AI-Driven Smart Farming: From Crop Prediction To Plant Disease Detection

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Submitted by

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CANDIDATE'S DECLARATION

I, **SHYAM KISHOR YADAV**, Roll No's – **2K23/AFI/25** student of M.Tech (COMPUTER SCIENCE AND ENGINEERING), hereby declare that the work that is presented in the thesis entitled **"AI-Driven Smart Farming: From Crop Prediction To Plant Disease Detection"** which is submitted by me in the Dapartment of Computer Science and Engineering, Delhi Technological University, Delhi under the supervision of **Dr. Prashant Giridhar Shambharkar** in partial fulfillment of the requirement for the award of degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any other degree of this or any other institute.

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CERTIFICATE

I hereby certify that the research workpresented in the thesis entitled **"AI-Driven Smart Farming: From Crop Prediction To Plant Disease Detection"** which is submitted by **Shyam Kishor Yadav**, Roll No's – **2K23/AFI/25**, Computer Science and Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology. The thesis embodies results of original work, and studies are carried out by the student himself under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

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Abstract

The escalating challenges to global food security, driven by climate change, limited natural resources, and rising population demands, necessitate the adoption of intelligent, data-driven solutions in agriculture. This thesis presents two complementary deep learning frameworks aimed at addressing key aspects of precision farming: accurate pre-season crop prediction and robust plant disease detection. For crop prediction, a hybrid model integrating Convolutional Neural Networks (CNNs) and Bidirectional Long Short-Term Memory (Bi-LSTM) networks is developed, effectively capturing spatial patterns and temporal trends from historical crop rotation data and synthetic field-level features. To ensure generalizability and prevent overfitting, the model leverages stratified k-fold cross-validation and dropout regularization, consistently outperforming conventional methods in terms of predictive accuracy and applicability to real-world scenarios. In parallel, this work introduces a novel Vision Transformer (ViT) combined with a modified High-Resolution Network (HRNet) for disease diagnosis across multiple plant species, addressing challenges such as variation in leaf venation, texture, and symptom presentation. By fusing global contextual reasoning from ViT with fine-grained spatial precision from HRNet, the proposed architecture achieves superior classification accuracy in both controlled and field environments. Together, these models provide an end-to-end framework for predictive and preventive crop management, advancing the goals of sustainable agriculture, early intervention, and resilient food systems.

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Chapter 1

INTRODUCTION

1.1 Background

Agriculture plays a vital role in ensuring global food security, providing livelihoods for billions and contributing significantly to the economy of developing nations. However, the sector faces growing challenges including climate change, declining arable land, unpredictable weather patterns, pests, and plant diseases. In the face of these issues, the integration of Artificial Intelligence (AI) in agriculture is emerging as a transformative approach to enable precision farming, efficient resource management, and sustainable practices.

The agricultural landscape is evolving from traditional labor-intensive methods to technology-driven solutions. AI, combined with Machine Learning (ML) and Deep Learning (DL), is reshaping farming systems through predictive analytics, automated disease detection, and smart decision-making. These technologies enable the processing of large-scale agricultural data, leading to timely interventions and optimized yields.

1.2 Problem Statement

Conventional agricultural practices often rely on manual observation and experience-based decisions, which are insufficient for handling complex and large-scale farm data. Crop prediction and disease detection are particularly challenging due to the variability in environmental factors, soil conditions, and crop characteristics. There is a need for intelligent systems that can predict suitable crop types before planting and identify plant diseases early to mitigate losses.

1.3 Motivation

With the global population projected to reach 9.7 billion by 2050, agricultural production must increase significantly. This demand calls for innovative solutions that maximize productivity while maintaining sustainability. AI-driven systems offer promising capabilities in addressing critical issues like crop type prediction and disease detection. The integration of hybrid deep learning models such as CNN, Bi-LSTM, ViT, and HRNet provides powerful tools for modeling complex agricultural data with high accuracy.

1.4 Objectives

The primary objectives of this thesis are:

1. To develop a hybrid CNN-BiLSTM model for accurate pre-season crop prediction.

2. To design an integrated ViT-HRNet model for effective multi-crop plant disease detection.

3. To evaluate and compare the performance of the proposed models with existing state-of-the-art approaches.

4. To contribute towards the development of scalable and interpretable AI systems for real-world agricultural applications.

1.5 Scope of the Thesis

This thesis focuses on two critical components of smart farming: crop prediction and disease detection. The study is based on two original research works:

1. An ensemble model using CNN and Bi-LSTM for pre-season crop prediction using historical agricultural data.
2. A hybrid model combining Vision Transformer and High-Resolution Network for precise plant disease detection across multiple crop types.

Both models are evaluated against benchmark datasets and are designed to be scalable and applicable to real-world scenarios.

1.6 Organization of the Thesis

The thesis is organized as follows:

1. **Chapter 2** reviews existing literature related to crop prediction and plant disease detection using AI and deep learning.
2. **Chapter 3** describes the methodology adopted for both models, including data preprocessing, model architecture, and implementation details.
3. **Chapter 4** presents experimental results and discusses the performance of the proposed models.
4. **Chapter 5** concludes the thesis with key findings, limitations, and future research directions.

Chapter 2

Literature Review

2.1 Introduction

The emergence of AI in agriculture has inspired a range of research efforts to solve persistent problems in crop management and plant health monitoring. This chapter critically examines the developments in AI-driven crop prediction and plant disease detection, analyzing classical approaches and contemporary deep learning methodologies. The review also identifies gaps and limitations that motivate the need for hybrid and scalable solutions.

2.2 Literature on Crop Prediction

Elbasi et al. [9] examined the role of GPS-equipped IoT sen sors in improving agricultural productivity through machine learning. By analyzing dynamic environmental parameters such as temperature, humidity, pH, and rainfall, their approach aids farmers in optimizing planting schedules, irrigation, and harvesting decisions. Baumert et al. [10] introduced a proba bilistic framework for crop type mapping in Europe, enhancing spatial and temporal resolution while aligning with adminis trative datasets. This model is particularly beneficial for areas where remote sensing data is sparse or impractical. Abernethy et al. [11]

proposed an alternative machine learning method that identifies crop sequence boundaries (CSBs) using field level polygons to summarize cropping patterns, streamlining computational demands while maintaining accuracy. Zhang et al. [12] integrated machine learning with crop phenology models, improving phenological predictions, particularly for rice, by considering climate variations across different growth phases. Dupuis et al. [13] developed a Seq2Seq-LSTM model for predicting crop rotation patterns and combined it with a conditional probability approach to refine forecasts. This paper discusses sustainable fertilization strategies that minimize chemical inputs while ensuring optimal yields. Raju et al. [14] introduced an advanced stacking ensemble (IML ASE) model tailored for agro-ecological zones, leveraging environmental and soil attributes to improve crop prediction accuracy. Romero et al. [15] explored the potential of high throughput phenotyping platforms (HTTP), which employ UAVs to estimate crop heading and maturity timelines under varying irrigation regimes. Using vegetation indices from RGB imagery, their model demonstrated predictive capabilities, ex plaining a significant proportion of variance in wheat and oat phenology. Lastly, Suruliandi et al. [16] proposed an ensemble deep learning framework, RFOERNN-CRYP, which combines LSTM, BiLSTM, and GRU models, optimized via Red Fox Optimization, for precise crop recommendations based on agro-parameters.

2.3 Literature on Plant Disease Detection

Nobela et al. [10] proposes a complex deep learning model for plant disease detection, introducing DenseNetMini with a learning resizer and Gradient Product (GP) optimization to improve accuracy and efficiency. Leygonie et. al. [11] presents a model that support decision for plant anomaly detection without requiring prior knowledge of the anomalies. Using an auxiliary prediction task, the model analyzes heatmap distributions to identify deviations in new observations. Dong et. al. [12] introduces plant disease anomaly detection by leveraging vision-language models and incorporating visual information to improve fine-grained classification. Traditional concept matching approaches struggle in this domain, so the proposed method refines prompt tuning to focus on visual cues. Calonea et. al [13] evaluates ChatGPT-3.5 Turbo and GPT-4 for plant disease risk forecasting. GPT-4 generates detailed adaptive messages for technical reports, while GPT 3.5 excels in concise, consistent communication for routine tasks. Both models require domain-specific training to improve accuracy and alignment with Integrated Pest Management principles. Dong jin et. al. [14] introduces Shuffle-PG, a lightweight model which extract features for plant disease and pest diagnosis using content-based image retrieval. By integrating ShuffleNet v2 with pointwise group convolution, Shuffle-PG significantly reduces computational costs while maintaining high search performance.The study also explores deep metric learning with contrastive loss to enhance feature extraction. Future research will address dataset imbalance, optimize deployment on mobile devices, and explore model compression techniques for improved efficiency. Tunio et. al. [15] proposes a novel Unsupervised Domain Adaptation (UDA) framework for plant disease classification, integrating CNNs for local features and MViTs for global features to en hance transferability. Using adversarial learning with Wasser stein distance, the model improves classification accuracy by 13.67Raghurama and Borah [16] presents a Hybrid Learning Model (HLM) for disease detection in tomato palnt, Deep Reinforcement Learning integrating with Transfer Learning (DRL-TL). High-resolution leaf images are preprocessed using an enhancement algorithm to improve clarity before being analyzed by a MobileNetV2-based model. Chaia et. al. [17] presents PlantAIM, a hybrid model combining Vision Trans former (ViT) and CNN for improved disease detection in plants. By fusing global attention with local feature extraction, it enhances crop-specific and disease-specific feature learning. Extensive evaluations show superior performance over state of-the-art models, establishing PlantAIM as a new benchmark in agricultural disease identification. Mahadevan et. al. [18] integrates image enhancement, segmentation, feature selec tion, and optimization to improve classification for rice plant disease detectio. Shwetha et. al. [19] presents LeafSpotNet, a MobileNetV3-based classifier for detecting leaf blight dis ease in Jasmine plants, achieving 97depthwise convolution, max pooling, CGAN-based data aug mentation, and Particle Swarm Optimization for enhanced feature extraction and selection. Its lightweight architecture, fast computation (30s) and small size (10MB), makes it suitable for real-time mobile deployment. Tejaswinia et. al. [20] explores CNN-based plant disease detection for tomato, potato, and bell pepper leaves, leveraging a pre-trained deep learning model on the Plant Village dataset. Rezaeia et. al. [21] proposes a few-shot learning (FSL) approach for disease detection in plants using a PMF+FA pipeline with Vision Transformers (ViT) and ResNet50. It demonstrates high efficiency (ViT: 1.11 ms/image) for real time applications. Peng et. al. [22] explores predicting Fusar ium Head Blight (FHB) Epidemics in Wheat Using Boosted Regression Trees (BRTs). BRTs significantly enhance classi f ication accuracy, reducing misclassification rates below 0.1, and efficiently handling non-linear relationships in weather related variables. While BRTs outperform traditional mod els, challenges include data quality dependency, overfitting risks, and interpretability issues. Perumal et. al. [23] explores FPGA-accelerated Convolutional Neural Networks (CNNs) for identification of plant disease in real time, leveraging the PYNQ FPGA platform for enhanced efficiency. Wang et. al. [24] presents a transformer-based model for automated plant disease identification, integrating BatchFormerV2, LAMB op timizer, and CIoU loss for improved accuracy and training sta bility. The model outperforms CNNs and vision transformers, achieving 56.3 mAP on a large-scale dataset. Its interpretable attention mechanism enhances transparency, supporting effi cient and accurate disease detection for precision agriculture.

Chapter 3

Proposed Methodology

3.1 Crop Prediction

The proposed methodology uses a hybrid deep learning model that combines CNN and Bi-LSTM layers. We trained and evaluated the model using a k-fold stratified cross-validation approach to ensure robust performance across diverse and unseen data distributions. The key steps in the methodology are detailed below.

3.1.1 Data Preprocessing and Model Architecture :

Step-1 : Dataset Loading:

The dataset, denoted as $D = \{X, y\}$, consists of:

- X: A matrix of dimensions $n \times m$, where n is the number of samples and m is the number of features.
- y: A vector of categorical crop labels, where each y_i represents the crop type corresponding to the sample i.

Step-2 : Label Encoding:

Categorical labels y are transformed into numerical labels y_{enc} using a mapping function f to convert crop categories into integers:

$$y_{enc} = f(y), \quad f : Categories \rightarrow Z \tag{3.1}$$

For example, if crops are $\{Wheat, Rice, Maize\}$, they are assigned to $\{0, 1, 2\}$.

Step-3 : Normalization:

Feature normalization ensures that input features are scaled to the range $[0, 1]$, enhancing the stability of the training:

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{3.2}$$

where $X_{\min}$ and $X_{\max}$ are the minimum and maximum values of each feature.

Step-4 : Re-shaping:

The normalized feature matrix is reshaped into a 3D tensor for compatibility with CNN and BiLSTM layers:

$$X_{reshaped} = reshape(X_{norm}, (n, m, 1)) \tag{3.3}$$

3.1.2 Model Overview:

Fig. 1 explains about model architecture that how we are designing, coding and integrating of our model. The model integrates CNN and Bi-LSTM layers to capture both spatial and temporal dependencies in agricultural data. CNN extracts spatial characteristics such as soil composition and vegetation indices, while Bi-LSTM models temporal relationships like historical pesticide use and weather patterns. Early-stage crops may recover from hazards better than mature crops, which are more vulnerable. This architecture is designed to support robust forecasting and mitigate agricultural risks.

Input Layer:

The input to the model is a 3D tensor:

$$X \in R^{n\times m\times 1} \tag{3.4}$$

Bi-LSTM Branch:

Each LSTM unit processes sequences bidirectionally, generating forward and backward hidden states:

$$\overrightarrow{h_t} = LSTM_{forward}(X_t), \quad \overleftarrow{h_t} = LSTM_{backward}(X_t) \tag{3.5}$$

Concatenation of hidden states:

$$h_t = \overrightarrow{h_t} \oplus \overleftarrow{h_t} \tag{3.6}$$

Two stacked BiLSTM layers are used: the first with 64 units, the second with 32 units. Dropout regularization with rate $p = 0.3$ is applied:

$$h_{drop} = Dropout(h, p) \tag{3.7}$$

CNN Branch:

1. First Conv1D layer with 64 filters and kernel size 2:

$$C_1 = Conv1D(X_{input}, 64, kernel\_size = 2) \in R^{n\times(m-1)\times 64} \tag{3.8}$$

2. MaxPooling1D with pool size 2:

$$P_1 = MaxPooling1D(C_1, pool\_size = 2) \in R^{n\times\frac{(m-1)}{2}\times 64} \tag{3.9}$$

3. Dropout with rate 0.3 applied.

4. Second Conv1D layer with 32 filters:

$$C_2 = Conv1D(P_1, 32, kernel\_size = 2) \in R^{n\times(\frac{(m-1)}{2}-1)\times 32} \tag{3.10}$$

5. MaxPooling1D with pool size 2:

$$P_2 = MaxPooling1D(C_2, pool\_size = 2) \in R^{n\times\frac{(m-3)}{4}\times 32} \tag{3.11}$$

6. Flattening the output:

$$F = Flatten(P_2) \in R^{n\times(8(m-3))} \tag{3.12}$$

Concatenation Layer:

Concatenation of Bi-LSTM output and CNN branch output:

$$h_{concat} = h_{BiLSTM} \oplus F \tag{3.13}$$

Fully Connected Layers:

Concatenated features passed through dense layer:

$$D = Dense(h_{concat}, 16, activation = ReLU) \tag{3.14}$$

Final softmax output layer:

$$\hat{y} = Dense(D, k, activation = softmax) \tag{3.15}$$

Loss Function:

The model is trained using sparse categorical cross-entropy:

$$L = -\frac{1}{n} \sum_{i=1}^{n} \log P(y_i \mid X_i) \tag{3.16}$$

where $P(y_i \mid X_i)$ is the predicted probability for the true label y_i given the input X_i.

Table I elaborates the whole architecture diagram and all hyperparameters of the proposed Bi-LSTM and CNN ensemble model for precise crop prediction. The model starts with an Input Layer that processes data in a shape of (n,m,1). It includes two Bidirectional LSTM (Bi-LSTM) layers, with 64 and 32 units, respectively, using the ReLU activation function to capture sequential dependencies. Dropout layers are added for regularization. The CNN component consists of two 1-D convolutional layers (64 and 32 filters), each followed by Max-Pooling layers to reduce dimensionality. The Flatten layer reshapes the output before concatenation with Bi-LSTM features.

Table 3.1: Hyperparameter of proposed model

Layer	**Type**	**Units/Filters**	**Activation**	**Output Shape**
Input Layer	Input	-	-	$(n, m, 1)$
Bi-LSTM (1)	Bidirectional LSTM	64	ReLU	$(n, m, 64)$
Dropout (1)	Dropout	-	-	$(n, m, 64)$
Bi-LSTM (2)	Bidirectional LSTM	32	ReLU	$(n, 32)$
Conv1D (1)	Convolutional 1D	64	ReLU	$(n, m-1, 64)$
MaxPooling (1)	MaxPooling 1D	-	-	$(n, \frac{m-1}{2}, 64)$
Dropout (2)	Dropout	-	-	$(n, \frac{m-1}{2}, 64)$
Conv1D (2)	Convolutional 1D	32	ReLU	$(n, \frac{m-1}{2} - 1, 32)$
MaxPooling (2)	MaxPooling 1D	-	-	$(n, \frac{m-1}{4}, 32)$
Flatten	Flatten	-	-	(n, f)
Concatenation	Concatenate	-	-	$(n, f + 32)$
Dense	Fully Connected	16	ReLU	$(n, 16)$
Output	Fully Connected (softmax)	k (categories)	softmax	(n, k)

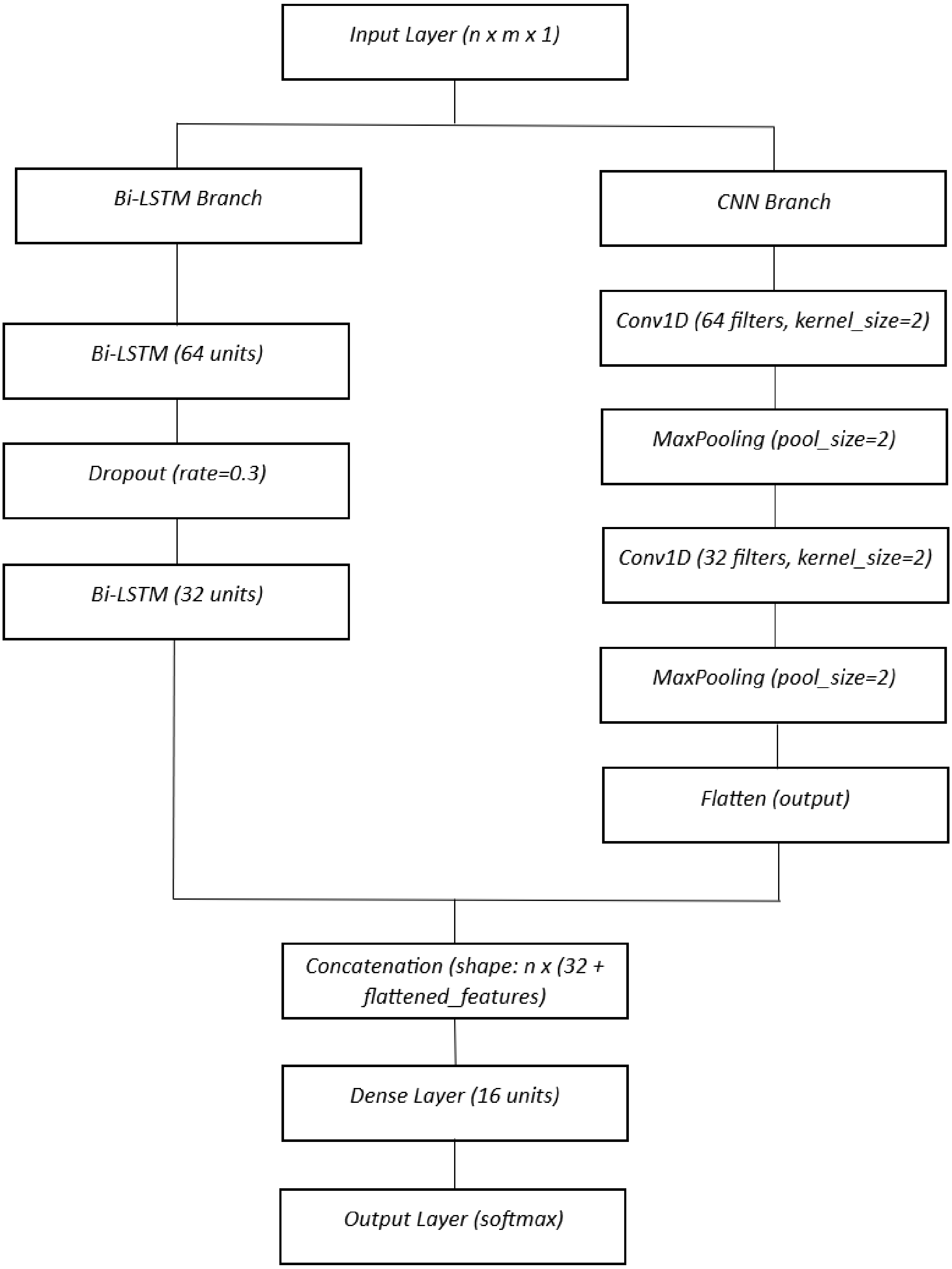

Figure 3.1: Architecture Diagram

Table 3.2: Hyperparameter Tuning of Different Models

ML Models	**Folds**	**Parameters Optimized**	**Values**
SVM	K-fold cross-validation = 5	Gamma	5
LR		Random state	2
		max_iteration	25
KNN		N_neighbours	2
DT		max_depth	5
RF		N_estimators	2
		random_state	0
ANN		Optimizer	Adam
		Loss	Binary Cross-Entropy
		max_iteration	25
Bi-LSTM + CNN (Proposed model)		Optimizer	Adam
		Loss Function	Binary Cross-Entropy
		Learning Rate	0.001
		Dropout Rate	0.5
		Batch Size	32
		Epochs	50

Table II presents the hyperparameter tuning details for different machine learning models, including the proposed Bi-LSTM + CNN model. A 5-fold cross-validation technique is applied to ensure robustness and minimize overfitting. Each model is fine-tuned using specific hyperparameters, such as gamma for SVM, maximum depth for Decision Trees, and learning rate, dropout rate, and batch size for Bi-LSTM + CNN. These hyperparameters are optimized to improve the performance of the model by balancing bias and variance. The proposed ensemble model takes advantage of both sequential and spatial feature extraction, making it more effective for precise crop prediction.

3.2 Disease Prediction

3.2.1 Dataset Preparation

Input

We have taken the Plant village dataset D containing plant leaf images, and Y be the corresponding disease labels. The dataset consists of:

- Disease symptoms & affected location (captured using ViT).
- Leaf shape & venation pattern (captured using HRNet).

The dataset can be represented as:

$$D = \{(X_i, Y_i)\}_{i=1}^{N} \tag{3.17}$$

where X_i represents an image, and Y_i is the associated label.

3.2.2 Data Preprocessing

To ensure consistent input to both ViT and HRNet, images undergo the following transformations:

Resizing

Images are re-shaped to 224×224 pixels.

Normalization

Normalized pixel values using ImageNet mean μ and standard deviation σ:

$$X_i' = \frac{X_i - \mu}{\sigma}, \quad X_i' \in R^{3\times224\times224} \tag{3.18}$$

Data Augmentation

Data augmentation techniques are applied to generalize the model and increase robustness for training images. These transformations help mitigate overfitting and improve performance on unseen data. The applied augmentations include:

- **Random Rotations** (θ): Ensure invariance to leaf orientation by randomly rotating images.
- **Horizontal Flips** (F_h): Reduces bias towards a fixed viewpoint by flipping images horizontally.
- **Color Jittering** (C_j): Enhances robustness to varying lighting conditions by modifying brightness, contrast, and saturation.

The final transformed image is obtained as:

$$X_i'' = C_j(F_h(R_\theta(X_i'))) \tag{3.19}$$

where X_i' is the normalized image, and X_i'' represents the augmented version.

3.2.3 Model Architecture

Our model integrates the two big deep learning architectures, one is Vision Transformer (ViT) and the other one is High-Resolution Network (HRNet) for the advantage of their complementary strengths for plant disease classification. The architecture consists of three main components:

Vision Transformer (ViT) Module

ViT is designed to capture global contextual information from images by dividing them into patches. ViT process them through a transformer-based self-attention mechanism. The ViT module follows these key steps:

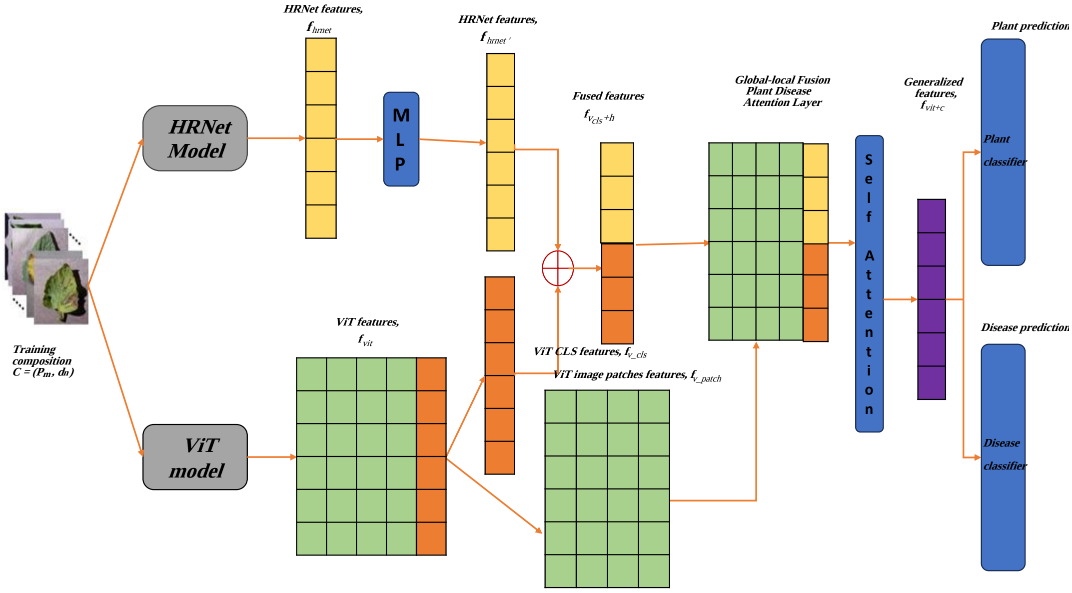

Figure 3.2: Model Architecture

- **Patch Embedding:** The input image $X \in R^{H\times W\times C}$ is divided into patches that are non-overlapping and linearly projected in an embedding space:

$$f_{v\_patch} = PatchEmbed(X) \in R^{N_p\times d} \tag{3.20}$$

  where N_p is the number of patches and d is the embedding dimension.

- **Self-Attention Mechanism:** The patch embeddings are processed through multiple transformer layers, where each layer applies Multi-Head Self-Attention (MSA):

$$Z = MSA(LN(f_{v\_patch})) + f_{v\_patch} \tag{3.21}$$

  where LN denotes Layer Normalization.

- **Feature Extraction:** The final ViT feature representation is computed as:

$$f_{ViT}(X) = W_{ViT}Z + b_{ViT} \tag{3.22}$$

High-Resolution Network (HRNet) Module

HRNet is specialized in maintaining high-resolution feature representations. HRNet ensures the preservation of structural details such as leaf shape and venation patterns. The HRNet module operates as follows:

- **Multi-Scale Feature Representation:** HRNet maintains multiple parallel feature streams at different resolutions. Feature maps at different resolutions are computed as:

$$H_1, H_2, H_3 = HRNet(X) \tag{3.23}$$

- **Feature Fusion:** The high-resolution representation is obtained by concatenating multi-resolution features:

$$f_{HRNet}(X) = W_{HRNet}[H_1 \oplus H_2 \oplus H_3] + b_{HRNet} \tag{3.24}$$

  where $\oplus$ denotes concatenation.

- **Feature Fusion and Classification** The features extracted from ViT and HRNet are concatenated to leverage both global contextual and fine-grained structural information:

$$F(X) = f_{ViT}(X) \oplus f_{HRNet}(X) \tag{3.25}$$

  A fully connected classification layer then maps these features to the final plant disease class:

$$\hat{Y} = W_{final}F(X) + b_{final} \tag{3.26}$$

  where W_{final} and b_{final} are the learned parameters.

3.2.4 Importance of ViT and HRNet in the Model

The combined proposed model (ViT and HRNet) plays a significant role. It integrates both global and local feature representations that enhances plant disease classification.

- **Vision Transformer (ViT):** Using self-attention mechanisms ViT excels in capturing disease-related patterns. When we provide a comprehensive global view of the leaf it effectively detects symptoms such as discoloration, lesions, and disease-affected region.

- **High-Resolution Network (HRNet):** HRNet make sure that structural details such as leaf shape, venation patterns, and fine texture details are preserved. These fine-grained details are particularly important for distinguishing between different plant diseases that exhibit subtle morphological differences.

- **Hybrid Feature Representation:** By combining the outputs of ViT and HRNet, the model benefits from both detailed structural information and rich contextual representations, leading to improved classification accuracy.

The integration of ViT and HRNet allows the model to perform robust and accurate plant disease classification, making it well-suited for real-world agricultural applications.

Table 3.3: Hyperparameter Settings for Plant Disease Classification Model

Hyperparameter	**Value**
Optimizer	Adam
Learning Rate	0.001
Batch Size	16
Number of Epochs	5
Loss Function	Cross-Entropy Loss
Image Size	224×224
Data Augmentation	Random Rotation, Horizontal Flip, Color Jitter
Train-Validation Split	80%-20%
Number of Classes	*(Based on dataset)*
ViT Model	vit_base_patch16_224 (Pretrained)
HRNet Model	hrnet_w18 (Pretrained)
Device	CPU

Chapter 4

Result and Discussion

4.1 Crop Prediction

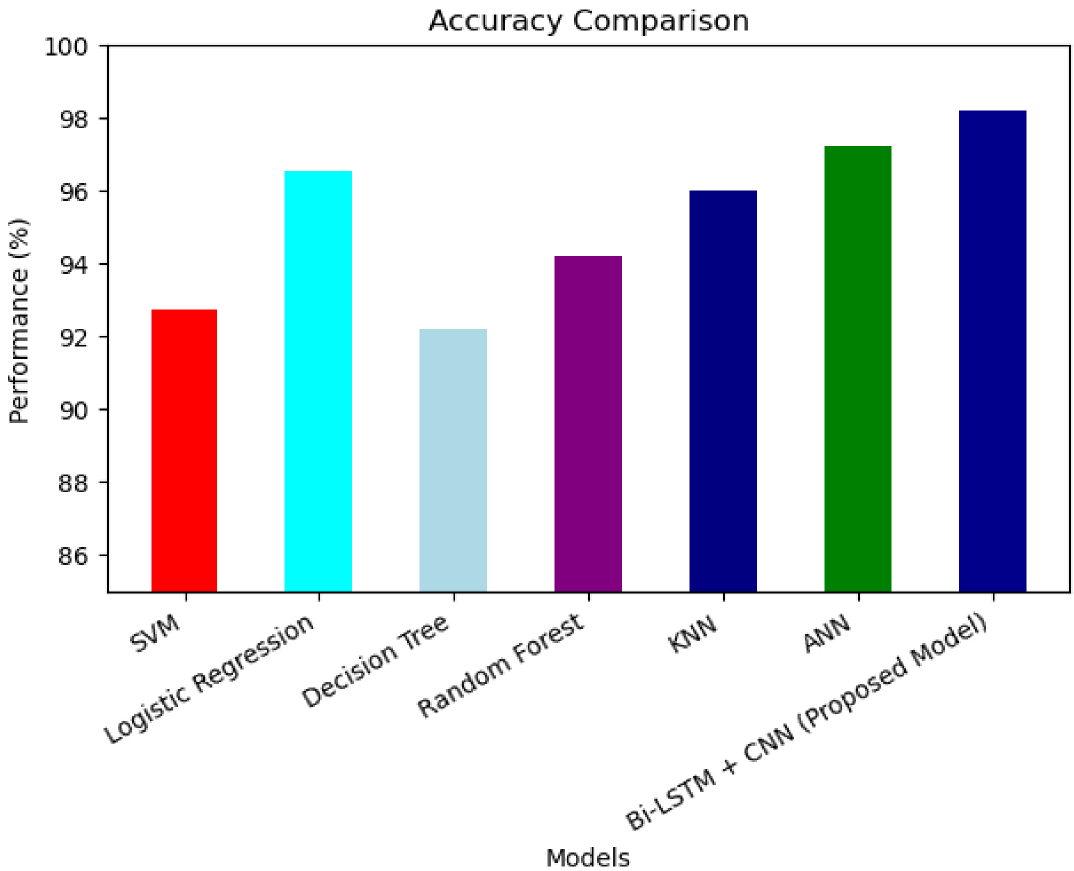

Figure 4.1: Accuracy comparison of different features

Table III presents the performance comparison of various machine learning

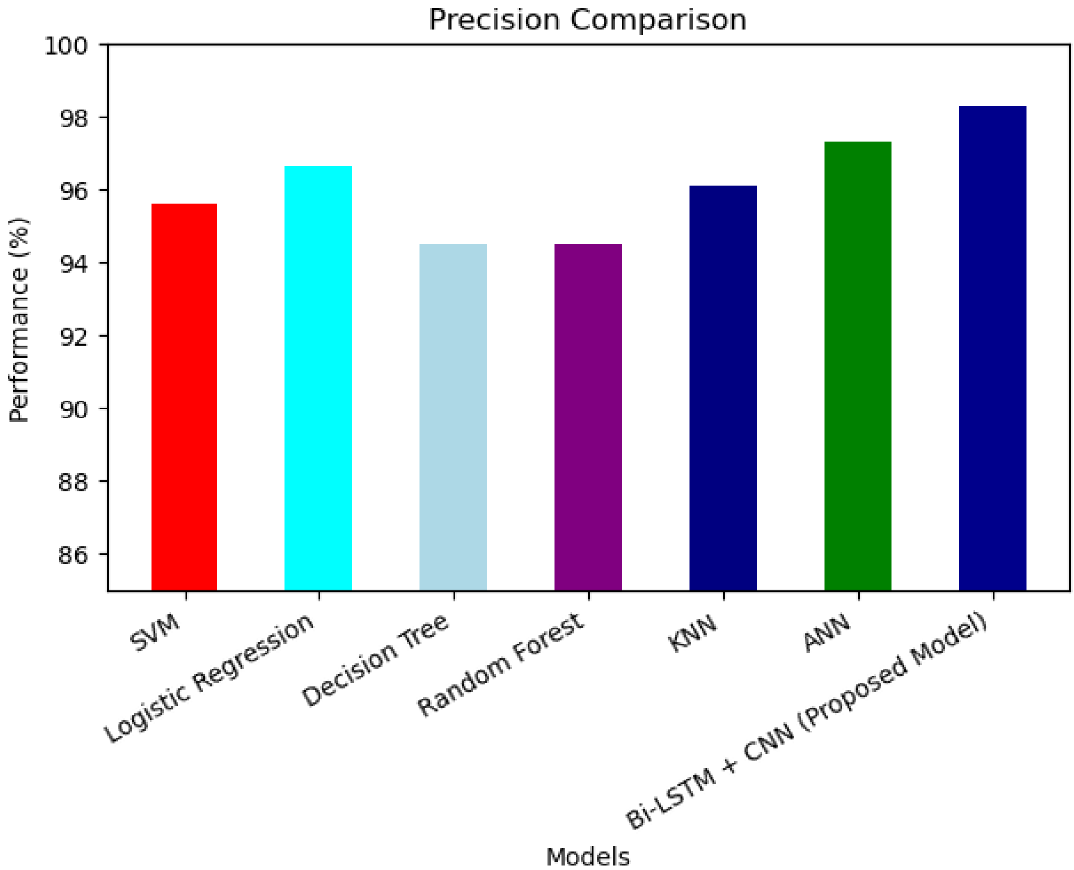

Figure 4.2: Precision comparison of different features

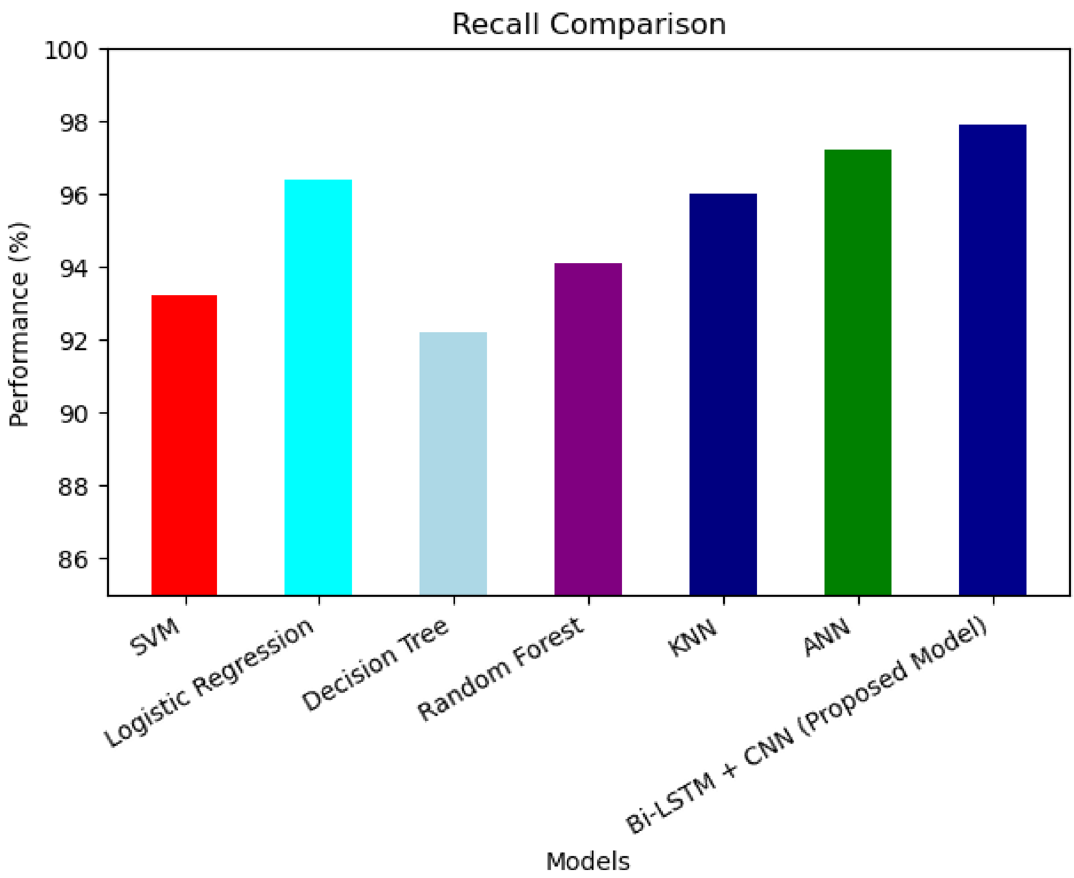

Figure 4.3: Recall comparison of different features

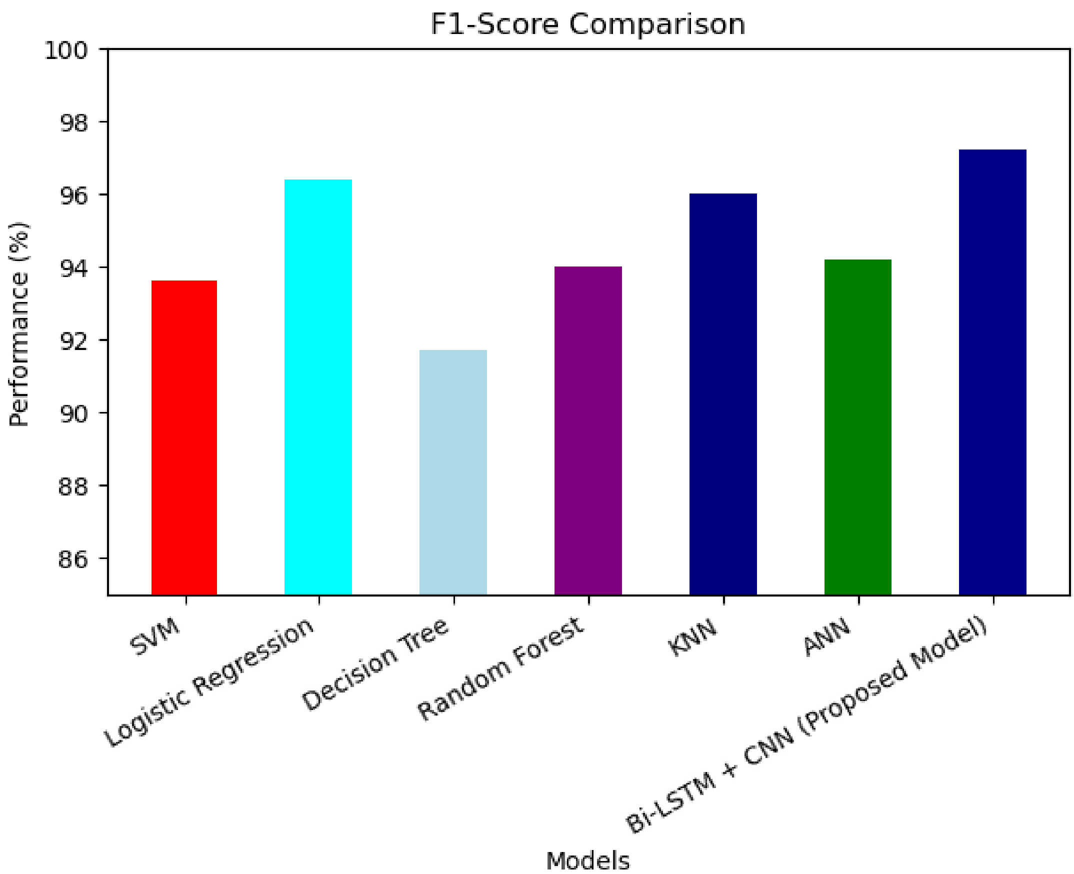

Figure 4.4: F1-score comparison of different features

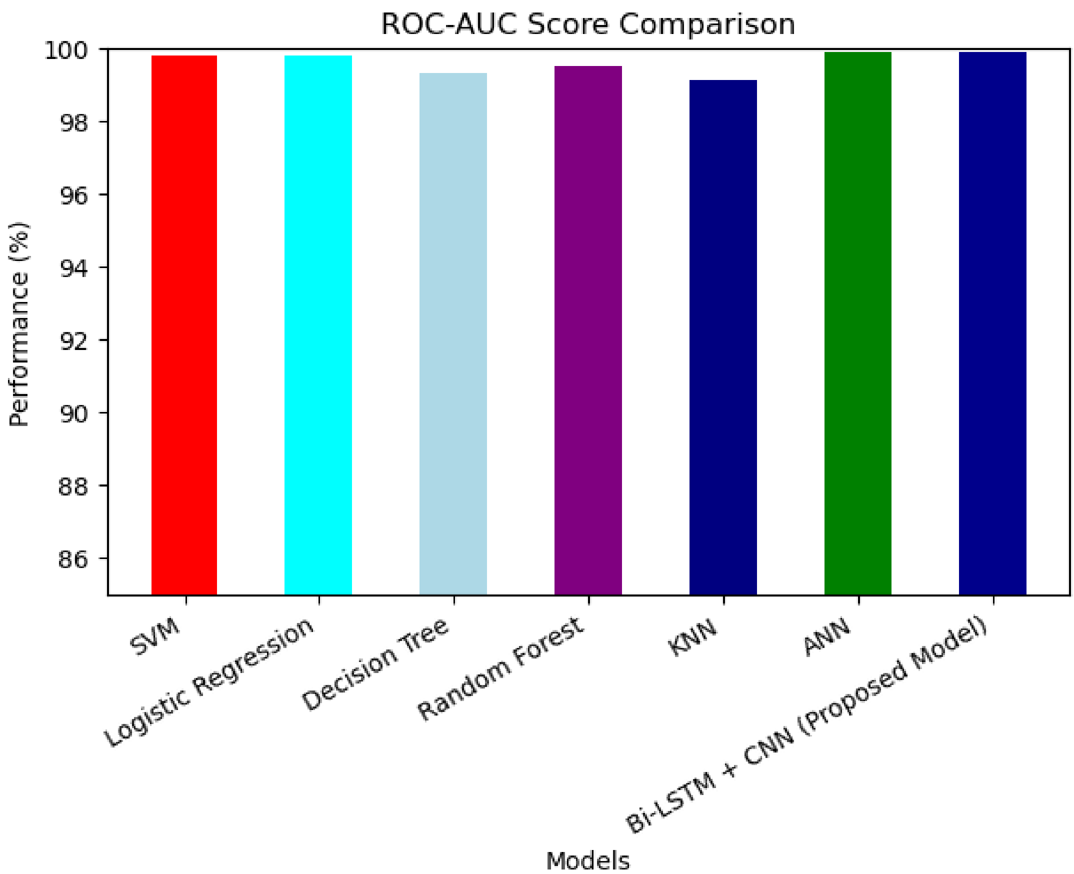

Figure 4.5: ROC-AUC score comparison of different features

and deep learning models based on accuracy, precision, recall, F1-score, and ROC-AUC score. The SVM model achieves an accuracy of 92.7%, with a high precision of 95.6% and an ROC-AUC score of 99.8%, indicating a strong classification ability. Logistic regression performs better, achieving 96.5% precision and a 96.63% precision rate. The Decision Tree model, with 92.2% accuracy, has the lowest F1 score (91.7%) among the models. Random Forest improves on this with accuracy 94.2% and a better F1 score (94.0%). KNN shows a strong balance with accuracy 96% and equal recall and F1 score. ANN outperforms most traditional models with 97.2% accuracy. Finally, the Bi-LSTM + CNN model achieves the highest accuracy (98.2%) and F1 score (97.2%), which proves to be the most effective technique. Due to its superior performance across all metrics, this method is proposed as the optimal approach for the given task.

Table 4.1: Performance Comparison of Models

Model	**Accuracy**	**Precision**	**Recall**	**F1-score**	**ROC-AUC Score**
SVM	92.7%	95.6%	93.2%	93.6%	99.8%
Logistic Regression	96.5%	96.63%	96.4%	96.4%	99.8%
KNN	96%	96.1%	96%	96%	99.1%
Decision Tree	92.2%	94.5%	92.2%	91.7%	99.3%
Random Forest	94.2%	94.5%	94.1%	94.0%	99.5%
ANN	97.2%	97.3%	97.2%	94.2%	99.9%
Bi-LSTM + CNN (Proposed model)	98.2%	98.3%	97.9%	97.2%	99.9%

Table IV presents a comparative analysis between the proposed model and existing techniques based on key performance metrics: accuracy, specificity, precision, recall, and F1-score. The referenced models exhibit varying performance levels, with accuracy ranging from 80.06% to 97.1%. Model [44] demonstrates the lowest accuracy (80.06%) and F1-score (85.37%), indicating suboptimal classification performance. Model [46] achieves strong results, with 97.1% accuracy and a perfect specificity score of 100%, demonstrating high reliability. However, the proposed model outperforms all prior approaches, achieving the highest accuracy (98.2%), specificity (99.3%), precision (97.04%), recall (97.5%), and F1-score (97.9%). These results suggest that the proposed approach enhances the classification performance and generalization capability, making it the most effective technique among the compared methods [44].

Table 4.2: Performance comparison with existing techniques.

References	**Accuracy**	**Specificity**	**Precision**	**Recall**	**F1-score**
[42]	89.7	98.83	94.14	93.24	93.68
[43]	94.43	97.68	92.37	93.64	93.62
[44]	80.06	82.11	82.7	83.19	85.37
[45]	84	94.63	89.11	88.53	88.81
[46]	97.1	100	97.03	97.12	97.09
[Proposed Model]	98.2	99.3	97.04	97.5	97.9

4.2 Disease Prediction

Table 4.3: Performance Comparison of Models

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**	**ROC-AUC (%)**
VGG16 + Inception-v3	97.6	98.0	98.0	97.0	98.2
ViT	98.8	98.8	98.6	98.7	99.2
ACO-CNN	99.2	99.1	99.1	99.0	99.2
CNN + Gradient Boosting	98.03	98.04	98.01	98.02	98.5
ResNet50 + Attention Fusion	98.7	98.53	98.56	98.57	98.8
ViT + HRNet (Proposed Model)	**99.82**	**99.71**	**99.69**	**99.72**	**99.80**

Table II presents a comparative analysis of different models which are used for plant diseases prediction. First one is VGG16 + Inception-v3 which is a 16 layer model and it gives 97% accuracy and after that I used Vision Transformer (ViT) which gives 98.8% accuracy. After that I take CNN with Ant Colony

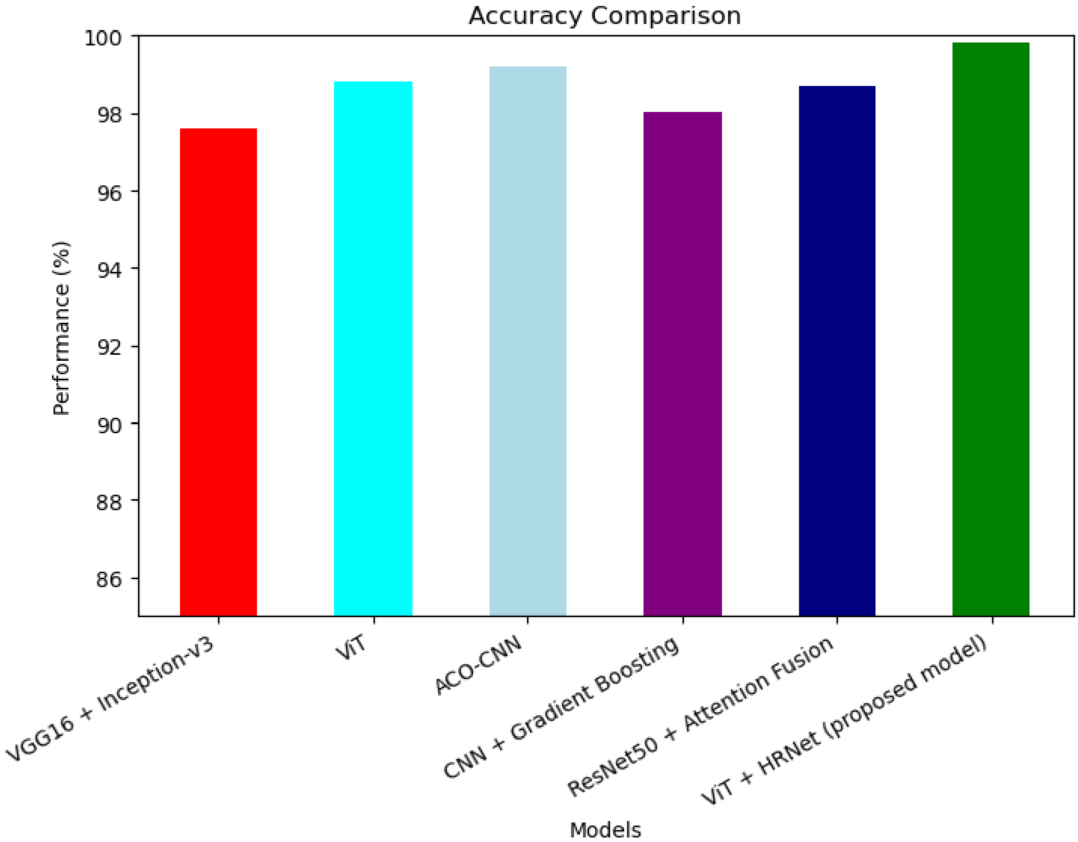

Figure 4.6: Accuracy comparison of different models

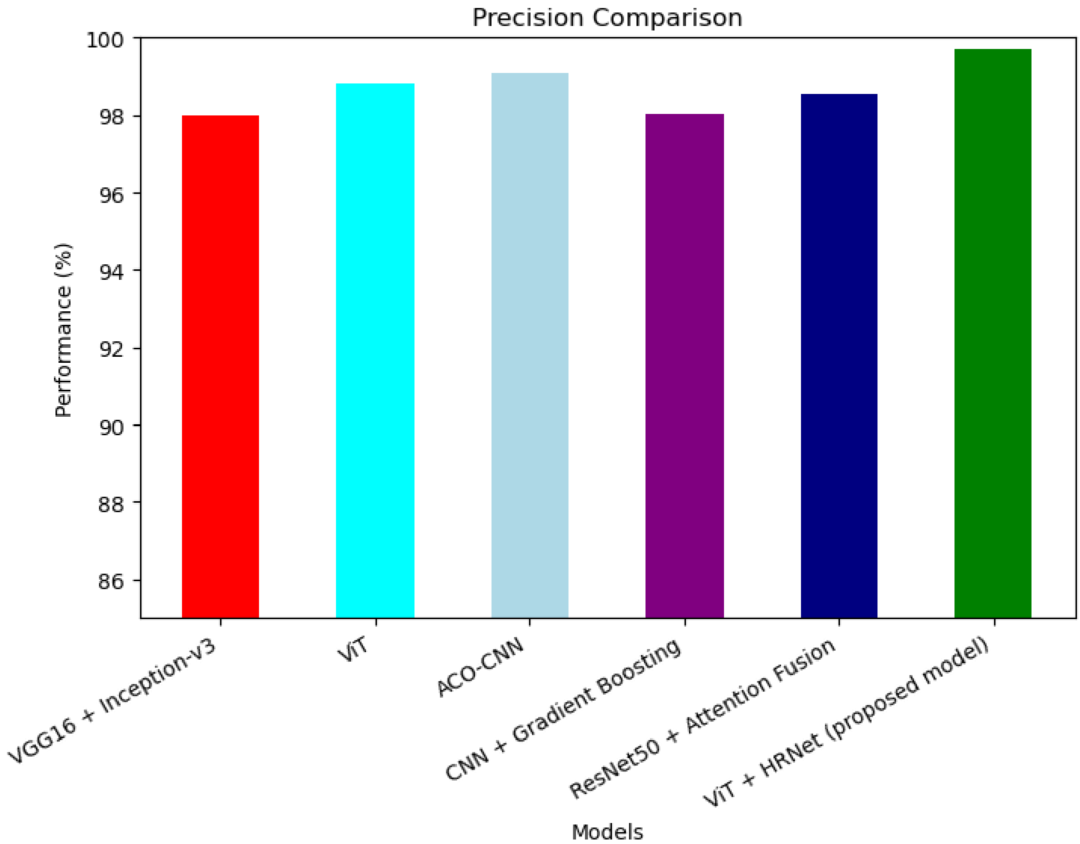

Figure 4.7: Precision comparison of different models

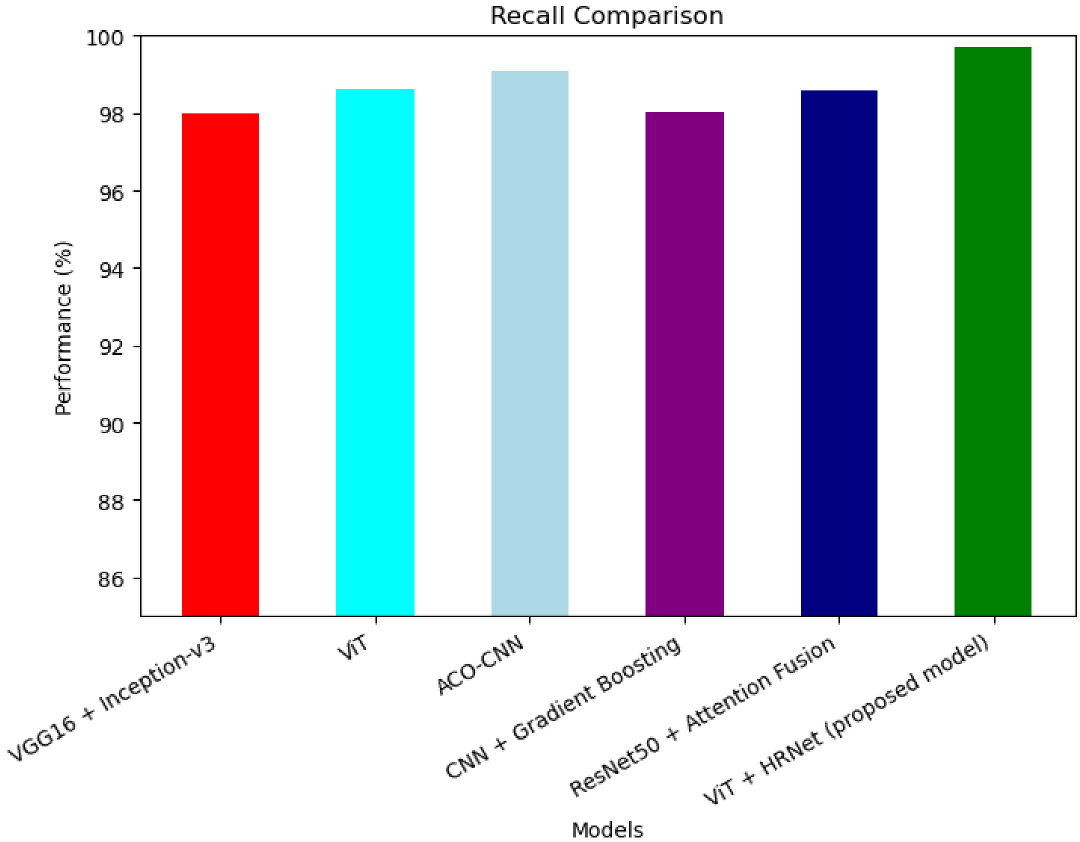

Figure 4.8: Recall comparison of different models

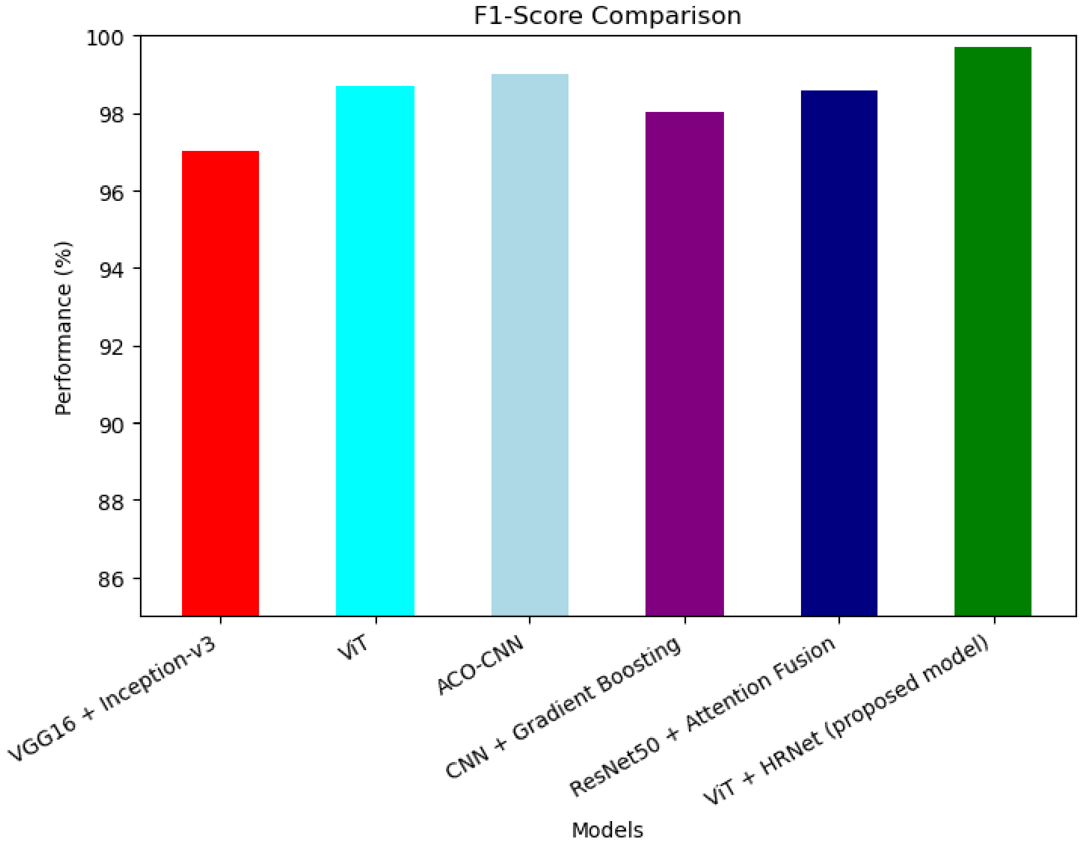

Figure 4.9: F1-score comparison of different models

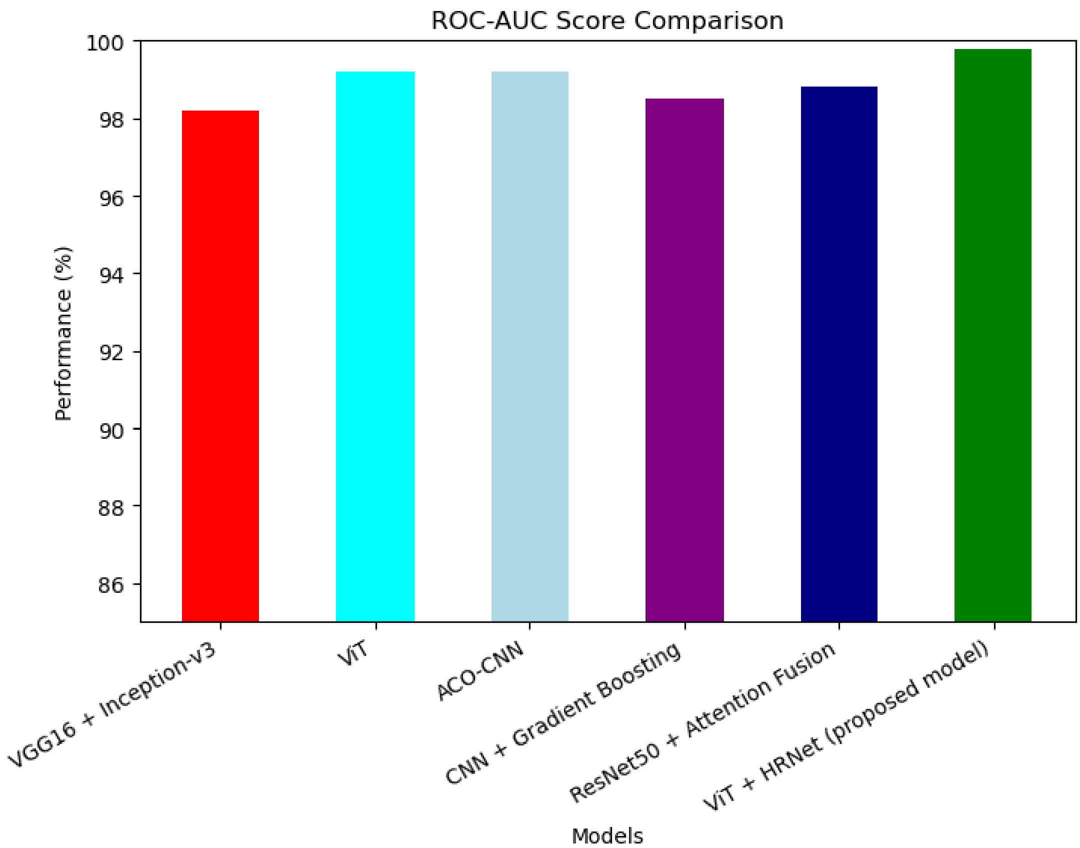

Figure 4.10: ROC-AUC score comparison of different models

Optmization(ACO) and Gradient Boosting and it gives a considerable accuracy which is 99.2% and 98.03% respectively and at last I used Vision Transformer with High Resolution Network (ViT + HRNet), which is my proposed model and it gives 99.82% accuracy.

Table III presents a comparative analysis of the proposed Fusion model of ViT and HRNet framework against several state-of-the-art (SOTA) models. The first category includes prior studies [25], [26], and [27], where models incorporating hybrid architectures, combining convolutional layers with attention mechanisms, were trained from the ground up. The highest accuracy observed in this category on the Plant Village dataset was 97.28%. The second category consists of approaches leveraging pretrained deep learning architectures, such as DenseNet121, MobileNetV2, and Vision Transformer (ViT) (vit_base_patch16_224). These models utilize transfer learning techniques, where CNN-based approaches integrate attention layers and ViT-based models incorporate convolutional layers to improve performance. The highest accuracy attained in this group reached 98.86% on the Plant Village dataset. Despite their effectiveness, these hierarchical architectures primarily focus on progressive feature extraction, which may pose challenges when generalizing across multiple crop species in plant disease classification.

In contrast, the proposed framework enhances feature extraction by integrating both pretrained ViT and HRNet architectures within a dual-stream processing mechanism. To further refine the extracted features, a novel Generalized Local Feature Aggregation (GLFA) layer is introduced, ensuring improved fusion of spatial and contextual information, thereby enhancing adaptability across diverse crop-disease combinations. Unlike previous studies that primarily depend on a single classifier, proposed model incorporates a dual-classifier mechanism to strengthen plant disease identification. For a rigorous evaluation. Specifically, ViT + HRNet employs a single classifier, aligning its structure with other SOTA models in Table II. The final classification result is obtained through a post-processing step that consolidates outputs from both classifiers.

Results of proposed model shows that it achieved outstanding performance attaining a peak accuracy of 99.72% on the Plant Village dataset, surpassing the highest-performing SOTA model by 0.80%. The combination of ViT + HRNet demonstrates superior precision, recall, and F1 score, that tells about its effectiveness. The improvement is significant in real-world agricultural applications and highlights the contribution of the GLFA layer to capture and generalize disease-specific features across multiple crops.

Table 4.4: Performance comparison between State of the models and proposed model.

Work	**Approach**	**Accuracy**	**Precision**	**Recall**	**F1 score**
[51]	Build from scratch	90.13	90.59	89.89	90.24
[53]	Build from scratch	97.28	97.49	97.06	97.27
[52]	Build from scratch	95.83	96.20	95.60	95.89
[57]	Pretrained ViT	98.61	98.24	98.33	98.28
[54]	Pretrained CNN	87.94	89.59	86.71	88.07
[55]	Pretrained CNN	96.61	97.09	96.11	75.03
[58]	Pretrained CNN	98.86	98.90	98.81	98.85
[56]	Pretrained CNN	96.68	97.49	95.83	96.64
ViT + HRNet (Proposed Model)	Pretrained ViT and HRNet	99.72	99.71	99.69	99.70

Chapter 5

Conclusion and Future Work

In this research paper, we introduce a novel hybrid model that enhances the identification of plant diseases by integrating the power of the Vision Transformer (ViT) and the High-Resolution Network (HRNet). The architecture we propose leverages a specialized feature fusion mechanism that effectively captures both global and local patterns, improving generalization capability for multi-crop disease classification.

After running our model, results show that the ViT and HRNet-based model outperforms state-of-the-art (SOTA) approaches present in the Plant Village dataset. By optimizing key parameters, we ensure the model's robustness for enhanced performance. These findings establish the proposed model as a strong candidate for advancing automated plant disease detection and classification techniques.

Accurate pre-season crop prediction plays a crucial role in strengthening global food security by facilitating data-driven decision-making, optimizing resource allocation, and promoting sustainable agricultural practices. In this paper, we introduce a hybrid deep learning approach that integrates CNN and Bi-LSTM networks to overcome the limitations of traditional prediction methods. The model effectively extracts spatial patterns using CNNs and employs Bi-LSTM to analyze temporal dependencies. This combination transforms raw agricultural data into meaningful spatiotemporal insights, improving its precision and reliability in crop forecasts. Additionally, we have used k-fold stratified cross-validation and dropout-based regularization to enhance the model's robustness, ensuring its capability to handle large-scale datasets while minimizing overfitting.

After running the model, metrics show that the CNN-BiLSTM hybrid model outperforms conventional approaches and achieves higher predictive accuracy aligned with practical agricultural requirements. This paper serves as a bridge to fill the gap between theoretical research and real-world farming applications, offering a scalable solution for pre-season planning. In an era of increasing global demand and climate change, improving prediction reliability supports sustainable farming, reduces environmental risks, and contributes to resilient food systems.

For further research, we can explore emerging techniques to continuously update data during the planting season and predict in-season and pre-season crops in real time for adaptive learning. Transfer learning techniques could also accelerate model adaptation in underrepresented regions and facilitate broader applicability. Additionally, for smallholder farmers, we can develop lightweight versions of the hybrid architecture. This lightweight design should be explored to ensure accessibility in resource-limited environments. Advancing these frameworks will enable a versatile and sustainable tool for global agriculture.

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Appendix A

List of Publications :

1. **Paper - 1**

   (a) Paper Title: A Hybrid Approach Integrating Global Attention And Local Features For Plant Disease Detection

   (b) Conference Name: International Conference on Artificial Intelligence and Sustainable Innovation-2025 (ICAISI-2025).

   (c) Organized by: Suresh Gyan Vihar University, Jaipur

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This is to certify that **Mr. SHYAM KISHOR YADAV** of **DELHI TECHNOLOGICAL UNIVERSITY** has presented his research paper titled ***"Harnessing The Future With An Ensemble Model Of Bi-LSTM And CNN For Precise Crop Prediction"*** at the 3rd International Conference on Networks and Cryptology (NetCrypt 2025) organized by School of Computer and Systems Sciences, Jawaharlal Nehru University, New Delhi, India, on May 29-31, 2025.

Dr. Karan Singh	**Prof. D. K. Lobiyal**	**Prof. Zahid Raza**
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2. **Paper - 2**

   (a) Paper Title: Harnessing The Future With An Ensemble Model Of Bi-LSTM And CNN For Precise Crop Prediction.

   (b) Conference Name: 3rd International Conference on Networks and Cryptology(NetCrypt 2025)

   (c) Organized by: School of Computer and Systems Sciences, Jawaharlal Nehru University, New Delhi.

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Certificate of Participation

This is to certify that **Shyam Kishor Yadav, Delhi Technological University** has presented his/her research paper titled **"A Hybrid Approach Integrating Global Attention And Local Features For Plant Disease Detection"** in the ICAISI-2025 organized by Suresh Gyan Vihar University, Jaipur held from **May 30th to 31st, 2025**.

S. Sharma

Prof (Dr.) Sohit Agarwal **Conference Chair**	**Prof (Dr.) Sandhya Sharma** **Conference Chair**	**Dr. Arunansu Haldar** **President**

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