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A Novel Marine Predators Optimization based Deep Neural Network for Quality and Shelf-Life Prediction of Shrimp

K. Prema[1], Visumathi J [2]

[1]Research Scholar,Department of Computer Science and Engineering
Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Chennai, Tamil Nadu, India.
premak@veltech.edu.in

[2]Professor, Department of Computer Science and Engineering
Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Chennai, Tamil Nadu, India.
drvisumathij@veltech.edu.in

Abstract— Consumer satisfaction and food safety are prime concerns for seafood retailers and wholesalers. Shrimp and its products are popular all over the world and play a significant part in maintaining a healthy diet by delivering a variety of nutrients and health benefits. Fresh shrimp and shrimp products, on the other hand, are very perishable and vulnerable to the rapid formation of disagreeable scents and tastes, as well as a rapid decay process. Shrimp freshness has previously been determined using a variety of techniques, but earlier techniques lacked adequate precision. To overcome this issue, in this manuscript, a Hybrid Convolutional Neural Network (Hyb-CNN) and Support Vector Machine (SVM) optimized with Marine Predators Algorithm (MPA) for shrimp freshness detection (SFD-Hyb-CNN-SVM-MPA) is proposed for classifying the freshness shrimp and non-freshness shrimp. The real time dataset is given to mean curvature Flow (MCF) filtering method and its pre-processed images are given to the Hybrid Convolutional Neural Network and Support Vector Machine classifier for classifying the freshness shrimp and non-freshness shrimp. Generally, The Hyb-CNN- does not demonstrate the implementation of any optimization techniques for identifying the ideal parameters and assuring correct classification. The proposed Marine Predators Algorithm (MPA) is considered for optimizing the hyper parameter of Hyb-CNN and SVM which is executed in MATLAB and certain performance measures are used to assess the effectiveness of the proposed approach such as precision, recall, f-measure, accuracy, computation time. The proposed method attains lower computational time39.89%, 43.78%, and 52.67%, higher accuracy 21.35%, 18.56%, and 13.56% compared with the existing methods, like shrimp freshness detection using Deep shrimp Net (SFD-D-SHNet), shrimp freshness detection using artificial neural network and k-neighbour network (SFD-ANN-KNN), shrimp freshness detection using convolutional neural network (SVM-FCCD) respectively.

Keywords- Convolutional Neural Network; Mean curvature flow; Marine Predators Algorithm; Support Vector Machine; Shrimp Freshness.

I. INTRODUCTION

The freshness of shrimp is a significant attribute that consumers paid attention, because decayed shrimp contain many spoilage microorganisms [1 Due to its distinctive qualities in terms of flavor and elegant nature, it is one of the most well-liked aquatic life forms among people globally [2-4]. Shrimp is a very perishable meal that includes essential elements such proteins, lipids, and vitamins that are quickly absorbed [5-7]. Storage, handling, and processing interfere with shrimp's quality and freshness throughout the post-harvest period [8–10]. This serious issue is brought on by a variety of environmental changes, such as changes in temperature, pressure, odor, color, and texture, which alter the chemical characteristics [11]. Freshness is regarded as a crucial indicator of shrimp quality for customers to use in conjunction or as a basic material for manufacturing by manufacturers [12–13]. It is extremely difficult to check the freshness fluctuations of shrimp sample

instantaneously because shrimps are tiny and elastic in structure, which hinders their quality and freshness in the post-harvest period [14]. Shrimps must be processed in an efficient and healthy manner to satisfy the demands and usage rates [15–16]. It might be challenging for average

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consumers to tell whether the shrimp is fresh or not. As a result, it is more necessary and crucial to develop a monitoring system that is straightforward, dependable, affordable, quick, and precise [17].

In this paper, the real time dataset is given to MCF filtering method for removing noise. These pre-processed imageries are fed to Hyb-CNN-SVM for classifying the freshness and non-freshness shrimp. Hyb-CNN-SVM did not show any optimization techniques for scaling the best parameters for classifying shrimp freshness detection. The hyper parameters of the Hyb-CNN-SVM are then optimized using the MPA technique.

Below is the summary of this research's significant contributions:

- The SFD-Hyb-CNN-SVM-MPA is proposed for classifying the Shrimp Freshness Detection.
- The high-resolution camera initially took pictures of the shrimp, which were then processed. To reduce noise from the acquired image during pre-processing, a Mean Curvature Flow filtering approach [18] is utilised.
- The pre-processed images are fed into Hyb-CNN-SVM [19] for shrimp freshness detection
- A Marine Predators Algorithm (MPA) [20] is utilised to optimise the Hyb-CNN-SVM classifier's parameters in order to increase classification accuracy.
- The performance of the proposed SFD-Hyb-CNN-SVM-MPA based classification process is examined under performances metrics, viz precision, recall, f-measure, specificity, computation time, accuracy.
- Finally, evaluate the proposed strategy by making comprehensive comparisons with three existing shrimp freshness detection using Deep shrimpNet (SFD-D-SHNet) [21], shrimp freshness detection using artificial neural network and k-neighbour network (SFD-ANN-KNN) [23], shrimp freshness detection using convolutional neural network (SVM-FCCD) [26] ,[27] respectively.

The rest with this paper is structured as follows: Recent investigations are outlined in Section 2, the proposed strategy is explained in Section 3, the findings are demonstrated with discussion in Section 4, and the conclusion is offered in Section 5.

II. LITERATURE REVIEW

This section discusses earlier research on determining shrimp freshness. The method for evaluating the freshness of shrimp has been the subject of several investigations.

In 2020, Liu. Z [21] have presented an identification of soft-shell shrimp based on an improved AlexNet for quality assessments. Several image processing techniques made it possible to normalise the picture of shrimp. The pre-processed output was given into deep convolutional neural networks. Then, hyper-parameters of Deep-ShrimpNet were optimized that was number of local receptive fields, batch-size, learning rate and dropout ratio. It gives more precision while requiring less computing time.

In 2021, Zhang, J et.al [22] demonstrated a shrimp identification network that is completely convolutional as well as a generative adversarial network A generative adversarial network-based synthetic dataset generation technique for circumventing the time-consuming manual labelling of the convolutional neural network (CNN) method for shrimp detection. It provides low computational time and high precision

In 2020, Khiem, N, M et.al [23] proposed a machine learning method for predicting acute hepatopancreatic necrosis disease (AHPND) in shrimp farms. Machine learning was used to predict the development of AHPND using data from shrimp farms. AHPND outbreaks in shrimp farms were predicted using logistic regression. It provides higher f-measure and lower computational time.

In 2020, Srinivasan, p., et.al [24] have developed a shrimp nose to extend the shelf life and preserve the perishable quality of cultivated Pacific white shrimp, where the melanosis was examined in dissimilar time periods to assess the shrimp samples' shelf life. Then the shrimp samples were given to the Pattern recognition approaches depending on multiple-variate analyses. It provides lower computational time and higher recall.

In 2022, jasmine S.A., et.al [25] have developed a machine learning-based intelligent framework for predicting dissolved oxygen levels in a shrimp cultivation system The study data were examined for prediction, and the structure for dissolved oxygen prediction and bio floc size was given in the shrimp-based bio floc culture scheme. Then the images were given to Random Forest, Adaboost, DNN. It provides lower computational time and higher accuracy.

III. PROPOSED METHODOLOGY

This paper discusses how a hybrid convolution neural network and support vector machine are optimised with the

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Marine predators Algorithm for detecting the freshness of shrimp (Hyb-CNN-SVM-MPA). Fig. 1 shows the architecture of proposed Hyb-CNN-SVM-MPA method. The detailed explanation of shrimp freshness detection utilizing Hyb-CNN-SVM optimized with MPA are given below.

A. Image Acquisition

In this work, Shrimp samples are collected from a fish landing Centre of Kasimedu, Chennai, Southeast coast of Tamil Nādu, India [21]. The input image acquisition is captured by the thermal imaging camera. In this dataset, total 656 samples are taken. 50% of these 656 samples are used for training and 50% for testing.

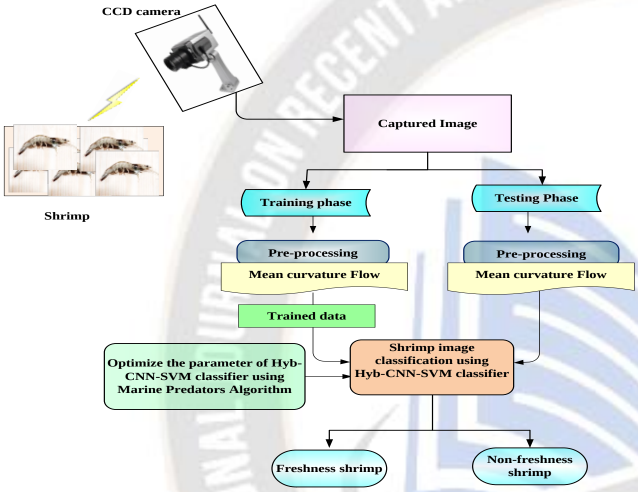

Figure 1. Block diagram of shrimp image classification using Hyb-CNN-SVM-MPA

B. *Pre-processing using Mean Curvature Flow (MCF) method*

Captured shrimp images are pretentious with noise while transmitting. Unwanted interference will cause the image quality to decline. Therefore, the Mean Curvature Flow (MCF) approach is employed to reduce noise and improve the clarity of the shrimp picture that was collected as input. The MCF partial differential equations (PDEs) and finds its credibility in several interdisciplinary scientific domains such as image processing, mathematical physics computer-aided design, PDE's theory, and geometric analysis. MCF can be expressed as in (1),

$$\bar{I}_{mcf} = \mathrm{N}\left|\nabla \bar{I}\right| \qquad (1)$$

Here, N represents the noise removal. The above equation (1) is mathematically represented as in (2),

$$N = \frac{u_a^2 u_{bb} - 2u_a u_b u_{ab} + u_b^2 u_{aa}}{\left(u_a^2 + u_b^2\right)}$$

(2)

Then, these pre-processed imageries are fed to the hybrid Convolutional Neural Network and Support Vector machines classifier to detect shrimp freshness accurately.

C. Classification using Hybrid-CNN-SVM

The hybrid model is utilized to detect the freshness of the shrimp. Detailed steps of Hyb-CNN-SVM are described below,

Convolutional Neural Network

This network contains input, output and hidden layer. Multiple function layers are present in the unseen layer. Most of the functional layers are convolutional, pooling, fully connected and normalized layers.

The main unit of convolutional neural network is the convolutional layer. This is the initial layer which contains filter that permits the shrimp's input quantity. During convolution process each filter calculating the input quantity of shrimp with dot operation. The convolutional layer does not perform manual operation to extract the image attributes. It can be calculated as in (3),

$$f(h(t)) \underline{def} \int_{-\alpha}^{\alpha} f(\Gamma) h(t-\Gamma) d\Gamma$$

(3)

From the above equation, the convolution is the multiplication of reversed and shifted function

The local and global pooling exists in CNN in the pooling layers. It lessens the measurement of the shrimp image that is attained by the consolidation of output neuron and particular neuron. Pooling scales the neuron's maximum and average value. The maximum and average pooling are exhibited in (4),

$$f_{MP1}(Y) = max_{j,i}(j,i) \qquad (4)$$
$$f_{AP1}(Y) = \frac{1}{m+n} \sum_{j=1}^{m} \sum_{i=1}^{m} Y(j,i)$$

From equation (4),$f_{MP1}(Y)$ represents maximum pooling, which maximises the value of each network, $f_{AP1}(Y)$ denotes average pooling, which averages the value of each.

The fully linked layer is also known as thick layer. It is situated at the last part of the CNN. Neurons present in this linked layer are fully linked to all activation layers in the earlier stage. The thick layer linked between the single layers of every neuron to another layer.

The Activation layer permits the network to plot the nonlinear function against the complex action. This is

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divided into two types that is saturated and non-saturated activation. Saturated activation states that the output has limited boundaries, if the output has unlimited boundaries, then it is said to be non-saturated functions.

Support Vector Machines

SVM classifier is added to last fully connected layer for classification. The proposed Hyb-CNN-SVM architecture is that the SVM classifier is connected to the fully connected layer that has been trained by the Soft-max classifier-based transfer learning network using the target dataset. SVM classifier is suggested to carry out the classification at the final layer. SVM is a direct learning computation that operates in hidden space based on class segmentation using planes or hyperplanes. The multiple dimensional data is classified into relevant categories based on SVM by calculating the optimal boundaries or hyper-planes.

The CNN fully connected layer concludes with an SVM classifier. The L1-SVM standard is used for a loss function that functions as a linear sum of slack variables using (5).

$$Min \frac{1}{n} m^t m + p \sum_{j=1}^{n} Max\left(0,1 - Rl_j\left(m^t y_j + a\right)\right) \quad (5)$$

Here, p represents the hyper parameter setting value that is penalty parameter, Rlindicates the shrimp real label, $m^t m$ denotes Manhattan (L1) standard, $m^t y_j + a$and represents the detective function. Unlike traditional computations that function by reducing the observational error size or the error's moment power, SVM reduces the basic risk for classifying the shrimp sample freshness. It may also generate nonlinear options by utilizing nonlinear bits.

After training, the parameters are updated to generate the final result, which is utilized to determine the freshness of shrimp. However, the ideal constraints of a hybrid model classifier that need to be tuned for efficient classification are employed to optimize the Hyb-CNN-SVM hyper parameter.

D. Proposed Marine Predators Algorithm for optimizing the hyper parameter of Hyb-CNN-SVM

In this study, the accuracy of Hyb-CNN-SVM is increased by using the Marine Predators Algorithm (MPA) to optimize the hyperparameter. The Marine Predators' intelligence and ability to tune their speed in different phases with their spiral trajectory for hunting served as inspiration for MPA, a meta-heuristic method derived from nature. This method is used to address issues with global optimization. In the early stages of the hunt, it exhibits increased interest in travelling widely and searching for prey, and in the closing stages of the hunt, it exhibits increased interest in attacking. Also, cruising and hunting behaviors of Marine Predators are considered for upgrading the classification parameters, which optimizes defective function for classification. Fig. 2 depicts the flow chart representation of MPA model.

Following is a step-by-step description of the MPA procedure.,

Step 1: Initialization

Here, a cluster of Marine Predators A, wherein the first trial's solution is evenly dispersed throughout the search space is described in (6)

$$A_0 = A_{\min} + rand\left(A_{\max} - A_{\min}\right) \quad (6)$$

Where $A_{min}$and $A_{max}$are denoted as the variable's upper bound, $rand$ as uniform random vector at 0 to 1range.

Step 2: Random Generation

Once the setup process is complete, the input parameters are created at random. With regard to the precise hyper parameter condition, the maximum fitness values have been selected. Create a population at random as well for precise shrimp freshness detection.

Step 3: Fitness Function

The initialized values are used to produce the random solution. The objective function indicates the parameter value of optimization for this solution for updating function of Hyb-CNN-SVM detective function is described in (7),

$$FitnessFunction = optimization[m^t y_j + a] \quad (7)$$

Step 4: High-velocity and low velocity ratio for optimizing $\mathbf{m^t y_j + a}$

In the high velocity ratio, during exploration phase, which lasts for the first third of the total number of generations, the predator moves more quickly than the prey. The low velocity is the last process in the optimization process

that is caused when the actions of predator are quicker than the prey. Hence, it is known as exploitation phase and it is formulated in (8),

$$m^t y_j + a = S_K \otimes (S_K \otimes El_i - A_i) i = 1,2, \dots n \quad (8)$$

Where $S \in [0,1]$ represents the vector uniform random numbers and a constant number,$S_K$specifies random

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numbers that specifies Brownian motion and⊗represents the process of element wise multiplication.

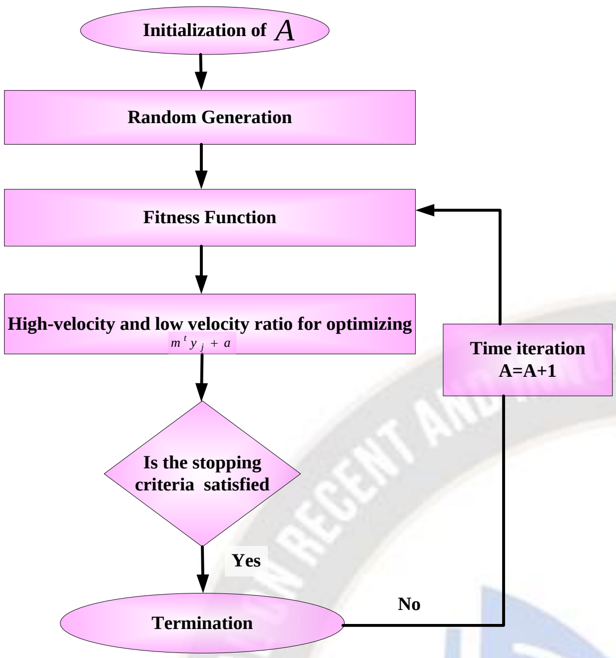


Figure 2. Flowchart of Marine Predators Algorithm

Step 5: Termination

The updated exploitation with exploration behaviour of MPA is upgrading the detective function of Hyb-CNN-SVM classifier. At last, the derived objective function is used to enhance the accuracy by lessening the computational time. Hyb-CNN-SVM using MPA is iteratively repeat step 3 till the halting criteria time iteration $A = A + 1$is met.

IV. RESULT AND DISCUSSION

SFD-Hyb-CNN-SVM-MPA, a hybrid deep learning model optimised with the MPA for shrimp freshness detection, is examined. MATLAB is used to carry out the suggested procedure. The MATLAB simulations are run on a computer with an Intel Core i5 processor running at 2.50 GHz, 8GB of RAM, and Windows 7. The proposed SFD-Hyb-CNN-SVM-MPA method's performance is evaluated using a number of performance metrics, including sensitivity, precision, recall, f-measure, specificity, computation time, and accuracy. In addition, the effectiveness is compared to previously developed methods for shrimp freshness detection, including Deep Shrimp Net (SFD-D-SHNet), Artificial Neural Network and K-Nearby Network (SFD-ANN-KNN), and Convolutional Neural Network.

A. Performance metrics

The proposed model's performance is validated by evaluating its sensitivity, specificity, precision, recall, f-measure, computation time, and accuracy performance measures. The definition of performance metrics and mathematical formulas are provided below. In order to scale the confusion matrix, the values of True Positive, True Negative, False Negative, and False Positive are required.

- True Positive(T_P) : Freshness was accurately identified.
- True Negative(T_N): Non-freshness was precisely identified as such.
- False Positive(F_P): Non-freshness that was identified as fresh.
- False Negative(F_N): Freshness was identified as being not fresh.

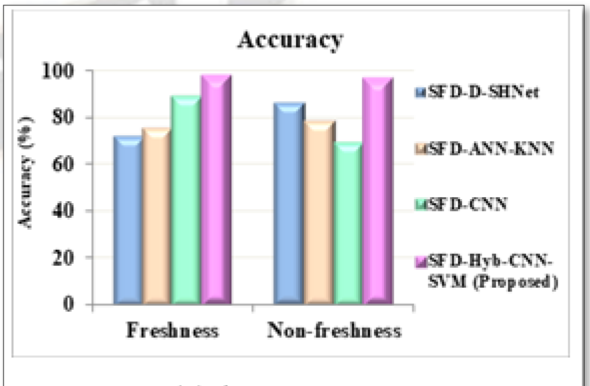
Equation (9) displays the accuracy, precision, recall, and f-measure formulas.

$$Accuracy = \frac{T_P+T_N}{T_P+T_N+F_P+F_N} \quad (9)$$

$$Pr\,e\,cision = \frac{T_p}{T_p + T_N}$$

$$Re\,c\,all = \frac{T_p}{T_p + F_N}$$

$$F - measure = 2 \times \frac{recall \times precision}{recall + precision}$$



(a) Accuracy

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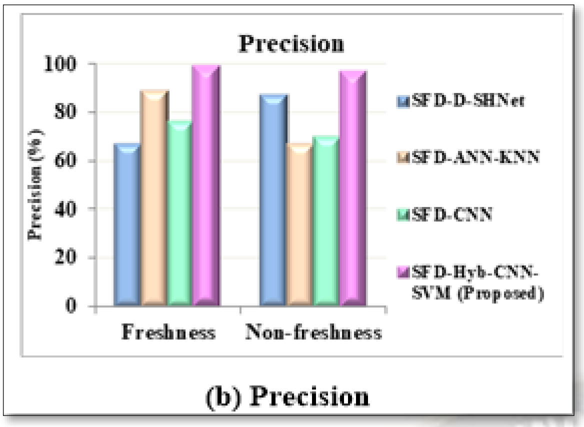

Figure 3. Performance analysis of accuracy and precision

Fig. 3 shows the accuracy analysis. When compared to existing methods like SFD-D-SHNet, SFD-ANN-KNN, and SFD-CNN, the performance of the proposed SFD-Hyb-CNN-SVM-MPA method performs 18.90%, 17.45%, and 15.67% higher accuracy for freshness; 22.34%, 32.56%, and 22.67% higher accuracy for non-freshness shrimp detection. In comparison to the current approaches, such as SFD-D-SHNet, SFD-ANN-KNN, and SFD-CNN, the performance of the proposed SFD-Hyb-CNN-SVM-MPA method gives 53.36%, 24.67%, and 12.47% greater precision for freshness; 19.69%, 28.98%, and 37.35% better precision for non-freshness shrimp.

The performance of the proposed SFD-Hyb-CNN-SVM-MPA approach gives 21.35%, 18.56%, and 13.56% higher f-measure for freshness; 11.45%, 33.67%, and 28.67% higher f-measure for non-freshness shrimp detection compared to the current techniques, such as SFD-D-SHNet, SFD-ANN-KNN, and SFD-CNN, respectively.

According to Fig. 4, the performance of the proposed SFD-Hyb-CNN-SVM-MPA method provides 15.90%, 12.34%, and 26.78% higher recall for freshness; 23.45%, 29.50%, and 17.46% higher recall for non-freshness shrimp detection when compared to the existing methods, such as SFD-D-SHNet, SFD-ANN-KNN, and SFD-CNN.

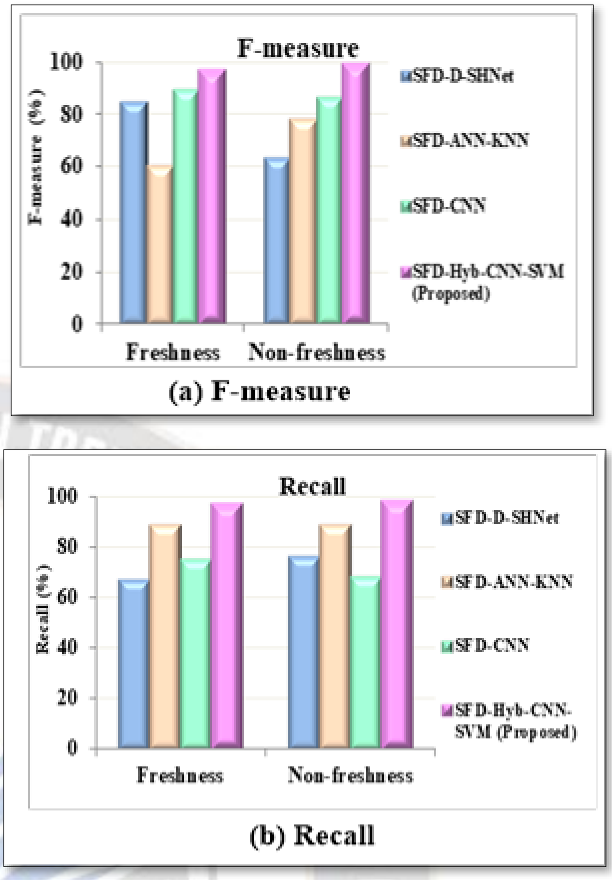

Figure 4. Performance analysis of F-measure and recall

Fig. 5 illustrates the computation time. In comparison to the current approaches, SFD-D-SHNet, SFD-ANN-KNN, and SFD-CNN, the performance of the SFD-Hyb-CNN-SVM-MPA method delivers 39.89%, 43.78%, and 52.67% reduced computing times for shrimp freshness detection, respectively.

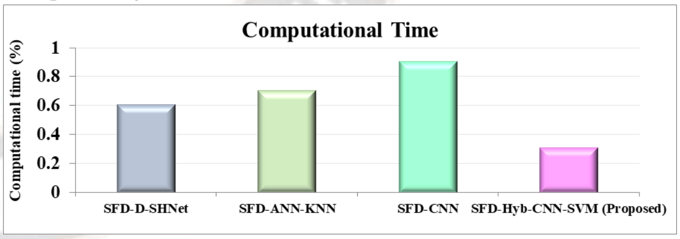

Figure 5. Computational time

Fig. 6 depicts the ROC curve for detecting shrimp freshness. The proposed model SFD-Hyb-CNN-SVM-MPA approach then delivers 2.89%, 6.59%, and 5.06% higher AUC over current methods such as SFD-D-SHNet, SFD-ANN-KNN, and SFD-CNN.

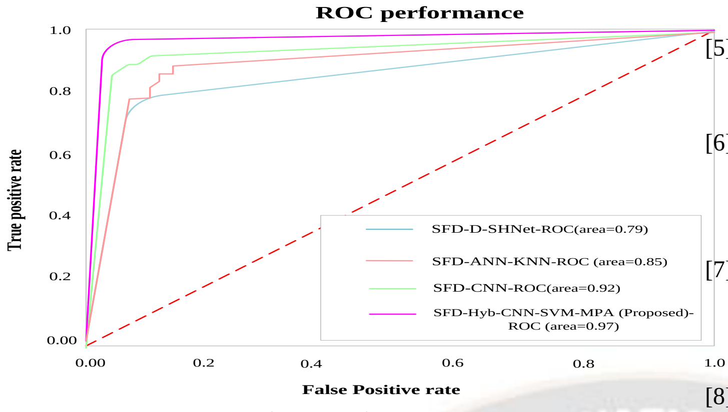

Figure 6. ROC curve for shrimp freshness detection

V. CONCLUSION

This paper proposes an Hyb-CNN-SVM-MPA classification strategy based on CNN parameter optimization utilising the MPA algorithm for shrimp freshness detection. The simulation is carried out in MATLAB, and the results are assessed using evaluation metrics. This study employs sophisticated categorization methods. These models perform very well with the MPA algorithm for meaningful classification results with enhanced accuracy and can improve classification process accuracy. In comparison to the current approaches, such as SFD-D-SHNet, SFD-ANN-KNN, and SFD-CNN, the suggested SFD-Hyb-CNN-SVM-MPA method achieves 2.89%, 6.59%, and 5.06% higher ROC, 15.90%, 12.34%, and 26.78% greater recall. Future research areas could consider merging the MPA with other machine learning classifiers to enhance searching parameters of these classifiers for optimal identification of freshness in aquaculture applications.

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