Classification of Ornamental Fishes in Bangladesh

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled "Classification of Ornamental Fishes in Bangladesh", submitted by **Ananna Saha Suchi** and **Md. Saif Ibne Jahid** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 15-07-2024.

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We hereby declare that, this project has been done by us under the supervision of **Professor Dr. Touhid Bhuiyan, Professor, Department of Computer Science and Engineering** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

There is a fascinating variety of decorative fish species hiding in Bangladesh's waterways, each with its own color and pattern scheme. This thesis sets out on an intensive expedition to discover the mysteries of these fascinating creatures by fusing scientific research with artistic expression. By utilizing underwater photography and digital images, we are able to fully convey the essence of every ornamental fish, revealing their intricate stories and illuminating their evolutionary wonders. We go beyond the realm of science to examine the cultural significance of these fishes, utilizing mythology and folklore to highlight their deep ties to Bangladeshi society. However, our investigation goes beyond observation. We take on the urgent problems of sustainability and conservation, looking for creative answers that strike a balance between the demands of people and the integrity of the environment. By empowering communities and practicing ecological stewardship, we set the path for a future in which ornamental fishes' vivid colours will continue to brighten our lives and protect the delicate habitats they call home. This thesis presents a complex portrayal of Bangladesh's ornamental fish community, honoring its beauty, diversity, and enduring legacy in the hearts and minds of everyone who enjoy the wonders of the aquatic world by linking creativity and science, tradition and innovation.

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CHAPTER 1

Introduction

1.1 Overview

Bangladesh’s waterways are teeming with an incredible variety of ornamental fishes, adding a splash of color and life to our tropical landscapes. These fishes, with their mesmerizing hues, intricate designs, and fascinating behaviors, have captured the imagination of hobbyists, researchers, and nature lovers alike. Despite Bangladesh’s reputation for biodiversity, there’s still much to learn about the ornamental fish species that call our rivers and ponds home. This thesis sets out to change that by taking a deep dive into the world of ornamental fishes in Bangladesh. We’re on a mission to identify and classify these fishes, understanding their shapes, sizes, and where they fit into our aquatic ecosystems. By studying them up close, we hope to uncover more about the hidden treasures lurking beneath the surface of our waters. We won’t just be relying on textbooks and lab work, though. We’ll be out in the field, exploring different habitats, and talking to local communities who have a special connection to these fishes. We want to understand how they’re viewed culturally and how they contribute to the lives and livelihoods of people across Bangladesh. But it’s not just about curiosity. There are real challenges facing these ornamental fishes, from habitat loss to overfishing. We’ll be looking at ways to protect and manage these species sustainably, ensuring they continue to thrive for generations to come. So, join us on this journey as we dive into the depths of Bangladesh's waterways, uncovering the mysteries of its ornamental fishes. Together, let’s celebrate the beauty and diversity of our aquatic heritage and work towards a future where these treasures remain a vibrant part of our natural world.

The unique contribution of this paper lies in the development of new dataset and a customized deep transfer learning framework for classifying ornamental fish species, providing an innovative solution to the challenges of traditional methods. By exploring this advanced technological approach, this paper contributes to ongoing efforts in biodiversity conservation and sustainable aquaculture practices. Delving into the intricacies of this innovative methodology, the next chapter describes the research methodology, experimental setup, results and discussion, and highlights the potential and limitations of the proposed deep transfer learning approach for ornamental fish classification. This will lead to a comprehensive understanding of the system’s capabilities and applications in enhancing species identification accuracy, ultimately supporting environmental sustainability and biodiversity preservation in Bangladesh.

1.2 Background and Present state

Bangladesh has a large number of ornamental fish species that are important to both local and international markets, contributing to the country's rich aquatic biodiversity. Bangladesh's ornamental fish market has expanded significantly over the years due to the growing demand for a wide variety of exotic species for public aquariums, home aquariums, and export markets. Numerous rivers, ponds, and wetlands are among the distinctive geographical features of the nation that offer an ideal habitat for the breeding and raising of a broad range of ornamental fish. Historically, manual techniques incorporating specialist knowledge and visual inspection have been mostly responsible for the identification and classification of ornamental fish species in Bangladesh. These conventional techniques, while somewhat successful, take a lot of time, are prone to human error, and frequently call for specific training. The growing complexity of differentiating between closely related species and the burgeoning ornamental fish business highlights the need for more precise and effective classification systems.

Technological developments in recent years, especially in the domains of machine learning and image processing, have created new opportunities for the classification of ornamental fish species. The promise for revolutionizing the identification and classification of fish species lies in automated systems that utilize deep learning models and sophisticated image processing techniques. These algorithms are capable of swiftly and reliably analyzing vast amounts of data, spotting minute variations in morphological traits, patterns, and colours that are frequently difficult to spot by manual inspection. Bangladesh continues to have a low acceptance rate for automated classification systems, despite these technological developments. The majority of fish categorization today is done using antiquated techniques, which are progressively unable to satisfy the needs of a developing sector. Several obstacles are impeding the widespread use of automated systems, including the limited availability of comprehensive, annotated datasets, inadequate training for local stakeholders, and restricted access to cutting-edge technological infrastructure. In addition to streamlining business processes within the sector, the creation and application of an automated system for Bangladesh's ornamental fish classification would support initiatives to conserve biodiversity. Such a system can monitor population dynamics, assist sustainable breeding techniques, and aid in avoiding the introduction of non-native species by offering accurate and trustworthy species identification.

1.3 Problem statement

Differentiating and categorizing ornamental angles is a surprising skill that is needed in Bangladesh's many conduits. This informational vacuum not only makes it difficult for us to understand the intricate biological systems that these angles inhabit, but it also poses a threat to their preservation and practical management. Efforts to protect species from threats such as overfishing and degradation of their living environments proved to be more problematic in the absence of a precise knowledge of which species are on display and where they are found. Furthermore, the lack of established methods for identifying and cataloguing ornamental angle species complicates preservation efforts and makes it challenging to modify management practices to meet their specific requirements. We also need to know how the neighborhood communities that are connected to these aspects contribute financially and socially to the complexity of preservation efforts. We urgently need to conduct additional research and involve the community in order to address these issues. With a deeper knowledge of the decorative angle species that are on display, their locations, and the ways in which neighboring people use them, more persuasive preservation strategies can be developed. This would not only help to ensure these amazing and socially significant aspects, but it will also ensure the health and adaptability of Bangladesh's marine biological systems for a long time to come.

1.4 Objective

The development of an automated system for the classification of ornamental fishes in Bangladesh through advanced image processing and machine learning represents a significant advancement in the field of aquaculture and biodiversity conservation. This innovative approach aims to provide accurate identification of fish species, supporting sustainable and cost-effective practices in the ornamental fish industry. By leveraging the capabilities of machine learning, the system can swiftly and accurately classify various species of ornamental fish based on their unique visual characteristics, which are often challenging to distinguish with the naked eye. With the use of state-of-the-art technology, this system provides fish breeders, enthusiasts, and conservationists with enhanced species identification precision, better breeding techniques, and biodiversity preservation. The system is dependable and effective since it employs sophisticated image processing algorithms to guarantee a high degree of accuracy in the classification process. The technology helps with effective resource management by encouraging accuracy in fish categorization, which lessens the environmental impact of fish identification techniques that rely on more conventional approaches. Aquatic ecosystems are generally healthier and more sustainable when artificial intelligence and image-processing technologies are combined. This also increases the accuracy of species identification. This system promises to bring in a new era of precision fish breeding and biodiversity protection through the integration of artificial intelligence and aquaculture, which will help both the ornamental fish market and environmental sustainability.

1.5 Scope and Limitations

The goal of the project "Classification of Ornamental Fishes in Bangladesh using Deep Transfer Learning" is to improve the use of cutting-edge AI techniques for the identification and classification of decorative fish species. The research aims to increase the precision and effectiveness of automated fish species categorization by utilizing pre-trained models including VGG-19, MobileNet-V2, ResNet-50, Xception and Inception-V3. Robust model training is facilitated by the carefully preprocessed and enhanced dataset, which is gathered from multiple sources, including field observations and web resources. For a thorough model evaluation using measures like accuracy, precision, recall, F1-score, and specificity, the dataset is divided into training, validation, and testing sets. This strategy aims to create a scalable and dependable classification system that can be used in Bangladesh's decorative fish market, supporting research on biodiversity, conservation initiatives, and the ornamental fish trade.

The study has significant shortcomings despite its thorough methodology. First off, despite the size of the dataset, it might not include all species of fish found in Bangladesh, which could restrict how broadly applicable the results can be. Moreover, differences in the dataset's image quality and resolution may have an impact on the model's performance and result in inconsistent classification accuracy. The reliance on transfer learning is another drawback; although it provides computational efficiency, it might not adequately represent the distinctive characteristics of particular fish species when contrasted with models created from scratch using specialized datasets. Furthermore, the model's applicability in real-world scenarios may not be fully reflected by the sole focus on classification accuracy. These restrictions might be overcome in the future by using higher-quality and more varied datasets, investigating different performance measures, and creating models especially designed for the categorization of ornamental fish.

1.6 Report Organization

The Proposed report has a thorough format that walks readers through the methodology, conclusions, and ramifications of the study. Every chapter has a distinct function and adds to the document's overall coherence and depth.

Chapter 1: Introduction

The introductory chapter sets the stage for the research, providing a background on the significance of fish species classification, the application of deep learning models, and the need for a comparative analysis of identification and segmentation approaches. It outlines the research questions, objectives, and the overall framework of the study.

Chapter 2: Background

In the background, a detailed exploration of relevant literature and prior research is presented. This section offers an in-depth understanding of the theoretical foundations, methodologies, and technological advancements related to fish species classification, and deep CNNs. It establishes the context for the current study and highlights gaps in existing knowledge.

Chapter 3: Research Methodology

The research methodology is described in the research methodology chapter. It provides an understanding of the model architecture, data gathering techniques, study design, and the justification for selecting a particular methodology. The chapter also covers any restrictions that might affect the study as well as ethical issues.

Chapter 4: Experimental Result

The experimental results from the use of deep learning for fish species classification are presented in this chapter. Visual representations and statistical measurements to validate the results are included, along with an in-depth analysis of the performance of various deep-learning models and image-processing approaches. The chapter sheds light on the potential uses of the suggested method in fish species identification by providing insights into its efficacy and accuracy.

Chapter 5: Impact on Society

The societal impact chapter delves into the far-reaching consequences of the research outcomes in the fields of aquaculture and environmental conservation. It examines how enhanced ornamental fish classification techniques can significantly benefit various stakeholders, including hobbyists, aquarists, conservationists, and commercial breeders. By elucidating the potential advancements in technology and their implications for the broader community, this chapter sheds light on the transformative potential of accurate fish species recognition in promoting sustainable aquatic ecosystems, supporting biodiversity conservation efforts, and fostering responsible aquaculture practices. Moreover, it underscores the role of technological innovation in empowering individuals and organizations to make informed decisions regarding ornamental fish management, thereby contributing to the overall welfare of aquatic life and the communities reliant upon it.

Chapter 6: Summary, Conclusion, Recommendation, and Implications for Future Research

This final chapter serves as a synthesis of the entire report. It summarizes the key findings, reiterates the conclusions drawn from the research, and offers recommendations forpractical applications and further studies. The implications for future research This structured layout ensure a logical flow of information, guiding the reader through the research journey from the introduction to the broader implications and recommendations. It allows for a comprehensive understanding of the research process and its potential impact on both the academic and practical aspects of fish species identification with deep learning.

1.7 Summary

The classification of ornamental fish in Bangladesh using cutting-edge image processing and machine learning approaches is the main topic of this study. The goal of the project is to create an automated system that uses deep learning models like VGG19, Inception-V3, ResNet-50, MobileNet-V2, and Xception to reliably identify and classify fish species. The study emphasizes how important precise fish classification is to maintaining biodiversity and implementing sustainable aquaculture methods. High-quality photos are gathered and annotated, and several deep learning models are trained to assess the models’ performance. The experimental design, findings, and advantages and disadvantages of the suggested strategy are all covered in the paper. In the end, this research aims to support environmental sustainability, improve species identification accuracy, and encourage biodiversity preservation in Bangladesh’s ornamental fish business.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

The literature review explores a wide range of research projects targeted at improving fish recognition algorithms with state-of-the-art deep learning and transfer learning approaches. These works cover a wide range of methodologies, from customized alterations of YOLOv3 models and CNN-based tactics to hybrid models combining YOLO deep neural networks. Importantly, obtaining data from actual environments such as fish farms and underwater settings is essential to building strong models. Furthermore, combining data augmentation, noise reduction, and dropout algorithms turns out to be one of the most important ways to improve model performance and counter overfitting. Pretrained CNNs are further optimized by utilizing transfer learning, which shows promise even in situations with a deficiency of training data. Taken as a whole, these investigations push the boundaries of fish recognition technology forward, providing priceless information that will help study, conservation efforts, and the identification of fish species of aesthetic value.

2.2 Related Works

A. Jalal et al [1], they developed a method to improve the accuracy of fish recognition and classification while addressing the difficulties of uncontrolled underwater recordings. They have used two datasets where the first dataset is taken from LifeCLEF 2015 fish task1 and the second dataset collect from Fish4Knowledge. They propose a hybrid model with YOLO deep neural network a unified approach to detect and classify fish. They achieve fish detection F-scores of 95.47% and 91.2%, while fish species classification accuracies of 91.64% and 79.8% on both datasets respectively. K. Cai et al [2], developed “A modified YOLOv3 model for fish detection based on MobileNetv1 as backbone”. They employed the k-means algorithm in addition to proposing YOLOv3 and MobileNet. A total of 2000 photos were gathered from actual fish farms, of which 1400 were used for training, 300 for validation, and 300 for testing. According to the paper, it has been shown that the recommended method is accurate in classifying fish species. S. Cui et al [3] proposed a CNN-based fish detection method and the dropout algorithm was selected to solve the overfitting problem. Using a digital camera, they gathered datasets from the Gulf of Mexico. The results showed how the proposed paradigm for different types of underwear could work and be promising. S. Villon et al [4], developed “A Deep learning method for accurate and fast identification of coral reef fishes in underwater images". Here, they present a method for identifying several fish species from underwater images, and they evaluate the model's performance in terms of speed and accuracy relative to human ability. Here, CNN models were suggested. They gathered information from the Mayotte island, covering barrier and bordering reefs, at depths ranging from 1 to 25 meters. The dataset they created includes 1197 photos of fish, which correspond to nine different species. A correct recognition rate of 94.9% was achieved. Allken, V. et al. [5], In order to automatically classify species discovered in images captured by the Deep Vision trawl camera system, they develop a deep learning neural network and apply it. Three CNN models based on convolutional neural networks are proposed here. The photos are a portion of the FRGT collection and were gathered from underwater movies. Their dataset comprises 22437 photos, of which 16800 were used to train the models and 5637 to test them. When training on a dataset with 15,000 photos based on 70 cropped images, the best accuracy of 94.1% was obtained on the test dataset. S. Pudaruth et al [6] proposed an inventive smartphone application has been created to identify fish species that are frequently found in Mauritius's lagoons, coastal areas, estuaries and outer reef zones. Many techniques, including as kNN, support vector machines, neural networks, decision trees, and random forests, were used to find which classifier performed the best. They collected images from open fish markets across the island, supermarkets, and the Central Fish Market in Port Louis. In total, they collected 1520 images, 40 of which were taken for each of the 38 fish species that were the subject of the study. A thresholding procedure was performed to eliminate the fish from each grayscale image in this collection, and Gaussian blur was applied to minimize noise. They discovered that the TensorFlow framework yielded an accuracy of 98% while the kNN algorithm gave an accuracy of 96%. V. KAYA et al [7], proposed a new model was developed in the classification process and the proposed model was compared with the ResNet50, ResNet101 and VGG16 models accepted in the literature to prove the success and accuracy of the model. The sVoNet8 model was suggested in this work. A total of 8000 fish photos were collected from Kaggle, of which 6400 were used for training, 800 for testing, and 800 for validation. Model training yielded success accuracy of 91.37% in the ResNet50 model, 86.12% in the ResNet101 model, 97.75% in the VGG16 model, and 98.62% in the proposed IsVoNet8 model, according to the validation data group. The proposed IsVoNet8 model has proven to have good success accuracy when compared to other models. In comparison to previous models, it has been noted that the suggested IsVoNet8 model has attained a high success accuracy. V. Huse et al [8], understanding the categorization of fish and non-fish image samples from the collection of intricate fish datasets is the aim of this effort. The k-mean approach was also employed in Artificial Intelligence techniques such as Principal Component Analysis, Self-Organizing Maps, and Local Binary Patterns. The dataset, which includes 500 fish photos from various families and species, was gathered from Fishbase and Fish4knowlage Ground-Truth databases since they offered a variety of fish families. This paper addresses many methods for improving the acquisition and preparation of fish images, such as local binary patterns (LBP) for image identification, principal component analysis (PCA) for dimension reduction, and Canny edge detection. In this investigation, an overall accuracy of 97% was achieved. Y. Xue et al [9], works on "Fish species recognition using an improved AlexNet model". This work aims to use new methods to enhance the fish recognition algorithm based on AlexNet. First, a soft attention mechanism based on things is added to improve accuracy. Second, the proposed model has a lower structural complexity with only four convolutional layers, one item-based soft attention layer, and two fully linked layers. Training becomes more effective in shorter amounts of time when transfer learning is used. Relation-based transfer learning, feature-based transfer learning, parameter-based transfer learning, and instance-based transfer learning are the four different forms of transfer learning. The QUT fish dataset and the LifeClef2019 fish dataset are the two datasets used in this study; 80% of each are used as training sets and the remaining 20% are used as test sets. While the latter contains 3960 fish images with a variety of backgrounds, the former contains 19717 fish images that are divided into 16 different types of fish. The three kinds of images in the QUT fish dataset are "captured," "natural environment," and "cropped." Where 0.1 and 0.01 were the corresponding learning rates selected. Both the FAN model and the AlexNet model obtained above 84% accuracy since 6000 iterative trainings were completed. The FAN model nevertheless produced accuracy values of 98.28% and 96.78% in these fish species. The article aims to utilize multiple item detection in real-time for underwater fish species recognition in murky seas and complex backdrop environments in future work. P. Mirunalini et al [10], propose a transfer learning technique using a pre-trained model that uses underwater fish images as input and applies a transfer learning technique to detect the fish species using a pre-trained Google Inception-v3 model. They have suggested three distinct approaches to categorizing the fish species in this research. With the Fish4knowledge (F4K) dataset, they tested their suggested approach and achieved an accuracy of 95.37%. The collection consists of 27370 images of fish taken from 5824 video clips. Of the total amount of photographs, training and test photos make up 16430 and 10940, respectively. The provided photographs were used to create 23 different classes. They obtained an accuracy of 95.37% for the test set, with a training accuracy of 97.9%. M. A. Iqbal et al [11], here a deep convolutional neural network-based automated method for fish species identification is presented. The proposed model is a simplified version of AlexNet, with four convolutional layers and two fully linked layers. A comparison between the two other deep learning models, AlexNet and VGGNet, considers factors such as the number of layers, batch size, dropout layer, and iterations needed to reach 100% training accuracy. The study makes use of the QUT fish dataset, and it includes 3960 photos taken in various settings. The findings demonstrate that, despite having fewer layers, the updated AlexNet performs better than the original model with a testing accuracy of 90.48% on an untrained fish dataset. The testing accuracy of the original model was 86.65%. Islam, S. M. M. et al. [12], A fish recognition system built on the combination of local and global features is presented in this research. This work uses five machine learning models for species prediction, LBP, SURF, and SIFT for local features, and CCV for global features. The 'QUT_fish_data' dataset is used for dataset collection, and 4,405 fish photos representing 465 fish species are used in the tests. The system consists of preprocessing, feature extraction, and training five machine learning models for classification. 256 photos distributed over 21 classes provide a promising 98.46% accuracy. Khalifa, N. E. M. et al. [13], This study presents a system for categorizing 191 subspecies and eight family fish species that are kept in aquariums. The system is built using two convolutional and two completely linked deep convolutional neural networks (CNNs) in four layers. Comparative findings with AlexNet and VggNet are shown based on parameters such as the number of layers, epochs for 100% accuracy, validation accuracy, and testing accuracy. With an untrained benchmark dataset, the proposed system achieves 85.59% testing accuracy, which is slightly higher than AlexNet's 85.41%. The 3,960 real-world fish photos from the QUT Robotics fish dataset are used in the study. The images in the dataset are classified as follows: "in situ" images show fish underwater in their natural habitat with no background or illumination control; "controlled" images show different fish specimens against a constant background with controlled illumination; and "out-of-the-water" images show fish specimens photographed outside with variable backgrounds and controlled illumination. J. A. Jose et al [14], proposes an automated system classifying Tuna species using image-based classification for enhanced accuracy. This work used ensemble approaches to predict outcomes using combined VGG16, VGG19, MobileNet, Xception, and region-based CNN-G2DLBP models. Images from the harbors of Vizhinjam, Cochin, and Thengapattanam along the Arabian Sea coast were collected for analysis by the paper. The dataset consists of 612 images: Images of 205 Bigeye, 200 Skipjack, and 207 Yellowfin tuna together with the Workflow: Stretching the contrast improves the edges, splits the image into the head, abdomen, and tail; the dataset is balanced and enlarged. In an independent test, the suggested system obtains 93.91% accuracy, whereas the super learning ensemble with random forest achieves 97.32% accuracy. H. ISMAIL et al [15], the article compares fish image classification benchmarks using various convolutional neural network (CNN) architectures for evaluation. In order to classify fish images, the work uses CNN architectures with different depths and assesses AlexNet, GoogLeNet, and ResNet-50. The QUT Fish dataset, the FishNet dataset, and the Dataset were gathered for this project via the Google search engine. 18,000 fish photos were categorized; of those, 5,400 were used for validation and 12,600 for training. Experiment: A total of 29,275 augmented images were produced by augmenting 736 images with 36 rotations (10º steps). Impressive accuracy is achieved by neural network models: 99.85% for AlexNet, 96.39% for GoogleNet, and 99.51% for ResNet-50. S. Ragab et al. [16]: A novel smartphone app that helps users find Mediterranean Sea fish species that are sold at nearby markets. The proposed work presents information through a mobile application and uses CNN based on AlexNet for fish identification. 128 fish species and 56 families were identified; 2670 images were captured using different smartphones while keeping the same resolution and preprocessing method: Images were separated into head, body, and tail segments, resized to 224 x 224 pixels, noise eliminated, and the dataset was normalized. In evaluation, the suggested model shows 80% accuracy, 0.788 precision, and 0.631 recall. A machine vision-based application for picture recognition and classification is introduced in work [17], which focuses on intelligent feeding in conventional ornamental fishkeeping. With the use of transfer learning, the study improved the classification accuracy of a Convolutional Neural Network (CNN) model for ornamental fish, resulting in an astounding 98.1% recognition accuracy. Three rare species of ornamental fish are represented by 3500 photos each, which are collected for TensorFlow model training. Low brightness and blur are addressed via a two-step preprocessing method that yields training and test data sets. With 120,000 iterations, the CNN model shows a promising 98.5% identification accuracy for ornamental fish recognition, with 99.57% accuracy on the training set and 96.67% accuracy on the test set. The study [18] uses an improved version of the YOLO detection method called YOLOv4-tiny on aquatic animals, with a particular emphasis on fish species including guppy, dwarf gourami, and zebrafish. Reliability is demonstrated by implementation on a Raspberry Pi 4 Model B with an 8MP camera. In addition to local photos, training uses a variety of datasets from sources such as FishBase, Kaggle, and the Global Biodiversity Information Facility. Each sample is subjected to 48 pictures during live testing on three different fish species as well as the unrelated petticoat tetra. The model's dependability is evaluated using a confusion matrix, which yields results such as a 91.67% global accuracy and a 97.81% mean average precision throughout training. With an average precision and accuracy of over 90% in all classes, the programme often achieves success.

2.3 Comparative Analysis and Summary

Existing works illustrate Numerous strategies have been used, such as ensemble methods, deep learning neural networks, CNN-based algorithms, customized YOLOv3, transfer learning strategies, and smartphone applications. The amount and source of datasets vary, with hundreds to tens of thousands of fish photos gathered from various sources such as open markets, fish farms, and underwater settings. A variety of techniques have also been used, including CNN designs like MobileNet, ResNet, AlexNet, and VGGNet, as well as k-means clustering, dropout, kNN, support vector machines, decision trees, and random forests. There are differences between studies in performance criteria such as accuracy, precision, recall, and speed. There are techniques that achieve great accuracy even in real-time or in murky underwater situations, with accuracy rates ranging from 80% to almost 100%. Overall, existing works demonstrate a diverse range of methodologies, datasets, and performance outcomes in the field of fish species classification, providing valuable insights for our research on ornamental fishes in Bangladesh.

TABLE 2.3.1: Comparative Analysis Table

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	A. Jalal et al [1]	A hybrid model with YOLO deep neural network	95%
2.	K. Cai et al [2]	YOLOv3 and MobileNet.	97%
3.	S. Cui et al [3]	CNN-based fish detection method and the dropout algorithm.	N/A
4.	S. Villon et al [4]	CNN	94.9%.
5.	V. Allken et al [5]	CNN	94.1%.
6.	S. Pudaruth et al [6]	kNN, Support Vector Machines, neural networks, decision trees and random forest	kNN algorithm is 96% TensorFlow framework produced an

			accuracy of 98%.
7.	V. KAYA et al [7]	IsVoNet8	N/A
8.	V. Huse et al [8]	Local Binary Patterns, Self-Organizing Maps, k-mean.	97%
9.	Y. Xue et al [9]	AlexNet	95%
10.	P. Mirunalini et al [10]	Google Inception-v3	97%

2.4 Open Issues

The scope of the problem addressed in this research, focusing on "Classification of Ornamental Fishes in Bangladesh," extends to the domain of aquaculture and biodiversity conservation, particularly within the context of ornamental fish species management. Ornamental fishes play a significant role in the socio-economic landscape of Bangladesh, contributing to trade, recreation, and cultural practices. However, accurate classification of these species poses a challenge due to the diverse array of species and morphological variations present. Furthermore, the research delves into the application of advanced techniques, including image processing and machine learning, to enhance the capabilities of ornamental fish classification. Traditional methods of fish classification may exhibit limitations in terms of accuracy and efficiency, especially when dealing with a large variety of species. The integration of these advanced techniques, such as transfer learning and deep Convolutional Neural Networks (CNNs), offers a promising avenue for improving the accuracy and speed of identification processes. The problem's scope also encompasses the comparative analysis of different classification approaches, including visual recognition and pattern analysis. Understanding the distinct visual characteristics and features of ornamental fish species is crucial for accurate classification and the research aims to explore the strengths and limitations of various classification methodologies. Moreover, the research aims to contribute to the conservation and sustainable management of ornamental fish species in Bangladesh. By enhancing our understanding of the diversity and distribution of ornamental fish species, the research can inform conservation efforts and support the development of policies and practices aimed at preserving these valuable aquatic resources. In essence, the scope of the problem encompasses the challenges inherent in ornamental fish classification in Bangladesh, the potential advancements offered by advanced techniques, and the comparative evaluation of different classification approaches. Through these endeavors, the research aims to contribute to the enhancement of ornamental fish management practices and the conservation of aquatic biodiversity in Bangladesh.

2.5 Summary

These studies contribute to the progress of fish recognition technologies for research and conservation by demonstrating the efficiency of deep learning and transfer learning techniques in reliably recognizing and categorizing fish species from diverse underwater image datasets. Here, a variety of deep learning-based model types are employed to achieve high accuracy in fish detection and categorization. A hybrid model that achieves good accuracy on datasets from LifeCLEF 2015 and Fish4Knowledge by merging YOLO deep neural networks for fish detection and classification. A YOLOv3 model that has been improved and uses MobileNetv1 as its foundation shows precise fish identification in real-world photos of fish farms. CNN-based technique for detecting fish, which uses data gathered from the Gulf of Mexico to mitigate overfitting using dropout algorithms and produce encouraging results. Data preprocessing techniques like augmentation, normalization, and noise reduction have proved crucial for improving CNN's performance. Through transfer learning, pretrained CNNs are optimized to produce better results with less training data. Deep learning applied to ornamental fish species literature could improve ornamental fish species classification and broaden our understanding of the subject.

CHAPTER 3

Research Methodology

3.1 Overview

The project's goal is to develop a potent deep learning model for species identification of ornamental fish. Data preparation and augmentation come first, followed by the accuracy-training of specialized models. The requirement analysis emphasizes the necessity of having deep learning knowledge and access to high-quality datasets. Clear objectives, resource allocation, and risk management are all guarantees of effective project management. By weighing costs and advantages, financial analysis guarantees the viability of projects. All things considered, these procedures are necessary to create a model that successfully and reliably recognizes species of ornamental fish.

The research "Classification of Ornamental Fishes in Bangladesh," delves into the application of advanced techniques in the field of aquaculture and biodiversity conservation, specifically targeting the accurate recognition of ornamental fish species. Ornamental fishes, integral to Bangladesh's socio-economic fabric, serve as the centric point for this investigation. The research explores the challenges associated with traditional methods of fish classification, aiming to address these limitations through the utilization of innovative approaches. Advanced image processing and deep learning techniques are employed to enhance the classification process. The research leverages transfer learning, a frontier concept in artificial intelligence, to adapt knowledge from unrelated tasks and apply it to the intricate domain of ornamental fish recognition. Deep Convolutional Neural Networks (CNNs), renowned for their proficiency in pattern recognition, are utilized to extract nuanced visual features from fish images, facilitating more accurate species classification. The comparative analysis aspect of the research investigates the divergences and synergies between different classification methodologies. This involves scrutinizing various visual recognition and pattern analysis approaches to discern their respective strengths and limitations. By elucidating these methodologies, the research aims to provide insights that inform the development of more effective and efficient tools for ornamental fish classification. In short, the research subject revolves around the convergence of advanced technologies, aquatic biology, and conservation efforts, with a specific focus on advancing the classification of ornamental fishes in Bangladesh. The outcomes of this research try aspire to enrich both the academic discourse and practical applications within the realm of aquaculture and biodiversity conservation, potentially leading to more sustainable management practices and enhanced preservation of aquatic ecosystems in Bangladesh. The experiments for this study were carried out on Google CoLab. For dealing with machine learning techniques on Python, TensorFlow, one of the best deep learning libraries, was employed. Each model was created by Google and made accessible through the Google Collaboratory framework after being trained in the cloud using a Tesla graphics processing unit (GPU). In this study, the fish species identification architectures used where the models are original VGG19, ResNet50, Inceptionv3, Xception and MobileNetv2. One architecture was chosen from each category.

3.2 Proposed Methodology

The flowchart provides a thorough blueprint for building a potent deep learning model intended to recognize species of ornamental fish. To improve the training process, it begins with meticulously cleaning, sizing, and augmenting the data. After that, it trains various deep learning models, each with a special architecture fit for the job at hand. To make sure these algorithms can correctly identify ornamental fish species, they go through a thorough review process. After being trained, the model may be used to accurately identify the species of fish in fresh photos, providing a dependable method for identifying different fish species. The methodical technique combined with cutting edge technology solves the difficult problem of accurately and efficiently identifying ornamental fish. This section ensures a comprehensive approach to the classification of ornamental fishes in Bangladesh, combining fieldwork, laboratory analysis, and data integration for accurate and useful outcomes.

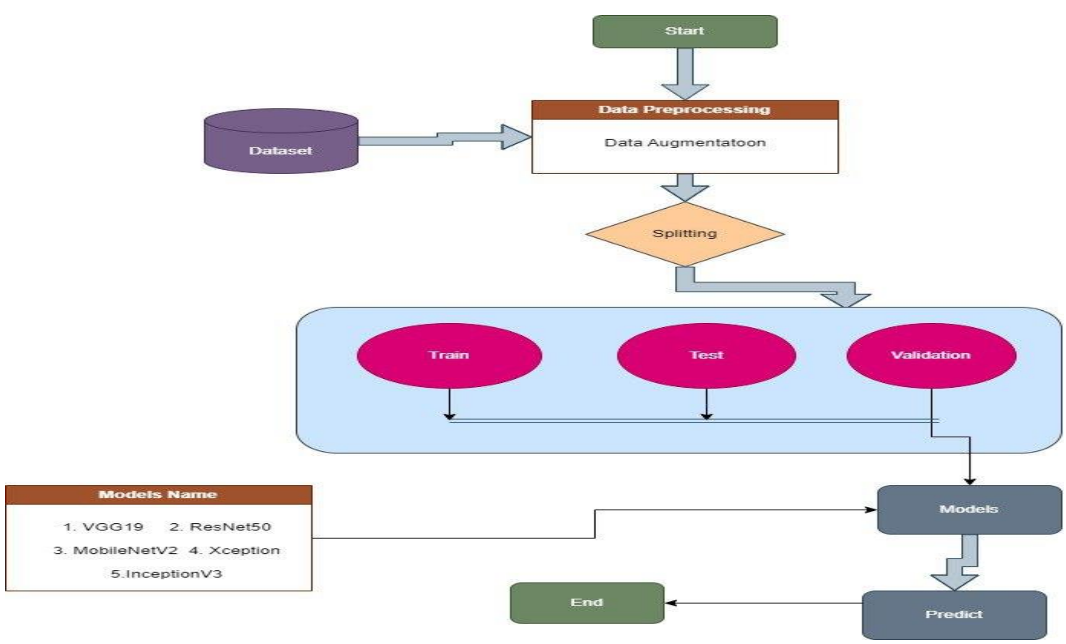


Figure 3.2.1: Working Flow

3.2.1 Datasets

A big part of this thesis paper is the dataset. The final result of our thesis will depend on this dataset. So, we want to collect raw data for this thesis. For this data collection we have to go to different types of ornamental fish shops. Go there and take videos and pictures of the fish. We can extract images from the video. Also, we can collect pictures of various ornamental fish from various Facebook pages or websites. We collect data of 19 classes of ornamental fish. Through these pictures we can show our expected output and the accuracy is likely to be better.

Figure 3.2.2: Some Raw Images of Dataset

TABLE 3.2.1: Images Used in the Train, Test and Validation Sets.

	Train	Test	Validation
Raw Dataset	553	158	79
Augment Data	2752	786	393

3.2.2 Process of Experiments

The first stage of this work is to collect data from the various fish shops. As deep neural networks need more data for training and improved performance,data augmentation technologies are sometimes utilized to overcome the problem of limiteddata. This is a rundown of how the experiment was designed to go:

Image Acquisition:

The Ornamental Fish Image Database provided data for model evaluation. This step required using pictures from particular websites. The dataset photos were carefully examined to make sure they had white backgrounds in order to assure consistency. For precise identification and analysis, the decorative fish were displayed in colours on white backgrounds in each image.

Image Augmentation:

Image enhancement is used in this stage. Picture augmentation adds fresh data to an existing dataset while preserving its label data. A bigger data set improves model generalization, creation it more lenient to unknown inputs.
Data augmentation helped us reach training data objectives. Brightness, scaling, flipping and revolution were utilized to improve color and position. Data augmentation included random spins from -15 to 15 degrees, inadvertent 90-degree rotations, distortion, bending, vertical and horizontal reversals, skate, and luminous intensity conversion. Each original picture was improved 6 times. Asubset of transformations improves a heterogeneous picture.

Figure 3.2.3: Augmented Image

3.3 Hardware / Software Requirements

The implementation of the research on "Classification of Ornamental Fishes in Bangladesh" entails specific requirements to ensure the successful execution of the Study. These implementation requirements encompass both hardware and software components, as well as considerations related to data collection and model evaluation.

Hardware Requirements:

- **High-performance computing resources:** Access to computational infrastructure with sufficient processing power and memory to handle the complex tasks involved in deep learning and image analysis.
- **Graphics Processing Unit (GPU):** A GPU is essential for accelerating the trainingof deep Convolutional Neural Networks (CNNs), significantly reducing the time required for model development.

Software Requirements:

- **Deep learning frameworks:** Utilization of popular deep learning frameworks such as ResNet50, VGG19 for the development, training and evaluation of the CNN models.
- **Python programming language:** Python provides a flexible and popular environment for data analysis and deep learning algorithm implementation.
- **Image processing libraries:** Integration of image processing libraries like OpenCV for pre-processing and augmenting fish images.

3.4 Project Management and Financial Analysis

3.4.1 Project Management

- **Project Objectives:**

A. Developed an innovative mobile application through which ornamental fish species can be classified.

B. Implement a user-friendly interface for ornamental fish businessmen and consumers to know the species of ornamental fish.

C. Simplify operations with a mobile application that makes profitable ornamental fish identification and care advice simple.

D. Ensure scalability and reliability of the mobile app for widespread adoption to identify ornamental fishes' species.

- **Project Timeline:**

A. Phase 1: Project Planning and Research (2-4 weeks)

B. Phase 2: Mobile Development and Testing (5-7 weeks)

C. Phase 3: Mobile App Design and Prototyping (1 week)

D. Phase 4: Front-End Development (Ongoing)

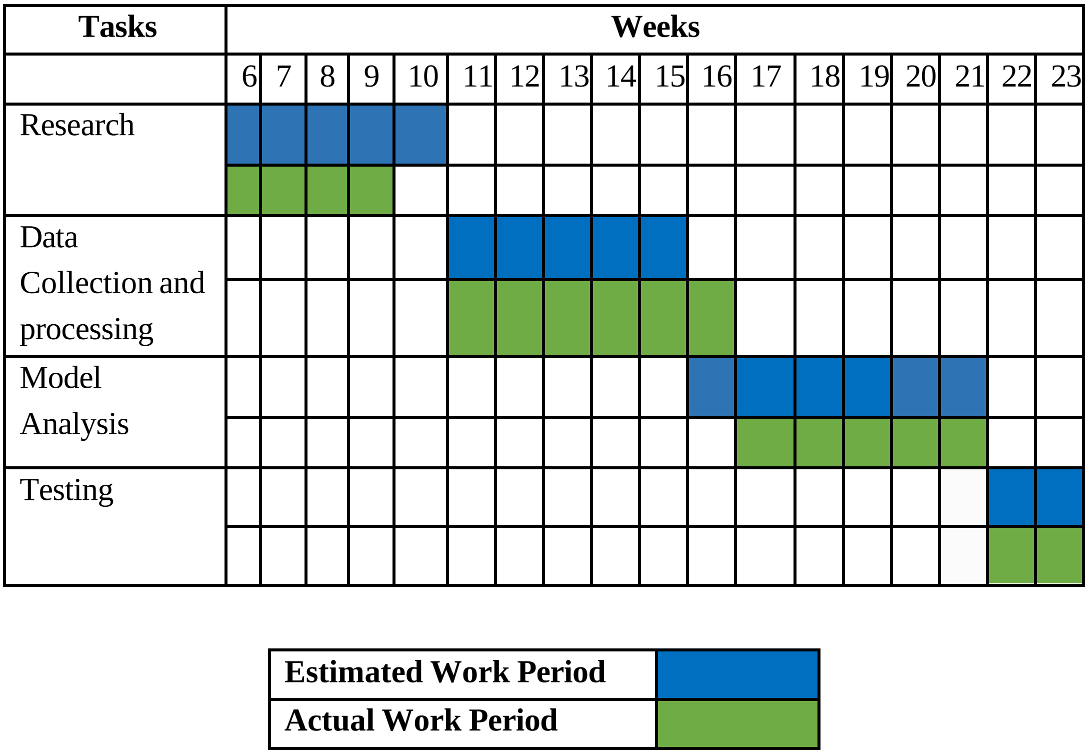
E. Phase 5: Back-End Development (Ongoing)

F. Phase 6: Testing (Under Planning)

G. Phase 7: Deployment (Under Planning)

H. Phase 8: Launch and Marketing (Under Planning)

Table 3.4.1: Project Management Gantt chart



- **Resource Planning:**

A. Equipment and Tools:

- Development and Testing Servers
- High-performance Computers for Development
- Mobile Device for App Testing (Android)
- Collaboration Tools (e.g., Slack, Trello, or project management software)
- Version Control System (Git)
- Testing Tools (e.g., Selenium for automated testing)

B. Software and Technologies:

- Deep Learning Frameworks (AlexNet, CNN, ResNet, VGG16)
- Mobile App Development (Flutter, Dart)
- Server Hosting.

C. Data and Content:

- Product Data: Manually collected image data from different ornamental fish shop.
- Product Images: Provided by sellers or obtained through agreements with suppliers.

D. Training and Skill Development:

- Ensure expertise in deep learning, mobile app development and cloud computing within the development team.
- Provide training on specific tools and frameworks used in the project.
- Continuous learning and skill enhancement throughout the project.

- **Risk Management:**

Here's a detailed SWOT analysis diagram including the Strengths, Weakness, Opportunities and Threats of this project:

Figure: 3.4.1 SWOT analysis

- **Communication Plan:**

A. Stakeholder Meetings:

- **Purpose:** Update stakeholders on project requirements gathering progress andgather feedback.

- **Participants:** Team members, and stakeholders.
- **Frequency:** Bi-weekly or as specified in the project plan.

B. **Change Control Meetings:**

- **Purpose:** Discuss and approve any changes to the project scope or requirements.
- **Participants:** Supervisor and team members.
- **Frequency:** Thrice in a week.

3.4.2 Financial Analysis:

- To evaluate project expenses, projected profits, return on investment (ROI), and risks, we will take out an in-depth financial study.
- This includes showing future source of income, estimating project costs, and detecting and reducing financial risks.
- Sensitivity analysis can help guide strategic decision-making for the best financial results by showing how sensitive the project is to changes in important variables.

Table 3.4.2: Estimated Cost for This Project

SN	Components	Estimated Cost (BDT)
01.	Visiting Stakeholders	1500-2000
02.	Data Collection and Processing	2000-2500
03.	Documentation and Report Writing	800-1000
04.	Miscellaneous (e.g., licenses, tools)	500-1000
05.	Contingency (10% of total)	5280-6500
Total Estimated Cost		10,080-13000

3.5 Summary

The study explores the complex field of species classification for ornamental fish, following a path designed with great care. It starts with a thorough preprocessing step and carefully cleans and enhances the dataset to improve the training process. A wide range of deep learning models with customized architectures are rigorously trained to guarantee the highest level of species identification accuracy. The requirements analysis emphasizes how important it is to have clean datasets, deep learning knowledge, and uncompromising ethical norms. This project offers not only innovation but a revolution in the accurate classification of ornamental fish species, with insightful financial analysis guiding the waters and competent project management driving the ship.

CHAPTER 4

Implementation

4.1 Overview

The implementation of the Classification of Ornamental Fishes in Bangladesh utilizes a comprehensive approach centered on advanced image processing and deep learning techniques. The research starts with gathering a heterogeneous dataset of photos of different species of ornamental fish, then carefully cleaning the data to make it consistent with models. Because they can be pretrained on big datasets like ImageNet, models like VGG-19, Inception-V3, ResNet-50, MobileNet-V2, Xception, and customized variations are used for their robust feature extraction capabilities. The latter layers of these models are tuned to identify particular traits and patterns that are particular to various fish species. The dataset is split into testing, validation, and training sets in order to evaluate the models' accuracy in classifying fish, validate their performance, and train the models. The models are assessed on the testing set after training to determine how effective they are. Monitoring model performance and maybe retraining the models with fresh data to improve accuracy over time are real-world deployment issues. This strategy supports Bangladesh's efforts to conserve biodiversity and promote sustainable aquaculture by ensuring the methodical establishment of a trustworthy categorization system for ornamental fish.

4.2 Train Model

For collecting images of ornamental fishes in Bangladesh, we followed two steps. Firstly, we collected images directly from various fish shops in Katabon where ornamental fishes are commonly found. These images provide a real-world representation of the diversity and variety of ornamental fish species in their natural habitats. Secondly, due to challenges in obtaining a sufficient number of images directly from the shops, we opted to supplement our dataset by leveraging available resources on Kaggle. Our model was trained by analyzing the gathered data using sophisticated image processing techniques, which improved our model's capacity to recognize and categories various species of ornamental fish. By integrating selected data from Kaggle with real-world observations, our method established a strong basis for our research and allowed for a more insightful analysis.

VGG19: VGG19 is an extension of the VGG16 model, consisting of 19 layers, which includes 16 convolutional layers and 3 fully connected layers. The architecture starts with a series of convolutional layers using small (3×3) filters and a fixed stride of 1 pixel, preserving spatial resolution and capturing detailed features. These layers are organized into five blocks, each followed by max-pooling layers with a 2×2 filter and a stride of 2, which reduce the spatial dimensions while maintaining critical information. The architecture also incorporates 1x1 convolutions as linear transformations followed by Rectified Linear Unit (ReLU) activations. The fixed convolution stride of 1 pixel ensures high spatial resolution, making it particularly effective for tasks requiring fine-grained image analysis, such as fish species classification.

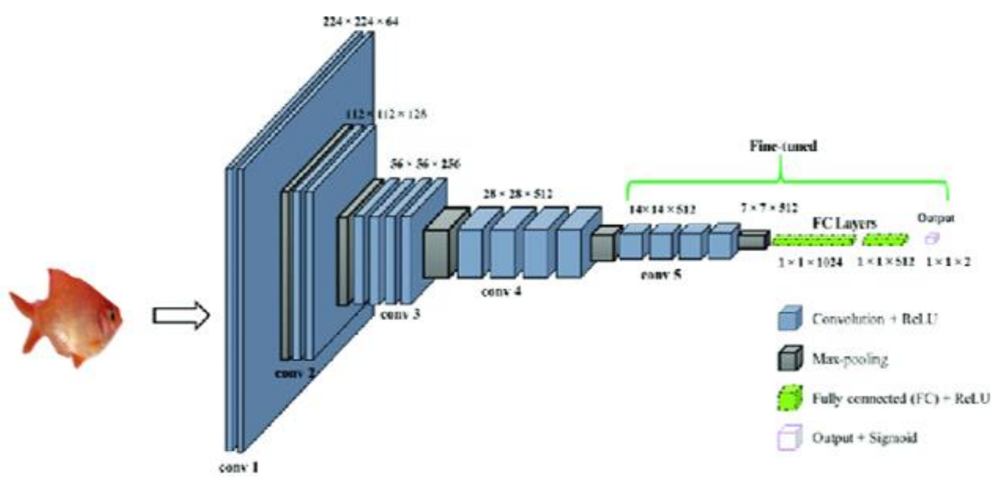


Figure 4.2.1: Schematic representation of VGG19 (**Resource Google**)

Inception-V3: A deep convolutional neural network architecture called Inception v3 is well-known for its effectiveness in image categorization applications. It uses an original module known as the inception module, which uses several convolutions of various sizes within the same layer in order to effectively represent spatial hierarchies. By using fewer parameters while maintaining a high level of accuracy, this architecture improves computing efficiency. In order to counter the vanishing gradient issue and promote gradient propagation, Inception-V3 further incorporates auxiliary classifiers at intermediate layers during training. Overall, Inception v3 balances depth and computational efficiency, making it suitable for various image recognition tasks, including fish species classification.

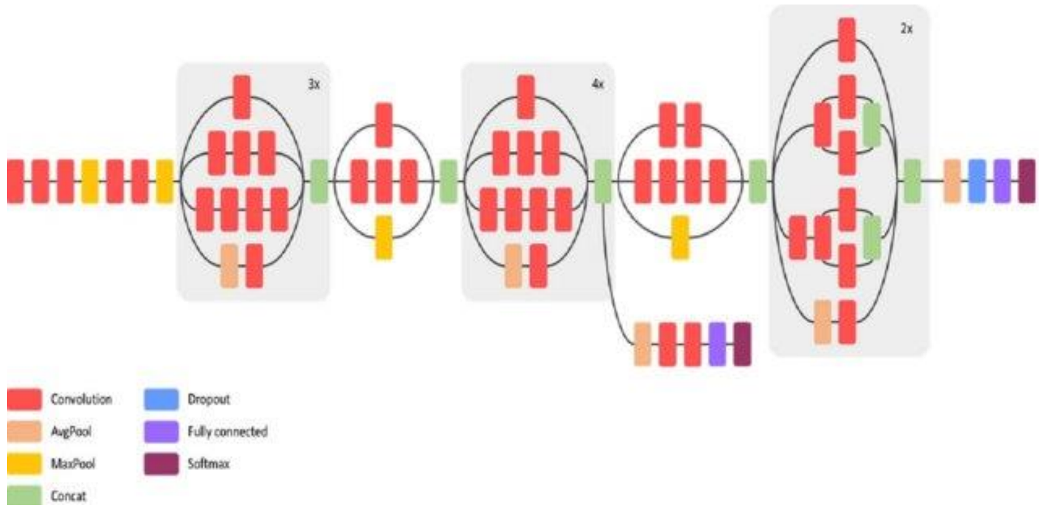


Figure 4.2.2: Schematic representation of Inception-V3 (**Resource Google**)

ResNet-50: Data augmentation helped us ResNet50 is a deep convolutional neural network architecture consisting of 50 layers which addresses the problem of vanishing gradients in deep networks by introducing residual learning. This makes ResNet50 highly effective for complex image classification tasks. ResNet50's deep architecture and innovative use of residual connections make it highly suitable for the classification of ornamental fishes in Bangladesh. Each residual block contains shortcut connections, bypassing one or more layers, facilitating the direct flow of information and enabling the network to learn residual mappings. Its success paved the way for even deeper and more complex neural network architectures.

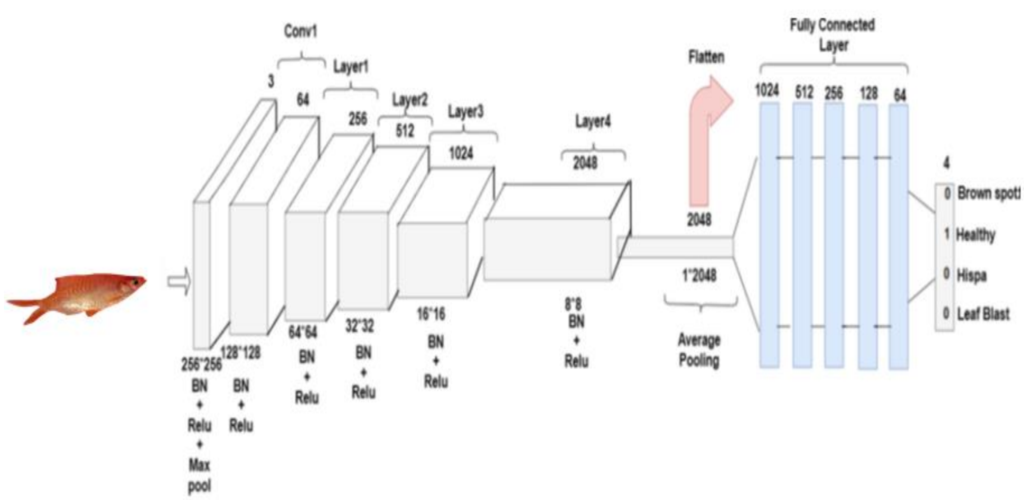


Figure 4.2.3: Schematic representation of ResNet-50 (**Resource Google**)

MobileNet-V2: MobileNet-V2 is a convolutional neural network designed for efficient mobile and embedded vision applications. It is characterized by its lightweight architecture, which provides a balance between model size, computational efficiency, and accuracy, making it ideal for tasks such as the classification. It introduces the concept of inverted residuals and linear bottlenecks, which are key innovations for maintaining performance while reducing computational complexity. The architecture utilizes depth wise separable convolutions to drastically reduce the number of parameters and multiplications compared to traditional convolution layers. Each layer in MobileNetV2 consists of a depth wise convolution followed by a pointwise convolution, enhancing efficiency. A significant feature of MobileNetV2 is the inverted residual block, were the input and output are connected by a shortcut, and the intermediate layers expand and then project back to a lower-dimensional space. This design helps in maintaining a high level of accuracy with fewer parameters. The linear bottleneck further aids in preserving the representational power of the network by ensuring that activations at the bottleneck layer are not distorted by non-linearities. These innovations collectively enable MobileNetV2 to achieve high performance in image classification tasks, making it particularly suitable for applications requiring a balance of accuracy and computational efficiency.

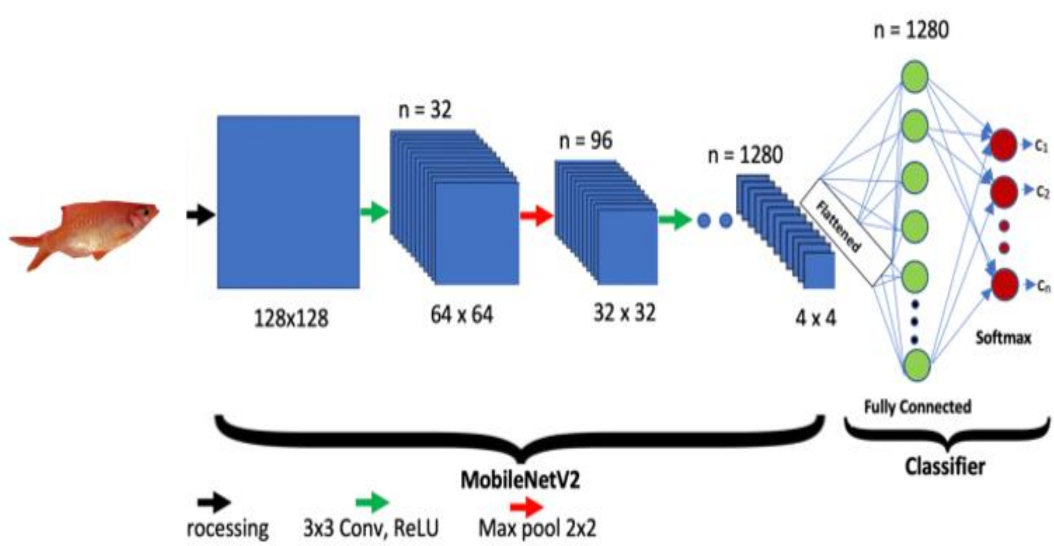


Figure 4.2.4: Schematic representation of MobileNet-V2 (**Resource Google**)

Xception: Xception is an advanced convolutional neural network (CNN) architecture known for its exceptional performance in image classification tasks. It employs an extreme version of inception modules, replacing standard convolutional layers with depth wise separable convolutions. This design significantly reduces the number of parameters while maintaining expressive power, leading to improved efficiency and accuracy. By decoupling spatial and channel-wise operations, Xception enhances feature learning and promotes better generalization. Its innovative architecture enables the network to capture intricate patterns and fine details in images, making it a preferred choice for various computer vision tasks.

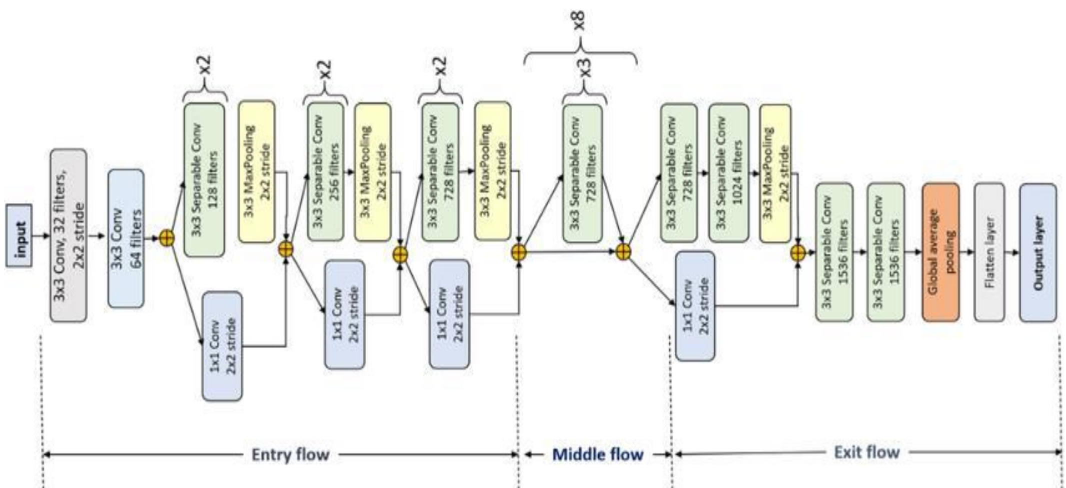


Figure 4.2.5: Schematic representation of Xception (**Resource Google**)

Training:

This step creates a CNN learner model. The dataset was used to train a model and test its classification accuracy using VGG19, MobileNetv2, ResNet50, Xception and Inception-V3. Early Stopping call-backs were used to train all representations for 20 epochs (10 iterations). Patience is the number of epochs without development before training ends. Learning rate = 0.0001, β1 = 0.9, β2 = 0.999, and ε=10^-7. An Adam optimizer uses momentum-SGD and RMSProp. The three representations received a similar optimizer and were saved as .h5 files. MobileNetV2 takes 45 seconds every epoch, whereas Xception takes 35 seconds.

The standard deviation was employed as a model performance metric in this investigationsince the dataset had no major imbalances. Categorical cross-entropy was selected as a lossgoal for all CNN architectures since this work involves multi-class sorting. These were the hyperparameters: There were 20 epochs, 17 batches, 0.3 dropouts, and 0.0001 learning. Adam optimized model weights. All photos were reduced to the architecture's default picture size before resizing.

4.3 System Testing / Model Evaluation

CNN base methods are evaluated using many machine learning classification model performance metrics. AC, precision, recall, F1-score, and confusion matrix are evaluated (CM). TP, TN, FP, and FN are also variables in those measurements (FN).

Accuracy:

Classification model accuracy is one metric. Accuracy is the model's predicted percentage.Accuracy is the percentage of properly classified pictures to total samples. Accuracy equation:

$$A = \frac{TP + TN}{TP + TN + FP + FN} \qquad (1)$$

Precision:

Precision is the chance of a positive label and how many are positive. Precision shows howmany accurately anticipated instances were positive. Precision is helpful when FP matters more than FN. Mathematically, it's this equation:

$$P = \frac{TP}{TP + FP} \qquad (2)$$

Recall:

Recall or Sensitivity measures how many positive expected occurrences were classified accurately. Recall is a helpful statistic when FN prevails over FP. F1-score is a further metric for classification accuracy that takes into account both recall and precision. Since precision and recall are harmonic means, the F1 score provides a comprehensive understanding of these two metrics. It reaches its optimum when Precision and Recall areequal. To figure it out, use the equation below:

$$R = \frac{TP}{TP + FN} \qquad (3)$$

F-1 Score:

F1 score is a recall-precision metric of categorization accuracy. As F1-score is the harmonic mean of Precision and Recall, it gives a complete picture. Precision and Recall are optimal when equal. Equation:

$$F1 = 2 \times \frac{P \times R}{P + R} \tag{4}$$

The percentage of people who do not have the ailment who have a negative test result is known as specificity. A highly specific test is effective in excluding the majority of individuals without the disease. Because of this, a positive outcome on a very precise test can definitively rule out the condition for a specific person. The equation is given below:

$$S = \frac{TN}{TN + FP} \tag{5}$$

However, there is a limit to how closely the model can mimic the training set of data before it loses its ability to generalize. An algorithm's performance can be assessed using a particular table format called the confusion matrix (CM). CM is used to illustrate crucial predictive parameters like recollection, specificity, precision, and accuracy. Confusion matrices are useful because they offer direct assessments of values like TP, FP, TN, and FN. The following parts respond to the research questions of this study based on the research questions.

4.4 Summary

The project on "Classification of Ornamental Fishes in Bangladesh using Deep Transfer Learning" employs cutting-edge AI techniques to enhance the identification and classification of ornamental fish species. It begins with the collection of a diverse dataset of ornamental fish images, complemented by additional data from online resources. Rigorous preprocessing and data augmentation techniques are applied to improve model training. Models such as VGG-19, MobileNet-V2, ResNet-50, Xception and Inception-V3 are fine-tuned for specific fish classification tasks. The dataset is divided into training, validation, and testing sets to ensure robust model evaluation through metrics like accuracy, precision, recall, F1-score, and specificity. This comprehensive approach aims to develop a reliable and scalable classification system for practical applications in the ornamental fish industry in Bangladesh.

CHAPTER 5

Result and Analysis

5.1 Overview

The study "Classification of Ornamental Fishes in Bangladesh" produced some interesting results about how well the following five algorithms performed: VGG19, MobileNetV2, ResNet50, Xception, and InceptionV3. A fair representation of the ornamental fish categories was ensured using stratified sampling, which divided the dataset into training, testing, and validation sets. The area under the receiver operating characteristic curve (AUC-ROC), accuracy, precision, recall, F1-score, and other suitable assessment metrics were used to assess the performance of the model. To find the best method for categorizing ornamental fish, a comparison analysis was done to evaluate the performance of several algorithms. With this experimental configuration in mind, the study sought to create dependable and accurate predictive models. With an astounding accuracy rate of 97%, the study discovered that VGG19, MobileNetV2 and ResNet50 outperformed the other algorithms in terms of accuracy. ResNet50 and VGG19 both proved to be efficient at correctly classifying ornamental fish. With an accuracy of 95%, Xception demonstrated its strong performance as well, demonstrating its capacity to handle intricate variables and data structures. With a 94% accuracy rate, InceptionV3 proved to be a reliable classifier for ornamental fish. These findings imply that these algorithms can make a substantial contribution to the efficiency and accuracy of fish ornamental classification. The study emphasizes how these models may increase categorization accuracy, which can benefit the ornamental fish business by improving inventory control and customer happiness. Through the use of these very effective algorithms, the study lays the groundwork for further investigation and advancement in the field of ornamental fish classification.

5.2 Experimental / Simulation Result

This section compares the five original CNN networks VGG19, MobileNetV2, Xception, ResNet50 and Inception-V3. Classification performance comes first. Then, those models' overall metrics are reviewed. collection, descriptions, probable reasons, andoutcomes improvement areas.

TABLE 5.2.1: Accuracy for Different Models

Architecture	Training Accuracy	Model Accuracy
VGG19	**95.88%**	**97%**
MobileNetV2	**95.73%**	**97%**
ResNet50	**97.55%**	**97%**
Xception	**96.40%**	**95%**
InceptionV3	**91.34%**	**94%**

The classification performance of the five original CNN networks is compared in this section. First, each model's important performance metrics—accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC)—are summarized. These metrics offer a thorough assessment of each model's performance in accurately classifying ornamental fishes. A comparative study is done to find the best algorithm for ornamental fish classification. This entails utilizing the summarized metrics to compare the various algorithms' performances. Furthermore, to further demonstrate the models' performance, visualizations including confusion matrices, ROC curves, and precision-recall curves are included. The distribution of predictions, trade-offs between true positive and false positive rates, and the harmony between recall and precision can all be better understood with the use of these graphic aids. A thorough discussion of each algorithm's advantages and disadvantages is provided. This comprises evaluating interpretability, computational efficiency, and forecast accuracy. For example, certain models might be more interpretable but marginally less accurate, while others might give more accuracy but demand more computing power. These trade-offs are emphasized in the discussion to give a clear picture of each model's applicability for real-world applications. All things considered, the research and experimental findings provide insightful information about how well various CNN models classify ornamental fishes. Through a thorough analysis of each algorithm's capabilities, limitations, and performance, the study offers a strong basis for choosing and fine-tuning models for use in the ornamental fish market.

TABLE 5.2.2: Precision, Recall, F1-Score, and Support (n) for original CNN networks (depending on thenumber of pictures, n=numbers).

VGG19				
	Precision	**Recall**	**F1-Score**	**Support**
Albino Rainbow Shark	1.00	1.00	1.00	39
Angel Fish	0.98	1.00	0.99	59
Barb	1.00	0.98	0.99	66
Betta	1.00	1.00	1.00	29
Comet	0.93	1.00	0.97	42
GoldFish	0.97	0.80	0.88	44
Gourami	0.97	0.94	0.96	70
Koi Carp	0.97	0.97	0.97	34
Molly	1.00	0.97	0.98	94
Oranda GoldFish	0.90	0.98	0.94	62
Panorama	1.00	1.00	1.00	31
Parrot	0.98	0.98	0.98	60
Pika	1.00	1.00	1.00	25
Silver Arowana	0.97	1.00	0.98	64
Sucker	0.98	0.98	0.98	49
Tiger Shark	0.92	0.97	0.94	34
Tinfoli Barb	0.98	0.95	0.97	62
Upside Down Catfish	0.98	1.00	0.99	61
Widow Tetra	0.95	1.00	0.97	19
Accuracy			0.97	944
Macro Avg	0.97	0.98	0.97	944
Weighted Avg	0.97	0.97	0.97	944

Xception				
	Precision	**Recall**	**F1-Score**	**Support**
Albino Rainbow Shark	1.00	1.00	1.00	20
Angel Fish	0.97	0.97	0.97	29
Barb	0.83	0.85	0.89	33
Betta	1.00	1.00	1.00	15
Comet	0.87	0.95	0.91	21
GoldFish	1.00	0.82	0.90	22
Gourami	1.00	0.94	0.97	35
Koi Carp	0.94	1.00	0.97	17
Molly	0.96	1.00	0.98	47
Oranda GoldFish	0.94	0.97	0.95	32
Panorama	1.00	1.00	1.00	15
Parrot	0.94	1.00	0.97	30
Pika	0.93	1.00	0.96	13
Silver Arowana	0.89	0.97	0.93	32
Sucker	0.92	1.00	0.96	24
Tiger Shark	0.93	0.76	0.84	17
Tinfoli Barb	0.97	.0.97	0.97	31
Upside Down Catfish	1.00	0.97	0.98	31
Widow Tetra	1.00	0.90	0.95	10
Accuracy			0.95	474
Macro Avg	0.96	0.95	0.95	474
Weighted Avg	0.96	0.95	0.95	474

InceptionV3				
	Precision	**Recall**	**F1-Score**	**Support**
Albino Rainbow Shark	1.00	1.00	1.00	39
Angel Fish	0.98	0.93	0.96	59
Barb	0.94	0.88	0.91	66
Betta	1.00	1.00	1.00	29
Comet	0.89	1.00	0.94	42
GoldFish	0.94	0.77	0.85	44
Gourami	0.97	0.84	0.90	70
Koi Carp	0.97	0.94	0.96	34
Molly	0.94	0.93	0.93	94
Oranda GoldFish	0.90	1.00	0.95	62
Panorama	1.00	1.00	1.00	31
Parrot	1.00	0.97	0.98	60
Pika	0.92	0.92	0.92	25
Silver Arowana	0.84	0.97	0.90	64
Sucker	0.94	0.92	0.93	49
Tiger Shark	1.00	0.97	0.99	34
Tinfoli Barb	0.90	0.98	0.94	62
Upside Down Catfish	0.92	0.95	0.94	61
Widow Tetra	1.00	1.00	1.00	19
Accuracy			0.94	944
Macro Avg	0.95	0.95	0.95	944
Weighted Avg	0.94	0.94	0.94	944

MobileNetV2				
	Precision	**Recall**	**F1-Score**	**Support**
Albino Rainbow Shark	1.00	1.00	1.00	39
Angel Fish	0.84	1.00	0.91	59
Barb	0.96	0.98	0.97	66
Betta	1.00	0.97	0.98	29
Comet	1.00	1.00	1.00	42
GoldFish	0.90	1.00	0.95	44
Gourami	0.96	0.99	0.97	70
Koi Carp	1.00	0.82	0.90	34
Molly	1.00	0.82	0.90	94
Oranda GoldFish	1.00	1.00	1.00	62
Panorama	0.97	1.00	0.98	31
Parrot	0.98	1.00	0.99	60
Pika	1.00	1.00	1.00	25
Silver Arowana	0.96	1.00	0.98	64
Sucker	0.98	0.98	0.98	49
Tiger Shark	1.00	1.00	1.00	34
Tinfoli Barb	1.00	0.98	0.99	62
Upside Down Catfish	0.98	0.98	0.98	61
Widow Tetra	1.00	1.00	1.00	19
Accuracy			0.97	944
Macro Avg	0.98	0.98	0.97	944
Weighted Avg	0.97	0.97	0.97	944

ResNet50				
	Precision	**Recall**	**F1-Score**	**Support**
Albino Rainbow Shark	1.00	1.00	1.00	39
Angel Fish	1.00	1.00	1.00	59
Barb	0.98	0.98	0.98	66
Betta	1.00	1.00	1.00	29
Comet	1.00	1.00	1.00	42
GoldFish	0.95	0.89	0.92	44
Gourami	0.99	0.96	0.97	70
Koi Carp	1.00	1.00	1.00	34
Molly	0.99	0.97	0.98	94
Oranda GoldFish	0.92	0.97	0.94	62
Panorama	1.00	0.97	0.98	31
Parrot	0.95	1.00	0.98	60
Pika	1.00	1.00	1.00	25
Silver Arowana	0.95	0.98	0.97	64
Sucker	0.98	0.98	0.98	49
Tiger Shark	0.89	0.94	0.91	34
Tinfoli Barb	1.00	0.97	0.98	62
Upside Down Catfish	0.95	0.97	0.96	61
Widow Tetra	1.00	0.95	0.97	19
Accuracy			0.97	944
Macro Avg	0.98	0.97	0.98	944
Weighted Avg	0.98	0.97	0.97	944

Table 5.2.2 provides a comprehensive overview of the training percentage and model accuracy achieved by five distinct original Convolutional Neural Network (CNN) architectures. Additionally, the table presents precision, recall, F1-score, and support values for each class, focusing on the VGG19, MobileNetV2, ResNet50, Xception and Inception-V3 models. Notably, the VGG19, ResNet50, and InceptionV3 architectures exhibit remarkable performance, particularly evident in their precision values when applied to the test dataset. Specifically,these three models consistently demonstrate superior precision, recall, and F1-score across various classes, affirming their effectiveness in accurate fish species classification. The VGG19, ResNet50 and Inception-V3 models exhibit commendable performance in categorizing detections, as highlighted in the detailed breakdown. However, it is noteworthy that the MobileNet-V2 model, while part of the comprehensive comparison, yields a comparatively lower identification rate, emphasizing the nuanced variations in performance among the considered CNN architectures.

Training and Validation Accuracy and loss of Original CNN Networks:

Represents the training and validation accuracy of the initial model, with the number of epochs on the x-axis and the accuracy and loss percentages on the y-axis. In the figure, training and validation data are adequately divided, and there is no overfitting.

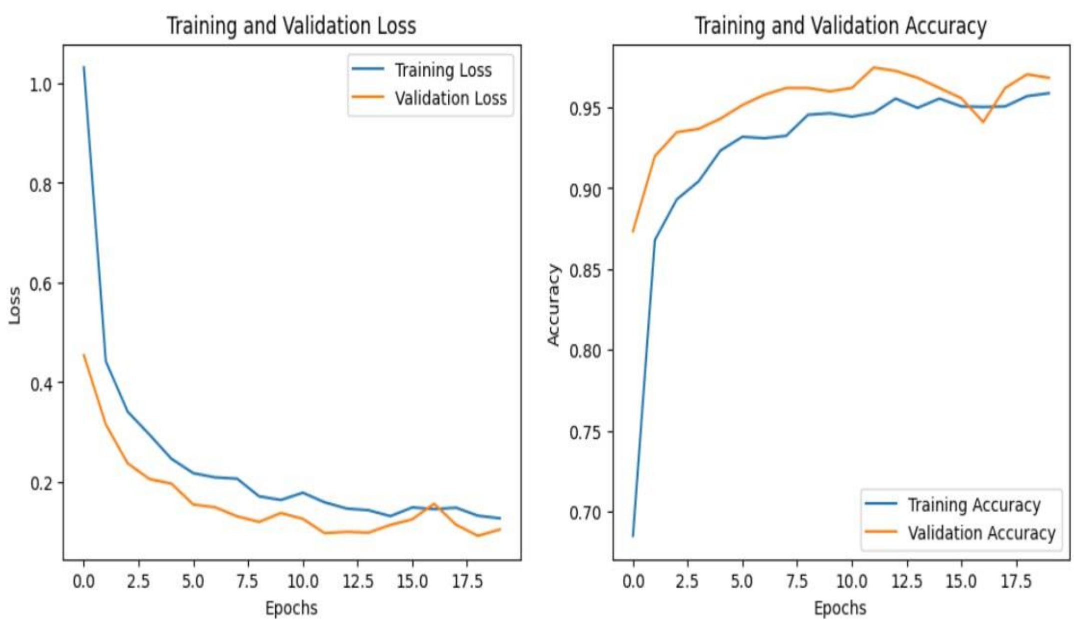


Figure 5.2.1: Training and validation accuracy and loss over the epochs (VGG19)

Figure 5.2.2: Training and validation accuracy and loss over the epochs (MobileNetV2)

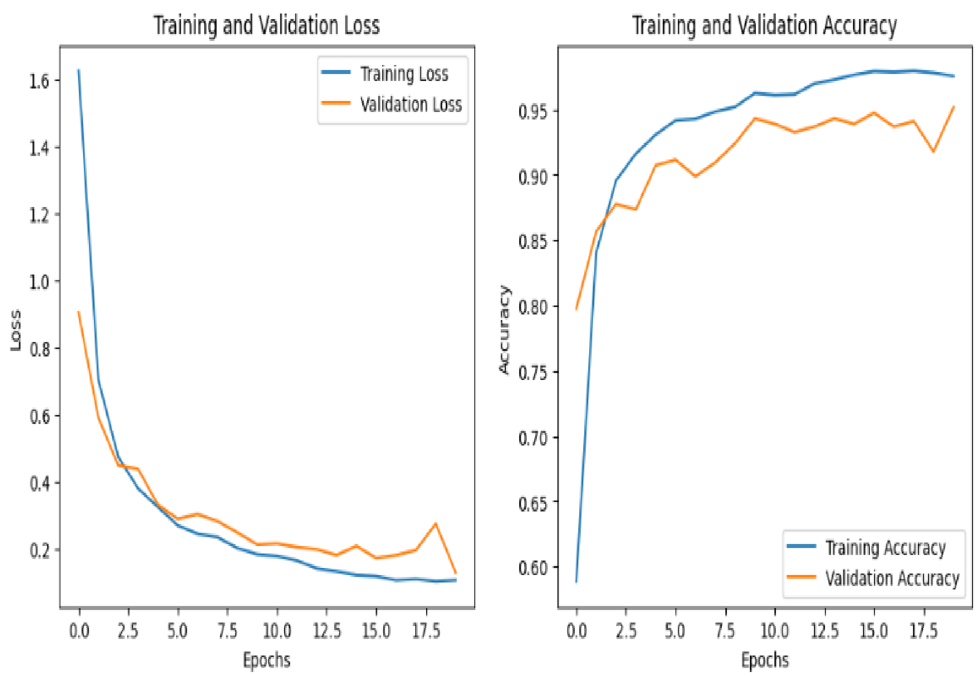


Figure 5.2.3: Training and validation accuracy and loss over the epochs (ResNet50)

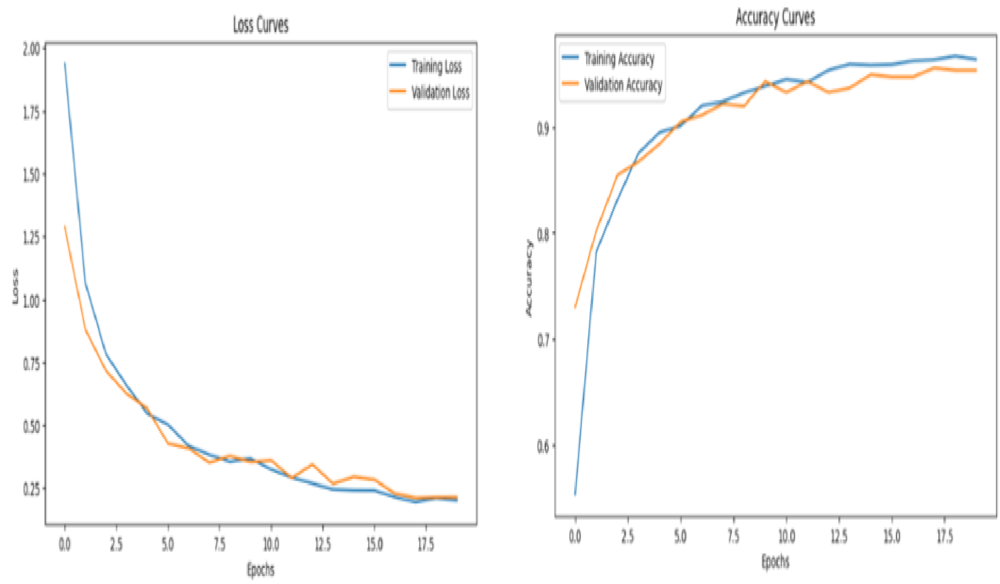


Figure 5.2.4: Training and validation accuracy and loss over the epochs (Xception)

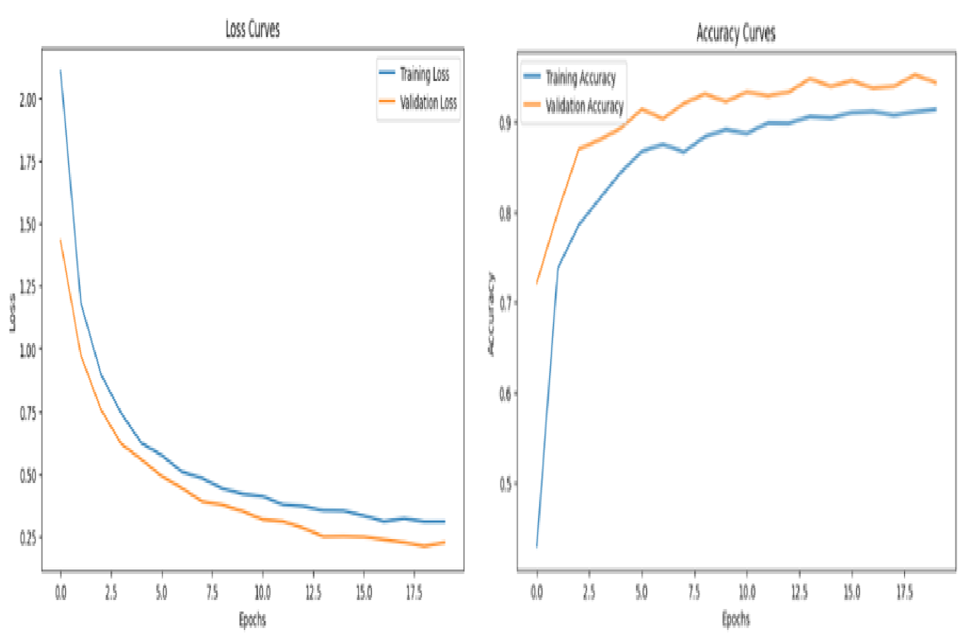


Figure 5.2.5: Training and validation accuracy and loss over the epochs (Inception-V3)

Confusion Matrix after Experiment:

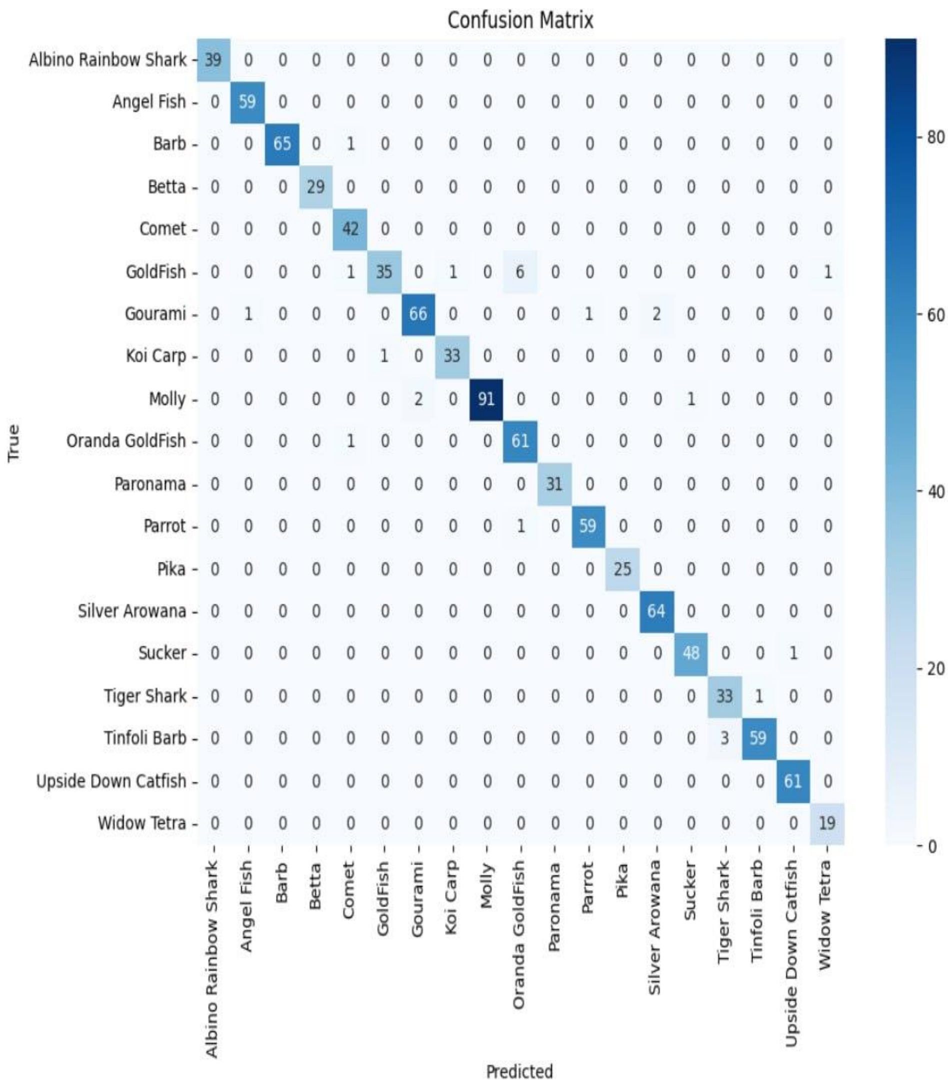


Figure 5.2.6: CM after Original Vgg19

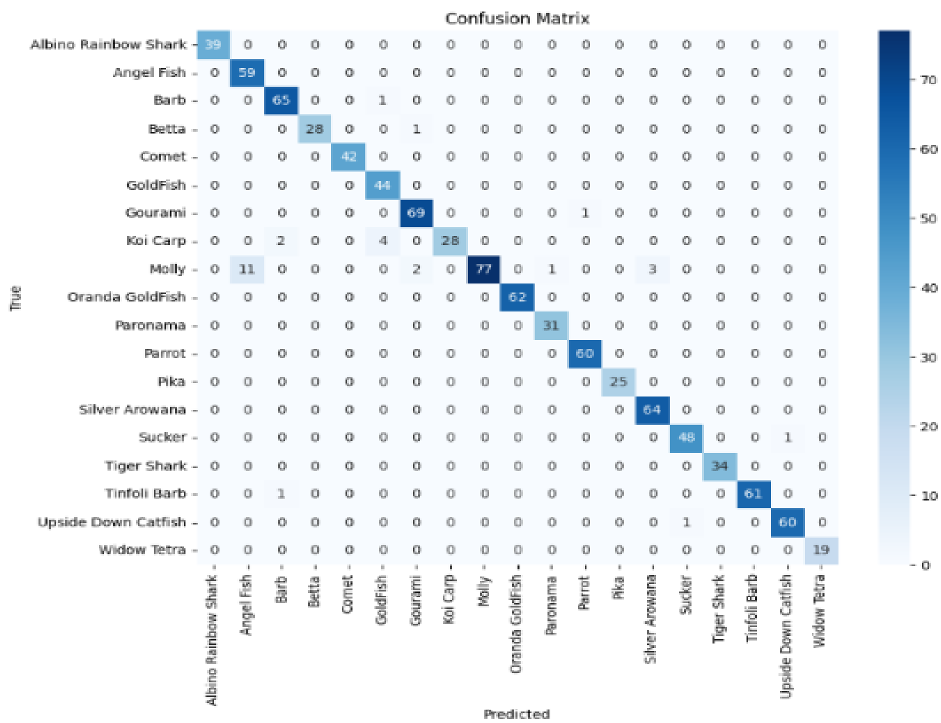


Figure 5.2.7: CM after Original MobileNetv2

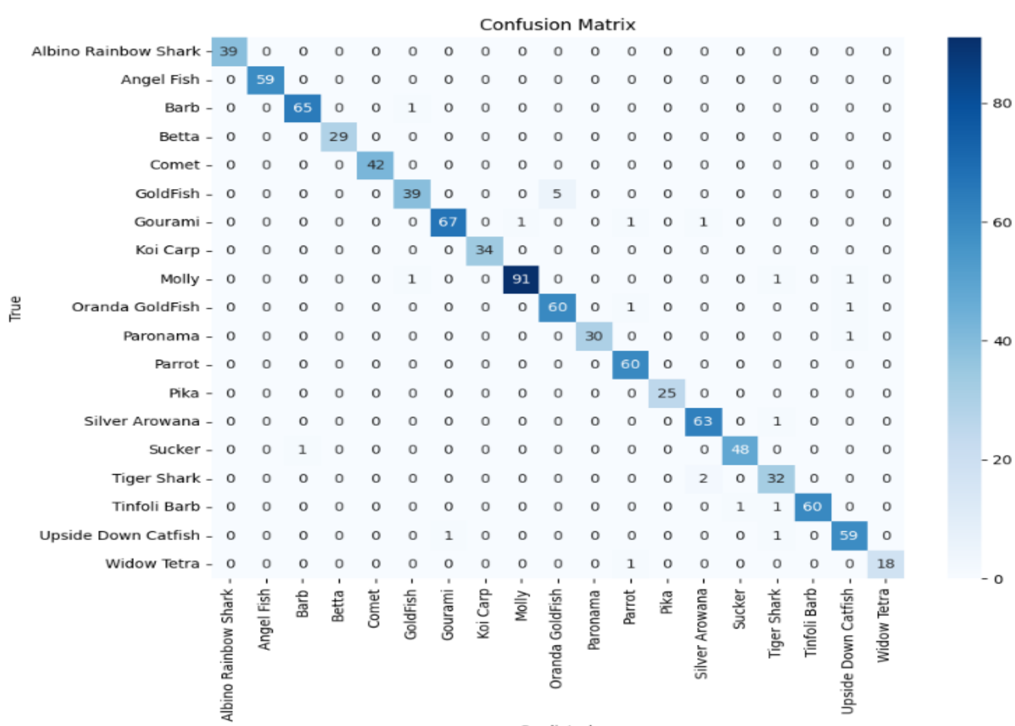


Figure 5.2.8: CM after Original ResNet50

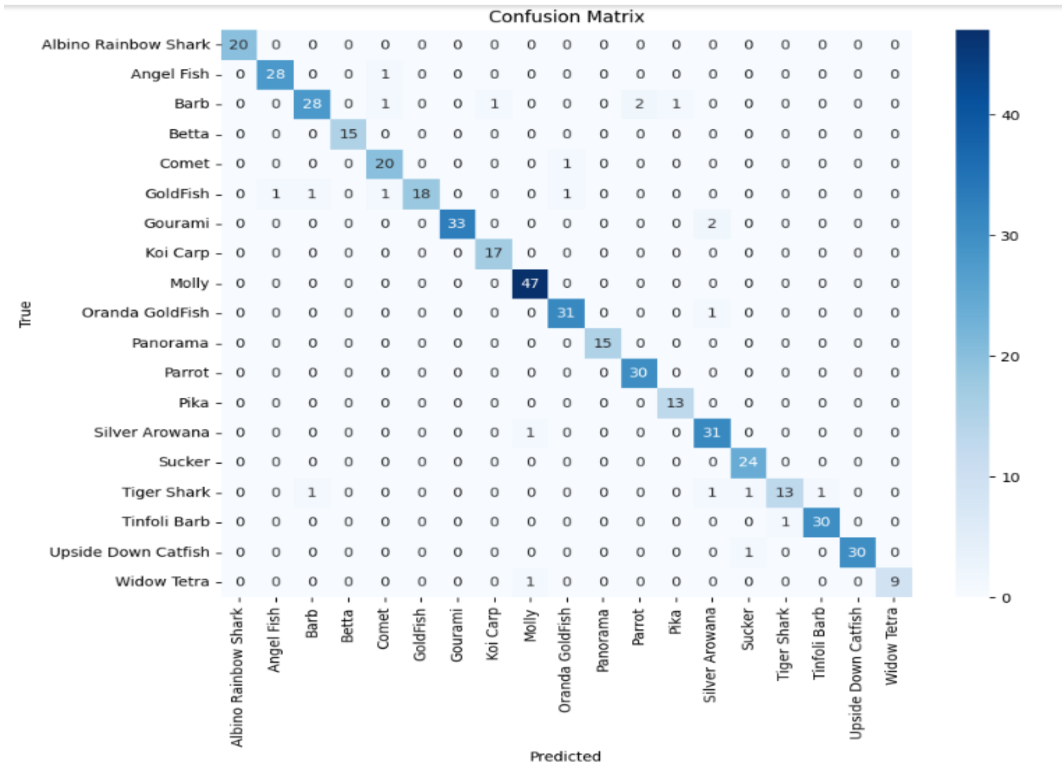


Figure 5.2.9: CM after Original Xception

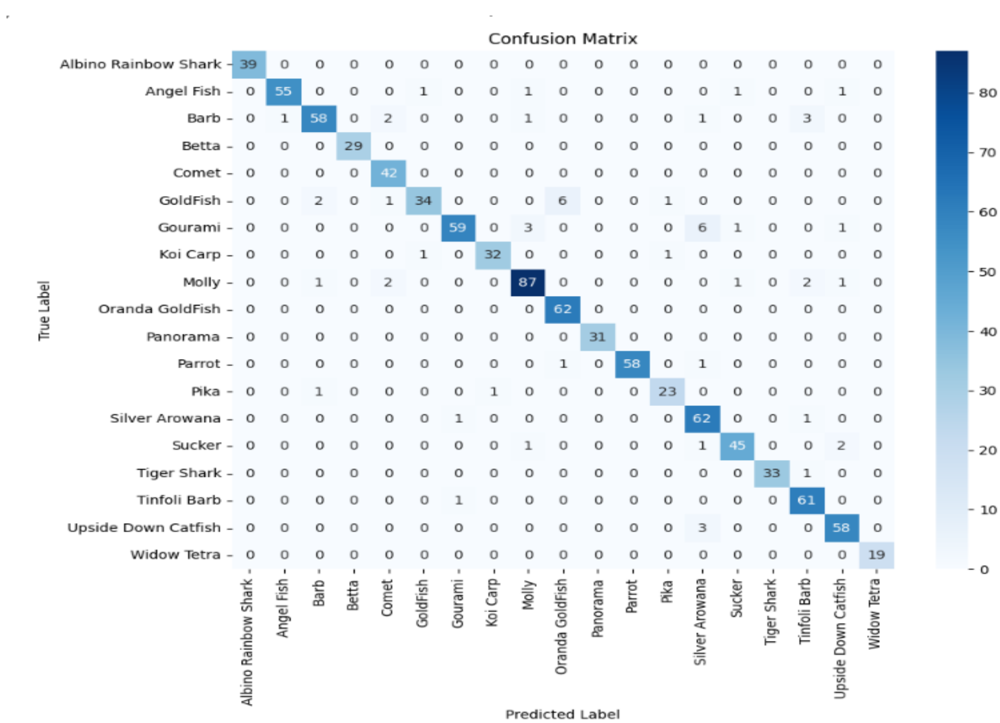


Figure 5.2.10: CM after Original Inception-V3

Overall, the classification of ornamental fishes in Bangladesh seems to be performing well, with a high number of true positives and true negatives across various fish categories. However, there are still a few false positives and false negatives. False positives could lead to the mislabeling of non-target fish as specific ornamental species, potentially causing customer dissatisfaction. False negatives could hinder the identification and sale of certain ornamental species, impacting inventory management and sales. It's important to note that this evaluation is based on a specific dataset, and the model's performance may vary with different datasets. Additionally, the confusion matrix only provides part of the story. Other metrics, such as precision, recall, and F1-score, offer more comprehensive insights into the model's performance. Overall, the confusion matrix offers a valuable visualization of the classification model's performance.

5.3 Performance / Comparative Analysis

This comprehensive study delves into the efficacy of various deep convolutional neural networks (CNNs) in recognizing and segmenting ornamental fishes, particularly focusing on different model architectures and their accuracy. Leveraging a substantial dataset of images of ornamental fishes, the research employs a sophisticated augmentation approach to enhance the dataset and improve model training. The study explores the utility of original CNNs, transfer learning techniques, and ensemble models in the context of classifying ornamental fishes.

Five prominent CNN-based models, including VGG19, MobileNetV2, ResNet50, Xception and InceptionV3, are rigorously tested on the classification of ornamental fish dataset. Notably, VGG19, ResNet50, MobileNetV2 and Xception, emerge as front-runners, achieving impressive accuracy scores of 97%, 97%, 97% and 95%, respectively, as visually depicted in the results section. Intriguingly, variations in background noise and the utilization of diverse augmentation strategies independently with test sets are identified as potential factors contributing to decreased performance.

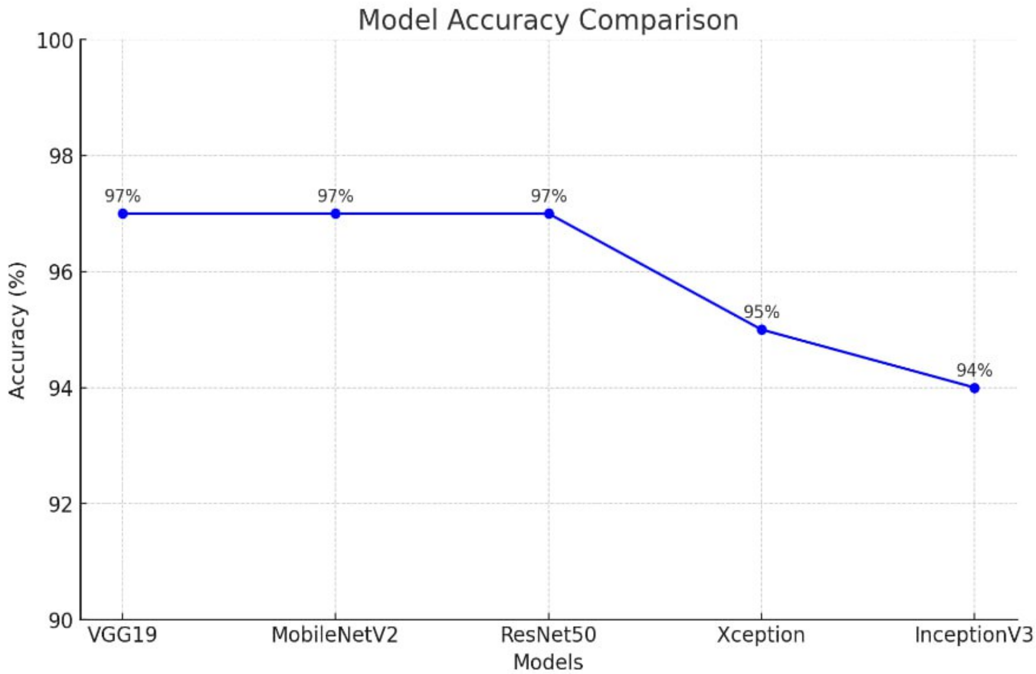


Figure 5.3.1: Accuracy comparison among individual models

In-depth analysis indicates that the original CNN model, when trained and evaluated using comparable input, exhibits enhanced predictive capabilities for unknown data. Nevertheless, the study recognizes limitations in dataset size, highlighting the potential impact on prediction capabilities, especially in the context of transfer learning. Insights from previous research reinforce the suggestion to increase dataset size, particularly when the input images undergo augmentation updates. The study underscores the potential superiority of ensemble models over individual CNN architectures, emphasizing that an ensemble of multiple models may outperform a single model, even if a specific CNN architecture exhibits suboptimal performance. In essence, this research provides a nuanced exploration of CNN-based models for classify ornamental fishes.

5.4 Summary

Results from the model created to categorize ornamental fish are shown in the Results and Analysis section, with an emphasis on the effectiveness of different algorithms. Using selected evaluation metrics, including accuracy, precision, recall, and other pertinent measures, we will examine the model's performance in more detail. This in-depth examination evaluates the model's precision in categorizing ornamental fish. The findings shed light on the model's advantages, investigate performance-influencing variables, point out possible areas for development, and visualize forecasts to comprehend the model's decision-making process. Five algorithms were assessed in this section: Xception, InceptionV3, ResNet50, MobileNetV2, and VGG19. The models with the highest accuracy were VGG19, MobileNetV2 and ResNet50, indicating their potent ability to classify ornamental fish. With an accuracy of 95%, Xception came in the second and InceptionV3 which had 94%. These findings suggest that within our dataset, VGG19, MobilNetV2 and ResNet50 are very good at classifying ornamental fish. This thorough assessment will demonstrate how well these models categorize ornamental fishes, providing insightful information about their behavior and pinpointing opportunities for further development. This section intends to provide a comprehensive knowledge of the models' effectiveness in this classification assignment by analyzing the elements impacting the models' performance and visualizing their decision-making processes.

CHAPTER 6

Impact on Society

6.1 Impact on Life

The implementation of a classification system for ornamental fishes in Bangladesh based on Convolutional Neural Networks (CNNs) has the potential to significantly impact various aspects of life, transforming the ornamental fish industry and the broader socio-economic and environmental landscape. By leveraging cutting-edge technology, this system can drive numerous positive changes. First off, the accuracy of fish identification can be significantly improved by an automated classification system. The method reduces the possibility of misidentification by reliably classifying several species of ornamental fish through the analysis of photos using sophisticated algorithms. Because of this accuracy, aquatic biodiversity is better managed and conserved, which benefits ecosystem health and sustainability. Second, the sector for ornamental fish might become more efficient thanks to technology. Fish species identification by hand can be labor-intensive and prone to mistakes, particularly in hectic breeding and trading settings. The technology can swiftly process and analyze photos thanks to automated classification, giving breeders and traders access to accurate and timely information. This effectiveness can simplify processes, resulting in quicker decision-making and lower operating expenses. The classification system can also make expert knowledge more accessible. By offering accurate classification of species remotely, this method can fill the gap in areas where access to ichthyologists and aquatic biologists is restricted. Technology can also support sustainability and economic expansion. The method can increase the quality and marketability of ornamental fish, creating new economic opportunities for nearby businesses and communities, by increasing the accuracy and efficiency of fish breeding and trading. For individuals working in the ornamental fish business, this may result in higher earnings and improved living conditions. In general, there could be a significant impact from a CNN-based classification system for ornamental fishes in Bangladesh. It can stimulate economic growth, help environmental protection, boost industry efficiency, provide access to specialized knowledge, and improve biodiversity management.

6.2 Impact on Society and Environment

Our aim with the "Classification of Ornamental Fishes in Bangladesh" study is to use state-of-the-art deep CNN-based classification technology to transform the ornamental fish market. We hope to assist scientists, hobbyists, and breeders in preserving and managing Bangladesh's aquatic biodiversity by creating an intelligent system for the precise identification and classification of ornamental fish. The ornamental fish sector will benefit financially from the implementation of our system, which will also provide new opportunities for local businesses and breeders by improving the quality of ornamental fish breeding and enabling accurate and efficient fish identification. Additionally, by protecting native species and upholding ecological equilibrium, our technology aids in conservation efforts. Our study aims to advance sustainable practices, modernize the sector, and enhance the lives of those who work in it. We want to use deep learning to optimize operations, minimize resource waste, and enhance environmental benefits while supporting regional ecosystems and advancing global sustainability goals. In the end, we hope to turn Bangladesh's ornamental fish market into a creative and sustainable industry where technological innovation, environmental preservation, and economic growth all coexist.

6.3 Ethical Aspects

The ethical principles underlying our project place a high priority on the welfare of those working in the ornamental fish sector, environmental sustainability, and biodiversity preservation. We are dedicated to giving breeders, enthusiasts, and academics access to cutting-edge technology, honoring their preferences, and assisting them in making decisions. We contribute to maintaining the ecological balance and sustainability of aquatic habitats by facilitating the appropriate classification and management of ornamental fish species. In an effort to close the digital divide and advance inclusivity in the ornamental fish business, we support universal access to technology. We help to preserve natural environments and treat aquatic life ethically by endorsing sustainable breeding and agricultural practices. Our ethical approach is guided by transparency, responsibility, and an emphasis on long-term advantages. Our goal is to advance a fair and sustainable future for Bangladesh's ornamental fish industry while also serving the interests of society and the environment.

6.4 Sustainability Plan

Our "Classification of Ornamental Fishes in Bangladesh" sustainability plan is a thorough approach intended to guarantee a favorable, long-lasting effect on the environment and society. From project conception to deployment, we are dedicated to using environmentally friendly technology and procedures. This involves minimizing waste, preserving resources, and, to the greatest extent feasible, lowering our carbon footprint. Another essential component of our strategy is economic sustainability. Our goal is to create jobs and increase resilience against economic uncertainty by empowering persons working in the ornamental fish sector and supporting local economies. By encouraging self-sufficiency and lowering reliance on outside assistance, we want to build community prosperity over the long run. In the end, our sustainability plan is about actively contributing to a better, more sustainable future for everybody, not just minimizing adverse effects.

6.5 Summary

Our research aims to create a deep CNN-based categorization system that will revolutionize Bangladesh's ornamental fish market. Accurate fish species identification is made possible by this technique, which benefits researchers, enthusiasts, and breeders in managing and conserving aquatic biodiversity. Our goal is to minimize the influence on the environment and preserve natural ecosystems. Our moral strategy puts the welfare of those working in the ornamental fish business first, guaranteeing data privacy, diversity, and equitable access to technology. The use of environmentally friendly practices and technologies, proactive community involvement, and economic resilience are all part of our sustainability plan. We help communities participating in the ornamental fish trade create jobs, become self-sufficient, and develop over the long term by supporting local economies and encouraging sustainable breeding practices. In order to ensure a sustainable and profitable future, we work to overcome difficulties within the ornamental fish business through collaboration and innovation. Our goal is to bring about significant, long-lasting change that will improve society and the environment.

CHAPTER 7

Conclusion and Future Research

7.1 Conclusions

This study, which focuses on cutting-edge deep CNN techniques, offers a thorough assessment of Bangladesh's ornamental fish taxonomy. The study fills a void in the literature by demonstrating the efficacy of this strategy, especially when applied to smaller and less sophisticated datasets. It also describes ornamental fish classification and management. Our study carefully assesses the efficacy of several CNN models, such as ResNet50, VGG19, MobileNetV2, Xception, and InceptionV3, in the classification of ornamental fish species. The results show that these models perform better as an ensemble stack than as individual models in terms of accuracy. Though the ensemble performed well overall, there were some cases of incorrect predictions, indicating that future study should consider different approaches like contrast augmentation or other image-processing techniques. Moreover, we suggest including picture segmentation before classification to improve the feature extraction performance of CNN models. The recommended ensemble is computationally demanding because it requires training many CNN models, but the potential for increased accuracy outweighs this expense. This work basically lays the groundwork for improving and developing methods for classifying ornamental fish, providing valuable information that could have a big influence on the ornamental fish market and spur more research into the rapidly developing field of automated species identification.

7.2 Further Suggested Work

The results of this investigation into the deep transfer learning approach for ornamental fish categorization provide insightful information and open new avenues for future research. An important recommendation for future research is to investigate different image-processing techniques, including adaptive thresholding, to deal with the incorrect classifications that the ensemble framework occasionally produces.

Furthermore, using segmentation methods prior to classification is proposed as a possible improvement for CNN models during feature extraction, enabling more accurate fish feature recognition. This emphasizes the necessity of developing more effective and scalable ensemble techniques in order to improve or preserve accuracy without sacrificing computing effectiveness. Even though the classification of ornamental fish was the study's primary focus, there is a strong need for additional focused research in this field. Developing new deep learning architectures, assembling a variety of datasets covering a broad range of fish species and circumstances, and evaluating these models in practical settings like fish farms and natural ecosystems are some ways to extend research endeavors. The management of aquatic biodiversity can benefit greatly from such thorough research, which will enhance the ecological and commercial elements of the ornamental fish trade.

7.3 Limitations

There are significant restrictions and possible conflicts of interest with our deep transfer learning research to classify ornamental fishes in Bangladesh. The quality and diversity of the training data, which may not include every potential species and variation of ornamental fish, are what determine how effective the model is. Due to the system's dependence on sophisticated equipment and high-quality photos, hobbyists and small-scale breeders with limited resources may not be able to use it. Overfitting is another possibility, in which the model performs well on training data but badly in practical applications. Widespread acceptance may be hampered by the need for substantial financial and technical resources for the technology's implementation and upkeep. Partnerships with aquaculture or tech businesses that put profit ahead of the sustainability of the environment and the well-being of the local community may give rise to conflicts of interest. It's also crucial to guarantee objective data collecting and handle any privacy issues. It is still very difficult to strike a balance between equal access, ethical concerns, and technological innovation.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Classification of Ornamental Fishes in Bangladesh

1. Student ID: 202-15-3821

2. Student ID: 202-15-3847

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to **Ornamental fish species classification** problem for the Final Year Design Project (FYDP).	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for the Final Year Design Project.	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish the goals for the Final Year Design Project.	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the Final Year Design Project.	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**

CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**
CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	The application of fundamental engineering (K3) principles is demonstrated in this project by deep neural networks, advanced techniques for enhancing data, and a variety of CNN designs specifically designed for image processing and classification tasks. Additionally, it demonstrates specialized knowledge (K4) by utilizing sophisticated CNN architectures such as VGG19 and Inception-V3 to execute transfer learning techniques. The goal of these initiatives is to improve fish species classification accuracy, which is essential for computer-aided diagnosis in aquaculture environments.	**Page no:** [22-23] **Section:** [3.2] **Page no:** [1-6] **Section:** [1.1]

				The project applies engineering practice & design (K5) by the figure of process of experiments. The project addresses engineering practice & technology (K6) by employing CNN model.	**Page no:** [22-23] **Section:** [3.2] **Page no:** [28] **Section:** [3.4]
				This project ensures to **K8 (Research Literature)** by synthesizing insights from recent studies, to advance fish species classification using deep learning, showcasing a comprehensive understanding of current methodologies.	**Page no:** [12-19] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project addresses **EP-2** by recognizing the hurdles in fish species classification, the complexities of integrating transfer learning and deep CNNs. Through comparative analysis, it confronts challenges in understanding spatial distributions, offering insights for refining diagnostic methodologies.	**Page no:** [19-20] **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This project addresses **EP-3** by meticulously comparing experimental outcomes, highlighting Transfer Learning as the chosen significant solution for enhancing fish species classification multiple potential approaches.	**Page no:** [36-49] **Section:** [5.2]

4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's interdisciplinary approach extends beyond computer science and engineering, impacting fish species classification which indicates **EP-4**.	**Page no:** [12-20] **Section:** [2.2, 2.3, 2.4]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	This project's comprehensive approach addresses high-level problems by integrating various components across data collection, statistical analysis, and proposed methodology which ensures **EP-7**.	**Page no:** [22-28] **Section:** [3.2, 3.3, 3.4]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements in fish species classification through transfer learning and deep learning CNNs.	**Page no:** [23-24] **Section:** [3.3]
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	No		N/A	N/A

4.	**EA4: Consequences for society and the environment**	Yes		This project his project contributes to society by enhancing biodiversity conservation and supporting sustainable fisheries management through accurate classification of ornamental fish species.	**Page no:** [52-54] **Section:** [6.1, 6.2, 6.3, 6.4]
5.	**EA-5: Familiarity**	Yes		This project expands upon existing research by examining a novel approach in fish species classification through transfer learning and deep CNNs, demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field.	**Page no:** [12-19] **Section:** [2.1, 2.2, 2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle.	**Page no:** [24-28] **Section:** [3.4]
2	CO9	Yes	The project demonstrates adherence to ethical principles by prioritizing patient privacy, obtaining informed consent, and transparently documenting the research process, ensuring responsible knowledge dissemination and societal well-being through the ethical application of	**Page no:** [53] **Section:** [6.3]

			advanced aquaculture technologies which comply with **CO9**.	
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges in fish species classification.	**Page no:** [29-35, 36-49, 54, 55] **Section:** [4.2, 4.3, 5.2, 6.4, 7.2]

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