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An improved deep CNN-based freshwater fish classification with cascaded bio-inspired networks

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ABSTRACT

Bangladesh has plentiful water, which is essential to its freshwater fish traditions. Environmental concerns and other causes have reduced the country's water resources, threatening many native freshwater fish species. Thus, the younger generation deficiencies recognition of local freshwater fish and struggles to recognize them. Traditional methods are very insufficient to overcome these issues. To address these research gaps, the research proposes an automatic system for categorizing Bangladesh's freshwater fish. The proposed methodology involves several key steps, including building a comprehensive dataset, extracting features from fish images using pre-trained Convolutional Neural Network (CNN) models, and employing typical ML approaches. Initially comprising eight classes, the dataset undergoes feature extraction using CNN algorithms, followed by the utilization of various feature selection methods such as Support Vector Classifier, Principal Component Analysis, Linear Discriminant Analysis, and optimization models like Particle Swarm Optimization, Bacterial Foraging Optimization, and Cat Swarm Optimization. In the final phase, seven conventional ML techniques are applied to classify the images of local fishes. Empirical measurements are gathered and analyzed to assess the proposed framework's performance. Particularly, the present approach achieves the highest accuracy of 98.71% through the utilization of the ML mechanism Logistic Regression with Resnet50, SVC, and CSO models.

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1. Introduction

In 1993, the international community created the Convention on Biological Diversity (CBD), whose goal is "To achieve a comprehensive global agreement for the preservation of biological diversity and an equal distribution of advantages generated by the productive use of the world's genetic materials." In order to accomplish this goal, numerous species are tracked all over the world. Specifically, the 10th Conference of the CBD members announced the importance of "To eliminate the exotic invasive species" all over the world [1,2]. Among 33,000 species, fishes are the most diverse vertebrate group [3]. Classifying fish is crucial for many reasons, including keeping tabs on marine species' ecological and behavioural status and determining how much food is available for human consumption [4–6]. Several environmental issues have a significant impact on fish populations. Some of these factors include pollution, overfishing, exploiting marine resources, and the effect that marine life has on changes in the climate. Besides that, Bangladesh is a riverine country that is well-known around the world. After India and China, the Bangladesh is Asia's third most aquatic fish-diverse country with fish species over 800 living in brackish, fresh, and marine waters [7–9].

Thus, around 265 different species of freshwater fish may be found in Bangladesh's inland waters, which cover 4.73 million hectares [10]. In addition, Bangladesh is home to around 795 indigenous fish and shrimp species, many of which are cultivated in the country. Additionally, as per the Food and Agriculture Organization, in 2018, Bangladesh ranked fifth in the production of aquaculture and third in freshwater capture production. Bangladesh's fisheries contribute significantly to the country's GDP (3.69 percent in the fiscal year 2015-2016) because the country has more than 700 rivers [11–14]. Furthermore, in the fiscal year 2015-2016, Bangladesh earned over 2% of its total foreign

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trade revenue from the inland fishing sector. The production of aquaculture grew from 712,640 metric tons in the year 2000–2,060,408 metric tons in the year 2016, a quantity that was significantly more than the production of wild catch (1.023 million metric tons) in 2016. In 2014-2015, Bangladesh produced fish of 3,684,245 metric tons, among these 27.79% (1,023,991 metric tons) of the total fish coming from fresh waters. On the other hand, 55.93% (2,060,408 metric tons) comes from the country's confined waters, and 16.28% (599,846 metric tons) are from the sector of marine fisheries [14,15].

The term "floodplain" refers to a low-lying terrain that is frequently flooded due to overflow from neighbouring rivers, beels, haors, and backed-up rain waters. Bangladesh is home to one of the world's largest and most expansive floodplains [16–18]. They cover a total area of 9.3 million hectares, among them 2.83 million are fields where paddy is cultivated that are submerged for three to four months of the year in water between 2 and 6 metres deep. However, in 2009, the floodplain area was 2,832,792 ha, but by 2017, the area is decreased to 2,712,618 ha, according to the Department of Forests in Bangladesh. It has been estimated that 60% of Bangladesh's freshwater fish species only exist in floodplains. The floodplain fisheries rely heavily on the 143 species, which comprise 40% of the inland fish catch. They are classified as "small fish" by the scientific community [10,19–21].

There are roughly 1.4 million individuals in Bangladesh who are actively engaged in fishing. Additionally, 11 million people make a living from fishing on a part-time basis, and aquaculture industry also involve around 3 million people. Fishes supply 63% of the country's total protein intake, around 5 percent of the country's GDP, and about 5% of revenue from exports. There is a wide variety of fisheries, with the sea sector accounting for 35% of the total amount of fish produced (2.1 million tons), inland closed water-based fisheries accounting for 44%, and inland open-water capture fisheries contributing 35% [12]. However, this diversity and quantity of freshwater fish in Bangladesh are presently threatened [22,23]. The freshwater environment is the most susceptible to several threats, including pollution of water, flow change, habitat loss, and invasions caused by biological substances. It has been already hypothesized that approximately 20% of the fauna fish in the world which is found on freshwater has been extinct or is about to gone from existence. Bangladesh's younger generation is suffering from an information gap about freshwater fish due to the country's rapid rate of fish extinction. When employing manual methods, species identification of fish is a time-consuming process that requires extensive sampling. However, automated systems for fish species classification will assist these people in identifying the freshwater fishes, and the framework will also determine the primary factors contributing to the extinction of these fish species [10,24–26].

Recent years have seen significant advancements in classifying fish in partially or fully uncontrolled environments using Image Processing, DL and ML frameworks. Study [13] presents a machine-vision-based method for identifying freshwater fish native to a given area. The system used a fish image acquired using handheld device or a mobile to determine its species. The work employs three different ML classifiers to accomplish the task of fish recognition; SVM achieves the highest accuracy (94.2%). To identify native freshwater fish, the authors of the paper [15] combined six CNN-based architectures with transfer learning. The best results (98.81%) were obtained using Inception-ResnetV2 and the Xception framework.

In order to identify species of fish in ecological systems such as inland lakes and rivers, the study [27] intends to develop a CNN based system that is resilient to the surrounding environment. This work analyzed and compared the CNNs GoogLeNet, AlexNet, and the recently utilized VGGNet (VGG16, VGG19). To optimize the task that was proposed, the Adam algorithm was applied. The AlexNet algorithm performed exceptionally well, with a 98.33% accuracy rate in Data Group I. Using Depthwise Separable Convolution, the research authors [28] propose Multi-Level Residual (MLR) as a novel network technique by fusing data from low-level in the first block and features from high-level in the last block. The research also suggested MLR-VGGNet, a new CNN framework that builds on VGGNet and adds Asymmetric Convolution, Multi-Layer Recurrent and Residual features, and Batch Normalization. According to the experimental results of the research, MLR-VGGNet has a 99.69% success rate on the datasets of Fish-gres and Fish4-Knowledge. In the study [29], the authors evaluate the feasibility of implementing a CNN to classify fish species. There are 12,859 fish photographs in the dataset utilized for this study, which comprises four different fish species. The study used the optimization technique RMSprop and the activation functions Tanh, Swish, Identity, and ReLU on hidden layers. As the suggested CNN model achieves an overall accuracy of 99.40% in classifying fish species, it is clearly superior to previous methods.

Seven different computer vision approaches integrated with data mining methods are thoroughly investigated in the paper [30] by evaluating their performance across nine different categories of fish species. Previously trained models such as VGG19, Xception, Inception V3, ResNet150 V2, EfficientNetB0, and a unique CNN Model, a data mining ANN Model constructed from the 20 features collected from the photos, are fine-tuned with accuracy 100%. In the publication

[31], the authors provide a benchmark for comparing different types of CNN in the context of fish picture categorization. Accuracy rates of 99.85% (AlexNet), 96.39% (GoogLeNet), and 99.51% (ResNet-50) are achieved by suggested neural network models. The authors of [32] explore the classification of live reef fish species in the context of the fishes' natural habitat. The research suggested implementing a deep CNN and training it with a novel incremental learning-based technique. In addition, many distinct optimization strategies were implemented, including SGD, Adam, Adamax, and RMSprop. An accuracy of 81.83 percent was achieved using the proposed method. The study [33] provided a computerized system for identifying and categorizing fish species. In order to create the proposed model, deep CNN model with a simplified AlexNet framework is used. A high testing accuracy of 90.48 percent was reached by the suggested and modified AlexNet architecture with fewer layers compared to 86.65 percent by the original AlexNet model.

In the publication [34], an innovative deep-learning approach was presented for the automatic categorization of eleven native Indian freshwater fish species using features derived from a pre-trained CNN framework. Researchers employed the initial three layers of a pre-trained Resnet-50 framework to extract fish photos features, and a "ones for all SVM" classifier was utilized to simulate and evaluate images according to the features. The suggested framework achieves the highest accuracy of 98.74% on the Fish-Pak dataset and 100% on its own dataset in terms of categorization fish species. Using Alexnet, the suggested work [7] shines a light on a wide range of fish species. Utilizing CNN, the accuracy for fish species categorization was 86%, whereas the accuracy of the suggested model was 90%. In order to identify fish species, the authors of [35] present a DL architecture based on the CNN technique. This research aims to create a system for categorizing fish species according to their appearance. Maximum accuracy of 96.63 percent was attained using the suggested 32-Layer CNN framework on body viewpoint datasets.

The suggested study [36] employs a pre-processing approach that combines Underwater Image Enhancement with Morphological-operations. In this study, researchers use the PatternNet approach to classify photos of fish into several categories using an algorithm for categorization that has proven to be both accurate and efficient. The proposed framework appears to achieve a 98% accuracy rate while only taking 3.64 s on average to calculate. In order to eliminate the need for a massive quantity of training data, the publication [37] proposes an approach that uses cross-convolutional layer pooling on an architecture of pre-trained CNN. This work is concerned with creating an automatic classification system to recognize and categorize fish in underwater videos. After conducting in-depth research on a picture dataset, the suggested model attained a validation accuracy of 98.03%. The researchers of the study [38] have developed a method of automatic fish detection and species categorization using an advanced neural network methodology called YOLO. The results of the proposed work showed that the F-scores for detecting fish are 95.47% and 91.2%, while the accuracies for classifying fish species were 91.64 and 79.8 percent. In addition, a hybrid CNN architecture has been suggested in the paper [39] that employs CNN for extracting features and ML techniques K-Nearest Neighbour and Support Vector Machine for categorization. Finally, a 98.79% accuracy is achieved by using the proposed framework DeepCNN-KNN.

The primary focus of the paper [40] is on categorizing traditional Bangladeshi fish and suggested an automatic system of fish categorization based on CNN models. On FishNet dataset VGG16 architecture outperforms in every way among the MobileNet and InceptionV3 models. In addition, the article [41] was used in order to categorize traditional Bangladeshi foods. A high test accuracy of 97% was achieved using the current Inception v3-based food recognition model, which is referred to as DeshiFoodBD-Net. Finding a workable approach for recognizing and categorizing fish species in Bangladesh using image processing techniques was the goal of this study [42]. In order to distinguish between fish and non-fish classes, the detection phase employs the Histogram of Oriented Gradient (HOG) descriptor and several ML models such as the Random Forest, Support Vector Machine, Naive Bayes classifier and Decision Tree. Fish species are sorted by utilizing an SVM classifier and a Color Co-occurrence Matrix (CCM) texture descriptor. Multi-image classification with DL techniques is explored in the study [43], which focuses on fish identification. To evaluate the validity of the work provided, researchers employ CNN, the most well-known deep-learning model for image identification. The present work has achieved the accuracy of 99.5%.

As a result, the following issues have arisen in developed systems. The collection of information about fish species is the first issue. Several researchers evaluated performance with minimal datasets and restricted resources. Secondly, the obtained fish photographs are not identical because of the visual effects caused by the varying depths and amounts of turbulence in the water. The amount of light present in a natural setting shifts often due to the interaction between the water and the sun. Additionally, the depth of the water and the cloudy appearance of the water both restrict the field of view. This makes it challenging to capture a significant number of fish in their natural habitat. Thirdly, there needs to be more information on the quantity and quality of fish photos, which is necessary for developing a fish

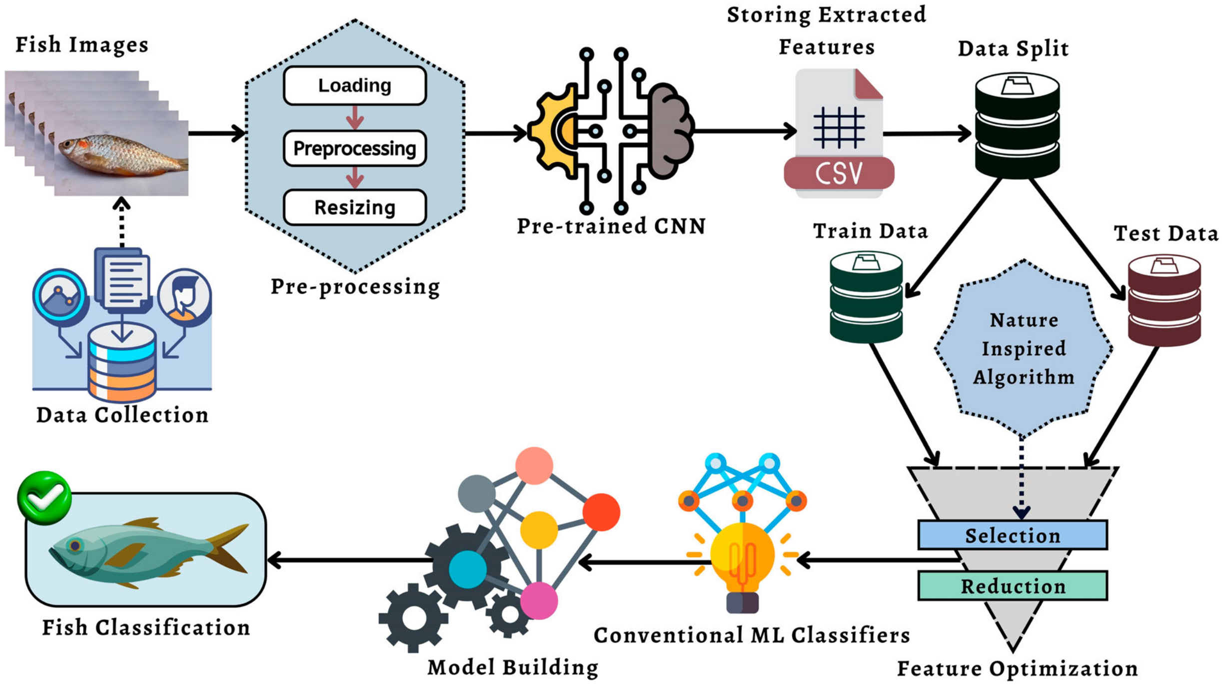


Figure 1. The proposed work's overall framework [44].

categorization system [27]. To address these limitations, the present research developed a DL-based model for freshwater fish classification.

In addition, the ML-based technique for classifying fish images based on their refined deep properties is considered in this investigation. Thus the contributions of this paper is given as follows:

- This study presents a machine learning method to classify fish images using advanced image features.
- Image features are extracted from fish images using pre-trained CNN models.
- Feature selection methods are applied to select the most dominant features from the extracted data.
- Optimization techniques are utilized to identify the best data attributes for improved classification performance.
- A lightweight application is developed using the trained model, integrated with Explainable AI (XAI) for better interpretability.

Four interconnected sections make up the manuscript. Section two provides the overall methodology of the proposed solution. Section 3 illustrates the rigorous result analysis with classifiers and feature optimization techniques. Finally, Section Four presents the conclusion of this manuscript along with the future scopes.

2. Materials and methodology

The methodology part of the current framework is presented in this segment. The research dataset collection, extract features with pre-trained CNN models, feature vector selectors and optimization algorithms, and fish categorization with the classic ML models are the inter-connected subsections which will represent this section.

The suggested system's overall framework is illustrated in Figure 1. At first, the dataset of the freshwater fish images will be built, as shown in Figure 1. In the second stage, many image pre-processing techniques, namely augmentation, pre-processing, resizing, and filtering, will be applied to the dataset. Pre-trained algorithms will work on feature extraction from the pre-processed image in the third stage. Afterward, feature selection algorithms and optimization techniques will be applied to the retrieved features to find out the highest quality features. Last step contains the classic ML algorithms to train the proposed method and also test the model to classify the fish images. As the ML model needs to feed the data and also needs data to test the model that's why this stage also has data splitting into training and testing.

2.1. Data collection and dataset building

A collection of samples which share the same characteristics are datasets. To execute the ML model, data should be fed into the model to train, and testing/validation data should be provided to measure the performance. The dataset for this proposed work is built by the authors. The authors collected freshwater fish images from the rivers and canals of Bangladesh. These freshwater fishes were purchased from different markets of Sirajganj district in Rajshahi division of Bangladesh and the additional location is Gazipur

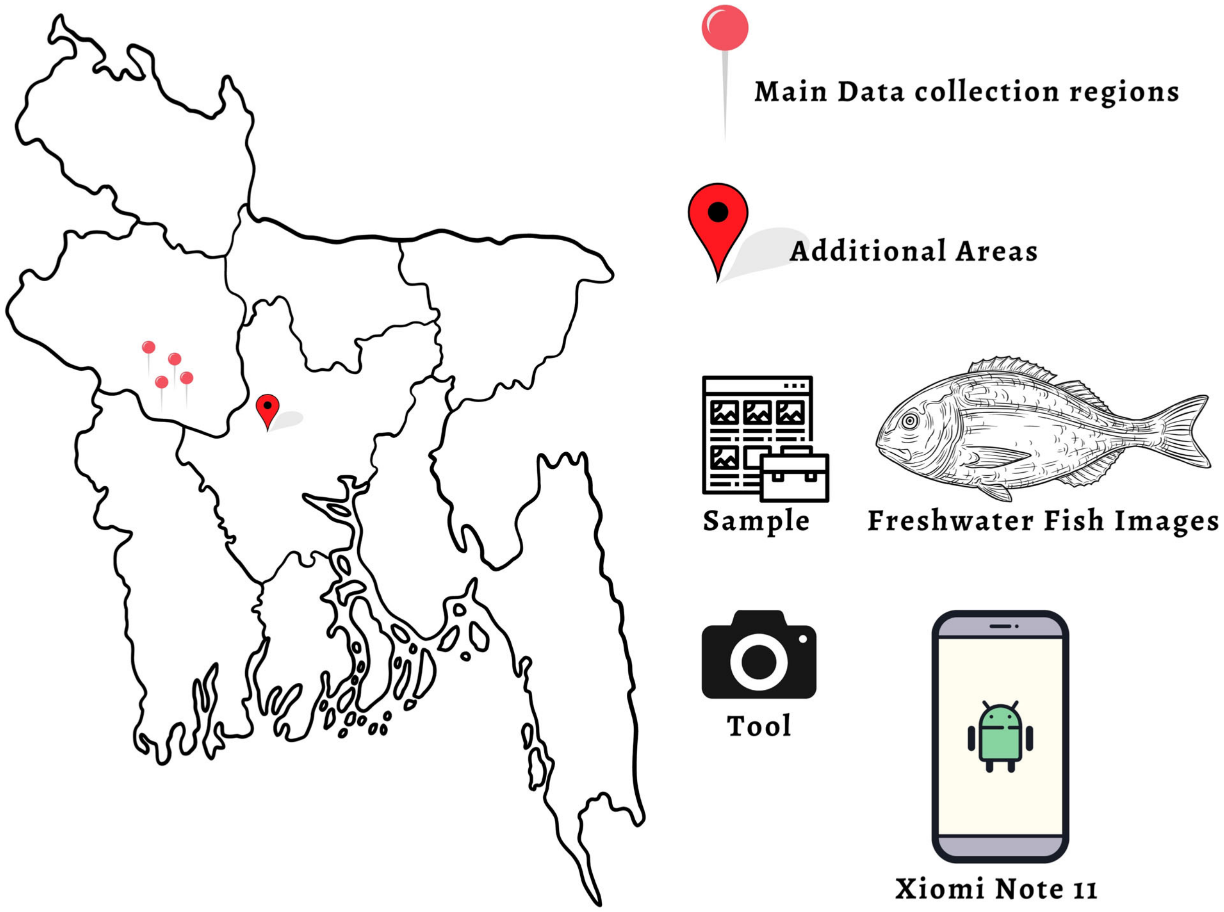


Figure 2. Data Collection and Dataset Building.

one of the districts of Dhaka division (see Figure 2). These fish images were taken with the camera of Xiaomi Note 10 and Note 11 Pro phones. The authors have placed the fishes on hard board, focused a mirror-based light, and captured the images from the different frontal views. The researchers have taken total 854 images including 8 species of Bangladeshi local freshwater fishes. In the dataset, authors have not applied the data augmentation system to enlarge the image data due to integrity of the proposed models and algorithms. Table 1 shows the local name of 8 species freshwater fishes along with the scientific name including a short description of their basic characteristics. Also, Table 2 shows the sample images of our own build dataset.

2.2. Image pre-processing

This section will focus on numerous approaches to preprocessing images. Performing image preprocessing before fish classification is essential for reliable outcomes. Multiple types of noise are present in the photos used in the dataset for the proposed model. These unwanted elements can be filtered out using image filtering techniques, and a lack of data can be compensated by applying augmentation techniques.

2.2.1. Image filtering

In order to enhance the results during the testing and training of present architecture, image filtering strategies have been implemented to reduce image noise. The images of the dataset will be filtered using a variety of methods, including:

Average Filter: The mean filter is a straightforward sliding window that changes the center value with an average of the pixel values inside the window when applied to an image. It has a wide variety of uses. The shape of a window or kernel does not have to be square; it can be any size or shape.

Gaussian Filter: The Gaussian filter is considered the most common filtering technique among linear filters. This method is utilized to blur an image or lessen noise within the image. Blurring edges and reducing contrast are fundamental characteristics of the Gaussian filter. The equation that corresponds to the Gaussian blur is displayed in Equation 1.

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}} \tag{1}$$

Median Filter: The median filter is a spatial filter that works like a sliding window, except it uses the median of the window's pixel values rather than its center value. The kernel of a mean filter is typically square but can take any shape.

Table 1. Data Description and quantity.

Serial No.	Local Name of the freshwater fishes	Scientific name	No. of collected images	Description to identify the fishes
1	Koi	*Anabus Testudineus*	100	The climbing perch, *Anabus Testudineus*, is a species of amphibious fish in the *Anabantidae* family which can be found on freshwater. Its range extends from Pakistan to Southern China and Southeast Asia. The length of the fish can reach upto 25 cm and has a brownish or green colouration with a long, cylindrical body and a large mouth. It is also known as a walking fish since it can survive out of water for several hours and move on land with the help of its pectoral fins and opercles. It's an omnivore that eats small fish, mollusks, insects, and plant debris.
2	Tengra	*Batasio Tengana*	125	The *Batasio Tengana* is a species of the family *Bagridae* that consists of freshwater catfish. Its scientific name is Batasio Tengana. Hillstreams and rivers with swift currents are its natural habitat, and it can be found throughout its native India, Bangladesh, Myanmar, and Thailand. It can reach a length of up to 9 centimetres and has a body that is long and cylindrical with a broad mouth. Its colour can range from brownish to green.
3	Taki	*Channa Puctata*	112	A very unusual fish, the *Channa Punctata*, commonly known as the spotted snakehead, has the ability to breathe air, walk on land, and climb trees. It is endemic to the region surrounding the Indian Subcontinent, where it is both a significant source of food and a popular pet fish in aquariums. It may be brownish or green in colour, and its body is long and cylindrical, with a broad mouth opening. Worms, insects, small fish, and things that have been partially digested make up its diet. It has a body that is long and cylindrical with a broad mouth, and it may grow to be as long as 25 centimetres in length. Its colour can range from brownish to green.
4	Shing	*Heteropneustes Fossilis*	102	*Heteropneustes Fossilis* is a catfish species that can lash, breathe air, and live outside of water. It is native to South and Southeast Asia, where it is a popular aquarium fish and an important sustenance fish. It is brownish or green in colour and has a cylindrical body with a wide aperture. It consumes worms, invertebrates, small fish, and partially digested matter. It can develop up to 30 centimetres (12 in.) in length.
5	Chingri	*Marcobrachium Malcoimsonii*	105	*Macrobrachium Malcolmsonii* is a freshwater prawn species belonging to the *Palaemonidae* family. It is called as the monsoon river prawn because it inhabits the rivers and waterways of South and Southeast Asia during the monsoon season. It is a bottom-dwelling, omnivorous prawn that consumes decomposing vegetation, small worms, animals, insects, and their larvae. It is also a cannibal and may consume newly-molted members of its own species. The maximum length of it can be of 16 cm, and also has a brownish or greenish hue, a long, cylindrical body, and a wide mouth.
6	Baim	*Mstacemblelus Armatus*	105	*Mastacembelus Armatus* is a fish species belonging to the family *Mastacembelidae* and found in the freshwater. It is also called as the tire-track eel, zig-zag eel, and marbled spiny eel. It is indigenous to the riverine fauna of Bangladesh, Vietnam, India, Sri Lanka, Pakistan, Thailand, and other Southeast Asian countries. It has a brownish or green body without genital fins and one to three darker longitudinal zigzag lines on its back. It can reach a maximum length of 90 centimetres and is a nocturnal, omnivorous fish that feeds on benthic invertebrates, worms, and some submerged plant matter.
7	Pabda	*Ompok Bimaculatus*	105	An Asian species of freshwater catfish called *Ompok Bimaculatus* is indigenous to nations including Bangladesh, India, Pakistan, and Sri Lanka. Due to its delicate meat and superior fish balls, it is also known as the "butter catfish". It has a brownish or green colour and a length of up to 45 cm and has three darker longitudinal zigzag lines on its back.
8	Puti	*Puntius*	100	*Puntius* is a genus of tiny freshwater fish belonging to the *Cyprinidae* family that are indigenous to South Asia, Mainland Southeast Asia, and Taiwan. They are sometimes referred to as barbs because barbels encircle their mouth. Typically, they are shorter than 25 centimetres (10 in.), but some species can grow larger. They come in a diversity of hues and patterns, and several of them are popular aquarium species.

2.3. Extraction of features with pre-trained CNN techniques

Feature extraction mechanism of the proposed method will be outlined in this section. At the beginning of this section, the process of characteristics extraction will be displayed together with its mathematical descriptions. After that, a demonstration of the feature selection will be shown in the following subsection. Afterward, the third subsection will explain the working procedure of the feature optimization algorithms like Artificial Bee Colony (ABC), Cat Swarm Optimization (CSO), Bacterial Foraging Optimization (BFO), and Particle Swarm Optimization (PSO) with appropriate algebraic annotations and explanations. Finally, the last subsection will discuss the internal workings of traditional ML classifiers used in the suggested model.

2.3.1. Feature extraction working principle

Nine distinct pre-trained CNN architectures have been utilized in the present framework to take out the

Table 2. Sample images of collected freshwater fishes.

Serial No.	Scientific name	Sample images	
1	*Anabus Testudineus*		
2	*Batasio Tengana*		
3	*Channa Puctata*		
4	*Heteropneustes Fossilis*		
5	*Marcobrachium Malcoimsonii*		
6	*Mstacemblelus Armatus*		
7	*Ompok Bimaculatus*		

(*continued*).

Table 2. Continued.

Serial No.	Scientific name	Sample images
8	*Puntius*	 

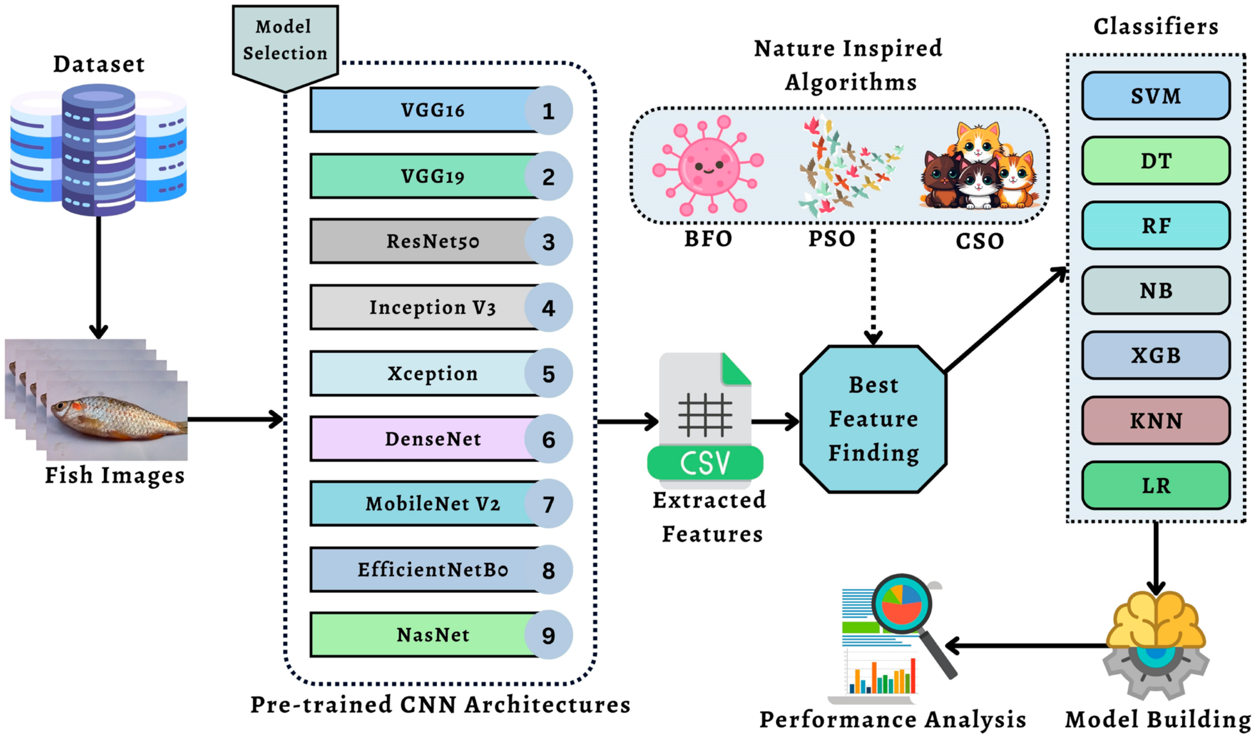


Figure 3. Working pipeline of the feature extraction for an image.

features from an individual photo. The pipeline of feature extraction technique used in the current investigation is portrayed graphically in Figure 3. The diagram on views that the system begins by directly obtaining the photos from the dataset and will pass them to the CNN techniques so that they can extract the features of the images. Nine different pre-trained models of CNN, namely, VGG16, VGG19, ResNet50, InceptionV3, DenseNet, MobileNetV2, EfficientNetB0, NasNet, and Xception, were applied to the dataset images to generate the feature vectors. Following extraction, 7 traditional ML methods were utilized to categorized the fish images. To classify the fish images with the best features, the proposed work performed four nature-inspired optimization algorithms and ran through the feature selection process. The system then evaluates the results according to the importance of each class.

The entire pipeline of extracting features from the dataset images is illustrated in Algorithm 1. Algorithm presents a clear and effective overview of feature pulling out technique from a specific image. The approach began by initializing the dataset with a predetermined number of photos, where *P* represents the image being input, and *Q* is the image generated as a result of performing image filtering and resizing, respectively. Next, a loop structure is represented by the pseudocode in order to calculate the feature vectors.

2.3.2. Pre-trained CNN model description

To accomplish feature extraction, the suggested research made use of the VGG16 and VGG19 pre-trained CNN models. Simoyan and Zisserman (2015) lay out the theoretical foundations of the VGG16 and VGG19 methods to investigate how network depth affects prediction accuracy [45]. During the ImageNet Challenge 2014, these two proposed models achieved the most outstanding accuracy in forecasting. The significant improvement was accomplished by using small-sized (3×3) convolutional filters in the VGG framework to increase the number of weight layers from 16 to 19. Among the 16 layers that make up VGG16, 13 are dedicated to the convolutional operation, 5 to the pooling operation, and 3 to be fully connected. On the other

Algorithm 1: Working procedure to extract feature vectors of the proposed work [44]

Input: 2D Images
Output: Feature Vectors

Initialization :
i. a = 2A-1, Where A = 1, 2,3, 4 … … … … .a
ii. X ← Input the Image
iii. Y_a ← Median filter is applied the on the input image *P* employing the kernel size a×a
iv. R_u ← Respective Characteristics Vector

Start :
i. **for** every A:
ii. Find out Y_a
iii. Employ (X, Y_a) to obtain R_a | R_a $V_0, V_1, \ldots, V_{14}$
iv. R_u ← R_a
v. **End for**
vi. Show R_u

End :

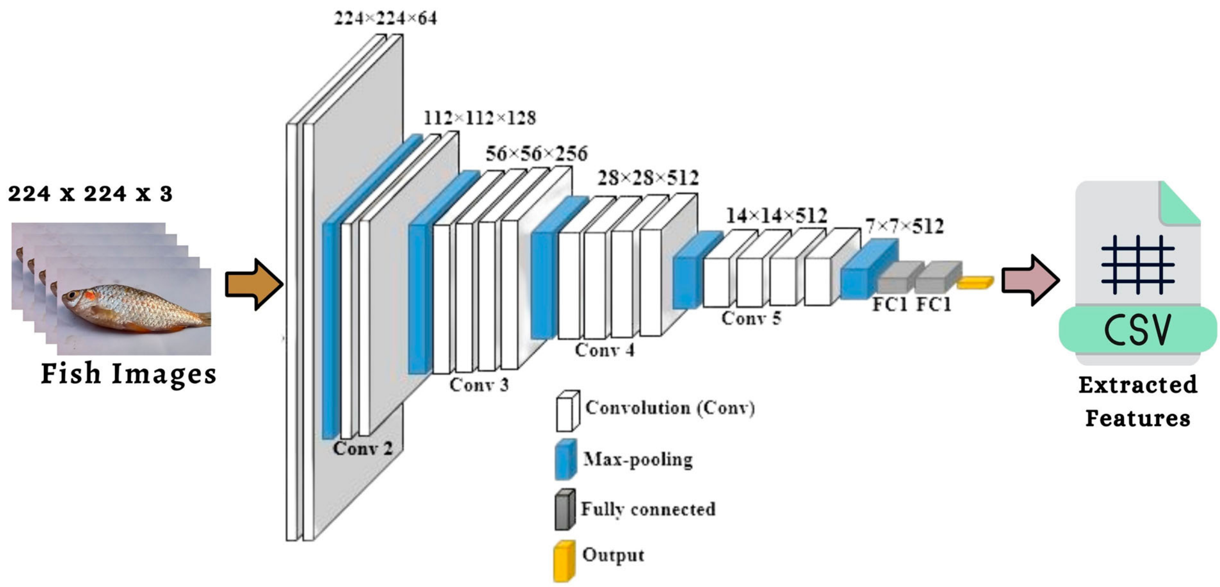


Figure 4. The architecture of VGG16 [44].

hand, VGG19 is built using three fully connected layers and five pooling layers in addition to 16 convolutional layers [46]. The output of the last layer of the feature extraction process (4096 features) is necessary for the VGG19 approach, which requires an input image with a 224 × 224 × 3 dimension. The architectures of the VGG16 and VGG19 are shown in Figure 4 and Figure 5, respectively.

Additionally, in the proposed research, a pre-trained CNN approach known as DenseNet was employed to pulling out the features of a dataset of fish image. Densely Connected Convolutional Networks (DenseNets) have direct connections between all its layers, as displayed in Figure 6. In this architecture, the number of direct links between any two levels with a value of "L" is L(L+1)/2. DenseBlocks, Connectivity layers, Bottleneck layers, and Growth Rate are the four individual components that come together to form the overall architecture of DenseNet. To improve efficiency and computation speed, a bottleneck layer might be included as a 1×1 convolutional layer before each 3×3 layer [47].

Figure 7 depicts the structure of the previously trained ResNet50 model utilized in the current investigation to extract the image characteristics. This pre-trained model has 50 layers and around 2M parameters. A number of components come together to form the ResNet50 framework. The first part consists of a fully connected layer, max pooling layer, 64 kernels, and convolutional layers. The augmentation layer makes it possible to deal with disappearing and dilapidation problems. Additionally, the skip connection acts as a super route. In present study, ResNet50 was exploited only for feature extraction, and the classifier component of the pre-built model was left out entirely. Images of fish at a resolution of 224 × 224 × 3 are the maximum size accepted by the proposed CNN model trained with ResNet50 [46], and the model's final layer is utilized to drag out 2048 features from every image.

After that, the suggested CNN model extracted features from the photos using a pre-trained version of the Inception V3 techniques (*also known as GoogleNet; see* Figure 8). The whole parameter set for this model is 5M, with 22 layers. To allow the extraction of features at

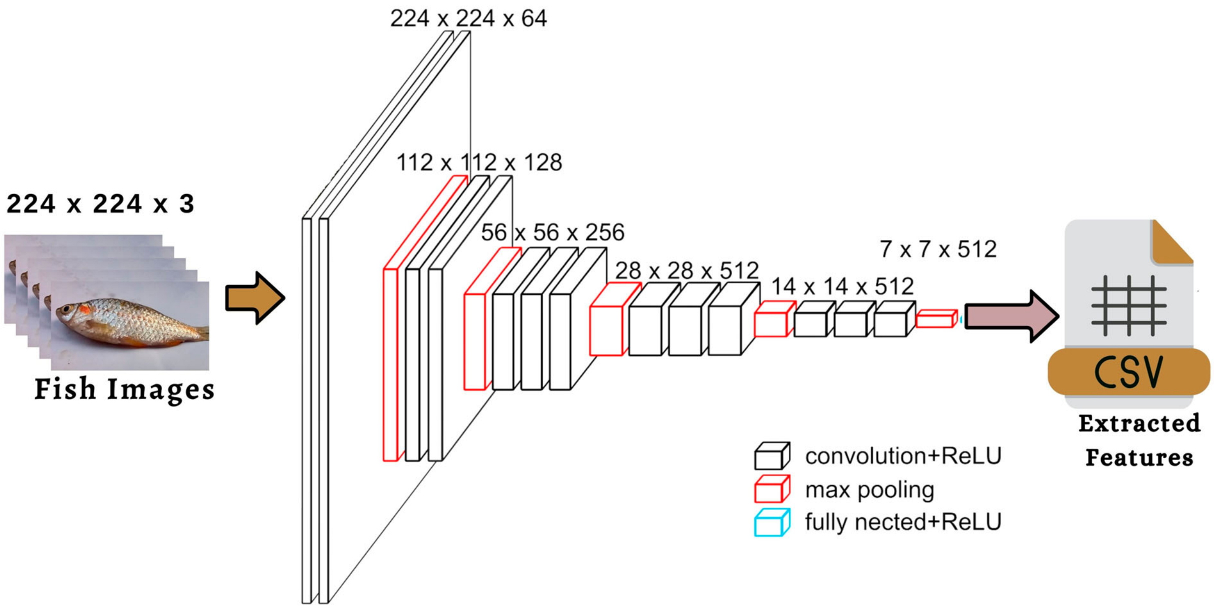


Figure 5. The architecture of VGG19 [46].

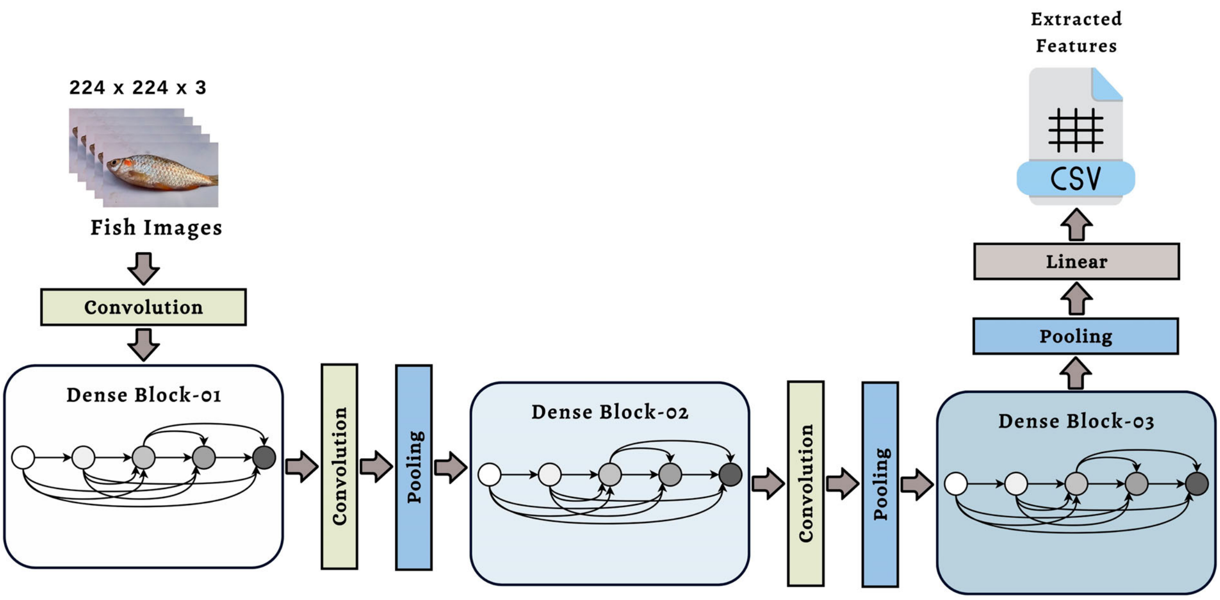


Figure 6. The architecture of DenseNet [47].

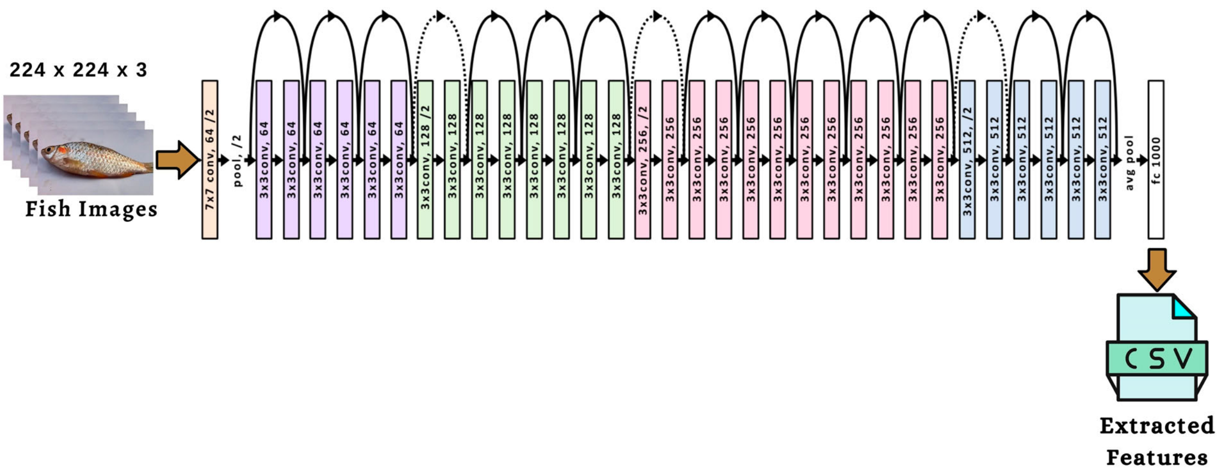


Figure 7. The architecture of ResNet50 [44,46].

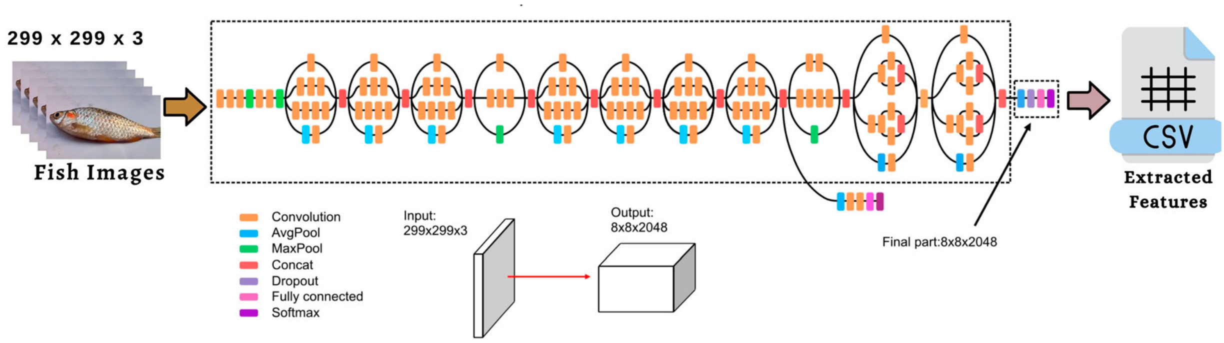


Figure 8. The architecture of InceptionV3 [46].

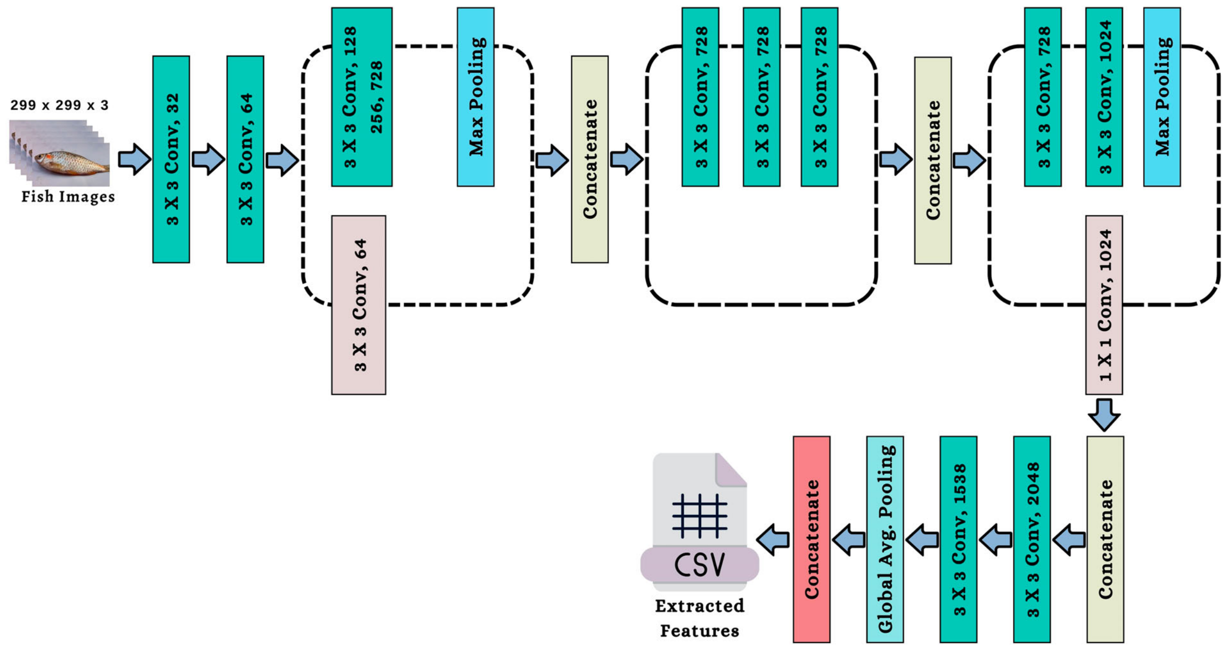


Figure 9. The architecture of Xception.

varying scales via max pooling, the model includes filters of sizes 1×1, 3×3, and 5×5. To improve the study's computational discarding performance, the convolutional filters of size 5×5 have been replaced with two filters of size 3×3. The model has a finely tuned structure comprising 48 layers to prevent it from overfitting. Images of fish at a resolution of 224 by 224 by 3 are the maximum size accepted by the proposed CNN model trained with Inception V3 [46], and the model's final layer is used to extract 2048 features for each image.

Furthermore, the Xception CNN algorithm, which has already been trained, is exploited to pull out the features from the fish photos in the suggested study. The framework of the Xception models is illustrated in Figure 9. To maximize efficiency, the Xception method framework included 36 convolutional layers for feature extraction. Except for the initial and final modules, all 14 modules that jointly comprise the 36 convolutional layers are enclosed by the linear residual connections. The Xception architecture [44] is composed of linearly stacked convolutional layers that may be trained separately in depth.

MobileNetV2 is a new deep neural network that has proven to be excellent for feature extraction, particularly in the areas of pattern categorization and segmentation. Google's employees are the first to create MobileNetV2. The architecture of MobileNetV2 is predicated on a residual structure turned on its head so that the residual links connect the bottleneck layers. Figure 10 displays the whole MobileNetV2 architecture. MobileNetV2 consists of 53 convolution layers and a single Average Pooling [48]. There are two key features that set apart MobileNetV2 from previous CNNs: the inverted residual block (IRB) and the bottleneck residual block (BRB). The framework of the MobileNet models is illustrated in Figure 10.

Feature extraction is a strength of EfficientNetB0, which was proposed by Google Brain in 2019. It makes inferences with the least amounts of FLOPS (the number of floating-point computations that an entity can compute in one second) compared to other typical convolutional neural networks, although having better accuracy and fewer parameters than those networks. The image that is received by the network

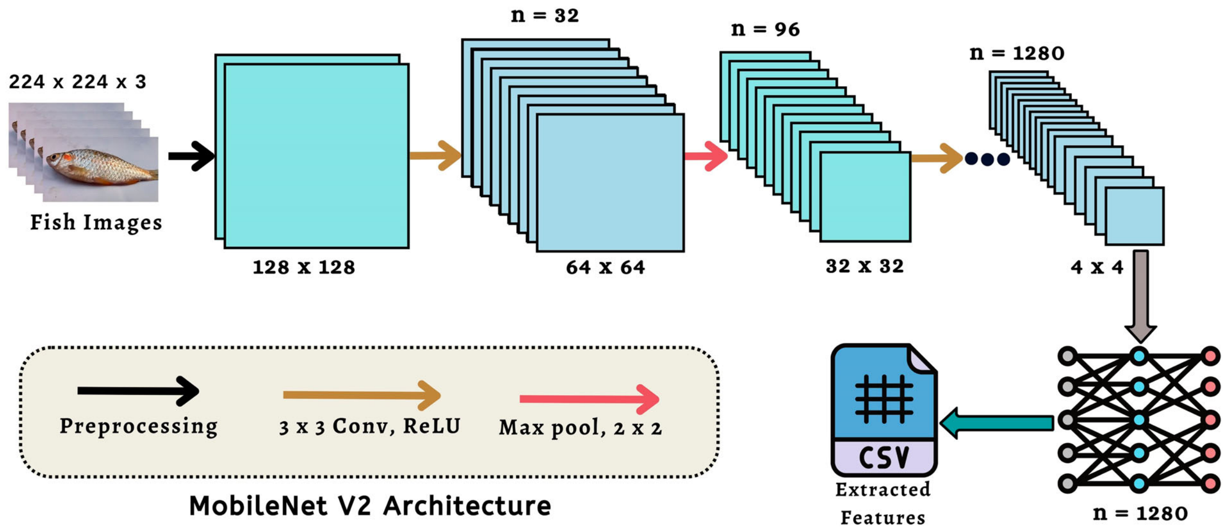


Figure 10. The architecture of MobileNetV2 [48].

has a resolution of (224 × 224) pixels. The EfficientNetB0 baseline network is built by searching for optimal neural architectures across many objectives and then scaled in depth, width, and resolution to achieve a compromise. The researchers at Google Brain created a deep CNN approach called Neural Architecture Search Network (NASNet) at the beginning of 2018. The design aimed to establish a building block that performed well in CIFAR-10's small-image classification task. Then, they expanded the block's applicability to a larger dataset (ImageNet). By limiting the number of factors, this architecture is able to produce accurate results with high classification capability (Figure 10).

2.3.3. Feature selection models

The feature selection models used by the current system are described in this section. Support Vector Classifier (SVC), Principal Component Analysis (PCA), and Linear Discriminant Analysis (LDA) feature selector were the primary models used to build the model during the research phase. To simplify the feature vectors the present work employed PCA and LDA techniques. PCA is an approach of unsupervised learning that enhances dataset variation. The LDA and SVC feature selectors, on the other hand, are supervised learning techniques that prioritize a feature vector subspace that enhances group categorization [49]. Some mathematical expressions of PCA, LDA, and SVC are given below.

A covariance matrix can be efficiently constructed using PCA. In order to build PCA, it is necessary to have a symmetric d × d- dimensional covariance, where d denotes the dimension numbers in a given dataset and can stores the pairwise co-variance value between various notable characteristics [49]. To illustrate, X_j and X_k represent two features of the study's focus group. The covariance is then found with the aid of the following equation (1).

$$\sigma_{jk} = \frac{1}{n}\sum_{i=1}^{n}(x_j^{(i)} - \mu_j)(x_k^{(i)} - \mu_k) \tag{2}$$

On the other hand, LDA works on the five interdependent procedures to function correctly. LDA begins by determining the average vectors of the d-dimensions. For the further work eigenvectors and scatter matrices are generated by LDA and then the descending order of the eigenvectors are arranged. Then, the appropriate feature reduction or feature selection is achieved using matrix multiplication.

However, the particular problem with Linear SVC can be effectively addressed by utilizing SVC. The primary goal of SVC is to find the best fit data among the dataset to produce the "best feature" hyperplane for categorization [49]. The operation of the feature selector technique SVC of the proposed model is described in Algorithm 2.

Figure 11 shows a block diagram of the feature selectors' preferred technique for determining the "Best Feature". To find out which features work best with conventional classifiers, the proposed framework gathers test data and converts it into feature vectors. Also, feeds those vectors into ML methods as shown in the diagram. Last but not least, ML classifiers help the model calculate the accuracy.

2.3.4. Working principles of nature inspired different optimization algorithms

In order to find out the best features that may optimized the accuracy level, the four essential inspired methods are shown in this segment. PSO, BFO, ABC, and CSO algorithms are included in the research pipeline to locate the best features and optimize for efficiency by using the fewest possible features.

Algorithm 2: LDA working procedure techniques for feature selection [44]

Input: Image Features
Output: Best Features

Start :
- i. Find the mean vector for the d-dimensional for each class of the dataset.
- ii. Construct the scatter matrices (in between the class and within the class scatter matrix).
- iii. Evaluate the eigenvectors of the scatter matrices' (e_1, e_2, e_3 … .e_d) and corresponding eigenvalues (λ_1,λ_2,λ_3,λ_4… … ..λ_d).
- iv. Sort out the eigenvectors by reducing eigenvalues, and then chose the k eigenvectors with the highest eigenvalues to form a d × k dimensional matrix W. (where every column stands for an eigenvector).
- v. The samples will be converted onto the new subspace, use this d × k eigenvector matrix. This outcome can be summarized using matrix multiplication: Y = X × W (where X is an n × d-dimensional matrix representing n samples and y are transformed n × k-dimensional samples in the new subspace).

End :

Algorithm 3: SVC working procedure techniques for feature selection [44]

Input: Extracted Image Features from the Pre-trained CNN Models
Output: Best Feature Vectors

Initialization :
- i. A = X-1, Where X = Feature Numbers of a specific CNN method.
- ii. B ← Classes numbers
- iii. P_u ← Number of training data
- iv. Q_u ← Number of testing data
- v. V_f ← Respective Best Feature Vectors
- vi. F_s ← Number of Best Selected Feature Vectors

Start :
- i. feature = SVMFeatureSelection ($P_{u,}$ Q_u)
- ii. **if** (Number of feature > 0.5):
- iii. $F_{s=}$ features
- iv. $V_{f=}$ sum(all the F_s)
- iv. **End if**
- v. | Show V_f

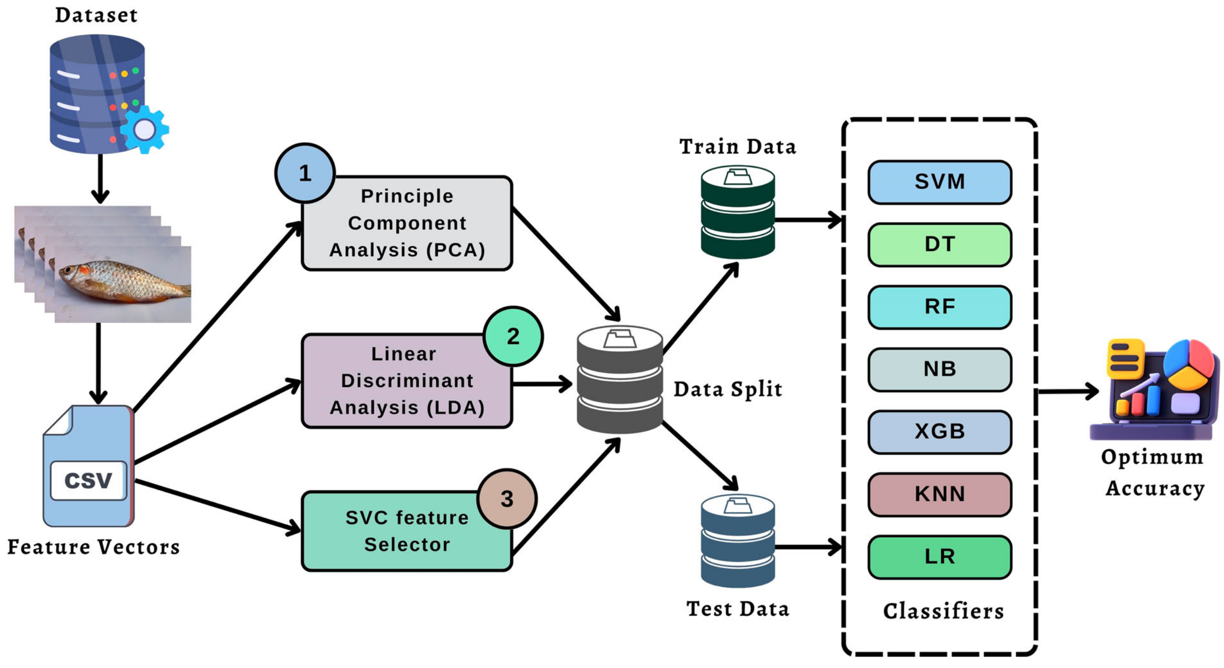


Figure 11. Feature selector model's framework of the proposed study..

2.3.4.1. Bacterial foraging optimization (BFO). Bacterial foraging optimization is an artificial intelligence (AI) based meta-heuristic search approach whose primary goal is finding optimal solutions to complex maximum and minimum problems [50]. Using E. coli's natural instinct to find food and propagate, the BFO solves the optimization issue numerically. Motivated by the foraging strategy of E. coli bacteria, the BFO method is a biologically motivated computer technique. Animals with inefficient foraging strategies are more likely to be eliminated by natural selection, whereas the genes of those with efficient foraging techniques are more likely to spread because those animals are more likely to reproduce successfully. Foraging methods that aren't optimal are gradually phased out or improved upon over many generations. During the process of

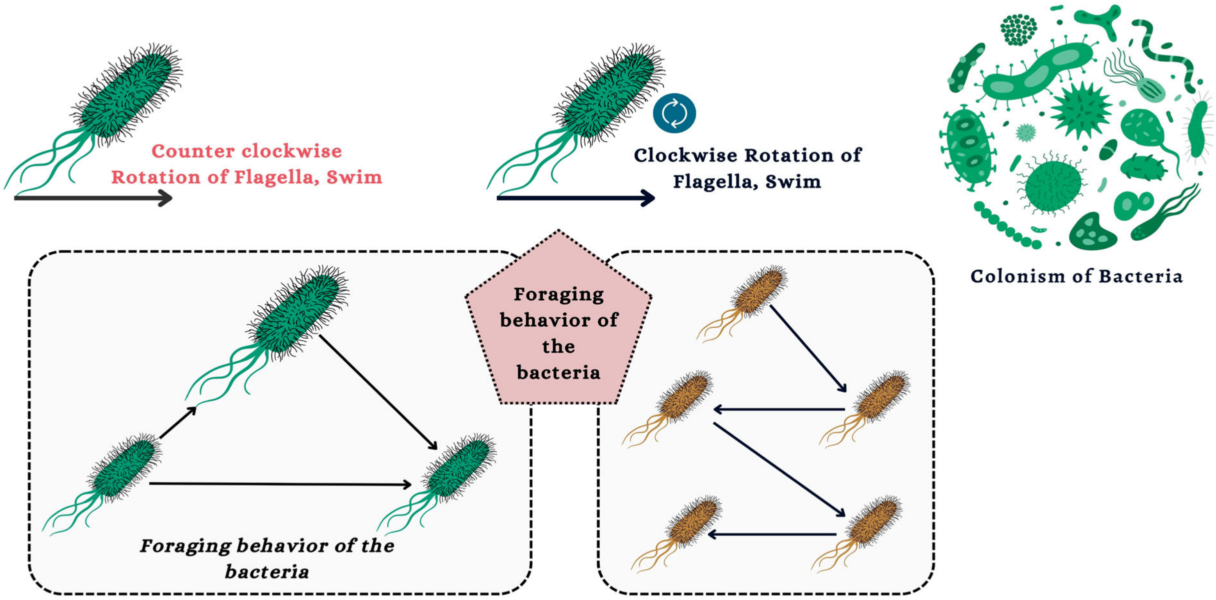


Figure 12. *E.coli* bacteria's foraging behaviour in BFO.

optimization, this characteristic of foraging is utilized. E. coli's foraging behaviour is depicted in Figure 12. The BFO has four major components: chemotaxis, reproduction, swarming, and elimination. In the Chemotaxis phase, the algorithms control the bacteria's forward motion by directing the flagellar motors that propel them forward. By forming complex and long-lasting spatiotemporal patterns, swarming bacteria can communicate with one another. In the Reproduction phase, the robust bacteria divide into a new set of two bacteria. However, this process results in the death of less healthy bacteria; hence, the size of the swarm does not change. Finally, a catastrophic shift in the population number is achieved in the Elimination process, at which point a group of bacteria can be eradicated. In order to find out the most useful characteristics for ML models, BFO has been incorporated into the algorithm used to do that work.

2.3.4.2. Particle swarm optimization (PSO). Among optimization models based on meta-heuristics, Particle Swarm Optimization has the most widespread recognition and application. The design of this algorithm was primarily motivated by the significant behaviours observed in nature, such as fish and bird schooling. The procedure is considered a heuristic since it assumes that the model would eventually converge on the global optimum. There is usually a significant distance between an observer and any bird in a flock. However, the presence of more than one of these birds makes the superior surface of a fitness function apparent to the entire swarm of birds [44].

Assume that the particles number is denoted as P and also, every iteration position is denoted by the letter i and written as Xi (t), varies from one iteration to the next. Consider Xi(t) to be a coordinate in the form Xi(t) = (xi (t), yi (t)). Additionally, the velocities of the particles can be written as Vi (t) = (vi x(t), vi y(t)). The position of the particle's then follows the formulas in Equations (2), (3), and (4) [44].

$$X^i(t+1) = X^i(t) + V^i(t+1) \tag{2}$$

$$x^i(t+1) = x^i(t) + v^i_x(t+1) \tag{3}$$

$$y^i(t+1) = y^i(t) + v^i_y(t+1) \tag{4}$$

Additionally, the below equation can be written like Equation (5),

$$V^i(t+1) = wV^i(t) + c_1 r_1 (pbest^i - X^i(t)) + c_2 r_2 (gbest - X^i(t)) \tag{5}$$

The numbers r_1 and r_2's value is in between in the interval [0,1] in Eq. (5). Particle i's best-fit F(x) value is located at position pbesti, and the other essential parameters of the PSO algorithm are w, c_1, and c_2. When all the particles in the swarm have been counted, the total value gbest will have been measured. The appropriate steps of the PSO method are displayed in Algorithm 3, and Figure 13 shows an overview of the algorithm.

2.3.4.3. Cat swarm optimization (CSO). In 2007, Chu and Tsai were the ones that came up with the idea for the cat swarm optimization method. This algorithm is able to function in both the Seeking Mode (SM) and the Tracking Mode (TM) depending on the situation. However, in TM, cats are observed to move to the subsequent location at different velocities, showcasing the resolute manner in which they chase their prey. For SM, cats don't move at all; they just stand there and wait to "feel" for the best course of action. The CSO method's working procedure is depicted in Figure 14.

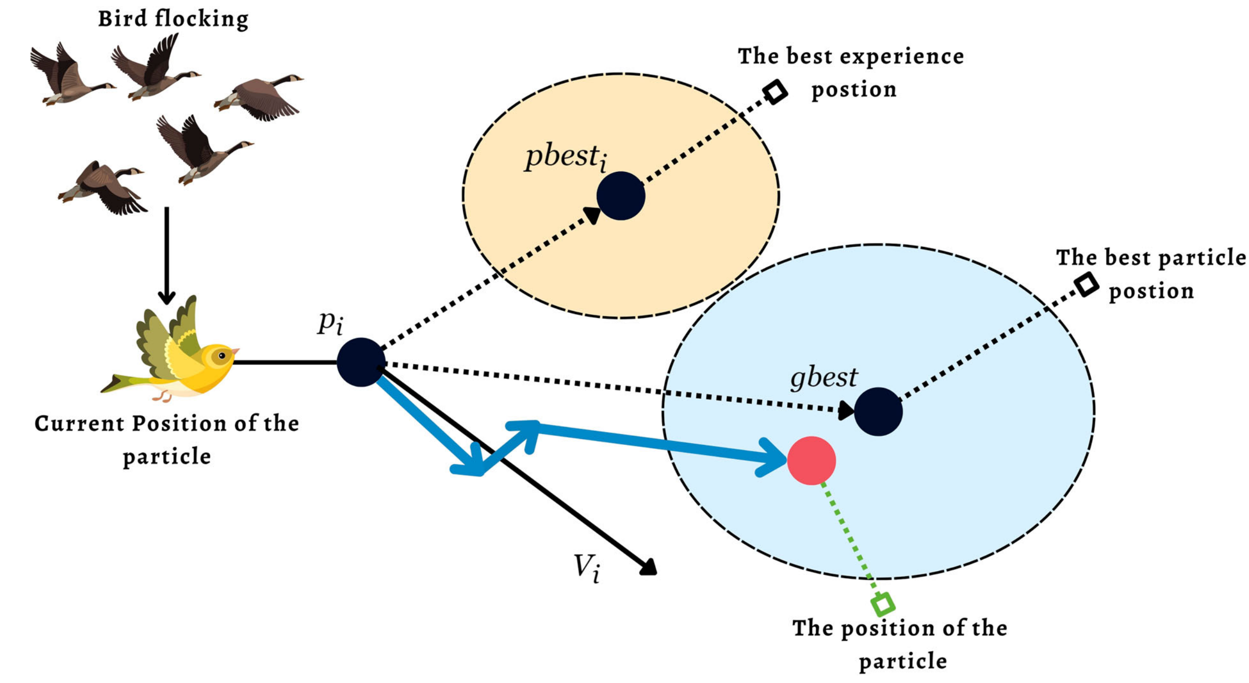


Figure 13. Working procedure of PSO.

Algorithm 4: PSO algorithm's working procedures for best particle calculation [44]

Input: Set of random particles
Output: Best fitted particles

Initialization :
1. Initialize random particle $P = P^1, P^2, P^3, \ldots P^i$.
2. t ⟵ Time
3. c_l ⟵ cognitive factor
4. c_2 ⟵ Social factors
5. r_1, r_2 ⟵ the value in the interval [0, 1]
6. w ⟵ inertia weight
7. $pbest^i$ ⟵ best position of P^i
8. gbest ⟵ global best position of the particle

Start :
1. **while** (best solution)
2. **for** each P^i
3. Update the velocity $V^i(t+1) = wV^i(t) + c_1 r_1 (pbest^i - X^i(t)) + c_2 r_2 (gbest - X^i(t))$
4. Update position $X^i(t+1) = X^i(t) + V^i(t+1)$
5. Use objective function f to evaluate the fitness value of P^i
5. Update $pbest^i(t) | pbest^i(t+1) = \begin{cases} pbest_i(t) & \text{if } f(pbest_i(t)) \le f(p_i(t+1)) \\ (p_i(t+1)) & \text{if } f(pbest_i(t)) > f(p_i(t+1)) \end{cases}$
6. Update $gbest(t) | gbest(t+1) = \max\{f(pbest^i(t)), f(ggest(t))\}$
7. **End for**

End while

End :

To effectively utilize the CSO, it is essential to keep track of several factors, including the Number of Duplicate Cats (SMP), Number of Dimensions of Variations (CDC), the Mutative Ratio for the Selected Dimensions (SRD) and the Passed Position as One of the Candidates (SPC). The following Equation (6) can be used to count the number of times each duplicate cat moves position:

$$X_{mn} = 1 + SRD \times R \times X_m \tag{6}$$

Where,
X_{mn} = The current Position
$R = [0, 1]$

A determination of the likelihood of each candidate's points will be made by the algorithm through the utilization of Eq. (7) to evaluate the Fitness Function (FS). In that case, the algorithm will select a value of 1 as its final result.

$$P_m = \frac{|FS_m - FS_{min}|}{FS_{max} - FS_{min}} \tag{7}$$

Where, $0 < m < j$

SM and TM are the primary search techniques supported by the CSO method. Algorithms 04 and 05 depict the inner workings of SM and TM, respectively. When using TM, Equation (8) can be used to express

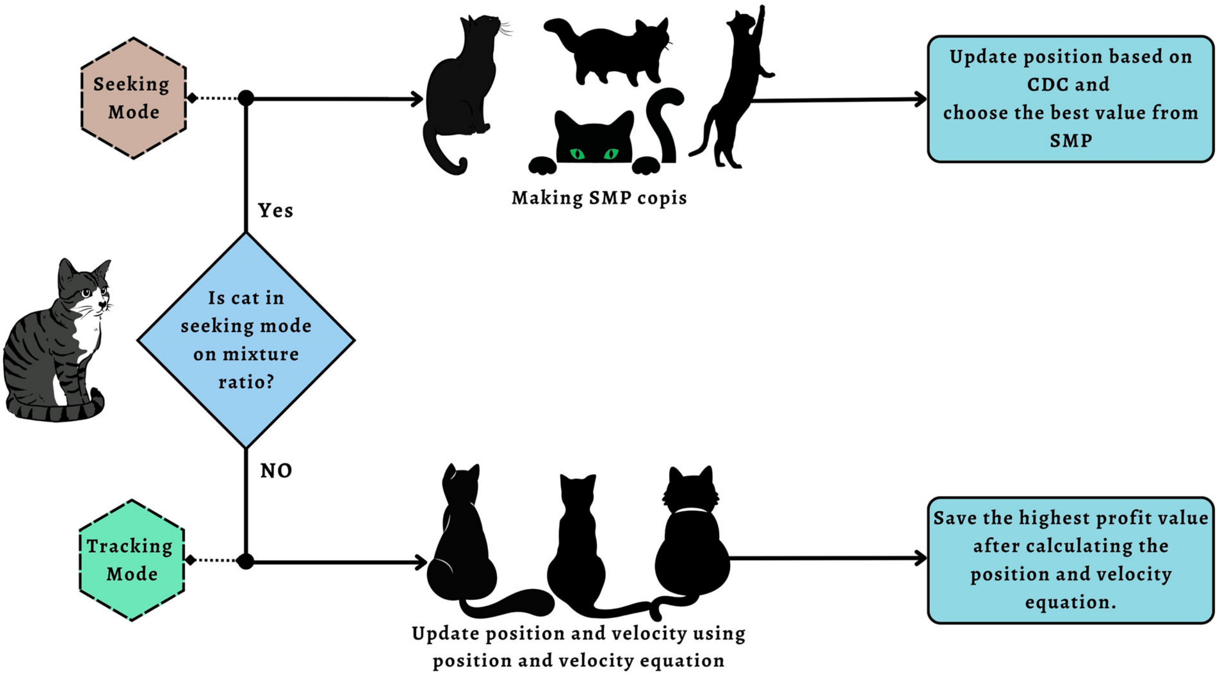


Figure 14. Working procedure of CSO [51].

Algorithm 5: CSO algorithm's working procedures of Seeking Mode (SM) [44]

Input: Set of random particles
Output: Best fitted particles

Initialization :
1. Initialize random particle the parameter SPC, SMP, SRD, SPC, and CDC.
2. j⟵ Duplicate cat position
3. m⟵ having value 0 < m < j

Start :
1. **If** (SPC! = 0)
2. J = SMP −1
3. **Else**
4. J = SMP
5. **End if**
6 Make J duplicate cat positions
7. **for** (m = 1 to SMP)
8. Compute the value of X_{mn} randomly using SRD & CDC using Equation (6)
9. Replace the old value
10. Calculate the probability P_m using *Equation (7)*
11. **End for**

End :

the speed of a single cat.

$$v_{l,i} = v_{l,i} + r \times q \times X_{\text{best},i} - X_{l,i} \tag{8}$$

Where,
$i = 1, 2, 3, 4 \ldots \ldots$ M, here M = cat number.
r = random value in a range of 0–1.
$X_{\text{best},i}$ = i-th best position of the cat.
$X_{l,i}$ = The current Position
$R = [0, 1]$
After that, the updated position of every cat will be presented by:

$$X_{l,i} = X_{l,i} + v_{l,i} \tag{9}$$

2.4. Classification with the conventional classifiers

The suggested research applied machine learning (ML) techniques to feature data gathered from various fish images. Extreme Gradient Boosting (XGB), Decision Tree (DT), Logistic Regression (LR), K-Nearest Neighbour (KNN), Support Vector Machine (SVM), Random Forest (RF), and Naive Bayes (NB) were the seven traditional ML classifiers employed in the proposed architecture [44].

3. Results and discussion

The following section of the paper demonstrates how ML-based classifiers are utilized to analyze this experiment's results. The first section shows the impressive

Algorithm 6: CSO algorithm's working procedures of Tracking Mode (TM) [44]

Input: Set of random particles
Output: Best fitted particles

Initialization :
1. Initialize random particles.
2. i ⟵ Cat number M = 1, 2, 3, 4 … .
3 r ⟵ the value in a range 0–1
4. M_{max} ⟵ Max Speed
5. v = velocity of the cat

Start :
1. Update the current velocity by using the *Equation (8)*
2. **for** (v < = r)
4. Execute the subsequent part with v
5. **Else**
6. v = M_{max}
7. **End if**
8. Update the position of the each cat by using *Equation (9)*

End :

Table 3. Proposed methods performance evaluation matrices' description [44].

Metrics	Description
Precision (*P*)	Represents a method for determining the level of quality of a model. $P = \frac{TP}{TP+FP} \times 100$
Accuracy (A)	Displays the overall proportion of correct predictions. $A = \frac{TP+TN}{FP+TP+FN+TN} \times 100$
Recall (R)	Defined as a way to measure the quantity in the model. $R = \frac{TP}{TP+FN} \times 100$
F1-score (F1)	Shows how precise and dependable a model is. $F1 = 2 \times \frac{R \times P}{R+P} \times 100$
NCM	Provides a tabular view of the detection rates (both right and incorrect) for different categories.

results of combining an ML-based model with the pre-trained CNN models. In the second step of the result section, the data from the experiment is analyzed by utilizing BFO, CSO, and PSO approaches, as well as several feature selector algorithms such as LDA, PCA, and SVC. This section comes to a close with an analysis and comparison of the effectiveness of numerous different classification methods.

To determine the present model's performance, a variety of assessment matrices, such as recall (R), F1-score (F1), precision (*P*), and accuracy (A), have been applied. Table 3 contains a variety of mathematical illustrations for the performance assessment matrices.

3.1. Performance analysis of different pre-trained CNN architectures

This part of the work represents the data assessments results using the previously trained CNN architectures and ML-based algorithms. The Google Colab, which is equipped with a specialized Graphics Processing Unit (GPU) and 53GB of RAM, was used to execute all of the code for the suggested work. For the proposed approach, the "pro" level of subscription of the Colab was recommended. Firstly, the present work pulled out the essential characteristics from the input photos. Following that, the amassed data was exploited as input into the ML-based methods to evaluate the model's accuracy. For the objectives of training and assessing the suggested model, the dataset was split into 80 and 20 percent.

Table 4. The overall results of various pre-trained techniques with SVM.

CNN model	A (%)	*P* (%)	R (%)	F1 (%)
VGG16	93.93	93.85	93.11	93.35
VGG19	97.45	97.54	97.64	97.52
ResNet50	**98.06**	**98.02**	**98.13**	**98.03**
InceptionV3	56.69	56.87	55.77	54.10
Xception	50.96	44.53	50.27	46.12
DenseNet	80.25	81.86	79.94	79.83
MobileNetV2	87.90	88.17	87.54	87.65
EfficientNetB0	94.90	94.90	94.86	94.81
NasNet	43.95	48.03	43.64	40.83

In the beginning, the present study decided to proceed with the CNN techniques that use the SVM algorithm. Table 4 displays the results obtained using the SVM and the proposed CNN models. Compared to the other CNN models, ResNet50 performs the best, with an accuracy of 98.06%. VGG16, VGG19, InceptionV3, Xception, DenseNet, MobileNetV2, EfficientNetB0, and NasNet only managed 93.93%, 97.45%, 56.69%, 50.96%, 80.25%, 87.90%, 94.90%, and 43.95% accuracy respectively. The proposed model employed 5-fold cross-validation strategies to determine the presence of overfitting problems, and the results are displayed in Table 5. Figure 15 and Figure 16 shows the experimental data analysis with the 09 previously trained CNN architectures without the optimization.

Seven classic ML-based classifiers -LR, DT, NB, SVM, RF, XGB, and KNN were used in the proposed study. Table 6 displays the whole set of outcomes from the ML algorithms trained on the VGG16 architecture. The best accuracy (95.54%) is acquired by the LR combined with VGG16, outperforming all other models. Table 7 displays the outputs of 5-fold cross-validation using ML models and VGG16. Figure 17 shows the

Table 5. The fold-wise results of various pre-trained techniques with SVM with SVM.

CNN model	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5
VGG16	76.42	80.87	84.08	84.05	86.03
VGG19	68.71	76.99	79.56	80.14	80.84
ResNet50	85.79	89.69	91.61	93.54	92.92
InceptionV3	23.56	24.17	24.19	29.91	27.37
Xception	22.33	19.81	21.73	21.73	25.52
DenseNet	34.41	53.51	58.62	57.33	59.28
MobileNetV2	40.80	56.66	60.49	63.24	63.69
EfficientNetB0	68.14	74.51	77.70	80.28	77.13
NasNet	23.56	24.80	26.07	29.91	28.06

Table 6. The overall results of various pre-trained techniques with VGG16.

Classifiers	*P* (%)	F1 (%)	A (%)	R (%)
SVC	93.85	93.35	93.93	93.11
RF	90.21	89.89	90.45	90.01
DT	65.86	64.67	64.97	65.32
NB	86.31	76.38	73.89	74.30
XGB	89.41	89.25	89.81	89.24
KNC	85.77	84.57	85.35	84.59
LR	**95.49**	**95.29**	**95.54**	**95.17**

Table 7. The fold-wise results of various pre-trained techniques with VGG16.

Classifiers	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5
SVC	76.42	80.87	84.08	84.05	86.03
RF	73.88	78.36	82.85	82.74	82.83
DT	44.62	42.01	38.18	43.30	43.30
NB	67.52	71.40	73.95	76.47	73.95
XGB	56.69	66.35	75.17	75.80	71.39
KNC	65.59	67.50	69.45	72.68	70.77
LR	83.34	86.61	86.60	87.86	85.94

Table 8. The overall results of various pre-trained techniques with VGG19.

Classifiers	A (%)	*P* (%)	R (%)	F1 (%)
SVC	**97.45**	**97.54**	**97.64**	**97.52**
RF	94.90	94.87	95.04	94.89
DT	70.06	69.71	69.64	69.39
NB	76.43	84.70	76.32	77.76
XGB	94.27	94.31	93.99	94.06
KNC	89.81	90.93	89.40	89.69
LR	97.45	97.48	97.38	97.39

Learning curve, ROC curve, and confusion matrix of LR+VGG16.

Additionally, Table 8 displays the outcomes from the ML algorithms trained on the VGG19 framework, where the SVC paired with VGG19 attained the best accuracy (97.45%), beating all other models. Table 9 displays the output of 5-fold cross-validation using ML models and VGG19. The ROC curve, learning curve, confusion matrix of SVC+VGG19 are shown in Figure 18.

Moreover, the results of all ML algorithms trained using the ResNet50 model are shown in Table 10. The combination of SVC and ResNet50 achieves the highest accuracy (98.06%), surpassing any other models. The outcomes of the 5-fold cross-validation of ML algorithms and ResNet50 are shown in Table 11. Figure 19 shows the Learning curve, ROC curve, and confusion matrix of SVC+ResNet50.

Table 9. The fold-wise results of various pre-trained techniques with VGG19.

Classifiers	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5
SVC	68.71	76.99	79.56	80.14	80.84
RF	74.48	73.22	79.53	80.76	78.32
DT	47.20	50.31	50.28	47.13	51.63
NB	66.17	71.95	67.46	71.97	66.80
XGB	69.42	70.70	76.42	74.43	71.96
KNC	71.30	77.01	75.76	76.39	76.48
LR	84.04	84.66	83.41	84.65	84.68

Table 10. The overall results of various pre-trained techniques with ResNet50.

Classifiers	A (%)	*P* (%)	R (%)	F1 (%)
SVC	**98.06**	**98.02**	**98.13**	**98.03**
RF	92.90	93.08	93.10	92.95
DT	69.03	72.64	68.82	69.30
NB	94.84	95.21	95.06	94.99
XGB	92.90	93.16	93.22	92.95
KNC	91.61	92.50	92.06	91.54
LR	96.77	96.60	97.10	96.82

Table 11. The fold-wise results of various pre-trained techniques with ResNet50.

Classifiers	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5
SVC	85.79	89.69	91.61	93.54	92.92
RF	83.87	83.23	83.87	87.06	89.69
DT	55.50	47.04	53.60	52.25	61.35
NB	56.15	68.99	71.59	73.54	79.35
XGB	67.08	72.87	74.24	72.90	79.99
KNC	76.76	76.72	76.06	77.41	81.89
LR	92.25	92.25	92.89	93.54	95.51

Lastly, the proposed study experimental results show that the pre-trained ResNet50 model with SVC ML algorithm performed best (98.06%) among the other models, VGG16+LR and VGG19+SVC, which got (95.54%) and (97.45%) accuracy, respectively.

3.2. *Result analysis with various feature selection techniques*

In this sub-segment, the overall performance between the feature selector algorithms with the pre-trained models of the proposed study is shown. Many feature selector algorithms such as SVC, PCA, and LDA feature selection were exploited in this work to find the most essential features from the pre-trained model's feature extraction. Table 12 displays the results of the different pre-trained models with PCA feature extractor where ResNet50 performs the best (98.71%) among all other models. Additionally, the results of the pre-trained models with LDA and SVC are shown in Table 13, and Table 14 where VGG16+LDA and ResNet50+SVC got the highest accuracy (97.45%), and (98.71%), surpassing any other models. The experimented results are the evaluated with the seven ML classifiers,

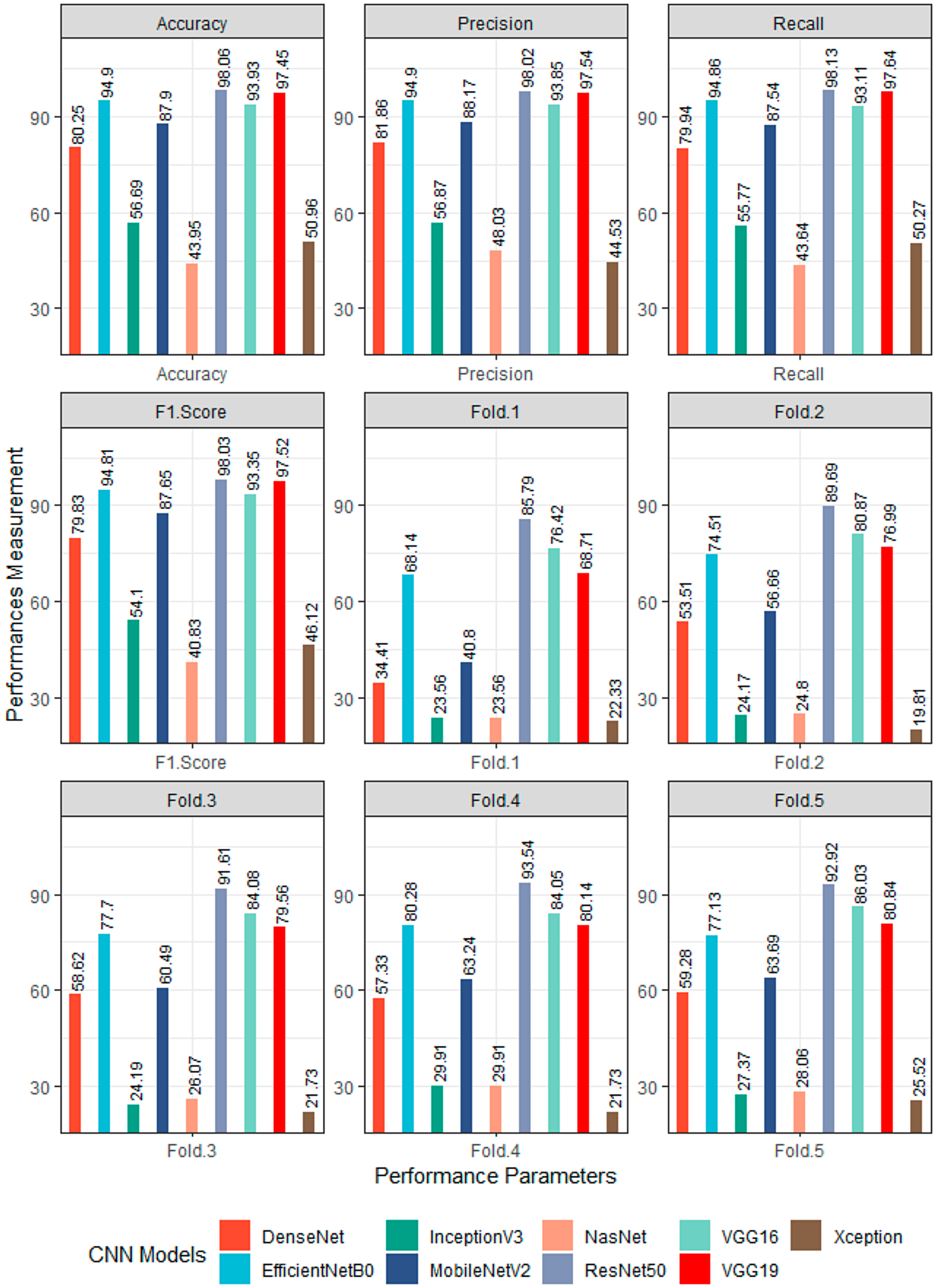


Figure 15. The overall results of various pre-trained techniques with SVM.

Lastly, the suggested study's results show that the pre-trained ResNet50 model with feature selector algorithms performed best (98.71%) among the other models. That's why the proposed pre-trained ResNet50 model with feature selector techniques have been chosen initially. Table 15 illustrate the overall results of the ResNet50 algorithm and the feature selection models.

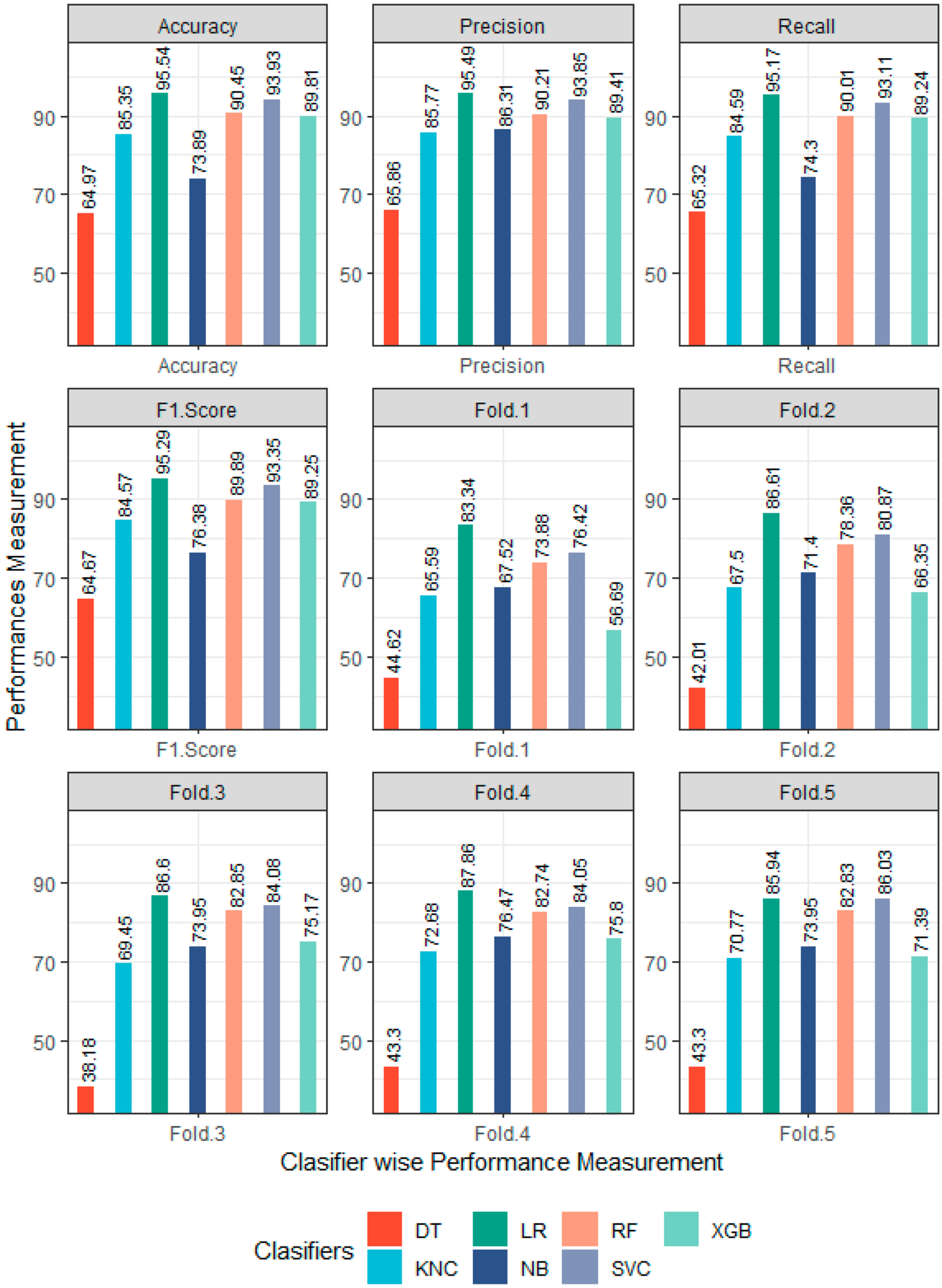
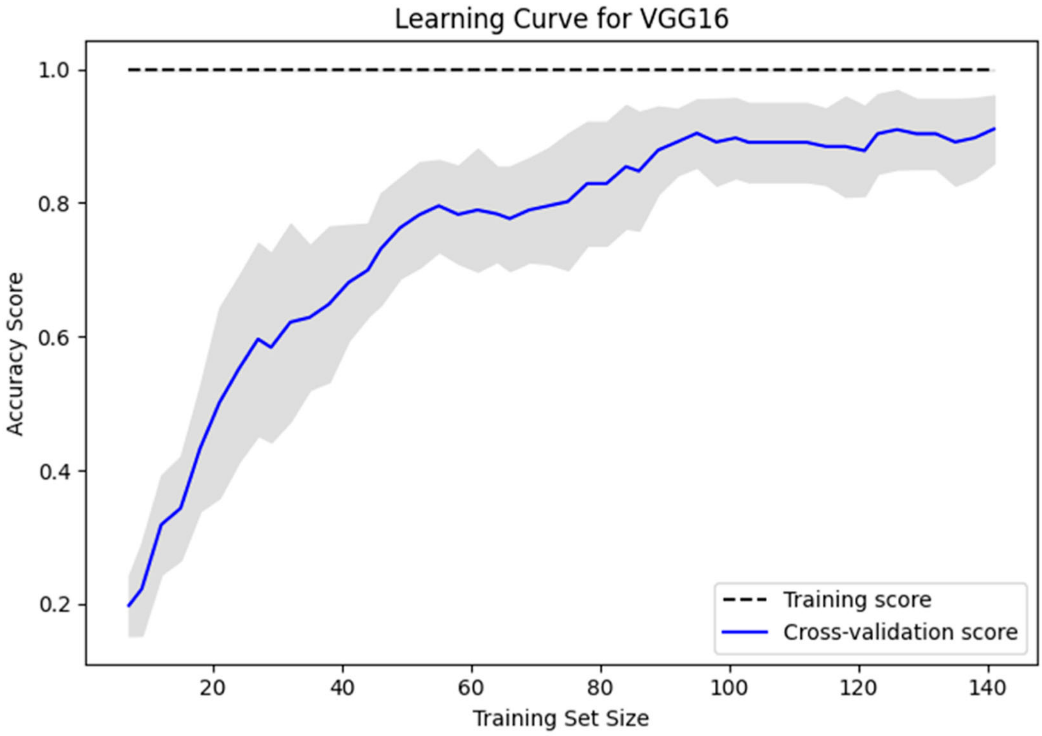
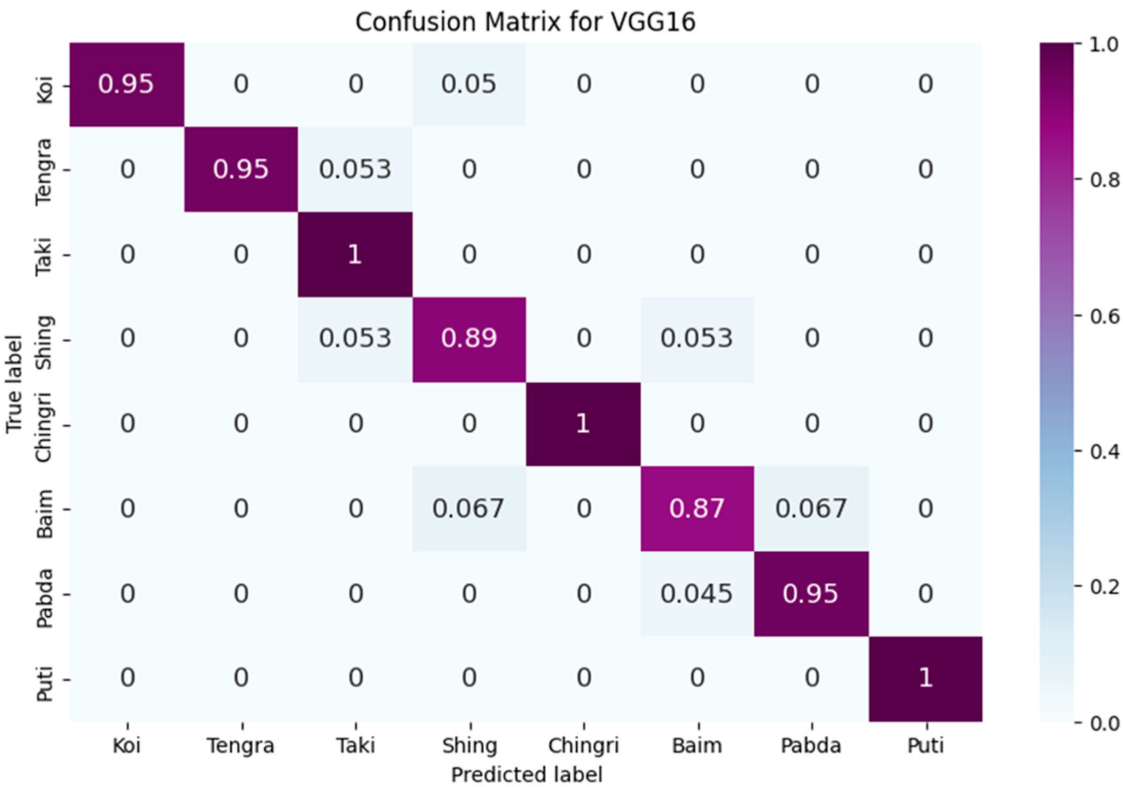


Figure 16. The overall results of various pre-trained techniques with VGG16.

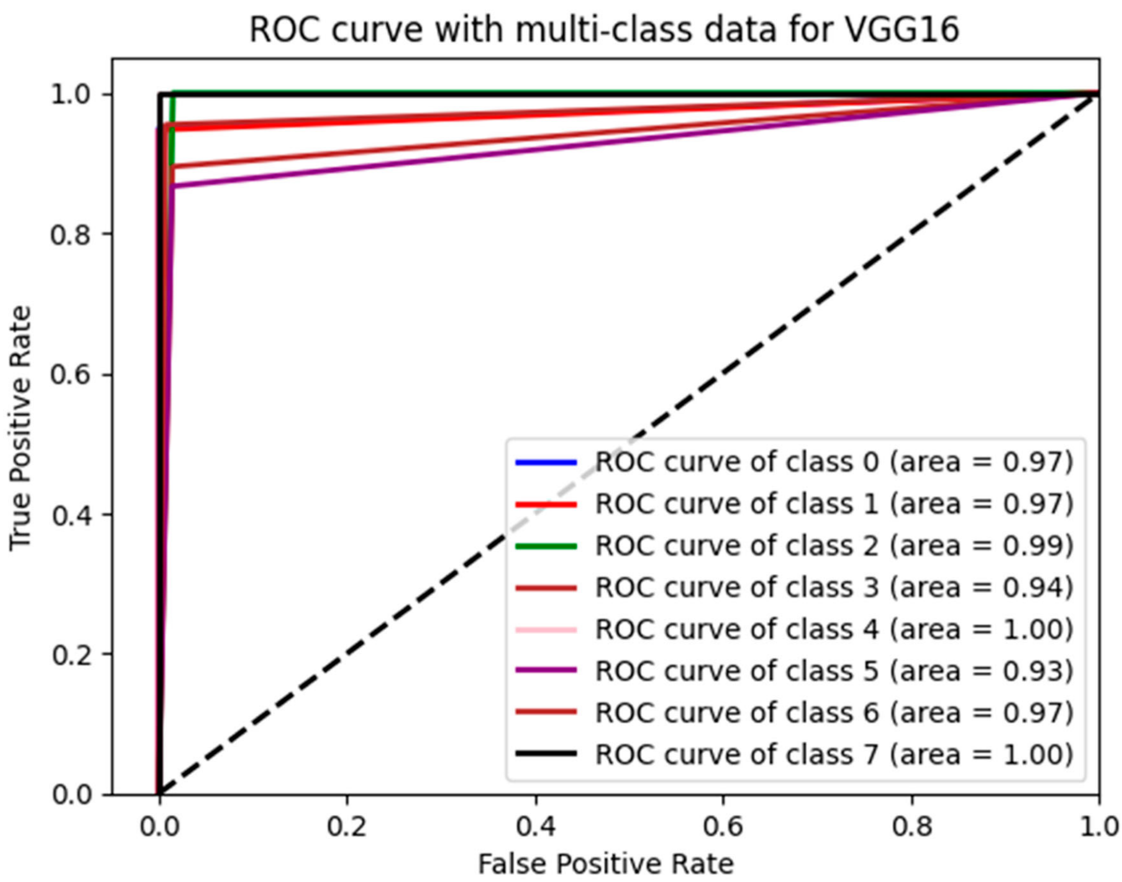


(a)



(b)

Figure 17. Best performance analysis of VGG16+LR with (a) Learning curve, (b) Confusion Matrix, (c) ROC curve.



(c)

Figure 17. Continued.

Table 12. The overall results of various pre-trained techniques with PCA feature extractor.

CNN model	A (%)	P (%)	R (%)	F1 (%)
VGG16	97.45	97.83	97.40	97.51
VGG19	97.45	96.98	96.84	96.87
ResNet50	**98.71**	**98.94**	**98.72**	**98.80**
InceptionV3	57.96	61.16	54.71	53.26
Xception	63.69	66.94	63.01	63.09
DenseNet	92.36	93.10	92.08	92.36
MobileNetV2	87.90	88.59	88.12	87.69
EfficientNetB0	94.90	94.69	95.31	94.88
NasNet	53.50	52.96	52.85	50.85

Table 13. The overall results of various pre-trained techniques with LDA feature extractor.

CNN model	A (%)	P (%)	R (%)	F1 (%)
VGG16	**97.45**	**97.53**	**97.73**	**97.52**
VGG19	94.27	95.57	93.98	94.54
ResNet50	96.13	96.13	95.68	95.51
InceptionV3	60.51	59.88	57.56	57.33
Xception	64.97	68.61	64.28	64.06
DenseNet	87.90	87.55	87.40	87.02
MobileNetV2	84.08	84.88	82.75	83.03
EfficientNetB0	97.45	97.54	97.21	97.34
NasNet	51.59	51.72	50.46	49.43

Table 14. The overall results of various pre-trained techniques with SVC feature extractor.

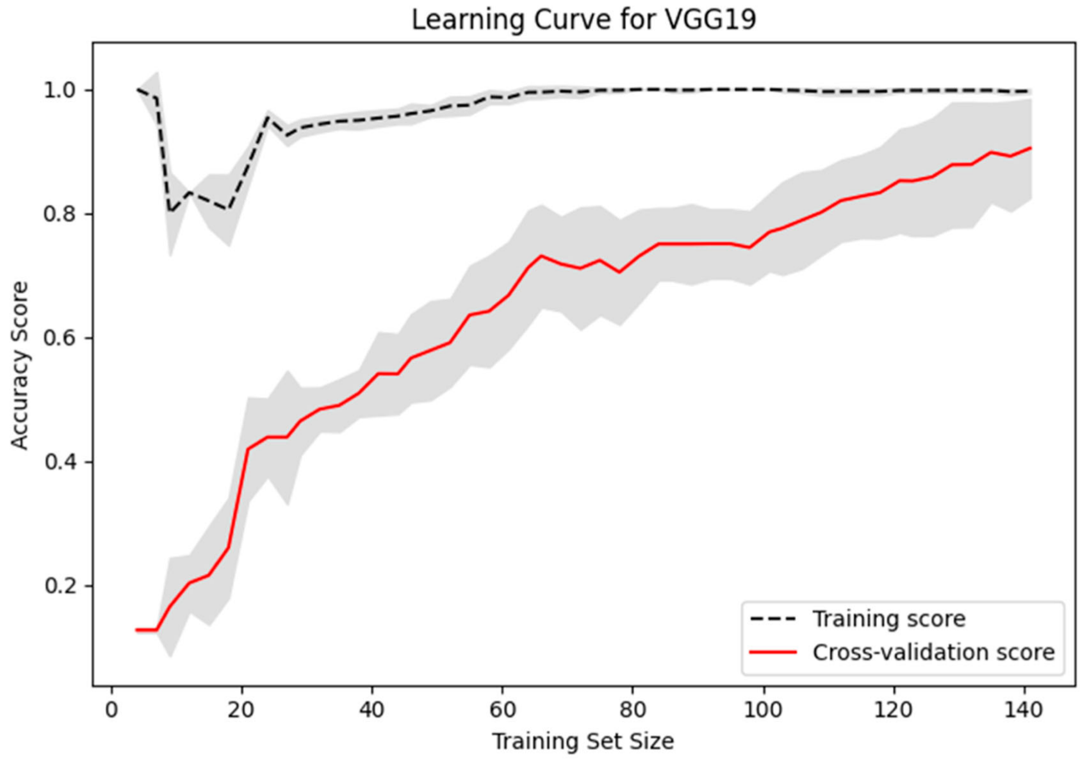
CNN model	A (%)	P (%)	R (%)	F1 (%)
VGG16	97.45	97.67	97.37	97.46
VGG19	96.82	96.83	96.48	96.57
ResNet50	**98.71**	**98.67**	**98.65**	**98.62**
InceptionV3	64.33	63.64	63.32	63.21
Xception	77.07	77.50	77.32	76.84
DenseNet	88.54	88.55	88.12	88.06
MobileNetV2	84.71	84.44	84.12	83.96
EfficientNetB0	94.90	94.64	94.54	94.54
NasNet	57.32	58.63	56.80	57.16

Table 15. The overall results of various feature selection techniques with ResNet50.

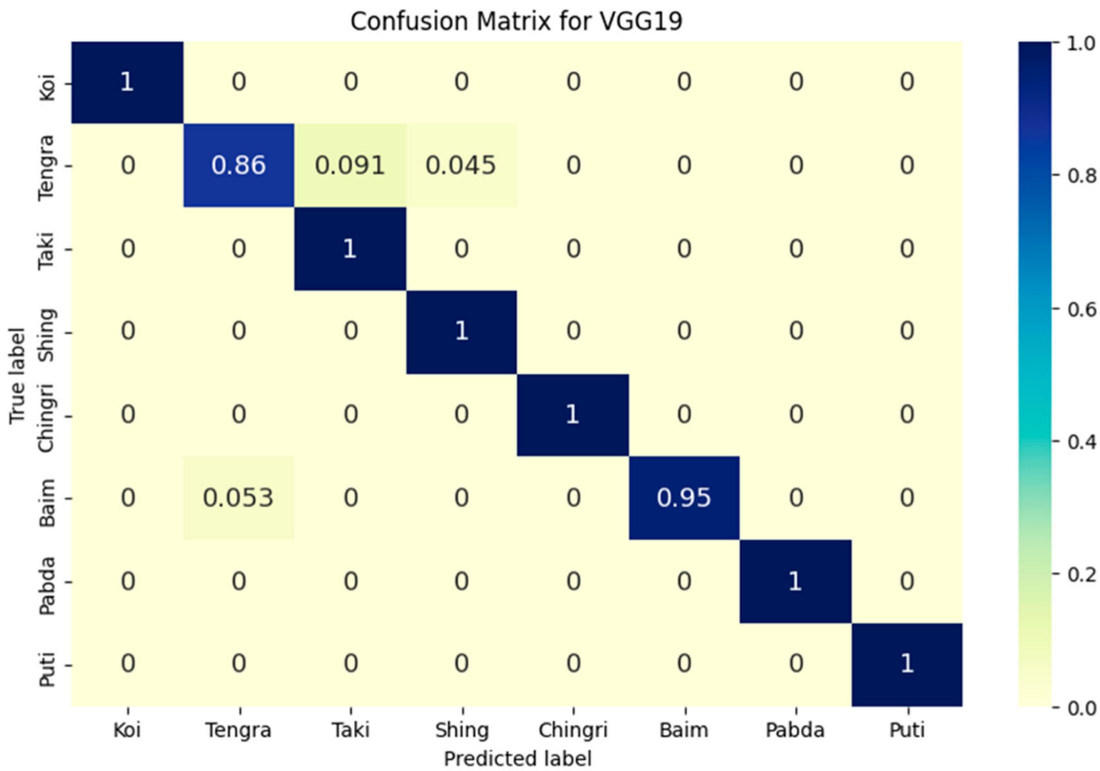
Serial No.	Feature selector	A (%)	P (%)	R (%)	F1 (%)
1	PCA	98.71	98.94	98.72	98.80
2	LDA	96.13	96.13	95.68	95.51
3	SVC Feature Selector	98.71	98.67	98.65	98.62

3.3. *Performance analysis with different nature inspired optimization algorithms*

The proposed research described the result analysis with the different Nature Inspired Optimization

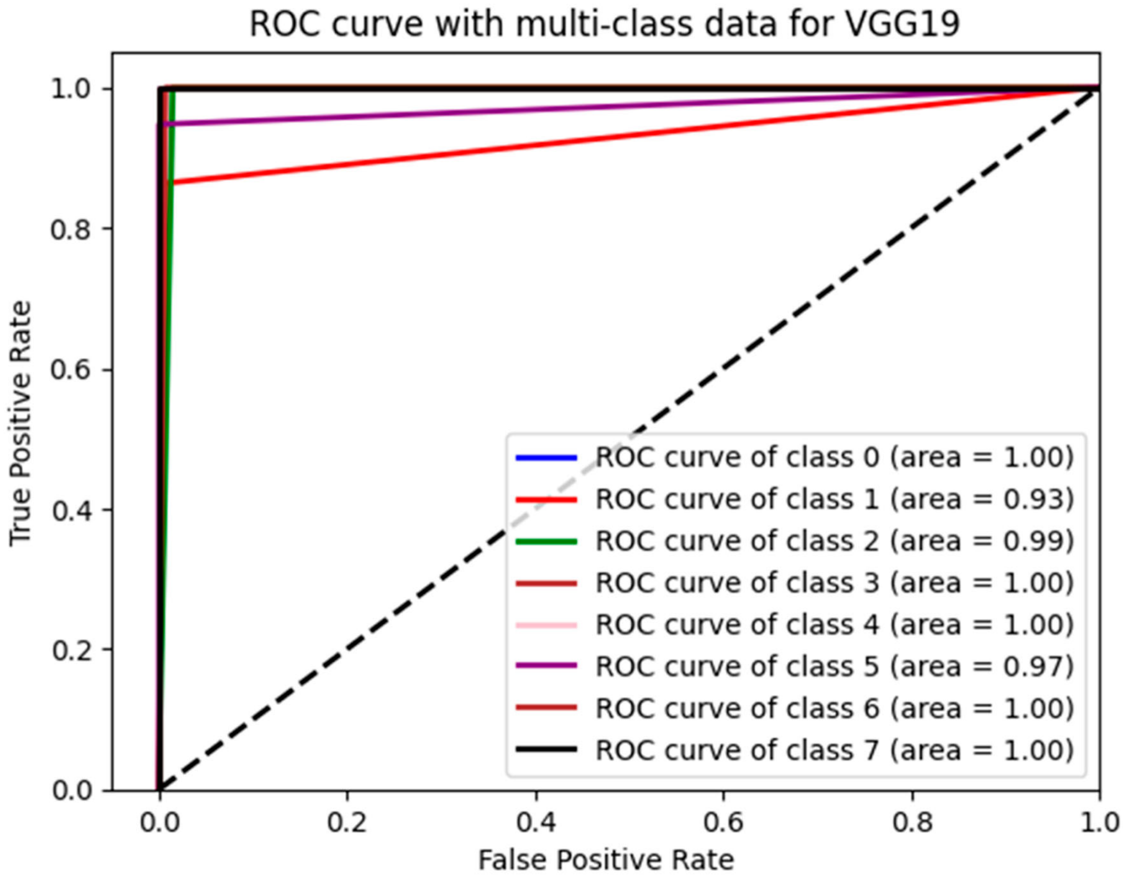


(a)



(b)

Figure 18. Best performance analysis of VGG19+SVC with (a) Learning curve, (b) Confusion Matrix, (c) ROC curve.



(c)

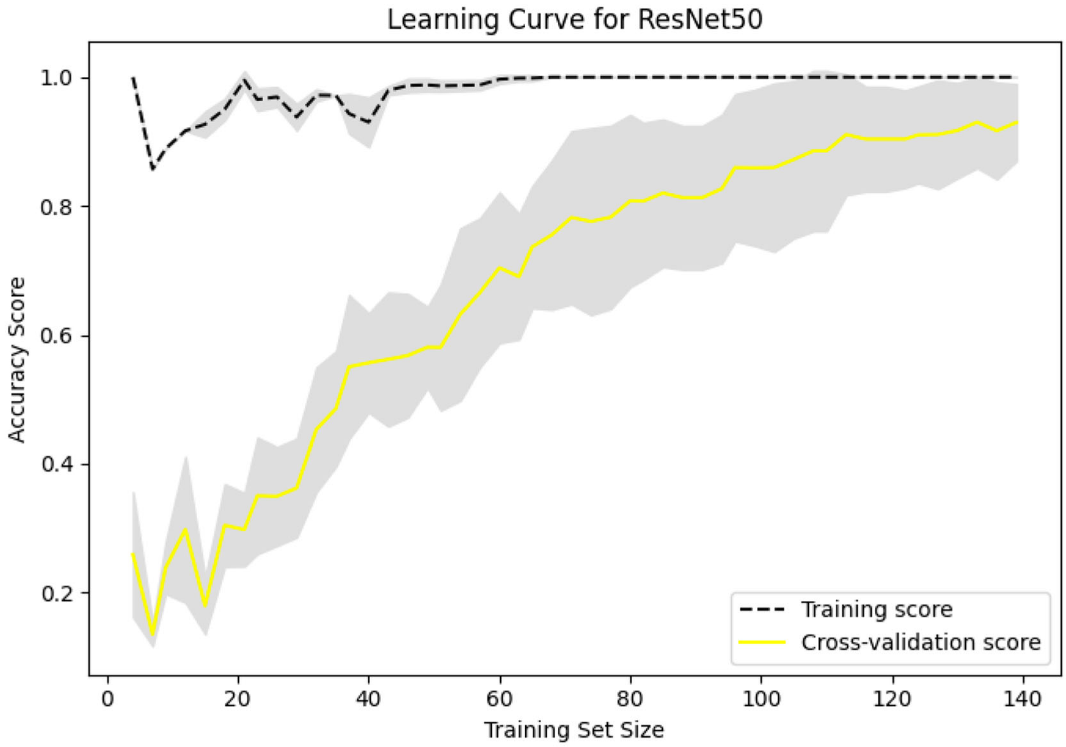
Figure 18. Continued.

algorithms in this subsection. Initially, the study pulled out characteristics with the help of previously trained CNN models and after that the feature selector algorithms with the Nature Inspired Optimization techniques were applied.

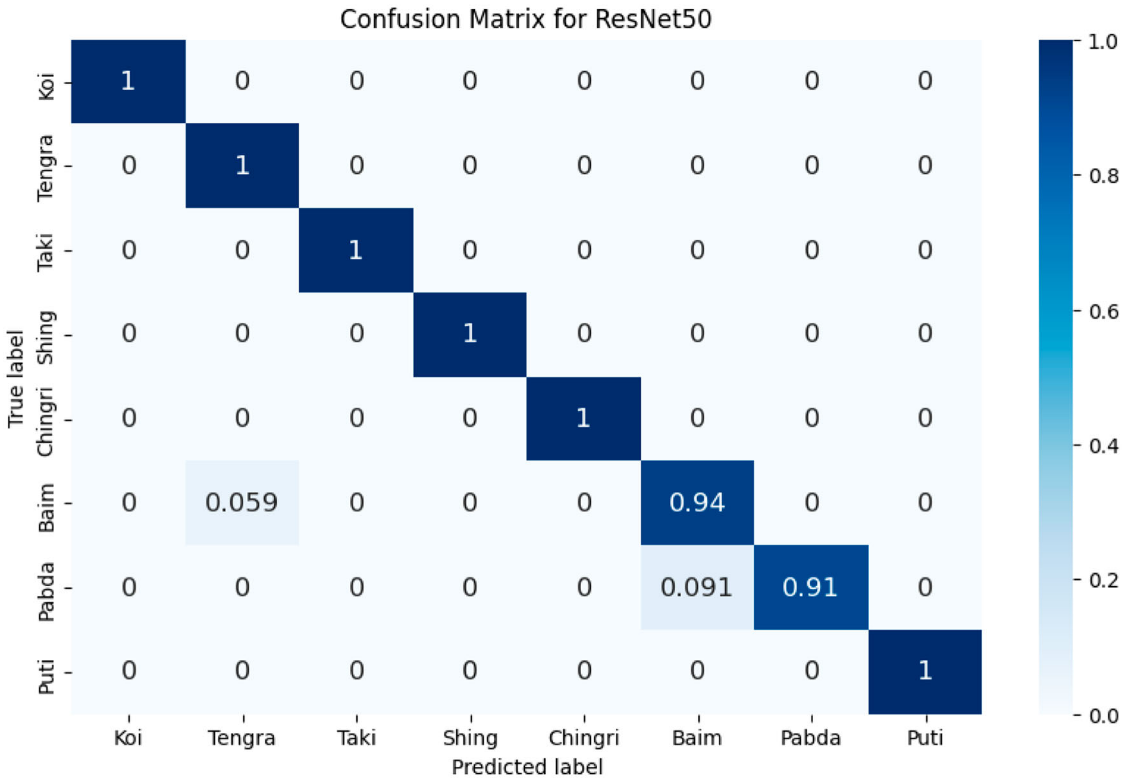
The data analysis summary of the suggested work with the ResNet50 model and the Nature Inspired Optimization techniques are displayed in Table 16. The both models such as PSO, CSO and BFO provide the best performance in fish classification and we found the highest accuracy of 98.71% between all other models. Though they provide the same accuracy but their performance can be differentiated in the number of the selected feature from ResNet50 model. We have found that the CSO algorithm utilized the less features compared to other two algorithms but gave the highest accuracy. Figure 20 shows the comparative performance from the different optimization algorithms and Figure 21 shows the ROC-curve obtained from these algorithms.

3.4. Comparison and discussion

This section demonstrates the comparison between the current system and the previous work which is illustrated in Table 17. The table clearly shows that, the CNN model of DL methods was the only method utilized in many earlier studies c for classifying the freshwater fish images. There was only two study that made use of ML and DL methods [34,39]. Previous works [27,29,38] only used a couple of pre-trained models or conventional algorithms when it came to CNN and ML models. The dataset sizes of several articles [27,30,34,35] are likewise not very large, and many of these papers [32,38] still need to apply image preprocessing techniques. In contrast, the suggested model classified freshwater fish images using nine pre-trained models of CNN architecture and seven traditional ML algorithms with several optimization approaches. The proposed model extensively uses image preprocessing techniques like filtering and enhancement. In addition,

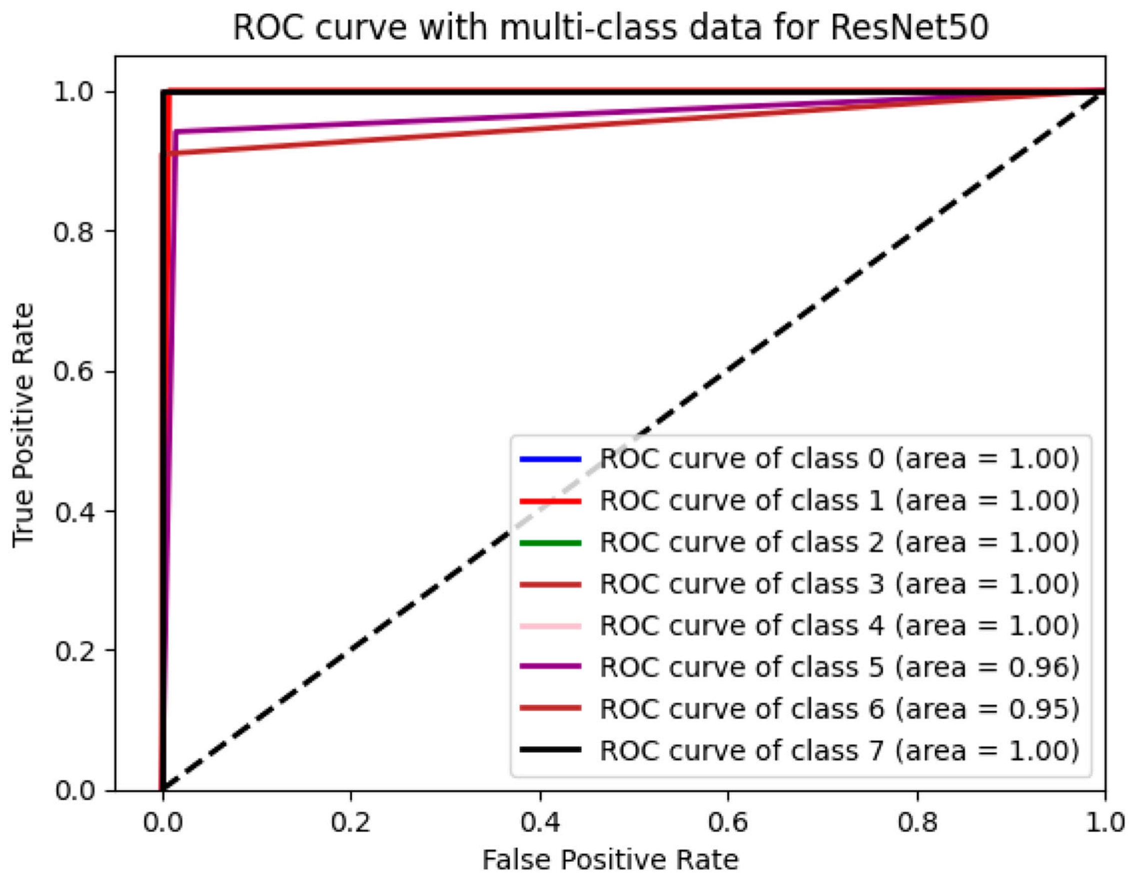


(a)



(b)

Figure 19. Best performance analysis of ResNet50+SVC with (a) Learning curve, (b) Confusion Matrix, (c) ROC curve.



(c)

Figure 19. Continued.

Table 16. The overall results of several natures inspired optimizer techniques with ResNet50 and the classifiers.

Serial No.	Nature inspired optimizer	Classifiers	Subset accuracy	No. best selected features	A (%)	*P* (%)	R (%)	F1 (%)
1	PSO	SVC	96.12	1005	97.42	97.32	97.30	97.29
		RF	97.41		94.19	94.28	94.03	94.02
		DT	72.25		67.74	68.68	67.93	68.06
		NB	93.19		94.19	94.93	93.77	94.14
		XGB	90.32		92.26	92.21	91.84	91.87
		LR	**98.06**		**98.71**	**98.67**	**98.65**	**98.62**
2	CSO	SVC	99.35	756	97.42	97.32	97.30	97.29
		RF	94.19		94.19	94.66	94.03	94.21
		DT	70.96		72.90	73.34	73.03	73.02
		NB	92.90		94.19	94.93	93.77	94.14
		XGB	94.19		92.26	92.21	91.84	91.87
		LR	**98.70**		**98.71**	**98.67**	**98.65**	**98.62**
3	BFO	SVC	96.77	998	97.42	97.32	97.30	97.29
		RF	93.48		94.19	94.95	93.84	94.18
		DT	67.09		69.68	70.50	70.38	69.85
		NB	93.54		94.19	94.93	93.77	94.14
		XGB	92.90		92.26	92.21	91.84	91.87
		LR	**98.06**		**98.71**	**98.67**	**98.65**	**98.62**

LDA, PCA, and SVC feature selection were employed as feature selector techniques to help get the most helpful information out of the dataset. Also, we have also applied the nature-inspired algorithm to track the highest accuracy.

3.5. The prototype development of the lightweight application (App)

We have applied the trained model and eXplainable AI (XAI) in order to check the efficacy of our proposed

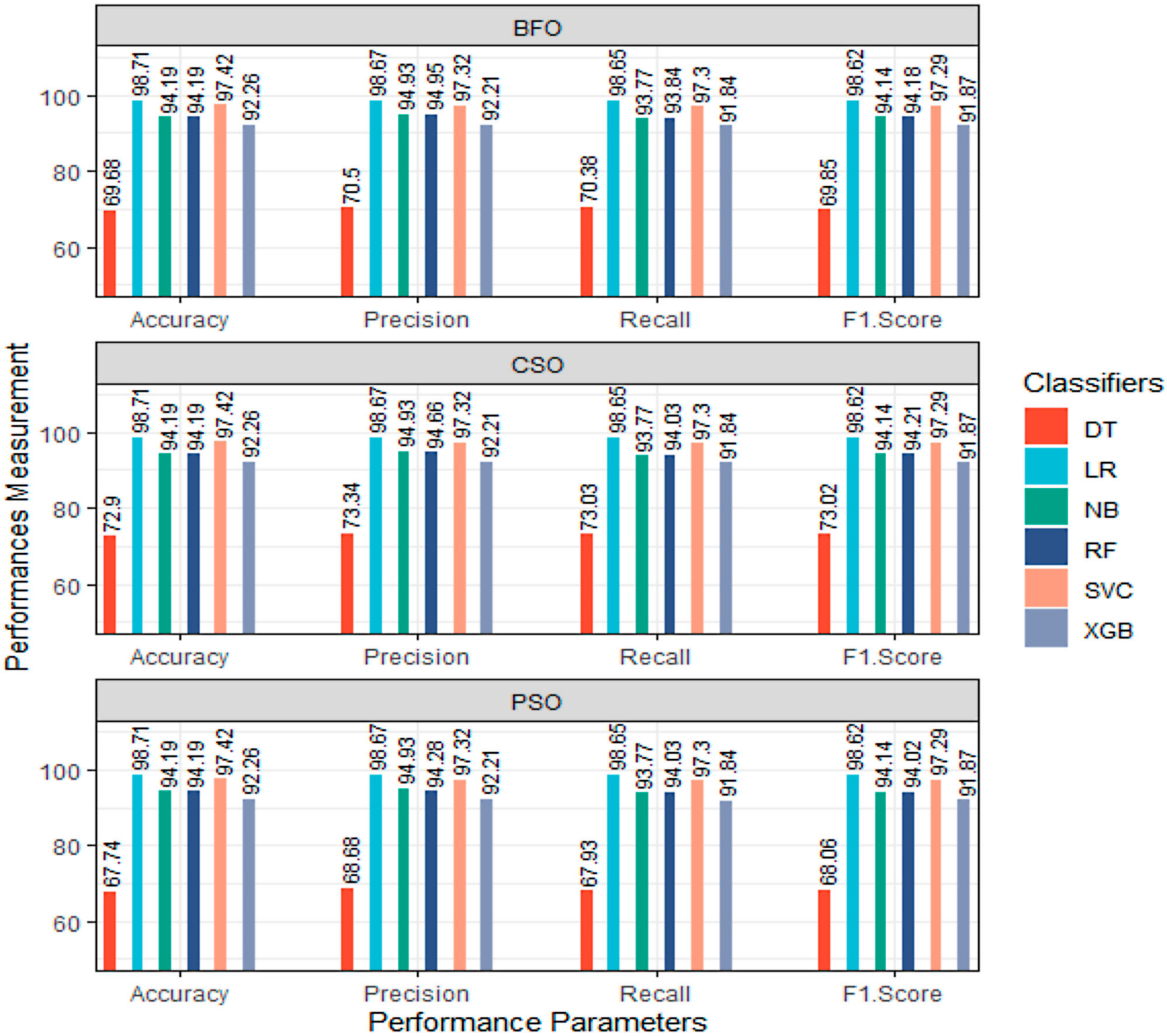


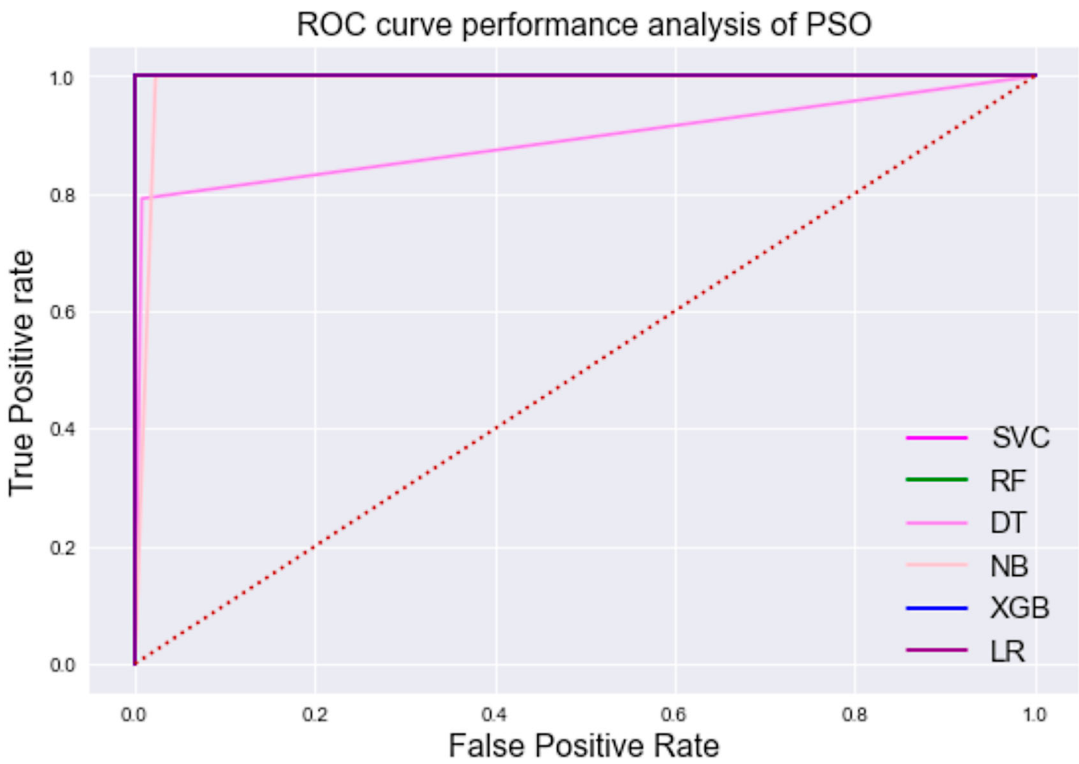
Figure 20. The collective effectiveness of diverse nature-inspired optimization techniques when applied to ResNet50 alongside various classifiers..

model. We have used the Python Flask environment to deploy the application, along with HTML, CSS, and JavaScript. First, Firstly, we saved the model in the ".pkl" format, which yielded the highest accuracy in multiclass classification after applying feature optimization techniques. we have built a lightweight web application to apply Grad-CAM visualization (as XAI) to fish classification. The following application accepts a fish image as input and uses Grad-CAM to provide the species name and significant features. Figure 22 shows the screenshots of the lightweight application.

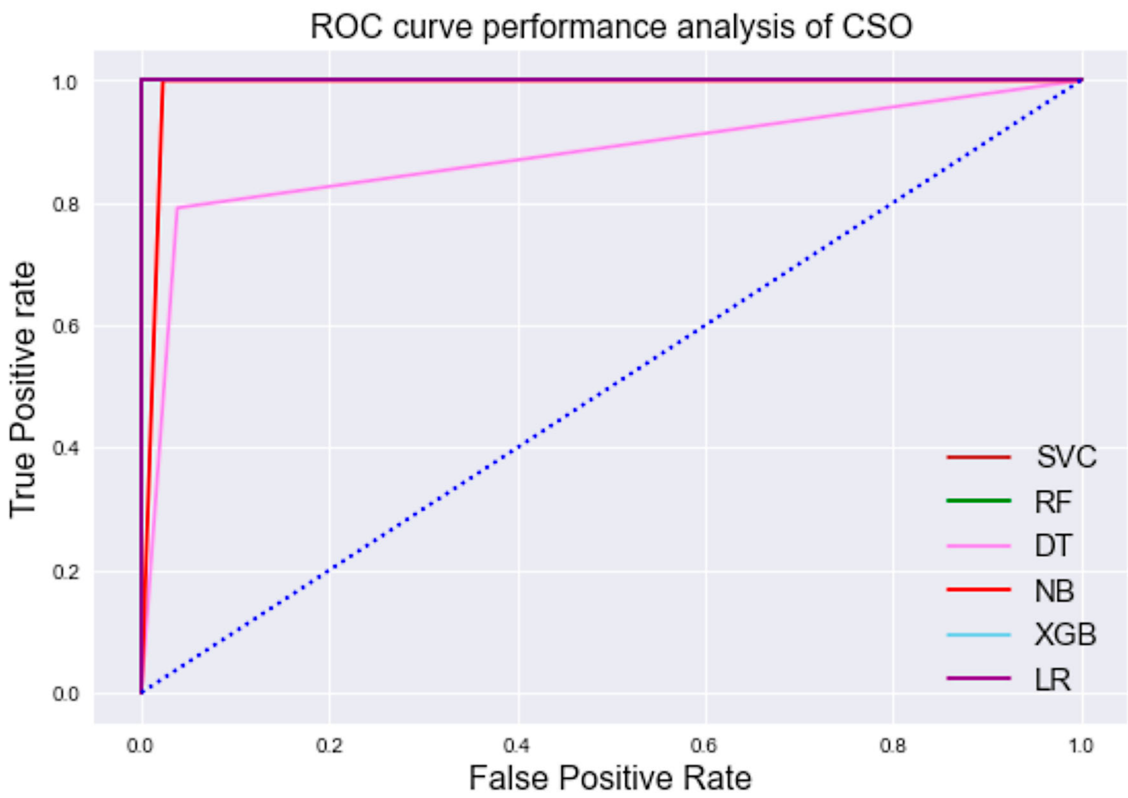
4. Conclusions and future work

The growth of fisheries faces significant challenges due to human activities altering riverine environments, disrupting ecological systems, intensifying agricultural practices, and polluting water bodies. As a result, native freshwater species in Bangladesh are at risk of extinction despite existing protective laws and regulations, which are difficult to enforce in the current socioeconomic context. To address these issues, this study explores the application of cutting-edge technologies such as Machine Learning (ML) and Deep Learning (DL) to categorize regional freshwater fish. Initially, features of local freshwater fish images are extracted using pre-trained Convolutional Neural Network (CNN) models. Subsequently, feature selection techniques including Bacterial Foraging Optimization (BFO), Particle Swarm Optimization (PSO), and Cuckoo Search Optimization (CSO) algorithms are employed. Experimental data analysis demonstrates the effectiveness of the proposed approach. Before integrating feature selectors or BFO, traditional ML techniques and pre-trained CNN models achieve an accuracy of 98.71%.

However, using the proposed architecture along with feature selection methods and BFO, the model achieves the same level of accuracy, showcasing its potential. Despite its success, the model has limitations.

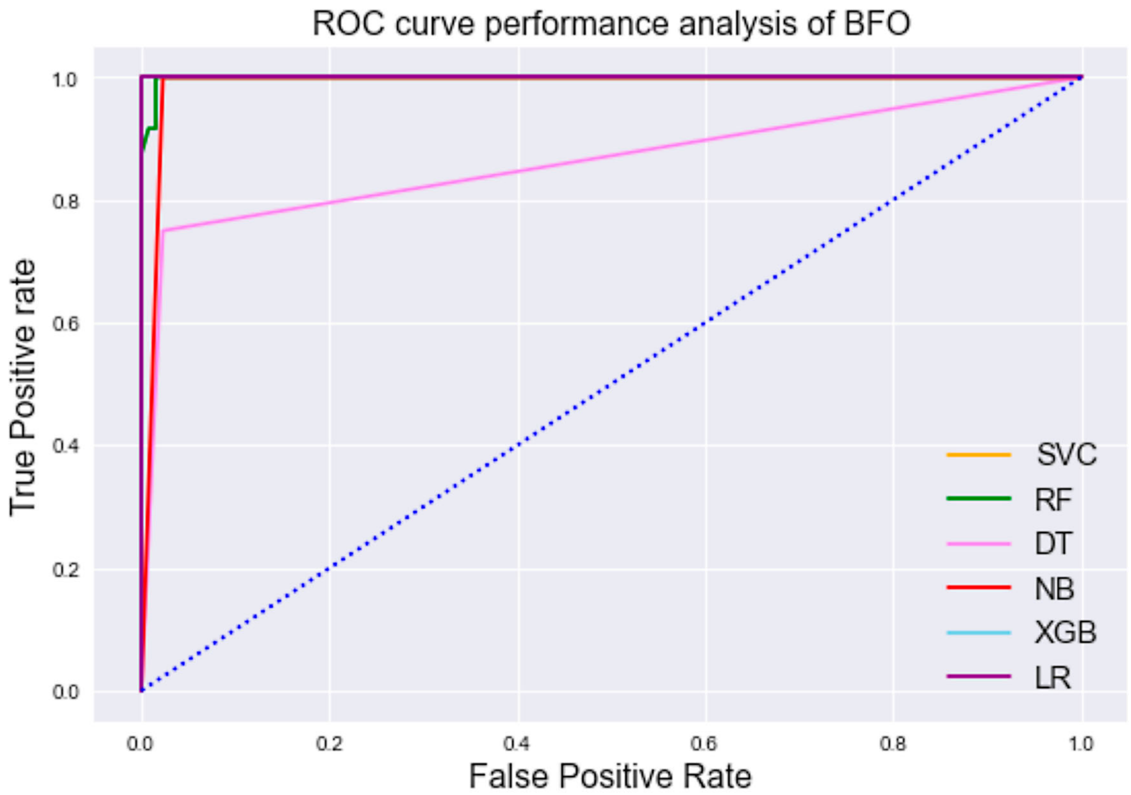


(a)



(b)

Figure 21. ROC curves of different nature inspired algorithm on ResNet50 and several classifiers (a) PSO (b) CSO (c) BFO.



(c)

Figure 21. Continued.

Table 17. Comparison among existing approaches and proposed model.

References	Algorithm/Model used	Techniques	Feature selector models	Optimization methods	Accuracy
[27]	GoogLeNet, AlexNet, VGG16, and VGG19	DL	–	Adam	98.33%
[28]	Multi-Level Residual (MLR), ResNet50, VGG16, VGG19, Xception, and Inception V3	DL	–	RMSProp	99.69%
[29]	Convolutional neural network (CNN)	DL	–	RMSprop, Adam, SGD	99.40%
[30]	VGG19, Xception, Inception V3, ResNet150 V2, EfficientNetB0, and ANN	DL	–	Adam	100%
[31]	AlexNet, GoogLeNet, and ResNet	DL	–	–	99.85%, 96.39%, and 99.51%
[32]	Deep Convolutional Neural Network	DL	–	SGD, Adam, Adamax or RMSprop	81.83%
[34]	SVM, Resnet-50, Transfer Learning	ML+DL	–	SGD	98.74%, 100%
[7]	AlexNet, Transfer Learning	DL	–	–	90%
[35]	VGG-16, Transfer Learning, LeNet-5, GoogleNet, AlexNet, and ResNet-50	DL	–	Momentum	96.63%
[37]	Transfer Learning, Convolutional Neural Networks (CNN), VGG-16 and ResNet-50	DL	–	Adamax	98.03%
[38]	YOLO deep neural network, ResNet-50, GMM	DL	–	–	91.64% and 79.8%
[39]	CNN, Support Vector Machine (SVM) and K-Nearest Neighbour (KNN)	ML+DL	–	–	98.79%
Proposed Model	Pre-trained CNNs: VGG16, VGG19, ResNet50, InceptionV3, Xception, DenseNet, MobileNetV2, EfficientNetB0, NasNet	ML+DL	PCA, LDA, SVC Feature Selectors	PSO, CSO and BFO	98.71%

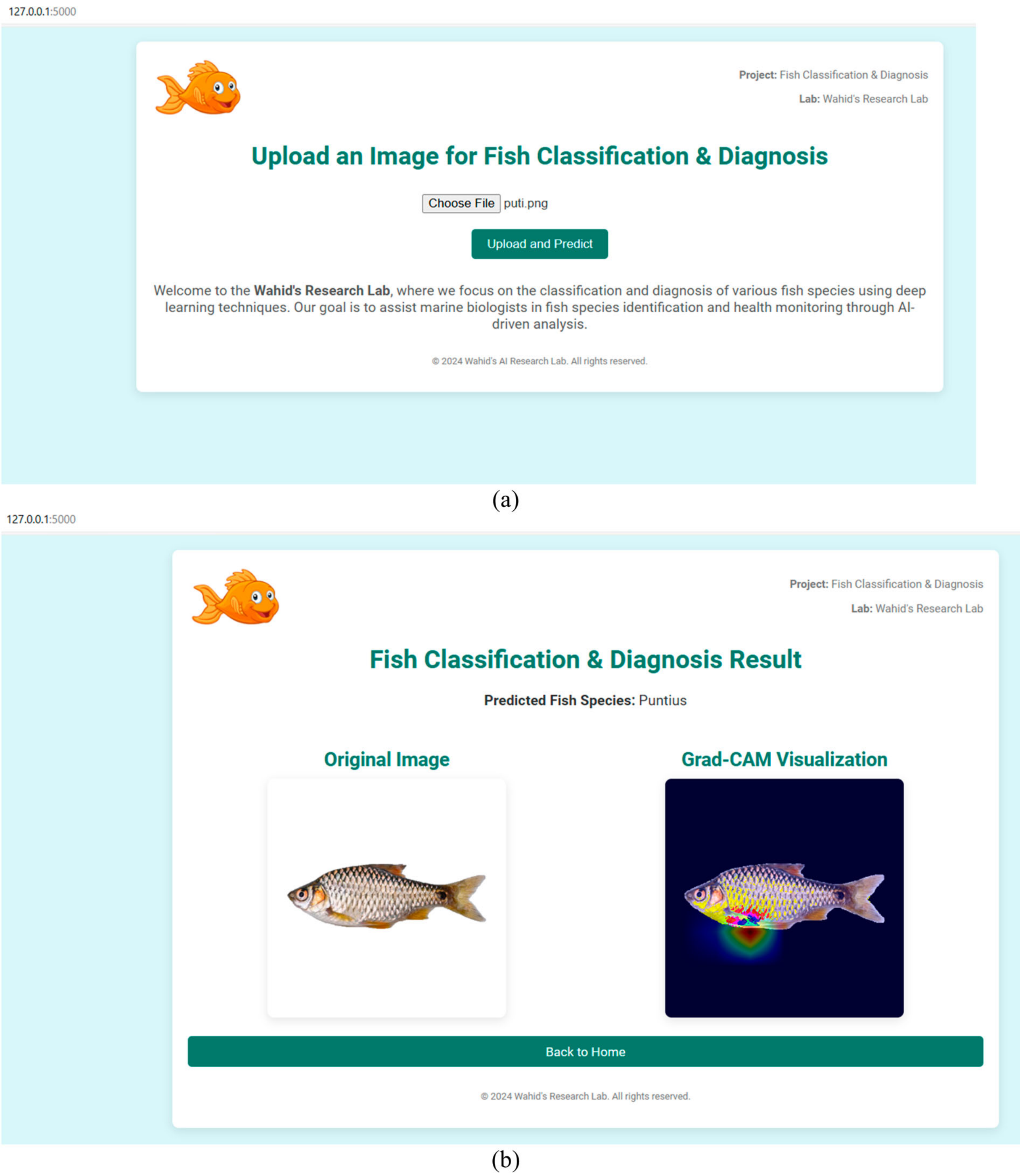


Figure 22. The development of lightweight web application using trained model with (a) landing page of application (b) Grad-CAM visualization on the extracted features.

It has yet to be implemented for categorizing freshwater fish in the area, and the optimization methods were only applied for straightforward attribute analysis. Future research aims to address these shortcomings by incorporating the optimization methods into modified CNN layers, enabling deployment on mobile devices and Internet of Things (IoT) devices. Additionally, future efforts will involve the use of more datasets to enhance the categorization of local freshwater fish.

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Data availability statement

All the data is available within the manuscript.

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