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Hierarchical Bayesian optimization based convolutional neural network for chest X-ray disease classification

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ABSTRACT

Pneumonia is an infection that affects the lungs, caused by bacteria or viruses inhaled through the air, leading to respiratory problems. The previous researches on this subject have limitations of high dimensional feature subspace and overfitting which minimize the classifier performance. In this research, hierarchical Bayesian optimization based convolutional neural network (HBO-CNN) method is proposed to effectively classify chest X-ray diseases. The proposed HBO algorithm optimizes hyperparameters of CNN which minimizes the overfitting issue and enhances the performance of classification. The hybrid Mexican axolotl optimization (MAO) and tuna swarm optimization (TSO) based feature selection method is used for selecting relevant features for classification that minimizes the high dimensional features. The ResNet 50 method is used for feature extraction to extract hierarchical features from the pre-processed images to differentiate the classes. The proposed HBO-CNN technique is estimated with performance metrics of accuracy, precision, recall, and F1-score. The proposed method attains the highest accuracy 97.95%, precision 92.00%, recall 89.00% and F1-score 92.00%, as opposed to the conventional methods, deep convolutional neural network (DCNN).

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1. INTRODUCTION

During the pandemic, COVID-19 emerged as the primary global emergency, impacting people worldwide. The virus was transferred from person to person through respiratory droplets and closest contact along the contaminated surface [1]. The major general symptoms of cough, fever, and dyspnea showed for 2-14 days after the virus exposure [2]. Chest X-rays (CXRs) and computed tomography (CT) scans are utilized to screen the chest X-ray diseases, and for the evaluation of disease progression in the admitted cases in the hospital [3]–[5]. However, the effective sensitivity detection of thoracic abnormalities by utilizing CT scans has numerous challenges [6]. The CT scanners are non-portable and need equipment sanitizing and imaging rooms between patients diagnoses [7], and also, their dose radiation is greater than the X-rays. In contrast, portable units of X-rays are majorly available with a feasible access in major hospitals [8]. In numerous cases, the clinical situation of the patient does not allow for CT scans, and therefore, the CXR is an effective choice for primary assessment [9]. Diseases like COVID-19 and pneumonia are detected and classified by using chest X-ray images. Recently, a wide range of researches for the automatic detection of pneumonia in chest X-ray images have been developed with deep learning methods [10], [11]. The classification of pneumonia gives relevant attention to pneumonia patients. Numerous researchers have developed automatic methods for pneumonia disease classification using chest X-ray images [12]. The deep learning technique is a completely automatic feature learning and extraction method that consumes more time for the complete of training [13]. Hence, such solutions are not robust due to the maximized amount of datasets. Deep learning methods like convolutional neural networks (CNN) have gained attention for pneumonia classification because of their good accuracy and representation of features [14], [15]. However, the existing researches have drawbacks of high dimensional feature subspace and overfitting issues which minimize the classifier's performance. In this research, an optimization-based feature selection method is employed to select relevant features which minimize the high dimensional features. The utilization of hyperparameter tuning of classifier parameters enhances the classification performance and minimizes the overfitting issue by finding the best combination of hyperparameters.

Haghanifar *et al.* [16] introduced a method to detect image features of pneumonia by utilizing the deep convolutional neural network in a huge dataset. In the introduced method, several chest X-ray images from numerous sources were gathered and the largest publicly accessible dataset was prepared. At last, the paradigm of transfer learning, the CheXNet method was used for developing the COVID-CXNet. The introduced method detected coronavirus pneumonia depending on the relevant significant features with accurate localization. However, the introduced method contained high dimensional features, including irrelevant or redundant features which minimized the classification performance. Chouat *et al.* [17] suggested a potential deep transfer learning to develop the classifier for detecting COVID-19 patients by utilizing CT scans and CXR images. The augmentation of data was utilized to maximize the training data size to solve the overfitting issue and improving generalization capability of the method. The suggested method included pre-trained deep neural networks such as ResNet50, InceptionV3, VGGNet-19, and Xception by utilizing data augmentation method. The suggested method had preferable generalization ability and robustness. However, the suggested method faced overfitting issues due to it having many layers and parameters. Agrwal and Choudhary [18] presented deep CNN depending on the structure to detect COVID-19 by utilizing chest radiographs. The datasets were utilized for training and testing the method on various public repositories. The presented method had high accuracy and the detection of COVID-19 was carried out in consultation with a medical clinician. Nonetheless, the presented method had lesser classification performance due to overfitting because the training data contained many irrelevant features, and did not consider image resizing because the different dimensions were difficult to be handled.

Aggarwal *et al.* [19] developed the transfer learning method with a combination of fine-tuned parameters to classify the chest X-ray images. The clipped adaptive histogram equalization (CLAHE) was used to enhance the contrast of images. Further, augmentation of data was performed to avoid the overfitting issue in the method. The developed transfer learning methods such as MobileNetV2, ResNet50, InceptionV3, NASNetMobile, VGG16, Xception, InceptionResNetV2, and DenseNet121 were performed. The developed method attained better performance in different classes of a small dataset. But it did not choose the relevant features, resulting in high dimensional issue of features and poor classification performance. Mousavi *et al.* [20] introduced a CNN-long short-term memory (LTSM) developed for extracting features from the raw data. To make it much more realistic and utilize the introduced model in the practical field, white Gaussian noise was added to the raw images. Moreover, the introduced method was tested and examined on six datasets and two additional datasets. The introduced method minimized the medical cost. Yet, the introduced method did not resize images, and these images with variant aspect ratios led the method to attaining a minimized performance. From the overall analysis of existing methods, it is seen that the existing methods have limitations of high dimensional features, issues of overfitting, and no consideration of image resizing which minimized the classification performance. The previous researches have limitations of high dimensional feature subspace and overfitting which also minimized the classifier performance. Hence, the proposed study includes image resizing for adjusting the size of the image uniformly for feasibility in handling. Then, the hybrid optimization-based feature selection method is employed to select the relevant features that minimize the high dimensionality of features while eliminating the irrelevant features, after which the overfitting issue is tackled through hyperparameter tuning of CNN hyperparameters using the hierarchical Bayesian optimization (HBO) algorithm. The major contributions of the research are given as below:

- The HBO-based CNN is proposed to classify the chest X-ray disease classes using chest X-ray images. The HBO optimizes the parameters of the CNN model to enhance the chest X-ray disease classification performance.
- The Mexican axolotl optimization (MAO) and tuna swarm optimization (TSO) algorithms are combined in feature selection phases to choose relevant features from the whole feature subset, which effectively minimize the dimensionality of features and enhances the classification performance.
- The ResNet 50-based feature extraction method is employed for extracting hierarchical features from the pre-processed images which differentiates features into different classes for classification.

The remaining section of the research is organized as follows: section 2 provides the proposed methodology details, while section 3 provides the results and discussion. At last, the conclusion of this research is given in section 4.

2. PROPOSED METHOD

This research proposes an HBO based CNN method to classify chest X-ray diseases using chest X-ray datasets. The raw images are pre-processed by using image resizing and min-max normalization techniques. Then, the hierarchical features are extracted by deploying the ResNet50 method, and the relevant features are chosen from the whole feature subset using the hybrid optimization algorithm. The selected relevant features are classified by utilizing the proposed HBO based CNN method. Additionally, the CNN parameters are optimized by employing the proposed HBO algorithm. Figure 1 represents the processes involved in the proposed method.

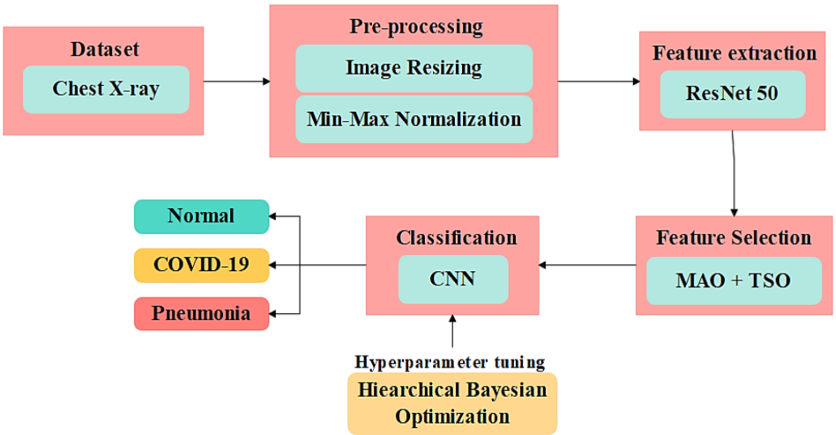

Figure 1. Process of proposed methodology

2.1. Dataset

The dataset used in this research is CXRs [21] image dataset which is publicly accessible. There are a total of 576 images in the COVID-19 class, 4,273 images in the pneumonia class, and 1,583 images in the normal class. The dataset is divided into training and testing set in the ratio of 80:20 and the description of the dataset is displayed in Table 1, while the sample images are given in Figure 2.

Table 1. Dataset description

Classes	Total images	Training	Testing
COVID-19	576	460	116
Pneumonia	4,273	3,418	855
Normal	1,583	1,266	317

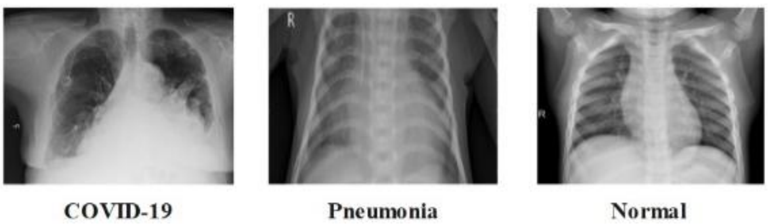

Figure 2. Sample images of the chest X-ray dataset

2.2. Pre-processing

The chest X-ray images from the dataset are pre-processed by resizing and normalization of images using min-max normalization [22]. The detailed explanation of these pre-processing techniques is explained here. The three classes of datasets namely, COVID-19, pneumonia, and normal have different sizes of 256×256 to 1024×1024 pixels. The images are resized to a defined size of 224×224 to ensure the uniform size of input data for feature extraction with the ResNet 50 method. Resizing of images minimizes the computational complexity. The normalization of images is a significant phase for preserving numerical stability. The normalization ensures quick learning with a stable gradient map in the image space. The resized images are normalized to a particular range [0,1] through min-max normalization which is significant for standardizing the input data. After the pre-processing, the images are given as input to the feature extraction phases to extract the pivotal features.

2.3. Feature extraction

The informative features are extracted from the pre-processed images by utilizing the CNN based pre-trained model (*i.e.*, ResNet 50) [23]. The ResNet 50-based feature extraction involves the usage of convolutional layers of the network for capturing hierarchical features from the chest X-ray images. The meaningful features are extracted from the pre-processed images by capturing different patterns and structures relevant to the chest X-ray disease. Furthermore, the ResNet 50 model includes skip connection which tackles the issue of vanishing gradient and helps in learning informative features. The ResNet 50 model processes the input image by their layers and extracts the low-level features of edges and textures in the initial layers and high-level semantic features, like the parts of objects in the deep layers. Finally, a total of 2048 features are extracted by using the global pooling layer of the ResNet 50 model. Figure 3 represents the process of feature extraction by the ResNet 50 method.

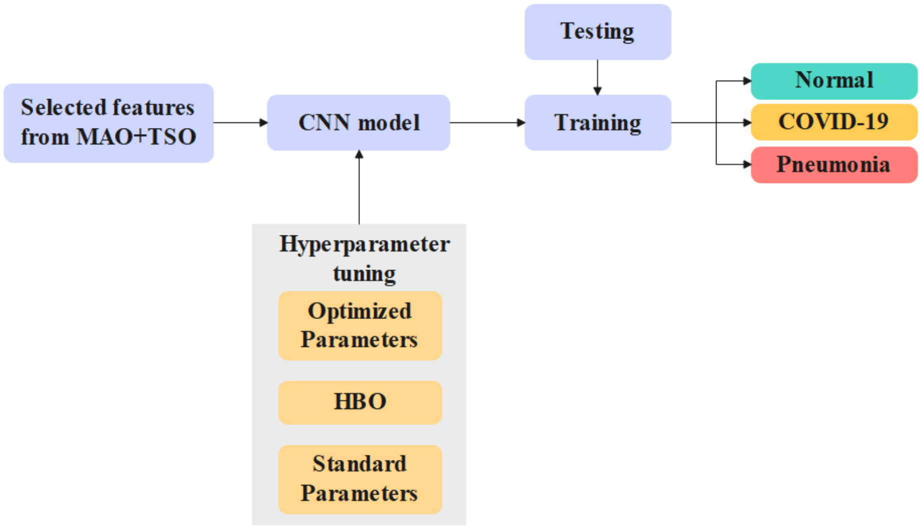

Figure 3. Process of HBO based CNN

2.4. Feature selection

The extracted 2048 features are given as input to feature selection by selecting the relevant features from the feature subset. In this research, optimization-based feature selection methods are used to select relevant features from the feature subset. The optimization algorithm searches the best features from whole feature subset which enhances the chest X-ray classification performance. The MAO and TSO algorithms are combined to choose the relevant features for classification. This step involves the combining of the exploration and exploitation strategies of MAO and TSO algorithms for feature selection to efficiently search the best feature subset and find the best optimal features. The MAO algorithm explores the feature subspace and searches various features by adjusting the features based on the exploration strategy of axolotl behavior. Then, the TSO algorithm exploits the feature subspaces found by the MAO algorithm and refines to the best features.

2.4.1. Mexican axolotl optimization

The Mexican axolotl optimization (MAO) algorithm is a nature-inspired algorithm that mimics the life of axolotl and its population is divided into male and female. The MAO algorithm has four iteration phases of transitioning from larvae to the adult stage, reproduction and assortment, injury, and restoration [24]. Initially, the population is initialized randomly, and next, every individual is allocated to a male or female because of axolotls developed by its sex, wherein 2 subpopulations are attained. The male individuals transmit water from adult larvae through adjusting its body parts' color towards male. The effective adapted individuals have superior camouflage and other individuals change their color. By that possibility, the axolotl is chosen to camouflage towards the superior. Considering the m_{best} as a superiorly adapted male, λ represents the transition parameter [0,1] for m_j male axolotl, further modifying their body parts, wherein the numerical expression is mathematically expressed as (1). The female axolotls modify the bodies from larvae to adults towards the females along a superior adaptation, whose numerical expression is formulated in (2).

$$m_{ji} \leftarrow m_{ji} + \left(m_{best,i} - m_{ji}\right) * \lambda \tag{1}$$

$$f_{ji} \leftarrow f_{ji} + \left(f_{best,i} - f_{ji}\right) * \lambda \tag{2}$$

Where, the f_{best} represents the best female and f_j represents the present female axolotl. However, by the inverse possibility of transition, individuals are unsuccessful in camouflaging themselves toward superiority, and have their colors chosen. If the random number $r \in [0,1]$ is lesser than the inverse transition possibility, the respective individual is chosen. To minimize the issue, the male axolotl m_j with an optimal value om_j is chosen. The numerical expression for inverse transition possibility is given as (3). Where, f_j represents the female axolotl with optimization value of of_j and the numerical formulated is given in (4), and the worst individuals have higher chances of random transitions. These individuals transit their ith body parts randomly and their numerical expression is given in (5) and (6).

$$pm_j = \frac{om_j}{\sum om_j} \tag{3}$$

$$pf_i = \frac{of_i}{\sum of_i} \tag{4}$$

$$m_{ji} \leftarrow min_i + (max_i - min_i) * r_i \tag{5}$$

$$f_{ji} \leftarrow min_i + (max_i - min_i) * r_i \tag{6}$$

From (5) and (6), the $r_i \in [0,1]$ represents the random number selected for every ith body part. The individuals with the random transmission are chosen by the optimization function value. By moving across water, axolotls suffer accidents and can be hurt. This procedure is represented as injury in the restoration stage. For every axolotl S_i in population, whether the possibility of damage (dp) is completed, axolotl loses a certain part of their body part. In this process, the regeneration possibility (rp) is utilized per bit.

2.4.2. Tuna swarm optimization

The tuna swarm optimization (TSO) algorithm is a nature-inspired algorithm that adopts the process of spiral foraging strategy, aggregates to the spiral shapes and determines the prey in shallow water regions [25]. The detailed explanation of population initialization, parabolic foraging and spiral foraging strategies are given below. There are *NP* tunas in the tuna swarm and at the swarm initialization stage, the TSO algorithm randomly generates the initial swarms in the search space. The numerical expression to initialize tuna individuals is given in (7).

$$X_i^{int} = rand \cdot (ub - lb) + lb \tag{7}$$

Where, X_i^{int} represents the ith tuna, ub and lb signify the upper and lower range boundaries in tuna exploration, while $rand$ denotes a random variable with uniform distribution from 0-1. Particularly, every individual X_i^{int} represents the candidate solution of TSO. Every individual tuna has a group of dimension numbers.

a. Parabolic foraging strategy

In the predation process, every tuna follows the past individuals and all tuna swarms form a parabola for surrounding the prey. Additionally, the tuna swarm utilizes a spiral foraging strategy, considering the possibility of the tuna swarm, selecting the strategy and a numerical expression is given as (8) and (9). The t represents the t^{th} iteration that is presently processed, and t_{max} represents the highest number of iterations that exist.

$$X_i^{t+1} = \begin{cases} X_{best}^t + rand \cdot (X_{best}^t - X_i^t) + TF \cdot p^2 \cdot (X_{best}^t - X_i^t), & if\ rand < 0.5 \\ TF \cdot p^2 \cdot X_i^t, & if\ rand \geq 0.5 \end{cases} \tag{8}$$

$$p = \left(1 - \frac{t}{t_{max}}\right)^{(t/t_{max})} \tag{9}$$

b. Spiral foraging strategy

The next effective cooperative foraging strategy is known as the spiral foraging strategy. When chasing prey, many tunas cannot select the correct direction, but a small amount of tuna guides the swarm to swim in the correct direction. The effective individuals are unable to cause the swarm to capture the prey efficiently. The tuna chose random individuals in a swarm to follow. The numerical expression for spiral foraging strategy is given as (10).

$$X_i^{t+1} = \begin{cases} \alpha_1 \cdot (X_{rand}^t + \tau \cdot |X_{rand}^t - X_i^t| + \alpha_2 \cdot X_i^t \\ \alpha_1 \cdot (X_{rand}^t + \tau \cdot |X_{rand}^t - X_i^t| + \alpha_2 \cdot X_{i-1}^t),\ if\ rand < \frac{t}{t_{max}} \\ \alpha_1 \cdot (X_{best}^t + \tau \cdot |X_{best}^t - X_i^t| + \alpha_2 \cdot X_i^t),\ ifrand \geq \frac{t}{t_{max}} \\ \alpha_1 \cdot (X_{best}^t + \tau \cdot |X_{best}^t - X_i^t| + \alpha_2 \cdot X_{i-1}^t) \end{cases} \tag{10}$$

The X_i^{t+1} represents the ith tuna in $t+1$ iteration. The X_{best}^t presents an optimal individual and X_{rand}^t denotes the randomly chosen tuna swarm. α_1 denotes the weight coefficient for controlling the swimming of tuna individuals for the optimum individual. The α_2 denotes the weight coefficient for controlling tuna individuals and τ denotes the distance parameter that manages the distance between tuna individuals and optimum individuals. Finally, the 1228 relevant features are selected from the whole feature subspace by using hybrid MOA and TSO algorithms.

2.5. Classification using HBO-based CNN

The selected relevant features are given as input to the CNN model for classifying the different classes of COVID-19, pneumonia, and normal. The CNN architecture includes five convolutions, five pooling, two fully connected and one dropout layer. The CNN model has fewer parameters as compared to certain conventional feedforward networks which result in a feasible training process. Here, the rectified linear unit (ReLU) is used as an activation function and the numerical expression is given as (11). Where, x represents the neuron input. The result of this activation function is 0 when the value of input is less than 0 or else, after which it returns a non-negative input value. The feature map of nth convolutional layer through utilizing the ReLU activation function is given as (12). In (12), the W^n and b_n denotes the weights and biases of n^{th} layer. The Max-pooling is a non-linear down-sampling method, separating the convolved data into $m \times n$ disjoint parts. This layer is next to the ReLU activation function and is utilized for executing the last feature vector. The output layer of n and the numerical expression is given in (13).

$$ReLU(x) = \max\{0, x\} \tag{11}$$

$$h_{ij}^n = ReLU\big((W^n x)_{ij} + b_n\big) \tag{12}$$

$$h_{ij}^n = ReLU\left(pool(x_{ij}^n)\right) \tag{13}$$

In (13), h_{ij}^n represents the nth feature map of size in a given convolutional layer with pixel coordinates. The dropout regularization method is implemented to avoid the over-fitting issue. At every convolutional layer block, the percentage of node is dropped to attain a minimized process of the network. The hyperparameters of batch size, optimizer, loss, learning rate, epoch, and activation function need to be optimized.

2.5.1. Hierarchical Bayesian optimization

The Bayesian optimization is an effective technique for global optimization of objective functions which is expensive for evaluation. In this research, HBO is proposed as an extension of standard Bayesian optimization by incorporating the hierarchical structure of hyperparameters that allow an effective exploration and optimization of difficult search spaces. The HBO captures the dependencies among the hyperparameters by utilizing probabilistic methods (Gaussian process) at every hierarchical level. The HBO is deployed for hyperparameter tuning of the CNN model which enhances the process of the CNN model and improves the chest X-ray classification performance. In HBO, the expected improvement (EI) is utilized due to its simplicity. Figure 3 represents the process of HBO based CNN method.

Considering that the optimization problem is optimizing the $\arg max_x f(x)$, the present best is at $x^+ = argmax_{x_i} \in X_{1:p} f(x_i)$. The numerical expression for the improved function is given as (14). The numerical expression for HBO on the expected value of $I(x)$ is given as (15). Here, $D_{1:p} = \{x_{1:p}, y_{1:p}\}$, the numerical expression for the $E(I(x))$ is formulated in (16).

$$I(x) = \max\{0, f(x) - f(x^+)\} \tag{14}$$

$$\arg \max_x E(I(x)|D_{1:p}) \tag{15}$$

$$E(I(x)) = \begin{cases} (\mu(x) - f(x^+))\Phi(z) + \sigma(x)\phi(z), & if\ \sigma(x) > 0 \\ 0, & if\ \sigma(x) = 0 \end{cases} \tag{16}$$

The proposed HBO-based CNN method effectively classifies the chest X-ray classes with high accuracy. The hyperparameters of CNN optimized are of the batch size: 32, Optimizer: Adam, loss: categorical cross entropy, learning rate: 0.001, epoch: 10 and activation function: ReLU. The data pre-processing of image resizing and min-max normalization methods resize the image in the same dimension and scales the image within the range of [0,1]. Then, the hierarchical features are extracted from the pre-processed images by using the ResNet 50 method, and the relevant features are selected from the whole feature subset by using MOA and TSO algorithms. Finally, the chest X-ray classes are classified by using the HBO-CNN method with high accuracy.

3. EXPERIMENTAL ANALYSIS

The performance of the proposed HBO-CNN is simulated with a Python environment and the system requirements are an i5 processor, 16 GB RAM and a Windows 10 operating system. The evaluation measures used to analyze the proposed HBO-CNN are, accuracy, precision, recall, and F1-score. In equations, TP denotes the correctly classified chest X-ray. TN denotes the correctly classified non-chest X-ray disease or normal class. Whereas, FP signifies the incorrectly classified chest X-ray class and FN signifies the incorrectly classified as the non-chest X-ray disease. The mathematical formula for evaluation metrics is given from (17) to (20).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{17}$$

$$Precision = \frac{TP}{TP+FP} \tag{18}$$

$$Recall = \frac{TP}{TP+FN} \tag{19}$$

$$F1 - score = \frac{2TP}{2TP+FP+FN} \tag{20}$$

3.1. Quantitative and qualitative analysis

The performance of HBO-CNN method is estimated with a chest X-ray dataset with accuracy, precision, recall, and F1-score. In this section, the proposed method is evaluated with different feature extraction techniques, different optimization algorithms and different classifiers. In Table 2 and Figure 4, the performance of the feature extraction method is estimated with the chest X-ray dataset in terms of the different evaluation measures. The conventional feature extraction techniques of ResNet 18, VGG 16, and CNN are considered for evaluation of the ResNet 50 method. The ResNet 50 method achieves the highest accuracy 97.94%, precision 92.00%, recall 89.00%, and F1-score 92.00%, while the ResNet 50 method attains maximized accuracy, as opposed to other methods. In Table 3 and Figure 5, the outcomes of the classification method-based MAO+TSO are evaluated with the chest X-ray dataset described. The conventional optimization techniques taken for evaluation of the MAO+TSO method is grey wolf optimization (GWO), MAO and TSO. The MAO+TSO method achieves the highest accuracy 97.94%, precision 92.00%, recall 89.00% and F1-score 92.00%, whereas the ResNet 50 method attains a maximized accuracy when compared to the other methods. In Table 4 and Figure 6, the results of the proposed HBO-CNN method is estimated with the chest X-ray dataset in terms of different evaluation measures is described. The conventional classifiers taken into consideration for the evaluation of the proposed HBO-CNN method are InceptionV2, VGG 19 and CNN techniques. The proposed HBO-CNN method attains a superior accuracy of 97.94%, precision of 92.00%, recall of 89.00% and F1-score of 92.00%, while on the other hand, the ResNet 50 method achieves a maximized accuracy when compared to the other methods. The hybrid optimization-based feature selection method is deployed in the proposed method to choose the relevant features from the whole feature subset, which further reduces the dimensionality of features by enhancing the classifier performance. Then, the parameters of CNN are optimized by utilizing HBO algorithm by tuning the optimized parameters of CNN to improve the classification performance.

Table 2. Performance of feature extraction method

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
ResNet 18	81.10	80.50	80.00	81.00
VGG16	79.20	75.80	73.40	70.00
CNN	73.00	72.89	72.65	72.90
ResNet 50	97.94	92.00	89.00	92.00

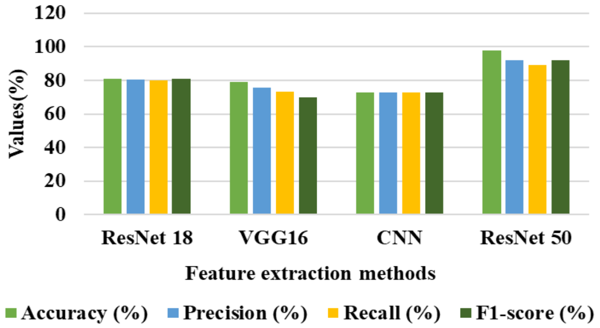

Figure 4. Performance of feature extraction method

Table 3. Performance of classification based on optimization algorithm

Algorithms	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
GWO	81.10	80.50	80.00	81.00
MAO	79.20	75.80	73.40	70.00
TSO	73.00	72.89	72.65	72.90
MAO+TSO	97.94	92.00	89.00	92.00

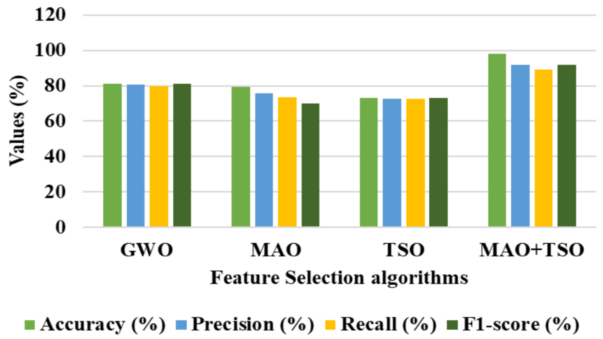

Figure 5. Performance of classification based on optimization algorithm

Table 4. Performance of classification based on different classifiers.

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
InceptionV2	80.05	82.00	80.00	80.00
VGG19	87.90	87.00	87.00	88.00
CNN	74.73	75.00	72.00	73.50
Proposed HBO-CNN	97.94	92.00	89.00	92.00

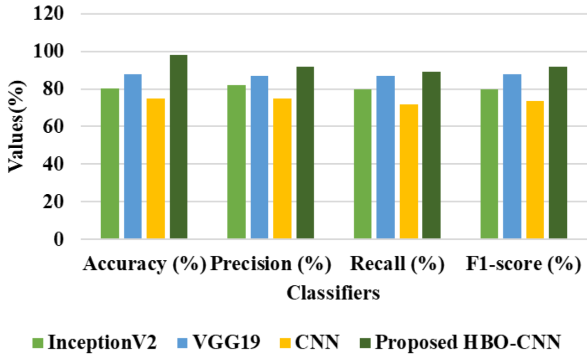

Figure 6. Performance of classification based on different classifiers

3.2. Comparative analysis

The proposed HBO-CNN method is compared with the existing methods, CheXNet [16], VGGNet 19 [17], DCNN [18] and DenseNet 121 [19], as presented in Table 5. The proposed HBO-based CNN method achieves a commendable accuracy of 97.94%, precision of 92.00%, recall of 89.00% and F1-score of 92.00%, which is more preferable than the other techniques. The hybrid optimization-based feature selection method is used in the proposed method to choose the relevant features from the whole feature subset, which further reduces the dimensionality of features and improves the classifier performance. Then, the parameters of CNN are optimized by utilizing the HBO algorithm which tunes the optimized parameters of CNN which further enhance the classification performance.

Table 5. Comparative analysis of the proposed method

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
CheXNet [16]	87.88	N/A	N/A	N/A
VGGNet 19 [17]	90.5	91.5	90.3	87
DCNN [18]	95.20	95.60	95.20	95.20
DenseNet 121 [19]	97	N/A	N/A	N/A
Proposed HBO-CNN	97.94	92.00	89.00	92.00

3.3. Discussion

The existing methods CheXNet [16], VGGNet 19 [17], DCNN [18] and DenseNet 121 [19] have the drawbacks of the overfitting issues, high dimensionality of features, and no consideration of resizing of images. In this research, the optimization of CNN hyperparameters tackles the issue of overfitting, and then, by using an optimization-based feature selection method, the high dimensional features are minimized by selecting relevant features from the whole feature subset. The image resizing is performed in the pre-processing stage to uniformly perform image resizing, ensuring an augmented classification output. The proposed HBO-CNN method exhibits an effective classification of chest X-rays with superior accuracy.

4. CONCLUSION

In this research, the HBO-CNN method is proposed to effectively classify the chest X-ray diseases. The proposed HBO algorithm optimizes the parameters of CNN, and minimizes the overfitting issue and enhances the performance of classification. The hybrid MAO and TSO-based feature selection method is employed for selecting the relevant features for classification, thereby minimizing the high dimensional features. The proposed HBO-CNN method effectively classifies chest X-ray disease with high accuracy. It also accomplishes the highest accuracy of 97.95%, precision of 92.00%, recall of 89.00% and F1-score of 92.00%, as opposed to the conventional methods. In the future, hybrid classifiers can be used for chest X-ray classification to further improve the performance.

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