BANGLADESHI SHRIMP SPECIES RECOGNITION BY DEEP CONVOLUTIONAL NEURAL NETWORK

BY
MD. SUJAN AHMMED
ID: 181-15-2017

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

Supervised By
Ms. Dristi Saha
Lecturer
Department of CSE
Daffodil International University

Co-Supervised By
Mr. Md. Mubtasim Fuad
Lecturer
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

13 July 2024

APPROVAL

This Project titled BANGLADESHI SHRIMP SPECIES RECOGNITION BY DEEP CONVOLUTIONAL NEURAL NETWORK, submitted by MD. SUJAN AHMMED to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation was held on 13 July 2024.

BOARD OF EXAMINERS

Hossain 13.07.2024

Dr. Md. Fokhray Hossain (MFH) — **Board Chairman**
Professor
Department of CSE
Daffodil International University

Mr. Shah Md. Tanvir Siddiquee (SMTS) — **Internal Examiner 1**
Assistant Professor
Department of CSE
Daffodil International University

13.07.24

Mr. Md Umaid Hasan (MUH) — **Internal Examiner 2**
Lecturer
Department of CSE
Daffodil International University

13/7/24

Dr. Shamim H Ripon (DSR) — **External Examiner**
Professor
Department of CSE
East West University

DECLARATION

We hereby declare that this project has been done by **Md. Sujan Ahmmed ID: 181-15-2017**, under the supervision of Ms. **Dristi Saha, Lecturer, Department of CSE** 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.

Supervised by:

Dristi

Ms. Dristi Saha
Lecturer
Department of CSE
Daffodil International University

Co-Supervised by:

Mr. Md. Mubtasim Fuad
Lecturer
Department of CSE
Daffodil International University

Submitted by:

SujanAhmmed

Md. Sujan Ahmmed
ID: 181-15-2017
Department of CSE
Daffodil International University

©Daffodil International University, Bangladesh ii

ACKNOWLEDGEMENT

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

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

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

We would like to thank our entire course mate in Daffodil International University, who took part in this discussion while completing the course work.

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

ABSTRACT

Shrimp, the most popular shellfish in Bangladesh, is rich in a variety of nutrients, giving it a great nutritional value. Some examples of such substances include iodine, protein, minerals, and vitamin D. This shellfish is named from the Bangladeshi word for "white gold" in its own language. It is the source of almost 70% of the agricultural food that the world consumes. The seas of Bangladesh are home to over 56 different species of prawn. Even seasoned fishers can't help but mix up different species when they see a superficial similarity. The authors of this research set out to address the problem of prawn identification, thus I built an AI system to help. I achieved our objectives by creating our own convolutional neural network (CNN) method for feature extraction and picture processing. In this work, I build three distinct convolutional neural network (CNN) designs, with distinct hyperparameters and convolutional layers for each, and one transfer learning approach vtgg19 is used. I got the highest accuracy from model 2 custom CNN architecture. The accuracy rate is 99.14%.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES	
FIGURES	**PAGE NO.**

CHAPTER 1
INTRODUCTION

1.1 Overview

In the seafood business, prawns are Bangladesh's most famous export. Shrimp output has accelerated in the last two years, going from 1.60 lakh MT in 2002–2003 to 2.41 lakh MT in 2004–2005. [1] No nation is more suited to coastal aquaculture than Bangladesh, thanks to its abundance of natural resources and favorable climate. [2] In fiscal year 2021–2022, frozen fish exports brought in $532 million, up 12% from $477 million the year before, according to statistics supplied by the Export Promotion Bureau. At around 2.5% of the global prawn trade, Bangladesh was the culprit. This highlights the significance of prawn farming to our nation's economy. Regrettably, no technology is used in either the cultivation or manufacturing of shrimp inside the shrimp business. Artificial intelligence's use in farming has been on the rise recently. the third Consequently, it is a great moment to deploy AI technology to boost prawn output without sacrificing quality. As a solution, I devised a deep learning-based intelligent picture classification system capable of accurately identifying each of the four prawn species. I set out to create three separate CNN architectures and, using as much objectivity as possible, assess their experimental performance. This project makes use of three distinct types of bespoke architecture: models 1, 2, and 3. Additionally, I used a transfer learning strategy similar to VGG19. Finally, they choose the model that does the best in a highly controlled setting. A score matrix comparison was therefore used to choose the models that would undergo testing. The model implementation makes use of a variety of tools and frameworks, including TensorFlow, Scikit-Learn, Pandas, and Keres. Since Python was the preferred language, it will be used to write the code for this research.

1.2 Problem Statement

The main objective of this work is to recognize Bangladeshi shrimp species by deep deep-learning approach. This research will help two sectors in our country. One is who did not recognize shrimp species my system can help by recognizing it. The second is in export field, as shrimp play a significant role in this sector so to maintain quality products my project can help by automatic recognition. The main non-technical challenges of this project is data collection, because if I did not collect and label data properly then the system finally failed so I was very sincere about it. Another this is it is very difficult to recognize different species of the same thing. Because all of the classes look similar so this coincident affect the performance of the deep learning model. I overcome this problem by designing deep and complex model in the algorithm section.

1.3 Motivation and Objective

It is still difficult to automatically identify shrimp using computer vision because of the similarity in shrimp colors and textures, the diversity of shrimp, and other features like their location or lighting conditions. The vast array of prawn varieties in terms of both color and texture is largely responsible for this. As it is very difficult to differentiate the species of shrimp so most people make mistakes in recognizing the shrimp's name. and this is the main point of my motivation. And my main objective is to help this kind of people who do not recognize shrimp species. The more brunch of objectives is given below:

- It is necessary to work on enhancing the fishing and agricultural industries.
- Gathering data and accurately labeling it.
- Find both the source and the remedy of the problem.
- so that the farmer may cut down on expenses.
- Provide the farmer with practical guidance to help him cultivate high-quality prawns.
- contributing significantly to the nation's economy in the overall context

1.4 Project Scope

The context of the study and specific objective, target population, and method is combined and represented by the project scope. In this project, my main context is recognizing shrimp species in Bangladesh through a deep learning approach. There are five different species is collected and evaluated in this work. Each class contains about 200 raw images collected by me. The deep convolutional neural network method is used in this work. 3 of the is custom designed and another is the transfer learning approach.

1.5 Project Outcome

One subset of optical recognition is prawn recognition, which in turn is a subset of fine-grained visual recognition. As an improved version of traditional image recognition, it is a kind of optical recognition. The classification of Shrimp inherently opens up the possibility of its use in several contexts, including commercial and scholarly ones. Think about a scenario where it was taught using a massive database. In this case, it may be used in apps for smartphones that identify the kind of prawn and then provide information about the prawn, such as how much it costs, what nutrients it has, how many calories it has, and anything else that might be needed. Furthermore, it may be able to identify endemic shrimp species, which are shrimp that are unique to a certain region and cannot be found anywhere else in the globe.

1.6 Report Organization

Each chapter of this paper describes itself as:

In the first chapter, I will lay out my program, its objectives, and the reasoning behind it. I will also describe the issue I want to answer, the subject I intend to research, the methodology I intend to use, and the expected completion date of the project. I explain the reasoning behind our investigation here.

The second Chapter summarizes the relevant material and includes a context analysis. This describes a substantial effort in deep learning, mostly focused on predictive work.

In Chapter 3, I will go into the specifics of how I will carry out the research. Here we may get a detailed description of the procedure. Read the "Methodology" section of this report for details on how it was put together.

In the fourth chapter, I will utilize a classification report and an accuracy table to evaluate the suggested model's performance.

In Chapter 5, I will go over the evaluation of this project. Environmental and ethical concerns related to this endeavor are also touched upon briefly here.

In Chapter 6 I will briefly go over the results of the model. I also quantify precision. Also included are the outcomes and the idea's online implementation. Problems with effort are examined in the chapter's last section. There are also plans for further developments.

1.7 Summary

The main parts that make up our organization's structure are laid out in this chapter. For us, the most important thing is what this chapter says. This chapter will serve as an introduction to our overall framework, touching on its inspirations, goals, and dedication, as well as a few related frameworks. Not only does this chapter examine our comprehensive framework approach, but it also explores the possibilities that may arise from this specific situation.

CHAPTER 2

BACKGROUND STUDY

2.1 Overview

When problems emerge when processing images, two common methods for solving them are machine learning and deep learning. When it comes to making people's lives easier and more comfortable, it's crucial. My topic and approach are novel, yet there have been other scholars who have followed directions that are quite similar to my work. Here are a few comparisons and case studies that may be used for review purposes.

2.2 Related Works

In order to identify and pinpoint the fish, Zhenxi et al. [3] presented an entirely new method. The FishNet approach was their name for it. Combining composite detection with an enhanced path aggressiveness network is the basis of this method. They improved the architecture of ResNet—which handled data on scene changes, fish species, and texture—in order to develop a composite backbone net. Because of this, they were able to gather data on the fish. To top it all off, they built a new route aggregation network with semantic data modification in mind. On average, FishNet achieves an accuracy of 81.1%, with a range of 75.2% to 92.8%.

A two-stage deep-learning approach for temperate fish identification was proposed by Knausgrd et al. [4]. With an accuracy of 89.95%, the final product outperforms the Faster R-CNN model by 7.25 percentage points. As a first stage, They used YOLO to identify objects. Then, they classified fish using CNN architecture mixed with Squeeze and Excitation architecture. Each of these phases is an independent part of the deep learning process. Their results were also more reliable since they used a method called transfer learning. Using the pre-trained transfer learning method, they attained a 99.27% accuracy rate. When they used the post-training model, their accuracy dropped to 83.68% and 87.34%, respectively.

Among the eight distinct fish species included in the suggested method of identification for aquarium fishes by Khalifa et al.[5] are a grand total of 191 subspecies. The system's backbone is a four-layer, lightweight deep convolutional neural network (CNN). This architecture has a lower computational complexity and uses less memory than other comparable systems. In order to examine the efficacy of their own CNN, two transfer learning architectures (AlexNet and VggNet), and their own network, they used all three networks. But using the AlexNet architecture, transfer learning managed to reach an accuracy of 85.41 percent. They discovered that the accuracy of their own model was 85.59%.

Sharmin et al. [6] planned to build a fish identification system for freshwater settings, and machine vision was proposed as the basis for it. Specifically, they zero down on four distinct types of features that may be present in a black and white image. some of these traits are: Furthermore, they used a technique based on histograms during feature extraction. Using principal component analysis (PCA), they accomplished dimensionality reduction. Out of the three classifiers tested, the SVM method had the greatest rate of accuracy at 94.2%.

2.3 Comparison between existing works

Deep learning (CNN) and computer vision seemed to have strong ties to several academic disciplines. Based on the findings of several research and investigations, it may be safely categorized as having relevance to numerous sectors, including ecology and agriculture. Based on our needs and interests, this is the greatest choice. Since CNN is the most trainable algorithm, it can be taught to achieve the greatest levels of accuracy in picture categorization. Table 2.1 represents the comparative analysis with my work and previous work. From this table they can see that authors used different algorithm to detect fish. The highest accuracy of previous work is about 99.27% where my works achieved 99.14% but the difference is this accuracy achieved by transfer learning pretrain model but I acquire accuracy by my custom cnn model.

TABLE 2.1 COMPARATIVE ANALYSIS WITH PREVIOUS WORK

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1	Zhenxi et al. [3]	FishNet method, composite detection, improved path aggressiveness network	75.2% - 92.8%, Avg: 81.1%
2	Knausgrd et al. [4]	Two-step deep learning, YOLO, CNN + Squeeze and Excitation, transfer learning	Pre-trained transfer learning: 99.27%
3	Khalifa et al. [5]	Lightweight deep CNN, AlexNet, VggNet with transfer learning	Own model: 85.59%, AlexNet: 85.41%
4	Sharmin et al. [6]	Machine vision, feature extraction, PCA, SVM	SVM: 94.2%

2.4 Gap Analysis

The hardest part of our work is preparing data sets for management. I employed powerful DL and image processing methods to determine our data set or future modification. The two main gap is described below:

2.4.1 Data Collection

Data gathering is of the utmost importance when it comes to deep learning. I was unable to get the massive amounts of data needed by deep learning since it relies on information gathered from a wide variety of wholesale and retail sources.

2.4.2 Model Selection

A wide variety of deep learning models are available. Choosing the right model is an extremely important responsibility on their part. In reality, picking the right model and excellent data is a breeze. I utilized three bespoke convolutional neural network (CNN) models and one transfer learning vgg19 model for feature extraction. On the other hand, there are several TL models (ResNet50, MobileNet) that are accessible.

2.5 Summary

In Chapter 2, I cover the prior research comparison analysis with previous work with my work. This chapter also included gap analysis and future scope to mitigate the gap.

CHAPTER 3
METHODOLOGY

3.1 Overview

Research methodology is a process by which we can analyze information regarding specific topics. My methodology steps are divided into 6 main steps fastest is data collection second is data preprocessing third is data set making 4th is applied learning 5th is the result experiment 6th is deployed in an open CV. In my work I use different CNN architectures first 3 models are custom Sain and model and another model is the vgg19 model. In the result experiment section, I used similar data for all algorithms for performance testing. The algorithm that performs best in the test data set I used this model as my final model.

3.2 Requirement Analysis

I divided my project requirements into three parts. first government is data requirement second is technical requirements and third is performance matrix.

3.2.1 Data requirements

The first condition of data requirements is data collection by my required data from field data can be collected by mobile camera or DSLR camera. After collecting data crop this data to make a square shape and all data must be resized into 224 by 224. This is the primary requirement of this project.

3.2.2 Technical requirements

In the technical requirement section hardware requirements are very important thing all of the requirement’s list is given below:

1. The Pc must need 50 GB of free space in the C drive.
2. Core i5 11Gen processor.
3. GPU NVIDIA 1650
4. Minimum 8 GB ram.

In software section I used different library and tools all of them is given below:

1. Python as programming Language
2. Jupiter notebook as IDE
3. Any image cropping software
4. Any internet browser

In the Library section all of the library name and versions is given below. I faced very difficult problem to create an environment for this project. Following the version of libraries is very important to create deep learning environment. Our guided Deep Learning Engineer told us if I tried to use different version then the environment will not work. I used joblib for future implementation of web-based or android-based work.

1. imageio==2.16.0
2. joblib==1.1.0
3. Keras==2.3.1
4. matplotlib==3.3.4
5. numpy==1.19.5
6. opencv-python==4.2.0.32
7. openpyxl==3.0.9
8. pandas==1.1.5
9. Pillow==8.4.0
10. pyxlsx==1.1.3
11. scikit-learn==0.24.2
12. seaborn==0.11.2
13. tensorflow-gpu==2.0.0
14. xlrd==2.0.1

In the performance matrix section I will use:

1. Confusion matrix
2. F1 score
3. Precision Score
4. Recall Score
5. Sensitivity

3.3 Proposed Methodology

My technique has six steps: data collecting, preprocessing, data set creation, applied learning, outcome experiment, and open CV deployment each and every step are dependent on each other's. If we bypass any steps then the entire system will fail. I utilize three custom cnn models and one vgg19 model in my CNN architecture. All methods were performance-tested with comparable data in the outcome experiment. The method that performed best in the test data set was my final model. Figure 3.1 represents the methodology diagram.

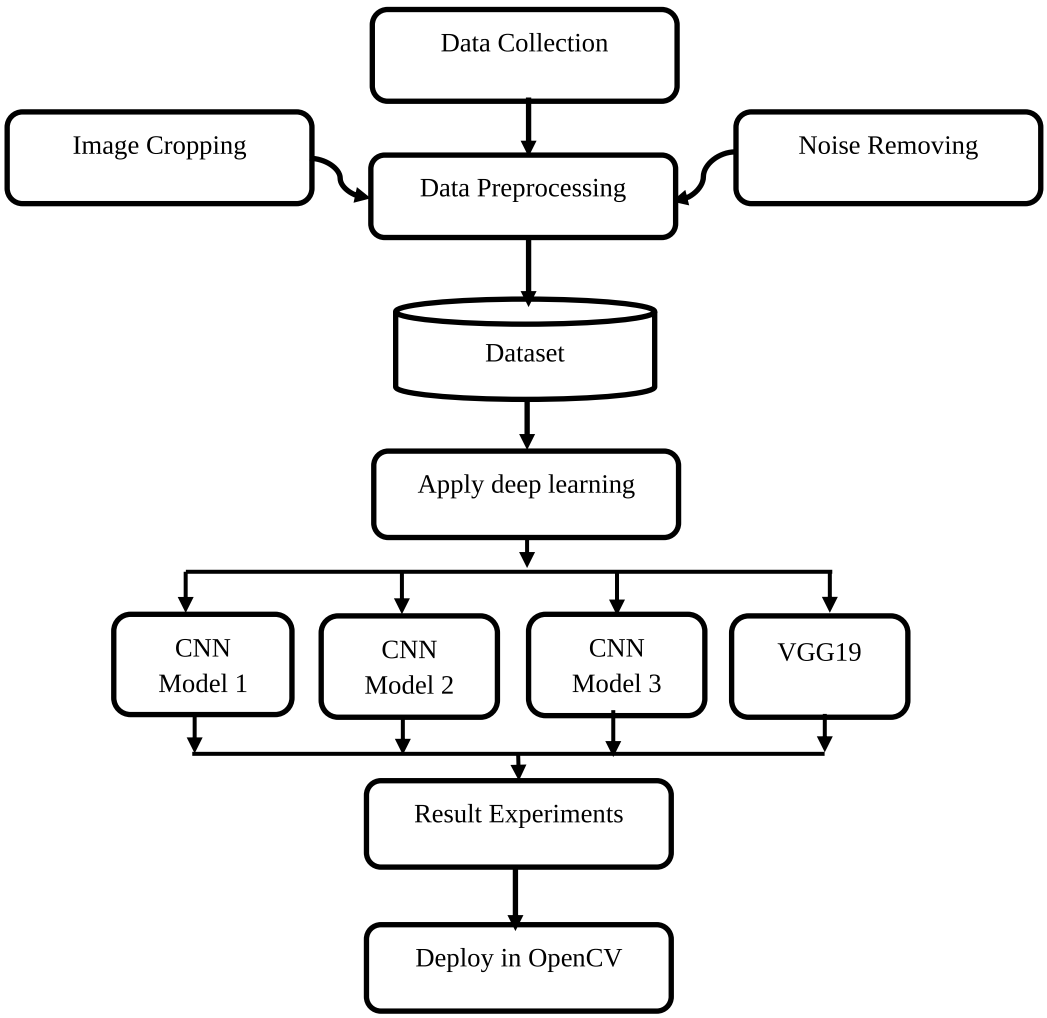


Figure 3.1 Methodology diagram

3.4 Data Collection

I collected all of my required data from the filed. There are 5 different shrimps species is collected. But initially, I did not find all species at a time. So it takes lots of time to collect all five species. The name of collected species is Bagda, Horina, Royal Red, Golda, and White shrimp. Table 3.1 represents all species images. The total size of our dataset is raw data about 1092, training data 5,260, validation data 705, and testing data 542.

TABLE 3.1 SHRIMP SPECIES

Name	Image
Bagda	
Horina	
Royal Red	
Golda	
White shrimp	

3.5 Project Management and Finance Analysis

The following table represents the project management timeline. This part was a very important and helpful part of our work. When I did not find all species at a time then I started parallel working to mitigate this problem.

TABLE 3.2 PROJECT MANAGEMENT ANALYSIS

	Oct 2023	**Nov 2023**	**Dec 2023**	**Jan 2023**	**Feb 2023**
Title defense					
Data collection					
Data annotation					
Report Writing					
Phase I					

The finance analysis table is given below:

TABLE 3.3 FINANCE ANALYSIS TABLE

Sl. No	Item Quantity & Unit	Unit Price	Total Price
1	1. Samsung 980 Pro 1TB PCIe 4.0 M.2 NVMe SSD.	12000	55600
	2. Core i5 11Gen processor.	21000	
	3. GPU NVIDIA 1650	20500	
	4. Minimum 16 GB ram.	2100	
2	Equipment	N/A	N/A
3	Labor and others	N/A	N/A
4	Thesis/Project Typing, Printing and Binding		3000.00
5	Miscellaneous cost		5000.00
		Total (In Figure):	63,600.
In words: sixty-three thousand six hundred taka only			

3.6 Summary

In this work, I discussed about methodology approach of my research. I also showed which challenges I faced to do this work and how to overcome research problems step by step by maintaining time.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

This chapter begins with a brief summary of the models. Every one of them is explained with its aims, and its characteristics are also highlighted. The initial part enumerates the equipment and software that are needed to build the models. The chapter explains the second part of how the models are being made available. This includes the data preparation, training of the models, and setting their parameters to ultimately get them to their working state. Also, it mentions a way to incorporate these models into the old systems that will work effectively and be economical. Moreover it tests the methods and demonstrates that they work properly in fact indicating the models are effective in practical applications.

4.2 Prototype Design

The element of the subsequent part of the chapter is the resulting models of shrimp sorting. Different types of testing were executed to meet the goals of being more accurate, faster, and also better than the class of other connected systems applicable at that time. The prototype development involved several key stages: the preliminary phase surely contains the coding, data migration, and functional testing in the early stage of the project. Accordingly, we could worry about many trouble data quality issues or model complication problems and their solutions. All of these difficult problems were dealt with by changing the algorithm right and other implemented optimization methods that helped in solving these issues.

4.2.1 Model 1

Figure 4.1 represents the architecture of model 1. It is an architecture that shows the two neural networks comprising the input layer (224x224 pixels) with three color channels, much like the ones that we can see in an RGB photograph. This step broke into a 4x4 convolutional layer with 64 filters, this later being combined with a 2x2 Max pooling layer with padding "same" size to meet the needs dimensionality.[7]. The second layer contains 4 by 4 convolutional layer with 128 filters. The strides of this layer is 2 by 2 with same padding. The model is built using the Adam optimizer, and the categorical cross-entropy

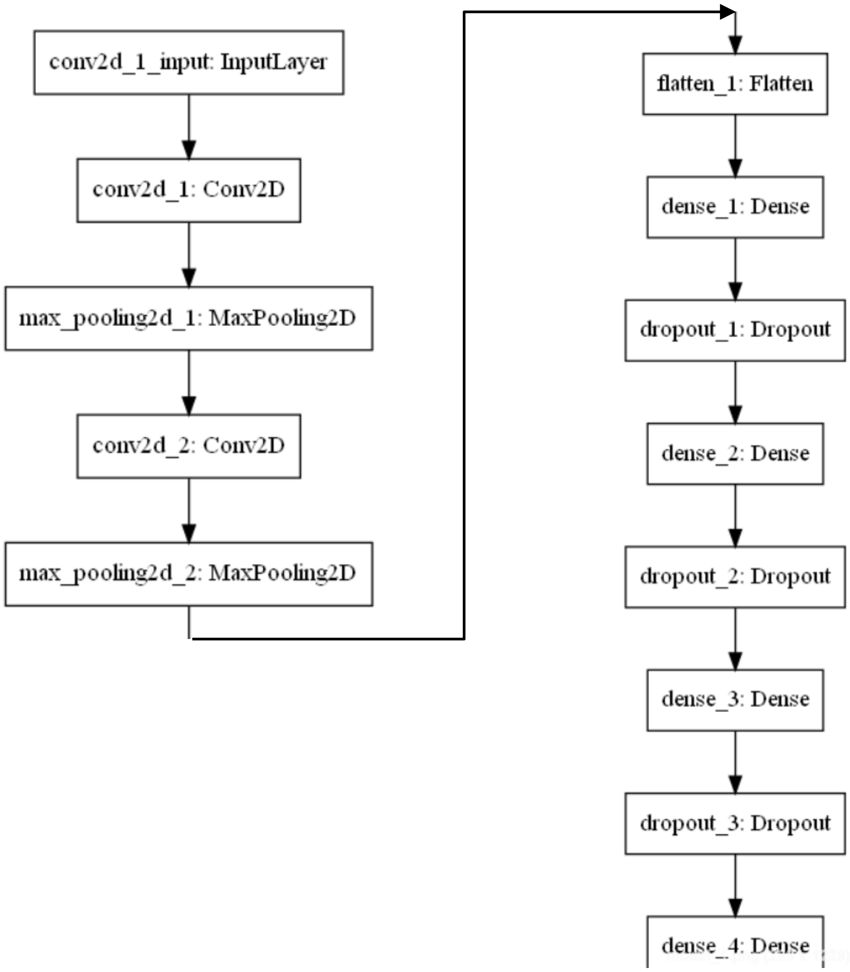


Figure 4.1: Model 1 Architecture

which minimizes, thus guaranteeing the correctness of the categorization and there will be no case of confusion as to which one of the five types is placed.

Figure 4.2 below shows the precision that can be reached via both the training and validation throughout the training process lasting for 10 epochs as part of the training phase of the model. Moreover, this graph also denotes the misunderstanding of the labeling inasmuch as the title in both plots is referred to as "accuracy", while the y-axis is directly connected with the "loss" which is another term implying not accuracy values but rather the losses. This graph is a fiction where the grey line (proposed) is the argument, whilst the blue line (the trained loss) declines indicating that the model becomes more suited with the more data that is fed. On the contrary, the first instance is obvious from the manner which is cyclic and brings back attention to the fact that mod is good at learning or remembering. Most of the time, as an intervention, we have to either use an adjustment in the model or tolerate a slight loss for cases of overfitting. The essence of this is that the model being trained experiences a larger loss on a validation dataset than on a training dataset which means that the model is not generalized well and there is need further investigations. The model manages to remember the datasets it learns from instead of generalizing well in a proper fashion

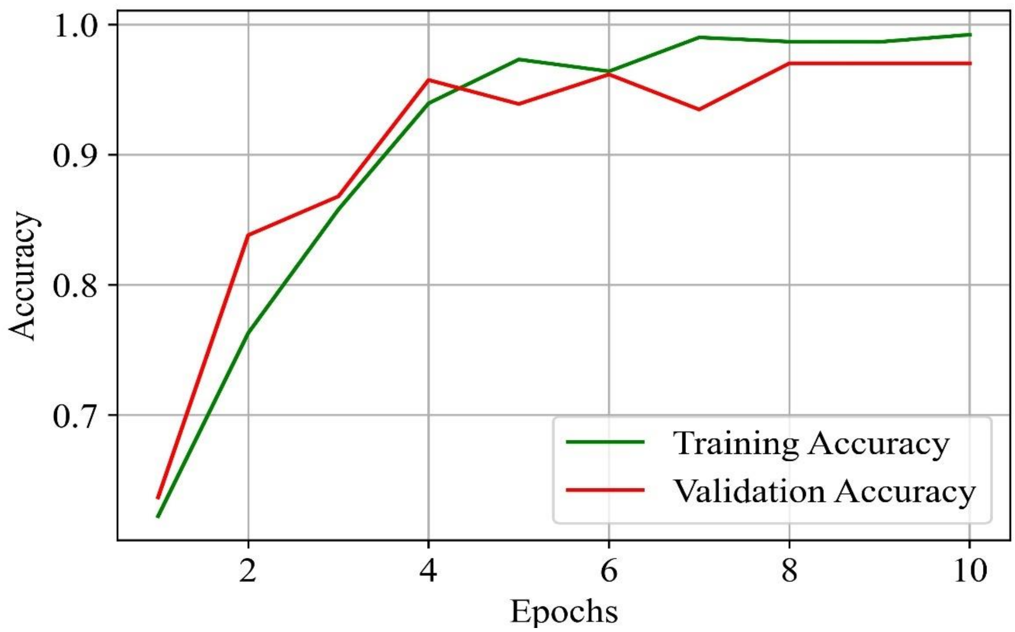


Figure 4.2 Training vs validation accuracy of model 1

Figure 4.3 shows the loss y-axis on training and validation loss of the neural networks in 10 epochs. Firstly, the figure shows that the loss function decreases rapidly from the point , and concludes with even faster acceleration. Next comes the training loss dip, and that stable line just partially with the noise level is the only thing that follows for the rest of the epochs. That result is expected, since there is nothing more the model can do to improve if it is fitted to the training data as well as it can be. The validation loss drops precipitously at the beginning and curbs, staying around 1 subsequently, with minor fluctuations around the range. The model is not overfitted. Indicating that the model exhibits exceptional response to training. In addition, this shows that our model does not suffer from bad learning or unspecific problems with data across epochs.

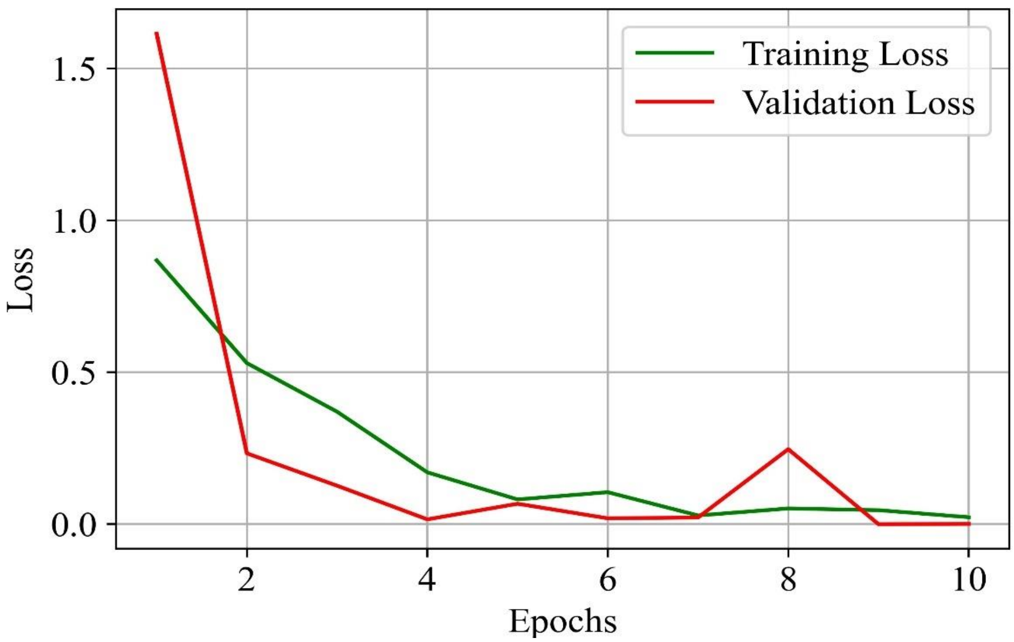


Figure 4.3: Training vs validation loss of model 1

4.2.2 Model 2

In order to visualize a convolutional neural network platform is employed. Similarly, so do other model is including image classification. Rather, this method is usually enforced by the function that splits the images into the components, each of which has the size of 224x224 and has 3 red, green, and blue (RGB) channels. The element consists of four convolutional blocks that operate sequentially by applying conv2d followed by feature extracting filters, and maxpooling2D which is used to spatially sub-sample that consequently improves the model capacity to abstract and fuse passed data. To start with the convolutional layers, 64 filters repeated are applied all the way to 512 finally and ReLu is applicable in the two that stride are set to 2. That is passing through the sliding windows of convolutional layers and flattening their output comes next. Coming next are the levels of deep layers with 1024, 512, and 256 neurons respectively, employing ReLU activations, and the Dropout as the approach for avoiding overfitting.[8] The last end-to-end layer where the Flatten layer followed by the Dense Layer with 5 neurons and SoftMax activation function is entered to be used with 5-classes classification purposes. In that case, it is shaped to serve this purpose which further allows for accuracy in prediction models

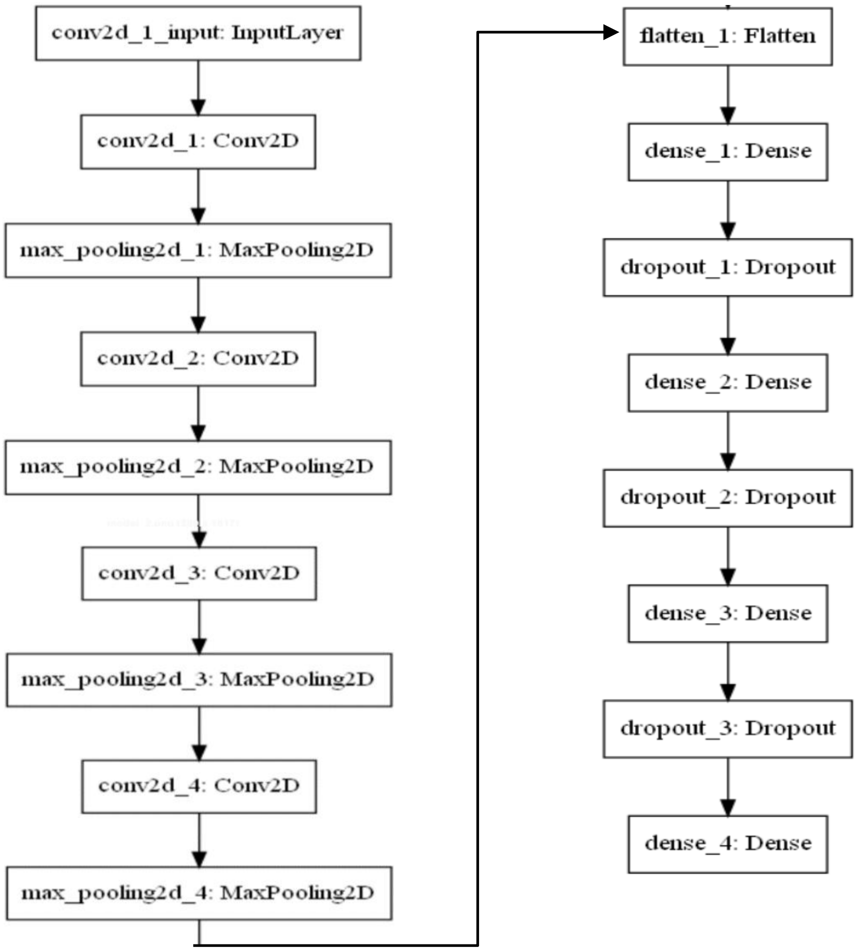


Figure 4.4: Model 2 ArchitectureThe

50 epochs graph is introduced to visualize the training and validation step accuracy of the machine learning model. Initially, both the accuracies move up exponentially, which means that the learning is very fast. In a process of increasing epochs the validation accuracy is little lower than the training accuracy. The purpose of this is to reveal that the model continues to provide high performance on both seen as well as unseen data without showcasing any sign of overfitting.

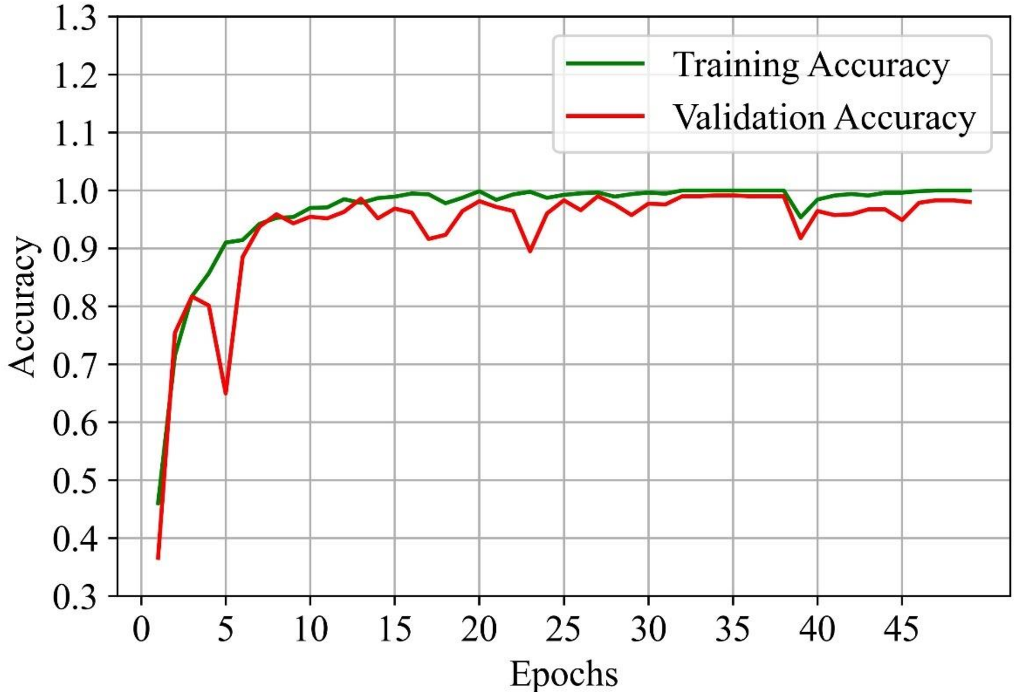


Figure 4.5: Training vs Validation Accuracy of Model 2

Through thirty epochs, this diagram indicates the training and validation loss that a neural network has managed to achieve. In the first losses' fluctuations go up and down with the most significant spike that happens towards the fifth turn. Training loss minimizes to zero with the overall epochs progressing, which is a signal that the model is rightly learning from the data. The later swings of the cost function are followed by a constant and low validation loss, that suggests good model generalization to new data. There are a few spikes in the validation loss, and this may indicate that the model diverts from anticipating predictions at moments.

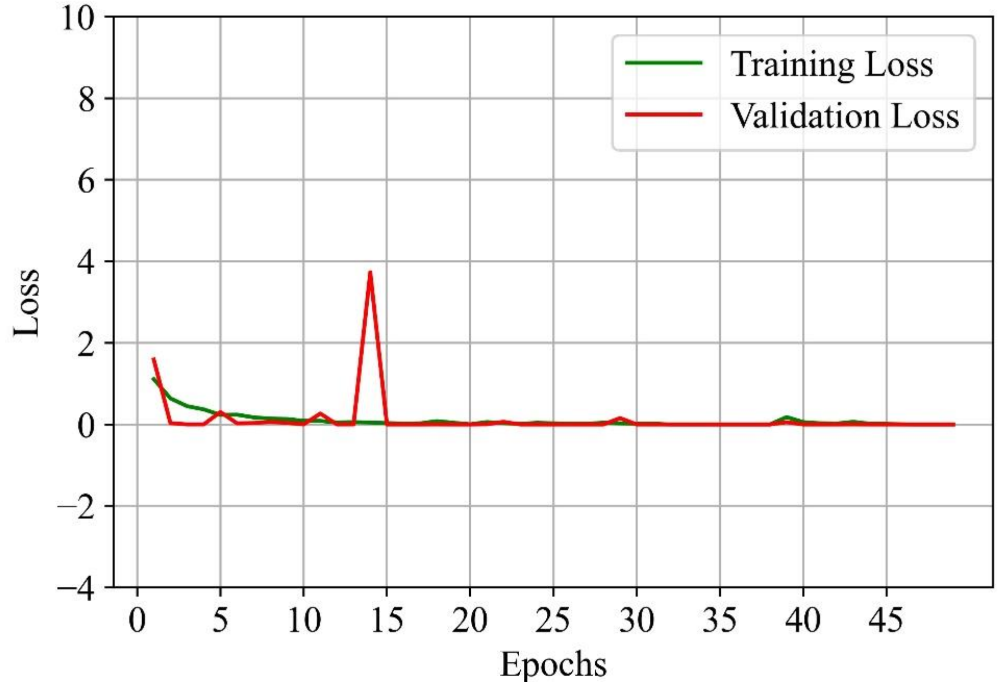


Figure 4.6: Training vs Validation Loss of Model 2

4.2.3 Model 3

A 224 × 224-pixel input serves as the basis for this CNN with three color channels and is created to classify our dataset. Convolutive blocks that build it encompass three. Conv2D layers are employed in each block for feature extraction and training stability,[9] MaxPooling2D for spatial dimensions decrease, as well as Dropout layers for eliminating overfitting. The amount of filters is increasing from 32 to 128 as filtration goes deeper through the blocks. Three densely connected layers with 512, 256 and 5 neurons respectively, unfolds after the convolution and pooling operations. The second to last Dense layer also was designed as five-category multi-class classifier, where it utilizes a softmax activation function. dense layers frequently conduct dropout to enhance generalization capability.

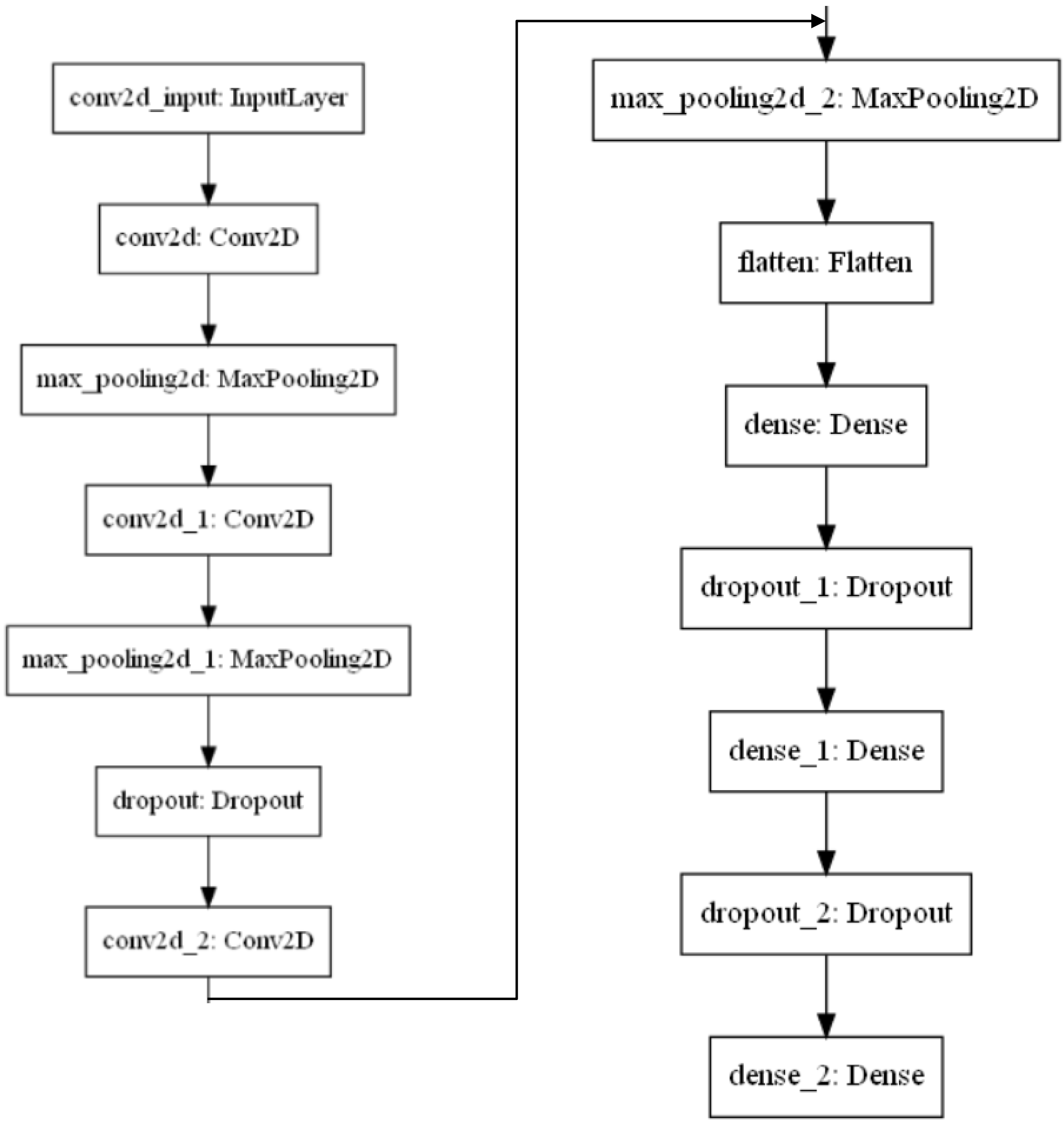


Figure 4.7: Architecture of Model 3

The graph illustrates that at10 epochs the model gave the training and validation accuracy and scores were highest for test data. To begin with, the training process deals with irregular performances that gradually get smoother until they reach the expected figure 4.8. on the other hand, the initial stage of talks will be accompanied by uncertainty on whether it will yield something good for many or rather disappear under 0. 6. The model manifests a close connection with the data however it has a high bias thus when it deals with new data it under fits instead of overfits new instances. Subsequently, if the validation data does not do better than the training set results, it becomes a real issue. The reliability of the methods could be compromised by different factors like the design or data ambiguity, the result of which may or may not lead to bizarre consequences that are ultimately influenced by the dates.

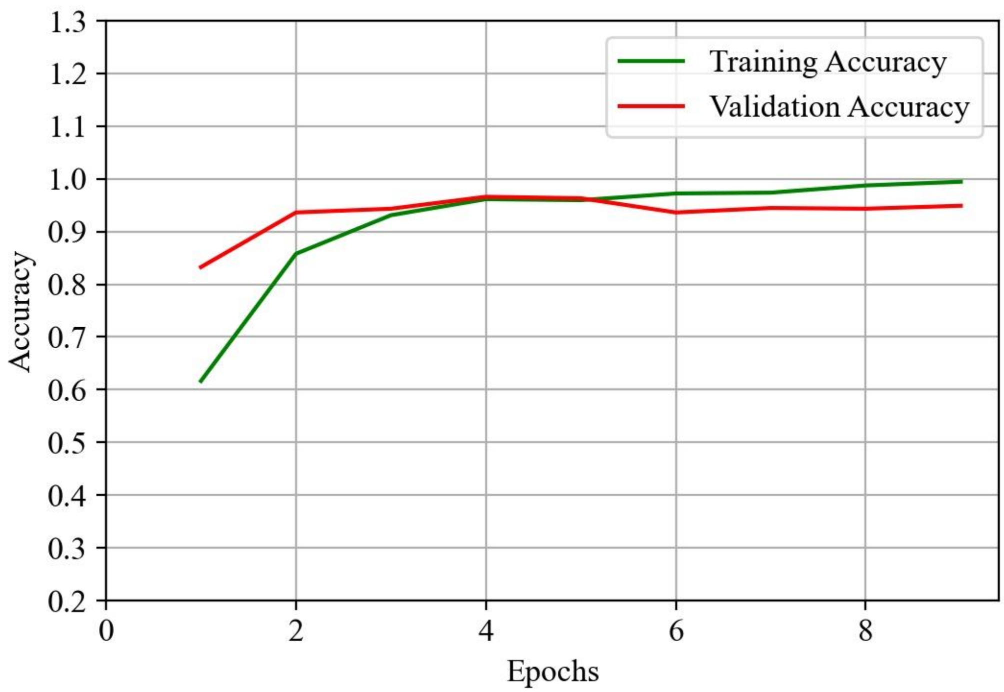


Figure 4.8: Training vs Validation Accuracy of Model 3

This graph plots both the training and the validation loss at each of the 10 epochs of model 3. To begin with, there is a big drop in both training and validation errors, which implies a fast learning rate. During the epochs, the loss function converges close to zero, which means that the model fits the data given in the training set quite well. While the training loss keeps on slightly wavering it stays quite close to the validation loss all the way during the training. This steady no gap between training and validation losses is indicative of the good generalization as there are no apparent indicate of overfitting. The negative loss values may show the problem of loss calculation or plotting.

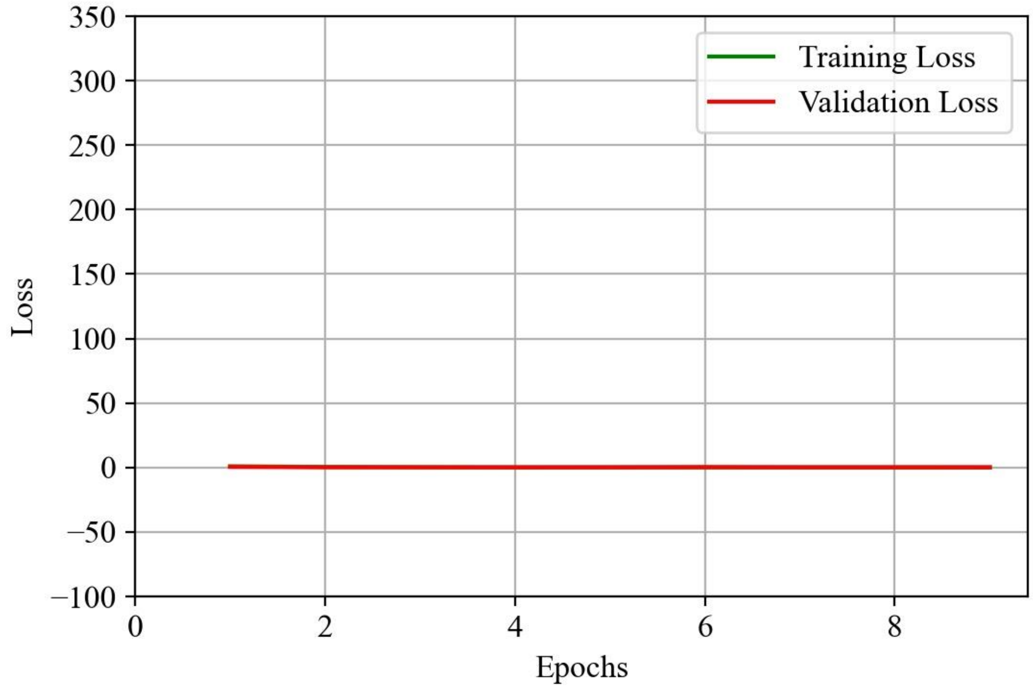


Figure 4.9: Training vs Validation Loss of Model 3

4.2.4 Model 4

The year 2012 saw the emergence of Alexnet which excelled the traditional Convolutional Neural networks as within this network there was more convolution and pooling layers. Since this group was formed by the Visual Geometry team from the University of Oxford, VGG as the name suggests is the successor of the Alexnet and it integrates ideas from its predecessor improves on them, and uses deep Conv So, let's examine VGG19, a VGG architecture version, and also compare it with some other VGG architecture versions by seeing some handy and practical applications of the VGG architecture.[10][11] The neural network here is purpose-built for high-resolution image classification with the ILSVRC challenge as a target; the size of the input window is fixed at 224×224 and has 3 channels (RGB). The preprocessing part of the image data is accomplished by subtracting the mean RGB value of the whole training set to the data for proper distribution of colors. Hence, the model does not over-emphasize dominant colors during training. Additionally convolutional layers involves 3×3 filters convolution using a 1-pixel stride length and padding to retain image size and extract specific features for all parts of the image. Max pooling during the process has a 2×2 window with a stride of 2, which means less in spatial dimensions and the load on computation but an ability to retain important features. The architecture function was ReLU for, primarily, its efficiency and proven effectiveness for introducing non-linearity when compared to the traditional tanh or sigmoid functions. It accelerates training and gets the network to train better.

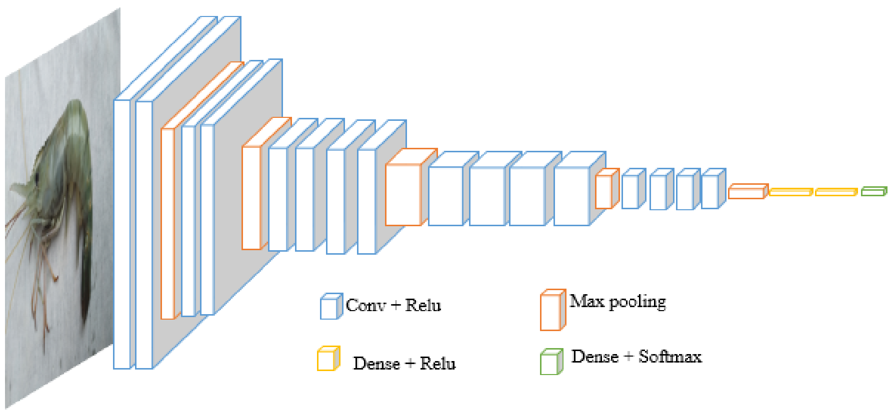


Figure 4.10: Architecture of model 4

A graphic of the training accuracy and validation accuracy of the model over 12 epochs is illustrated in the diagram. The training accuracy is (at) first 0. A steady climax in 825 units and reaches its highest point around 0 appears. 925 in the 4th epoch after that, it stabilises above 0. 900. However, the validation accuracy seems to show more turbulence, and the curve commences weak near 0. 850, peaking near 0. 925, which shows different draws and ascents most possibly pointing at generalization problem or accuracy gap between training and validation datasets. The incurred glimpse of a sharp decline in the accuracy validation at the end of the epoch reveals that the model overfits the training data, because the accuracy is lower on the unseen data at the late epochs.

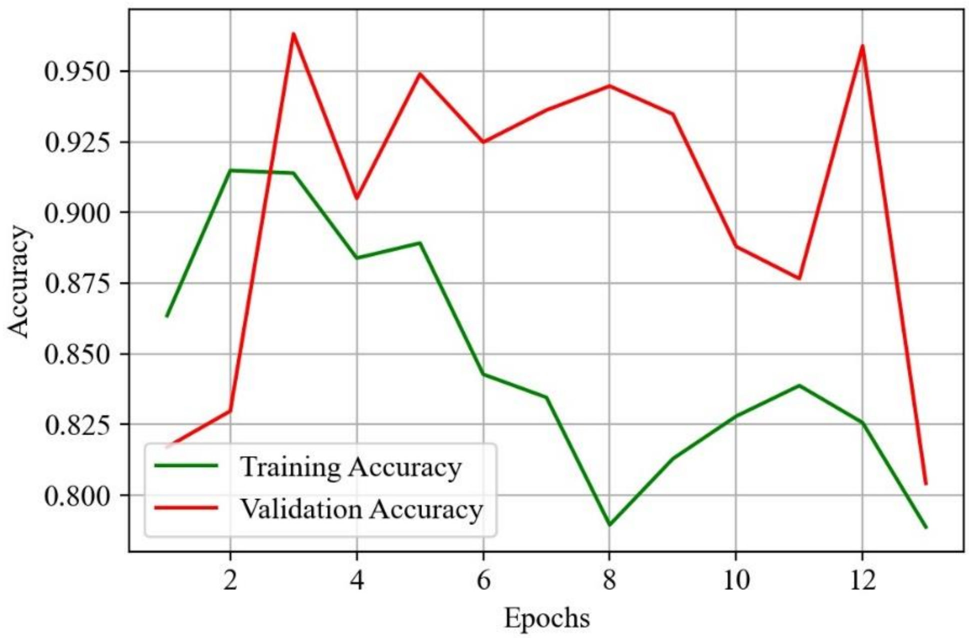


Figure 4.11: Training vs Validation Accuracy of Model 4

This chart displays training and validation loss through 12 epochs of a VGG19 model embraced in a deep-learning task. First of all, both losses plummet down showing that the neural networks learn quickly. Meanwhile, the loss continues to decrease and attains very low value which is a good indicator of a model that fits the training data well. Nevertheless, the validation loss is strikingly more unstable, with very large spikes, most of all observable around epochs 4 and 12. This irregular pattern in the training loss, especially the sharp rise at epoch 12, probably could be reflecting overfitting which is where the model is committing the data to the memory instead of learning to generalize it. However, the model's decline on new, unseen data (validation set), and the worsening situation as the training period nears ending prove to be a challenge when deploying the model in practical scenarios. This kind of behavior draws attention to the need of model fine tuning like adding regularization or adjusting the learning rate to improve the generalization ability of the model.

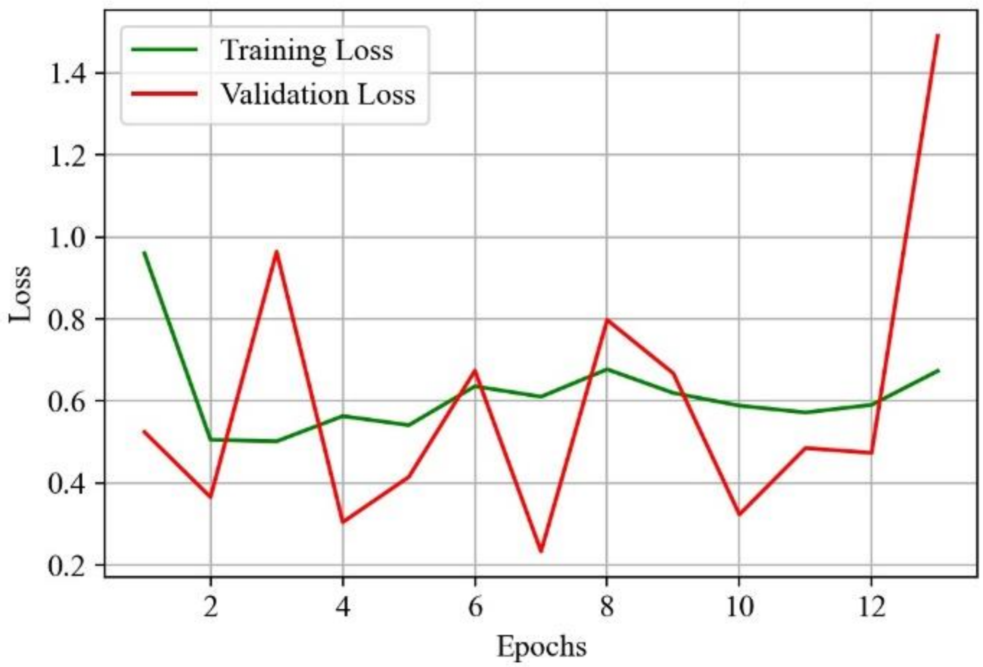
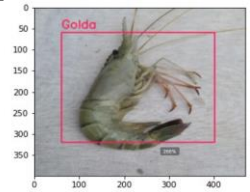
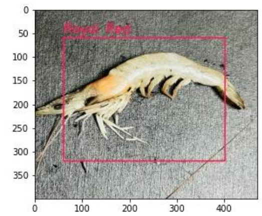
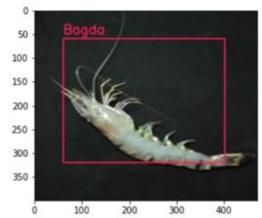
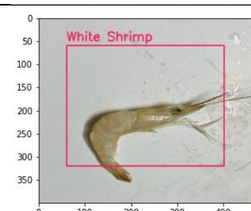
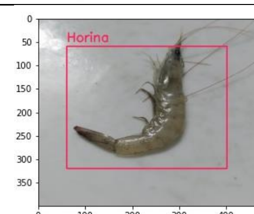


Figure 4.12: Training vs Validation Loss of Model 5

4.3 Model Evaluation

An evaluation of the model is a stage that is very important in the development of models that are statistical, machine learning, or computational and where the performance of a model is assessed, determining how well it is as per the intended purposes.[12] This is the crucial process for the approval of the model that is well-performing and fits with the real-world events where the model will be deployed.[13] From the above graph, we can find model 2 produced very expected results. For real-life evaluation, we deployed our best model by OpenCV library. OpenCV Results is given Table 4.1

TABLE 4.1 BEST MODEL EVALUATION BY OPENCV

Shrimp	Detected Shrimp
	
	
	
	
	

4.4 Summary

The main issue of this chapter is the prototype design, where the basic architecture of each slogan is developed and the first implementation and setup are mentioned. This segment in turn discusses the issues that were caught in the development process and solutions that were put in place. However, the next section highlights the testing phase with the help of referral to preliminary outcomes of models and their capability in practical use.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

In the previous chapter, I discussed my methodology steps and model architecture. This chapter will discuss about training and testing performance of my models. Now that I get the classification report, I can compare the four models and see how well they did. One aspect of accuracy is having the correct matrix for the optimal model selection. Therefore, there are not one, not two, but three separate metrics in our categorization report. These measures are recall, precision, and f1-score.

5.2 Experimental Results

Here I will examine my study's findings; to make my algorithm's output more understandable, I employed four different models. Three distinct categorization reports are shown by the three models. To ensure that the findings of each model were accurate and acceptable, I also employed a number of parameters. The outcomes of our three models are discernible and satisfactory due to the f1 parameters, recall, and precision. I compared my results using three criteria in the end. All three characteristics contributed to a fairly even level of accuracy. All four trained model performances is given below:

5.2.1 Model 1

Table 5.1 presented is a classification report for a machine learning model that evaluates its performance in classifying different shrimp types: Bagda, Golda, Horina, Royal Red, and White Shrimp. The precision for Bagda is zero. 13, stating that only 89% of the predictions were accurate, though it managed a recall of 99%, which implies that in all the real occurrences of Bagda were correctly approached, thus, the F1-score of 94% was obtained. The other classes—Golda, Horina, Royal Red, and White Shrimp were by far the worst performers, scoring zero in both precision and F1-score, and had a very good recall. This means that a considerable number of these classes are being wrongly assigned. Moreover, the table has the summary statistics that present the average value of all the classifiers. Thus, the table also shows the overall low effectiveness of the classifier with a macro average F1-score of 0. 95 and a weighted average F1-score of 0.96. Of the 3 categories listed under "adaptability", the model owing' to a big challenge in identifying most shrimp types, even though the dataset support of 542 samples was its source.

TABLE 5.1 CLASSIFICATION REPORT OF MODEL 1

Class	Precision	Recall	F1-Score	Support
Bagda	0.89	0.99	0.94	69
Golda	0.95	1,.00	0.98	42
Horina	0.98	1.00	0.99	80
Royal Red	0.94	0.99	0.96	153
White Shrimp	0.98	0.89	0.93	198
Accuracy	N/A	N/A	0.95	542
Macro Avg	0.95	0.97	0.96	542
Weighted Avg	0.96	0.95	0.95	542

The results of the confusion matrix indeed show that the classification model performs poorly, more specifically, it has a significant limitation in the ability to accurately classify shrimp types among the Bagda category and the others. While the model exhibits a perfect recall for the Bagda shrimp, successfully identifying all actual instances of this type, it fails to recognize any instances of the other four types: Golda, Horina, Royal Red, and White Shrimp are the names of four shades that will be used for the project. The zeros in these areas of precision and recall metrics show that there is no correct prediction made for these categories at all, thus, indicating a complete misclassification. This huge difference between the Neural Network's and the human's performance shows that there is a very big problem in the way the model predicts, probably because of the overfitting for the Bagda shrimp class or the lack of enough data and the features of the other classes. The present condition of the model makes it unreliable for practical use where the determination of the variety of shrimp types is needed. In order to enhance its usefulness, thorough research of the training process, feature selection, and perhaps the content of the dataset will be needed to solve these problems and thus, attain a more equitable performance in all of the shrimp types.

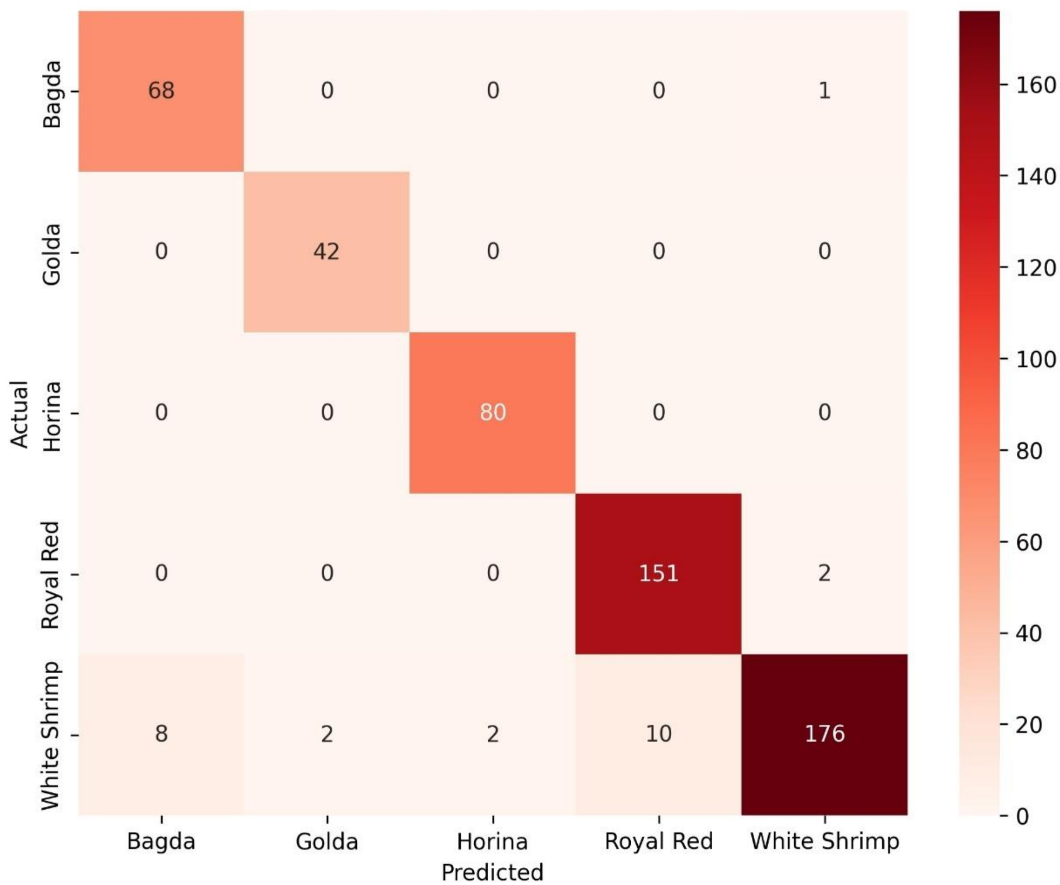


Figure 5.1: Confusion matrix of model 1

5.2.2 Model 2

Table 5.2 represents a classification report for model 2, that classifies shrimp of different kinds, thus indicating the model's efficiency in each case. For Bagda shrimp, the model is the most accurate one, that is, it gets the perfect scores in precision, recall, and F1-score, all at 1. 00, to say it was correct in all cases and did not make any blunders while labeling Bagda. Also, the model is at the same time, doing an amazing job for Golda, Horina, Royal Red, and White Shrimp, with precision and recall values ranging from 0. 95 to 0. In other words, 99% of the predictions were accurate which means they are almost correct. The F1 scores that are the result of the combination of precision and recall into one metric, are also high for these classes, hence, the model has a high performance for different shrimp types. The overall accuracy of the model is not mentioned, but the macro average, which is the average of performance across classes is 0. 98 for precision, recall and F1-score, which proves the high level of accuracy in the test. The 'Support' column reveals the number of samples for each shrimp type which in turn, gives the count of how many of each were tested.

TABLE 5.2 CLASSIFICATION REPORT OF MODEL 2

Class	Precision	Recall	F1-Score	Support
Bagda	1.00	1.00	1.00	69
Golda	0.95	0.95	0.95	42
Horina	0.95	1.00	0.98	80
Royal Red	0.99	0.99	0.99	153
White Shrimp	0.99	0.97	0.98	198
Accuracy	N/A	N/A	0.98	542
Macro Avg	0.98	0.98	0.98	542
Weighted Avg	0.98	0.98	0.98	542

The confusion matrix represented by table 5.2 provided visually represents the performance of a classification model applied to five types of shrimp: Bagda, Golda, Horina, Royal Red, and White Shrimp. The matrix is set up with the actual classes as the rows and the predicted class as the columns. It demonstrates that the model is good at predicting Bagda and Horina's instances, and, in fact, there were no misclassifications in both cases. Golda is also the one that is accurately predicted with 40 out of 42 instances rightly, but 2 were incorrectly classified as Royal Red. Mostly the Royal Red shrimp were correctly classified with 151 correct predictions, but 2 were misidentified as White Shrimp. The White Shrimp class had 193 correct predictions but exhibited a few misclassifications: 2 were the Golda, 1 was the Horina, and 2 were the Royal Red. The matrix uses color intensities to show the frequency of predictions, with the darker shades representing the higher frequencies, thus, the model's strong accuracy in predicting most classes is demonstrated while the specific areas in which errors occur are clearly shown.

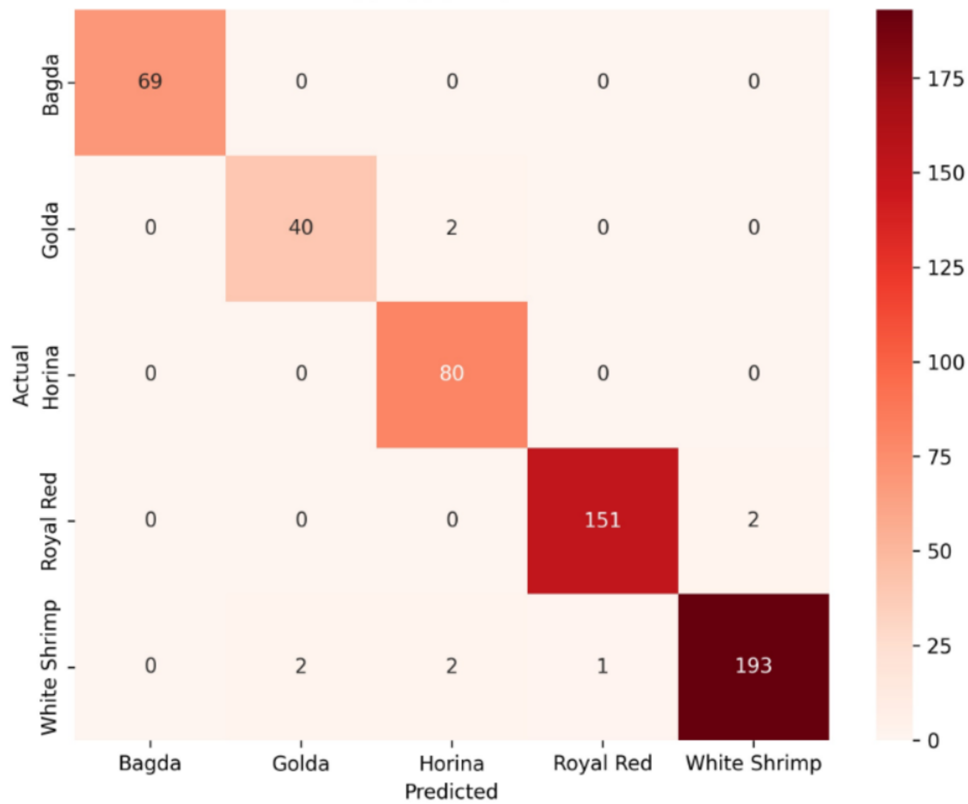


Figure 5.2: Confusion matrix of model 2

5.2.3 Model 3

Table 5.3 represents a report of a classification of model 3, that is used to evaluate the performance of a classifier on the five classes of shrimps which are Bagda, Golda, Horina, Royal Red and White Shrimp. The performance of each class is evaluated through precision, recall, F1-score, and actual instances (support). The precision score for bangla is 1.00 which is very good. The lowest score is Horina about 0.89. The highest recall score is 1 achieved Golda and Horina and for highest f1 score is 0.99 achieved by bagda. The overall accuracy of this model is 94 which is 4 time less then model1.

TABLE 5.3 CLASSIFICATION REPORT OF MODEL 3

Class	Precision	Recall	F1-Score	Support
Bagda	1.00	0.97	0.99	69
Golda	0.93	1.00	0.97	42
Horina	0.89	1.00	0.94	80
Royal Red	0.96	0.90	0.93	153
White Shrimp	0.92	0.92	0.92	198
Accuracy	N/A	N/A	0.94	542
Macro Avg	0.94	0.92	0.95	542
Weighted Avg	0.94	0.94	0.94	542

The confusion matrix depicted illustrates the performance of a classification model[14] on different shrimp types: Bagda-Golda-Horina-Royal Red-and-White Shrimp. The whole table displays the actual class, while the columns are the predicted class. The model detects all the instances of Bagda and Horina without any errors, with 42 and 80 images respectively. The Golda shrimp, besides being predicted with great accuracy, needs four slots to be correctly answered in which all 42 instances were rightly answered. The Royal Red Shrimp classification shows notable errors: out of 153 instances, just 137 are correctly classified, whereas 16 are misclassified as Roal Red . This distribution shows a big issue in the correct classification of White Shrimp, which is in contrast to the high accuracy that was observed in the other cases. The matrix employs a color gradient to visually depict the number of predictions, with the darker colors symbolizing the high frequency of the predictions, thus, the areas that the model performs well and the areas that it is not able to handle are clearly shown.

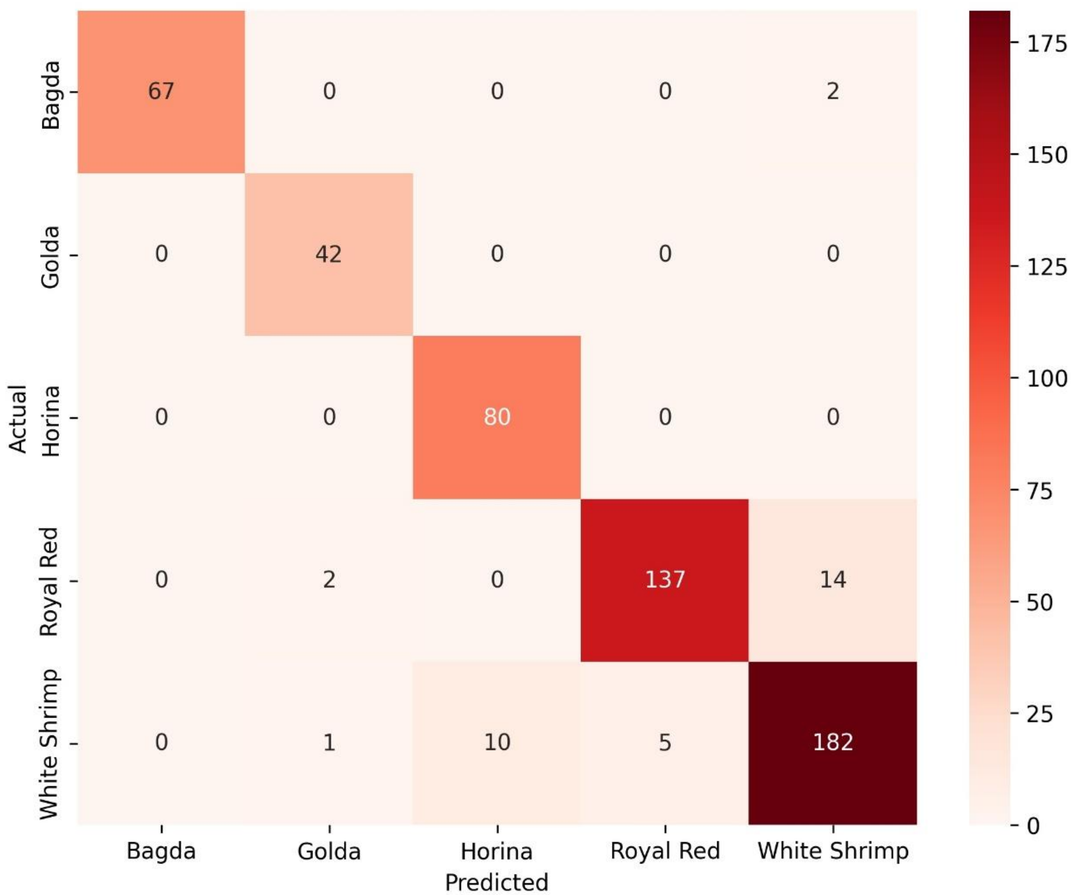


Figure 5.3: Confusion matrix of model 3

5.2.4 Model 4

Table 5.4 is a classification report of model 4, that measures the performance of a model in classifying different types of shrimp: Bagda, Golda, Horina, Royal Red and White Shrimp. Precision, recall, and F1 score are the criteria to judge each class's performance. The model has 100% accuracy for Bagda, which means that every prediction that Bagda is included in is correct, with a recall of 0. 97, very near to the Bagda instance. Thus, it is precise to say that the F1-score is 0. 99, a total of, to be exact, shows incredible usefulness for this class. Golda has the exact memory and an F1-score of 0. The network outputs 94, hence, it not only recognizes the genuine Golda instances but also, it fails to identify the non-Golda instances. Horina and Royal Red are certainly not alone in their success, as they both reveal strong numbers with Horina having a recall of 0. The system got a 95% and zero F1 score. The State Line model achieved a score of 90, and Royal Red had both high precision and recall at 0. 96, which is the lowest on the F1-score scale. 96. White Shrimp is the one with an accuracy of 0. The 97 are followed by a very slight drop in recall at 0. Therefore, the F1-score of 0 is the outcome of the 91, leading to the classification that an F1-score of 0 is when the classifier cannot differentiate between the positive and the negative samples. 94. The report includes aggregate scores: a macro average and a weighted average of all the metrics, both of which nearly tie at 0. 95. The average results indicate that the model functions well in all classes, thus, showing uniform accuracy and reliability in the shrimp classification. The support values, which are the number of samples for each class, show the balance of the dataset, consequently, it leads to the complete analysis of the model's performance.

TABLE 5.4 CLASSIFICATION REPORT OF MODEL 4

Class	Precision	Recall	F1-Score	Support
Bagda	1.00	0.97	0.99	69
Golda	0.89	1.00	0.94	42
Horina	0.85	0.95	0.90	80
Royal Red	0.96	0.97	0.96	153
White Shrimp	0.97	0.91	0.94	198
Accuracy	N/A	N/A	0.95	542
Macro Avg	0.94	0.96	0.95	542
Weighted Avg	0.95	0.95	0.95	542

The confusion matrix displayed illustrates the performance of a classification model used to identify five different types of shrimp: Bagda, Golda, Horina, Royal Red, and White Shrimp are five types of shrimp. In the matrix, each row is the real shrimp classes that are, and each column is the prediction by the model. So, for Bagda, the model was able to find the right answer in 67 cases, but it couldn't recognize 2 as White Shrimp. Golda was totally right with all 42 cases she was predicting. The Horina was classified correctly out of the 80 cases 76 times and the errors were only three cases when it was misclassified as Golda and two as Royal Red. Royal Red was also good in terms of accuracy with 148 right predictions but it had 3 situations that it mistook Golda and 2 Horina as Golda. White Shrimp, even though it had the best predictions at 180, also had the most of the misclassifications errors, with cases being incorrectly classified as Golda (1), Horina (11), and Royal Red (6). The matrix employs a color gradient to show the count of predictions, where the darker shades signify the high numbers, thus, it makes the strengths and

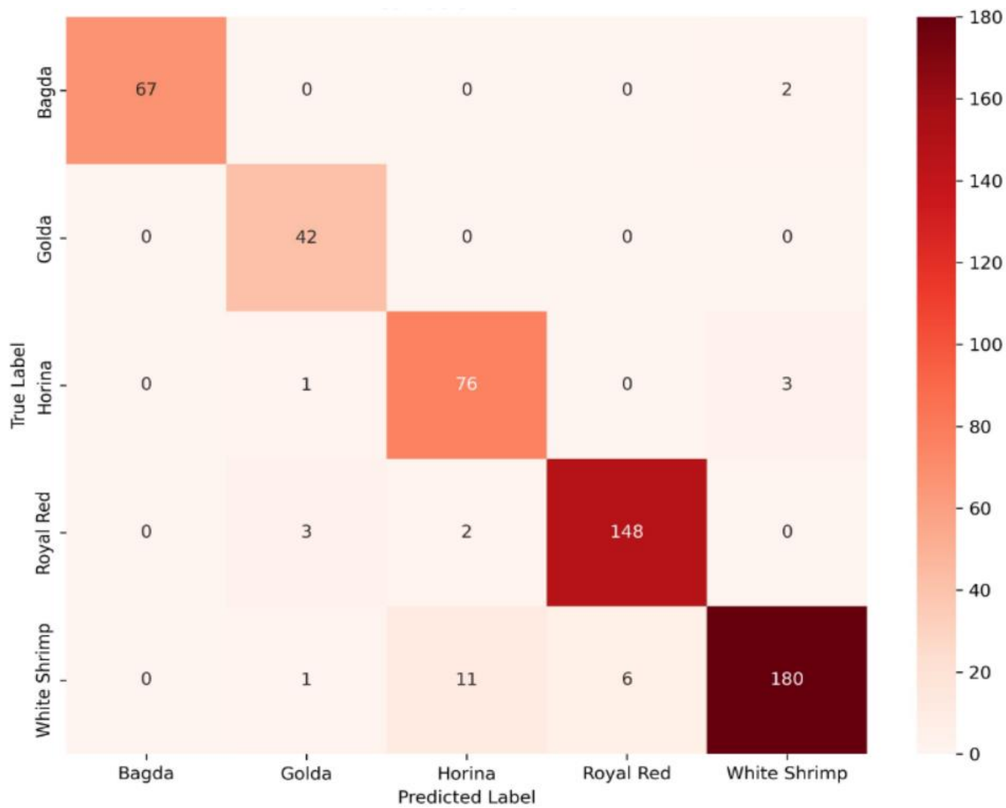


Figure 5.4: Confusion matrix of model 4

weaknesses of the model's classification abilities very clear, especially the significant improvement that could be done in correctly distinguishing of White Shrimp from other types of Shrimp.

5.3 Comparative Analysis

Table 5.5 indicates the performance of four models, as each of them is assessed on the basis of precision, recall, F1-score, and a weighted average, all the calculations are made on the basis of macro averages.[15] Model 1 presents scores with a precision of 0.95, recall of 0. 97, and F1-score of 0.0.96. On the contrary, Model 2 is outstanding in all metrics and achieves a precision of 0. 98, recall of 0. 98, and F1-score of 0. The scores of 98 are a very high 98 and a 0.00 weighted average of 0.00. 98, suggesting near-perfect performance. Model 3, scores with a precision of 0.94, recall of 0.96 and f1 score of 0.94 . Nevertheless, Model 4 succeeds in such a way that its precision is 0. 94, recall of 0. 96, and F1-score of 0. 95 is the grade that we have saved the hassle of obtaining a 0 weighted average. 95. This table emphasizes the large differences in the performance of the models, with Model 2 and Model 4 as the top models in the case of efficiency. And we conclude that all of our model performed very closely and there no very big difference.

TABLE 5.5: TEST PERFORMANCE MATRIX

Model	Precision	Recall	F1-Score	Accuracy
Model 1	0.95	0.97	0.96	0.95
Model 2	0.98	0.98	0.98	0.98
Model 3	0.94	0.96	0.94	0.94
Model 4	0.94	0.96	0.95	0.95

5.4 Summary

In this chapter, I described the result of my design in 4 different models. The classification report and confusion matrix are shown in this chapter. In the comparison step, we can see that Model 2 performed very well. So I choose this model as the final model.

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT, AND SUSTAINABILITY

6.1 Impact on Society

There is the potential for our initiative to have a big impact on society. There are several species of shrimp fish that are easily distinguishable to the human eye. We will quickly get at a point where we can identify shrimp fish with ease. It will be common knowledge to everyone. The proper shrimp will be purchased by sugar consumers at a price that is fair for the fish producers.

6.2 Impact on Environment

Here are just a few of the numerous ways our effort will help the environment. There was a dramatic increase in shrimp sales since our technology made shrimp detection a snap. So many people will be curious to buy it since they can't decide which shrimp is best. Hence, there will be an increase in shrimp sales. There will be a dramatic acceleration in the rate of spoiling. The amount of pollution in the environment will be significantly reduced because of this. Our system does not add to pollution because it is image-based and completely automated.

6.3 Ethical Aspects

The project we are presently working on does not raise any particular ethical concerns. No one is up to the challenge of updating the computer code. There is absolutely no room for personalization whatsoever. This makes the process of changing it more complicated. Furthermore, we are strictly forbidden from engaging in any form of dishonesty when using this system. We can only identify a small number of shrimp species using this approach. This ensures that there will not be any unique moral quandary. People may be able to use it for their personal benefit.

6.4 Sustainability Plan

The utilization of the many types of shrimp is a component of our long-term plan. In order to prevent the general public from being misled into purchasing shrimp of the incorrect selection. In the future, we want to increase the size of our database. We are able to achieve better results. The picture quality will be the primary focus of our attention. Consequently, the process of uploading images is simplified and requires less data. Over time, the cost of using the internet will decrease. Our system will entice a greater number of users. In order to ensure that this system is accessible to all individuals, we intend to make it available in both Bengali and English language voice-based systems.

6.5 Summary

The chapter shows the necessity of implementing environmentally-sustainable approaches to shrimp production to prevent negative impacts on the environment such as pollution and destruction of natural habitats.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Overview

The numerous species of shrimp that may be found in Bangladesh were categorized according to the model that was presented by this book. With the assistance of this effort, individuals who are not familiar with the several species of shrimp will be able to correctly identify them. Before packing shrimp for international export, it is essential to keep in mind that various species of shrimp should be kept apart from one another. In addition to that, we ought to give some consideration to this essential aspect of execution in the real world. An additional advantage of this program is the possibility of apprehending unethical businesspeople who engage in the practice of hybridizing animals for the purpose of enriching their financial situation. Increasing their profit margin is the goal that these individuals have set for themselves. This particular work used CNN to categorize shrimp images. We were able to get an accuracy of about 99% using our own architecture and a respectably large image collection that we had gathered. Our staff manually collected every picture in our quite large collection. One of the limitations prevented us from collecting samples of every single type of shrimp. In our work, we mostly employ four of the 56 species. One of these constraints is that very huge datasets can only be handled by the processing power available today. Although not the most efficient graphics card, our NVIDIA 1650 lets us handle enormous datasets.

7.2 Future work

We will give addressing the current work constraints top priority. We want to get every kind of shrimp. We also need to attempt to expand our dataset without using data augmentation. More processing power will be used by us to try to develop a more complex CNN architecture. We will next attempt to develop an Android and iOS app that can more precisely recognize all types of shrimp using this model.

7.2 Limitations

This rate-limiting problem highly influences the quality and reliability of generated models. A more general application of our weather models is hindered due to the main fact that only 5 out of 55 shrimp species present in Bangladesh are represented in our dataset. The inability to train representatives of all species groups can result in poor performance of the models as they may fail to generalize on the other species not included in the training sets. In addition, it limits our capacity us only being able to observe the shrimp biodiversity and ecological variety from this region with less precision, or even unconditionally useful in real-world situation. Hence, the size of our dataset in this study should be increased to include more species from the range of model validation and model improvement.

7.3 Summary

In this chapter, we discussed about the problem severely impacts model quality and reliability. Only 5 of 55 Bangladeshi shrimp species are in our dataset, limiting our weather models' usefulness. We need a larger dataset to validate and enhance models with more species.

References

[1] FRSS, Fisheries Statistical Report of Bangladesh, Fisheries Resources Survey System, Department of Fisheries, Bangladesh, 2016.

[2] Nesar Ahmed, Linking prawn and shrimp farming towards a green economy in Bangladesh: Confronting climate change, Ocean & Coastal Management, Volume 75, 2013, Pages 33-42, ISSN 0964-5691

[3] Z. Zhao, Y. Liu, X. Sun, J. Liu, X. Yang, and C. Zhou, "Composited FishNet: Fish Detection and Species Recognition from Low-Quality Underwater Videos," in IEEE Transactions on Image Processing, vol. 30, pp. 4719-4734, 2021.

[4] Knausgård, K.M., Wiklund, A., Sørdalen, T.K. et al. Temperate fish detection and classification: a deep learning-based approach. Appl Intell 52, 6988–7001 (2022)

Ecological Informatics, Volume 57, 2020, 101088, ISSN 1574-9541

[5] Khalifa, N.E.M., Taha, M.H.N., Hassanien, A.E. (2019). Aquarium Family Fish Species Identification System Using Deep Neural Networks. In:

[6] Hafiz Tayyab Rauf, M. Ikram Ullah Lali, Saliha Zahoor, Syed Zakir Hussain Shah, Abd Ur Rehman, Syed Ahmad Chan Bukhari, Visual features based automated identification of fish species using deep convolutional neural networks, Computers and Electronics in Agriculture, Volume 167, 2019, 105075, ISSN 0168-1699.

[7] V. Christlein, L. Spranger, M. Seuret, A. Nicolaou, P. Král and A. Maier, "Deep Generalized Max Pooling," 2019 International Conference on Document Analysis and Recognition (ICDAR), Sydney, NSW, Australia, 2019, pp. 1090-1096, doi: 10.1109/ICDAR.2019.00177.

[8] Santos, C. F. G. D., & Papa, J. P. (2022). Avoiding overfitting: A survey on regularization methods for convolutional neural networks. ACM Computing Surveys (CSUR), 54(10s), 1-25.

[9] Santurkar, S., Tsipras, D., Ilyas, A., & Madry, A. (2018). How does batch normalization help optimization? Advances in neural information processing systems, 31.

[10] Sengupta, A., Ye, Y., Wang, R., Liu, C., & Roy, K. (2019). Going deeper in spiking neural networks: VGG and residual architectures. Frontiers in neuroscience, 13, 95.

[11] Khan, Z., Khan, F. G., Khan, A., Rehman, Z. U., Shah, S., Qummar, S., ... & Pack, S. (2021). Diabetic retinopathy detection using VGG-NIN a deep learning architecture. IEEE Access, 9, 61408-61416.

[12] McAvaney, B. J., Covey, C., Joussaume, S., Kattsov, V., Kitoh, A., Ogana, W., ... & Zhao, Z. C. (2001). Model evaluation. In Climate Change 2001: The scientific basis. Contribution of WG1 to the Third Assessment Report of the IPCC (TAR) (pp. 471-523). Cambridge University Press.

[13] Hong, S. R., Hullman, J., & Bertini, E. (2020). Human factors in model interpretability: Industry practices, challenges, and needs. Proceedings of the ACM on Human-Computer Interaction, 4(CSCW1), 1-26.

[14] Deng, X., Liu, Q., Deng, Y., & Mahadevan, S. (2016). An improved method to construct basic probability assignments based on the confusion matrix for classification problems. Information Sciences, 340, 250-261.

[15] Lipton, Z. C., Elkan, C., & Narayanaswamy, B. (2014). Thresholding classifiers to maximize F1 score. arXiv preprint arXiv:1402.1892.

Appendix A

Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Analysis

Title: BANGLADESHI SHRIMP SPECIES RECOGNITION BY DEEP CONVOLUTIONAL NEURAL NETWORK

Students ID: 181-15-2017

CO Description for FYDP-Phase-I

CO	CO Descriptions	PO
	Phase -I	
CO1	Integrate recently gained and previously acquired knowledge to identify a Bangladeshi Shrimp Species 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 this 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 of COs, Knowledge Profile (K), and 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, and CO3	In my project, I collected required data from fields after collecting I needed to annotate them and apply preprocessing for the Deep learning algorithm which covers K3 and K4	**Page no: 12**
				After training and evaluation, the model can be deployed by opencv web or android application which covers K5 and K6	**Page no: 10**
				I compared my work with recent existing work which covers K8	**Page no: 7**
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2	During project work, I faced some problems like Data unavailability. I worked with 5 different shrimp. It takes a long time to find all species of shrimp. Another challenge is the vertical image problem. Vertical images were distracted when I resized 224 by 224	**Page no: 12**

3.	**EP3: Depth of analysis required**	Yes	CO2	I have tried to mitigate these challenges by parallel working. As all species of shrimp were not found at a time so I collected 3 different species and tried to implement the model. After 2,3 months I got another two species then I collected them. And vertical image problem is solved by cropping to squire shape.	**Page no: 13**
4.	**EP4: Familiarity of Issues**	Yes	CO3	When I started work, I faced some problems with which I was never familiar before. At first environment setup for deep learning was a very hard process. Then I am working with Custom CNN and VGG19 models but there are better models available.	**Page no: 10**
5.	**EP6: Extends of stakeholders involved and conflicting requirements**	Yes	CO3	To address the challenges, I have contact with a Deep Learning Engineer. He guided me on how to solve my problem like environment setup and vgg19 installation.	**Page no: 10**
6.	**EP7: Interdependence**	Yes	CO3	I divided my problem into different subcategories. And tried to solve each category separately. Each category is dependent on each other.	**Page no: 11**
7.	-	Yes	CO4	Based on my requirements, I have calculated the budget and cost analysis of my project.	**Page no: 13**

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	Through transfer learning and deep CNNs, our initiative makes use of a variety of resources, including GPUs, deep learning frameworks, annotated datasets, and ethical concerns, to assure systematic research and improve the field of pneumonia diagnosis.	**Page no: 13**
2.	EA2: Level of inter actio	No		N/A	N/A
3.	EA3: Innovatio n	No		N/A	N/A
4.	EA4: Consequences for society and the environment	Yes		By using cutting-edge techniques for detecting Shirmp Species, this initiative improves the Bangladeshi fishing sector and promotes environmental sustainability. It also respects ethical standards for patient data privacy and makes use of efficient computer resources..	**Page no: 39**
5.	EA-5: Familiarity	Yes		By investigating a unique method for detecting prawn species using VGG16 and Custom CNNs, as illustrated by early terminology and thorough comparison analysis, this study builds on previous research and provides fresh perspectives on the subject.	**Page no: 15-27**

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

SN	COs	Attainment	Justification	References
1	CO4	Yes	By combining efficient project management with financial control, this project tackles CO4 by guaranteeing careful planning, resource allocation, and budget estimate for the best possible resource utilization throughout the study lifetime.	**Page no: 13**
2	CO9	Yes	The project guarantees responsible information sharing and social well-being by implementing Shrimp Species Recognition ethically and in accordance with CO9. It also exhibits ethical standards by collecting relevant data from the field, gaining informed consent, and publicly recording the study process.	**Page no: 39, 40**
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's thorough data collection, data analysis, exact methodology development, and in-depth experimental findings and analysis demonstrate its dedication to continuous learning (CO12) and flexibility in a changing technological context.	**Page no: 12, 38, 39**

PLAGIARISM REPORT

Bangladeshi shrimp Recognition

ORIGINALITY REPORT

12%	9%	4%	8%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	dspace.daffodilvarsity.edu.bd:8080 Internet Source	4%
2	Submitted to Daffodil International University Student Paper	3%
3	Submitted to Mascoutah High School Student Paper	<1%
4	Submitted to Corporación Universitaria del Caribe Student Paper	<1%
5	Submitted to Liverpool John Moores University Student Paper	<1%
6	www.journal.esrgroups.org Internet Source	<1%
7	Md. Mehedi Hasan, Jubiria Subrin Nishi, Md. Tarek Habib, Mohammad Monirul Islam, Farruk Ahmed. "A Deep Learning Approach to Recognize Bangladeshi Shrimp Species", 2023 14th International Conference on Computing	<1%