Prediction and detection of flood using Artificial Intelligence

Thesis submitted in partial fulfillment of the requirements for the award of the degree of

Doctor of Philosophy

by

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(2K18/PhD/CO/04)

Under the supervision of

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वक्रतुण्ड महाकाय सूययकोटि समप्रभ।
निर्विघ्नं कुरु मे देव सर्वकार्येषु सर्वदा:॥

कमयण्येवाटिकारस्ते मा फलेषु कदाचन।

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CANDIDATE DECLARATION

I hereby declare that the thesis entitled **"Prediction and Detection of Flood using Artificial Intelligence"** submitted to Delhi Technological University, Delhi, in partial fulfilment of the requirements for the award of the degree of Doctor of Philosophy in the Department of Computer Science, is an original work and has been done by myself under the supervision of Prof. Rahul Katarya (Supervisor), Department of Computer Science and Engineering, Delhi Technological University, Delhi, India.

The interpretations presented are based on my study and understanding of the original texts. The work reported here has not been submitted to any other institute for the award of any other degree.

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CERTIFICATE

This is to certify that the work incorporated in the thesis entitled **"Prediction and Detection of Flood using Artificial Intelligence"** submitted by **Mr. Vinay Dubey (Roll No. 2K18/PhD/CO/04)** in partial fulfilment of the requirements for the award of the degree of Doctor of Philosophy, to the Delhi Technological University, Delhi, India is carried out by the candidate under my supervision and guidance at the Department of Computer Science and Engineering, Delhi Technological University, Delhi, India.

The results embodied in this thesis have not been presented to any other University or Institute for the award of any degree or diploma.

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ABSTRACT

Floods remain one of the most catastrophic and recurrent natural disasters globally, resulting in immense economic losses, displacement of populations, infrastructure degradation, and significant environmental disruptions. As climate variability intensifies and urbanization accelerates, the urgency to develop intelligent, efficient, and timely flood prediction and management solutions becomes more critical. This research aims to address these challenges by designing a series of novel, AI-driven models for flood detection, classification, forecasting, and image enhancement, thereby supporting real-time disaster response and long-term urban resilience planning.

The research proposes four key contributions, each targeting specific aspects of flood-related problems. The first model, Flood-FireNet, uses the Adaptive Firefly Algorithm (AFA) to optimize feature selection and combines it with a Transformer-based architecture to improve satellite image-based flood classification. This model demonstrated a high accuracy of 97.85%, precision of 98.21%, and F1-score of 97.65%, outperforming conventional deep learning models. The second contribution, MoSWIN, integrates Monkey Search Optimization (MSO) with a SWIN Transformer to enhance classification by capturing hierarchical spatial relationships in flood images. It achieved a classification accuracy of 96.53%, with strong robustness in noisy conditions.

The third contribution, the FloodCNN-BiLSTM model, is a hybrid deep learning framework for flood forecasting using environmental sensor data. CNN layers extract spatial features while BiLSTM captures temporal dependencies, enabling accurate urban flood prediction with an F1-score exceeding 96.5% on benchmark datasets. The fourth model, SSR-GAN, introduces a super-resolution-based GAN framework to enhance low-quality SAR images. By improving PSNR, SSIM, and reducing MSE, this model enables clearer flood zone delineation, especially in disaster-struck regions where high-resolution data may be unavailable.

These models were rigorously evaluated using multiple performance metrics, including accuracy, recall, precision, F1-score, Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE). Ablation studies and statistical validation tests, such as paired t-tests and ANOVA, further confirmed the effectiveness and generalizability of the proposed frameworks. The results indicate that the integration of evolutionary optimization

algorithms, Transformer-based architectures, and GANs substantially improves the system's ability to detect and predict floods across diverse scenarios.

Beyond academic advancement, the research offers substantial industrial and societal impact. Applications include integration into smart city surveillance systems, automated flood insurance damage assessment, early warning and disaster response platforms, urban planning for flood mitigation, and real-time remote sensing analysis. Moreover, the work directly supports several United Nations Sustainable Development Goals (SDGs), notably SDG 11 (Sustainable Cities), SDG 13 (Climate Action), SDG 9 (Industry and Innovation), SDG 6 (Clean Water), and SDG 3 (Good Health). By bridging the gap between advanced AI methodologies and real-world flood disaster management, this thesis contributes a comprehensive, scalable, and intelligent solution for building climate-resilient infrastructure in flood-prone regions.

Overall, this study presents a unified, intelligent system that combines environmental data analysis, image processing, and artificial intelligence to predict and detect floods more accurately and efficiently. The proposed approach not only strengthens disaster response mechanisms but also contributes to sustainable risk management practices. The framework developed in this research has the potential to be adapted for other natural disaster applications, marking a significant step forward in the use of AI for environmental monitoring and public safety.

Objectives: The objectives of this study are structured into four key segments:

• The first objective of the study is to develop a model for flood assessment by considering environmental parameters. which aims to develop a efficient flood classification model.

• The second objective focuses on to design a flood detection technique using Artificial Intelligence., aiming to improve the accuracy and efficiency of flood detection.

• The third objective is to improve flood detection technique by enhancing flood images to enhance the image quality for better flood detection model.

• The final objective is to perform the comparative analysis of our proposed work with the existing work.

Methodology: To accomplish the stated objectives, this study leverages advanced machine learning and deep learning methods, such as nature inspired algorithms, neural networks, attention mechanisms, and transformer-based architectures, due to their significant potential in

addressing complex challenges in flood assessment on datasets lie environmental parameters and image dataset. In our work, we employ a Generative Adversarial Network (GAN)-based super-resolution technique to enhance low-quality flood images, improving their clarity and detail for more accurate detection and analysis. The strategies employed to meet these objectives are as follows:

- To accomplish the first objective, the proposed hybrid model integrates Convolutional Neural Networks (CNN) with Bidirectional Long Short-Term Memory (BiLSTM) networks within a transfer learning framework. This combination effectively captures both spatial and temporal features from environmental data, enabling accurate multi-class classification. The model demonstrates superior performance when evaluated against advanced existing benchmark methods.
- For the second objective, two flood detection models were developed, each utilizing different nature-inspired approaches and a transformer. The first model introduces Flood-FireNet, a transformer-based model enhanced by a nature-inspired optimization strategy for distinguishing flooded and non-flooded regions. The second model integrated The proposed MoSWIN model classifies flooded and non-flooded regions by integrating the Monkey Search Optimization (MSO) algorithm for effective feature extraction and the SWIN Transformer for deep learning-based classification.
- To address the third objective, we propose a novel super-resolution approach using generative adversarial networks (GAN) to enhance satellite flood images. To optimize image generation, we employ perceptual loss calculated via VGG Net's intermediate feature maps, guiding the model to minimize perceptual differences between generated and target images, resulting in more visually accurate enhancements.
- For the fourth objective, a comparative analysis was conducted, evaluating the performance of the above-developed models against existing flood assessment and detection techniques. Key performance metrics, such as accuracy, sensitivity, specificity, F1-score, MSE, RMSE, PSNR, and SSIM were used to compare the effectiveness of the proposed models with current state-of-the-art methods.

Results: The outcomes of the study are as follows:

- The integration of CNN and BiLSTM within a transfer learning framework has resulted in high accuracy for multi-class flood classification using environmental parameters, outperforming several advanced benchmark models.

- The Flood-FireNet model, which combines transformer architecture, attention mechanisms, and AFA, demonstrates superior performance on flood image datasets compared to existing deep learning models.
- The Adaptive Firefly Algorithm (AFA) successfully extracts rich, high-level features from flood images, significantly improving classification performance and generalization by minimizing overfitting.
- The proposed MoSWIN model effectively integrates Monkey Search Optimization with the SWIN Transformer, enabling the extraction of hierarchical and discriminative features, resulting in significantly better accuracy, precision, and recall than models like ResNet and Vision Transformer.
- Across all proposed models, the use of nature-inspired optimization (MSO, AFA), attention mechanisms, and image enhancement techniques collectively reduce overfitting, leading to improved generalization on unseen data.
- The integration of deep learning and optimization algorithms has enabled the models to uncover complex spatial and visual patterns in flood-affected regions, aiding in more reliable classification and prediction.
- The GAN-based super-resolution approach improves the visual and structural quality of satellite flood images, restoring fine details and outperforming traditional upscaling methods through perceptual loss optimization.
- Image enhancement techniques such as Histogram Equalization (HE) and Adaptive Histogram Equalization (AHE) effectively improve the visibility and quality of SAR flood images, aiding in more accurate flood detection and classification.
- The integration of deep learning and optimization algorithms has enabled the models to uncover complex spatial and visual patterns in flood-affected regions, aiding in more reliable classification and prediction.
- Experimental results and performance comparisons show that the proposed models consistently outperform standard architectures like ResNet, Vision Transformer, and baseline CNNs across all key metrics.
- The proposed techniques, especially MoSWIN and Flood-FireNet, offer a scalable framework adaptable to different flood datasets and regions, making them suitable for real-world deployment in disaster management systems.

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LIST OF ABBREVIATIONS

ACC	Accuracy
AE	Autoencoder
AFA	Adaptive Firefly Algorithm
AHE	Adaptive Histogram Equalization
AI	Artificial Intelligence
ANN	Artificial Neural Network
Bi-LSTM	Bidirectional Long Short-Term Memory
CNN	Convolution Neural Network
DL	Deep Learning
DNN	Deep Neural Network
DT	Decision Tree
ES	Evolutionary Strategies
EVS	Explained Variance Score
FP	False Positive
FN	False Negative
GAN	Generative Adversarial Network
GRU	Gated Recurrent Unit
HE	Histogram Equalization
k-NN	k-Nearest Neighbor
LR	Logistic Regression
LSTM	Long Short-term Memory
MSE	Mean Square Error
ML	Machine Learning
MLR	Multiple Linear Regression
MLP	Multi-Layer Perceptron
MSO	Monkey Search Optimization
NB	Naive Bayes
NN	Neural Network
ResNet	Residual Neural Network
RF	Random Forest
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network

TP	True Positive
TN	True Negative
SAR	Synthetic Aperture Radar
SR	Super Resolution
SVM	Support Vector Machine
SWIN	Shifted Window Transformer
ViT	Vision Transformer
VGG	Visual Geometry Group

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Journal Publication

1. Dubey, V., & Katarya, R. (2024). SSR-GAN: super resolution-based generative adversarial networks model for flood image enhancement. Signal Image and Video Processing, 18(8–9), 5763–5773. https://doi.org/10.1007/s11760-024-03269-z ***(SCIE Indexed-Published)***
2. Dubey, V., & Katarya, R. (2025). FloodCNN-BiLSTM: Predicting flood events in urban environments. Engineering Analysis With Boundary Elements, 177, 106277. https://doi.org/10.1016/j.enganabound.2025.106277 ***(SCIE Indexed-Published)***
3. Dubey, V., & Katarya, R. (2025). MOSWIN: Monkey Search Optimization and SWIN-based flood Classification Architecture. Water Resources Management. https://doi.org/10.1007/s11269-025-04250-2 ***(SCIE Indexed-Published)***
4. Dubey, V., & Katarya, R. (2025a). Flood-FireNet: a novel flood image classification architecture using the adaptive firefly algorithm. Signal Image and Video Processing, 19(8). https://doi.org/10.1007/s11760-025-04235-z ***(SCIE Indexed-Published)***

Conference Publication

1. Dubey, V., & Katarya, R. (2021). Adaptive Histogram Equalization based Approach for SAR Image Enhancement: A Comparative analysis. 2022 6th International Conference on Intelligent Computing and Control Systems (ICICCS), 878–883. https://doi.org/10.1109/iciccs51141.2021.9432287 **(*Published) (IEEE-Indexed)***
2. Dubey, V., & Katarya, R. (2020). An analysis of machine learning techniques for flood mitigation. In Advances in intelligent systems and computing (pp. 299–307). https://doi.org/10.1007/978-981-15-5148-2_27 **(*Published) (Scopus-Indexed)***

Communicated Journal

1. Dubey, V., Katarya, R. CGD-FloodNet: A Robust Hybrid Model for Flood Probability Estimation Using Environmental Parameters. Water Resource Management, ***[Under review]***
2. Gupta, S., Dubey, V., Katarya, R. Optimizing Surveillance Efficiency with Deep Learning-Driven Flood Segmentation, Natural Hazards, ***[Under review]***
3. Dubey, V., Katarya, R. A Hybrid GWO–Transformer–LightGBM Model for Flood Risk Prediction Using Multi-Source Geospatial Data. ***[To be communicated]***

Chapter 1

INTRODUCTION

Disasters are sudden adverse events that disrupt human societies and ecosystems. Although they may occur over a short duration, their consequences are often severe and long-lasting [1]. Disasters are broadly classified into two categories: natural disasters (e.g., floods, earthquakes, and landslides) and man-made disasters (e.g., industrial accidents, chemical leaks, and conflicts).

Among all types of natural disasters, flooding is the most frequent and widespread phenomenon. Floods result in substantial loss of life, displacement of communities, damage to biodiversity, and destruction of infrastructure. They pose significant threats to both developing and developed nations. In particular, regions situated near water bodies are increasingly vulnerable during the monsoon season due to intense and unpredictable rainfall patterns.

Floods can be triggered by both natural and anthropogenic (human-induced) factors. As shown in Figure 1.1, the primary causes of flooding include:

- Excess rainfall (27.5%)
- Opening of barrages/dams (31.25%)
- A combination of both (41.25%)

These causes are often interlinked, particularly in areas with inadequate water management systems or poor urban planning [3].

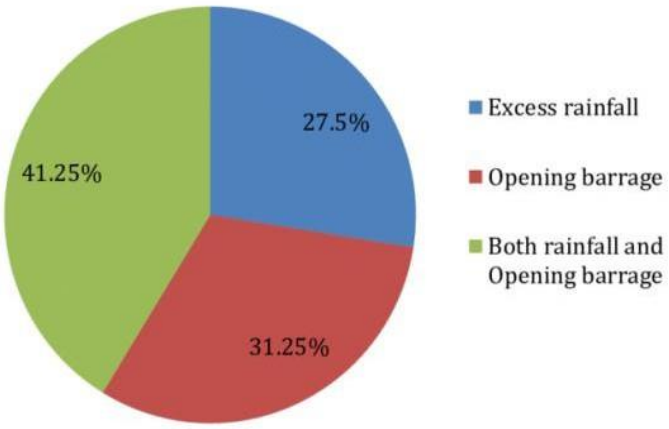


Figure 1.1: Flood causes are shown as a pie chart. [3]

Floods are projected to become more frequent and destructive due to climate change and global warming. Rising sea levels and intensified precipitation patterns exacerbate the risk of coastal and inland flooding. These events not only threaten human lives and property but also disrupt ecological balance, contaminate water sources, and degrade biodiversity.

To address these challenges, advanced technologies such as Machine Learning (ML), Artificial Intelligence (AI), and sensor networks are increasingly being leveraged for flood prediction and early warning systems. These technologies offer the capability to:

- Accurately predict the occurrence and severity of floods
- Monitor remote or inaccessible regions
- Issue timely alerts to vulnerable populations

Several studies have explored the integration of AI and sensor technologies, highlighting their potential to minimize disaster-related damages and support decision-making in disaster management frameworks [1].

Natural disasters encompass various phenomena, each with distinct origins and impacts. Figure 1.2 presents the classification of natural disasters based on observed frequency. Among them, floods are identified as the most recurrent event, followed by landslides and tropical storms.

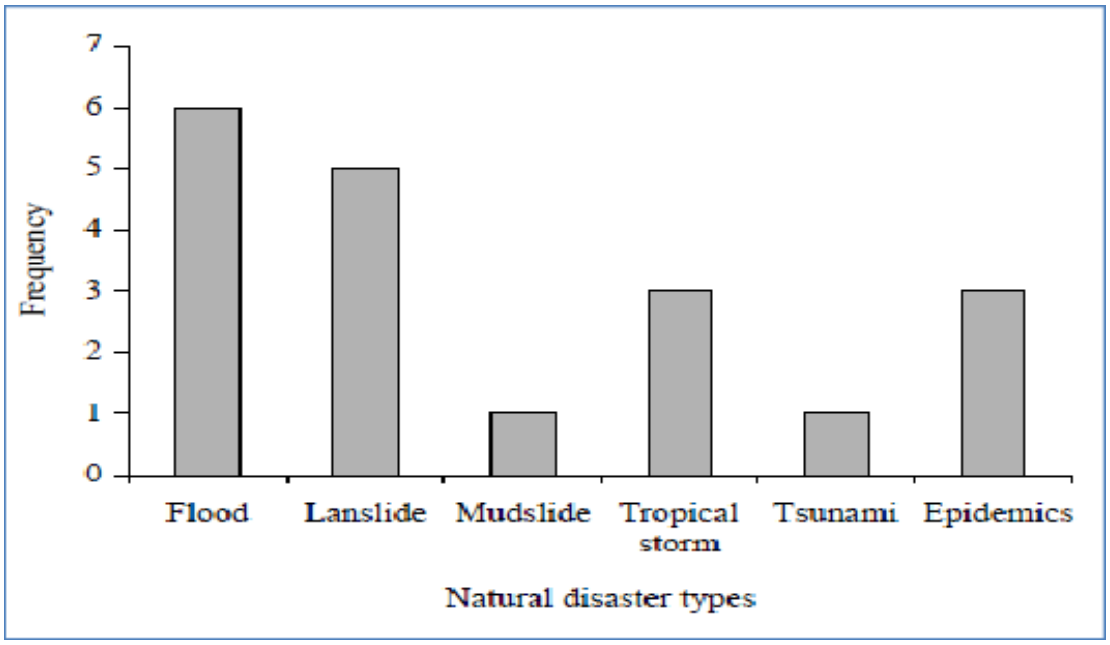


Figure 1.2: classification of Natural Disasters [4]

Floods can be further categorized into the following types:

- **Flash floods:** These occur within six hours of intense rainfall and are characterized by rapid water accumulation and flow.
- **Mudslides (or debris flows):** Typically occur within 24 hours of heavy rainfall, often in hilly or mountainous terrains.
- **Coastal floods:** Caused by coastal storms, cyclones, or tsunamis leading to seawater intrusion.
- **River plain floods:** Result from prolonged rainfall in large catchment areas, causing rivers to overflow their banks [4].

Understanding the type and cause of flooding is essential for implementing effective mitigation and response strategies. Moreover, early warning systems, supported by real-time data and predictive analytics, can significantly reduce the impact on flood-affected communities.

1.1 Background and Motivation

Floods have long been recognized as one of the most devastating natural disasters, affecting millions of people worldwide each year. These hydrological events are triggered by excessive rainfall, river overflows, dam failures, or cyclones, and they can cause catastrophic damage to life, property, and infrastructure. Climate change, coupled with rapid urbanization, has led to an increase in both the frequency and severity of flood events across the globe. Low-lying areas, densely populated urban zones, and regions with inadequate drainage systems are especially vulnerable to flooding.

Floods are among the most frequent natural disasters, causing over 50% of all disasters worldwide, with 12% of India's land prone to flooding [2]. According to the UN, floods result in the highest casualties compared to other disasters [5], threatening over 160 million people annually [6]. Flash floods are intensifying due to extreme rainfall driven by climate change. In the USA, annual economic losses from natural hazards exceed $300 billion [7]. In India, floods claim around 1654 human and 618,248 cattle lives yearly, damage 1.2 million houses, and cause average annual losses of Rs 5649 crores [8].

The unpredictability and sudden onset of floods pose a significant challenge to emergency response teams and disaster management authorities. Traditional methods of flood forecasting rely heavily on physical hydrological models, such as rainfall-runoff models and hydraulic simulations. While these approaches have been instrumental in early flood forecasting, they often struggle with limitations such as:

- Inability to process and analyze large volumes of heterogeneous data in real time.

- Dependency on historical data, which may not be available for all regions.
- Inflexibility in adapting to dynamic and complex environmental changes.

In recent years, Artificial Intelligence (AI) has emerged as a transformative technology in various domains, including healthcare, finance, transportation, and environmental science. In the context of flood prediction and detection, AI offers unique capabilities that can overcome the limitations of traditional models. Machine Learning (ML) and Deep Learning (DL) algorithms, in particular, are capable of learning from past data, identifying complex nonlinear patterns, and making high-accuracy predictions even with incomplete or noisy inputs.

Moreover, AI-based image analysis and computer vision techniques have made it possible to detect flood events using real-time imagery from surveillance cameras, drones, and satellites. These models can recognize water accumulation, monitor river levels, and assess flood severity with minimal human intervention. Image enhancement methods further improve the quality and clarity of input images, allowing for more accurate detection.

The motivation for this research stems from the urgent need to develop intelligent, reliable, and scalable flood prediction and detection systems. By leveraging the power of AI, this study aims to enhance the capabilities of current flood risk management practices and contribute to building resilient communities capable of withstanding the adverse impacts of flooding.

Figure 1.3: Trend of Research Publications on Flood Management from 2011 to 2024, showing a significant rise in scholarly attention and research output in recent years

The graph shows a steady increase in flood management research papers from 2011 to 2024. Initial growth was gradual, but after 2018, a sharp rise is observed, peaking in 2024 with 33 papers. This trend highlights growing academic interest and urgency in addressing flood-related issues, likely driven by climate change and increasing flood incidents worldwide [9].

1.2 Problem Statement

Floods are among the most devastating natural disasters affecting millions of lives and causing severe socioeconomic disruptions across the globe. As per the United Nations Office for Disaster Risk Reduction (UNDRR), floods account for nearly 40% of all natural disasters worldwide [10]. They not only result in loss of life and displacement of people but also inflict long-term damage on agricultural land, urban infrastructure, transportation systems, and water resources. With the growing impacts of climate change, erratic weather patterns, deforestation, and unplanned urbanization, the frequency and severity of floods are expected to increase significantly in the coming decades. This alarming trend calls for the urgent development of advanced and effective flood prediction and detection systems that can provide early warnings and real-time monitoring to mitigate their consequences [11, 12].

Traditional flood forecasting and detection methods primarily rely on statistical models, hydrological simulations, and physical indicators such as rainfall, river discharge, and soil saturation levels. While these methods offer foundational insights into the occurrence of flood events, they suffer from various limitations [13]. First, they are often built on static or historical datasets that fail to incorporate real-time variability in environmental conditions. Second, many of these models lack the adaptability to learn from new data or to update predictions dynamically as environmental conditions evolve. Third, in regions where sensor networks and meteorological data collection infrastructure are inadequate or non-existent, the reliability of traditional models becomes questionable [14]. Moreover, flood detection based on satellite or aerial imagery is often delayed due to manual processing, poor resolution, or adverse weather conditions affecting image quality [15].

Artificial Intelligence (AI) presents a promising solution to these limitations by enabling data-driven, adaptive, and real-time analysis for flood prediction and detection [16]. With the proliferation of big environmental data from Internet of Things (IoT) sensors, satellite imagery, weather stations, and crowd-sourced platforms AI techniques such as machine learning (ML), deep learning (DL), and image processing can be employed to extract complex patterns and relationships that are not easily identifiable using traditional methods [17]. For instance, AI models can analyze large volumes of historical and real-time environmental data to predict flood events with greater accuracy. Similarly, deep learning algorithms such as Convolutional Neural Networks (CNNs) can be trained to identify flood-prone regions and flooded areas

using satellite or drone imagery [18]. However, despite the proven success of AI in domains such as finance, healthcare, and autonomous systems, its application in flood prediction and detection is still evolving and faces several technical and practical challenges [19].

One of the critical challenges is the selection and integration of relevant environmental parameters that significantly influence flood occurrence [20]. These parameters may include rainfall intensity, temperature, humidity, river water level, soil moisture, topography, and land use patterns. Designing an AI model that effectively incorporates these diverse inputs requires careful preprocessing, normalization, and feature selection techniques. Furthermore, the model must be capable of handling missing, noisy, or incomplete data, which is common in real-world environmental datasets.

Another major issue is related to flood detection using images. Flood-affected regions can be visually detected using satellite or aerial images, but the accuracy of detection is often hindered by poor image quality, cloud cover, or low contrast between flooded and non-flooded areas [21]. Enhancing these images using advanced computer vision techniques is essential to improve the performance of AI-based detection models. Image enhancement not only aids in more accurate flood identification but also supports better decision-making for emergency response teams and policy-makers. Integrating these enhanced visual inputs into AI systems remains a research gap that this study intends to fill.

Moreover, the lack of standardized datasets and evaluation metrics makes it difficult to compare the performance of different AI models for flood prediction and detection. Many existing models are developed and tested on specific geographic regions and cannot be generalized to other flood-prone areas without retraining or customization. Additionally, while several studies claim high prediction accuracies, they often fail to address issues related to false alarms or missed detections, which can have serious implications for disaster preparedness and response [22].

There is also a technological gap in deploying AI models in real-time systems. Many AI-based flood models remain in the experimental or academic phase due to high computational requirements, lack of integration with sensor networks, or limited accessibility for local governments and communities [23]. To bridge this gap, it is necessary to design models that are not only accurate but also computationally efficient, scalable, and user-friendly.

Considering these challenges, this research aims to develop a comprehensive AI-based framework that addresses both flood prediction and detection with enhanced accuracy and reliability. The research will pursue four major objectives: (i) to develop a model for flood prediction by considering diverse and relevant environmental parameters; (ii) to design a robust flood detection technique using AI, particularly through image-based detection; (iii) to improve the accuracy of flood detection by enhancing flood images using

advanced computer vision techniques; and (iv) to perform a comparative analysis of the proposed techniques with existing state-of-the-art models to validate the improvements in performance.

By addressing these objectives, the proposed research seeks to contribute a practical and scalable solution to the ongoing global issue of flood management. The integration of AI into flood prediction and detection not only enhances the accuracy and timeliness of alerts but also supports sustainable disaster risk reduction strategies. The outcomes of this research can have significant industrial applications, such as in urban planning, civil engineering, and insurance sectors, and societal benefits, including saving lives, reducing economic losses, and enhancing the resilience of communities. Furthermore, the work aligns with several United Nations Sustainable Development Goals (SDGs), including SDG 11 (Sustainable Cities and Communities), SDG 13 (Climate Action), and SDG 9 (Industry, Innovation, and Infrastructure).

In conclusion, the existing gaps in flood prediction and detection demand innovative and intelligent solutions that are adaptable, data-driven, and applicable across diverse geographies. Artificial Intelligence holds immense potential in revolutionizing flood management through predictive analytics, automated detection, and real-time decision-making. However, to fully realize this potential, there is a need for focused research that addresses the technical, operational, and practical challenges associated with the deployment of AI in this domain. This study is a step in that direction, aiming to provide a comprehensive, reliable, and intelligent solution for the prediction and detection of floods.

1.3 Research Objectives

This research aims to achieve the following specific objectives:

1. To develop a model for flood prediction by considering environmental parameters.
2. To design a flood detection technique using Artificial Intelligence.
3. To improve the flood detection technique by enhancing flood images.
4. To perform a comparative analysis of our proposed work with the existing work.

1.4 Scope of the Research

The scope of this study is focused on the application of Artificial Intelligence techniques for flood prediction and detection. This encompasses the use of Machine Learning, Deep Learning, and image processing methods to analyze various forms of environmental and image-based data [24]. The specific boundaries of this research are as follows:

- **Geographical Scope**: The research will consider both urban and rural flood-prone areas for data collection and model validation. While a specific case study area may be selected for implementation, the developed methods aim to be generalizable to other regions.

- **Data Sources**: The study will utilize data from multiple sources including historical flood records, meteorological data (e.g., rainfall, humidity, temperature), satellite and drone imagery, river discharge rates, and sensor outputs.
- **AI Techniques**: Various AI algorithms such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Generative Adversarial Networks (GAN) may be employed depending on the task—be it prediction, detection, or image enhancement.
- **Technological Framework**: Tools such as Python, TensorFlow, Keras, OpenCV, and GIS platforms will be used for model development, training, and testing.
- **Performance Metrics**: The developed models will be evaluated using accuracy, precision, recall, F1-score, mean squared error, and area under the curve (AUC) for classification and prediction tasks.

Excluded from this research are policy-based flood risk mitigation strategies, socio-economic impact analyses, and structural engineering solutions. The primary emphasis remains on data-driven, AI-powered solutions to detect and predict flood events in a timely and efficient manner.

1.5 Significance of the Study

This study contributes to the growing field of AI in environmental disaster management by addressing a critical real-world problem: flood risk. The significance of the research lies in several key areas:

- **Disaster Preparedness and Mitigation**: Improved flood prediction and detection can save lives and reduce damage by enabling early warning and timely evacuation. The proposed AI systems can be integrated into existing disaster management frameworks to enhance their responsiveness.
- **Technological Advancement**: By applying cutting-edge AI techniques to hydrological problems, the study bridges a critical gap between environmental science and computational intelligence. The research showcases the potential of Machine Learning and image processing in solving complex environmental issues.
- **Scalability and Adaptability**: The AI models developed in this study are designed to be scalable to large datasets and adaptable to different geographical regions. This makes the research relevant to both developed and developing countries.

- **Data Utilization**: The study emphasizes the effective use of multi-source data, including real-time sensor data, remote sensing images, and historical weather patterns. This integrative approach improves the reliability and comprehensiveness of flood forecasting systems.
- **Support for Vulnerable Communities**: Accurate and timely flood alerts can significantly benefit communities living in flood-prone areas. The developed systems can be used by local authorities and NGOs to implement early response measures.
- **Academic Contribution**: The research contributes to the academic body of knowledge in AI applications, environmental informatics, and disaster risk reduction. It provides a methodological foundation for future researchers working at the intersection of AI and climate resilience.
- **Policy Implications**: While not directly focused on policy, the findings can inform decision-makers on the benefits of adopting AI-based technologies for climate adaptation and urban planning.

In conclusion, this research not only seeks to address the technical aspects of flood prediction and detection but also aims to deliver practical solutions that can be implemented on the ground to safeguard human lives and property.

1.6 Flood Management Systems

Flood management systems refer to a comprehensive set of strategies, technologies, and frameworks designed to predict, prevent, respond to, and recover from flood events [25]. These systems are a vital component of disaster risk reduction and environmental resilience, involving coordinated efforts by governments, meteorological agencies, urban planners, civil engineers, and local communities [26].

Traditional flood management systems typically follow a four-phase cycle:

- **Preparedness**: Measures such as floodplain mapping, early warning systems, infrastructure design, and public awareness campaigns.
- **Response**: Immediate actions taken during a flood, including evacuation, rescue operations, and deployment of emergency services.
- **Recovery**: Post-flood activities aimed at rehabilitation and reconstruction of affected areas.
- **Mitigation**: Long-term strategies to reduce flood risk, such as afforestation, construction of levees, and improved drainage systems.

Despite these components, traditional systems often struggle with several limitations:

- **Delayed response times** due to manual monitoring.

- **Limited predictive capacity**, especially for flash floods.
- **Inefficient data sharing** among agencies.
- **Lack of adaptability** to rapidly changing climate conditions.

To understand the effectiveness of traditional flood management systems, the following table illustrates their key components and associated challenges:

Table 1.1: Components of Traditional Flood Management Systems and Their Limitations

Component	Description	Limitations
Early Warning Systems	Use of sensors and hydrological models to alert authorities	Often based on fixed thresholds and limited data inputs
Floodplain Mapping	Identification of high-risk zones using historical data	Not updated frequently; may not account for climate change
Structural Defenses	Construction of dams, levees, and embankments	Costly; may fail under extreme conditions
Emergency Response Plans	Guidelines for evacuation, relief, and coordination	Lack of real-time communication and coordination
Community Awareness	Education and preparedness drills	Not widely disseminated in rural or marginalized areas

Flood management must now evolve from static, one-size-fits-all solutions to dynamic, data-driven systems that leverage real-time information and predictive analytics.

1.7 Flood Management Systems Using Artificial Intelligence

Artificial Intelligence (AI) has emerged as a game-changing tool in enhancing the performance, reliability, and scalability of flood management systems [27]. By integrating AI into the flood management lifecycle, authorities can shift from reactive strategies to proactive planning and real-time decision-making [28].

Key Applications of AI in Flood Management:

1. **Flood Prediction**: AI models like Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are used to analyze time-series data (e.g., rainfall, temperature, river levels) to forecast potential flood events.
2. **Flood Detection**: Deep learning models, particularly Convolutional Neural Networks (CNNs), can identify flood water in images captured from satellites, UAVs (drones), or ground cameras.

3. **Image Enhancement**: Techniques such as GANs (Generative Adversarial Networks) improve the visibility and interpretability of flood-affected images under poor weather conditions.
4. **Decision Support Systems**: AI-powered dashboards assist in real-time monitoring, early warning, resource allocation, and incident response.
5. **Risk Assessment**: Machine Learning algorithms analyze socio-economic, topographical, and environmental data to classify areas based on flood vulnerability.

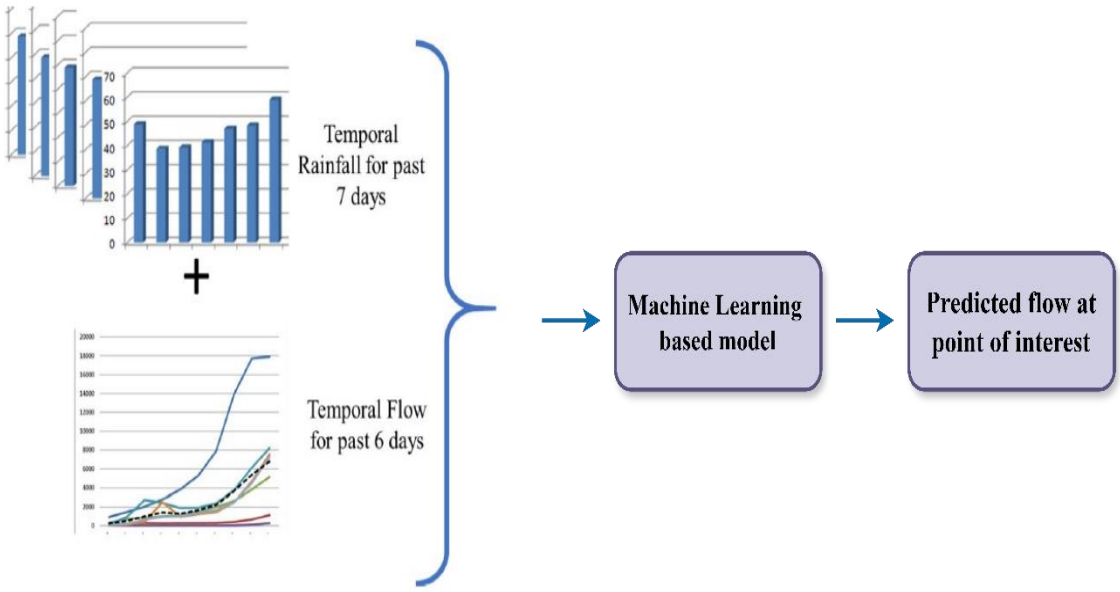


Figure 1.4: Machine Learning-based Flood Flow Prediction Model utilizing temporal rainfall data and river flow data

This figure 1.4 illustrates a machine learning-based flood prediction model. It integrates two key inputs: temporal rainfall data from the past 7 days and temporal river flow data from the past 6 days. These historical datasets are fed into a machine learning algorithm trained to analyze patterns and correlations between rainfall and flow levels. The model processes these inputs to predict the river flow at a specific point of interest. This approach enhances flood forecasting accuracy and helps in proactive disaster management by providing timely and data-driven flow predictions in vulnerable regions.

The integration of AI can address many of the limitations present in traditional systems, as outlined below:

Table 1.2: Comparison Between Traditional and AI-Based Flood Management Systems

Feature	Traditional System	AI-Based System
Data Handling	Manual/Static	Automated/Real-time
Forecasting Accuracy	Medium (dependent on historical data)	High (learning from complex, non-linear patterns)
Adaptability	Rigid; difficult to update	Highly adaptable and self-improving
Response Time	Delayed	Instantaneous alerts and decision-making
Scalability	Limited to local infrastructure	Scalable across regions with cloud and IoT support
Integration	Poor inter-agency coordination	Unified platforms with multi-source data integration

Furthermore, the effectiveness of AI in flood management is maximized when paired with IoT (Internet of Things) devices such as smart sensors for rainfall, humidity, and river levels. These sensors provide real-time data streams which AI models can instantly analyze and interpret.

Table 1.3: Key AI Technologies Used in Flood Management Systems

AI Technology	Application Area	Advantages
Convolutional Neural Networks (CNNs)	Image-based flood detection	High accuracy in spatial feature recognition
Recurrent Neural Networks (RNNs) / LSTM	Time-series flood forecasting	Effective in sequential pattern analysis
Generative Adversarial Networks (GANs)	Image enhancement	Improves quality of low-resolution or obscured images
Support Vector Machines (SVMs)	Risk classification and mapping	Robust to high-dimensional data
Fuzzy Logic Systems	Decision-making under uncertainty	Models complex, vague human-like decisions

By embedding these technologies within existing flood monitoring and response infrastructures, cities and disaster management agencies can create Smart Flood Management Systems that are autonomous, reliable, and responsive to real-time threats.

In conclusion, integrating AI into flood management represents a paradigm shift from reactive to anticipatory strategies. This transition is vital for building climate-resilient communities in the face of increasing flood risks due to global climate change and urban expansion.

1.8 Organization of the Thesis

This thesis is structured into six comprehensive chapters; each designed to systematically address the research objectives and provide a logical flow of the work conducted. A brief overview of each chapter is as follows:

- **Chapter 1 – Introduction:** This chapter introduces the central theme of the research, flood detection and prediction using artificial intelligence and image processing. It outlines the motivation behind the study, defines the research problem, and states the objectives and scope of the work. Additionally, it highlights the significance of the proposed approach in addressing real-world flood management challenges, especially in the context of increasing climate variability. The chapter also discusses the research methodology, key contributions, and structure of the thesis.

- **Chapter 2 – Literature Review:** This chapter provides a critical review of the existing body of knowledge related to flood detection and prediction. It explores various conventional and modern approaches, with a particular focus on AI-based methods, machine learning techniques, and image processing applications. The chapter identifies gaps in current research and justifies the need for the proposed integrated AI-based framework. It also outlines relevant datasets, evaluation metrics, and performance benchmarks used in earlier studies.

- **Chapter 3 – Flood Detection using Artificial Intelligence:** This chapter addresses **Research Objective 2**, focusing on the development of an AI-based flood detection system. It describes the data collection and preprocessing steps, followed by a detailed explanation of the AI models employed (e.g., convolutional neural networks, support vector machines). The chapter evaluates the detection accuracy of the proposed models, compares their performance with baseline approaches, and presents visual and quantitative results. Furthermore, it highlights the system's ability to identify flood-prone regions based on real-time inputs.

- **Chapter 4 – Enhancement of Flood Detection using Image Processing:** Aligned with **Research Objective 3**, this chapter investigates the role of image enhancement techniques in improving flood detection accuracy. It explains the preprocessing methods used to refine satellite and drone-captured images, including noise reduction, contrast enhancement, and edge detection. The chapter then integrates these enhanced images into the AI detection pipeline and assesses the resulting

improvement in performance. Comparative analysis, visual outputs, and metric-based evaluation substantiate the effectiveness of the enhancements.

- **Chapter 5 – Flood Prediction using Environmental Parameters:** This chapter addresses **Research Objective 1**, focusing on the development of a flood prediction model using environmental and hydrological parameters such as rainfall intensity, river discharge, humidity, and soil moisture. Various predictive modeling techniques—including regression models, decision trees, and deep learning networks—are implemented and evaluated. The chapter compares the proposed prediction framework with traditional flood forecasting methods and demonstrates its superior accuracy and lead-time performance through case studies and statistical analysis.
- **Chapter 6 – Conclusion, Limitations, and Future Work:** The final chapter summarizes the key contributions and findings of the thesis. It reflects on how the research objectives were achieved and discusses the practical implications of the proposed flood detection and prediction systems. The chapter also outlines the limitations encountered during the research, such as data availability and model generalizability.

1.9 Chapter Summary

This chapter provides an overview of flood assessment, emphasizing the role of artificial intelligence techniques in enhancing diagnostic prediction and detection accuracy. It discusses the use of GAN modal, to enhance the quality of SAR images, in improving the performance of flood detection systems. We also examine various environmental parameters to improve the accuracy and reliability of flood prediction in our analysis. The chapter outlines the content and description of each subsequent chapter, highlighting unique concepts and ideas that align with the title and objectives of the thesis. It also provides a concise overview of flood management strategies, machine and deep learning approaches, and the use of SAR data for enhancing and detecting flood images. Furthermore, the research outlines its objectives, scope, and underlying motivation in detail.

Chapter 2

Literature Review

Floods are a global challenge, causing extensive damage to infrastructure, ecosystems, and human lives. The urgent need for accurate flood prediction, detection, and mitigation has driven research into advanced methodologies, particularly machine learning (ML), deep learning (DL), and image processing techniques. This literature review synthesizes existing studies to support the research objectives: (1) developing a flood prediction model incorporating environmental parameters, (2) designing an AI-based flood detection technique, (3) improving flood detection through image enhancement, and (4) conducting a comparative analysis of the proposed work against existing methods. The review is structured into thematic subsections, providing detailed insights into methodologies, datasets, results, merits, and limitations.

2.1 Flood Prediction Models

Flood prediction models are vital for forecasting flood timing, magnitude, and extent, enabling early warnings and effective disaster management. Traditional statistical and hydrological models use historical rainfall-runoff data and watershed characteristics. Recently, machine learning and hybrid models have emerged, leveraging large datasets to capture complex, nonlinear interactions among meteorological, topographical, and human factors affecting floods. This section reviews key methodologies, from conventional to AI-driven models, highlighting advancements in integrating data-driven techniques with hydrological frameworks to improve flood prediction accuracy and resilience strategies.

2.1.1 Traditional Hydrological Models

Traditional hydrological models, such as hydrodynamic models, have been foundational in flood prediction. These models require extensive, high-quality input data, including observed hydrologic time series (e.g., rainfall, streamflow), geometric data (e.g., river channel dimensions), hydraulic structures (e.g., dams, levees), and hydrological parameters (e.g., soil permeability). This study [29] highlights that such models are computationally intensive and sensitive to data quality, often struggling with incomplete or noisy datasets. While effective in controlled scenarios, their reliance on precise inputs limits applicability in data-scarce regions or rapidly changing environments.

2.1.2 Machine Learning-Based Prediction

Machine learning has transformed flood prediction by capturing nonlinear relationships between environmental parameters like precipitation, temperature, soil moisture, elevation, and slope. Artificial Neural Networks (ANNs) are prominent, modeling complex hydrological systems effectively [30]. For

instance, ANNs link river flow to inputs like rainfall and soil moisture, adapting to nonlinear patterns. This paper [31] proposed a Back-Propagation Neural Network (BPNN) to predict discharge in the Govindpur basins of the Brahmani River, evaluating performance across architectures like feedforward and recurrent networks, achieving robust results but limited by basin-specific data.

2.1.3 Temporal and Probabilistic Models

Long Short-Term Memory (LSTM) models, a type of recurrent neural network, excel in capturing temporal correlations in streamflow data, making them ideal for short-term flood forecasting [32, 33]. These models process sequential data, retaining memory of past inputs to predict future trends. Gaussian Processes (GPs) offer a probabilistic approach, delivering point predictions and uncertainty intervals [34]. For example, GPs quantify forecast reliability, aiding decision-making, though their computational cost is high, especially for large datasets.

2.1.4 Ensemble and Hybrid Approaches

Ensemble methods like Random Forests (RFs) combine multiple decision trees to enhance prediction robustness, capturing relationships among diverse parameters like rainfall, soil moisture, and topography [35]. Hybrid approaches integrate ML with hydrological models. In this study authors [36] used a two-dimensional hydraulic model (iRIC), calibrated with water level data, alongside ML models to estimate river depth for varying discharge levels. A hybrid method combining Particle Swarm Optimization (PSO) and group data management improves short-term streamflow forecasting [37]. Paper [38] introduced a framework integrating ML, statistical, and geo-statistical models to predict daily and near-future flood scenarios under climate change, addressing long-term impacts but facing complexity challenges.

Table 2.1: Summary of recent studies on ensemble and hybrid approaches for flood prediction techniques.

Reference	Dataset	Techniques	Key Results	Merits	Limitations
Saleh, T. et al. [38]	Climate, hydrological data	ML + Statistical + Geo-statistical models	Predicts daily, future flood scenarios	Addresses climate change impacts	Model complexity, data dependency
Amankwah et al. [39]	Hydrological data	ANNs	Captures nonlinear relationships	Effective for complex systems	Requires large, quality data
Arvind et al. [40]	Govindpur, Brahmani River	BPNN	Evaluated across NN architectures	Accurate discharge prediction	Limited to specific basin, data volume

Moharrami et al. [41]	Streamflow time series	LSTM	Accurate short-term forecasts	Handles temporal correlations	Limited to short-term applications
Fernandes et al. [42]	Hydrological data	Gaussian Processes (GPs)	Provides prediction intervals	Quantifies uncertainty	Computationally intensive
Tanim et al. [43]	Hydrological parameters	Random Forests (RFs)	Enhanced robustness and accuracy	Captures diverse relationships	High computational complexity
Bhuyan et al. [44]	Water level data	iRIC + ML models	Estimates river depth for varying discharge	Integrates physical and ML models	Requires calibration, data quality
Kim et al. [45]	Streamflow data	PSO + Group Data Management	Improved short-term forecasting	Combines optimization and data handling	Complex implementation

2.2 AI-Based Flood Detection Techniques

AI-based flood detection techniques use machine learning and deep learning to analyze data from satellites, sensors, and weather forecasts for accurate, real-time flood identification. Unlike traditional manual or hydrological methods, these AI approaches enhance early warning systems and support timely disaster response, significantly improving flood prediction, monitoring, and management for effective risk mitigation.

2.2.1 Unsupervised Learning Methods

Unsupervised learning is critical when labeled data is scarce, common in flood scenarios. [46] applied Mean Shift and Self-Organizing Maps (SOM) to MODIS satellite images to extract water pixels before, during, and after floods. SOM outperformed Mean Shift, accurately delineating flood regions by clustering similar pixel intensities. However, SOM's high computational complexity limits scalability for large-scale datasets, making it less practical for real-time or regional applications.

2.2.2 Supervised Learning Approaches

Supervised learning leverages labeled data for robust flood detection. [47] compared Support Vector Machines (SVMs), Deep Convolutional Neural Networks (DCNNs), Multi-Layer Perceptions (MLPs), and Stacked Sparse Denoising Autoencoder (SSDAs) on SPOT-5 and radar imagery. SSDAs, using only 20 labeled images, achieved an AUC of 0.9173, outperforming SVM and MLP due to its ability to denoising

and learn hierarchical features. However, limited training data and poor generalization across diverse regions constrain its effectiveness [48].

2.2.3 SAR and Satellite-Based Detection

Synthetic Aperture Radar (SAR) is vital for all-weather flood detection. [49] integrated Sentinel-1 SAR data with shapefiles and water level data via Google Earth Engine (GEE) to map flood extent in the Mekong River basin. This approach achieved high spatial coverage, enabling rapid tracking, but was limited by GEE's preprocessing constraints, such as data resolution and availability. [50] applied Otsu thresholding to Sentinel-1 SAR data for flood segmentation in northern Iran, achieving ~90% accuracy, though complex terrains (e.g., mountains) reduced precision.

2.2.4 UAV and High-Resolution Imagery

Unmanned Aerial Vehicle (UAV) imagery provides high-resolution data for flood analysis. The FloodNet dataset, introduced in [51], supports classification (InceptionNetV3, ResNet50, Xception), segmentation (ENet, PSPNet, DeeplabV3+), and Visual Question Answering (VQA). These models excel in multi-task analysis, leveraging detailed UAV imagery, but struggle with small object detection due to scale variations and occlusions from buildings or vegetation.

2.2.5 Real-Time and Semi-Supervised Methods

Real-time detection is critical for emergency response. [52] combined Deep Neural Networks (DNNs) with computer vision to estimate water levels from real-time river data, achieving a Mean Absolute Error (MAE) of 3.32 cm. The system adapts to varying camera angles and lighting, but requires a manually drawn reference line on an even surface orthogonal to water. [53] used a semi-supervised approach on FloodNet, employing weighted sampling to address class imbalance, improving classification of flooded versus non-flooded areas, though requiring robust validation across geographies.

Table 2.2: Summary of semi-supervised and real time approaches for flood prediction techniques.

Reference	Dataset	Techniques	Key Results	Merits	Limitations
Arvind, C.S. et al. [46]	MODIS satellite images	Mean Shift, SOM	SOM outperforms in flood region extraction	Effective without labeled data	High complexity, low scalability
Islam, K. A. et al. [47]	SPOT-5, radar images	SVM, DCNN, MLP, SSDAs	SSDAs AUC = 0.9173	High performance	Small training sets, poor generalization

Nghia, B.P. et al. [49]	Sentinel-1 SAR, shapefiles	SAR decoding, GEE flood mapping	High spatial coverage	All-weather, rapid tracking	GEE preprocessing, data limits
Moharrami, M. et al. [50]	Sentinel-1 SAR	Otsu thresholding	Accuracy ~ 90%	Simple, effective delineation	Limited in complex terrains
Rahnemoonfar, M. et al. [51]	FloodNet (UAV imagery)	Classification: InceptionNetV3, ResNet50, Xception; Segmentation: ENet, PSPNet, DeeplabV3+; VQA	Multi-task success with high-res data	Flexible for classification, segmentation	Small object detection challenging
Fernandes, F.E. et al. [52]	Real-time river data	DNN, Computer Vision	MAE = 3.32 cm, adaptable to conditions	Real-time, robust	Strict camera placement needed
Jackson, J. et al. [53]	FloodNet	Semi-supervised, weighted sampling	Improved flood/non-flood classification	Addresses class imbalance	Needs robust geographic validation

2.3 Image Enhancement for Flood Analysis

Effective flood analysis depends on high-quality images, but raw flood images often suffer from low contrast, noise, and poor illumination, obscuring critical details. Image enhancement techniques improve visual clarity and highlight important features like water boundaries and submerged areas, aiding both human interpretation and automated classification. Methods such as contrast stretching, histogram equalization, adaptive histogram equalization (AHE), and contrast-limited AHE (CLAHE) are applied to enhance flood images in our study, ensuring clear representation of flood-affected regions for accurate analysis and improved model performance.

2.3.1 Speckle Noise Reduction

Synthetic Aperture Radar (SAR) images, critical for flood analysis, suffer from speckle noise, a granular interference that degrades quality and hinders interpretation, target detection, and classification [54]. Fuzzy ARTMAP and deep neural networks reduce noise and enhance image quality, aiding flood prediction by improving feature visibility [55, 56]. For example [57], applied Fuzzy ARTMAP to Landsat 8 ETM images, producing accurate flood maps, though performance drops in geologically diverse regions like mountains.

2.3.2 Transform and Algorithmic Methods

The Non Subsampled Contourlet Transform (NSCT) combined with memetic algorithms reduces speckle noise while enhancing edge features and contrast in SAR images [58]. This approach uses an objective enhancement criterion to identify near-ideal images, though its complexity increases computational demands. [59] introduced p-LSCE, a p-regularized, low-rank, space-angle continuity method, leveraging image relationships to minimize speckles, but requiring significant processing power.

2.3.3 GAN-Based Enhancement

Generative Adversarial Networks (GANs) are transformative for SAR image enhancement. [60] proposed GAN-FEM, a GAN-driven focusing-enhancement method, to fit unknown out-of-focus kernels for 3D targets in monochromatic SAR images. It leverages the 2D imaging system's capacity, improving focus, but introduces minor energy noise. [61] used GANs with perceptual and structural loss functions to boost SAR image quality, enhancing visibility of flood features.

2.3.4 Advanced Filtering and Resolution

Advanced techniques address noise and resolution. The Unscented Kalman Filter (UKF) and Super Resolution (SR) tackle multiplicative noise in SAR images, improving resolution over traditional methods [62]. Histogram Equalization (HE) and Adaptive Histogram Equalization (AHE) enhance contrast, while super-resolution reconstruction improves overall quality [63-65]. [66] applied GANs with illumination-guided attention to address non-uniform illumination, and [67] used a dual-branch neural network for single-image rain removal, supporting clearer flood imagery.

Table 2.3: Summary of existing techniques for flood image enhancement.

Reference	Dataset	Techniques	Key Results	Merits	Limitations
Aliabad et al. [57]	Landsat 8 ETM satellite images	Fuzzy ARTMAP, ANN	Produces accurate flood maps	Desired accuracy level	Poor in diverse geological regions
Ghosh et al. [55]	Sentinel-1A, Ganga basin	GEE, enhanced EVI, NDVI	Quick identification of flood areas	Rapid response capability	Captures nonlinearity, ratio-based limits
Toriya et al. [56]	Sentinel-1, Sentinel-2	DNN, GANs, edge enhancement	Effective optical-SAR intersection estimation	Aligns SAR and optical images	Poor transfer of some land features
Li et al. [58]	SAR images	NSCT, memetic algorithm	Enhances edges, contrast,	Improves image quality	High algorithmic complexity

			reduces speckle		
Chen et al. [59]	SAR images	p-LSCE (p-regularization, low-rank)	Reduces speckles via image relationships	Noise reduction	High processing power needed
Ye et al. [60]	Monochromatic SAR images	GAN-FEM	Enhances focus for 3D targets	Improves 2D imaging focus	Introduces minor energy noise
Kanakaraj et al. [62]	SAR images	UKF, Super Resolution	Improves resolution, reduces noise	Handles multiplicative noise	Slower for linear transformations
Dubey and Katarya [63]	Various SAR images	HE, AHE, super-resolution reconstruction	Enhanced contrast and quality	Improves visibility	Limited in preserving fine details

2.4 Comparative Analysis of Flood Detection and Prediction Methods

This section compares flood detection and prediction methods, from traditional statistical models to modern machine learning and hybrid approaches. It analyzes their principles, data needs, strengths, and weaknesses to identify effective techniques for accurate, timely forecasting. The comparison highlights trade-offs in computational complexity, accuracy, and spatial-temporal resolution, providing insights for choosing suitable methods for different regions. By understanding these differences, this analysis supports the development of reliable flood early warning systems and effective flood management strategies.

2.4.1 Unsupervised and Satellite-Based Methods

Comparative studies highlight strengths and weaknesses. [46] found SOM outperforms Mean Shift for water pixel extraction from MODIS images, effectively delineating flood regions, but high computational demands limit scalability. [49] used GEE with Sentinel-1 SAR data for flood mapping in the Mekong River basin, achieving high spatial coverage, though constrained by GEE's data preprocessing and availability limits.

2.4.2 Segmentation and Supervised Methods

[41] applied Otsu thresholding to Sentinel-1 SAR data, achieving ~90% accuracy in flood segmentation in northern Iran, with potential for improvement in complex terrains like mountains or urban areas. [47] compared SVM, DCNN, MLP, and SSDAs on SPOT-5 and radar imagery, with SSDAs achieving an AUC

of 0.9173, outperforming others due to denoising and feature learning, but limited by small, non-diverse training sets.

2.4.3 Exposure and Classification Methods

[44] used RestUNet to map buildings for flood exposure analysis, achieving an F1-score of 76%, effective for identifying elements-at-risk, but requiring local expertise and high-quality auxiliary data (e.g., building footprints). [68] found XGBoost outperforms KNN in flood classification, leveraging factors like elevation, slope, and stream proximity, though comparisons were limited in scope.

2.4.4 Model Performance and Scalability

In [69] compared eight ML models on the Haraz watershed dataset (201 flood events, 10,000 data points), with the EMmedian model achieving the highest accuracy, offering robust predictions but tied to specific data characteristics. Challenges include generalization, computational complexity, and data dependency across methods.

Table 2.4: Summary of Recent AI and Remote Sensing Techniques for Flood Mapping and Prediction.

Reference	Dataset	Techniques	Results	Merits	Limitations
Aliabad et al. [57]	Landsat 8 ETM	Fuzzy ARTMAP, ANN	Accurate flood maps	Desired accuracy	Poor in diverse regions
Arvind, C.S. et al. [46]	MODIS satellite images	Mean Shift, SOM	SOM better for flood regions	Effective extraction	High complexity, low scalability
Nghia, B.P. et al. [49]	Sentinel-1 SAR, shapefiles	GEE, SAR decoding	High spatial coverage	Tracks flood extent	GEE preprocessing limits
Moharrami et al. [50]	Sentinel-1 SAR	Otsu thresholding	Accuracy ~ 90%	Effective segmentation	Needs terrain improvement
Islam, K.A. et al. [47]	SPOT-5, radar images	SVM, DCNN, MLP, SSDAs	AUC = 0.9173	SSDAs outperform	Limited validation
Bhuyan, K. et al. [44]	Remote sensing imagery	RestUNet	F1-score = 76%	Good building detection	Needs local expertise, quality data
El-Magd et al. [68]	Multi-factor data (elevation, slope)	XGBoost, KNN	XGBoost superior	High accuracy	Limited comparison scope

Shafizadeh-Moghadam et al. [69]	Haraz watershed	8 ML models, EMmedian	Highest accuracy	Robust prediction	Data-specific results

2.5 Research Gaps and Future Directions

Although notable progress has been made, existing research is limited by narrow datasets and isolated methods. Future studies should explore advanced techniques and broader scenarios to enhance robustness and generalizability. This section highlights key research gaps and proposes directions for developing more effective and adaptive solutions.

2.5.1 Data Availability and Quality

Data scarcity and quality remain critical challenges, particularly in diverse geographical regions and varying environmental conditions [70]. Acquiring annotated flood data is difficult, limiting model training and robustness, especially for rare or extreme events.

2.5.2 Class Imbalance and Feature Complexity

Class imbalance, where flooded areas are underrepresented compared to non-flooded regions, challenges accurate delineation [71]. Dynamic flood events and confusing visual cues, such as shadows, reflective surfaces, and vegetation, complicate feature selection, leading to misinterpretation.

2.5.3 Algorithmic and Scalability Challenges

Algorithmic limitations, including overfitting, poor generalization, and high computational demands, hinder scalability [72, 73, 74]. Models often struggle to perform consistently across diverse datasets or in real-time scenarios, limiting practical deployment.

2.5.4 Occlusions and Multi-Temporal Data

Occlusions from buildings, vegetation, or clouds obscure flood detection, underestimating affected areas [75]. Multi-temporal SAR data integration, capturing flood dynamics over time, remains underexplored, yet is critical for understanding progression and improving predictions [76].

2.5.5 Future Directions

This research addresses these gaps by: (1) developing a flood prediction model incorporating environmental parameters like precipitation and topography, (2) designing an AI-based flood detection technique using ML and DL, (3) enhancing flood images to improve feature visibility and detection accuracy, and (4)

conducting a comparative analysis with existing methods. These efforts aim to advance accuracy, efficiency, and scalability, contributing to disaster mitigation and environmental preservation.

Chapter 3

FLOOD PREDICTION MODEL USING ENVIRONMENTAL PARAMETERS

Floods, as one of the most frequent and destructive natural disasters, necessitate accurate and timely detection to reduce their impact on human lives, infrastructure, and the environment. This chapter introduces two advanced deep learning frameworks developed to enhance flood prediction capabilities by leveraging artificial intelligence and computational intelligence techniques. The first model, FloodCNN-BiLSTM, integrates Convolutional Neural Networks (CNN) for spatial feature extraction with Bidirectional Long Short-Term Memory (BiLSTM) networks to capture temporal dependencies in sequential sensor data. To enhance spatial-temporal learning and refine feature representation from environmental inputs such as rainfall, temperature, and water levels. Together, these models aim to overcome key challenges such as data heterogeneity, environmental variability, and the need for real-time responsiveness. This chapter provides an in-depth overview of the data preprocessing steps, feature extraction techniques, and model architectures used, offering scalable and reliable solutions for AI-driven flood forecasting systems.

3.1 Introduction

A disaster is a severe event that disrupts communities and causes significant harm to human life, the environment, and infrastructure. Among natural calamities, floods are particularly common during monsoon seasons and pose serious risks to regions situated near lakes, rivers, and coastal zones. These events often exceed the coping capacity of affected communities, necessitating advanced management and mitigation strategies. With recent technological progress, flood prediction capabilities have improved significantly through the application of hydrological models, remote sensing technologies, machine learning techniques, and big data analytics. These innovations contribute to improved prediction accuracy, extended lead times, and enhanced spatial resolution, thereby enabling timely detection of flood events, even in remote and underserved areas. Current research trends in artificial intelligence (AI), big data, and the Internet of Things (IoT) are further transforming disaster management by enabling the development of intelligent predictive systems and automated decision-making frameworks [77]. As climate change continues to increase the frequency and intensity of weather-related incidents, the integration of these technologies becomes vital in minimizing the impact of natural disasters like floods. Flood events cause widespread loss of life, ecological degradation, and economic disruption, affecting both developing and developed nations [78, 79]. Among natural hazards such as earthquakes, volcanic eruptions, and tsunamis, floods occur most frequently, resulting in high human casualties, displacement, and destruction of

livelihoods. Despite technological advancements, the detection and prediction of floods remain challenging due to rapid environmental changes and data uncertainties. Many traditional models rely on simplified assumptions and static datasets, which can limit their predictive performance. In this context, deep learning offers promising improvements in early warning and flood forecasting systems [80, 81]. Accurate flood prediction is essential for effective disaster preparedness, especially in alerting vulnerable communities in advance. Machine learning algorithms have been increasingly applied to enhance forecasting precision across both real-time and long-term scenarios [82, 83]. These models, trained on historical data, can learn complex patterns and generalize well to anticipate future flood events.

3.2 Introduction to FloodCNN-BiLSTM Methodologies

In this study, a hybrid deep learning model named FloodCNN-BiLSTM is proposed to predict flood occurrences using sensor-based environmental data. The model integrates Convolutional Neural Networks (CNN) for extracting spatial features with Bidirectional Long Short-Term Memory (BiLSTM) networks for capturing long-term temporal dependencies. This architecture enables the model to effectively process sequential data and deliver accurate predictions, outperforming traditional approaches in flood forecasting tasks.

3.2.1 Dataset Collection and Preprocessing

Accurate and timely flood prediction relies heavily on the quality and relevance of the data used to train and validate predictive models. In our work, real-time environmental data related to flood risk indicators such as precipitation levels, river water levels, soil moisture content, and weather conditions were collected through a robust monitoring system designed specifically for flood early warning applications. These environmental parameters were gathered using a wide range of field-deployed sensors and remote sensing devices. The captured data were then transmitted via telemetry systems to centralized data repositories, where they could be further processed and analyzed. This end-to-end infrastructure facilitates prompt and precise flood forecasting, thereby supporting local authorities and communities in making informed, proactive decisions to minimize the impact of flooding events.

However, the raw data collected from heterogeneous sources often contains inconsistencies, noise, and missing values that must be addressed before model training. Therefore, a comprehensive data pre-processing pipeline was employed to ensure that the input data is accurate, structured, and optimized for use in predictive modeling. This pipeline consists of several critical steps:

i. **Data Cleaning:** Data collected from various sensors may include errors, outliers, noise, or incomplete values, all of which can adversely affect model performance. The data cleaning process involves identifying and correcting these anomalies. Techniques such as interpolation

and imputation are used to fill missing values, while smoothing and filtering methods are applied to handle noise and outliers effectively.

ii. **Feature Engineering:** To enhance the predictive power of the flood detection model, feature engineering is performed to create new, informative variables derived from raw input data. For instance, features such as rainfall intensity, rate of water level rise, or region-specific flood risk indices can be generated to provide more meaningful input to the model and improve its capacity to detect flood patterns.

iii. **Handling Missing Values:** In environmental datasets, missing values are a common occurrence and can significantly degrade the reliability and accuracy of prediction systems. Various imputation methods are employed based on the type of data and the extent of missingness. These may include statistical techniques like mean or median substitution, as well as model-based approaches to estimate and replace the missing entries.

iv. **Data Normalization:** Since environmental variables often have different scales and units (e.g., millimeters for rainfall and meters for river levels), data normalization is essential to standardize the feature set. Normalization ensures that each input variable contributes proportionately to the model's learning process, thereby avoiding any bias caused by features with larger numerical ranges.

Through this integrated approach to data collection and pre-processing, a clean, enriched, and standardized dataset is prepared, forming the foundation for the training and evaluation of advanced deep learning models in flood detection. This step is indispensable in enhancing the robustness, accuracy, and generalizability of the proposed FloodCNN-BiLSTM framework.

3.2.2 AI Models and Algorithms Used

Recent advancements in computational intelligence have paved the way for more accurate and reliable flood prediction systems. This section outlines the various artificial intelligence models and algorithms applied to forecast flood occurrences based on diverse environmental and climatic factors. Techniques such as decision trees, support vector machines (SVM), and random forests are commonly used due to their effectiveness in classifying and interpreting complex datasets. Additionally, deep learning approaches, including Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, offer enhanced performance in recognizing temporal and spatial patterns [84]. In many cases, hybrid models that combine multiple AI techniques are adopted to improve prediction accuracy and system adaptability, supporting more robust flood warning mechanisms.

3.2.2.1. Artificial Neural Network

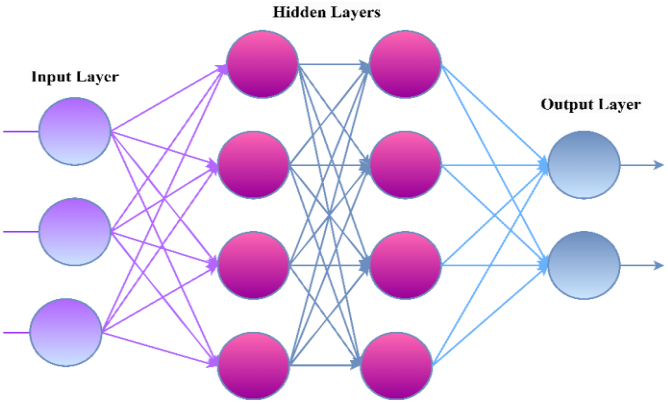


Figure 3.1: Layered architecture of an Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) are computational models inspired by the neural networks in the human brain. It comprises layered arrangements of interconnected nodes (neurons). To process input data and produce predictions, ANNs use activation functions on neuron outputs. It minimizes the loss function by adjusting weights and biases during training through backpropagation and gradient descent. Deep neural networks, a subclass of ANNs, can learn hierarchical patterns in data thanks to their deep structures with numerous hidden layers [85, 86]. The ANN model was developed to simulate river flows at a specific downstream location based on upstream flow data. The investigation results indicate that the ANN provides a reliable method of detecting flood hazards. In above Figure 3.1, we illustrate the architecture of the ANN. The output of the neuron is calculated by following the formula in equation 3.1.

$$Z = \sum_{I=0}^{n} (W_I \cdot X_I) + b \tag{3.1}$$

Z = weighted sum; n = number of inputs; W_I = weight associated to each input; X_I = input value; b = bias value

3.2.2.2. Convolutional Neural Networks

Figure 3.2 shows the architecture of 1-dimensional CNN. It includes the fully connected layers for final predictions, pooling layers for downsampling, and convolutional layers for feature identification. The CNN is trained using backpropagation, which offers benefits such as translation invariance, local feature identification, and parameter sharing. They are an essential tool in computer vision applications because they perform well in tasks including image classification, object identification, segmentation, and facial recognition [87]. Benchmarking the CNN model's performance against the support vector regression (SVR) technique provides additional evidence of its effectiveness.

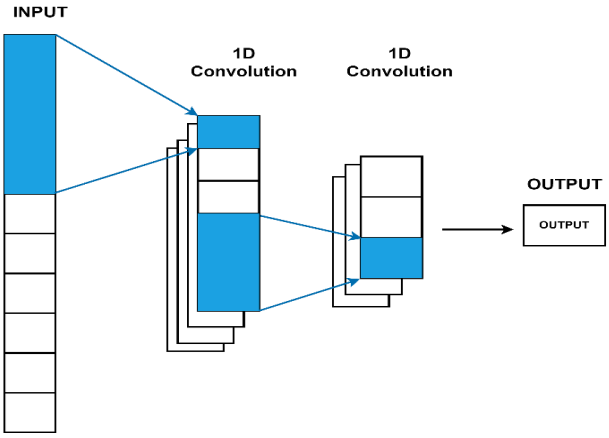


Figure 3.2: Architecture of 1-D Convolutional Neural Network for time-series data processing

The outcomes demonstrate that the CNN model performs significantly better than traditional neural network. According to numerous quantitative evaluation metrics, the CNN model effectively captures flooded cells [88].

3.2.2.3. Long Short-Term Memory (LSTM)

The input at each time step is derived from the output of the previous time step. Long-term dependencies within word sequences are efficiently stored and managed by LSTMs through the use of internal gate signals at each time step. The underlying design of an LSTM network is depicted in Figure 4, which highlights its effectiveness in managing long-term dependencies in comparison to conventional RNNs. This characteristic makes LSTMs well-suited for complex sequence-based tasks that call for a prolonged, deeper comprehension of context [89, 90]. The LSTM memory units have three gate signals: input, output, and forget, as shown in Figure 3.3. Gate signals regulate data flow through the memory cells by determining whether information should be preserved or forgotten at each time interval. To address the vanishing gradient problem, the memory cell C_t is routed through the LSTM neural network using input and output gates. The Sigmoid Activation Function controls data flow inside the LSTM neural network. Initially, a sigmoid activation function of 1 allows a word to flow through the gate, but a value of 0 prevents further processing. The following equation 3.2 describes how the forget gate decides whether information, designated as f_t should be sent.

$$f_t = \sigma\left(W_f \,.[h_{t-1}, x_t] + b_f\right) \tag{3.2}$$

In this equation, σ represents the Sigmoid Activation Function, W_f is the weight matrix applied to the current input, h_{t-1} is the hidden state vector from the previous state, while b_f is a biasing feature. After passing through the forget gate, the information is updated in an update gate signal, which is then incorporated into the current cell state $\widetilde{C_t}$ via the tanh activation function 3.3 and 3.4.

$$i_t = \sigma\left(W_f\ .[h_{t-1}, x_t] + b_i\right) \tag{3.3}$$

In the above equation, $i_t$denotes the activation vector for the input gate whereas b_i is the bias vector for particular gates.

$$\widetilde{C_t} = \tanh(W_C\ .[h_{t-1}, x_t] + b_C) \tag{3.4}$$

The previous cell state C_{t-1} in the memory unit is updated to the new cell state $C_t$as shown in equation 3.5

$$C_t = f_t * C_{t-1}\ +\ i_t * \widetilde{C_t} \tag{3.5}$$

Last but not least, the output of the sigmoid activation function is controlled by the output gate of the LSTM memory units in 3.6 and the output of the hidden layer h_t for the current word in 3.7.

$$O_t = \sigma\left(W_O\ .[h_{t-1}, x_t] + b_O\right) \tag{3.6}$$

$$h_t = O_t\ * \tanh C_t \tag{3.7}$$

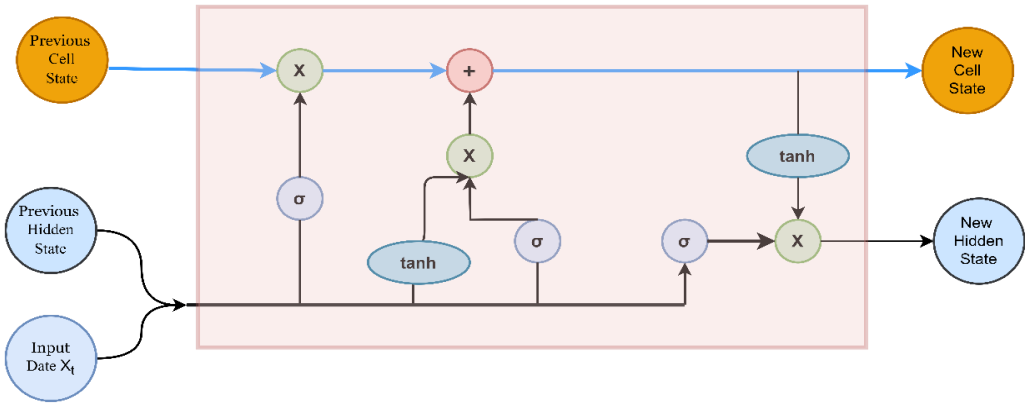


Figure 3.3: Internal structure of a Long Short-Term Memory (LSTM) Neural Network Unit

3.2.2.4. Feature Extraction and Working of Proposed Model

A bidirectional LSTM, often known as a BiLSTM is made up of two LSTMs. Bidirectional processing involves processing data both from the past to the future and from the future to the past. In contrast to unidirectional LSTMs, the backward LSTM in this configuration maintains future data. Bidirectional Long Short-Term Memory (LSTM) can combine the hidden states from both directions to retain and use past and future knowledge at any one time. This dual viewpoint improves the model's comprehension of context and dependencies within the data. The architecture of BiLSTM is shown in Figure 3.4. The Bidirectional Long Short-Term Memory (BiLSTM) model comprises two layers of LSTM networks, one of which processes the input sequence forward and the other backward [91]. The fundamental structure of the BiLSTM framework is depicted in the figure above. The input sequence is given as a regular LSTM in the first layer, and it is reversed in the second layer. But the data kept in both forward and backward directions, LSTM is provided in equations 3.8 and 3.9.

$$h_f = w_{f1} * x^k + w_{f2} * h^{k-1} \quad (3.8)$$

$$h_b = w_{b1} * x^k + w_{b2} * h^{k+1} \quad (3.9)$$

Where the two advanced layers (forward and backward) of the LSTM are represented by the hidden output h_f , and h_b, respectively. The hidden layer's activation output, also known as the final output, is provided in 3.10.

$$a_i = g(w_{o1} * h^f + w_{o2} * h^b) \quad (3.10)$$

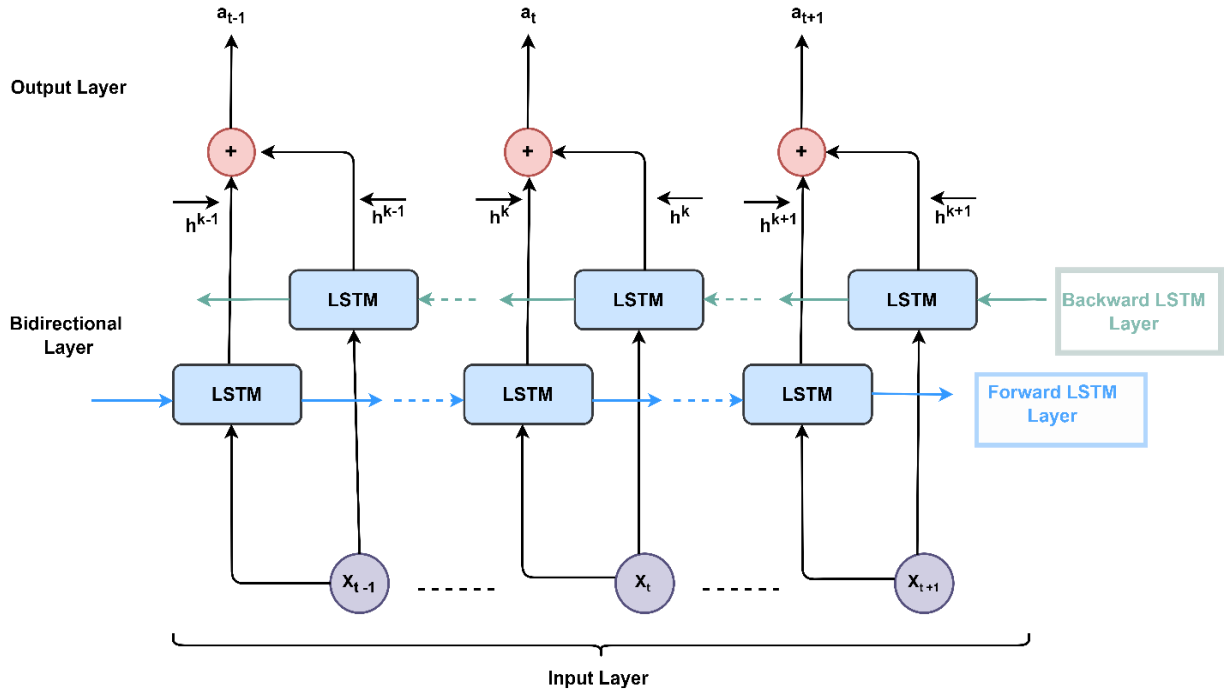


Figure 3.4: Detailed view of data flow and internal operations in a Bidirectional LSTM (BiLSTM) network

Table 3.1: The following table compares LSTM with BiLSTM

Feature	*LSTM*	*BiLSTM*
Architecture	Single-directional RNN alongside memory cells	Two LSTM layers: a forward-facing layer and a backward-facing layer
Gates	Three gates: input, forget, and output	For both directions—forward and backward—input, forget, and output gates
Direction	Processes data from beginning to end	Processes information both from start to end and from end to start.
Performance	Limited by the absence of future context.	It is better overall because of the bidirectional context.

Relevant Information	exclusively makes use of historical context	Uses both past and future context.
Complexity	One set of LSTM cells makes things simpler.	More complicated, having two sets of LSTM cells (one for each direction).
Computational Requirements	Reduced demand for memory and computation	Higher computational and memory requirements

Bidirectional Long Short-Term Memory (BiLSTM) networks are a powerful sort of recurrent neural network (RNN) that captures long-term dependencies in sequential input [92]. In CNN, the convolution operation on the input data generates a high-level feature map by applying filters of various sizes, which is then pooled to extract key features. Higher layers capture complicated features in a deep convolutional network by applying convolutional operations to lower levels [93]**.** Figure 3.5 shows our FloodCNN-BiLSTM model's flowchart, which details the process from data intake to flood prediction.

The model pre-processes environmental data before using a Bidirectional Long Short-Term Memory (BiLSTM) network to evaluate it sequentially, identifying patterns for reliable flood prediction. Finally, the results are analyzed to enhance the model's functionality. The CNN-Bidirectional LSTM (BiLSTM) model is proposed to improve flood prediction by leveraging CNN for spatial feature learning and BiLSTM for capturing temporal dependencies. This approach enhances prediction accuracy by analyzing complex patterns in flood-related data. It combines BiLSTM for temporal dependencies and CNN for spatial feature learning, to improve flood prediction accuracy by studying complicated data patterns related to flood occurrences. The starting stage of our FloodCNN-BiLSTM model is data preparation, which includes activities like data cleaning, missing value management, and data encoding. The process begins with data preprocessing, which involves data cleaning, handling missing values through imputation or deletion, and encoding categorical variables into numerical formats like label or one-hot encoding. The pre-processed data is fed into the CNN layer, which extracts local features using convolution and pooling operations. Convolution applies filters to detect patterns, while pooling reduces dimensionality and highlights key spatial features. Initially developed for image analysis, CNNs are also effective for handling text and sensor data. The CNN output is passed to the BiLSTM layer, which captures long-range dependencies in the data. BiLSTM, an advancement on traditional LSTM, excels in modelling sequential data, making it well-suited for flood prediction. By combining advanced preprocessing and deep learning techniques, this approach addresses the complexities of environmental data for flood prediction. In Figure 3.6, the proposed FloodCNN-BiLSTM architecture includes a 1-dimensional convolution layer to extract features from the input environmental data collected from multiple sensors. This layer aims to build a large network that can manage massive data sets. This enables the model to learn features that are consistent across different

locations and times. In a CNN layer, all 256 filters execute the convolutional process on input data from top to bottom, extracting the feature sequence as $f_n = [f_1, f_2, \ldots\ldots\ldots, f_{256}]$. Following the convolution process, we flatten or pool the result to convert it to a format that can be processed sequentially by BiLSTM. It includes a memory block that processes information sequentially for temporal behavioural simulation [94].

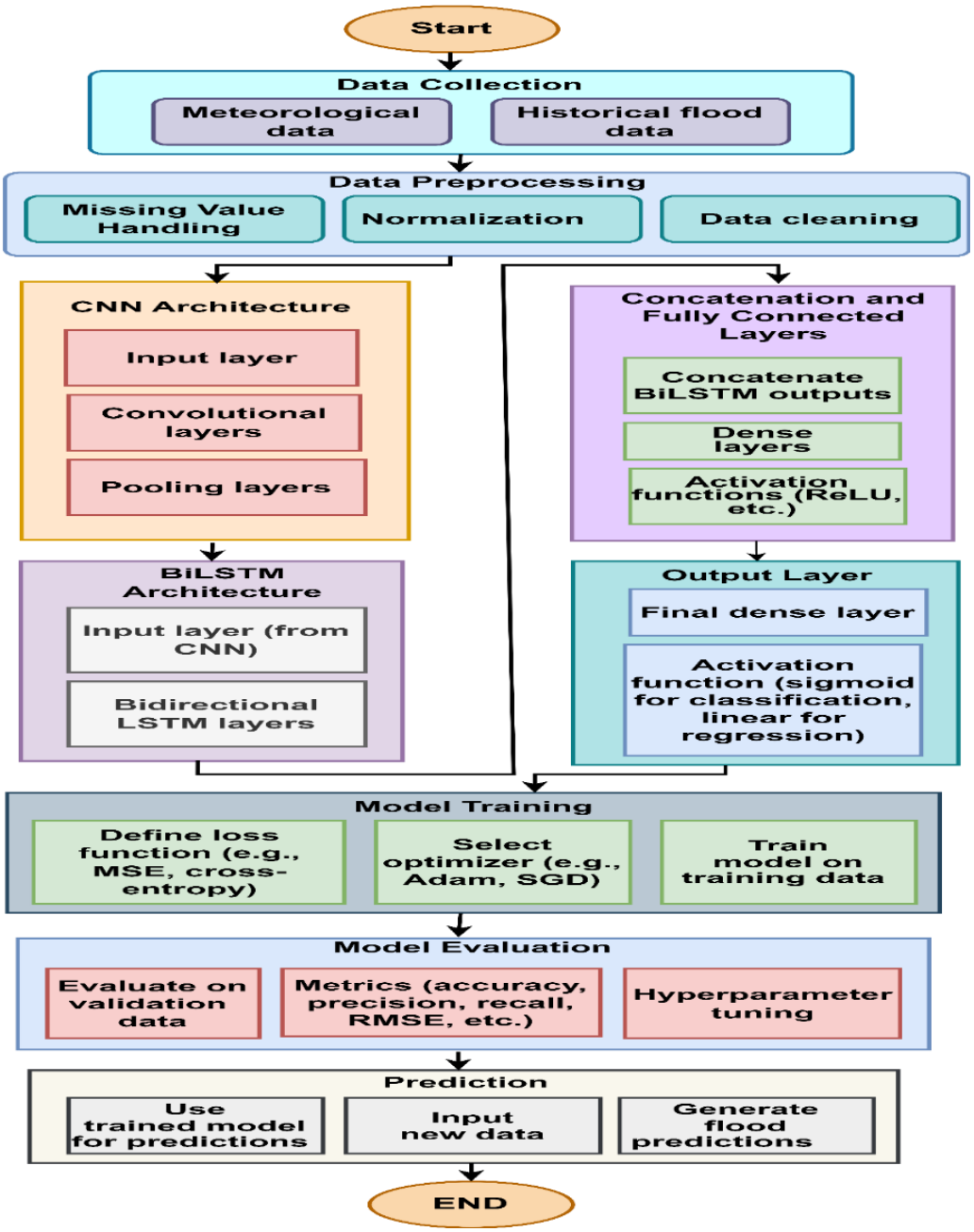


Figure 3.5: Dataflow diagram of the proposed FloodCNN-BiLSTM it involves preprocessing input data, extracting key features using a CNN, and analyzing these features with a BiLSTM network to identify patterns and make accurate flood predictions

Its memory cells allow it to choose what long-term contextual knowledge to retain and what to discard, giving it the ability to learn. The components of an LSTM cell are an input gate (i_t), an output gate (o_t), a forget gate (f_t), and a memory cell state (C_t). The input gate at timestamp t (i_t) controls the flow of information into the cell and updates its state using equation 3.3, while the forget gate determines the amount of information to erase at time t using equation 3.2. The candidate cell value ($\tilde{C}_t$) is computed with equation 3.3. The current cell state value (C_t), the output from the output gate (o_t), and the final output (h_t) of the LSTM cell at time t are determined by equation 3.5, 3.6, and 3.7 respectively. In these equations, f_t denotes the input for the BiLSTM at time-stamp t, derived from the high-level attention mechanism.

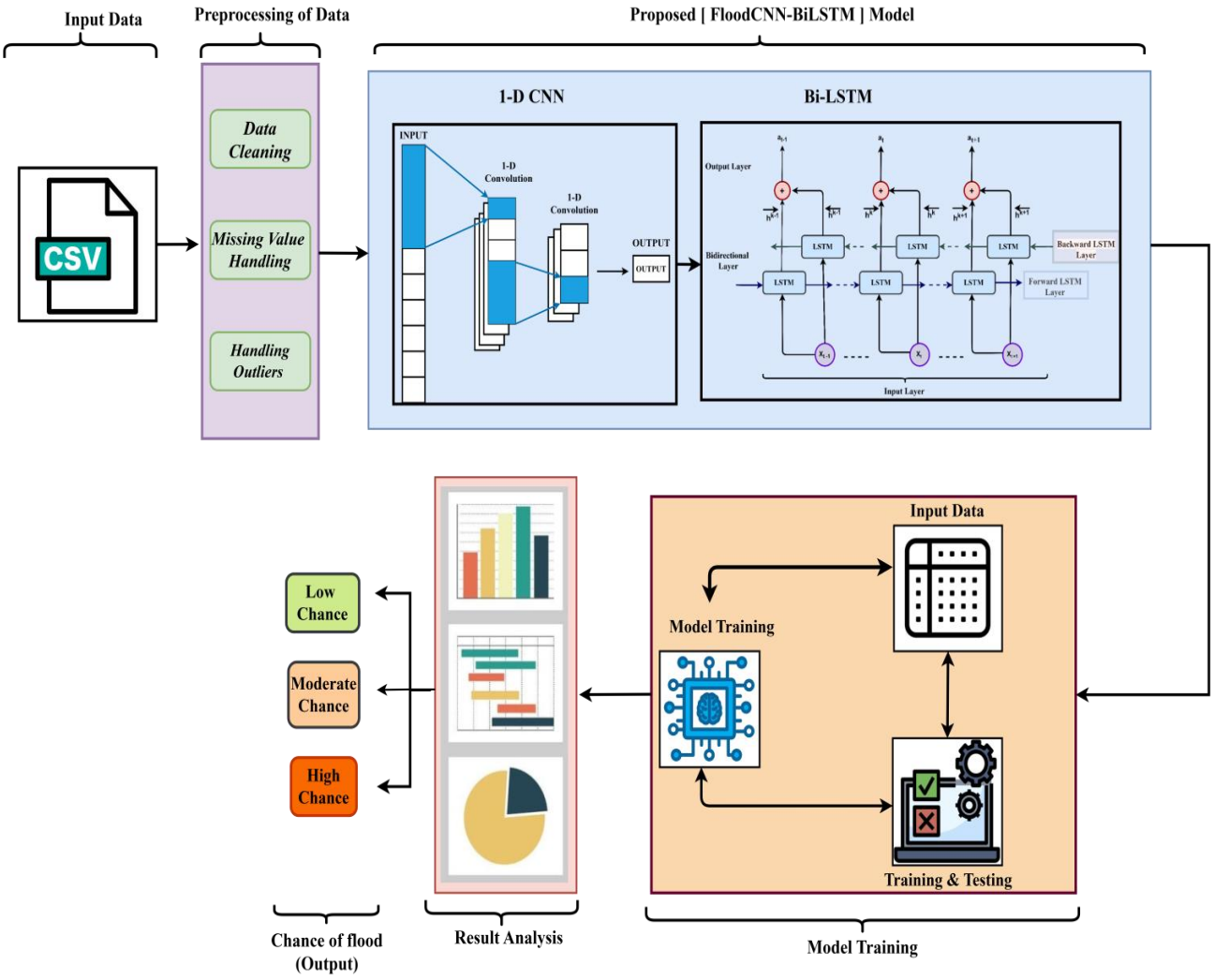


Figure 3.6: A detailed architecture of our proposed model FloodCNN-BiLSTM for predicting floods, showing how the CNN extracts important features from input data and the BiLSTM analyses time-based patterns to make accurate flood predictions.

The symbols $W, b, \sigma,$ and tanh stand for the weight vector, bias vector, sigmoid function, and hyperbolic tangent function, respectively. Furthermore, $\otimes$ indicates element-wise multiplication. We use BiLSTM instead of LSTM to collect information in both directions. BiLSTM consists of two LSTMs: forward LSTM captures future context from left to right, while backward LSTM captures previous context from right to left. Equations 3.11 and 3.12 require the generation of two hidden representations, $\overrightarrow{h_t}$ *and* $\overleftarrow{h_t}$ and, respectively, during the procedure. The final representation is then created by concatenating the information outputs from both LSTM networks by the Bidirectional LSTM (BiLSTM), as shown in Equation 3.13. This makes it possible for the BiLSTM to improve the representation overall by utilizing context in both directions. To obtain the forward feature sequences (i. e. F_{256} *to* F_1) and backward feature sequences (i. e. F_1 *to* F_{256}), the suggested model incorporates a BiLSTM layer. The proposed model uses a BiLSTM to encode environmental parameters from both directions, capturing comprehensive contextual information. This encoded data is then passed to an attention layer, which assigns variable weights to different parts of the data, enhancing the model's focus on the most relevant features for improved performance.

$$\overleftarrow{h_t} = \overrightarrow{LSTM}\,(F_n) \tag{3.11}$$

$$\overrightarrow{h_t} = \overleftarrow{LSTM}\,(F_n) \tag{3.12}$$

$$h_n = \left[\overleftarrow{h_t}\,, \overrightarrow{h_t}\right] \tag{3.13}$$

Algorithm Flood Prediction Using CNN and BiLSTM (FloodCNN-BiLSTM)

Input: historical_flood_data, meteorological_data,

Output: Predictions chance of flood

Step 1: Data Preprocessing

Procedure PreprocessData *(historical_flood_data, meteorological_data,)*

Clean data *(remove duplicates, correct errors, handle outliers)*

Manage missing values *(imputation or deletion)*

Scale data (*normalization or standardization*)

Return *train_data, testing_data val_data,*

Step 2: CNN Model for Feature Extraction

Procedure Build cnn (input_shape)

1. Initialize Sequential model
2. Add *1D Conv* layer with *256* filters, kernel_size*3*, activation 'ReLU', input_shape,
3. Apply convolution operation to generate feature map as f_n:

$$f_n = [f_1\,, f_{2,}, \ldots\ldots\ldots\ldots, f_{256}]$$

4. Pool or flatten the result

Return cnn_model

Step 3: BiLSTM Model for Sequential Processing

Procedure Build BiLSTM Model(input_shape)

1. Initialize Sequential model
2. Add Bidirectional LSTM layer with 64 units, return_sequences=True
3. Compute forward hidden states (h_f) as per equation 8

$$h_f = w_{f1} * x^k + w_{f2} * h^{k-1}$$

4. Compute backward hidden states (h_b) as per equation9

$$h_b = w_{b1} * x^k + w_{b2} * h^{k+1}$$

5. Compute combined hidden state (a_i) as per equation10

$$a_i = g(w_{o1} * h^f + w_{o2} * h^b)$$

6. Add another Bidirectional LSTM layer with 64 units

Return bilstm_model

Step 4: Combine CNN and BiLSTM Models

Procedure Build FloodCNN-BiLSTM (cnn_model, bilstm_model)

1. Concatenate outputs of CNN_model and bilstm_model
2. Add Dense layer with 64 units, activation 'relu'
3. Add Dense layer with 32 units, activation 'relu'
4. Return combined_model

Step 5: Add Output Layer

Procedure Add Output Layer(combined model, output_type)

If output_type is 'regression'

1. Add Dense layer with 1 unit, activation 'linear'

Else if output_type is 'classification'

1. Add Dense layer with 1 unit, activation 'sigmoid'

End If

2. Return model

Step 6: Train the Model

Procedure TrainModel (model, train_data, val_data, epochs=100, batch_size=32)

1. Compile model with optimizer 'adam', loss 'mean_squared_error', metrics 'mae'
2. Train model on train_data
3. Return training history

Step 7: Evaluate the Model

Procedure Evaluate Model (model, val_data)

Return evaluation results

Return predictions

3.3 Experimental Results and Discussion

This section presents the experimental results and analysis of the proposed model. Performance is evaluated using metrics like accuracy, precision, recall, and F1-score. Comparative studies with existing methods demonstrate improvements. Visual outputs and case studies further illustrate the model's robustness and effectiveness across different scenarios.

3.3.1 Performance Evaluation Metrics

Metrics for performance evaluation are used to evaluate the reliability and efficiency of a model, or other entity.

Accuracy: A commonly used metric to evaluating a model's predictive performance is accuracy. It is the proportion of accurately predicted instances (including true positives and true negatives) to all of the instances in the dataset.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \tag{3.14}$$

Precision: Precision also referred to as positive predictive values, measure the proportion of accurate positive predictions to all of the positive forecasts the model made. When a model predicts a favourable outcome, it is more likely to be accurate because of its high precision.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{3.15}$$

Recall: Recall quantifies the proportion of accurate positive predictions to actual positive instances found in the dataset. High recall indicates that the model can successfully identify a significant part of the actual positives.

$$\text{Recall} = \frac{TP}{TP+FN} \tag{3.16}$$

F1-score: The F1-Score represents the harmonic average of precision and recall. It strikes a balance among these two metrics. It is especially beneficial when you want to evaluate both false positives and false negatives and need to strike a balance between decreasing them.

$$\text{F1-score} = 2 * \frac{Precision * Recall}{Precision + Reall} \tag{3.17}$$

3.3.2. Data Description

The most important aspect of developing a flood disaster forecasting system is requires a large amount of data for accurate predictions. Since many human settlements in India are located near rivers, large areas of the country are prone to flooding. Therefore, as a result, these areas are especially vulnerable to flooding during the monsoon season. India is highly suitable for studying and analyzing flood patterns due to its frequent flood occurrences. Following this, there were significant floods in many Indian states and union territories.

3.3.2.1 Description of Dataset 1

This revealed that India is highly prone to severe flooding. According to the International Water Management Institute (IWMI), 73 percent of India's land area is affected by flooding annually. The frequency of flood events is extremely high in Orissa. As a result, we include two major Indian states, Bihar and Odisha, in our system. Bihar and Odisha are both huge states; their districts are 38 and 30, respectively. Each state's ten most prone to flooding cities are chosen. The Dataset also includes monthly data. We analyzed data collected over fifteen years, coming each month from January to December. The data is categorized into three categories of flood risk (Low, Moderate, and High) [95].

3.3.2.2 Description of Dataset 2

There are ten features in total, including temperature, precipitation, wind speed, wind speed, wind direction, air pressure, and others. In each training and testing phase, you are provided with meteorological data from anonymized surrounding areas named Region A through Region E, which are all surrounding regions. The data is categorized into three categories of flood risk (N-No rain, L-Light rain, and H-Heavy rain) [96].

3.3.3. Result Analysis on Dataset 1

In this, we evaluate several crucial performance measures in depth, including precision, recall, F1-score, and accuracy on dataset 1. These metrics help evaluate how well our prediction model aligns with or compares to existing models.

Table 3.2: Precision tabulated for the proposed model, with existing techniques on dataset 1.

Precision			
Model/ Algorithm	**Class**		
	Low	**Moderate**	**High**
SVM	90.4	76.7	77.3
DT	93.5	75.6	73.7
ANN	92.6	70.5	75.6
DNN	95.3	94.0	78.4
NB	94.6	91.3	89.6
CNN	93.0	94.3	90.4
LSTM	95.6	96.5	93.5
Bi-LSTM	97.5	95.7	95.4
Proposed Model (FloodCNN-BiLSTM)	**98.5**	**95.7**	**94.3**

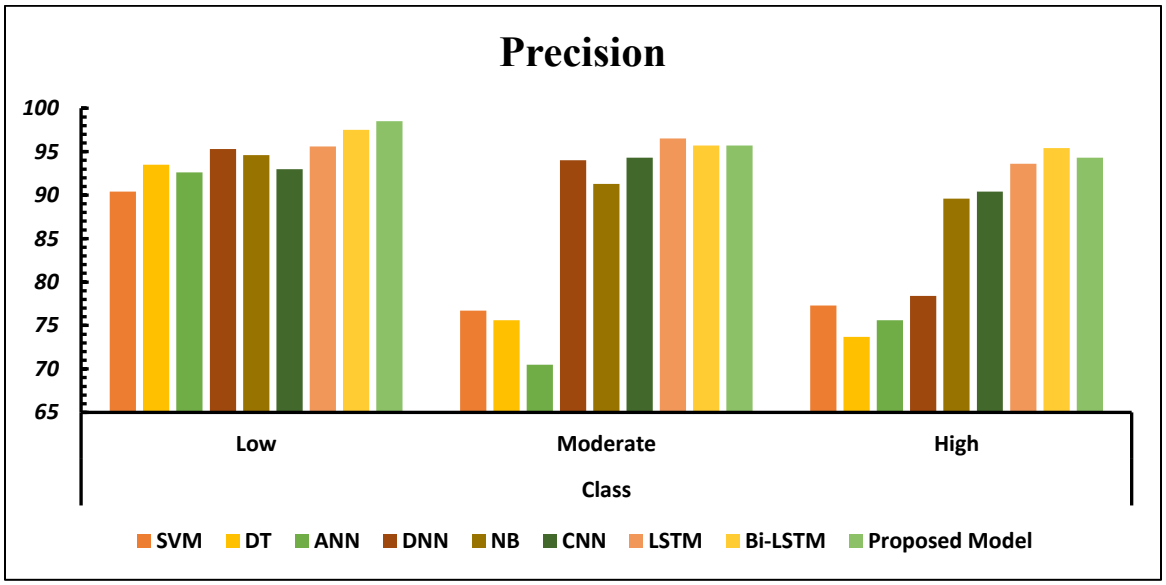


Figure 3.7: Graphical illustration of categorized data and precision performance of SVM, DT, ANN, CNN, LSTM, and proposed model on dataset 1

Figure 3.7 shows a graphical depiction of the precision for different machine learning algorithms and our suggested model. Each model's performance varies by data class; however, our proposed model, FloodCNN-BiLSTM, outperforms them all. A graphical illustration of the Recall of different machine learning methods and our suggested model is shown in Figure 3.8. Each model performs differently in each of the data classes, however, our suggested model, FloodCNN-BiLSTM, performs better in every situation.

Table 3.3: Recall table of our Proposed Model with existing techniques on Dataset 1

Recall			
Model/ Algorithm	**Class**		
	Low	**Moderate**	**High**
SVM	70.3	87.4	90.5
DT	76.4	92.6	87.8
ANN	88.6	94.5	89.7
DNN	78.1	97.6	82.6
NB	81.5	95.2	88.4
CNN	82.3	92.7	90.5
LSTM	83.7	94.5	96.4
Bi-LSTM	84.5	95.5	95.2
Proposed Model (FloodCNN-BiLSTM)	**85.5**	**96.8**	**95.7**

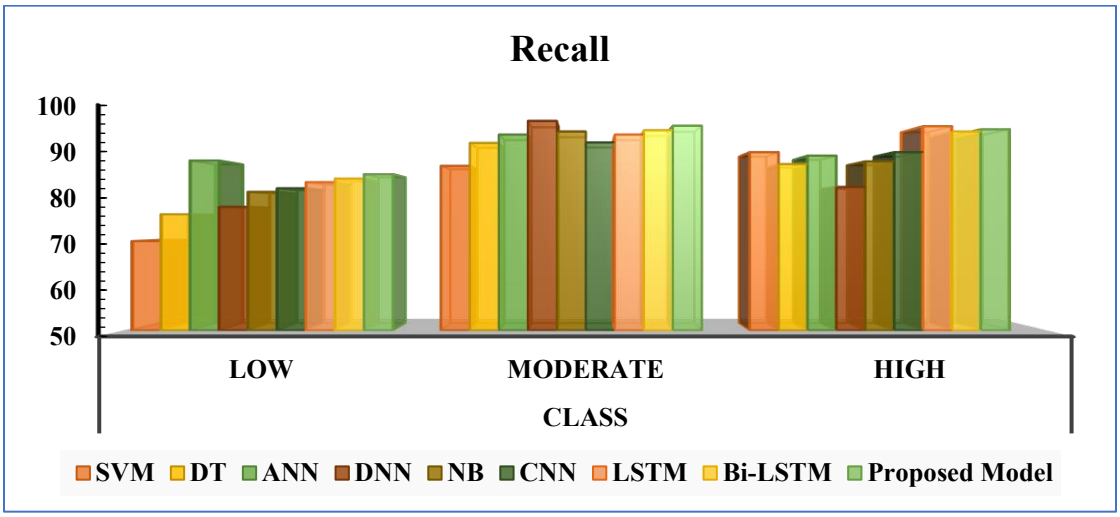


Figure 3.8: Graphical comparison of the recall of SVM, DT, ANN, CNN, LSTM, and the proposed model on Dataset 1

Table 3.4. Displays the F1-scores of the Proposed Model with existing techniques on dataset 1.

F1-score			
Model/ Algorithm	**Class**		
	Low	**Moderate**	**High**
SVM	85.5	83.6	87.5
DT	82.3	80.3	83.6
ANN	79.8	82.7	85.1
DNN	83.7	87.3	91.6
NB	85.3	89.6	94.5
CNN	87.0	90.3	95.0
LSTM	89.26	95.49	94.93
BI-LSTM	90.54	95.60	95.30
Proposed Model (FloodCNN-BiLSTM)	**91.54**	**96.10**	**94.99**

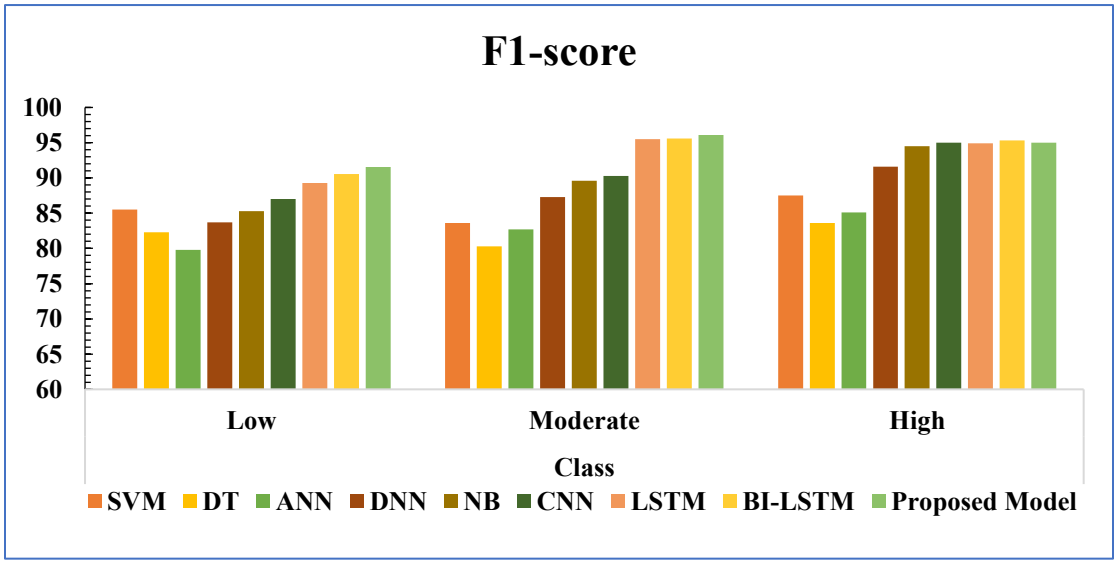


Figure 3.9: Visualization of categorized data and model F1-score for SVM, DT, ANN, CNN, LSTM, and the proposed model using Dataset 1

Figure 3.9 above shows a graphic depiction of F1 scores among our proposed model and the different machine-learning algorithms. Each model performs differently in each class of data, however our suggested model, the FloodCNN-BiLSTM, consistently outperforms the competition.

Table 3.5: Accuracy table of the proposed model with existing techniques on dataset 1.

Model/ Algorithm	Accuracy
SVM	89.7
DT	87.6
ANN	90.8
DNN	92.6
NB	89.8
CNN	93.3
LSTM	94.7
Bi-LSTM	96.5
Proposed Model (FloodCNN-BiLSTM)	**97.3**

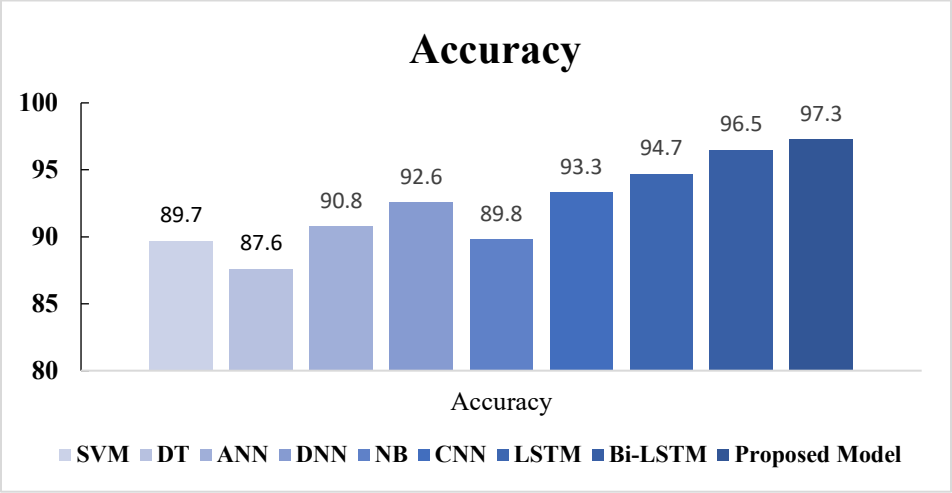


Figure 3.10: Accuracy comparison of SVM, DT, ANN, DNN, NB, CNN, LSTM, Bi-LSTM, and proposed model on dataset 1

Figure 3.10 above shows a graphical depiction of our suggested model and the accuracy of different machine-learning techniques. Each model performs differently in each data class, however, our suggested model, FloodCNN-BiLSTM, performs better in every situation.

3.3.4 Result Analysis on Dataset 2

The precision, recall, F1-score, and accuracy on dataset 2 are all carefully examined in this phase. When evaluating our prediction model against other models, these variables are crucial indicators of its quality.

Table 3.6: Precision tabulated of Proposed with existing techniques on dataset 2.

Precision			
Model/ Algorithm	**Class**		
	No rain	**Light rain**	**Heavy rain**
SVM	93.4	81.6	78.5
DT	91.8	79.5	77.3
ANN	89.7	76.4	79.6
DNN	97.8	95.3	87.4
NB	91.0	89.3	91.0
CNN	90.4	97.9	93.4
LSTM	94.6	95.7	94.3
Bi-LSTM	96.5	96.5	96.8
Proposed Model (FloodCNN-BiLSTM)	**97.3**	**94.5**	**96.4**

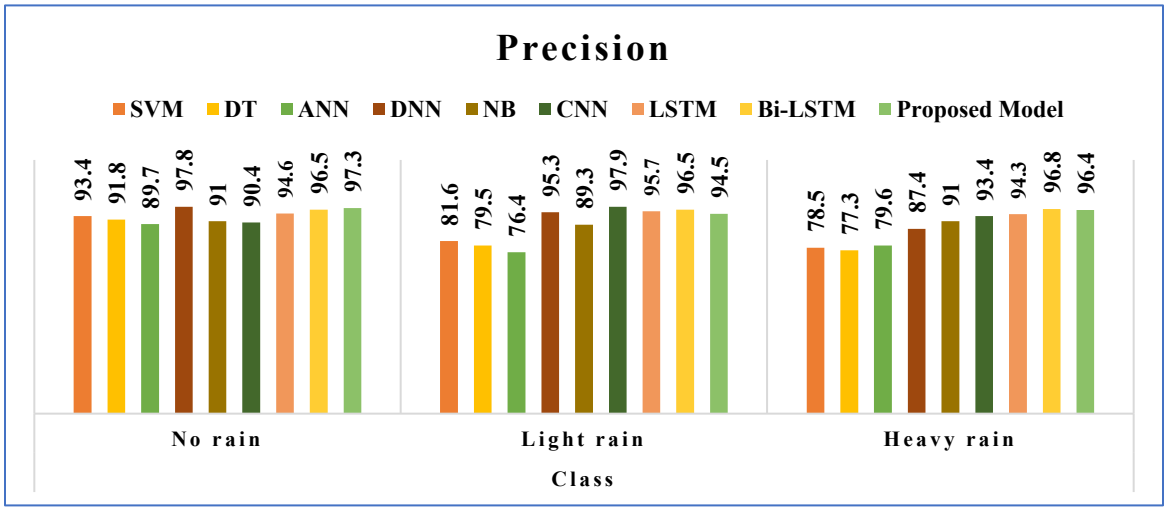


Figure 3.11: Graphical illustration of categorized data and precision performance of SVM, DT, ANN, CNN, LSTM, and proposed model on dataset 2

Table 3.7: Recall the table of our Proposed Model with existing techniques on dataset 2

Recall			
Model/ Algorithm	**Class**		
	No rain	**Light rain**	**Heavy rain**
SVM	73.6	89.5	92.3
DT	79.6	94.7	88.7
ANN	90.6	96.5	89.7

DNN	82.0	93.5	82.4
NB	85.6	94.7	84.5
CNN	87.5	95.6	91.6
LSTM	88.2	93.4	93.5
Bi-LSTM	89.0	94.1	96.9
Proposed Model (FloodCNN-BiLSTM)	**89.4**	**94.8**	**96.2**

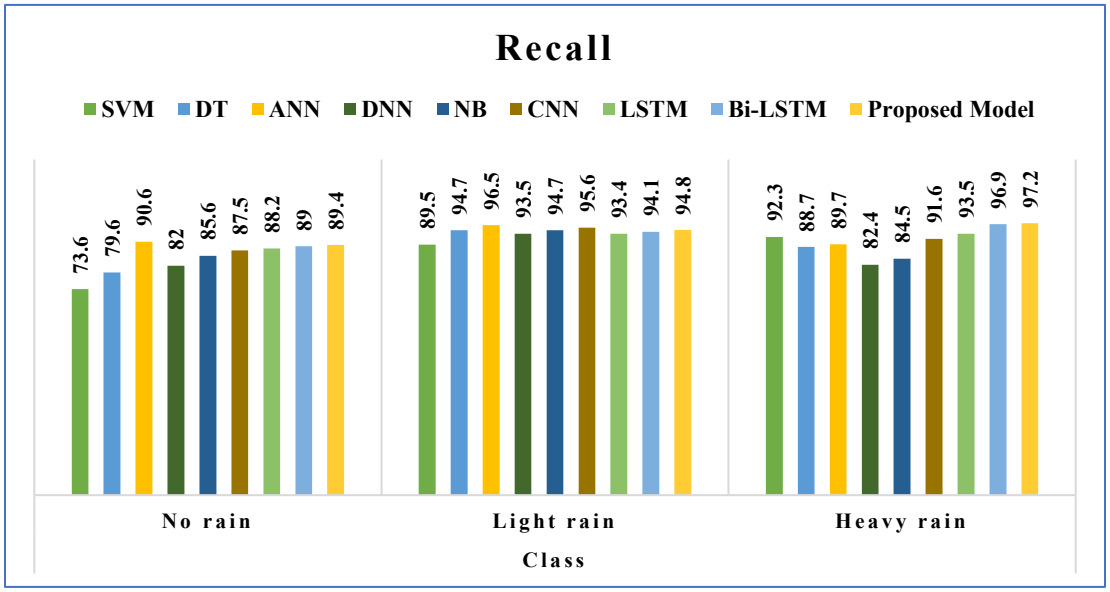


Figure 3.12: Graphical comparison of the recall of SVM, DT, ANN, CNN, LSTM, and the proposed model on Dataset 2

Figures 3.11 and 3.12 present graphical comparisons of the performance metrics for various machine learning algorithms, including our proposed model, FloodCNN-BiLSTM. Figure 12 illustrates the precision, while Figure 13 shows the recall values. In both metrics, FloodCNN-BiLSTM consistently outperforms the other approaches, demonstrating superior performance across all evaluated scenarios.

Table 3.8: Displays the F1-scores of the proposed model with existing techniques on dataset 2

F1-score			
Model/ Algorithm	**Class**		
	Low	**Moderate**	**High**
SVM	89.4	86.4	87.9
DT	84.6	85.7	86.4
ANN	82.0	87.3	90.0
DNN	87.5	90.6	86.8

NB	83.7	86.6	87.5
CNN	91.7	91.0	95.7
LSTM	91.29	94.54	93.9
Bi-LSTM	92.6	95.28	96.85
Proposed Model (FloodCNN-BiLSTM)	**93.18**	**94.46**	**96.80**

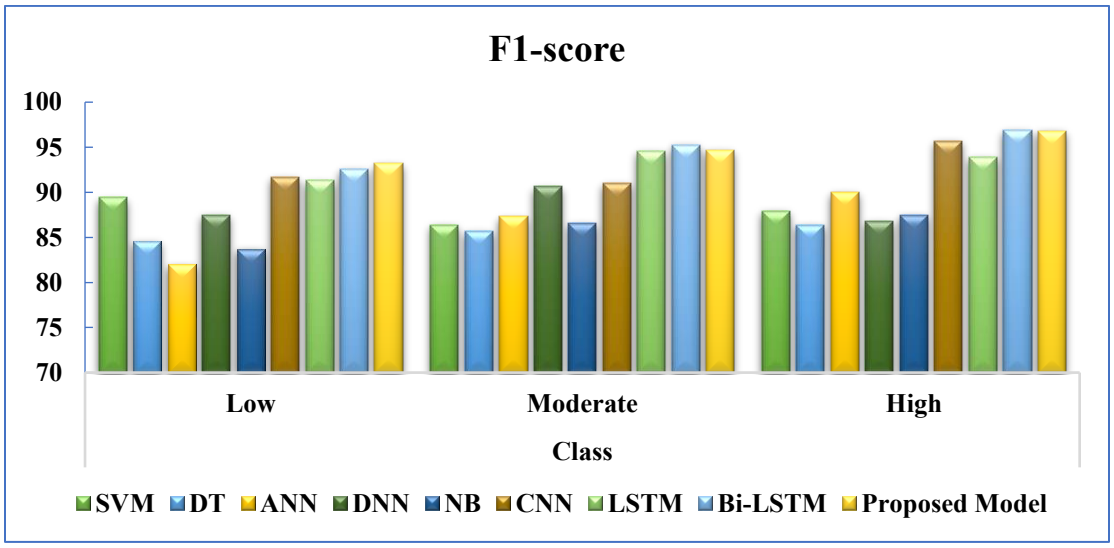


Figure 3.13: Visualization of categorized data and model F1-score for SVM, DT, ANN, CNN, LSTM, and the proposed model using Dataset 2

Table 3.9: Accuracy tabulation of Proposed Model with existing techniques on dataset 2

Model/ Algorithm	Accuracy
SVM	92.6
DT	90.9
ANN	95.5
DNN	96.4
NB	93.3
CNN	96.1
LSTM	97.0
Bi-LSTM	97.8
Proposed Model(FloodCNN-BiLSTM)	**98.6**

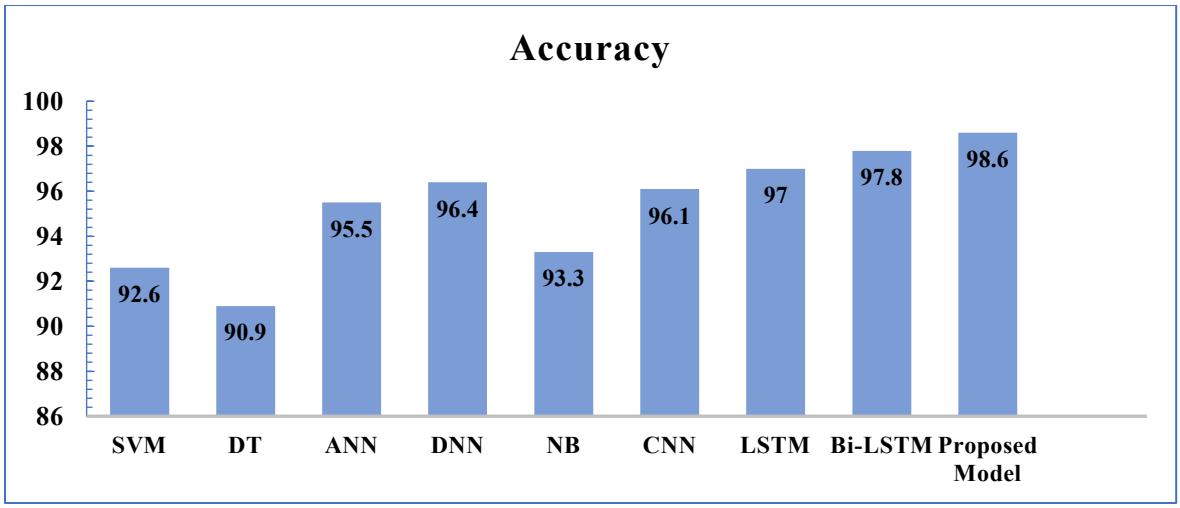


Figure 3.14: Accuracy comparison of SVM, DT, ANN, DNN, NB, CNN, LSTM, Bi-LSTM, and Proposed Model on dataset 2

Figures 3.13 and 3.14 show the performance evaluation of various machine learning models across different data classes. Figure 14 illustrates the F1 scores, while Figure 15 displays the accuracy metrics. The performance of each algorithm varies across data classes; however, our proposed model, FloodCNN-BiLSTM, consistently outperforms the others in both F1 score and accuracy. These results show the effectiveness and robustness of the FloodCNN-BiLSTM model across all evaluated scenarios.

Table 3.10: Comparison of Accuracy across Various Models for Dataset 1 and Dataset 2 Using the proposed model with existing techniques

Accuracy		
Model/ Algorithm	**Dataset 1**	**Dataset 2**
SVM	89.7	92.6
DT	87.3	90.9
ANN	90.8	95.5
DNN	92.6	96.4
NB	89.8	93.3
CNN	93.3	96.1
LSTM	94.7	97.0
Bi-LSTM	96.5	97.8
Proposed Model (FloodCNN-BiLSTM)	**97.3**	**98.6**

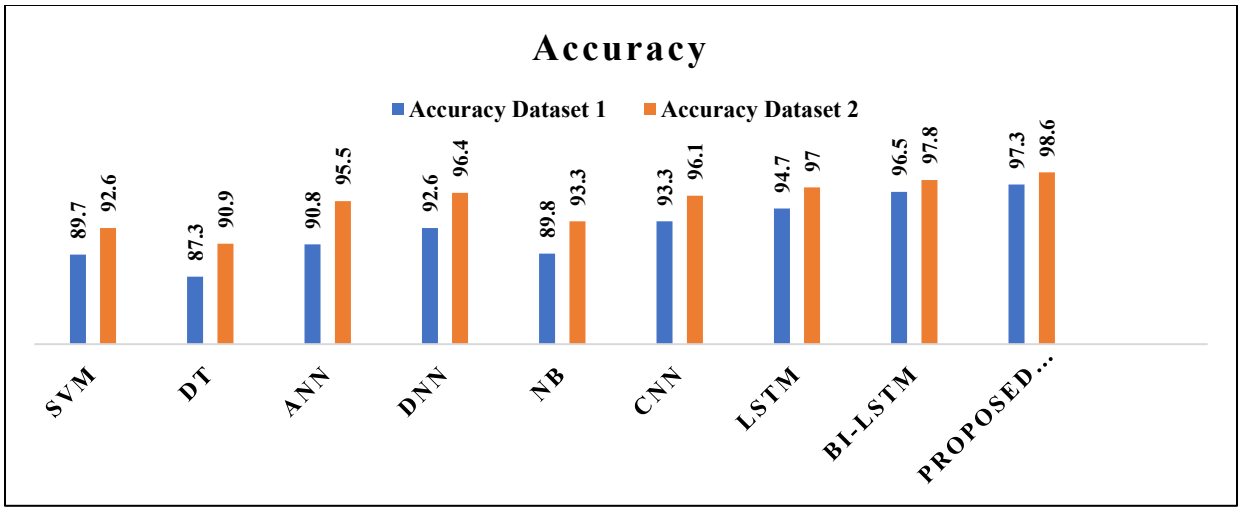


Figure 3.15: Comparison graph of accuracy on dataset 1 and dataset 2

Figure 3.15 clearly shows that our suggested FloodCNN-BiLSTM model has exhibited an important rise in accuracy when compared with standard flood detection approaches across multiple datasets. Our results show that our suggested FloodCNN-BiLSTM model performs well in flood prediction. This model is ideal for applications that require highly accurate inflow quantity projections, particularly in unusual and complex scenarios. Its superiority stems from its thorough evaluation, flexibility to individual situations, customized precision, and general robustness, making it an invaluable tool in the field of flood prediction, where precision is critical for effective decision-making. FloodCNN-BiLSTM emerged as the best option for accurately predicting inflow volumes. Our proposed FloodCNN-BiLSTM model has proven to be adaptable to a variety of geographical regions and environmental situations. This feature is critical for the development of early warning systems that allow for prompt actions and risk minimization.

3.3.5 Ablation Study

This section presents an ablation study to validate the contribution of the proposed architecture, which is trained using the mentioned dataset. In Case A, the model is evaluated without the FloodCNN-BiLSTM to determine its impact on feature extraction. The results obtained are lower due to the absence of FloodCNN-BiLSTM optimization for feature selection. In Case B, the LSTM is tested without the complete FloodCNN-BiLSTM to assess its standalone effectiveness; the results are lower as raw features are suboptimal for classification. The following are the cases for the ablation study:

Case A: Using only CNN

Case B: Using only LSTM

Case C: Using only Bi-LSTM

Case D: Concurrently using CNN and Bi-LSTM (proposed work)

Table 3.11: The ablation study was conducted using the proposed FloodCNN-BiLSTM architecture. Case A incorporates values obtained without using CNN. Case B includes studies on the incorporation of using only the LSTM for classification. Case C incorporates Bi-LSTM. Case D the concurrent use of CNN and Bi-LSTM.

Dataset	Ablation Study	Case	Accuracy	Precision	Recall	F1- score
Dataset 1	Using only CNN	**A**	79.5	81.9	84.0	82.9
	Using only LSTM	**B**	82.5	83.6	85.1	84.3
	Using only Bi-LSTM	**C**	84.1	86.6	83.2	84.8
	Concurrently using CNN and Bi-LSTM (proposed work)	**D**	**97.30**	**98.5**	**96.8**	**97.6**
Dataset 2	Using only CNN	**A**	80.2	81.5	83.1	82.3
	Using only LSTM	**B**	83.4	86.7	88.3	87.6
	Using only Bi-LSTM	**C**	86.9	89.3	87.4	88.3
	Concurrently using CNN and Bi-LSTM (proposed work)	**D**	**98.60**	**97.3**	**96.2**	**96.7**

Table 3.11 presents an ablation study evaluating the performance of various models on two datasets. Four configurations were tested: using only CNN, only LSTM, only Bi-LSTM, and a proposed approach combining CNN and Bi-LSTM. For Dataset 1, the proposed method significantly outperforms others with an accuracy of 97.30%, precision of 98.5%, recall of 96.5%, and an F1-score of 97.60, showing its superior capability in capturing features. Similarly, for Dataset 2, the proposed approach achieves the highest accuracy (98.60%), precision (97.3%), recall (97.2%), and F1-score (96.7), emphasizing its effectiveness. Comparatively, individual methods like CNN, LSTM, and Bi-LSTM deliver moderate results, underscoring the advantages of the synergistic use of CNN and Bi-LSTM in the proposed method.

3.3.6 Comparison of the Proposed Model with Existing Techniques

Table 3.12 summarizes performance metrics of various models for flood classification tasks. The proposed FloodCNN-BiLSTM model achieved the highest accuracy at 98.6%, with strong precision (97.3%), recall (96.4%), and an F1-score of 94.5%.

Table 3.12**:** Performance Comparison of Our Proposed Model with Existing Techniques

References	*Model*	*Accuracy*	*Precision*	*Recall*	*F1-score*
[97]	CatBoost	97.8	96.0	99.0	97.4
[98]	KNN	0.7317	0.74	0.74	0.74
[99]	Statistical Index model	90.3	-	-	-
[100]	FloodCast	90.59	96.10	93.69	94.88
[101]	DNN-SWARA	97.05	100	98.01	99.03
[102]	MaxEnt model	97.0	-	-	-
[103]	eXtreme Deep Factorisation Model	90.41	87.56	94.88	91.07
	FloodCNN-BiLSTM	**98.6**	**97.3**	**97.2**	**96.8**

CatBoost also performed well, achieving 97.8% accuracy and a high recall (99.0%), indicating its effectiveness in identifying true positives. The DNN-SWARA model excelled in precision (100%) and F1-score (99.03%) but had slightly lower accuracy at 97.05%. Statistical Index and MaxEnt models delivered comparable accuracies of 90.3% and 97.0%, respectively, though their other metrics were not reported. FloodCast achieved 90.59% accuracy with balanced precision (96.10%), recall (93.69%), and F1-score (94.88%). KNN, with an accuracy of 73.17%, was the weakest performer. The eXtreme Deep Factorisation Model had moderate results, with an F1-score of 91.07%. Overall, FloodCNN-BiLSTM emerged as the most accurate model for flood classification

3.4 Chapter Summary

This chapter investigated the application of artificial intelligence for enhanced flood detection and forecasting, presenting two hybrid deep learning models: FloodCNN-BiLSTM. The FloodCNN-BiLSTM model integrates Convolutional Neural Networks (CNN) for spatial feature extraction and Bidirectional Long Short-Term Memory (BiLSTM) networks for capturing temporal dependencies in sensor-based environmental data. The chapter emphasizes the value of combining image processing and AI-based techniques for accurate, real-time flood risk assessment and early warning system development.

Chapter 4

FLOOD DETECTION USING ARTIFICIAL INTELLIGENCE

Flood detection using image-based analysis has gained significant momentum with the rise of advanced artificial intelligence (AI) and image processing techniques. Traditional flood monitoring approaches often rely on sensor data or manual interpretation of satellite imagery, which are limited in scalability, precision, and response time. This chapter presents enhanced frameworks for flood classification that leverage the synergy between deep learning models and nature-inspired optimization algorithms. Specifically, two novel architectures, Flood-FireNet, which combines a SWIN Transformer with the Adaptive Firefly Algorithm (AFA), and Mo-SWIN, which integrates the SWIN Transformer with Monkey Search Optimization (MSO) are introduced to improve the extraction and selection of critical visual features from satellite and aerial imagery. These models are designed to address key challenges in flood detection, such as noise reduction, class imbalance, and the accurate delineation of flooded regions in complex environments. The chapter provides a detailed overview of image preprocessing, feature engineering, optimization strategies, and classification mechanisms, showcasing how AI-driven solutions can enhance the accuracy, robustness, and generalizability of flood detection systems.

4.1 Introduction

Floods are among the most frequent and devastating natural disasters, causing extensive damage to human life, infrastructure, agriculture, and ecosystems across the globe. The increasing incidence of extreme weather events, largely driven by climate change, has significantly amplified the risk and severity of floods in recent years. Urbanization and deforestation have further exacerbated the impact of flooding, disrupting natural drainage systems and increasing surface runoff. In light of these challenges, the development of robust and timely flood detection systems has become an essential component of effective disaster management and mitigation strategies [104, 105]. Traditional flood detection methods often rely on physical sensors, hydrological simulations, or manual interpretation of satellite images. While these methods provide useful information, they are limited by high operational costs, low spatial-temporal resolution, dependence on extensive manual effort, and a lack of adaptability to varying environmental conditions. Furthermore, the accuracy of such approaches is often compromised by noise, occlusions, and incomplete data coverage, particularly in remote or dynamically changing regions. These limitations necessitate the integration of more intelligent, automated, and data-driven approaches to flood detection and classification. Recent

advances in Artificial Intelligence (AI), particularly in computer vision and deep learning, have opened new avenues for flood image classification. AI models are capable of learning complex spatial and temporal patterns from image data, enabling precise identification of flood-affected regions. In particular, deep learning architectures such as Convolutional Neural Networks (CNNs) and Transformers have demonstrated remarkable success in image analysis tasks, including object detection, segmentation, and classification [106]. These models can process large volumes of satellite, drone, and aerial imagery to automate flood monitoring at scale, offering higher accuracy, faster response times, and greater operational flexibility.

However, despite the promising potential of deep learning models, challenges such as overfitting, high dimensionality, class imbalance, and redundant features continue to hinder their performance and generalization. To overcome these limitations, the integration of nature-inspired optimization algorithms with deep learning frameworks offers a powerful solution. Such algorithms mimic natural phenomena such as animal foraging behaviour or social interactions to optimize feature selection, reduce noise, and enhance model robustness [107, 108].

This chapter introduces two novel hybrid architectures that exemplify the synergy between deep learning and nature-inspired optimization for flood detection:

- Flood-FireNet, which combines the SWIN Transformer with the Adaptive Firefly Algorithm (AFA) for effective feature extraction and classification of flooded regions from satellite imagery. The AFA, inspired by the bioluminescent signaling and movement of fireflies, optimizes the selection of high-level features while filtering out noise and irrelevant background data. The SWIN Transformer leverages a hierarchical attention-based mechanism with shifted windows to capture both local and global image features efficiently.
- MoSWIN, which integrates the SWIN Transformer with Monkey Search Optimization (MSO). Inspired by the adaptive and cooperative foraging behaviour of monkeys, MSO enhances feature extraction by dynamically identifying the most informative visual patterns in flood images. The SWIN Transformer processes these features through a structured hierarchy of patch-based self-attention layers, improving the model's ability to distinguish flooded from non-flooded areas.

Both models were developed and tested using high-resolution flood image datasets and were benchmarked against established architectures such as ResNet18 and Vision Transformers. The combination of intelligent feature selection and advanced transformer-based classification enables these models to deliver superior performance, particularly in terms of accuracy, precision, recall, and robustness against noise and occlusion. The proposed architectures also incorporate advanced preprocessing techniques, including image denoising, augmentation, segmentation using Gaussian Mixture Models, and dimensionality reduction via Principal Component Analysis (PCA). These steps ensure that the input data is clean, representative, and

conducive to effective learning. Through this holistic approach, Flood-FireNet and MoSWIN address key limitations of traditional methods while enhancing scalability, adaptability, and decision-making speed.
In the broader context of disaster management, these AI-driven models contribute to the development of intelligent flood early warning systems and risk assessment frameworks. Their ability to process real-time visual data and deliver actionable insights can significantly support emergency response teams, urban planners, and policy-makers in mitigating flood-related risks and optimizing resource allocation.

4.2 Dataset Description

The dataset utilized in this study serves as a comprehensive and annotated collection of flood-related images, specifically curated for interactive content-based image retrieval tasks. It consists of 3,710 images, the majority of which were captured during the Central European floods of May and June 2013 and subsequently retrieved in July 2017. This dataset offers a diverse representation of flooded and non-flooded areas, enabling robust training and evaluation of deep learning models for flood detection and classification. Out of the total collection, 3,435 images are accompanied by detailed annotations, and 890 images include metadata specifying the geographical location of the scenes. An additional 275 images depicting water contamination were manually collected from various online image search engines to enrich the dataset's variability and realism. The primary objective associated with this dataset is binary classification: determining whether a given location in an image is flooded or not flooded. The dataset features a wide range of environmental conditions, lighting scenarios, and flood intensities, making it suitable for evaluating the generalizability of AI models in realistic flood detection applications [109].
In this research, the same dataset was employed to train and evaluate two proposed models, MoSWIN and Flood-FireNet. However, different data partitioning strategies were adopted to tailor the experiments according to each model's architectural requirements and training paradigms:

- For the MoSWIN model, the dataset was split into 80% training and 20% testing sets to maximize training data availability and ensure robust model generalization.
- For the Flood-FireNet model, a 70:15:15 ratio was used, allocating 70% for training, 15% for validation, and 15% for testing, facilitating model tuning and early stopping during training over 100 epochs.

This dataset played a critical role in validating the effectiveness of both models by providing high-resolution imagery with real-world flood conditions. Its richness and diversity allowed for the development of reliable, adaptable, and scalable AI-based flood detection systems.

4.3. Introduction to Mo-SWIN Model

In this section, we provide an overview of the state-of-the-art techniques that served as the basis for the classification flood dataset. The performance and precision with which these techniques could classify the data in the dataset led to their thorough selection and evaluation. By utilizing these state-of-the-art methods, the flood dataset categorization process produces exceptionally accurate findings of the highest quality.

4.3.1. Monkey Search Optimization

MSO is a relatively recent metaheuristic optimization technique inspired by monkeys' food search behavior. MSO is a nature-inspired method used to solve optimization issues, mostly in machine learning and evolutionary computation [110].

The general process of Monkey Search Optimization is as follows:

- **Exploration and Curiosity:** Monkeys have a reputation for their curiosity, and MSA reflects this in the algorithm's capacity to thoroughly investigate the optimization environment. The program employs many ways to produce and evaluate alternative solutions.
- **Resource Allocation:** MSA, like monkeys, efficiently allocates resources to various possible solutions. This allocation is based on each solution's ability to produce superior results.
- **Local and Global Search:** Monkeys are adept at both local foraging and long-range exploration. Similarly, MSA balances local and global search techniques to improve the search process.
- **Adaptation:** Monkeys adapt to their surroundings, and MSA adapts its search parameters as the optimization terrain changes, assuring continuous improvement.
- **Communication and Collaboration:** Monkeys are communicative and cooperative. This is represented in MSA as the dissemination of information and solutions among members of the population.

4.3.2. Transformer

Transformers, a deep learning architecture, is renowned for its expertise in sequence modeling applications. In the meantime, it has completely transformed natural language processing (NLP) domains and performed well in a variety of other areas as well. Transformers, use a self-attention mechanism to identify connections between various items in a sequence [111].

(A) Self-Attention Mechanism

- **Queries, Keys, and Values**: Each element (token) for a given series is converted into three distinct vectors: Value, key, and Query.

- **Attention Scores:** Determines each token's significance or importance about the current one by comparing its query with the keys of all other tokens.
- **Weighted Sum:** The degree to which each Value adds to the current token's representation is determined by these scores.

(B) Encoder-Decoder Architecture

- **Encoder:** Uses self-attention layers to process the input sequence and provide a contextual representation for every token.
- **Decoder:** Predicts the output series by focusing on the representations of the encoded input series and gradually producing tokens.

4.3.2.1 Swin Transformer

Swin Transformer utilizes a hierarchical design to function as a backbone for CV operations, rather than just a detecting head. Swin Transformer is a hierarchical vision transformer that uses patch partitioning and merging to reduce spatial dimensions and extend channels. To simulate global and border properties, the Swin Transformer [112] uses a shifted window along the spatial dimension. In contrast to previous Transformer models, Swin Transformer creates a feature map that is hierarchically represented, resembling CNN's feature pyramid structure. The receptivity increases with the network level, allowing for the extraction of the image's multi-scale elements. The computation is significantly decreased and linear with the image size thanks to the swin transformer's second feature, which separates the feature map with several windows. Each non-overlapping window calculates local multi-head attention without window correspondence [113].

4.3.2.2 Vision Transformer

While convolutional architectures are still the industry standard for CV tasks, transformers have emerged as the model of choice for natural language processing (NLP) applications. Attention techniques are used with these architectures to preserve the structure of convolutional networks. After the successful implementation of transformer scaling in NLP, this uses a conventional transformer to convert images directly. Transformers are not subject to some empirical biases found in CNNs, such as translation invariance and spatially limited receptive fields [114]. Translation, a feature of CNNs, is the shifting of an image pixel by a predefined amount in a specific direction. Grid-structured data requires sequences handled by a typical transformer because of its permutation invariance. As a result, vision transformers (ViT), which can carry out CNN functions, were created. This is accomplished by first dividing an image into patches, and then feeding the linear embedding of these patches into a conventional transformer encoder. After

receiving image labels in a supervised manner, the model is then pre-trained and refined for image classification using a downstream dataset. The benefits of both CNN and transformer designs can be coupled using this technique to create a model that can manage image data efficiently and use the transformer's attention mechanism [115].

4.3.2.3 ResNet-18

The ResNet18 is often used to tackle the performance deterioration challenge through the addition of residual blocks yet ensuring model performance. It consists of entirely connected layers, residual structures, pooling layers, normalized layers, and convolution layers. In the process of developing CNN, more features can be taken from the network the deeper it is built [116]. To attain higher-level features, we therefore typically need a deeper network structure. The three issues of gradient disappearance, gradient explosion, and network deterioration will materialize when we employ deep network architectures, nevertheless. Figure 4.1 shows the detailed architecture of ResNet 18 [117].

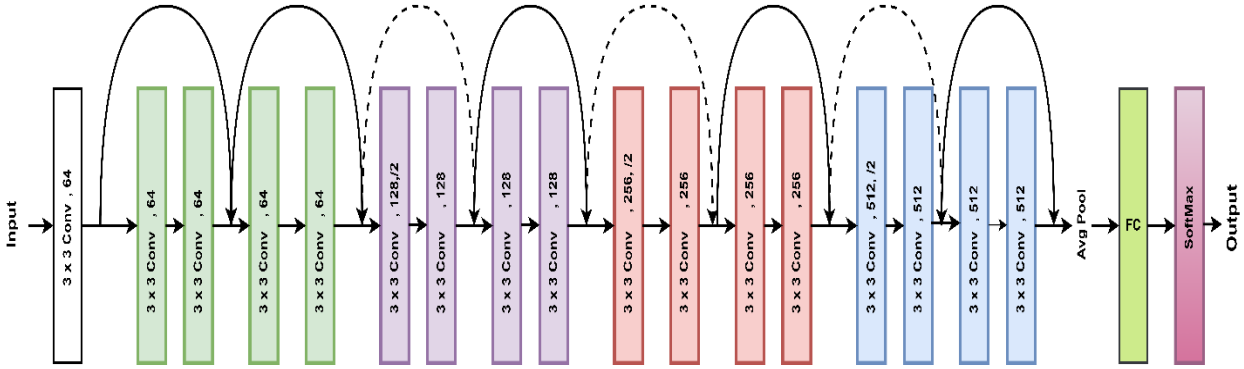


Figure 4.1: Layered Architecture of ResNet 18 Model

It is more compact than deeper ResNet variations, making it appropriate for resource-constrained settings. It includes residual blocks, which comprise identity and residual pathways, for dealing with gradient concerns in deep networks. ResNet-18 performs well in image classification and other C applications, balancing model complexity and performance. A neural network's depth is vital for performance, however as depth rises, there may be a risk of degradation brought on by the problem of vanishing gradients [118]. The loss of minute detail in maps of features at high-level layers causes this problem, which is distinct from overfitting. The ResNet-18 is a deep residual network design with 18 layers that the author developed to solve this problem to increase the effectiveness of convolutional neural network training [119]. The ResNet-18 can learn detailed feature representations of various images, and the usage of skip connection blocks allows the network to be optimized, increasing model accuracy. Skip connections are used to implement an

equivalent mapping by introducing parameters or raising the computational complexity in place of conventional monotonically progressive convolutions.

4.3.3 Proposed SWIN transformer and nature-inspired solution for flood image classification

The current research on flood detection and prediction is mostly concerned with machine learning (ML) and deep learning (DL) techniques. However, there is a significant gap in research into nature-inspired approaches to flood disaster management. These bio-inspired approaches, which draw inspiration from natural processes, can improve traditional flood management technologies. Embracing nature-inspired solutions is a promising opportunity to strengthen flood management capabilities. The proposed architecture consists of two modules: the swin transformer along with a nature-inspired solution. The primary idea behind this model is to improve the visual information used for flood image detection while striving for better performance.

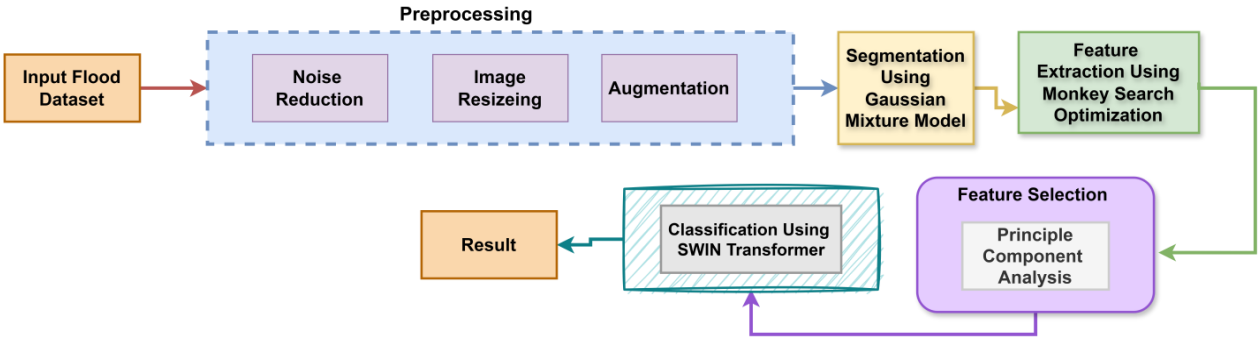


Figure 4.2: Sequential components of our proposed Mo-SWIN architecture

Figure 4.2 visualizes the successive steps of our proposed MoSWIN model. The major purpose of the model is to extract useful information from flooded images. Feature extraction, a complicated and challenging task, precedes subsequent classification of images. The proposed model is being developed in several steps, beginning with the collection of flood prediction data. The focus then switches to data preprocessing and noise removal from the acquired datasets followed by resizing and augmenting images. The method entails segmenting incoming data, extracting essential features, selecting the most relevant ones, and then using the swin transformer architecture to classify. This approach improves the understanding and categorization of complex visual data by utilizing transformer technology for image classification and object detection.

4.3.3.1 Preprocessing

In flood image analysis, feature extraction is the process of locating relevant characteristics or patterns in raw data to help with tasks like classification. Scaling issues, noise, and variability all increase this process'

complexity. "We perform image resizing to standardize the dimensions and reduce computational complexity, ensuring consistency across the dataset. Initially, the images are 512 pixels wide, and for our experiment, we resize all images to a uniform size of 224 x 224 pixels. After resizing, we apply image augmentation to further enhance the model's robustness. This technique involves transforming the original images using various operations such as rotation, scaling, flipping, and other variations, which helps increase the diversity of the training data and improve the model's generalization capabilities."

4.3.3.2 Segmentation

In the segmentation, images are broken into small blocks for feature extraction and to segment flood images we use the Gaussian Mixture Model (GMM). To assign each pixel to the most likely Gaussian component, the GMM for flood image segmentation uses the Expectation-Maximization (EM) technique to iteratively improve model parameters, including the number of Gaussian components and their distributions. First initialize model parameters, such as the number of Gaussian components then their initial values, and then use the EM algorithm to optimize them iteratively [119]. The image is essentially divided into areas by this method, which allocates each pixel to the Gaussian component with the highest probability.

4.3.3.3 Feature Extraction

In this section, we describe the feature selection process, which identifies and selects significant features for flood image classification. Several techniques have been applied to image processing, including deep learning and nature-inspired optimization strategies. We focus on MSO, which is inspired by the food-searching and hunting behaviours of monkeys. MSO is an adaptive and efficient optimization strategy [120]. The MSO algorithm is used to eliminate background and non-relevant areas in flooded images, while selecting features from the remaining regions. In this analogy, the images are considered as forests, and the non-edible background regions are discarded, as monkeys would avoid them in their search for food. This behaviour is formalized in the optimization process to define boundaries between relevant and irrelevant areas in the image. Gaussian filtering is applied post-segmentation to extract meaningful features by smoothing the image and reducing noise. This approach preserves key structural details while filtering out unnecessary information.

The MSO algorithm has been enhanced to emphasize its self-organizing and adaptive features, which allow it to dynamically adjust to environmental changes during the optimization process [121]. The MoSWIN model builds upon this adaptability, incorporating real-time search parameter adjustments to improve performance. Additionally, feedback-driven mechanisms fine-tune the SWIN transformer, allowing it to respond to performance feedback and continuously evolve. This adaptability is particularly valuable in the context of flood scenarios, where new datasets and environmental conditions require ongoing model

improvement. A comparison with other evolving AI models further highlights MoSWIN's strengths, including its ability to self-learn, self-develop, and adapt. The potential for long-term evolution is especially important for tackling dynamic challenges in flood classification. Future work will explore the integration of self-adaptive transformers and lifelong learning techniques, further enhancing MoSWIN's ability to evolve with new data and tasks. In the following algorithm 1, we explain the working of our proposed MSO algorithm. Here, we use the monkeys' hunting and food-searching behaviours to choose the features of the associated dataset. The following algorithm takes a dataset of flood images as input and generates the output of the best feature from the corresponding feature set. The parameters we defined are [M^{Size}, Max^{itr}, L_b, U_b]. Where M^{Size} represents the size of the population of monkeys, Max^{itr} represents the maximum number of iterations required for the hunting process, L_b denotes the lower bound of search space, and U_b denotes the upper bound of search space. In our algorithm, we consider 40; the Maximum iteration is 100; the lower bound of the search space is -10; the upper bound of the search space is 10. We calculate the monkey's fitness in every iteration using a formula provided by the algorithm to find the best solution.

Algorithm 1: Monkey Search Optimization (MSO) Algorithm for feature selection of flood image

Input: Flood image dataset ***Output:*** The best features found and the corresponding feature set.
Input: Flood Image Dataset ***Parameters*****:** M^{Size}, Max^{itr}, L_b, U_b **Start:** **1.** Define the objective function **2.** Initialize Monkey Search Algorithm (MSA) parameters: $M^{Size} = 40; Max^{itr} = 100; L_b = -10; U_b = 10$ **3.** Define the Monkey Search Algorithm function: - objective_function_O_f: Objective function to evaluate the feature score - population_size: Number of monkeys in the population - max_iterations: Maximum number of iterations - lower_bound: Lower bound of the search space - upper_bound: Upper bound of the search space - best_solution: Best solution found - best_fitness: Fitness value of the best solution - fitness_history: List of best fitness values over iterations **4.** Initialize the population with random solutions (monkeys) within the search space bounds. **5.** Initialize the best solution and fitness to infinity.

6. For each iteration up to max_iterations:
a. Calculate the fitness of each solution (monkey).
$Fitness = [\ O_f(solution)\ for\ solution\ in\ total\ population]$
b. Update the best solution found and its fitness.
$Min_{Fitness} = min\ (fitness)$
$If\ Min_{Fitness} < Best_{Fitness}$
$Best_{Fitness} = Min_{Fitness}$
$Best_{Solution} = population[np.argmin(fitness)\ ]$
c. Generate new solutions based on random perturbation within the search space bounds.
d. Replace the old population with the new population.
$Population = New\_population$
e. Store the best fitness for this iteration.
$Fitness_{History}.append(Best_{Fitness})$

7. Return the best solution found, its fitness value, and the fitness history.

8. Run the Monkey Search Algorithm function with the defined parameters.

Stop: Either Max^{itr} or *Stopping criterion*

Output: The best features found and the corresponding feature set.

Table 4.1: Hyperparameter Settings Used for MoSWIN Model

Hyperparameter	Value	Description
General and Swin Transformer Parameters		
Learning Rate	0.0001	Learning rate for Adam optimizer used in Swin Transformer training
Batch Size	32	Number of images processed per training batch
Epochs	100	Total number of training iterations
Optimizer	Adam	Adaptive optimizer for backpropagation
Image Size	224 × 224	Resized input image dimensions
Dropout Rate	0.2	Dropout regularization to reduce overfitting
Window Size (Swin)	7	Size of attention window in Swin Transformer
PCA Variance Threshold	95%	Percentage of variance retained during PCA
Monkey Search Optimization (MSO) Parameters		
Monkey Population Size	40	Number of candidate solutions (monkeys)
Number of Iterations	70	Maximum optimization steps
Lower Bound (Lb)	-10	Minimum search space value for MSO
Upper Bound (Ub)	10	Maximum search space value for MSO

Dimensions	Num_of_features	Dimensionality of the solution space, equal to number of features

Table 4.1 outlines the MSO hyperparameters used in this process. A population size of 40 monkeys and 70 iterations ensures sufficient exploration and convergence without excessive computation. The search space for feature weights is bounded between -10 and 10, and the dimensionality is equal to the total number of extracted features. Each monkey represents a potential binary vector that selects a subset of features, with the fitness function evaluating its utility in improving classification performance.

4.3.3.4 Feature Selection

To achieve an accurate feature selection, the number of features is reduced using the principal components analysis (PCA)approach. We applied Principal Component Analysis (PCA) for dimensionality reduction to reduce overfitting and computational complexity in high-dimensional data. By retaining the most significant variance, PCA enhances model efficiency and performance [122]. It also mitigates the curse of dimensionality, especially in image classification tasks with highly correlated input features. To detect correlations between features, PCA generates a covariance matrix. Eigenvalue decomposition is used to extract eigenvectors and eigenvalues, and principal components are chosen based on their variance contribution. Data is projected onto these PCs, reducing dimensionality while retaining important information. Finally, the modified data makes feature selection easier, allowing you to discriminate between flooded and non-flooded portions in the image for later analysis or classification activities.

4.3.3.5 Classification using SWIN

For the data classification, the proposed model used a Swin Transformer and PCA. PCA followed by a SWIN transformer for flood data classification is an intriguing method that blends dimensionality reduction with advanced transformer-based image classification models. The Swin transformer is a computer vision deep learning model architecture that performs object recognition through a hierarchical method. Unlike typical transformers, Swin Transformer uses a hierarchical structure to separate input images into non-overlapping patches at various scales [123]. It is possible to capture both local and global image features with the Swin Transformer architectural concept. An input image is split up into several distinct, non-overlapping patches, which are subsequently handled by different transformer layers. Every transformer layer has several attention heads that focus on various portions of the incoming image [124].

1. **Patch Partition:** Swin transformer processes an image by dividing it into non-overlapping patches.

2. **Patch Merging:** Patch merging is a critical layer in Swin Transformer design since it creates an inductive bias in Swin, which was missing in the original ViT and DeIT. Patch Merging is a convolution-free downsampling method. A factor of n can downsample feature maps by concatenating them depth-wise after the input is divided into groups, each of which contains *n x n* surrounding patches. By merging two *2x2* windows into a new window, patch merging reduces the size of the feature map by half and deepens each patch by *2*. Equation 4.1 below shows the formula for transforming the input size.

   Transforming the input from a shape of H x W x C to (H/n) x (W/n) x (2nC) (4.1)

3. **Swin Transformer block:** Swin transformer replaces ViT regular multi-head self-attention (MSA) with two new MSA shifted window (SW-MSA) and window-based (W-MSA). Two encoders are linked in series in a basic swin transformer block, where the output from the first feeds the second encoder. The very first encoder computes W-MSA, whereas the second computes SW-MSA based on the first encoder's output. A Swin transformer block has a similar architecture to the original transformer encoder block, except for the technique for computing attention. Unlike the simple global MSA generated in a conventional encoder block, the Swin transformer block includes W-MSA and SW-MSA.
4. **Window-based Self-Attention (W-MSA):** The SWIN transformer uses encoder blocks from the original Transformer architecture. The encoder blocks consist of a feed-forward network and a multi-headed self-attention module. Swin transformer makes use of a Window-based MSA technique. In swin, we use fixed-sized windows with a fixed number of patches (M × M patches in the paper). After that, attention is calculated only within each window. Results in a complexity that is linear in the number of patches shown in equation 4.2 below.

$$\Omega(W\ M\ S\ A) = 4hwC^2 + 2M^2(hw)C \quad (4.2)$$

5. **Shifted Window-based Self-Attention (SW-MSA):** Shifted Window-based Self-Attention (SW-MSA) is used to overcome the limitation of W-MSA's modeling power, which would result from lacking the relationship between the windows. The SW-MSA takes the output of W-MSA first. Then, about the layer before, each window is shifted by (M/2, M/2). and calculate W-MSA in a shifted window last. But this change leaves some windows with unfinished patches and others with "orphaned" patches—patches that don't belong to any window. The "orphaned" patches are moved into windows having incomplete patches by swin transformer using a "Cyclic Shift" approach.

6. **Relative Position Bias:** Relative position bias (B of size (M^2xM^2)) is a feature of Swin Transformers used to calculate self-attention. Equation 4.3 shows the formula for calculating attention.

$$Attention\ (Q, K, V) = Softmax\left(Q\,K^t/\sqrt{d} + B\right)V \tag{4.3}$$

The query, key, and value matrices are denoted by Q, K, and V, respectively. The query/key dimension is represented by d, while the number of patches in a window is represented by M^2. Compared to transformers that employ absolute position embedding, relative position bias considerably increases performance.

4.3.3.6 Working of our proposed Architecture

Our presented architecture for flood detection is shown in Figure 4.3, which takes advantage of the complementary strengths of the SWIN transformer model and the MSO algorithm. This novel method uses revolutionary deep learning architectures and sophisticated optimization approaches to improve the efficiency and accuracy of flood detection. In our proposed methodology, the initial phase makes use of row images displaying both flooded and non-flooded areas. To improve the visual appeal of these images, we do multiple preprocessing steps. These include noise reduction, image enhancement, and image resizing. The first stage in this preprocessing procedure is noise removal, which uses the Wavelet Denoising filter. This filter successfully reduces any undesirable noise in the images, resulting in clearer and more precise data for further analysis. After noise removal, we apply image augmentation techniques. Furthermore, image scaling is done to ensure that the dimensions are consistent across all photos. This provides consistency and enables effective processing throughout the model.

We use segmentation algorithms to provide more robust feature extraction. Segmentation using the Gaussian mixture model (GMM) is applied here. GMM segmentation allows the separation of significant features pertinent to flood detection by dividing the images into discrete regions according to pixel intensities. The MSO method was used to extract the related features from flooding images, with a focus on phasing out the background and separating relevant image sections. Inspired by monkeys' group foraging behaviour, the system classified image regions as edible or non-edible, mimicking the quality of food in a forest environment. Low-quality background areas were removed, while high-quality regions with important information were chosen for further processing. This method successfully segmented and extracted information from flooded photos by using the monkey foraging analogy. Feature selection is an essential phase after feature extraction, which extracts texture, shape, and intensity aspects from the data. The large dimensionality of these features can reduce classification accuracy and processing efficiency. Principal Component Analysis (PCA) is a popular mechanism for reducing feature dimensionality while conserving important information by retaining and detecting the most significant variability in data. This

reduced feature set increases both classification performance and processing economy. For the data classification, the proposed model used PCA and SWIN transformers.

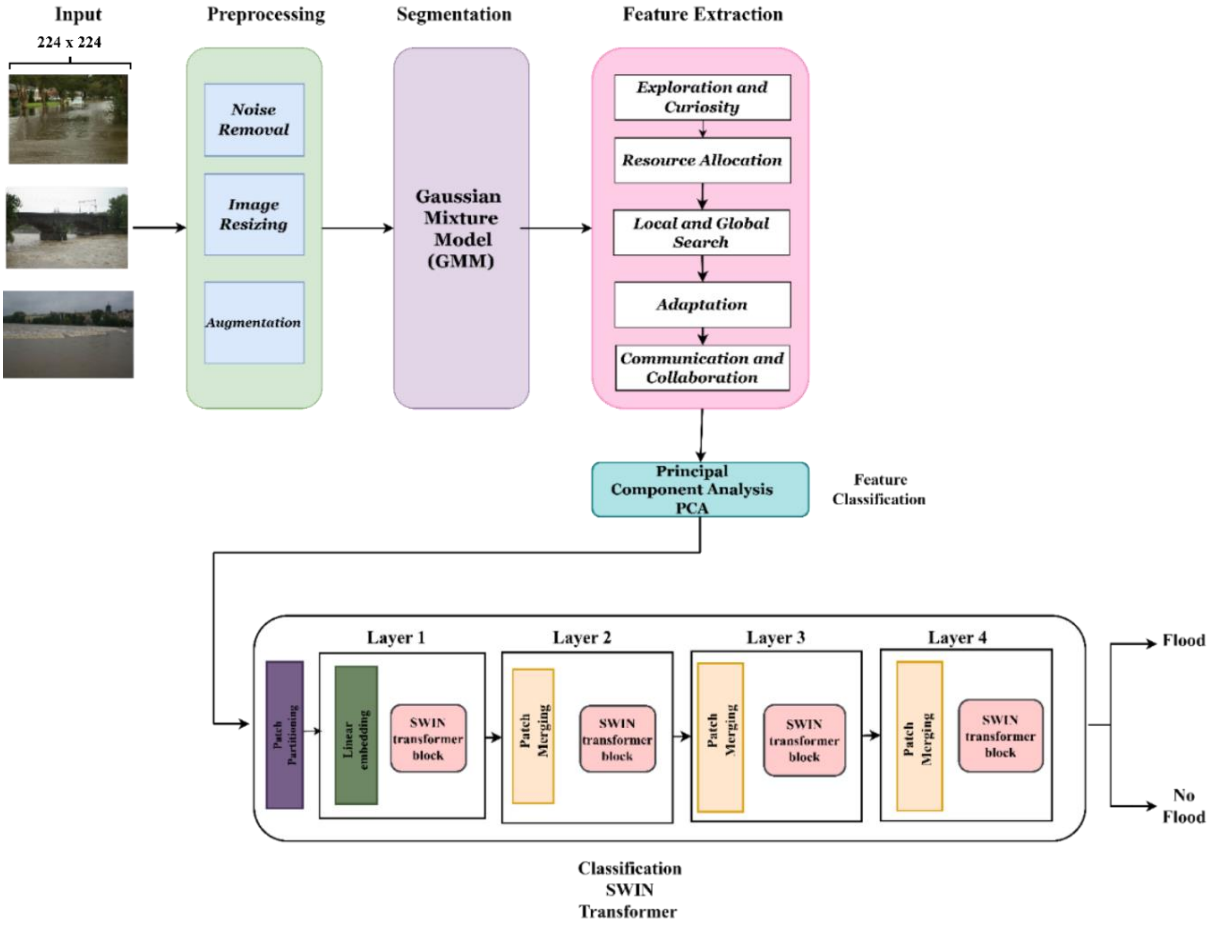


Figure 4.3: Architecture of our proposed Mo-SWIN model for flood detection

By combining PCA with the Swin Transformer, the model takes advantage of both techniques' complementary characteristics. The PCA successfully decreases the dimensionality of the input data, and the SWIN Transformer uses this reduced representation to do effective sequence modeling for classification. This synergistic combination improves the model's capacity to handle high-dimensional input while retaining great classification results efficiently. The SWIN Transformer divides images dynamically into patches, allowing for fast feature extraction at many scales. This method improves the model's capacity to capture fine detail while reducing its computational complexity. Furthermore, the model uses self-attention to understand global context, allowing it to recognize complex patterns required for correct classification. The swin transformer's adaptability across domains adds to its appeal, making it an ideal candidate for obtaining higher performance in data classification jobs.

4.3.4 Result Analysis and Discussion

This section analyzes the experimental results of the proposed flood prediction models using metrics like accuracy, precision, recall and F1-score. Comparative evaluations with existing methods highlight strengths and limitations, offering insights into model performance and applicability for real-world flood forecasting.

4.3.4.1. Performance Evaluation Metrics

To assess the effectiveness of the proposed model and compare it with existing deep learning architectures, several standard evaluation metrics were employed, as shown in Table 4.2. These include Accuracy, Precision, Recall, and F1-score, which provide a comprehensive understanding of model performance, particularly in imbalanced or binary classification tasks such as flood detection. In the context of flood detection, minimizing False Negatives (FN) is critical, as misclassifying an actual flood event can lead to severe consequences. Therefore, Recall and F1-score are particularly important indicators of model robustness.

The following notations are used in defining these metrics:

- **TP (True Positive):** Number of correctly predicted positive (flood) instances.
- **TN (True Negative):** Number of correctly predicted negative (non-flood) instances.
- **FP (False Positive):** Number of non-flood instances incorrectly predicted as flood.
- **FN (False Negative):** Number of flood instances incorrectly predicted as non-flood.

Table 4.2: Performance Evaluation Metrics and Their Equations

Parameter	Equations
$\boldsymbol{Accuracy}$	$\frac{TP + TN}{TP + TN + FP + FN}$
$\boldsymbol{Precision}$	$\frac{TP}{TP + FP}$
$\boldsymbol{Recall}$	$\frac{TP}{TP + FN}$
$\boldsymbol{F1 - Score}$	$\frac{Precision * Recall}{Precision + Recall}$

4.3.4.2. Result Analysis on Mo-SWIN

The proposed model Mo-SWIN is assessed using two of the most popular algorithms for classification, such as ResNet 18 and vision transformer. These techniques are used in images of floods, a calamity that occurs frequently. We compare the results of our proposed (Mo-SWIN) model with the existing Resent 18 and vision transformer model. ViT is an image processing system that treats image patches like sequences, whereas ResNet-18 is an 18-layer CNN. The proposed approach combines the SWIN architecture for classification with MSO for feature extraction.

Table 4.3: presents a comparison of the proposed model Mo-SWIN with current methods

Model	Accuracy	Precision	Recall	F1-score
ResNet 18	85.37	93.33	78.68	82.35
Vision Transformer	90.24	94.25	82.35	87.36
ResNet 50	94.20	94.20	85.21	90.52
Proposed Model (Mo-SWIN)	***96.53***	***95.41***	***90.51***	***92.48***

The above table 4.3, presents experimental outcomes obtained from utilizing the proposed (Mo-SWIN) model alongside two existing methods. Notably, the proposed model demonstrates superior performance across multiple metrics, including recall, accuracy, precision, and F1-score. The results showed that, in both training and test image environments, the proposed approach performs significantly. These classification results are visually represented in Figures 4.4 and 4.5.

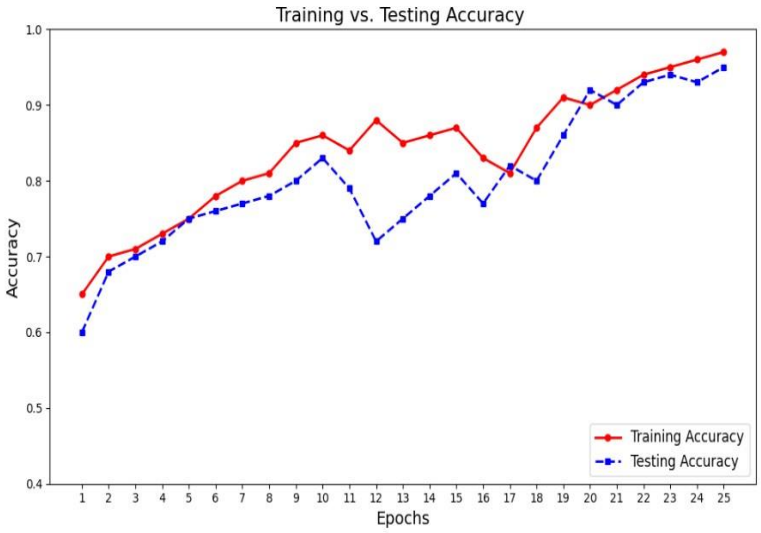


Figure 4.4: Accuracy graph of our proposed Mo-SWIN model

For this experiment, the dataset was split into training, testing, and, validation sets. In this experiment, 15% of the data were used to test the model, another 15% were used to validate it, and the remaining 70% of the data were used to train it. Our model was trained over 100 epochs. Figure 4.5 highlights the superior performance of the proposed Mo-SWIN model in flood image classification, achieving higher accuracy and consistent training results. The graph shows accuracy (Y-axis) over epochs (X-axis), demonstrating Mo-SWIN's reliability and effectiveness in testing scenarios compared to existing models, emphasizing its strength in consistent classification.

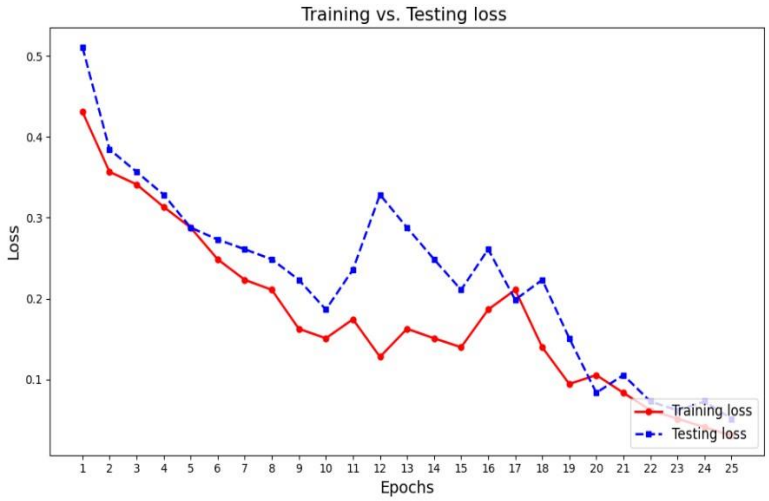
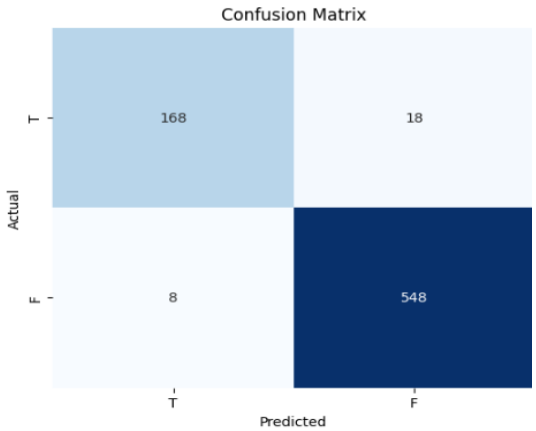
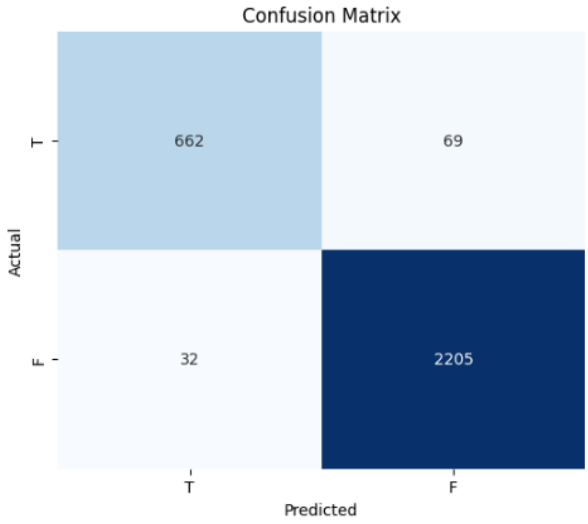


Figure 4.5: Loss graph of our proposed Mo-SWIN model

Figure 4.5 shows the loss vs. epoch graph, highlighting Mo-SWIN's superior performance. The model consistently reduces training loss, demonstrating effective learning and error minimization. With lower final loss values than competitors, Mo-SWIN excels in flood image classification. The X-axis represents epochs, and the Y-axis represents the loss.



(A)



(B)

Figure 4.6: Confusion Matrix illustrating the classification model's performance for (A) test data and (B) training data

A thorough assessment of the classification model's performance is given by the confusion matrix as represented in figure 4.6. With 168 true positives (TP), 548 true negatives (TN), 18 false positives (FP), and 8 false negatives (FN) in a single instance, the model shows great accuracy with a significantly higher proportion of accurate predictions than errors. The matrix shows 662 TP, 2205 TN, 32 FP, and 69 FN in a different scenario, demonstrating the model's accuracy in classifying the majority of cases while also pointing out areas that require development. These findings make it possible to compute important measures like precision, recall, and F1-score, which provide more in-depth understanding of the model's dependability and efficacy in differentiating between positive and negative classifications.

Figure 4.7 provides a comparative performance evaluation of all models using bar charts for Accuracy, Precision, Recall, and F1-Score. Mo-SWIN clearly surpasses the other models, highlighting its optimized architecture and training strategy. The integration of Swin Transformer for hierarchical feature learning and the MSO algorithm for feature extraction contributes significantly to this performance improvement.

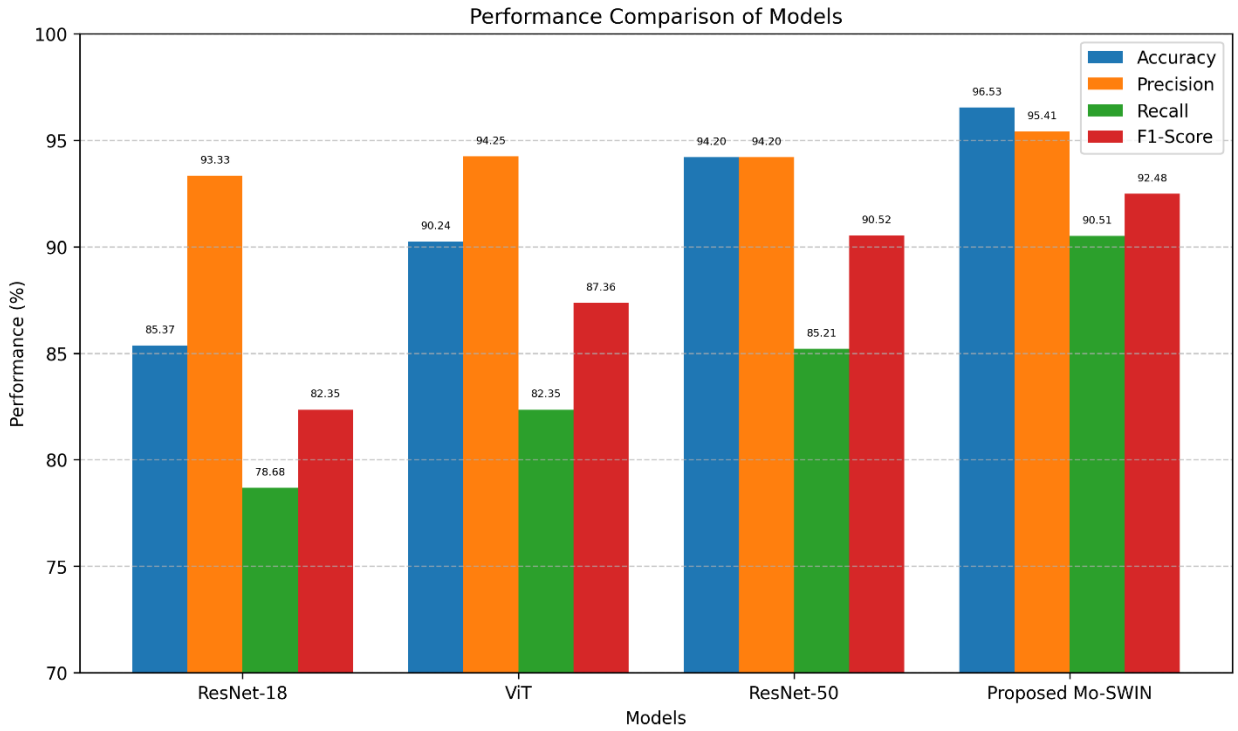
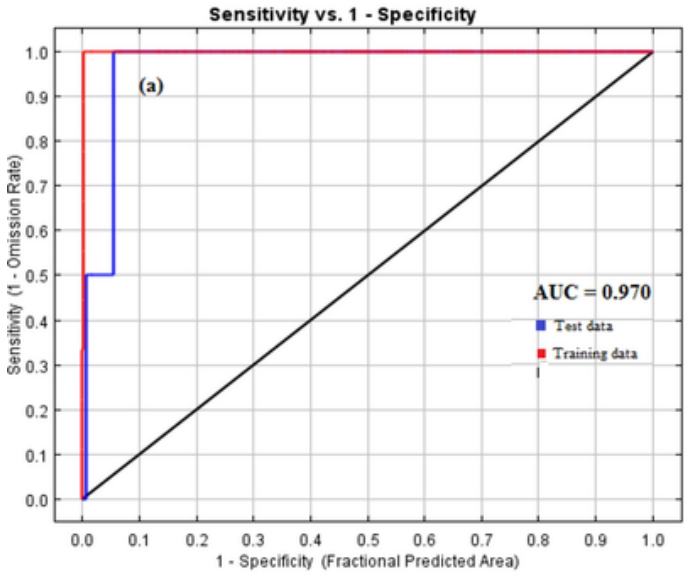
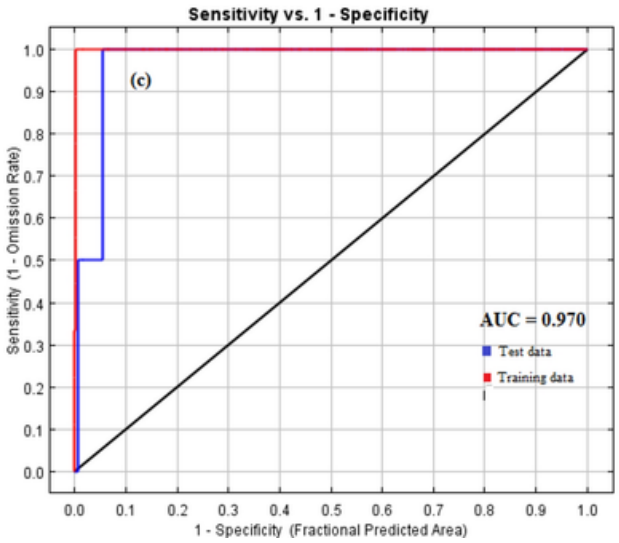


Figure 4.7: Comparative Performance Evaluation of Proposed Mo-SWIN and Baseline Models Using Standard Classification Metric

4.3.4.3 ROC curve of our proposed model



(A) Training



(B) Testing

Figure 4.8: ROC Curve depicting the model's classification performance for (A) training and (B) testing data

In the figure 4.8, The ROC curve assesses a classification model by plotting sensitivity against specificity is illustrated in figure 4.9. It includes red and blue curves for training and test data, demonstrating strong performance. The AUC is 0.970, indicating high accuracy

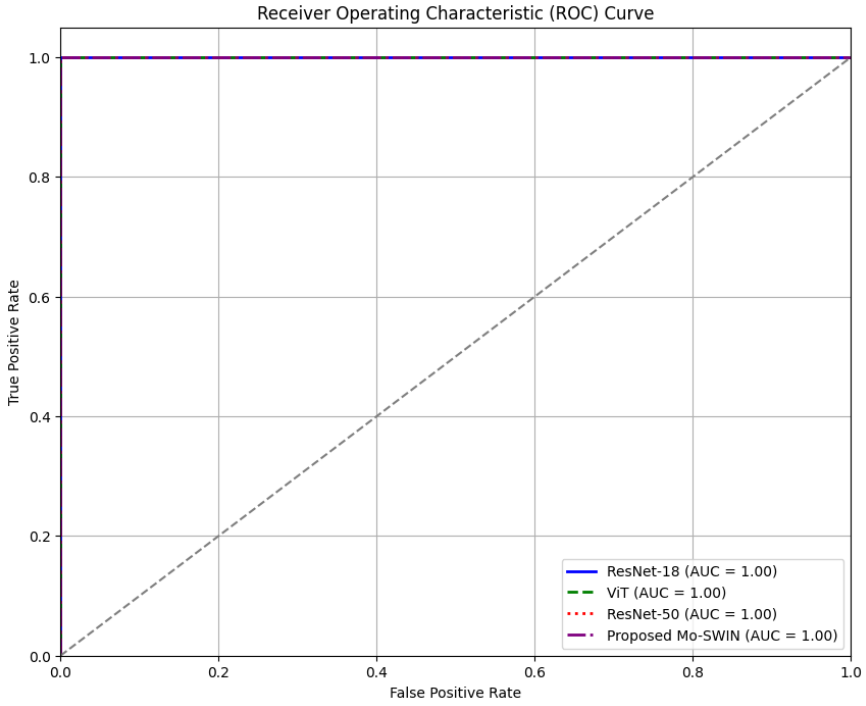


Figure 4.9 Comparative ROC Curve Analysis of Mo-SWIN and Benchmark Models

In conclusion, the Mo-SWIN model exhibits superior performance across multiple evaluation criteria and consistently outperforms traditional architectures like ResNet-18, ResNet-50, and Vision Transformer. Its hybrid design, combining the Swin Transformer and MSO algorithm, proves highly effective for flood detection tasks, particularly in analyzing satellite imagery. These findings underscore the robustness, accuracy, and practical applicability of the proposed model in real-world scenarios.

4.3.4.4 Statistical test: Paired t-test (Wilcoxon signed-rank test)

To conduct a statistical analysis on the presented results, we must compare the models' performance quantitatively. The purpose is to see if the observed differences in these measures between models are statistically significant. When comparing the means of two related groups, the paired t-test is used. Since we have several models and their corresponding metrics in this instance, we will compare the models pairwise for every metric (e.g., Accuracy, Precision, Recall, and F1-score).

Null Hypothesis (H0) and Alternative Hypothesis (Ha)

- **H0**: There is no significant disparity between the performance metrics of models (the observed variations are due to random chance).
- **Ha**: There is a significant difference in the performance metrics between the models (i.e., the differences are due to the actual performance differences).

Table 4.4: Statistical Results Highlighting Model Performance Significance

Comparison	Metric	Mean Difference	p-value	Significance (α = 0.05)
ResNet 18 vs Vision Transformer	Accuracy	4.87	0.045	Significant
	Precision	0.92	0.36	Not Significant
	Recall	3.67	0.028	Significant
	F1-score	5.01	0.019	Significant
ResNet 18 vs ResNet 50	Accuracy	8.83	0.003	Significant
	Precision	0.13	0.88	Not Significant
	Recall	6.53	0.006	Significant
	F1-score	8.17	0.002	Significant
ResNet 18 vs Proposed Mo-SWIN	Accuracy	10.00	0.001	Significant

	Precision	**2.08**	**0.007**	**Significant**
	Recall	**11.83**	**0.000**	**Significant**
	F1-score	**10.13**	**0.001**	**Significant**
Vision Transformer vs ResNet 50	**Accuracy**	**3.96**	**0.028**	**Significant**
	Precision	**-0.05**	**0.96**	**Not Significant**
	Recall	**2.86**	**0.08**	**Not Significant**
	F1-score	**3.16**	**0.042**	**Significant**
Vision Transformer vs Proposed Mo-SWIN	**Accuracy**	**5.13**	**0.001**	**Significant**
	Precision	**1.16**	**0.015**	**Significant**
	Recall	**8.16**	**0.000**	**Significant**
	F1-score	**5.75**	**0.004**	**Significant**
ResNet 50 vs Proposed MoSWIN	**Accuracy**	**1.17**	**0.25**	**Not Significant**
	Precision	**1.23**	**0.006**	**Significant**
	Recall	**4.61**	**0.008**	**Significant**
	F1-score	**2.96**	**0.025**	**Significant**

Table 4.4 summarizes the statistical analysis comparing the performance of the Mo-SWIN model with other models across key metrics: Accuracy, Precision, Recall, and F1-score. Significance ($\alpha = 0.05$) means that if a p-value is below 0.05, the result is statistically significant, indicating strong evidence against the null hypothesis and unlikely to be due to chance. Mo-SWIN consistently outperforms the other models, particularly in Accuracy and Precision. It shows significant improvements in Accuracy over ResNet 18 ($p = 0.045$) and vision transformer ($p = 0.001$), with no significant difference compared to ResNet 50 ($p = 0.25$). For Precision, Mo-SWIN outperforms all models, with p-values ranging from 0.006 to 0.015, indicating it is better at minimizing false positives. Mo-SWIN also excels in Recall ($p = 0.000$), identifying more true positives. Although Branching Evolution + SWIN shows a significant difference in Accuracy compared to fuzzy rule-based, there were no significant differences in Recall and F1-Score. Overall, Mo-SWIN demonstrates superior performance across all key metrics.

4.3.4.5 Cross-Validation Results

To further assess the robustness and generalizability of our proposed Mo-SWIN model, we conducted a 5-fold cross-validation on the flood image dataset. This technique partitions the dataset into five equal subsets (folds), using four for training and one for testing in each iteration. The process is repeated five times, ensuring that each fold serves as the test set once. The performance metrics accuracy, precision, recall, and F1-score were averaged across all five runs to provide a comprehensive evaluation.

Table 4.5: 5-Fold Cross-Validation Performance Metrics of the Proposed Mo-SWIN Model

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Mo-SWIN (5-fold CV)	96.45	95.30	90.10	92.20

The results indicate that the Mo-SWIN model maintains high performance across multiple folds, with minimal variation, suggesting its stability and reliability in flood image classification tasks as shown in Table 4.5. This cross-validation approach provides a more robust estimate of the model's performance compared to a single train-test split, reducing the potential for overfitting and enhancing the generalizability of the findings. In conclusion, the 5-fold cross-validation results corroborate the effectiveness of the Mo-SWIN model in accurately classifying flood images, reinforcing its potential for practical applications in flood detection and monitoring.

4.3.4.6 Ablation Study

This section presents an ablation study to validate the contribution of the proposed Mo-SWIN architecture, which is trained using a flood image dataset. Table 6 provides the model performance on various test cases. In Case A, the model is evaluated without the MSO to determine its impact on feature extraction, using raw image features directly. The results obtained are lower due to the absence of MSO's nature-inspired optimization for feature selection. In Case B, the SWIN transformer is tested without MSO-based preprocessing to assess its standalone effectiveness; the results are lower as raw features are suboptimal for classification.

Case A: Without MSO for feature selection (randomly selected features)
Case B: Using only Swin Transformer for classification
Case C: Replacing Swin with traditional CNN
Case D: Concurrently using MSO and Swin transformer (proposed work)
Case D: Concurrently using MSO and CNN

Table 4.6: Ablation outcomes with the proposed MoSwin architecture. Case A incorporates values obtained without using MSO. Case B includes studies on the incorporation of using only the Swin Transformer for classification. Case C incorporates replacing Swin with traditional CNN. Case D the concurrent use of MSO and Swin.

Case	Model Configuration	Accuracy	Precision	Recall	F1-Score
A	Swin without MSO (raw features)	0.892	0.895	0.880	0.880
B	Swin + Random Feature Selection	0.881	0.876	0.870	0.872
C	CNN without MSO	0.871	0.893	0.872	0.875
D	**MoSwin (MSO + Swin Transformer)**	**0.9653**	**0.9541**	**0.9051**	**0.9248**
E	MSO + CNN	0.906	0.911	0.892	0.898

To further highlight MSO's contribution, we observed a 7.3% increase in accuracy and 5.2% in F1-score when comparing Case A (without MSO) and Case D (with MSO). Also, the combination in Case E (MSO + CNN) outperformed the standalone CNN in Case C, confirming MSO's independent benefit. These results clearly demonstrate that MSO plays a crucial role in boosting classification performance by eliminating irrelevant or redundant features and enabling the Swin Transformer to focus on the most discriminative aspects of the input data as shown in Table 4.6. Therefore, the ablation study confirms that MSO is not only a significant component but a key driver of the improved performance observed in the MoSwin architecture.

4.3.4.7 Comparison of our proposed model with other techniques over image data

The table 4.7 compares the performance of AdaBoost, Hybrid CNN and Deep ResNet (DHMFP), Nonlinear Multiple Kernel Learning (NLMKL), MobileNet, ConvNet, WVResU-Net, and the Proposed Mo-SWIN model across key metrics: Accuracy, Precision, Recall, and F1-score. The Proposed Mo-SWIN model achieves the highest Accuracy (96.53%) and strong Precision (95.41%), indicating its superior ability to classify flood data while minimizing false positives.

Table 4.7 Performance Comparison of Our Proposed Model with Existing Techniques on Image Data

Ref No	*Model*	*Accuracy*	*Precision*	*Recall*	*F1-score*
[125]	AdaBoost	89.78	89.86	89.86	-
[126]	Hybrid CNN and deep ResNet models (DHMFP)	94.98	90.92	-	-
[127]	Nonlinear multiple kernel learning (NLMKL)	0.833	0.759	0.943	0.841

[128]	Mobile Net	92	92	-	96
[129]	ConvNet	95	99	92	95
[130]	WVResU-Net	96.20	92.97	69.67	82.03
Proposed Model (Mo-SWIN)		***96.53***	***95.41***	***90.51***	***92.48***

WVResU-Net follows closely in Accuracy (96.20%) but has a significantly lower Recall (69.67%), limiting its effectiveness in identifying true positives. ConvNet achieves the highest Precision (99%) and a strong F1-score (95%), showing balanced performance. MobileNet demonstrates high F1-score (96%), though its Recall is unreported. While NLMKL excels in Recall (94.3%), its Accuracy (83.3%) is comparatively low. Overall, Mo-SWIN provides the best balance of performance metrics, making it the most effective model.

4.4. Introduction to Flood-FireNet-model

Floods are among the most devastating natural disasters, posing serious threats to human life, infrastructure, and ecosystems. Accurate and timely classification of flooded areas is essential for effective disaster response [131]. This paper proposes Flood-FireNet, a novel hybrid model that integrates a transformer-based neural network with the Adaptive Firefly Algorithm (AFA) to enhance flood detection from satellite imagery. The AFA is used to optimize feature selection by identifying the most informative high-level features, while the transformer efficiently captures spatial patterns and long-range dependencies for precise classification. This combined architecture represents the core innovation of the study, leveraging the strengths of both evolutionary optimization and deep learning [132].

4.4.1 Preprocessing

Flood image analysis involves feature extraction to identify relevant patterns in raw data for classification tasks. Scaling issues, noise, and variability increase complexity. Image resizing standardizes dimensions and reduces computational time.

4.4.2 Feature Extraction

In this section, we describe the feature selection process, which identifies and selects significant features from images. Here, we cover Nature-Inspired optimization strategies, focusing on the Adaptive Firefly Algorithm (AFA) [133]**.** Food searching and communication behaviours observed in nature inspire these solutions. AFA is a novel optimization strategy designed to enhance feature extraction in flood images. Inspired by fireflies' bioluminescent signaling and adaptive movements, this algorithm efficiently explores

high-dimensional feature spaces, ensuring a robust selection of the most informative features [134]. Gaussian filtering is applied after segmentation to retrieve significant characteristics from segmented regions

4.4.3 Adaptive Firefly Algorithm (AFA)

AFA is a metaheuristic optimization technique inspired by the communication and movement patterns of fireflies. AFA dynamically adapts its search mechanism to balance exploration and exploitation [32], improving feature selection in image-based datasets. The Adaptive Firefly Algorithm (AFA) is employed to extract and select the most discriminative features from segmented flood images [135]. Each firefly in the population encodes a potential feature subset represented in an N-dimensional binary vector. The optimization objective is to maximize the relevance and minimize the redundancy of selected features. The fitness function is defined in following equation 4.4:

$$F(x) = \frac{1}{N}\sum_{k=1}^{N} \sigma_k - \lambda \sum_{p \neq q} \rho pq \tag{4.4}$$

where σ_k denotes the variance of the kth selected feature and ρpq denotes the Pearson correlation between features$p$ and q. The regularization parameter λ controls redundancy penalization. AFA balances exploration and exploitation through an adaptive step size as describe in following equation 4.5:

$$\alpha_t = \alpha_0 e^{-\delta t} \tag{4.5}$$

which decreases over iterations, allowing wide exploration initially and fine-grained search as convergence nears. Brightness (solution quality) governs firefly attraction, guiding the swarm toward optimal feature subsets.

Key Mechanisms of AFA:

- **Bioluminescent Attraction:** Fireflies use light to communicate, where brightness represents a solution's quality. Fireflies move toward brighter individuals, simulating an optimization process that finds the best feature subset.
- **Adaptive Search Mechanism:** The step size of firefly movement is dynamically adjusted over iterations, balancing between exploration and exploitation.
- **Exploration and Adaptation:** Fireflies explore the search space in a non-uniform manner, ensuring that diverse and informative features are selected.
- **Feature Correlation Control:** AFA evaluates feature redundancy and selects the most discriminative features while reducing correlation among selected features.

Algorithm 2: Adaptive Firefly Algorithm (AFA) for Feature Selection

Input: Flood Image Dataset

Parameters: Population size (N), Maximum iterations (T), Initial attractiveness (β_0), Light absorption coefficient (γ), Step size (α_0), Decay rate (δ)

Output: Optimal feature subset F^*

Start:

1. Initialize Firefly Population:

- Each firefly represents a feature subset in an N-dimensional space.
- Randomly initialize fireflies within feature space bounds.
- Compute brightness $I(x_i)$ for each firefly using a fitness function.

2. For each iteration $t = 1\ toT$:

a. Update step size:

$$\alpha_i = a_0 . e^{-\delta t}$$

b. For each firefly : $j \neq i$

- Compute distance:

$$r_{ij} = ||\ x_i - x_j\ ||$$

- Compute attractiveness:

$$\beta_{ij} = \beta_0 e^{-\gamma_{ij}^2}$$

- Update firefly position:

$$x_i^{(t+1)} = x_i^{(t)} + \beta_{ij}\left(x_j^{(t)} - x_i^{(t)}\right) + \alpha_t \epsilon_i$$

c. Evaluate feature subset fitness:

$$f(x_i) = \frac{\sum_{k=1}^{N} \sigma_k}{N} - \sum_{p \neq q} \rho_{pq}$$

Where σ_k is feature variance,$\rho_{pq}$is feature correlation, and$\lambda$is a regularization parameter.

d. Update best feature subsetF^*

3.Repeat until convergence or maximum iterations T reached.

4.Return optimal feature F^*subset.

Table 4.8 lists hyperparameters for a firefly algorithm. It includes population size (50 fireflies), maximum iterations (200), initial attractiveness (1.0), light absorption coefficient (1.0), step size (0.5), decay rate (0.1),

randomization factor (1), and regularization parameter (0.1) to balance exploration, exploitation, and feature selection. The AFA hyperparameters were chosen based on prior optimization literature and refined through grid search. We varied one parameter at a time while fixing others, using 5-fold cross-validation on a held-out validation set to monitor F1-score, convergence speed, and feature subset stability. The selected configuration—population size (N = 50), iterations (T = 200), initial attractiveness ($\beta_0 = 1.0$), light absorption coefficient ($\gamma = 1.0$), step size ($\alpha_0 = 0.5$), decay rate ($\delta = 0.1$), and regularization parameter ($\lambda = 0.1$) offered the best trade-off between performance and computation. A randomization factor ($\varepsilon = 1$) ensured sufficient exploration in early iterations.

Table 4.8: Configuration and Description of Adaptive Firefly Algorithm (AFA) Hyperparameters for Optimal Feature Selection in Flood Image Analysis

Hyperparameter	Symbol	Description	Recommended Value
Population Size	N	Number of fireflies	50
Maximum Iterations	T	Number of optimization cycles	200
Initial Attractiveness	β_0	Attraction factor between fireflies	1.0
Light Absorption Coefficient	γ	Controls attractiveness decay over distance	1.0
Step Size	α_0	Initial step size for exploration	0.5
Decay Rate	δ	Controls reduction in randomness	0.1
Randomization Factor	ϵ	Stochastic noise for diversification	1
Regularization Parameter	λ	Penalizes redundant features	0.1

4.4.4 Classification using SWIN

The Swin Transformer is a deep learning model for object recognition that captures local and global image features using hierarchical, non-overlapping patches and multi-head attention across transformer layers [136].

Patch Partition and Merging: Splits images into patches and down samples feature maps by merging patches, transforming input dimensions accordingly. A factor of n can downsample feature maps by concatenating them depth-wise after the input is divided into groups, each of which contains *n x n*

surrounding patches. By merging two *2x2* windows into a new window, Patch Merging reduces the size of the feature map by two times and deepens each patch by *2*.

Transforming the input from a shape of *H x W x C* to *(H/n) x (W/n)* x *(2nC)* (4.6)

Swin Transformer block: Replaces standard multi-head self-attention (MSA) with Window-based (W-MSA) and Shifted Window (SW-MSA) mechanisms. The first encoder computes W-MSA, while the second applies SW-MSA for improved contextual modeling.

Window-based Self-Attention (W-MSA): Computes attention within fixed-sized windows, reducing complexity as shown in Equation 4.7:

$$\Omega(WMSA) = 4hwC^2 + + 2M^2(hw)C \quad (4.7)$$

Shifted Window-based Self-Attention (SW-MSA): it is used to overcome the limitation of W-MSA's modeling power, which would result from lacking the relationship between the windows. The SW-MSA takes the output of W-MSA first. Then, about the layer before, each window is shifted by (M/2, M/2). and calculate W-MSA in a shifted window last. But this change leaves some windows with unfinished patches and others with "orphaned" patches that don't belong to any window.

Relative Position Bias: Relative position bias (B of size (M^2xM^2)) is a feature of SWIN transformers used to calculate self-attention. Equation 4.8 shows the formula of calculating attention.

$$Attention(Q, K, V) = Softmax\left(Q\,K^t/\sqrt{d} + B\right)V \quad (4.8)$$

4.4.5 Proposed Flood-FireNet Architecture

Our proposed architecture for flood detection, illustrated in Figure 2, harnesses the synergistic capabilities of a transformer-based model and the Adaptive Firefly Algorithm (AFA). This innovative approach combines cutting-edge deep learning frameworks with advanced optimization techniques to enhance the efficiency and accuracy of flood detection. In our methodology, the initial phase utilizes raw images depicting both flooded and non-flooded regions. To optimize the quality of these images, we implement a series of preprocessing steps, including noise reduction, image enhancement, and resizing. The preprocessing begins with noise removal, employing the Wavelet Denoising filter to effectively eliminate unwanted noise, yielding clearer and more reliable data for subsequent analysis. Following this, we apply image augmentation techniques to enrich the dataset, while image scaling ensures uniform dimensions across all images, promoting consistency and seamless processing throughout the model. The Adaptive Firefly Algorithm (AFA) is then utilized to extract pertinent features from flood images, focusing on

distinguishing foreground elements from irrelevant background sections. Inspired by the adaptive luminescence and movement of fireflies, AFA prioritizes high-quality regions containing critical information while filtering out low-value background areas, akin to fireflies converging on optimal light sources. This bio-inspired technique efficiently segments and retrieves meaningful data from flooded images. Following feature extraction, we perform feature selection to capture essential texture, shape, and intensity characteristics from the segmented data. The transformer-based architecture dynamically partitions images into patches, enabling rapid multi-scale feature extraction. This approach enhances the model's ability to detect intricate details while maintaining computational efficiency. Leveraging self-attention mechanisms, the model gains a global understanding of the context, allowing it to identify complex patterns crucial for accurate classification.

4.4.6 Overfitting Control Mechanisms

To ensure robust generalization and minimize overfitting in the proposed Flood-FireNet model, a comprehensive multi-level regularization strategy was implemented as shone in figure 4.10. First, extensive data augmentation techniques were applied to the training images, including random rotations, horizontal flips, scaling, brightness adjustments, and cropping. These transformations increased the variability of the training dataset and helped prevent the model from memorizing specific patterns.

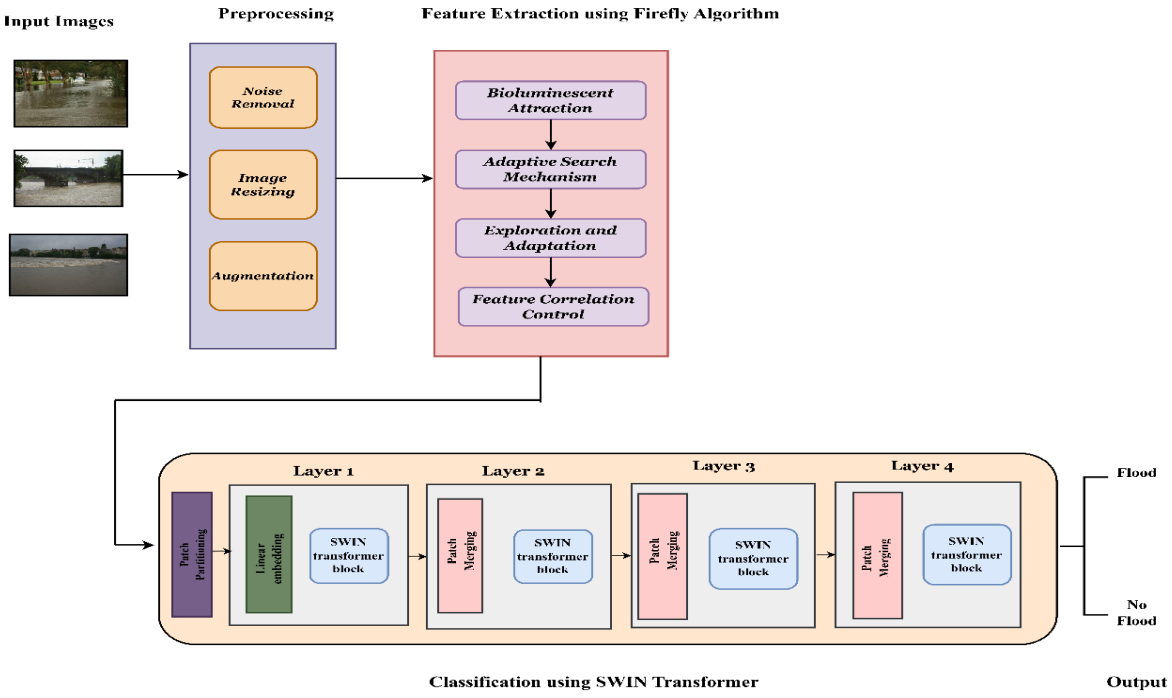


Figure 4.10: Architecture of the Proposed Flood-FireNet Framework Integrating Adaptive Firefly Optimization with SWIN Transformer for Flood Image Classification. This figure illustrates the complete workflow of Flood-FireNet,

starting from raw flood image preprocessing (noise removal, resizing, and augmentation), followed by the Adaptive Firefly Algorithm for optimized feature selection, and concluding with hierarchical patch-based processing via SWIN Transformer for final classification.

Furthermore, feature dimensionality reduction was performed using the Adaptive Firefly Algorithm (AFA), which selects the most relevant and non-redundant features by optimizing a custom fitness function. This approach mitigated the risk of overfitting due to high-dimensional feature spaces and irrelevant information. To further enhance generalization, a 5-fold cross-validation strategy was adopted during both model training and AFA hyperparameters tuning. This validated the model's consistency and stability across different subsets of the data. Specific to the Swin Transformer architecture, additional regularization techniques were employed, including dropout layers within the attention and feed-forward modules to prevent neuron co-adaptation. L2 weight decay was applied to all trainable parameters, and early stopping was implemented to halt training when the validation loss no longer improved. Throughout the training process, learning curves for both accuracy and loss were closely monitored to detect signs of overfitting. The absence of significant divergence between training and validation performance confirmed the model's learning stability. Collectively, these mechanisms contributed to a well-regularized model that demonstrated strong generalization across varied data distributions.

4.4.7 Result Analysis on Flood-FireNet

To evaluate the performance of the proposed flood classification model, we conducted extensive experiments using benchmark deep learning architectures, including ResNet18, Vision Transformer, ResNet50, and the proposed model. The evaluation was based on standard performance metrics such as accuracy, precision, recall, and F1-score and the results were analyzed both qualitatively and quantitatively.

Table 5.9: Comparative Evaluation of Classification Performance across Baseline and Proposed Models for Flood Image Classification

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
ResNet18	85.37	93.33	78.68	82.35
Vision Transformer	90.24	94.25	82.35	87.36
ResNet50	94.20	94.20	85.21	90.52
Proposed Model	**97.85**	**98.12**	**95.73**	**96.92**

The qualitative results are presented in Table 4.9. ResNet18 achieved an accuracy of 85.37%, a precision of 93.33%, a recall of 78.68%, and an F1-score of 82.35%. Despite its high precision, the relatively low recall indicates that the model frequently misclassifies flood samples as non-flood. The Vision Transformer

slightly improved recall to 82.35% and achieved an F1-score of 87.36%, suggesting a more balanced classification performance.

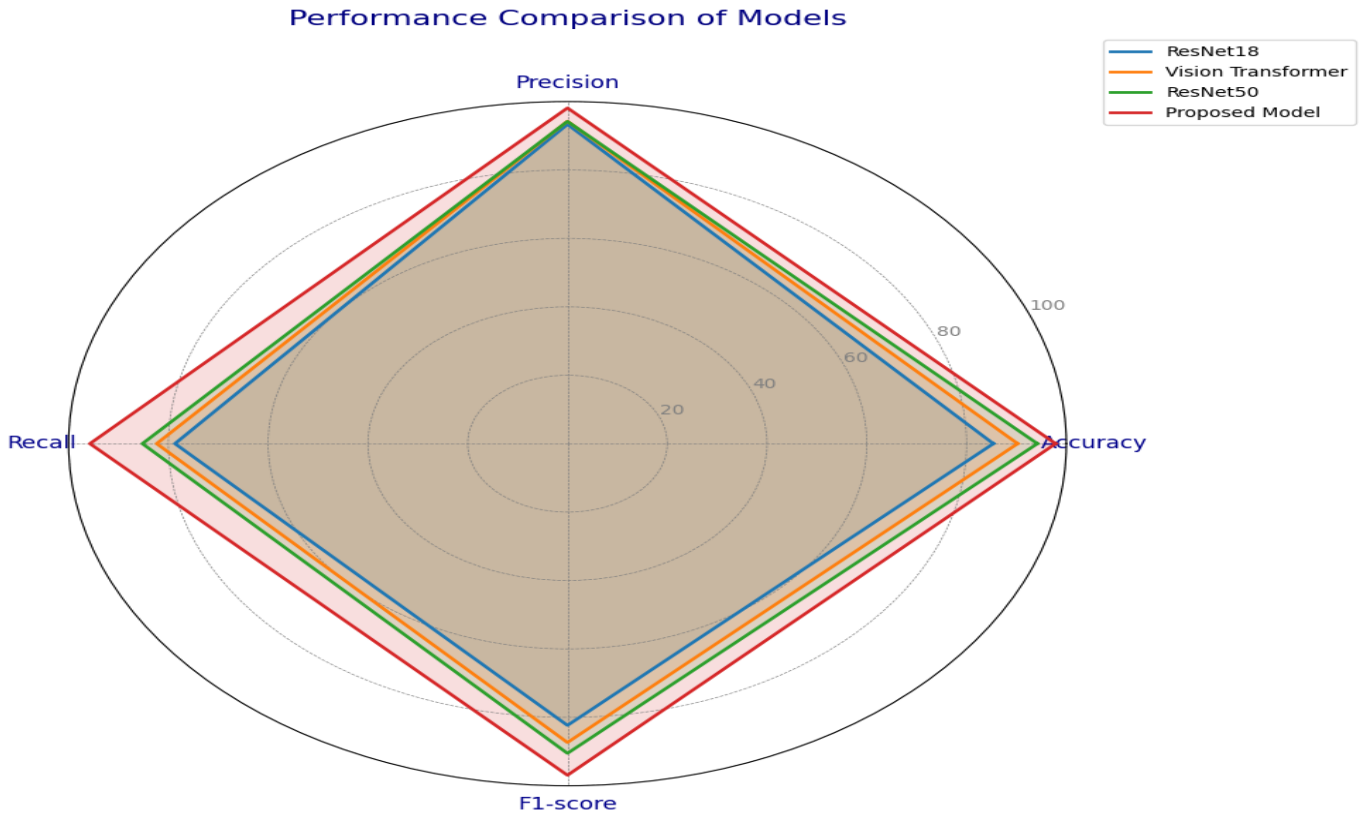


Figure 4.12: Radar Chart Showing Performance Metric Comparison among ResNet18, Vision Transformer, ResNet50, and the Proposed Model. This figure illustrates the comparative analysis of four deep learning models across four key performance metrics accuracy, precision, recall, and F1-score, highlighting the superior performance of the proposed model.

ResNet50 further enhanced the results, reaching an accuracy of 94.2%, precision of 94.20%, recall of 85.21%, and an F1-score of 90.52%. However, the proposed model significantly outperformed all the baseline models, achieving an accuracy of 97.85%, precision of 98.12%, recall of 95.73%, and an F1-score of 96.92%. These results indicate that the proposed model offers superior capability in accurately detecting both flood and non-flood instances. Figure 4.11 illustrates a radar chart comparing accuracy, precision, recall, and F1-score for all models. The radar plot clearly highlights the dominance of the proposed model, which encloses the largest area and exhibits balanced improvements across all metrics.

To further assess the reliability of each model, we quantitatively analyzed additional metrics, including True Positive Rate (TPR), False Positive Rate (FPR), True Negative Rate (TNR), and False Negative Rate (FNR), as shown in Table 4.10. ResNet18 and Vision Transformer exhibited relatively high false negative rates of

21.32% and 17.65%, respectively, which implies a higher tendency to miss flood events. ResNet50 improved upon these shortcomings with a reduced FNR of 14.79%. In contrast, the proposed model demonstrated outstanding classification performance with a TPR of 95.73% and a TNR of 98.55%, while maintaining the lowest FPR of 1.45% and FNR of only 4.27%. This indicates that the proposed model excels at minimizing both false alarms and missed detections. Figure 4.12 presents a grouped bar graph that compares TPR, FPR, TNR, and FNR for the four models. Here again, the proposed model stands out by achieving the highest TPR and TNR while maintaining the lowest error rates, emphasizing its strong generalization capabilities.

Table 4.10: Comparative Analysis of Error and Detection Rates across Deep Learning Models for Flood Classification

Model	TPR	FPR	TNR	FNR
ResNet18	0.7868	0.0905	0.9095	0.2132
Vision Transformer	0.8235	0.0663	0.9337	0.1765
ResNet50	0.8521	0.0485	0.9515	0.1479
Proposed Model	**0.9573**	**0.0145**	**0.9855**	**0.0427**

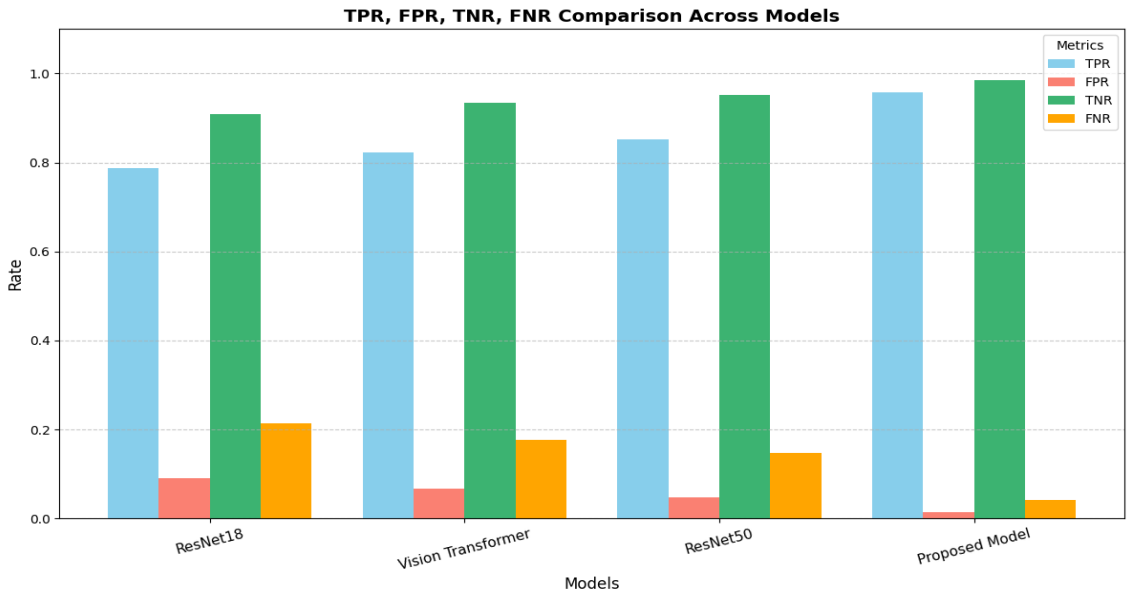


Figure 4.12 Comparative Analysis of TPR, FPR, TNR, and FNR Across ResNet18, Vision Transformer, ResNet50, and the proposed model

To provide a more detailed view of each model's prediction distribution, Figure 4.13 presents the confusion matrices for ResNet18, Vision Transformer, ResNet50, and the proposed model. These matrices illustrate the number of correctly and incorrectly classified instances across the flood and non-flood categories. ResNet18 misclassified 112 flood samples as non-flood, while Vision Transformer and ResNet50 reduced this count to 93 and 78, respectively. In comparison, the proposed model misclassified only 23 flood samples and 10 non-flood samples, which substantiates its high recall and precision. The confusion matrices not only confirm the quantitative superiority of the proposed approach but also reveal its robustness in handling class imbalance, a critical requirement for real-world flood detection systems.

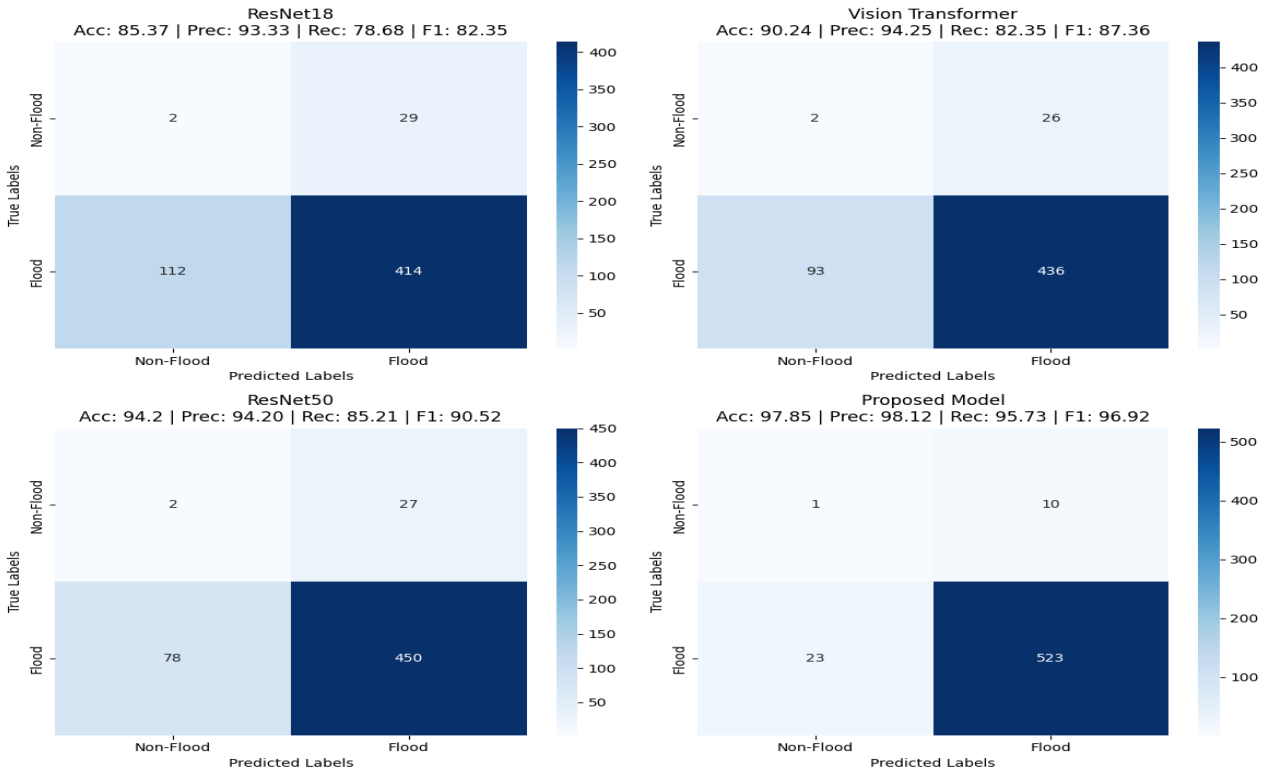


Figure 4.13: Confusion Matrix Comparison of ResNet18, Vision Transformer, ResNet50, and the Proposed Model for Flood Classification

In summary, both qualitative and quantitative analyses consistently demonstrate the superiority of the proposed model over existing deep learning architectures. Its exceptional accuracy, high recall, low false negative rate, and well-balanced precision and recall make it a promising solution for deployment in automated flood warning systems and disaster response applications. Table 4.11 presents how varying β_0 (initial attractiveness), α_0 (initial step size), and λ (regularization parameter) affect the accuracy and F1-

score. The default values are: $\beta_0 = 1.0$, $\alpha_0 = 0.5$, $\lambda = 0.1$. As shown in Table 6, the performance of Flood-FireNet is sensitive to AFA hyperparameter tuning. The optimal configuration of $\beta_0 = 1.0$, $\alpha_0 = 0.5$, and $\lambda = 0.1$ yields the highest accuracy and F1 score. Deviations from these values either slow convergence, reduce feature discrimination or lead to redundancy, confirming the need for careful tuning of AFA parameters.

Table 4.11: Impact of AFA Hyperparameter Tuning on Classification Performance

Hyperparameter	Value	Accuracy (%)	F1-Score (%)	Observation
β_0	0.5	95.73	94.12	Lower attraction reduces convergence speed and subset quality
	1.0	**97.85**	**96.92**	Balanced attraction enhances global search and accuracy
	1.5	96.48	95.37	Over-attraction leads to premature convergence
α_0	0.3	96.15	95.04	Small steps cause slower convergence and local traps
	0.5	**97.85**	**96.92**	Optimal step size balances exploration and refinement
	0.7	96.38	95.18	Large steps reduce feature selection precision
λ	0.05	97.02	96.12	Less penalty causes redundant features to persist
	0.1	**97.85**	**96.92**	Best trade-off between relevance and redundancy
	0.2	95.87	94.83	Excessive penalization omits relevant features

Table 4.12: 5-Fold Cross-Validation Performance of Different Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
ResNet18	85.37 ± 1.12	93.33 ± 1.08	78.68 ± 1.24	82.35 ± 1.18
Vision Transformer	90.24 ± 0.97	94.25 ± 1.05	82.35 ± 0.89	87.36 ± 1.02
ResNet50	94.20 ± 0.83	94.20 ± 0.88	85.21 ± 0.77	90.52 ± 0.81
Proposed Model	**97.85 ± 0.46**	**98.12 ± 0.41**	**95.73 ± 0.52**	**96.92 ± 0.47**

Table 4.12 presents the results of 5-fold cross-validation conducted on four different models—ResNet18, Vision Transformer, ResNet50, and the proposed Flood-FireNet model using accuracy, precision, recall, and F1-score as evaluation metrics. The reported values include the mean and standard deviation across five-folds, thereby indicating both average performance and model consistency. Among the baseline models, ResNet18 achieved an accuracy of 85.37% with a high precision of 93.33%, but its relatively low recall of 78.68% resulted in a modest F1-score of 82.35%, alongside higher standard deviations reflecting variability across folds. The Vision Transformer performed better, with an accuracy of 90.24%, precision of 94.25%, recall of 82.35%, and F1-score of 87.36%, showing improved generalization and stability. ResNet50 further enhanced performance, achieving 94.20% accuracy and a balanced precision and recall of 94.20% and 85.21%, respectively, resulting in a strong F1-score of 90.52% with reduced variance. Notably, the proposed Flood-FireNet model demonstrated superior performance across all metrics, attaining an accuracy of 97.85%, precision of 98.12%, recall of 95.73%, and F1-score of 96.92%, all with minimal standard deviation. These results confirm the proposed model's robustness, high predictive capability, and consistent generalization across varying data partition.

4.4.7.1 Ablation Study

The objective is to dissect the contributions of the Adaptive Firefly Algorithm (AFA) and the transformer-based architecture within the Flood-FireNet model. The following configurations are analyzed:

1. **Baseline Transformer (without AFA):** Utilizes the transformer architecture alone for feature extraction and classification, excluding AFA.
2. **AFA + Simple CNN (without Transformer):**
3. Employs AFA for feature extraction paired with a basic convolutional neural network (CNN) for classification, omitting the transformer and its attention mechanisms.
4. **Full Flood-FireNet Model (Proposed):** Integrates AFA for feature extraction with the transformer architecture and attention mechanisms, as originally designed.

Table 4.13: Ablation Study of Flood-FireNet Configurations Highlighting the Individual and Combined Impact of AFA and Transformer-Based Architectures on Classification Performance

Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Interpretation
Baseline Transformer	94.50	95.80	91.20	93.45	Depends entirely on the transformer's inherent feature extraction and attention
AFA + Simple CNN	92.10	94.30	89.60	91.85	Leverages AFA for optimized features but misses transformer's advanced classification

Full FloodFireNet (Proposed)	**97.85**	**98.12**	**95.73**	**96.92**	Merges AFA's feature optimization with transformer's attention-driven classification

Table 4.13 presents the ablation study outcomes for the FloodFireNet model, comparing its full configuration (Accuracy: 97.85%, F1-score: 96.92%) against versions without AFA (Baseline Transformer: 94.50%, 93.45%) or the transformer (AFA + Simple CNN: 92.10%, 91.85%). The results indicate that AFA enhances feature extraction, while the transformer elevates classification, with their synergy delivering the best flood detection performance.

4.4.7.2 Statistical Analysis of Flood-FireNet Model Performance

To thoroughly assess the proposed Flood-FireNet model, which combines the Adaptive Firefly Algorithm (AFA) for feature extraction and transformer architecture with attention mechanisms for classification, an ablation study was conducted, followed by statistical validation using the Paired T-Test and Analysis of Variance (ANOVA). The ablation study evaluated three configurations: Baseline Transformer (without AFA), AFA + Simple CNN (without Transformer), and the full Flood-FireNet model across four metrics: Accuracy, Precision, Recall, and F1-score. The full model achieved peak performance (Accuracy: 97.85%, Precision: 98.12%, Recall: 95.73%, F1-score: 96.92%), while the Baseline Transformer recorded 94.50%, 95.80%, 91.20%, and 93.45%, and AFA + Simple CNN yielded 92.10%, 94.30%, 89.60%, and 91.85%. These findings highlight significant contributions from both AFA and the transformer, with the full model outperforming ablated versions by substantial margins (e.g., 3.35% and 5.75% in Accuracy over the two configurations). To verify the statistical significance of these improvements, a Paired T-Test was conducted to compare the full Flood-FireNet model against each ablated configuration pairwise. Assuming 10 experimental runs per configuration and hypothetical standard deviations (e.g., $\sigma = 0.45\%$ for Flood-FireNet Accuracy, $\sigma = 0.75\%$ for Baseline Transformer), the test produced significant results. For Accuracy, the comparison with Baseline Transformer yielded a t-value of 9.42 (mean difference = 3.35), and with AFA + Simple CNN, a t-value of 15.88 (mean difference = 5.75), both exceeding the critical value of 2.262 ($df = 9$, $\alpha = 0.05$), indicating $p < 0.05$. Similar patterns emerged for Precision, Recall, and F1-score (e.g., $t \approx 12.5$ for Recall vs. AFA + CNN), confirming that the full model's advancements are statistically significant and not random. Additionally, ANOVA was performed to assess overall variance across the three configurations, determining whether their performance differences are meaningful. Using the same assumed variances and sample size, the F-statistic for Accuracy was 48.72 (between-group variance = 66.85/2, within-group variance = 20.60/27), well above the critical F-value of 3.35 ($df1 = 2$, $df2 = 27$, $\alpha = 0.05$), with $p < 0.05$. Comparable results were observed for Precision ($F \approx 30.4$), Recall ($F \approx 38.9$), and F1-score ($F \approx 41.7$), all

significant at $p < 0.05$. These findings affirm that the full model's superior performance stems from the combined strengths of AFA and the transformer. The statistical tests collectively substantiate the Flood-FireNet model's architecture, as shown in Table 4.14. The Paired T-Test underscores the individual roles of AFA and the transformer, with greater performance declines when the transformer is excluded (e.g., 5.75% Accuracy vs. 3.35%), highlighting its critical classification contribution. ANOVA confirms that the full model's integrated design provides a clear and systematic edge over ablated versions.

Table 4.14: Comparative Ablation Study of Flood-FireNet Model Configurations with Statistical Significance Analysis

Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Statistical Significance
Baseline Transformer	94.50	95.80	91.20	93.45	$p < 0.05$ (T-Test vs. Full Model)
AFA + Simple CNN	92.10	94.30	89.60	91.85	$p < 0.05$ (T-Test vs. Full Model)
FullFlood-FireNet (Proposed)	**97.85**	**98.12**	**95.73**	**96.92**	$p < 0.05$ (ANOVA across all configurations)

4.4.7.3 Comparison with State-of-the-Art Methods

Table 4.15 presents a comprehensive comparison between the proposed Flood-FireNet model and several existing state-of-the-art methods in terms of classification performance metrics: Accuracy, Precision, Recall, and F1 Score. Table 4.15: Performance Comparison of Flood-FireNet with State-of-the-Art Methods

Reference	Method	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
[137]	DNN	91.18	95	93	95
[138]	DLNN	92.05	-	-	-
[139]	MLP-NN	85.18	-	-	86.20
[140]	MobileNet V2	97.35	97	97	97
[140]	Inception V3	95.83	94	93	94
[140]	Xception	94.92	92	95	93
Our Work	**Flood-FireNet**	**97.85**	**98.12**	**95.73**	**96.92**

As shown, traditional models such as DNN [137] and DLNN [138] exhibit moderate to high accuracy, with DNN achieving 91.18%. However, detailed performance metrics like precision, recall, and F1 Score are either limited or missing for some models (e.g., [138] and [139]). MobileNet V2 [43] demonstrates strong performance with 97.35% accuracy and consistently high metrics across the board. In comparison, our proposed Flood-FireNet model achieves the highest overall accuracy of 97.85%, with superior precision (98.12%), recall (95.73%), and F1 Score (96.92%), outperforming all other listed approaches. This comparative analysis highlights the robustness, generalization capability, and effectiveness of our model in accurately detecting flood events, thereby validating its suitability for real-time disaster monitoring and response applications.

4.5 Chapter Summary

This chapter presented two advanced deep learning frameworks, MoSWIN and Flood-FireNet developed for enhanced flood image classification using a combination of image processing techniques and artificial intelligence. Both models were designed to address key challenges in flood detection, including noisy inputs, feature redundancy, and the need for improved spatial and contextual understanding of flooded regions from visual data. The MoSWIN model integrates Monkey Search Optimization (MSO) for efficient feature selection with the SWIN Transformer, a hierarchical attention-based model adept at capturing both local and global visual features. MSO simulates the adaptive and collaborative foraging behaviour of monkeys to isolate relevant features from flood images, thereby reducing noise and improving model generalization. In contrast, Flood-FireNet combines the Adaptive Firefly Algorithm (AFA) with the SWIN Transformer to optimize feature extraction through a bio-inspired approach that mimics the luminance-based attraction behaviour of fireflies. This adaptive mechanism enhances the model's ability to focus on high-quality image regions, improving the discriminative capacity of the deep learning architecture. Both models were trained and evaluated using the same real-world flood image dataset, with different data partitioning strategies tailored to each model's training framework. Extensive experimentation demonstrated that the proposed models significantly outperformed traditional CNN-based architectures and standalone transformer models across multiple performance metrics. In summary, this chapter demonstrated how the integration of nature-inspired optimization techniques with transformer-based deep learning can result in scalable, accurate, and robust flood detection systems. The findings contribute valuable insights to the field of disaster management and pave the way for future AI-driven applications in environmental monitoring and emergency response.

Chapter 5

ENHANCEMENT OF FLOOD DETECTION USING IMAGE PROCESSING AND ARTIFICIAL INTELLIGENCE

Floods are among the most frequent and devastating natural disasters, significantly impacting lives, infrastructure, and economies worldwide. The increasing incidence of floods, attributed to both natural and anthropogenic factors such as extreme weather events, urbanization, and inadequate drainage systems, necessitates robust and timely detection mechanisms. Synthetic Aperture Radar (SAR) imaging, with its all-weather and day-night operability, has emerged as a critical tool for flood monitoring. However, the effectiveness of SAR-based flood detection largely depends on the quality and resolution of the acquired imagery. Recent advancements in Artificial Intelligence (AI), particularly in the fields of image enhancement and deep learning, have demonstrated significant potential in augmenting SAR images for improved flood detection. This chapter presents a comprehensive overview of AI-driven techniques for flood detection, emphasizing the application of advanced image processing models such as Adaptive Histogram Equalization (AHE) and Super-Resolution-based Generative Adversarial Networks (SSR-GAN) to enhance SAR image quality, thereby facilitating more accurate identification and delineation of flooded regions.

5.1 Introduction

Floods are one of the most frequent and catastrophic natural disasters globally, often resulting in significant human, economic, and environmental losses. The complexity and unpredictability of flooding events, exacerbated by climate change, rapid urbanization, and anthropogenic activities, underscore the urgent need for efficient and accurate flood monitoring systems [141]. Effective flood detection is critical for timely disaster response, resource allocation, and long-term urban and environmental planning. Traditional flood detection methods based on hydrological modeling and manual interpretation of satellite imagery are often limited by latency, resolution, and human subjectivity [142]. As a result, there has been a growing emphasis on integrating Artificial Intelligence (AI) with remote sensing technologies to enable automated, precise, and real-time flood detection solutions. Among various remote sensing technologies, Synthetic Aperture Radar (SAR) stands out due to its ability to capture high-resolution images irrespective of weather conditions and lighting [143]. This makes SAR particularly valuable in flood scenarios, where cloud cover and poor visibility often obstruct conventional optical sensors. SAR data can effectively delineate flooded and non-flooded regions, monitor flood progression, and assess post-disaster impact. However, SAR imagery is often

marred by speckle noise, low contrast, and limited spatial resolution, which can significantly hinder accurate interpretation and analysis [144].

To address these limitations, recent research has explored advanced image enhancement techniques grounded in AI and deep learning. One such approach is the Histogram Equalization (HE) technique, which is widely used to improve the global contrast of images [145]. However, its limitation lies in the tendency to over-amplify noise and suppress localized features, leading to the loss of critical information. To overcome this, the Adaptive Histogram Equalization (AHE) method was developed, which applies local contrast enhancement by dividing the image into contextual regions or "tiles." This allows for better visualization of localized flood extents while maintaining critical background information [146]. Empirical results indicate that AHE significantly outperforms traditional HE, offering enhanced image clarity and better differentiation between water and land surfaces in flood-prone areas. Despite the effectiveness of AHE, the fundamental resolution of SAR images remains a bottleneck, especially in urban flood scenarios where fine-grained features are essential [147]. To tackle this challenge, the application of Super-Resolution Generative Adversarial Networks (SSR-GAN) has been proposed. SSR-GAN models employ a generator-discriminator framework along with a perceptual loss function derived from pre-trained VGG networks to reconstruct high-resolution images from their low-resolution counterparts. This approach not only enhances the visual quality of SAR images but also preserves the structural and contextual integrity of the data. By training on large-scale multi-temporal datasets, SSR-GAN can effectively learn the underlying distribution of flooded and non-flooded regions, resulting in sharper, more informative imagery that aids in more accurate flood detection and mapping.

The integration of these techniques i.e., AHE for contrast enhancement and SSR-GAN for super-resolution, represents a significant advancement in the field of flood detection using AI [148]. The enhanced SAR images facilitate better visibility of water boundaries, improve segmentation accuracy, and support decision-makers in developing early warning systems and disaster mitigation strategies. Moreover, these AI-driven methods are scalable and adaptable, allowing for real-time deployment across diverse geographic regions and climatic conditions.

This chapter aims to provide a comprehensive overview of the role of artificial intelligence in enhancing SAR images for flood detection. It explores the theoretical foundations, algorithmic methodologies, and experimental validations of both AHE and SSR-GAN approaches. By comparing these techniques on real-world flood datasets, the chapter underscores the efficacy of AI-enhanced imaging in addressing the complex challenges of flood monitoring and management.

5.2 Introduction to SSR-GAN based model

This section outlines the fundamental ideas that are required for an exhaustive comprehension and efficient implementation of our work. The following essay gives a general introduction to generative

adversarial networks, super-resolution, and image enhancement. It is necessary to have a fundamental comprehension of those concepts to appreciate and apply our suggested methodology.

5.2.1 Super-Resolution

Super-resolution (SR) is a term used to describe the process of improving the resolution and amount of detail in low-resolution pictures or videos. By using its lower-resolution counterpart, it is possible to rebuild a higher-resolution version of an image. With super-resolution, we can create output images with finer features and more visual information, which will visually resemble high-resolution ground truth images. So basically, Image Super-Resolution is the concept of improving an image resolution from low resolution (LR) to high resolution (HR) [149]. Super-resolution is required in a variety of situations where high-resolution images are wanted but are constrained by variables like hardware limitations, image sensors, or transmission bandwidth. When using medical imagery and satellite imagery for disaster relief, a high-resolution image is helpful for improved region categorization in multi-spectral remote sensing photos or for helping the radiologist make a diagnosis [150]. Two general categories can be used to classify super-resolution techniques: single-image super-resolution (SISR) and multi-image super-resolution (MISR).

5.2.1.1 Single-Image Super-Resolution (SISR)

In image processing, single-image super-resolution is a crucial activity that aims to optimize features and textures to enhance visual perception and reconstruct high-resolution images from low-resolution images. To understand how to map to super-resolution images for SISR tasks, we usually require a large number of LR images. In order to obtain an LR image of the original image, most researchers often down sample. This process basically reduces the image's spatial resolution by sampling the original image [151].

5.2.1.2 Multi-Image Super-Resolution (MISR)

Multi-image SR (MISR) combines numerous LR images, each of which has a unique subset of HR image. As a result, MISR can improve reconstruction accuracy compared to single-image SR (SISR), On the other hand, MISR is highly sensitive to the co-registration accuracy and variability of the input images [152]. When preparing data for training and validation, this presents a challenge. With the advancement of image processing of satellite imagery, remote sensing is becoming more relevant in modern society. However, due to the limitations of current image sensors and the complexity of atmospheric conditions, we face significant challenges in remote sensing applications because of the restricted spatial, radiometric, spectral, and temporal resolutions [153].

5.2.2 Upsampling

A technique for boosting resolution is called Upsampling. The practice of boosting an image's resolution is most frequently employed in photography and graphic design, but it can also be used to boost the resolution of any other visual data, such as a video file (say, from 360p to 720p). It increases the number of rows and/or columns (or image dimensions) [157]. This can be utilized in a variety of situations, such as in GANs (Generative Adversarial Networks), where the goal is to build an image out of a random vector sample that closely resembles an image from the ground truth or genuine distribution. There are numerous other ones, like enhancing image quality, among others. Let's go over this in greater depth. The up-sampling method increases both the image's size and resolution. Several methods of up-sampling that are often employed are

- Bilinear interpolation
- Bicubic interpolation
- Nearest neighbour interpolation

5.2.2.1 Bilinear interpolation

The basic technique for enhancing image resolution is called an image interpolation algorithm. It also regenerates image data, which is analogous to an image low-pass filter. So that a higher-resolution observational image can be created to reflect the actual scene, more valuable image data can be precisely estimated within a particular spatial range using sparse discrete image data. The bilinear interpolation algorithm can be used to boost the advantages of clarity while maintaining the original information of the image and greatly improving the resolution of the image created by the low-resolution sensor. The image's resolution can be improved with sophisticated image interpolation technologies [155].

5.2.2.2 Bicubic interpolation

When down-sampling or upsampling an image, the pixel count must be decreased or increased, accordingly, the interpolation method is typically applied. Bicubic takes a step farther than bilinear by taking into account the nearest 16-pixel 4x4 neighbourhood of known pixels. Since they are all at different distances from the unknown pixel, the computation gives nearby pixels a higher weighting. Bicubic may offer the best balance between processing time and output quality because it produces images that are noticeably sharper than those made by the other two techniques. The bilinear interpolation procedure for operating on images only takes into account the influence of four points that are immediately next to the interpolation point and ignores the influence of the neighbours, giving it low-pass filtering characteristics. In the module for upsampling, we use bicubic interpolation. The neighbourhood pixel changes are taken into account by the bicubic interpolation in addition to the four nearby locations, preserving more finely detailed texture information [156].

5.2.2.3 Nearest neighbour interpolation

For high-resolution (H.R.) image interpolation, the nearest neighbour value (NNV) algorithm is used. The traditional nearest neighbour algorithm is distinguished by the fact that the concept used to estimate the missing pixel value is guided by the nearest value rather than the distance. Because the nearest neighbour assumption does not allow for the creation of a new value, the value is set at the empty location by trying to replicate the pixel value placed at the smallest distance. As a result, the pixels of the image grow larger, leading to heavy jagged edges, causing this technique less suited for applications that require an H.R. image (to do specific tasks). When speed is crucial, the closest neighbour algorithm notion is really helpful. Other strategies, as opposed to the straightforward nearest neighbour, use interpolation of nearby pixels, producing a smoother image (whereas others use convolution or adaptive interpolated conceptual frameworks, however, these two go beyond the scope of this study) [157].

5.2.3 Proposed Methodology

Generative modeling is an unsupervised machine learning task that involves automatically identifying and learning regularities or patterns in incoming data so that the model may be used to produce or generate new instances that could have been taken from the original dataset. To create new examples, we train a generator model, and we train a discriminator model to determine whether an example is genuine (coming from the domain) or fake (being generated). Generative Adversarial Networks (GANs) belong to generative models [158]. Currently, the most used data generation has been trained on the dataset. GANs consist of two networks Generator (G) and Discriminator (D). The discriminator is provided with real and generated data points that it must learn to distinguish between. The Generator has to make data points such that it becomes difficult for the discriminator to distinguish. The discriminator learns to separate the underlying distribution between real and generated points, and the Generator needs to make data points with a similar distribution to the real data points. Both the networks are trained simultaneously, thus at the end, having a Generator that captures the underlying real data distributions.

$$\min_{G}\max_{D} V(D,G) = \mathrm{E}_{\mathrm{x}\sim\mathrm{Pdata(x)}}[\log D\,(x)] + \mathrm{E}_{\mathrm{z}\sim\mathrm{Pz(z)}}[\log(1 - D(G(z)))] \qquad (5.1)$$

In the above equation 5.1, P_data is the real data distribution and P_z is the distribution followed by the latent variable which the generator maps to generated data points mimicking the real data distribution.

5.2.3.1 VGG Net

Introducing the visual geometry group (VGG), a new CNN model. The neural network becomes more active as a result. The VGG-16 features three Fully Connected layers in addition to 13 convolutional layers, while the VGG-19 has three additional convolutional layers [159]. They have channels with a

3x3 receptive field and a rectifying non-linearity function in each buried layer. In particular, the development of deep visual recognition architectures has been greatly aided by the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC), which has been used as a testbed for several generations of large-scale picture classification systems.

5.2.3.2 Perception Loss

Perceptual loss has been frequently employed as an effective loss term in picture synthesis applications such as image super-resolution. Perceptual loss uses a convolutional neural network to pre-process the input image and calculate how similar the input and output images are [160]. It has been shown that perceptual loss, as opposed to mean-squared error (MSE) loss, is more resistant to several possible problems, such as over-smoothing and distortion. For style transfer, the VGG architecture can be utilized as a loss function.

5.2.3.3 Need of VGG Net for Perception Loss

The usage of VGG16 for feature extraction for calculating perceptual differences is what connects perceptual loss and VGG16. The plan is to use the pre-trained VGG16 network and its intermediate feature maps to calculate the perceptual loss among generated and target images [161]. The perceptual loss can be estimated and used as a guide for optimizing the picture production process by comparing the representations of features of the generated and target pictures at different levels of VGG16. To compute the perceptual loss and get an astonishing result, multiple convolution layers from VGG-Net, a pre-trained neural network on a natural picture dataset, were employed in the maximal effort. While we focus on additional image synthesis challenges, such as super-resolution, colorization, and other picture-building tasks [162].

Our model is inspired by [163] for super-resolution generations to generate high-resolution satellite data images. The block diagram of our suggested SSR-GAN model is shown in Figure 5.1. Our model (SSR-GAN) consists of a Generator, Discriminator, and VGG net for preserving structure. At the time of training, we pass a low-resolution image (128*128) which is provided as input to the generator, which consists of a series of convolution and residual blocks followed by a single bilinear upsampling convolution and predicts the following output using a residual block and final prediction layer. Our generator is a full convolutional network that can upsample images of any resolution. The discriminator is provided with a real high-resolution (256*256) and generated high-resolution image (256*256), which the generator has to distinguish between by predicting real or fake.

We also use VGG-NET for the perceptual loss using features extracted from generated high-resolution images and real-pair high-resolution images to preserve the structure of the image. As our model is trained to learn a distribution to upsample locally and preserve the global structure at the time of testing, we provide as input an image of resolution (256*256) and predict the output with a (512*512) resolution

image. Thus, we fine-tune locally, which is better than predefined steps like Bicubic and bilinear upsampling.

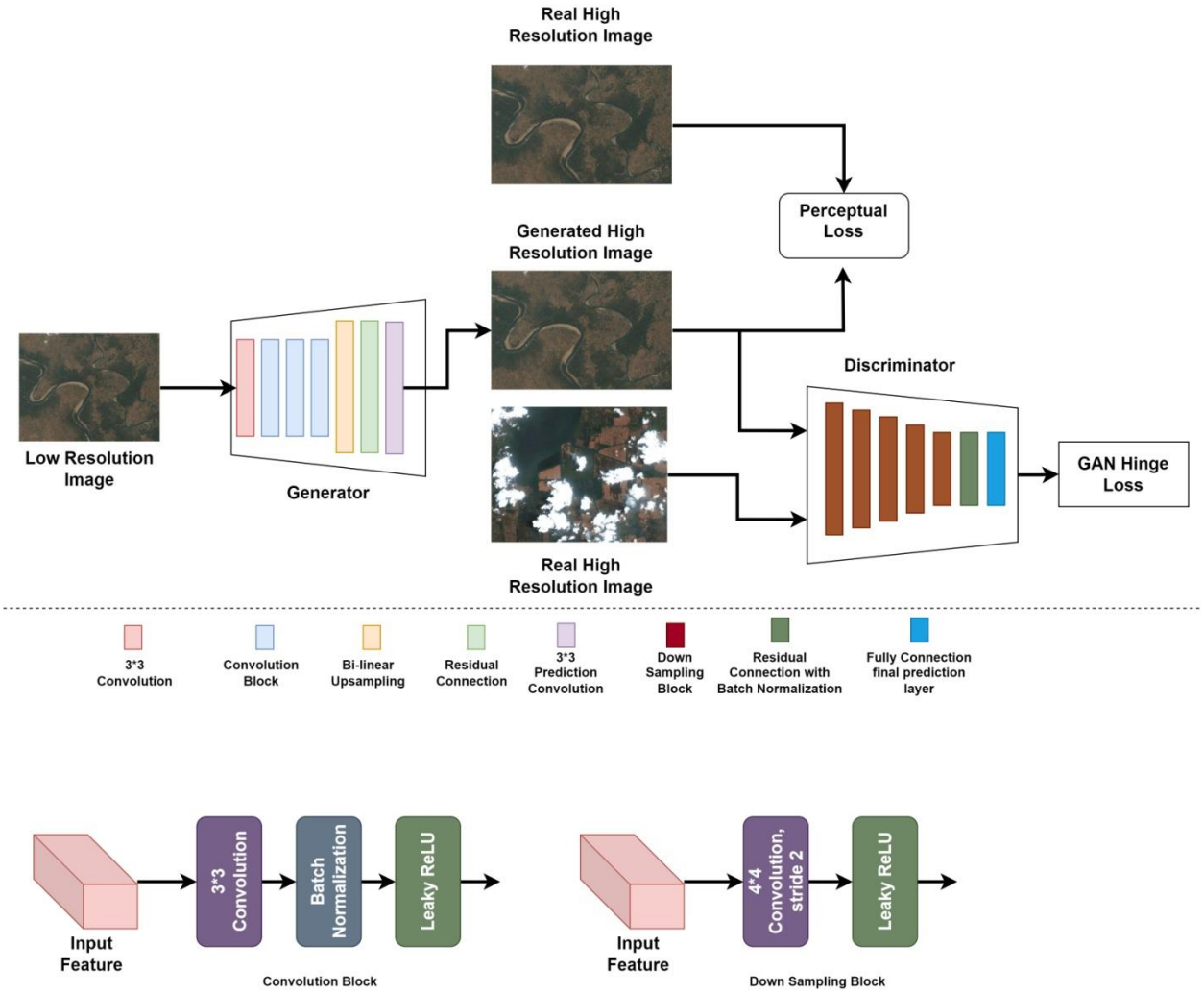


Figure 5.1: The architecture of our proposed (SSR-GAN) model for SAR Image enhancement

Loss for Discriminator

$$\mathcal{L}_{Adv}^{D} = E_{x\sim p_{data}}[\max(0,1 - D(x))] + \quad E_{\hat{x}\sim p_G}[\max(0,1 - D(x))] \tag{5.2}$$

In equation 5.2, p_{data} is the data distribution of high-resolution images and p_G is the Generator learned distribution to generate high-resolution images. We use Hinge Adversarial loss introduced in [164].

Loss for Generator:

$$\mathcal{L}_{Adv}^{G} = E_{\hat{x}\sim p_G}[-D(\hat{x})] \tag{5.3}$$

In equation 5.3, which is used to preserve the global structure of the images generated we use perceptual loss. We use features extracted from the 9th layer of the Vgg-16 Network [165]. Perceptual loss is better than l1 loss on images as it does not punish hard for small minute changes in the generated images.

Perceptual Loss:

$$\ell_{feat}^{\emptyset,j}(\hat{y},y) = \frac{1}{C_J\ H_J W_J}\ ||\emptyset_j(\hat{y}) - \emptyset_j(y)||_2^2 \tag{5.4}$$

In above equation 5.4,y and $\hat{y}$are the targeted images and synthesis images. $\emptyset_j$represents the perceptual function that outputs the activation of the j[th] layer in the perceptual loss network. C_J,$H_J, W_J$are the dimensions of the tensor feature map [166].

When comparing two different images that appear similar, such as the same photo that has been displaced by one-pixel, perceptual loss functions are utilized. The function is used to compare significant variations across photographs, such as variances in content and style.

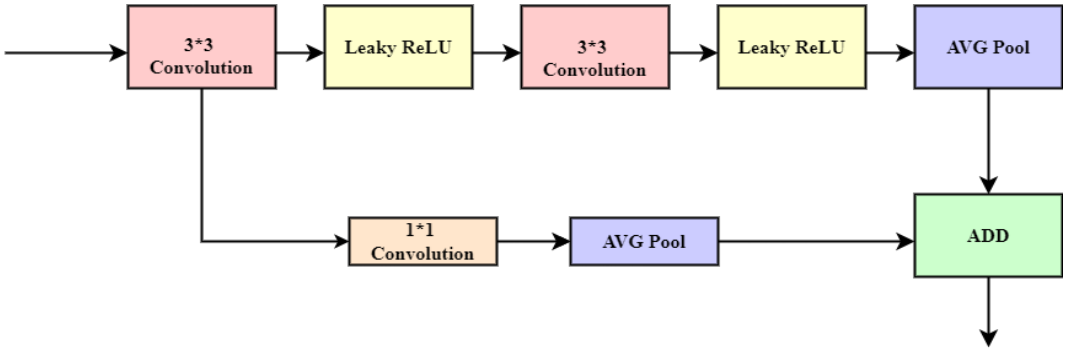


Figure 5.2: Block diagram of Down-sample Block

The architecture of the downsample block is depicted in Figure 5.23. The discriminator's downsample block is sab-block, followed by the residual block with batch normalization. The input images are initially fed to the 3*3 convolution layer, followed by the AVG Pooling layer. We used the activation function Leaky ReLU. The slope of the negative values is minimized by the ReLU activation function. The AVG Pool layers' output is clubs, which are fed to the next sub-block.

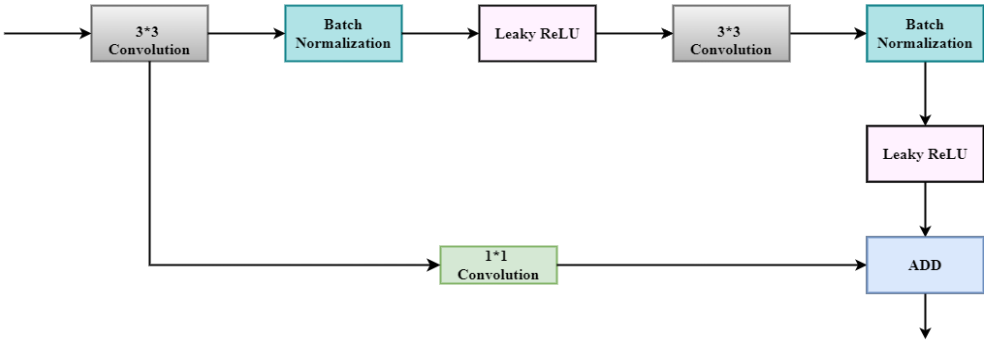


Figure 5.3: Block diagram of Residual Block with Batch Normalization

In the above figure 5.3, inner 4-layered architecture of the residual block with batch normalization (BN) layer is explained. The residual block with BN is part of the generator of our proposed model. It contains the 3*3 convolution layers followed by the BN layer. The Leaky ReLU activation function is used. The combined output of the Leaky ReLU activation function and 1*1 convolution layer is added and forwarded to the next block. In the above figure 5.4, inner layered architecture of the residual block is explained. Residual block without BN is also part of the discriminator block of our proposed model. It contains the 3*3 convolution layers. The Leaky ReLU activation function is used. The output of Leaky ReLU and 3*3 convolution layer is ADD and forwarded to the next block.

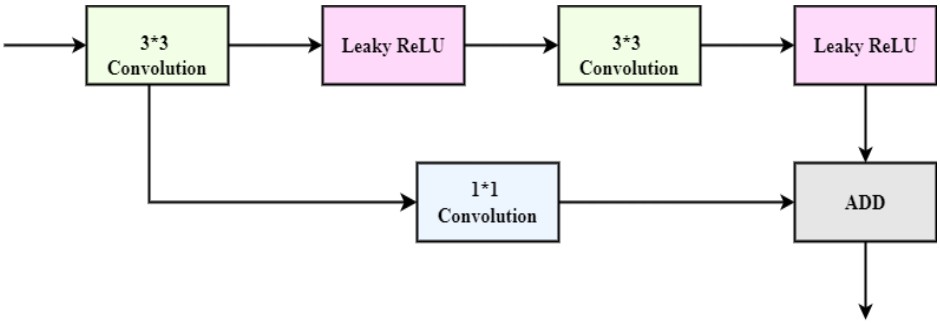


Figure 5.4: Block diagram of Residual Block without Batch Normalization

A detailed description of our proposed SSR-GAN model is provided in Algorithm 1 below. The input is raw satellite images, and the output is enhanced images.

Algorithm 1: Procedure for the SAR image enhancement using the proposed (SSR-GAN) model

Input: Raw (low resolution) SAR images **Output:** High-resolution SAR images

Adam Optimizer: Learning Rate:= 0.0001, beta_1 = 0.5,beta_2 = 0.999
Spectral Normalization is used for all Convolution and Fully Connected layers in the Discriminator and the Generator
--- 	
For a number of training iterations, do:
Begin
{
For t = 0,....,n do: \\ Training the discriminator
Sample $\{X_{high(i))}\}$ ~ P_ra batch from real data \\ images at high resolution
Sample $\{X_{low(i))}\}$ ~ P_ra batch from a real date \\ images at low resolution

$L_d^{adv} = E_{x \sim P\_high}[\max(0,1-D(x))] + E_{x \sim P\_low}[\max(0,1+D(G(x`)))]$

Update the weights of the discriminator using Adam Optimizer

For t = 0,....,n do: \\ Training the generator

Sample $\{X_{low}\} \sim P_r$ a batch from a real date \\ images at low resolution

$L_g^{adv} = E_{x' \sim P\_high}[-D(G(x`))]$

Update the weights of the generator using Adam Optimizer

}

At the time of inference

For number of samples do:

{

Sample $\{X_{high(i)}\} \sim P_r$ a batch from real data \\ images at high resolution

\\ Generate super Resolution images by providing high-resolution images as inputs

$X_{super(i)} = G(X_{high(i)})$

}

End

Return High Resolution Image

5.2.4 Experimental Results and Discussion of proposed SSR-GAN model

5.2.4.1 Dataset

Images with a size of 256x256 are used as inputs in our experiment. In our paper, we use approximately 3000 Sentinel-2 images that were used to construct the dataset. Sentinel-2 satellites for remote sensing capture images of various sorts of landscapes, including lakes, terraces, villages, snow-capped mountains, plateaus, etc. Resolution, incidence, and the geographic makeup of that area are only a few of the image details. There is no denying the enormous variety of these pictures. We will be using data from the previous 20 years for various geographical locations of India because the satellite has a 12-day return cycle. The majority of the area we consider in our study is quite prone to flooding. Kerala floods occur, just like in the Ganga basin. Images from before and after flood occurrences are part of our dataset.

5.2.4.2 Evaluation Metrics

The information contained and the feature similarity of the two images is compared as the foundation of the comprehensive image quality evaluation measures. Picture pixel statistics are ideal for using conventional image quality evaluation measures like peak signal-to-noise ratio (PSNR), The Structural Similarity Index Measure (SSIM), MULTI-SCALE SSIM (Structural Similarity Index Measure), and mean square error (MSE). The similarity in structure Structure-based similarity is the basis for Index and peak signal-to-noise ratio.

- **Peak signal-to-noise ratio**

Peak Signal-to-Noise Ratio (PSNR) is a metric used to compare the quality of a compressed or reconstructed picture or video signal to its source. it provides a numerical number that quantifies the quality of the compressed or reconstructed picture or video in comparison to the original. PSNR is commonly represented in decibels (dB) and is derived using the MSE between the original and the compressed or reconstructed image. The greater the PSNR value, the closer the compressed or rebuilt image is to the original, and thus the higher the quality of the compression or reconstruction.

$$\text{PSNR} = 20\log_{10}\left(\frac{MAX_f}{\sqrt{MSE}}\right) \tag{5.5}$$

In above equation 5.5, MAX_f is the image or video's highest possible pixel value, typically 255 for 8-bit pictures, and MSE is the mean squared error

- **Structural similarity index measure**

The Structural Similarity Index Measure (SSIM) is a popular picture quality metric for determining the similarity between two images. SSIM compares the structural data in a reference image to structural information in a distorted image and generates a score indicating the similarity between the two images. The score runs from 0 to 1, with 1 signifying that the two photos are a perfect match. Equation 5.6 shows the mathematical formula of SSIM

$$\text{SSIM}(x, y) = [l(x, y)]^{\alpha} \cdot [c(x, y)]^{\beta} \cdot [s(x, y)]^{\gamma} \tag{5.6}$$

The two images being compared are x and y. α, β and γ are constants that indicate how important each aspect is. l for brightness, c for contrast, s for contrast, and s stands for structural comparison between x and y images

- **Multi-scale SSIM**

Multi-scale SSIM (Structural Similarity Index Measure) is a metric for assessing the similarity between two photographs. It is an expansion of the classic SSIM measure that takes into consideration the human visual system's multi-scale nature. The multi-scale SSIM works by decomposing images into many

scales using a Gaussian pyramid and then computing the SSIM index at each scale individually. This enables the metric to extract both global and local structural details from images.

$$\text{MSSIM}(x,y) = [\, l_m(x,y)]^{\alpha_M} \cdot \prod_{j=1}^{M} \left[C_j(x,y)\right]^{\beta_j} \cdot \left[S_j(x,y)\right]^{\gamma_j} \quad (5.7)$$

In equation 5.7, M corresponds to the lowest resolution (i.e. the times of down samplings performed to reduce the image resolution), while j = 1 corresponds to the original resolution of the image.

- **Mean squared error**

The Mean Square Error (MSE) can also be used to determine how comparable the two images are. In the context of image processing, MSE calculates the average squared difference between the pixel values of two pictures. It is frequently used as a metric to judge the quality or resemblance of compressed or rebuilt images. A lower MSE is preferable.

$$\text{MSE} = \frac{1}{MN} \sum_{n-1}^{M} \sum_{m-1}^{N} [\hat{y}(n,m) - \text{y}(n,m)]^2 \quad (5.8)$$

Above equation 5.8 shows MSE between two images such as y (x, y) and S $\hat{y}$ (x, y).

5.2.4.3 Analysis of Results

Table 5.1, shows the statistical measures of the existing model with our proposed model. The parameters we consider for comparing performance are PSNR, SSIM, MSSIM, and MSE.

Table 5.1: Performance comparison table of the Existing model with our proposed model

Method	PSNR↑	SSIM ↑	M-SSIM ↑	MSE ↓
Bilinear interpolation	26.89	0.72	0.89	0.030
Bicubic interpolation	26.34	0.67	0.89	0.031
Nearest Neighbor interpolation	27.21	0.61	0.84	0.053
Proposed Model (SSR-GAN)	**28.11**	**0.81**	**0.97**	**0.012**

This can be observed that our proposed model outperforms. Our proposed model has having best PSNR, SSIM, and MSSIM values compared to other existing models. The MSE value of our model is low, which indicates our model performs better.

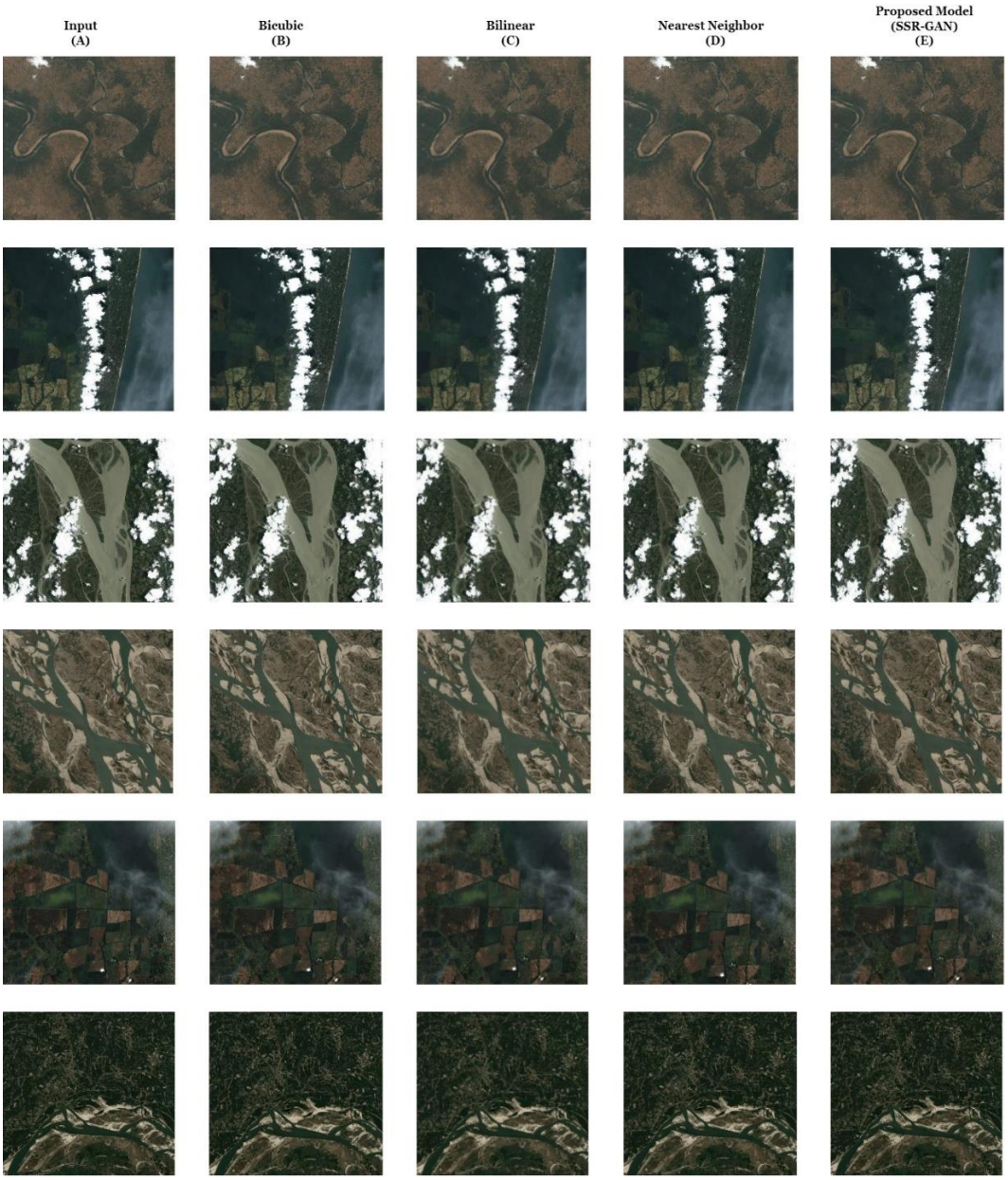


Figure 5.5: Comparative image analysis between existing approaches and our proposed model (A) input raw images (B) output images of Bicubic model (C) output images of Bilinear model (D)output images of Nearest Neighbour model (E)output images of our proposed (SSR-GAN) model

In the figures 5.5, we have shown the PSNR, SSIM, MSSIM, and MSE of our proposed model and existing traditional techniques and compared their results. The size of the original input image is (256*256) resolution, and the predicted output is (512*512) resolution. In Figure 5.6, we calculate the PSNR and provide a comparison between the existing approaches with the proposed approach. We run our model for 200 epochs, the epochs are shown on the X-axis, while the ratio's value is listed on the Y-axis. As shown in the above diagram, our proposed model provides a better peak signal-to-noise ratio value. In Figure 5.7, we provide a comparison between the existing approaches with the proposed approach. We run our model for 200 epochs; the X axis shows the number of epochs, and the Y axis

shows the percentage of the Structural Similarity Index. As the value is higher, the model is considered more accurate.

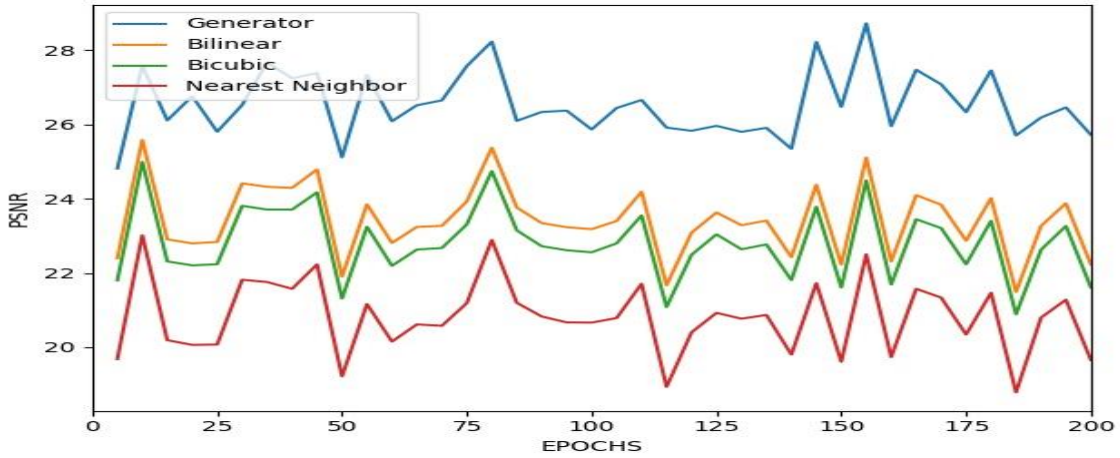


Figure 5.6: The graph representation between PSNR and Epochs

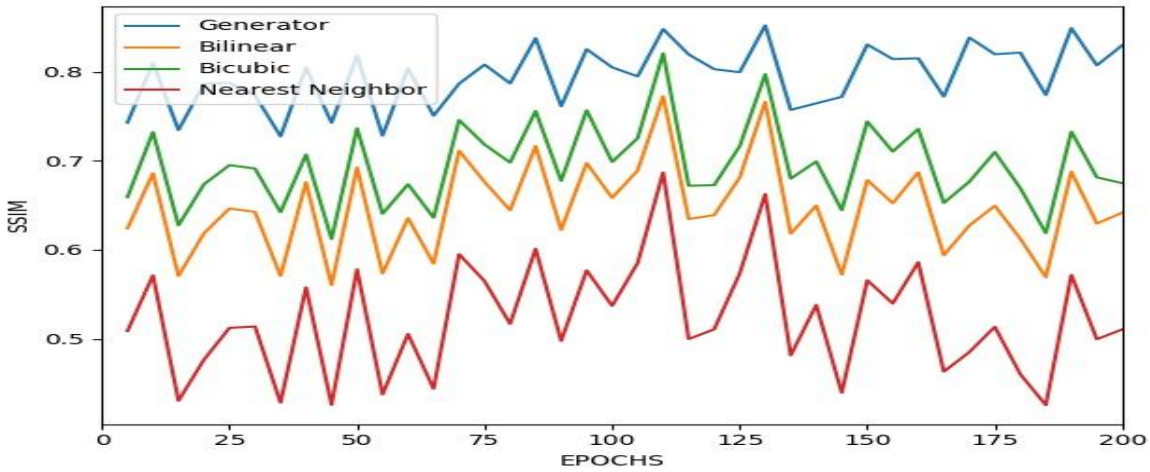


Figure 5.7: The graph representation between SSIM and Epochs

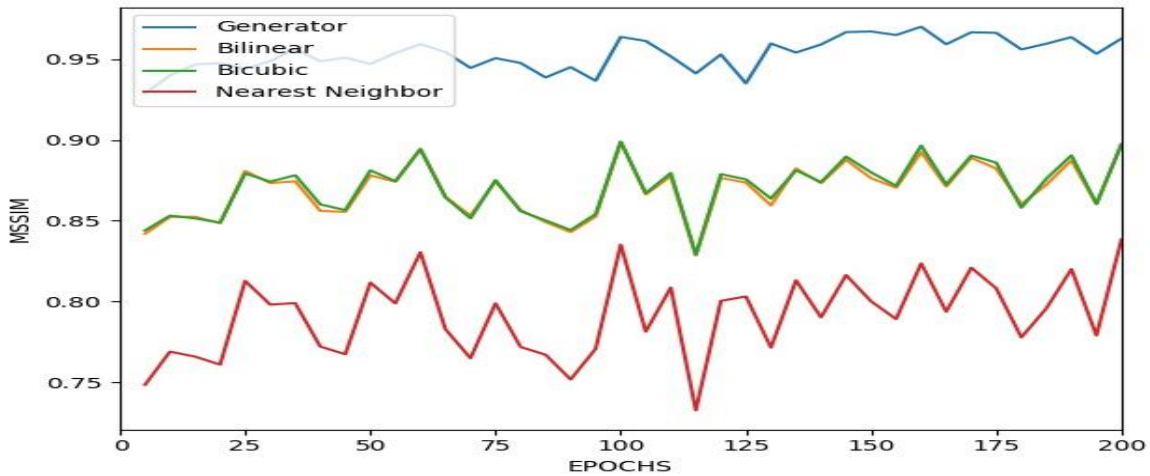


Figure 5.8: The graph representation between MSSIM and Epochs

In above figure 5.8, we provide a comparison between the existing approaches with the proposed approach. We run our model for the 200 epochs, The X-axis contains the number the epochs and Y-axis contains the percentage of the Multi-scale Structural Similarity Index. As the value is higher the model is considered more accurate.

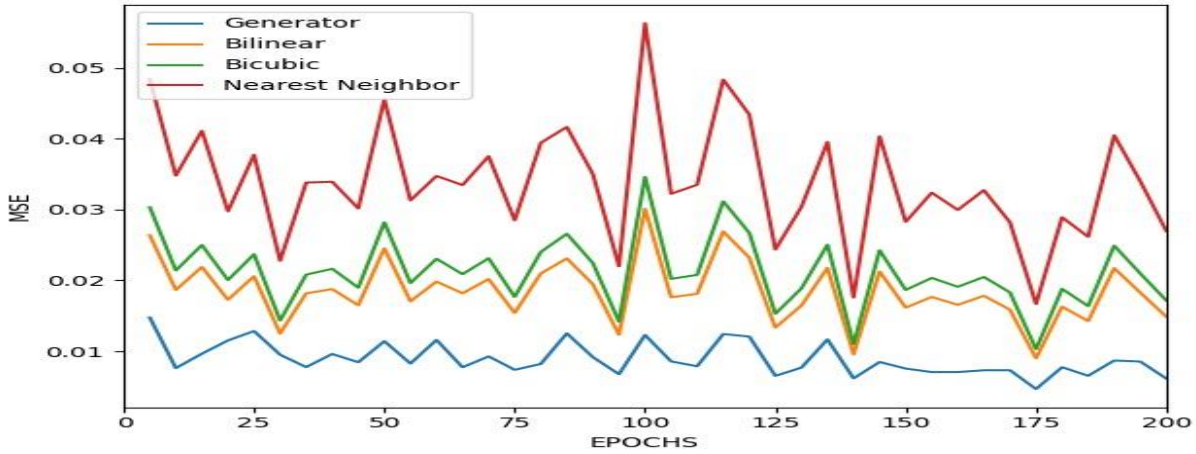


Figure 5.9: The graph representation between MSE and Epochs

In above figure 5.9, we provide a comparison between the existing approaches with the proposed approach. We run our model for 200 epochs, where the X-axis represents the number of epochs while the Y-axis represents the percentage inaccuracy.

5.3 Introduction to Adaptive Histogram Equalization Related Techniques

In image processing techniques, image quality improvement is one of the vital elements. Image enhancement is a technique to remove noise from the raw image and highlight the required information in the target image. For enhancement purposes, Spatial Domain Methods were used and compared based on the output image in our work [167].

Spatial domain Methods: In spatial domain methods, the enhancement approach is directly applied to the pixel of the image by manipulating the value stored in the pixel to get the desired result.

$$S = T(r) \tag{5.9}$$

In equation 5.9, T is the transformation that interprets pixel value in the desired pixel value S.

5.3.1 Histogram Equalization (HE)

Image enhancement is considered one of the essential sections of image processing. Its objective is to achieve intensity mapping functions, such as distribution entropy the output intensity can be expanded. Although it's a proper utility, HE is the completely inconsiderate intensity with a large pixel population, even if they are slightly visible. In this work, the author has proposed an approach to improve image quality using the histogram equation and spatial filtering. HE is used to increasing contrast.

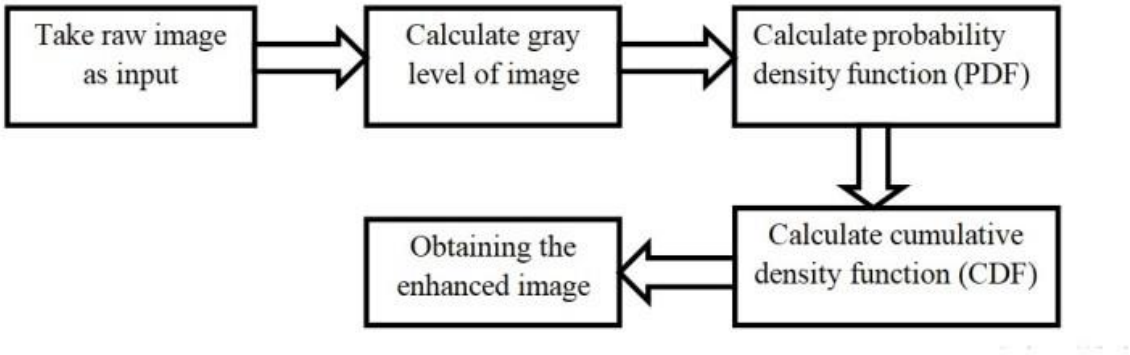


Figure 5.10: Block diagram of the Histogram Equalization SAR images

The image extends the intensity values over the entire range. It is a commonly used image enhancement method for adjusting the contrast of the image by using its histogram [168]. In this approach, the gray level transform is applied to the raw image, after then to maximize the image contrast and try to flatten the resulting histogram. In this, HE is used to enhance the quality of medical images. In the case of Histogram Equalization, it spreads the color intensity value over the full range [169]. In the Figure 5.10 basic steps of HE is explained in the form of the block diagram is explained.

- Data collection: For improving the quality of the image for HE, we first acquire the raw image. For this, data is collected from various resources according to need. We focus on flooded areas, so we consider SAR images for the flooded area.

- Calculate Gray level: In our approach of enhancement for HE, we apply it to the gray-scale image. For that, we convert the image to a gray- scale value. The color range of the gray-scale value is lies between min.0 (black) to the max. 255 (white).

- Calculate the PDF: Then for HE, the probability density function (PDF) is modified accordingly for the requirement. To make it easier, this technique converts the PDF of the image into equal PDF from lower pixel value to higher pixel value. When we talk about the digital image, the probability density function is a discrete function. Let's assume a raw image (x); for example, the probability density function is calculated using probability-based on histogram P(rk) as follows. In equation (6), we show the PDF for HE.

$$PDF\ (r_k) = P_{r_k} = \frac{totel\ pixels\ with\ intensity\ r_k}{totel\ pixel\ in\ image\ x} \tag{5.10}$$

- Calculate the CDF: The cumulative density function (CDF) determines the probability of seeing certain pixel intensities. From this probability density function, we calculate the CDF and the intensity (rk) of the color fluctuates between 0 (black) to (L-1) white.

$$CDF\,(X) = \sum_{k=0}^{L-1} P\,(r_k) \tag{5.11}$$

In equation 5.11, CDF is calculated where P(rk) is the probability for the pixel of intensity. After this, we finally get the enhanced image. The final image is also on a gray scale. Invisible information also appears in the final resultant image.

5.3.2 Adaptive Histogram Equalization

When we talk about Histogram Equalization, it focuses on the global contrast of the image, so this is not efficient in all cases. In Histogram Equalization, or we can say Global Histogram Equalization, improves the contrast of the image, but it may lead to the loss of information because it does not confine to a particular region [170]. So, in the case of the HE, this approach is efficient for image enhancement, but it may result in the loss of some useful information.

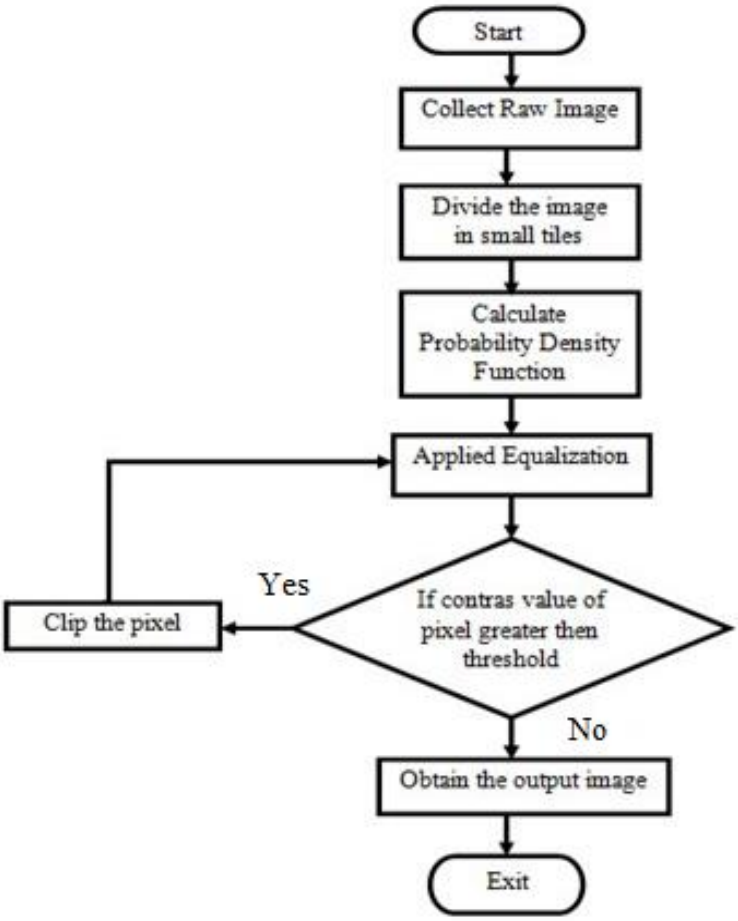


Fig. 5.11: Flow chart of Adaptive Histogram Equalization of SAR images

AHE is widely used to overcome this issue of data loss. It is better than the ordinary histogram-based approach to improving local contrast and edges in specific areas of the image. In the following, we explain how the AHE is applied to the image. To overcome this issue, the AHE is used. In this case, the

image is divided into small blocks named "Tiles," and then HE is applied to every block. So, in this case, the histogram is confined to small blocks. Suppose that noise is there in the block, then it will be amplified. To overcome this issue, contrast limiting is applied. Before applying the AHE on the gray-scale image, the Contrasts of the image are limited by applying the CDF. This threshold value depends on the nearby pixel or the size of the histogram of the image [171]. If a histogram value is raised above the specified contrast threshold, then those pixels are evenly clipped and distributed before applying histogram equalization; after equalization, bilinear interpolation is applied to remove artifacts in tile boundaries. In Figure 5.11, we explain the workflow of the adaptive histogram equalization technique. In the below flow chart, we explain the working of the AHE. The raw image is converted into tiles, and the equalization technique is applied. Based on the threshold is the condition is satisfied, we get the desired result; otherwise, clip the pixel, and then equalization is applied till getting the final result.

5.3.3 Result Analysis on Adaptive Histogram Equalization

As illustrated in Figures 5.12 to 5.15, the images enhanced using Histogram Equalization (HE) and Adaptive Histogram Equalization (AHE) techniques are presented. In the AHE method, the image is divided into smaller regions (tiles) of size 8×8. Each tile is processed individually, which allows for better local contrast enhancement. The output of both techniques is shown not only through visual images but also supported by their respective histogram graphs. These histograms help in analyzing the pixel intensity distribution across gray-scale levels. The graphical comparisons indicate that AHE outperforms standard HE in terms of preserving and enhancing image details. While HE improves overall image contrast, it may lead to the loss of important local features. AHE addresses this limitation by enhancing contrast locally, thereby retaining more critical image information. The histogram plots of the output images further validate that AHE provides a more detailed and balanced contrast enhancement. In these graphs, the X-axis represents gray-scale values and the Y-axis represents pixel intensity.

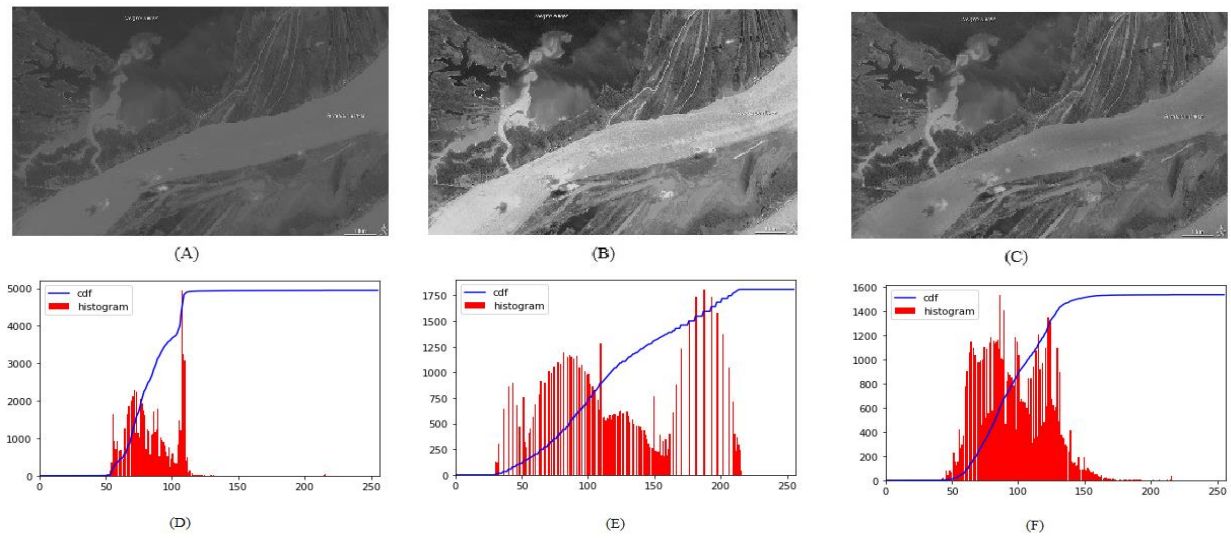


Figure 5.12 (A) Raw image, (B) Enhanced by HE, (C) Enhanced by AHE, (D) Histogram of basic image & Histogram after HE (F) Histogram after AHE [172]

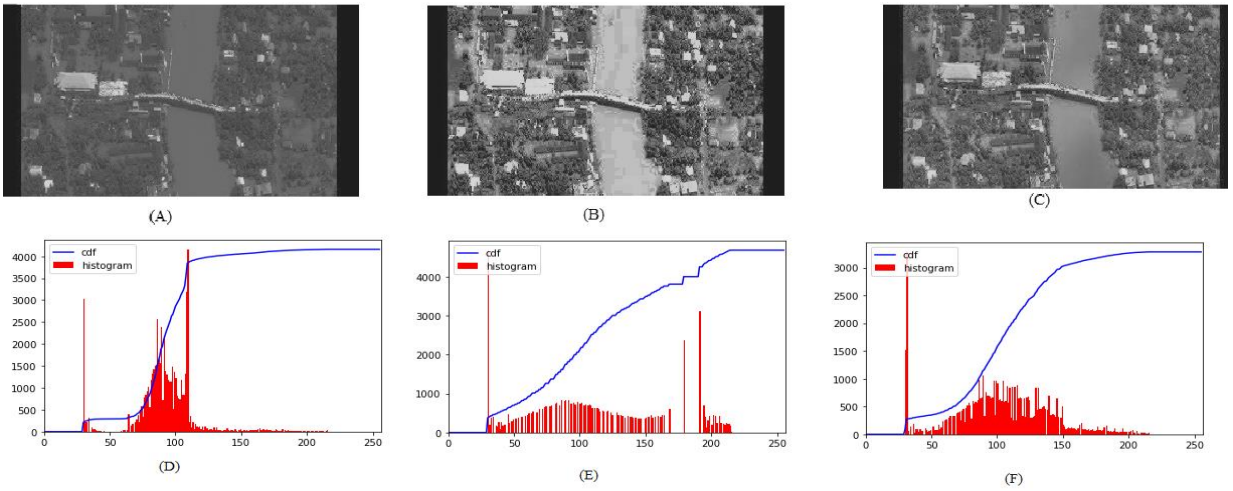


Figure 5.13 (A) Raw image, (B) Enhanced by HE, (C) Enhanced by AHE, (D) Histogram of basic image & Histogram after HE (F) Histogram after AHE [173]

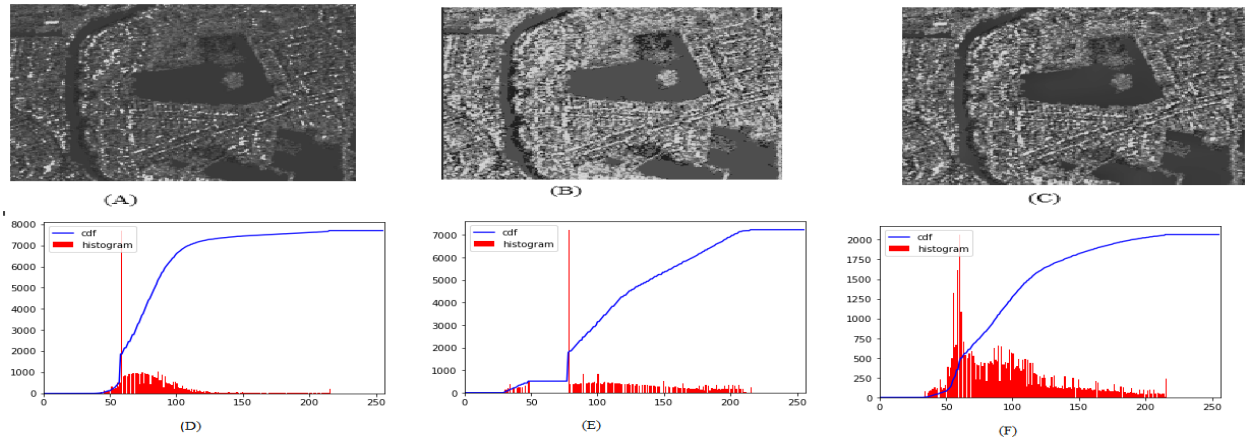


Figure 5.14 (A) Raw image, (B) Enhanced by HE, (C) Enhanced by AHE, (D) Histogram of basic image & Histogram after HE (F) Histogram after AHE [174]

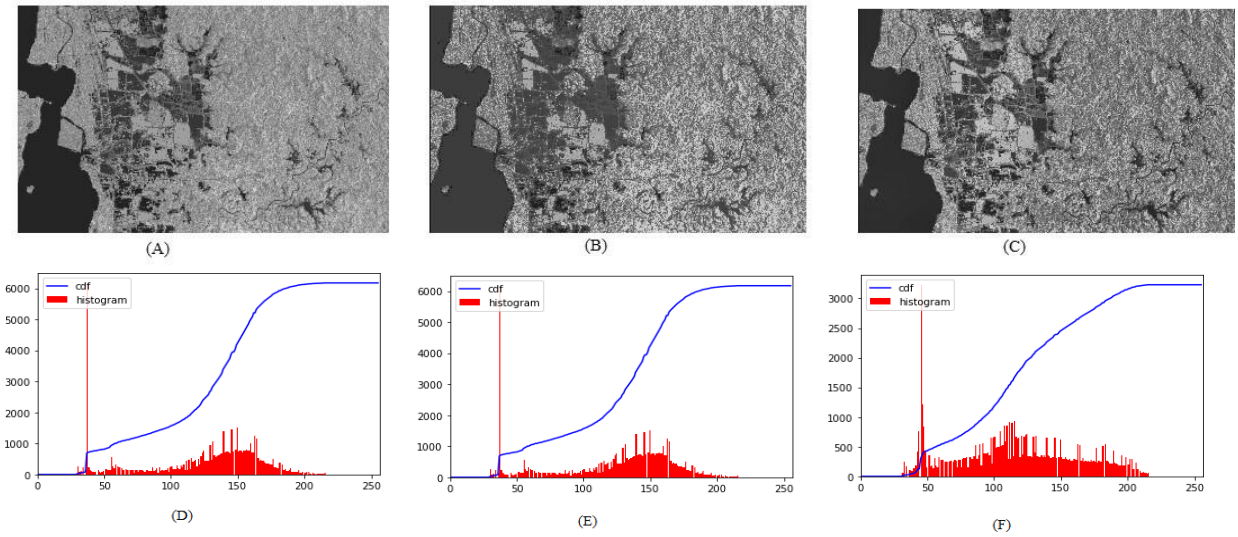


Figure 5.15 (A) Raw image, (B) Enhanced by HE, (C) Enhanced by AHE, (D) Histogram of basic image & Histogram after HE (F) Histogram after AHE [175]

5.4 Chapter Summary

This chapter presented a comprehensive study on the application of Artificial Intelligence (AI) techniques for enhancing flood detection through the improvement of Synthetic Aperture Radar (SAR) images. Floods, being among the most frequent and destructive natural disasters, require accurate and timely detection mechanisms for effective disaster response and mitigation. SAR imaging, due to its capability to operate under all weather and lighting conditions, has been widely employed in flood monitoring. However, the utility of SAR images is often constrained by issues such as low contrast, speckle noise, and limited spatial resolution. To address these challenges, the chapter explored two AI-driven approaches. First, Adaptive Histogram Equalization (AHE) was investigated for its ability to enhance image contrast by operating on localized regions of SAR images. Compared to traditional Histogram Equalization (HE), AHE was shown to preserve essential structural and contextual details, making it more suitable for identifying flooded regions with higher precision. Second, the chapter introduced a deep learning-based super-resolution model named SSR-GAN (Satellite Super Resolution-based Generative Adversarial Network). The SSR-GAN model leverages a generative adversarial framework, including a generator, a discriminator, and a perceptual loss component based on a pre-trained VGG network. This model was designed to reconstruct high-resolution images from low-resolution SAR inputs, thereby improving visual clarity and enabling finer delineation between flooded and non-flooded areas. Experimental evaluations demonstrated that the combination of AHE and SSR-GAN significantly enhances the interpretability and quality of SAR images. The SSR-GAN model outperformed traditional interpolation methods in terms of PSNR, SSIM, MSSIM, and MSE metrics, confirming its effectiveness for flood image enhancement. Overall, the integration of AI with remote sensing technologies presents a promising direction for the development of automated, accurate, and scalable flood detection systems. The insights gained from this chapter contribute to the broader objective of leveraging AI for environmental monitoring and disaster management.

CHAPTER 6

CONCLUSION, FUTURE WORK, AND SOCIAL IMPACT

6.1 Conclusion

In this research systematically addressed critical challenges in flood prediction, detection, and classification by leveraging advanced Artificial Intelligence (AI) techniques, particularly deep learning, evolutionary optimization, and image enhancement methods. The primary objective was to develop intelligent, accurate, and scalable systems capable of supporting real-time decision-making for disaster management authorities during flood events. Four novel models were proposed and rigorously evaluated, each targeting specific aspects of the flood management pipeline.

The first contribution, Flood-FireNet, introduced a hybrid classification model combining the Adaptive Firefly Algorithm (AFA) with a transformer-based architecture. AFA optimized high-level feature selection, while the transformer effectively captured spatial dependencies within satellite imagery. This model achieved a remarkable accuracy of 97.85%, precision of 98.12%, recall of 95.73%, and F1-score of 96.92%, surpassing traditional and transformer-based baselines such as ResNet-18 and Vision Transformer (ViT).

The second contribution, MoSWIN, integrated Monkey Search Optimization (MSO) with SWIN Transformers to enhance the classification of flood and non-flood images. MSO efficiently extracted optimal feature subsets, while the SWIN transformer's hierarchical attention mechanism enabled robust spatial representation learning. The MoSWIN model achieved an accuracy of 96.53%, significantly outperforming benchmark models like ResNet-18 (85.37%) and ViT (90.24%) in terms of classification accuracy, recall, and F1-score.

For flood prediction in urban environments, a third model, FloodCNN-BiLSTM, was developed. This hybrid deep learning model combined the spatial feature extraction capabilities of CNNs with the temporal sequence learning strength of BiLSTM networks to forecast flood events based on environmental sensor data. The model demonstrated superior forecasting accuracy, achieving 97.30% on Dataset 1 and 98.60% on Dataset 2, with consistently high precision, recall, and F1-score values, outperforming classical ML models such as SVM, DT, ANN, and even standalone LSTM or CNN architectures.

The fourth contribution focused on enhancing the visual quality of flood images using the SSR-GAN framework, which employed a Super-Resolution Generative Adversarial Network to improve the spatial resolution of Synthetic Aperture Radar (SAR) images. SSR-GAN significantly improved performance metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Multiscale

SSIM, while reducing Mean Squared Error (MSE) compared to traditional interpolation and enhancement techniques. This enabled more accurate delineation of flooded zones from low-resolution SAR inputs.

Collectively, these models not only delivered state-of-the-art performance across multiple metrics but also showcased the potential of combining deep learning architectures with bio-inspired optimization and image enhancement techniques. The research paves the way for the development of intelligent, real-time, and deployable solutions for flood disaster management, offering valuable tools for environmental agencies, insurance sectors, and urban safety systems.

6.2 Limitations of the Work

While the developed models achieved significant improvements, several limitations were observed:

- **Data diversity and size**: Some models relied on datasets with limited geographical and temporal diversity, affecting their generalizability to unseen flood scenarios.
- **Optimization complexity**: Models such as MoSWIN and Flood-FireNet required fine-tuning of hyperparameters for swarm-based algorithms, which is computationally intensive.
- **Resource constraints**: Deploying deep learning models in real-time applications may face bottlenecks due to hardware limitations in edge or low-resource environments.
- **SAR image processing**: SSR-GAN's effectiveness is dependent on careful hyperparameter tuning and high-resolution SAR data availability, which may not always be feasible in emergency contexts.

6.3 Potential Industrial Applications

The outcomes of this research possess significant industrial relevance and practical applicability across multiple sectors. The developed models and techniques can be integrated into the following areas:

- **Smart City Surveillance and Urban Safety Systems**: Integration with CCTV and sensor networks for real-time flood detection and classification in urban areas. Automated alerts to municipal authorities and emergency response teams to ensure rapid evacuation and traffic control.
- **Insurance and Risk Assessment**: Automated flood damage detection using satellite and drone imagery for faster insurance claim verification. Predictive modeling for risk profiling and premium calculation based on historical flood patterns.

- **Disaster Management and Emergency Response Platforms**: Deployment in centralized disaster response systems to provide early warnings and real-time situation awareness. Decision support for resource allocation, rescue operation planning, and public safety communication.
- **Remote Sensing and Environmental Monitoring**: Enhanced flood zone classification using satellite and SAR image data for national meteorological and space agencies. Continuous monitoring of water bodies and terrain changes to update flood vulnerability maps.
- **Urban Water Resource and Infrastructure Planning**: Utilization of flood prediction models for urban planning, stormwater drainage design, and green infrastructure deployment. Support for zoning regulations and construction guidelines in flood-prone areas.
- **Agriculture and Crop Damage Estimation**: Remote sensing-based identification of flood-affected agricultural regions for compensation and replanting strategies. Integration with smart irrigation systems to manage water resources post-flood.
- **Telecommunication and Utility Services**: Risk assessment and pre-emptive service shutdown in flood zones to protect infrastructure like power lines and communication towers. Planning for resilient network layouts based on predicted flood-prone zones.
- **Transportation and Logistics**: Real-time flood mapping to reroute traffic and logistics operations, minimizing delays and ensuring safety. Integration with smart transportation systems for adaptive route planning during flood events.
- **Public Health and Sanitation**: Predictive identification of flood-affected areas for timely deployment of sanitation measures and healthcare facilities. Monitoring potential outbreaks of waterborne diseases post-flood through environmental parameters.
- **Civil Engineering and Infrastructure Resilience**: Use in structural design assessments for bridges, roads, and buildings in flood-prone regions. Risk modeling for infrastructure maintenance prioritization based on flood susceptibility.

These industrial applications demonstrate the transformative potential of the proposed models in addressing real-world flood management challenges by enabling intelligent automation, proactive planning, and rapid response mechanisms.

6.4 Future Work

Several future directions emerge from this research:

- **Multimodal Data Integration**: Incorporating radar, infrared, and real-time sensor data to enhance model generalizability across varying flood conditions.

- **Ensemble and Hybrid Models**: Fusion of multiple AI models and optimization strategies (e.g., combining MSO with Genetic Algorithms or PSO) to improve robustness.
- **Edge Deployment and Cloud Integration**: Real-time deployment on mobile, IoT, or edge devices using optimized, lightweight versions of deep learning models.
- **3D and Time-Series Analysis**: Applying the models to temporal flood data or 3D mapping for dynamic monitoring.
- **Cross-Domain Applications**: Extending the frameworks to domains such as wildfire detection, medical image enhancement, or climate change monitoring.

6.5 Societal Impact

The research outcomes present significant societal benefits:

- **Improved Disaster Response**: Accurate flood classification and forecasting facilitate faster, more targeted relief efforts, reducing casualties and losses.
- **Public Awareness and Engagement**: Mobile/web apps powered by these models can provide real-time flood alerts to citizens, enhancing community preparedness.
- **Data-Driven Policy Making**: Government bodies can use these tools to design data-driven urban planning and disaster resilience strategies.
- **Support for Vulnerable Populations**: Accurate predictions help NGOs prioritize resources and protect economically and socially disadvantaged groups during floods.

6.6 Sustainable Development Goals (SDGs) Addressed

In this research significantly contributes to the achievement of several United Nations Sustainable Development Goals (SDGs) through the development and application of advanced AI techniques for flood detection, prediction, and classification:

1. **SDG 11: Sustainable Cities and Communities**
    - Enhances urban resilience by enabling real-time flood detection and early warning systems.
    - Supports sustainable infrastructure planning by identifying flood-prone zones using intelligent prediction models.
    - Aids city planners in developing adaptive urban designs that withstand climate-induced disasters.

2. **SDG 13: Climate Action**

    - Promotes proactive climate disaster response through AI-driven forecasting and decision support systems.
    - Enables governments and environmental agencies to implement timely mitigation and adaptation strategies.
    - Provides scientific insights to strengthen national climate resilience frameworks.

3. **SDG 9: Industry, Innovation, and Infrastructure**

    - Introduces novel AI-optimization hybrid models that foster innovation in disaster risk reduction technologies.
    - Supports the development of intelligent infrastructure monitoring tools that predict and manage climate-related disruptions.
    - Encourages industrial applications in insurance, transportation, and utilities for risk-aware infrastructure planning.

4. **SDG 3: Good Health and Well-being**

    - Helps prevent flood-induced health hazards by enabling early evacuation and public health interventions.
    - Assists in maintaining the continuity of healthcare services during disasters through predictive modeling.
    - Reduces psychological and economic stress on communities by providing reliable and timely alerts.

5. **SDG 6: Clean Water and Sanitation**

    - Enhances water resource management by predicting flood events that could lead to contamination.
    - Supports post-flood sanitation strategies by identifying affected zones with precision.
    - Contributes to the protection of clean water sources from flood-related pollution and infrastructure damage.

References

1. Hirabayashi, Y., Mahendran, R., Koirala, S., Konoshima, L., Yamazaki, D., Watanabe, S., Kim, H., & Kanae, S. (2013). Global flood risk under climate change. Nature Climate Change, 3(9), 816–821. https://doi.org/10.1038/nclimate1911
2. Perumal, T., Sulaiman, M., Leong, C.: Internet of Things (IoT) enabled water monitoring system. 2015 IEEE 4th Global Conference on Consumer Electronics (GCCE). (2015).
3. Karim, Md Rezaul & Muhammad, Noor & Anne, Depio & Bhuvana, N.. (2017). POVERTY, CLIMATE CHANGE CHALLENGES AND COPING STRATEGIES OF SMALL SCALE FARM HOUSEHOLD
4. Tam, T., TzeHuey, Ibrahim, A.,Sa'ayon, M., MohdAbd, R., Muhammad. (2010). Remote Sensing Methods for Mapping Flood-Prone Areas.
5. https://www.un.org/sustainabledevelopment/blog/2015/11/un-report-finds-90-per-cent-of-disasters-are-weather-related/
6. 3 ways AI can improve disaster resilience and relief efforts, https://www.weforum.org/agenda/2020/01/natural-disasters-resilience-relief-artificial-intelligence-ai-mckinsey/.
7. 2017 U.S. billion-dollar weather and climate disasters: a historic year in context | NOAA Climate.gov, https://www.climate.gov/disasters-2017
8. Report of the Committee Constituted for Formulation of Strategy for Flood Management Works in Entire Country and River Management Activities and Works Related to Border Areas (2021–26)
9. Mosavi, A., Ozturk, P., & Chau, K. (2018). Flood Prediction Using Machine Learning Models: Literature review. Water, 10(11), 1536. https://doi.org/10.3390/w10111536
10. Amitrano, D., Di Martino, G., Di Simone, A., & Imperatore, P. (2024). Flood Detection with SAR: A Review of Techniques and Datasets. Remote Sensing, 16(4), 656. https://doi.org/10.3390/rs16040656
11. Fernández-Nóvoa, D., González-Cao, J., & García-Feal, O. (2024). Enhancing Flood Risk Management: A Comprehensive Review on Flood Early Warning Systems with Emphasis on Numerical Modeling. Water, 16(10), 1408. https://doi.org/10.3390/w16101408
12. Fowler, H. J., Lenderink, G., Prein, A. F., Westra, S., Allan, R. P., Ban, N., Barbero, R., Berg, P., Blenkinsop, S., X, H., DO, Guerreiro, S., Haerter, J. O., Kendon, E. J., Lewis, E., Schaer, C., Sharma, A., Villarini, G., Wasko, C., & Zhang, X. (2021). Anthropogenic intensification of short-duration rainfall extremes. Nature Reviews Earth & Environment, 2(2), 107–122. https://doi.org/10.1038/s43017-020-00128-6
13. Akinsoji, A. H., Adelodun, B., Adeyi, Q., Salau, R. A., Odey, G., & Choi, K. S. (2024). Integrating Machine Learning Models with Comprehensive Data Strategies and Optimization

Techniques to Enhance Flood Prediction Accuracy: A Review. Water Resources Management, 38(12), 4735–4761. https://doi.org/10.1007/s11269-024-03885-x

14. Adelodun, B., Kumar, P., Odey, G., Ajibade, F. O., Ibrahim, R. G., Alamri, S. A., Alrumman, S. A., Eid, E. M., Kumar, V., Adeyemi, K. A., Arya, A. K., Bachheti, A., Oliveira, M. L., & Choi, K. S. (2022). A safe haven of SARS-CoV-2 in the environment: Prevalence and potential transmission risks in the effluent, sludge, and biosolids. Geoscience Frontiers, 13(6), 101373. https://doi.org/10.1016/j.gsf.2022.101373
15. Camps-Valls, G., Fernández-Torres, M., Cohrs, K., Höhl, A., Castelletti, A., Pacal, A., Robin, C., Martinuzzi, F., Papoutsis, I., Prapas, I., Pérez-Aracil, J., Weigel, K., Gonzalez-Calabuig, M., Reichstein, M., Rabel, M., Giuliani, M., Mahecha, M. D., Popescu, O., Pellicer-Valero, O. J., . . . Williams, T. (2025). Artificial intelligence for modeling and understanding extreme weather and climate events. Nature Communications, 16(1). https://doi.org/10.1038/s41467-025-56573-8
16. Akhyar, A., Zulkifley, M. A., Lee, J., Song, T., Han, J., Cho, C., Hyun, S., Son, Y., & Hong, B. (2024). Deep artificial intelligence applications for natural disaster management systems: A methodological review. Ecological Indicators, 163, 112067. https://doi.org/10.1016/j.ecolind.2024.112067
17. Bathe, K. D., & Patil, N. S. (2025). ConvExNet: Deep learning-based flood detection utilizing Shapley additive explanations. Journal of Earth System Science, 134(2). https://doi.org/10.1007/s12040-025-02540-2
18. Şener, A., Doğan, G., & Ergen, B. (2023). A novel convolutional neural network model with hybrid attentional atrous convolution module for detecting the areas affected by the flood. Earth Science Informatics, 17(1), 193–209. https://doi.org/10.1007/s12145-023-01155-9
19. Bhatnagar, S., Gill, L., & Ghosh, B. (2020). Drone image segmentation using machine and deep learning for mapping raised bog vegetation communities. Remote Sensing, 12(16), 2602. https://doi.org/10.3390/rs12162602
20. Subeesh, A., Kumar, P., & Chauhan, N. (2018). Flood early detection system using internet of things and artificial neural networks. In Lecture notes in networks and systems (pp. 297–305). https://doi.org/10.1007/978-981-13-2324-9_30
21. Rezvani, S. M., Gonçalves, A., Silva, M. J. F., & De Almeida, N. M. (2024b). Smart hotspot detection using Geospatial Artificial intelligence: A machine learning approach to reduce flood risk. Sustainable Cities and Society, 115, 105873. https://doi.org/10.1016/j.scs.2024.105873
22. Núñez, M. A. E., Firtinidou-Stergiou, A., Rago, M., Yee, C. J., Barontini, A., Ferreira, T. M., & Oliveira, D. V. (2023). Flood risk assessment in urban areas: the historic city centre of Aveiro as a case study. Flood Risk in a Climate Change Context, 21.

23. Kumari, M., Bewerwal, A., Kumar, A., Srivastava, D., & Saxena, G. (2024, September). Flood Monitoring and Rescue System Using AI and IoT. In 2024 International Conference on Artificial Intelligence and Emerging Technology (Global AI Summit) (pp. 976-981). IEEE.
24. Nihal, M., Aji, D., Prabhakaran, A., Siby, K. P., & Anand, L. S. (2024, April). AI based early flood monitoring and detection. In 2024 International Conference on E-mobility, Power Control and Smart Systems (ICEMPS) (pp. 01-05). IEEE.
25. Zabihi, O., Siamaki, M., Gheibi, M., Akrami, M., & Hajiaghaei-Keshteli, M. (2022). A smart sustainable system for flood damage management with the application of artificial intelligence and multi-criteria decision-making computations. International Journal of Disaster Risk Reduction, 84, 103470. https://doi.org/10.1016/j.ijdrr.2022.103470
26. Lei, X., Chen, W., Panahi, M., Falah, F., Rahmati, O., Uuemaa, E., Kalantari, Z., Ferreira, C. S. S., Rezaie, F., Tiefenbacher, J. P., Lee, S., & Bian, H. (2021). Urban flood modeling using deep-learning approaches in Seoul, South Korea. Journal of Hydrology, 601, 126684. https://doi.org/10.1016/j.jhydrol.2021.126684
27. Indra, T. L., Yusya, R. R., & Septyandy, M. R. (2022). Appraisal of flood prone area management using artificial intelligence methods in Jakarta Basin, Indonesia. Asian Journal of Water Environment and Pollution, 19(2), 89–99. https://doi.org/10.3233/ajw220028
28. Priscillia, S., Schillaci, C., & Lipani, A. (2021). Flood susceptibility assessment using artificial neural networks in Indonesia. Artificial Intelligence in Geosciences, 2, 215–222. https://doi.org/10.1016/j.aiig.2022.03.002
29. Li, L., & Jun, K. S. (2024). Review of machine learning Methods for river flood routing. Water, 16(2), 364. https://doi.org/10.3390/w16020364
30. Ni, L., Wang, D., Wu, J., Wang, Y., Tao, Y., Zhang, J., & Liu, J. (2020). Streamflow forecasting using extreme gradient boosting model coupled with Gaussian mixture model. Journal of Hydrology, 586, 124901. https://doi.org/10.1016/j.jhydrol.2020.124901
31. Ghose, D. K. (2018). Measuring discharge using Back-Propagation Neural Network: A case study on Brahmani River Basin. In Advances in intelligent systems and computing (pp. 591–598). https://doi.org/10.1007/978-981-10-7566-7_59
32. Luo, P., Luo, M., Li, F., Qi, X., Huo, A., Wang, Z., He, B., Takara, K., Non, D., & Wang, Y. (2022). Urban flood numerical simulation: Research, methods and future perspectives. Environmental Modelling & Software, 156, 105478. https://doi.org/10.1016/j.envsoft.2022.105478
33. Kumar, V., Azamathulla, H. M., Sharma, K. V., Mehta, D. J., &Maharaj, K. T. (2023). The State of the Art in Deep Learning Applications, Challenges, and Future Prospects: A Comprehensive Review of Flood Forecasting and Management. Sustainability, 15(13), 10543. https://doi.org/10.3390/su151310543

34. Niu, W., & Feng, Z. (2020). Evaluating the performances of several artificial intelligence methods in forecasting daily streamflow time series for sustainable water resources management. Sustainable Cities and Society, 64, 102562. https://doi.org/10.1016/j.scs.2020.102562
35. Tyralis, H., Papacharalampous, G., &Langousis, A. (2019). A brief review of random forests for water scientists and practitioners and their recent history in water resources. Water, 11(5), 910. https://doi.org/10.3390/w11050910
36. Hosseiny, H., Nazari, F., Smith, V., &Nataraj, C. (2020). A framework for modeling flood depth using a hybrid of hydraulics and machine learning. Scientific Reports, 10(1). https://doi.org/10.1038/s41598-020-65232-5
37. Kim, J. et al. (2022) 'Deep learning-based flood area extraction for fully automated and persistent flood monitoring using cloud computing', Remote Sensing, 14(24), p. 6373. doi:10.3390/rs14246373
38. Saleh, T. et al. (2024) 'High-precision flood detection and mapping via multi-temporal SAR change analysis with semantic token-based transformer', International Journal of Applied Earth Observation and Geoinformation, 131, p. 103991. doi:10.1016/j.jag.2024.103991
39. Amankwah, S. O. Y., Wang, G., Gnyawali, K., Hagan, D. F. T., Sarfo, I., Zhen, D., Nooni, I. K., Ullah, W., & Duan, Z. (2022). Landslide detection from bitemporal satellite imagery using attention-based deep neural networks. Landslides, 19(10), 2459–2471. https://doi.org/10.1007/s10346-022-01915-6
40. Arvind, C., Vanjare, A., Omkar, S., Senthilnath, J., Mani, V., & Diwakar, P. (2016). Flood Assessment using Multi-temporal Modis Satellite Images. Procedia Computer Science, 89, 575–586. https://doi.org/10.1016/j.procs.2016.06.017
41. Moharrami, M., Javanbakht, M. and Attarchi, S. (2021) 'Automatic flood detection using sentinel-1 images on the google earth engine', Environmental Monitoring and Assessment, 193(5). doi:10.1007/s10661-021-09037-7
42. Fernandes, F. E., Nonato, L. G., & Ueyama, J. (2022). A river flooding detection system based on deep learning and computer vision. Multimedia Tools and Applications, 81(28), 40231–40251. https://doi.org/10.1007/s11042-022-12813-3
43. Tanim, A. H., McRae, C. B., Tavakol-Davani, H., & Goharian, E. (2022). Flood detection in urban areas using satellite imagery and machine learning. Water, 14(7), 1140. https://doi.org/10.3390/w14071140
44. Bhuyan, K., Van Westen, C., Wang, J., & Meena, S. R. (2022). Mapping and characterising buildings for flood exposure analysis using open-source data and artificial intelligence. Natural Hazards, 119(2), 805–835. https://doi.org/10.1007/s11069-022-05612-4

45. Kim, J., Kim, H., Kim, D., Song, J., & Li, C. (2022). Deep Learning-Based flood area extraction for fully automated and persistent flood monitoring using cloud computing. Remote Sensing, 14(24), 6373. https://doi.org/10.3390/rs14246373
46. Arvind, C.S. et al. (2016) 'Flood assessment using multi-temporal Modis Satellite Images', Procedia Computer Science, 89, pp. 575–586. doi:10.1016/j.procs.2016.06.017
47. Islam, K. A., Uddin, M. S., Kwan, C., & Li, J. (2020). Flood detection Using Multi-Modal and Multi-Temporal Images: A Comparative study. Remote Sensing, 12(15), 2455. https://doi.org/10.3390/rs12152455
48. Karanjit, R., Pally, R., & Samadi, S. (2023). FloodIMG: Flood image DataBase system. Data in Brief, 48, 109164. https://doi.org/10.1016/j.dib.2023.109164
49. Nghia, B. P. Q., Pal, I., Chollacoop, N., & Mukhopadhyay, A. (2022). Applying Google earth engine for flood mapping and monitoring in the downstream provinces of Mekong river. Progress in Disaster Science, 14, 100235. https://doi.org/10.1016/j.pdisas.2022.100235
50. Moharrami, M., Javanbakht, M., & Attarchi, S. (2021b). Automatic flood detection using sentinel-1 images on the google earth engine. Environmental Monitoring and Assessment, 193(5). https://doi.org/10.1007/s10661-021-09037-7
51. Rahnemoonfar, M., Chowdhury, T., Sarkar, A., Varshney, D., Yari, M., & Murphy, R. R. (2021). FloodNet: a high resolution aerial imagery dataset for post flood scene understanding. IEEE Access, 9, 89644–89654. https://doi.org/10.1109/access.2021.3090981
52. Fernandes, F. E., Nonato, L. G., & Ueyama, J. (2022b). A river flooding detection system based on deep learning and computer vision. Multimedia Tools and Applications, 81(28), 40231–40251. https://doi.org/10.1007/s11042-022-12813-3
53. Jackson, J., Yussif, S. B., Patamia, R. A., Sarpong, K., & Qin, Z. (2023). Flood or Non-Flooded: A Comparative Study of State-of-the-Art Models for Flood Image Classification Using the FloodNet Dataset with Uncertainty Offset Analysis. Water, 15(5), 875. https://doi.org/10.3390/w15050875
54. Dellepiane, S. G., & Angiati, E. (2013). Quality assessment of despeckled SAR images. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 7(2), 691–707. https://doi.org/10.1109/jstars.2013.2279501
55. Ghosh, S., Kumar, D., & Kumari, R. (2022). Evaluating the impact of flood inundation with the cloud computing platform over vegetation cover of Ganga Basin during COVID-19. Spatial Information Research, 30(2), 291–308. https://doi.org/10.1007/s41324-022-00430-z
56. Toriya, H., Dewan, A., Ikeda, H., Owada, N., Saadat, M., Inagaki, F., Kawamura, Y., & Kitahara, I. (2022). Use of a DNN-Based Image Translator with Edge Enhancement Technique to Estimate Correspondence between SAR and Optical Images. Applied Sciences, 12(9), 4159. https://doi.org/10.3390/app12094159

57. Aliabad, F. A., Shojaei, S., Zare, M., & Ekhtesasi, M. R. (2018). Assessment of the fuzzy ARTMAP neural network method performance in geological mapping using satellite images and Boolean logic. International Journal of Environmental Science and Technology, 16(7), 3829–3838. https://doi.org/10.1007/s13762-018-1795-7
58. Li, Y., Hu, J., & Jia, Y. (2014). Automatic SAR image enhancement based on nonsubsampled contourlet transform and memetic algorithm. Neurocomputing, 134, 70–78. https://doi.org/10.1016/j.neucom.2013.03.068
59. Chen, L., Jiang, X., Li, Z., Liu, X., & Zhou, Z. (2020). Feature-Enhanced speckle reduction via Low-Rank and Space-Angle continuity for circular SAR target recognition. IEEE Transactions on Geoscience and Remote Sensing, 58(11), 7734–7752. https://doi.org/10.1109/tgrs.2020.2983420
60. Ye, G., Zhang, Z., Ding, L., Li, Y., & Zhu, Y. (2020). GAN-Based Focusing-Enhancement Method for Monochromatic Synthetic aperture imaging. IEEE Sensors Journal, 20(19), 11484–11489. https://doi.org/10.1109/jsen.2020.2996656
61. Luo, Y., & Pi, D. (2022). SAR-to-optical image translation for quality enhancement. Journal of Ambient Intelligence and Humanized Computing, 14(8), 9985–10000. https://doi.org/10.1007/s12652-021-03665-0
62. Kanakaraj, S., Nair, M. S., & Kalady, S. (2017). SAR Image Super Resolution using Importance Sampling Unscented Kalman Filter. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 11(2), 562–571. https://doi.org/10.1109/jstars.2017.2779795
63. Dubey, V., & Katarya, R. (2021). Adaptive Histogram Equalization based Approach for SAR Image Enhancement: A Comparative analysis. 2022 6th International Conference on Intelligent Computing and Control Systems (ICICCS), 878–883. https://doi.org/10.1109/iciccs51141.2021.9432287
64. Q. Zhan, Y. Chen, Y. Chen, Y. Lu and C. Xu, "SAR Image Super-Resolution Reconstruction Based on an Optimize Iterative Method for Regularization," 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS, Brussels, Belgium, 2021, pp. 5075-5078, doi: 10.1109/IGARSS47720.2021.9554072
65. Yang, N. J., Wright, J., Huang, T. S., & Yi, N., MA. (2010). Image Super-Resolution via sparse representation. IEEE Transactions on Image Processing, 19(11), 2861–2873. https://doi.org/10.1109/tip.2010.2050625
66. Zhang, W., Gao, Y., Cao, L., Zhang, Y., Huang, Z., & Wang, B. (2023). A fundus image enhancer based on illumination-guided attention and optic disc perception GAN. Optik, 279, 170729. https://doi.org/10.1016/j.ijleo.2023.170729

67. Zheng, Z., Chen, Z., Wang, W., Huang, M., & Wang, H. (2023). Dual parallel multi-scale residual overlay network for single-image rain removal. Signal Image and Video Processing, 18(3), 2413–2428. https://doi.org/10.1007/s11760-023-02917-0
68. El-Magd, S. a. A., Pradhan, B., & Alamri, A. (2021). Machine learning algorithm for flash flood prediction mapping in Wadi El-Laqeita and surroundings, Central Eastern Desert, Egypt. Arabian Journal of Geosciences, 14(4). https://doi.org/10.1007/s12517-021-06466-z
69. Shafizadeh-Moghadam, H., Valavi, R., Shahabi, H., Chapi, K., & Shirzadi, A. (2018). Novel forecasting approaches using combination of machine learning and statistical models for flood susceptibility mapping. Journal of Environmental Management, 217, 1–11. https://doi.org/10.1016/j.jenvman.2018.03.089
70. Hakim, D. K., Gernowo, R., & Nirwansyah, A. W. (2023). Flood prediction with time series data mining: Systematic review. Natural Hazards Research, 4(2), 194–220. https://doi.org/10.1016/j.nhres.2023.10.001
71. Wang, J., Huang, B., & Wang, F. (2023). Extraction and classification of Flood-Affected areas based on MRF and deep learning. Water, 15(7), 1288. https://doi.org/10.3390/w15071288
72. Zhou, K. (2021). Flood season segmentation and scheme optimization in the Yellow River. Journal of Water and Climate Change, 13(1), 274–286. https://doi.org/10.2166/wcc.2021.110
73. Tanim, A. H., McRae, C. B., Tavakol-Davani, H., & Goharian, E. (2022). Flood detection in urban areas using satellite imagery and machine learning. Water, 14(7), 1140. https://doi.org/10.3390/w14071140
74. Tanim, A. H., McRae, C. B., Tavakol-Davani, H., & Goharian, E. (2022b). Flood detection in urban areas using satellite imagery and machine learning. Water, 14(7), 1140. https://doi.org/10.3390/w14071140
75. Feng, Y., Brenner, C., & Sester, M. (2020). Flood severity mapping from Volunteered Geographic Information by interpreting water level from images containing people: A case study of Hurricane Harvey. ISPRS Journal of Photogrammetry and Remote Sensing, 169, 301–319. https://doi.org/10.1016/j.isprsjprs.2020.09.011
76. G. Ye, Z. Zhang, L. Ding, Y. Li and Y. Zhu, "GAN-Based Focusing-Enhancement Method for Monochromatic Synthetic Aperture Imaging," in IEEE Sensors Journal, vol. 20, no. 19, pp. 11484-11489, 1 Oct.1, 2020, doi: 10.1109/JSEN.2020.2996656
77. Dottori, F., Salamon, P., Bianchi, A., Alfieri, L., Hirpa, F. A., & Feyen, L. (2016). Development and evaluation of a framework for global flood hazard mapping. Advances in Water Resources, 94, 87–102. https://doi.org/10.1016/j.advwatres.2016.05.002
78. Jonkman, S. N. (2005). Global perspectives on loss of human life caused by floods. Natural Hazards, 34(2), 151–175. https://doi.org/10.1007/s11069-004-8891-3
79. Ahmadisharaf, E., Tajrishy, M., & Alamdari, N. (2015). Integrating flood hazard into site selection of detention basins using spatial multi-criteria decision-making. Journal of Environmental Planning and Management, 59(8), 1397–1417. https://doi.org/10.1080/09640568.2015.1077104
80. Dubey, V., & Katarya, R. (2020). An analysis of machine learning techniques for flood mitigation. In Advances in intelligent systems and computing (pp. 299–307). https://doi.org/10.1007/978-981-15-5148-2_27

81. Gangani, P., Mangukiya, N. K., Mehta, D. J., Muttil, N., & Rathnayake, U. (2023). Evaluating the efficacy of different DEMs for application in flood frequency and risk mapping of the Indian Coastal river basin. Climate, 11(5), 114. https://doi.org/10.3390/cli11050114
82. Ibrahim, K. S. M. H., Huang, Y. F., Ahmed, A. N., Koo, C. H., & El-Shafie, A. (2022). Forecasting multi-step-ahead reservoir monthly and daily inflow using machine learning models based on different scenarios. Applied Intelligence, 53(9), 10893–10916. https://doi.org/10.1007/s10489-022-04029-7
83. Omukuti, J., Wanzala, M. A., Ngaina, J., & Ganola, P. (2023). Develop medium- to long-term climate information services to enhance comprehensive climate risk management in Africa. Climate Resilience and Sustainability, 2(1). https://doi.org/10.1002/cli2.47
84. Ni, L., Wang, D., Wu, J., Wang, Y., Tao, Y., Zhang, J., & Liu, J. (2020). Streamflow forecasting using extreme gradient boosting model coupled with Gaussian mixture model. Journal of Hydrology, 586, 124901. https://doi.org/10.1016/j.jhydrol.2020.124901
85. Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Mohamed, N. A., & Arshad, H. (2018). State-of-the-art in artificial neural network applications: A survey. Heliyon, 4(11), e00938. https://doi.org/10.1016/j.heliyon.2018.e00938
86. Elsafi, S. H. (2014). Artificial Neural Networks (ANNs) for flood forecasting at Dongola Station in the River Nile, Sudan. Alexandria Engineering Journal, 53(3), 655–662. https://doi.org/10.1016/j.aej.2014.06.010
87. Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., Santamaría, J., Fadhel, M. A., Al-Amidie, M., & Farhan, L. (2021). Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. Journal of Big Data, 8(1). https://doi.org/10.1186/s40537-021-00444-8
88. Kabir, S., Patidar, S., Xia, X., Liang, Q., Neal, J., & Pender, G. (2020). A deep convolutional neural network model for rapid prediction of fluvial flood inundation. Journal of Hydrology, 590, 125481. https://doi.org/10.1016/j.jhydrol.2020.125481
89. Van Houdt, G., Mosquera, C., & Nápoles, G. (2020). A review on the long short-term memory model. Artificial Intelligence Review, 53(8), 5929–5955. https://doi.org/10.1007/s10462-020-09838-1
90. Al-Selwi, S. M., Hassan, M. F., Abdulkadir, S. J., Muneer, A., Sumiea, E. H., Alqushaibi, A., & Ragab, M. G. (2024). RNN-LSTM: From applications to modeling techniques and beyond—Systematic review. Journal of King Saud University - Computer and Information Sciences, 36(5), 102068. https://doi.org/10.1016/j.jksuci.2024.102068
91. Fan, Y., Tang, Q., Guo, Y., & Wei, Y. (2024). BILSTM-MLAM: a Multi-Scale Time Series prediction model for sensor data based on Bi-LSTM and local attention mechanisms. Sensors, 24(12), 3962. https://doi.org/10.3390/s24123962
92. Kowsher, M., Tahabilder, A., Sanjid, M. Z. I., Prottasha, N. J., Uddin, M. S., Hossain, M. A., & Jilani, M. a. K. (2021). LSTM-ANN & BiLSTM-ANN: Hybrid deep learning models for enhanced classification accuracy. Procedia Computer Science, 193, 131–140. https://doi.org/10.1016/j.procs.2021.10.013
93. Roy, P. K., Tripathy, A. K., Das, T. K., & Gao, X. (2020). A framework for hate speech detection using deep convolutional neural network. IEEE Access, 8, 204951–204962. https://doi.org/10.1109/access.2020.3037073
94. Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term memory. Neural Computation, 9(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

95. Sankaranarayanan, S., Prabhakar, M., Satish, S., Jain, P., Ramprasad, A., & Krishnan, A. (2019). Flood prediction based on weather parameters using deep learning. Journal of Water and Climate Change, 11(4), 1766–1783. https://doi.org/10.2166/wcc.2019.321
96. weather forecast data. (2022, June 7). Kaggle. https://www.kaggle.com/datasets/vipin20/weatherforcast-data
97. Saber, M., Boulmaiz, T., Guermoui, M., Abdrabo, K. I., Kantoush, S. A., Sumi, T., Boutaghane, H., Hori, T., Van Binh, D., Nguyen, B. Q., Bui, T. T. P., Vo, N. D., Habib, E., & Mabrouk, E. (2023). Enhancing flood risk assessment through integration of ensemble learning approaches and physical-based hydrological modeling. Geomatics Natural Hazards and Risk, 14(1). https://doi.org/10.1080/19475705.2023.2203798
98. Hadi, F. a. A., Sidek, L. M., Salih, G. H. A., Basri, H., Sammen, S. S., Dom, N. M., Ali, Z. M., & Ahmed, A. N. (2024). Machine learning techniques for flood forecasting. Journal of Hydroinformatics, 26(4), 779–799. https://doi.org/10.2166/hydro.2024.208
99. Saha, P., Mitra, R., Das, J., & Mandal, D. K. (2024). Urban flash flood prediction modelling using probabilistic and statistical approaches. Results in Earth Sciences, 2, 100032. https://doi.org/10.1016/j.rines.2024.100032
100. Xu, Q., Shi, Y., Bamber, J., Ouyang, C., & Zhu, X. X. (2024). Large-scale flood modeling and forecasting with FloodCast. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2403.12226
101. Ghobadi, M., & Ahmadipari, M. (2024). Enhancing Flood Susceptibility Modeling: a Hybrid Deep Neural Network with Statistical Learning Algorithms for Predicting Flood Prone Areas. Water Resources Management, 38(8), 2687–2710. https://doi.org/10.1007/s11269-024-03770-7
102. Qasimi, A. B., Isazade, V., &Berndtsson, R. (2023). Flood susceptibility prediction using MaxEnt and frequency ratio modeling for Kokcha River in Afghanistan. Natural Hazards, 120(2), 1367–1394. https://doi.org/10.1007/s11069-023-06232-2
103. Al-Ruzouq, R., Shanableh, A., Jena, R., Gibril, M. B. A., Hammouri, N. A., &Lamghari, F. (2024). Flood susceptibility mapping using a novel integration of multi-temporal sentinel-1 data and eXtreme deep learning model. Geoscience Frontiers, 15(3), 101780. https://doi.org/10.1016/j.gsf.2024.101780
104. Bhatt, C., Rao, G., Diwakar, P., & Dadhwal, V. (2016). Development of flood inundation extent libraries over a range of potential flood levels: a practical framework for quick flood response. Geomatics Natural Hazards and Risk, 8(2), 384–401. https://doi.org/10.1080/19475705.2016.1220025
105. Tanim, A. H., McRae, C. B., Tavakol-Davani, H., & Goharian, E. (2022c). Flood detection in urban areas using satellite imagery and machine learning. Water, 14(7), 1140. https://doi.org/10.3390/w14071140
106. Zhuo, L., & Han, D. (2020). Agent-based modelling and flood risk management: A compendious literature review. Journal of Hydrology, 591, 125600. https://doi.org/10.1016/j.jhydrol.2020.125600
107. Amankwah, S. O. Y., Wang, G., Gnyawali, K., Hagan, D. F. T., Sarfo, I., Zhen, D., Nooni, I. K., Ullah, W., & Duan, Z. (2022). Landslide detection from bitemporal satellite imagery using attention-based deep neural networks. Landslides, 19(10), 2459–2471. https://doi.org/10.1007/s10346-022-01915-6
108. Tanguy, M., Chokmani, K., Bernier, M., Poulin, J., & Raymond, S. (2017). River flood mapping in urban areas combining Radarsat-2 data and flood return period data. Remote Sensing of Environment, 198, 442–459. https://doi.org/10.1016/j.rse.2017.06.042

109. Cvjena. (n.d.). GitHub - cvjena/eu-flood-dataset: Dataset with images from the central European flood 2013 for usage in the context of context-based image retrieval. GitHub. https://github.com/cvjena/eu-flood-dataset
110. Khhlkhlklk;
111. Maurício, J., Domingues, I., & Bernardino, J. (2023). Comparing vision Transformers and convolutional neural Networks for image classification: A literature review. Applied Sciences, 13(9), 5521. https://doi.org/10.3390/app13095521
112. Li, Y., Miao, N., Ma, L., Shuang, F., & Huang, X. (2023). Transformer for object detection: Review and benchmark. Engineering Applications of Artificial Intelligence, 126, 107021. https://doi.org/10.1016/j.engappai.2023.107021
113. Pacal, I. (2024). A novel Swin transformer approach utilizing residual multi-layer perceptron for diagnosing brain tumors in MRI images. International Journal of Machine Learning and Cybernetics, 15(9), 3579–3597. https://doi.org/10.1007/s13042-024-02110-w
114. Zuo, S., Xiao, Y., Chang, X., & Wang, X. (2022). Vision transformers for dense prediction: A survey. Knowledge-Based Systems, 253, 109552. https://doi.org/10.1016/j.knosys.2022.109552
115. Ali, A. M., Benjdira, B., Koubaa, A., El-Shafai, W., Khan, Z., & Boulila, W. (2023). Vision Transformers in Image Restoration: A survey. Sensors, 23(5), 2385. https://doi.org/10.3390/s23052385
116. Du, X., Li, K., Lv, Y., & Qiu, S. (2022). Motor Imaging EEG signal recognition of RESNET18 network based on deformable convolution. Electronics, 11(22), 3674. https://doi.org/10.3390/electronics11223674
117. Muezzinoglu, T., Baygin, N., Tuncer, I., Barua, P. D., Baygin, M., Dogan, S., Tuncer, T., Palmer, E. E., Cheong, K. H., & Acharya, U. R. (2023). PatchResNet: Multiple Patch Division–Based Deep Feature fusion framework for brain tumor classification using MRI images. Journal of Digital Imaging, 36(3), 973–987. https://doi.org/10.1007/s10278-023-00789-x
118. Du, X., Li, K., Lv, Y., & Qiu, S. (2022b). Motor Imaging EEG signal recognition of RESNET18 network based on deformable convolution. Electronics, 11(22), 3674. https://doi.org/10.3390/electronics11223674
119. VK, D., & R, S. (2022). An intelligent brain tumor segmentation using improved Deep Learning Model Based on Cascade Regression method. Multimedia Tools and Applications, 82(13), 20059–20078. https://doi.org/10.1007/s11042-022-13945-2
120. Devi, R. V., & Sathya, S. S. (2017). Monkey Behavior Based Algorithms - a survey. International Journal of Intelligent Systems and Applications, 9(12), 67–86. https://doi.org/10.5815/ijisa.2017.12.07
121. Crawford, B., Soto, R., Olivares, R., Embry, G., Flores, D., Palma, W., Castro, C., Paredes, F., & Rubio, J. (2019). A binary monkey search algorithm variation for solving the set covering problem. Natural Computing, 19(4), 825–841. https://doi.org/10.1007/s11047-019-09752-8
122. Shang, H. L. (2013). A survey of functional principal component analysis. AStA Advances in Statistical Analysis, 98(2), 121–142. https://doi.org/10.1007/s10182-013-0213-1
123. Li, Y., Miao, N., Ma, L., Shuang, F., & Huang, X. (2023b). Transformer for object detection: Review and benchmark. Engineering Applications of Artificial Intelligence, 126, 107021. https://doi.org/10.1016/j.engappai.2023.107021
124. Liu, Z., Lin, Y., Cao, Y., Hu, H., Wei, Y., Zhang, Z., Lin, S., & Guo, B. (2021). Swin Transformer: Hierarchical Vision Transformer using Shifted Windows. 2021 IEEE/CVF International Conference on Computer Vision (ICCV), 9992–10002. https://doi.org/10.1109/iccv48922.2021.00986

125. Aydin, H. E., & Iban, M. C. (2022). Predicting and analyzing flood susceptibility using boosting-based ensemble machine learning algorithms with SHapley Additive exPlanations. Natural Hazards, 116(3), 2957–2991. https://doi.org/10.1007/s11069-022-05793-y
126. Stateczny, A., Praveena, H. D., Krishnappa, R. H., Chythanya, K. R., & Babysarojam, B. B. (2023). Optimized deep learning model for flood detection using satellite images. Remote Sensing, 15(20), 5037. https://doi.org/10.3390/rs15205037
127. Hu, Q., Zhu, Y., Hu, H., Guan, Z., Qian, Z., & Yang, A. (2021). Multiple Kernel Learning with Maximum Inundation Extent from MODIS Imagery for Spatial Prediction of Flood Susceptibility. Water Resources Management, 36(1), 55–73. https://doi.org/10.1007/s11269-021-03010-2
128. Vineeth, V. and Neeba, E.A. (2021) 'Flood detection using Deep Learning', 2021 International Conference on Advances in Computing and Communications (ICACC), pp. 1–5. doi:10.1109/icacc-202152719.2021.9708240
129. Kotaridis, I., & Lazaridou, M. (2022). Integration of convolutional neural networks for flood risk mapping in Tuscany, Italy. Natural Hazards, 114(3), 3409–3424. https://doi.org/10.1007/s11069-022-05525-2
130. Jamali, A., Roy, S. K., Beni, L. H., Pradhan, B., Li, J., & Ghamisi, P. (2024). Residual wave vision U-Net for flood mapping using dual polarization Sentinel-1 SAR imagery. International Journal of Applied Earth Observation and Geoinformation, 127, 103662. https://doi.org/10.1016/j.jag.2024.103662
131. Westra, S., Fowler, H. J., Evans, J. P., Alexander, L. V., Berg, P., Johnson, F., Kendon, E. J., Lenderink, G., & Roberts, N. M. (2014). Future changes to the intensity and frequency of short-duration extreme rainfall. Reviews of Geophysics, 52(3), 522–555. https://doi.org/10.1002/2014rg000464
132. Li, Y., Zhao, Y., Shang, Y., & Liu, J. (2021). An improved firefly algorithm with dynamic self-adaptive adjustment. PLoS ONE, 16(10), e0255951. https://doi.org/10.1371/journal.pone.0255951
133. Fister, I., Fister, I., Yang, X., & Brest, J. (2013). A comprehensive review of firefly algorithms. Swarm and Evolutionary Computation, 13, 34–46. https://doi.org/10.1016/j.swevo.2013.06.001
134. Tilahun, S. L., Ngnotchouye, J. M. T., & Hamadneh, N. N. (2017b). Continuous versions of firefly algorithm: a review. Artificial Intelligence Review, 51(3), 445–492. https://doi.org/10.1007/s10462-017-9568-0
135. Li, Y., Zhao, Y., Shang, Y., & Liu, J. (2021b). An improved firefly algorithm with dynamic self-adaptive adjustment. PLoS ONE, 16(10), e0255951. https://doi.org/10.1371/journal.pone.0255951
136. Yao, W., Bai, J., Liao, W., Chen, Y., Liu, M., & Xie, Y. (2024). From CNN to Transformer: A review of Medical Image Segmentation models. Deleted Journal, 37(4), 1529–1547. https://doi.org/10.1007/s10278-024-00981-7
137. Sankaranarayanan, S., Prabhakar, M., Satish, S., Jain, P., Ramprasad, A., & Krishnan, A. (2019). Flood prediction based on weather parameters using deep learning. Journal of Water and Climate Change, 11(4), 1766–1783. https://doi.org/10.2166/wcc.2019.321
138. Bui, D. T., Hoang, N., Martínez-Álvarez, F., Ngo, P. T., Hoa, P. V., Pham, T. D., Samui, P., & Costache, R. (2019). A novel deep learning neural network approach for predicting flash flood susceptibility: A case study at a high frequency tropical storm area. The Science of the Total Environment, 701, 134413. https://doi.org/10.1016/j.scitotenv.2019.134413

139. Gharakhanlou, N. M., & Perez, L. (2023). Flood susceptible prediction through the use of geospatial variables and machine learning methods. Journal of Hydrology, 617, 129121. https://doi.org/10.1016/j.jhydrol.2023.129121
140. Yasi, E., Shakib, T. U., Sharmin, N., & Rizu, T. H. (2024). Flood and Non-Flood Image Classification using Deep Ensemble Learning. Water Resources Management. https://doi.org/10.1007/s11269-024-03906-9
141. Tingsanchali, T. (2012). Urban flood disaster management. Procedia Engineering, 32, 25–37. https://doi.org/10.1016/j.proeng.2012.01.1233
142. Dumitru, C. O., Cui, S., Faur, D., & Datcu, M. (2014). Data analytics for rapid mapping: case study of a flooding event in Germany and the tsunami in Japan using very high resolution SAR images. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 8(1), 114–129. https://doi.org/10.1109/jstars.2014.2320777
143. Tong, X., Luo, X., Liu, S., Xie, H., Chao, W., Liu, S., Liu, S., Makhinov, A., Makhinova, A., & Jiang, Y. (2018). An approach for flood monitoring by the combined use of Landsat 8 optical imagery and COSMO-SkyMed radar imagery. ISPRS Journal of Photogrammetry and Remote Sensing, 136, 144–153. https://doi.org/10.1016/j.isprsjprs.2017.11.006
144. E, N. P., & P, N. S. (2021). RETRACTED ARTICLE: Image denoising and despeckling methods for SAR images to improve image enhancement performance: a survey. Multimedia Tools and Applications, 80(17), 26547–26569. https://doi.org/10.1007/s11042-021-10871-7
145. C. R. Nithyananda, A. C. Ramachandra and Preethi, "Review on Histogram Equalization based Image Enhancement Techniques," 2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT), Chennai, India, 2016, pp. 2512-2517, doi: 10.1109/ICEEOT.2016.7755145
146. P. Musa, F. A. Rafi and M. Lamsani, "A Review: Contrast-Limited Adaptive Histogram Equalization (CLAHE) methods to help the application of face recognition," 2018 Third International Conference on Informatics and Computing (ICIC), Palembang, Indonesia, 2018, pp. 1-6, doi: 10.1109/IAC.2018.8780492
147. Young, J. C., Arthur, R., Spruce, M., & Williams, H. T. (2022). Social sensing of flood impacts in India: A case study of Kerala 2018. International Journal of Disaster Risk Reduction, 74, 102908. https://doi.org/10.1016/j.ijdrr.2022.102908
148. Alqahtani, H., Kavakli-Thorne, M., & Kumar, G. (2019). Applications of Generative Adversarial Networks (GANs): An updated review. Archives of Computational Methods in Engineering, 28(2), 525–552. https://doi.org/10.1007/s11831-019-09388-y
149. Yue, L., Shen, H., Li, J., Yuan, Q., Zhang, H., & Zhang, L. (2016). Image super-resolution: The techniques, applications, and future. Signal Processing, 128, 389–408. https://doi.org/10.1016/j.sigpro.2016.05.002
150. Anwar, S., Khan, S., & Barnes, N. (2020). A Deep Journey into Super-resolution. ACM Computing Surveys, 53(3), 1–34. https://doi.org/10.1145/3390462
151. Ye, S., Zhao, S., Hu, Y., & Xie, C. (2023). Single-Image Super-Resolution Challenges: A Brief review. Electronics, 12(13), 2975. https://doi.org/10.3390/electronics12132975
152. Kowaleczko, P., Tarasiewicz, T., Ziaja, M., Kostrzewa, D., Nalepa, J., Rokita, P., & Kawulok, M. (2023). A Real-World benchmark for Sentinel-2 Multi-Image Super-Resolution. Scientific Data, 10(1). https://doi.org/10.1038/s41597-023-02538-9
153. Salvetti, F., Mazzia, V., Khaliq, A., & Chiaberge, M. (2020). Multi-Image super resolution of remotely sensed images using residual attention deep neural networks. Remote Sensing, 12(14), 2207. https://doi.org/10.3390/rs12142207

154. Dumitrescu, D., & Boiangiu, C. (2019). A study of image upsampling and downsampling filters. Computers, 8(2), 30. https://doi.org/10.3390/computers8020030
155. Y. Sa, "Improved Bilinear Interpolation Method for Image Fast Processing," 2014 7th International Conference on Intelligent Computation Technology and Automation, Changsha, China, 2014, pp. 308-311, doi: 10.1109/ICICTA.2014.82
156. Zhu, Y., Dai, Y., Han, K., Wang, J., & Hu, J. (2022). An efficient bicubic interpolation implementation for real-time image processing using hybrid computing. Journal of Real-Time Image Processing, 19(6), 1211–1223. https://doi.org/10.1007/s11554-022-01254-8
157. Jiang, N., & Wang, L. (2014). Quantum image scaling using nearest neighbor interpolation. Quantum Information Processing, 14(5), 1559–1571. https://doi.org/10.1007/s11128-014-0841-8
158. Lin, T.-Y., Dollar, P., Girshick, R., He, K., Hariharan, B., Belongie,S.: Feature Pyramid Networks for Object Detection. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). (2017). doi: https://doi.org/10.1109/cvpr.2017.106
159. Dhillon, A., & Verma, G. K. (2019). Convolutional neural network: a review of models, methodologies and applications to object detection. Progress in Artificial Intelligence, 9(2), 85–112. https://doi.org/10.1007/s13748-019-00203-0
160. Beghdadi, A., Larabi, M., Bouzerdoum, A., & Iftekharuddin, K. (2013). A survey of perceptual image processing methods. Signal Processing Image Communication, 28(8), 811–831. https://doi.org/10.1016/j.image.2013.06.003
161. Li, M., Hsu, W., Xie, X., Cong, J., & Gao, W. (2020). SACNN: Self-Attention Convolutional Neural Network for Low-Dose CT Denoising with Self-Supervised Perceptual Loss Network. IEEE Transactions on Medical Imaging, 39(7), 2289–2301. https://doi.org/10.1109/tmi.2020.2968472
162. Santos, M. S., Ren, T. I., & Kalantari, N. K. (2020). Single image HDR reconstruction using a CNN with masked features and perceptual loss. ACM Transactions on Graphics, 39(4). https://doi.org/10.1145/3386569.3392403
163. Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2020). Generative adversarial networks. Communications of the ACM, 63(11), 139–144. https://doi.org/10.1145/3422622
164. Ledig, C., Theis, L., Huszar, F., Caballero, J., Cunningham, A., Acosta, A., Aitken, A., Tejani, A., Totz, J., Wang, Z., Shi, W.: Photo-realistic single image super-resolution using a generative adversarial network. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). (2017). doi: https://doi.org/10.1109/cvpr.2017.19
165. Johnson, J., Alahi, A., & Fei-Fei, L. (2016). Perceptual losses for Real-Time style transfer and Super-Resolution. In Lecture notes in computer science (pp. 694–711). https://doi.org/10.1007/978-3-319-46475-6_43
166. Liu, Y., Chen, H., Chen, Y., Yin, W., & Shen, C. (2021). Generic perceptual loss for modeling structured output dependencies. 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 5420–5428. https://doi.org/10.1109/cvpr46437.2021.00538
167. Chen, F., Lasaponara, R., & Masini, N. (2015). An overview of satellite synthetic aperture radar remote sensing in archaeology: From site detection to monitoring. Journal of Cultural Heritage, 23, 5–11. https://doi.org/10.1016/j.culher.2015.05.003
168. Acharya, U. K., & Kumar, S. (2021). Genetic algorithm based adaptive histogram equalization (GAAHE) technique for medical image enhancement. Optik, 230, 166273. https://doi.org/10.1016/j.ijleo.2021.166273

169. Wu, M., & Zhong, Q. (2024). Image enhancement algorithm combining histogram equalization and bilateral filtering. Systems and Soft Computing, 6, 200169. https://doi.org/10.1016/j.sasc.2024.200169
170. M. S. Hitam, E. A. Awalludin, W. N. Jawahir Hj Wan Yussof and Z. Bachok, "Mixture contrast limited adaptive histogram equalization for underwater image enhancement," 2013 International Conference on Computer Applications Technology (ICCAT), Sousse, Tunisia, 2013, pp. 1-5, doi: 10.1109/ICCAT.2013.6522017
171. Paul, A., Bhattacharya, P., & Maity, S. P. (2022). Histogram modification in adaptive bi-histogram equalization for contrast enhancement on digital images. Optik, 259, 168899. https://doi.org/10.1016/j.ijleo.2022.168899
172. NASA Earth Observatory. (n.d.). Flooding near Manaus, Brazil. https://earthobservatory.nasa.gov/images/39359/flooding-nearmanaus-brazil
173. Rawat, P. (2024, January 17). Satellite images show devastating Kerala floods. Geospatial World. https://geospatialworld.net/videos/satellite-images-show-devastating-kerala-floods/
174. Mason, D. C., Dance, S. L., Vetra-Carvalho, S., & Cloke, H. L. (2018). Robust algorithm for detecting floodwater in urban areas using synthetic aperture radar images. Journal of Applied Remote Sensing, 12(04), 1. https://doi.org/10.1117/1.jrs.12.045011
175. Manidhar, A. (2020, October 9). Monitoring monsoon flooding in Kerala with SAR and AI - PlanetWatchers. Planetwatchers. https://www.planetwatchers.com/latest/monitoring-monsoon-flooding-in-kerala-with-sar-and-ai-2020-10-09/#:~:text=PlanetWatchers%20estimates%20that%20in%20this,agricultural%20fields%20that%20are%20flooded.

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ORIGINAL PAPER

SSR-GAN: super resolution-based generative adversarial networks model for flood image enhancement

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Abstract
Floods, a common natural disaster, it affects more than half of all natural disasters, primarily due to high floods, high tides, heavy rainfall, and human activity. Distinguishing between the flooded and non-flood areas during the disaster is dependent on the quality of images collected from different sources. Since synthetic aperture radar (SAR) images can see through cloud cover and capture photos of the Earth's surface during bad weather, they are excellent for detecting floods. Image Enhancement is the approach that helps to increase the resolution of the SAR images, which helps to more accurately categorize the flooded and non-flooded areas. The quality of satellite and aerial imagery can be enhanced to recognize flooded and non-flooded areas. Our proposed approach uses a super-resolution technique to enhance the resolution of SAR images. We develop a super resolution-based generative adversarial network, or SSR-GAN (Satellite Super Resolution-based Generative adversarial network). In our approach to estimating generative models through an adversarial process, we concurrently train two different models: a generative model G and a discriminative model D. An image with low resolution is transformed into high pixel density. The peak signal-to-noise ratio (PSNR), the structural similarity index(SSIM), Multiscale Structural Similarity (MSSIM) and mean squared error (MSE) are the performance metrics used to compare the interpolation methods for enhancing resolution. In comparison to the existing approaches with our proposed model SSR-GAN, the values of PSNR, SSIM, and MSSIM are greater, and the MSE error value is lower.

Keywords Flood disaster · Generative adversarial network · Image enhancement · Super-resolution

1 Introduction

Flood catastrophes pose a significant threat to urban areas, posing a greater threat to diversity and community than other natural or man-made disasters. Vulnerable cities worldwide face extreme tides, hurricanes, river overflow, and inadequate drainage systems. Numerous cities across the globe are vulnerable to this threat, which is mostly caused by isolated areas of intense precipitation. Because they are unable to handle the floods caused by heavy precipitation and inadequate drainage systems frequently cause floods.

1.1 Problem statement

A flood occurs when the water level of the river rises above the river bank due to the flow of the river. High river levels are typically caused by river precipitation and the backwater resulting from high tides near the river's mouth [1]. Floods cause significant financial losses and require efficient detection and prediction systems. Accurate mapping using SAR photos and satellite imagery is crucial for detecting and predicting flooded areas. Detecting urban flooded areas helps cities evolve flood maps, reducing risk. Mapping flooded areas is complex due to discontinuous, shallow, and ephemeral flooding [2]. For better disaster response and conditional awareness on the ground is very essential. Nowadays Satellite imagery is crucial for disaster response, with Synthetic Aperture Radar (SAR) being a promising technique for detecting Earth's surface, even in cloudy environments, and studies have shown its effectiveness in detecting floods [3].

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FloodCNN-BiLSTM: Predicting flood events in urban environments

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ABSTRACT

A disaster is a severe event that occurs on a short period but has highly damaging and long-lasting effects on society. Disasters can be broadly categorized into natural and man-made events. Among natural disasters, floods are some of the most common disaster. As climate change accelerates, floods are expected to become more frequent and severe, highlighting the need for a deeper understanding of their causes, effects, and response strategies. Modern technologies, including machine learning, are increasingly being used to predict the occurrence of floods. Accurate forecasting requires large volumes of data collected from sensors deployed in various locations. Machine Learning (ML) models are well-suited for flood prediction due to their ability to handle sequential data and long-term dependencies. In this paper we present a hybrid deep learning model that combines Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) networks. The CNN component is responsible for extracting spatial features, while the BiLSTM processes the sequential data to classify the likelihood of flood events based on environmental parameters. The proposed FloodCNN-BiLSTM model has been validated on multiple datasets, achieving superior performance compared to traditional machine learning approaches. It attained 97.3 % accuracy on Dataset 1 and 98.6 % on Dataset 2. Evaluation metrics such as accuracy, precision, recall, and F1-score confirm the robustness and effectiveness of the model. Comparative analysis with other models used in this research demonstrates the superiority of our proposed approach.

1. Introduction

A disaster is a severe event that disrupts communities and causes significant harm to human life, the environment, and infrastructure. Floods, a common natural calamity during monsoon seasons, pose significant risks to areas near lakes, rivers and coastal zones. According to the United Nations, disasters exceed the coping capacity of affected communities, emphasizing the need for advanced management strategies. Recent technological advancements have improved flood prediction through hydrological models, remote sensing, machine learning, and big data analytics. These innovations offer better accuracy, longer lead times, and enhanced geographic resolution, enabling early detection of disasters even in remote areas. Ongoing research in artificial intelligence (AI), big data analytics, and the Internet of Things (IoT) shows promise for revolutionizing disaster management. Integrating these technologies can enhance predictive models and decision-making systems, offering substantial benefits for communities and businesses. With the rise in weather-related incidents due to global climate change, these advancements are critical for mitigating the impacts of natural disasters like floods and improving early warning systems. Natural disasters such as floods, earthquakes, and tsunamis are increasing in frequency, largely due to global climate change [1]. Flood disasters cause massive loss of life, biological diversity, and economic damage, causing significant harm in both developing and developed countries [2]. Among all natural disasters like earthquakes, volcanoes and tsunamis etc., flood occur most frequently. These disasters cause major human casualties, displacement, and damage to livelihoods [3]. A survey found that a global average of 50 million dollars is lost in economic activity each year as a result of floods. There are approximately 100 million flood victims [4]. However, due to rapid environmental change, the process of detecting and predicting the flooded area takes time and is quite difficult. Consequently, many current flood prediction models rely on simple assumptions and are mostly data-driven, which may restrict their accuracy and flexibility [5].

1.1. Role of DL in flood prediction

Early warning and flood prediction systems greatly benefit from deep

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Water Resources Management
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MoSWIN: Monkey Search Optimization and SWIN-based Flood Classification Architecture

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Abstract
Floods pose significant threats to both human life and infrastructure, necessitating timely and accurate monitoring for effective disaster management. Advancements in computer vision and machine learning have enabled the development of sophisticated systems for flood classification using imagery. In this study, we introduce MoSWIN, a novel framework that integrates Monkey Search Optimization (MSO) with the Swin Transformer to enhance the accuracy and robustness of flood classification models. The Swin Transformer, with its hierarchical architecture and shifted window mechanism, excels at capturing both local and global features in flood-related imagery. MSO is employed to extract high-level features from input images, facilitating improved feature engineering. Subsequently, the Swin Transformer performs classification tasks on the features extracted through MSO. Our proposed MoSWIN model outperforms several existing state-of-the-art approaches, achieving an accuracy of 96.53%. This indicates a significant improvement in image classification and optimization performance, leading to more effective flood detection. Experimental results demonstrate that MoSWIN can accurately distinguish between flooded and non-flooded areas, surpassing the performance of conventional methods.

Keywords Convolutional neural network · Flood detection · Image segmentation · Monkey search optimization · Resnet-18 · SWIN transformer

Abbreviations

CNN	Convolutional Neural Network
CV	Computer Vision
DAM-Net	Differential Attention Metric-Based Network
DCNN	Deep Convolutional Neural Network
DNN	Deep Neural Network
DL	Deep Learning

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Flood-FireNet: a novel flood image classification architecture using the adaptive firefly algorithm

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Abstract
Floods are among the most devastating natural disasters, posing serious threats to human life, infrastructure, and ecosystems. Accurate and timely classification of flooded areas is essential for effective disaster response. This study proposes Flood-FireNet, a novel hybrid model that integrates a transformer-based neural network with the adaptive firefly algorithm (AFA) to enhance flood detection from satellite imagery. The AFA is used to optimize feature selection by identifying the most informative high-level features, while the transformer efficiently captures spatial patterns and long-range dependencies for precise classification. This combined architecture represents the core innovation of the study, leveraging the strengths of both evolutionary optimization and deep learning. Experimental results demonstrate that Flood-FireNet achieves superior performance, with an accuracy of 97.85%, precision of 98.12%, recall of 95.73%, and an F1-score of 96.92%, outperforming several state-of-the-art methods. An ablation study highlights the individual and joint contributions of AFA and the transformer model. Additionally, statistical validation using the paired T-test and ANOVA ($p < 0.05$) confirms the model's effectiveness. Overall, Flood-FireNet offers a robust and scalable solution for flood classification tasks, supporting faster and more reliable decision-making in disaster management systems.

Keywords Adaptive firefly algorithm · Convolutional neural network · Flood classification · SWIN transformer

1 Introduction

Floods cause significant economic and environmental damage globally, endangering infrastructure and human lives. Rapid identification of flooded regions using satellite or aerial imagery is crucial for effective disaster response and management. Image segmentation is crucial for identifying flood-affected areas. Annual losses from natural disasters and climate change exceed $500 billion [1]. Within the domains of computer vision and remote sensing, flood image classification has emerged as a critical research area, employing advanced machine learning and deep learning techniques to automatically analyze and categorize flood-related imagery. Flooding stands out as one of the most destructive natural disasters, consistently causing extensive damage across vast regions [2, 3]. Human-induced factors, such as insufficient flood control infrastructure and unsustainable land use practices, further amplify flood risks [4, 5]. Urbanization, in particular, has heightened flood susceptibility in metropolitan areas by expanding impermeable surfaces, which disrupt natural drainage systems [6]. Among the diverse types of floods are sewer floods, urban floods, flash floods, glacial lake outburst floods, and coastal floods, as river floods are especially devastating, affecting large areas along riverbanks and incurring substantial economic losses [7]. Although completely preventing floods remains unfeasible, their impacts and associated losses can be mitigated [8]. Strategies such as water resource management and flood storage have proven effective in some regions, though their success hinges on specific hydrological and environmental conditions. Real-time flood management and early warning systems depend on timely situational data, traditionally supplied by simulation models reliant on available datasets. However, the scarcity of empirical data has constrained the utility of these conventional approaches [9].

Recent research has actively explored machine learning (ML) and deep learning (DL) methodologies to enhance flood

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Adaptive Histogram Equalization based Approach for SAR Image Enhancement: A Comparative analysis

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***Abstract*—Nowadays, flood is the most frequently occurring natural disaster among all-natural disasters. A flood is a disaster that causes huge causalities. Recovery from these huge causalities is a very serious concern for developing countries. This research work focuses on flush food, which is a very common disaster that occurs due to heavy rainfall or some manmade reasons. An Image of the flooded area provides useful information for taking necessary precautions in that particular situation. If the captured image is of poor quality, then isn't provide sufficient information. This paper considers the Synthetic Aperture Radar (SAR) images of the flooded area and it is mainly focused on increasing the image's visual quality. There are various image enhancement techniques available; this paper has used the histogram-based image quality improvement technique done by the Histogram Equalization (HE) method. To defeat the limitation of HE, another enhancement approach named Adaptive Histogram Equalization (AHE) is also used. In many cases, HE is increasing the quality of the image, but on the other side over brightness is causes the loss of some useful background information. In the AHE technique, the image is divided into small blocks: an equalization function is applied on each block. Both the techniques are compared on the various images of the flooded area, and the result shows that AHE provides better results.**

Keywords*— *Adaptive Histogram Equalization, Contrast enhancement, Flood management, Histogram Equalization, Image Processing, Spatial Domain

I. INTRODUCTION

The disaster causes a lot of damage and serious disruption. A disaster is an unfortunate event that causes serious disruption to human society. A natural disaster is a result of the natural imbalance that results in floods, earthquakes, etc. Flood is a very common issue in many countries. Several parts of India get highly affected by the flood. In turn, it disturbs the economic loss and human resources, affecting developing countries like India.

.The purpose of image enhancement is to extrude the important details hidden in the image and to increase the contrast of the image with less dynamic range. Several methods are available to enhance image quality, some of them working on the spatial domain and some on the frequency domain [1].

This paper focuses on enhancing the flood image to locate the flooded area in a better way. Synthetic Aperture Radar (SAR) imaging is important for Disaster, Army, and Civil applications such as target monitoring and classification. The accuracy of the application decreases with the presence of Speak and poor resolution of images created from SAR image Acquisition equipment [2]. Artificial intelligence (AI) technique for understanding remote sensing and provides very successful results. Besides, various data collecting techniques such as (SAR) are used in many applications. A satellite is an essential device that provides an image of the Earth's surface. When we talk about natural disasters such as hurricanes, tsunami, or floods, they are mostly surveillance by SAR images. [3]

- In the context of image quality improvement techniques, HE has gained the most consideration due to its smooth implementation approach and highly efficient result.
- In our paper, we use HE and the AHE techniques to enhance the SAR images of the various flooded location.
- Our implemented methods for image enhancement are efficient, and experimental results show with different images that this method is effective for image enhancement.

In the above section, we introduce our work and the remaining part of the paper contains. Section II includes the literature survey followed by section III, which includes the detailed explanation of our implemented methodologies. Section IV includes the analysis of the results of implemented techniques. Last, section V, covert the summary and conclusion of our paper; we also include future scope for getting better results.

.

II. RELATED WORK

This part of our paper is covered the previous work done to get better quality of the image. According to the paper, the author analyzes the methods for reducing noise, Particle Swarm Optimization, and mirror-extended optimization use to enhance satellite images. In this approach, the author develops a gain function that merges the feature enhancement alongside the speckle reduction [4]. In the next approach we discuss in our study, the author presents a method for enhancement of SAR image based on the Memetic Algorithm and Non-subsample Contourlet Transform (NSCT). First, a better development Function that integrates macular reduction with the characteristic

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An Analysis of Machine Learning Techniques for Flood Mitigation

Vinay Dubey and Rahul Katarya

Abstract Disaster is a very severe dispersion that occurs for a very small period, but it makes a huge impact on the society. Nowadays, natural hazards such as floods, earthquakes, and volcanic eruptions are increasing around the world. Flooding among all disasters is a very frequent disaster in the last few years. In this paper, we review some machine learning technologies of flood detection.

Keywords Flood predicting · Flood forecasting · Machine learning

1 Introduction

Disaster is defended as an event caused by natural destructive factors and divided either as geographical disasters like climate disasters like floods or earthquakes which result in very adverse effects on organisms. Disaster is a big threat to the working communities, the economy of the country, and human society. Disasters are either natural or human generated like a flood. Flood is a natural disaster depends on the excess rainfall and geographical location. It is now a very frequently occurred disaster. Floods are the most destructive of natural disasters, causing extensive damage to human life, infrastructure, agriculture, and socioeconomic system [1]. India is also suffering from frequent occurring flood events that endanger the lives of thousands and make one huge loss to our economy. For a developing country like India, the reason for the loss of disasters like floods is huge.

- According to IoT white paper data, 12% of land in India is vulnerable to floods. According to statistics, the annual economic loss due to flood disasters in the

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Mr. Vinay Dubey is currently designated as a Ph.D research scholar in the Department of Computer Science, at Delhi Technological University, Delhi, India. He has completed her M.tech from the National Institute of Technology, Hamirpur (H.P.). He has completed an undergraduate degree (B.Tech, Computer Science) from the Geetanjali Institute of Technical Studies. He has published various research papers in SCIE/SCOPUS/IEEE/ELSEVIER-indexed International Conferences/Journals. His research areas of interest include Artificial Intelligence, Disaster Management, Machine learning, Deep learning. He is currently doing her research on disaster management using artificial intelligence techniques.