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Explainable Deep Learning for Bangladeshi Prawn Species Identification

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Abstract

Aquaculture Shrimp and prawn account for a significant share of the market in Bangladesh, with a 70% share of the agricultural sector. Accounting for 70h is exported in this sector. The species are morphologically indistinguishable, and farmers and exporters report misidentification. Accurate species identification is crucial for promoting species-specific farming, ensuring export quality, and supporting sustainable aquaculture. In this paper, we introduced and evaluated the performance of three DL models: VGG19, ResNet50, and a Custom CNN model for four species (Bagda, Deshi, Golda, Horina) with 6,000 images. We pre-processed and labelled the dataset with augmentation for robustness and evaluated the model using positive and negative precision, recall, and F1-score. We study the thermoregulation of honey bees and utilise SHAP explainability to confirm the models on biologically interpretable features: antennae and body shape. The results showed that the Custom CNN achieved the highest accuracy (97%), followed by VGG19 (96%), and was inferior to ResNet50 (79%). The precision fluctuated slightly in the Custom CNN, but it made the most accurate predictions. Additionally, VGG19 was trained and performed well in prediction. In conclusion, the proposed work results showed that deep learning, specifically VGG19 and a custom CNN, can be effectively explained and is impressively useful practically for prawn species identification, which can be helpful in monitoring and positively impacting the export of shrimp from Bangladesh.

Keywords: Deep Learning; Prawn Species Identification; VGG19; ResNet50; Custom CNN; Aquaculture; Computer Vision; SHAP Explainability; Bangladesh; Image Classification

1. Introduction

Aquaculture is one of the fastest-growing sectors in Bangladesh, making significant contributions to food security, employment, and foreign exchange earnings. Among the aquatic resources, prawns have a unique importance as they are highly demanded in both national and international markets. Staple varieties, like Bagda (black tiger prawn), Golda (giant freshwater prawn), Deshi (native species), and Horina, present significant means of livelihood for coastal and rural communities' people. Bangladesh is considered to be one of the largest exporters of prawns and shrimps in the world. The contribution of the fisheries and aquaculture sector to the national GDP is about 2.5%, and to the agricultural GDP it is above 22%. In the fiscal year 2024–24, fish and fisheries products brought about BDT 6,145 crore (approximately USD 600–620 million) worth of exports to the country, with shrimp and prawn contributing more than

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USD 300 million annually [1]. Such exports are vital to the foreign exchange of the country, both supporting the balance of trade and the balance of payments, the net worth of which was estimated at USD 23.9 billion at the end of 2023–24. Improving the quality of the exportable items and competing in global marketplaces is of utmost importance to sustain the economic growth and the favorable balance of payments in the country [2]. Despite this economic significance, prawn species differentiation is a serious issue in the aquaculture industry. Because field buying is based primarily on gross morphology (size, color, body markings), farmers and merchants who specialize in buying are usually required to make do with a manual inspection. This method is laborious, needs expertise, and is error-prone; it results in misclassification, low market value, and sometimes export refusal. Reliable, automatic methods for identification are necessary to ensure quality control and compliance with international trade standards. New developments in machine learning and artificial intelligence provide powerful tools for addressing this issue. CNNs have achieved great success in different application fields such as medical image, plant disease diagnosis, and fish species classification. However, the deployment of these technologies in Bangladesh is limited by a fundamental obstacle: most of the current deep learning methods are computationally expensive and also need high-performance infrastructure. In rural agriculture settings with limited resources, a lightweight, cheap, easy-to-deploy model is more appropriate. The current study focuses on the construction of disposable deep learning models to distinguish Bangladeshi prawn species. The idea of expendable highlights non-expensive, efficient, and portable models that can be deployed on low-power devices like smartphones or tablets, which means farmers, hatchery workers, and quality inspectors can have a real-time and accurate species recognition experience.

The rest of this paper is organised as follows. Section II presents related works. The Methodology was detailed in Section III. Section 4 presents the experimental results, and Section 5 discusses the effectiveness of our model. We provide a Model Implementation in Section VI and describe the results in Section VII, along with next steps.

2. Literature review

In recent years, their growing interest has been in applying deep learning and machine learning methods to solve image processing tasks. Although the problem and technique in our paper are different, a similar technique and model have been used in the related work. The comparisons below are done so as:

M. M. Hasan el. at.[3] The study pays particular attention to shrimp's importance to Bangladesh (known locally as "white gold"), where shrimp makes up close to 70 per cent of national agricultural exports. They are tolerant to salinity and can be reared in hypersaline environments. Model 1 and Model 3 achieved an accuracy of 99.01%. They decided to use Model 3 for integration into the computer vision system.

Yang el. at.[4] They introduced intelligent types in the progress of digital aquaculture, emphasizing automatic fish detection for precision farming. Challenges such as illumination variation, occlusion, noise, and dynamic backgrounds are illustrated. The review also compiles a list of open-source datasets, applications, and research prospects for enhanced aquaculture, eased by both (D)CF and CTP.

Barbedo el. at.[5] They summarised the development of computer vision in fish recognition, from early techniques to the breakthrough of deep learning during the 2010s. The article concludes by discussing recommendations and future research initiatives aimed at linking the advancement of academia to industry's requirements.

Yang el. at.[6] This review includes three potential applications of AI in aquaculture: water quality management, feed handling, and disease prediction. Some of the issues include data quality, non-scalability, and socioeconomic challenges. It states that a focus on interdisciplinary work and the development of better frameworks is necessary to enable AI to reach its full potential in aquaculture.

Hao el. at.[7] This paper describes the application of computer vision technology to a smart-feeding system breeding development, utilizing computer vision technology in the water products food industry. It presents practical applications in breeding and prospects for future breeding production efficiency. It applies in general, indicating how technological progress influences and promotes the development of intelligent feeding systems.

Xiao et al.[8] This paper investigates the problem and presents an improvement on Object Detection Underwater (ODUW), where several critical issues, including noise, poor visibility, and color degradation, deteriorate the performance of the algorithms. Constraints and the prospects for this subject are emphasized—discussion: Underwater detection directions guide.

Zhang el. at.[9] This review consolidates the available literature on the environmental context of prawn and shrimp farming in the country, with a special focus on the upper global warming potential of freshwater prawn culture. The review highlighted the scarcity of studies related to IMTA in prawn farms and recommended that on-site level studies be developed around sustainable aquaculture systems in Bangladesh.

Alam el. at.[10] The study analyses the Life Cycle Assessments carried out on shrimp aquaculture to evaluate the environmental impacts of each stage of the production process. The review suggests sustainable feed sources, improved feed conversion ratios, and renewable energy investments to curb the industry's environmental impact.

Pazmiño el. at.[11] proposed in this paper an original two-stage deep learning pipeline for the automatic detection and classification of fish in underwater images. The ODU object detection is based on the YOLO block for object detection, whereas the SCU species classification uses a CNN with a Squeeze-and-Excitation structure. Through pre-training, they achieved state-of-the-art performance with an accuracy of 99.27%, indicating the potential for practical application in marine ecology.

From the above discussion, image classification methods have been heavily used, and many of them are based on sub-integer multiples of block size, with most being designed with fish detection in mind. Instead, our work adds a new perspective to this area by utilising deep learning to classify the same type of aquatic animals across different species.

3. Materials and methods

Figure 1 shows the methodology diagram of this project. In the prawn image dataset, we have collected a dataset of 6000 raw images (Horina, Deshi, Bagda, Golda) for Bangladeshi shrimp from diversified sources. Preprocessing: The original images were preprocessed by removing undesired or low-quality images and applying data augmentation (rotation, flipping, and brightness) to emphasise different patterns. This provided higher-quality, better-balanced, and more robust datasets.:

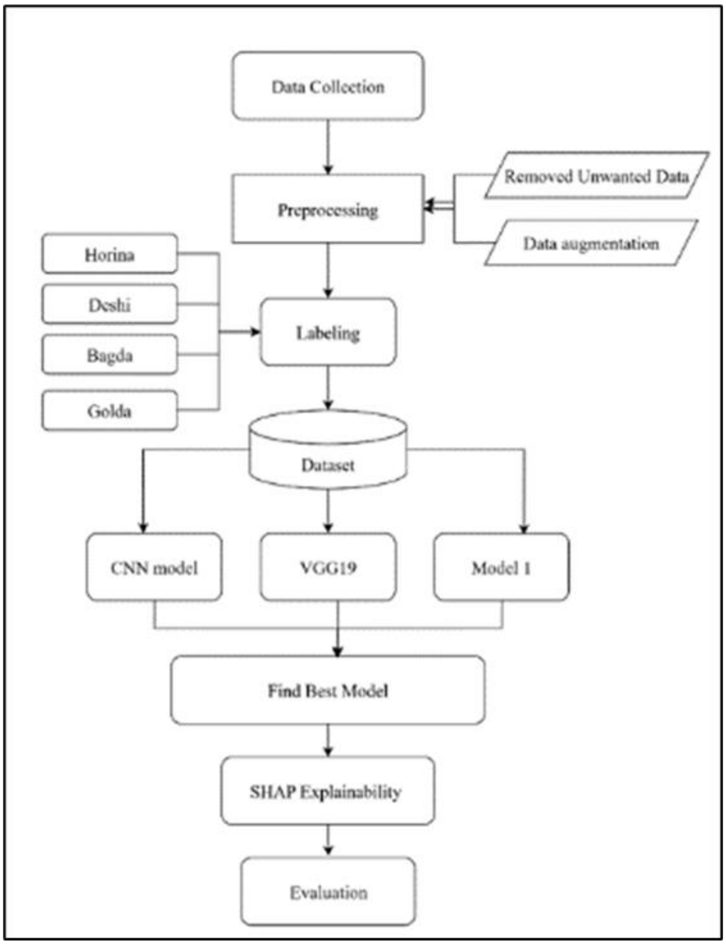

Figure 1 Methodology Diagram

3.1. Data Collection

The research was conducted using six thousand raw images of Bangladeshi prawn, which were already collected, representing four broader types of prawn: Bagda (Black tiger prawn), Golda (Giant freshwater prawn), Deshi (Local species), and Horina. The images were sourced from a variety of locations, all featuring different local fish markets, hatcheries, and farms, with a patchy natural diversity in terms of size, color, orientation, and background features [12]. Augmentation of the dataset involved flipping, rotation, cropping, scaling, and adjusting brightness.

3.2. Preprocessing

The preprocessing function, as input with the PRC case data, is essential to the model for training or evaluating the dataset. Synthesis dataset. Here, 6,000 raw images of four species of prawn were utilized; irrelevant, duplicated, and blurred images were abandoned to ensure quality and consistency [13]. To balance the classes and represent real-life data, we applied all typical data augmentation methods, including rotation, flipping, cropping, scaling, and brightness adjustments, to each image. These transformations enabled the model to learn the approximation of camera angle, light, and scale, and we no longer had to worry as much about overfitting to particular pixels [14].

3.3. Labelling and dataset representation

The obtained images were pre-processed and classified according to their species (prawn), namely Bagda (Black tiger prawn), Golda (Giant freshwater prawn), Deshi (Local), and Horina. The dataset sample is shown in Figure 2. For deep learning methods that require labeled images for training, the image categories were manually labeled to ensure that each image was assigned to the correct category. And with labels of that sort comes ground truth (for training and evaluating models) and knowledge of how accurate and reliable those results will be.

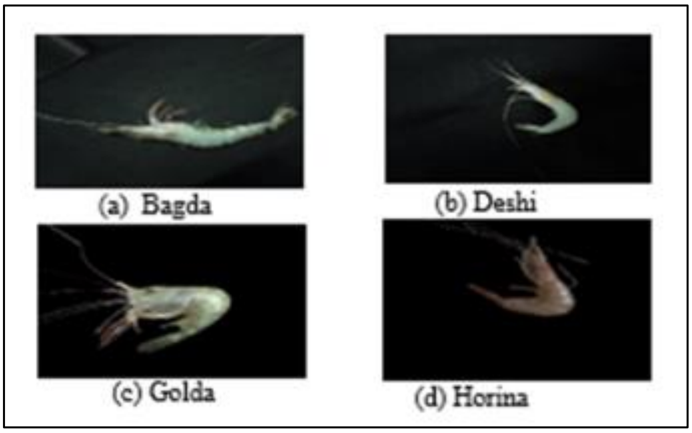

Figure 2 Sample of the dataset.

3.4. Model Comparison and Selection

The three models were evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. Models 1 and 3 both achieved an accuracy of 99.01%, which is close to the 96% accuracy of VGG19. Model 3 produced similar prediction accuracy to the selected Model 1 and was chosen as the final model due to its higher robustness across species classes and its superior validation generalisation trend.

3.5. Explainability (SHAP):

SHAP (Shapley Additive exPlanations) was applied to enhance the interpretability of the model. SHAP is a method for explaining the prediction of any model at the observation level [15]. Figure 3 shows the SHAP image representation. In prawn classification, the SHAP localisations showed which parts of an image were relevant to determining the species. The inclusion of SHAP allowed the model to predict with high performance, yet still enabled interpretability, allowing aquaculturists and researchers to have confidence in the models. We can observe in visualizations that the attention model focuses on the most informative morphological structures of species, including the head, antennae, and tail segments [16].

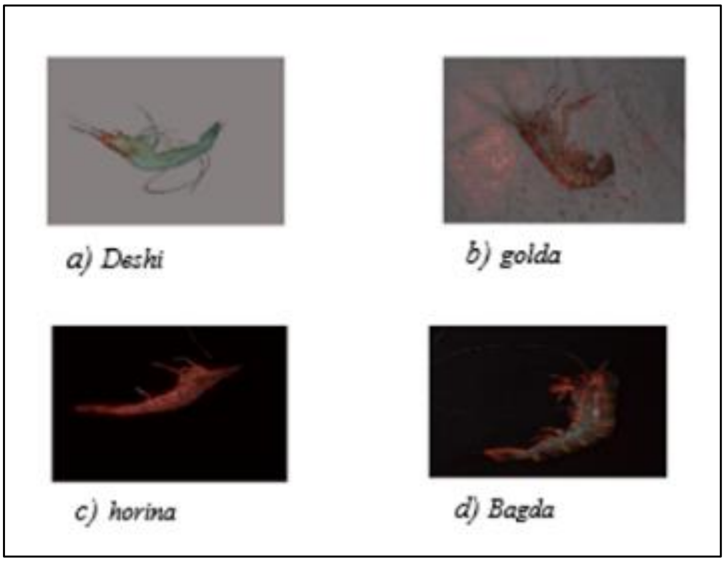

Figure 3 Representation of the SHAP image

3.6. Evaluation

For the final model, the confusion matrix as well as precision, recall, F1-score, and the overall accuracy were determined. These figures ensured that models were validated equally across all species grades of prawns. The F1-score could provide a trade-off between precision and recall [17]. This sort of comprehensive evaluation is common in computer vision literature to measure robustness against adversaries before deployment.

4. Results and discussion

The VGG16 model showed excellent performance, as shown in Table 1, for the classification of the four prawn species—Bagda, Deshi, Golda, and Horina. The total accuracy was 96% and macro-precision, recall, and F1-score were 0.96, 0.95, and 0.96, respectively. On the class-wise examination, Bagda was predicted with a precision and recall of 0.93, indicating stable recognition even for a moderate training set size. The Deshi class was the most well-classified class (Precision = 0.99 and Recall = 0.97), which means that the model performed exceptionally well in distinguishing this species [18]. Golda had a precision of 0.94 and a recall of 0.96, while Horina achieved a balance between precision of 0.96 and a recall of 0.96. The similarity between the macro and weighted averages of the models indicates that the taxa were treated equally, without bias towards those with greater class sizes, which contributed to maintaining performance across the species.

Table 1 DESIGN OF VGG16

Labels	Precision Scores	Recall Scores	F1-Score	Support
Bagda	0.93	0.93	0.93	569
Deshi	0.99	0.97	0.98	874
Golda	0.94	0.96	0.95	1067
Horina	0.96	0.96	0.96	612
Accuracy			0.96	0.96
Macro Avg	0.96	0.95	0.96	3122
Weighted Avg	0.96	0.96	0.96	3122

The results for the prawn species, as shown in Table 2, indicate that the overall accuracy of the ResNet50 model in classifying the dataset reached 79%, which is an acceptable result. In terms of the classes, Bagda has a 1.00 recall, indicating that all the actual thrown Bagdas were identified. The precision was, however, inferior (0.51), showing the considerable amount of errors (misclassifications) by other species in this class. Deshi, on the other hand, could achieve complete precision (1.00) at the cost of only 0.60 recall, indicating that many real Deshi prawns were not covered despite being predicted correctly. Overall, the Golda and Horina systems had balanced performance, achieving F1-scores of 0.87 each. The macro-average F1 score was 0.79, and the weighted average LME was 0.80, which reflects the bias in the model's performance across different species. In general, ResNet50 performed well in some classes, but it did not generalise well, especially in the precision-recall tradeoff.

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Table 2 DESIGN OF RESNET50

Class	Precision	Recall	F1-Score	Support
Bagda	0.51	1.00	0.68	569
Deshi	1.00	0.60	0.75	874
Golda	0.97	0.79	0.87	1067
Horina	0.87	0.87	0.87	612
Accuracy			0.79	0.79
Macro Avg	0.84	0.82	0.79	3122
Weighted Avg	0.87	0.79	0.80	3122

The overall accuracy of the Custom CNN shown as table 3 was 97% and was effective for four species of prawn. On a per-class basis, classes Deshi and Golda are recognised almost perfectly with precision and recall of approximately 1 by the model; F1-scores were 0.99 and 0.98, respectively. Bagda also had very high precision (0.99) but a slightly lower recall (0.93), indicating that some detections were missing. Chatfield performed slightly better than the RF model, but achieved an abysmal recall (0.64) for missing complete trails. Horina compared retaining full recall (1.00) at the expense of dropping precision (0.89), that is, by classifying other species as Horina. Otherwise, both Marco's and weighted averages were 0.97, indicating the performance balance on the dataset. Ours: The competitive ability of the Custom CNN in species classification is evident in our results

Table 3 DESIGN OF CNN

Class	Precision	Recall	F1-Score	Support
Bagda	0.99	0.93	0.96	569
Deshi	1.00	0.99	0.99	874
Golda	1.00	0.97	0.98	1067
Horina	0.89	1.00	0.94	612
Accuracy			0.97	0.97
Macro Avg	0.97	0.97	0.97	3122
Weighted Avg	0.98	0.97	0.97	3122

5. Evaluation

The loss curves of the VGG16 model, as shown in Figure 4, indicate perfect convergence and stability as the model is trained. The training loss and validation loss are both relatively low throughout the entire 30 epochs, with minimal fluctuation. More importantly, the validation loss closely follows the training loss, indicating that the model is well-generalised for unseen data and not overfitting. The rapid decay of the loss during the early epochs, which then stabilises, demonstrates the effectiveness of practical training and optimisation. These results demonstrate that the VGG16 model not only achieves excellent performance with high accuracy but also exhibits stable learning dynamics, making it suitable for the classification of prawn species.

The training and validation accuracy for the VGG16 model, as shown in Figure 5, demonstrates the model's good classification and generalisation. During the first few iterations, training accuracy grew steadily and settled at around 0.90; however, validation accuracy remained consistently higher, at around 0.99, throughout training [21]. This persistent accuracy between training and validation indicates that there is no overfitting, but rather generalisation, as validation accuracy did not drop or fluctuate wildly.

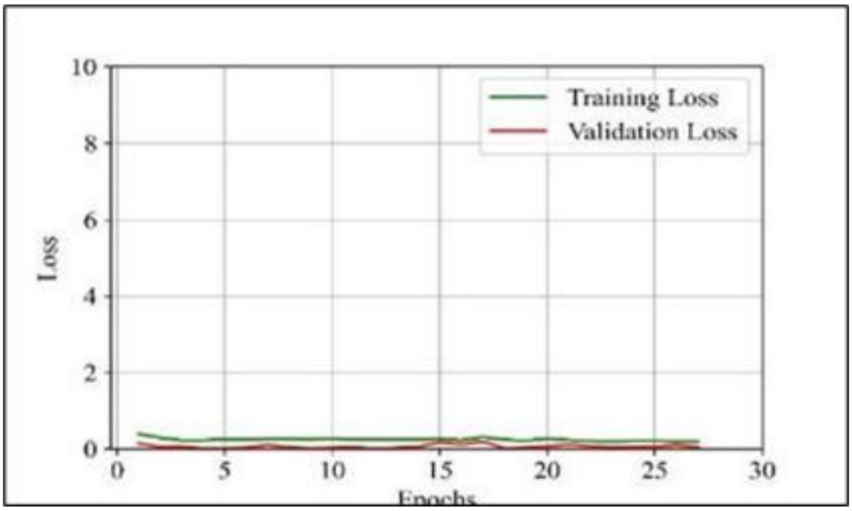

Figure 4 VGG16 training vs. validation loss.

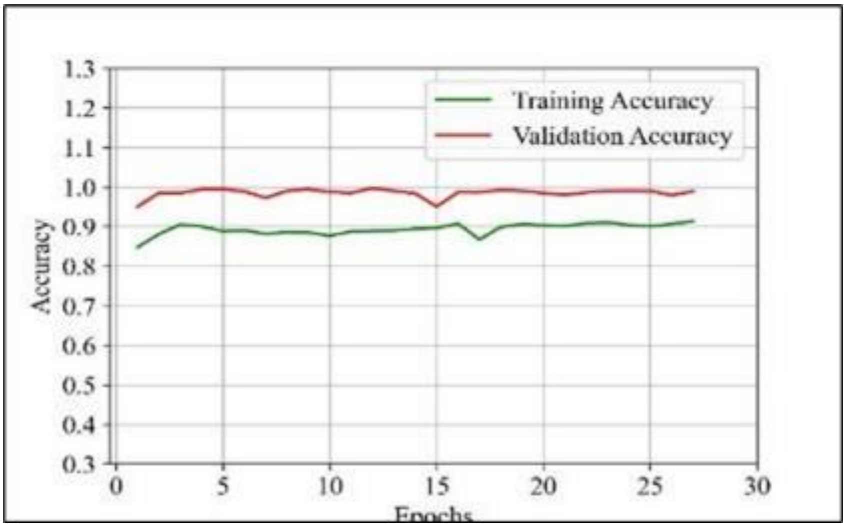

Figure 5 VGG16 Training vs Validation Accuracy

The training and validation loss curve obtained by the ResNet50 model (Fig. 6) indicates that the model has potential for early loss reduction; however, noise persisted until the end of training. The training loss value reduced steadily and plateaued at a low level, suggesting that the dataset was well learnt [22]. This suggests that there was possibly a well-fitted model, such as ResNet50, that underfitted less average convergence was slower and steadier than that of ResNet50.

The ResNet50 and accuracy plots. On that model, we have deployed (Figure 7 presents the training and validation accuracy curves for the ResNet50 model); we notice that performance is irregular, as the number of epochs is dependent. The accuracy on the training data plateaued at around 0.85 after the first few epochs of training, suggesting that our model has effectively learned the training data [23]. Validation accuracy was lower but still reasonable, fluctuating widely between epochs (approximately 0.75–0.78)

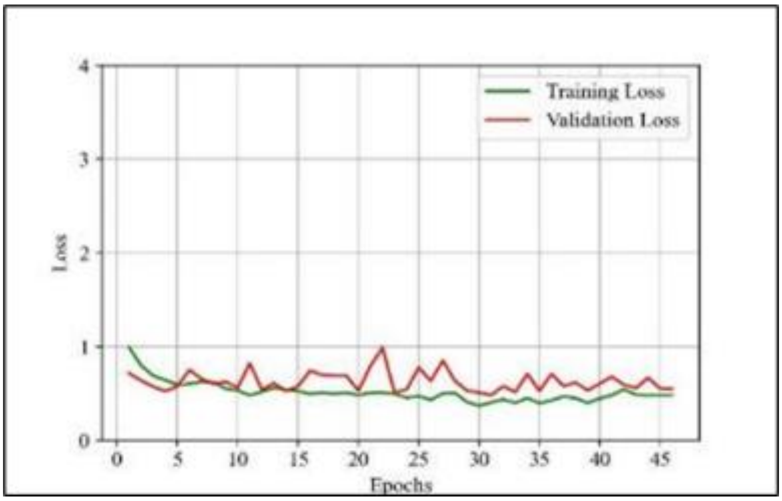

Figure 6 ResNet50 training vs. validation loss.

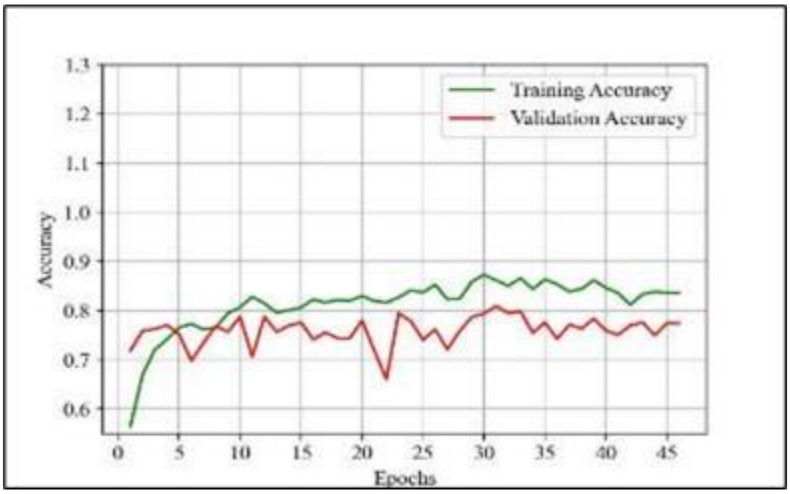

Figure 7 ResNet50 Training vs Validation Accuracy.

The training and validation accuracy plots of the Custom CNN model (refer to Figure 8) exhibit an interesting pattern. The collection turns out to be high immediately (using Resim pack may result in a high value from the beginning, ~ 0.99). The training accuracy can be quickly raised to a very high but tolerable level and maintained at a high level after a few epochs, indicating the good learning ability of the training set [24]. However, the validation results are volatile and not smooth at all, particularly at the start/middle of the epochs; the validation accuracy varies significantly, ranging from 0.30 to 1.00. This instability had it that, while the model was able to learn a high-performance solution, it was also sensitive to overfitting and the differences in the data.[25]

The loss curves of the training and validation processes for the Custom CNN model, depicted in Figure 9, show that the model learned very quickly, with its training loss reaching an extremely low value at the beginning of training and remaining nearly zero over the epochs. The validation loss, however, was unstable, particularly during the early and middle stages of training, and exhibited some spikes. Moreover, another outlier appeared around epoch 44, where the validation loss rises considerably before returning to its previous level. However, despite this high final accuracy, both the low training loss for all classes and the converging validation loss in later epochs provide support for the achieved high accuracy seen in the classification results of later epochs (97%)

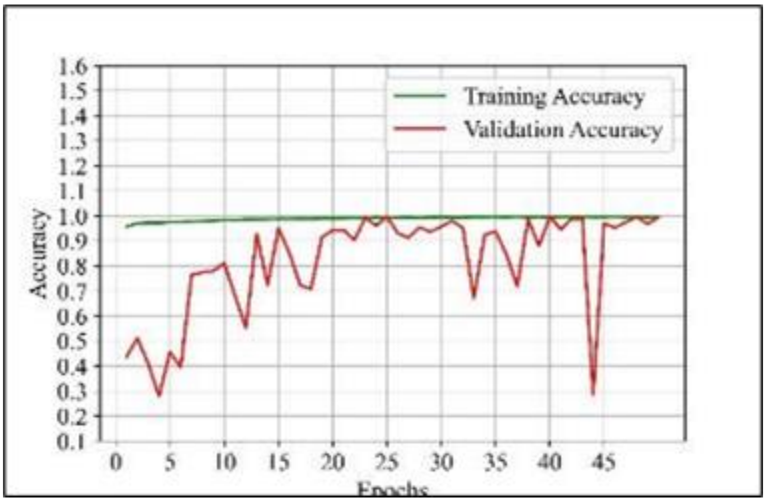

Figure 8 CNN training vs. validation loss.

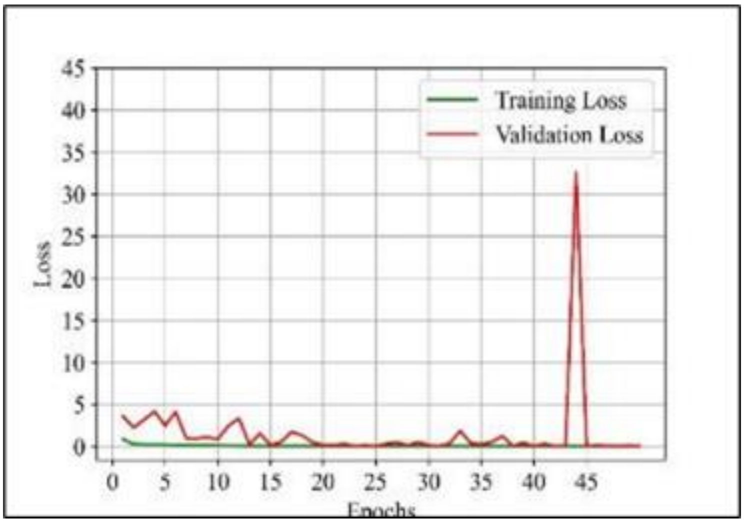

Figure 9 CNN Training vs Validation Accuracy.

5.1. Decision

The highest accuracy of 97% was achieved by the Custom CNN, which yields a promising classification, particularly for Deshi and Golda. The performance of the model fluctuated and varied by class, with IncRec performing well, exhibiting better precision and high recall for Bagda. In short, VGG16 was more balanced and stable, and Custom CNN was the most accurate but least stable. ResNet50 did not generalise well, and some species that resemble one another were misclassified. Therefore, VGG16 is feasible to deploy, leading to the exploration of a customised CNN.

6. Model Implementation

Figure 10 demonstrates the application of the learned CNN model, which learns to detect and label (with the Prwan species name) different types of prawn.[26] Every species of prawn is correctly identified. This experiment demonstrates the model's potential usability in aquaculture that demands in-situ species detection and classification for process control and monitoring of shrimp farming/export.

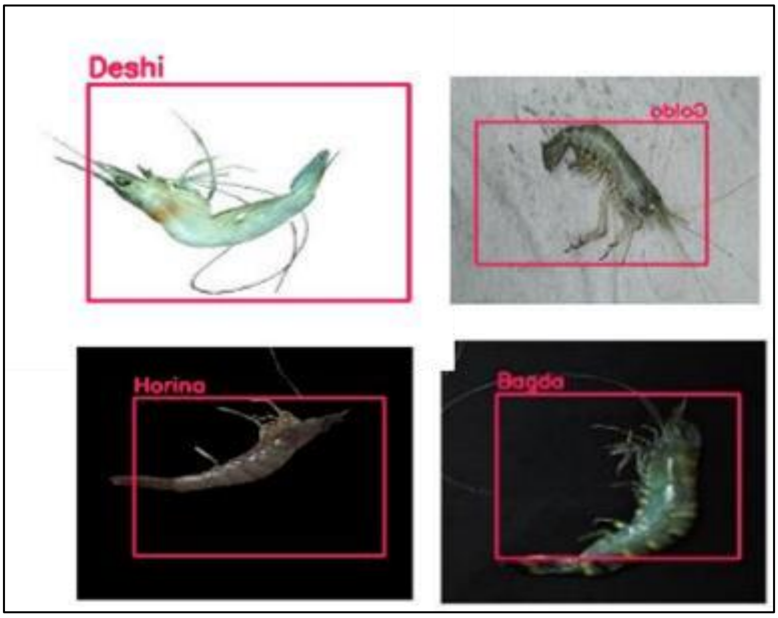

Figure 10 OpenCV implementation

7. Conclusion & Future work

This study examines the application of deep learning for the automated classification of prawn species in Bangladesh. Three models, VGG16, ResNet50, and A Custom CNN, were trained and evaluated on a dataset of 6,000 images. The Custom CNN achieves the best accuracy of 97%, followed by VGG16, which shows an accuracy of 96%. It also exhibits generalisation and generalisation ability. ResNet50 performed the worst, with 79% accuracy, mainly due to its less informative internal feature structure and class-wise imbalance. For practice usage, we decided that VGG16 was the best model; however, a custom CNN showed a promising possibility with further development.[27][28] First, new and more diverse data are being collected to provide the system with larger training sets, and hence the capacity to extend the model's robustness across more non-ideal lighting, backgrounds, and environments. Second, the variability in Custom CNN training can be minimised through hyperparameter optimisation of data augmentation and regularisation techniques. Third, the possibility of integrating the models into real-time detection systems on mobile or IoT-related platforms would reduce the distance of the models to the farmers and exporters.[29] In addition, future comparisons with the state-of-the-art architectures such as EfficientNet, Vision Transformers (ViT), and the model that combines CNN with an attention mechanism would help improve the performance.[30] Lastly, by integrating explainable AI libraries, like SHAP, with end-to-end systems, we'll be able to build confidence with users and decision makers who might have domain expertise, as they can inspect the predictions themselves.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed

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