Research Square

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Skin Cancer Diagnosis Using CNN Features with Genetic Algorithm and Particle Swarm Optimization Methods

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Abstract

If skin cancer is not treated early, it also affects the diseased area under the skin and this threatens the treatment of the disease. In recent years many diseases have been rapidly detected with high accuracy with artificial intelligence methods and the treatment process has accelerated. Convolutional neural networks one of the artificial intelligence methods provide very detailed information about images and extremely successful results are obtained in classifying images. In this study firstly the data set was trained with the EfficientNetB0 model which is one of the convolutional neural networks models. Then, with the fully connected layer of this model, deep features of the images were obtained. These deep features were obtained by selecting with PSO and GA optimization algorithms, and different feature combinations were created. Each of these selected feature sets were classified by the SVM method and the best performance results were tried to be obtained. As a result, the success of the proposed model has been proven by obtaining an accuracy rate of 89,17%.

1. Introduction

Skin cancer is the most common type of cancer among cancer types, and the number of those diagnosed is increasing day by day. This type of cancer has two main types, melanoma and non-melanoma, which corresponds to 95% of this disease [1]. Early diagnosis of the disease is essential in the treatment of the disease. Late diagnosis of the disease causes the lesion to pass under the skin and adversely affects the treatment [2].

One of the traditional diagnostic methods, dermoscopic examination, is performed by imaging the lesion with a device called a dermoscope with a particular light system. With the advanced illumination system, the upper layers of the lesion can be viewed and examined in detail, and dermatologists can make early diagnoses. In order to perform histopathological examination, which is the other method, the tumorous lesion must be removed entirely and examined by pathologists in the laboratory environment. First, local anaesthesia is applied to the area where the lesion will be removed, and then the suspicious tissue is removed from the skin by drawing the proper boundaries. This method is a significant diagnostic method to confirm the diagnosis of melanoma.

In addition, developing computer technologies and artificial intelligence methods [2] [3][4][5] have also begun to gain popularity in diagnosing this disease. Image processing [6][7], machine learning [8][9][10], deep learning methods [2][11][12][13] and optimization methods [14][15][16] frequently used of the methods.

In this study, performed that deep feature selection using Convolutional neural network (CNN) feature-based deep feature extraction, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) + K-Nearest Neighbor (KNN) deep learning methods for effective diagnosis of skin cancer. A hybrid method is proposed that classifies them with the Support Vector Machine (SVM).

In recent years, many methods have been used to diagnose skin cancer using artificial intelligence techniques. These methods can be considered under two main headings, feature extraction and classification. Feature extraction was obtained by training CNN methods on the MobilNetV2 International Skin Imaging Collaboration (ISIC) dataset. Then these features were used together with a convolutional model to classify these features with an accuracy rate of 95.27% [17]. In another study, to classify the data set consisting of skin cancer images, the noise in the images was removed. The features were extracted with the AlexNet CNN model after the images were resized. Finally, the ECOC SVM method was used to classify the data set, and an accuracy rate of 95.1% was obtained [18]. The hybrid study, which was done by combining the artificial intelligence method and human interpretation, determined that superior results were obtained compared to the computer-based and expert interpretation-based model. This study, it was made by considering CNN networks and human interpretation [19]. In another proposed model for diagnosing skin cancer, images are first subjected to HSV color conversion and Laplacian filter. Then, after the lesion area was determined with the CNN method, the features were extracted with the InceptionV3 CNN model before using Hamming feature merging. Then the classification was done by selecting the features [20]. When looking at another study performed outside of the deep learning method, after the lesion area was obtained with the watershed segmentation method, the shape features of the region, Gray level co-occurrence matrix, and the feature set with the ABCD method were obtained. Then the classification was made with SVM, Random Forest, kNN methods [21].

The following sections of the article are organized as follows. In Chapter 2, studies on the materials and methods used, Chapter 3 describes the proposed model and the hyperparameters used. In Chapter 4, the performance results of the model are mentioned. In the following section, discussion and conclusion sections are given, respectively.

2. Material And Methods

This section will give information about deep learning, optimization algorithms, and classification methods used in our proposed method.

2.1. Dataset

This study used a dataset consisting of processed skin cancer images from the ISIC archive [22]. The dataset consists of a total of 3297 color images, including 1497 Malignant and 1800 Benign. Example images of the selected data set are given in Figure 1.

2.2. EfficientNetB0

EfficientNet is one of the CNN methods developed by the Google AI team, which is very successful in image classification processes [22]. It is a very successful method with an accuracy rate of 84% on the ImageNet dataset. This model can be considered a group convolutional neural network model, but it is more effective and efficient than the others. The main building block for EfficientNet is the mobile inverted bottleneck MBConv, first introduced in MobileNetV2. It is combined with deep separable

convolution, using direct shortcuts between bottlenecks connecting far fewer channels than expansion layers and reducing computation by almost k^2 times compared to traditional layers. Here k stands for kernel size, which specifies the height and width of the 2D convolution window [23]. This network also uses squeeze-and-excitation(SE) optimization, which contributes to performance improvements [24].

This method scales more efficiently by carefully balancing the network depth, width, and resolution, resulting in better performance. The architecture of the EfficientNetB0 network is given in Figure 2.

2.3. Genetic Algorithm

Genetic Algorithm (GA) is an optimization method that works using mechanisms similar to evolutionary mechanisms observed in nature. It works with the principle of searching for the best solution based on the principle of survival of the chromosome, which iterates in multidimensional space for optimization according to a specific cost function and produces the best result in each iteration. After the initial population is generated, the algorithm improves the current population with Mutation, Crossover, Selection (Roulette Wheel, Rank, Tournament, Elitism, Boltzmann, Steady State) operations in iterations and chooses the final optimal solution [24].

2.4. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is an optimization method developed by Kenedy and Eberhart (1995), inspired by fish and insects moving in swarms [25]. PSO is based on approximating the position of individuals in the herd to the best-positioned individual in the herd. This approach speed is a situation that develops randomly and most of the time, individuals in the herd are better positioned in their new movements than the previous position. This process continues until they reach the target [26][27][28].

2.5. K-Nearest Neighbor

The K-Nearest Neighbor (K-NN) algorithm is one of the simplest and most widely used classification algorithms. This algorithm does not learn the training data, instead, it searches for nearest neighbors in the entire dataset when we want to predict by memorizing the training dataset. A K value is determined for the neighbourhood search, which represents the number of elements to look for. When a value comes in, the distance between the incoming value is calculated by taking the nearest K element. The Euclidean function is generally used in distance calculation. As an alternative to the Euclidean function, Manhattan, Minkowski and Hamming functions can also be used. After the distance is calculated, it is sorted, and the incoming value is assigned to the appropriate class [29].

2.6. Support Vector Machine

Support Vector Machine is one of the supervised learning methods generally used in classification problems [30]. It draws a line to separate points placed on a plane. It aims to have this line at the maximum distance for the points of both classes. Suitable for complex but small to medium datasets.

3. The Proposed Model

CNN was introduced as an image feature extraction module because convolutional neural network (CNN) has an excellent performance in extracting image features.

Our study, in which deep learning, optimization algorithms and classification methods are used, consists of 4 stages. These are deep feature extraction, feature selection, combining best features, and classification steps (Figure 3).

As shown in Figure 3, the skin cancer images dataset is first trained using one of the CNN methods, EfficientNetB0. Then, 1000 deep features of EfficientNetB0 fully connected (FC) layer (MatMul) were obtained. GA and PSO optimization algorithms were used to select the most effective features among these features. K-NN classification algorithm was used to calculate the fitness value of the solutions obtained in both algorithms [31]. The results obtained in each optimization algorithm are brought together and made into a single input and then classified by giving them to the SVM.

The parameters used for the feature selection algorithms are as follows;

Common Parameters:

- Population Dimension: D=1000 (Extreacted feature size 1000),
- Population Size : N=10 number of population,
- Population Matrix : X (N,D), each element in the matrix x_i^d.
- Number of function evaluations: NFE = Number of iterations (100) * N = 1000,
- Number of KNN : k=5,

PSO Parameters:

- Cognitive factor =2,
- Social factor = 2,
- Inertia weight =0.9,

GA paramters:

- Selection method = Roulette Wheel,
- Crossover rate =0.8,
- Mutation rate=0.01,

The initial X(N,D) population matrix was obtained randomly between 0>x_i^d>1 values. In the case of x_i^d> 0,5 selected 1 is taken as 0, otherwise unselected, and fitness values are calculated. The fitness calculation formulation (Equation 1) is as follows.

$$EroorRate = 1 - ACC$$

$$SF = \sum_{i=0}^{D} x_i = 1$$

1

$$FitnessFunction = alpha * ErrorRate + beta * (SelectedFeatures/D)$$

Here, the accuracy rate obtained in the K-NN classification of the ACC selected features was taken as alpha=0.99, beta=0.01. SF refers to the sum of the selected features. The pseudo-codes of the optimization algorithms to which the K-NN-based fitness calculation is adapted are given in Figure 4.

1000 deep features obtained with EfficientNetB0 are given to the selected optimization algorithms to select the best features. According to the algorithm results, deep features of GA (DFGA) = 442 and deep features of PSO (DFPSO) = 479 feature sets were selected. According to these results, DFGA + DFPSO = 442 + 479 = 921 results were obtained. Since DFGA ∩ DFPSO = 210 of them are in both clusters, DFGA ∪ DFPSO = 711 different deep features were selected and these selected features were classified with SVM.

Detailed explanations and data of the experimental test results of our proposed method are given in the next section.

4. Experimental Results

This study used confusion matrix (CM) and cross-validation for performance measurements of studies to diagnose skin cancer images. A confusion matrix is a table used to describe the performance of a classification model on a set of test data for which the true values are known. There are four values in the confusion matrix: true positive (TP), false positive (FP), true negative (TN), and false negative (FN). To measure model performance, accuracy, sensitivity, specificity, precision and F-Score values were obtained from CM. These performance metrics are given mathematically in Formula 2-6, respectively. Cross-validation k value was chosen as 10. In this method, the data in the data set is randomly divided into k parts, and each time the k-1 value of the data set is used for training, while one part is used as a test.

$$\text{Accuracy (Acc)} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

2

$$\text{Sensitivity (Se)} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

3

$$\text{Specificty (Sp)} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

4

$$\text{Precision (Prec)} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

5

$$\text{Fscore}(\text{F} - \text{Sc}) = \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}}$$

6

The proposed model consists of 4 steps. First, the skin cancer dataset was trained with the EfficientnetB0 CNN model and its experimental results were examined. To train the CNN model, 70% of the data set was used for training and 30% was trained by randomly dividing it as a test. Since the skin cancer images were trained directly with EfficientNetB0, an accuracy rate of 86.25% was obtained when looking at the experimental results. The performance results obtained from the EfficientNetB0 model are given in Table 1, and the ROC curve is given in Figure 4.

Table 1
%70-%30 EfficientnetB0

Model	Accuracy	Sensitivity	Specificity	Precision	F-Score
EfficiennetB0	86.25	85.37	87.31	89.00	87.15

In the second step of the experimental study, 442 features were selected from 1000 deep features obtained from the EfficientNetB0 CNN model fully connected (FC) and support vector machines classified these features. In order to perform the classification process, the data set was randomly divided into 70% training and 30% testing, then classified, and the experimental results were analyzed by cross-validation. Considering the performance results obtained using only the Genetic Algorithm (GA), 90.09% accuracy was obtained with the holdout (70% training-30% test) method, while 88.69% accuracy was obtained with cross-validation. Experimental results obtained from feature selection with GA are given in Table 2, Receiving Operating Curve (ROC) curves in Figure 5 and convergence performance of GA in Figure 6.

Tablo 2 Genetic Algorithm %70 training and %30 testing

Model	Accuracy	Sensitivity	Specificity	Precision	F-Score
GA-Holdout	90.09	90.00	90.20	91.70	90.84
GA-Cross-validation	88.69	89.06	88.24	90.11	89.587

In order to determine the most effective features from the feature set obtained by the FC layer of the CNN model, this feature set was trained with the PSO algorithm method in the third stage of the experimental study. As a result of the training of deep features with PSO, it was determined that 479 deep features were selected. This feature set was given as an input to the support vector machines. When the experimental results were examined, it was seen that an accuracy rate of 87.77% was obtained with the holdout

method. In comparison, the accuracy rate of 88.38% was obtained with cross-validation (Table 3). The ROC graph obtained by using the PSO features is given in Figure 7, and the graph of the convergence performance of the PSO algorithm is given in Figure 8.

Table 3
Performance results obtained using the PSO algorithm

Model	Accuracy	Sensitivity	Specificity	Precision	F-Score
PSO-Holdout	87.77	89.63	85.52	88.16	88.89
PSO-cross	88.38	89.50	87.04	89.25	89.38

At the last stage of the experimental study, a new feature set was created from the selected features with GA and PSO optimization algorithms. 442 and 479 features were selected with GA and PSO, respectively. Since 210 features were selected in both optimization algorithms, these features were used only once. As a result, a new feature set consisting of 711 features was obtained as an input to the support vector machines. Considering the performance results of the deep features selected by the optimization algorithms, 89.08% accuracy was obtained with the Holdout method, while 89.17% accuracy was obtained with the cross-validation. The experimental results obtained with the deep properties of GA and PSO are given in Table 4, and the CM and ROC curves are given in Figure 9-10.

Table 4
PSO+GA Selected Deep Features

Model	Accuracy	Sensitivity	Specificity	Precision	F-Score
GA+PSO-Holdout	89.08	89.44	88.64	90.45	89.94
GA+PSO-Cross-validation	89.17	89.67	88.58	90.42	90.04

5. Discussion

Physiological changes on the skin manifest skin cancer. It can be life-threatening if not diagnosed and intervened early. It is a disease that can be seen in everyone, although it is more common in people with fair skin and exposed to ultraviolet rays. In this study, the deep features of the EfficientNetB0 deep convolutional neural network were used to classify benign and malignant skin cancer images in the ISIC dataset. The performance results of the model have been increased by using the deep features of the EfficientNetB0 model, GA and PSO optimization algorithms. In addition, in this study, it has been seen that it is a correct method in the selection of features obtained from the deep CNN model with optimization algorithms. When looking at the studies done with the same data set in the literature, Jayalakshmi et al [32]. After using the resizing and edge-smooting algorithm on the dataset, they proposed a CNN model consisting of 6 convolutions and then batch normalization and drop-out layers. The results were analyzed by changing the hyperparameters by using different training and test data ratios to train the dataset. As a result, an accuracy rate of 89.3% was obtained. Using a transfer learning

strategy on CNN models that have been previously trained on a large data set is a rather laborious task compared to testing a new CNN model. Classification using the weights of the pre-trained CNN model gives better results [33]. Similarly, in another study, the hairs were removed by applying a sharpening filter on the data set, and then the InceptionV3 and MobileNetV2 CNN models were trained with 75% training and 25% testing. As a result, 86% accuracy was obtained. In this study, although a smaller number of data was used for the network's training, a higher accuracy rate was obtained. Using the EfficientNet model transfer learning strategy, an accuracy rate of 86.25% was obtained. Although it is not correct to directly compare since the same hyperparameters are not used, it can be said that the CNN model used is a suitable model for training the ISIC dataset. In another study with deep learning [17] the same number of images were taken from both classes in the ISIC dataset, and the original dataset was reproduced with Autoencoder networks, and a model based on the spiking network and CNN networks were proposed and an accuracy rate of 95.27% was obtained.

Since feature selection with GA and PSO optimization algorithms is used in this study, it is seen as an advantage that the machine requires less computational load.

6. Conclusion

In this study, the classification process of benign and malignant cancerous cells in the ISIC dataset was performed to diagnose skin cancer. For this purpose, a diagnostic model based on CNN, GA and PSO has been proposed. First, the data set was trained with the EfficientNetB0 CNN model and an accuracy rate of 86.25% was obtained. Then, feature selection method with GA was used to increase the performance results and an accuracy rate of 90.09% was obtained. The feature selection method was used with the PSO algorithm, another optimization method. When the features selected with this algorithm were classified by the SVM method, an accuracy rate of 87.77% was obtained. An accuracy rate of 89.08% was obtained when the classification was made with the feature set consisting of common and specifically selected features with both optimization algorithms. Since the results obtained by dividing the data set into small-sized datasets may be biased, cross-validation tests were also carried out, and 89.17% accuracy was obtained by using the deep features of the EfficientNetB0 CNN model together with GA and PSO algorithms, and the accuracy of the EfficientNet model was increased.

Future studies are planned to use different CNN models, feature selection algorithms and optimization algorithms.

Declarations

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author Contrubition

Conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing and visualization made Erdal BAŞARAN and Yüksel ÇELİK.

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Figures

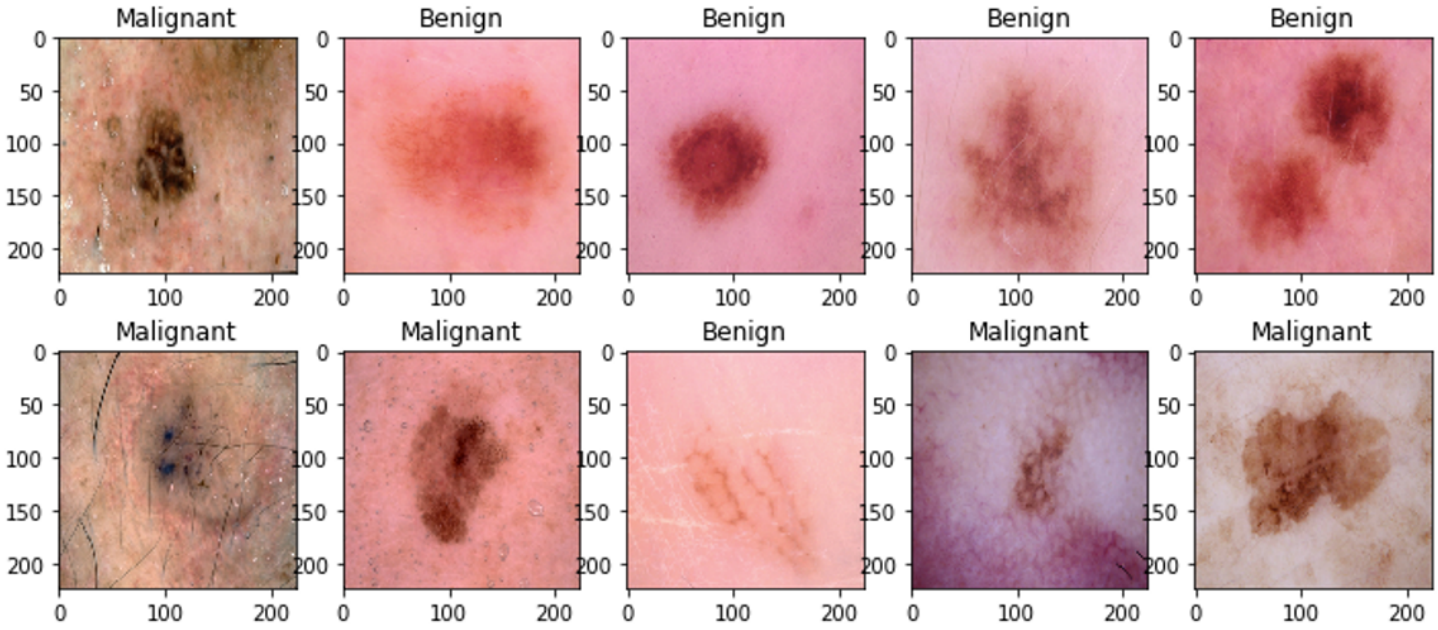

Figure 1

Randomly Selected Malignant and Benign images from Processed Skin Cancer pictures of the ISIC Archive dataset

Figure 2

The architectural structure of EfficientNetB0's CNN model.

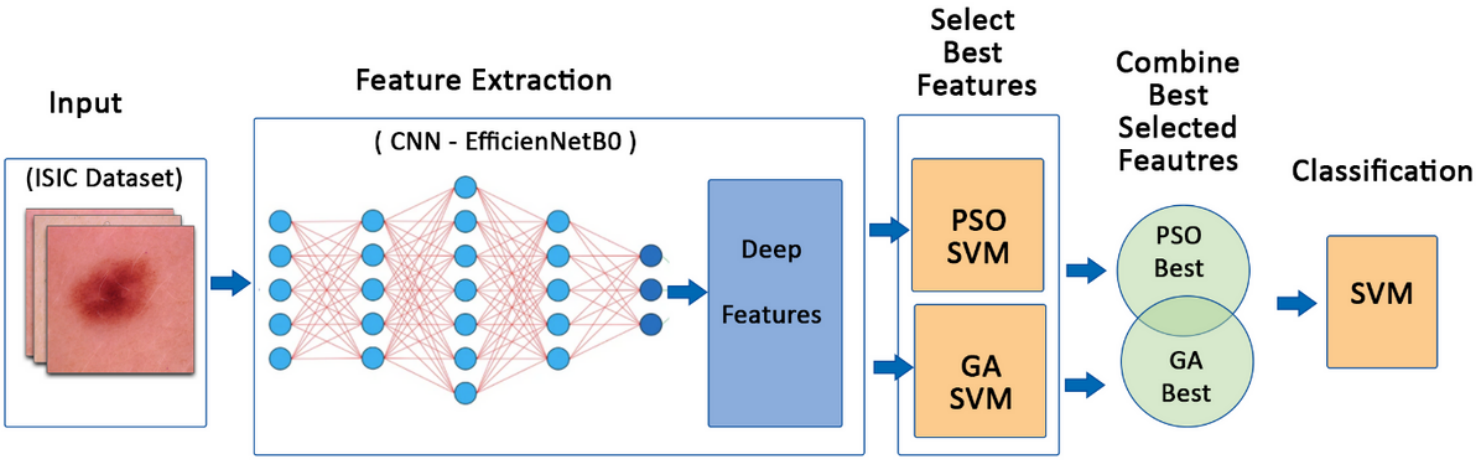

Figure 3

Skin Cancer classification Framework

Genetic Algorithm

Generate the initial population
Compute fitness by using ***(Eq.1)***
Select local best as global best
Repeat
Selection by using Roulette Wheel
Crossover
Mutation
Compute fitness by using (Eq.1)
Select local best
If *local best<global best*
globalbest=localbest
endif
Until *population has converged*

(a)

Particle Swarm Optimization

Generate the initial position and velocity of Particles
Compute fitness by using ***(Eq.1)***
Select local best as global best
while *(Until Stopping Criteria)*
for *(Each particles)*
Calculate fitness value by using ***(Eq.1)****;*
Selection (Survival of strong individuals);
Crossover (Here, new generation produced);
if *(There are same chromosomes)*
Mutation (Changing some genes for new and different individuals);
endif
endfor
Select local best
If *local best<global best*
globalbest=localbest
endif
endwhile

(b)

Figure 4

Pseudo Code for Genetic Algorithm (a) and Particle Swarm Optimization (b)

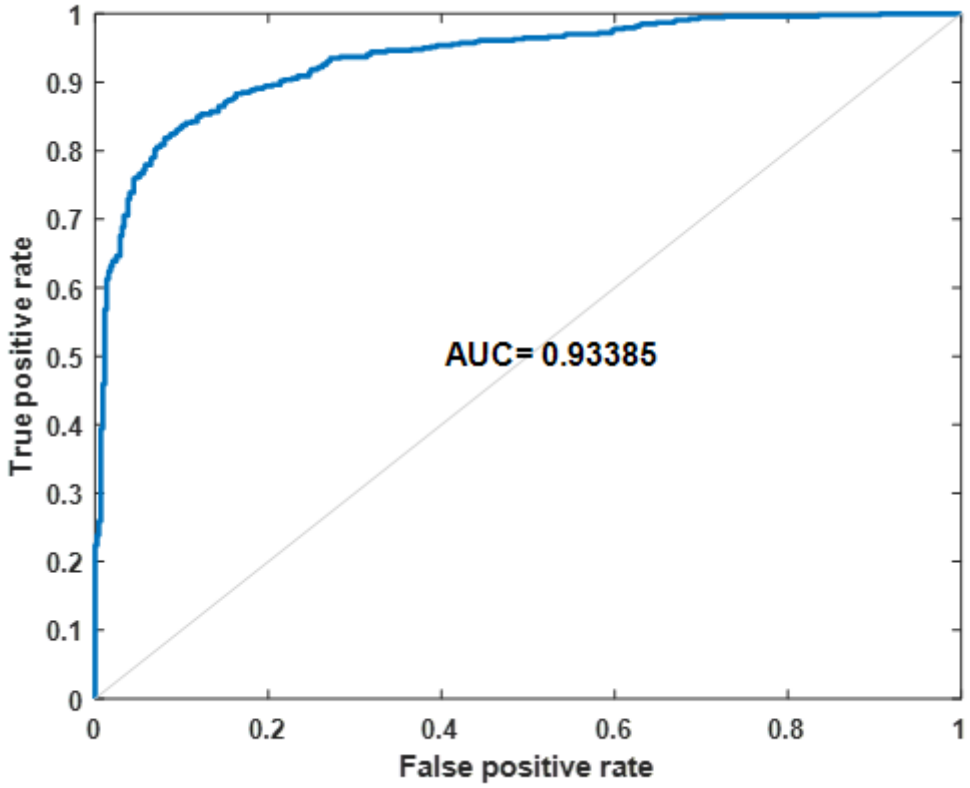

Figure 5

ROC curve of EfficientNetB0

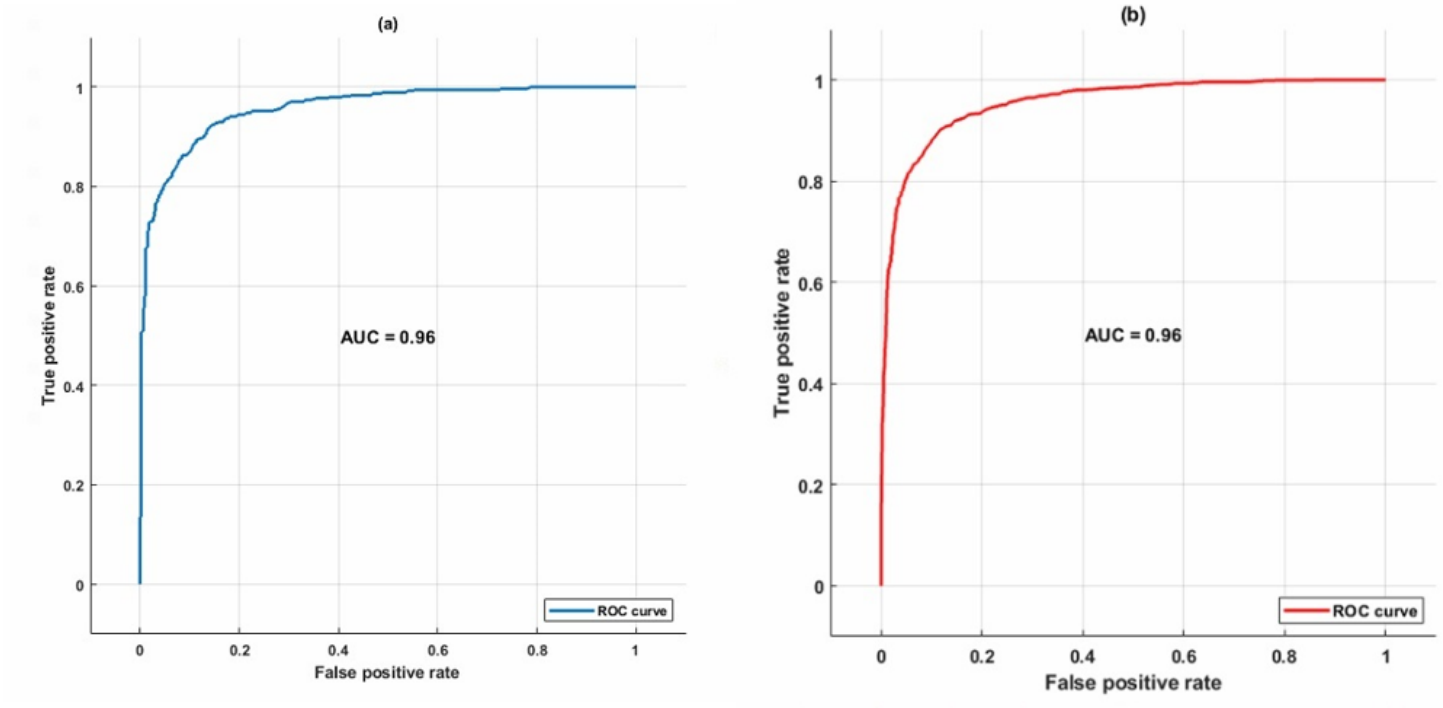

Figure 6

ROC curves of the feature set selected with GA, a) Holdout, b) Cross-validation

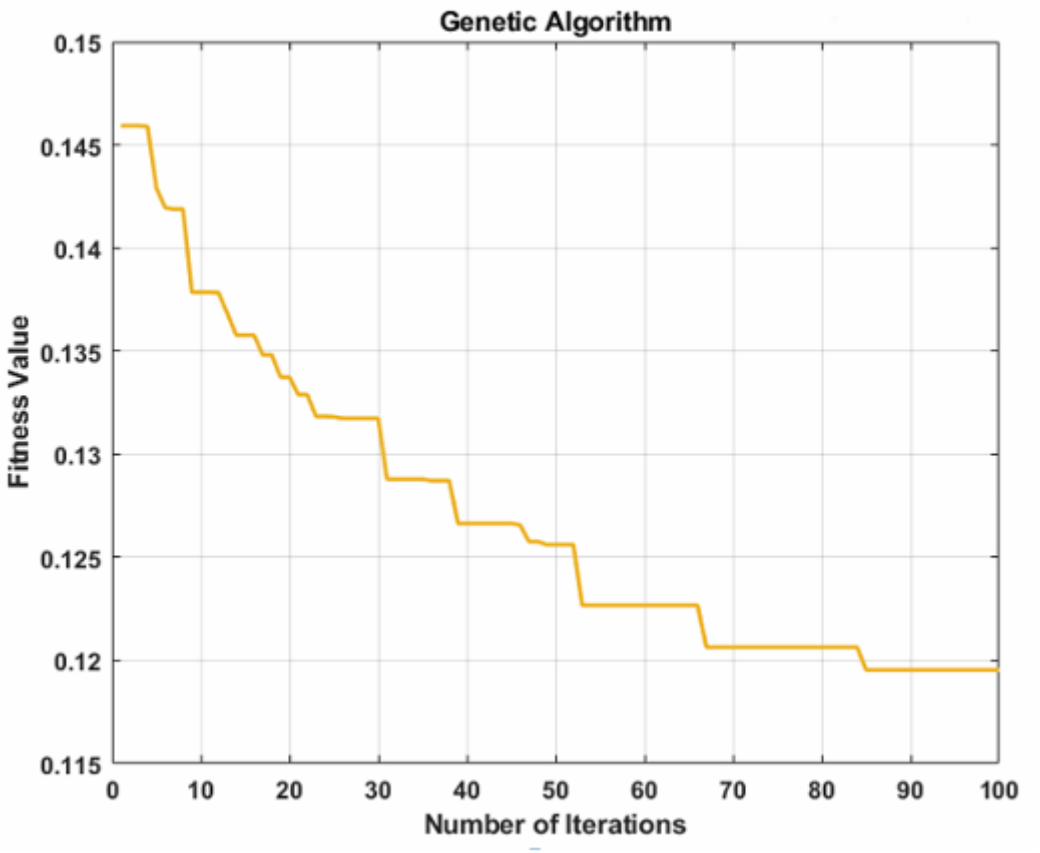

Figure 7

The convergence performance of GA

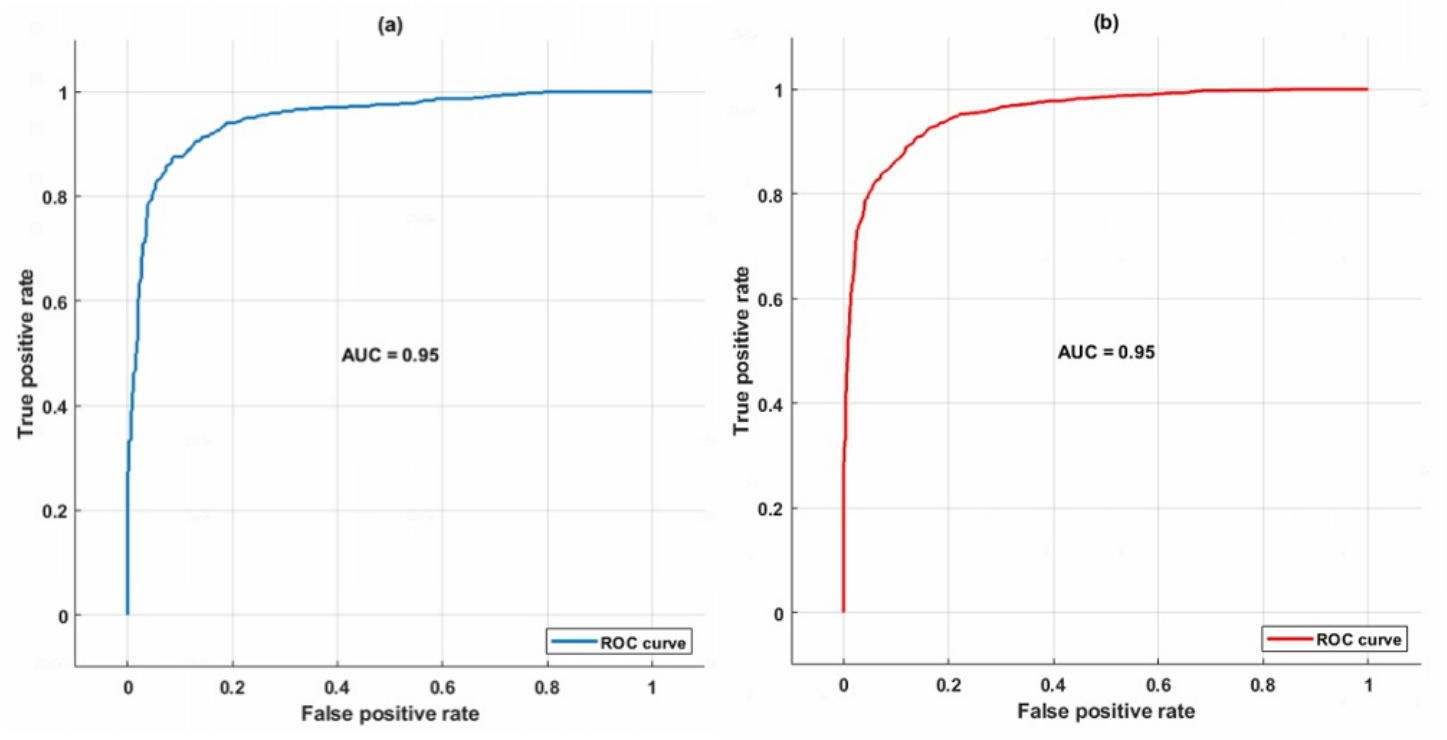

Figure 8

ROC curves of the feature set selected with PSO, a) Holdout, b) Cross-validation

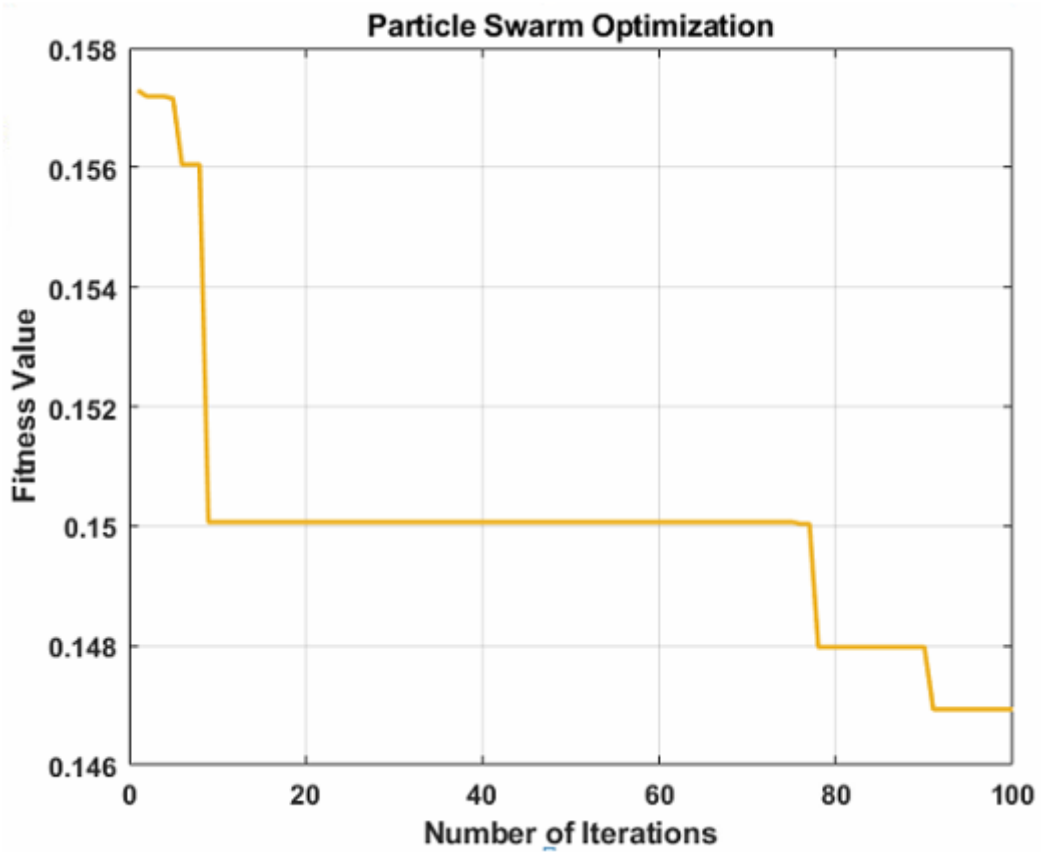

Figure 9

The convergence performance of PSO Algorithm

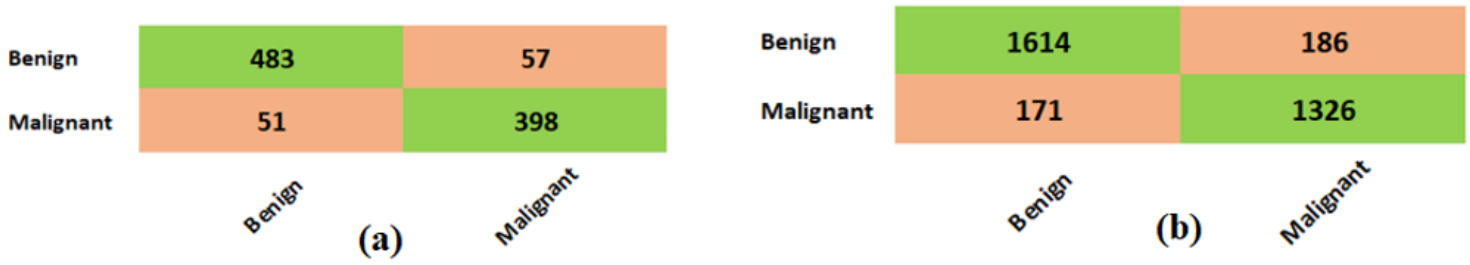

Figure 10

Confusion matrix of PSO+GA, a) Holdout, b) Cross-validation

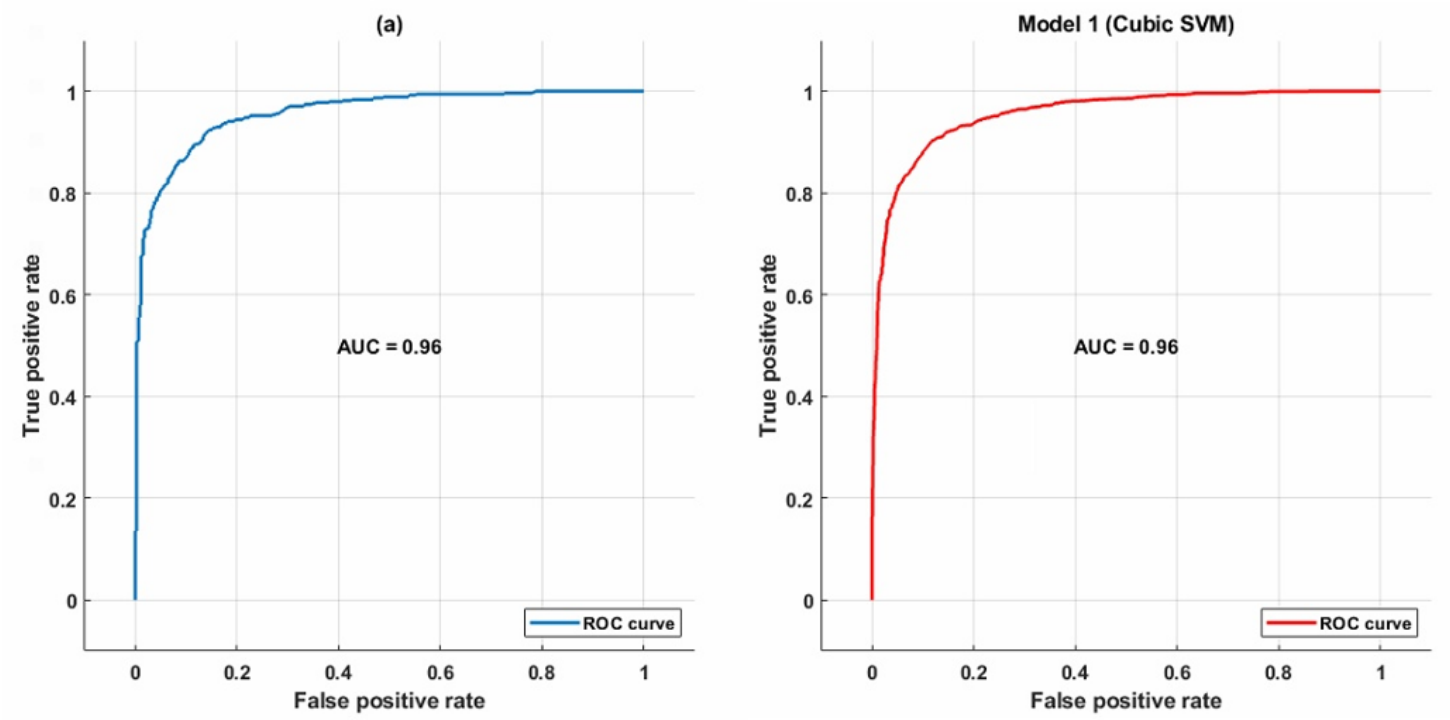

Figure 11

ROC curve of PSO+GA

Supplementary Files

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- graphicalabstract.docx