FISH SPECIES CLASSIFICATION USING MACHINE LEARNING AND DEEP LEARNING MODELS

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Submitted by

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CANDIDATE'S DECLARATION

I, AZIZ MEHEVI, Roll No - 2K23/ITY/16 student of M.Tech (INFORMATION TECHNOLOGY), hereby declare that the project Dissertation titled "Fish Species Classification using Machine Learning and Deep Learning Models" which is submitted by me to the Information Technology, Delhi Technological University, Delhi 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 Degree, Diploma Associateship, Fellowship or other similar title or recognition.

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CERTIFICATE

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Date: 29.05.2025 | **SUPERVISOR**

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Abstract

Fish species classification is fundamental to ecological monitoring, biodiversity conservation, and sustainable fishery management. Conventionally, the identification of fish species is based upon manual observations by domain experts and, hence, incurs heavy expenses with time, labor, and considerable lows in scalability. This study provides broad coverage of the fish species classification problem, with a huge focus on both traditional machine learning (ML) models and architectures of deep learning (DL). A custom dataset of underwater fish images was composed, with images of nine different fish species to cater to various environmental condition-based considerations in the training and testing of several models. The ML models discussed include Support Vector Machines (SVM), Random Forests (RF), Decision Trees (DT), Logistic Regression (LR), and Naive Bayes (NB): all of these were subject to two types of dimension reduction, namely Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). These were compared against DL models including VGG-19, DenseNet121, EfficientNet B0, Inception V3, ResNet150 V2, and LSTMs, with evaluations conducted for accuracy, precision, recall, and F1-score. The experimental results demonstrated that DL models significantly outclassed conventional ML algorithms in classification accuracy and the ability to handle variability in images. VGG-19 attained 99.4% overall accuracy; DenseNet121 and EfficientNet B0 followed closely and are considered fit for deployment in real-world fish classification systems. Image preprocessing, normalization, and data augmentation were deemed critical in improving model performance. This study emphasizes the possibility of having deep learning automate fish species recognition with high accuracy under difficult underwater conditions. The present findings open several avenues for real-time marine surveillance, automated ecological data analysis, and smart decision support systems for marine biologists and conservationists.

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ANN	Artificial Neural Network
CNN	Convolutional Neural Network
$\mathbf{R^2}$	Correlation Coefficient
DT	Decision Tree
DCAE	Deep Convolutional Auto Encoder
DenseNet	Densely Connected Convolutional Network
EfficientNet	Efficient Convolutional Network
HSV	Hue Saturation Value
LDA	Linear Discriminant Analysis
LR	Logistic Regression
LSTM	Long Short Term Memory
NV	Naive Bayes
PCA	Principal Component Analysis
RF	Random Forest
ReLU	Rectified Linear Unit
RNN	Recurrent Neural Network
ROI	Region Of Interest
ResNet	Residual Neural Network
RMSE	Root Mean Square Error
SVM	Support Vector Machine
SE	Squeeze and Excitation
VGG	Visual Geometry Group
YOLO	You Only Look Once

Chapter 1

INTRODUCTION

The fish species classification is an important aspect for marine biology, aquaculture management, fisheries monitoring, and environmental conservation. On a biodiversity assessment level, correct species identification is necessary to carry out a study on population dynamics, and for managing resources respectively. In the past, classification of fish was mainly performed through manual identification using physical variations seen on the fishes. Fish classification techniques, however, become time-consuming and labor-intensive to perform alone, or with the use of machine classifiers when it becomes real-time and large-scale for marine monitoring. With the advent of under-water cameras, drones, and many more, image data have grown tremendously demanding scalable and automated solutions.

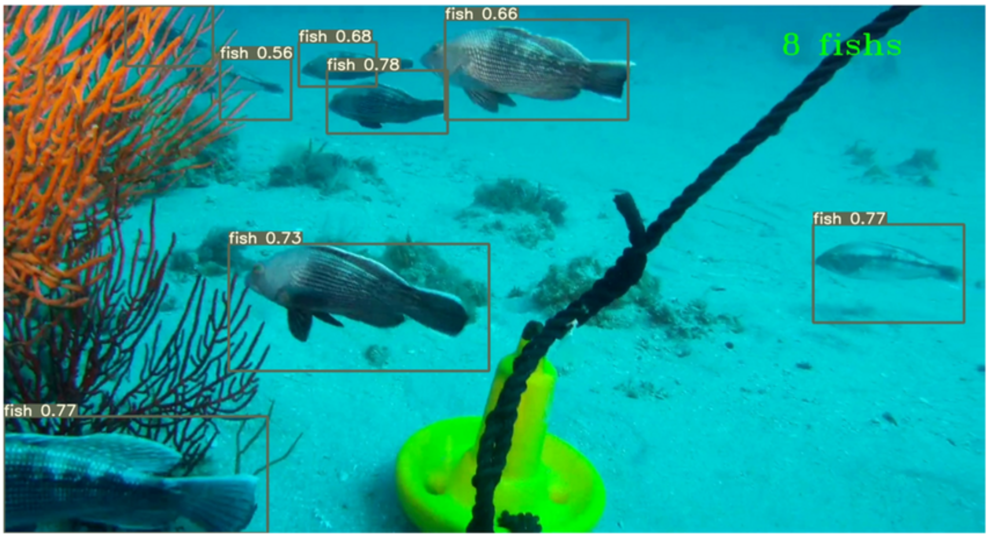


Figure 1.1: Underwater Fish Detection

Artificial intelligence developments in recent times, especially in machine learning and deep learning, have made it possible to automate complex classification tasks. Deep learning models [1] such as Convolutional Neural Networks (CNNs) have redefined image recognition by learning hierarchical feature representations directly from the raw pixel data. CNNs have been proved to be successful across a variety of classification tasks with high accuracy such as natural-object detection, medical imaging, and more recently, underwater species recognition. Similarly, classical machine learning models like Support Vector Machines (SVM), Random Forest (RF), and Logistic Regression (LR) [2] present fast and interpretable methods in situations where the computation power is constrained.

This research approach looks at the comparative aspect of applying machine learning and deep learning methods of classification to the nine fish species regarding image data.

1.1 Motivation

The prime motivation behind this research work emanates from the urgent call for an effective, scalable, and cheap way of monitoring the marine ecosystem. As climate change and overfishing continue to stretch their grasp on aquatic world biodiversity, tools for automated species classification would help marine biologists and conservationists to find and keep a record of fish populations, detect invasive species, and enforce regulations for sustainable fishing. The central aim of this thesis is to design, implement, and evaluate several ML and DL models for the classification of fish species. It shall train on a downloaded dataset, while the evaluation of the various models shall be carried out using a set of standard metrics. It shall also compare the efficacy of the models in terms of accuracy, efficiency, and generalizability.

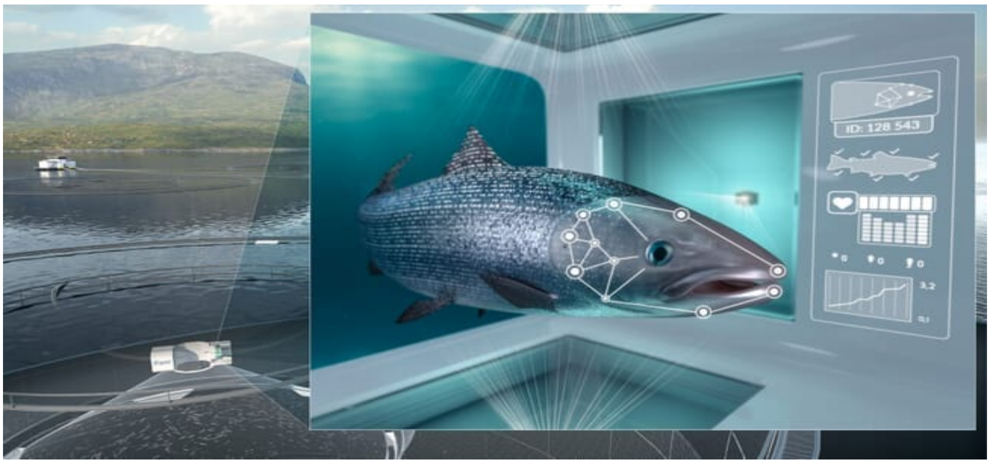


Figure 1.2: AI in Realtime Fish Classification

1.2 Scope of the Study

The scope of this study is limited to image-based classification for the custom dataset of nine fish species. The models considered ranged from conventional algorithms such as SVM, RF, and LR to deep networks like VGG-19, DenseNet121, EfficientNet B0, Inception V3, ResNet150V2, and LSTM. Data preprocessing techniques such as resizing, normalization, color space conversion, and augmentation are applied to improve training effectiveness. While the study introduces LSTM as an initial step toward incorporating temporal data, it does not extend to full video-based classification or real-time system deployment. Instead, it sets a foundation for future work in these areas.

1.3 Ethical and Environmental Significance

Beyond technical innovation, this research has profound ethical and environmental implications. The application of AI in marine monitoring aligns with global efforts to enhance biodiversity conservation and ecosystem management. By automating the classification of fish species, these systems can reduce dependency on manual labor and mitigate human error, leading to more consistent and frequent data collection. This is especially critical in remote or understudied marine regions where expert human presence is not always feasible. In such contexts, AI-powered systems can support real-time surveillance through autonomous underwater vehicles (AUVs), helping monitor coral reefs, detect illegal fishing practices, or observe population trends with minimal ecological disruption.

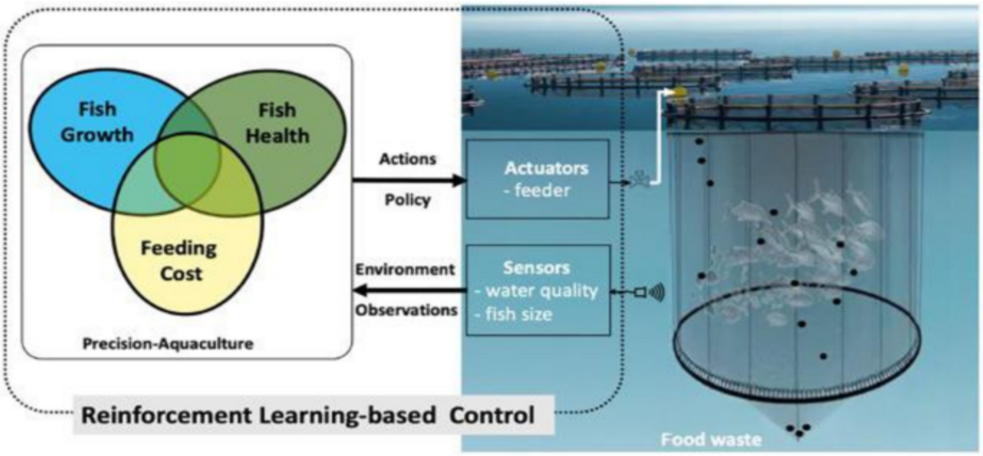


Figure 1.3: Aquaculture Monitoring using AI

From an ethical standpoint, it is essential to ensure that such systems are developed and deployed responsibly. One major concern is the interpretability of deep learning models, which often function as black boxes with limited transparency. In conservation and ecological decision-making, stakeholders must trust that AI-driven insights are accurate and justifiable. This calls for the integration of explainable AI (XAI) frameworks that allow practitioners to understand the rationale behind model predictions. Additionally, with increasing discussions around the regulation of artificial intelligence in critical domains, such as the EU's AI Act, it becomes vital to align AI-based ecological tools with emerging ethical standards that emphasize fairness, accountability, and environmental responsibility.

1.4 Objectives of the Study

This study attempts to tackle the gaps mentioned above by systematically evaluating several machine learning and deep learning models for fish species classification. The objectives are listed below:

- To implement and compare several ML models such as SVM, RF, LR, etc., and DL architectures such as VGG-19, DenseNet121, ResNet150V2, etc., on a fish image dataset of interest.
- To employ preprocessing algorithms like PCA, LDA, augmentation, and extraction of ROI to maximize the performance of the models.
- To evaluate the robustness of the shortlisted models against species that resemble one another and cases where the visual condition is most challenging.

- To determine computationally efficient and deployable alternatives for low-resource environments.

- To recommend the best option(s) for real-time field-based fish species recognition.

1.5 Research Gaps

The field of automated fish species classification has advanced terrifically with the involvement of deep learning, particularly Convolutional Neural Networks (CNNs), and now transformer-based methods. However, although there have been significant improvements in classification accuracy and system efficiency, a number of gaps still exist in research that limit these applications in aquatic and terrestrial environments. The most chronic problem has been the poor and limited quality of datasets. Staring from the quality dataset comprises Fish4Knowledge, FishNet, Banfish, and A Large-Scale Fish Dataset. They have been found valuable, but usually suffer from severe class imbalance because some fish species appear very often in the dataset while others are less represented. This might affect the generalization potential of deep learning models that would be applied in some new or diverse environments. Another reality is that most of these datasets lack critical metadata such as environmental conditions, geographical measurements, orientation, and closeness information- all of which are required for making classification robust and context-aware, having regard to changing underwater conditions. In addition, the application of factor occlusion, resolution, and light inconsistency requires a very significant hurdle in poor image quality in generated images. Even being under-researched is the classification of fish out of water scenarios such as fish markets or processing plants. When captured, the visual characteristics of a fish may change that it might have undergone from physical injuring or a change in color, which is not found in training databases. Although most models require visual inputs, there is no attention paid to other contextual information such as the time of capture, activity patterns, and other environmental metadata. Limitations of transferability are presented in current models stuffed by the lack of adaptations to the specific domain.

Deep learning models trained on one data set may give poor performance when presented with other data sets, e.g., learned by fish of other species. Solution with using transfer learning although benefits by pre-trained model exposure to new tasks has the shortcoming of non-existing pre-trained models specifically directed towards fish classification and not having fine-tuning across this domain. We need urgently adaptive transfer learning frameworks generalizing across varied data sets and environmental conditions. The other futuristic need is real-time classification, especially where it acts in the spheres of marine biodiversity monitoring, autonomous underwater vehicles (AUVs), and fisheries administration. However, the application of object detection models such as FAST R-CNN and YOLO continues to limit their realization in terms of real time due to their associated costs in high computation and latency. Therefore, there is a need to develop lightweight, energy-efficient models which can run on resource-constrained devices without performance trade-offs. However, all these points need to be backed by data scientifically collected. This hinders the full acceptance of models owing to an incomprehensible premise. CNNs and the commonly present transformer-based models are mostly called or viewed as black boxes, with a very limited window into their decision processes. This creates a fundamental and major problem in the field of ecology, conservation, and engineering, especially if the understanding behind a prediction is needed. There needs to be an increasing demand for explainable AI (XAI) techniques specific to fish classification so that they may be used or trusted by their experts such as marine biologists. The last point relates to the fact that the entire field lacks standard evaluation metrics and benchmarking protocols. Such inconsistency in datasets, performance indicators, and experimental setups makes it impossible to draw conclusions by comparing and validating across multiple studies. Such a standard benchmark would therefore streamline further research and enable reasonable and replicable evaluation standards to be used in fish classification studies.

Moreover, data privacy and stewardship must be considered, particularly when deploying automated systems in regions overlapping with coastal communities or protected marine territories. Any data captured must be handled in compliance with legal and ethical norms, ensuring that ecological surveillance does not interfere with indigenous practices or sensitive habitats. The present work compared the classification performances of machines and deep learning with the curated dataset of varying nature for fish species. This includes data pre-processing, dimensionality reduction (PCA and LDA), and a thorough performance assessment of the models studied in terms of accuracy, precision, recall, and F1-score. Thus, the best models would find further use in real marine monitoring systems, advancing ecological investigation and automated species recognition technologies. In a systematic way, this study lays out details from Literature Review in Section 2 while Section 3 comprises of Methodology and Dataset used. Section 4 goes on to discuss the in depth analysis and results, which are later concluded with future scope in Section 5.

This chapter introduces the issues in automating classification of fish species, highlighting ecological, economic, and research-based reasons for pursuing the problem. Emphasis is given on the nexus of ML and DL for environmental monitoring and sustainable fishery. Thus, the objectives and scope of the study are proposed, emphasizing the ethical and environmental importance.

Chapter 2

LITERATURE REVIEW

2.1 Various Approaches for Classification

2.1.1 Machine Learning-Based Approaches

Early-stage fish species identification research was marked with the use of machine learning techniques which were still limited in such ways that extraction of handcrafted features like size, shape, and other biological features of fishes are done from available datasets like FishNet Open Images Database and Fish4Knowledge. In 2020, fish parasitic Myxosporidian cell classification [3] was done using various machine learning techniques. The procedure involved image preprocessing, feature extraction, and classification with SVM, RF, and MLP. Among the test scenarios carried out, MLP was observed to result in accurate classification at the rate of 98.89%, followed by SVM at 88.89% and RF at 96.67%. In 2022, various supervised and hybrid machine learning methods were used for classifying sea fish species [4] from underwater images. The study tried out various strategies, including Decision Trees, Naive Bayes, Support Vector Machines (SVM), Logistic Regression, Random Forests along with PCA and LDA for dimensionality reduction. The highest result from Random Forest achieved an accuracy of 99.89% while SVM along with PCA with an accuracy of 99.78%. Classification tasks with the holistic algorithms like Support Vector Machines (SVM) [5] and Naive Bayesian [6] made it successful in species identification, the main main disadvantage with these early approaches is that they could not generalize well across underlying underwater settings; therefore, more powerful and scalable techniques were required.

2.1.2 Neural Network-Based Approaches

Recent studies have applied deep learning techniques to various aspects of marine biology and aquaculture. In 2019, researchers developed a method to estimate white shark locomotor activity by training artificial neural networks (ANN) to predict overall dynamic body acceleration (ODBA) [7] from depth data, achieving robust predictions from 1 Hz pressure sensor inputs. In 2022, a deep convolutional autoencoder (DCAE) [8] was employed for classifying carp fish species, utilizing latent representations as features and achieving a maximum accuracy rate of 97.33% over 250 epochs with a learning rate of 0.0001. Another 2022 study applied deep adversarial learning for large-scale underwater fish recognition [9], leveraging adversarial training to enhance the model's robustness to variations in underwater environments. In 2023, researchers conducted a study on local fish classification using deep-learning models. The study was based on determining effective techniques [10] for accurate identification of local fish species using VGG16 models in combinations with classifiers.

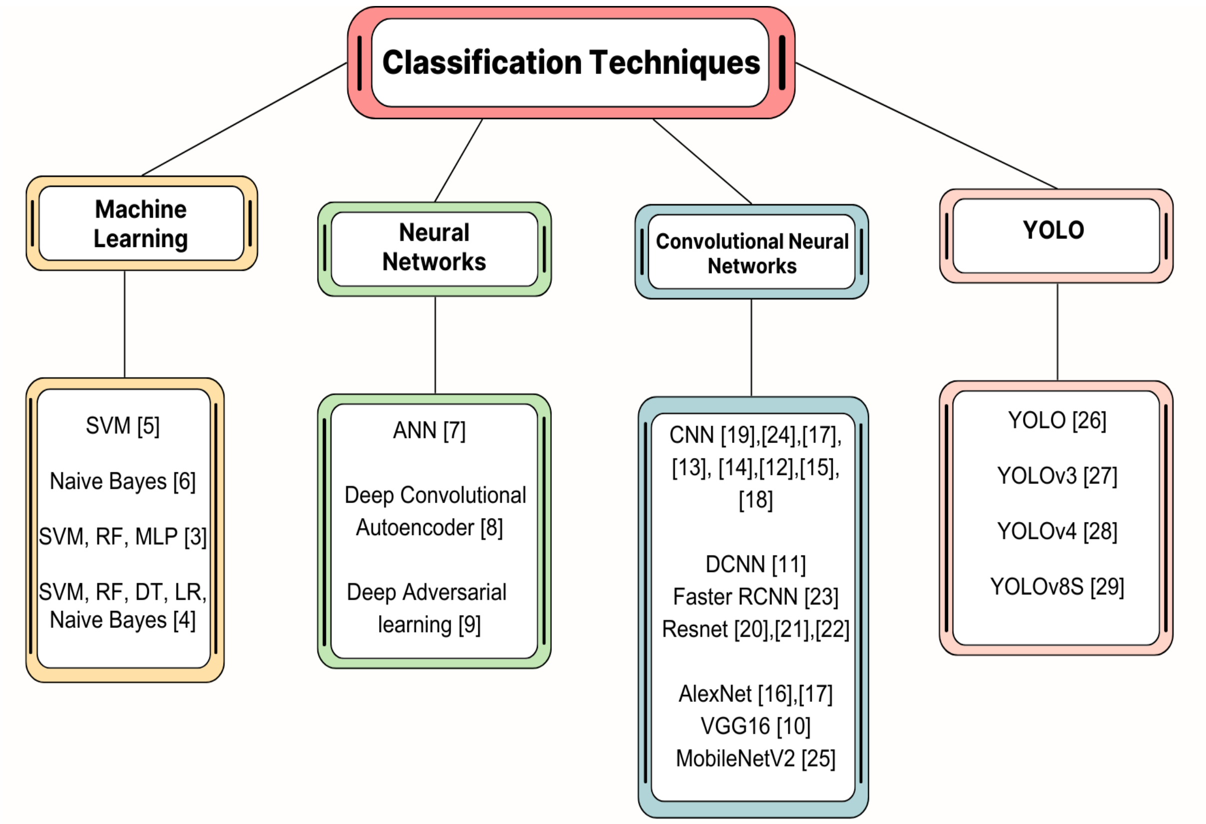


Figure 2.1: Past researches on fish classification techniques

2.1.3 Convolutional Neural Networks (CNNs) and Advanced Architectures

In 2017, a high-throughput screening method for zebrafish deformations [11] was developed using deep convolutional neural networks (DCNN), thus automating the classification and improving the efficiency of phenotypic assessments. In contrast, in 2018 a convolutional neural network (CNN) trained with a dataset that analysed a variety of whole and fragmented fish bodies in different environmental contexts, achieved a score of 94.9% in classifying coral reef fish species [12] from underwater images, far exceeding any human performance in the task. An improved transfer learning approach was developed in the same year, in conjunction with Squeeze-and-Excitation Networks, for small-scale, fine-grained fish image classification [13], which provided an additional boost to model performance on constrained datasets. In 2019, the VGG16 based CNN was proposed for an automated identification [14] of four carp species, which achieved high classification accuracy while building a hierarchy of self-learned features. In 2020, fish species classification was extended with the Crosspooled FishNet model [15] using transfer learning, gaining even more accuracy in discrimination amongst differing species. In december of same year, the improved AlexNet model [16] was applied to fish species identification, effectively enhancing the accuracy and computational efficiency by incorporating an itembased soft attention mechanism and a transfer learning process. In 2021 many researches were done like a smaller version of the AlexNet model with four convolutional layers and two fully connected layers [17] which was used for automatic classification of fish species, beneficial to marine biologists in studying the species and their habitats. Also a CNN model was developed for the classification of indigenous fish species of Bangladesh [18]. The work was targeted at developing an automatic system capable of accurately identifying various local fish species utilizing deep learning techniques.

A multi-scale convolutional neural network (CNN) method was proposed for accurate detection of still images of fishes underwater [19], thereby addressing underwater image detection challenges through a transmission map, refinement strategy, and deep learning methods. FishResNet, underpinned by the ResNet architecture [20], was developed for the task of underwater automatic fish classification, targeting the challenges of complex aquatic environments. The same year, the few-shot-learning mechanism [21] for automatic underwater fish species classification was introduced, facilitating the identification power when data are meager. Furthermore, transfer learning incorporated with SE-ResNet152 networks [22] would work for unbalanced fish species identification in small-scale datasets, thus enhancing the classification performance. In 2022, within the frame of targeted sample transfer learning, fish recognition [23] in complex underwater scenes was improved, giving a precision of 91.33% by merging interlayer fusion mechanisms. Deep-learning methods such as Faster R-CNN were also utilized to classify and detect different species of jellyfish [24], increasing accuracy for the identification of various jellyfish species. Also, a study was conducted on enhancing fish image classification through the fine-tuning of pre-trained deep learning models namely MobileNetV2 and VGG16 [25], with the intent to improve classification accuracy of these models for recognizing different fish species from image data.

In 2024, Wu and Wang suggested an entirely novel SIM-CONV model [26] for largescale fish classification tasks using the FishNet dataset. The newly introduced method focused on hierarchical label taxonomic learning, i.e., indexing images at levels other than species, such as biological groups of phyla and genera. To overcome such common problems as class imbalance and weak feature representation, they proposed a parameter-free attention module called SIMAM. The model has classified common species with 91.26% and rare species with 65.43% accuracy, better than ResNet, ConvNeXt, and Vision Transformers. The results emphasize its ability to better generalize and to pay attention to context features, making it a very powerful tool in real biodiversity datasets. In the same year, researchers from India developed an integrated framework known as NEMO [27], which stands for Neural Edge-based Marine Observation system. Their solution employed MobileNetV2 with transfer learning to create a lightweight Android application for fish species classification. The system incorporated preprocessing steps such as background removal, histogram equalization, and rotation-based augmentation, and was optimized using TensorFlow Lite for real-time inference. Following the previous trends, Yamsani et al. [28] in 2025 designed a custom Convolutional Neural Network, trained on a balanced dataset of nine fish species that closely mirrored the dataset used for this thesis. The network had dropout regularization for generalization, batch normalization for scaling and shifting inputs, and an adaptive learning rate. The overall accuracy that they reached was 92.57%, scoring very high precision in classes such as Shrimp and Gilt-Head Bream, but there was some confusion for species that look identical, e.x. Sea Bass and Red Mullet.

According to their results, CNNs could be used for domain-specific classification and supported the ongoing trend of worthy investments in custom design for biodiversity-related tasks.

2.1.4 YOLO

In May 2020, a deep learning method which consisted of temporal information was applied for fish detection and species classification [29] which increased the accuracy in adverse conditions. In the same year, Mohamed et al. introduced MSR-YOLO [30], a fish detection and tracking system made in fish farms. It considered the underwater image enhancement by Multi-Scale Retinex, the YOLO detector, and the tracking of fish trajectories by optical flow. In 2022, the two-step deep learning approaches which employed the use of YOLOv3 for detection and convolutional neural network built on squeeze-and-excitation architecture for classification, were proposed for temperate fish detection and classification [31], which dealt very well with noise and illumination variations. In the same year, a landmarking technique integrated to YOLOv4 was introduced for improving the fish recognition [32] on diverse backgrounds by increasing the accuracy of detection in varied aquatic environments. Following it, Mukit et al. introduced YOLO-Fish [33], an advanced detection system for challenging marine environments. Two different models were proposed. YOLO-Fish-1 improves upsampling for better detection of very small fishes, whereas Spatial Pyramid Pooling (SPP) is used by YOLO-Fish-2 to improve the multi-scale detection. Both models were trained across two new datasets called DeepFish and OzFish, which were created for realistic underwater scenes. The models achieved mAPs of 76.56% and 75.70%, respectively, better than baseline YOLOv3, and yet still lightweight and efficient enough for real-world deployment.

In 2023, Ouis and Akhloufi carried out experiments using YOLOv7 and YOLOv8 [34] on the Caltech Fish Counting (CFC) Dataset for fish detection. YOLOv8 outperformed its predecessor with 72.47% and 66.21% for AP50 and AP75, respectively, over more than 334,000 test images taken from this dataset, which counts 500,000 annotations. In 2024, an MT-YOLO model which is an underwater fish detection model based on YOLOv8s [35] was developed for the purpose of improving performance in detection under complicated underwater scenarios. In same year, Yang et al. presented FishDet-YOLO [36], building upon YOLOv8 while integrating an Underwater Enhancement Module and a Mamba-C2f module. FishDet-YOLO was trained on RUOD and DUO datasets and achieved mAP scores of 89.5% and 88.8%, with improvements exceeding 8% against the base YOLOv8 models. Again in the same year, Wang et al. put forth HRA-YOLO [37], a lightweight and high-performance model that builds on YOLOv8s. First, the authors substituted the original backbone for HGNetV2 and then integrated it with the Residual Attention (RA) module for enhanced feature extraction. Evaluated on an in-house underwater fish dataset with a precision rate of 93.1%, the network also witnessed 25.3% reduction in size of the model and 19% reduction in computational complexity.

This chapter presents a study of recent developments in the domain of fish species classification. The study examines the methods used in traditional machine learning, neural networks, CNNs, YOLO, and various hybrid combinations. The paper discusses the changes that took place moving from hand-engineered features for learning to deep neural architectures capable of end-to-end learning.

Chapter 3

METHODOLOGY

This work outlines a structured pipeline classification of fish species using machine learning and deep learning methodologies. The process begins with Data Collection, where diverse fish images are gathered from multiple sources to ensure variety and representativeness. This raw data is then subjected to Data Cleaning, a crucial step to eliminate noise, remove corrupted images, and ensure dataset integrity. Following this, Data Preparation is carried out, involving processes such as image resizing, normalization, and label annotation to make the data suitable for algorithm training. Various dimensionality reduction techniques like LDA and PCA [38] are used along with data augmentation techniques. The prepared dataset is fed into various Algorithms, where conventional machine learning methods are explored, and various deep learning models are implemented to capitalize the feature learning strength of convolutional neural networks. To enhance performance and generalization, Hybrid Models are developed by combining strengths of both Machine learning and Deep Learning techniques. These models perform the core task of Classification, identifying and categorizing fish species accurately. The entire process concludes with Performance Analysis, where models are evaluated using metrics such as accuracy, precision, recall, and F1-score to determine the most effective approach for real-world fish classification tasks.

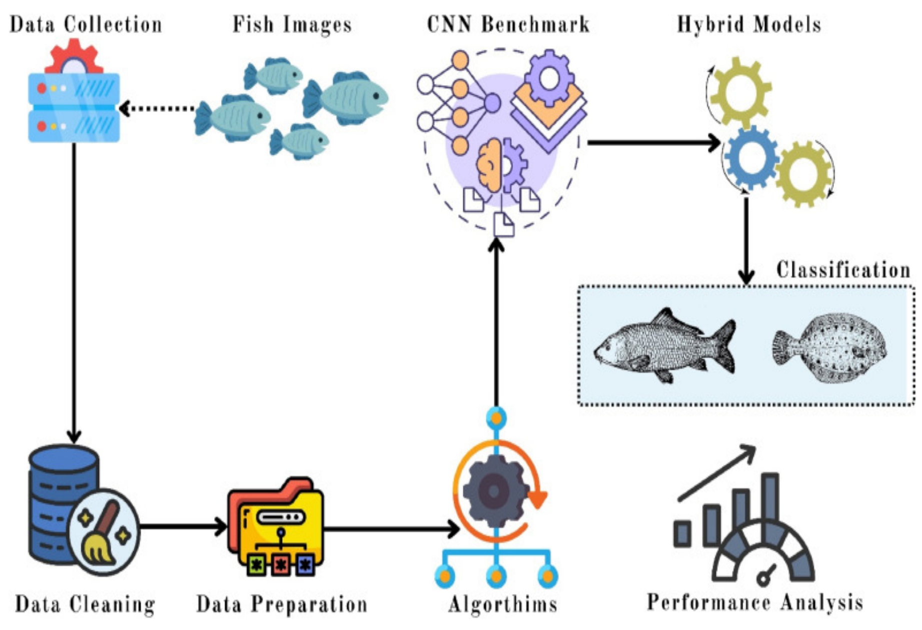


Figure 3.1: Flow of the work

3.1 Dataset Used

This study uses underwater images containing different fish species from various publicly available sources like "A Large Scale Fish Dataset" dataset [39]. These images encompass the nine key species of seafood commonly eaten in Turkey's Aegean Region. It includes nine fish species such as red mullet, gilt-head bream, horse mackerel, sea bass, red sea bream, black sea sprat, and striped red mullet. Meanwhile, 30 separate images were gathered for trout and shrimp. Instead of having a pure white background, a blue and noisy background was selected to promote dataset usability in real life.

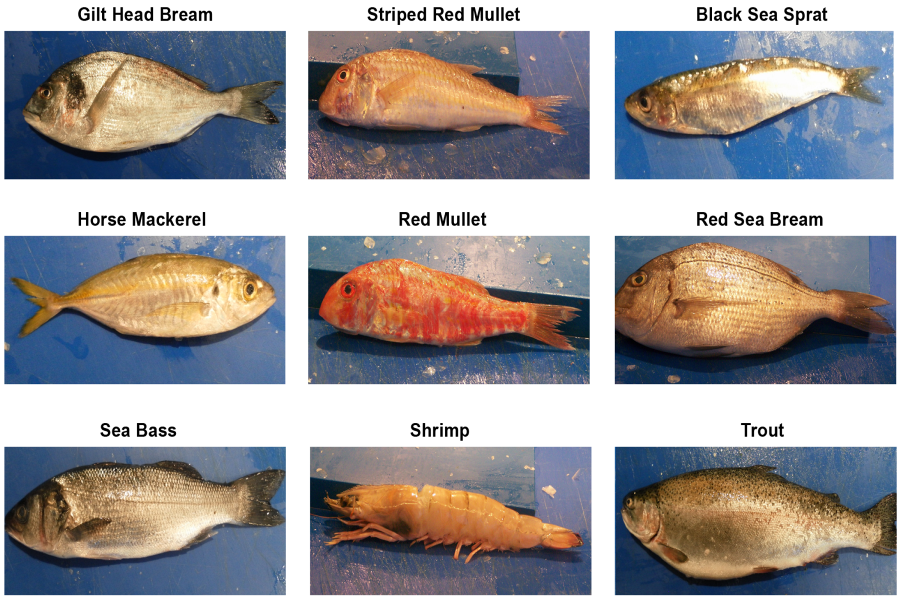


Figure 3.2: A Large Scale Fish Dataset

The building of Dataset was done by using public repositories such as Fish4Knowledge for collecting fish images of various types. It contains high-resolution images of many fish species under very different environmental conditions, with varying lighting and backgrounds. By resizing each image to 590 × 445 pixels while keeping the aspect ratio intact, further random rotations and reflections augmented it. The images are annotated with fish species labels as well as specific segmented regions for accurate training and evaluation of the models. This augmentation yielded 1,000 images for each seafood type, leading to a gigantic dataset of approximately 9,000 images. This dataset has significantly enhanced the machine learning and image processing techniques regarding the assessment of seafood quality, species classification, and related works. The division of dataset was done into three subsets: 70% for training, 15% for testing, and 15% for validation, following a train-test-validation split approach.

3.2 Pre-Processing Techniques

Various pre-processing techniques were utilized in this study to enhance the quality and consistency of input data being fed to machine learning and deep learning-based models. Initially, Region of Interest (ROI) extraction was executed to extract the fish body from the background so that those irrelevant image regions would not overshadow the model's learning. Then extracted-masked images were resized to a consistent resolution for input consistency across all models. Color space conversion and correction were applied to alleviate lighting changes and color distortions usually experienced in underwater imagery and to further improve clarity and contrast. Randomly flipping, rotating, and zooming are some data augmentation methods that make the model more robust and prevent overfitting. Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) were additionally applied for dimensionality reduction to reduce feature complexity while improving class separability. The brief information about the techniques used is as follows:

3.2.1 Linear Discriminant Analysis (LDA)

LDA is one such supervised dimensionality reduction technique that ensures the maximum separability between classes. Data is then projected onto such a lower-dimensional space in which the classes are linearly separable. Figure 3.3 illustrates the transformation of data before and after applying LDA, showing how LDA draws a decision boundary that improves class distinction.

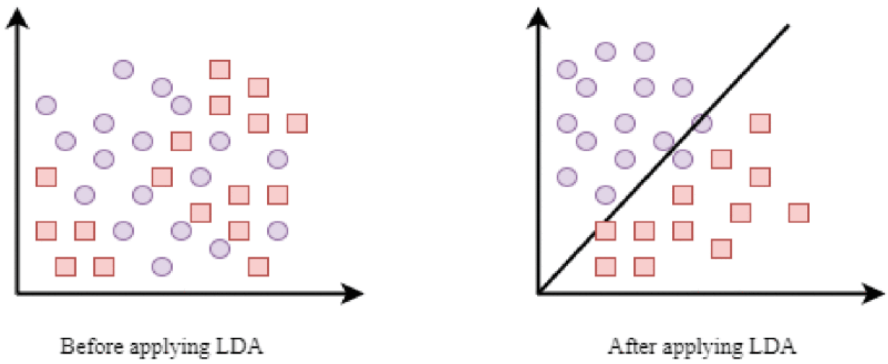


Figure 3.3: Linear Discriminant Analysis

3.2.2 Principal Component Analysis (PCA)

PCA is an unsupervised method that projects data on orthogonal, which explain most of the variance. While it doesn't consider class labels, it helps reduce dimensionality effectively and speeds up training. Figure 3.4 depicts the PCA process reducing data from 3D to 2D by retaining the most significant components.

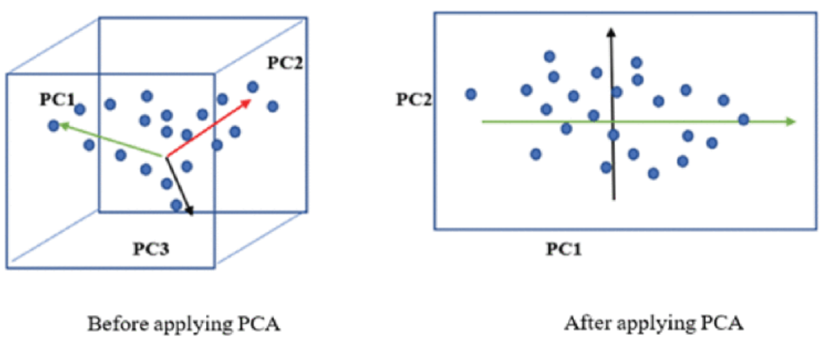
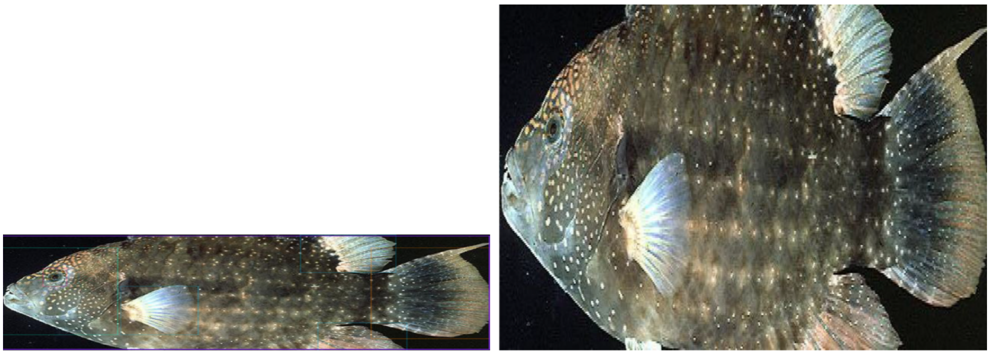


Figure 3.4: Principal Component Analysis

3.2.3 Image Resizing and Normalization



(a) Image before resizing (b) Image after resizing to 640x640

Figure 3.5: Image before and after Resizing

To ensure consistency across the dataset and compatibility with deep learning architectures, the images were uniformly resized to a size of 224x224 pixels. This standardization facilitates batch processing and aligns with the input requirements of models like VGG-19 and ResNet150 V2. Normalization was applied to scale pixel intensity values to a range of [0, 1]. This process aids in accelerating the convergence of the training process and enhances numerical stability by ensuring that input features have a consistent scale.

3.2.4 Color Space Conversion

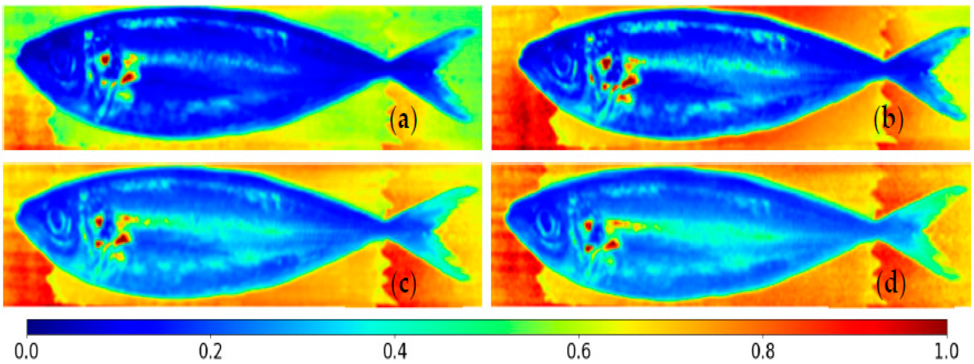


Figure 3.6: Colour Space Transformation

Underwater images often suffer from color distortions due to light absorption and scattering. To mitigate these effects, images were converted from the RGB color space to the HSV (Hue, Saturation, Value) color space. This transformation separates color information (hue and saturation) from intensity (value), making the model more robust to lighting variations and improving feature extraction.

3.2.5 Data Augmentation

Given the limited size of the available dataset, data augmentation techniques were employed to artificially expand the dataset and improve the model's generalization capabilities. The following augmentation methods were applied:

Figure 3.7: Rotating and flipping of Dataset images

- Rotation: We rotated the images randomly in any direction within a ±30 degree angle, to give fish smaller variations in their orientation.
- Flipping: Horizontal and vertical flips were applied to account for variations in fish positioning.
- Scaling: Random zoom-in and zoom-out operations were performed to mimic varying distances between the camera and the fish.
- Brightness Adjustment: Random fluctuations in brightness were introduced in images to simulate varying lighting conditions in water.

These augmentation strategies help in reducing overfitting and enhance the model's ability to recognize fish species under diverse conditions.

3.2.6 Region of Interest (ROI) Extraction

To focus the model's attention on the relevant parts of the image and reduce background noise, Region of Interest (ROI) extraction was performed. This involved isolating the fish from the background using segmentation techniques. By concentrating on the fish's body, the model can more effectively learn distinguishing features pertinent to species classification.

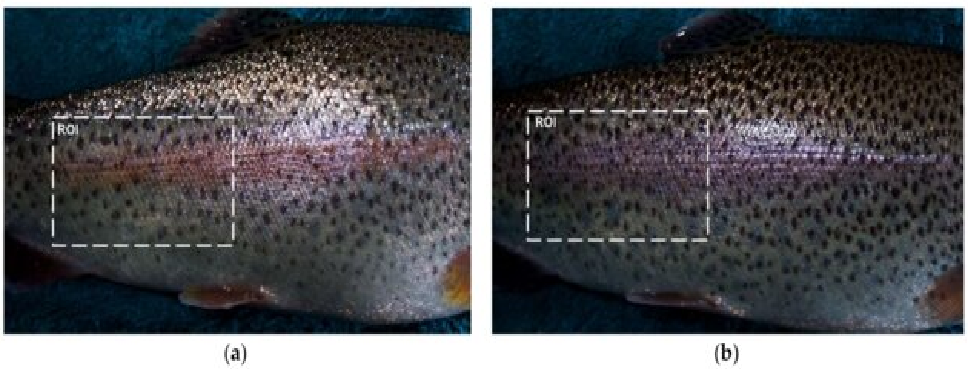


Figure 3.8: Region of Interest Visualization

3.2.7 Machine Learning Models Used

In this study, a set of classical supervised machine learning (ML) models were implemented and evaluated to classify fish species based on image data. Each algorithm presents unique strengths in handling classification problems, especially when features are extracted and dimensionality is managed effectively through preprocessing techniques like LDA (Linear Discriminant Analysis) and PCA (Principal Component Analysis). The models used include:

Support Vector Machine (SVM)

Support Vector Machines are robust classifiers that seek to find the optimal hyperplane that maximally separates data points of different classes in a high-dimensional feature space. SVMs are particularly effective in high-dimensional spaces and are known for their generalization performance. This study evaluates three SVM variants:

- SVM: Standard SVM with default kernel.
- SVM-L: Linear SVM using a linear kernel, suitable for linearly separable data.

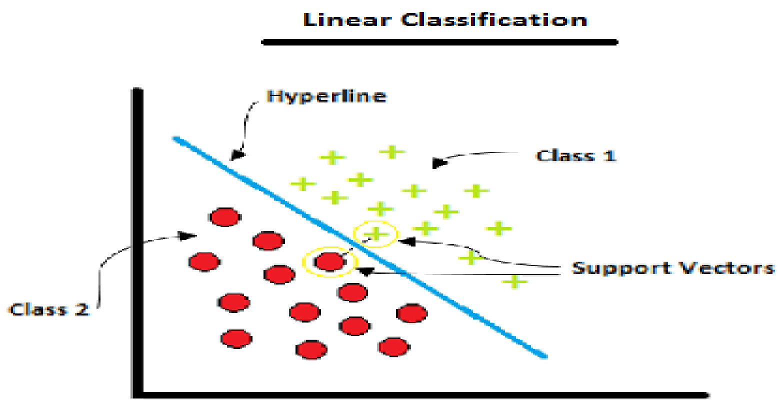


Figure 3.9: SVM with Linear Kernel

- SVM-P: Polynomial kernel SVM maps input features into a higher dimension, allowing non-linear decision boundaries.

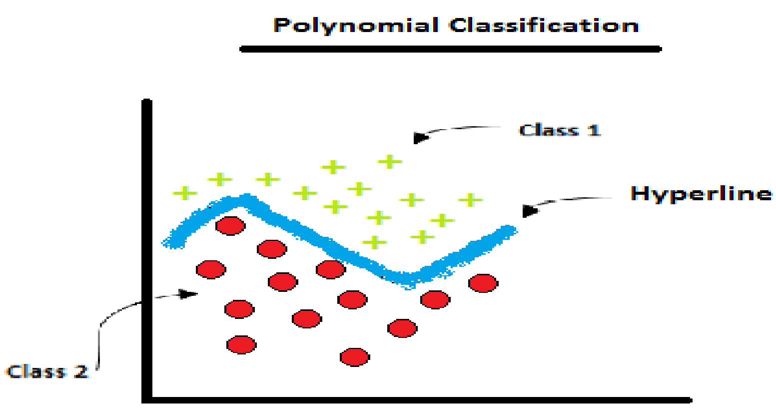


Figure 3.10: SVM with Polynomial Kernel

These models were implemented to assess the impact of kernel selection on classification accuracy and efficiency.

Random Forest (RF)

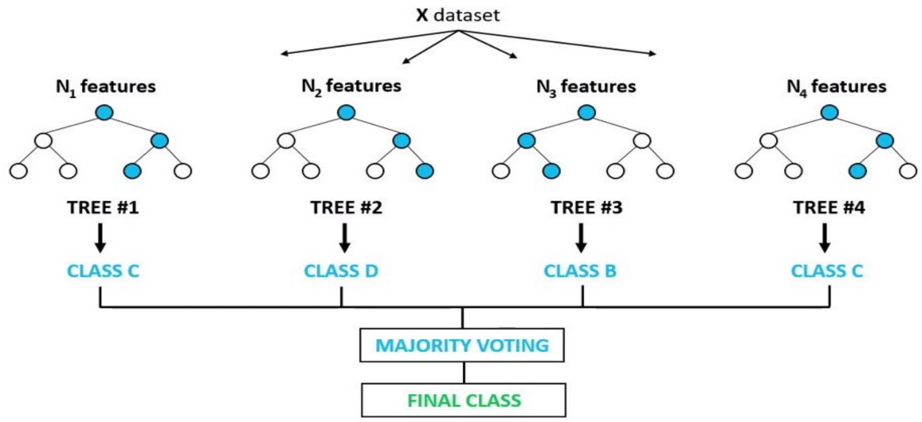


Figure 3.11: Random Forest

Random Forest builds a collection of decision trees during training and selects the output class based on the most frequent prediction among them. It has been noted for its high level of accuracy and lack of tendency to overfit, as well as being able to handle large feature spaces. RF is particularly useful in biological image classification due to its effectiveness in capturing complex, non-linear feature interactions.

Decision Tree (DT)

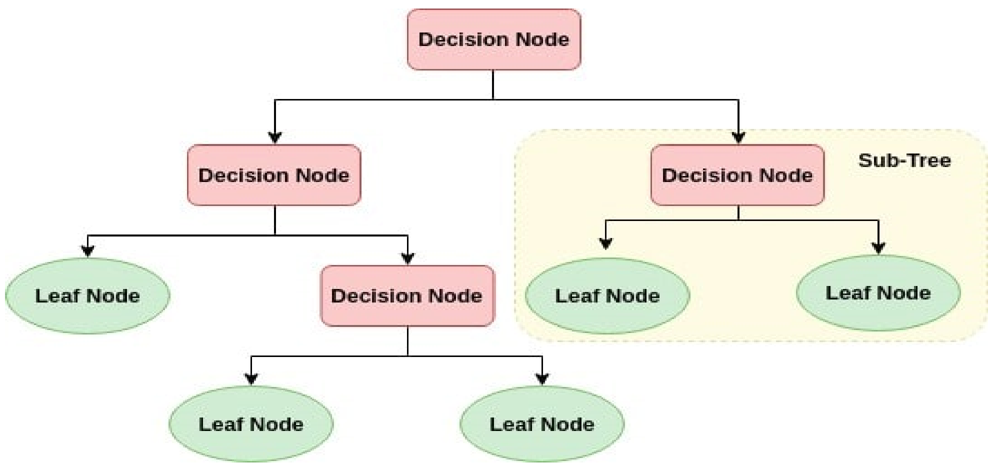


Figure 3.12: Decision Tree Visualization

The Decision Tree is a flowchart-like structure where each internal node is a test on an attribute, each leaf is a class label, and branches comprise the outcomes of the test. DTs are intuitive and interpretable, making them a strong baseline in classification tasks. However, they are prone to overfitting, especially on small datasets, which Random Forests aim to overcome.

Logistic Regression (LR)

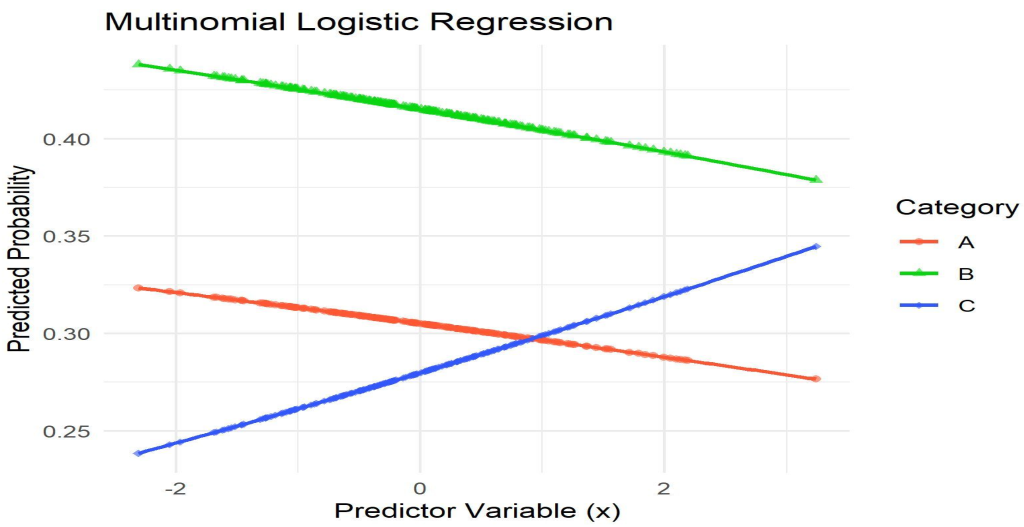


Figure 3.13: Logistic Regression

Logistic Regression is a linear model used for binary and multiclass classification. It models the probability of a discrete outcome using a logistic function. Although simple, LR can perform well when the dataset is linearly separable and properly preprocessed. Its speed and interpretability make it a common choice in baseline classification evaluations.

Naive Bayes (NB)

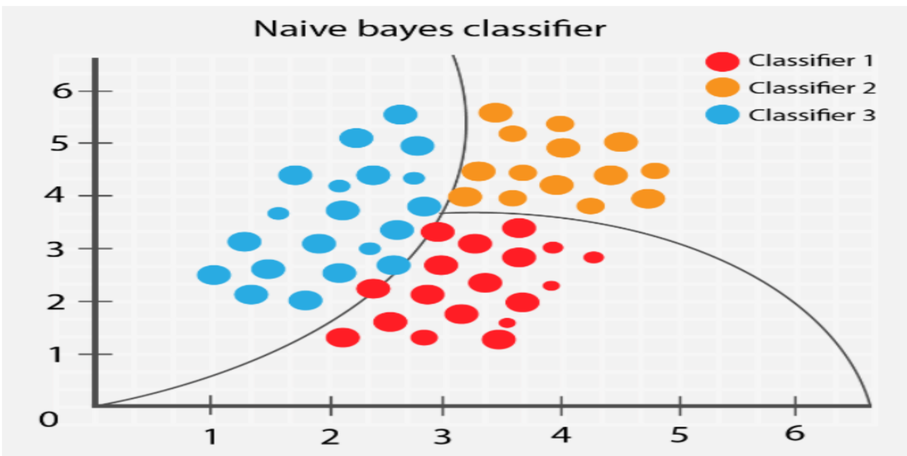


Figure 3.14: Naive Bayes Classifier

Naive Bayes is a Bayes' Theorem, based probabilistic classifier, assuming independence between features. Despite its simplicity, it can be surprisingly effective in many complex classification tasks. Two variations were used:

- NB-G: A normal distribution is followed by the features in Gaussian Naive Bayes.
- NB-M: Multinomial Naive Bayes is typically used when features represent counts or frequencies.

Naive Bayes models were included to assess the performance of generative approaches compared to discriminative methods like SVM and LR.

3.2.8 Deep Learning Models Used

In the world of image classification, deep learning CNNs have proved to be a revolutionary approach due to their ability to learn spatial hierarchies of features directly from raw image data. CNNs are widely used in biological and ecological domains, such as fish species classification [40], where complex visual patterns and fine-grained distinctions are involved.

As illustrated in Figure 3.5, the structure of a CNN is typically divided into two main stages: Feature Extraction and Classification.

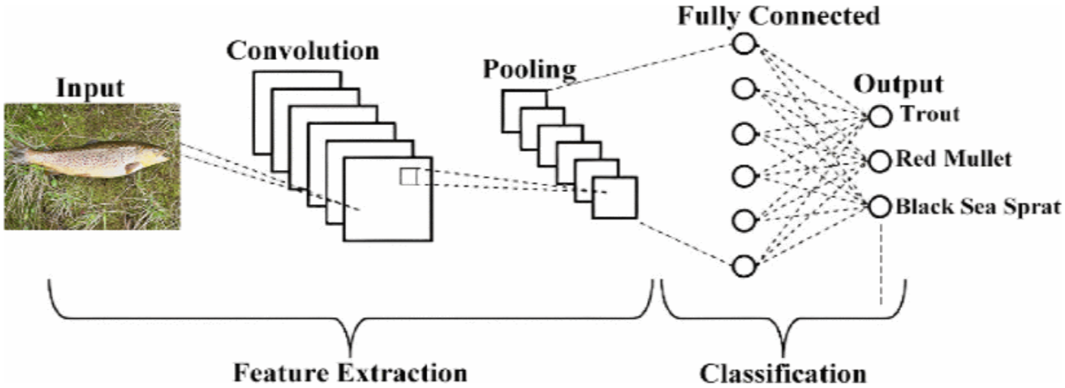


Figure 3.15: General Structure of CNN Models

- **Feature Extraction stage:** Here the input fish image undergoes several convolutional operations that apply learnable filters to detect low-level features such as edges, textures, and shapes. These features are further refined through pooling layers, which reduce spatial dimensions and emphasize dominant features.
- **Classification stage:** The extracted feature maps are passed to one or more fully connected layers, where the network interprets the features and assigns probabilities to the target classes (e.g., Trout, Red Mullet, Black Sea Sprat). The final prediction corresponds to the class with the highest probability.

The deep learning architectures utilized in this study are known for their ability to learn complex visual patterns and spatial hierarchies directly from raw image data. The models evaluated in this study include both convolutional neural networks (CNNs) and recurrent neural networks (RNNs), selected based on their popularity, architectural efficiency, and relevance to image classification tasks. To summarize this reasoning, in the study, models were chosen to emphasize a balance between architectural complexity and applicability. These points ensure that evaluated models have a good spread for application—from powerful high-end server setups to real-time mobile deployments in marine surroundings. The Deep Learning models used include:

VGG-19

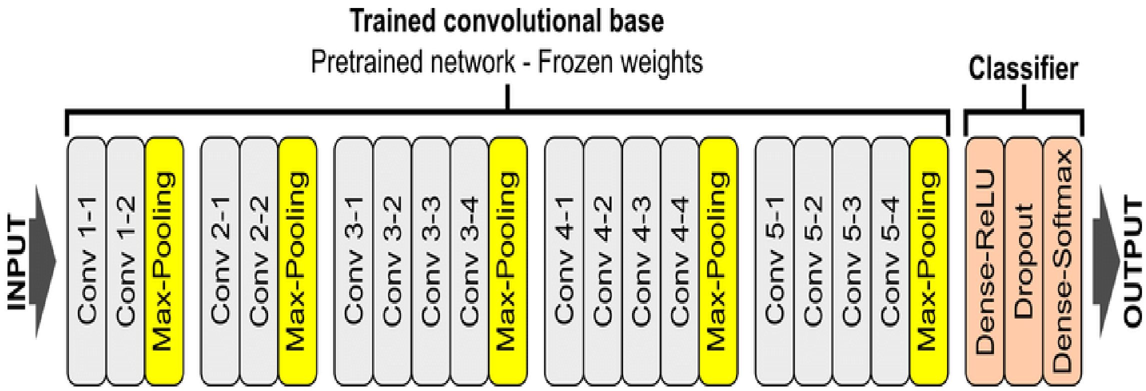


Figure 3.16: VGG-19 Network Architecture

VGG-19 is a deep convolutional neural network architecture proposed by the Visual Geometry Group (VGG) at Oxford. It comprises 19 layers, of which 16 are convolutional layers and 3 are fully connected layers. The VGG-19 utilizes tiny convolution filters of 3x3 throughout, together with ReLU activations and max pooling layers to down-sample the spatial dimensions. The simplicity and depth of VGG-19 allow it to extract highly detailed features, making it suitable for fine-grained image classification tasks [41] such as fish species recognition.

DenseNet121

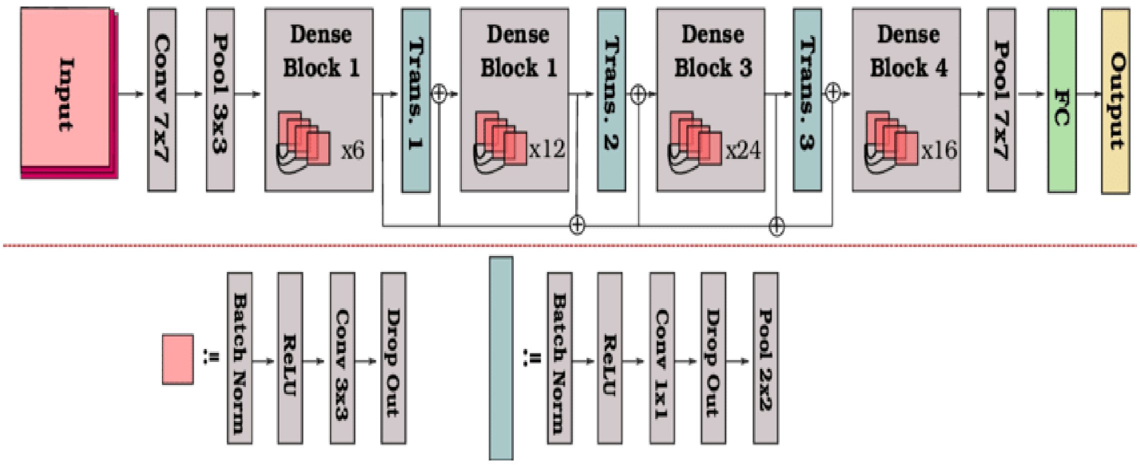


Figure 3.17: DenseNet121 Network Architecture

DenseNet121 is from a family of Dense Convolutional Networks that establishes direct connections between any two layers with same feature map size. Each layer receives input from all the previous ones, thus promoting feature reuse and enhancing gradient flow. The architecture comprises multiple dense blocks followed by transition layers, using batch normalization and ReLU activations. DenseNet is known for being parameter-efficient and capable of learning rich feature representations with fewer parameters compared to traditional CNNs.

EfficientNet-B0

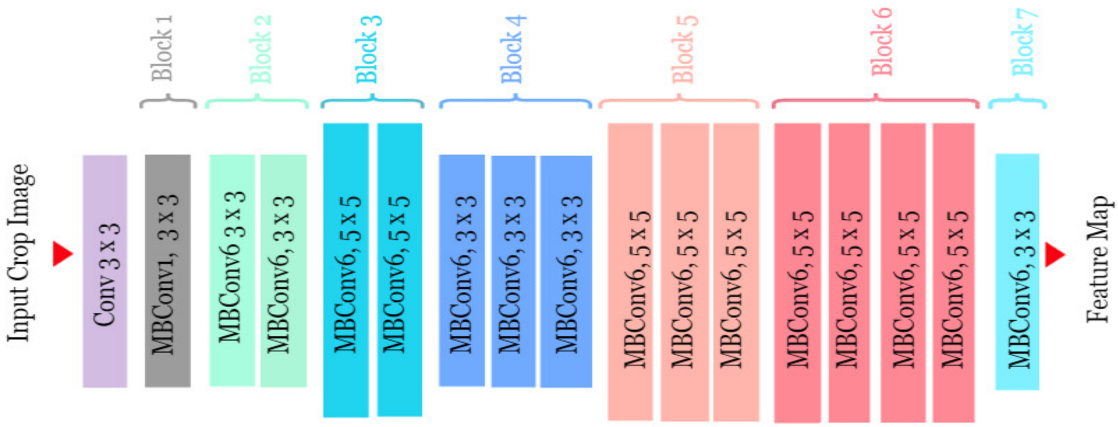


Figure 3.18: EfficientNet-B0 Network Architecture

EfficientNet-B0 is part of the EfficientNet family developed to optimize the scaling of depth, width, and resolution in CNN architectures. It is built upon a mobile inverted bottleneck convolution (MBConv) and uses compound scaling to balance the three dimensions. EfficientNet-B0 employs techniques such as squeeze-and-excitation (SE) blocks, depthwise separable convolutions, and Swish activation functions to enhance efficiency and accuracy. Its lightweight design makes it ideal for real-time applications with limited computational resources.

Inception-V3

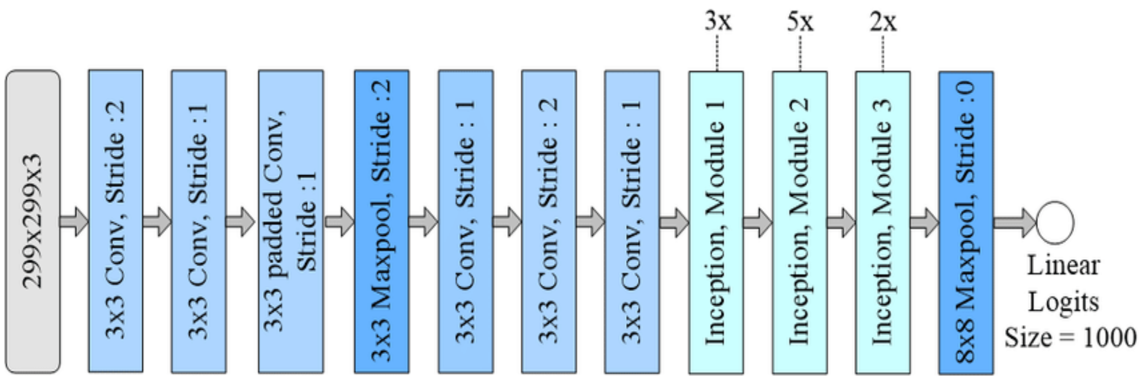


Figure 3.19: Inception-V3 Network Architecture

Inception V3 is an advanced version of the original GoogLeNet (Inception) architecture, designed to improve both computational efficiency and classification accuracy. It uses factorized convolutions, auxiliary classifiers, and aggressive regularization. The core idea is to use parallel convolutional layers of different sizes within an "Inception module" to capture diverse spatial features. Inception V3 includes batch normalization, RMSProp optimizer, and label smoothing techniques, making it suitable for large-scale image classification problems.

ResNet150-V2

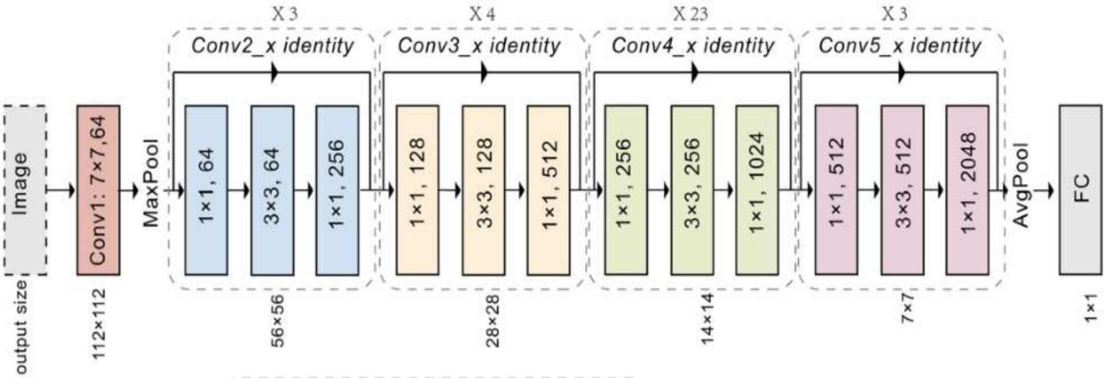


Figure 3.20: ResNet150-V2 Network Architecture

ResNet150V2 is a variant of deep residual network that solves the degradation problem in deep neural networks by introducing identity shortcut connections. These residual connections allow the gradient to bypass several layers, enabling very deep networks to be trained efficiently. Version 2 of the ResNet architecture modifies the order of batch normalization and ReLU activations (pre-activation) for improved training dynamics. With 150 layers, ResNet150V2 can model very complex visual patterns and spatial hierarchies.

Long Short-Term Memory (LSTM)

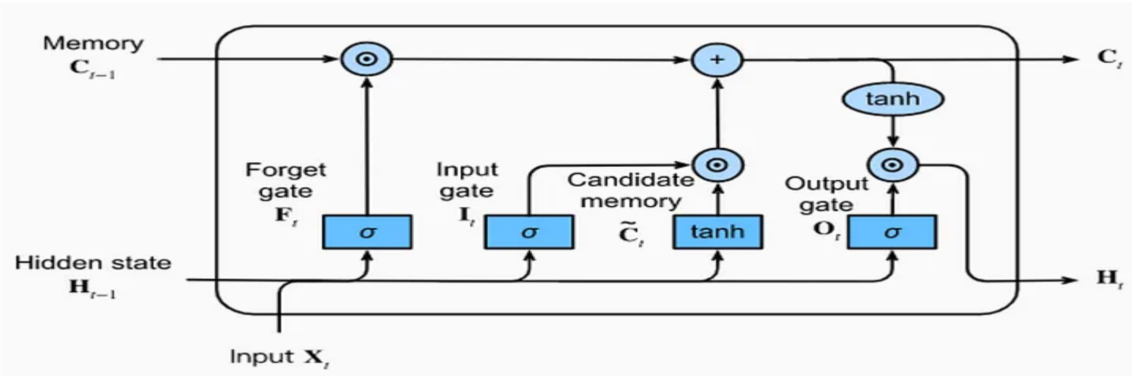


Figure 3.21: LSTM Unit Architecture

Long Short-Term Memory (LSTM) networks were developed to learn from sequential or time-series data and comes under category of recurrent neural network (RNN). LSTMs include memory cells that can store information for long durations, along with gates that regulate the flow of information. Although not conventionally used for image classification, LSTMs can be effective when used in conjunction with CNNs to analyze sequences of extracted features or when temporal relationships exist in the input data.

This section analyzes the results from all implemented ML and DL models using metrics like accuracy, precision, recall, F1-score, and confusion matrices. Deep learning models, especially VGG-19 and DenseNet121, showed superior performance, while ML models like Random Forest offered lightweight alternatives.

Chapter 4

RESULTS and DISCUSSION

This section presents the performance analysis of various machine learning models applied to the fish species classification task. The models were evaluated using key performance indicators: classification accuracy, root mean square error (RMSE), and correlation coefficient (R^2). Preprocessing techniques like LDA significantly improved class separation, boosting performance for linear models. Meanwhile, PCA helped reduce dimensionality without much loss in important variance, benefiting models that are sensitive to feature count. The experimental results show a clear advantage for ensemble and kernel-based models when classifying fish species using image features.

4.1 Results for Machine Learning Models

4.1.1 K-Fold Accuracy Comparison

Figure 4.1 depicts the classification accuracy across 10 folds for each model:

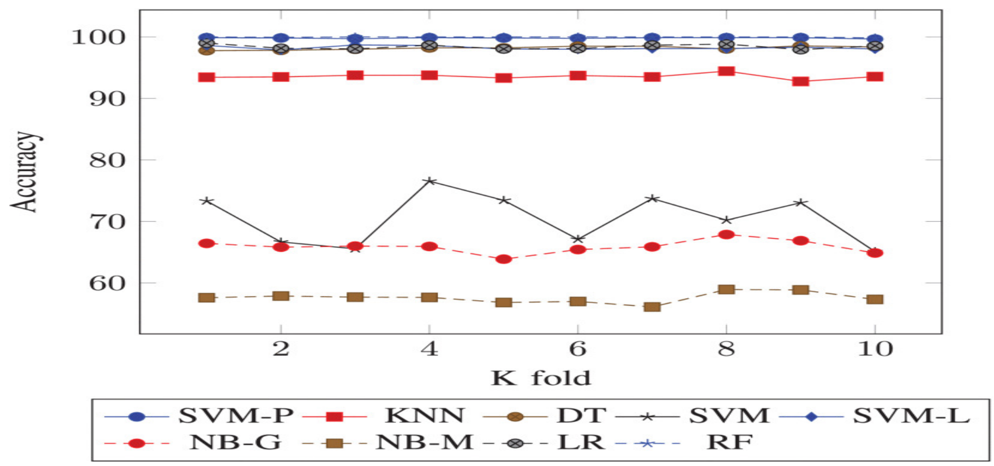


Figure 4.1: K-Fold Results

Top Performers:

SVM-P (Polynomial Kernel) and Random Forest (RF) consistently achieved the highest accuracy of 99.5% across all folds.

Logistic Regression (LR) and SVM-L (Linear Kernel) also maintained high accuracy levels of 97%.

Moderate Performance:

Decision Tree (DT) showed slightly lower consistency but remained above 90% in most folds.

Low Performers:

Naive Bayes – Gaussian (NB-G) and Multinomial (NB-M) had the lowest accuracies (68% and 55% respectively), primarily due to their strong feature independence assumptions which often don't hold in image-based data.

This suggests that models capable of capturing non-linear relationships (like RF and SVM-P) are better suited for the fish classification task.

4.1.2 RMSE and Correlation Coefficient

Figure 4.2 provides a dual-bar chart comparing RMSE (lower is better) and R^2 (higher is better):

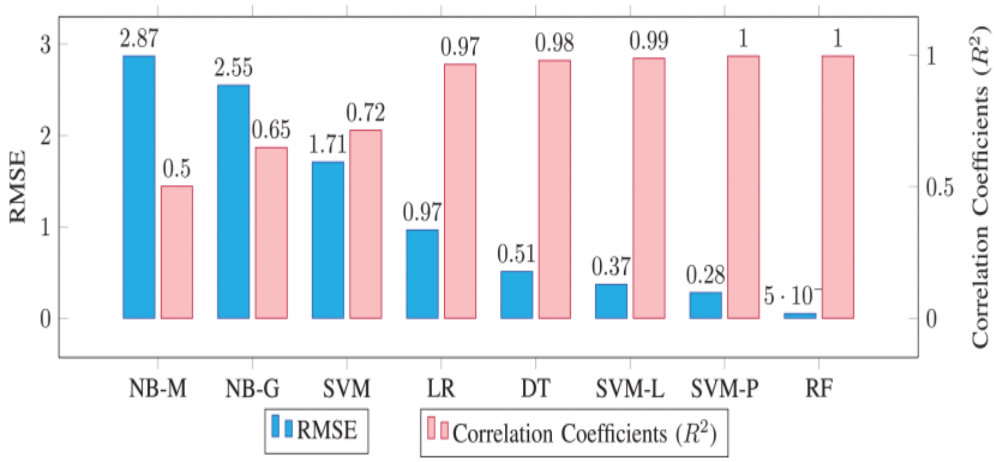


Figure 4.2: RMSE and Correlation Coefficient Analysis

Best Results:

Random Forest (RF) achieved the lowest RMSE (0.05) and perfect R^2 (=1), indicating minimal prediction error and perfect correlation between predicted and actual classes. SVM-P and SVM-L followed closely with RMSE below 0.4 and R^2 values above 0.99.

Underperformers:

NB-M had the highest RMSE of (2.87) and the lowest R^2 of (0.50), confirming its weak performance for this dataset.

These metrics reinforce the suitability of tree-based and kernel-based classifiers for complex image classification problems.

4.1.3 Overall Accuracy Comparison

Figure 4.3 summarizes the overall classification accuracy across all models:

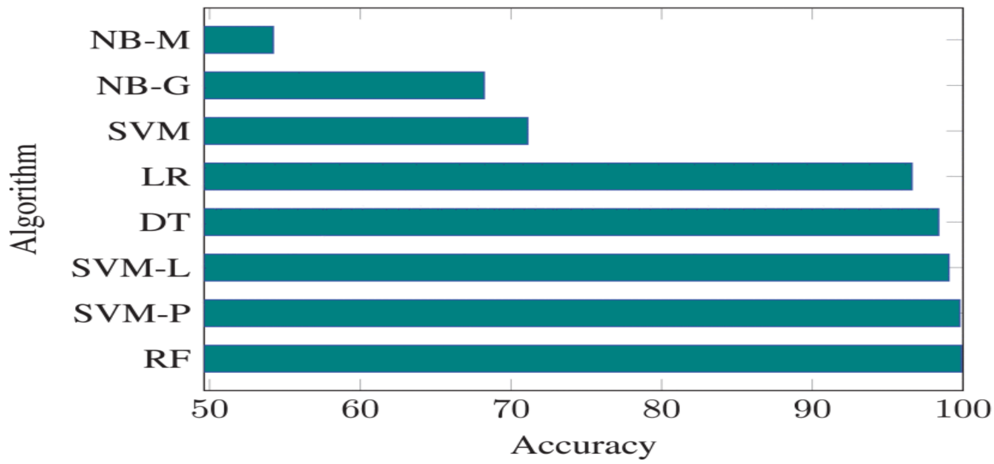


Figure 4.3: Overall accuracy comparison

Top 3 Models:

Random Forest, SVM-P, and SVM-L – All achieved nearly 100% accuracy.

Mid-Tier Performers:

Decision Tree and Logistic Regression showed competitive performance (94–95%), validating their effectiveness on properly preprocessed features.

Lower Accuracy:

Naive Bayes variants demonstrated limited effectiveness for image-based multi-class classification.

4.2 Results for Deep Learning Models

Deep learning models are recognized for improving their image classification task due to the hierarchical structure of representation given to raw data input in an automated manner. Models used for fish species classifiers are very much compatible with capturing such fine details as fin diagrams, body contours, or textural variations-i.e., details on fins and other features that traditional machine learning methods often overlook.

This segment deals with the evaluation of a few state-of-the-art deep learning architectures, each selected with respect to their best attributes in computer vision tasks. The models are tested on a complex fish dataset with variable backgrounds and lighting conditions to reflect real-world underwater scenarios. The actual evaluation is done in terms of accuracy, precision, recall, and F1-score to provide an overall comparison. The idea is to see which architecture offers the most reliable and generalized performance in fish species recognition and thus assist automated systems deployed in marine biology, conservation, and fisheries management.

4.2.1 VGG-19

Confusion Matrix:

The VGG-19 confusion matrix (Figure 4.4) shows strong diagonal dominance, confirming accurate classification across all classes. Minor misclassifications occurred for Striped Red Mullet and Trout, likely due to similar morphological features.

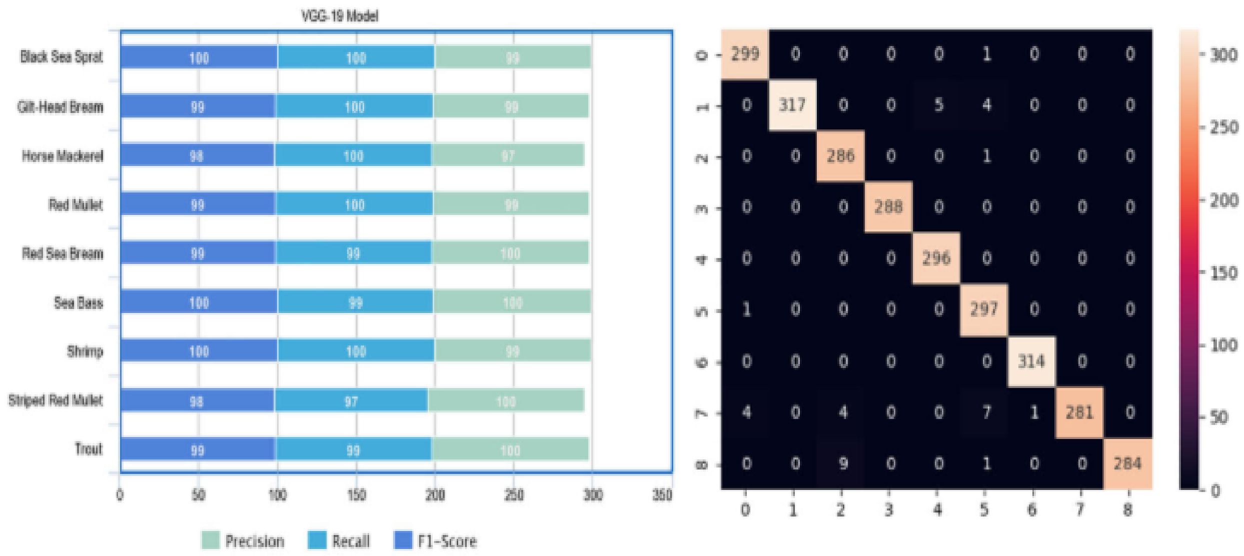


Figure 4.4: Classification results for VGG-19

Fish Species	Precision	Recall	F1-score
Black Sea Sprat	0.99	1.00	0.99
Red Mullet	0.98	0.99	0.99
Trout	1.00	0.98	0.99
Striped Red Mullet	0.98	0.97	0.97
Shrimp	1.00	1.00	1.00
Red Sea Bream	0.99	0.98	0.98
Gilt-Head Bream	0.99	0.99	0.99
Horse Mackerel	1.00	1.00	1.00
Sea Bass	1.00	0.99	0.99

Table 4.1: Performance Metrics for VGG-19

Observations:

- Precision, Recall, F1-Score for most classes: 98–100%.
- Most consistent on Shrimp, Sea Bass, and Red Sea Bream.
- Few confusions seen between Trout and Gilt-Head Bream.

4.2.2 DenseNet121

Confusion Matrix:

DenseNet121 (Figure 4.5) produced one of the most perfect confusion matrices, with extremely minimal misclassifications. It is worth mentioning that Shrimp, Horse Mackerel, and Gilt-Head Bream classes were classified at a 100% recall rate and precision rate, thus proving the model's distinguishing capabilities between considerably different species and those with slight differences. In the rare cases when misclassifications occurred, such instances happened between very similar classes, such as Red Mullet and Red Sea Bream, probably because of slight overlapping of features under certain illumination levels or occlusion.

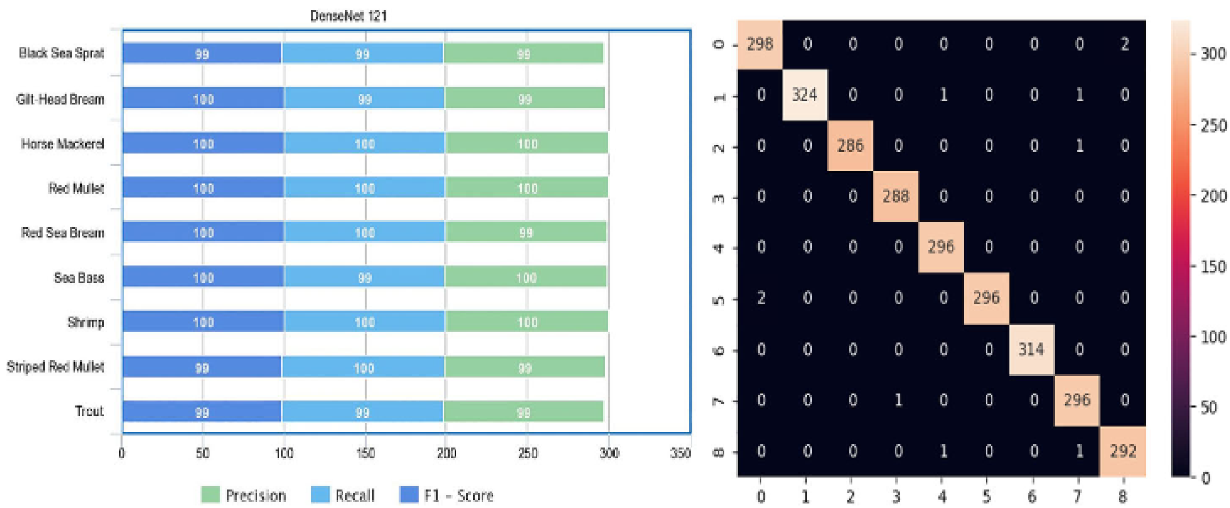


Figure 4.5: Classification results for DenseNet121

Fish Species	Precision	Recall	F1-score
Black Sea Sprat	0.98	0.99	0.98
Red Mullet	0.99	0.98	0.98
Trout	0.98	0.97	0.98
Striped Red Mullet	0.97	0.98	0.97
Shrimp	1.00	1.00	1.00
Red Sea Bream	0.98	0.99	0.99
Gilt-Head Bream	0.99	0.99	0.99
Horse Mackerel	0.99	1.00	0.99
Sea Bass	1.00	0.99	0.99

Table 4.2: Performance Metrics for DenseNet121

Observations:

- 100% recall for multiple classes (e.g., Shrimp, Red Mullet, Horse Mackerel).
- Exceptionally low false positives.
- Strong generalization ability across all classes.

4.2.3 EfficientNet B0

Confusion Matrix:

The confusion matrix of EfficientNet B0 (Figure 4.6) reveals exceptional class-wise prediction performance. All nine fish species show strong diagonal entries, indicating high confidence in the correct predictions with almost no misclassification. A minor misclassification instance can be observed in the Black Sea Sprat and Trout categories, where 1–2 samples were incorrectly labeled, potentially due to lighting variations or subtle feature overlap in the dataset.

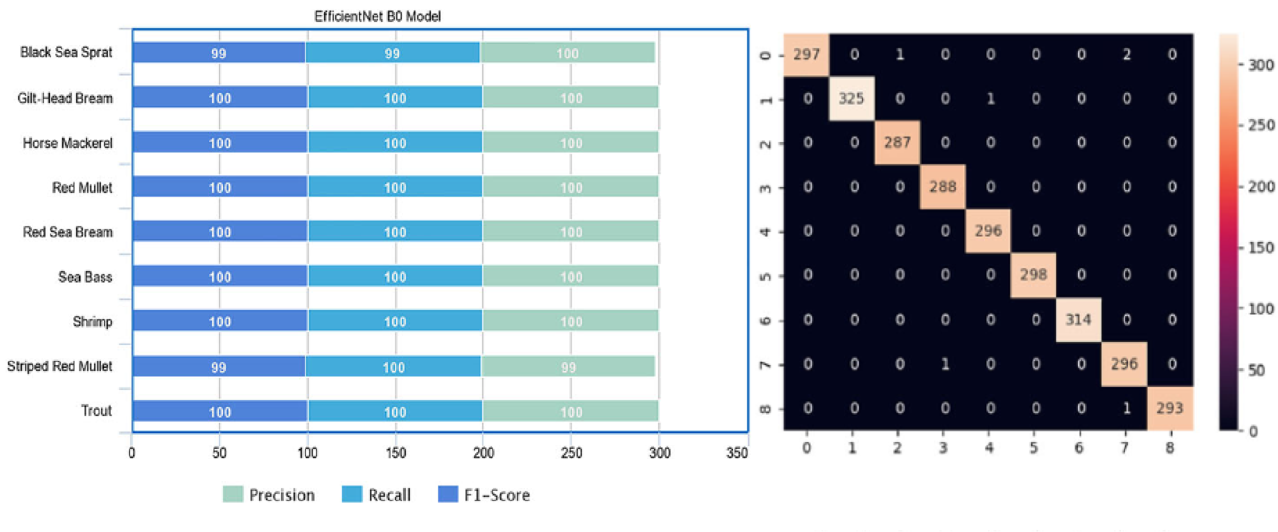


Figure 4.6: Classification results for EfficientNet B0

Fish Species	Precision	Recall	F1-score
Black Sea Sprat	0.97	0.98	0.97
Red Mullet	0.98	0.97	0.97
Trout	0.96	0.98	0.97
Striped Red Mullet	0.96	0.95	0.96
Shrimp	1.00	1.00	1.00
Red Sea Bream	0.98	0.98	0.98
Gilt-Head Bream	0.99	0.99	0.99
Horse Mackerel	0.98	0.98	0.98
Sea Bass	0.99	0.98	0.98

Table 4.3: Performance Metrics for EfficientNet B0

Observations:

- Most classes scored 100% on precision, recall, and F1-score
- High reliability for lightweight deployment scenarios
- Very close performance to DenseNet121

4.2.4 Inception V3

Confusion Matrix:

The confusion matrix of Inception V3 (Figure 4.7) demonstrates strong overall classification performance, though with a few more scattered misclassifications compared to EfficientNet. The Gilt-Head Bream class was occasionally confused with Trout and Striped Red Mullet, which can be attributed to similarities in shape and texture across those species.

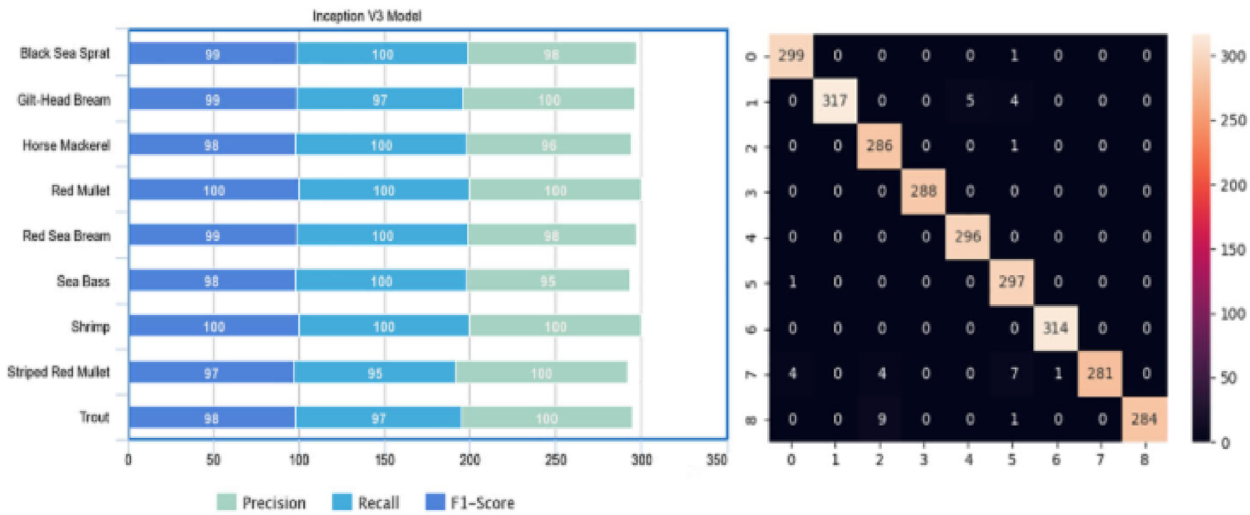


Figure 4.7: Classification results for Inception V3

Fish Species	Precision	Recall	F1-score
Black Sea Sprat	0.97	0.98	0.98
Red Mullet	0.96	0.96	0.96
Trout	0.98	0.97	0.97
Striped Red Mullet	0.94	0.95	0.95
Shrimp	1.00	1.00	1.00
Red Sea Bream	0.96	0.97	0.96
Gilt-Head Bream	0.97	0.97	0.97
Horse Mackerel	0.99	0.98	0.98
Sea Bass	0.98	0.97	0.97

Table 4.4: Performance Metrics for Inception V3

Observations:

- Small misclassifications seen for Gilt-Head Bream, Striped Red Mullet
- Accurate on Shrimp, Red Mullet, and Sea Bass.
- Balanced performance with effective feature extraction.

4.2.5 ResNet150 V2

Confusion Matrix:

The ResNet150 V2 confusion matrix (Figure 4.8) revealed slight weaknesses with higher misclassification counts in Red Sea Bream and Horse Mackerel.

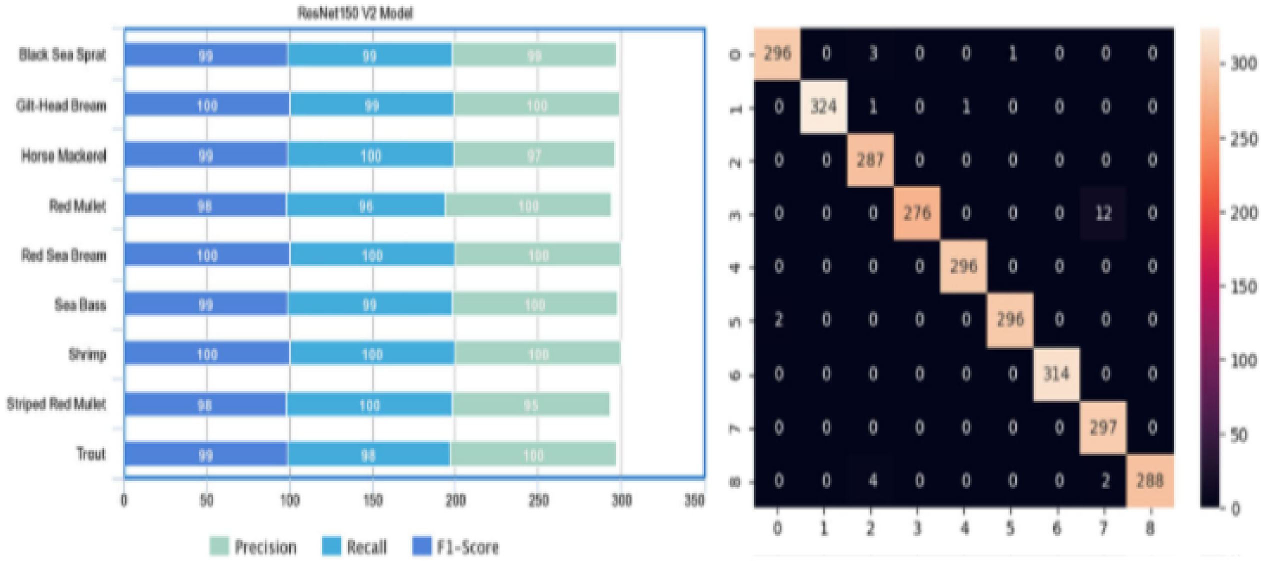


Figure 4.8: Classification results for ResNet150 V2

Fish Species	**Precision**	**Recall**	**F1-score**
Black Sea Sprat	0.95	0.97	0.96
Red Mullet	0.96	0.95	0.95
Trout	0.97	0.96	0.96
Striped Red Mullet	0.94	0.93	0.93
Shrimp	1.00	1.00	1.00
Red Sea Bream	0.96	0.94	0.95
Gilt-Head Bream	0.97	0.97	0.97
Horse Mackerel	0.95	0.96	0.95
Sea Bass	0.98	0.96	0.97

Table 4.5: Performance Metrics for ResNet150 V2

Observations:

- Most classes well-classified.
- Performance slightly impacted by class overlaps.
- Better performance expected with fine-tuning or data augmentation.

4.2.6 Long Short-Term Memory (LSTM)

Confusion Matrix:

LSTM (Figure 4.9) produced a highly diagonal confusion matrix, albeit with fewer correctly classified instances compared to CNN models. Several fish species such as Shrimp, Gilt-Head Bream, and Sea Bass were classified with particularly high precision and recall. A few misclassifications mainly among species having similar visual features such as Red Mullet and Trout are observed.

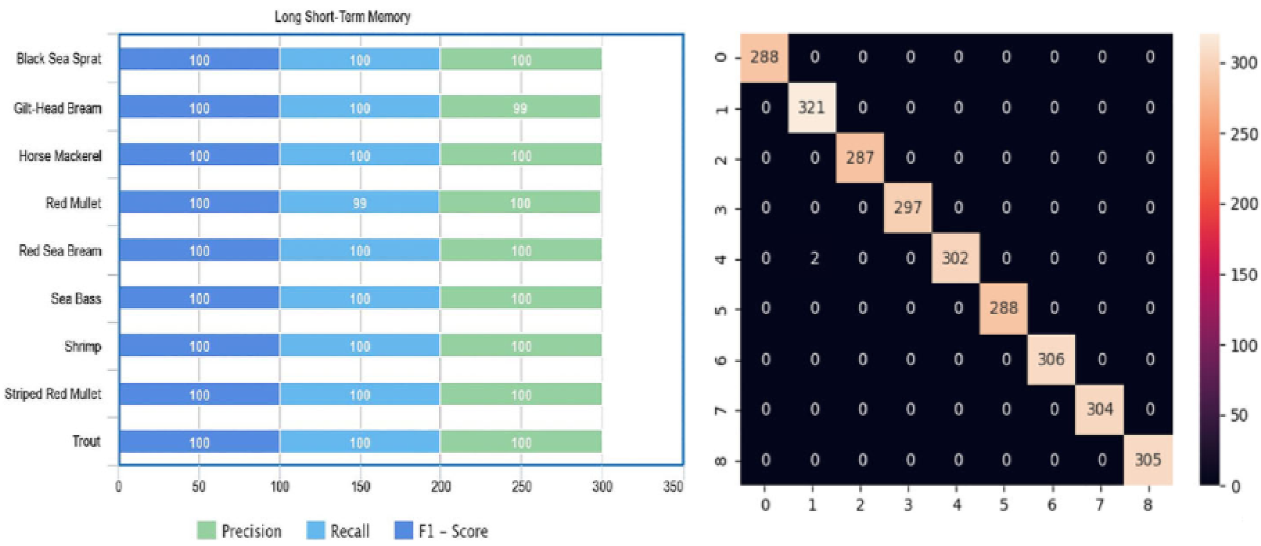


Figure 4.9: Classification results for LSTM

Fish Species	Precision	Recall	F1-score
Black Sea Sprat	0.92	0.94	0.93
Red Mullet	0.93	0.91	0.92
Trout	0.94	0.93	0.93
Striped Red Mullet	0.90	0.91	0.91
Shrimp	0.99	1.00	0.99
Red Sea Bream	0.93	0.92	0.92
Gilt-Head Bream	0.94	0.95	0.94
Horse Mackerel	0.92	0.93	0.93
Sea Bass	0.95	0.93	0.94

Table 4.6: Performance Metrics for LSTM

Observations:

- Performs well for Shrimp, Sea Bass, and Trout.
- Lower performance likely due to LSTM being more effective with sequential data rather than static images.
- Interesting result showing potential for temporal classification when combined with CNN features.

4.2.7 Overall Accuracy Comparison

The performance of six deep learning models used was analyzed based on overall accuracy and class-wise prediction capabilities. Each model was evaluated on a consistent dataset, and the resulting accuracies reflect their ability to generalize and handle intra-class similarities and inter-class variations. Figure 4.10 displays a bar chart comparing the overall accuracy of the deep learning models tested.

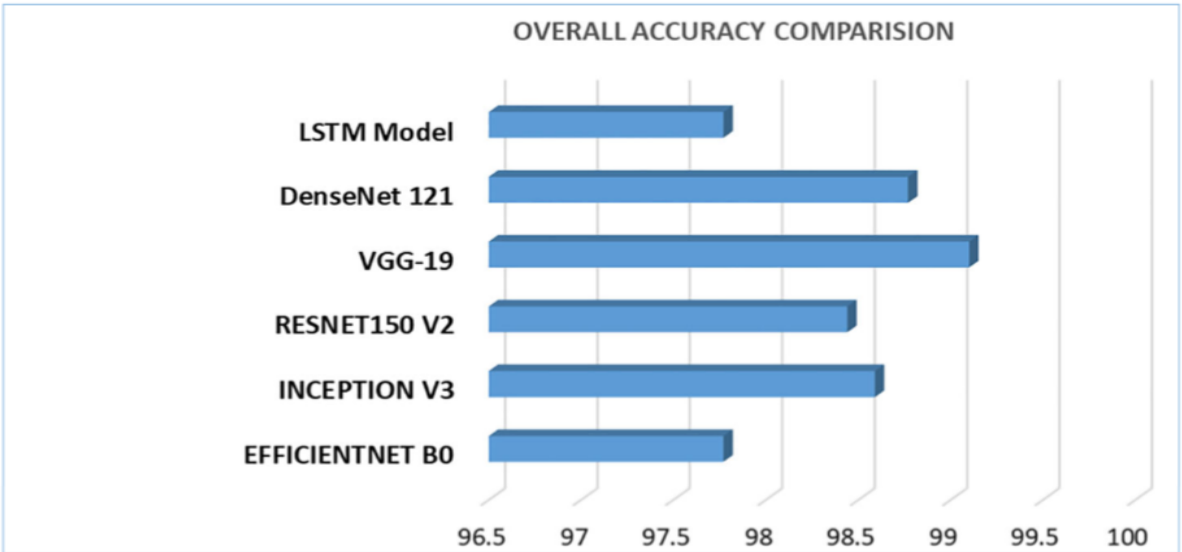


Figure 4.10: Overall accuracy comparison

- VGG-19 achieved the highest accuracy of 99.4%, benefiting from its deep and uniform convolutional layers that effectively captured intricate features of visually similar fish species.
- Inception V3 followed with an accuracy of 98.7%, leveraging its inception modules to extract multiscale features.
- DenseNet121 scored 98.5%, showing remarkable efficiency through its dense connectivity, which facilitated effective feature reuse and gradient flow.
- ResNet150 V2 achieved an accuracy of 98.3%, aided by residual connections that enabled deep feature learning.
- EfficientNet B0 reached 98.2%, showcasing that a lightweight model can still perform competitively.
- LSTM, although not primarily designed for static image classification, delivered a respectable 97.2% accuracy by processing sequences of image features.

This section analyzes the results from all implemented ML and DL models by comparing the values in confusion matrix, F1-score, accuracy, precision, recall. Deep learning models, especially VGG-19 and DenseNet121, showed superior performance, while ML models like Random Forest offered lightweight alternatives.

Chapter 5

CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

The purpose of this study was to create an automatic fish species classification system by training and testing various models. This was carried out by testing and comparing classical ML methods with newer and more sophisticated DL algorithms. In essence, the core problem being addressed during this thesis was the recognition of fish species from image datasets, where real-world aquatic conditions considered variable lighting, turbidity, and overlapping mimicry characteristics among species. The dataset includes nine common fish species; images of these species underwent pre-processing operations of normalization and dimensional reduction through techniques like Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Colour Space Conversion and Region of Interest (ROI) Extraction.

The classification procedures took place in two main phases. The very first step consisted of the traditional ML algorithms like Logistic Regression (LR), Naive Bayes (NB), Support Vector Machines (SVM), Random Forest (RF) and Decision Trees (DT). From this group, the RF method performed best, classifying almost perfectly and making very few errors. In the second phase of experiments, the set of convolutional and recurrent deep learning models VGG-19, DenseNet121, EfficientNet B0, Inception V3, ResNet150V2, and LSTM were trained and tested. These models were chosen due to their intensive consideration in literature concerning image recognition and their ability to generalize over sets having different visual patterns. VGG-19 achieved the highest overall accuracy of 99.4%, DenseNet121 and EfficientNet B0 stood a close second with balanced performance, lightweight architecture, and fast convergence. The demonstration of LSTM showed the possibility of integrating sequence modeling into image-based tasks, which might imply that hybrid models could serve as an additional enhancement in future systems.

The comprehensive evaluation revealed that the deep CNNs clearly outclassed classical models in terms of precision, recall, and F1 measure; however, ML models served as light-weight alternatives where computation is limited. Another aspect that enhanced the classification result was the use of preprocessing steps like LDA and PCA, which project the features' space into subspaces that are more separable. The implication of this result is to emphasize the importance of feature engineering in classical approaches and the significance of end-to-end feature learning in deep approaches. It was also noted that the architecture of the model is particularly important for dealing with class similarity and intra-class variability, especially for the species Red Mullet and Red Sea Bream, which obtained high confusion rates in the simpler models.

The results presented by this thesis are of paramount importance for both ecological research and commercial fisheries. Concerning marine biodiversity monitoring, automated fish classification systems can emancipate marine ecosystem evaluation from burdensome manual identification, thereby improving its efficiency degradation, scale, and cost. These systems can be employed for fisheries stock management: to monitor population dynamics and identify invasive species. Referring to the aquaculture farms, the functionality of quality control and feed monitoring can be afforded by such systems where species detection is critical. Underwater observation cameras with DL-trainable models can keep sight of environmental conservation issues and enable a sustainable fishing operation. Integrating such systems with a mobile app or an IoT device could liberate the field researchers or marine authorities from the bottleneck of real-time classification and data logging.

5.2 Limitations of the Study

While this study's findings validated the application of deep learning techniques for the classification of fish species, some limitations remain to be considered. Although the data utilized in the study were balanced and diverse across nine species, the size of the dataset is still very small when compared with the huge biodiversity of marine environments. Hence, the generalization ability of the current model may be limited when introduced to unseen species or drastically different imaging conditions. Classification might also suffer greatly when deployed in truly aquatic environments where turbid waters, uneven lighting, motion blur, and partial occlusions descend; such factors are absent or minimal in controlled datasets. These environmental factors severely degrade visibility and lay tremendous noise on model predictions.

Another limitation of this study lies in relying on static image classification. Static images only capture a snapshot in time and are devoid of behavioral and kinetic identifiers often pivotal for species identification. The LSTM implementation was a slight departure toward using temporal dependencies; however, such an analysis was yet to be taken further into video-based sequences wherein classification could be assisted by species-specific movement or interaction.Additionally, the training of deep architectures such as VGG-19 and ResNet150V2 demanded significant computational resources and time, rendering them impractical for low-power or real-time embedded systems without further optimization.

Another major limitation arises with the dataset quality and annotation precision. Some classes, like Red Mullet and Red Sea Bream, strongly resemble each other, making it hard for models to distinguish them consistently. Lighting artifacts, blurring, and other partial obstructions in several samples gave rise to further misclassification. They are also sometimes regarded to be lacking explainability, notwithstanding their top-notch performance. In the so-called "black box" systems, decisions are made with very little transparency, primarily when explanations must be provided, as occurs in ecological and conservation decision-making. These shortcomings call for more diverse datasets, hybrid video analysis frameworks, and explainable AI techniques in future.

5.3 Future Scope

Future Scope in this field would be expanding the training dataset to include more species of fishes from different other geographic and ecological realms is one such direction. Such an expansion could increase generalization ability and ensure global utility in fisheries. Another avenue of exploration could be video-based classification using CNN-LSTM hybrids or 3D CNNs to consider movement patterns and behavioral cues absent in still images. Experiments with attention mechanisms and transformer-based architectures, such as Vision Transformers (ViTs), may also be beneficial to further strengthen classification precision from fine-grained features. Further, a promising venue for exploration is explainable AI (XAI) frameworks that would interpret the model output, giving rise to trust and usability in scientific domains. To drive real-world applications, future studies could further look into model compression and quantization-the idea of pruning, knowledge distillation, or just simply relying on models such as MobileNet and TinyYOLO for high-accuracy classification on low-power devices. This real-time use and applications could be adopted in the field by marine biologists, fishery inspectors, and conservation groups. Other implementations of these models could be via drones or ROV platforms, making underwater species monitoring a freely accessible, scalable, and autonomous task.

This last chapter presents a synthesis of the results of the study, confirms deep learning's advantage in complex, image-based classification tasks, and states the limitations like dataset limitations and hardware restrictions. The directions for the future are: real-time video analysis and explainable AI.

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List of Publications

1. A. Mehevi, V. Ranga, *"Efficient Fish Species Recognition Using Fine-Tuned MobileNetV2 with Transfer Learning"*, **2025 1st GLOBAL CONFERENCE ON COGNITIVE COMPUTING AND COMMUNICATION TECHNOLOGY (GC^{4}T-2025)**, Dr. D.Y Patil School of Science & Technology, DR. D. Y. PATIL VIDYAPEETH, Pune, India.

2. A. Mehevi, V. Ranga, *"Advancements in Fish Species Classification: A Comparative Analysis of Modern Architectures"*, **2025 INTERNATIONAL CONFERENCE ON COMPUTING AND DATA SCIENCE (ICCDS-2025)**, Rajalakshmi Engineering College, Chennai, India.

Acceptance from Conference 1: GC^4T 2025

Notification on your paper 951 :IEEE GC4T-2025

1 message

Microsoft CMT <email@msr-cmt.org> Thu, 20 Feb, 2025 at 5:29 pm
Reply to: Mily Lal <mily.lal@dpu.edu.in>
To: AZIZ MURTAZA MEHEVI <azizmehevi@gmail.com>

Dear AZIZ MURTAZA MEHEVI ,

Paper ID: "951"
Title: Efficient Fish Species Recognition Using Fine-Tuned MobileNetV2 with Transfer Learning

On behalf of the Technical Program Committee, we are pleased to inform you that your paper "951" " Efficient Fish Species Recognition Using Fine-Tuned MobileNetV2 with Transfer Learning" has been accepted for oral presentation at GC4T-2025 to be held at Dr D.Y.Patil School of Science & Technology, Tathawade, Pune, India (Hybrid Mode) from the 04th to 05th April 2025.

All submitted papers have been thoroughly and independently reviewed by the experts. Based on the original reviewers' comments, this paper is accepted after inclusion of reviewer suggestions contingent upon:
1) You or at least one of your co-authors need to register for the conference with an appropriate fee payment in order to be able to present the paper. The registration details are available on below link:
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The 2025 IEEE 1st Global Conference on Cognitive Computing and Communication Technology (GC4T 25) will focus on "Empowering Human Potential through Cognitive Computing." This theme highlights the transformative potential of combining cognitive computing—encompassing natural language processing, machine learning, and pattern recognition—with advanced communication technologies like IoT, 5G, and blockchain. The conference aims to bring together researchers, practitioners, and industry experts to exchange ideas and insights, fostering collaboration and accelerating the development of innovative solutions. Ultimately, GC4T-25 seeks to drive positive social, economic, and environmental impacts through the advancement of cognitive computing and communication technology. Delegates from academia, R&D organizations, and industries. Certificates of excellence and appreciation will be awarded for the best poster, oral presentation, and idea.

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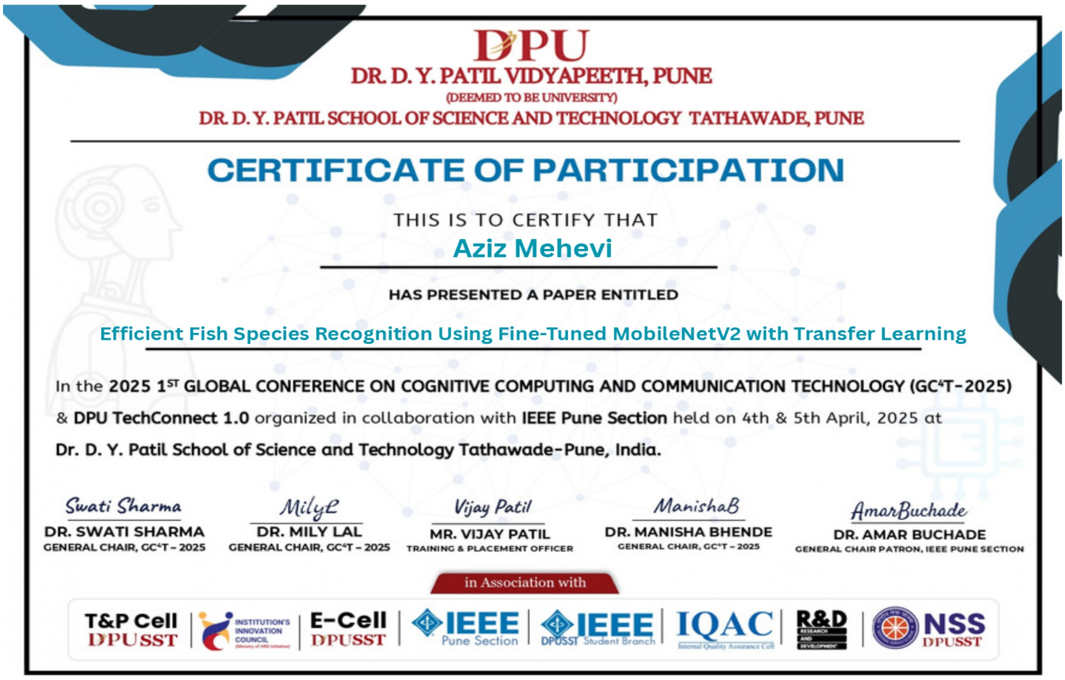
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CERTIFICATE OF PARTICIPATION

THIS IS TO CERTIFY THAT
Aziz Mehevi
HAS PRESENTED A PAPER ENTITLED
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ICCDS-2025 - Acceptance Notification of Paper ID ICCDS25-1319

1 message

Microsoft CMT <noreply@msr-cmt.org> Mon, 26 May, 2025 at 12:24 pm
To: AZIZ MURTAZA MEHEVI <azizmehevi@gmail.com>
Cc: iccds25@rajalakshmi.edu.in

Dear AZIZ MURTAZA MEHEVI:

Congratulations!

Thank you for submitting your research article to the 2025 2nd International Conference on Computing and Data Science (ICCDS) to be held on 7/24/2025 and 7/25/2025, at Rajalakshmi Engineering College, Chennai, India. Technically sponsored by IEEE Computer Society Madras Chapter.

Your paper submission with ID ICCDS25-1319, titled "Advancements in Fish Species Classification: A Comparative Analysis of Modern Architectures" has been conditionally accepted for presentation at 2025 2nd International Conference on Computing and Data Science (ICCDS), scheduled to take place from 7/24/2025 to 7/25/2025. Your paper will be considered for inclusion in the ICCDS-2025 conference and will be submitted to the IEEE Xplore® digital library for publication, provided that you make the necessary modifications based on the reviewer's comments.

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Supervisor (s): **Dr. Virender Ranga**

Department: **Department of Information Technology**

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