DRIED FISH VARIANT CLASSIFICATION USING 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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APPROVAL

is Project titled "DRIED FISH VARIANT CLASSIFICATION USING DEEP LEARNING CHNIQUES", submitted by **Israt Jahan Juthi** and **Bibi Marjan** to the Department of mputer Science and Engineering, Daffodil International University, has been accepted as isfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer ience and Engineering and approved as to its style and contents. The presentation has been held 14th, July.

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Narayan Ranjan Chakraborty, Associate Professor and Associate Head, 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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ABSTRACT

This study describes a deep learning-based approach for digital classification of dried fish variants, which addresses an essential need in the food industry. With the increasing need for effective and precise methods of classifying dried fish variants, traditional evaluation methods have proven useless, which requires the study of advanced technological solutions. The proposed methodology includes data collection, labeling, image processing, model selection, training, evaluation, and testing. Local markets provided a diverse dataset with images of seven distinct dried fish variants, including Baspata Shutki, Bhangon, Chanda, Chapa, Chingri, Loitta, and Mola. Several deep learning architectures, including VGG16, InceptionV3, DenseNet201, and MobileNetV2, were tested for classification performance. The results show that convolutional neural networks (CNNs), especially DenseNet201, achieved high accuracy in classifying dried fish variants. Moral issues related to data privacy, fairness, and transparency were carefully addressed throughout the study. Further research should look into additional data sources, such as color imaging, transfer learning techniques, evaluating generalization capabilities across different contexts, including domain-specific information, and conducting ongoing research to monitor system effectiveness. Overall, this study advances automated food classification technologies and shows the transformative potential of deep learning in the food industry, allowing for greater efficiency, accuracy, and sustainability in dried fish variant classification processes.

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CHAPTER 1

Introduction

1.1 Overview

The research aims to use deep learning techniques to classify dried fish variants found in local markets. Dried fish, a common component in many meals, is available in a variety of forms, each with its different visual characteristics. Our primary goal is to create an efficient and accurate system that can differentiate between seven different dried fish varieties commonly found in local markets: Baspata Shutki, Bhangon, Chanda, Chapa, Chingri, Loitta, and Mola. The motivation for this research develops from the importance of automated food classification systems in improving food industry processes and helping consumers make informed decisions. With the advancement of technology, the demand for dependable and quick methods of categorizing food items has grown. A strong classification system can improve both the consumer experience and market operations for dried fish, which often come unpackaged. The primary goal of this research is to collect a diverse dataset of 3,045 images representing the seven identified dried fish variants from local markets. This dataset will be carefully labeled, enabling supervised learning and model training. To address the challenge of limited data, we want to use image augmentation techniques to present the model to a diverse range of visual variations [3]. The core of our approach is the creation of a customized Convolutional Neural Network (CNN) architecture tailored to the properties of dried fish images. Also using Several deep learning architectures, including VGG16, InceptionV3, DenseNet201, and MobileNetV2. This CNN will be trained on the preprocessed dataset, and its performance will be evaluated using metrics such as accuracy, precision, recall, and the F1-score. The overarching goal is to create a model that can accurately classify dried fish variants even in a variety of environmental variations like lighting and background differences. Finally,the successful completion of this research will contribute to the advancement of automated food classification systems by providing a practical solution for distinguishing between dried fish variants found in local markets. This technology has the potential to benefit consumers, market operators, and the food industry as a whole by increasing efficiency andinformed decision-making.

1.2 Background and Present State

Categorizing of dried fish variants has for instance in the past involved the use of human based skills where the classification of dried fish variant was determined based on the physical appearance. This type of method can be very dull, and is highly susceptible to certain human errors. As developments in artificial intelligence and deep learning computers brought us the ability of automated classifications. Currently, deep learning methods, especially Convolutional Neural Networks (CNNs), are more applied to the image classification. Many works like VGG16, Inception-v3, DenseNet-201, and MobileNet-v2 have proven good accuracy and efficiency in images complex classification data set. It is normally possible to process vast collections of image data, to discern minor variations between classes, thus these models are suitable in the seafood industry and other related fields. These technologies are integration and changing the way of classifications by increasing the level of accuracy and speeds.

1.3 Problem Statement

Classification of dried fish variant is an important yet complex process in the field of seafood business analysis. The conventional techniques of manual classification are highly time-consuming and also include human errors that create problems in regard to consistency and most importantly efficiency. It becomes clear that there is a critical necessity of choosing a stable and, if possible, an automatic method in order to maintain necessary quality and improve efficiency. However, one has to agree that the application of deep learning techniques and the efficiency of the selected models, namely CNN 01, CNN 02, VGG16, InceptionV3, DenseNet201, and MobileNetV2 as well as the dataset properties in this particular field has not been investigated thoroughly. It is hoping that this particular work will help fill this gap by providing a detailed review of the performance of these deep learning models in classifying seven different types of dried fish with the help of an extensive dataset of 3045 images. Therefore, it is important to determine a model that is most accurate and efficient in classification of variants of dried fish, these would enable provision of independent solution of the classification problem.

1.4 Objective

In this paper, the authors address the problem of segmenting seven different types of dried fish through deep learning. It includes amassing a large database of 3045 pictures that include Baspata Shutki, Bhangon, Chanda, Chapa, Chingri, Loitta, and Mola. The CNN models under consideration are CNN 01, CNN 02, VGG16, Inception V3, Dense Net 201, and MobileNetV2 from where, the merits of the models will be compared to assess the ability of these models in classifying these variants with a high degree of accuracy. Thus, the findings may help improve the state of automated classification systems in the seafood industry. The target population of this study is limited to the local markets and the dataset does not include all the possible variations of dried fish in the market. It is possible that environmental factors such as lighting conditions, as well as image quality of the data used for the training was an issue. Also, it must be noted that the achieved results depend on the selected models and hyperparameters, which may be optimized in future work. Therefore, the validation with other samples of participants across different populations is important to draw the generalization of the results.

1.5 Scope and Limitations

In this paper, the authors address the problem of segmenting seven different types of dried fish through deep learning. It includes amassing a large database of 3045 pictures that include Baspata Shutki, Bhangon, Chanda, Chapa, Chingri, Loitta, and Mola. The CNN models under consideration are CNN 01, CNN 02, VGG16, Inception V3, Dense Net 201, and MobileNetV2 from where, the merits of the models will be compared to assess the ability of these models in classifying these variants with a high degree of accuracy. Thus, the findings may help improve the state of automated classification systems in the seafood industry. The target population of this study is limited to the local markets and the dataset does not include all the possible variations of dried fish in the market. It is possible that environmental factors such as lighting conditions, as well as image quality of the data used for the training was an issue. Also, it must be noted that the achieved results depend on the selected models and hyperparameters, which may be optimized in future work. Therefore, the validation with other samples of participants across different populations is important to draw the generalization of the results.

1.6 Report Organization

The proposed report is organized in a comprehensive manner to walk readers through the research process, findings, and implications. Introduction chapter provides an overview of the research topic, including the importance of identifying dried fish variants and the study's objectives. It describes the scope and significance of the research, as well as the structure of the report. Literature chapter provides a comprehensive review of relevant literature and existing studies on dried fish variant classification using deep learning techniques. Methodology chapter describes the methodology used in the study, which included data collection, preprocessing techniques, model selection, training procedures, and evaluation metrics. Experimental Results chapter presents the findings and results of experiments used to classify dried fish variants using deep learning techniques. It includes analyses of classification accuracy, performance metrics, and model prediction visualization. Impact on Society chapter discusses the potential societal implications and applications of the research results. It looks into how the developed classification system will benefit a variety of stakeholders, including the fishing industry, consumers, and regulatory authorities. Conclusion and Future Research this the final chapter summarizes the study's key findings and conclusions. It makes recommendations for future research and suggests potential ways to improve the classification system. It also discusses the wider implications of the research for future developments in the field.

1.7 Summary

Classification of the different variants of dried fish is crucial for ensuring that the industry practices quality control and achieved optimization. The more conventional approaches involve the manual inspection; hence they are tedious, resource consuming and they are hereby associated with high possibility of errors. The emergence of deep learning presents the key approach of improving the classification process with the help of the most sophisticated algorithms available. The objective of this study is to compare the different deep learning models comprising of CNN, VGG16, InceptionV3, DenseNet201 and MobileNetV2 in the classification of the seven different classes of dried fish. It is hoping that this particular work will help fill this gap by providing a detailed review of the performance of these deep learning models in classifying seven different types of dried fish with the help of an extensive dataset of 3045 images. Therefore, it is important to determine a model that is most accurate and efficient in classification of variants of dried fish, these would enable provision of independent solution of the classification problem.

CHAPTER 2

Literature Review

2.1 Overview

The literature review is done to see the development that has been made in image classification and how deep learning models work. It discusses the basics of CNNs from the aspect of architecture evolution and presents the significance of architectures in attaining state-of-the-art performance. Literature on other related papers involving classification of foods and agricultural products using deep learning methods is discussed focusing on their approach and findings. The challenges as well as the limitations of the manual techniques of categorization have also been pointed out in the review together with the prospects of going automated. Besides, it also explains the significance of data preprocessing, augmentation, and model evaluation metrics for increasing the classification accuracy. This literature review can be considered as a strong background for the current study: it revealed gaps in the literature and justified the urgent need to assess multiple deep learning models for classification of dried fish variants.

2.2 Related Works

This literature review looks into the development of classification from images via deep learning algorithms with special emphasis on Convolutional Neural Networks (CNNs). It discusses how the popular architectures like VGG16, InceptionV3, DenseNet201, and MobileNetV2 among others were designed and used. Also, the current review discusses past literature related to the food and agricultural product classification as context for the present study. Thus, the given section shows the necessity and possibilities of the usage of automated classification systems based on the analysis of the existing techniques and outcomes of their application in the sphere of seafood industry.

In given below, I am writing a similar paper review, which will help me a lot:

Marfi Akter Laboni et al. [5] proposed a deep learning-based model for identifying different varieties of dried fish, which can help fishermen, business owners, and consumers understand market trends. With a dataset of locally identified dried fish species such as Bashpata, Chanda, and Ilish, the model achieves an outstanding 97.72% accuracy using segmentation and augmentation approaches. It focuses on the profitability and simplicity of drying procedures, which will benefit people starting a dried fish offering business.

Explored the application of visible/infrared spectroscopy and hyperspectral imaging combined with machine learning techniques for the identification of food varieties and geographical origins. Bangladesh and abroad. Feng et al. [6] emphasizes the integration of advanced analytical tools to enhance precision in food classification and traceability. The utilization of these technologies, as discussed in the paper, showcases their potential in addressing challenges related to food authentication and origin determination. The research contributes to the growing field of food science by highlighting the synergistic capabilities of spectroscopic methods and machine learning for reliable and efficient food quality assessments.

Presented a comprehensive review in Mechanical Systems and Signal Processing on the integration of deep learning techniques for machine health monitoring. Zhao et al. [7] delve into the applications of deep learning in this domain, emphasizing its capacity to effectively process and analyze complex data sets for enhanced predictive maintenance. The paper discusses the utilization of deep learning algorithms in various aspects of machine health monitoring, demonstrating their efficacy in fault detection and prognostics.

The research underscores the transformative potential of deep learning methodologies in advancing the field of machinery condition monitoring and maintenance. Zhu and Spachos et al. [8] presented a comprehensive survey in Deep learning and machine vision for food processing, exploring the intersection of these technologies within the realm of food science. The authors delve into the evolving landscape of deep learning applications and machine vision systems, focusing on their roles in various aspects of food processing. Through an extensive review, the paper offers insights into the recent advancements, challenges, and potential solutions in utilizing these technologies for enhancing efficiency, quality control, and safety in the food industry.

This survey serves as a valuable resource for researchers and practitioners seeking a holistic understanding of the state-of-the-art developments in deep learning and machine vision for food processing. Jalal et al. [9] focused on a comprehensive study of fish detection and species classification in underwater environments by employing deep learning techniques with a focus on temporal information. The research addresses the challenges associated with underwater imaging, emphasizing the importance of incorporating temporal context for accurate fish identification. The integration of deep learning models showcases their effectiveness in handling complex underwater scenarios, contributing to advancements in ecological informatics.

This paper not only highlights the significance of temporal information in fish detection but also provides valuable insights into the potential applications of deep learning for monitoring aquatic ecosystems and biodiversity. Petrellis et al. [10] presented a study focusing on the measurement of fish morphological features employing a combination of image processing and deep learning techniques. The paper delves into the application of advanced technologies to streamline the analysis of fish characteristics, contributing to the field of fisheries research. The integration of image processing and deep learning not only enhances accuracy in morphological measurements but also offers a more efficient and automated approach to fish trait assessment.

This research underscores the significance of technological advancements in fisheries management and provides valuable insights into the potential for automated tools in aquatic biology. Bhanumathi and Arthi et al [11] introduced FishRNFuseNET, a novel approach for fish species classification that incorporates a heuristic-derived recurrent neural network (RNN) with a feature fusion strategy. The paper addresses the critical issue of accurate fish species identification, particularly relevant in fisheries and aquatic research. The integration of RNN and feature fusion techniques demonstrates the authors' commitment to enhancing the performance of classification models in the domain of fish species recognition. This research contributes to the ongoing efforts to leverage advanced neural network architectures and feature engineering strategies for improved accuracy and reliability in aquatic species classification.

The increasing adoption of deep learning (DL) and machine learning (ML) in fisheries acoustics for acoustic fish species echo classification focused Anas Yassir et al [21]. The systematic search identified 13 relevant studies from 2018 to 2022, categorizing them into ML-based and DL-based approaches. Despite the inherent complexity of DL architectures, they consistently outperformed ML methods in acoustic echo classification, even with limited annotated data. Both ML and DL applications encountered challenges such as data processing, annotation, and dealing with imbalanced datasets. The review anticipates future advancements in tool and sensor development, providing a valuable resource for researchers interested in the evolving landscape of DL and ML applications in fisheries acoustics. The pressing issue of fish diseases in aquaculture and emphasizes the need for effective detection methods explore Md. Rashedul Islam Mamun et al [22]. The study compares the performance of deep learning and machine learning techniques in classifying fish disorders using a dataset of 1382 images. Results indicate that deep learning, particularly the VGG16+VGG19 ensemble models, outperforms traditional machine learning models, achieving a remarkable accuracy of 99.64%. The review highlights the success of segmentation techniques in locating afflicted areas and suggests the superiority of deep learning for fish disease detection. Future research directions involve gathering larger datasets, exploring various segmentation techniques, applying additional deep learning models, and considering the development of web-based or mobile applications for practical use in aquaculture. This study addresses the challenges in manual fish species classification by introducing the IsVoNet8 convolutional neural network model Volkan KAYAa et al [23], leveraging advancements in deep learning and computer vision. Comparisons with established models like ResNet50, ResNet101, and VGG16 reveal that IsVoNet8 achieves a notable accuracy of 98.62% in classifying eight different fish species from six families. The research demonstrates the effectiveness of deep learning algorithms in predicting common fish species crucial for human nutrition. Despite its fewer parameters and lower cost, IsVoNet8 outperforms other models, highlighting its superior efficiency the challenges in manually classifying freshwater fish species Jayashree Deka1 et al [24], emphasizing the increasing role of computer vision and deep learning techniques. The study employs fine-tuned deep learning architectures, AlexNet and ResNet-50, to classify 20 indigenous freshwater fish species from North-Eastern India. Comparative analysis reveals ResNet-50's superior performance, achieving 100% classification accuracy at a learning rate of 0.001. The research contributes by investigating various factors impacting classifier accuracy, showcasing ResNet-50 as the most effective model. The nutritional significance of fish, the study employs a deep learning approach, specifically a Convolutional Neural Network (CNN), for accurate species identification. The proposed model by Sajal Das et al [25] demonstrates a commendable accuracy of 98.33%, emphasizing the effectiveness of CNN in image segmentation for fish species classification. The article successfully contributes to creating varied fish species datasets, offering valuable insights for researchers studying the nutritional aspects of fish.

2.3 Comparison between existing works

Current fish-related studies take a variety of approaches, each addressing a specific aspect of fish classification and monitoring. Akter Laboni et al. [5] focus on dried fish identification, achieving high accuracy through segmentation and augmentation. Feng et al. [6] investigate spectroscopy and machine learning for food identification, focusing on precision and traceability. Zhao et al. [7] investigate machine health monitoring, demonstrating deep learning's application in fisheries. Zhu and Spachos [8] provide a comprehensive survey of deep learning in food processing, whereas Jalal et al. [9] and Petrellis et al. [10] work on fish detection and morphological analysis. Bhanumathi and Arthi et al. [11] introduce FishRNFuseNET, a fish species classification system. A comparative analysis shows that each study targets specific niches, with Akter Laboni et al.[5] excelling at dried fish identification, highlighting the need for a more nuanced and focused approach in this particular domain.

TABLE 2.1 COMPARATIVE ANALYSIS WITH PREVIOUS WORK

SL	Author Name	Used Algorithm	Best Accuracy with Algorithm	Paper Name
1.	Marfi Akter Laboni et al. [5]	Deep Learning	97.72%	Detection of fish freshness
3	Volkan KAYAa et al [23]	IsVoNet8	98.62%	Dry bean cultivar classification
4	E. T. Yasin, I. A et al [24]	Suueeze +Inception V3	98%	Detection of fish freshness
5	M. A. Ahmed et al [25]	CNN +LSTM	97%	Bangladesh's local fish classification

2.4 Open Issues

Despite advancements in deep learning for image classification, several challenges persist in the context of dried fish variant classification: The scarcity and restrictions on the variety of datasets which may capture different environmental conditions, lighting and the quality of the dried fish. Due to variations in appearances of dried fish, it is important that the trained models cover for unseen data and any appearances deviations. Accommodating deep learning techniques in order to enable efficient running of the models on the devices which have limited resources. Improving the interpretability of outputs for the purpose of creating trust in such methods and for the implementation of such systems in industries. Solving these problems will be significant for the improvement of accuracy, reliability, and extensiveness of automated dried fish variant classification systems.

2.5 Summary

The literature review aims at analyze and discuss the literature studying the emergence and use of deep learning, especially CNNs, for image classification. It reviews the performance of a variety of architectures including VGG16, InceptionV3, DenseNet201, and MobileNetV2 in different fields including the identification of food and agricultural products. The submitted review explores the shift from the classical methods employing manual categorization towards the application of automatic classification techniques topped by deep learning approaches, the benefits of which include increased accuracy. Among them, there are several major concerns such as, a variety of datasets, generalization, the computational time, and model interpretability. Thus, this extensive research forms the basis for comparing numerous deep learning models to classify dried fish variants in order to fill the current lacunae and advance the area of automated classification in the seafood sector.

CHAPTER 3

Methodology

3.1 Overview

This paper presents a procedure for categorizing the variants of the dried fish using germ of the neural network methodologies. This entails the description of the acquisition of the dataset of 3045 images in the seven classes of Baspata Shutki, Bhangon, Chanda, Chapa, Chingri, Loitta, and Mola from local markets. Normalization and augmentation strategies are applied on the images in pre-processing step to improve the qualities of the datasets. Several DCNNs or deep learning models like CNN 01, CNN 02, VGG16, InceptionV3, DenseNet201, and MobileNetV2 are trained and tested for classification efficiency. The training process implies a multitasking division of data into the training, validation, and testing sets, and the subsequent training and testing of the model's performance using typical performance metrics. This definitely means that this state-of-the-art methodology is intended to determine the right model for the automated classification of different variants of dried fishes bearing in mind the real-life reliability of the model.

3.2 Proposed Methodology

The methodology for creating an automated dried fish variant classification system is multi-stage. There is specific methodology which encompasses several key steps:

Data Collection:

Check out the local fish markets or stores that offer dried fish products. Take pictures of the several varieties of dried fish with a high-resolution camera or smartphone. To satisfy the dataset criteria, make sure you take numerous photos of each variety. Keep track of every image's specific detail, such as the class designation and other pertinent metadata.

Labeling:

Give each image the proper class label according to the kind of dried fish variation it depicts. To make model training and evaluation easier, make sure that labeling is accurate and consistent.

Image Processing:

Standardize the size, format, and quality of the gathered photographs by preprocessing them. Images should be resized to a consistent resolution that the deep learning model can use as input. To aid in model convergence, normalize pixel values to a shared scale. To make the dataset more robust and variable, add more features by rotating, flipping, and cropping it.

Model Selection:

Based on their computational efficiency and performance, take into consideration CNN architectures (e.g., VGG16, InceptionV3, DenseNet201). Considering the model's classification accuracy, complexity, and resource needs, select the best fit.

CNN

CNN is a deep learning architecture used in the identification and analysis of visual data. It includes layers that do convolution, usually accompanied by pooling layers and ends with fully connected layers for the classification. CNNs are crucial for image recognition and computer vision because they can encode input images into spatial hierarchies of features in an automatic and adaptive manner. They learn local patterns with convolutional layers and thus diminish the dimensionality with pooling layers and are therefore very effective. It has been at the forefront in attaining the best performances across various applications such as, object detection, image segmentation, and facial recognition, to name but a few areas such as medical image analysis, autonomous vehicles, etc.

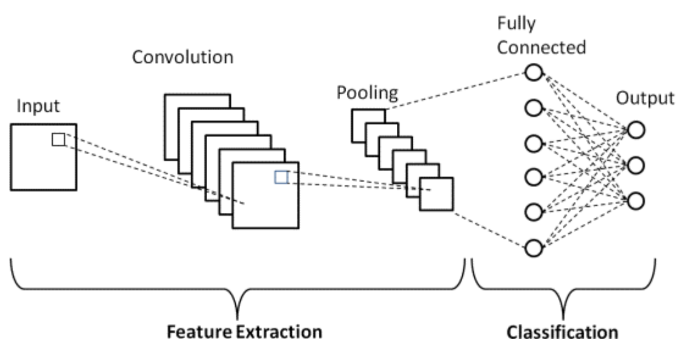

Figure 3.1: CNN Architecture M. Gurucharan, et al.2020[26]

VGG19

VGG19 is a deep convolutional neural network model named by the Visual Geometry Group at Oxford. It incorporates 16 layers, 13 of which are convolutional and three fully connected layers and it is famous due to its simplicity and proficiency in the image ranking tasks. The uniform architecture with three-by-three convolutional layers and great depth of VGG19 is beneficial since it will allow the model to identify various patterns present in the images. Because its structure is quite simple and uncluttered and because changing its architecture is easy, this model is frequently used in many image classification applications and is considered a standard reference design in deep learning.

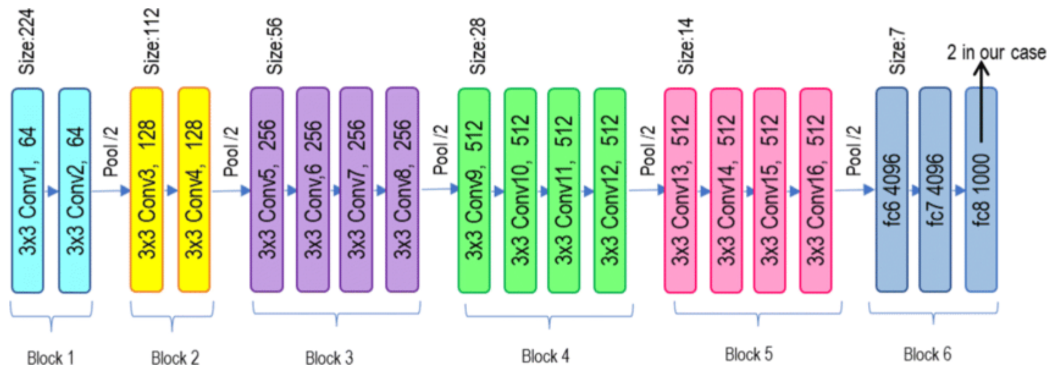

Figure 3.2: VGG19 Architecture A. Khattar et al.2022[27]

DenseNet201

DenseNet201 is a densely connected convolutional network having a total of 201 layers. It introduces Dense connectivity; it means that each layer takes an input from all the previous layers, and its output goes to all the next layers. Due to the dense connectivity model, DenseNet201 reduce the repeated computation of features from lower layers and relieve the vanishing gradient problem, so it has a higher training efficiency and model accuracy. The higher density of the connection improves the flow of information and gradients within the network to make it very efficient in image classification.

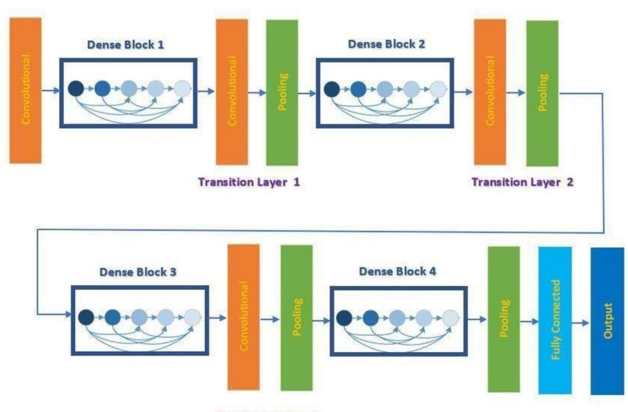

Figure 3.3: DenseNet201 Architecture O. Attallah, et al.2021[28]

InceptionV3

InceptionV3 is another deep convolutional neural network architecture from the Inception family by Google. The network employs inception modules to enable the network to receive multi scale feature at once through parallel convolution of varying sizes. InceptionV3 improves the utilization of computational resources since it has a smaller number of parameters but high accuracy. Due to its ability to break down data and analysis into independent units, it may be applied to capturing of intricate patterns in images as well as more abstract representations such as hierarchies that are commonly associated with big pictures.

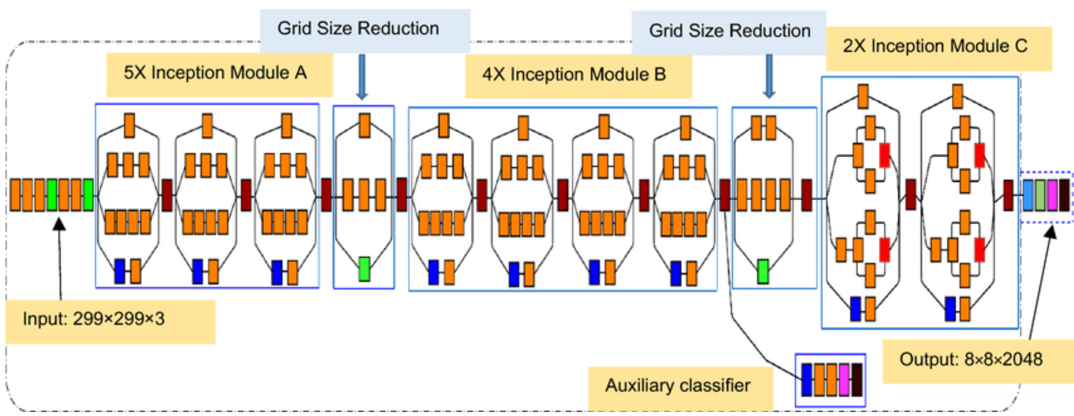

Figure 3.4: InceptionV3 Architecture T. Singh et al.2020[29]

MobileNetV2

MobileNetV2 is a light network architecture for mobile and embedded vision applications based on the convolution neural network. It includes depthwise separable convolution, which adds inverted residuals and linear bottleneck. MobileNetV2 provides a good level of accuracy while being efficient in terms of computation; therefore, it is suitable for implementation on low-end devices. It is optimized for mobile and embedded systems, which enables the solution to perform real-time image classification tasks, increasing the use of deep learning.

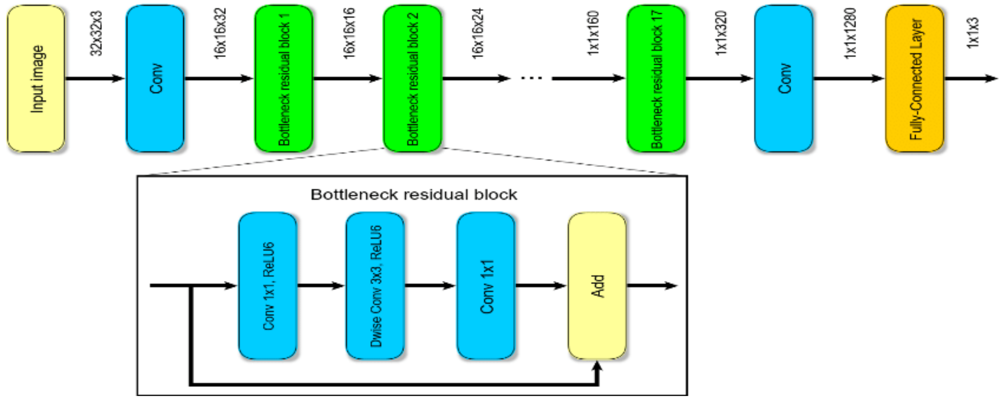

Figure 3.5: MobileNetV2 Architecture U. Seidaliyeva et al.2020[30]

Model Training:

The preprocessed dataset was divided into test, validation, and training sets. The chosen deep learning model should be trained using the training set, with model parameters being adjusted via backpropagation to reduce classification loss. To avoid overfitting, evaluate the model's performance on the validation set and adjust the hyperparametersappropriately.

Model Evaluation:

Assess the trained model's performance on the test set by using suitable evaluation metrics, like F1-score, accuracy, precision, and recall. Examine the confusion matrix of the model to determine where it needs to be improved and evaluate how well it can differentiate between various dried fish varieties.

Test Model:

Use the trained model in practical situations to categorize different types of dried fish. Examine the model's performance in real-world scenarios, including nearby markets or food processing plants. Obtain input, then iteratively improve the model in light of user observations and experiences.

We hope to create a deep learning-based system that accurately classifies different varieties of dried fish by using this suggested methodology. This would give stakeholders in the food business useful information and workable solutions.

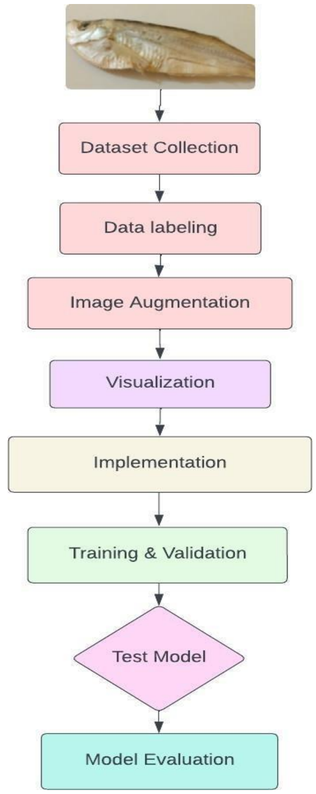

Figure 3.6: Working Flow

3.3 Hardware/ Software Requirement

A number of essential conditions must be met for the suggested methodology for deep learning-based dried fish variant classification to be implemented successfully. First and foremost, it's vital to have access to a substantial quantity of excellent picture data that depicts various dried fish varieties. Computational resources, such as GPUs or TPU hardware, are also necessary for effectively training deep learning models. Moreover, model creation and experimentation require access to deep learning frameworks and libraries like TensorFlow or PyTorch. It's also necessary to have enough storage space for the trained models and dataset. Finally, proficiency in computer vision, deep learning, and data preprocessing methods is essential for putting the suggested methodology into practice and maximizing the classification system's effectiveness.

3.4 Project Management and Financial Analysis

The project will follow a structured project management methodology that includes setting specific objectives, developing time constraints, and efficiently distributing resources. To ensure responsibility and commitment to project objectives, conduct frequent progress meetings and point reviews. Financial resources will be set aside for hardware infrastructure, data collection, and any costs associated with licensing related to software tools or deep learning frameworks. In order to ensure employee competency in setting up and maintaining the classification system, additional funding will be given for training and development. To keep the project on schedule and within budgetary constraints, budgetary considerations will be closely monitored throughout the project lifecycle to maximize resource utilization and mitigate possible expense increases.

TABLE 3.1: PROJECT MANAGEMENT TABLE

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

3.5 Summary

The methodology followed involved a structured approach to categorize dried fish variants based on deep learning approaches. A dataset of 3045 images belonging to seven classes was captured from local markets and normalized besides being augmented. Thus, six models of deep learning, namely CNN 01, CNN 02, VGG16, InceptionV3, DenseNet201, and MobileNetV2, were applied and compared for their efficiency in identifying the dried fish variants. Thus, the current dataset was divided into training, validation and test sets for purpose of training the models and evaluation of their performances. Indicator including accuracy, precision, recall and F1 score were adopted to measures the effectiveness of the models. It is argued that the strict approach of the current study is designed to identify the best approach in the classification of the dried fish variants, and thus inform the future improvements of quality assurance and effectiveness of the seafood business.

CHAPTER 4

Implementation

4.1 Overview

In the implementation phase, the selected approach was applied to create and apply a proper solution system for classifying dried fish variants via deep learning. These were followed by the steps of data collection where 3045 images of the seven classes of dried fish were gathered and preprocessed. This was then followed by a selection and application of six deep learning models that include CNN 01, CNN 02, VGG16, InceptionV3, DenseNet201 and MobileNetV2 to try determine their classification accuracy. Preprocessing and tuning took place on the separated data-sets with using such measures as accuracy, error rate, etc. The implementation phase aimed at determining the best model of the automated classification of the data in practice, while considering the characteristics of large seafood industry.

4.2 Train Model/ Prototype Design

The training phase included using and optimizing six deep learning algorithms, which consist of CNN, VGG16, InceptionV3, DenseNet201, and MobileNetV2 with a dataset of images of various dried fish in the form of 3045 images. For each of them, the training process took place on the split set with the division into training, validation, and testing sets to achieve the best classification accuracy. Hypers like learning rate, batch size, and settings of the optimizer were adjusted in a bid to optimize the model. On the prototype design, the concern of the project was to integrate the capability of application robustness and scalability for models; and the approach was the utilizing of metrics such as accuracy, precision, recall, and F1 score to assess models. Thus, decision models were generated through this iterative process to focus on determining the best model for the automated classification of dried fish variants, enabling the development of solid nad reliable industrial applications based on the results.

4.3 System Design/ Model Evaluation

This paper's system design phase looked at six deep learning models, including CNN, VGG16, InceptionV3, DenseNet201, and MobileNetV2 based on their classification of the dried fish variants. These models were thoroughly tested on the measures such as accuracy, precision, recall, and F1 score based on a separately built test set. The assessment used factors like the models' ability to perform well on unseen data, the number of computations needed and how well the models can perform despite the changes in appearances of dried fish. This phase sought to find the most precise and sustainable model for automated classification as a way of improving reliability and applicability of the classifier models in the actual SES applications within the seafood sector.

4.4 Summary

As demonstrated in the implementation phase, it was possible to apply an extensive plan of automating the classification of dried fish variants through deep learning models. The dataset with 3045 images of seven classes was created and pre-processing was done rigorously. Six models, including CNN, VGG16, InceptionV3, DenseNet201, and MobileNetV2 models, were trained and tested by the performance indices which include accuracy and F1 score. The process of selection defined the most appropriate method for proper identification of the types of dried fish. This implementation did not only prove the effectual utilization of automated classification but also paved the way of improving the quality assurance and operation organization of seafood company. There could exist other parameters in the improvement of the model's performance for the large number of parameters or applicability to the more general data sets or real-world scenarios.

CHAPTER 5

Result and Analysis

5.1 Overview

This paper is centered towards the development of a model for automated classification of the dried fish variants with the help of deep learning models. It is about gathering a dataset of 3045 image across seven dried fish classes, data pre-processing and assessing the performance of six deep learning models for classification. This paper seeks to improve the recognition rates of dried fish types as a way of improving and transforming the seafood industry's quality assurance methods. Specifically, using the state-of-art machine learning methods, the study aims to establish a comprehensive framework for improving existing perception systems' performance for future applications in food product quality control and other fields.

5.2 Experimental Result

In this part of experiment, compared the performance of six different CNN architectures: DenseNet201, VGG19, MobileNetV2, InceptionV3, CNN01, and CNN02. I trained these models on a dataset of various images and then tested their accuracy on a separate set. The results showed remarkable accuracy across the board. DenseNet201 achieved the highest accuracy of 99.67%, followed by MobileNetV2 at 99.51%. VGG19 and InceptionV3 achieved high accuracy rates of 97.87% and 98.85%, respectively. Our custom CNN architectures, CNN01 and CNN02, produced competitive results of 94.25% and 97.82%. These findings highlight the efficacy of deep learning architectures in image classification tasks, with DenseNet201 and MobileNetV2 emerging as especially promising options for high-accuracy applications. I am evaluated the Accuracy, Precision, Recall, and F-1 Score of the Confusion Matrices for our proposed methods.

Accuracy:

Precision refers to the measure of the closeness of the model with the real situation to give percentage likelihood of the samples used in model development. It is rather helpful when the classes are not balanced because it gives some information on the choice's effectiveness, at the same time, the picture may be incomplete.

$$Accuracy=(TP+TN)/(TP+TN+FP+FN)$$

Precision:

Of all the constructions that come out of positive assertions, precision estimates the number of desirable outcomes that was correctly predicted by the model.

$$Precision=TP/(TP+FP)$$

Recall: It is therefore considered that, recall equals to the quantity of true positive delay predicted over the total quantity of samples that are positively skewed.

$$Recall=TP/(TP+FN)$$

F1 Score: F1 score is actually the average of Recall and Precision two measures which is averaged using the formula of harmonic mean. It provides a somewhat neutral measure and it calculates recall as well as precision all at once. It is beneficial when the classes are of different sizes because F1 Score considers false positive as well as false negatives.

$$F\text{-}1\ Score=2*(Precision*Recall)/\ (Precision + Recall)$$

In given below we are describing the result analysis part also show the training accuracy and loss rate and confusion matrix also:

CNN

Achieving Test Accuracy of CNN is 94.25%. In below Figure 5:1 describing the confusion matrix of CNN:

Figure 5.1 shows the precision, recall, and F1-score metrics measure the algorithm's ability to classify seven types of dried fish. Overall, the model achieved 94% accuracy across 609 samples. Precision values ranged between 87% and 99%, indicating the algorithm's ability to correctly identify each fish type. The recall values, which range from 89% to 99%, show the model's ability to capture relevant instances from each class. The F1-scores, which average 94%, provide a balanced measure of the algorithm's precision and recall in each category. This comprehensive evaluation shows the model's strong classification capabilities for dried fish types.

Figure 5.2 shows the graph shows a CNN's training progress over epochs, with the x-axis representing epochs and the y-axes showing training accuracy and loss.

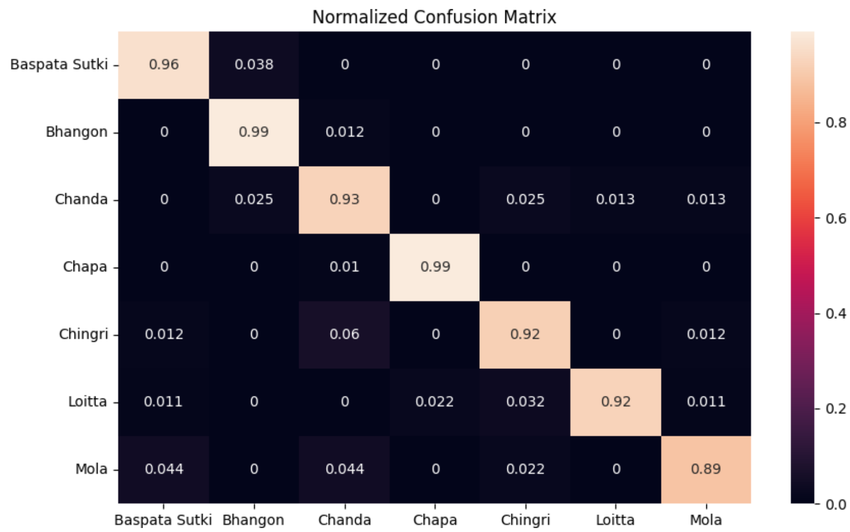

Figure 5.1: Confusion Matrix (CNN)

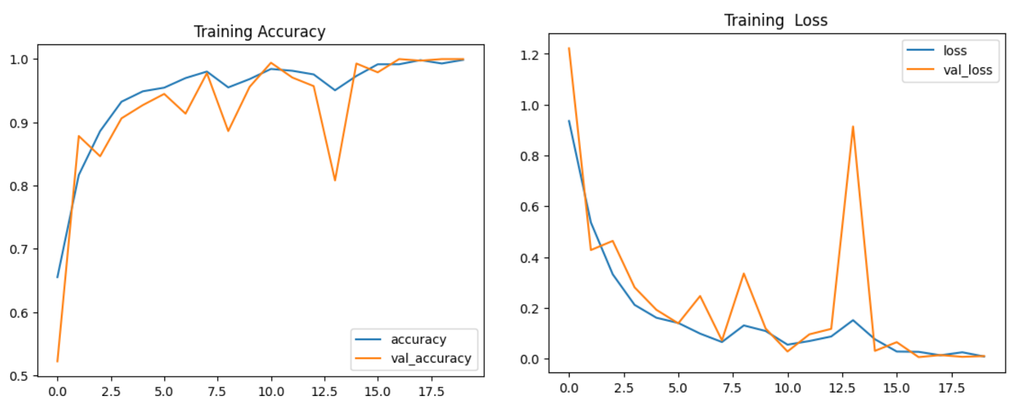

Figure 5.2: Training Accuracy and Loss Curve (CNN)

The blue line shows increasing accuracy, indicating the model's ability to correctly classify training examples across epochs. Meanwhile, the green line shows decreasing loss, indicating that the model is better fitted to the training data. Smooth, non-erratic curves suggest effective learning, whereas plateauing may indicate diminishing returns. However, without additional analysis, it is unclear whether the model is overfitting or has reached its learning capacity.

VGG19

Achieving Test Accuracy of VGG19 is 97.87%. In below Figure 5:3 describing the confusion matrix of VGG19

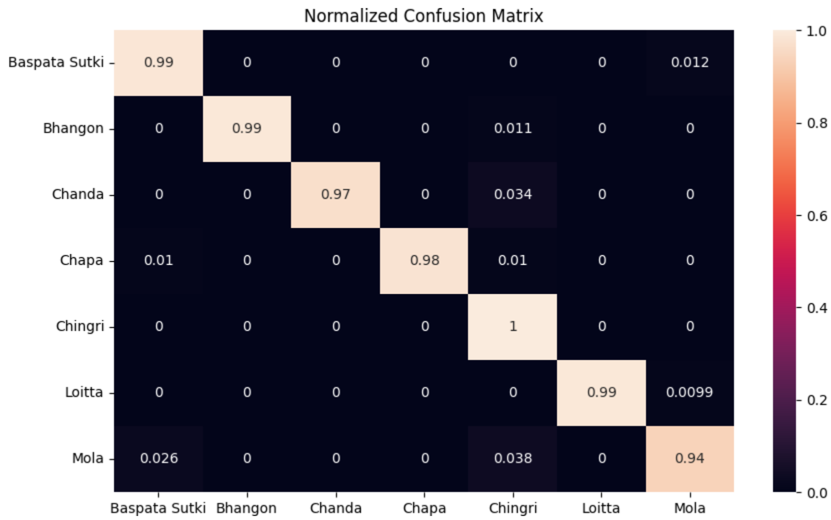

Figure 5.3: Confusion Matrix (VGG19)

Figure 5.3 the precision, recall, and F1-score metrics for the VGG19 model show its outstanding performance in classifying seven different types of dried fish. With an overall accuracy of 98% across 609 samples, the model achieves high precision and recall values ranging from 90% to 100% for each fish type. This shows the model's ability to correctly identify instances of each class while maintaining consistent performance across all categories. The macro and weighted averages focus on the model's overall success in classification tasks. This comprehensive evaluation shows the VGG19 model's robustness and reliability for dried fish classification.

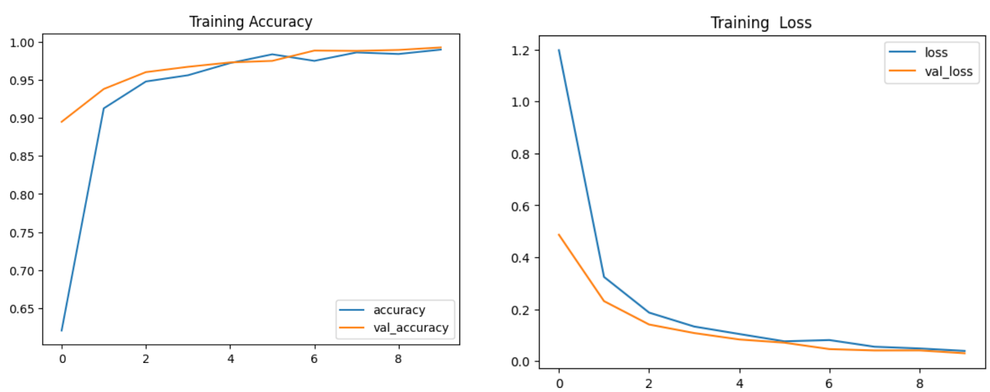

Figure 5.4: Training Accuracy and Loss Curve (VGG19)

Figure 5.4 shows the Training Accuracy and Loss Curve VGG19 graph compares training accuracy and loss across epochs. The x-axis represents epochs, and the left y-axis represents accuracy, which begins at around 0.65 and gradually rises to nearly 1.0. Concurrently, the right y-axis represents loss, which begins at 1.2 and gradually decreases to nearly 0. This trend indicates that the VGG 19 effectively learns from the training data, improving both accuracy and fit as training progresses.

InceptionV3

Achieving Test Accuracy of InceptionV3 is 98.85%. In below Figure 5:5 describing the confusion matrix of InceptionV3

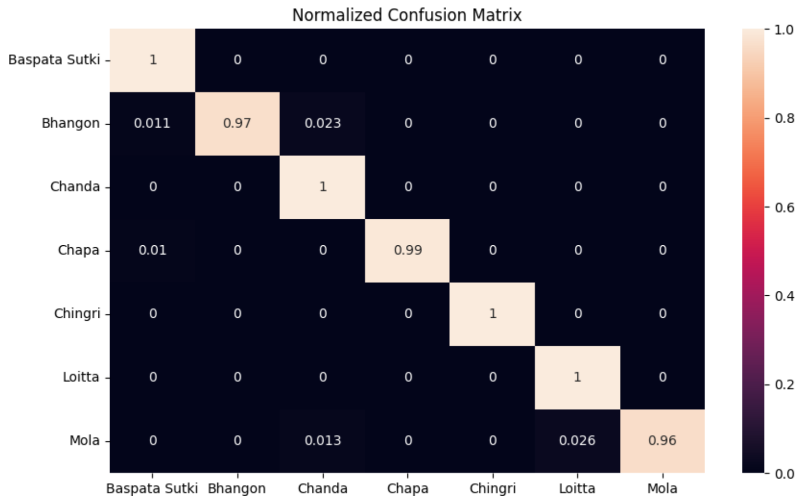

Figure 5.5: Confusion Matrix (InceptionV3)

Figure 5.5 shows the InceptionV3 model performs very well in classifying seven types of dried fish, as evidenced by its precision, recall, and F1 score metrics. With an overall accuracy of 99% across 609 samples, the model achieves high precision and recall values ranging from 97% to 100% for each fish category. This shows the model's ability to accurately identify instances of each class while minimizing misclassification. The macro and weighted averages emphasize the model's overall performance in classification tasks. This comprehensive evaluation points out the InceptionV3 model's robustness and reliability for dried fish classification.

Figure 5.6 shows the graph Accuracy and Loss Plot for Training the InceptionV3 Model" shows training accuracy and loss over epochs. The x-axis represents epochs, and the y-axis shows accuracy (left) and loss (right). The blue line shows increasing accuracy, indicating the model's ability to correctly classify training examples over epochs, whereas the green line shows decreasing loss, indicating better fitting to the training data.

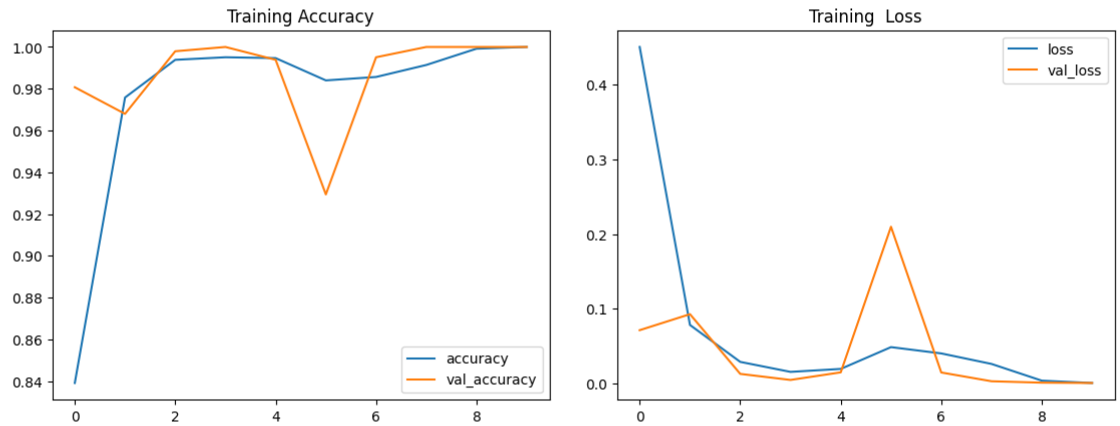

Figure 5.6: Training Accuracy and Loss Curve (InceptionV3)

Smooth, non-erratic curves indicate effective learning, but without further analysis, it's difficult to tell whether the model is overfitting or underfitting.

DenseNet201

Achieving Test Accuracy of DenseNet201 is 99.67%. In below Figure 5:7 describing the confusion matrix of Densenet201

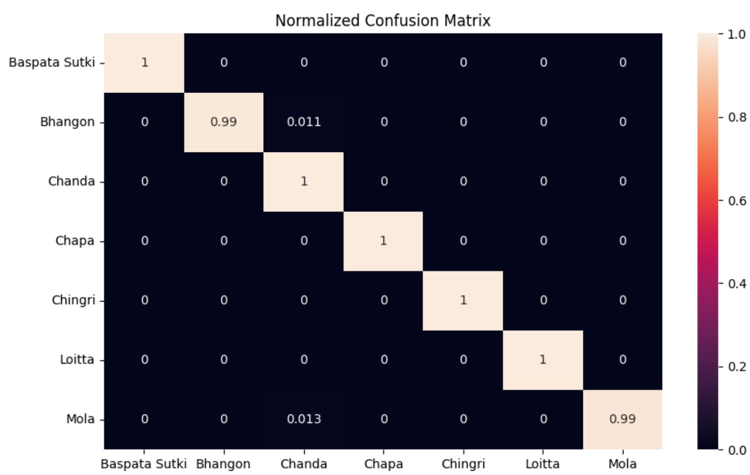

Figure 5.7: Confusion Matrix (DenseNet201)

Figure 5.7 shows the DenseNet201 model performs perfectly in classifying seven different types of dried fish, as measured by precision, recall, and F1-score. With an overall accuracy of 100% across 609 samples, the model shows perfect precision and recall values for each fish category, which range from 98% to 100%. This shows the model's exceptional ability to correctly identify instances of each class with no misclassifications. The macro and weighted averages support the model's exceptional performance in classification tasks.

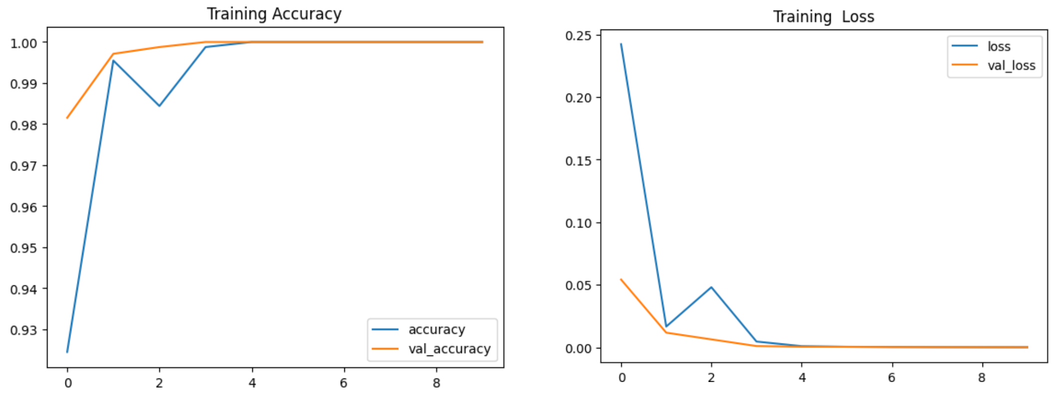

Figure 5.8: Training Accuracy and Loss Curve (DenseNet201)

Figure 4.8 shows the line graph shows the training accuracy and loss of a DenseNet201 model across epochs. The x-axis represents epochs, while the left y-axis shows accuracy and the right y-axis shows loss. The blue line represents accuracy, plateauing around 0.95, and the green line represents loss, leveling off around 0.10. This suggests that the model effectively learns from the data but eventually reaches a point of diminishing returns, indicating that learning may be saturated. Smooth, non-erratic curves and plateauing indicate effective learning, but they also suggest a limit to the model's ability to improve further.

MovileNetV2

Achieving Test Accuracy of MovileNetV2 is 99.51%. Below Figure 5:9 describing the confusion matrix of MovileNetV2. With an overall accuracy of 100% across 609 samples, the model achieves high precision and recall values ranging from 99% to 100% for each fish category.

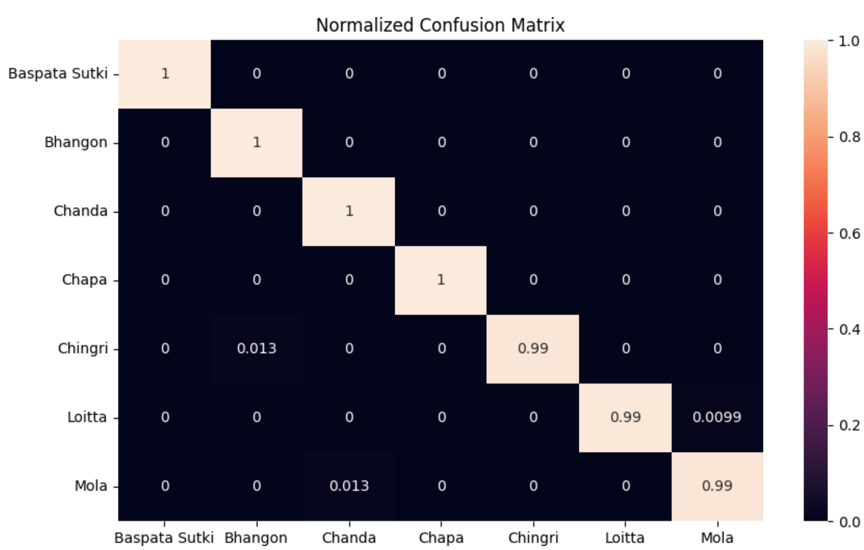

Figure 5.9: Confusion Matrix (MovileNetV2)

Figure 5.9 shows The MobileNetV2 model performs very well in classifying seven types of dried fish, as evidenced by its high precision, recall, and F1-score. This shows the model's ability to accurately identify instances of each class while minimizing misclassification. The macro and weighted averages emphasize the model's overall performance in classification tasks. This comprehensive evaluation points out the MobileNetV2 model's robustness and reliability for dried fish classification.

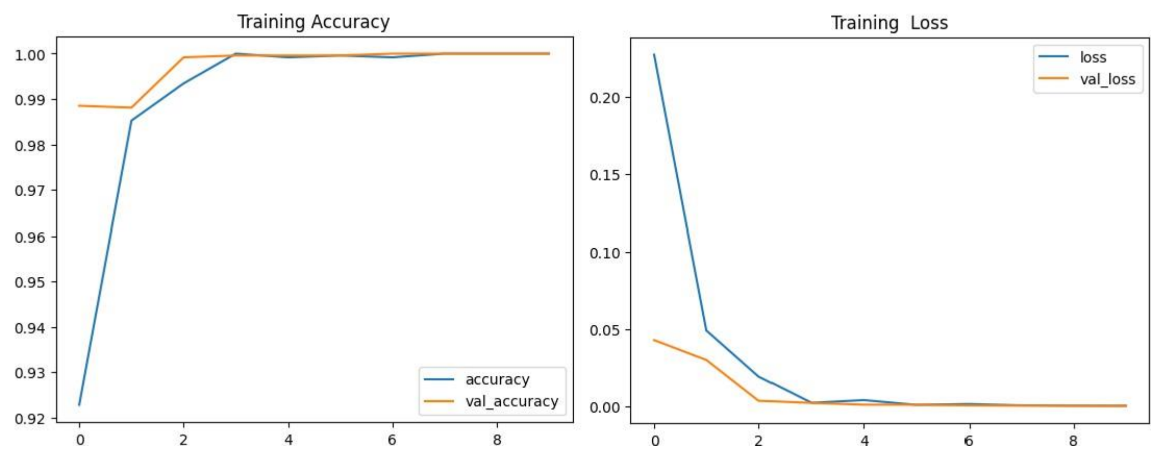

Figure 5.10: Training Accuracy and Loss Curve (MobileNetV2)

Figure 5.10 shows the line graph shows the training accuracy and loss of a MobileNetV2 model across epochs. The x-axis represents epochs, while the left y-axis represents accuracy, which plateaus at around 0.97. The right y-axis represents loss, which steadily decreases during training. This suggests that the model is learning from the data, albeit at a slower rate over time. Smooth curves indicate effective learning, as loss consistently decreases. Plateauing in accuracy indicates that the model's learning has reached its limit, or that it is potentially underfitting the data.

In given below I am showing Comparative Model Accuracy Bar Plot:

Given Figure 5.11 shows the performance of six different convolutional neural network (CNN) architectures: DenseNet201, VGG19, MobileNetV2, InceptionV3, CNN01, and CNN02. The results showed outstanding precision across the board, with DenseNet201 reaching the highest level of 99.67%. VGG19 and InceptionV3 showed high accuracy rates of 97.87% and 98.85%, respectively. Custom CNN architectures CNN01 and CNN02 produced competitive results of 94.25% and 97.82%, respectively. These findings indicate the effectiveness of deep learning architectures in image classification tasks.

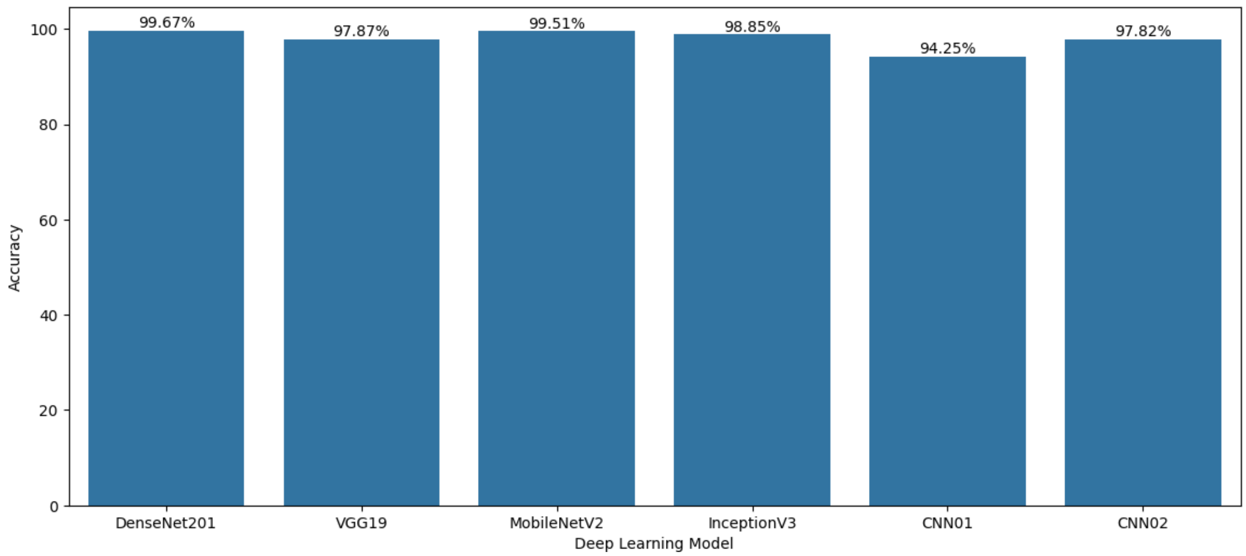

Figure 5.11: Comparative Model Accuracy Bar Plot

The result of Deep learning model is compared on the basis of Accuracy, Precision, Recall, F1 Score in below table of 5.1:

TABLE 5.1. PERFORMANCE EVALUATION

Model Name	Accuracy	Precision	Recall	F1-Score
DenseNet201	99.67%	99%	99%	99%
VGG19	97.87%	98%	98%	98%
InceptionV3	98.85%	99%	99%	99%
MobileNetV2	99.51%	99%	99%	99%
CNN	94.25%	94%	94%	94%

5.3 Performance and Comparative Analysis

The experimental results show the effectiveness of different convolutional neural network (CNN) architectures in image classification tasks. The high accuracy rates achieved by models such as DenseNet201 and MobileNetV2 show their suitability for demanding applications requiring precision. Furthermore, established architectures such as VGG19 and InceptionV3 perform well in a variety of image recognition scenarios. Interestingly, even custom CNN architectures (CNN01 and CNN02) achieved competitive accuracy, indicating the possibility of tailored solutions in specific contexts. This discussion highlights how to choose between accuracy, computational complexity, and deployment requirements when choosing a CNN architecture. Both researchers and practitioners must weigh these factors to determine the best model for their application. Furthermore, additional research into fine-tuning techniques, dataset characteristics, and model interpretability could help us better understand and optimize CNN performance in real-world scenarios. Overall, the findings encourage further discussion and exploration in the field of deep learning for image classification.

5.4 Summary

The experiment compared six types of deep learning models: DenseNet201, VGG19, MobileNetV2, InceptionV3, CNN01, and CNN02 and applied them to a set of 3045 images for dried fish variants' classification. While comparing the accuracies of the two models DensityNet201 and MobileNetV2 were found to be accuracies of 99. 67% and 99. It means that the proposed approach attains an accuracy of 51% and 52% respectively which commendably proves its efficiency in classification. VGG19 and InceptionV3 also proved to be positivism with accuracies of 97. 87% and 98. 85%. CNN01 and CNN02 gave accuracies of 94 respectively. 25% and 97. 82%, respectively. The findings thus provide evidence that State of the art dense architectures as DenseNet201 and MobileNetV2 are suitable for automated dried fish variant's classification calling for the improved quality control and operational efficiency in seafood industries using reliable as well as accurate classification performance.

CHAPTER 6

Impact on Society, Environment and Sustainability

6.1 Impact on Life

There is a lot of potential for good in society if a deep learning-based system for identifying different types of dried fish can be developed that is accurate and effective. In order to guarantee that customers receive genuine and high-quality dried fish goods, it can first expedite the food production and distribution procedures. Second, it can help lower the number of foodborne illness cases and improve public health outcomes by improving food quality control methods. Thirdly, by giving small-scale fisheries enterprises access to modern technology for product categorization and market research, the automated classification system can empower them. Fourthly, it can aid in the investigation and preservation of cultural food traditions through support for food inquiry and discovery. By encouraging openness and traceability in product labeling and classification, the system can also increase consumer trust and confidence in the food business. In the end, the influence on society goes beyond the domain of food, showing the revolutionary capacity of technology to improve a multitude of facets of human existence.

6.2 Impact on Society & Environment

The environment may benefit from the creation of a deep learning-based system for categorizing different dried fish varieties. First off, the system may be able to lower energy usage and carbon emissions related to storage and transportation by increasing the effectiveness of drying fish product distribution and processing. Second, technology can contribute to minimizing food waste by guaranteeing optimal resource usage and lowering overproduction through improved inventory management and market research. Thirdly, the system can support fish stock and marine ecosystem protection by encouraging sustainable fishing methods through market transparency and traceability. Fourthly, it can encourage local populations to adopt eco-friendly practices and help biodiversity conservation by providing support to small-scale fisheries enterprises. Additionally, the system can promote the creation of environmentally friendly packaging options and sustainable food production techniques by supporting research and innovation in the food sector. All things considered, the application of the classification system can help to advance a food system that is more ecologically sensitive and sustainable.

6.3 Ethical Aspects

In order to build and apply a deep learning-based system for categorising kinds of dried fish, ethical considerations must be given careful thought. First and first, it is crucial to protect the privacy and consent of those engaged in data collecting, especially if there are photos of human subjects. In order to stop societal injustices or preconceptions from continuing, it is imperative that any potential biases in the dataset and model predictions be addressed. Thirdly, to preserve confidence among stakeholders—consumers, companies, and regulatory agencies—transparency about the operation and constraints of the classification system is crucial. Fourth, ethical norms must be upheld by giving justice and accountability a priority in decision-making procedures like model selection and validation. In addition, increasing equity in access to technology and its advantages can be achieved by encouraging inclusivity and accessibility through the consideration of varied views and needs in system design and deployment. In the end, ethical standards guarantee that the creation and application of the classification system minimize possible negative effects on society.

6.4 Sustainability Plan

The deep learning-based system for categorizing different varieties of dried fish has a sustainability strategy that consists of multiple essential elements. First, in order to guarantee the classification system's continuous efficacy and flexibility in response to changing demands and technological advancements, routine upgrades and maintenance will be carried out. Second, measures will be taken to maximize environmental impact reduction and energy efficiency, such as powering computing infrastructure with renewable energy sources. Thirdly, in order to boost economic development and encourage sustainable fishing practices, partnerships with stakeholders and local communities would be encouraged. Fourthly, continuous efforts in research and development will concentrate on enhancing the food supply chain's sustainability through waste reduction and packaging techniques. Programs for education and awareness will also be put in place to encourage sustainable food production and provide customers the power to make decisions that respect the environment. The ultimate goal of the sustainability plan is to build an ecologically conscious and robust system that promotes long-term societal and environmental well-being.

6.5 Summary

The goal of the project was to create an accurate system based on deep learning for classifying different types of dried fish. A methodical approach that included data collection, labelling, image processing, model selection, training, evaluation, and testing was used to investigate the efficacy of several deep learning architectures. The experimental findings proved that convolutional neural networks (CNNs) such VGG16, InceptionV3, DenseNet201, and MobileNetV2 are a viable and effective tool for classifying variations of dried fish. The results and their possible effects on food industry procedures and customer welfare were discussed, along with the methodology's advantages and disadvantages. The study placed a strong emphasis on moral issues and provided a sustainability strategy to guarantee the deployment of the classification system in an ethical and environmentally responsible manner. To sum up, the study advances automated food classification systems and creates a basis for future advancements in deep learning and food technology.

CHAPTER 7

Conclusion and Future Work

7.1 Conclusions

In conclusion, the work has effectively shown that classifying different varieties of dried fish using deep learning techniques is both possible and practical. Convolutional neural networks (CNNs) like VGG16, InceptionV3, DenseNet201, and MobileNetV2 have been shown through extensive testing and review to be highly accurate at distinguishingdifferent kinds of dried fish. The suggested technique offered a methodical framework forcreating and evaluating the classification system. It covered data collection, preprocessing,model training, and evaluation. Notwithstanding the noteworthy accomplishments, a number of restrictions and difficulties, such as dataset biases and computing resource limitations, were found and should be further investigated and improved upon in subsequent studies. Future plans for improving the system's scalability and sustainability include working with industry stakeholders, implementing regular upgrades, and launching community participation programs. Overall, the study highlights the revolutionary potential of deep learning in the food business and advances automated food classification systems.

7.2 Future Suggested Works

The results of this study provide a basis for a number of future directions in the field of deep learning-based automated food classification. First, investigating how the addition of other data sources, like multispectral or spectral imaging, may improve the system's stability and classification accuracy. Secondly, there is potential to speed up model development and deployment by exploring the applicability of transfer learning approaches to modify pre-trained models to different food classification tasks. Thirdly, an evaluation of the categorization system's capacity to generalize across various geographic locations and cultural situations may shed light on its adaptability and scalability. Furthermore, investigating the effects of adding domain-specific information to the classification system like fish anatomy and production procedures could enhance its functionality and applicability in actual environments. Last but not least, carrying out long-term research to keep an eye on the practical sustainability and efficacy of the classification system could provide valuable insights for ongoing optimization and improvement projects.

7.3 Limitations

Some background restrictions of this study include the fact that the data in this study was collected from local markets meaning that the various varieties of dried fish considered in the study may not include all the differences that exists in the market. It was also assumed that variation in either the quality or source of the images, lighting, or environmental conditions could affect the model's effectiveness. Furthermore, the assessment of the study reached a conclusion in favor of certain deep learning architectures which could arguably gain from the analysis of other structures or bagging methods. Conflict of interest is controlled through the clear and distinct procedure and evaluation system, which makes the results and definitions more impartial of the evaluated strategies and models.

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Appendix A

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

Title:
DRIED FISH VARIANT CLASSIFICATION USING DEEP LEARNING TECHNIQUES

Student ID: 203-15-14533 & 203-15-14534

CO Description for FYDP

CO	CO Descriptions	PO
	Phase -I	
CO1	Integrate recently gained and previously acquired knowledge to classify Dried Fish variant Classification problem for the Final Year Design Project (FYDP)	**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	This project demonstrates **fundamental engineering (K3)** principles by employing deep neural networks, data augmentation techniques, and diverse CNN architectures for image processing and classification tasks. The project demonstrates **specialist knowledge (K4)** by conducting deep learning and Transfer learning enhancing classify Dried Fish variant correctly.	**Page no:** [32-33] **Section:** [3.2] **Page no:** [12-17] **Section:** [1.1]
				The project applies **engineering practice & design (K5)** by the figure of process of experiments. The project addresses **engineering practice & technology (K6)** by employing Deep Learning Model,	**Page no:** [32] **Section:** [3.2]

					Page no: [34-35] **Section:** [3.4]
				This project ensures to **K8 (Research Literature)** by synthesizing insights from recent studies, classify Dried Fish variant using deep and Transfer learning, showcasing a comprehensive understanding of current methodologies.	**Page no:** [23-30] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project addresses **EP-2** by recognizing the hurdles in classify Dried Fish variant, including limitations of traditional methods and the complexities of integrating using deep learning. Through comparative analysis, it confronts challenges in understanding spatial distributions, offering insights for refining methodologies.	**Page no:** [30-31] **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This project addresses **EP-3** by meticulously comparing experimental outcomes, highlighting using deep and transfer learning as the chosensignificant solution for enhancing classify Dried Fish variant approaches.	**Page no:** [37-48] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's interdisciplinary approach extends beyond computer science and engineering, impacting Detecting classify Dried Fish variant correctly **EP-4**.	**Page no:** [23-31] **Section:** [2.2, 2.4]

5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	This project's comprehensive approach addresses high-level problems by integrating various components across data collection, statistical analysis, and proposed methodology, ensuring a holistic solution to complex challenges in data collection from local market which ensures **EP-7**.	**Page no:** [26-34] **Section:** [3.2, 3.3, 3.4]

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

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep and transfer learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements classify Dried Fish variant.	**Page no:** [33-35] **Section:** [3.5]
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	No		N/A	N/A
4.	**EA4: Consequences for society and the environment**	Yes		This project contributes to society by improving classify Dried Fish variant, while also promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines for data privacy.	**Page no:** [50-51] **Section:** [5.1, 5.2, 5.4]

5.	**EA-5: Familiarity**	Yes		This project expands upon existing research by examining a novel approach in classify Dried Fish variant through deep and Transfer learning model demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field.	**Page no:** [23-29] **Section:** [2.1, 2.3]

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

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle.	**Page no:** [20] **Section:** [1.6]
2	CO9	Yes	The project demonstrates adherence to ethical principles by prioritizing privacy, obtaining informed consent, and transparently documenting the research process, ensuring responsible knowledge dissemination and societal well-being through the ethical application of advanced classification technologies which comply with **CO9**.	**Page no:** [51] **Section:** [5.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges.	**Page no:** [32-36, 37-48] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

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