EAST WEST UNIVERSITY

Department of Computer Science and Engineering

Course Code: Capstone 400C

Project Title: Classification of Dried Fish Types with Convolutional Neural Networks

Name	Student Id
Subah Nuzhat	2020-1-60-129
Shajia Hossain	2020-1-60-050
Sadia Tasnim Shifa	2020-1-68-013
Lamia Haider	2020-1-60-049

Supervised By:

Dr. Md. Hasanul Ferdaus

Assistant Professor, Department of Computer Science and Engineering

Declaration

We, **Subah Nuzhat, Shajia Hossain, Sadia Tasnim Shifa**, and **Lamia Haider** hereby, declare that the work presented in this capstone project report is the outcome of the investigation performed by us under the supervision of **Dr. Md. Hasanul Ferdaus**, Assistant Professor, Department of Computer Science and engineering, East West University. We also declare that no part of this project has been or is being submitted elsewhere for the award of any degree or diploma, except for publication.

Countersigned

…………………………

Dr. Md. Hasanul Ferdaus

Supervisor

Signature

………………

Subah Nuzhat

2020-1-60-129

Signature

………………

Shajia Hossain

2020-1-60-050

Signature

………………

Sadia Tasnim Shifa

2020-1-68-013

Signature

………………

Lamia Haider

2020-1-60-049

Letter of Acceptance

The capstone project report entitled **"Advanced Classification of Dried Fish Types with Convolutional Neural Networks"** is submitted by Subah Nuzhat (2020-1-60-129), Shajia Hossain (2020-1-60-050), Sadia Tasnim Shifa (2020-1-68-013), and Lamia Haider (2020-1-60-049) to the Department of Computer Science and Engineering, East West University, Dhaka, Bangladesh. The requirement for the Bachelor of Science in Computer Science and Engineering is partially satisfied by this report.

Board of Examiners

1. ____

Dr. Md. Hasanul Ferdaus
(Research Project Supervisor)
Assistant Professor
Department of Computer Science and Engineering
East West University

2. ____

Dr. Maheen Islam

(Chairperson)

Department of Computer Science and Engineering

East West University

Abstract

Dried fish are an important source of nutrition, offering high protein content and essential vitamins and are widely consumed across various countries. These fish are also vital for the economy, supporting incomes through trade and providing a long-lasting food option. However, classifying different dried fish species is a multifaceted task due to their similar visual characteristics and the need for accurate analysis from multiple perspectives such as a bulk, head, tail and single fish view. In our study, we employ deep learning models to classify dried fish to tackle these challenges. A dataset was created with images of eight different dried fish species- Baim, Chela, Chapla, Kachki, Tengra, Chepa and Loitta captured from different angles. Four deep learning models- MobileNetV2, Xception, ResNet50V2 and EfficientNetV2 were evaluated for performance. The result showed that MobileNetV2 performed best for bulk fish classification achieving 100% accuracy and a loss of 0.000031. RestNet50V2 and Xception also showed strong performance for single fish and head perspectives with accuracies of 98.84% and 100% respectively. This work highlights the potential of deep learning to improve the classification process of dried fish leading to enchanted quality control and market efficiency while offering benefits to both producers and consumers.

Key Words: Dried fish, Deep learning, Classification, MobileNetV2, Xception, ResNet50V2, EfficientNetV2.

Acknowledgment

First and foremost, we express our deepest gratitude to the Almighty for his boundless blessing. And guidance throughout our journey. We extend our heartfelt thanks to our esteemed supervisor Dr. Md. Hasanul Ferdaus whose mentorship, insights and unwavering support have been instrumental in the successful completion of this work. His encouragement, thoughtful feedback and ability to challenge us intellectually have greatly enriched our learning experience and fostered our growth. We are profoundly grateful to our parents for their unconditional love, sacrifice and constant encouragement. We also thank the Computer Science and Engineering Department at East West University for their essential support in facilitating this project. Finally, we extend our appreciation to our friend and everyone who supported us directly or indirectly. This work is dedicated to all who have guided, inspired and supported us on this journey.

Table of Contents

List of Figures

List of Tables

List of Models

Chapter 1

Introduction

Dried fish is a very popular food item in all over the country. This is easily transportable, marketable, storable and has good market demand in the country or abroad. The fisheries sector plays a very important role in the national economy as a result it contributes 3.57% to the Gross Domestic Product (GDP) of the country and 26.50% to the agricultural GDP (DoF, 2022) [1]. Norway exported 5200 tons of stockfish to mainly Italy and other countries like Nigeria, Sweden, and France. Other than stockfish, Norway also mass produces clip fish, which is. essentially salted dried fish. Overall, dried fish is accepted and consumed all over the globe and produced in varying ways depending on the cultures involved in the product. Hence, the characteristics of dried fish highly depend on such cultures as the type of fish, ingredients used. and drying methods readily affect the characteristics of the product in terms of its nutritional contents and texture [7].

Bangladesh possesses vast aquatic resources in the form of inland waters, rivers, brackish and marine waters and ranks among the top five fish producing countries in the world (FAO, 2016). As per the FAO's latest report in 2018, Bangladesh now holds the 3rd position among freshwater fish producing countries in the world after China and India [2]. Dry fish (Shutki) is one of the popular food items and is widely consumed in Bangladesh. Bangladesh exported 3144 metrics tons of dried fish, valued at 425.9 million Taka (DoF, 2019) during 2018-19[3]. The legendary Kuakata and Barisal are the largest dry fish processing area in the coastal region of Bangladesh [4]. The role of fisheries and aquaculture in the national economy, food security and-nutrition of Bangladesh is enormous. Bangladesh exports dried fish globally, with the main markets being India, Singapore, Hong Kong, Malaysia, the UK, the USA and United Arab Emirates [5], The sector contributes 2.43% to the GDP 22.14% to the agricultural GDP and 1.05% to the total national exports; some 5.74% of the GDP growth was achieved from the fisheries sub-sector (Bangladesh Economic Review 2023) [6].

The increasing demand for dried fish has led to extensive research into production methods and species classification. Both of which are essential for ensuring quality, fair trading and accurate. pricing in the fisheries and aquaculture sector. Traditional classification techniques for dried fish are often labor-intensive, time-consuming, and prone to errors. In contrast, deep learning offers a faster, more accurate and cost-effective approach. This study explores the application of deep learning models to develop efficient and precise methods for classifying dried fish species.

The primary contribution of this study is accomplishing high classification accuracy for dried fish species using our collected dataset. We used deep learning methods to demonstrate notable performance improvements. For a detailed perspective, we outlined the utilized dataset as follows:

Dried Fish Species: This dataset encompasses images of various dried fish species. collected from wholesale markets. The data includes a varied range of dried fish. categorized by:

Size: Including both small and large species.

Shape: Considering lengthened, round, or irregular forms.

Thickness: Covering thin, medium, and thick slices of dried fish.

Species Variety: Encompassing a combination of common and less common

dried fish species found in local wholesale markets.

In this paper, research similar to our study is presented in the Literature Review section. Data collection, preprocessing and models are shown in the Methodology section. On this basis accuracy rate, training model and comparison between the models are presented in the Result and Discussion section. At last, we conclude our paper in the Conclusions section.

Chapter 2

Literature Review

Research on dried fish classification has been done by researchers in [8]. They used deep learning and CNN model to classify the dried fish dataset and achieved an accuracy of 98.27%. In another research [9] machine learning models are applied on dried fish dataset collection which resulted in 42.67% of highest accuracy before training the model and 95.23% of highest accuracy after training amongst all the model and that is EfficientNetB0 model.

Another work [10] focuses on fish species classification in unconstrained underwater environments using shape and texture features. The study began with images captured in real- world aquatic settings, where various preprocessing techniques were applied to extract the fish's region of interest. The authors employed Local Binary Patterns (LBP) and Gabor filters for feature extraction, while Support Vector Machines (SVMs) were utilized as the primary classification model. The research achieved an overall accuracy of 98.43% in identifying fish species under varying underwater conditions. However, the presence of low lighting reduced the classification performance.

Study [11] is based on fish species classification using machine learning techniques in constrained environments. It utilizes a dataset of fish images where color and texture features were extracted using the Gray-Level Co-occurrence Matrix (GLCM). Inception is used as a deep learning framework and a k-Nearest Neighbors (k-NN) classifier was employed as the primary model, achieving an accuracy of 94% under controlled environmental conditions. However, classification performance declined when images included variations in illumination and background noise.

A fish classification system based on recognized image bounding boxes is discussed in [12]. It describes a 2D affine object recognition technique that uses invariant features derived from the fish's contour and texture. These affine-invariant features remain unaffected by the object's position, orientation, or scale. Texture analysis is performed using the gray-level histogram, Gabor filters and gray-level co-occurrence matrices (GLCM). The system classifies fish images into 1 of 10 supported species, achieving a success rate of 85% in average.

Larsen et al. in [13], introduced a fish classification method that uses both shape and texture features, designed to work with various images and species. The approach includes separating shape and texture characteristics using an active appearance model, which relies on principal component scores and linear discriminant analysis. This method shows the integration of statistical modeling techniques to enhance the accuracy and robustness of fish species identification.

Rova et al. in [14], implemented a Support Vector Machine (SVM) algorithm for fish recognition, focusing on differentiating between the Striped Trumpeter and the Western Butterfish species. Their method involved developing a texture-based classification system, where a unique template was created for each species. For classification, each query image was aligned and warped to both templates, enabling the texture-based classifier to accurately differentiate between the two species. This approach highlights the effectiveness of combining template matching with advanced machine learning techniques for species identification.

The work in [15] presents an automatic fish classification system for underwater environments toad marine biologists in studying fish behavior. The system combines texture features (from gray level histograms, Gabor filters, and co-occurrence matrices) and shape features (from curvature scale space transforms and Fourier descriptors). It uses affine transformations for 3D representation and achieves 92% accuracy on a dataset of 360 images across ten species.

This study [16] reviews machine vision-based methods for fish classification, highlighting their speed, non-destructive nature, and the impact of deep learning advancements. It discusses applications, challenges, and future research directions, aiming to guide researchers in developing advanced models for improving fish classification in marine ecology, aquaculture, and health monitoring. Among all the model VGGNet achieved the highest accuracy 0f 100% evaluating model performance using cross-validation.

Kaya et al. [17] proposed a CNN-based model named IsVoNet8 for classifying eight fish species from six families commonly consumed in Türkiye. The model outperforms ResNet50, ResNet101, and VGG16 in accuracy and loss rate, achieving a 98.62% accuracy with a loss rate of 0.0568. Comparatively, ResNet50, ResNet101, and VGG16 achieved accuracies of 91.37%, 86.12%, and 97.75%, respectively. This shows IsVoNet8's effectiveness in fish classification using deep learning techniques.

By using CNN and training it to use as a novel method that is based on incremental learning, Ben et al. [18] were able to classify live reef fish species in an unrestricted underwater environment. The method of gradual learning was important in bringing on this successful outcome. According to the results of the calculations that were carried out, the suggested method had an accuracy of 81.83% when applied to the LifeClef 2015 Fish benchmark dataset.

In [19] a novel multimodal convolutional neural network (MMCNN) is approached for predicting fish age using Fourier transform near-infrared (FT-NIR) spectra of otoliths, combined with biological and geospatial data from nearly 9,000 walleye pollock specimens. The model automatically extracts spectral features and reveals structural relationships linked to fish growth, achieving high accuracy of $R^2 = 0.93$, RMSE = 0.83 for training; $R^2 = 0.92$, RMSE = 0.91 for testing. Absorbance in the 7000–4000 cm^{-1} range, along with fish length, latitude, depth, and temperature, significantly influenced predictions. The MMCNN outperformed traditional methods and also improved accuracy for older fish age predictions.

Another study [20], introduces a low-cost fish species identification tool combining a custom- built multispectral camera and machine learning. It examines small fish regions using reflectance spectroscopy, focusing on three abundant species in Portugal that are horse mackerel, Atlantic mackerel, and sardines. Overall, 48,741 spectra from 5×5 pixel regions were captured across 12 wavelength bands (390–970 nm) using cost-effective high-pass filters and Teflon tape as a white reference. Support vector machines achieved the best classification accuracy of 63.8%, and similar results are possible with 10 cameras instead of 12.

Alsmadi et al. [21] proposed a fish classification prototype that combines features extracted from shape and size measurements using distance and geometric calculations. The study used a dataset of 350 different type of fish images from 20 different families, splitting the data into 257 images for training and 93 for testing. By developing a neural network with a back-propagation algorithm, the model achieved an accuracy of 86% on the test dataset. The results proved the classifiers effectiveness in accurately identifying fish species, differentiating between poisonous and non-poisonous fish, and classifying them into their respective families.

The study [22], focuses on detecting diseases in salmon, a key species in the rapidly growing aquaculture industry. By using a combination of image processing and machine learning, the work applies pre-processing and segmentation techniques to enhance images with feature extraction and disease classification using an SVM algorithm followed by a kernel function. This experiment on a novel salmon image dataset achieved an accuracy rate of 91.42% with image augmentation and 94.12% without it, representing the effectiveness of the proposed approach.

Hasan et al. [23], proposed a study on fish diseases detection using Convolutional Neural Network (CNN). It studies the use of CNNs for detecting fish diseases, testing 90 images that include healthy fish and two diseases; White Spot and Red Spot. The CNN achieved a high detection accuracy of 94.44%, representing its capability to effectively identify and classify fish diseases. Nevertheless, future studies with larger datasets could more enhance detection performance.

We can conclude that none has performed any depth research work on different features of dried fish classification regarding the research obligations described above. In contrast, most of the research works involved typical fish classification but not dried fish. Furthermore, only one research on this topic has been conducted in Bangladesh. Our study focuses on this area, using locally sourced dried fish collected from markets within the region.

Chapter 3

Research Questions and Objectives

In this study, we aim to apply a Convolutional Neural Network (CNN) model to classify dried fish images into different categories based on their species and segments.

The questions we are considering for this study are as follows:

1. What methods can be used to classify different types of dried fish?

Classifying dried fish by species involves several approaches, including data collection, preprocessing, image segmentation, selecting suitable machine learning models, training and testing the models, and implementing them for automated classification.

2. How can dried fish species be classified autonomously?

Classifying dried fish species autonomously can be achieved using a combination of techniques, such as image acquisition, preprocessing, feature extraction, machine learning model training, real-time classification, and deployment.

3. What are the image processing steps required before utilizing images in deep learning models for dried fish classification?

The essential image processing steps include Image Rotation, Image Resizing, Contrast Enhancement, Noise Reduction, Edge Detection, Feature Extraction, Data Augmentation, and Dataset Splitting to ensure optimal performance in deep learning-based classification.

4. Are there any high-quality dataset available that specifically focuses on dried fish in Bangladesh?

The performance of a deep learning model in classification of dried fish species depends on a premium quality dataset. A region-specific dried fish dataset is also essential for capturing local variations, species, and preparation methods.

5. How can automation in dried fish classification enhance industry operations?

Exploring how automated classification systems can improve efficiency, accuracy, and scalability in sorting processes for dried fish in real-world scenarios.

3.2 Research Objectives:

1. To develop CNN-based deep learning models for the classification of dried fish species and quality.

This objective focuses on designing and training some convolutional neural network to analyze dried fish images, aiming to differentiate between different species and quality grades based on specific properties of their appearance.

2. To utilize advanced deep learning models for classifying and categorizing various types of dried fish.

This objective aims to employ advanced deep learning techniques to automatically recognize and classify dried fish varieties. The trained model will serve as a reliable and efficient system for sorting and categorization based on specific features.

3. To identify the most effective image preprocessing techniques for improving the accuracy of dried fish classification.

The goal here is to experiment with and determine optimal image processing methods to enhance the performance of deep learning models in identifying and classifying the properties of dried fish accurately.

4. To collect and prepare high quality dried fish image dataset focusing on the diverse varieties across Bangladesh.

The objective of this study is to develop a high-quality image dataset of dried fish, representing the various species and preparation techniques focusing on Bangladesh, to support accurate classification and analysis.

5. To contribute to the automation of dried fish sorting and quality assessment using AI-driven solutions.

These objective objects to prove the potential of AI and deep learning technologies in creating scalable, automated solutions for the seafood industry, improving efficiency and consistency in dried fish classification.

Chapter 4

Materials & Proposed Methodology

4.1 Materials

4.1.1 Dataset Collection

The dataset used in this study comprises 3,313 original images of dried fish, sourced from the local market. The dataset contains eight type of small-sized dried fish species, which were photographed using high-definition smartphone cameras under natural lighting conditions to ensure clarity and authenticity in the visual representation. To capture a comprehensive range of perspectives, the images were taken from multiple angles, including close-up shots of the head, tail, individual fish, and bulk fish arrangements. This variability in image capture helps the model generalize better across different viewing perspectives. This dataset contains images of eight small-sized dried fish species, which are common in the local market: Baim, Chela, Chapila, Chepa, Chanda, Kachki, Loitta, Tengra. Each species was carefully selected to represent a variety of common dried fish found in the market, ensuring the dataset is well-rounded and diverse.

The images were captured with a resolution of 1920x1080 pixels, offering high-definition quality suitable for detailed feature extraction. The high resolution allows the model to recognize fine textures and variations in the fish's surface, which are important for classification.

The images if the dataset vary in the positioning of fish, ensuring that the model can identify species regardless of their orientation or clustering. Additionally, the dataset includes different lighting conditions, further improving its robustness by simulating real-world variations.

To augment the dataset and improve model performance, the images were subjected to multiple augmentation techniques. These included random rotations, flipping, and adjusting brightness and noise resulting in a total of 9,939 images, which enhances the model's ability to handle unseen data and prevent overfitting.
This comprehensive dataset provides a solid foundation for training machine learning models to accurately classify and discriminate between different species of dried fish.

4.1.2 Dataset Description

After collation, the dataset was visually analyzed for clarity and distinctiveness of fish features. Species were reviewed for differentiating characteristics.

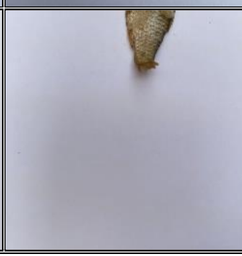
Category	Single	Head	Tail	Bulk
Baim				
Chanda				
Chapila				
Chela				
Chepa				

Figure 1: Sample Images of each category

Table 1: Dataset collection

Fish Type	Genus	Species	Total Images	Single	Bulk	Head	Tail
Chela	Chela	Chela cachius	400	100	100	100	100
Chepa	Hilsa	Hilsa ilisha	400	100	100	100	100
Chanda	Parambassis	Parambassis ranga	400	100	100	100	100
Chapila	Gudusia	Gudusia chapra	423	121	100	102	100
Loitta	Harpadon	Harpadon nehereus	400	100	100	100	100
Baim	Mastacembelus	Mastacembelus armatus	428	106	108	103	111
Tengra	Batasio	Batasio tengana	407	101	100	100	106
Kachki	Corica	Corica soborna	455	133	107	107	108

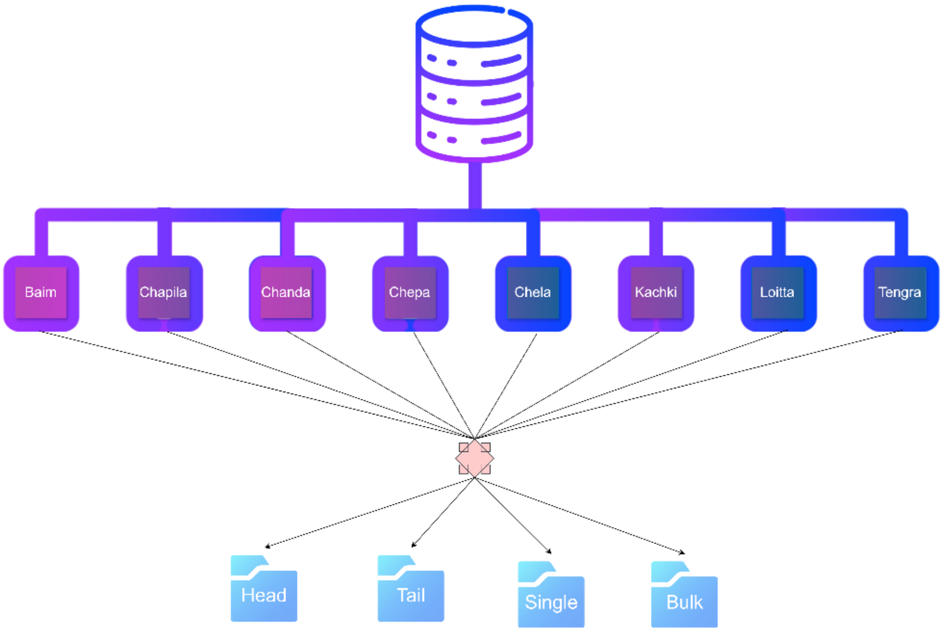


Figure 2: Dataset Organization

4.1.3 Dataset Sampling

To ensure consistency and minimize biases during model training, the dataset was carefully partitioned into three subsets training, validation, and testing. The dataset was split into training 80%, validation 10% and testing 10%. Stratified sampling was employed to maintain class proportions across all subsets, ensuring that the representation of each fish species remained consistent. This approach prevented any single class from dominating a subset, thereby preserving the dataset's diversity and enabling the model to generalize effectively. The training set comprised 2,319 images, including both original and augmented data. This subset formed the core of the model's learning process, exposing it to a wide range of scenarios and variations, such as fish orientations, lighting conditions, and background settings. The use of augmented images in this subset enhanced the model's ability to recognize fish under diverse conditions, improving its robustness. The validation images, serving as a checkpoint during training to monitor the model's performance on unseen data. By evaluating metrics such as accuracy and loss on the validation set, adjustments were made to hyperparameters like learning rate and dropout to fine-tune the model and prevent overfitting. The testing set images, was reserved exclusively for the final evaluation of the trained model. This subset was used to assess the model's real-world performance, providing a true measure of its accuracy, precision, recall, and overall robustness. By keeping the testing set independent and untouched during training, the evaluation results offered an unbiased view of the model's ability to classify dried fish species in practical scenarios. This stratified and balanced sampling strategy ensured that the dataset was utilized effectively, promoting fairness and reliability in the training and evaluation process.

4.1.4 Dataset Processing

The dataset underwent a series of preprocessing steps to ensure uniformity and prepare it effectively for use in machine learning models. These preprocessing steps addressed inconsistencies in image dimensions, pixel intensity values, and class representation while introducing variability to enhance the model's ability to generalize. Below is a detailed breakdown of each step:

Resizing: All images were resized to a fixed dimension of 256x256 pixels to meet the input size requirement of all architecture. This resizing step ensured that all input data was of uniform size, which is crucial for maintaining consistency during model training and reducing computational overhead. Resizing also made the dataset compatible with the pre-trained model's structure, which was designed to accept this specific input resolution.

Augmentation: To enhance dataset diversity and improve the model's ability to generalize to unseen data, data augmentation techniques were applied. These augmentations introduced variations in the dataset while preserving the core features of the images. The transformations included:

Rotation: Random rotations within a range of -10° to +10° were applied to simulate variations in fish orientation during photography. This transformation mimics real-world conditions where fish may not always be aligned in the same way.

Flipping: Both horizontal and vertical flips were applied randomly to create mirrored versions of the images. Horizontal flipping helps the model handle left-right asymmetries, while vertical flipping addresses variations in fish positioning.

Brightness Adjustment: Random brightness changes within -15% to +15% were applied to simulate different lighting conditions. This augmentation helped the model learn to recognize fish under varying illumination levels, improving robustness to environmental factors.

Noise: Up to 1.5% of pixels were randomly altered in each image to introduce subtle distortions. This noise injection simulates imperfections in the image acquisition process, such as camera artifacts, and improves the model's resilience to noisy inputs.

Table 2: Augmentation Methods

Methods	Values
Flip	Horizontal, Vertical
Rotation	Between - 10 degree and +10 degree
Brightness	Between - 15% and +15%
Noise	Up to 1.5% of pixels

These preprocessing and augmentation techniques collectively ensured that the dataset was not only prepared for effective model training but also enriched with variability to improve generalization. By addressing potential biases and diversifying the training data, these steps contributed to the robustness and accuracy of the fish classification model.

The dataset utilized in this study, comprising high-quality images of small-sized dried fish from the local market, has been made publicly available on Mendeley Data [24]. This dataset includes 3,313 original images and 9,939 augmented images, capturing various angles and characteristics of eight different dried fish species: Chela, Chapila, Chepa, Loitta, Chanda, Baim, Tangra, and Kachki.

4.1.5 Research Environment and Devices

We have worked on a total of four deep learning models which were implemented in most of the previous researches lately for classifying different image types precisely. We trained the models in the Google Colab environment, a running environment for running python codes. Our training was done on the T4 GPU card, with the GPU memory size of 15 GB, 12.7 GB of system memory and the disk size of 112.6 GB. Methods of investigated prediction in the testing phase which are often equivalent to training for more valuation

4.2 Method

4.2.1 Proposed Model

For classifying dried fish species is based on deep learning techniques, utilizing four well-known convolutional neural network (CNN) models: MobileNetV2, Xception, ResNet50V2, and EfficientNetV2BO. These models were selected due to their ability to handle complex image classification tasks with high accuracy while also providing computational efficiency, especially when working with large datasets such as the one used in this research. Each model was trained on a dataset prepared using Roboflow, which allowed for effective image preprocessing, augmentation, and management of the image data. The models were chosen based on their performance in image classification tasks and their varying architectures, which provide an opportunity to compare and analyze their effectiveness for the task at hand.

MobileNetV2: It is a lightweight deep learning architecture designed for efficient image processing on mobile and edge devices. It uses depth-wise separable convolutions to reduce computational cost while maintaining decent performance. The model employs inverted residual blocks and linear bottleneck layers to further enhance efficiency, making it ideal for resource-constrained environments.

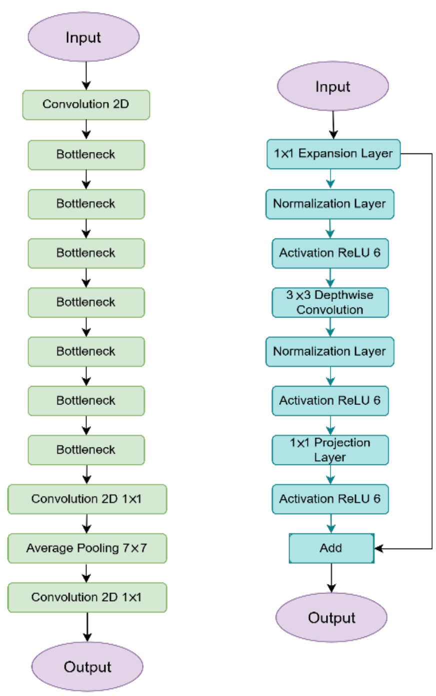


Figure 3: MobileNetV2 Model Architecture

With 53 layers, MobileNetV2 excels in tasks like object detection, image classification, and semantic segmentation, offering high performance despite its reduced computational footprint. It is widely used in applications requiring real-time image recognition on mobile and embedded system.

Xception: It is an advanced convolutional neural network (CNN) architecture that builds upon the concept of depth wise separable convolutions, offering significant efficiency gains for large datasets. It is designed to optimize feature extraction by using a series of convolution layers, each divisible by depth, which allows it to learn complex patterns and relationships in the data. Compared to traditional CNNs, Xception reduces computational costs, improves boundary detection, and optimizes resource usage, making it ideal for resource-constrained environments like mobile and embedded devices.

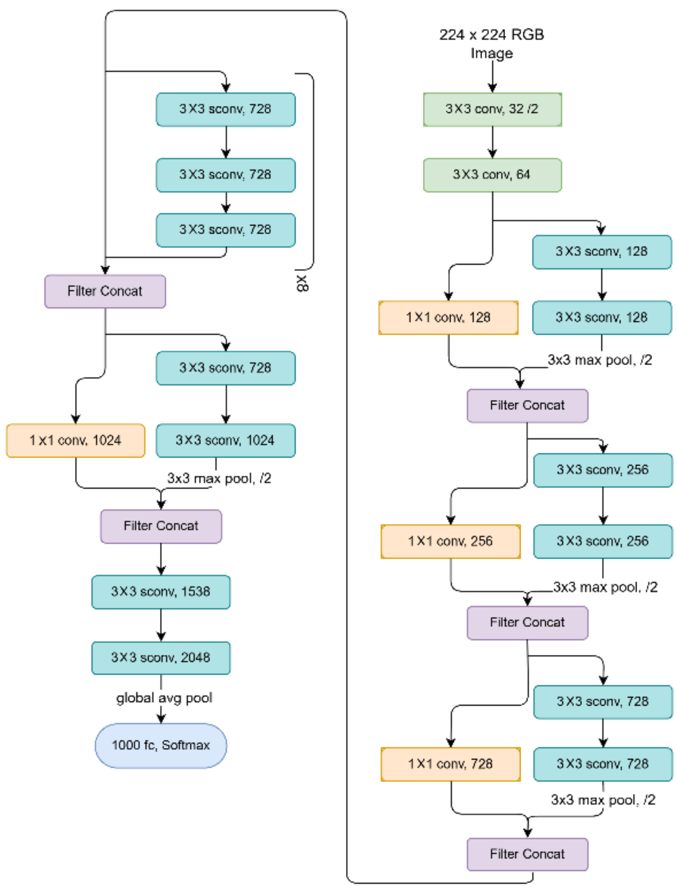


Figure 4: Xception Model Architecture

ResNet50V2: ResNet50V2, or "Residual Network with 50 layers," is an expansion of the original ResNet (Residual Network) design. A change was made to the propagation concept of the block-to-block links in ResNet50V2. ResNet50V2 performs admirably on the ImageNet dataset as well. In General, ResNet50V2 is superior to the original. ResNet50 architecture in terms of accuracy and 14 convergence speed. A number of computer vision tasks, such as segmentation, object identification and image classification, are extensively exploited. It is known for its deep residual networks that help to combat the vanishing gradient problem, allowing for better generalization.

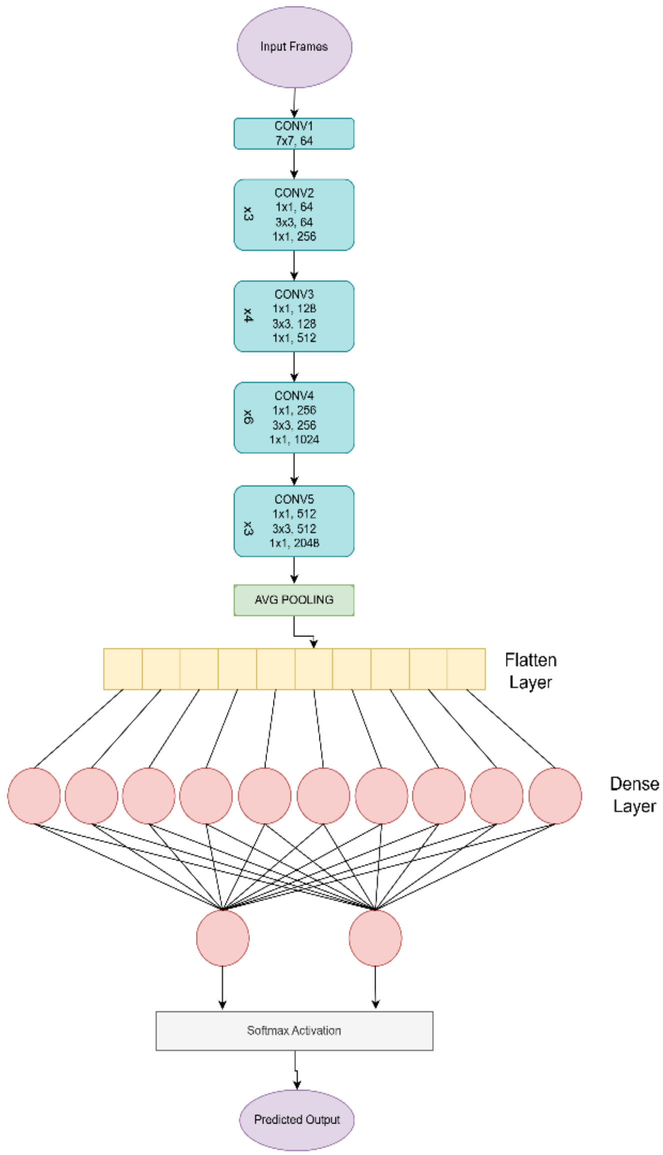


Figure 5: ResNet50V2 Model Architecture

EfficientNetV2BO: This model is designed for high performance with a smaller computational footprint, offering a balance of speed and accuracy, making it ideal for scalable image classification tasks. The model uses a compound scaling technique, which optimally scales the network's depth, breadth, and resolution, allowing for better utilization of model parameters and resources. This optimization makes EfficientNetV2B0 well-suited for deployment on resource-constrained devices and real-time inference applications.

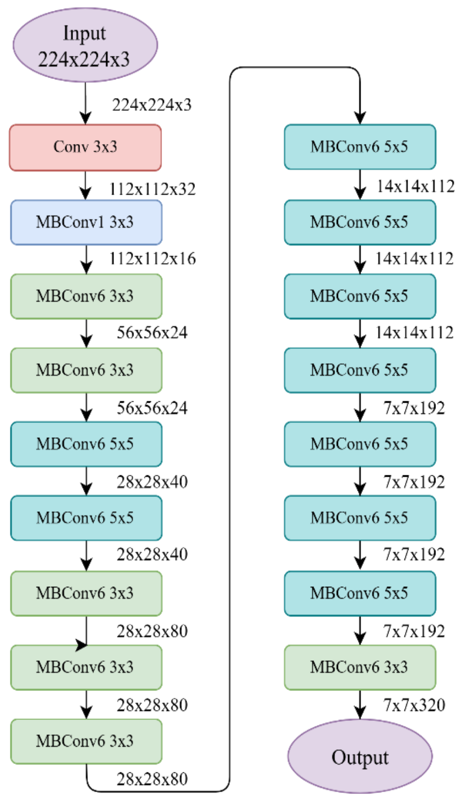


Figure 6: EfficientNetV2BO Model Architecture

These models were evaluated based on their ability to classify the dried fish species across different orientations, including head, tail, single fish, and bulk images, which were all annotated and preprocessed using Roboflow.

4.2.2 Design/Framework

The proposed system follows a standard deep learning pipeline for image classification, leveraging Google Colab for an efficient and scalable training environment. The overall framework of the classification system is divided into three primary components:

dataset preparation, model architecture, and training and evaluation. These components work synergistically to ensure that the system is both efficient and accurate in classifying the dried fish species.

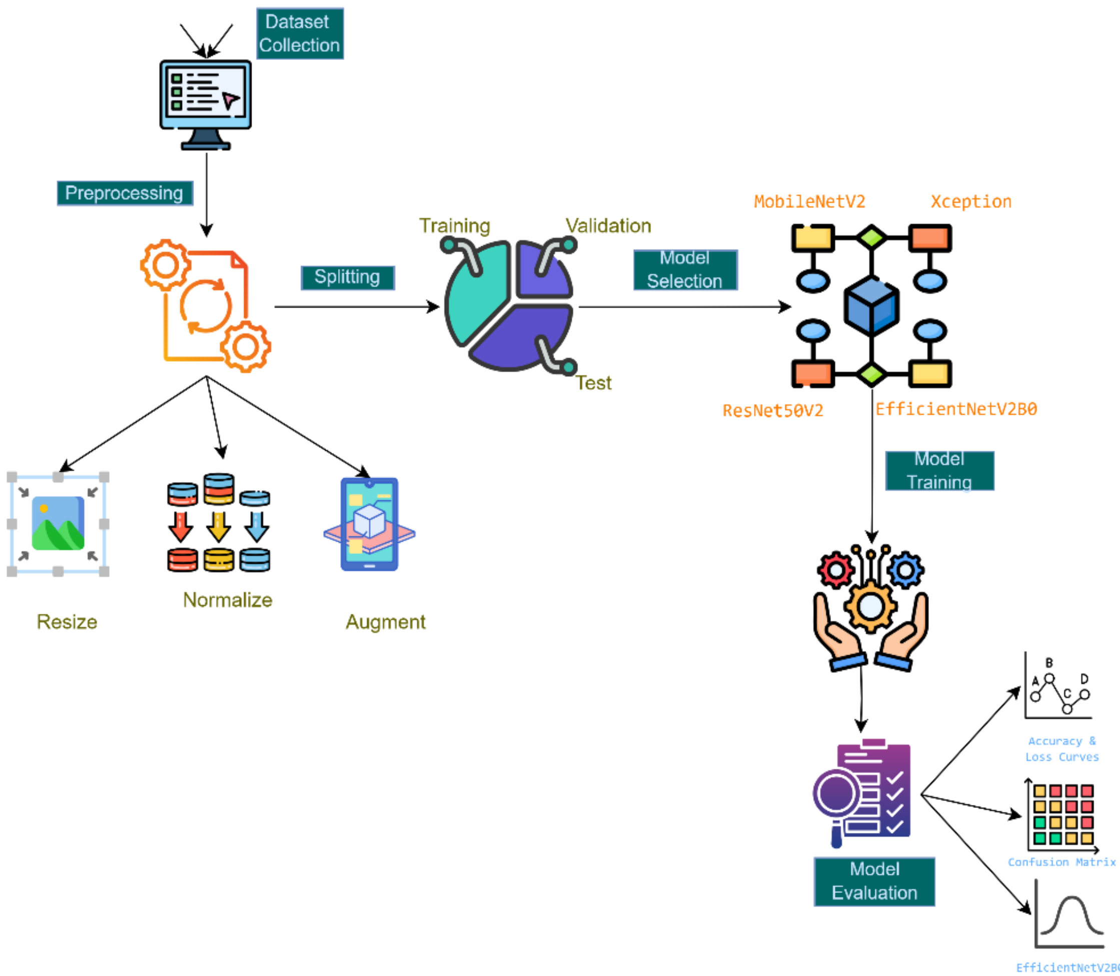


Figure 7: Workflow diagram of Proposed models

Dataset Preparation

The dataset preparation phase is crucial to ensuring high-quality data for training the models. The dataset was organized and augmented using Roboflow for single, head, tail and bulk individually, which helped streamline the process of data structuring and augmentation. Initially, all images were resized to 256x256 pixels, a standard size suitable for input into deep learning models. Additionally, the pixel values of the images were normalized to the range of [0, 1] by dividing each pixel value by 255, which helped stabilize the training process and improve model performance.

To increase data diversity and enhance the model's generalization ability, various augmentation techniques were applied in all types of images data. These included random horizontal and vertical flipping, rotation (within a -10-degree to +10-degree range), and brightness adjustments (between +15% and -15%). These transformations simulated real-world variations, such as different lighting conditions or orientations, helping the model generalize better and avoid overfitting.

After preprocessing and augmentation, the dataset was divided into three subsets using stratified sampling to maintain the same class distribution across the sets: 80% for training, 10% for validation, and 10% for testing. This ensures that each subset has a balanced representation of all classes, preventing any bias toward specific classes during model training.

Model Architecture

The model architecture phase focuses on selecting the right deep learning models to achieve optimal classification performance. For this task, we chose MobileNetV2 and Efficient NetV2BO for their lightweight and computationally efficient architectures. These models are ideal for deployment in resource-constrained environments, where memory and processing power are limited. They use depth-wise separable convolutions, significantly reducing the number of parameters and computational cost while maintaining good classification performance.

In contrast, Xception and ResNet50V2 were selected for their ability to handle complex image patterns, thanks to their deep and advanced feature extraction capabilities. Xception uses depth wise separable convolutions and is effective at capturing detailed features, while ResNet50V2 uses residual connections to mitigate the vanishing gradient problem, allowing for deeper networks and improved learning.

Each of these models was adapted by adding custom classification layers. These layers consisted of either a global average pooling layer or a flatten layer, which transformed the feature maps output by the convolutional layers into a 1D vector. A dense layer with 8 neurons (one for each class) and a softmax activation function was then added to output the probability distribution for each of the 8 species.

Training and Evaluation

The models were trained using the Adam optimizer, which dynamically adjusts the learning rate, allowing for efficient training and faster convergence. Early stopping was employed during training to prevent overfitting. The early stopping mechanism monitored validation accuracy and stopped training if no improvement was observed for 50-60 epochs, ensuring that the model did not overfit the training data and that it generalized well to unseen data.

During training, the process was visualized by plotting accuracy and loss curves to observe how the model's performance improved over time. To assess the model's classification performance, a range of metrics were used, including accuracy, precision, recall, and F1-score, which provided a comprehensive view of the model's effectiveness. Additionally, confusion matrices were generated to identify misclassifications between classes, and Receiver Operating Characteristic (ROC) curves were plotted to evaluate the model's ability to distinguish between different fish species across all classification thresholds.

This systematic approach ensured that the model was well-prepared for training and capable of providing meaningful insights into its classification performance, ultimately achieving accurate and reliable predictions for dried fish species classification.

4.2.3 Algorithm/Model Formulation

The image classification pipeline follows a well-defined sequence of steps, starting with the preprocessing of input data and continuing through feature extraction, classification, and evaluation.

Input Data

The input images are resized to 256x256 pixels, ensuring they fit the input requirements of the deep learning models. The images are also normalized by scaling the pixel values from the range [0, 255] to [0, 1]. This normalization step helps stabilize the training process by ensuring the input values are on a similar scale, which is crucial for faster convergence and more efficient training.

Feature Extraction with Pre-trained Models

The pre-trained models MobileNetV2, Xception, ResNet50V2, and EfficientNetV2B0 are used to extract features from the images. These models act as feature extractors, where their convolutional layers automatically detect and learn hierarchical features such as textures, shapes, edges, and patterns within the images. Convolutional layers are particularly effective at capturing spatial hierarchies of patterns in the image, such as the body shape, scales, and fin structure of the fish species.

Global Average Pooling (GAP) or Flatten Layer
After the convolutional layers extract meaningful features from the images, the output is passed through a Global Average Pooling (GAP) layer or a Flatten layer, depending on the model.

Global Average Pooling: This layer calculates the average of all the values in the feature maps generated by the convolutional layers, reducing each feature map to a single value. GAP is used to reduce the dimensionality of the feature maps, making it easier for the subsequent classification layers to handle the data.

Flatten Layer: In contrast to GAP, the flatten layer simply reshapes the feature maps into a 1D vector, preserving all spatial information in the process.

Dense Layer with Softmax Activation
The output from the GAP or Flatten layer is passed to a Dense layer with 8 neurons, where each neuron corresponds to one of the eight fish species classes. This dense layer applies a softmax activation function, which converts the raw output values into a probability distribution. The softmax function ensures that the output values sum to 1, making them interpretable as class probabilities.

Model Compilation and Optimization
The models are compiled using the Adam optimizer, which is an adaptive optimization algorithm that adjusts the learning rate during training to improve convergence.

Sparse categorical cross-entropy
It is used as the loss function because the task involves multi-class classification with integer labels. This loss function measures the difference between the true class labels and the predicted probabilities and helps guide the model's learning by adjusting its weights during training.

Evaluation Metrics
Accuracy: The proportion of correct predictions over the total number of predictions.

Precision: The proportion of true positive predictions over all positive predictions, measuring the accuracy of the positive predictions.

Recall: The proportion of true positive predictions over all actual positives, measuring how well the model identifies positive instances.

F1-Score: The harmonic means of precision and recall, providing a balance between the two and useful in cases of imbalanced datasets.

ROC: The ROC curve evaluates the ability of the model to discriminate between the classes at various thresholds. The curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at different classification thresholds. The Area Under the Curve (AUC) score quantifies the overall ability of the model to separate the classes. A higher AUC score indicates better model performance in distinguishing between the different classes.

Confusion Matrix: It is a performance measurement tool that shows how well the model's predictions match the true labels. It helps in identifying specific misclassifications, such as whether the model is confusing one class with another. The confusion matrix is normalized to account for imbalanced class distributions, providing a clear view of the model's classification errors across different fish species.

4.2.4 Experiment Setup

The experiments were carried out on Google Colab, leveraging its GPU runtime to accelerate the training process and optimize computational efficiency. The classification task focused on 8 distinct types of dried fish species—Baim, Chanda, Chapila, Chela, Chepa, Kachki, Loitta, and Tengra. The dataset included images of the fishes categorized into four perspectives: head, tail, single fish, and bulk fish. Each category was processed individually to capture unique distinguishing features and improve the robustness of the classification models. The experimental setup included the following configurations:

Table 3: Image Processing

Step	Description	Details
Input Image	Resizing and Normalization	Images resized to 256x256 pixels and normalized to the range [0, 1].
Pretrained Model	Feature Extraction	Models used: MobileNetV2, Xception, ResNet50V2, and EfficientNetV2B0.
Optimization	Weight Adjustment	Adam optimizer adjusts model weights during training to minimize the loss function.
Batch Size	Memory Optimization	Training performed in batches of size 4.
Epochs	Training Iterations	Maximum of 500 epochs with early stopping to prevent overfitting.
Evaluation Metrics	Performance Assessment	Accuracy, precision, recall, F1-score, ROC curve, and confusion matrix are used.

Chapter 5

Result & Discussion

5.1 Model's Strengths and Weakness

For analyzing the overall value of four deep learning models we scanned their performance, convenience, and disadvantages because of its enlightened feature extraction and compound scaling procedure.

EfficientNetV2B0:

EfiicientNetV2B0 exhibited magnificent accuracy and calculating productivity, even so complex textures may demand domain-specific-fine-tuning, its convolutional layers require use of MBConv blocks which unite compress-and-excitation layers with in depth distinguishable convolution to contribute powerful feature extraction at a cheap measurable cost. Layer depth, width, and input resolution are all continuously balanced by the compound scaling which give an assurance the best possible stability between strength and performance.

Xception:

In spite of being speculation, Xception depth wise distinct convolutions offered steady performance allowing it to excel in feature extraction and split regional and channel-wise process, in place of traditional convolutional layers. By limiting the number of parameters and calculating attempt, this fragmenting develops performance and create Xception exceptionally good at studying complicated hierarchical features.

ResNet50V2:

ResNet50V2 which advantages from lasting connections that boost gradient flow, displayed resilience for wide feature discovery but malfunctioned with complex character discrimination. Its convolutional layers are assembled by identity mappings into bottleneck blocks. With the advantage of omit connections, these blocks permit the model to obtain deep attributes while stopping disappearing gradient problems, assuring harmonious training even with a deep architecture.

MobileNetV2:

Accompanied by the small number of parameters, MobileNetV2 provided a very essential that was good enough for the surroundings with sparse assets. Transposed residual box with depth wise divisible convolutions are a feature of its architecture that beneath processing demands without giving up important features. The transparent architecture of MobileNetv2 permits for real time applications by maintaining ambitious accuracy.

Following equations presents the result of this research paper, that are average accuracy, precision, recall, and F score, in that order. Normally every architecture run 500 epochs but because of quick finishing all architecture did not reach 500 epochs, quick finishing is a coordination technique for dep learning networks that finish training when adaptions to parameters no longer achieves on a validation set. The accuracy of every trial was recorded and table 4 and 5 shows the acreages.

$$Accuracy = \frac{(True\ positives + True\ Negatives)}{(True\ positives + True\ negatives + False\ positives + False\ negatives)} \quad (1)$$

$$Precision = \frac{true\ positive}{true\ positive + false\ positive} \quad (2)$$

$$Recall = \frac{true\ positive}{true\ positive + false\ positive} \quad (3)$$

$$F1\ Score = \frac{2 \times (precision \times recall)}{precision + recall} \quad (4)$$

In formula (1) The Accuracy is used as a statistical measure of how well a binary classification test correctly identifies or excludes a condition. That is, the accuracy is the proportion of correct predictions (both true positives and true negatives) among the total number of cases examined.

In formula (2) The precision of a model is determined by how well it makes positive predictions. True Positive is the number of times the model predicts the positive class with accuracy. The number of times the model wrongly predicts the positive class is known as the False Positive count.

In formula (3) The model's recall measures how well it can catch every relevant positive case. Few false negatives occur when a model has a high recall because it captures the majority of positive cases.

In formula (4) When handling unequal class sizes, the F1 Score—a test accuracy metric—becomes very helpful. Precision and recall's harmonic mean is the F1 Score. Extreme values are punished by it. Therefore, only when both accuracy and recall are good can one get a high F1 Score.

5.2 Model's Performance Analysis for Dried Fish Classification

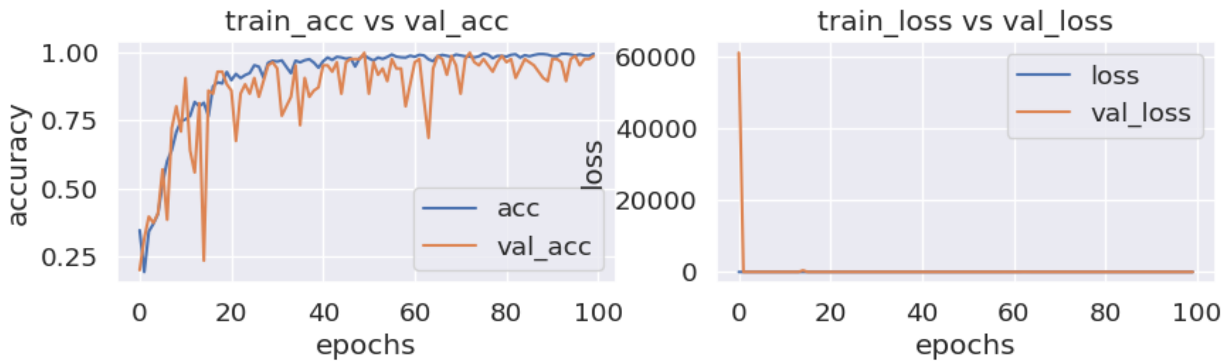
The train_loss vs val_loss curve shows training and validation accomplishment of a deep learning model over provided epochs. Accuracy curve displays how perfectly the model predicts the exacts outputs on training as well as validation datasets across time. The error or variation in the middle of the predicted and real outputs as long as a recognition of how precisely the model is enhancing is calculated by loss curve. This curve also detect overfitting and underfitting. Overfitting happens when a model perfectly on training data but terrible on the validation data, showing that it has remembered the training set in place of generalizing good to unseen data.

Key Indicators of Overfitting:

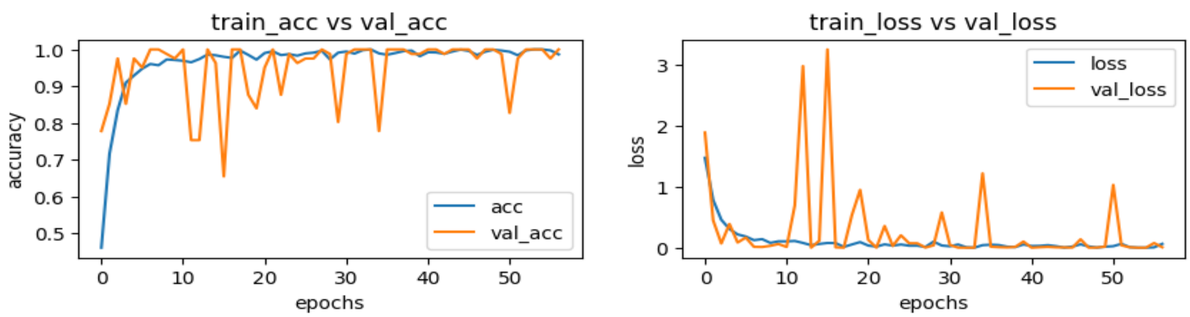
1. Huge gap between training and validation accuracy:
   A continuous high training accuracy along with lower validation accuracy over epochs.

2. Districted Loss Curve:
   Diminishing training loss consistently but validation loss either stop flowing or increase over time.

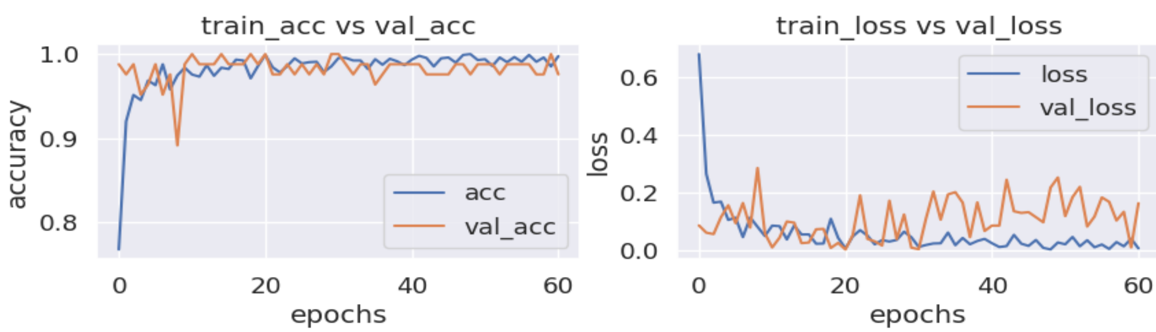
Underfitting is another issue in which both training and validation accuracy remains low, this situation also can be identified by this curve the graph has also the ability to stop the model early if the model's accuracy stabilized which is convergence. In figure 8 and 9 (Train Accuracy) throughout each epoch blue line (Train Accuracy) shows the accuracy of the model on the training dataset. Stable increasing is shown until it acknowledges the pattern of the training data. The orange line (loss graph) the validation loss frequently follows a related tendency but may show minor variations initially on before stabilizing. The model will successfully generalize to new data or not it relies on whether the validation loss is low and fixed.



Single Dried Fish (EfficientNetV2B0 Model)

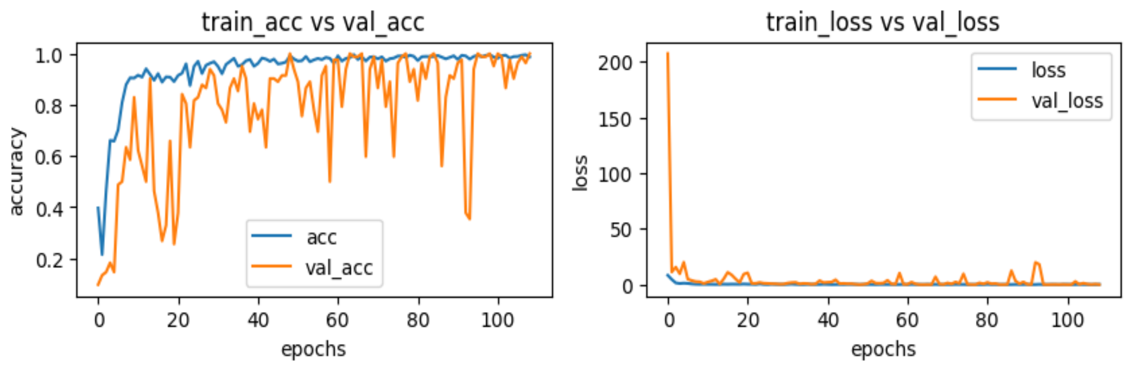


Dried Fish's Head (Xception Model)

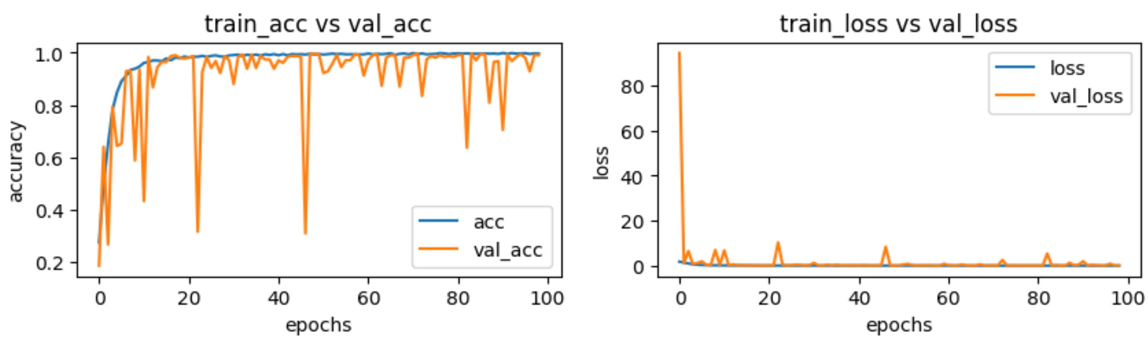


Dried Fish's Tail (EfficientNetV2B0 Model)

Figure 8: Best Model for All Categories' on basis accuracy and value loss curve



Bulk Dried Fish (MobileNetV2 Model)



All types of Fish Including all category (ResNet50V2 Model)

Figure 9: Best Model for All Categories on basis accuracy and value loss curve

Figure 8 and 9 represents best models on basis of its accuracy and train _acc vs val_acc and train_loss vs val_loss curve as we implemented four models for five categories.

At first, Single dried fish's train _acc vs val_acc curve graph is shown in left and EfficientNetV2B0 model is best for this category as the accuracy is 98.84% and loss is 0.0197 and it's classification time is also less than other model, it is shown in table 4.The training datasets stabilizes nearly 1.0 here and the latest accuracy determines best performance on the validation set proposing the model overview well to unseen data. In train_loss vs val_loss curve at right because of rapid increasing in training loss it stabilizes nearly to zero. Although validation loss behaves similarly it spikes sometimes and that's why orange line is visible. Finally, the model is trained well as the final loss is very low and there is minimal overfitting.

In dried fish's head, Xception model has amazing training accuracy, surpassing 95%, and validation accuracy in consecutive epochs which sink inside a corresponding range. In spite of that there are repeat variation in the validation curve, which specify occurrences of data variability and a little overfitting. Whereas, the validation loss differs before mounting, the training loss regularly rejects. Despite the fact that the model displays great ability, it also points out the certainty of regularization approaches (Data augmentation) to decrease validation achievement inconstancy.

For fish tail classification, EffitienNetV2B0 functions properly, with training accuracy upcoming 99% and validation accuracy nearly 97%. The adjacent association of both curve implies that the model does not overfit as well as the generalization is good. The loss curve exhibits that training and validation losses balance and fall rapidly over time, remaining low. This indicates the model is capable of acknowledge particular features of fish tails.

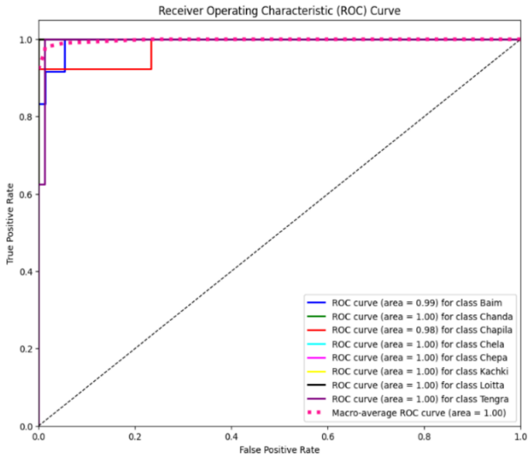
In bulk dried fish classification, the MobileNetV2 accomplishes of validation accuracy over 95% and training accuracy over 98%. There is slight alteration in the middle of the training and validation accuracy curves, which are both strong. The validation loss is even now minimally greater than the training loss but the loss curve displays a slow fall, for its balance between analytical providence, the model is good for bulk category but the small gap indicates minimal degree of overfitting.

The ResNetV2B0 performs well in all fish classification and shows extraordinary multi classification abilities and the training accuracy stabilizes at 100%. Although the model was best among all model there was slight overfitting.

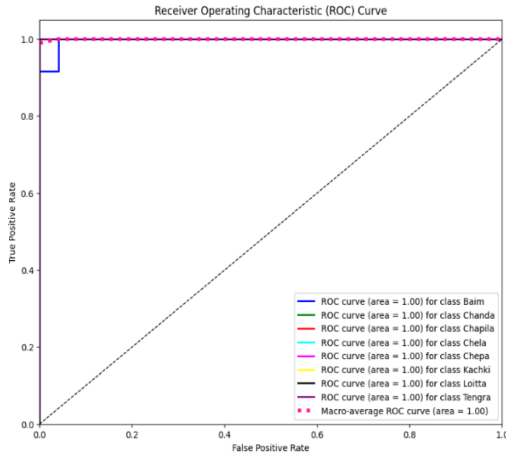
In table 4, four models' size, classification time and other efficiency factors like Accuracy, Precision, Re-call and F1-score are given for single dried fish classification. Out of all of them ResNet50V2 outperforms all the models and next Xception has second highest accuracy although its size is the largest.

Table 4: Model Accuracy, Efficiency, and Size for Single Dried Fish Classification

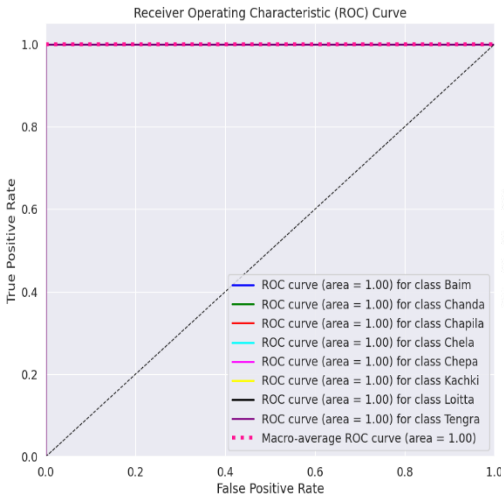
Model	Model Size	Classification Time (Time/step)	Accuracy	Loss	Precision	Re-call	F1-score
EfficientNetV2B0	9.44 MB	3s	95.72%	0.1553	0.95	0.95	0.96
Xception	178.41 MB	5s	98.45%	0.0425	0.98	0.98	0.98
ResNet50V2	79.40 MB	3s	98.84%	0.0197	0.98	0.98	0.98
MobileNetV2	91.25 MB	2s	96.11%	0.3142	0.95	0.96	0.95



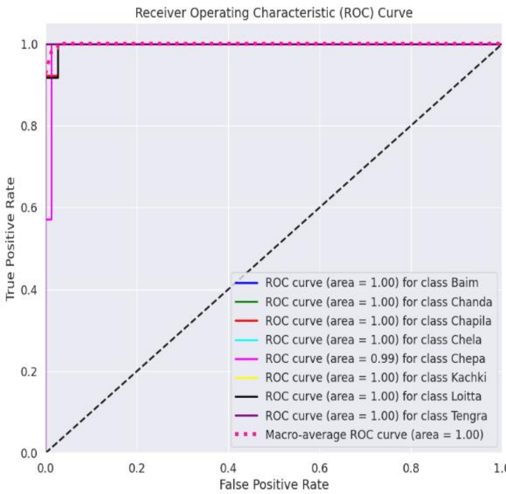
EfficientNetV2B0



Xception



ResNet50V2



MobileNetV2

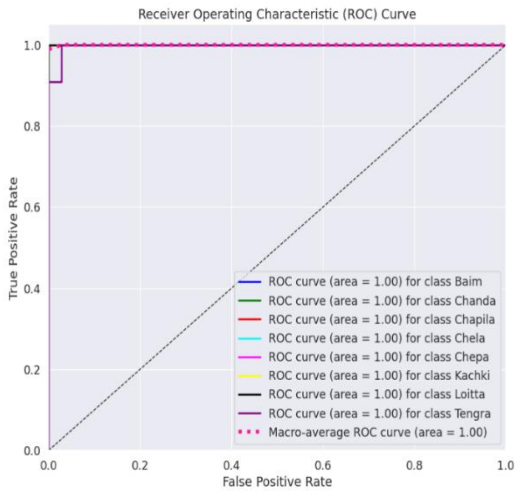
Figure 10: ROC Curve of Single Dried Fish

A classifier performance over various threshold is revealed graphically by the ROC (Receiver operating characteristics). ROC is basically plotted by a One-Versus-Rest (OVR) procedure while tackling with Multi-class classification like we are dealing with 8 classes classification where every class is known as binary classification Problem. If AUC value is closes to 1.0 or it is 1.0 it specifies excellent performance, while 0.5 suggests random guessing. High positive rate review model's capacity to classify dried fish precisely.

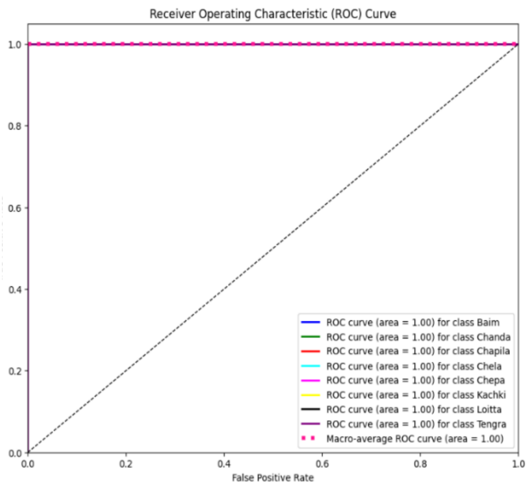
Single Dried fish ROC Curve Analysis from figure (10):

❖ High AUC values which is 1.0 were illustrated by RestNet50V2 and Xception, proposing better discrimination.

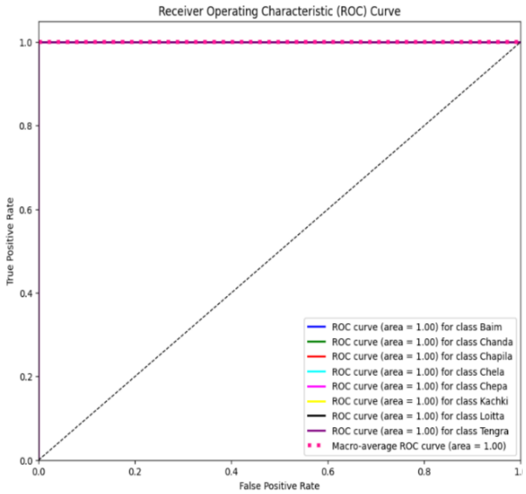
❖ Higher loss for EfficientNetV2B0 and slight loss for MobileNetV2 suggested that the ROC curve sometimes misclassified data. In EfficientNetV2B0 Baim, Chapila and Tengra showed false positive rate and Tengra has highest false positive rate but not less than 0.5. On the other Hand, in MobileNetV2 has less than 0.2 false positive rate for Loitta and Chepa.



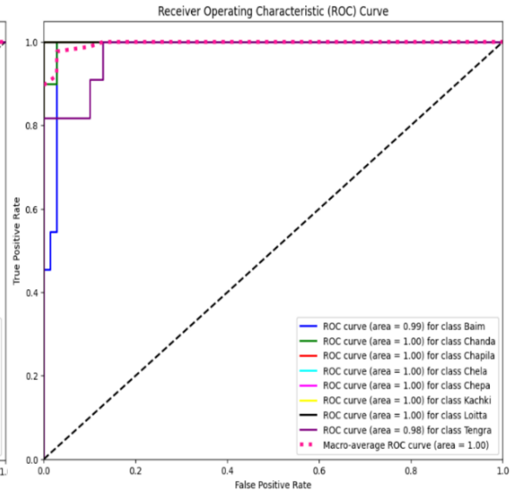
EfficientNetV2B0



Xception



ResNet50V2



MobileNetV2

Figure 11: ROC Curve of Dried Fish's Head

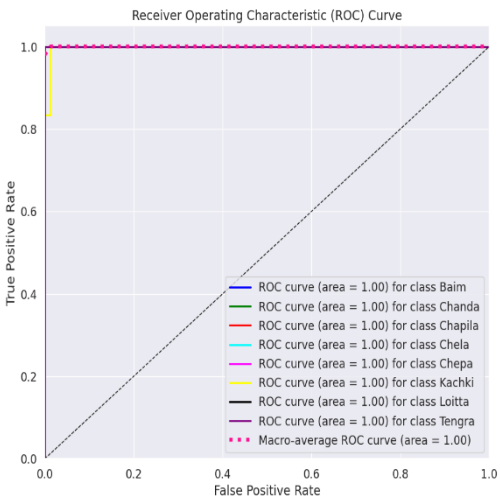
Head of Dried Fish Classification Analysis from figure (11):

❖ Xception Distributed ideal classification (AUC)
❖ EfficientNet50V2 also displayed powerful accomplishment
❖ But Tengra, Baim and Chanda showed misclassification specially Tengra and its Roc is not 1.0, it is 0.98.
❖ MobileNetV2 showed poorer performance as it has 3 classes which has AUC which is less than 1.0 which are Baim, Chanda and Tengra. Specially Tengra has less than 0.5 AUC which indicates poorer generalizations.

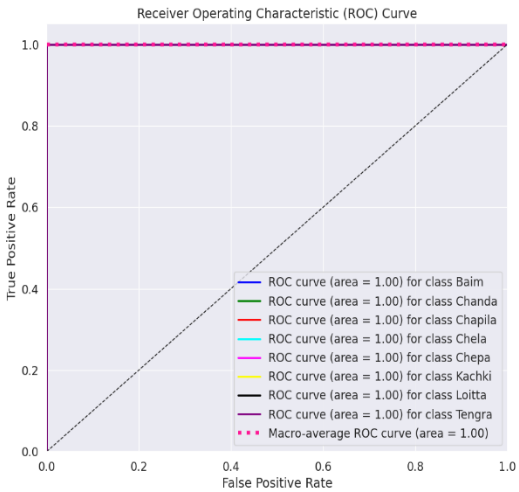
In table 5, all model's accuracy, size, classification time and other efficiencies like Precision, Re-call and F1-score are given. Xception model is proven best for its highest accuracy and other higher efficiency but the classification time of this model is slightly higher than the other models for dried fish's' head. On the other hand, EfficientNetV2B0 has the lowest accuracy and MobileNetV2 has the second lowest accuracy and other efficiencies are also lower than EfficientNetV2B0.

Table 5: Model Accuracy, Efficiency, and Size for Dried Fish's Head Classification

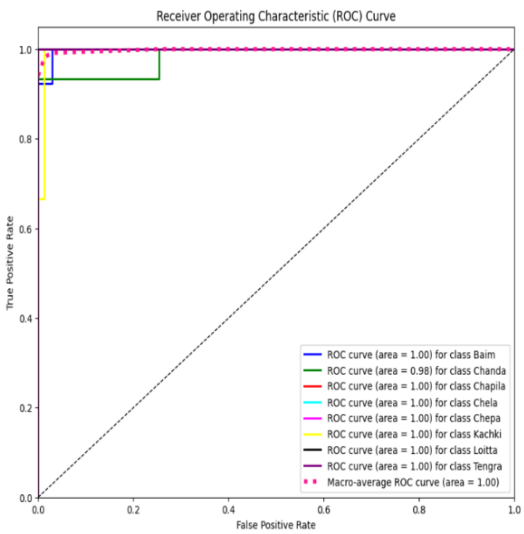
Model	Model Size	Classification Time (Time/step)	Accuracy	Loss	Precision	Re-call	F1-score
EfficientNet V2B0	9.44 MB	2s	96.42%	0.1134	0.98	0.98	0.98
Xception	79.64 MB	4s	100%	0.0181	1.0	1.0	1.0
ResNet50V2	89.96 MB	827ms	98.21%	0.313	0.99	0.99	0.99
MobileNetV2	11.11 MB	2s	96.75%	0.2068	0.95	0.96	0.95



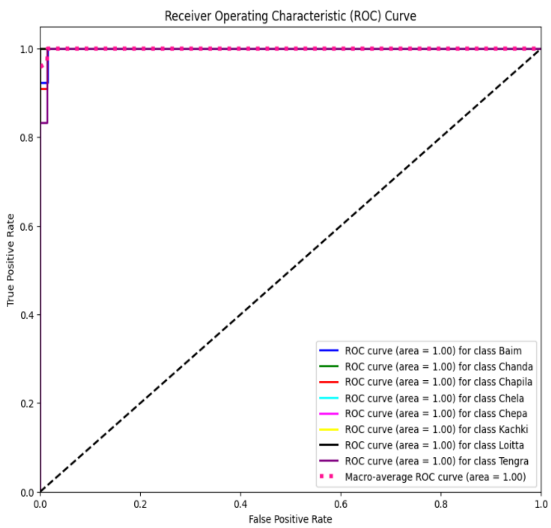
EfficientNetV2B0



Xception



ResNet50V2



MobileNetV2

Figure 12: ROC Curve of Dried Fish's Tail

Tail of Dried Fish Classification Analysis for figure (12):

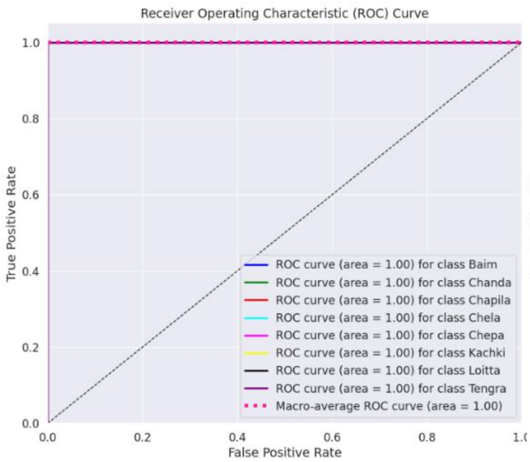
❖ EfficientNet50V2 and Xception displayed high AUC values which provide ideal classification (AUC)

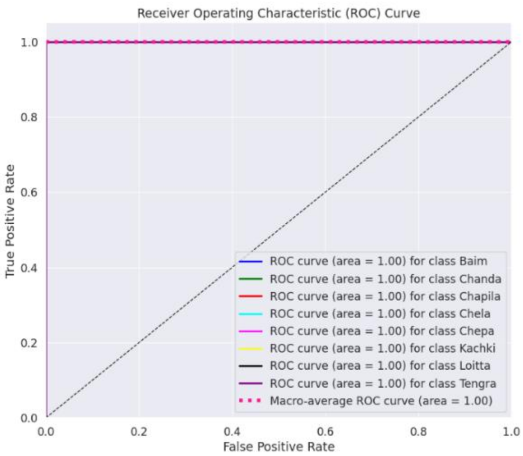
❖ ResNet50V2 and MobileNetV2 indicate lower performance as these have misclassifications sometimes and that's why Chanda, Baim showed slight misclassification which impacts overall macro average ROC curve. It is not visible and AUC is 1.0 because of overall performance is good and it neglects the specific instances of confusion metrics.

In table 6, EfficientNetv2B0 and Xception has the highest accuracy and classification time is less than Xception too but Precision, Re-call are lower than Xception. Besides, MobileNetV2 has the lowest accuracy and the other efficiencies are lower too but it takes less time and size is smaller than other models too.

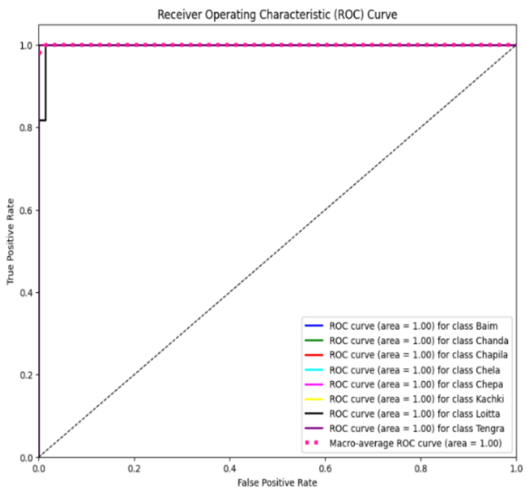
Table 6: Model Accuracy, Efficiency, and Size for Dried Fish's Tail Classification

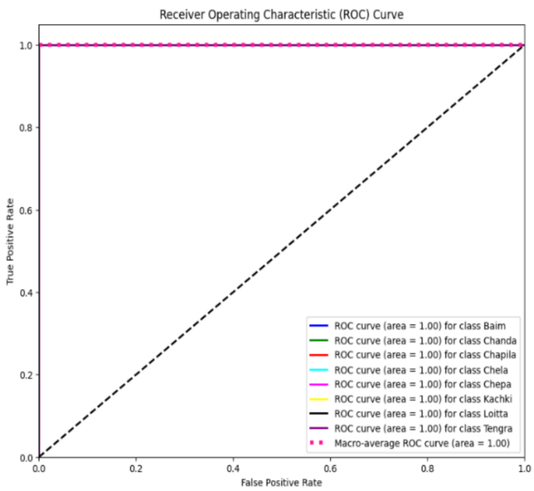
Model	Model Size	Classification Time (Time/step)	Accuracy	Loss	Precision	Re-call	F1-score
EfficientNetV2 B0	22.62 MB	3s	98.22%	0.0322	0.98	0.98	0.99
Xception	79.64 MB	4s	98.22%	0.1184	0.99	0.99	0.99
ResNet50V2	93.89 MB	2s	95.83%	0.2185	0.96	0.97	0.96
MobileNetV2	11.11 MB	2s	93.61%	0.2073	0.94	0.93	0.93





EfficientNetV2B0 **Xception**





ResNet50V2 **EfficientNetV2B0**

Figure 13: ROC Curve of Bulk Dried Fishes

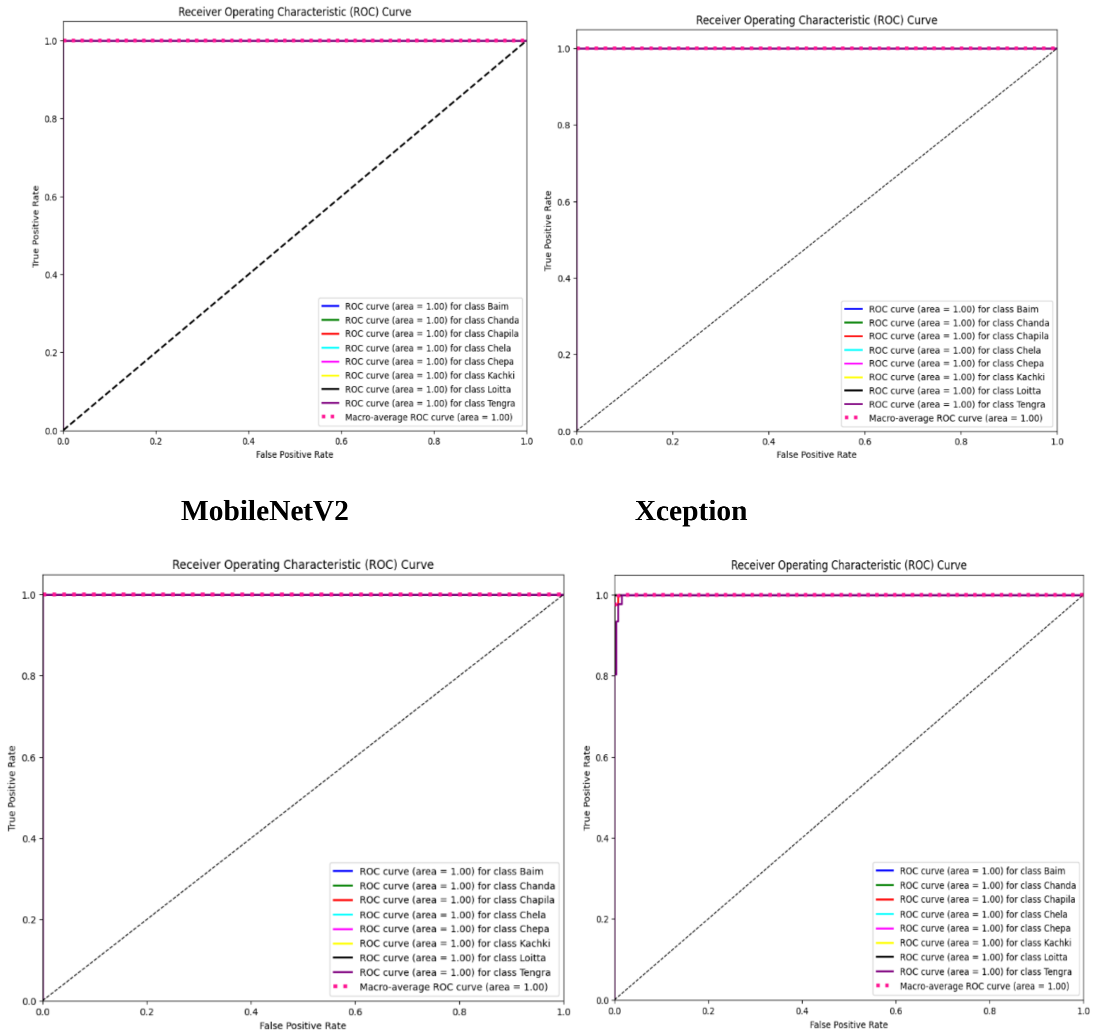
Bulk Dried Fish Classification Analysis for figure (13):

All models performed well based on ROC curve while ResNet50V2 have slightly misclassification because Loitta has less than 0.1 false positive rate.

In table 7, both MobileNetV2 and EfficientnetV2B0 has the highest accuracy for bulk classification and other properties like Precision, Re-call, F1-Score are also the same but the MobileNetV2's classification time is less and the model size is also smaller than the other. ResNet50v2's accuracy is lowest but it takes less time than MobileNetV2 during classification.

Table 7: Model Accuracy, Efficiency, and Size for Bulk Dried Fish Classification

Model	**Model Size**	**Classification Time (Time/step)**	**Accuracy**	**Loss**	**Precision**	**Re-call**	**F1-score**
EfficientNetV2B0	22.62 MB	3s	100%	0.0101	1.0	1.0	1.0
Xception	79.64 MB	4s	97.20%	0.0445	0.97	0.97	0.98
ResNet50V2	93.89 MB	3s	95.41%	0.2110	0.96	0.97	0.96
MobileNetV2	11.11 MB	2s	100%	0.2233	1.0	1.0	1.0



MobileNetV2 **Xception**

ResNet50V2 **EfficientNetV2B0**

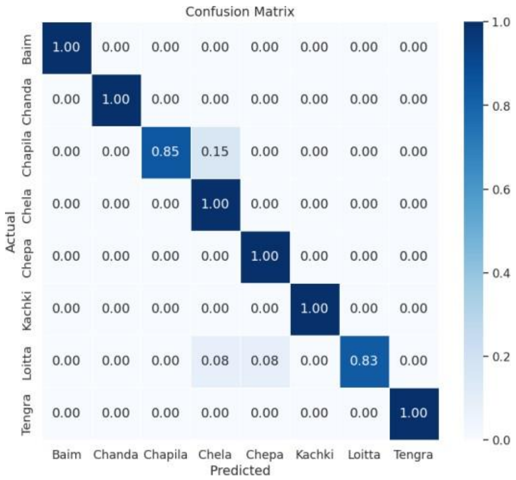
Figure 14: ROC Curve of All categories' Dried Fishes

All models performed well based on ROC curve while have slightly misclassification in EfficientNetV2B0 as Tengra has slight spiking over time in the graph.

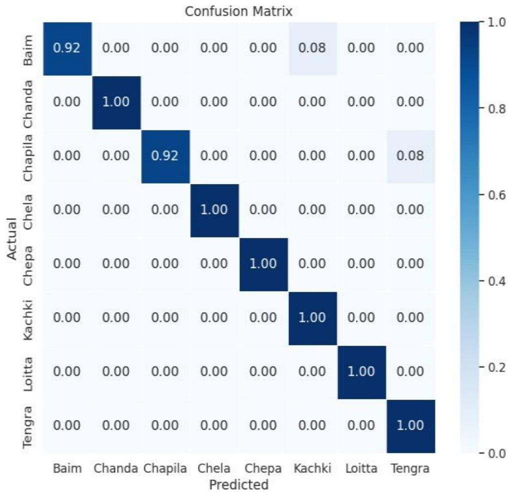
Table 8: Model Accuracy, Efficiency, and Size for all Types of Fish Classification

Model	**Model Size**	**Classification Time (Time/step)**	**Accuracy**	**Loss**	**Precision**	**Re-call**	**F1-score**
EfficientNetV2B0	22.62 MB	3s	99.54%	0.0211	0.99	0.99	0.99
Xception	89.96 MB	789ms	99.40%	0.0125	0.99	0.99	0.99
ResNet50V2	93.89 MB	590ms	100%	0.0011	1.0	1.0	1.0
MobileNetV2	8.69 MB	425ms	99.79%	0.0037	1.0	1.0	1.0

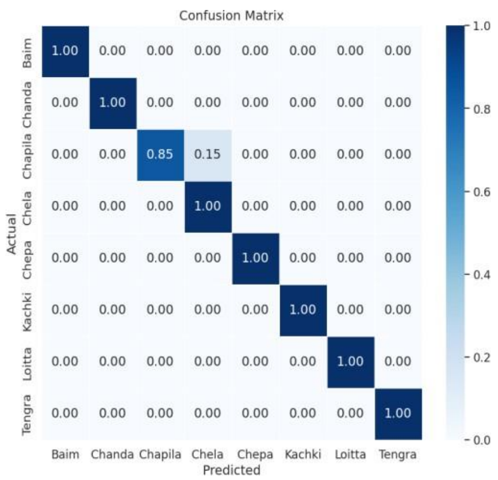
In table 8, ResNetV2B0 has the highest accuracy but the classification time is less than it in MobileNetV2 and the size of it is also less than other model. On the other hand,the size of Xception model is the highest and accuracy is lower too.



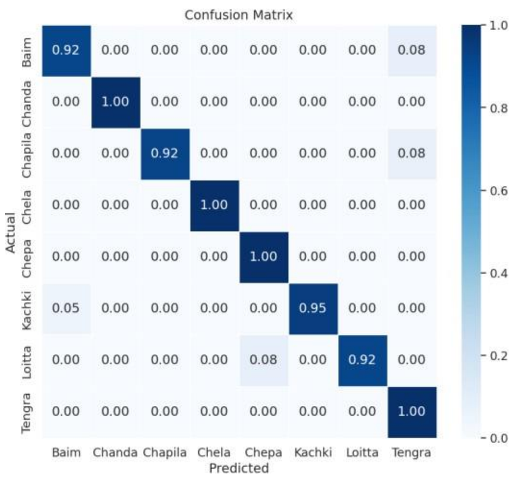
MobileNetV2



Xception



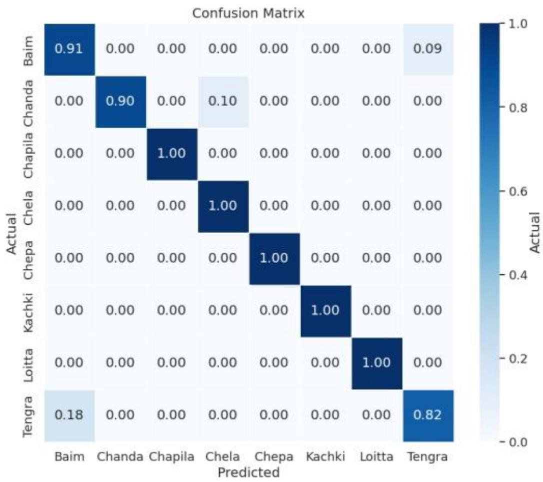
ResNet50V2



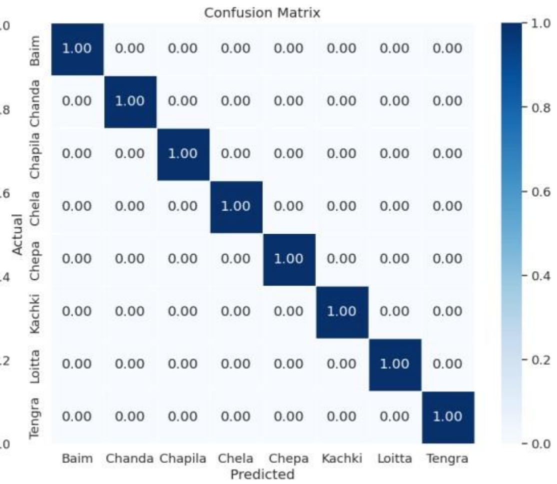
EfficieNetV2B0

Figure 15: Confusion Matrix of Single of Dried Fish for all Models

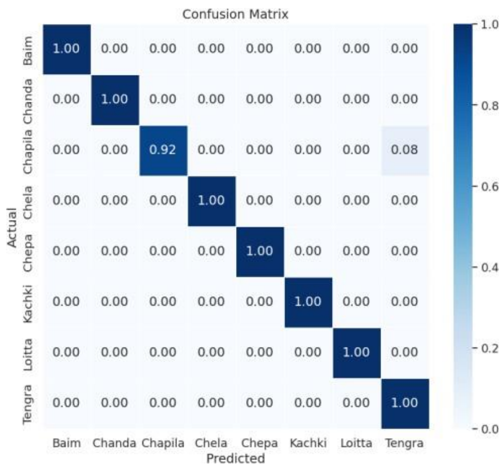
In figure 15, MobileNetV2 Baim, Chanda, Chela, Chepa, Kachki and Tengra give 1.0 classification value and Chapila and Loitta give 0.85 and 0.83 prediction on diagonal position. For this 15% Chapila is misclassified as Loitta was misclassified by Chela as well as 8% of Chela and 8% of Chepa.



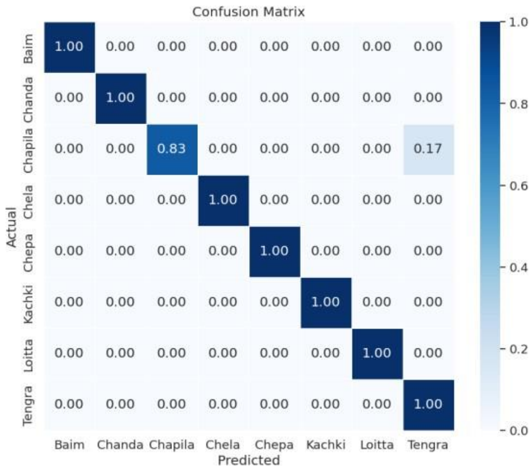
MobileNetV2



Xception



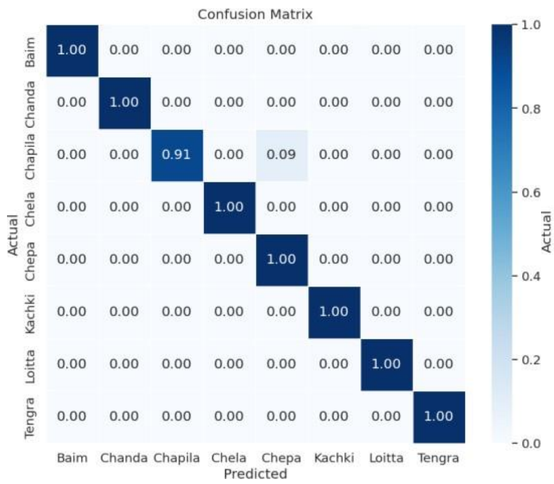
ResNet50V2



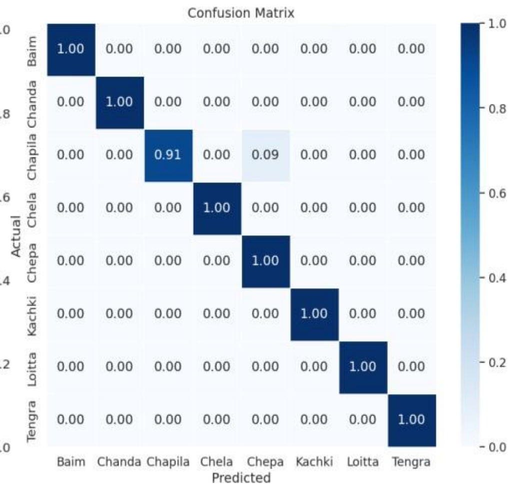
EfficientNetV2B0

Figure 16: Confusion Matrix of Head of Dried Fish for all Models

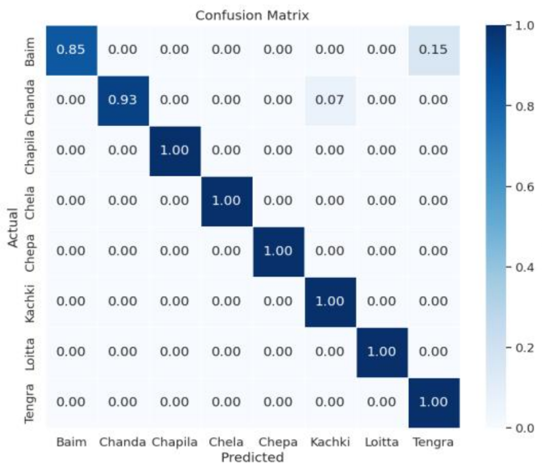
In figure 16, Xception models all dried fishes give the highest classification value 1.0. In MobileNetV2 Baim gives 0.91 classification on diagonal value and it's 9% value is misclassified by Tengra on off diagonal. Diagonally 0.90 classification value is classified by Chanda on diagonal whereas 10% value is misclassified by Chela.0.82 value on diagonal is classified by Tengra but 18% is misclassified by Baim. 0.92 classification value is indicated by Chapila in ResNet50V2 and 8% value is misclassified by Tengra. In EfficientNetv2B0 Chapila classified 0.83 value and 17% value is misclassified by Tengra.



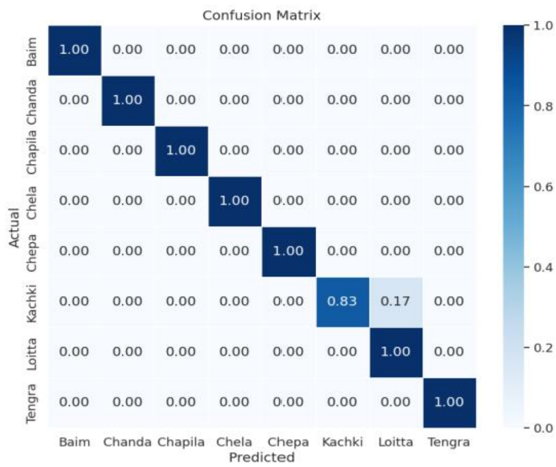
MobileNetV2



Xception



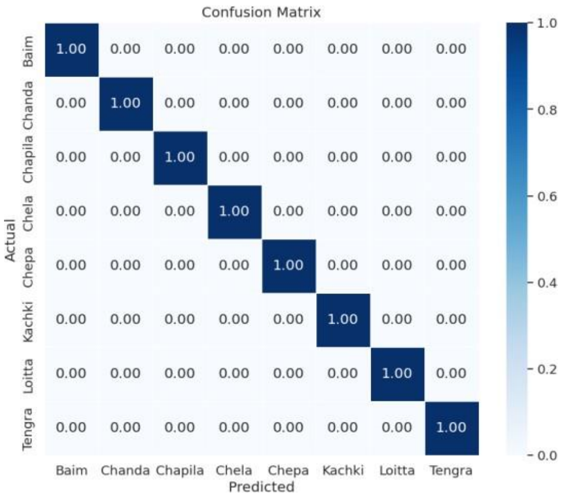
ResNet50V2



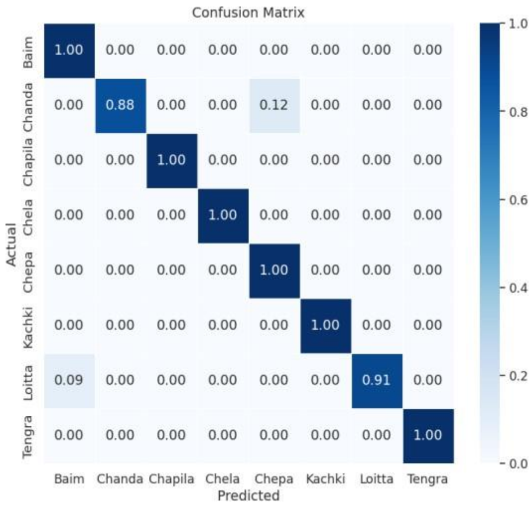
EfficientNetV2B0

Fig 17: Confusion Matrix of Tail of Dried Fish for all Models

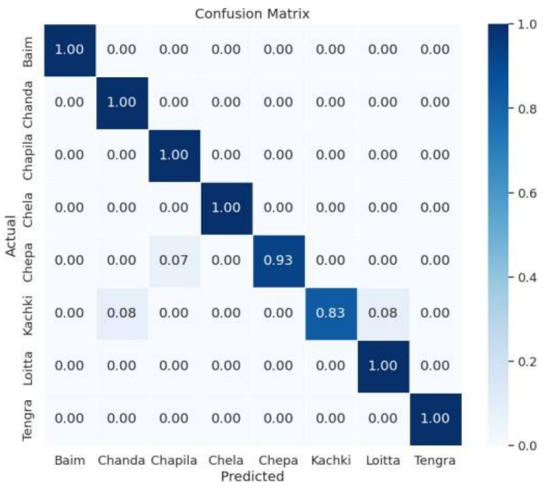
In figure 17, MobileNetV2's Chapila class classified 0.91 value and 9% value was misclassified by Chepa. Same goes for Xception. In ResNet50V2 0.85 value was classified by Baim and 15% value is misclassified by Tengra. Loitta misclassified 17% value of Kachki and 0.83 value of Kachki class was classified.



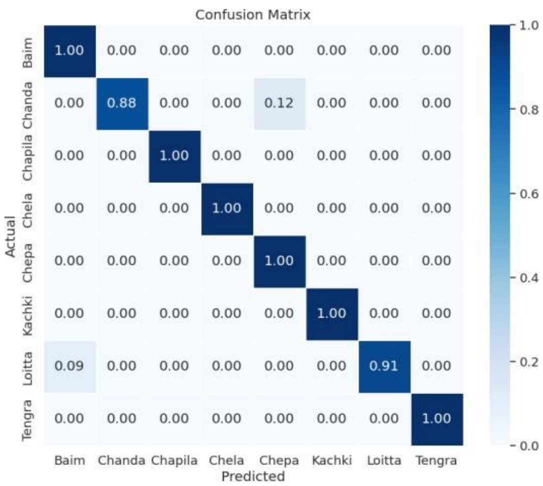
MobileNetV2



Xception



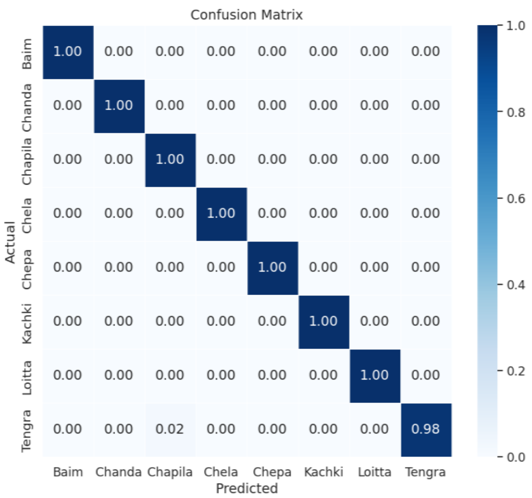
ResNet50V2



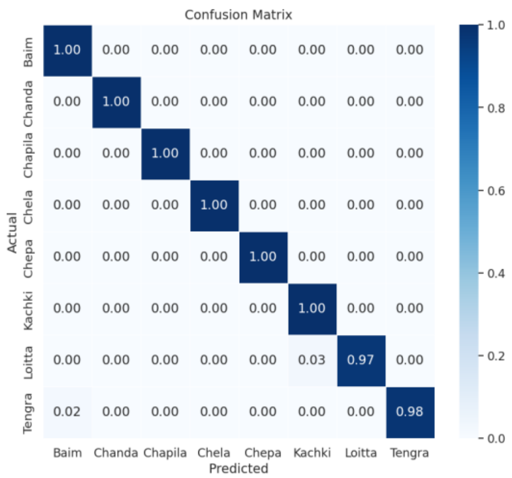
EfficientNetV2B0

Figure 18: Confusion Matrix of Bulk Dried Fish for all Models

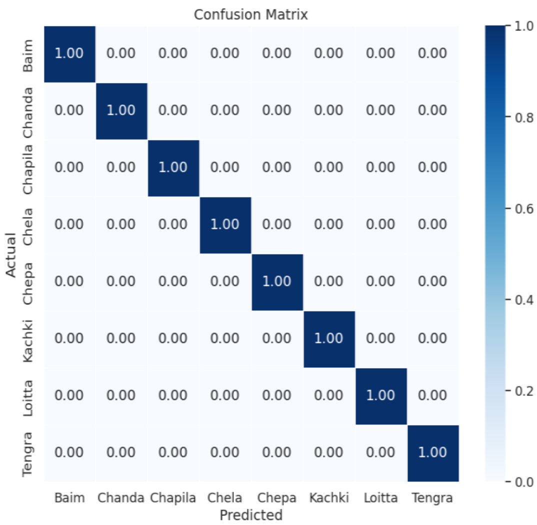
In figure 18, MobileNetV2 give the highest accuracy value 1.0 for all classes diagonally. Chanda classified 0.88 value and 12% value was misclassified by Chepa for Xception model. In ResNet50V2 0.93 value was classified by Chepa and 7% was misclassified by Chapila and 0.83 value was classified by Kachki but 8% value was misclassified by both Chanda and Loitta.0.88 value was classified by Chanda and 12% was misclassified by Chepa as well as 0.91 value was classified by Loitta and 9% was misclassified by Baim.



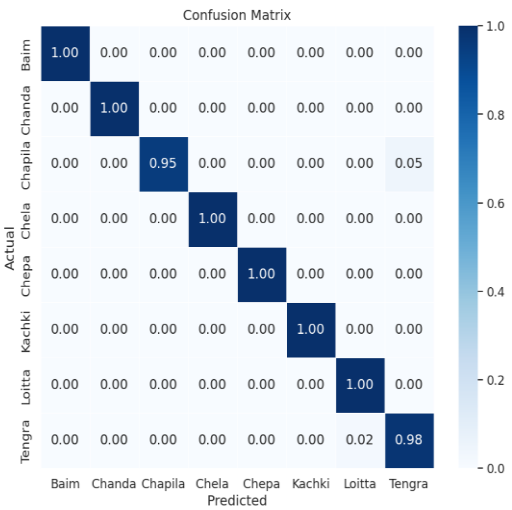
MobileNetV2



Xception



ResNetV2B0



EfficientNetV2B0

Figure 19: Confusion Matrix of All Dried Fish's' for all Models

In figure 19, both MobileNetV2 and EfficientNetV2B0 and Xception has same classification value for class Tengra which is 0.98 but Chapila misclassified 2% value in MobileNetv2.Besides, EfficientNetV2B0's class Loitta misclassified 25 data of Loitta. In Xception 0.97 value was classified by Loitta but 0.03 value was misclassified by Kachki. On the contrary Best accuracy model RestNetV2B0's all classes' classified value is 1.0.

Discussion of the Classification of Dried Fish in every aspect:

Although every model performed well in dried fish classification which is quite impressive as our dataset is unique because we collected the dataset on our own. There are three categories of figures in this report and the result of all the figure is different and sometimes it is slightly similar.

For an instance in figure 9, we have taken five best curves on basis of its accuracy among all four models and we have observed that the best model among all categories is Xception model which is performed for dried fish head categories is best as it has amazing generalization, stability and less overfitting. On the other hand, MobileNetV2 performs bad for notable overfitting and its performance for unseen and test data although it performs well on training data.

After observing all ROC curve All dried fish categories' all ROC curves are perfect for four models,8 classes have 1.0 positive and negative rate for all classes but there is slight misclassification in Tengra in EfficientNetV2B0 model which can be ignored negative rate, that indicates no imperfect generalization and it is shown in figure 14. Xception Model shows great result in Head, Tail, Bulk and all types of fish categories (figure 11,12,13,14) ROC Curve as the AUC value were one in all these categories. The Model among all the ROC curves from all categories which displayed poor result is MobileNetV2 (Figure 11) for Dried fishes' head category. Single dried fishes (figure 10) show poorer result as it's three models has misclassification whereas rest of the models have one or two models have misclassifications.

Confusion matrix shows immense diversity in these 5 categories but the best performing model basis of classes and diagonal and non-diagonal is Xception as it gives 1.0 classification value for both Single Dried Fish and Dried fishes' Head category. Single dried fish's category displays less appealing result as it's all classes have multiple misclassifications. Unfortunately, MobileNetV2 is considered poorest model on basis of confusion matrix as Dried Fishes' Head class has 3 misclassifications for 3 classes (figure 16) and this model has showed misclassification in every category except Bulk Dried Fish class.

Finally, two types of aspect show different result because one is accuracy of all categories and other is the description of graphs. If we see the accuracy from all the table is the best model on basis of accuracy (100%) and mild loss (0.0011) (table 8). On basis of graphs Xception is best among all models for it's amazing performance and it is the convenient model for our Dried Fish Dataset

Reasons of misclassifications:

Familiar appearances: Particular classes may share visual traits like Baim and Tengra or Kachki and Chapila.

Intra-Class Variability: Fishes can vary drastically in terms of size, position or condition even in a single class.

Insufficient Data Per class: Spilliting Data into different categories hinders the number of samples for particular class preventing the model's capability to generalize.

Complicated Dataset: This design can be difficult for lightweight models to detect fine-grained optical differences throughout eight classes

Overfitting occurs if model does good on training dataset but does not generalize unseen data.

Steps that can be taken for increasing models' performance:

Advanced Architecture: For better performance we can try combining EfficientNetv2 and Xception for developed classification

Multilevel Classification: Fishes that are similar can be grouped together like small and long dried fishes and then we can perform finer classification.

Change in Data Labeling: To minimize ambiguity, we need to ensure that the dataset is labeled accurately.

Mechanisms of Attentions: To focus on smooth features, we can rely on Vision Transformers (Vit) or add modules like SE blocks.

Cross Category Learning: To make advantage of mutual learning among categories, we can train single for each eight classes instead of dividing into distinct categories.

Class Specific pre-processing: Modifying data augmentation to focus on variations between that are often mistaken.

Chapter 6

Conclusion

This research paper evaluated four deep learning models which are MobileNetV2, EfficientNetV2B0, Xception, and ResNet50V2 for their capacity to classify dried fish into four categories: Single, Head, Tail, Bulk. Important indicators like Accuracy, loss graphs, detection time, precision, recall, and F1-score were the main elements for the assessment. MobileNetV2 is the best possible model for real time applications and edge devices as it displayed the best balance between accuracy, speed and calculation effectiveness. It continuously performed well in categories like bulk and others EfficientNetV2B0 positioned itself as an easy option for circumstances ordinary assets consumption is supportable by contributing estimated tradeoff between accuracy and calculating cost. ResNet50V2 was restricted in its use for real time tasks because of its poor speed and regulation in spite of its good performance in Single classification.

Finally, the outcome is that EfficientnetV2B0 has the highest accuracy and it is the best model among all the categories because Tail and Bulk and classes after classifying. The ResNet50V2 has the highest accuracy for single dried fish as well as all types of fish classification. Xception model has highest accuracy for Head classification. But all models are good and has expertise for different type of classification. Besides the graphs shows different type of results from which we can declare Xception the best model if we compare all models and categories.

Moreover, Data Article on the collected dataset will be submitted in “Data Brief” which will open new doors for our paper and dataset for further research and development or it would help others to take ideas to do more updated research.

Future work can focus on enlarging the dataset to add more dried fish species and categories, improving the model’s using quantization and trimming methods for margin arrangement, and inspecting broader architectures as attention-based model and architecture. In upcoming future, research can develop systems for classification of dried fish by managing these issues, launching the door to helpful adaptable industrial applications.

References

1. Amin, Redwan. (2023). Dried and Dehydrated Fishery Products. 10.13140/RG.2.2.27689.16485

2. Paul, P. C., Reza, M. S., Islam, M. N., & Kamal, M. (2018). A review on dried fish processing and marketing in the coastal region of Bangladesh. Research in Agriculture Livestock and Fisheries, 5(3), 381-390.

3. Mansur, M. A., Rahman, S., Khan, M. N. A., Reza, M. S., & Uga, S. (2013). Study on the quality and safety aspect of three sun-dried fish. African Journal of Agricultural Research, 8(41), 5149-5155

4. Kubra, K., Hoque, M. S., Hossen, S., Husna, A. U., Azam, M., Sharker, M. R., & Ali, M. M. (2020). Fish drying and socio-economic condition of dried fish producers in the coastal region of Bangladesh. Middle-East J. Sci. Res, 28(3), 182-192.

5. Hoque, M. S., Tamanna, F., Hasan, M. M., Al Banna, M. H., Mondal, P., Prodhan, M. D. H., ... & van Brakel, M. L. (2022). Probabilistic public health risks associated with pesticides and heavy metal exposure through consumption of common dried fish in coastal regions of Bangladesh. Environmental Science and Pollution Research, 1-16.

6. Sujit Krishna Das,"DRIED FISH INDUSTRY IN BANGLADESH: ISSUES AND CONCERNS,"INFOFISH,Apr,4,2024[Available online athttps://v4.infofish.org/index.php/article-ii-4-2024-dried-fish-industry-in-bangladesh-issues-and-concerns]

7. Fitri, N., Chan, S. X. Y., Che Lah, N. H., Jam, F. A., Misnan, N. M., Kamal, N., ... & Abas, F. (2022). A comprehensive review on the processing of dried fish and the associated chemical and nutritional changes. Foods, 11(19), 2938.

8. Laboni, M. A., Rimi, I. F., Deb, S., Afrin, F., & Hena, M. H. (2022, April). Dried Fish Classification Using Deep Learning. In 2022 Second International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT) (pp. 1-6). IEEE.

9. Paygude, P., Gayakwad, M., Wategaonkar, D., Pawar, R., Pujeri, R., & Joshi, R. (2024). Dried Fish dataset for Indian Seafood: A machine learning application. Data in Brief, 110563.

10. Salman, A., Jalal, A., Shafait, F., Mian, A., Shortis, M., Seager, J., & Harvey, E. (2016). Fish species classification in unconstrained underwater environments based on deep learning. Limnology and Oceanography: Methods, 14(9), 570-585.

11. Allken, V., Handegard, N. O., Rosen, S., Schreyeck, T., Mahiout, T., & Malde, K. (2019). Fish species identification using a convolutional neural network trained on synthetic data. ICES Journal of Marine Science, 76(1), 342-349.

12. Spampinato, C., Chen-Burger, Y. H., Nadarajan, G., & Fisher, R. B. (2008, January). Detecting, tracking and counting fish in low quality unconstrained underwater videos. In International Conference on Computer Vision Theory and Applications (Vol. 2, pp. 514-519). SciTePress.

13. Larsen, R., Olafsdottir, H., & Ersbøll, B. K. (2009). Shape and texture based classification of fish species. In Image Analysis: 16th Scandinavian Conference, SCIA 2009, Oslo, Norway, June 15-18, 2009. Proceedings 16 (pp. 745-749). Springer Berlin Heidelberg.

14. Rova, A., Mori, G., & Dill, L. M. (2007, May). One fish, two fish, butterfish, trumpeter: Recognizing fish in underwater video. In MVA (pp. 404-407).

15. Islam, S. M., Bani, S. I., & Ghosh, R. (2021). Content-based fish classification using combination of machine learning methods. International Journal of Information Technology and Computer Science (IJITCS), 13(8), 62-68.

16. Li, D., Wang, Q., Li, X., Niu, M., Wang, H., & Liu, C. (2022). Recent advances of machine vision technology in fish classification. ICES Journal of Marine Science, 79(2), 263-284.

17. Kaya, V., Akgül, İ., & Tanır, Ö. Z. (2023). IsVoNet8: a proposed deep learning model for classification of some fish species. Journal of Agricultural Sciences, 29(1), 298-307.

18. Ben Tamou, A., Benzinou, A., & Nasreddine, K. (2022). Live fish species classification in underwater images by using convolutional neural networks based on incremental learning with knowledge distillation loss. Machine Learning and Knowledge Extraction, 4(3), 753-767.

19. Benson, I. M., Helser, T. E., Marchetti, G., & Barnett, B. K. (2023). The future of fish age estimation: deep machine learning coupled with Fourier transform near-infrared spectroscopy of otoliths. Canadian Journal of Fisheries and Aquatic Sciences, 80(9), 1482-1494.

20. Monteiro, F., Bexiga, V., Chaves, P., Godinho, J., Henriques, D., Melo-Pinto, P., ... & Fernandes, A. M. (2023). Classification of Fish Species Using Multispectral

Data from a Low-Cost Camera and Machine Learning. Remote Sensing, 15(16), 3952.

21. Alsmadi, M. K., Omar, K. B., Noah, S. A., & Almarashdeh, I. (2010). Fish recognition based on robust features extraction from size and shape measurements using neural network. Journal of Computer Science, 6(10), 1088.

22. Ahmed, M. S., Aurpa, T. T., & Azad, M. A. K. (2022). Fish disease detection using image based machine learning technique in aquaculture. Journal of King Saud University-Computer and Information Sciences, 34(8), 5170-5182.

23. Ahmed, M. S., Aurpa, T. T., & Azad, M. A. K. (2022). Fish disease detection using image based machine learning technique in aquaculture. Journal of King Saud University-Computer and Information Sciences, 34(8), 5170-5182.

24. Ferdaus, Md Hasanul; Ahmed, Masud; Prito, Rizvee Hassan; Haider, Lamia; Hossain, Shajia; Nuzhat, Subah; Shifa, Sadia Tasnim; Islam, Mohammad Manzurul; Ali, Sawkat; Islam, Maheen; Rasel, Ahmed Abdal Shafi; Rahoman, Md Mizanur (2024), “DriedFishBD: A Detailed Image Dataset of Common Small-sized Dried Fish Varieties in Bangladesh for Identification and Classification.”, Mendeley Data, V1, doi: 10.17632/vz4xgybxr2.1