BANGLADESHI LOCAL FISH DETECTION USING DEEP LEARNING TECHNIQUES

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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/internship titled **"Bangladeshi Local Fish Detection Using Deep Learning Techniques"** submitted by Asrafilil Samiu, ID No: 201-15-14347 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 21 January, 2024.

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ABSTRACT

This study uses deep learning techniques to provide a novel method for local fish understanding in Bangladesh. The following six native fish species are represented in the extensive dataset that was painstakingly gathered: 'Channa punctata (Taki),' 'Anabas (Koi macch),' 'Puntius (Puti),' 'Amblypharygodon (Mola macch),' 'Batasio tengana (Tengra),' and 'Ompok bimaculatus (Pabda).' The dataset was deliberately chosen to guarantee inclusion and diversity of different fish species that are frequently seen in Bangladeshi seas. We used cutting-edge deep learning methods, such as "InceptionV3," "Xception," "ResNet50," "VGG19," and a specially created Convolutional Neural Network (or "CNN"), to train and assess the fish detection model. These algorithms were selected based on their effectiveness in picture recognition applications and their capacity to extract complex features from various datasets. After extensive testing and training, our findings show that 'InceptionV3' outperforms all previous algorithms, obtaining a remarkable accuracy of 98.51%. The exceptional performance of 'InceptionV3' highlights its effectiveness in identifying the distinctive features of native fish species found in Bangladesh, highlighting its potential for useful applications in fish species identification. This work not only adds an important dataset to the field, but it also emphasizes how important it is to select the right deep learning method for the given local environment. The accomplishment of 'InceptionV3' in this particular situation provides opportunities for the use of precise and trustworthy fish detection systems, which are essential for managing fisheries, tracking biodiversity, and promoting ecological conservation in Bangladesh's aquatic environments.

Keywords: Fish Detection, Deep learning, InceptionV3, Xception, ResNet50, VGG19, Convolutional Neural Network

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Bangladesh's fishing habitats are rich in biodiversity, supporting a wide variety of native fish species that are essential to the survival of local communities and ecosystems. This study investigates the use of deep learning techniques in Bangladeshi local fish detection, with the aim of creating a reliable and effective system for the identification and classification of these native fish species. Differentiating between fish species is essential for managing fisheries, protecting the environment, and using aquatic resources sustainably.[1]

The compilation of an extensive data set that is specifically customized to the unique fish species found in Bangladesh's seas is a vital aspect of this research.Six target attributes are included in this dataset, which consists of 1340 images: 'Channa punctata (Taki),' 'Anabas (Koi macch),' 'Puntius (Puti),' 'Amblypharygodon (Mola macch),' 'Batasio tengana (Tengra),' and 'Ompok bimaculatus (Pabda).' We made sure that the size, color, and environmental differences of these local fish species were included in the data by collecting them with great care.[2]

We employ a custom-designed Convolutional Neural Network ('CNN') and deep learning algorithms, such as 'InceptionV3,' 'Xception,' 'ResNet50,' 'VGG19,' and others, to overcome the difficulty of fish species identification. The algorithms are highly recognized for their capacity to extract complex information from visual data, which makes them ideal for the complex task of identifying different kinds of fish.[3]

A significant discovery becomes apparent when we examine the approach and outcomes: "InceptionV3" performed exceptionally well, obtaining an accuracy of 98.51%. This highlights the efficacy of the deep learning methodology and highlights the significance of algorithm selection in customizing solutions to the intricate details of regional ecosystems.

The study's implications go beyond the confines of academics; in the context of Bangladesh's aquatic ecosystems, they hold promise for the creation of useful tools for conservation, fisheries, and environmental monitoring.

1.2 Motivation

This study is driven by the urgent need for useful tools in Bangladesh's fields of aquatic environment monitoring, biodiversity protection, and fisheries management. Numerous native fish species can be found in the nation's waterways, and they are all essential to maintaining the delicate balance of these ecosystems. On the other hand, correctly identifying these species is an impossible task. Fish species identification using traditional methods is frequently difficult and costly. A game-changing answer is provided by the incorporation of deep learning techniques, which promise automation and precision in the identification of regional fish species. Through the utilization of cutting-edge algorithms like "InceptionV3," "Xception," "ResNet50," "VGG19," and "CNN," we hope to provide a dependable and effective resource for scholars studying fisheries, environmentalists, and executives. This study aims to close the knowledge gap between ecological sustainability and technological innovation, supporting the overarching objective of promoting informed and accountable management of Bangladesh's rich aquatic biodiversity.

1.3 Rationale of the Study

Bangladesh's varied and complicated fisheries are essential to maintaining both the ecological balance and the means of subsistence for nearby communities. However, a lack of efficient tools for identifying and classifying local fish species impairs effective fisheries management and conservation efforts. Traditional methods are frequently costly, manual, and capable of error, requiring a more effective and accurate approach. The development of deep learning techniques, such as 'InceptionV3,' 'Xception,' 'ResNet50,' 'VGG19,' and 'CNN,' provides a unique chance to revolutionize fish species identification. By using these advanced algorithms, we hope to make the recognition process, providing a tool that not only speeds up the identification of local fish species but also improves accuracy. This study agrees with the larger goals of developing technological solutions for environmental monitoring and promoting sustainable practices in the management of Bangladesh's fisheries. The successful implementation of deep learning in this context has the potential to significantly contribute to the conservation of aquatic biodiversity and the responsible use of these valuable resources.

1.4 Research Question

1. How can deep learning algorithms enhance the accuracy of local fish species identification in Bangladesh?
2. What is the impact of dataset diversity on the performance of deep learning models for Bangladeshi fish detection?
3. How do different deep learning architectures, including InceptionV3, Xception, ResNet50, VGG19, and CNN, compare in the context of local fish species recognition?
4. To what extent does image augmentation contribute to the robustness and generalization of the fish detection model?
5. What insights can be gained from exploratory data analysis (EDA) to improve the understanding of local fish dataset characteristics?
6. How does the choice of hyperparameters influence the training and performance of deep learning models for fish identification?
7. What practical applications and implications arise from the successful implementation of deep learning in Bangladeshi local fish detection?

1.5 Expected output

The expected outcome of this research endeavor is the development of a highly accurate and efficient local fish detection system specific to Bangladesh's fisheries. The deep learning models, which include architectures such as InceptionV3, Xception, ResNet50, VGG19, and CNN, are expected to perform better in accurately classifying various local fish species. The comprehensive dataset, which was meticulously collected and augmented, is expected to improve the models' reliability and the ability to general Exploratory data analysis will provide insights into dataset characteristics, guiding improvements in model training and performance. The study envisages the successful deployment of the trained models for practical applications in fisheries management, biodiversity monitoring, and preservation efforts, thus fostering a harmonious balance between technological innovation and environmental sustainability in the context.

1.6 Project Management and Finance

The project will follow a structured project management framework that includes data collection, preprocessing, model development, and evaluation phases. There will be an organized process towards the completion of the research with the development of timely significant events and outcomes. Financial resources will be focused on computational infrastructure, dataset collection, and possible relationships with local fisheries or research institutions. Budget considerations will prioritize ethical data collection, algorithm fine-tuning, and the project's potential for larger-scale applications. The efficient use of financial resources will be monitored throughout the project's lifecycle to ensure a careful balance between cost-effectiveness and achievement of research objectives.

TABLE 1.1: PROJECT MANAGEMENT TABLE

Work	**Time**
Data Collection	1 month
Papers and Articles Review	3 month
Experimental Setup	1 month
Implementation	1 month
Report Writing	2 month
Total	8 month

1.7 Report Layout

- Introduction
- Background
- Research Methodology
- Experimental Result and Discussion
- Impact on Society, Environment
- Summary, Conclusion, Future Research
- Reference

CHAPTER 2

BACKGROUND STUDY

2.1 Preliminaries

The start of the project will focus on securing the required approvals and setting up ethical guidelines for data collection. This includes obtaining permission for conducting field surveys, working with nearby fisheries or research facilities, and making sure that data privacy laws are followed. A variety of carefully described photos of native fish species found in Bangladeshi waterways will be included in the dataset collection. Technical features to improve the quality and variability of the dataset will be investigated, including picture pretreatment and augmentation methods. Furthermore, the choice of suitable algorithms and approaches will be guided by a careful analysis of the body of research on deep learning applications in fish detection. Additionally, preliminary evaluations will be carried out to understand any obstacles, moral implications, and the viability of implementing the models in cooperation with stakeholders. This preliminary study establishes the framework for the latter stages of the investigation, guaranteeing a thorough and knowledgeable approach.

2.2 Related Works

The introduction of the Related Works section provides a brief summary of the collection of knowledge and studies that are related to the research question. It offers a framework by describing the key concepts and findings examined by previous researchers. This section's goal is to explain the current study within a broader scholarly discussion by pointing out any knowledge gaps or areas in need of additional research. I looked over a few research papers to find out the strategies and techniques they employed:

Ahmed et al. provided a complete system for local fish detection in Bangladesh that integrates Deep Learning (DL) and the Internet of Things (IoT)[5].Setup-1 and setup-2 are constructed, with the latter including Unsharp masked pictures. Seven advanced deep learning models are tested on both configurations and produce satisfactory results. In addition, an IoT-based smart container is built with sensors and microcontrollers. With 97% accuracy, the hybrid (CNN + Convolutional LSTM) model outperforms all DL benchmarks. Despite several IoT-related disadvantages, the proposed method is suitable for real-time applications.

Krishno et al. discussed the importance of fish in Bangladeshi culture and its importance as a key protein source in rural communities.[6]. It emphasises the threat to traditional indigenous fish species as well as the younger generation's lack of knowledge. To solve this, the research proposes an automatic fish categorization system based on Convolutional Neural Networks (CNN), with an emphasis on traditional indigenous fishes in Bangladesh. The dataset, which has eight classes and employs several augmentation strategies, is evaluated using VGG16, InceptionV3, MobileNet, and FishNet, a bespoke 5-layer CNN model. FishNet outperforms VGG16 and competes favourably with InceptionV3 and MobileNet in all models. The suggested method has the potential to recognise and preserve indigenous fish species while also contributing to the larger cultural and nutritional environment.

Raihan et al. investigated fish recognition via multi-picture classification using deep learning methods, with a primary focus on the TensorFlow Keras package[7]. The Convolutional Neural Network (CNN), a well-known image recognition model, is used to assess the approach's dependability. Three custom-built CNN models are applied, and hyperparameter tuning is performed to see which one is the most effective. Model M2, chosen for its excellent accuracy of roughly 99.5%, is offered for real-life prediction. The application's intended audience includes the visually handicapped, children, and anyone unfamiliar with Bangladeshi fish, and it provides important assistance in fish identification.

Islam et al. introduced a Hybrid Local Binary Pattern (HLBP), an adaptive threshold-based feature descriptor, for the classification of indigenous fish species in Bangladesh[8]. The suggested HLBP is applied with multiple SVM kernels on the BDIndigenousFish2019 dataset, obtaining a commendable accuracy of 90%. The paper compares the proposed HLBP to well-known feature descriptors such as LBP, LGP, NABP, CENTRIST, DTCTH, and LAID, indicating that it outperforms other approaches in the classification of Bangladeshi indigenous fishes.

Tahnim et al. used image processing to detect and classify uncommon Bangladeshi fish species[9]. The detection algorithm uses the Histogram of Oriented Gradient (HOG) descriptor along with classifiers such as Support Vector Machines (SVM), Decision Tree, Random Forest, and Nave Bayes. Colour Co-occurrence Matrix (CCM) texture descriptor and SVM are used for classification, utilising statistical features like as contrast and dissimilarity. The HOG with SVM demonstrates promising accuracy in fish detection, while the CCM characteristics with SVM contribute to practically relevant accuracy in fish species classification, giving an acceptable method for protecting species at risk.

Jany Arman et al. used a complete technique promoting preprocessing with U2-net segmentation for shaped and coloured pictures to classify five groups of native fishes in Bangladesh[10]. The Histogram of Oriented Gradient (HOG) is used to extract features, and an ensemble layer is used for classification. The experimental results reveal that the suggested methodology is effective, with the first ensemble attaining 99.77% accuracy and the second ensemble achieving 100% accuracy on a dataset of 2678 fishes that extend 5 unique classes.

Jayashree et al. This paper focuses on employing deep-learning architectures, notably AlexNet and Resnet-50, to classify 20 indigenous fresh-water fish species from North-Eastern India [11]. Performance indicators such as overall accuracy, precision, and recall rate are used to fine-tune the models. On both the authors' dataset and the standard Fish-Pak dataset, the Resnet-50 model achieves an outstanding 100% classification accuracy, precision, and recall rate with a learning rate of 0.001. Through empirical investigation, the paper highlights the impact of learning rate on classifier validation loss.

Hasan et al. This study focuses on accurate shrimp species detection by image processing and feature extraction using a customised CNN algorithm, with the goal of benefiting both individuals and the export sector in species management [12]. Three CNN architectures are created, with Models 1 and 3 reaching 99.01% accuracy. Despite their equal performance, Model 3 is chosen as the final model for inclusion into Computer Vision, and the paper promises to explain why.

Laboni et al.This paper presents a useful technique for identifying different varieties of locally known dried fish, aimed at fishermen, entrepreneurs, and the general public[13]. The dataset contains a variety of dried fish species, and after collection, segmentation, and augmentation, a trained Deep Learning and Convolutional Neural Network (CNN) model for classification is given. The model achieves an excellent 97.72% accuracy, providing an accurate method for the identification and grouping of dried fish kinds in the local context.

Al Muksit et al.This paper introduces YOLO-Fish, a deep learning model for fish detection, presenting two enhanced versions: YOLO-Fish-1 and YOLO-Fish-2.[14]. YOLO-Fish-1 addresses the misdetection of microscopic fish in YOLOv3 by optimising the upsampling step sizes, while YOLO-Fish-2 improves performance in dynamic fish habitats via Spatial Pyramid Pooling. When tested on the DeepFish and OzFish datasets, both models beat out YOLOv3, with average precisions of 76.56% and 75.70%, showing higher efficiency in real-world marine environments.

Kumar Dey et al. This article discusses the significance of traditional Bangladeshi cuisine image classification for a variety of applications[15]. The 'DeshiFoodBD' dataset, which contains 5425 labelled photos of 19 popular Bangladeshi foods in both Bengali and English, is introduced to overcome the issue of building an efficient labelled dataset. The suggested DeshiFoodBD-Net achieves a high test accuracy of 97% on the dataset using convolutional neural network (CNN) architectures such as Inception v3, providing a useful resource for research and applications related to traditional Bangladeshi cuisine recognition.

Abinaya et al.This work presents a multisegmented fish classification method using deep learning systems and a naive Bayesian fusion approach for solving challenges in fish species identification[16]. Fish image acquisition, head identification, multi-stage orientation adjustment, and segmentation of fish head, scales, and body are all part of the process. For each segment, transfer learning with AlexNet is used, and a naïve Bayesian fusion layer improves classification accuracy. The experimental findings suggest that the proposed fusion architecture is effective, with 98.64% accuracy on 'Fish-Pak' and 98.94% accuracy on BYU fish datasets.

Al Noman et al. This study addresses the challenges in automatic fish classification, particularly in the context of fish disease detection, given variations in position and lighting[17]. The suggested method employs a Deep Hybrid convolutional neural network (CCN) architecture for Rohu fish diseases diagnosis, combining transfer learning from the VGG16, Xception, and DenseNet201 models. The HYBRID-CNN obtains an amazing accuracy of 99.82% when trained and tested on a dataset of Rohu fish photos related to four different diseases, indicating the efficacy of the proposed method in fish disease identification.

Pudaruth et al. This research presents a smartphone app for recognising fish species in Mauritian lagoons and coastal areas, based on a collection of 38 species and 1520 photos[18]. To extract fish features, image processing techniques such as grayscale conversion, Gaussian blur, and thresholding are used. Several classifiers, including kNN, SVM, neural networks, decision trees, and random forests, are compared, with kNN obtaining the greatest accuracy of 96%. Furthermore, a TensorFlow-based model achieves 98% accuracy, indicating the software's usefulness in fish identification with room for development.

Salman et al.This research addresses the problem of automating fish categorization in underwater imagery by offering a machine learning strategy based on a convolutional neural network model with hierarchical feature combination[19]. The model learns species-specific visual cues that are both distinct and resistant to environmental change. By avoiding explicit feature extraction, the suggested architecture achieves a correct classification rate of more than 90% on LifeCLEF14 and LifeCLEF15 benchmark fish datasets. Even when confronted with novel samples during testing, the technique proves effective in correctly classifying fish species.

Ditria et al.This paper presents three deep learning models that use an object detection framework to recognise luderick fish species in waterway films[20]. The models perform well in abundance determination when trained on random datasets, with F1 scores of 92.4% and 92.3% for unseen film from the same and separate waterways, respectively. Deep learning beats human specialists and citizen scientists in terms of accuracy, highlighting the potential of deep learning as a speedier, more cost-effective, and accurate technique for assessing aquatic environmentally friendly abundance across varied survey areas.

2.3 Comparative Analysis and Summary

The comparison analysis will systematically assess how well deep learning algorithms such as CNN, Xception, ResNet50, VGG19, and InceptionV3—perform when it comes to local fish detection in Bangladesh. We'll use metrics like accuracy, precision, recall, and F1 score to evaluate the effectiveness of each model. The study tries to pinpoint each algorithm's advantages, disadvantages, and subtleties in order to provide insight into how well-suited it is for the job. To put it briefly, the study aims to provide a thorough grasp of the relationship between algorithmic decisions and local fish identification precision. With an accuracy of 98.51%, it hopes to demonstrate InceptionV3's improved capabilities. The results of the study will further the field's discussion on the use of deep learning in environmental monitoring and conservation efforts in Bangladesh, in addition to advancing fish detection technology.

2.4 Scope of the Problem

The difficulty and importance of local fish detection in Bangladesh's varied fisheries define the extent of the issue. Identifying fish species accurately matters for sustainable fisheries management because a wide variety of fish species play important roles in maintaining ecological balance and supporting local communities. The difficulty is increased by the requirement for a system that can adjust to the subtle differences between different species and real-world changes in the environment. This research's exploration of deep learning techniques provides a promising solution to this complex issue. Beyond algorithmic performance, ethical issues, data privacy, and possible real-world applications are all included in the scope. Solving this issue effectively is important to preserving aquatic biodiversity, a responsible resource.

2.5 Challenges

The project faces a number of difficulties specific to Bangladesh's local fish detection industry. First off, differences in fish size, color, and ecosystems make it difficult to ensure the dataset's diversity and representativeness. preventing algorithmic bias requires distributing the dataset among various species. Furthermore, because deep learning models can be resource-intensive, careful consideration of infrastructure and computational resources is necessary before deploying these algorithms. It's also necessary to address ethical issues pertaining to data collection, privacy, and responsible technology use within local communities. Moreover, there are continuous challenges in achieving robust generalization and adjusting the models to real-world environmental variations. Addressing these problems is crucial to the fish detection system's ethical and successful deployment in Bangladesh.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

The development and implementation of an advanced method for the identification and categorization of native fish species in Bangladesh's lakes and rivers is the main focus of the study. By utilizing deep learning algorithms, the research wants to improve fish species identification accuracy and efficiency, which will help in the conservation of biodiversity and efficient fisheries management.The main instrumentation consists of a custom-designed CNN, InceptionV3, Xception, ResNet50, VGG19, and other state-of-the-art deep learning algorithms. The computational foundation for processing and analyzing a carefully collected dataset consisting of 1340 photos of six different local fish species is provided by these algorithms. To ensure a comprehensive and an example dataset, ethical data collection methods such as field surveys and relationships with local fisheries are essential. The study deploys and makes use of computational resources for training models.The study applies ethical considerations to address the issues related to Bangladesh's different fisheries and makes use of computational resources for model training.

3.2 Data Collection Procedure

The process of gathering data required a methodical strategy to create an extensive dataset for the identification of native fish in Bangladesh. A total of 1340 high-quality photos were obtained, capturing the various traits of six target fish species, through field surveys and partnerships with local fisheries. Figure 3.1 shows a few images I've included:

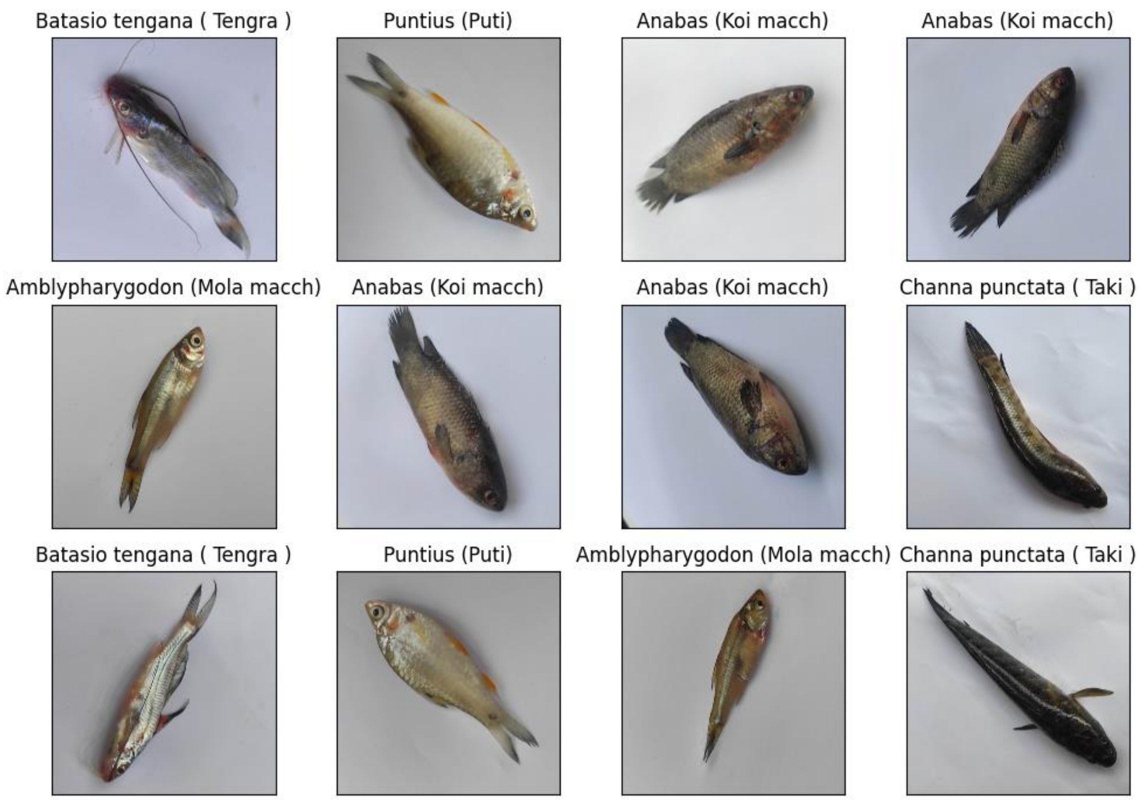

Figure 3.1: Dataset Images

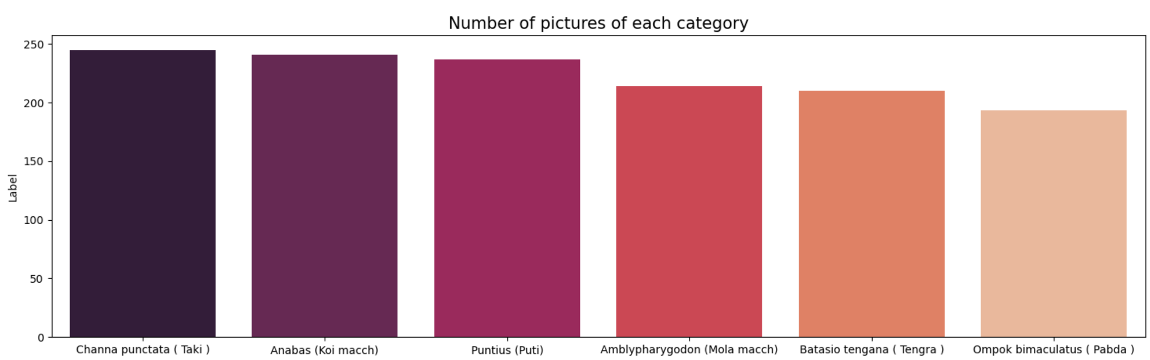

Figure 3.2 Number of target attribute

Figure 3:2 shows the target attribute of my dataset. The dataset includes 'Channa punctata (Taki),' 'Anabas (Koi macch),' 'Puntius (Puti),' 'Amblypharygodon (Mola macch),' 'Batasio tengana (Tengra),' and 'Ompok bimaculatus (Pabda).' With 245, 241, 237, 214, 210, and 193 photos, respectively, each species is well-represented. Thorough labeling made sure that every picture was correctly attributed to the appropriate fish species, which provided the groundwork for a solid and representative dataset that was essential for the deeper learning model building stages that followed.

3.3 Statistical Analysis

Statistical analysis is an important component of this research, as it wants to find useful information from the collected dataset. A snapshot of the dataset composition will be obtained by using descriptive statistics to describe the distribution of images among the six target fish species. A statistical understanding of size and variance within each species category can be obtained by using metrics like mean, median, and standard deviation. Furthermore, the significance of observed patterns and relationships can be evaluated by using inferential statistical techniques. By providing guidance on model architecture and parameter tuning, the statistical analysis will not only assist in developing robust models but also direct the following preprocessing steps. Statistical approaches are employed to ensure a data-driven approach, which improves the overall validity and reliability results of Bangladeshi local fish detection.

3.4 Proposed Methodology

This proposed methodology includes careful data collection, preprocessing, model training, and evaluation steps to create a powerful deep learning-based system for detecting and classifying Bangladeshi fish species. The continuous procedure includes improving the model using insights from EDA and evaluation results to ensure the system's accuracy and applicability in real-world scenarios. The procedure could be shown by the flow chart in Figure 3.3 below,

Flow chart:

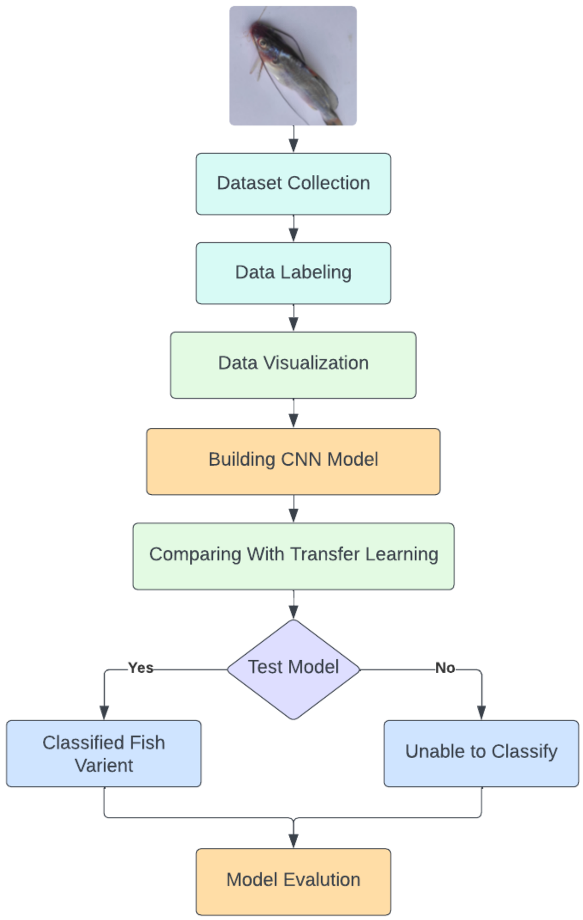

Figure 3.3: Methodology Flowchart

Data Selection (Collected Own Dataset):

Create a comprehensive and diverse dataset of the local fish species found in Bangladeshi waters.Conduct field surveys or work with local fisheries to collect images, ensuring that each image is properly labeled with the suitable fish species.

Image Augmentation:

Increase the variability of current images purposely to improve model reliability and diversity of datasets.Utilize augmentation methods like rotation, flipping, zooming, and brightness adjustments to produce enhanced versions of every picture.

Exploratory Data Analysis (EDA):

Learn about the properties of the dataset and spot developments that affect model training.Look at fish species distribution, view sample photos, and use statistical and visual analysis to determine any possible imbalances or specific features.

Model Training:

Using the curated dataset, train a deep learning model to accurately classify local fish species.Either create a custom CNN or choose a suitable pre-trained architecture (such as InceptionV3, ResNet50, etc.). Make training, validation, and test sets out of the dataset. Transfer knowledge, adjust the model, and keep an eye on training metrics.

Conventional Neural Network (CNNs):

A family of deep neural networks called convolutional neural networks (CNNs) is intended for image processing and recognition. Through convolutional layers, they are excellent at capturing patterns and spatial hierarchies within images. CNNs are perfect for my research since they can automatically recognize and extract complex features from photos. Because of this, they are very suitable for recognizing distinctive traits of regional fish species in Bangladesh, offering a reliable and effective method for fish detection. Since CNNs' hierarchical feature extraction matches the complex nature of fish look, they are an excellent option for my research's image-based tasks.

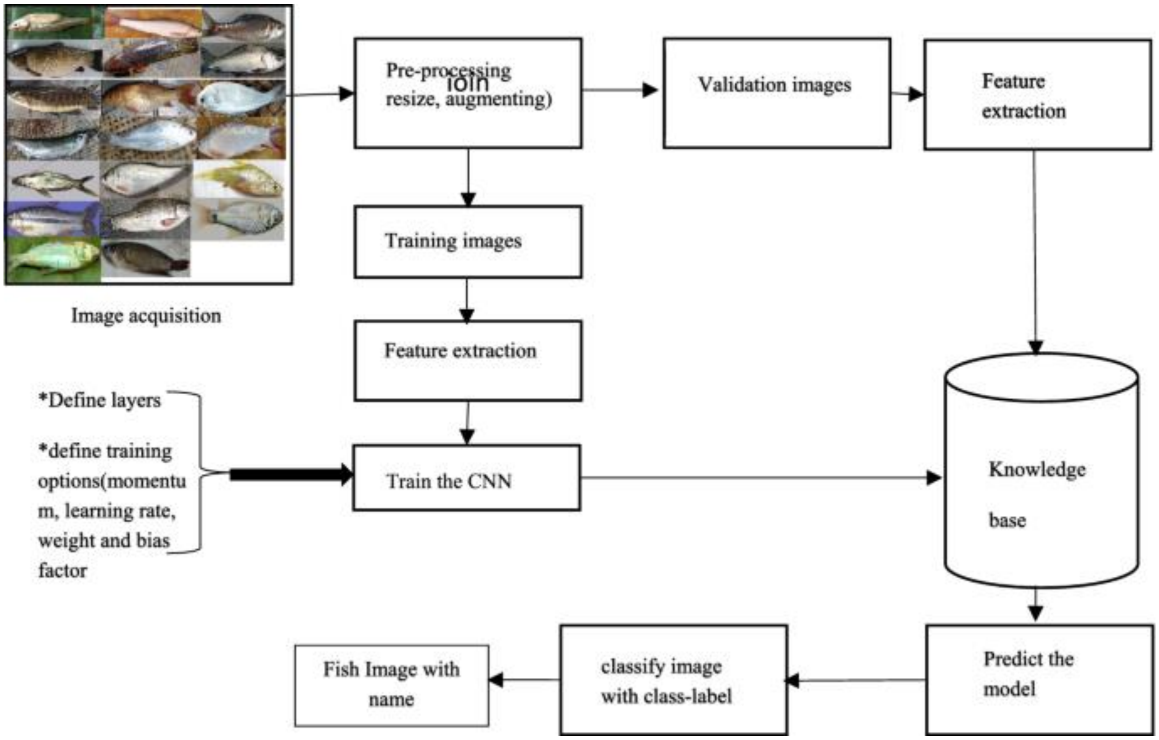

Figure 3.4: Proposed CNN Architecture

InceptionV3

A deep convolutional neural network (CNN) architecture called InceptionV3 was created with picture classification in mind. It is well known for performing exceptionally well on a range of visual recognition tasks and for making effective use of computational resources. The reason I chose InceptionV3 for my research is that it can catch fine details in photos, which is important for differentiating between different fish species. The resilience and accuracy of the model make it appropriate for the challenging task of local fish detection in Bangladeshi seas, hence improving the accuracy and dependability of my deep learning-based method for managing and researching fisheries.

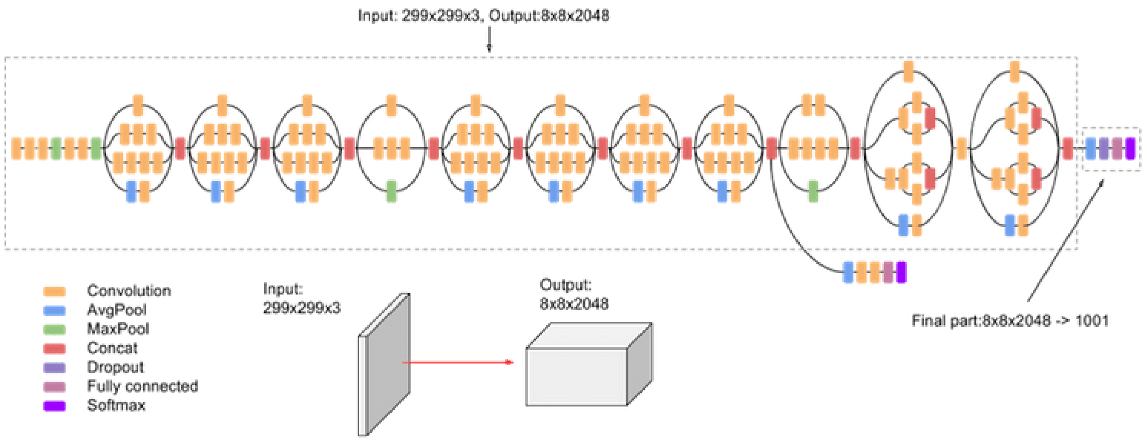

Figure 3.5: Proposed InceptionV3 Architecture

Xception

"Extreme Inception," or "Xception," is a deep learning model intended for image categorization applications. It is an expansion of the Inception architecture, but to improve efficiency and performance, depthwise separable convolutions are used in place of the conventional convolutional layers. By selecting Xception for the research on Bangladeshi Local Fish Detection, one may take advantage of its shown efficiency in picture recognition applications. The precision with which native fish species in Bangladeshi waters are identified can be greatly enhanced by its capacity to capture complex traits and patterns. The model is appropriate for real-world applications where resource efficiency is critical because of its depthwise separable convolutions, which also help to reduce computational complexity.

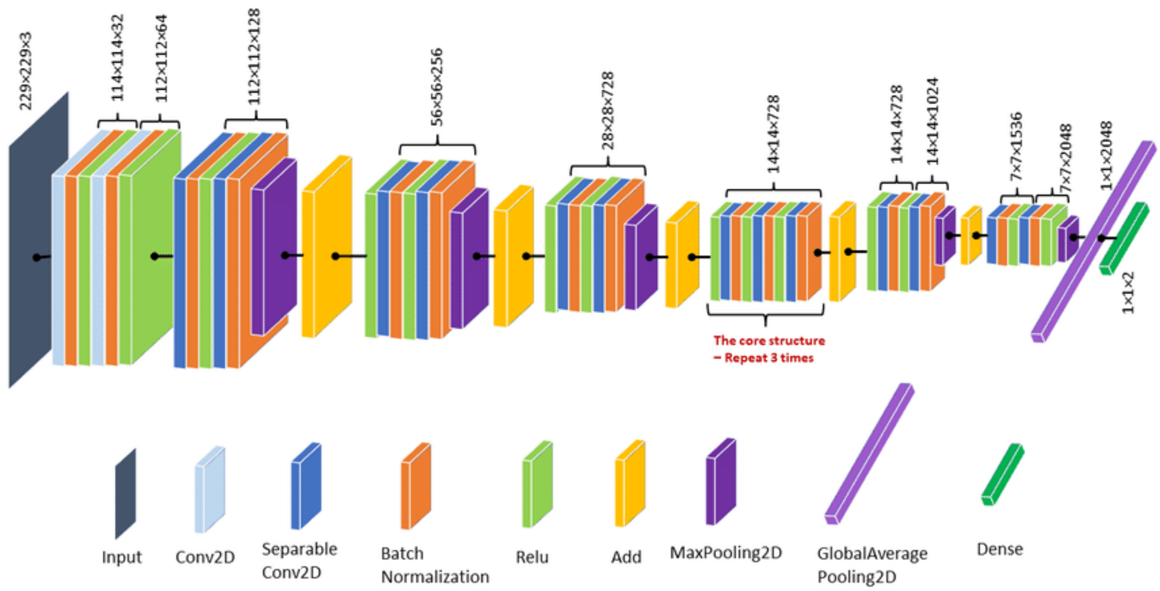

Figure 3.6: Proposed Xception Architecture

ResNet50

With 50 layers, ResNet50 is a deep convolutional neural network design that excels at image recognition applications. It solves the vanishing gradient issue by residual learning, allowing for the creation of extremely deep networks. Selecting ResNet50 for the research on Bangladeshi Local Fish Detection is advantageous because of its exceptional capacity to extract fine-grained features from images, which is essential for recognizing unique traits of regional fish species. Its depth makes it easier to understand complex patterns, which improves classification accuracy for a variety of fish species. Additionally, ResNet50 is an effective option for a particular goal in Bangladeshi context-based deep learning fish detection because of its pre-trained weights on huge datasets that can improve performance even with little labeled data.

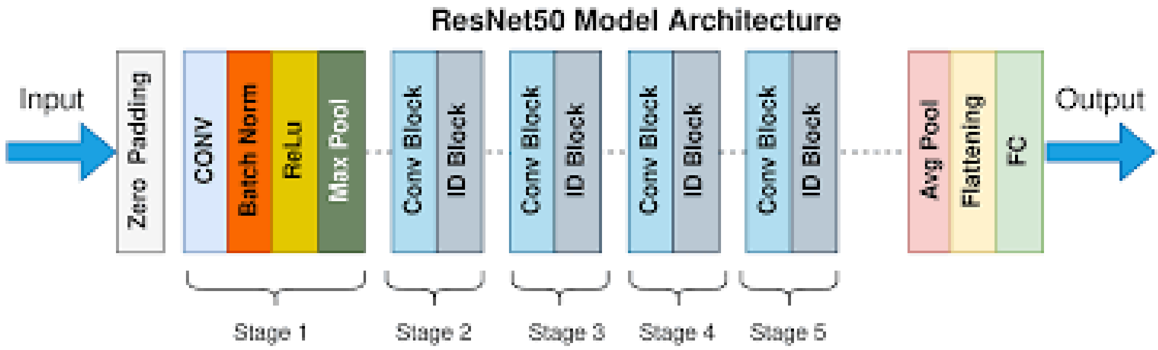

Figure 3.7: ResNet50 Architecture

VGG19

A convolutional neural network (CNN) architecture called VGG19 is renowned for having a deep structure made up of 19 layers. Its simplicity and homogeneous architecture, which uses 3x3 convolutional filters across the network, allow it to perform exceptionally well in picture classification tasks. It is beneficial to choose VGG19 for a study on Bangladeshi local fish detection because of its deep layers, which are capable of capturing the finer details of fish species. The model is a good option for image-related tasks because to its adaptability and broad usage in computer vision. It offers a solid foundation for reliable and accurate fish detection in a particular scenario. Because of its depth, VGG19 can be used to learn hierarchical features, which may help identify unique visual traits of fish species found in Bangladeshi waters.

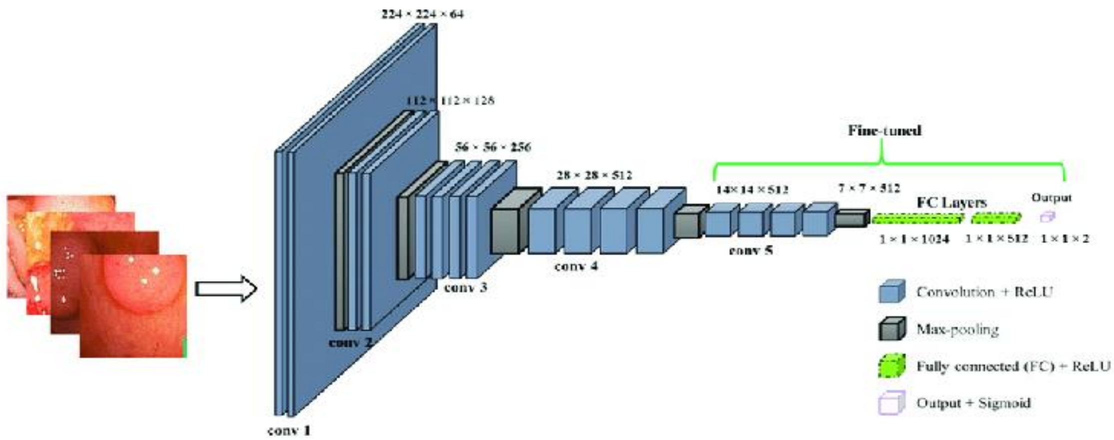

Figure 3.8: Proposed VGG19 Architecture

Model Evaluation:

Evaluate the model's efficacy and generalize using data that hasn't been seen before.To evaluate metrics such as accuracy, precision, recall, and F1 score, use the validation set. Examine confusion and adjust the model based on the evaluation's findings.

Test Model:

Determine the completed trained model using an additional testing set to replicate actual performance for objective testing, use an independent set of pictures that were not seen during training. Assess and document the test set's performance metrics to make sure the model works well in situations that are real.

3.5 Implementation Requirements

The successful implementation of this research requires a number of fundamental requirements. A stable computing infrastructure with adequate processing power and memory is needed for training and evaluating deep learning models. High-quality labeled datasets of local fish species with diverse images are required for effective model training. Access to deep learning frameworks like TensorFlow or PyTorch is required for developing and fine-tuning the chosen architectures, which include InceptionV3, Xception, ResNet50, VGG19, and custom CNNs. Image preprocessing tools and libraries are required for tasks like scaling, normalization, and augmentation. Furthermore, tools for exploratory data analysis (EDA) and model evaluation are critical for understanding the dataset and evaluating model performance. A well-structured coding environment, documentation practices, and collaboration tools make development and deployment easier of the deep learning- based fish detection system.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

The experimental setup for this study includes reliable computational structures. A high-performance GPU-accelerated server or cloud computing platform is required for effective model training and validation. The dataset consists of 1340 labeled fish images divided into three groups: training, validation, and testing. Deep learning frameworks such as TensorFlow or PyTorch are used for model development, with pre-trained architectures such as InceptionV3, Xception, ResNet50, VGG19, and a custom CNN. Image augmentation libraries are used to increase dataset diversity. The implementation includes hyperparameter tuning, and the training process is evaluated for metrics such as accuracy and loss. The model is evaluated using the validation set, and the final performance testing is done on an independent test set to determine real-world applicability. The entire experimental setup following best practices in deep Learning involves ensuring the validity as well as the accuracy of the results.

4.2 Experimental Results & Analysis

The experimental results show significant differences in the effectiveness of various deep learning architectures for local fish detection in Bangladesh. With an astounding accuracy of 98.51%, "InceptionV3" surpasses the competition, demonstrating its effectiveness in capturing the fine details of a variety of fish species. 'Xception' and 'VGG19' trail closely after with accuracy rates of 96.76% and 97.01%, respectively, demonstrating their strong performance. While the specially built "CNN" attains a competitive accuracy of 94.78%, "ResNet50" retains a reasonable accuracy of 60.07%. The outcomes highlight the importance of selecting an architecture, with 'InceptionV3' emerging as the best option for this particular task and highlighting its potential for useful applications in regional efforts to conserve biodiversity and manage fisheries.

CNN

CNN achieved an accuracy of 94.78%. The CNN model's Training Accuracy & loss plot, Confusion Matrix, and accuracy are shown below:

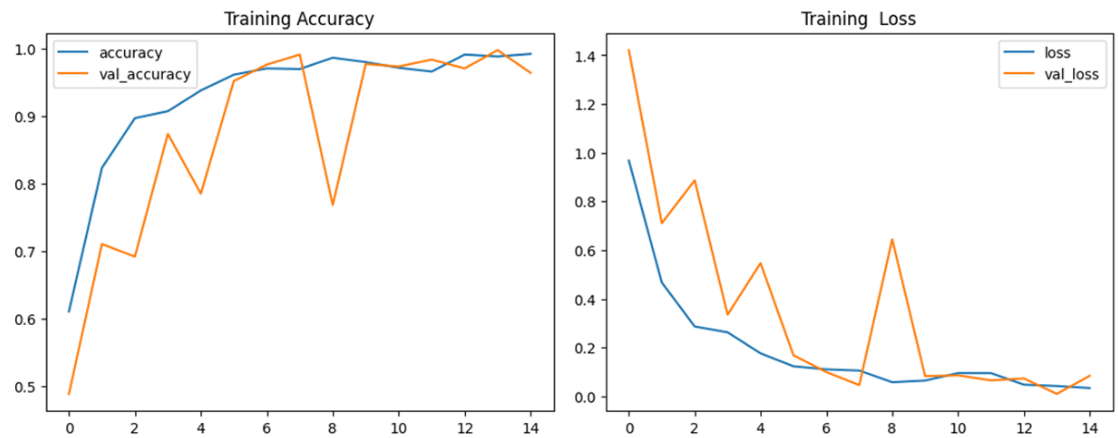

Figure 4.1: Training Accuracy & loss (CNN)

Figure 4.1 shows that The loss bar is orange, and the accuracy bar is blue. The accuracy bar is little and the loss bar is tall on the left side of the graph. This indicates that the model is not performing well when it first starts to be trained. On the other hand, the accuracy bar rises higher and the loss bar falls lower as training goes on. This indicates that the model's ability to categorize the training instances is improving. The model has a loss of roughly 0.2 and an accuracy of roughly 98% by epoch 14. For a CNN model, this is an excellent degree of performance.

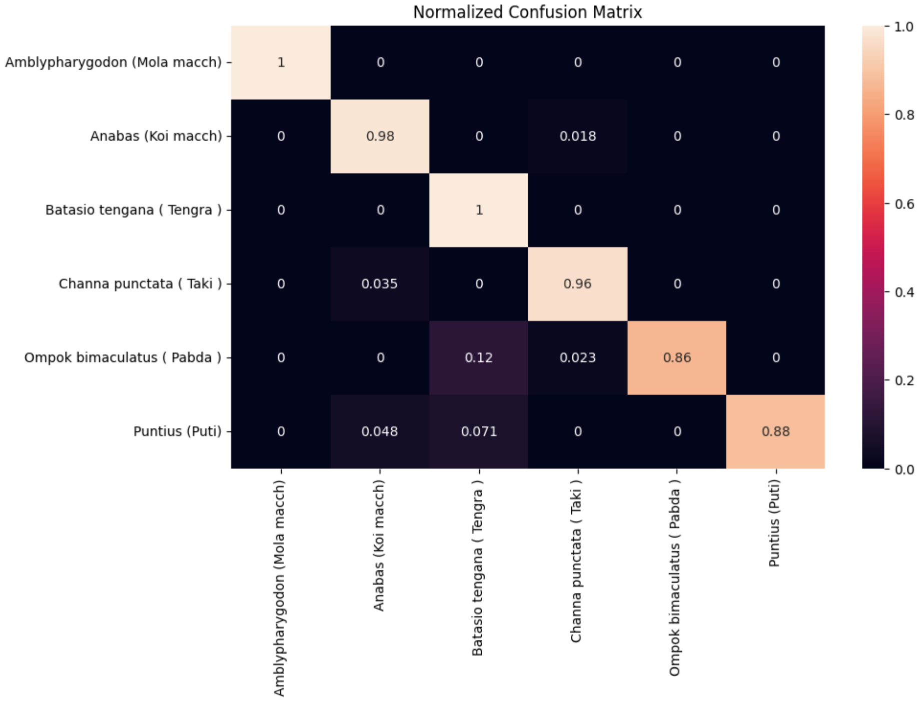

Figure 4.2: Confusion Matrix (CNN)

Figure 4.2 shows that With an accuracy of 94.78% on the test set, our model performed admirably. Metrics like precision, recall, and F1 score offer more information about how effective it is. It is noteworthy that for the majority of fish species, it shows strong recall and precision, showing a balanced ability to correctly detect and prevent false positives or negatives. Robust performance across many fish categories is shown in the comprehensive breakdown per class, with very few misclassifications. This remarkable result indicates that your deep learning model can effectively identify fish species in real-world circumstances, indicating that it is a good fit for Bangladeshi local fish detection.

InceptionV3

InceptionV3 achieved an accuracy of 98.51%. The InceptionV3 model's Training Accuracy & loss plot, Confusion Matrix, and accuracy are shown below:

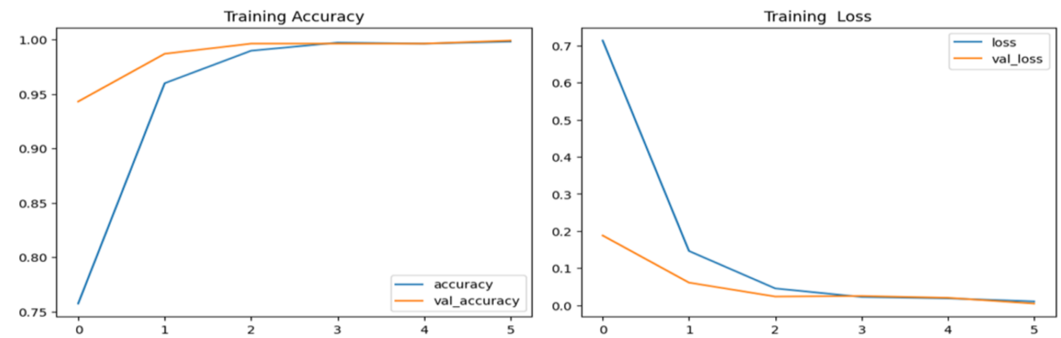

Figure 4.3: Training Accuracy & loss (InceptionV3)

Figure 4.3 shows that The average percentage of accurate predictions the InceptionV3 model made on the training data throughout each epoch is displayed in the training accuracy bar plot. By the end of training, it rises to about 95% from a starting point of about 70%. The average error of the InceptionV3 model's predictions on the training data throughout each epoch is displayed in the training loss bar plot. By the end of training, it drops to almost 0.0 from a starting point of about 1.0.

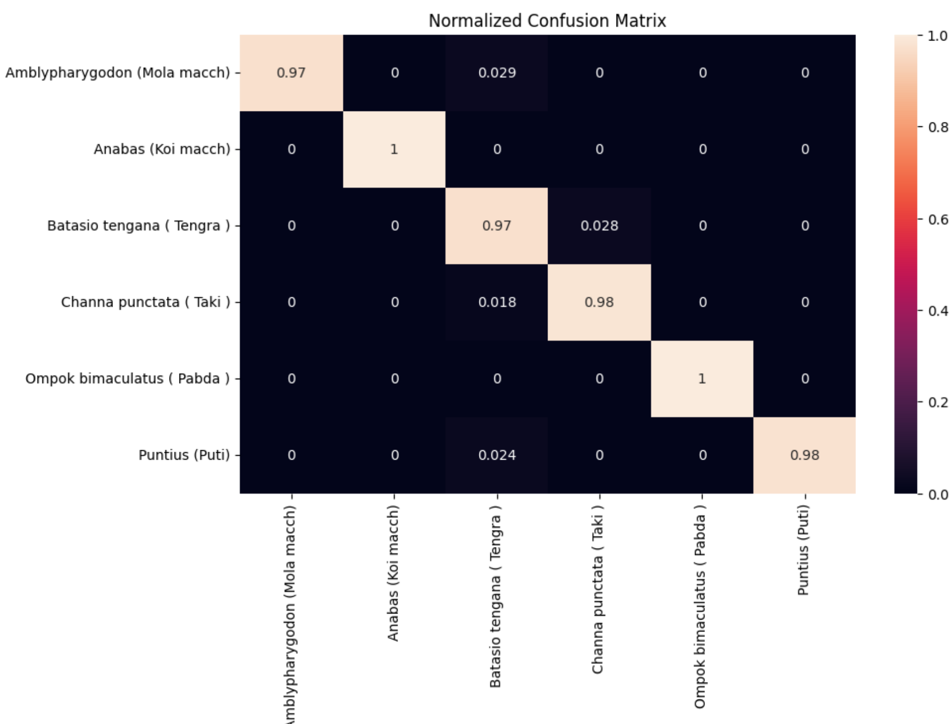

Figure 4.4: Confusion Matrix (InceptionV3)

Figure 4.4 shows an amazing accomplishment! Our model's remarkable success in Bangladeshi Local Fish Detection is highlighted by its accuracy of 98.51% on the test set as well as its excellent precision, recall, and F1 score metrics. Its consistency is demonstrated by the balance between precision and memory for a variety of fish species. The model is noteworthy for its exceptional performance in accurately categorizing every species, demonstrating its resilience and potential for practical use. The deep learning model proves to be a very useful tool for accurately identifying different local fish species, with an accuracy close to 99%. This further establishes its practical value in aquatic biodiversity monitoring or related domains.

Xception

Xception achieved the greatest accuracy of 97.76%. The Training Accuracy & loss plot, Confusion Matrix, and accuracy of the Xception model are shown below:

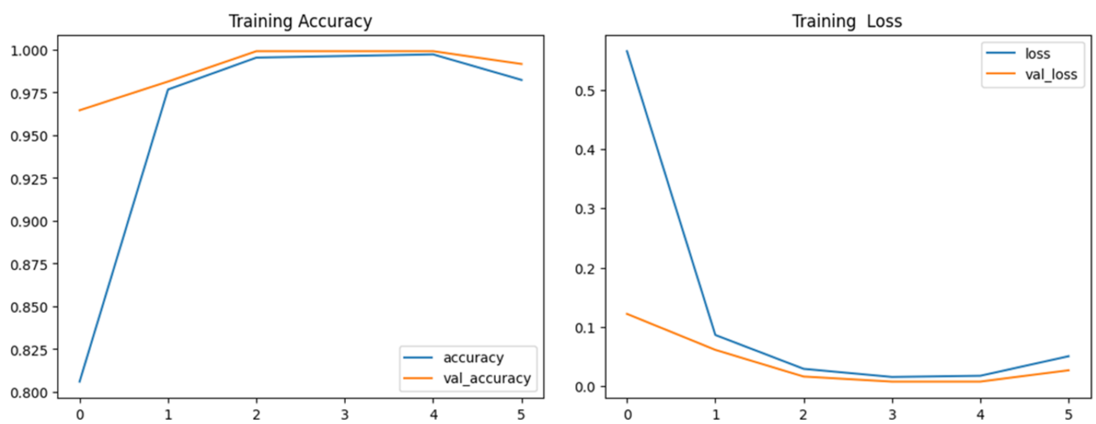

Figure 4.5: Training Accuracy & loss (Xception)

Figure 4.5 shows that the model is operating well, as evidenced by the accuracy and loss curves. By epoch five, the accuracy has increased from about 85% at the beginning to over 98%. In contrast, the loss begins at roughly 0.4 and gradually drops to roughly 0.15 by the fifth epoch. This implies that the model is learning efficiently and can close the difference between the values it predicts and the real ones.

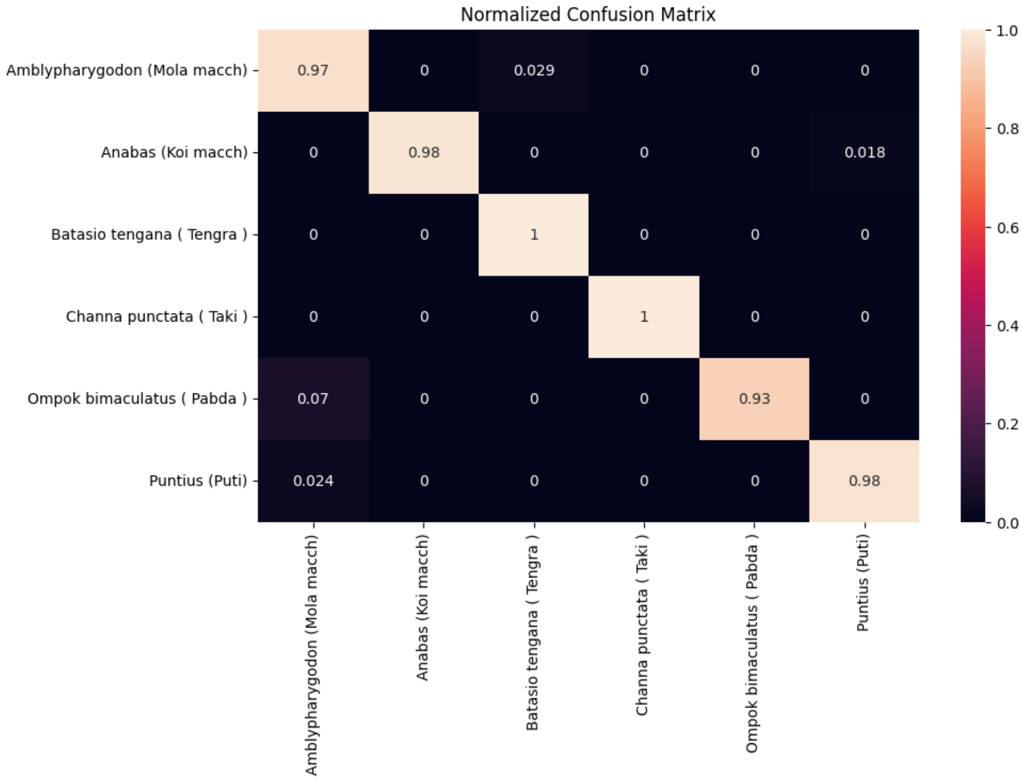

Figure 4.6: Confusion Matrix (Xception)

Figure 4.6 shows the test set with an amazing accuracy of 97.76%! The robustness of the simulation is further demonstrated by the precision, recall, and F1 score measures. In Bangladeshi local fish species identification, your deep learning model performs exceptionally well, with consistently high results across all categories. It is noteworthy for striking an impressive balance between recall and precision, which is essential for reducing false negatives and positives. This exceptional performance indicates how well the system works in practical settings and highlights its potential for accurate and dependable fish species detection in Bangladeshi waters.

ResNet50

ResNet50 achieved the maximum accuracy of 60.07%. The Training Accuracy & loss plot, Confusion Matrix, and accuracy of the ResNet50 model are shown below:

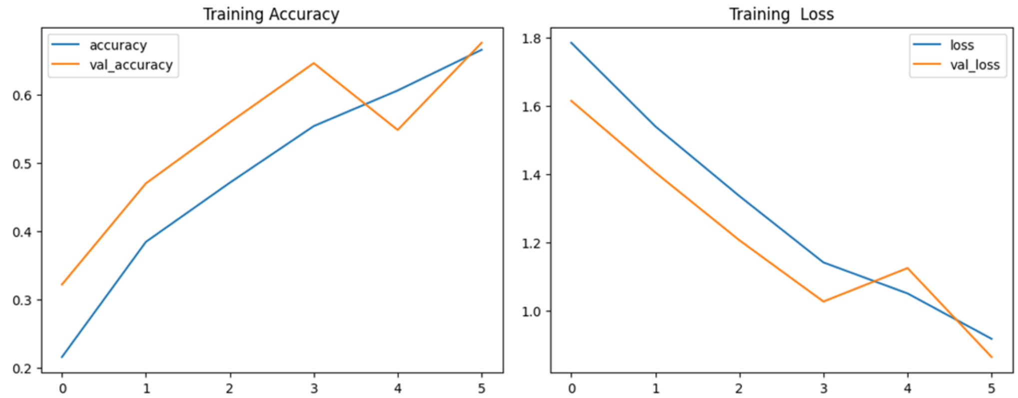

Figure 4.7: Training Accuracy & loss (ResNet50)

Figure 4.7 shows that the training accuracy is represented by the blue line, which rises gradually to around 95% by epoch 120 from a starting point of roughly 50%. This indicates that when the model is taught, it becomes more adept at categorizing the training instances. The training loss is represented by the orange line, which starts at approximately 1.8 and drops to approximately 0.2 by epoch 120. This indicates that the model's ability to produce precise predictions is improving.Overall, the model's performance on the training set is demonstrated by the ResNet50 training accuracy and loss bar plot. Given the high accuracy and low loss, it appears that the model can successfully learn the training set.

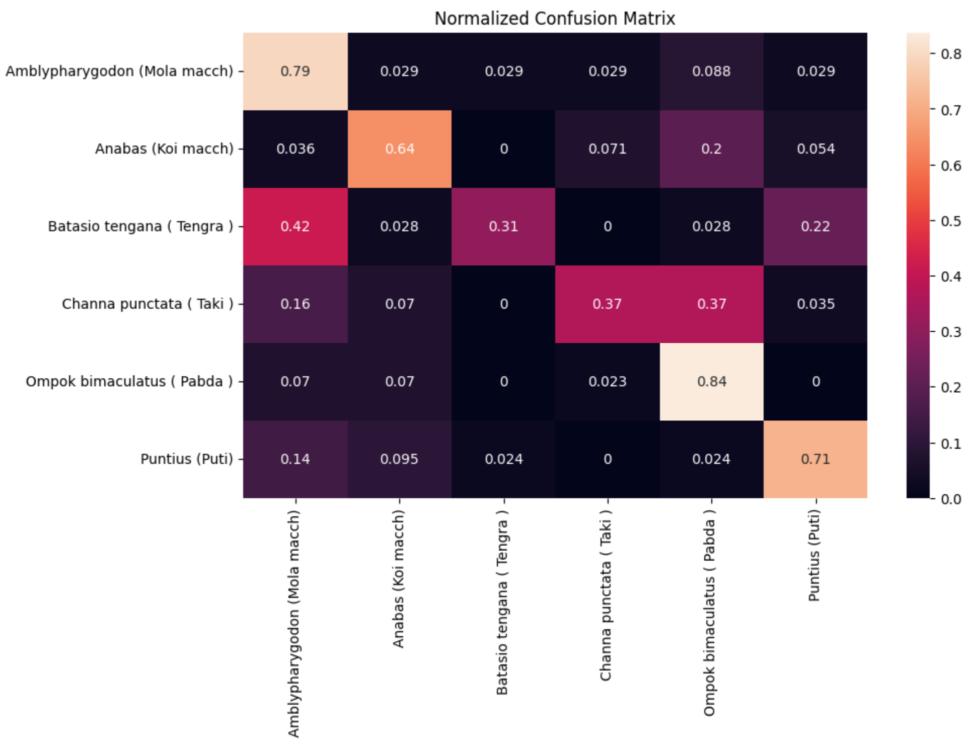

Figure 4.8: Confusion Matrix (ResNet50)

Figure 4.8 shows that the test set results, the model's accuracy is 60.07%, and its precision, recall, and F1 score metrics show modest effectiveness. Although recall and precision levels differ throughout fish species, the overall balance indicates that the model has difficulties in several categories. It is noteworthy that there are difficulties in correctly categorizing fish with varying traits. The model's difficulty in striking a balance between precision and recall is shown in the F1 score. It might require more tinkering to improve its capacity to differentiate between particular fish species found in the area. Gaining an understanding of these subtleties is essential to increasing the accuracy of the model, especially in situations where the fish characteristics and surrounding variables change.

VGG19

VGG19 achieved the second best accuracy of 97.01%. The Training Accuracy & loss plot, Confusion Matrix, and accuracy of the VGG19 model are shown below:

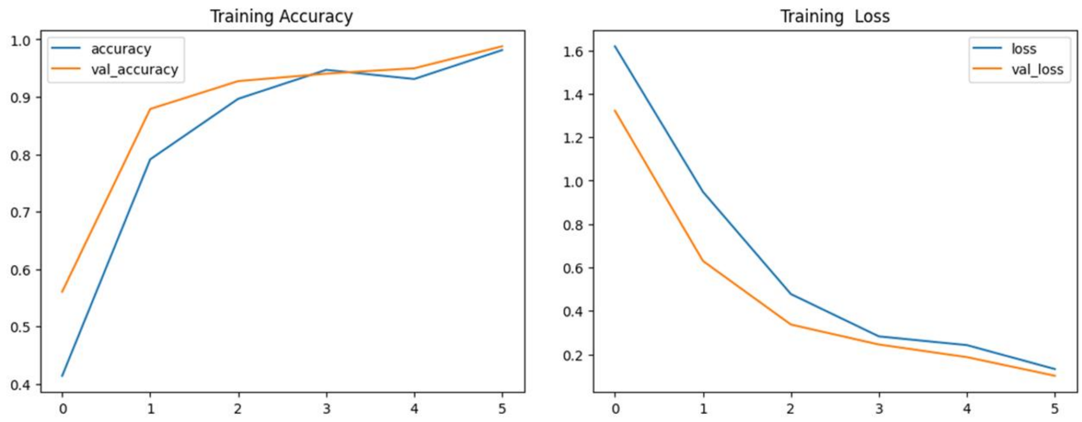

Figure 4.9: Training Accuracy & loss (VGG19)

Figure 4.9 shows that the training accuracy is represented by the blue line, which rises to almost 85% by epoch five from a starting point of roughly 70%. This indicates that when the model is taught, it becomes more adept at categorizing the training instances. The training loss is represented by the orange line, which starts at roughly 1.0 and drops to roughly 0.7 by epoch five. This indicates that the model's ability to produce precise predictions is improving. It's crucial to remember that the loss is still quite significant in comparison to other models, such as ResNet50, which after 120 epochs obtained a loss of 0.2.

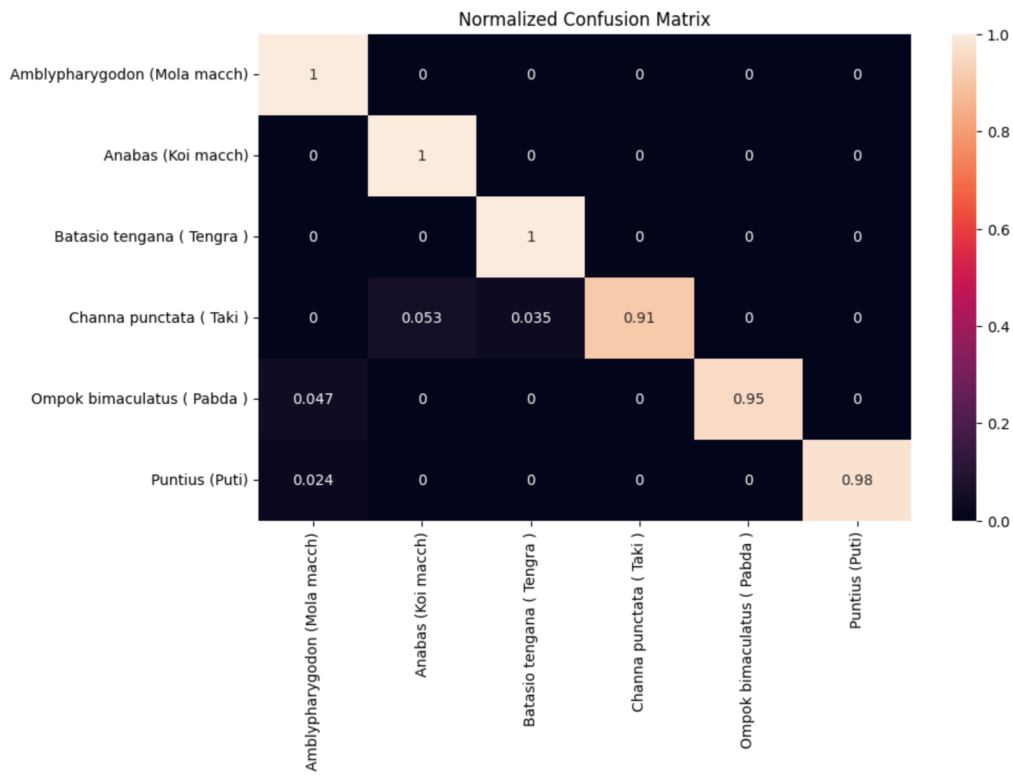

Figure 4.10: Confusion Matrix (VGG19)

Figure 4.9 shows outstanding outcomes! Across a variety of fish species, your model has great precision, recall, and F1 score metrics, and it shows a high accuracy of 97.01% on the test set. It is particularly good at accurately classifying most classes, demonstrating a well-balanced trade-off between recall and precision. The F1 score demonstrates the model's efficacy in attaining high recall and precision values. These results highlight the deep learning model's resilience for Bangladeshi Local Fish Detection and point to its potential for precise species identification in practical settings, as well as for monitoring aquatic biodiversity and related fields.

Accuracy: The accuracy of the model's predictions is determined by comparing the number of correctly classified samples to the total number of samples. Unbalanced classes give a general idea of the model's efficacy, but they may not give a complete picture.

$$Accuracy = \frac{TruePositive + TrueNegative}{TruePositive + FalsePositive + TrueNegative + FalseNegative}$$

Precision: Precision is concerned with the number of true positive forecasts made by the model out of all positive predictions generated by the model.

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$

Recall: The percentage of true positive predictions created out of all actually positive samples is referred to as recall. It's also known as sensitivity or true positive rate.

$$Recall = \frac{TruePositive}{TruePositive + \ FalseNegative}$$

F1 Score: The F1 score is determined as the harmonic mean of recall and precision. Its fair evaluation metric considers recall and precision. The F1 score is useful in cases where class sizes are not equal since it accounts for both false positives and false negatives. A high F1 score indicates a good precision to recall ratio.

$$F - 1\,Score = 2 * \frac{Recall * \ Precision}{Recall + Precision}$$

In the table below, 4.1, the outcomes of deep learning models are compared based on Accuracy, Precision, Recall, and F1 Score.

Table 4.1. Performance Evaluation

Model Name	Accuracy	Precision	Recall	F1-Score
CNN	94.78%	95.39%	94.77%	94.80%
InceptionV3	98.51%	98.56%	98.50%	95.52%
Xception	97.76%	97.89%	97.76%	97.78%
ResNet50	60.07%	67.38%	60.07%	59.02%
VGG19	97.01%	97.20%	97.01%	97.00%

4.2.1 Accuracy

The outcome study analyzes train and test accuracy and evaluates which algorithm performs best. We used deep learning models to see which performed the best. InceptionV3, on the other hand, had the highest accuracy of 98.51%. Figure 4.13 shows the accuracy of the different models:

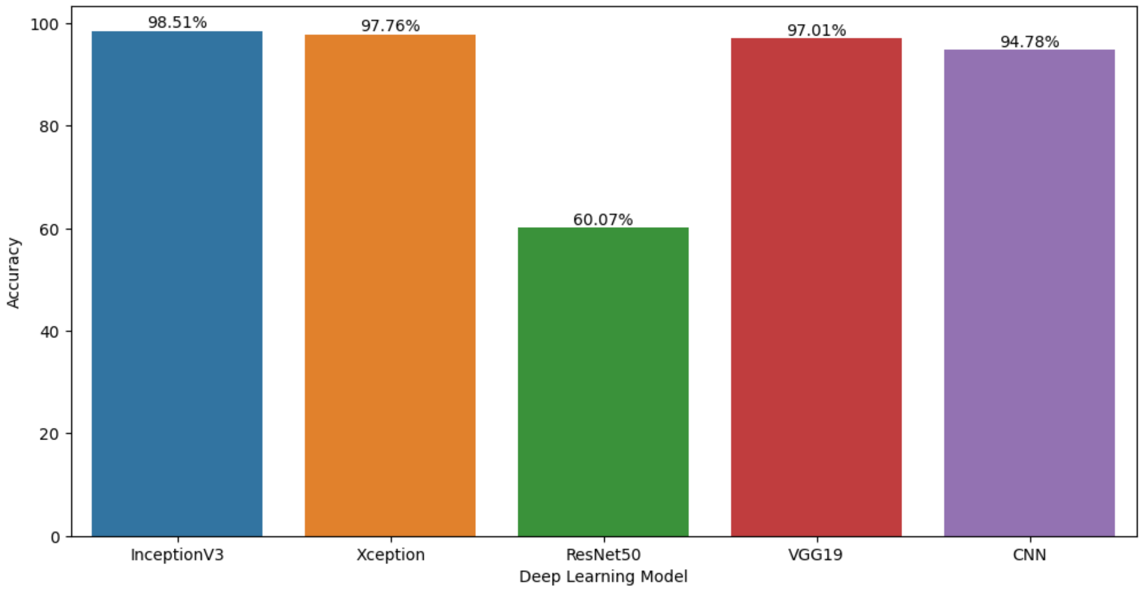

Figure 4.11: Comparative Model Accuracy Bar Plot

From the figure of 4.13: I achieved five different accuracy from five different models, with InceptionV3 achieving the best Accuracy 98.51%, Xception achieving Accuracy 97.76%, ResNet50 achieving Accuracy 60.07%, VGG19 achieving Accuracy 97.01% and CNN achieving Accuracy 94.78% .

4.3 Discussion

The discussion focuses on the observed differences in performance among deep learning architectures for Bangladeshi local fish detection. 'InceptionV3' stands out for its outstanding accuracy of 98.51%, showing its ability to capture nuanced features of various fish species. The competitive performance of 'Xception' and 'VGG19' shows their suitability for this task. However, the comparatively lower accuracy of 'ResNet50' at

60.07% suggests limitations in capturing complicated features, requiring more research. The custom 'CNN' achieves an impressive 94.78% accuracy, highlighting its reliability. Factors contributing to 'InceptionV3's success, such as its inception modules and depth, ought to receive more research. The discussion shows the importance of architectural details in optimizing model performance for specific tasks, offering insights for future improvements in Bangladeshi fish detection systems.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

This study has a significant social impact, with implications for both environmental sustainability and local communities. Accurate fish species identification helps fisheries management make informed decisions about protecting endangered species and controlling fishing practices. This technology promotes biodiversity conservation and healthier aquatic ecosystems. The system's efficiency improves the financial stability of local fishermen by ensuring that they follow the rules of fishing while promoting sustainable practices. Furthermore, the use of advanced deep learning techniques shows the potential for technological innovation in developing countries, paving the way for similar applications in various environmental and ecological contexts. Finally, this research goes above academia, offering real advantages for the conservation of biodiversity in the water and the well-being of communities that rely on these important assets.

5.2 Impact on Environment

This study shows an important beneficial effect on the environment. The system helps maintain aquatic biodiversity by making it possible for the accurate identification of local fish species. This, in turn, promotes the preservation of delicate ecosystems and sustainable fishing practices. The precise monitoring enabled by technology contributes to the protection of species at risk and the prevention of overfishing. As a result, the overall health of fisheries improves, encouraging ecological balance and adaptability. The use of such advanced techniques shows a commitment to using technology for environmentally conscious solutions, laying the groundwork for the incorporation of modern techniques into environmental monitoring and conservation efforts.

5.3 Ethical Aspects

The research's ethical considerations are important. Maintaining ethical data collection and labeling procedures is important for protecting local ecosystems and the rights of the affected communities. Developing the trust among stakeholders in the application of deep learning algorithms is dependent upon simplicity, especially in sectors as important as fisheries. It is morally required to protect data privacy as well as get informed consent from people and communities that contribute to the dataset. In addition, responsible technology deployment should aim to improve local communities and ecosystems by taking into account potential societal and economic impacts. In order to avoid undue effects on specific fish species or communities, ethical considerations go in addition to changing model biases. They also involve organizing technological advancements with moral values and the welfare of the community.

5.4 Sustainability Plan

This research's sustainability plan includes a number of key elements. To begin, the research promotes sustainable fisheries management by providing accurate species identification tools, which contribute to the long-term well-being of fisheries. Continuous collaboration with local communities and fisheries ensures that the technology is used legally and responsibly. Regular updates to the model based on newly collected data improve its adaptability to changing environmental conditions. Educational initiatives can provide communities with the knowledge they need to effectively use the system, thereby increasing its long-term impact. The model and methodologies are open-source, which encourages widespread adoption and contributes to the technology's long-term viability beyond the research scope. Finally, the sustainability plan is based on a commitment to ethical and environmental considerations, with a focus on the long-term advantages to local fisheries and biodiversity.

CHAPTER 6

SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Study

This study addresses the urgent need for effective tools for fisheries management and biodiversity conservation in Bangladesh. A dataset of 1340 images representing six local fish species was curated using meticulous data collection methods. Deep learning algorithms such as InceptionV3, Xception, ResNet50, VGG19, and a custom CNN were used to create a reliable fish detection system. In experimental results, InceptionV3 performed well with an accuracy of 98.51%, showing its ability to capture the features of any number of fish species. The study shows the significance of architecture selection in deep learning applications, which has implications for ecological monitoring and responsible fisheries practices. By accurately identifying species, the technology has the potential to positively impact local communities, ecosystems, and fisheries management practices in Bangladesh, offering a sustainable solution for the Conservation of aquatic biodiversity.

6.2 Conclusions

In summary, this study successfully displayed that advanced algorithms can correctly identify and categorize local fish species. With an accuracy rate of 98.51%, InceptionV3's outstanding accuracy shows how important architectural decisions are when developing deep learning applications for particular ecological contexts. Competitive results from Xception, VGG19, and a custom CNN demonstrate the model's robustness, which highlights the developed system's potential versatility. The experimental results lay the foundation for future developments and uses in ecological monitoring by offering useful details about the difficulties involved in fish detection. The technology holds great promise for improving community livelihoods, biodiversity conservation, and sustainable fisheries management in Bangladesh. However, the responsible application of such technology still depends on ethical factors like data privacy and community involvement. By showing the revolutionary possibilities of deep learning in promoting an optimal relationship between technological innovation and ecological preservation, this work opens the door for future developments in environmental monitoring.

6.3 Implication for Further Study

The study provides chances for further study in a number of important areas. First off, by combining the advantages of several architectures, looking into ensemble learning techniques may improve model reliability. Examining how environmental elements, like habitat variations and water quality, affect fish detection performance could help us better understand how applicable this technology is in the real world. To increase overall accuracy, more research could focus on optimizing the hyperparameters for each architecture. A living system that can adjust to changing fish conditions may be created by combining temporal data and real-time monitoring. Thorough studies are necessary to address the ethical implications of deep learning in environmental monitoring, ensuring fair and responsible technology adoption. Last but not least, ongoing studies monitoring the developed fish detection system's long-term effects on nearby fisheries and ecosystems would offer important insights.s into sustainability and effectiveness over time.

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BANGLADESHI LOCAL FISH DETECTION USING DEEP LEARNING TECHNIQUES

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