A Deep Learning Approach to Recognize Bangladeshi Shrimp Species

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ABSTRACT

The nutritional value of shrimp, the most consumed shellfish in Bangladesh, is high because of its abundance of various nutrients. Protein, minerals, vitamin D, and iodine are all examples of such things. The name of this seafood means "white gold" in its native Bangladeshi language. More than 70% of the world's agricultural food supply comes from this. Roughly 56 distinct species of shrimp can be found in American waters. Unfortunately, most people only have a cursory understanding of the wide variety of life on our planet. Experienced fishermen sometimes make the mistake of confusing one species with another because of their superficial resemblance. We developed an AI system to aid in shrimp identification to solve the difficulty presented by this paper. We anticipate that this study will also help the export sector in distinguishing between the numerous shrimp species under observation. To accomplish our goals, we developed an in-house convolutional neural network (CNN) algorithm for extracting features and processing images. Here, we construct three unique CNN architectures, each with its own unique hyperparameters and convolutional layers. Model 3 was chosen as the final model for computer vision integration, despite the fact that both Model 1 and Model 3 attained an accuracy of 99.01%. Models 1 and 3 produce the same answer; if model 3 is more accurate, why would we pick it as the final model? Furthermore, we will offer a rational justification for this study's findings.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Bangladesh's most well-known export in the seafood industry is shrimp. In the years 2002–2003, the rate of shrimp production was 1.60 lakh MT, but in the most recent two years, that number has increased to 2.41 lakh MT. [1] Because it has a wealth of natural resources and a climate that is suitable for aquaculture, Bangladesh is the finest country in the world to practice coastal aquaculture. [2] According to data provided by the Export Promotion Bureau, frozen fish exports raked in a total of $532 million during the fiscal year 2021-2022, representing a 12 percent increase over the $477 million achieved the previous year. Because of this, exports of frozen food now make up Bangladesh's second most valuable commodity. Shrimp makes up the majority of the frozen seafood that is available. Bangladesh was responsible for around 2.5% of the world's total shrimp trade. This demonstrates how important the production of shrimp is to the economy of our country. Unfortunately, neither the cultivation nor the production of shrimp in the shrimp sector makes use of any kind of technology. The application of AI in agricultural contexts has increased rapidly in recent years. [3] As a result, this is an excellent time to make use of artificial intelligence technologies to increase shrimp production while maintaining a high level of quality. To put it another way, shrimp are classified as arthropods. Sadly, the majority of people in our country are unable to differentiate between the many types of shrimp. Particularly challenging to differentiate are species with common names such as Golda and Bagda, Horina and Deshi, and the like. And while Golda and Bagda have some similar physical characteristics, the dilemma for Horina and Deshi is the exact reverse. Our team came up with the idea of creating a deep learning-based intelligent image classification system that can correctly identify all four species of shrimp to address this issue. Our objective was to design three distinct CNN architectures and evaluate the experimental performance of each of them in as objective a manner as feasible. Both Model 1, which has a very deep CNN structure, and Model 3, which is lighter in weight than

Model 1, offered the same level of accuracy, making it challenging to select the model that is best suited for the task. In the end, we choose the model that performs the best in an environment that has been carefully regulated. As a result, we selected the models that would be put through testing using a score matrix comparison method. Tensorflow, Scikit-Learn, Pandas, and Keres are some examples of libraries and frameworks that are utilized in the process of implementing models. This project's code will be written in Python, as that was the language of choice.

In this paper, we will be discussing the following topics. The literature review can be found in Section II. In the third section, we provided even more specifics about our process. The results of the experiments are discussed in Section IV, and an evaluation of the usefulness of our model may be found in Section V. In Section VI, the implementation of the model is presented, and in Section VII, a summary and discussion of potential future possibilities are presented.

1.2 Motivation

Due to the similarities in the colors and textures of shrimp, the variety of shrimp, and other characteristics such as their position or the lighting conditions, it is still challenging to automatically recognize shrimp using computer vision. This is due to the fact that shrimp come in a wide variety of colors and textures. The following is a list of the five well-known designs for image recognition that we plan to study. Each of these architectures makes use of a deep convolutional neural network in some capacity. The native shrimp species of Bangladesh are the focus of these designs, the objective of which is to identify them. If we go about things in this manner, both of these models, which represent distinctive approaches, will be tested out on the Bangladeshi shrimp that we have available to us in order to gain an understanding of how successfully they function.

1.3 Research Question

- How does the ability to recognize shrimp have an impact on the way we go about our daily lives?
- Can ML and DL (machine learning and deep learning) models be combined in one application?
- How do applications for Shrimp Recognition deal with the challenges they face?
- Which technique for identifying shrimp is the most effective?
- Where can I get more information about the specialized areas of Shrimp Recognition that are most pertinent to my research interests?

1.4 Research Objectives

The following is a list of the primary goals that we have:

- Efforts should be made to improve the Fishing and agriculture sectors.
- Data collecting.
- Determine the cause of the issue as well as the solution.
- In order to reduce the costs incurred by the farmer.
- Give the farmer some sound advice so that he can raise shrimp that is of superior quality.
- In the grand scheme of things, making a significant contribution to the economy of the nation.

1.5 Expected Outcome

Shrimp recognition is a subclass of fine-grained visual recognition, which is a subcategory of optical recognition. It is a form of optical recognition that is more advanced than conventional image recognition. Shrimp recognition was developed in the 1990s. The categorization of Shrimp inevitably brings with it the prospect of use in a variety of settings, including academic and commercial ones. Consider, for example, the situation in which it was trained with the help of a vast database. In this instance, it might be utilized in smartphone applications that instantly recognize the kind of Shrimp and provide information about the Shrimp, such as its price, the nutritional benefits it delivers, the calorie count, and any other essential information that might be required. In addition to this, it has the potential to recognize rare species of Shrimp that are endemic to a certain place and cannot be found in any other part of the world.

1.6 Summary

This chapter provides an overview of the major components that work together to form the framework of our organization. The content of this specific chapter is of the utmost significance to us. In this chapter, we will provide an overview of our general framework, as well as a few related frameworks, our inspirations, our ambitions, and our commitments to this framework. In addition, we will discuss a few related frameworks. In addition, we will talk about a few frameworks that are connected to this topic. In this chapter, we look not just at the overarching framework approach that we have devised but also at the potential exists that we might take from this particular predicament.

1.7 Report layout

Chapter 1: In this first chapter, we will present our program, its goals and rationale, the nature of the problem we hope to solve, the topic we hope to study, the approach we will follow, and the timetable we anticipate for finishing the project. Here, we detail the rationale behind our study.

Chapter 2: The second chapter sets the stage for the investigation, discusses related studies, and evaluates the current situation in Bangladesh. The larger setting is discussed, as well as the piece itself.

Chapter 3: Methods for conducting the study will be detailed in Chapter 3. You'll find a more in-depth explanation of the process here. To learn more about the process that went into compiling this report, please refer to the "Methodology" section.

Chapter 4: Fourth, the effectiveness of the proposed model will be assessed with the use of a classification report and an accuracy table.

Chapter 5: This chapter discusses the critical analysis of this project. Here also briefly discussed the environmental and ethical issues of this project.

Chapter 6: There will be one more chapter in this report, and it will be numbered 5. In this section, we will briefly review the results of the model. We also include a comparison of accuracy. The results and online application of the concept are also discussed. The chapter concludes by analyzing the issues that have arisen from the effort. Details on planned further endeavors are also provided.

CHAPTER 2

BACKGROUND STUDY

2.1 Literature Review

Machine learning and deep learning are two approaches that are frequently utilized to find solutions to issues that arise during the process of image processing. It is vital in helping individuals live their lives in a more comfortable manner and assist people in doing so. In spite of the fact that both our subject matter and methodology are entirely original, a number of researchers in the past have pursued lines of inquiry that are strikingly analogous to ours. The following are some case studies and comparisons that can serve as examples for review:

Zhenxi et al. [4] introduced a completely novel approach to recognizing and localizing the fish. They referred to it as the FishNet method. This technique employs composite detection in conjunction with an improved path aggressiveness network. They were able to create a composite backbone net by improving the design of ResNet, which was responsible for information on scene changes as well as fish species and texture. This allowed them to obtain the information about the fish. In addition to that, a redesigned path aggregation network was developed specifically for the purpose of semantic information modification. The accuracy of FishNet ranges from 75.2 percent to 92.8 percent, with an average of 81.1 percent.

Xiu Li and his colleagues [5] suggested using neural networks for the analysis of pictures of fish swimming in the ocean because of their ability to be both powerful and versatile. This particular investigation makes use of 24, 277 records drawn from the datasets of 12 separate classes for the purpose of training. They contributed an idea for a CNN architecture that they came up with and came up with the name PVAnet fish detector for it. They included it in their work. The structure of the Faster R-CNN Model was responsible for its conception. As a result, they implemented a number of different convolutional architectures by using the core component of Relu, Inception, and HyperNet in that order.

Knausgrd et al.[6] suggested a two-step deep learning strategy for the detection of temperate fish. The end result has an accuracy of 89.95%, which is 7.25 percentage points higher than the performance of the Faster R-CNN model. The first phase is the detection of objects using YOLO, and the second step is the classification of fish using CNN architecture combined with Squeeze and Excitation architecture. The process of deep learning includes each of these stages as individual steps. In addition to this, they employed a strategy known as transfer learning in order to improve the accuracy of their findings. They were able to achieve an accuracy rate of 99.27% when they implemented the pre-trained transfer learning approach. They were only able to achieve an accuracy of 83.68 percent and 87.74 percent, respectively, when they utilized the post-training model.

Jalal et al. [7] created a hybrid method to recognize and categorize fish in unconstrained underwater video as part of their YOLO project by merging optical flow and Gaussian mixture models with deep neural networks. This approach was used to recognize and classify fish. This was done in order to ensure that the outcomes were as good as they could possibly be. In the beginning, YOLO-based object recognition algorithms were mainly used to capture fish that were staying in one place and were easily visible to the naked eye. We get around the limitations of YOLO by employing Gaussian mixture models in conjunction with the temporal information gained from optical flow. This allows us to recognize fish that are free-swimming but are hidden in the background, which is impossible with YOLO alone. They put the proposed model to the test by utilizing two different sets of data. The accuracies and the f1 values both came in at 95.47%, while the difference between the two was 91.2%.

The identification system for aquarium family fish species was proposed by Khalifa et al.[8] has a total of 191 subspecies of the eight different species of fish that are included. The foundation of the whole system is made up of a lightweight deep CNN architecture that is comprised of a total of four layers. When compared to other systems of a similar kind, this design requires less amount of memory and has a lower level of computational complexity. They employed their own CNN, as well as AlexNet and VggNet, which are both transfer learning architectures, and compared the results of all three networks. On the other hand, transfer learning was able to achieve an accuracy of 85.41% while utilizing the AlexNet architecture. They found that their own model had an accuracy of 85.59%.

Rauf et al.[9] proposed using a CNN-based architecture with 32 levels of depth to identify fish species based on their morphology as a means to accomplish this task. The fishpak dataset was utilized in order to accomplish the objectives of this investigation. This collection features 915 distinct fish photographs that are organized into six distinct categories. They compared the results obtained from their own bespoke CNN design to those obtained from transfer learning architectures like as VGG, LeNet-5, AlexNet, GoogleNet, and ResNet-50. In addition to this, their very own bespoke CNN architecture was also implemented. In addition, the findings of the comparative study revealed that the proposed model is capable of achieving higher levels of performance than the model that is currently in use.

Machine vision was suggested as the foundation for the fish detection system that Sharmin et al. [10] intended to construct for freshwater environments. They concentrate largely on four different kinds of qualities that might be discovered in a grayscale picture. these characteristics include: In addition to this, during the process of feature extraction, they applied a strategy that was predicated on the use of histograms. They were able to successfully perform dimensionality reduction by utilizing PCA. The SVM algorithm had the highest rate of accuracy, which came in at 94.2%, out of the three different classifiers that were used.

Machine learning and deep learning models were recommended to be used by Rimi et al. [11] in order to identify the various species of leguminous plants. During the deep learning phase of the research, in addition to their own CNN, they used transfer learning architectures including VGG-16, Inception v3, and ResNet-50. This was done in conjunction with the deep learning they developed. The accuracy reached by Inception v3, which clocks in at 98.6%, is the greatest among all of the algorithms that have been developed.

The previous conversation has illuminated for us the fact that a substantial amount of work is being carried out making use of a variety of methods for the classification of photographs, the bulk of which are concerned with the identification of fish. As was recently mentioned, we have found a new issue with the solution that we produced by utilizing Deep Learning, and this issue has caused us some concern. The issue is that we are focusing on different species of fish while dealing with the same kind of fish.

2.2 Comparative Analysis and Summary

Computer vision and deep learning (also known as CNN) seemed to tie in well with other fields of study,

- It can be securely classified as relevant to ecology, agriculture, and other sectors based on the results of various studies and investigations. This option is the one that best fits our preferences and requirements.
- CNN can be trained to attain the highest levels of accuracy in image classification since it is the most trainable method.
- It's easy to deploy and may be enhanced using the many resources available.
- Incorrect use of CNN layers and insufficient training can lead to subpar outcomes and accuracy.
- If we use CNN layers correctly and train them sufficiently, we should be able to achieve respectable results and accuracy.

2.3 Summary

Prior studies are discussed in Chapter 2. Research encompasses a wide range of fields, including English language studies, machine learning, deep learning, and computer vision,

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

Therefore in part of the article, we will go through the steps that we took in order to conduct the tests that were required for this study. These steps were important in order to get accurate results. The schematic of the process overview is included for your convenience in Figure 3.1 An in-depth review of the following specifics is offered for your perusal:

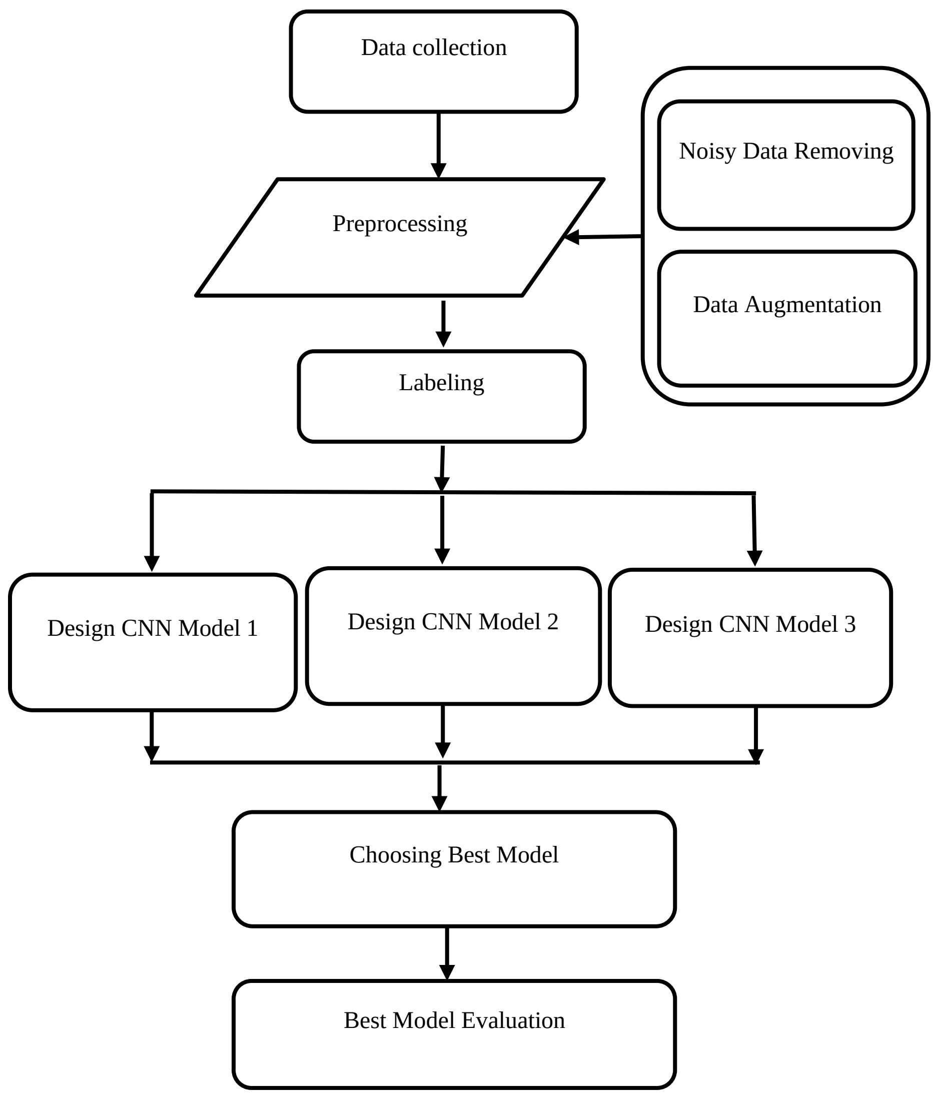

Figure 3.1 Methodology diagram

3.2 Data Collection

The photographs that were used in the creation of our dataset were taken in an area that was surrounded by shrimp enclosures. We utilized a cell phone whenever there was a need for us to take a photograph. We gathered images of the Golda, Bagda, and Deshi species of shrimp, as well as the Horina species. While we were taking the picture, we did everything in our power to ensure that the dataset remained in a stable and even state. It is estimated that there are 11,500 photos in all. Depending on which of the images was selected, the background of each picture was either black or white.

Data preprocessing

In order to improve the approach taken to the analysis of the data. The approach of preparing data for images is one that bears a great deal of significance. You need to take care of things like background removal, image compression, dead pixels, and spiky regions before beginning the training of the model [12]. During the stage where the data was being preprocessed, we made use of methods for the enhancement of data as well as the elimination of noisy data.

Data Augmentation

Given the scope of the information that we have obtained, which is quite limited. As a result, we aimed to broaden the scope of our dataset by employing a variety of strategies for data enhancement. The expansion of data can be accomplished with an approach known as data augmentation, which is both efficient and successful. Using this strategy, we are able to modify the image in a variety of ways, including adjusting the angles and rotations, which helps the algorithm acquire knowledge of all of the potential scenarios that could occur with an image. Figure 3.2 contains a depiction of the extended data sample that may be found in the database. (a) signifies Bagda, (b) represents Deshi, (c) represents Golda and (d) represents Horina species. After the improvements were finished being made, the total number of photos was 38,042.

(a) Bagda (b) Deshi

(c) Golda (d) Horina

Figure 3.2: Augmented images.

3.3 Data labeling

In order for the classification method to work as intended, the dataset needs to have accurate labels applied to it. There is a possibility that the weight and bias value will change as a result of the combination of one class with another. As a result, we carried out these processes with an extreme amount of prudence. Figure 3.3 is where you can find the representation of the labeling % for our balanced dataset.

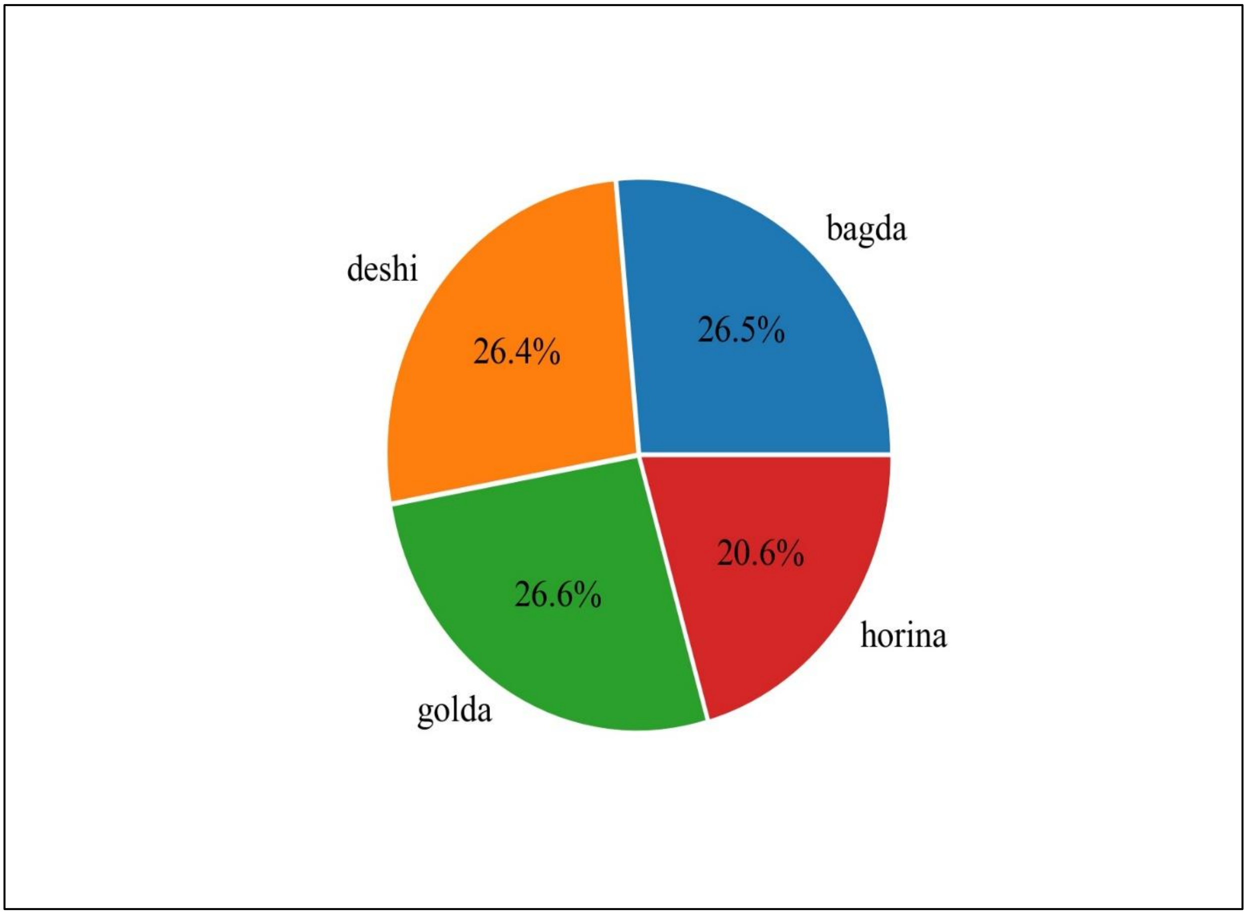

Figure 3.3 Representation of the dataset

The major representation of our dataset is shown here in this figure. Here, we can see that our dataset has four levels: deshi contains 26.4% of the data, golda gained 26.6%, horina achieved 20.6%, and bagda has 26.5% of the data. There is not a significant difference between the levels of our dataset. Therefore, it is an even-handed dataset. Additionally, it indicates the precision of our dataset once the preprocessing has been done.

3.4 Implemented Algorithm

Convolutional networks do not understand images as having patterns in two dimensions but rather as having volumes in three dimensions. This stands in stark contrast to the capabilities of humans to sense the world that they are surrounded by. When compared to the two-dimensional field of vision that each of us possesses, the capacity of convolutional networks to detect the depth of information included within an image is a significant advantage. Convolutional networks can read the depth of information included inside an image.

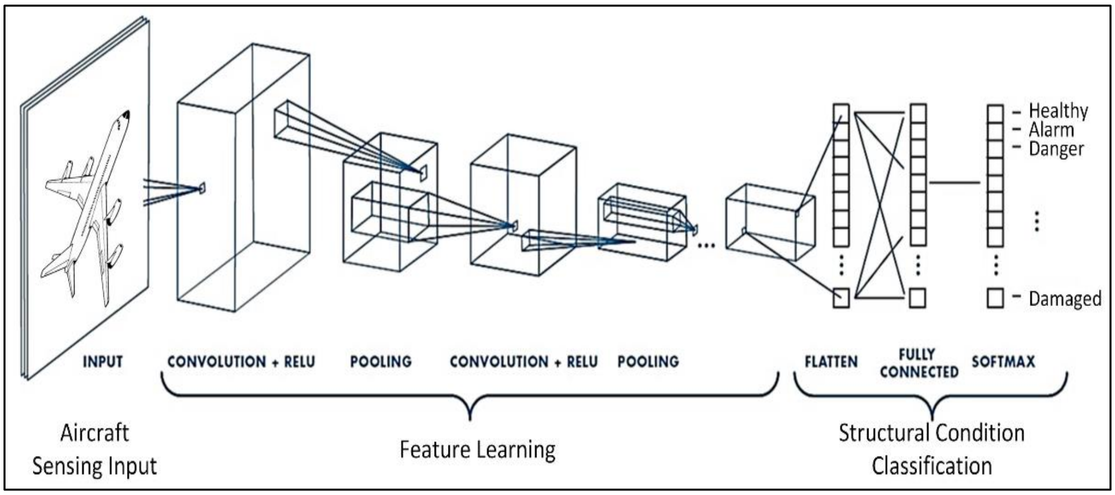

Figure 3.4 CNN architecture

A convolutional network is required to first consume an image in three distinct depth layers or channels before it can analyze an image since a picture is encoded using the RGB color model. This is necessary before the network can process the picture. This is essential for the network to accomplish in order for it to correctly analyze the image. Before the pixel squares are used in the calculations of the convolutional network, they go through a filtering process first. It is the job of a filter, which is also known as a kernel in some contexts, to scan through a group of pixels in order to locate patterns that appear repeatedly. The number of steps that a filter's path takes through an input image is used to determine the activation map for that path, and the size of the map is proportional to the number of steps that the path takes through the image. The creation of images is accomplished mostly via a method that involves the utilization of patterned pixels. These patterns paved the way for the creation of new activation maps, which in turn paved the way for the formation of this new volume. This new volume came about as a result of the formation of this new volume. Both the amount of time required to process these images as well as the number of computer resources that are required have considerably increased as a direct result of the increased dimensionality of these images. Convolutional neural networks were able to successfully address and fix this issue because they made use of dimensionality reduction tactics such as filter stride and downsampling. Those two techniques are examples.

3.5 Prerequisites for Implementation

We utilized a wide variety of machine-learning libraries all during the course of the project's execution. The numerous incarnations of these libraries are displayed further down in this section.

Python's most recent release, version 3.8, is the most up-to-date version of this computer language. It is a programming language that excels in every conceivable way and achieves the height of achievement. At this time, the research for the majority of studies is being carried out with the assistance of it. It is highly recommended for programming languages that are used in jobs that are dependent on AI owing to how easy it is to learn due to how easy it is to pick up due to how easy it is to understand. In addition, younger generations of programmers are especially fond of using it as a result of the broad adoption of it among their peers.

Google CoLab:

Users of Google CoLab are not need to pay a fee in order to make use of the open-source Python programming language distribution. Users can access this feature whenever they want, whenever they need it. Everyone who uses the Google CoLab platform has access to this advantage of the service. Even if we can finish our work online by utilizing Jupiter Notebook, we also have unrestricted access to a virtual GPU. This gives us a lot of flexibility. This affords us a great deal of leeway in our decisions. The following is a summary of the most significant benefits that result from participating in this Google CoLab activity:

The following are some of the criteria that need to be met, not only for the software but also for the hardware: RAM, a web browser with more than 4 gigabytes of memory, an operating system (it is recommended that you use Windows 10), and an operating system (more than 4 GB)

3.6 Recapitulation

In Chapter 3, we discuss analysis approaches, which help to contribute to the development of mathematical methodologies that are used throughout the rest of this book. These mathematical methodologies are used in a variety of contexts. Within the context of the growth of the mathematical methodology covered in this book, these methods are covered in depth. In addition, the following chapter will walk you through the process of how the Machine Learning classifier works its way through it step by step. Access can be granted to the raw data, data that has been preprocessed, data processing, algorithms for the classifier, and all of the other steps that are necessary. This encompasses anything and everything, from the data in its raw form to the data after it has been preprocessed.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Introduction

At this stage, we analyzed the classification report in order to evaluate how well each of our three models performed. Due to the fact that accuracy does not simply consist of possessing the appropriate matrix for the most effective model selection. [14] Therefore, the categorization report that we present includes not one, not two, but three separate metrics. These measurements are recall, precision, and f1-score.

Table 5 contains the report that may be obtained for the model 1 classification system. The best possible F1 score goes to Deshi, whose precision rate has a maximum of one, whereas Bagda's recall rate has a maximum of one. Deshi has the highest possible accuracy rate. In addition, the overall accuracy is 96% based on the 3122 data points that were considered.

4.2 Experimental Result

In this step, we analyze the results of our research, and we use three models to clarify the results of our algorithm. The three models display three different classification reports. In addition, we used several parameters for the accuracy and acceptability of each model's results. Precision, recall, and f1 parameters make the results of our three models apparent and acceptable. Finally, we used three parameters to compare our accuracy. The accuracy was reasonably balanced with the three parameters.

Model 1

The report on Model 1's classification can be seen in Table 4.1 below. For the purpose of our research, we selected four different shrimp. Bagda's recall Score came back with uniform results of 1, which is the same as the height value of the other two Metrix Precision contents, which came in at 0.87, and the F1 Score, which was 0.92. In the instance of Deshi, three metrics are operating at a satisfactory level, with Precision equal to 1, Recall equal to 0.98, and F1-Score equal to 0.99%. Both Golda and Horina made significant improvements to their scores. Horina did not gain more than 0.95 percent of any of the three matrices combined. The other two metrics, Macro avg, and Weighted avg provided results for accuracy that were equal to one another, with the exception of Recall. This indicates that our algorithms have successfully produced accurate and reliable results. Based on the findings of our research, Model 1 had an accuracy of 96% out of a total of 3132 data sets.

Table 4.1: Model 1 Accuracy Table

Label name	**Precision**	**Recall**	**F1-Score**	**Support**
Bagda	0.87	1.00	0.93	569
Deshi	1.00	0.98	0.99	874
Golda	0.99	0.94	0.97	1067
Horina	0.95	0.95	0.95	612
Accuracy			0.96	3122
Macro avg	0.95	0.97	0.96	3122
Weighted avg	0.97	0.96	0.96	3122

Model 1 shows well accuracy but it is the lowest accuracy of the three models. So we do not take this model for our future implementation.

Model 2

The analysis of Model 2's classification is presented in Table 4.2, which can be found below. In order to facilitate the completion of our study, we chose four distinct kinds of shrimp. The accuracy Score that Deshi was given was Recall with consistent findings of 1, which is the same as the height value of the other two Metrix Recall contents, which was measured to be 0.97, and the F1 Score, which was measured to be 0.98. In the case of

Horina, the Precision meter is equal to 0.95, the Recall metric is equal to 0.98, and the F1-Score metric is equal to 0.97%. These three measures are operating at a level that is satisfactory. The Bangda team has shown substantial growth in their score improvement. The precision value for Bagda is 0.99, the recall value is 0.93, and the F1 Score gained 0.96 from Model 1. Except for recall, the outcomes of the other two measures, macro average, and weighted average were identical to one another in terms of accuracy. Memory was the only metric that differed. The second model has an accuracy of 0.97%. This demonstrates that our algorithms have been successful in Model 2 and exhibit well accuracy. However, it is less than Model three. Therefore, we will not be adopting this paradigm for our subsequent application.

Table 4.2: Model 2 Accuracy Table

Label name	**Precision**	**Recall**	**F1-Score**	**Support**
Bagda	0.99	0.93	0.96	569
Deshi	1.00	0.97	0.98	874
Golda	0.94	0.97	0.95	1067
Horina	0.95	0.98	0.97	612
Accuracy			0.97	3122
Macro avg	0.97	0.96	0.97	3122
Weighted avg	0.97	0.97	0.97	3122

Model 3

The findings of the inquiry into the categorization of Model 3 are presented in Table 4.3, which may be found further down this page for your perusal. We came to the conclusion that using four distinct kinds of shrimp would make it much simpler for us to carry out the remainder of our research endeavor. The accuracy Score that was given to Bagda was a recall with consistent findings of 1, which is the same as the height value of the other two Metrix precision contents, which was measured to be 0.97, and the F1 Score, which was measured to be 0.98. In addition, the F1 Score was the same as the height value of the other two Metrix precision contents. Bagda's F1 Score was also determined to be 0.98 after being measured. When it comes to Deshi, the Precision meter has a value of 1, the Recall metric has a value of 0.96, and the F1-Score measure has a value of 0.98%. The performance of these three indicators has reached a level that is regarded as satisfactory at this point. The Golda team has shown tremendous improvement in terms of their overall Score, demonstrating that they are making significant headway. Golda has a precision score of 0.98%, a recall score of 0.98%, and a first-place finish score of 0.98%. Horina was able to get a substantial advantage as a result of the work that was done by other Models. The findings that were drawn through the use of the other two measures, the macro average and the weighted average, were accurate to the same degree as one another. The one and only deviation from this rule was the memory. The third model has an accuracy of 0.98 percent, according to the results. There was a three-model rise in the height value of model number three. Because of this, we are going to continue our research using this model.

Table 4.3: Model 3 Accuracy Table

Label name	Precision	Recall	F1-Score	Support
Bagda	0.97	1.00	0.98	569
Deshi	1.00	0.96	0.98	874
Golda	0.98	0.98	0.98	1067
Horina	0.97	0.99	0.98	612
Accuracy			0.98	3122
Macro avg	0.98	0.98	0.98	3122
Weighted avg	0.98	0.98	0.98	3122

4.3 Evaluation

The third model seemed to have the most potential, all things considered. During the evaluation phase, we will show how well the model worked by using both the training data and the test data. This will allow us to compare the two sets of data. Our Model 3 was operational for a total of 45 epochs. The accuracy of the training is depicted by the green line in Figure 4, while the accuracy of the validation is depicted by the red line in the same figure. The precision of training is continuously getting better, and at the same time, the accuracy of validation is also getting better:

Model 1

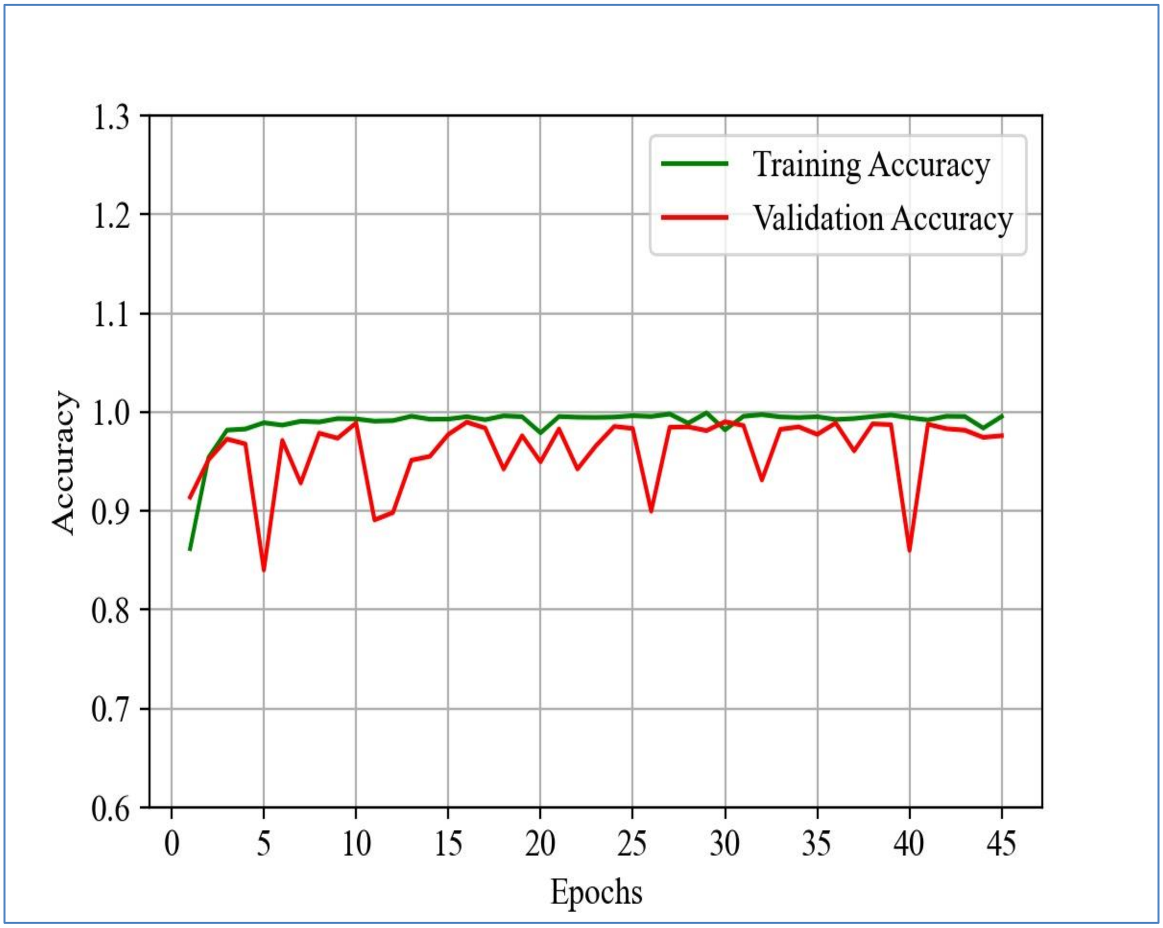

Figure 4.1: Training accuracy vs validation accuracy Model 1

An overview of the level of precision that could be obtained by training the first model is presented in Figure 4.1. The validity of the validation is indicated by the red line, while the reliability of the training is displayed by the green line. In the context of this particular model, the level of accuracy achieved in both the training and the validation phases steadily improves over the course of time. The training and validation processes need a large amount of moving in the opposite direction and regularly swapping gears. In addition to this, there is not a significant amount of distinction that can be seen between the two lines. This incidence is illustrative of the rapid rate of learning that our dataset has been demonstrating, and it is what drew our attention to the issue in the first place. Because our model 1 has a validation accuracy of 96.0 percent, it is the model that has the lowest percentage that may be equaled by the accuracy of another model. This means that it is the most accurate model.

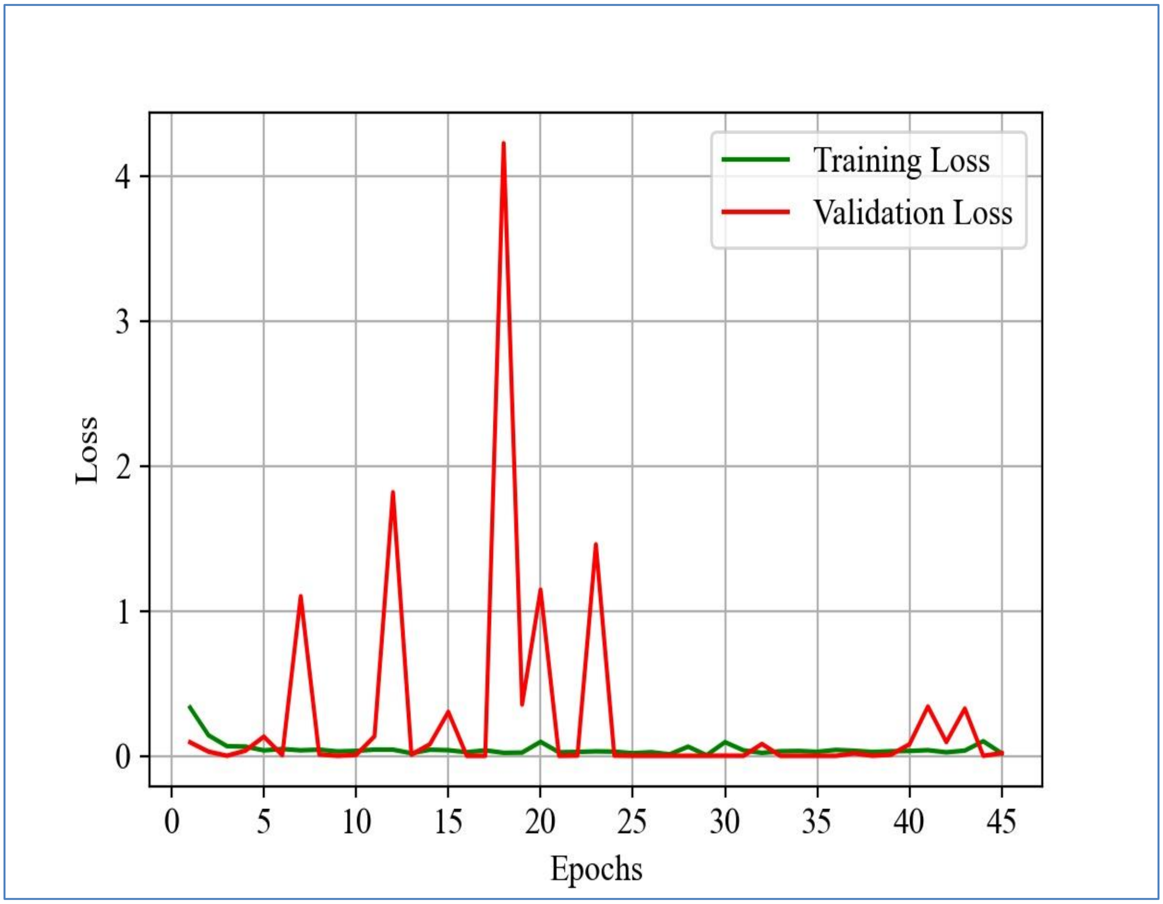

Figure 4.1: Training accuracy vs validation loss Model 1

Training loss and validation loss are often combined in a time-dependent evaluation. In contrast to the training loss, the validation loss demonstrates model 1's ability to produce its own data. Using this study, we consider how well the initial model can come up with novel results. If we take a look at Figure 4.4, for instance, we can see a potential setting in which the loss model 1 is being trained or verified. Model 1's validation loss was significantly higher than its training loss. It could quickly ascend to a skyscraping level from a somewhat high one. In a similar vein, decreasing the losses during training and validation may be accomplished by lengthening the period. Model 1 can train quickly and shows no signs of overfitting the data. The outcomes, however, show that significant information was lost during validation. However, the line of training loss accurately reflects the state, making this model inappropriate for the dataset I've decided to use for my analysis. I've decided not to use it in the field ever since.

Model 2

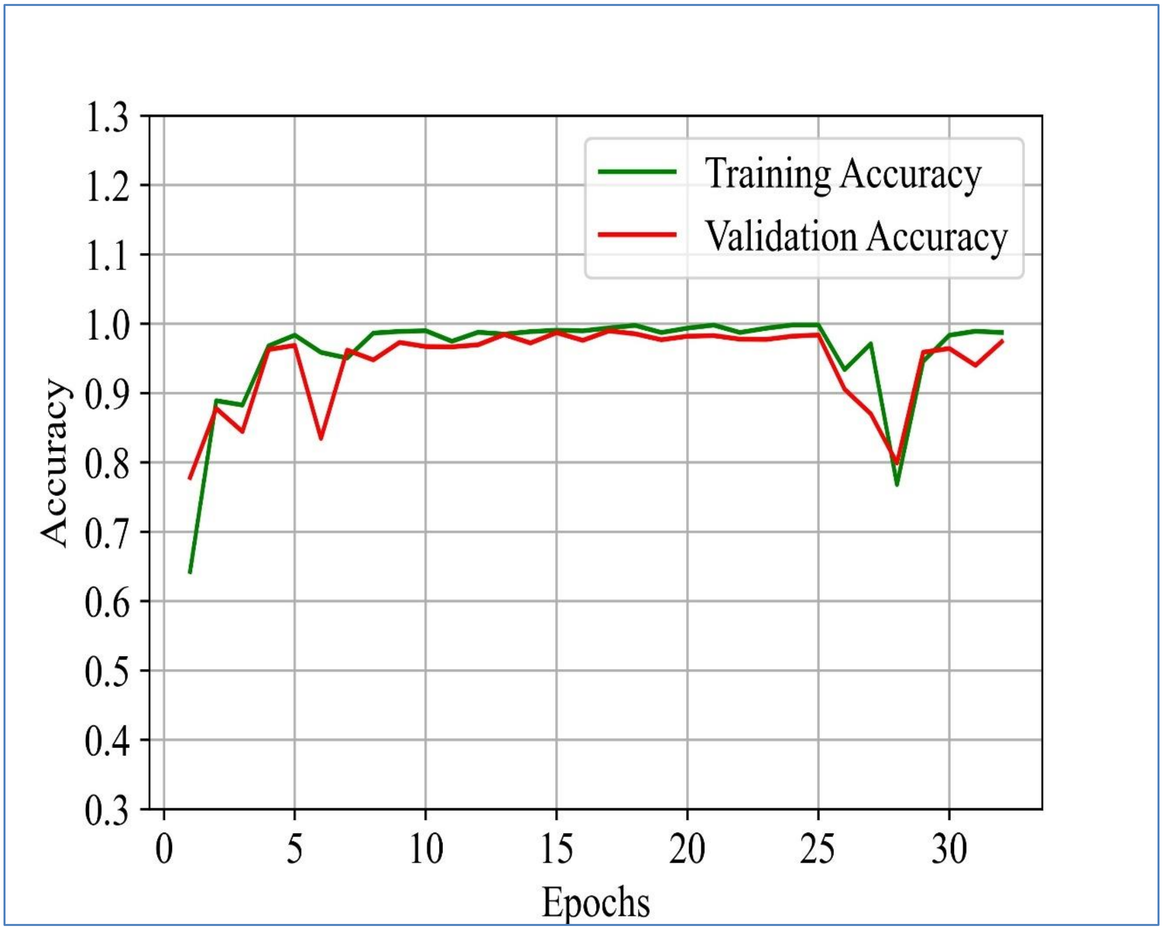

Figure 4.3: Training accuracy vs validation accuracy Model 2

The Model 2 training and validation processes are shown side-by-side in Figure 4.2 for easy comparison. The green line shows the accuracy during training, whereas the red line shows the accuracy during validation. Through training and validation, this algorithm's accuracy is improved incrementally. Both the verification and the instruction went off without a hitch. Visually, the two lines are indistinguishable. Both the validation and the training accuracy significantly deviate from one another. This demonstrates that they are continuing to advance along the same route. This incident is illustrative of the remarkable development of our data set. Describes the algorithm's effectiveness in generating desirable results. Our Model 2 validation has a 97.0% success rate, making it the second most accurate approach out there.

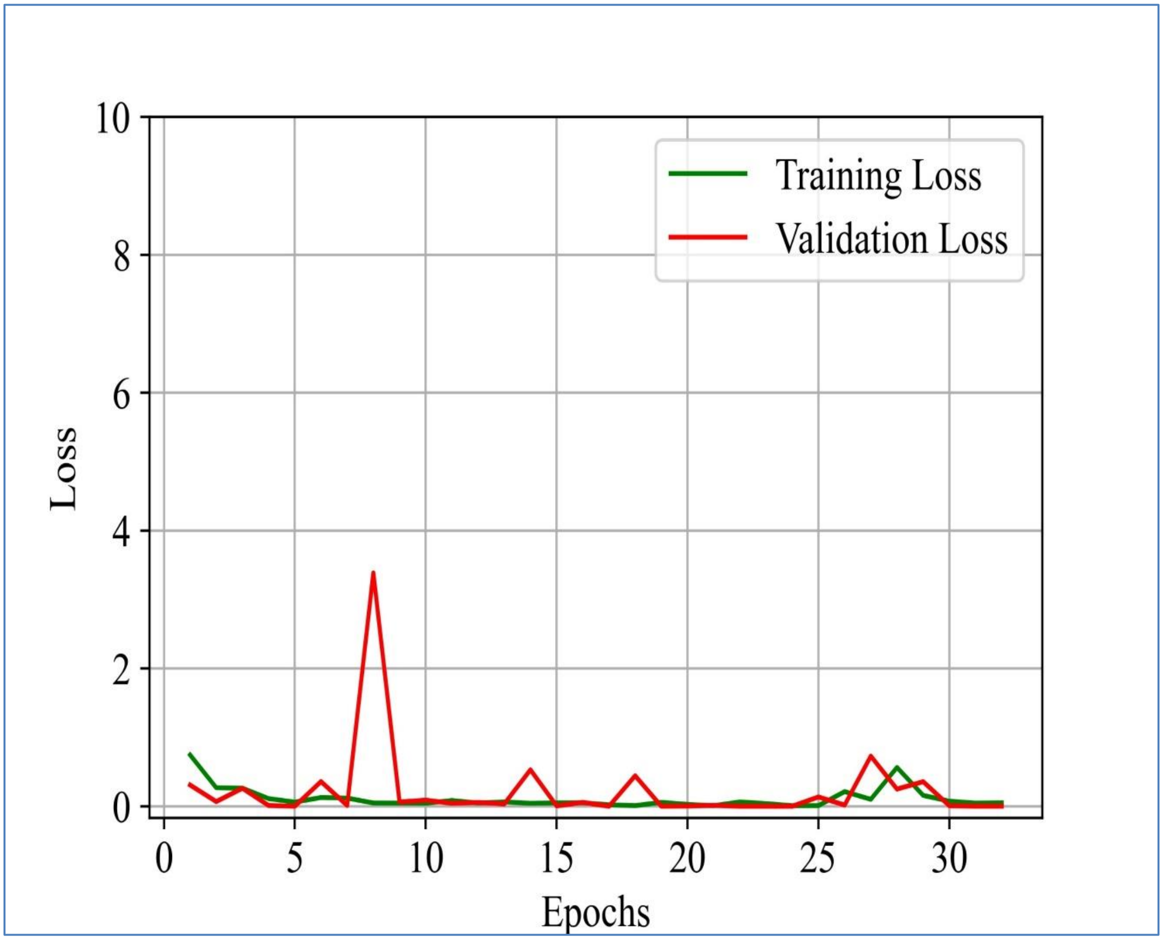

Figure 4.1: Training accuracy vs validation loss Model 2

One of the most common combinations of metrics is a comparison of the training loss and the validation loss. Whereas the training loss shows how faithfully Model 2 reproduces the original data, the validation loss shows how faithfully Model 2 generates new data. In other words, it measures how well model 2 can come up with new information. Figure 4.4 depicts an instance of training and validating loss model 2. Guarantee losses and activity losses both came out with somewhat undulating curves from Model 2. As with training loss, validation loss can be mitigated by increasing the number of epochs. Model 2 appears to have not been overfitting to the dataset, and it learns quickly. However, the findings show that a sizable amount of data was lost throughout the verification procedure. The current scenario is best described by the line of training loss. However, there was a substantial loss of data during validation. Therefore, it was ultimately.

Model 3

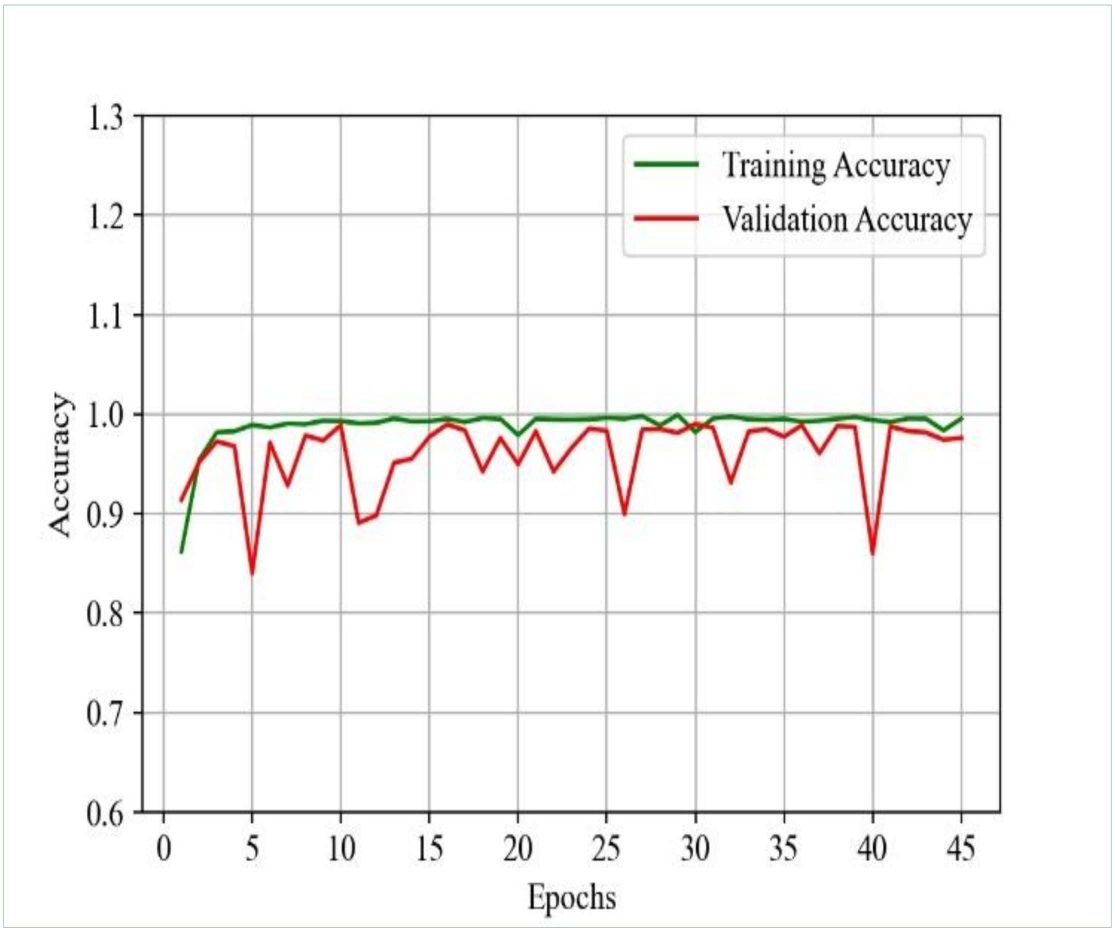

Figure 4.5. Training vs. validation accuracy Model 3.

In Figure 4.5, we see a side-by-side representation of the Model 3 training and validation procedures. The training accuracy is shown as a green line, while the validation accuracy is shown as a red line. This algorithm improves in precision over time as it is trained and validated. There were no hiccups during the presentation or the training. The two lines appear identical to the untrained eye. There is only a slight discrepancy between validation and training accuracy. This shows that they are still developing their ideas along the same lines. This is a prime example of the exponential expansion of our data set. Exhibits the algorithm's ability to provide the desired outcomes. No other technique can equal the 98.0% precision and accuracy of our Model 3 validation.

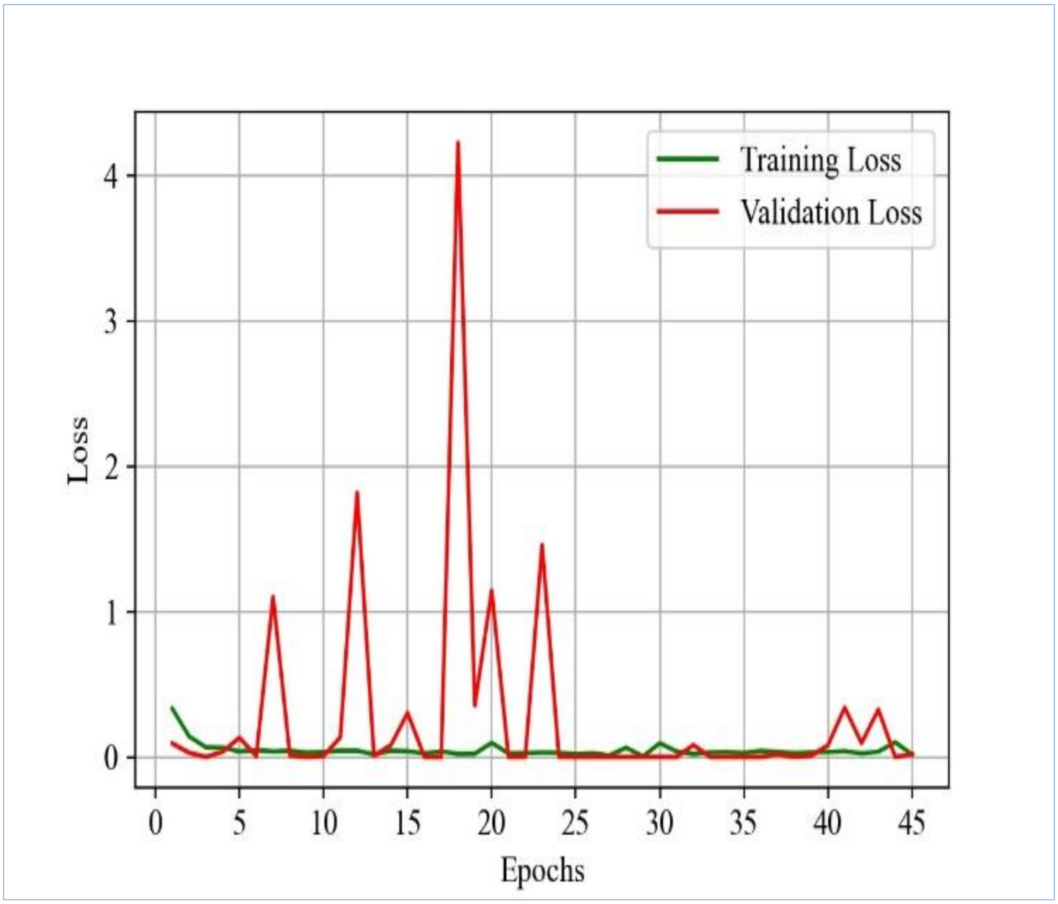

Figure 4.6: Training accuracy vs validation loss Model 2

Training loss is gradually decreasing while at the same time, the first 24 epochs of the validation line produced a zigzag line, but after 24 epochs, it nearly overlaps with training loss, and after 24 epochs, validation loss is nearly 0. Training loss is gradually decreasing, while at the same time, validation loss is nearly 0. Based on what has been said so far, our study does not involve any instances of overfitting with regard to model three. Which one is the more successful model.

Test Result

The graph that compares the actual to the predicted is shown in figure 4.6. In order to validate our model, we employed a test dataset consisting of 3122 picture data. The actual number is represented by the blue bar, while the number that was predicted by our model is given by the orange bar. In the Bagda class, 569 out of 569 photos have been correctly predicted. According to Deshi, around 839 out of 874 photos may be predicted correctly. 1046 out of 1067 photos can be recognized correctly by Golda. Horina is able to correctly identify 606 of the 612 photos it has been shown.

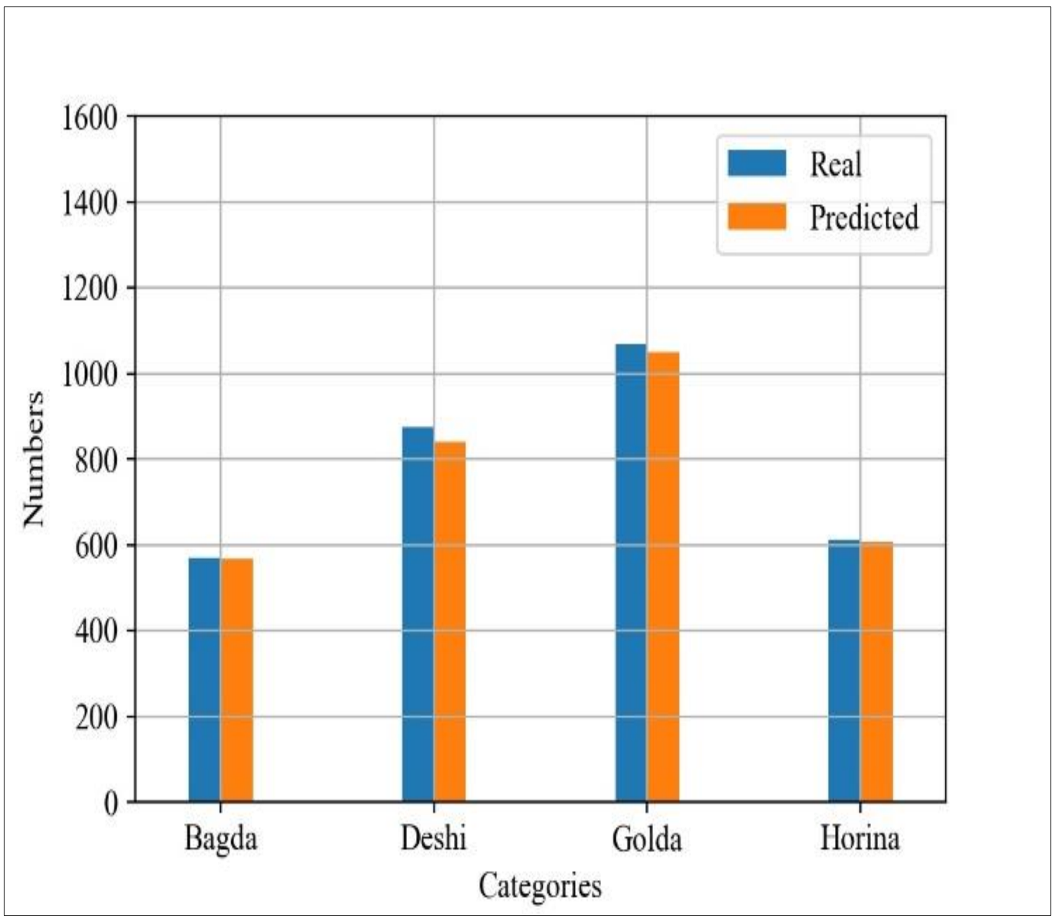

Figure 4.7: Test Result

The graph that compares the actual to the predicted is shown in figure 4.7. In order to validate our model, we employed a test dataset consisting of 3122 picture data. The actual number is represented by the blue bar, while the number that was predicted by our model is given by the orange bar. In the Bagda class, 569 out of 569 photos have been correctly predicted. According to Deshi, around 839 out of 874 photos may be predicted correctly. 1046 out of 1067 photos can be recognized correctly by Golda. Horina is able to correctly identify 606 of the 612 photos it has been shown.

It is clear from looking at this graph that our model does quite well when it comes to making predictions about the real world.

4.4 Model Implementation

Figure 4.8 presents an illustration of the application of our conceptual framework. The implementation of our model made use of OpenCV, which is widely considered to be the most well-known computer vision library. In order to produce the mask, we utilized a narrower color range of (30,30,30), however, for the rest of the costume, we utilized a wider color range (170, 200, 200). After that, we determined the contour of the shrimp by utilizing an algorithm known as finding contours. After that, we generated a rectangle that was based on the highest possible coordination value that the shrimp's contour had. In addition, the forecast from our model served as the basis for the name of the label. When you take a look at Figure 4.8, it becomes immediately apparent that our model is able to accurately identify each species.

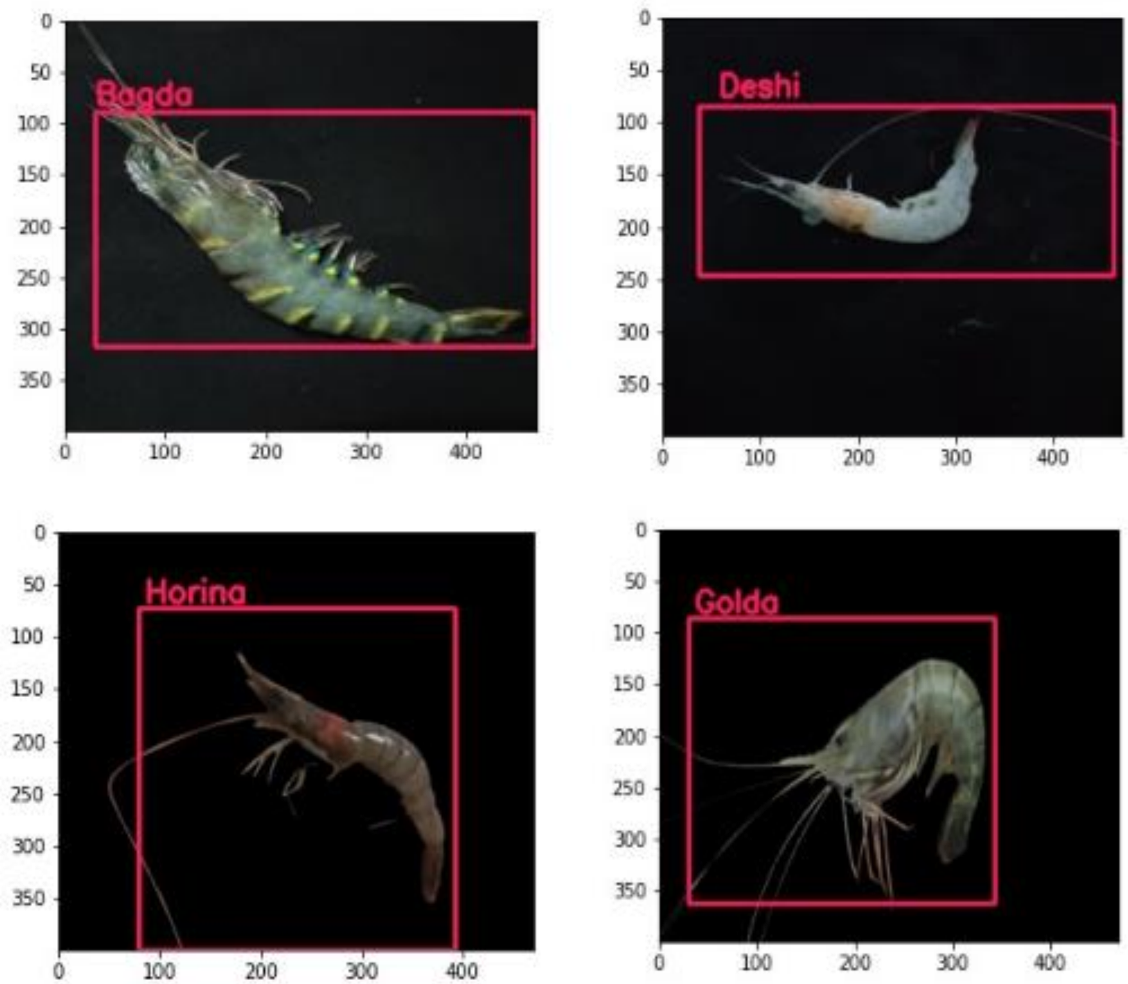

Figure 4.8: Model Implementation

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT, AND SUSTAINABILITY

5.1 Impact on society

- Our project can have a lot of impact on society.
- People can easily understand the species of shrimp fish.
- You will be able to identify shrimp fish correctly.
- No one will be deceived.
- The fish farmers will get a fair price from the sugar consumers for the right shrimp fish.

5.2 Impact on the environment

The following is a list of the beneficial effects that our project will have on the surrounding environment.

- By using our system, shrimp can be easily detected, so the sale of shrimp will increase from before. Those who do not know the right shrimp will be interested in buying it. This will increase the sale of shrimp. Its rotting will be reduced many times. This will significantly reduce the pollution in the environment.
- Our system does not cause environmental pollution because it is an automatic system that works with images.

5.3 Ethical Aspects

The project we are working on does not raise any particular ethical concerns.

It is difficult for anyone to update the programming code. It will not have the ability to be customized in any way. Therefore, its transformation won't be an easy process. In addition, we are not allowed to utilize this system in a dishonest manner. Only species of shrimp can be identified with our approach. As a result, there won't be any kind of unique ethical problem. People are able to make use of it to their benefit.

5.4 Sustainably plan

- Our sustainable plans are,
- Working with the remaining varieties of shrimp. So that ordinary people cannot be deceived into buying other types of shrimp.
- We want to enrich our database. Our results will be better.
- We will work with image quality. So that images can be uploaded easily with less data. It will reduce the cost of the internet. Interest in using our system will increase.
- We want to make the language of this system Bengali and English so that everyone can use it.

CHAPTER 6

CONCLUSION, FUTURE WORK

6.1 Conclusion

An example of a method for classifying the many species of shrimp that can be found in Bangladesh was offered in this publication. With the support of this endeavor, individuals who are not well-versed in the many species of shrimp will be able to correctly identify them. When shrimp of various species are packaged together for the purpose of being shipped overseas, it is necessary to ensure that these shrimp do not become mixed up with one another. This is another important real-life implementation area to consider. Through the utilization of this initiative, there is also the chance to capture shady businesspeople who crossbreed different species in order to improve their profit margin. The goal of these individuals is to enhance their profit margin. In this particular piece of work, the classification of shrimp images was accomplished through the application of the CNN algorithm. We used our own personally acquired and reasonably sized image dataset, and with the help of our own architecture, we were able to achieve an accuracy of about 99%. Our image dataset was manually acquired by us, and it was fairly large. As a result of one of the limitations, we were unable to collect representatives of all of the different species of shrimp. Only four of the 56 species are regularly utilized in the work that we do. One of these restrictions is that the dataset has to be too vast for the processing resources that are now available. We worked with enormous datasets using a graphics card that had an NVIDIA 1650, which isn't the most efficient way to do things.

6.2 Future Work

In the future,

- Our primary focus will be on finding a solution to the work constraints we currently face.
- We are going to make an effort to acquire all of the different kinds of shrimp. And we should make an effort to expand our dataset without resorting to data augmentation approaches.

- We are going to make an effort to develop a CNN architecture that is deeper by utilizing more processing resources.
- After that, we will make an effort to create an app for Android and iOS based on this model in order to improve the accuracy with which we recognize all shrimp 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] Tanha Talaviya, Dhara Shah, Nivedita Patel, Hiteshri Yagnik, Manan Shah, Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides, Artificial Intelligence in Agriculture, Volume 4, 2020, Pages 58-73, ISSN 2589-7217.

[4] 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.

[5] X. Li, Y. Tang and T. Gao, "Deep but lightweight neural networks for fish detection," OCEANS 2017 - Aberdeen, 2017, pp. 1-5.

[6] 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)

[7] Ahsan Jalal, Ahmad Salman, Ajmal Mian, Mark Shortis, Faisal Shafait,Fish detection and species classification in underwater environments using deep learning with temporal information, Ecological Informatics, Volume 57, 2020, 101088, ISSN 1574-9541

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

[9] Hassanien, A., Tolba, M., Shaalan, K., Azar, A. (eds) Proceedings of the International Conference on Advanced Intelligent Systems and Informatics 2018. AISI 2018. Advances in Intelligent Systems and Computing, vol 845. Springer

[10] 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.

[11] Sharmin, I., Islam, N.F., Jahan, I. et al. Machine vision based local fish recognition. SN Appl. Sci. 1, 1529 (2019)

[12] Rimi, I.F., Habib, M.T., Supriya, S. et al. Traditional Machine Learning and Deep Learning Modeling for Legume Species Recognition. SN COMPUT. SCI. 3, 430 (2022)

[13] Maider Vidal, José Manuel Amigo, Pre-processing of hyperspectral images. Essential steps before image analysis, Chemometrics and Intelligent Laboratory Systems, Volume 117, 2012, Pages 138-148, ISSN 0169-7439

[14] V. Thakkar, S. Tewary and C. Chakraborty, "Batch Normalization in Convolutional Neural Networks — A comparative study with CIFAR-10 data," 2018 Fifth International Conference on Emerging Applications of Information Technology (EAIT), 2018, pp. 1-5,

[15] Sturm, B.L. Classification accuracy is not enough. J Intell Inf Syst 41, 371–406 (2013)

APPENDIX

The first was to outline the procedures for the analysis, which presented a number of difficulties. The report was the first. Furthermore, no progress has been made in this area previously. Indeed. It wasn't your typical job. We couldn't find someone who could help us that much. Another stumbling block was data collection, which proved to be a huge issue for us.

- We created a data-gathering corpus because we couldn't locate an open-source Bangladesh text pre-processing program.
- We've begun manually collecting data. Furthermore, classifying the various postings is a difficult task.
- We might be able to achieve it after a lengthy time of hard labor.

PLAGIARISM REPORT

Plagiarism Report

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