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Optimal Feature Selection and Classification of Respiratory Diseases by Novel EFICNN-EBOA Algorithm: A Real Time Implementation Concept

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Abstract: Currently, many people pass away every day as a result of various respiratory illnesses. The ability to precisely identify various kinds of disorders has been made possible through respiratory sound evaluation. Till now, lung disorders were detected manually by listening for breathing sounds, but this method is no longer practical for a number of factors, including audio quality and medical preferences. With the use of recent computer evaluation, illnesses may be more accurately diagnosed and treated early for patients. Hence, it is crucial to use Artificial Intelligence (AI) approaches to totally simplify the detection of respiratory disorders. This research work aims to perform optimal feature selection and classification of respiratory diseases using novel deep learning methodology. In the initial step, the respiratory data are collected in real time from the abnormal and normal persons with the help of a breathing sensor. Next, the gathered data undergo the data augmentation process for eradicating the overfitting problems. The output attained from this data augmentation process is subjected to the feature extraction phase for extracting the features. From these extracted features, the optimal features are selected. These optimal features undergo the final classification phase done by the novel Enhanced Feature Interpreted Convolutional Neural Network (EFICNN). The parameter tuning in both the optimal feature selection and the classification phases is performed by a nature inspired meta heuristic optimization algorithm referred as Election-Based Optimization Algorithm (EBOA) in order to derive the accuracy maximization as the fitness function. The final output is done on the basis of different ranges of the Peak Expiratory Flow Rate (PEFR) values. This research indicates an efficient and effective method for early detection and remote monitoring of respiratory problems, ultimately resulting in enhanced patient care and quick response to situations of emergency. It does this by integrating the ESP8266 microcontroller with the robust Internet of Things (IoT) platform from Ubidots and using a Peak Flow Meter to input data.

Keywords: *Convolutional Neural Network, Enhanced Feature Interpreted, Election-Based Optimization Algorithm, ESP8266 microcontroller, Internet of Things, Optimal Feature Selection, Real Time Implementation, Respiratory Diseases Classification*.

1. Introduction

The WHO reports that respiratory disease, which includes TB, lung cancer, COPD, asthma, and LRTI, constitutes a large percentage of global fatality [1]. Early identification is critical in dealing with respiratory infections because it improves the efficacy of therapy, particularly diagnosis and restricting transmission [2]. Lung auscultation (paying attention to the sounds of breathing with a stethoscope throughout a respiratory check-up) describes an essential part of respiratory illness screening [3]. Specialists recognize spontaneous noises (which includes Wheezes and Crackles) during the respiratory process by focusing on respiratory noises throughout lung auscultation [4]. These unusual breathing noises are common in people with pulmonary diseases. If automated techniques for detecting these aberrant sounds may be created, it will increase the early diagnosis of respiratory illness and allow testing of more individuals than conventional screening [5]. There are certain antecedents regarding studies on inspection of respiratory sounds, yet it has gained traction in recent years as powerful machine hearing approaches have been created, utilizing increasingly more competent DL algorithms [6].

A globally trustworthy and widely available machine learning methodology implemented throughout hospitals may help in the diagnosis as well as prevention of concurrent respiratory diseases [7]. However, the institutions' unwillingness to provide information owing to privacy considerations, as well as the considerable heterogeneity and diversity of these information, renders it difficult to build a worldwide methodology, leading in a costly and time-consuming diagnostic method [8]. Though DL-oriented medical chest X-ray image evaluation (also referred as detection/classification) methods for respiratory

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diseases have proven cost-efficient solutions and better accuracy for medical detection, studies in this area is lessened owing to the shortage of coordination among medical facilities [9].

DL classifiers are resilient and efficient, according to a performance evaluation of traditional respiratory noise identification algorithms [10]. Nevertheless, certain DL-oriented methods have extraordinarily complex structures, making them difficult to deploy in wearable devices or mobile for real-time applications [11]. Naturally cutting-edge techniques require a growing degree of model complexity [12]. The inability to compare methodologies owing to a limitation of standardized datasets for assessment has been a more significant concern in this study area [13] [14]. The majority of the sources conduct evaluations using proprietary datasets that are not accessible to the general population [15].

The paper contribution is as follows.

- To perform the optimal feature selection and classification of respiratory diseases using novel deep learning methodology.
- To collect the respiratory data in real time from the abnormal and normal persons with the help of a breathing sensor and to undergo the data augmentation process for eradicating the overfitting problems.
- To extract the features such as Mean, Energy, Standard deviation, Kurtosis, Skewness, Peak Max Index Feature, Peak Min Index Feature and Linear Index Feature and to select the optimal features by the EBOA.
- To perform the classification by the novel EFICNN, in which the parameter tuning is performed by the nature inspired meta heuristic optimization algorithm referred as EBOA.
- To derive the accuracy maximization as the major objective function by optimizing the features as well as the parameters of FICNN by the EBOA algorithm.

The paper organization is as below. Section 1 is the introduction of the respiratory disease classification model. Section 2 is literature survey. Section 3 is proposed methodology involving data acquisition, data augmentation, feature extraction, optimal feature selection, classification by EFICNN, and EBOA algorithm. Section 4 is results. Section 5 is conclusion.

2. Related Work

In 2018, Rubio et al. [16] have proposed EM-PSEQ, a revolutionary EM-based approach for efficiently estimating genuine designs. A simulation research looked at how the accuracies of MV, EM-PSEQ, and IS changed as the count of studies increased. EM-PSEQ outperformed both IS and MV, while requiring only a little amount of computing work. As a result, it was believed that EM-PSEQ would be a highly helpful platform for clinical investigations since it could significantly increase the accuracy of manual respiratory research at a low cost.

In 2023, Roy and Satija [17] have suggested a unique lightweight inception framework for exploiting lung sound signals to categorize a broad range of respiratory disorders. The suggested methodology was divided into three phases: 1) pre-processing; 2) Mel spectrogram extraction and transformation into a three-channel image; and 3) categorization of the Mel spectrogram images into distinct pathological classes utilizing the suggested RDLINet. Excellent classification accuracy of 99.6%, 96.6%, and 94.0% was attained using the suggested methodology for six-class classification, seven-class classification, and asthma vs healthy classification. To the greatest extent of the ability, this was the initial study to use lung noises to classify seven types of respiratory diseases. The suggested framework, on the other hand, beats entire previously published research for binary and six-class classifications. The proposed system employs DL algorithms and provides standardized assessment with good classification skills. The study was a groundbreaking one that concentrated solely on lung noises to discriminate among a broad spectrum of respiratory disorders. The suggested architecture may be turned into a real-time clinical application, paving the way for automated respiratory health monitoring with lung noises.

In 2021, Shuvo et al. [18] have presented a lightweight CNN framework for classifying respiratory illnesses from individual breath cycles employing hybrid scalogram-oriented characteristics of lung noises. The EMD and CWT are used in the suggested feature collection. The suggested strategy's effectiveness was evaluated utilizing a patient-independent train-validation-test group from the publically accessible ICBHI 2017 lung sound dataset. Weighted accuracy ratings of 98.70% for six-class pathological classification and 98.92% for three-class chronic classification were obtained using the suggested system, outperforming familiar and considerably bigger VGG16 with respect to accuracy by significant margins of 1.11% and 1.10%, correspondingly. While being economically equivalent, the suggested CNN methodology beats remaining existing lightweight methods.

In 2018, Nousias [19] demonstrated a combined mHealth solution that offers patients real-time personalized feedback for monitoring correct medicine administration, teaching them, and assisting them in avoiding frequent errors. Traditional and data-driven classification and feature extraction approaches are used to identify four phases (exhalation, inhalation, inhaler actuation, and background noise) for optimal inhaler usage. The suggested technique outperforms modern and related conventional techniques by 98% classification accuracy. Furthermore, intuitive feedback systems in the format of a virtual guiding agent coupled with the mobile application were introduced to assist patients in following their action plan and assessing their inhaler approach in an improved way. Vast simulation experiments with 12 people confirmed the effectiveness of the developed methodologies in both outdoor as well as indoor settings.

In 2021, Pham et al. [20] have proposed and investigated a strong DL architecture for auscultation assessment. This project uses respiratory noise recordings to categorize irregularities in respiratory phases and diagnose illnesses. The system starts with feature extraction at the front end, which converts input noise into a spectrogram description. The spectrogram characteristics are next classified using a back-end DL framework into classifications of respiratory abnormality phases or disorders. Studies on the ICBHI respiratory-noise benchmark dataset indicate three major improvements to respiratory-noise research. To begin, we investigate the impact of spectral-time resolution, spectrogram types, non-overlapping/overlapping windows, and data augmentation on final prediction accuracy. As a result, we offer a unique DL framework based on the suggested methodology that exceeds existing approaches. Furthermore, we use a Teacher-Student method to create a trade-off between model efficiency and model complexity that offers potential for real-time application development.

In 2023, Ahmed et al. [21] have employed machine learning to classify and forecast chronic respiratory and cardiovascular disorders. Carers as well as healthcare providers could be informed when a patient's health situation is predicted. Utilizing real-world vital sign information, vital indicators was forecasted for 180 seconds. Carers could save a person's life if they respond promptly and foresee situations. Rather than individually tweaking machine learning classifiers, the TPOT was utilized. This research concentrated on improving classification accuracy by integrating machine learning methods and featuring pre-processors with predicting crucial indicators and TPOT genetic programming using Prophet and linear methods. The TPOT tuning parameter mixes forecasted values with traditional classification methods like SVMs, NB, and RFs. This research demonstrates the significance of categorizing and improving prediction accuracy. The suggested method's adaptive behavior is achieved by essentially integrating several machine learning classifiers. Utilizing a substantial quantity of training information, the developed method was compared to many conventional techniques. The developed method outperformed traditional methods in tests at the University of Queensland, enhancing the categorization of chronic respiratory disease from 0.49 to 0.70, and cardiovascular disease from 0.58 to 0.71 correspondingly, while minimizing the mean percent error in health indicators. The findings indicate that the Facebook Prophet prediction method, when combined with the TPOT classification method, may properly identify a patient's health state on the basis of anomalous vital signs, allowing patients to obtain immediate medical assistance.

In 2023, Jalehi and Albaker [22] have suggested a deep CNN methodology to diagnose respiratory framework disorders from X-ray images employing a transfer learning approach on the basis of the EfficientNetV2 methodology, which serves as a foundation to improve the accuracy and efficacy of CAD efficiency. Furthermore, the most recent data augmentation techniques and fine-tuning for the last block in the convolutional base have been implemented. Grad-CAM was also utilized to emphasize critical characteristics to render the DL methodology more understandable. The suggested methodology has been trained to recognize normal, COVID-19, and pneumonia. It makes use of CXR images from three freely available databases. On the testing group, the below results were obtained: specificity = 99.51%, sensitivity = 98.66%, and accuracy = 99.4%. As a result, the approach outperforms the four major recently published classification approaches.

In 2023, All et al. [23] have suggested a federated learning technique capable of learning from heterogeneous and multi-class respiratory medical information. The suggested approach aggregated and trained the local method using blockchain methodology while maintaining anonymity. The weight manipulation strategy was presented when combining the local methods, which, unlike previous researches, employs the local method test accuracy as the primary parameter. The metric scores reveal that, while learning from varied as well as heterogeneous information, the developed federated method performs similarly to a single-source method (learning from single source information). The maximum testing accuracy of 88.10% was reached for five classes utilizing the innovative aggregation approach, compared to the minimal sophisticated single source method, which attained 88.60% validation accuracy. A similar pattern has been discovered for three as well as four class methods. This research proposes an incentive framework for the participating organization in order to improve organizational synergy, while the blockchain keeps the data to render the framework trustworthy and transparent. The suggested method was put into impact in the form of a web framework, demonstrating how the weight manipulation approach could efficiently learn from multi-sourced and heterogeneous information while maintaining anonymity.

In 2022, Leng et al. [24] have suggested a bi-level AI approach for acute respiratory illness risk categorization. It is divided into two tiers. The initial level was a specialized model of the DL method "BiLSTM+Dilated Convolution+3D Attention+CRF" for CCNER for extracting significant data from unstructured information in CEMRs. The developed DL method provides improved effectiveness and accuracy in the CCNER challenge than the familiar "Bert+BiLSTM+CRF" strategy by using semi-supervised learning and transfer learning techniques. The next level was a customized XGBoost that combines the retrieved entity information with remaining structured information in the CEMRs to realize the risk categorization of acute respiratory illnesses. According to the research results, the suggested methodology might give real technical help for enhancing diagnostic accuracy. The work demonstrates the feasibility of using hybrid AI-oriented technology as a platform to assist doctors in dealing with CEMR information and improving diagnostic assessment beneath diagnostic ambiguity.

In 2022, Revathi et al. [25] have developed RRDCBS by extracting multiple features from sounds, developing multiple modelling approaches, and conducting experimental disease detection employing proper evaluation processes for binary and multi-class respiratory disease categorization. The decision level combination of characteristics for the VQ modelling approach yielded 100% accuracy in categorizing five respiratory illnesses and healthy people. To execute binary categorization of the respiratory disease versus healthy information noise, decision level fusion of indices on the features offered 100% accuracy for SVM, VQ, and KNN modelling approaches. Deep recurrent as well as CNNs were also being tested for binary/multiple respiratory illness categorization.

3. Proposed Methodology

The proposed respiratory disease classification model includes various phases such as data acquisition, data augmentation, feature extraction, optimal feature selection, and classification. In the first stage, respiratory information from abnormal and normal people are acquired in real time using a breathing sensor. The collected information is then subjected to data augmentation in order to eliminate overfitting issues. The result of this data augmentation method is submitted to the feature extraction step for feature extraction. Mean, Energy, Standard deviation, Kurtosis, Skewness, Peak Max Index Feature, Peak Min Index Feature, and Linear Index Feature are all extracted here. The best features are chosen from the retrieved features. The innovative EFICNN performs the final classification phase on these ideal features. The nature-inspired meta heuristic optimization method EBOA performs parameter tweaking in both the optimum feature selection and classification stages in order to determine the accuracy maximization as the fitness function. The final result is calculated using various ranges of PEFR values. Normal pulmonary function is defined as a PEFR value between 450 and 550 L/min. Furthermore, a minor pulmonary disease is defined as a PEFR score between 50 and 75 L/min. Similarly, acute severe pulmonary disease is defined as a PEFR score between 33 and 50 L/min. Furthermore, if the PEFR value is less than 33L/min, the condition is regarded as life threatening. This proposed method demonstrates an efficient and successful strategy for early diagnosis and remote monitoring of respiratory issues, resulting in improved patient care and faster response to emergency situations. It does this by combining the ESP8266 microcontroller with Ubidots' strong IoT environment and employing a Peak Flow Metre to collect information. The overall proposed methodology of the developed respiratory disease classification model is shown in Figure 1.

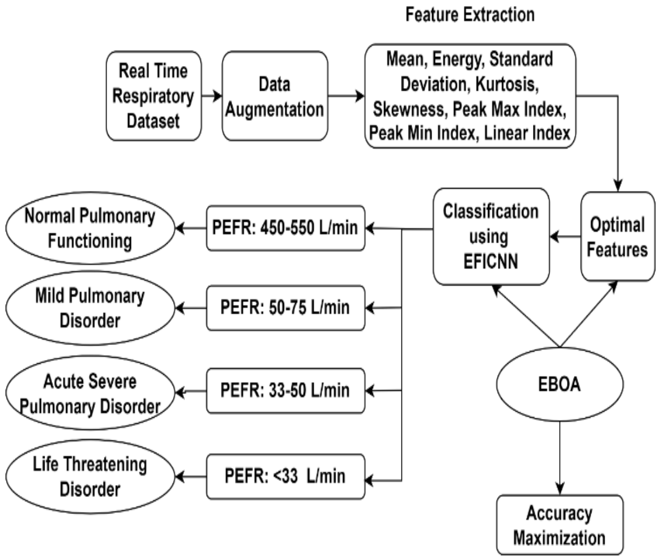

Fig 1. Overall methodology of the proposed respiratory disease classification model

3.1 Data acquisition

The respiratory/pulmonary information from normal as well as disordered people are acquired in real time in this study utilizing two separate sensing devices known as breathing sensors. The traditional breathing sensor is just a breath-o-meter that measures breathing blow values and transforms them to digital measurements. In this traditional breath-o-meter, as shown in Fig. 2(a), only the maximum digital value is taken into account. CIPLA describes the maker of this traditional breath-o-meter. All of the breathing blow data are required for the classification procedure in order to provide a greater respiratory illnesses classification rate. As a result, the breathing sensor module shown in Fig. 2(b) is built, which includes an Arduino microcontroller, an A/D converter, a breathing sensor, and an RS232 interface module. The breathing sensor collects the breathing-blow, and these analog values are transformed into digital values using an A/D converter, and these digital values are handled by the microcontroller for normalization of the collected digital information. Utilizing an RS232 interface module attached among the Laptop/PC and the microcontroller, this processed information is delivered to a PC or laptop for further information categorization.

(a) Traditional breathing sensor (Breath-o-meter) | (b) Developed breathing sensor

Fig 2. Traditional and developed breathing sensor

3.2 Data augmentation

Because of overfitting issues, the acquired respiratory information cannot be directly subjected to the CNN methodology. As a result, the gathered respiratory information or specimens are information supplemented in order to avoid overfitting issues. The gathered respiratory specimens are kept in a $Q * R$ matrix, with Q rows and R columns, in this study. Furthermore, this matrix is rotated left by single position (utilizing the left shifting function) to make a left shifted data matrix, and it is turned right by single position (employing the right shifting function) to generate a right shifted data matrix. The original specimen matrix, as well as the left along with the right shift matrices, are combined to form the DAM.

3.3 Feature extraction

In this research, the main criteria for signal categorization represents the features. In this study, automated signal classifications are performed using characteristics like Peak Min Index Feature, Energy, Mean, Kurtosis, Standard deviation, Peak Max Index Feature, Skewness, and Linear Index Feature. These characteristics are taken from the DAM, whose rows as well as columns are described by the letters j and k. These characteristics are taken from the DAM and trained by the EFICNN classification method. Each of these features is listed below.

Kurtosis: Kurtosis describes a statistical term that measures the form of the endpoints of a probability distribution in comparison to the form of the endpoints of a normal distribution. It indicates whether a distribution is flat or peaked in comparison to the normal distribution, often referred to as the bell curve. Normally, the kurtosis is determined utilizing the fourth standardized moment, which is provided by the equation:

$$Kurtosis = \frac{\left(\Sigma \quad \left(\frac{yj-\underline{y}}{o}\right)^4\right)}{t^4} \quad (1)$$

Here, the standard deviation associated with the data is shown by t, total count of data points is shown by o, mean associated with the data is shown by $\underline{y}$, every data point linked with the distribution is shown by yj, and the summation symbol is given by Σ respectively.

Peak Min Index Feature: A "peak min" might possibly describe to the minimal point in an area of interest when the values of a dataset or signal grow and subsequently fall. Peaks are commonly connected with local maxima, or the highest points in the area. The feature that indicates the index or location of data points inside a signal or dataset might be referred to here. Integrating these assumptions, "Peak Min Index Feature" shall describe a feature extraction approach that includes detecting the minimum values inside peaks of a dataset or signal and utilizing their related indices as features.

Peak Max Index Feature: A peak represents a high point or local maximum in a signal or dataset in signal processing and general data analysis. The location or position of the highest value in sequence or an array is referred to as the maximum index. A feature in machine learning is often trait or an individual input variable that is employed to create forecasts or categorize information pieces. On the basis of these elements, it is feasible that the expression "Peak Maximum Index Feature" refers to a particular feature engineering or feature selection technique that includes recognizing peaks in information, determining their maximum indices, and employing them as potential features for a machine learning method.

Linear Index Feature: The linear index feature represents a straightforward and widely utilized feature in a variety of applications, including signal processing, time series analysis, and some forms of data preparation. While it does not directly give data on the data's qualities, it may be beneficial for maintaining the sequence or order of data points, particularly when working with sequential or time series data. Linear index features are seldom employed as forecasters on their self in machine learning, but they may be coupled with remaining features or utilized in feature engineering to build multiple informative features for methods to learn from.

Standard deviation: The standard deviation quantifies the spread of data points around the mean. If the standard deviation is large, it suggests that the data points are dispersed throughout a broad range, signaling greater variability. A low standard deviation, on the other hand, indicates that the data points are grouped tightly around the mean, meaning lesser variability. The standard deviation may be utilized as a feature on itself in feature extraction, or it may be paired with remaining statistical metrics like the median, mean, or range to build multiple useful features for machine learning methods. Furthermore, standard deviation is widely employed in data preparation stages such as outlier identification and data normalization.

The standard deviation associated with a specific feature is often determined in feature extraction employing the below equation:

$$standard\ deviation\ (\sigma) = \sqrt{\left(\sum \quad \frac{\left(yj-\underline{y}\right)^2}{o}\right)} \qquad (2)$$

Here, the total count of data points linked with the feature is given by o, the mean (average) associated with the feature is given by $\underline{y}$, every data point related to the feature is given by yj, and the summation symbol is given by Σ correspondingly.

Mean: The meaning gives useful information about the average or usual value of the information in the feature. It defines an adequate metric that may provide an overview of data dispersion. When employed as a feature, the mean serves to attain the data's fundamental behavior and may be utilized as a concise description of the feature's qualities. The below formula is used to compute a feature's mean:

$$Mean\left(\underline{y}\right) = \sum \quad \frac{(yj)}{o} \qquad (3)$$

Here, the total count of data points linked with the feature is shown by o, every data point associated with the feature is shown by yj, and the summation symbol is represented by Σ respectively.

Energy: "Energy" represents a statistical term utilized in feature extraction to assess the signal intensity or amplitude of a given frequency element in a time series or signal data. Energy is frequently related with the subject of signal processing and is employed in applications like image processing, audio processing, and vibration analysis. The energy associated with a signal is determined in the framework of feature extraction from signals by adding the squared amplitude values linked with the signal throughout a particular frequency range or time frame. The energy element is utilized to attain the overall magnitude related to the signal and is especially effective in jobs involving particular frequency elements.

The computation of energy related to a discrete signal $y[o]$ over a time frame or frequency range looks like this:

$$Energy = \sum \quad |y[o]|^2 \qquad (4)$$

Here, the magnitude associated with the signal at sample o is shown by $|y[o]|$, and the summation over entire specimens o in the frequency range or time window is shown by Σ respectively.

3.4 Optimal feature selection

The extracted features attained from the considered feature extraction techniques seems to be lengthy. Hence, it is necessary to select the optimal features in order to derive the maximization of accuracy as the main fitness function. Here, the features are optimally selected using the considered EBOA algorithm. Optimal Feature Selection decreases incorrectly chosen features in half while keeping real positive rates constant. This implies it is more effective in selecting the appropriate variables, giving in a simpler, more accessible, and more appropriate method. It minimizes the number of features to reduce computing complexity while also improving the deep learning model's effectiveness.

3.5 Classification by EFICNN

The classification of the respiratory diseases is done here in this study by the proposed novel EFICNN model. Here, the parameters of FICNN are tuned by EBOA algorithm for evaluating the accuracy maximization as the major objective function. The various specifications considered for the traditional FICNN model is shown in the table below.

Table 1. Specifications of traditional FICNN model

Layer	***Activation***	***Feature size***	***specifications***	***Remarks***
Conv-Lay-1	tanh	256 features	256 kernels, 3*3 mask window	-
Pool-Lay-1	-	-	2*2 pool window	-
Conv-Lay-2	tanh	512 features	512 kernels, 3*3 mask window	-
Pool-Lay-2	-	-	2*2 pool window	-
Conv-Lay-3	tanh	512 features	512 kernels, 3*3 mask window	-
Pool-Lay-4	-	-	2*2 pool window	-
Dense-Lay-1	SoftMax	-	-	1024 neurons
Dense-Lay-2	SoftMax	-	-	512 neurons

Three Convolutional as well as three Pooling layers make up the developed EFICNN. The DAM is used on Conv-Lay-1, which has 256 filters and a 3*3 mask window size. Conv-Lay-1 output is ReLu-1, which removes negative outcomes, and this layer output is sent via Pool-Lay-1 to create size minimized direct information. At the same time, the findings of Conv-Lay-1 are sent via Conv-Lay-2, which has 512 filters and a mask window size of roughly 5*5. ReLu-2 removes the negative in this layer's reactions. This layer output is routed via Pool-Lay-2 to generate size-minimized direct information. The resulting information is then sent via Conv-Lay-2, which has 512 filters as well as a 7*7 mask window size. The characteristics from Pool-Lay-1 as well as Pool-Lay-3 are interpreted, and the interpretation findings are then processed via three thick layers to generate the final classification outcomes, as shown in Fig. 3.

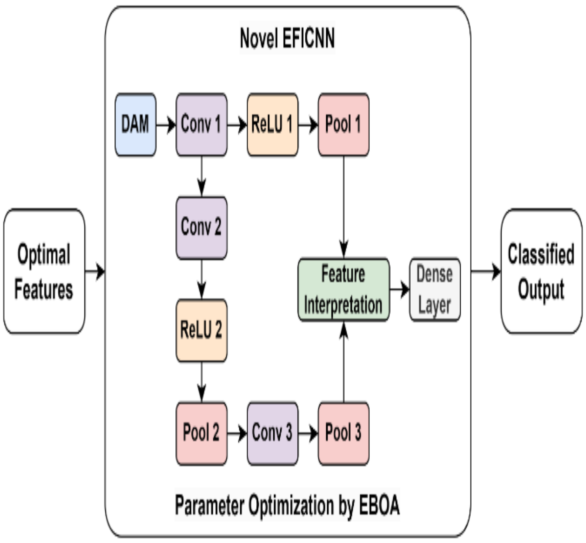

Fig 3. Proposed EFICNN for the respiratory disease classification

The EFICNN is proposed here in order to overcome the limitations of the traditional FICNN model. The conventional FICNN has various advantages such as it classifies each and every pixel into distinct classes, detects objects within an image, etc. But it limits from the fact that it needs a vast amount of labeled data to perform the training in an efficient manner and also requires high computational necessities. Therefore, to limit the shortcomings, the parameters of existing FICNN are optimized by considered EBOA algorithm for attaining the fitness or the objective function, thus referred as proposed EFICNN. This developed EFICNN saves time and also eradicates the time complexity. The final outcome is calculated by the developed EFICNN using several ranges of PEFR values. Normal pulmonary function is defined as a PEFR value between 450 and 550 L/min. Furthermore, a minor pulmonary disease is defined as a PEFR score between 50 and 75 L/min. Additionally, acute severe pulmonary disease is defined as a PEFR score between 33 and 50 L/min. Furthermore, if the PEFR value is less than 33L/min, the condition is regarded as life threatening. The below Algorithm describes the full method of the developed EFICNN for respiratory disease classification.

Algorithm 1: Proposed EFICNN for the respiratory disease classification
Begin
Input: *Respiratory sensor readings/outputs*
Output: *Normal pulmonary functioning, Mild pulmonary disorder, Acute severe pulmonary disorder, and Life-threatening disorder*
Stage 1: The data is read from the developed breathing sensor
Stage 2: Describe the maximum value associated with the gathered data utilizing the following equation. $peak_{value} = max(information\ from\ the\ developed\ breathing\ se$
Stage 3: The data is pre-processed utilizing the data augmentation technique
Stage 4: Subject the DAM to the developed EFICNN model
Stage 5: Classify the final data as Normal pulmonary functioning, Mild pulmonary disorder, Acute severe pulmonary disorder, and Life-threatening disorder
Stop

3.6 EBOA algorithm

The EBOA algorithm is considered here for enhancing the feature selection as well as the classification phase of the proposed respiratory disease classification model. This EBOA optimizes the features as well as the parameters of the proposed respiratory disease classification model for deriving the accuracy maximization as the main fitness function. EBOA simulates the election procedure to choose the leader. The voting procedure, the selection of the leader, and the influence of public knowledge on the selection of the leader were the primary inspirations for EBOA. The EBOA population is governed by the search space, which is overseen by the elected leader. The EBOA procedure is analytically divided into two stages: exploration as well as exploitation.

EBOA represents a population-oriented metaheuristic method including community members. Every member associated with the population in the EBOA symbolizes a potential solution to the issue. Utilizing Eq. (5), the EBOA population is described mathematically by a matrix referred to as the population matrix.

$$Y = \left[Y_1 \ \vdots \ Y_j \ \vdots \ Y_O \ \right]_{O\times n} = \left[y_{1,1} \ \vdots \ y_{j,1} \ \vdots \ y_{O,1} \ \cdots \ \ddots \ \cdots \ \therefore \ \cdots \ y_{1,k} \ \vdots \ y_{j,k} \ \vdots \ y_{O,k} \ \cdots \ \therefore \ \cdots \ \ddots \ \cdots \ y_{1,n} \ \vdots \ y_{j,n} \ \vdots \ y_{O,n} \ \right]_{O\times n} \quad (5)$$

Here, Y shows the EBOA population matrix, Y_j shows the j^{th} EBOA member (i.e., the suggested solution), $y_{j,k}$ shows the value of the k^{th} issue variable provided by the j^{th} EBOA member, O shows the size associated with the EBOA population, and n shows the count of decision variables. Individuals' beginning positions in the search space are described at random using Eq. (6).

$$y_{j,k} = LB_k + s \cdot (UB_k - LB_k), j =$$

$1,2,\cdots,O, k = 1,2,\cdots,n$ (6)

Here LB_k as well as UB_k are the lower as well as upper bounds linked with the k^{th} variable, and s shows a random integer in the range [0;1]. A value associated with the objective function may be calculated on the basis of the values suggested by every EBO individual for the problem variables. As per Eq. (7), these assessed values related to the problem's objective function are stated utilizing a vector.

$$OBF = \left[OBF_1 \ \vdots \ OBF_j \ \vdots \ OBF_O \ \right]_{O\times 1} = \left[OBF(Y_1) \ \vdots \ OBF(Y_j) \ \vdots \ OBF(Y_O) \ \right]_{O\times 1} \quad (7)$$

Here, OBF is the vector of EBOA individual attained objective function values and OBF_j is the attained objective function value linked with the j^{th} EBOA individual. The values associated with the objective function serve as a standard for judging the effectiveness related to the suggested solutions, with the optimal value related to the objective function indicating the optimal individual and the worst value indicating the worst individual.

The key distinction among metaheuristic methods is how individuals associated with the population are updated and how the developed solutions are improved in every iteration. The method of updating the algorithmic individual in EBOA is divided into two stages: exploitation and exploration, which are explained further beneath.

Stage 1: Holding elections and voting procedure (exploration): On the basis of their knowledge, EBOA individuals vote for one among the candidates in the election. Individual's consciousness may be seen as being reliant on the goodness and quality of the objective function's value. As a result, Eq. (8) is used to imitate community members' knowledge. Individuals having higher values related to the objective function are more conscious regarding this awareness simulation procedure.

$$B_j = \{\frac{OBF_j - OBF_{worst}}{OBF_{best} - OBF_{worst}}, OBF_{best} \neq OBF_{worst} \ \ 1, else \quad (8)$$

Here, B_j shows the awareness related to the j^{th} EBOA individual, and OBF_{best} and OBF_{worst} represents the objective function's best as well as worst values, correspondingly. It must be observed that in minimization problems, OBF_{best} is associated with the minimum value of the objective function, whereas in maximization problems, OBF_{best} is associated with the maximum value of the objective function, and OBF_{worst} is associated with the minimum value of the objective function.

Amongst the individuals of the community, 10% of the most aware persons are regarded election contenders. In the EBOA, the minimum count of candidates (O_D) is considered to be two (i.e., $O_D \geq 2$), implying that at least two candidates would sign up for the election.

In EBOA, the voting procedure is implemented in such a way that every individual's degree of awareness is compared to a random count; if an individual's level of awareness is more than that random count, the individual is capable of voting for the optimal candidate (referred as D_1). Alternatively, that individual will vote for one among the remaining candidates in a random manner. This voting procedure is analytically represented in Eq. (9).

$$W_j = \{D_1, B_j > s \ \ D_l, else \quad (9)$$

Here, W_j denotes the vote linked with the j^{th} member of the community, D_1 denotes the optimal candidate, and D_l denotes the l^{th} candidate, in which l describes a randomly chosen integer from the group $\{2,3,\cdots,O_D\}$.

At the completion of the voting procedure, depending on the total count of votes cast, the candidate with the most votes is chosen (leader). This elected leader has an impact on entire individuals of society, including those who did not vote for him. Individuals' positions in the EBOA are updated beneath the leadership and supervision of the chosen leader. This leader leads the algorithm population to various sections of the search space, increasing the EBOA's capacity to explore in the global search. The leader directs the procedure of updating the EBOA member in such a manner that every member is assigned a novel location. If the newly created location enhances the value linked with the goal function, it is appropriate for updating. Alternatively, the prior place is retained by the matching member. Eqs. (10) and (11) are used to represent the EBOA's updating procedure.

$$y_{j,k}^{new,Q1} = \{y_{j,k} + s\cdot\left(M_k - J\cdot y_{j,k}\right), OBF_M < OBF_j \ \ y_{j,k} + s\cdot\left(y_{j,k} - M_k\right), else \quad (10)$$

$$Y_j = \{Y_j^{new\cdot Q1}, OBF_j^{new,Q1} < OBF_j \ \ Y_j, else \quad (11)$$

Here, $Y_j^{new\cdot Q1}$ shows a newly produced location for the j^{th} EBOA individual, $y_{j,k}^{new,Q1}$ shows its k^{th} dimension, $OBF_j^{new,Q1}$ shows its objective function value, J shows an integer chosen at random between 1 and 2, M shows the elected leader, M_k shows its k^{th} dimension, and OBF_M shows its objective function value.

Stage 2: Public movement to increase awareness (exploitation): Individual's awareness involves a significant influence on their accurate judgements during the election as well as voting procedure. Aside from the leader's effect on individual's awareness, any individual's ideas as well as acts may raise that individual's knowledge. A better answer can be determined mathematically by doing a local search nearby to any given solution. Therefore, community members' efforts to raise awareness led to an increase in the EBOA's capacity to utilize the local search and identify optimal solutions to the issue. To replicate this local search procedure, a random point in the search space is evaluated in the neighborhood of every individual. The objective function associated with the problem is next determined on the basis of this novel circumstance to see if it is better when compared to the individual's current condition. If the novel location provides a higher value for the goal function, the local search proves effective, and the relevant individual's location is changed. Enhancing the value of the goal function will raise that individual's knowledge, allowing them to make better decisions in the next election (in the next cycle). Eqs. (12) and (13) are used to represent this updating procedure to raise individual's knowledge of the EBOA.

$$y_{j,k}^{new,Q2} = y_{j,k} + (1-2s)\cdot S\cdot\left(1-\frac{u}{U}\right)\cdot y_{j,k} \qquad (12)$$

$$Y_j = \begin{cases} Y_j^{new.Q2}, & OBF_j^{new,Q2} < OBF_j \\ Y_j, & else \end{cases} \qquad (13)$$

Here, $Y_j^{new.Q2}$ shows a newly produced location for the j^{th} EBOA individual, $y_{j,k}^{new,Q2}$ shows its k^{th} dimension, $OBF_j^{new,Q2}$ shows its objective function value, S shows a constant equal to 0.02, u shows the iteration contour, and U shows the maximum count of rounds.

After changing the status of the entire population individuals, an EBOA iteration is finished. The EBOA starts the next iteration with the newly modified values, and the population update procedure is continued till the final iteration on the basis of the first as well as second stages as per Eqs. (8) to (13). EBOA provides the optimal suggested solution obtained throughout the algorithm rounds as the answer to the problem after the entire execution of the method is completed. Algorithm 2 specifies the pseudocode of complete EBOA implementation processes.

Algorithm 2: EBOA				
Begin EBOA				
	Input problem data: objective function (accuracy maximization), variables, and conditions [optimally selected features of the proposed respiratory data classification model]			
	Set iterations (U) and EBOA population size (O)			
	Randomly produce the initial population matrix			
	Determine the objective function (accuracy maximization)			
		For $u = 1\ to\ U$		
			Update the best as well as worst population members (different classified diseases of the developed respiratory model)	
			Perform the exploration process	
			$B_j = \begin{cases} \frac{OBF_j - OBF_{worst}}{OBF_{best} - OBF_{worst}}, & OBF_{best} \neq OBF_{worst} \\ 1, & else \end{cases}$	
			Describe the candidates (different diseases) on the basis of awareness condition	
			$W_j = \begin{cases} D_1, & B_j > s \\ D_l, & else \end{cases}$	
			Count the votes (number of optimal solution of the proposed respiratory disease classification model) and describe the election winner as leader	
			For $j = 1\ to\ O$	
				$y_{j,k}^{new,Q1} = \begin{cases} y_{j,k} + s\cdot(M_k - J\cdot y_{j,k}), & OBF_M < OBF_j \\ y_{j,k} + s\cdot(y_{j,k} - M_k), & else \end{cases}$
				$Y_j = \begin{cases} Y_j^{new\cdot Q1}, & OBF_j^{new,Q1} < OBF_j \\ Y_j, & else \end{cases}$
				Perform the exploitation process
				$y_{j,k}^{new,Q2} = y_{j,k} + (1-2s)\cdot S\cdot\left(1-\frac{u}{U}\right)\cdot y_{j,k}$
				$Y_j = \begin{cases} Y_j^{new.Q2}, & OBF_j^{new,Q2} < OBF_j \\ Y_j, & else \end{cases}$
			end	
			Save best developed solution (best classified disease of the developed respiratory model) attained so far	
		end		
	Output best quasi-optimal solution (best classified output of the considered diseases of the respiratory model) attained with the EBOA			
Stop EBOA				

4. Results

4.1 Experimental Setup

The developed respiratory disease classification model is run in a MATLAB R2020 platform having 8 GB of RAM and a 1TB hard drive. This effort creates a real-time dataset that includes normal pulmonary functioning, mild pulmonary disorder, acute severe pulmonary disorder, and life-threatening disorder. This information is obtained from the Upgraded Government Primary Health Centre in Srimushnam, where 550 males and 475 females are participating in the production of respiratory information in this dataset gathering procedure. Out of these 550 males, 400 had normal respiratory information and no symptoms for any respiratory issue, according to clinician reports, while the remaining 150 had mild pulmonary disorder, acute severe pulmonary disorder, and life-threatening disorder as well as signs for any respiratory issue, according to clinician reports. Furthermore, out of these 475 females, 300 generated normal respiratory information and did not show signs for any respiratory issue, according to clinician reports, while the other 175 generated mild pulmonary disorder, acute severe pulmonary disorder, and life-threatening disorder as well as did show signs for any respiratory issue, according to clinician reports.

4.2 Simulation output

The developed research entails utilizing an ESP8266 microcontroller for tracking PEFR and importing information from a Peak Flow Meter. The ESP8266 interfaces to a local Wi-Fi network and uses MQTT to deliver the PEFR data to Ubidots. These PEFR results are categorized, taken into consideration, and supplied to Ubidots for visualization. SMS instances in Ubidots are set up using predetermined PEFR thresholds for every group. Ubidots sends an SMS alert whenever the PEFR value falls under a certain range, like the Life-threatening group. This occurrence is connected to a predefined cellphone number, assuring that crucial alerts are sent on time.

The developed respiratory disease classification model provides real-time monitoring of PEFR, allowing healthcare providers or carers to follow the patient's respiratory health using data from the Peak Flow Meter. The system's features are enhanced by the automated SMS notifications, which provide quick alerts when the PEFR values suggest possible health hazards. This study indicates an efficient and effective solution for early detection and remote monitoring of respiratory problems by integrating the ESP8266 with Ubidots' powerful IoT environment and using a Peak Flow Meter for data input, thereby leading to quick response and enhanced patient care to situations of emergency. An illustration of an SMS alert describing the condition of the respiratory disease of the patient is shown in the figure below.

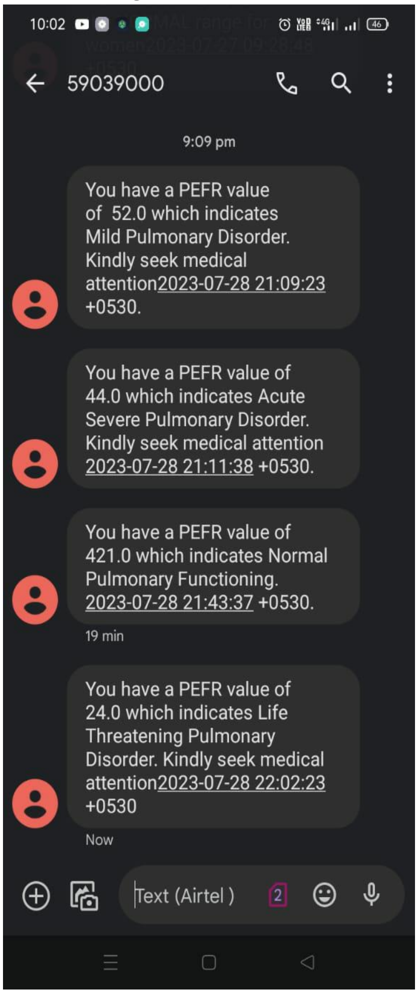

Fig 4. Illustration of an SMS alert showing the condition of the respiratory disease of the patient

4.3 Accuracy analysis

The accurate analysis of the proposed respiratory disease classification model with respect to the proposed EFICNN-EBOA and the existing methods is shown in the table and figure below. The degree of accuracy is how near a computed or evaluated number is to the real value. It calculates statistical error as the variation between the computed and real value. It can be seen clearly that the proposed EFICNN-EBOA outperforms the other considered measures in terms of accuracy, thereby revealing its superiority. The proposed EFICNN-EBOA is 6.84% better than ANFIS, 4.20% better than SVM, 2.55% better than LeNet, and 0.02% better than FICNN. Therefore, it can be demonstrated clearly that the developed EFICNN-EBOA is better with respect to the accuracy measure than the other state-of-the-art works respectively for the developed respiratory disease classification model.

Table 2. Accuracy analysis

Methods	***Epochs***				
	20	40	60	80	100
ANFIS [26]	85.49	87.85	89.60	91.91	93.58
SVM [27]	87.85	89.38	91.72	93.30	95.95
LeNet [28]	89.84	91.39	93.87	95.39	97.49
FICNN [29]	90.59	92.93	94.29	96.05	99.96
Proposed EFICNN-EBOA	91.50	93.04	95.29	97.74	99.98

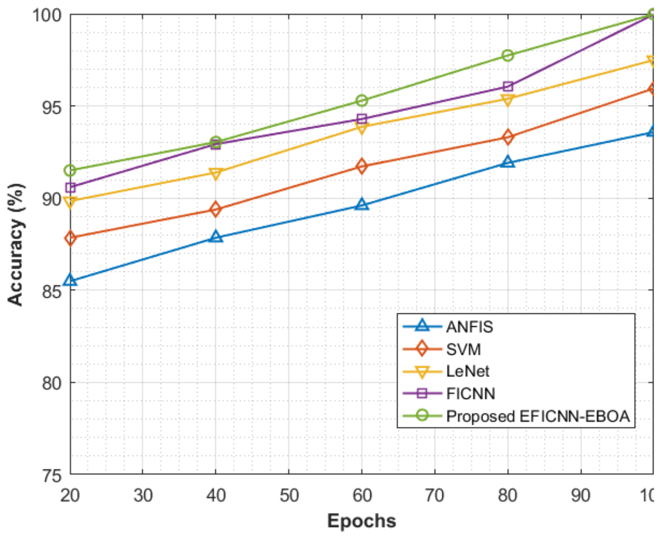

Fig. 5. Accuracy analysis

4.4 Specificity analysis

The table and figure below illustrate the specificity analysis of the suggested respiratory disease classification model in comparison to the developed EFICNN-EBOA and the conventional approaches. Specificity, defined as the percentage of individuals accurately assigned a negative allocation out of entire samples who are genuinely negative for the result, reflects how better an evaluation may categorize samples that do not have the desired result. The suggested EFICNN-EBOA clearly exceeds the remaining evaluated metrics with respect to specificity, demonstrating its betterment. The suggested EFICNN-EBOA is 6.04 percent superior to ANFIS, 3.61 percent superior to SVM, 1.51 percent superior to LeNet, and 0.02 percent superior to FICNN. As a result, it is obvious that the produced EFICNN-EBOA is superior in terms of specificity to the remaining existing works for the established respiratory disease classification model.

Table 3. Specificity analysis

Methods	***Epochs***				
	20	40	60	80	100
ANFIS [26]	86.40	88.85	90.39	92.95	94.28
SVM [27]	87.59	89.85	91.38	93.01	96.49
LeNet [28]	90.58	92.82	94.10	96.04	98.48
FICNN [29]	91.49	93.85	95.10	97.09	99.95
Proposed EFICNN-EBOA	92.49	94.85	96.39	98.01	99.97

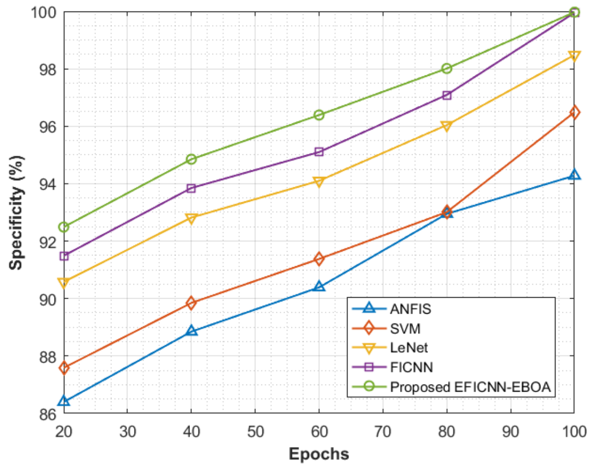

Fig 6. Specificity analysis

4.5 Sensitivity analysis

The table and figure below show the sensitivity analysis of the proposed respiratory disease classification model compared to the introduced EFICNN-EBOA and traditional techniques. Sensitivity is described as the fraction of variations in a technique's outcome to variations in the value of the amount being monitored. It represents the technique's response to the minimal variation in the computed variable. The proposed EFICNN-EBOA clearly outperforms the remaining examined measures in terms of sensitivity, proving its superiority. The proposed EFICNN-EBOA is 8% advanced than ANFIS, 5.55% advanced than SVM, 3.63% advanced than LeNet, and 0.02% advanced than FICNN. As a consequence, it is clear that the created EFICNN-EBOA outperforms the remaining current works for the created respiratory disease classification model with respect to sensitivity.

Table 4. Sensitivity analysis

Methods	***Epochs***				
	20	40	60	80	100
ANFIS [26]	84.49	86.85	88.29	90.03	92.57
SVM [27]	85.40	87.84	89.50	91.81	94.72

LeNet [28]	88.40	90.81	92.40	94.93	96.48
FICNN [29]	91.40	93.92	95.40	97.85	99.96
Proposed EFICNN-EBOA	92.48	94.75	96.49	98.83	99.98

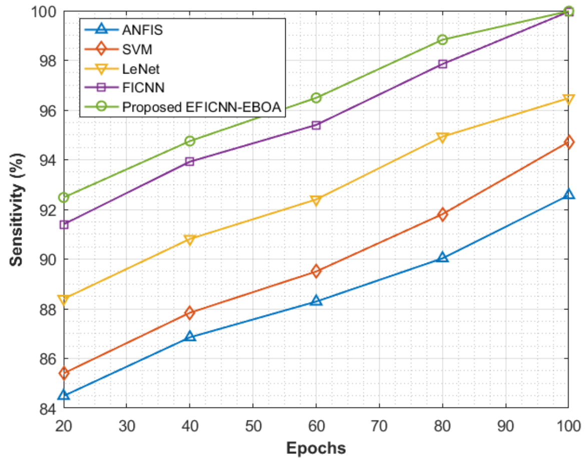

Fig 7. Sensitivity analysis

4.6 Computational time analysis

The table and image below compare the computational time of the suggested respiratory disease classification model to the recommended EFICNN-EBOA and conventional approaches. The time it requires a computer algorithm to complete its work (computation time) is an important performance indicator used by software developers and scientists to assess if a method is capable of finishing its objective in a realistic time range. In terms of computational time, the suggested EFICNN-EBOA significantly beats the other investigated metrics, demonstrating its supremacy. As a result, it is obvious that the generated EFICNN-EBOA surpasses the state-of-the-art works in terms of computational time for the constructed respiratory disease classification model.

Table 5. Computational time analysis

Methods	***Epochs***				
	20	40	60	80	100
ANFIS [26]	2.54	2.65	2.76	2.87	1.98
SVM [27]	2.	1.	1.	1.	1.

	09	98	87	76	65
LeNet [28]	1.36	1.25	1.14	1.03	0.92
FICNN [29]	0.49	0.38	0.27	0.16	0.05
Proposed EFICNN-EBOA	0.46	0.35	0.24	0.13	0.02

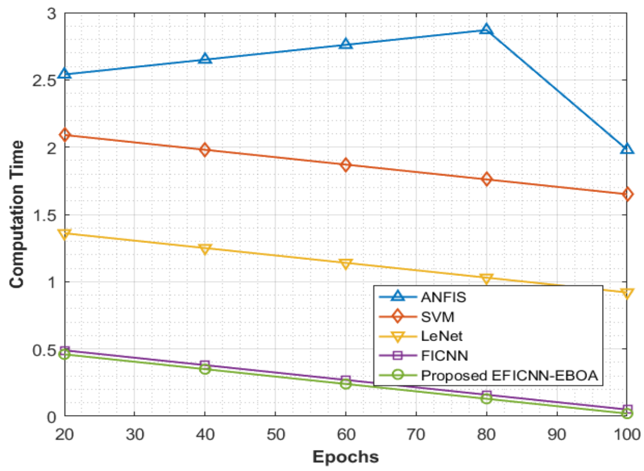

Fig 8. Computational time analysis

4.7 Respiratory Detection Rate (RDR) analysis

The table and graphic below contrast the RDR of the proposed respiratory disease classification model to the proposed EFICNN-EBOA and traditional techniques. With respect to RDR, the proposed EFICNN-EBOA greatly outperforms the remaining measures studied, proving its superiority. The newly developed EFICNN-EBOA is 14.17% more than ANFIS, 8.94% more than SVM, 7.65% more than LeNet, and 0.20% more than FICNN. As a consequence, the developed EFICNN-EBOA clearly outperforms the existing methods in consideration of RDR for the developed respiratory disease classification model.

Table 6. RDR analysis

Methods	***Epochs***				
	20	40	60	80	100
ANFIS [26]	79.04	81.30	83.75	85.49	87.5
SVM [27]	83.	85.	87.	89.	91

	59	75	20	37	.7
LeNet [28]	84.59	86.71	88.50	90.04	92.8
FICNN [29]	91.50	93.84	95.30	97.84	99.7
Proposed EFICNN-EBOA	92.40	94.84	96.61	98.40	99.9

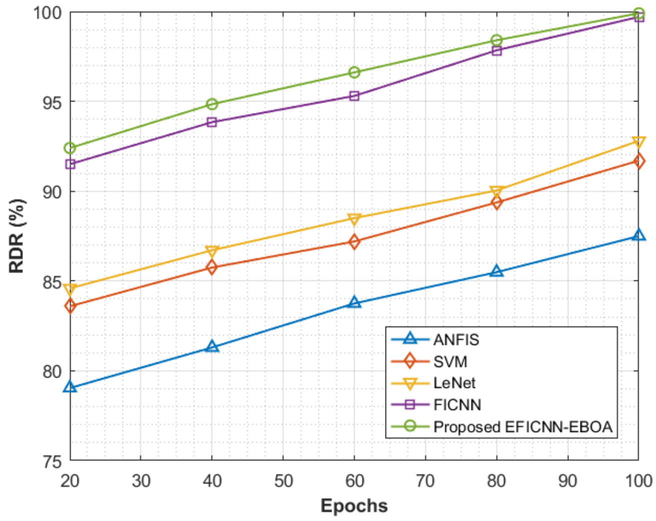

Fig. 9. RDR analysis

5. Conclusion

This research intended to use unique DL technology to conduct optimum feature selection and classification of respiratory illnesses. In the first stage, respiratory data from abnormal and normal people were acquired in real time using a breathing sensor. The collected data was then subjected to data augmentation in order to eliminate overfitting issues. The result of this data augmentation method was submitted to the feature extraction step for feature extraction. Mean, Energy, Standard deviation, Kurtosis, Skewness, Peak Max Index Feature, Peak Min Index Feature, and Linear Index Feature were all extracted there. The best features were chosen from the retrieved features. The innovative EFICNN performed the final classification phase on these ideal features. The nature-inspired meta heuristic optimization method EBOA performed parameter tweaking in both the optimum feature selection and classification phases in order to determine the accuracy maximization as the fitness function. The final result was based on several ranges of PEFR values, which were classified as normal lung functioning, moderate pulmonary disorder, acute severe pulmonary disorder, and life-threatening disorder. It did this by combining the ESP8266 microcontroller with Ubidots' strong IoT platform and employing a Peak Flow Metre to collect data.

Author contributions

Rampriya R: Conceptualization, Methodology, Software, Field study, Writing-Original draft preparation **Dr. Suguna N:** Data curation, Software, Validation., Field study **Dr. Suresh Kumar R.G:** Data Visualisation, Logical Reasoning, Optimization., Field study **Dr. Sudhakar P:** Visualization, Investigation, Writing-Reviewing and Editing., Field study.

Conflicts of interest

The authors declare no conflicts of interest.

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