FISHNET28: BANGLADESHI FISH CLASSIFICATION USING MACHINE LEARNING AND DEEP LEARNING TECHNIQUES

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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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DHAKA, BANGLADESH

July 2024

APPROVAL

This Project titled "FishNet28: Bangladeshi Fish Classification using machine learning and deep learning techniques", submitted by Arnob Dey and Saied Hasan 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 15th July,2024.

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Amir Sohel, Senior Lecturer, 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 the award of any degree or diploma.

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ACKNOWLEDGEMENT

First, we express our heartiest thanks and gratefulness to almighty for His divine blessing making it possible for us to complete the final year project/internship successfully.

We are grateful and wish our profound indebtedness to **Amir Sohel**, **Senior Lecturer**, Department of CSE Daffodil International University, Dhaka. Deep Knowledge & keen interest of our supervisor in the field of "*Machine Learning, Deep Learning & AI*" to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting them at all stages have made it possible to complete this project.

We would like to express our heartiest gratitude to the **Dr. Sheak Rashed Haider Noori, Professor & Head of CSE**, Daffodil International University for his kind help in finishing our project and also to other faculty members and the staff of the Department of CSE, Daffodil International University.

We would also like to thank the Upazila Fisheries office of Austagram, Kishoreganj for taking the time to validate our work and dataset

Finally, we must acknowledge with due respect the constant support and patience of our parents.

ABSTRACT

As urbanization advances, technological integration has become a necessity for the sustainable management of diverse ecosystems, where the fish world or the aquatic realm is no exception. This study introduces "FishNet28," an approach aiming to classify Bangladeshi indigenous fish species and decrease the information gap in Bangladesh. The primary objectives of FishNet28 encompass dataset construction, accurate species classification, custom machine learning model development, and the creation of a user-friendly mobile application, addressing critical gaps in fish identification methodologies and knowledge dissemination systems. At present, many indigenous fish species in Bangladesh are on the verge of extinction due to overfishing or false identification. Our methodology for FishNet28 addresses these fish identification gaps by involving the collection of a large dataset of fish images and classifying them with the help of machine learning and deep learning techniques. This study compares the performance of four pre-trained models: DenseNet201, Xception, ResNet50V2, and InceptionV3. Each model was classified, and their performance metrics were recorded for comparative analysis. Additionally, a custom layered DenseNet201 model was developed and evaluated. The custom FishNet28 model demonstrated superior performance with a training accuracy of 99.53% and a validation accuracy of 99.86%, highlighting its potential for accurate species classification in practical applications.

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CHAPTER 1
INTRODUCTION

1.1 Overview

Fish is a common ingredient in the diet of people in Bangladesh, who are often referred to as "Mache Bhate Bengali" because they cannot imagine a meal without fish. Historically, Bangladesh was self-sufficient in fish and boasted a diverse selection of species due to its favorable climate. However, climate degradation has led to a decline in fish diversity. The fisheries sector plays a vital role in the economy, supporting entrepreneurship, employment, and poverty alleviation. FishNet28 proposes an application to provide detailed information on fish species, including local names, scientific names, habitats, nutritional values, and endangerment status, contributing to informed decision-making in fisheries and conservation efforts.

1.2 Background and Present State

The fisheries sector in Bangladesh faces significant challenges due to the decline of native fish populations. Overfishing, capturing endangered species, and fishing during mating seasons have led to the endangerment of various fish species. A primary issue is the knowledge gap regarding fish species, leading to misidentification and overexploitation. Additionally, construction, soil erosion, and siltation have further threatened aquatic life. Many native fish species, such as veduri, folli, baim, Gutum, Chital, and Guicha, are on the verge of extinction, with high prices in local markets due to their scarcity. The current generation lacks knowledge about most fish species, contributing to a lack of informed purchasing decisions.

1.3 Problem Statement

The fisheries sector in Bangladesh is experiencing a decline in native fish populations due to overfishing, misidentification of fish species, and environmental changes. There is a significant knowledge gap among the general public, fishermen, and fish farmers regarding fish species, their nutritional values, and the impact of overfishing. This lack of awareness contributes to the overexploitation of vulnerable species and poses a challenge for sustainable fisheries management.

1.4 Objectives

The primary objective of FishNet28 is to create a reliable and accurate classification method for identifying a wide variety of fish species. The study aims to develop a comprehensive dataset of Bangladeshi indigenous fish, particularly those available under different names, and use this dataset to create an accurate machine-learning model for fish identification. The model should be efficient and adaptable for implementation with IoT devices to ensure accessibility for non-technical users and those without high-end devices.

1.5 Scope and Limitations

The scope of the study includes the creation of a large and diverse dataset of indigenous Bangladeshi fish species, the development of a robust data preprocessing pipeline, and the creation and validation of a machine-learning model for fish identification. The study also aims to raise public awareness and contribute to conservation efforts. However, limitations include the potential lack of high-quality images for all fish species and the need for significant funding for data collection and model development.

1.6 Report Organization

The report is structured into seven chapters, each focusing on different aspects of FishNet28 study. The introduction provides a comprehensive overview of the study, setting the stage for the subsequent chapters. It includes sections on the background and present state of the fisheries sector in Bangladesh, the problem statement, the objectives of the study, the scope and limitations, the organization of the report, and a summary. Chapter 2, literature review is based on existing literature related to fish species identification and conservation. It begins with an overview, followed by a detailed examination of related works. It also includes a comparison between existing works, highlighting open issues in the field. The chapter concludes with a summary of key findings from the literature.

1.7 Summary

The fisheries sector in Bangladesh faces challenges due to declining fish populations, overfishing, and misidentification of fish species. FishNet28 proposes a solution to create a comprehensive dataset and develop a machine-learning model for accurate fish identification. The study aims to raise public awareness, contribute to conservation efforts, and promote sustainable fisheries management. The report is structured to provide a detailed account of the research process, findings, and implications for future work.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

This chapter reviews the literature on fish consumption and classification, highlighting the significance of knowledge and technological advancements in these areas. The chapter then delves into various research efforts aimed at improving fish classification techniques. Significant contributions include the integration of Deep Learning (DL) and Internet of Things (IoT) for automated fish processing, hybrid models combining Convolutional Neural Networks (CNNs) with other architectures, and the application of transfer learning to achieve high accuracy rates in fish classification. Each study is evaluated in terms of dataset size, model accuracy, limitations, and contributions. The literature review identifies research gaps, societal needs to build FishNet28 for broader applicability, better results and efficiency.

2.2 Related Works

Md.A. Ahmed et al. [4] proposed an integrated system for fish classification using Deep Learning (DL) and Internet of Things (IoT) on "An advanced Bangladeshi local fish classification system based on the combination of deep learning and the internet of things (IoT)". It involves creating datasets from original and Unsharp masked fish images where they used a dataset containing Bangladeshi fish image based on eight different classes; then they implemented seven state-of-the-art Deep Learning models. They used a hybrid CNN + Convolutional LSTM model and achieved 97% accuracy for fish classification. The proposed model can be utilized to automate fish processing and packing. Kristian Muri Knausgard et al. [5] presented a two-step deep learning-based approach to detect and classify temperate fishes using You Only Look Once (YOLO) and a Convolutional Neural Network with the Squeeze-and-Excitation architecture. They also applied transfer learning as a part of post-processing to achieve a state-of-the-art accuracy of 99.27%. Their work is highly valuable for classifying fish in marine ecology research and conservation efforts, such as monitoring nursing and feeding behaviors of temperate fishes. Deka et al. [6] has provided a fine-tuned resnet-50 architecture to achieve a remarkable accuracy of 100% on freshwater 20 fish species of the south Asian regions. They reported a learning rate of 0.001 with the resnet-50 model based on their own images and Fish-Pak dataset in images. Their work is significant in the context of classifying fishes to aid in stock management and fish preservation. Sharmin et al. [7] conducted an extensive study of current research in fish recognition, emphasizing the scarcity of studies dedicated to fish from Bangladesh. Their analysis involved 96 datasets encompassing 6 fish species, with the Support Vector Machine achieving the highest accuracy at 94.2%. The study also explores the application of machine vision in recognizing aquatic foods and delves into the utilization of deep convolutional networks. It underscores the imperative for more comprehensive studies on fish recognition in Bangladesh, emphasizing the novelty and significance of their proposed machine-vision-based local fish recognition system. Alaba SY et al. [8] proposed a deep learning model for fish species recognition using a loss function to handle an imbalanced dataset. The model trained on the SEAMAPD21 dataset with 228,328 images across 130 species but focused on 82 fish species for experimentation. to address imbalances, the authors fine-tuned the dataset and removed unavailable classes, adhering to the 512x512 standard for VGG512. They achieved a loss result of 0.5164 (51.64%) and an accuracy of 80.61% with the VGG512 architecture. Xu and Li et al. [9] have taken a deep learning-based approach to identify small-scale fish species by creating a transfer learning and SE-ResNet152 network framework. Remarkably, their approach has produced an accuracy result of 98.80% when applied to a dataset with images of full fish images containing fish bodies, heads, and scales. Notably, their finely tuned model surpassed the performance of well-established frameworks, including SENet154, DenseNet121, ResNet18, ResNet152, and VGG16. Mathur et al. [10] has proposed an eco-friendly and cost-effective approach to classify underwater fishes without catching them by using a transfer learning-based approach. Their approach achieved a high accuracy (98.44%) on a big dataset and a relatively good accuracy (84.92%) on a smaller dataset. For their two datasets, the proposed FishResNet method outperformed existing state-of-the-art models used for fish species classification. To help conserve endangered species and help marine park managers, M. A. Iqbal et al [11] has proposed a modified version of AlexNet, which on their dataset has given a higher accuracy (90.48%) than the original AlexNet (86.65%). They reduced the number of layers to achieve a better overall performance. Moreover, the modified or fine-tuned AlexNet can be used more efficiently and it is less complex to compute due to its architecture. Malik H. et al. [12] proposed FD_Net, a dilated Convolutional Network to classify 9 species of fish. They compared FD_Net, YOLOv3, YOLOv3-TL, YOLOv3-BL, YOLOv4, YOLOv5, Faster-RCNN & YOLOv7 to obtain accuracy over various image resolutions. Here, FD_Net outperformed all other models by generating a 95.30% accuracy on 299 x 299 x 3 image resolution and also having very similar accuracy on other image resolutions as well. Jalal A et al. (2020) [13] proposed a hybrid model combined of Gaussian Mixture Models, optical flow, and a YOLO neural network for detection and classification in underwater videos. They used LCF-15 and UWA dataset. Their proposed model achieved accuracies 91.64% and 79.8%on two dataset respectively. Suharto et al. (2020) [14] introduced MobileNet V1 model for freshwater fish detection focusing on pomfret, carp and tilapia fish. Their usages dataset was derived from Google Image. They trained the model with learning rate parameters 0.0004 and epoch 20.000.They obtained the accuracy rate 90%.() Volcan et al. (2023) [15] introduced the IsVoNet8 deep learning model for the classification of fishes. They used a Large-Scale

Fish Dataset which contained 8 species belonging to 6 families. Comparing the introduced model with ResNet50, ResNet101, and VGG16, they found that it achieved a better accuracy rate. It achieved 98.62% accuracy with IsVoNet8 and the loss rate is 0.0568. Sarigul et al. (2017) [16] researched CNN models with different numbers of convolution layers and filter sizes for fish classification. They found that less deep architectures with larger filters gave better performance on the test dataset. They achieved a 40.73% performance boost by increasing the size of filters. Monika et al. (2020) [17] proposed Cross pooled FishNet model to develop automatic fish classification from underwater images captured through videos. They used Fish4Knowledge dataset containing 27,370 images of 23 species but the dataset is highly imbalanced. They achieved 98.03% accuracy with the Cross pooled Fishnet model utilizing ResNet-50 feature extraction. Pooja et al. (2022) [18] proposed a combinational technique of the firefly algorithm and neural network. In their research, they used a Ground Truth database containing 27,370 images categorized into 23 fish classes. By employing UWIE with FFA optimization, they achieved a remarkable accuracy of 99.008% in fish classification.

2.3 Comparison between existing works

Here is a simpler tabular format of comparison between existing works.

TABLE 2.3.1: Comparative Analysis Table

Author Name and year	Dataset	Model	Accuracy	Limitations	Contributions
Ahmed (2023) [4]	8 classes of fish dataset	DenseNet201+ConvLSTM hybrid model	97%	Small dataset containing 800 images only.	Proposed an IoT-based deep learning model.
Knausgard (2021) [5]	Total Image: 23275	CNN-SENet	99.27%	Only worked on Temperate species and did not consider other fish types.	Their model is powerful and they used the YOLO approach.
Deka (2023) [6]	Species: 20 Size: 587 Raw: 316	Resnet-50	100%	Very small dataset	Remarkable accuracy of 100%.
Sharmin (2019) [7]	6 Species 96 Images	Support vector machine	94.2%	Very small dataset containing 6 species and 96 images	Proposed solution to save freshwater species in Bangladesh.

Alaba (2022) [8]	SEAMAPD21 Dataset:	VGG512	80.61%	Very imbalanced dataset No of images: Unspecified	Handling fish recognition and imbalance problems.
Xu (2021) [9]	Fish Species: 6 Total fish: 915	SE-ResNet152	98.80%	Small-scale imbalanced dataset with specific features	Fine-tuned model to classify small datasets of fish images with good accuracy.
Mathur (2021) [10]	Fish4Knowledge & QUT Dataset	Modified ResNet-50	98.44% & 84.92%	Very high accuracy on big dataset	Efficient & cost-effective classification solution.
Malik (2023) [11]	Total images: 410 Augmented images: 9000	FD_Net	95.30%	Less efficient in larger datasets.	High accuracy with image segmentation.
Iqbal (2019) [12]	The QUT fish dataset and LifeClef2015 Fish dataset Total images: 1334	Modified AlexNet model (Reduced layers)	Modified AlexNet model (Reduce d layers): 90.48%	Better performance with unseen data than the seen data.	Helping fish stockiest and marine park managers to conserve endangered species.
Jalal (2020) [13]	LCF-15 dataset Images: 42,778 fish patches and 29,965 for training and 12,813 for testing. UWA dataset Images: 4418	Hybrid model (GMM, optical flow with YOLO)	91.6 %	The system's performance has not been tested across diverse underwater environment	They achieved high accuracy (91.6%) with their hybrid model for detection and classification of underwater fishes.
Suharto (2020) [14]	Total Images:700 Training:469 Testing:201 validation 30	MobileNet V1	90%	Small dataset and less fish classes. They faced limitations in error detection for certain fish images.	They achieved 90% accuracy using MobileNet V1 and trained on specific learning rate and epoch parameters.

Volkan (2023) [15]	Large-Scale Fish Dataset Total images:8000	IsVoNet8	98.62%	Lack of diversity of fish species	They achieved highest accuracy with IsVoNet8 that Resnet and VGG model
Sarigül (2017) [16]	QUT Fish Dataset 3960 images of 468 species	CNN model		insufficient images for some species and limited dataset diversity.	They achieved a 40.73% performance boost by increasing the size of filters
Monika (2020) [17]	Fish4Knowledge 27,370 images for 23 classes	Cross pooled FishNet with ResNet-50	98.03%	Highly Imbalanced dataset	They achieved 98.03% accuracy with Cross pooled Fishnet model utilizing ResNet-50 feature extraction.
Pooja (2022) [18]	Ground Truth database Total 27,370 images for 23 classes	UWIE with FFA optimizati on	99.008%	Scalability challenge with larger datasets.	Combination of FFA optimization with UWIE achieved 99.008% accuracy

2.4 Open Issues

Here are some open issues we can explore with our FishNet28 study:

- Existing machine learning and deep learning models lack robust classification for a wide variety of fish species.
- Many studies used small or highly imbalanced datasets.
- There is a lack of raw fish images for comprehensive datasets.
- Most research focused on regional species, potentially introducing bias.
- There is a need for the integration of IoT into fish classification systes for broader applicability.

2.5 Summary

The literature highlights significant advancements in fish classification using deep learning models but also points out several limitations, including dataset size and diversity, and the need for comprehensive and unbiased datasets. Future research should focus on developing large, diverse datasets and integrating IoT to enhance the efficiency and applicability of fish classification systems.

CHAPTER 3
METHODOLOGY

3.1 Overview

The research subject of the "FishNet28" study focuses on developing an accurate and efficient fish classification system for indigenous fish species in Bangladesh. The primary objective is to create a comprehensive dataset encompassing a wide variety of fish classes found in the region. By leveraging advanced computer vision techniques, specifically Convolutional Neural Networks (CNNs), this study aims to build a robust model capable of classifying fish species with high accuracy.

3.2 Proposed Methodology

The study addresses the critical need for improving indigenous fish knowledge among the general population of Bangladesh. Accurate identification of fish species is essential for various applications, including conservation efforts, aquaculture practices, and educational purposes. Traditional methods of fish identification often rely on manual examination by experts, which can be time-consuming and prone to human error.
The research explores the use of state-of-the-art CNN architectures, such as DenseNet201, Xception, ResNet50V2, InceptionV3, to develop an automated and scalable fish classification system. These architectures have demonstrated exceptional performance in image recognition tasks and are well-suited for handling the diversity and complexity of fish imagery.

To handle the computational demands of training deep learning models on large datasets, the study leverages the Google Collab cloud computing platform, which offers scalable and efficient environments for training and evaluating the proposed CNN models.

The study incorporates performance evaluation metrics, such as accuracy, precision, recall, and AUC score, to assess the effectiveness of the developed fish classification system. These metrics assist in quantifying the model's performance and guiding further refinements or adjustments as needed.

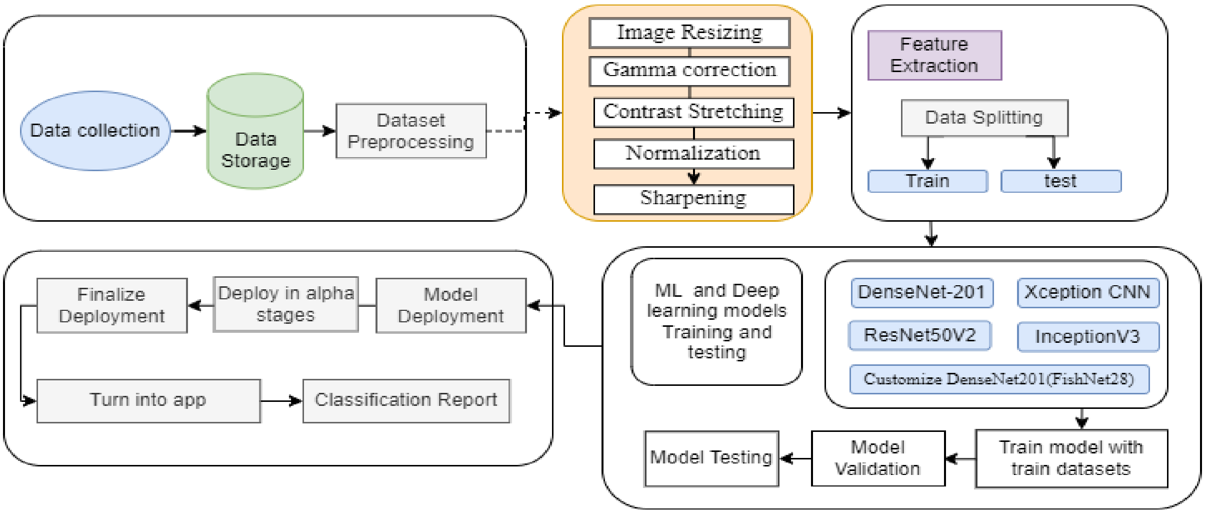


Figure 3.2.1: FishNet28 Methodology flowchart

3.2.1 Data Collection Procedure

For dataset collection, we used multiple methods. Firstly, we captured fish in village ponds, acquiring around 20-30 specimens of various fish species during this process. For each fish, we captured 5-6 images. Since this approach provided us with a limited number of fish, we extended our efforts to local markets known as "Fish Bazar" to gather more fish images. However, at these fish markets, vendors prohibited us from touching or holding the fish for photography, making our work more challenging. Additionally, we scheduled our visits either early in the morning or during the evening, impacting the overall picture quality. Despite these challenges, we managed to capture images of the fish and deleted any blurred or unusable pictures that were taken there.

To improve and collect more fish images for our dataset, we had to bribe some fishermen or purchase fish from them to secure permission to take images for the dataset. Another effective but costly solution involved bringing fish home for photography, even though this required real-world currency. For each fish, we captured 5-6 images using every method. To diversify our dataset further, we photographed fish against different backgrounds, especially for smaller species that were difficult to identify using the same camera or equipment.

Given the regional variations in fish species, some were found exclusively in certain areas of our country.

For instance, certain fish species were more prevalent in Mymensingh, Barisal, or specific districts. To ensure the authenticity of our dataset, we refrained from importing fish, as it could compromise their quality. Instead, we traveled to specific locations, used the local fish market method, and captured images. We also collected fish of the same species from various locations, including Rajshahi, Savar, Khulna, Kishorgonj, Pabna, Kushtia, Mirpur, Mymensingh, and Netrokona in Bangladesh. However, there were still some places we could not visit or might take a longer time to travel to. In such cases, we enlisted the help of friends to collect data/images for us, saving both time and money.

3.2.2 Dataset Description and Statistical Analysis

To build our FishNet28 dataset, we collected images for 28 unique Bangladeshi indigenous fish species. For each species there are around 1000 raw images. For each unique fish we took 5 to 7 images per fish. The highest number of images are taken for Katol fish of 1090 images and the lowest number of images are for Boyal fish with 968 images. In total, we have collected over 29000 images for 28 species. Here is a basic introduction to our fish species based on their availability environments, country they can be found in and body description**:**

Olive barb fish measures approximately 0.6m, features a silvery or pale body with red or orange-hued fins. Two pairs of tactile barbels on its face enhance sensory perception. It is found in rivers, streams, lakes and backwaters of Bangladesh, Afghanistan, India, Nepal, Pakistan, Bhutan, Sri Lanka, Thailand, Myanmar.

The Zig-zag eel fish has a large dark body and circular patterns, showcases an elongated, compressed form with upward-lifted jaws and distinctive whitish eyes. It is found in highland Streams, Lowland Wetlands, Still Waters, Coastal Marshes, and Rivers of Bangladesh, India, Pakistan, Sri Lanka, Thailand, Vietnam, Indonesia.

The Potasi fish features an elongated and compressed body with an upwards lifted jaw. The eyes are large and have a whitish color. It has four pairs of barbels in its body with lateral patterns on its body. It is found in freshwaters and tidal rivers of Bangladesh, Pakistan, India, Myanmar and Nepal.

The snakehead fish features an elongated, cylindrical body with small anterior eyes with a lower jaw on a large body. These fishes come in many different colors while yellow to brown colors are most prominent. It is found in rivers, canals, ponds, lakes, doba, and streams of Bangladesh, Pakistan, India and Sri Lanka [19].

The Guntea Loach fish species has a long, cylindrical body with straight dorsal-ventral sides, three pairs of tactile organs, and no lateral line. Its small, clear anal fin is covered in mucous. It is found in Swift streams, freshwater, swamps, lakes of Bangladesh, Pakistan, northern India, Nepal, Myanmar and Thailand.

The Freshwater Gar has an elongated body with a beaklike jaw with teeth. It has a silvery green body with teeth and anal fins positioned near its tail. The male fishes have black edged anal or fins. It is found in both freshwater and brackish water of Bangladesh, India, Sri Lanka, Malaysia.

Climbing Perch fishes generally attain a maximum length of 0.3m. In life, it exhibits colors ranging from dark to pale greenish, with a very pale underside. It has longitudinal stripes are present ventrally on the head and it is marked with a dark spot on its posterior margin. It is found in freshwater, Canals, Beels, Haors, Baors, and Ponds of Pakistan, India, Bangladesh, Sri Lanka, Southern China, Indonesia, Papua New Guinea, Northern Australia.

The Pool barb species has a body size of 0.2m approx. with female fishes being 4.7-5 cm. They are found in rivers, streams, and ponds in plains and submontane regions. It is found in both freshwater and brackish water of Bangladesh, Pakistan, India, Nepal, Myanmar and Yunnan province of China.

Bata is a small indigenous fish species that has a slightly convex body, a large, gray surface and silvery ventral and lateral surfaces. It has a small body size and a slow growth rate. It is found in ponds, rivers etc. of Bangladesh and India [20].

The body of Mola fish is covered with thin fibers and is light silver, the thorns are soft. It is a fresh fish, with bright appearance, soft and firm texture with characteristic fresh odor. It is found in Rivers, Beels, Canals, Streams, Ponds of Bangladesh and India [21].

Sing fish are found in Ponds, Ditches, Swamps, Marshlands, Muddy rivers of Bangladesh, India, Laos, Myanmar, Nepal, Pakistan, Sri Lanka, and Thailand. They have a body that is long and pressed, the abdomen is rounded, and the head is miniature. The fins are long, the dorsal fin is rounded, the dorsal fin is deeply notched, and the snout is absent [22].

The sea bass fish features an elongated body with a large mouth and ctenoid scales. The Fish in our dataset has a maximum length around 0.2-0.5 m and it has silver scales on its body. It is found in Marine water, Freshwater, Brackish water of Bangladesh, India [23].

Catla are large fishes with a broad head, a jaw, and an upturned mouth. An adult Catla can reach 6.6m whereas our dataset had a maximum size of 0.4m. It is found in Freshwater of Bangladesh, India, Myanmar, Nepal and Pakistan.

The body of Baili fish is like a roller, the head is round, the mouth has long jaws, the lips are thick, the teeth are on the jaws, the color is gray and the body is covered with thin scales. It is found in Marine water, Freshwater of Bangladesh, India, Pakistan.

Rui is a species of freshwater fish in the carp family. It is a fish of reddish and silvery color, which can weigh from 2-3 kg to 45 kg. It is found in freshwater, brackish of Bangladesh, India, Pakistan, Nepal, Myanmar, and Sri Lanka.

Tengra fish species feature an elongated and compressed body with a pointy head and mouth. The body is ash colored and has four pairs of barbels on its face. It is found in the River, Canal, Pond, Lake, Doba, Stream of Bangladesh, India, Myanmar and Thailand.

The Pangas fish has a broad, rounded head, narrow fleshy eyes, a tail, yellowish-green upper surface, silvery-red flanks, golden-brown head sides, and reddish-yellow fins, with a strong pectoral fin. It is found in freshwater and brackish water of Bangladesh, Pakistan, India, Myanmar, Thailand, Malaysia and Indonesia.

Boyal is large predatory freshwater catfish found in Rivers, Reservoirs and in connected watersheds of Bangladesh, India, Pakistan, Nepal, Burma, Sri Lanka, Thailand, Vietnam, Kampuchea and Indonesia. This species has a flat-sided body without scales and a distinctive appearance living in the floodplain ecosystem, earning it the name "Monster Fish" [24].

The Mrigal fish features a large, deep freshwater carp fish with a long, deep body, cycloid scales, and no teeth. It has a large mouth, anal fin, dark gray hindwing, silvery flanks, and belly. It is found in Freshwater lakes & River’s water of Bangladesh, India, Pakistan, Myanmar.

Hilsa, the national fish of Bangladesh, is a freshwater fish with a thick, muscular body. The Hilsa is characterized by its silvery-yellow color, medium size, and thick skin on the upper part of the head. It is found in freshwater, brackish water of Bangladesh, India and Pakistan and some other Asian countries.

Resembling the Rohu fish, the Calibos features thick black or gray scales, a small head, red eyes, and a pair of whiskers. It is found in Freshwater lakes & Rivers water of Bangladesh, India & other South Asian countries.

Foli fish features a long, compressed body with a convex dorsal profile, coppery green dorsal portion, silvery bars, and a 120 cm long anal fin. It is found in freshwater, brackish water of Bangladesh, India, Nepal, and Pakistan.

Ompok Pabda is a freshwater fish found in South Asian rivers and ponds, has an elongated body with a flattened head, rounded snout, superior mouth, two pairs of barbells, and a forked caudal fin. It is found in freshwater, brackish water of Bangladesh and India [25].

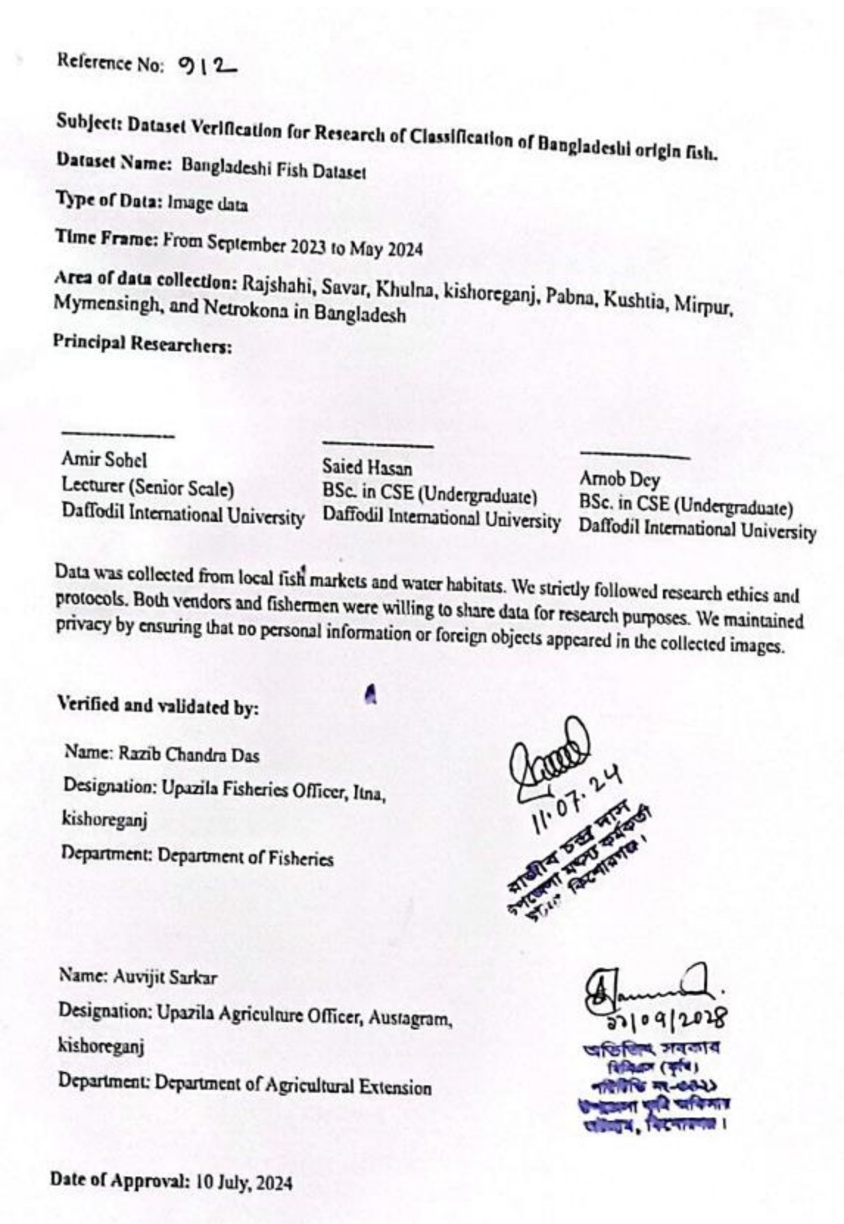
The Corsula fish has a sub-cylindrical anterior body, a moderately compressed posterior, a straight dorsal profile, a flat head, compressed sides, a ventral mouth position, and elevated eye. It is found in freshwater, brackish water of Bangladesh [26].

The Soal fish features elongated body with depressed head, moderated eyes, rounded caudal and large scales on head. It is found in freshwater of Bangladesh, India, Malay Archipelago, Myanmar, Nepal, Pakistan, Sri Lanka, south China and Thailand. The Garua fish has elongated and compressed body, moderate and sub-terminal mouth, 4 pair barbel, gill opening widely and absence of adipose fin in adult fish. It is found in freshwater of Bangladesh, Pakistan, India, Myanmar and Nepal. [27]

The Chapila fish are short, relatively deep, sides are very tight, mouth is small, eyes with bard adipose leaflets. It is found in freshwater of Bangladesh, India, Sri Lanka. Chanda nama is found in Bangladesh, Pakistan, Burma and Indonesia. It can be found in both fresh and brackish water. But they're also found in the marginal area of the jute and paddy fields. It is a small sized fish that grows to a max length of 11 CM. [28]

Table 3.2.2.1: FishNet28 Dataset Overview

SL no	Dataset Name	Local Names	English name	Scientific name	Images
1	Katol	কাতল	Catla	Catla	1090
2	Tengra	ট্যাঁপারি	Batasio	Batasio tengana	1080
3	Puti	কসুয়াটি, কসুয়াতি	Pool barb	Puntius sophore	1071
4	Pangas	পাঙাশ, পাংগাস	Yellowtail catfish	Pangasius	1065
5	Taki	লাটি , ছাইতান, শাটি	Spotted snakehead	Channa punctatus	1064
6	Bata	বাটা	Bata	Labeo Bata	1054
7	Gautam	গুতুম, বুতুম, বইচ্যা	Guntea Loach	Lepidocephalichthys guntea	1051
8	Mola	মৌরোলা	Amblypharyngodon mola	Amblypharyngodon mola	1050
9	Rui	রহু, রউ, রহিতি	Rohu carp	Labeo rohita	1049
10	Baim	বাইম, মাব, সল বাইম	Zig-zag eel	Mastacembelus armatus	1048
11	Khorsola	খড়শলা	Corsula mullet	Rhinomugil corsula	1041
12	Soal	শোল	Snakehead murrel	Channa striata	1040
13	Ghaura	ঘাইরি	Garua Bachcha	Clupisoma garua	1040
14	Veduri [29]	ভেটকি, ভ্যাদা	Sea bass	Lates calcarifer	1037
15	Pabda	পাবদা	Butterfish	Ompok pabda	1035
16	Sorputi	সরপুঁটি,, সরাল, কুর্টি	Olive barb	Puntius sarana	1032
17	Ilish [30]	ইলিশী, মোদেন	Hilsa	Tenualosa ilisha	1030
18	Baili	বেলে মাছ	Tank goby	Glossogobius giuris	1023
19	Mrigal	মিড়কা, সির্হিনা্	Mrigal	Cirrhinus cirrhosus	1022
20	Chanda	চান্দা,নামাচান্দা	Elongate glass-perchlet	Chanda nama	1020
21	Chapila	খইরা,গণি চাপিলা	Indian River Shad	Gudusia chapra	1020
22	Koi	কৈ	Climbing Perch	Anabas testudineus	1015
23	Kaklas	কাইক্যা, কাকিলা	Freshwater Gar	Xenentodon cancila	1015
24	Batashi	পতাসি, দোয়া, পটাসি,	Indian potasi	Pseudeutropius atherinoides	1013
25	Kalabaus	কালিবাউশ	Orange-fin labeo	Labeo calbasu	1013
26	Sing	শিংঘি	Stinging catfish	Silurus fossilis	1012
27	Foli	ফলই	bronze featherback	Notopterus	1002
28	Boyal	ইকান তাপাহ	Freshwater shark	Wallago attu	968
Total Species: 28				Total Images: 29000	



Reference No: 912

Subject: Dataset Verification for Research of Classification of Bangladeshi origin fish.

Dataset Name: Bangladeshi Fish Dataset

Type of Data: Image data

Time Frame: From September 2023 to May 2024

Area of data collection: Rajshahi, Savar, Khulna, kishoreganj, Pabna, Kushtia, Mirpur, Mymensingh, and Netrokona in Bangladesh

Principal Researchers:

Amir Sohel Lecturer (Senior Scale) Daffodil International University	Saied Hasan BSc. in CSE (Undergraduate) Daffodil International University	Arnob Dey BSc. in CSE (Undergraduate) Daffodil International University

Data was collected from local fish markets and water habitats. We strictly followed research ethics and protocols. Both vendors and fishermen were willing to share data for research purposes. We maintained privacy by ensuring that no personal information or foreign objects appeared in the collected images.

Verified and validated by:

Name: Razib Chandra Das
Designation: Upazila Fisheries Officer, Itna, kishoreganj
Department: Department of Fisheries

11.07.24

Name: Auvijit Sarkar
Designation: Upazila Agriculture Officer, Austagram, kishoreganj
Department: Department of Agricultural Extension

Date of Approval: 10 July, 2024

Figure 3.2.2.1: FishNet28 dataset validation document

3.2.3 Pre-processing techniques used:

1. Image Resizing: The images for this dataset were taken with different phones in different environments. Images were also in different formats such as jpg, png, etc. We converted all images into “jpg” format with the help of Python Imaging Library or Pillow. After preprocessing the shape becomes 224x224x3.

2. Gamma correction: Due to differences in lighting conditions, some images became dark and the fish became hard to identify. So, to enhance the visual quality of images, we used the gamma correction technique. Gamma correction

is used to adjust the brightness and contrast ratio based on their pixel intensities. For calculating gamma correction image input value is raised to the power of the inverse of gamma. This means the formula for gamma correction is,

$$I' = 255 \times (\frac{I'}{255})^{\gamma} \text{ or } I = 255 \times (\frac{I'}{255})^{\frac{1}{\gamma}} \quad (1)$$

Which is the formula for inverse gamma correction. In gamma correction the higher the value from 1, the image will get brighter, and less the value from 1, the image will get darker. Again, for values higher than 1, the image will get brighter in reverse gamma correction.

3. Contrast Stretching: Contrast stretching an image improves the overall contrast in the input image by spreading the pixel intensity range. Since we have some low-contrast or blurred images in our datasets, we used the contrast stretching formula for the images. The formula for contrast stretching is:

$$O(x, y) = \frac{I(x,y) - Imin}{Imax - Imin} \times 255 \quad (2)$$

Here, I(x,y) is the original intensity value at pixel (x,y), Imin Imax are the minimum and maximum

intensity values for the images and O(x,y) is the contrast stretched intensity value.

4. Normalization: Normalization is a common technique used to scale the pixel values of an image to a standard range. This helps in improving the training of deep learning models. Typically, pixel values are scaled to be between 0 and 1. For fish images, we normalize the pixel values of the images to a range between 0 and 1.

$$Normalized\ pixel\ value = \frac{255}{Original\ pixel\ value} \quad (3)$$

5. Sharpening: Sharpening is used to enhance the edges and details in an image to make it appear clearer. One of the most common sharpening methods is called unsharp masking. Even though its name is unsharp masking, it does not involve actually creating a mask. Instead, it involves creating a sharpened version of the image by subtracting a blurred version of the image from the original. This process involves blurring the image, subtracting the blurred image and then adding the Sharpened Image.

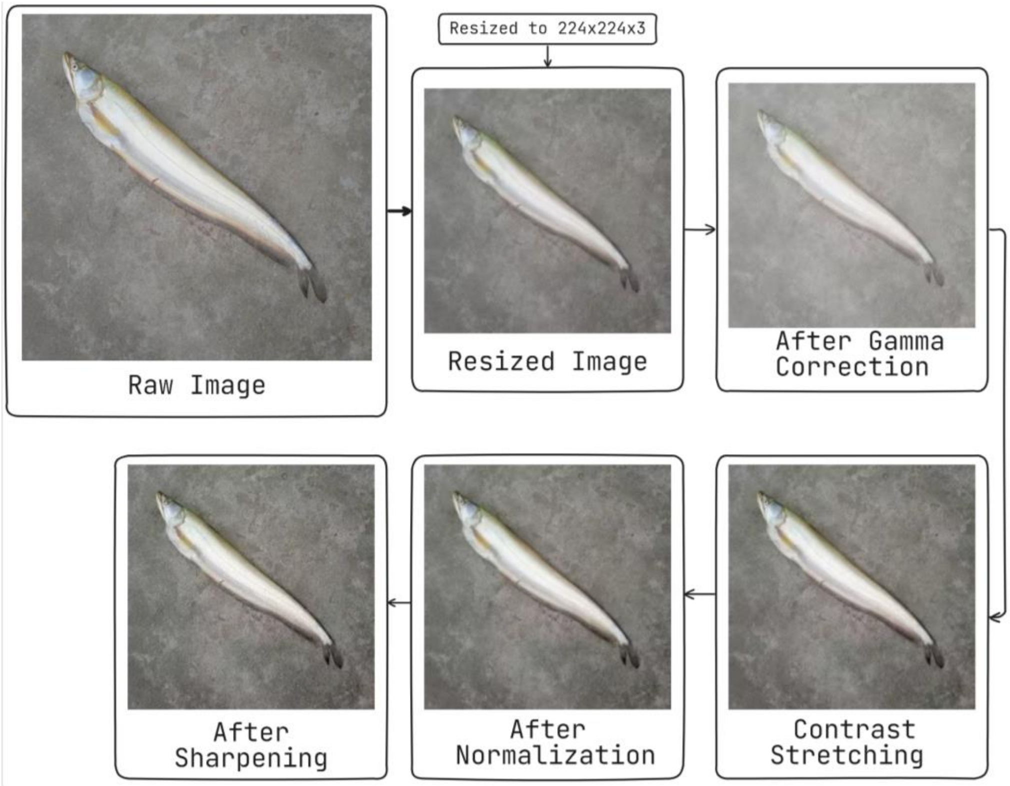


Figure 3.2.3.1: FishNet28 Preprocessing techniques

3.2.4 Data validation and verification:

In machine learning and deep learning models, assessing the quality of images after compression or preprocessing techniques are required. Several metrics are used to evaluate image quality, including Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), Root Mean Squared Error (RMSE) to provide a comprehensive assessment of image quality post-preprocessing [31].

Structural Similarity Index (SSIM):

The Structural Similarity Index (SSIM) is a perceptual metric that quantifies image quality degradation by considering changes in structural information. SSIM is designed to model the image degradation in terms of perceived changes in structural information to evaluate three aspects of the image: luminance, contrast, and structure.

$$SSIM(x,y) = [l(x,y)]^{\alpha} \cdot [c(x,y)]^{\beta} \cdot [s(x,y)]^{\gamma} \qquad (4)$$

Where, α, β and γ are parameters for relative importance of Luminance Comparison (l (x , y)), Contrast Comparison (c (x , y)), Structure Comparison (s (x , y)).

SSIM values range from -1 to 1. A value of 1 indicates perfect structural similarity between the two images whereas value of 0 indicates no structural similarity.

$l(x,y)$: Luminance comparison

$c(x,y)$: Contrast comparison

$s(x, y)$: Structure comparison

Peak Signal-to-Noise Ratio (PSNR):

PSNR is a ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. It is most commonly used to measure the quality of reconstruction of lossy compression codecs.

$$PSNR = \frac{10\log_{10}(peakval^2)}{MSE} \quad (5)$$

where $\boldsymbol{peakval}$ (Peak Value) is the maximal in the image data.

- PSNR is expressed in decibels (dB).
- Higher PSNR generally indicates better quality.
- Commonly, PSNR values above 30 dB indicate high fidelity, while the range of 20-30 dB signifies moderate to good quality for images.

Mean Squared Error (MSE):

MSE is a risk function corresponding to the expected value of the squared error loss or quadratic loss, and it is almost always positive due to randomness or incomplete information. In machine learning's empirical risk minimization, MSE estimates the true MSE by averaging losses on observed data, offering insight into model performance on unseen date. The formula of MSE is:

$$MSE = \frac{1}{MN}\sum_{n=0}^{M}\sum_{m=1}^{N}[g\hat{}'\,(n,m) - g(n,m)]^2 \quad (6)$$

where M is the number of rows (height) and N is the number of columns (width) of the image, g (n,m) represents the pixel value at position (n,m).

- $\boldsymbol{g'(n,m)}$ and $\boldsymbol{g(n,m)}$ are the pixel values at position (n,m) of the predicted and original images, respectively.
- For MSE, lower MSE indicates lower error.
- M is the number of rows (height) and N is the number of columns (width) of the image.

Root Mean Squared Error (RMSE):

RMSE is the square root of the average of squared differences between the prediction and actual observation. It is a good measure of how accurately a model predicts the response. RMSE is particularly useful for comparing prediction errors across different models or datasets. The formula of RMSE is:

$$RMSE = \sqrt{MSE} \quad (7)$$

where, MSE is Mean Squared Error.

- Lower RMSE indicates better fit and accuracy
- RMSE values are non-negative, with 0 indicating a perfect match.

TABLE 3.2.4: Verification table

Fish name	Sample Data	SSIM	PSNR	MSE	RMSE
Mrigal		0.9798	21.95	414.62	20.36
Pangas		0.9628	21.06	509.39	22.57
Soal		0.9502	20.55	572.70	23.93
Baili		0.9329	18.77	864.11	29.40
Baim		0.9223	14.45	2333.97	48.31
Bata		0.9659	21.82	427.44	20.67
Batashi		0.9631	29.07	80.52	8.97

Sorputi		0.9478	30.23	61.65	7.85
Tengra		0.9497	32.09	40.18	6.34

3.3 Hardware/ Software Requirement

To implement proper research on "FishNet28: Bangladeshi Fish Classification using machine learning and deep learning techniques", some requirements are filled in order to ensure execution and implementation of the study.

Hardware Requirements:

- High-Performance Computing Resources: Access to computational infrastructure with sufficient processing power and memory to handle deep learning tasks and large-scale image analysis.
- Graphics Processing Unit (GPU): Utilization of GPUs to accelerate training processes and reduce model development time.

Software Requirements:

- Deep Learning Frameworks: Utilization of deep learning frameworks such as TensorFlow or PyTorch for model development, training, and evaluation.
- Google Colab: Leveraging Google Colab for cloud-based development, which provides free access to GPUs and TPUs, allowing for faster model training without the need for expensive hardware.
- Image Processing Libraries: Integration of libraries like OpenCV for preprocessing and augmenting fish images.
- Pandas: For efficient handling of data, especially if metadata or additional information about the fish species is involved.
- NumPy: For numerical operations and efficient data handling, especially with image data.

Model Implementation:

- Training and Validation: Training CNN models using collected data and validating model performance to ensure accuracy.
- Testing and Evaluation: Conducting rigorous testing and evaluation of models

using appropriate metrics such as accuracy, precision, recall, and F1 score.

Non-Functional Requirements:

- Performance: Achieving high accuracy and performance metrics while considering hardware limitations for model integrability.
- Scalability: Choosing scalable models and techniques to accommodate varying dataset sizes.
- Security: Ensuring data security and privacy by restricting access to the dataset and implementing secure storage solutions.

3.4 Project Management and Financial Analysis

Financial Analysis:

For this study, we have developed an entire dataset by taking raw images of fishes. For data collection, we had to travel to different parts of Bangladesh and take images. Moreover, we had to either pay fishermen or buy fish from them to take pictures of fishes. So, funding is essential to our FishNet28 project.

Table 3.4.1: Financial Analysis and total cost

SN	Components	Estimated Cost (BDT)
1	Travel expenses (Visiting Stakeholders)	7000-7500
2	Fishes Bought	25000-26000
3	Image collection	10000
4	Organizing data, Documentation and Report Writing	5000
5	Data storage (offline and online) (Monthly subscription)	3000
6	Miscellaneous (Paid fishermen, background cloths etc.)	5000 - 6000
7	Contingency (10% of total)	5000 - 5500
	Total Estimated Cost	60000 - 63000

Project Management:

- Agile methodology for iterative development and testing.
- Version control using Google Colab’s share feature for code management.

3.5 Summary

The study aims to accurately classify fish species using a dataset of fish images processed through advanced CNN models. The proposed methodology involves comprehensive pre-processing, model validation, and leveraging powerful hardware and software tools. Efficient project management and careful financial planning ensure the project's success and sustainability.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

In this chapter, we delve into the implementation details of our machine-learning models. We discuss the training process for various architectures, including DenseNet201, Xception, ResNet50V2, and InceptionV3, as well as our customized DenseNet201 model, naked FishNet28. Each model is described in terms of its layers, convolutional blocks, and how they process input images for classification tasks. We also cover the evaluation metrics used to assess model performance, such as accuracy, precision, recall, and the F1 score.

4.2 Train Model

DenseNet201: DenseNet201 is a convolutional neural network with 201 layers that processes images of size 224x224x3. It starts with an input layer, followed by a convolution layer (7x7, stride 2) and a max pooling layer (3x3, stride 2). The network then progresses through four dense blocks, where each block contains a series of 1x1 and 3x3 convolution layers: the first block has 6 layers, the second 12 layers, the third 48 layers, and the fourth 32 layers. Between dense blocks are transition layers featuring 1x1 convolutions and 2x2 average pooling. After the final dense block, the network performs global average pooling, followed by a dense layer with 512 units (ReLU), and concludes with an output dense layer of 28 units using softmax activation for classification.

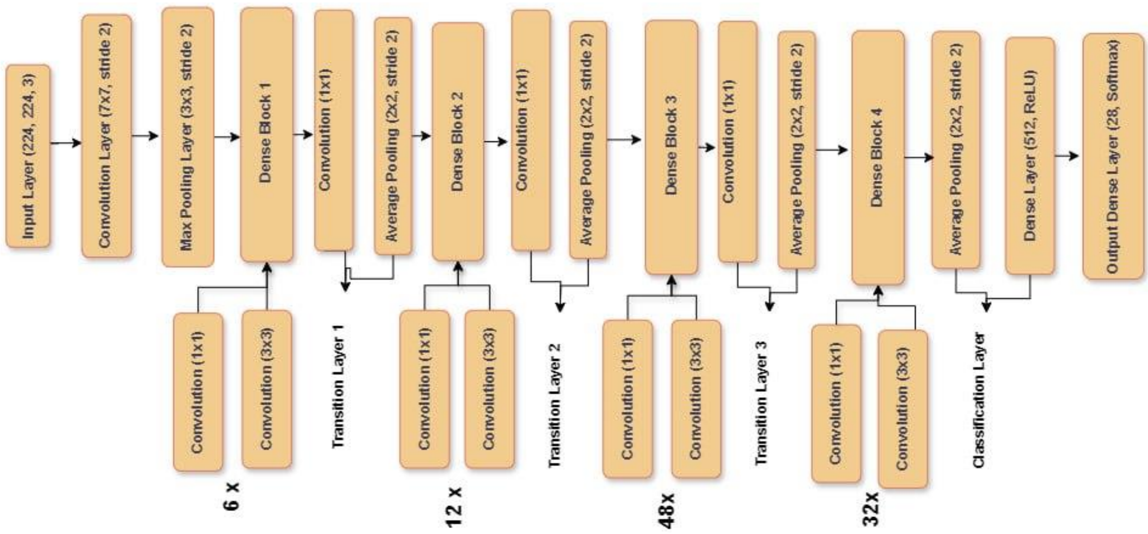


Figure 4.2.1: DenseNet201 layer architecture

Xception: Also known as Xception, is a convolutional neural network architecture that leverages depth-wise separable convolutions. It was designed to be computationally efficient while maintaining high performance. Xception processes images of size 224x224x3 through three main flows. The entry flow includes an input layer, two convolution layers with 3x3 filters and 2x2 stride, followed by three residual blocks with 1x1 and 3x3 convolutions. The middle flow consists of eight blocks, each containing separable convolutions, batch normalization, and ReLU activation. The exit flow comprises final convolution layers, global average pooling, a dense layer with 512 units (ReLU), and a dense layer with 28 units (SoftMax) for classification.

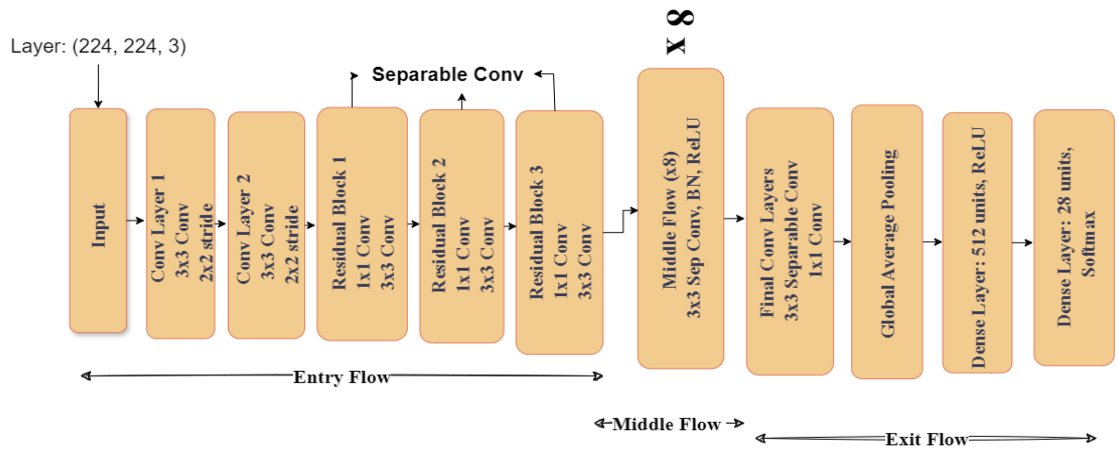


Figure 4.2.2: Xception layer architecture

ResNet50V2: Our custom model, based on ResNet50V2 which is a variant of the ResNet50 architecture with 50 convolutional layers., processes input images of shape (224x224x3) through multiple phases. Phase 1 includes zero padding, convolution, batch normalization, ReLU activation, and max pooling. Phase 2 consists of a convolution block followed by 4 identity blocks, while Phase 3 includes a convolution block followed by 6 identity blocks. Phase 4 contains a convolution block followed by 3 identity blocks, and Phase 5 includes two convolution blocks. The output is then passed through average pooling, flattened, and processed by a Dense layer with 512 units (ReLU activation). Finally, a Dense layer with 28 units and softmax activation produces the probability distribution over 28 classes.

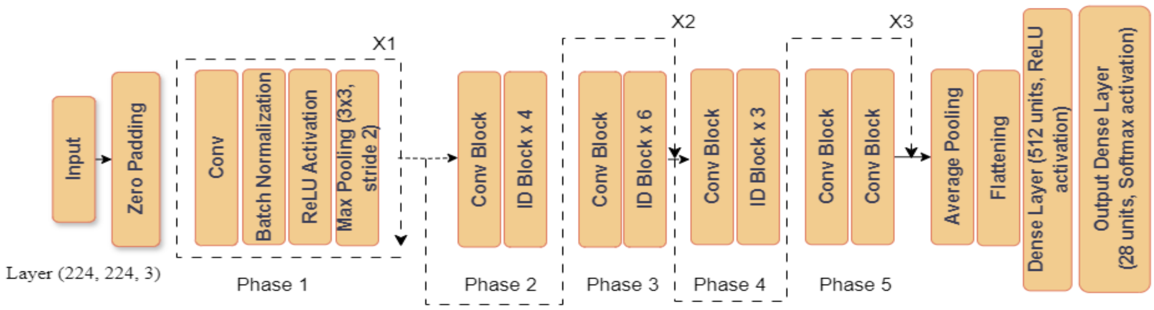


Figure 4.2.3: ResNet50V2 layer architecture

InceptionV3: InceptionV3 is a CNN designed to capture features at multiple scales. It starts with an input layer for (224x224x3) images, followed by the InceptionV3 base model with convolutional and max-pooling layers. It then processes data through Inception modules A to E, capturing multi-scale features. A global average pooling layer reduces the feature maps to a single vector. Finally, a Dense layer with 512 units (ReLU) and a Dense layer with 28 units (SoftMax) produce the probability distribution over 28 classes.

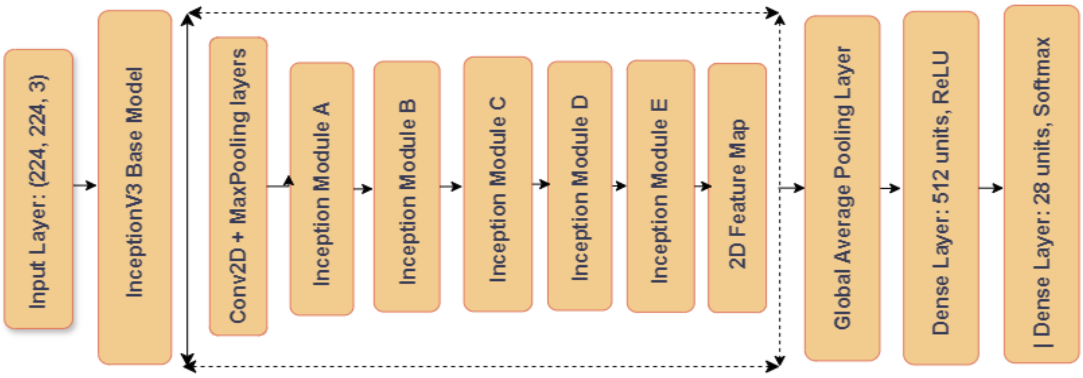


Figure 4.2.4: InceptionV3 layer architecture

Customize DenseNet201(FishNet28): Our custom model is based on DenseNet201, enhanced with additional Conv2D, MaxPooling2D, Batch Normalization, Dropout, Flatten, and Dense layers for superior image classification. It processes an input image (224x224x3) through DenseNet201, followed by a Conv2D layer (32 filters), MaxPooling2D, Batch Normalization, and a Dropout layer (rate 0.5). The output is then flattened and passed through a Dense layer with 512 units (ReLU activation) and another Dropout layer (rate 0.5). Finally, it passes through a Dense layer with 28 units and softmax activation. The model employs data augmentation and preprocessing for robust training, using Categorical Cross entropy loss, RMSprop optimizer, and metrics like accuracy, precision, recall, and AUC. It freezes the first 100 layers of DenseNet201 to leverage pre-trained features and fine-tunes the remaining layers on a dataset with 28 classes.

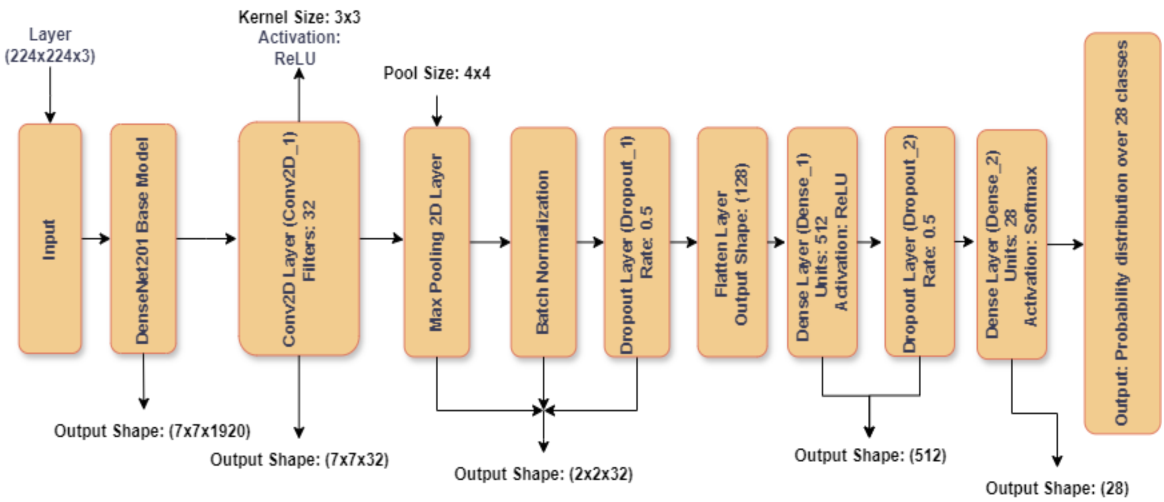


Figure 4.2.5: Customize DenseNet201(FishNet28) layer architecture

4.3 Model Evaluation

Here are the evaluation metrics and their results, where we will be using precision, recall. F1-score and categorical accuracy to evaluate the results.

Accuracy:

Accuracy is the fraction of predictions that a model got right. Categorical accuracy measures the proportion of correctly predicted instances among the total instances, used in multiclass classification techniques. The formula for categorical accuracy is:

$$Accuracy = \frac{\sum_{i=1}^{N} 1(y'i=yi)}{N} \qquad (8)$$

Where:

- N is the total number of instances.
- y'i is the predicted class for the ith instance.
- yi is the true class for the ith instance.
- 1(y'i=yi) is an indicator function that equals 1 if the prediction is correct and 0 otherwise.

Precision:

Precision is the ratio of correctly predicted positive observations to the total predicted positives.

It is used to measure the accuracy of the positive predictions made by the model. The formula is:

$$Precision = \frac{True\ Positives}{True\ Positives+False\ Positives} \qquad (9)$$

Where:

- True Positives (TP) are the instances correctly classified as positive.
- False Positives (FP) are the instances incorrectly classified as positive.

Recall:

Recall is known as true positive rate which is the ratio of correctly predicted positive observations

to all the observations in the actual class. The formula for recall is:

$$Recall = \frac{True\ Positives}{True\ Positives+False\ Negatives} \qquad (10)$$

Where:

- False Negatives (FN) are the instances that were not classified as positive but should have been.

F1 Score:

The F1 score is the harmonic mean of precision and recall. It provides a single metric that

balances both precision and recall, especially useful in cases where there is an uneven class distribution.

The formula for the F1 score is:

$$F1\ Score = \frac{2(Precision\ .Recall)}{Precision+Recall} \tag{11}$$

Model Training results across these metrics:

Table 4.3.1: Model evaluation

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
DenseNet201	98.90	98.98	98.84	98.91
Xception	96.30	96.78	94.95	96.36
ResNet50V2	97.74	97.94	97.58	97.76
InceptionV3	94.73	95.42	94.02	94.71
Custom FishNet28	99.53	99.62	99.45	99.54

4.4 Summary

This chapter provided an in-depth look at the implementation and training of multiple convolutional neural network architectures for image classification. We explored the structural components of DenseNet201, Xception, ResNet50V2, and InceptionV3, along with our custom model, FishNet28. We highlighted the performance metrics used to evaluate these models, demonstrating their effectiveness in achieving high accuracy, precision, recall, and F1 scores. This comprehensive analysis underscores the robustness and efficiency of our custom model compared to standard architectures.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

In this chapter, we provide a detailed examination of the results and analysis from the various models tested. This includes the performance metrics of each model, a comparative analysis, and a summary of the findings. We specifically highlight the performance of our custom FishNet28 model in comparison to other state-of-the-art models.

5.2 Experimental & Simulation Result

Using CNN based existing pre trained models we can experiment on which model can serve our use case best for FishNet28. If we can gain more accuracy with modifying any high performing model, we can choose that as our best performing model.

5.2.1 Experimental Result:

This section presents the experimental results of the models evaluated:

DenseNet201:

DenseNet201 achieves high performance metrics with a training accuracy of 98.90% and a validation accuracy of 98.26%. The precision is 98.98% on the train data and 98.36% on the validation data, suggesting strong positive instance identification. Recall values are 98.84% for the train set and 98.19% for the validation set, showing the model's ability to capture most relevant instances. The F1 score is 98.91% for the training data and 98.27% for the validation data, maintaining a good balance between precision and recall.

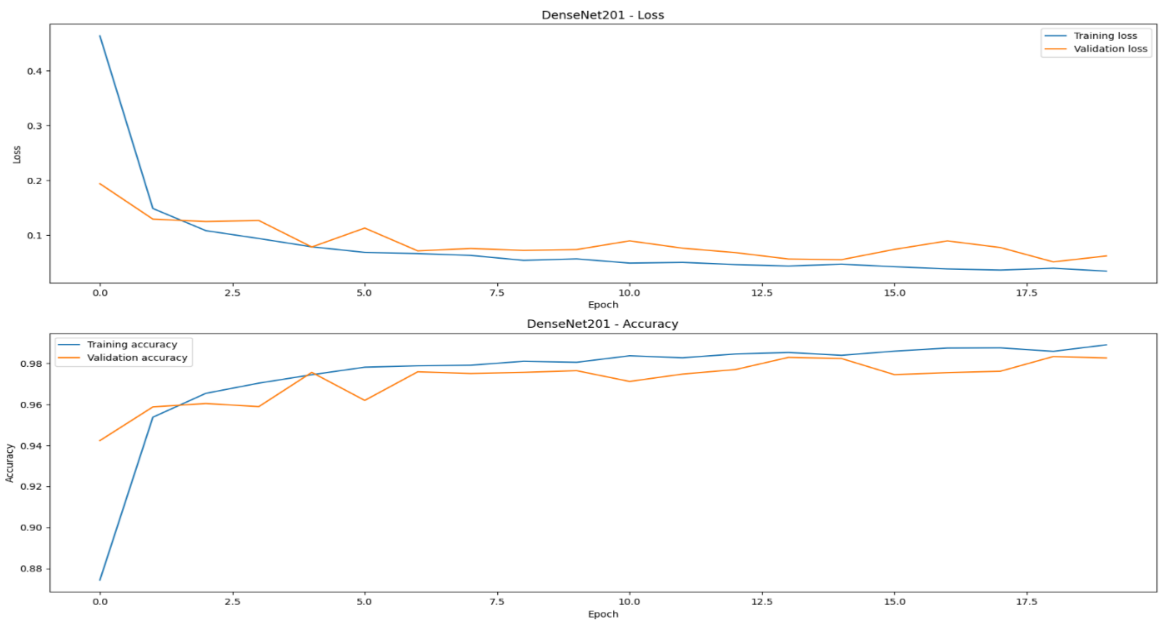


Figure 5.2.1.1: DenseNet201 loss-accuracy curve

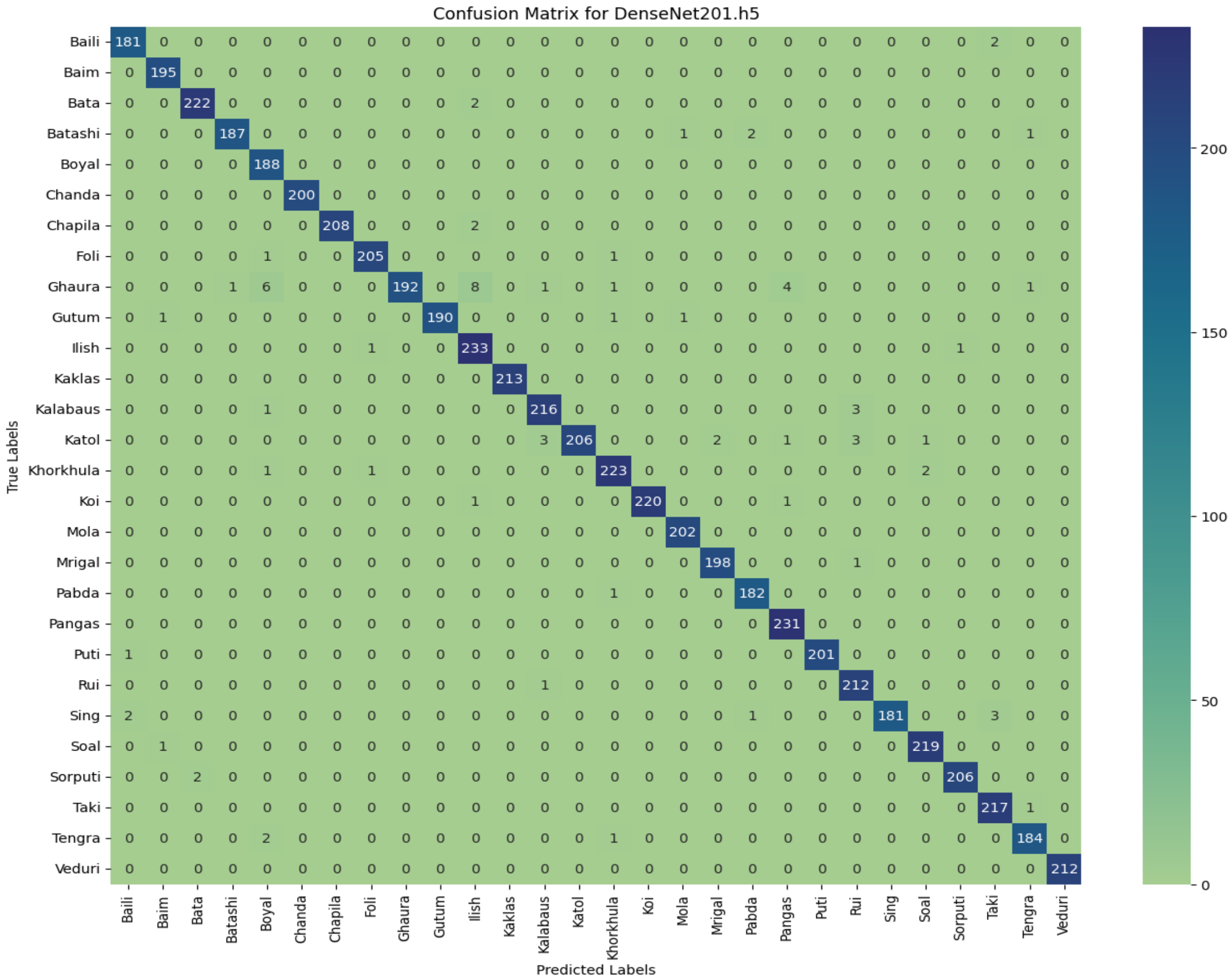


Figure 5.2.1.2: DenseNet201 confusion matrix

Xception:

Xception shows notable differences between train and validation metrics. Training accuracy is 96.30%, whereas the validation accuracy is 94.87%. The precision is 96.78% on the training dataset and 95.46% on the validation set, demonstrating the model's effectiveness in correctly identifying positive instances. Recall values are 95.95% for the training dataset and 94.46% for the validation set, indicating a slightly lower ability to capture all relevant instances. The F1 score is 96.36% for the training data and 94.95% for the validation data, reflecting the balance between precision and recall. Loss values differ significantly, with a training loss of 1.082% and a validation loss of 15.74%, indicating a substantial increase in miss on the validation data.

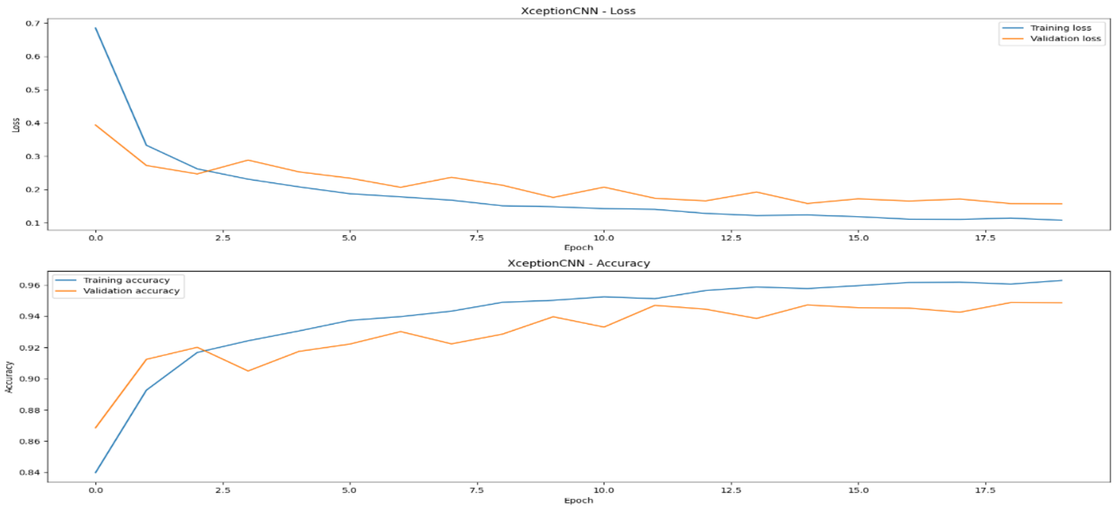


Figure 5.2.1.3: Xception loss-accuracy curve

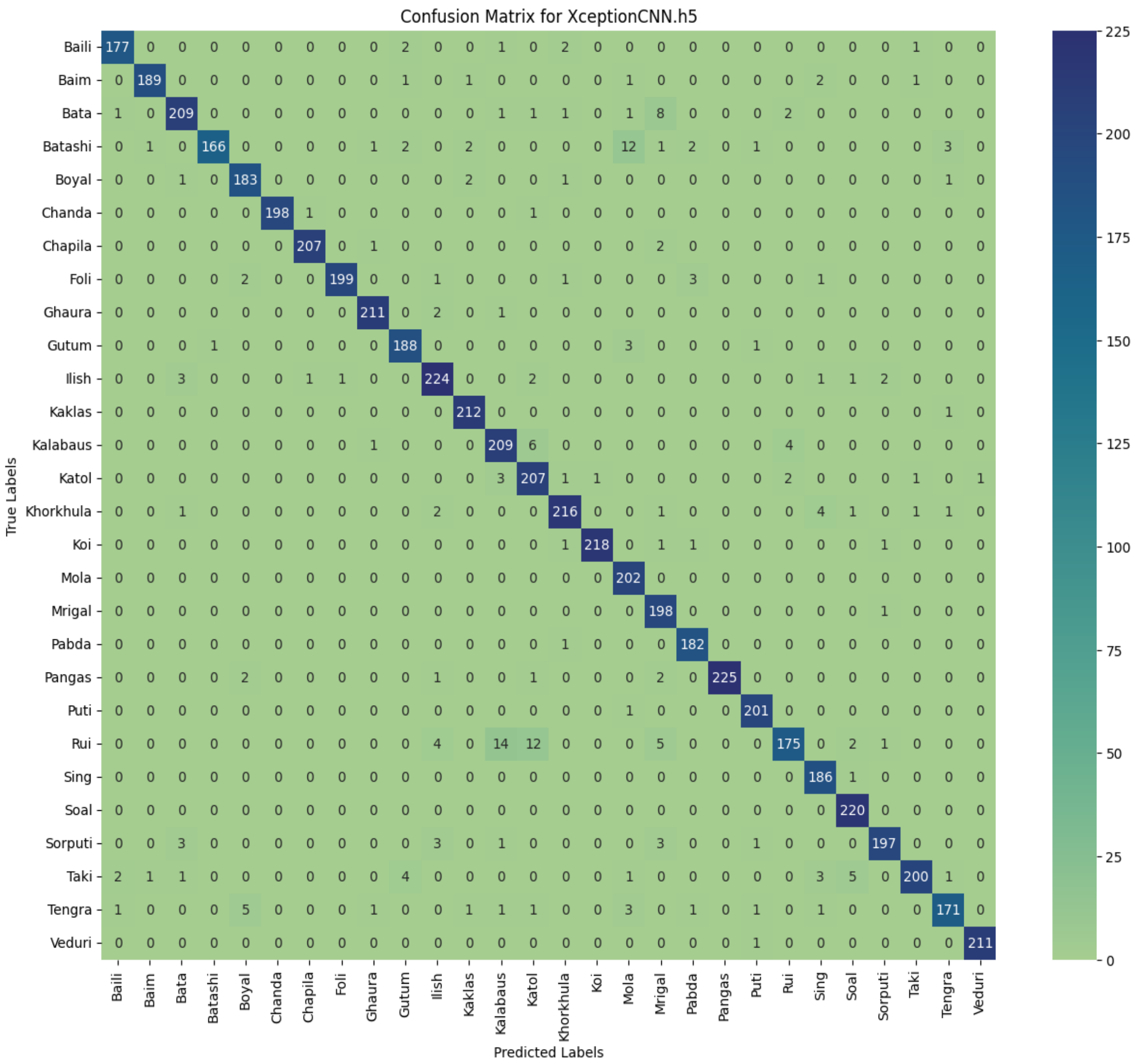


Figure 5.2.1.4: Xception confusion matrix

ResNet50V2:

ResNet50V2 achieves high performance metrics with a training accuracy of 97.74% and a validation accuracy of 96.19%. The precision is 97.94% on the training data and 96.40% on the validation data, suggesting strong positive instance identification. Recall values are 97.58% for the training set and 96.03% for the validation set, showing the model's ability to capture most relevant instances. The F1 score is 97.76% for the training data and 96.21% for the validation data, maintaining a good balance between precision and recall.

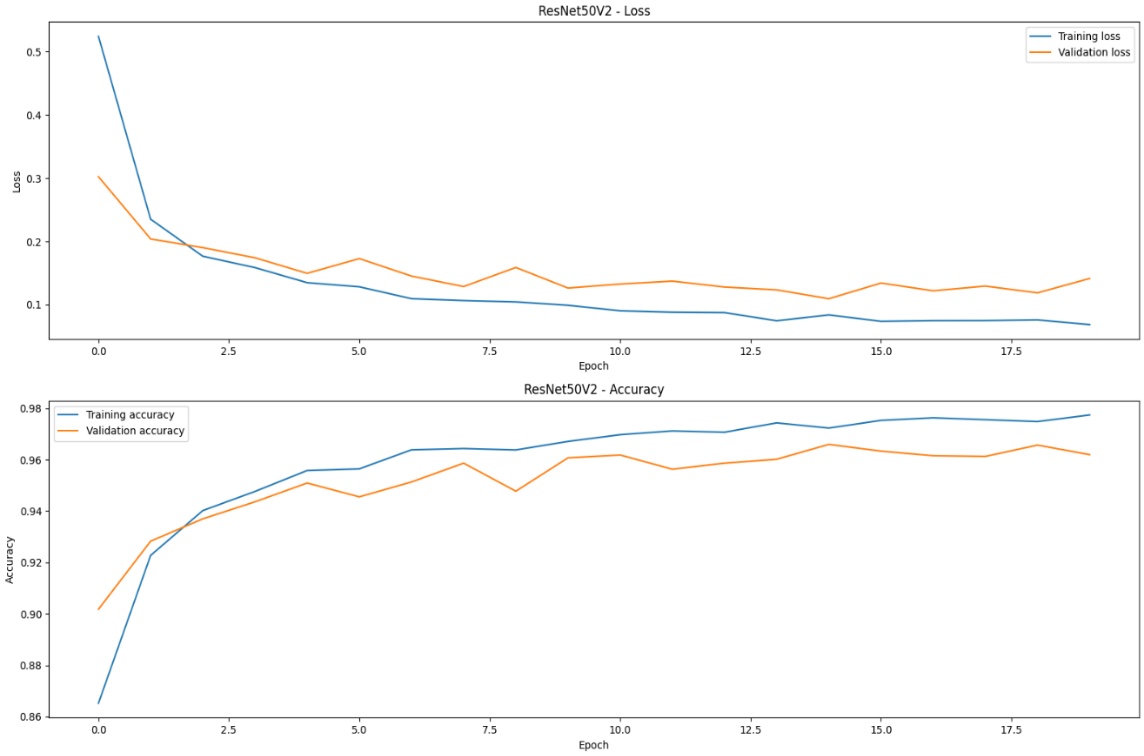


Figure 5.2.1.5: ResNet50V2 loss-accuracy curve

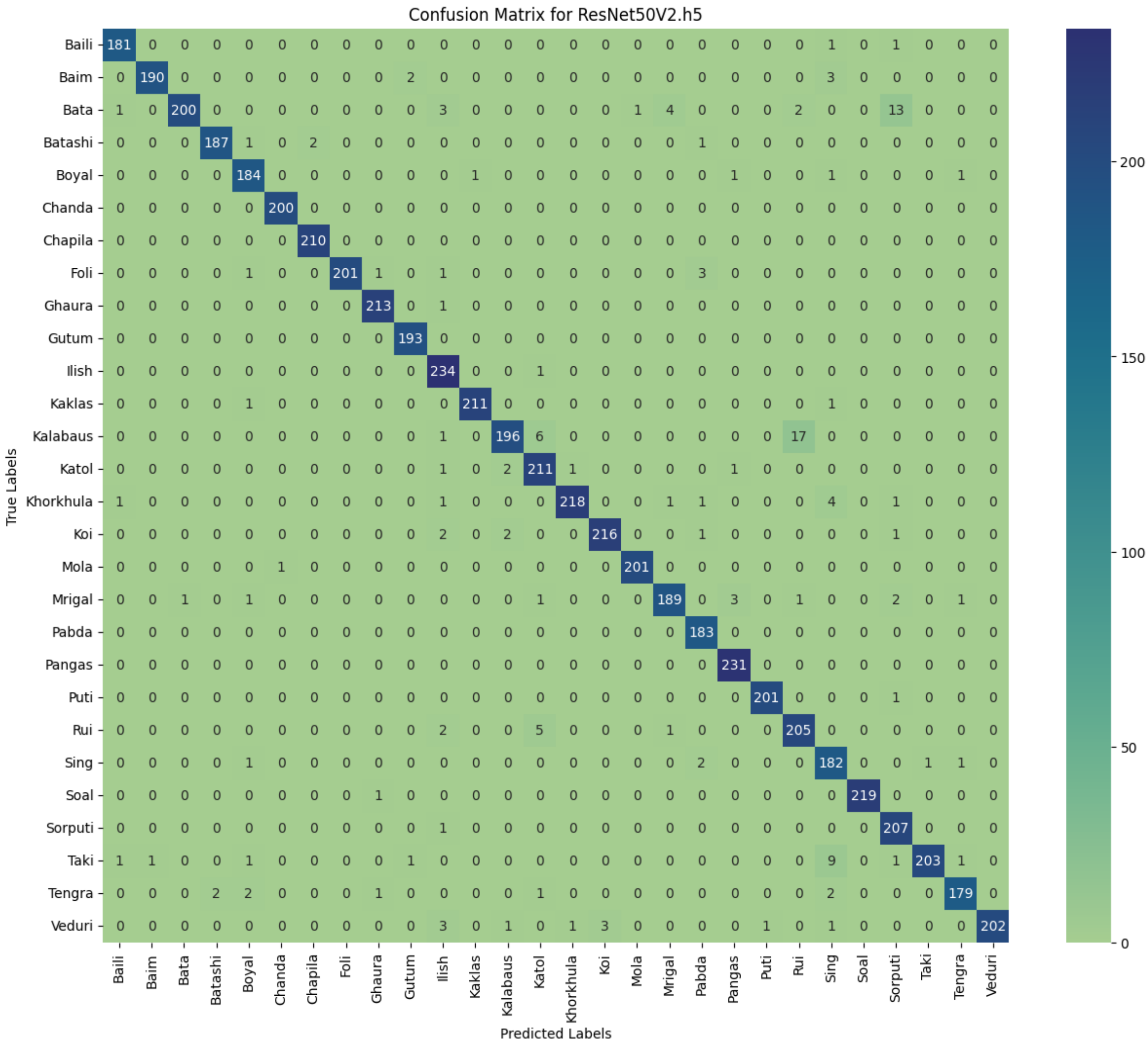


Figure 5.2.1.6: ResNet50V2 confusion matrix

InceptionV3:

InceptionV3 displays relatively lower performance metrics. The training accuracy is 94.73% and the validation accuracy is 94.06%. Precision values are 95.42% for the training set and 94.82% for the validation set, reflecting the model's ability to correctly identify positive instances. Recall is 94.02% for the training data and 93.38% for the validation data, indicating the model's effectiveness in capturing relevant instances. The F1 score is 94.71% for the training data and 94.09% for the validation data, balancing precision and recall. Loss values are higher, with 15.95% for the training data and 18.78% for the validation data, showing increased error rates

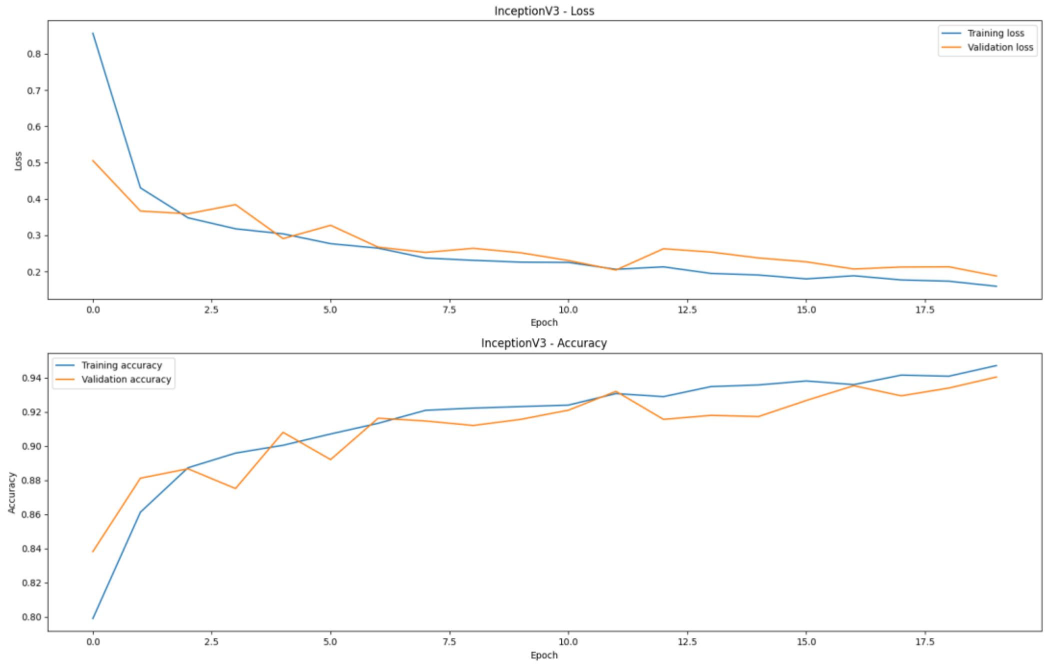


Figure 5.2.1.7: InceptionV3 loss-accuracy curve

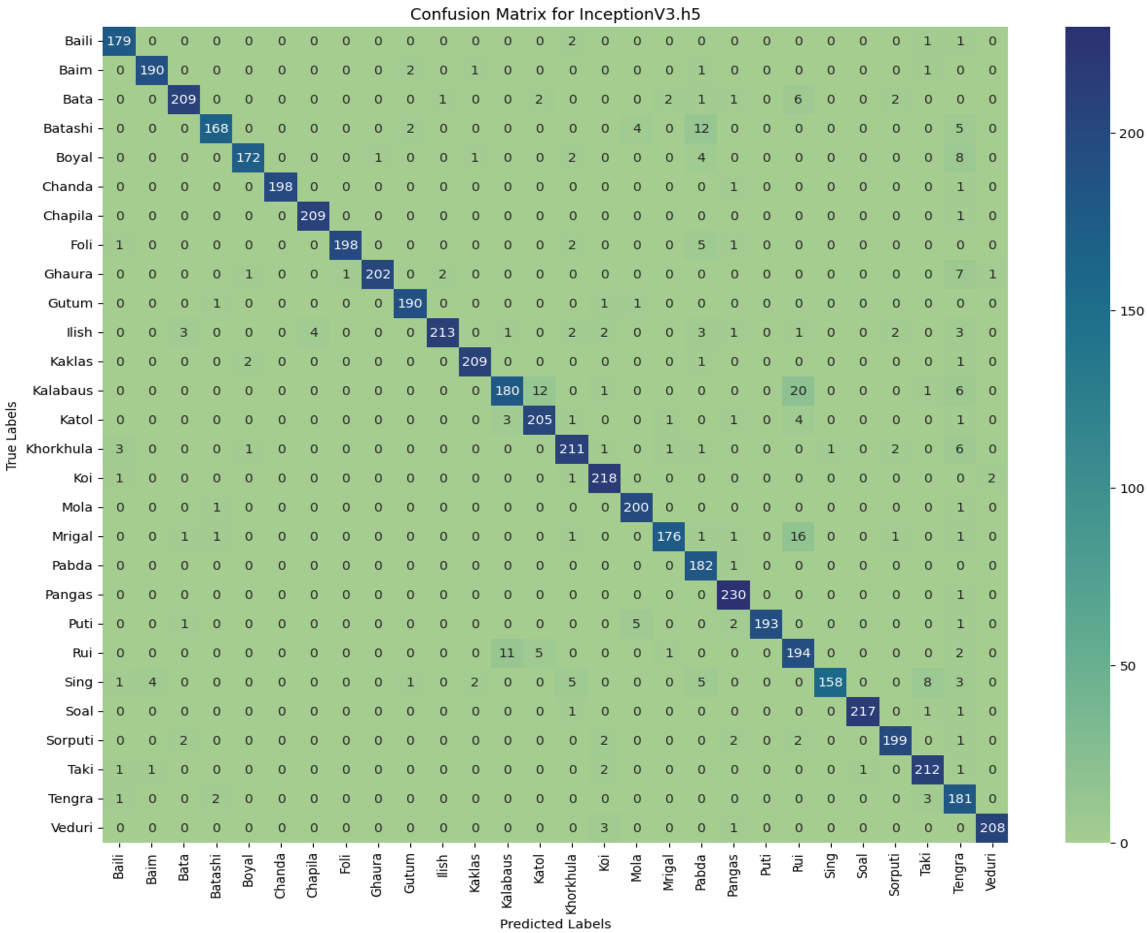


Figure 5.2.1.8: InceptionV3 confusion matrix

FishNet28 or Custom DenseNet201:

The FishNet28 model or the custom DenseNet201 model outperforms all other models, with a training accuracy of 99.53% and a validation accuracy of 99.86%. Precision is extremely high, at 99.62% for the training set and 99.88% for the validation set, indicating the model's exceptional ability to identify positive instances correctly. Recall values are 99.45% for the training data and 99.84% for the validation data, demonstrating the model's effectiveness in capturing nearly all relevant instances. The F1 score is 99.54% for the training data and 99.86% for the validation data, highlighting the model's balanced precision and recall. Loss values are very low, with 2.16% for the training data and 0.77% for the validation data, indicating minimal error and excellent overall performance.

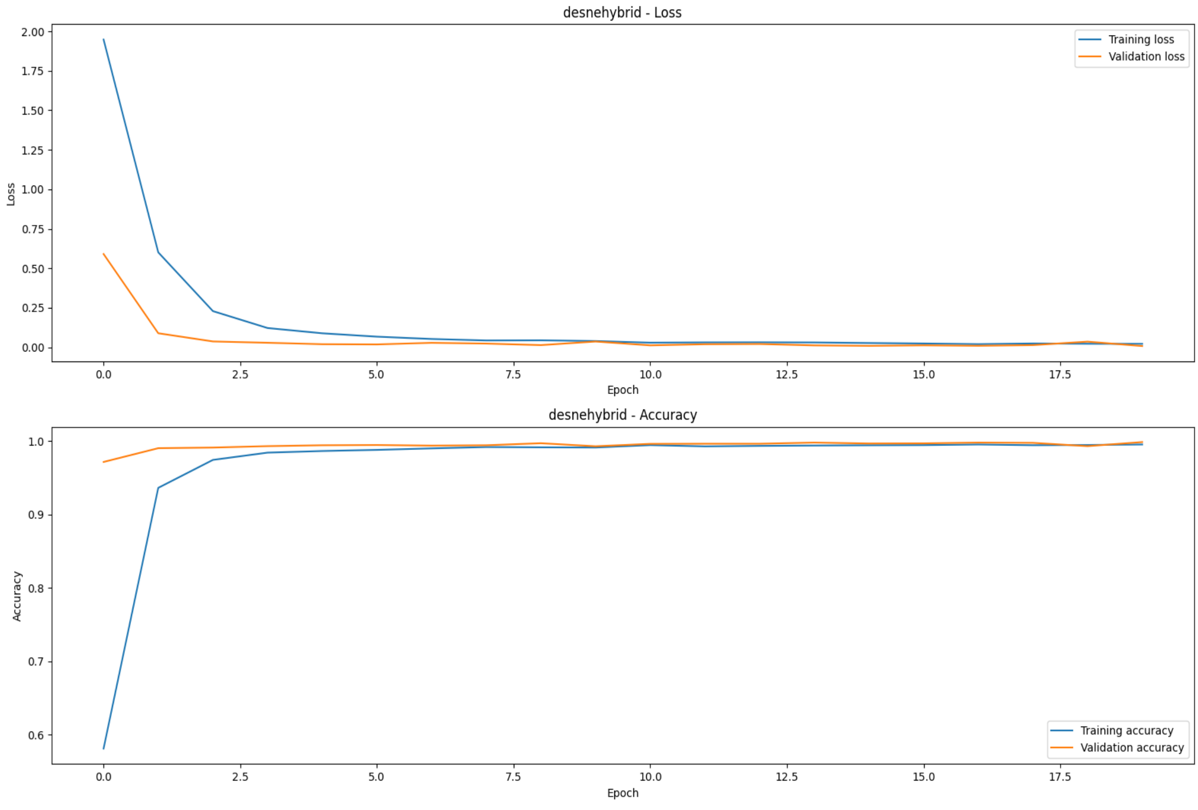


Figure 5.2.1.9: FishNet28 loss-accuracy curve

FishNet28 is our custom model, a modified and hybrid version of DenseNet201, surpasses the pre-trained model by integrating additional layers such as Conv2D, MaxPooling2D, BatchNormalization, Dropout, Flatten, and Dense layers. These added layers enable the model to capture more intricate patterns from input images, crucial for improved performance, especially in datasets with specific challenges. Adding Dropout layers with a rate of 0.5 aids in regularization, mitigating overfitting by encouraging the learning of more robust features. The final Dense layer with 28 units and SoftMax activation is tailored to our dataset of 28 classes, enhancing classification accuracy by specifically addressing the task at hand. Leveraging data augmentation and preprocessing techniques enhances the model's resilience to input variations, leading to better generalization.

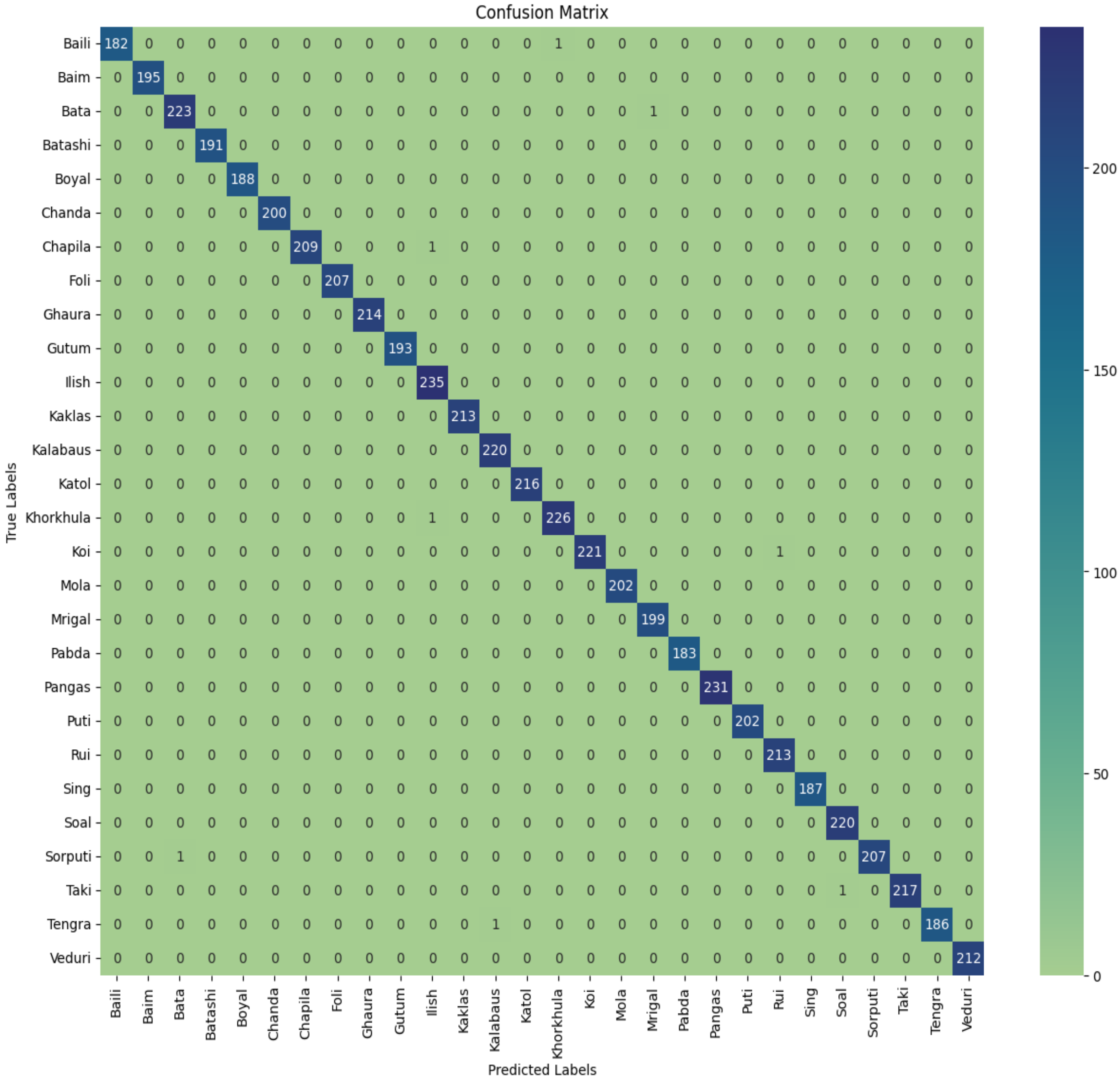


Figure 5.2.1.10: FishNet28 confusion matrix

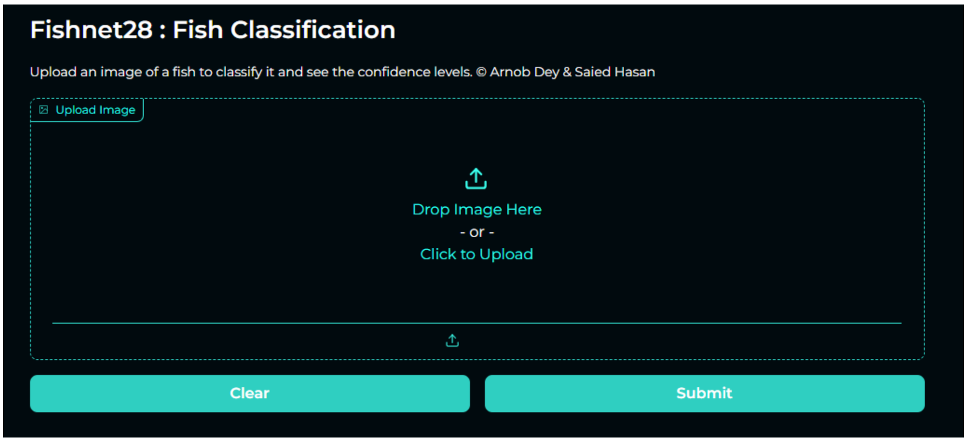
5.2.2 Simulation Result:

With the FishNet28 model, a WebApp or android app can be built using python libraries or existing industry standard frameworks. The FishNet28 web application is implemented using Python, leveraging the Gradio library to create an interactive web-based interface.

- Model Loading: The application starts by loading the pre-trained FishNet28 model from a previously saved .h5 file. This model has been meticulously trained and optimized for achieving high accuracy in the classification of various fish species. Utilizing this pre-trained model allows for quick and reliable predictions, leveraging the extensive training it has undergone.

- Image Preprocessing: Once an image is uploaded by the user, it undergoes a series of preprocessing steps to ensure it is in the correct format for classification. The image is resized to 224x224 pixels to match the input size expected by the model. Additionally, the pixel values are normalized to fall within the range of 0 to 1, which helps in achieving consistent and accurate predictions. This preprocessing is performed using the Keras and Pillow libraries for Python.
- Image Classification: After preprocessing, the image is passed to the FishNet28 model for classification. The model processes the image and outputs a confidence score for each fish species. These scores indicate the model's certainty regarding the presence of each species in the image, allowing for a ranked list of potential matches.
- Results Formatting: The classification results are then formatted into an HTML structure. This structured format displays the fish species names alongside their respective confidence levels in a visually appealing manner. The use of HTML and CSS ensures that the results are both informative and aesthetically pleasing.
- User Interface: A user-friendly interface is created using Gradio, along with HTML and CSS. This interface allows users to upload an image of a fish and view the predicted fish species along with confidence levels. The intuitive design ensures that users can easily interact with the application and understand the results provided by the model.

Web Interface:



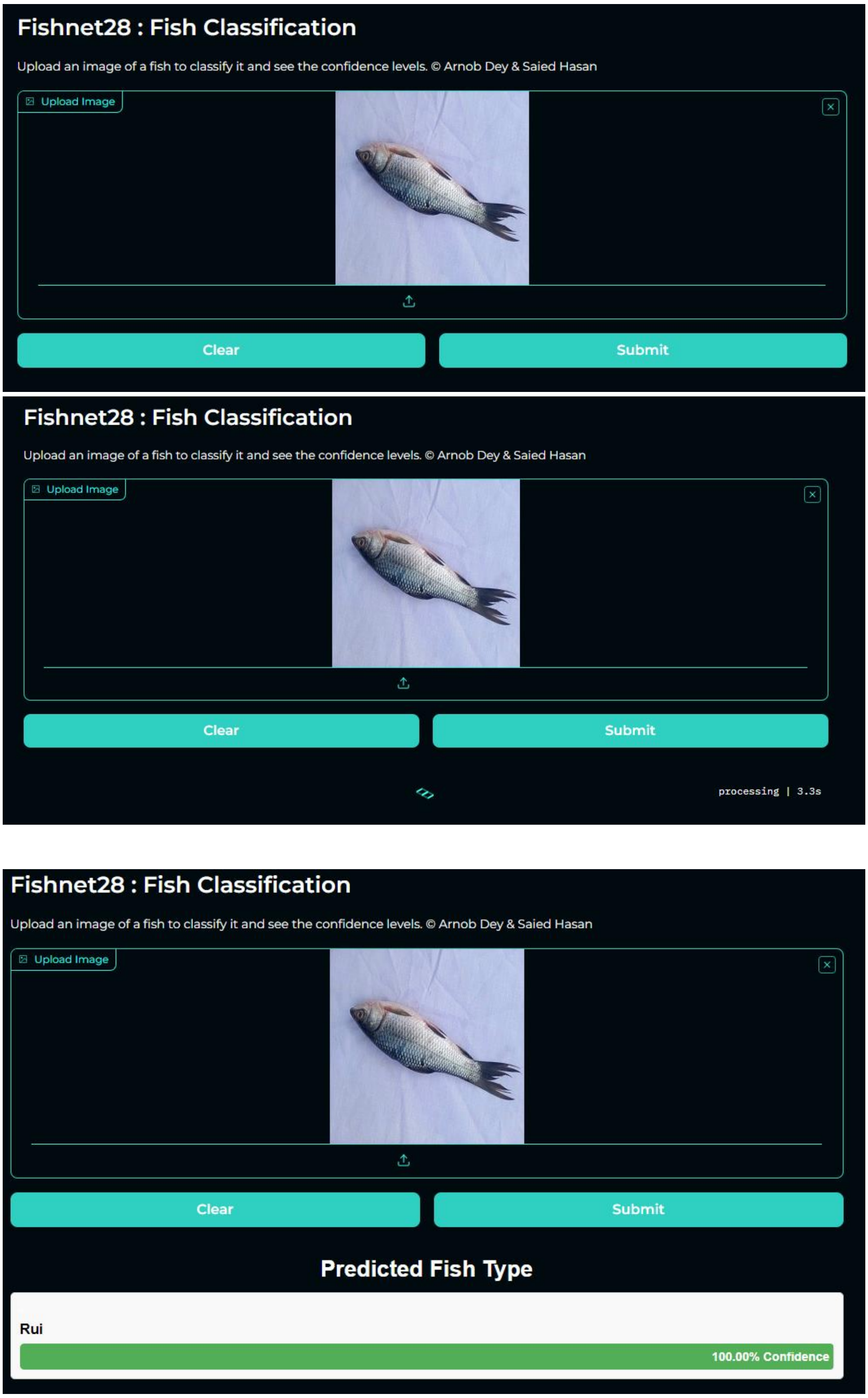


Figure 5.2.2.1-4: Web interface and UI

5.3 Comparative Analysis

By fine-tuning the pre-trained DenseNet201 while freezing its initial layers, FishNet28 effectively combines the strengths of pre-trained features with adaptations tailored to our dataset, facilitating improved feature extraction and overall performance. Utilizing Categorical Cross entropy loss and RMSprop optimizer optimizes the model's training process, ensuring effective weight updates and minimizing classification errors. These enhancements collectively empower FishNet28 to excel in feature extraction, generalization, and classification accuracy compared to the pre-trained model. The FishNet28 or custom DenseNet model achieves the highest performance across all evaluated metrics, with near-perfect accuracy, precision, recall, and F1 scores, and minimal loss. DenseNet201 and ResNet50V2 also perform well but show minor differences between test and validation metrics. Xception and InceptionV3 exhibit lower performance, with more significant differences between training and validation metrics, reflecting the variability in their effectiveness.

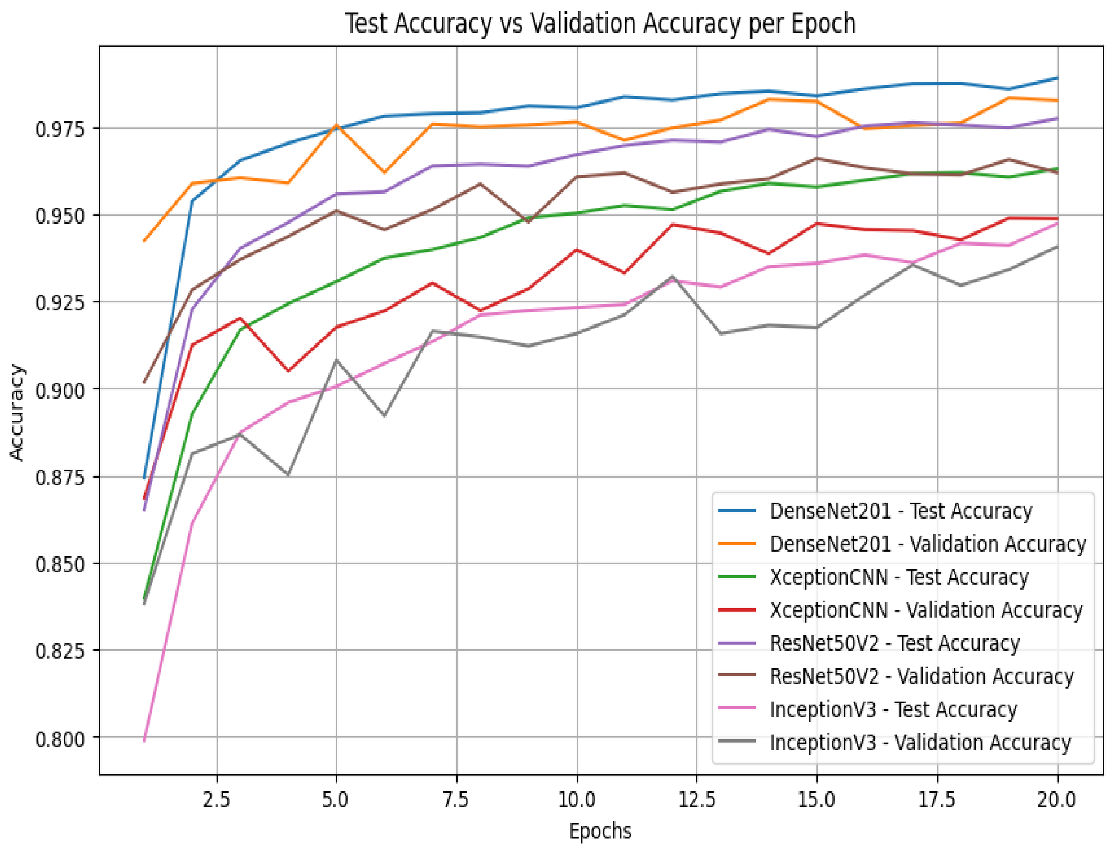


Figure 5.3.1: comparative analysis on test vs validation accuracy per epoch

Here is a comparative table of classification models:

TABLE 5.3.1: Model validation results across all metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
DenseNet201	98.26	98.36	98.19	98.27
Xception	94.87	95.96	94.46	94.95
ResNet50V2	96.19	96.40	96.03	96.21
InceptionV3	94.06	94.82	93.38	94.09
Custom FishNet28	99.86	99.88	99.84	99.86

5.4 Summary

The analysis concludes that the FishNet28 model significantly outperforms other models in terms of accuracy, precision, recall, and F1 scores, with the added benefit of minimal loss values. The modifications and enhancements in FishNet28, such as additional layers and regularization techniques, contribute to its superior performance. This comprehensive evaluation underscores the FishNet28 model's capability to deliver high accuracy and reliable predictions, making it an excellent choice for real-world applications.

CHAPTER 6
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

The research on “FishNet28: Bangladeshi Fish Classification using Machine Learning and Deep Learning Techniques” holds the potential to profoundly impact various aspects of life in Bangladesh. By addressing critical issues in fisheries management and conservation, this project directly influences both human and ecological well-being.

- Enhanced Nutritional Health: FishNet28 aids in the identification and preservation of diverse fish species, which are essential to the diet of many Bangladeshis. By providing accurate information about the nutritional value of different fish species, the project promotes better dietary choices, enhancing the nutritional health of consumers
- Sustainable Livelihoods: The project supports sustainable fishing practices, ensuring that fish populations are not depleted. This sustainability is crucial for the long-term livelihoods of fishermen and fish farmers, who rely on healthy fish populations for their income and food security. By preventing the overexploitation of fish species, FishNet28 helps secure the economic stability of communities dependent on fishing.
- Healthier Ecosystems: By promoting the conservation of fish species and mitigating environmental degradation, FishNet28 contributes to healthier aquatic ecosystems. This ecological balance is essential for maintaining biodiversity and ensuring the resilience of natural habitats against environmental changes.

6.2 Impact on Society & Environment

The research on “FishNet28: Bangladeshi Fish Classification using Machine Learning and Deep Learning Techniques" has the potential to have a significant impact on Bangladeshi society, particularly in the realms of fisheries management, conservation efforts, public awareness, and technological accessibility. FishNet28's impact on the environment extends to the conservation of fish species, preservation of biodiversity, and mitigation of environmental degradation. To explain further,

- Increased Awareness and Education: FishNet28 provides detailed information about fish species, their habitats, and nutritional value, empowering consumers, fishermen, and fish farmers with knowledge about the importance of preserving fish diversity. This increased awareness fosters a culture of conservation and responsible consumption within Bangladeshi society.
- Improved Livelihoods: By promoting sustainable fishing practices and

preventing the overexploitation of fish species, FishNet28 helps protect the livelihoods of fishermen and fish farmers who rely on healthy fish populations for income and food security. Additionally, the accessibility of fish species information can facilitate informed decision-making in the fish market, benefiting both sellers and buyers.

- Technological Empowerment: Through the development of a user-friendly mobile application and integration with IoT devices, FishNet28 empowers non-technical users to access advanced fish species identification tools. This technological empowerment enhances the capabilities of fishermen, fish farmers, and consumers, leading to more efficient and sustainable fishing practices.
- Preservation of Biodiversity: By raising awareness about the importance of preserving fish diversity, FishNet28 supports efforts to protect the rich biodiversity of Bangladesh's rivers and water bodies. Preserving diverse fish species ensures the resilience of aquatic ecosystems and maintains essential ecosystem services.
- Mitigation of Environmental Degradation: By promoting sustainable fisheries management practices, FishNet28 mitigates the environmental degradation caused by overfishing, habitat destruction, and pollution. This contributes to the overall health and resilience of Bangladesh's aquatic environments.

6.3 Ethical Aspects

Ethical considerations play a crucial role in the FishNet28 study, ensuring responsible data use, respect for indigenous knowledge, and transparency in methodologies. FishNet28 adheres to ethical guidelines for data collection, ensuring that fish images are obtained and used responsibly, with respect for the rights and privacy of individuals like fishermen involved. Also, no fish were harmed or damaged while collecting the dataset. Transparency and accountability are maintained throughout the study, with clear documentation of methodologies, model development, and data usage, allowing for accountability to stakeholders and ensuring that the study's outcomes benefit society and the environment.

6.4 Sustainability Plan

The sustainability plan for FishNet28 encompasses several key strategies to ensure the long-term effectiveness and impact of the study's outcomes. FishNet28 implements a robust plan for collecting, curating, and maintaining fish species data. This includes regular updates to the dataset to account for changes in fish populations, habitats, and conservation statuses. By continuously updating and expanding the dataset, FishNet28 ensures that the classification model remains accurate and relevant over time. The study prioritizes community engagement and capacity-building initiatives to empower local stakeholders in fisheries management and conservation efforts. FishNet28 implements a continuous monitoring and evaluation system of its impact and effectiveness.

6.5 Summary

FishNet28 aims to significantly impact Bangladeshi society by increasing awareness about fish species, improving the livelihoods of fishermen and fish farmers, and providing technological empowerment through a user-friendly mobile application and IoT integration. The project focuses on environmental conservation by identifying endangered species, promoting responsible fishing practices, preserving biodiversity, and mitigating environmental degradation. Ethical considerations ensure responsible data use and respect for indigenous knowledge. A sustainability plan ensures the long-term relevance of FishNet28 through continuous data collection, community engagement, and impact evaluation.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Conclusions

The fisheries sector in Bangladesh faces challenges such as declining native fish populations, overfishing, and low public awareness of fish species diversity and conservation. Our "FishNet28" study aims to address these issues by creating a comprehensive dataset of Bangladeshi indigenous fish species, including those found in local markets and those under-identified or mislabeled. This dataset will train machine learning models to accurately classify various fish species from images. The study adopts a holistic approach to tackle fisheries sector challenges in Bangladesh by using machine learning and deep learning techniques to develop a reliable fish classification system. This system will aid fisheries management, conservation efforts, public awareness, and technological accessibility. FishNet28 aims to educate stakeholders on fish species diversity and promote sustainable fishing practices. It also seeks to conserve native fish populations and preserve biodiversity in Bangladesh's aquatic ecosystems. Ethical considerations are integral to the study, ensuring responsible data use, respect for indigenous knowledge, and transparency in methodologies. The sustainability plan includes strategies for continuous data updates, community engagement, capacity building, and monitoring and evaluation to maintain the study's effectiveness over time. Collaborations with governmental and non-governmental organizations could help implement fish classification systems on a larger scale and support broader conservation and sustainability initiatives.

7.2 Further Suggested Works

Future research could explore additional applications of machine learning and deep learning techniques in the fisheries sector, such as fish disease detection, stock assessment, and ecosystem modeling. Additionally, efforts to expand the dataset to include more fish species and improve model performance could enhance the accuracy and applicability of fish classification systems. Further studies may also investigate the integration of emerging technologies, such as blockchain and satellite imaging, to improve traceability, monitoring, and management of fish stocks and fishing activities. Collaborations with governmental and non-governmental organizations could facilitate the implementation of fish classification systems at scale and support broader conservation and sustainability initiatives.

7.3 Limitations of the study

- **Computational Resources**: Training deep learning models on large-scale image datasets requires significant computational resources, including high-performance GPUs. Limited access to such resources can slow down the training process and impact the overall development timeline.

- **Data Collection and Quality**: The FishNet28 project relies heavily on the collection of raw fish images from various regions in Bangladesh. Ensuring the quality and consistency of these images can be challenging due to varying environmental conditions, camera quality, and fish handling practices. This variability may affect the accuracy and robustness of the machine learning models.

- **Ethical and Privacy Concerns**: Collecting data from fishermen and local communities involves ethical considerations, including obtaining consent and ensuring the privacy and rights of individuals involved in the data collection process.

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

Title: FISHNET28: BANGLADESHI FISH CLASSIFICATION USING MACHINE LEARNING AND DEEP LEARNING TECHNIQUES
Student ID: 203-15-3906 & 203-15-3903

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a real-life complex engineering problem for the Final Year Design Project	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish these goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**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 FishNet28 project requires an in-depth understanding of both existing and emerging knowledge in areas such as computer vision, machine learning, and species classification. Identifying the real-life problem of fish species misidentification and its consequences on biodiversity showcases the integration of various knowledge domains covering **K1 [Natural Science], K3** [Engineering Fundamentals]**, K4 [Specialist Knowledge]**.	**Page no:** [1-2,9,8-12] **Section:** [1.1,1.2,1.2 3,1.5,3.2,3.2.2] **Page no:** [21-25] **Section:** [4.2, 4.3]
				As part of fish image classification, we have to draw diagrams for the proposed methodology, create figures and tables for classification models that cover **K5 [Engineering Design]**. We choose certain machine learning models, classified images, used python as a programming language, used different libraries and preprocessing techniques that reflect our knowledge from **K6[Engineering Practice]**.	**Page no:** [9,17,21-24] **Section:** [3.2,3.2.3,4.2]
				To find the research scope and compare our methodology, we studied existing research and compared their models and techniques. Which covers **K8 [Research Literature]**.	**Page no:** [3-7] **Section:** [2.2, 2.3,2.4]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	During fish image Classification we will face significant challenges such as time period to train models, storage to contain dataset. We may also face challenges regarding training and validation accuracy across different models.	**Page no:** [19] **Section:** [3.3]

3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	We will have to choose a classification model based on the result obtained after training the dataset and comparing evaluation metrics like accuracy, precision, recall, F1 score.	**Page no:** [27-38] **Section:** [5.2,5.3]
4.	**EP4: Familiarity of Issues**	Yes	CO8	For fish image classification and building a proper dataset, we need knowledge on zoological characteristics of fish, which is also known as Ichthyology. Building and classifying fish images will also have an impact on Fisheries, Aquaculture, Environmental Conservation sectors as well.	**Page no:** [1-2.39-40] **Section:** [1.2,1.3,1.4, 1.5,6.1,6.2, 6.3,6.4]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting requirements**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	The design and development of FishNet28 involve a synergy between different fields. Ichthyology provide insights into fish species characteristics, data scientists develop and fine-tune machine learning models, and software engineers create the mobile application. This collaboration ensures that the technical solutions are robust, scientifically accurate, and user-friendly.	**Page no:** [1,2,3-5] **Section:** [1.2,1.5,2.2]

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	The FishNet28 project leverages a wide array of resources, including advanced machine learning frameworks such as TensorFlow and Keras, pre-trained models like DenseNet201, XceptionCNN, ResNet50V2, and InceptionV3. A large, diverse dataset of fish images also have been collected from various sources, ensuring comprehensive coverage of Bangladeshi indigenous fish species.	**Page no:** [21-24] **Section:** [4.2]
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	Yes		FishNet28 simply demonstrates innovation through the creation of a custom layered DenseNet201 model that outperforms existing pre-trained models in accuracy. It also innovates by combining machine learning techniques with practical knowledge and implementation.	Page no: [21-24,27-34] Section: [4.2,5.2]
4.	**EA4: Consequences for society and the environment**	Yes		This projects emphasizes social impact and environmental sustainability by enhancing trip efficiency, promoting sustainable travel practices, and ensuring ethical considerations such as strong security, privacy, and transparent business practices, fostering societal well-being and environmental stewardship.	**Page no:** [39-41] **Section:** [6.2,6.3, 6.4]

5.	**EA-5: Familiarity**	Yes		The project has significant positive impacts on society and the environment, likewise by accurately identifying fish species and preventing misidentification, the project supports efforts to protect endangered species and maintain ecological balance. It also promote sustainable fishing practices by providing accurate data on fish populations, helping to prevent overfishing.	**Page no:** [1-2, 40] **Section:** [1.2, 1.3,1.4,1.5,6.4]

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

SN	COs	Attainment	Justification	References
1	CO4	Yes	We have prepared a budget to manage, evaluate and estimate the cost required for our FYDP covering CO4.	**Page no:** [20] **Section:** [3.4]
2	CO9	Yes	The FishNet28 project is rooted in ethical considerations, such as the preservation of biodiversity and preventing the extinction of indigenous fish species. By ensuring accurate species identification, the project promotes ethical fishing practices and conservation efforts. The project also promotes transparency by keeping dataset collection procedure public and keeping transparency in methodologies.	**Page no:** [40] **Section:** [6.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The field of machine learning and technology is rapidly evolving. The FishNet28 project fosters a mindset of continuous learning by building a custom FishNet28 model that can classify fish images more accurately.	**Page no:** [21-24,27-34] **Section:** [4.2,5.2]

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