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Parallel Mirrors Based Marine Predator Optimization Algorithm with Deep Learning Model for Quality and Shelf-Life Prediction of Shrimp

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ABSTRACT- Automatic classification and assessment of shrimp freshness plays a major role in aquaculture industry. Shrimp is one of the highly perishable seafood, because of its flavor and excellent nutritional content. Given the high amount of industrial production, determining the freshness of shrimp quickly and precisely is difficult. Instead of using feature-engineering-based techniques, a novel hybrid classification approach is proposed by combining the strength of convolutional neural networks (CNN) and Marine Predators Algorithm (MPA) for shrimp freshness diagnosis. In order to choose the best hyperparameter values, marine predator algorithm is improved using Parallel Mirrors Technique (PMPA). The proposed methodology employs a pretrained CNN model termed EfficientNet (ENet), which is combined with the PMPA algorithm to form the PMPA-ENet architecture. The proposed approach yields high performance while also reducing computational complexity. The result showed that proposed model achieved an accuracy and F-score of 98.62% and 97.25% for assessment of freshness in shrimp. PMPA's effectiveness in determining optimal values is compared to four different meta-heuristic algorithms hybridized with ENet including Particle Swarm Optimization (PSO), Simple Genetic Algorithm (SGA), Whale Optimization Algorithm (WOA), and traditional Marine Predator Algorithm (MPA). The results indicated that PMPA-ENet algorithm provides better classification compared with other algorithms.

Keywords: Deep learning, Hyperparameters optimization, Parallel mirrors technique, Marine predator's algorithm, Shrimp freshness diagnosis.

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1. INTRODUCTION

The importance of the aquaculture industry for 21st-century nutrition and food security is being recognized more and more. Future development of this contribution will require an acceleration of revolutionary breakthroughs in innovation in order to realize sustainable and equitable aquaculture. A balanced diet must include items that are found in the ocean. Aquatic food, even in little amounts, will have essential nutritious values [1]. Consumer behavior has been impacted by significant socioeconomic developments, particularly in wealthy countries. As a result of increased obesity rates and obesity-related concerns, eating good nutrition has become a well-known. Consumers and corporate distributors have shifted their attention to aquatic food systems which resulted in increased demand.

Consumers desire ease in addition to healthy and sustainable aquatic goods. Nowadays, the commodities are professionally prepared and packed, requiring minimum preparation by food sector, and through digital platforms for placing order. Purchasing through internet sites are becoming routine due to the increasing use of smartphones and mobile applications.

Numerous approaches have helped to contribute aquaculture production efficiency. Utilizing knowledge and technology has resulted in an increase in marine aquaculture productivity. Innovations and new technology will determine the rate at which aquaculture transforms to meet demand [2].

According to the World Health Organization, foodborne and waterborne illnesses kill over 2.2 million people globally each year. Seafood-borne disease is mostly caused by eating seafood that has been polluted at the source or that has gotten infected during the processing and packing. Thus, the use of science and technology has a considerable impact on molding aquaculture's industrialization and its growth as a key food security outlet.

Shrimp is widely regarded as the major ingredient in high-end, well-known cuisines around the country. Shrimp is high in various microelements and vitamins, and it also has greater healing properties, making it useful in the treatment of skin ulcers, breast bruising, and neurasthenia [3]. It is vital to accurately and immediately evaluate the freshness and shelf life of shrimp so that consumers and business may avoid health concerns and food waste.

Currently, the traditional method of assessing the freshness of shrimp is widely used. It entails human interaction in the form of direct contact with shrimp samples and analysis of quality based on visual examination and odor evaluation [4-5]. Human intervention assessment is challenging to evaluate because routine quality application measurement is uneven, error-prone, expensive, and labor-intensive. Following that, numerous well-established methods and processes for measuring shrimp freshness are introduced [6-7]. All of these procedures have advantages and limitations, with the sensory evaluation being very sensitive and selective. On the other hand, output produced through sensors is unreliable because of components used and external ecological troubles, and it also produces anomalies since it is weak and vulnerable to subjectivity [8–9]. There are now independent shrimp freshness techniques in use. Even while these stand-alone methods are helpful, a single platform that combines real-time vision-based methods with other techniques will be more effective and have a big impact on the solutions for quality monitoring that are developed in the future. Deep Learning (DL) techniques for determining shrimp freshness have recently been described. Because of its ability to learn independently, it mainly focuses on the image features that are too complicated. To increase feature extraction from data, DL techniques employ a variety of newly created models. DL is made up of multilayer neural networks that build hierarchical feature structure from raw pictures.

A common method for classifying and detecting images that uses layer-wise automatic feature extraction [11] is CNNs. Hyperparameter information is needed to prepare for classification objectives. One of the best solutions for image classification applications is deep learning using CNN. The datasets that are readily available in some situations are insufficient for creating and training a CNN. Transfer learning may be utilized in this situation to save computation expenses while still utilizing CNN's capabilities. The quality of the classification images may suffer as a result of some of the collected characteristics using CNN being inadequate. As a consequence, the task may be finished by eliminating unnecessary features using a feature selection approach.

With these factors in mind, this paper, a novel, effective method for improving deep learning-based architectures for freshness classification in aquaculture applications is proposed., in conjunction with a newly improved metaheuristic algorithm [12-13] called PMPA, which is used to select best hyperparameters from images for CNN to perform image classification. The suggested technique is PMPA-ENet, which relies on the EfficientNet model [14] to diagnose shrimp image quality and shelf life.

The following are the key contributions:

- By considering the traditional Generative adversarial network architecture (GAN), a modified GAN is proposed that improves the unbalanced data problem using image data augmentation
- An efficient architecture combining the strength of convolutional neural networks (CNN) and a meta heuristic algorithm called Marine Predators Algorithm (MPA) for shrimp freshness diagnosis
- A new robust optimizer called Parallel Mirror Technique [15] combined with Marine Predator algorithm (PMPA) to choose the best hyperparameter values appropriately for CNN to assess shrimp quality. The results are contrasted to other optimization algorithms.

The following sections are organized as stated: *Section 2* includes several literary evaluations. *Section 3* goes into depth regarding the dataset utilized. *Section 4* discusses the approach and techniques employed in this paper, as well as proposed model framework. *Section 5* displays the experimental results and discusses them. Finally, in *Section 6*, the conclusion is described, along with future study in this field directions.

2. RELATED WORKS

This section highlights prior work on shrimp freshness determination. Many studies have been carried out on the shrimp freshness assessment method.

An approach for evaluating the freshness of frozen seafood utilizing an excitation emission matrix and a charge coupled camera was reported by Md. Mizanur Rahman et al. in their study [16]. In this experiment, the shrimp sample is gathered, refrigerated and maintained. The hydrogen potential and ATP mixes in the frozen shrimp were checked using a fibre optic assisted fluorescence spectrophotometer. The K-value and PH esteem of the solidified shrimp elevated, according to chemical examination. Several super chilling procedures were successfully used at that time to authorize K-value visualization, and the forecast accuracy was 95% with an error of 5%.

Ainaz Khodanazary [17] provided periodic analysis methodology which employed regression and index method to assess the duration for storage, and employed principal component analysis to interpret chemical and bacteriological quality factors. Scores ranging from 0 to 3 were assigned to each quality attribute. Based on QIM, the output is linked to biological and physicochemical alterations that occurred. Analysis of variance is detected and used to compare average values. Metapenaeus affinis placed on ice has a 9-day shelf life, during which it is safe to use, according to bacteriological and physicochemical findings.

To enhance shrimp quality and lengthen shelf life, A. Taheri-Garavand et al. [18] demonstrated the synergistic effects of ozone invention and a modified air bundling procedure. Water that has been ozonated and chlorinated is used to pre-treat the samples. Samples were obtained for each designated day (third day) for analysis. Ozonated water, followed by modified barometric bundling, ensured low microbiological counts, extended shelf life and maintained acceptable sensory characteristics, and ultimately protected chemical parameters.
A method for assessing shrimp quality while they are being stored in the freezer was created by Xinjie Yu et al. [19] combines hyperspectral imaging and deep learning. The images that were gathered were used as examples, which were then split into two groups, new and old. Stacked auto-encoders (SAEs) was utilized for extracting phantom properties and were then entered to determine the shrimp's freshness grade. The data is classified using a deep learning method based on logistic

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regression (LR). A classification map-based image processing method was developed to display the freshness grade. Finally, the findings clearly show how a may be used to quickly and non-destructively determine the freshness grade of shrimp.

An internet of things based electronic nose system were used in a study by Huanhuan Feng et al. [20] to analyze changes in quality characteristics and freshness measures. At various temperatures, the specified qualities, including texture, color, sensory, and pH value, were measured and examined. To gather and combine sensory data and find patterns and correlations, principal component analysis is utilized.

According to study of Rongke Ye et al. [21], the freshness of shrimp was assessed using a number of spectrum processing techniques. The entire demonstration is based on savitzky-golay initial subsidiary, multivariate adjustment, and standard variate. Its wavelength calculations to dissect the characteristics are also used, along with four discriminant models and fractional least squares separation. The model gave the best result on SNV-CARS-ELM for shrimp quality after comparing all the calculations and methods.

3. DATA SET

3.1 Dataset Collection

Fresh samples of Pacific white shrimp (Litopenaeus Vannamei) brought from kasimedu seashore in Chennai district, Tamil Nadu. On an average, the weight of the shrimp is determined, in which one shrimp will be around 15 g per shrimp. All shrimps were cleaned immediately after purchase in pure water. Once drained, it is placed at 4 degrees celsius in a plastic container with depleted gaps. Every day for five days, shrimp samples were collected and examined. Once examined, the samples will be placed back into the refrigerator on a regular basis to preserve the same ratio. Input parameter specification are given in *table 1*.

Table 1: Input parameter specification of Shrimp data

Parameter	Values
Image Size	384×256
Zoom	No Zoom
ISO Speed	200
Focal ratio	f/4.5
Dots per inch	600
Type of image	jpeg

3.2 Data Acquisition

The image capture system is made up of hardware components such as the Raspberry Pi Zero and the Pi Camera. A pi camera is used for acquisition maintaining a distance between 10 cm to 20 cm. JPEG pictures with dimensions of 3024×3024 pixels were used in a variety of orientations. The samples are returned to the refrigerator after being photographed. During acquisition, all the components are placed in a proper to avoid external disturbances. To ensure that samples are captured with appropriate light distribution for reliable testing, the ambient lighting conditions are suitably maintained while taking images with the Pi camera for testing purposes. *Figure 1* shows hardware setup used for acquisition.

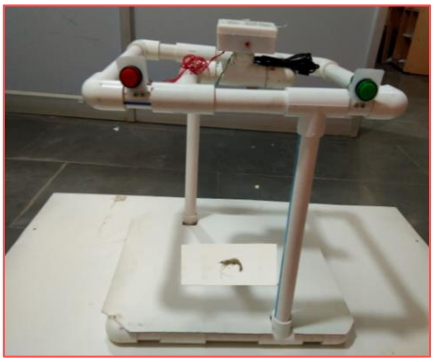

Figure 1(a): Data Acquisition System

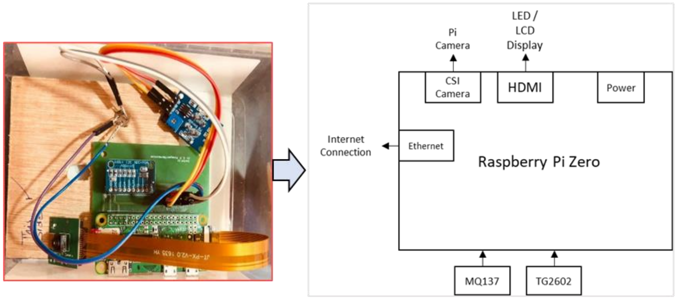

Figure 1(b): System Hardware and schematic diagram

3.3 Dataset Creation

We collected shrimp samples as image dataset and downscaled the images to 224×224 pixels because they were not all the same size. As a result, the computational load during training is reduced. Our dataset, called the Shrimp Freshness dataset, is divided into five categories: Very Fresh, Fresh, Early Spoiled, Half Spoiled, and Completely Spoiled. *Table 2* contains information about the original dataset. The class name represents all five classes utilized in this work and the number of images represents total images under each class.

Table 2: Dataset Specification

Class	Number of Images
Very Fresh	159
Fresh	138
Early Spoiled	81
Half Spoiled	76
Completely Spoiled	52

4. PROPOSED METHODOLOGY

This section introduces hybridized PMPA algorithm with ENet model for hyper parameter optimization and classification. The CNN model's hyperparameters are optimized [22] using the PMPA technique to get the optimum performance. The EfficientNet model is trained and tested with datasets. The proposed framework's process is depicted in *figure 2*. The

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subsequent sections provide thorough description of proposed approach.

4.1 Data preprocessing and Data Augmentation

Before applying data augmentation techniques to the shrimp datasets, data preprocessing techniques were used to remove the noise and resize them to 224×224 resolution, hence limiting storage space and lowering computing time. After data preprocessing, both traditional and generative adversarial network (GAN) procedures have been applied. In this framework, multiple data augmentation strategies were used to enhance training sets, reduce overfitting, accelerate the convergence process, and improve generalization.

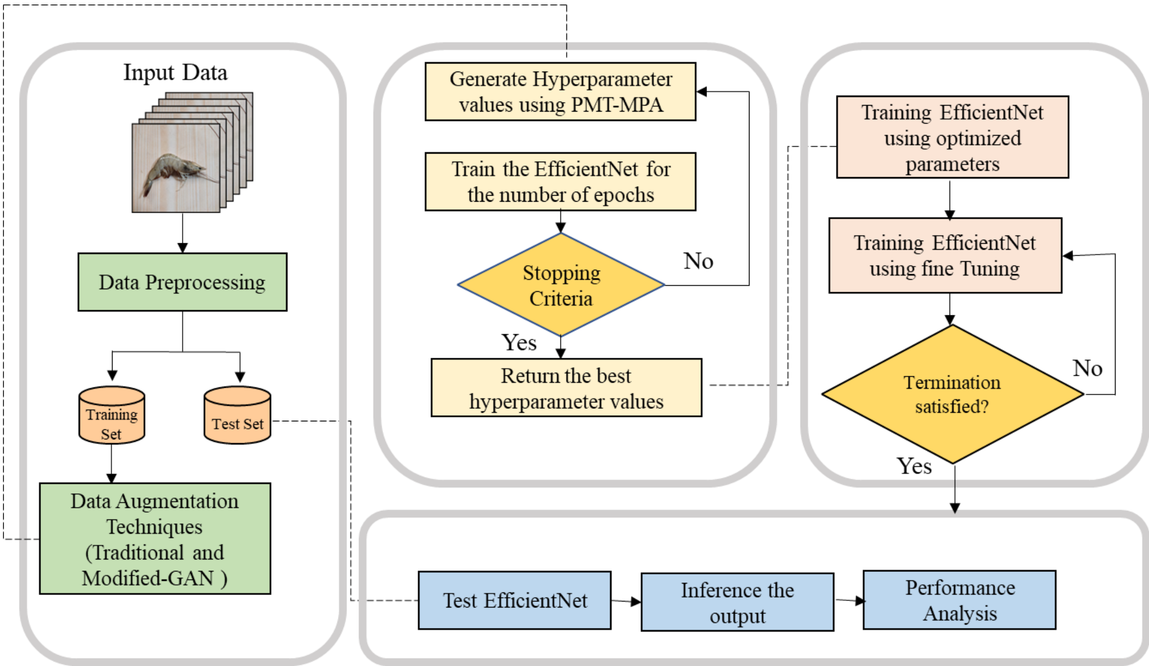

Figure 2: Block diagram of proposed framework

4.1.1 Standard Data Augmentation Strategies

In this section, standard data augmentation strategies were implemented using Image Data Generator by considering challenges like restricted datasets, as well as how imbalances and data expansion might aid in oversampling solutions. *Table 3* represents the data augmentation approaches applied and it corresponding ranges.

Table 3: Strategies used for augmentation and its ranges

Strategies used for augmentation	Range
Rotation	20
Width_Shift	0.2
Height_Shift	0.2
Zoom	0.1
Horizontal_Flip	True
Vertical_Flip	True
Shear	0.1

4.1.2 Modified generative adversarial network augmentation technique

In this section, a modified GAN is used which helps in getting sufficient and balanced dataset containing good quality images for diagnosis. GAN is an interconnection of neural networks. Totally there are two networks called as generator and discriminator [23-24]. Generator trained to form closely genuine images similar to original image whereas discriminator

is trained to find out whether the instances created by former network is real or fake.

However, the basic approach has a lot of limitations. Because the generator strives to maximize the loss and the discriminator wants to minimize the loss, there is a continual oscillation between the two. Additionally, vanishing gradients are a concern. However, it also introduces mode collapse, in which the generator intelligently chooses what to create. As a solution, numerous loss functions are employed in the discriminator in place of only one. A modified loss function is presented to regularize the discriminator weights by selecting popular and appropriate losses by integrating them with fuzzy weights. The general equation of proposed fuzzy loss function is described in *equation (1).*

$$LF = \alpha 1.Loss1 + \alpha 2.Loss2 + \cdots + \alpha n.Lossn; \quad (1)$$

where αi represents fuzzy value and $Loss_i$ represents loss functions.

Here, based on nature of our research work, we have considered three loss functions such as adversarial loss, perceptual loss and mean square error loss. These loss functions are described below in *equation (2).*

$$L_{Adv} = E_{x\sim PG}[D(x)] - E_{x-pdata}[D(x)] + \lambda E_{x\sim penalty}[(||\nabla_x D(x)|| - 1)^2];$$

$$L_{Per} = \frac{1}{WijHij}\sum_{x=1}^{Wij}\sum_{y=1}^{Hij}(\emptyset^{ij}(I^{HR})x,y - \emptyset^{ij}(G(I^{LR}))x,y)^2; \quad (2)$$

$$L_{MSE} = \frac{1}{N}\sum_{i=1}^{N}||I_i^H - G(I_i^L, \theta)||^2;$$

4.2 Proposed Optimization Method

4.2.1 Standard Marine Predator Algorithm

An optimization algorithm driven by nature based on predator motion in marine. [25]. The Levy and Brownian movements are two well-known predator types of motions. Small steps are followed by high hops in the Levy motion, which encourages exploration. In contrast, to optimize exploitation, fixed steps are followed to optimize exploitation in the Brownian motion.

During the initialization process, prey matrix is constructed with random variable position and elite matrix with position vector based on fitness value is generated. Algorithm follows iterative technique in which the instructions are executed into three stages. In the initial one-third iterations, the prey updates the prey matrix as it moves utilizing the Brownian movement as in *equation (3)*.

$$\overrightarrow{stepsizei} = \overrightarrow{R_B} \otimes (\overrightarrow{Elitei} - \overrightarrow{R_B} \otimes \overrightarrow{Preyi}) \quad (3)$$
$$\overrightarrow{Preyi} = \overrightarrow{Preyi} + P * \overrightarrow{R_B} \otimes \overrightarrow{stepsizei}$$

where $stepsizei$ denotes ith member step of a population. R_B denotes a vector using Brownian motion which is of random numbers.

Next, the prey uses Levy movement and predator uses Brownian in the second third of iterations, and the population's initial half is updated as in *equation (4)*.

$$\overrightarrow{stepsizei} = \overrightarrow{R_L} \otimes (\overrightarrow{Elitei} - \overrightarrow{R_L} \otimes \overrightarrow{Preyi}) \quad (4)$$
$$\overrightarrow{Preyi} = \overrightarrow{Preyi} + P * \vec{R} \otimes \overrightarrow{stepsizei}$$
$$\overrightarrow{stepsizei} = \overrightarrow{R_B} \otimes (\overrightarrow{R_B} \otimes \overrightarrow{Elitei} - \overrightarrow{Preyi})$$
$$\overrightarrow{Elitei} = \overrightarrow{Elitei} + P * \overrightarrow{CF} \otimes \overrightarrow{stepsizei}$$

Here, *RL* denotes a vector using levy motion which is of random numbers, while *R* denotes a random vector created using uniform distribution ranges from 0 to 1 and P is a constant parameter assigned as 0.5.

During the last third of iterations, the Prey matrix is refreshed and the Predator moves utilizing Levy motion as mentioned in equation (5).

$$\overrightarrow{stepsizei} = \overrightarrow{R_L} \otimes (\overrightarrow{R_L} \otimes \overrightarrow{Elitei} - \overrightarrow{Preyi}) \quad (5)$$
$$\overrightarrow{Elitei} = \overrightarrow{Elitei} + P * \overrightarrow{CF} \otimes \overrightarrow{stepsizei}$$

4.2.2 Improved Marine Predator Algorithm (PMPA)

The proposed marine predator algorithm is explained in this section. When the performance of generic MPA is examined, it is seen that it does not effectively search all search space options. It also suffers from a low convergence rate due to the use of discrete sections in the optimization process. Thus, the generic MPA algorithm is improved by using the parallel mirrors technique to optimize the CNN model's hyperparameters. Pseudocode of proposed algorithm is depicted in *Algorithm 1*.

Algorithm 1: Pseudocode of proposed PMPA algorithm

Input: Max_Iter, P = 0.5, Population Size N, Dimension dim, lower bound lb, upper bound ub.
Output: Best fitness and best position in search space
1. Initialize population x_i^0 randomly with dimension
2. On the initial population apply PMT using equation (7) and save result in v
3. while Iter <= Max_Iter do
4. for i <= N do
5.Using Fitness Function, evaluate x_i and save results in fit_i
6. Calculate the fitness value
7. if $fit_i < fit_v$, *then*
8. x_i = v
9. end if
10. Save memory
11.If the value of Iter is less than the value of (Max_Iter/3)
12. Prey should be updated depending on the equation (3)
13. else if Max_Iter/3 less than Iter less than 2*Max_Iter/3
14. Update the first part and second part of the solution based on equation (4)
15. else if Iter value is greater than value of (2*Max_Iter/3)
16. Prey should be updated depending on the equation (5)
17. end if
18. Save memory and update Elite
19. Apply eddy and save results
20. end while
21. Return the best solution

To improve marine predator algorithm, an opposite based learning strategy called parallel mirrors technique is used. An endless number of pictures are formed into each mirror in a parallel mirrors system. The images will be created each other successively based on the angle based on the mirrors and the angle. By following the initial image, another image will be formed constantly into the opposite mirror in the virtual space which forms unlimited number of comparable images. The PMT replicates this process in order to create new possibilities by presuming two mirrors, one on each side of the candidate. As a result, it enables dispersion of candidates over search space, boosting possibility of getting global optimal solution while eliminating locally optimal constraints. The position of each defined mirror is represented using the *equation (6)*.

$$Position\ (M1) = v - d1; \quad (6)$$
$$Position\ (M2) = v + d2;$$

where M1, M2 represents the location of the mirror, d1 and d2 are distance between each mirror, v is the original value belongs to lower and upper bound.

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Hence, images can be generated using the current candidate value as mentioned in *equation (7)*. As shown in *equation (7)*, The range in between mirror position and value affects the location of PMT. The mirrors may be controlled to recreate near or distant pictures simultaneously and will disperse images in the space dependent on the range in between mirror and value.

$$v_i = v_{i-1} \pm 2(\mathrm{i} * \mathrm{d1} + (\mathrm{i}-1)\mathrm{d2}) \qquad (7)$$

The initialization phase is the first stage of the algorithm. Three phases will be used to accomplish the optimization procedure in the following steps, as described in *Section 4.2.1*. The fitness function for each solution is then calculated using the PMT approach to update the overall best solution. Once these three steps are finished, Elite matrices are updated, and the proposed approach then chooses the best solution. We can determine the hyperparameters that this method can optimize by using it. Learning rate, batch size, dropout, number of epochs, and optimization solver are hyperparameters optimized.

4.3 Proposed Classification Method

To get the optimum performance, the PMPA method is utilized in pretrained CNN models for tuning the hyperparameters. The CNN model used to achieve classification is EfficientNet-B0 [26]. After selecting the optimal parameter values, the EfficientNet-B0 model was trained. The model is validated using dataset once it has been trained.

EfficientNet, a deep CNN which employs scaling technique by computing compound coefficient to consistently scale the parameters [27]. This technique equally increases network width, depth, and resolution using specified set of coefficients randomly. Squeeze-and-excite blocks from MobileNetV2 as well as inverted bottleneck residual blocks are used to construct the EfficientNet-B0 network. EfficientNet-block B0's diagram is seen in *figure 3*.

CNN model performance is enhanced by performing fine tuning in the pretrained model. Here, the CNN model is finetuned by replacing the fully connected layers of pre trained model with new ones and retrained. The model is composed of input layer followed by EfficientNet-B0 architecture as second layer. Following that is a completely linked layer with two thick layers and two dropout layers. The output layer employs neurons with softmax activation proportional to the input class categories. Following the construction of the CNN model, chosen hyperparameters are used to test it. *Figure 4* represents the fine-tuned model.

5. EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

This section summarizes and examines the findings obtained to validate the performance of the proposed PMPA-ENet model for determining shrimp freshness. The following is how this section is organized: *Section 5.1* describes the dataset, *Section 5.2* describes the platform utilized for this study, *Section 5.3* describes the hyperparameter settings for the optimization method, *Section 5.4* describes the proposed model analysis, and *Section 5.5* compares it to other optimization techniques.

5.1 Dataset Description

In this study, custom datasets are used for evaluation. Initially the dataset is composed of about 506 images divided into five categories. By applying data augmentation approaches, the dataset gets expanded as shown in *table 4*.

Table 4: Detailed Specification of Dataset after Augmentation

Class	Number of Images
Very Fresh	636
Fresh	552
Early Spoiled	324
Half Spoiled	304
Completely Spoiled	208

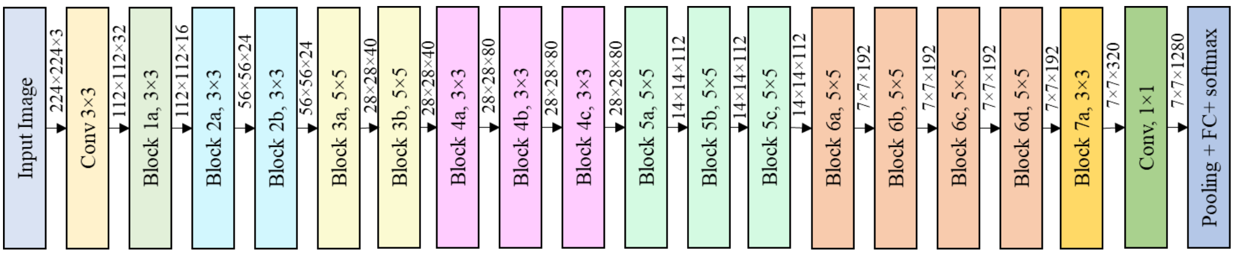

Figure 3: Block diagram of EfficientNet-B0

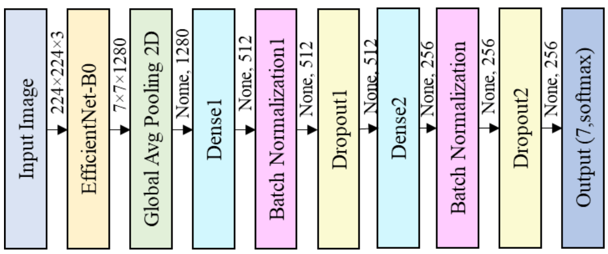

Figure 4: Proposed EfficientNet-B0

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Model performance is assessed using various sets of training, testing, and validation data. There are 2024 total food photos in the collection. A total of 506 photos were utilized for validation, or about 25%, while 1518 images, or about 75%, were used to train the model. Model learning is done using corresponding dataset. The learning process is analyzed by validating the accuracy of the model which is examined to adjust the hyperparameters. Five different random photos of shrimps are utilized following the training are shown in *figure 5*.

Figure 5: Shrimp Categories

5.2 Experimental Platform

The system development environment including both hardware and software settings utilized for the experiment are described in *table 5*.

Table 5: System development environment

System Requirement	Description
Processor	Intel Core i5
Graphics card	NVIDIA
Memory card	16 GB
Operating System	Windows 10
Development Platform	Google Colaboratory
Programming Language/ Interface/ Library/	Python 3, Keras with TensorFlow

5.3 Hyperparameter Settings

Table 6 depicts hyperparameters along with range chosen for optimization and the optimal value chosen for model training. The population is limited to 30, and 50 iterations is the maximum. The proposed optimization technique seeks to optimize the learning rate in order to fit into the optimal region. The learning rate's range should be narrower in the fine-tuning strategy since there won't be many modifications made to the model, which is necessary to prevent losing the features discovered during extraction. While searching, an upper constraint restricts the batch size. The epochs were set in such a way that the training process takes an exponential amount of time.

Table 6: Hyper parameter Settings

Hyperparameter	Range	Optimal value
Learning rate	[0.001,0.01,0.1,0.2]	0.001
Batch Size	[1,30]	30
Epochs	[10,20,30]	30
Dropout rate	[0.2,0.3,0.4]	0.2
Optimization solver	[SGD, Adam, RMSprop]	Adam

5.4 Performance Analysis of PMPA-ENet model

In this part, the appropriateness of the proposed methodology is addressed along with a thorough analysis and discussion of the outcomes. Through the use of the Marine Predator Algorithm and Parallel Mirrors Technique, an effort has been made in this work to examine and enhance the classification performance of the suggested model for classifying shrimp freshness. Accuracy, sensitivity, specificity and precision have been used as performance assessment metrics for assessing the performance of algorithms. These metrics are summarized in the section below.

Accuracy: calculates the number of successfully identified test samples. It is expressed using *equation (8)*.

$$Accuracy = \frac{(TP+TN)}{(TP+FN+TN+FP)} \times 100 \tag{8}$$

where TP defines True Positive, TN defines True Negative, FP defines False Positive and FN defines False Negative.

Sensitivity: calculates the proportion of overall positive cases that are correctly identified. It can be measured using *equation (9)*.

$$Sensitivity = \frac{TP}{(TP+FN)} \times 100 \tag{9}$$

Specificity: This demonstrates how accurate the general negative predictions were as well as how accurate the normal predictions were. It can be measured using *equation (10)*.

$$Specificity = \frac{TN}{(TN+FP)} \times 100 \tag{10}$$

Precision: calculates actual positive classes from total predicted classes. It can be expressed using *equation (11)*.

$$Precision = \frac{TP}{(TP+FP)} \times 100 \tag{11}$$

F-score: It is calculated to measure the test accuracy. It can be expressed using *equation (12)*.

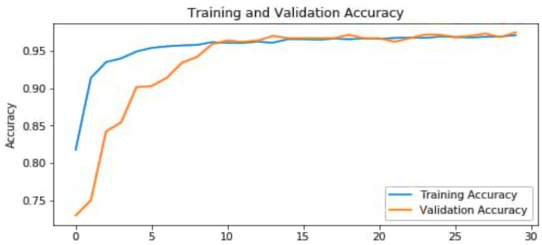
$$F - score = \frac{2*TP}{(2*TP+FP+FN)} \times 100 \tag{12}$$

Table 7 signifies proposed model perform PMPA-ENet which has achieved a classification accuracy of 98.62% on the test set. The average sensitivity, specificity, precision and F-Score were 97.24%, 98.83%, 98.71%, 97.25%.

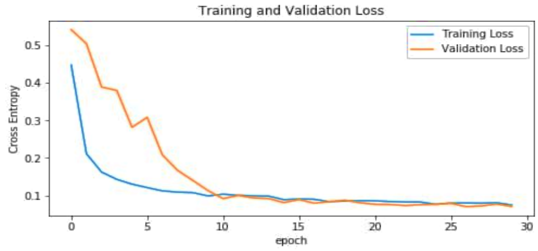
Table 7: Performance of Proposed PMPA-ENet Model

Metrics	PMAP-ENet %
Accuracy	98.62%
Sensitivity	97.24%
Specificity	98.83%
Precision	98.71%
F-Score	97.25%

The suggested model achieved an accuracy of 98.62% for the test dataset after executing 30 epochs. A high successive rate was successfully attained using the model. Analysis of the outcome and confusion matrix leads to the conclusion that this model performs satisfactorily. *Figure 6* provides an illustration of the model's overall performance. The training and validation accuracy of overall model performance are presented in *figure 6(a)*. The entire model performance's training loss and validation loss are shown in *figure 6(b)*. The model's minimized loss for both training and testing is shown on a very simple graph. Therefore, both the loss and accuracy of training and testing the model for datasets are quite well represented in the graph of *figure 6*.



(a)



(b)

Figure 6: (a) Accuracy of Training and Validation
(b) Loss of Training and Validation

The computed confusion matrix with normalisation is shown in *figure 7* along with its performance metrics, which are used to evaluate the effectiveness of the classifier in assigning freshness classes.

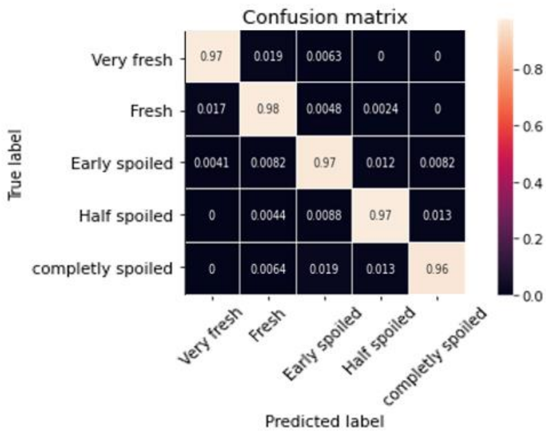


Figure 7: Confusion Matrix

Additionally, evaluation is done to compare classification outcomes of three cutting-edge classifiers. The results of the computed categorization are shown in a *Table 8*.

We contrasted the outcomes of the proposed model with those of previous studies reported in the literature, as shown in *Table 9*. However, compared to the previous similar investigations, the proposed technique shows higher superiority in freshness detecting states.

Table 8: Comparison of proposed model with other pre-trained model

Metrics	ResNet 50	InceptionV 3	VGG16	PMPA-ENet
Accuracy	87.15%	90.16%	92.36%	98.62%
Sensitivity	88.26%	91.37%	92.82%	97.24%
Specificity	89.21%	92.17%	93.21%	98.83%
Precision	87.76%	90.41%	92.54%	98.71%
F-Score	86.75%	89.34%	91.63%	97.25%

5.5 Comparison with other Optimization Algorithm

Furthermore, to show that the PMPA algorithm chooses the optimum settings for the EfficientNet model to achieve high accuracy, it is contrasted with other meta heuristic algorithms. The Simple Genetic Algorithm (SGA), Particle Swarm Optimization (PSO), Whale Optimization Algorithm (WOA), and Basic Marine Predator Algorithm were all put up against the PMPA algorithm (MPA). *Figure 8* indicates that PMPA has a more effective and quicker convergence than the other optimization techniques.

The proposed approach is compared to various optimization techniques that have been hybridized with EfficientNet which is shown in *table 10*. The comparison findings show that PMPA is more effective when combined with EfficientNet to categorize shrimp freshness.

Table 9: Comparison of proposed model with other related work

Author	Data/ Sensor	Samples Used	Approach	Prediction Accuracy
Md.M. Rahman, et al.	Excitation Emission matrix from frozen raw shrimp	48	Fluoresce imaging by partial least square regression	80%
Ainaz Khodanazary	Sensor data	200g	Quality Index method and Partial least square	96.3%
P.Srinivasan, et al.	Gas sensors	6	Pattern recognition algorithms	95.7%
Xinjie Yu, et al.	Hyperspectral image	32	Stacked auto encoders with logistic regression	93.9%

Linong Du, et al.	Sensory data	38	Principal Component analysis	91.7%
Mahdi Ghasemi-Varnamkhasti, et al.	Image data	80	Linear discriminant analysis, Nearest neighbors and Regression	90%
Proposed Work	Image data	50	EffiicientNet-B0 and Marine predator algorithm with Parallel Mirror Technique	98.62%

Table 10: Comparison of Proposed model PMPA-ENet with other optimization algorithms

Model	Accuracy	Sensitivity	Specificity	Precision	F-score
PMPA-ENet	98.62%	97.24%	98.83%	98.71%	97.25%
MPA-ENet	95.85%	93.64%	95.34%	94.34%	92.91%
WOA-ENet	94.58%	94.16%	94.82%	94.22%	95.00%
PSO-ENet	94.13%	93.10%	93.38%	94.16%	93.25%
SGA-ENet	93.38%	93.50%	93.69%	93.00%	93.21%

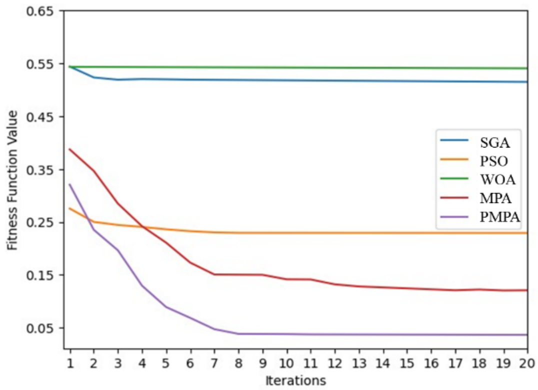


Figure 8: Convergence Curves

6. CONCLUSION

Computational image analysis is critical in determining freshness for a variety of applications. In this work, a novel classification method is presented based on a deep convolutional neural network EfficientNet-B0 that has been hybridized with the marine predator algorithm and enhanced by the parallel mirrors methodology. The proposed approach outperformed existing state-of-the-art techniques in classification performance, showing that the classification model performs best for freshness diagnosis when the hyperparameters of the EfficientNet architecture are determined using a meta-heuristic optimization process. All metrics have improved by around 3% to 4%, showing that the proposed model is reliable and efficient for determining shrimp freshness. In order to prevent health risks and food waste, the proposed effort serves to reduce quality loss and contribute to the creation of an industry4.0 feedback system.

Future applications might include chic nutritional-related organizations and clever freshness discoveries outside of the aquaculture industry. Future smartphone apps might be developed using the information gathered so that users could only take a photo of a shrimp to verify its freshness. The proposed model, which combines CNN for classification and a meta-heuristic approach for parameter optimization, has shown promising results and may be beneficial and successful in other image classification applications.

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