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Optimized DEC: An effective cough detection framework using optimal weighted Features-aided deep Ensemble classifier for COVID-19

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ABSTRACT

Since the year 2019, the entire world has been facing the most hazardous and contagious disease as Corona Virus Disease 2019 (COVID-19). Based on the symptoms, the virus can be identified and diagnosed. Amongst, cough is the primary syndrome to detect COVID-19. Existing method requires a long processing time. Early screening and detection is a complex task. To surmount the research drawbacks, a novel ensemble-based deep learning model is designed on heuristic development. The prime intention of the designed work is to detect COVID-19 disease using cough audio signals. At the initial stage, the source signals are fetched and undergo for signal decomposition phase by Empirical Mean Curve Decomposition (EMCD). Consequently, the decomposed signal is called “Mel Frequency Cepstral Coefficients (MFCC), spectral features, and statistical features”. Further, all three features are fused and provide the optimal weighted features with the optimal weight value with the help of “Modified Cat and Mouse Based Optimizer (MCMBO)”. Lastly, the optimal weighted features are fed as input to the Optimized Deep Ensemble Classifier (ODEC) that is fused together with various classifiers such as “Radial Basis Function (RBF), Long-Short Term Memory (LSTM), and Deep Neural Network (DNN)”. In order to attain the best detection results, the parameters in ODEC are optimized by the MCMBO algorithm. Throughout the validation, the designed method attains 96% and 92% concerning accuracy and precision. Thus, result analysis elucidates that the proposed work achieves the desired detective value that aids practitioners to early diagnose COVID-19 ailments.

1. Introduction

During the end period of 2019 and throughout 2020, a very disastrous virus is spread widely and rapidly worldwide as it is contagious in nature. It is identified as one kind of disease as “Severe Acute Respiratory Syndrome Corona Virus 2 (SARS-CoV-2)” [1]. In 2020th February, the World Health Organization (WHO) named this virus as COVID-19. The entire world stumbles by the outbreak of this virus. Over the world, due to its quick spread, around 434,150,000 cases were confirmed in February 2022 [2], in which 5,940,000 cases were reported as deaths. Major notable syndromes are reported as follows (i) Ear, Nose, and Throat (ENT) and respiratory issues like cough and less breathness [3], head pain and sore throat, (ii) general symptoms like muscle pain, fever, and weakness and (iii) lack of taste and smelling sense. Further, the common ENT symptoms are noticed along with COVID-19 that lead to other ailments like nasal congestion, upper respiratory tract infection, rhinorrhea, pharyngeal erythema, and tonsil inflammation [4]. Subsequently, the analysis of cough detection becomes recent attention in COVID-19 disorder as it directly affects the lung parts of the human. Predominantly, cough is the prime identification for confirming COVID-19 patients [5]. Therefore, the lung disorder causes an impact in the glottis to do the metabolism process in a way of either being obstructed or restricts. This disease could be influenced by considering the acoustic signals of breath, cough, and speech [6].

For COVID-19 patients, the cough becomes the second most notable syndrome as fever is in prior symptoms. While diagnosing the cough for COVID patients, it is firstly in the dry and non-productive state that is the same as like a tickle in their throat region [7], whereas the most affected individuals get wet in the throat as well as productive in nature, which leads to cause the flu or cold. From the acoustic perspective, the cough

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sound is defined as a "forced expulsive maneuver" that exhibits against the closed glottis with a cough sound [8]. In nature, the cough sounds can be distinguished into three phases; they are phase 1 – explosive, phase 2 – intermediate, and phase 3 – voiced, correspondingly. The voiced phase is always not existed [9], but due to its absence, the identification of the intermediate is critical one. Therefore, as always, the presence of the explosive phase, it is used for primarily diagnosing the disease [10]. Over the recent few years, several scholars have examined the performance analysis for cough and respiratory sounds to reach the attention for earlier treatment of COVID-19. The cough in COVID-19 differs from other normal respiratory causes of cough syndromes [11].

In order to develop an effective cough detection model, cough acoustic sounds are initially considered. Certain experts have filed the cough audio datasets, where the acoustic signals are presented in short record samples of breath and cough [12]. Owing to the audio signals, the cough detection model is processed with frequency domain features, and then, classification is done by either machine or deep learning approaches [13]. Conversely, some machine learning approaches are employed to diagnose the COVID-19 disease by considering the images. In [14], Computed Tomography (CT) image is utilized to analyze cough detection, where the ResNet50 classifier is used to acquire more accurate values. Using chest X-ray images, the detection is performed with promising results. Yet, rather than the image representation, the signals can be used to easily identify as every individual varies with acoustic signals of cough or respiratory [15]. Over the past two to three years, the automated cough detection model has been implemented with respiratory or cough signals. Furthermore, other transfer learning approaches are deployed with significant features to do the classification tasks [13]. Hence, the deep learning model emerges with its beneficial traits to diagnose COVID-19 disorder and the respiratory audio signals [17].

The prime contributions for the new detection work are listed as below.

- To adopt a novel cough detection model by optimized deep learning model with heuristic improvement for COVID-19 disorder that is helpful for a medical institution to sustain their reputation for diagnosing the disease in an appropriate way. The recommended cough detection model can be suitable for different applications like healthcare and mobile-based applications.
- To extract the most informative features of cough audio signal by the concept inference of MFCC, spectral and statistical features, to enhance the performance of the cough detection model. Hence, the MFCC can be performed to minimize the error, and also it provides a significant feature when the signal is affected by noise.
- To concatenate all the resultant features to select the weighted-based optimal features. It is upgraded into the weighted features, where the weight factor is optimally determined by a novel MCMBO algorithm that resolves the dimensionality issues. Moreover, the developed MCMBO algorithm can be used to resolve the issues in local optima. Consequently, it can resolve complex optimization problems.
- To frame the optimized DEC model for classifying the features into the presence or absence of COVID-19. Here, it possesses LSTM, DNN, and RBF to do the classification task, in turn, the hidden neurons and epochs are tuned using the MCMBO algorithm. The optimized DEC method solves the gradient vanishing and underfitting issues. Moreover, the accuracy rate can be improved by the developed method.
- To analyze the performance with different measures and compare over traditional heuristic algorithms and other classifier models. The comparative analysis provides effective results for improving the system's robustness.

The rest parts are explored. Part II describes the existing research works on the cough detection model in COVID-19. It is followed by explaining the novel intelligence cough detection framework in Part III. Part IV demonstrates the weighted feature selection with a modified heuristic approach. Part V illustrates the optimized ensemble learning model for classification purposes. Part VI implements the proposed concept and its respective results. Finally, the conclusion and future scope are described in Part VII.

2. Existing works

2.1. Literature papers

In 2020, Laguarta et al. [18] have implemented the Artificial Intelligence (AI)-based detection model for COVID-19. Here, the experimentation was done using acoustic signals and recordings of cough audio. Thus, it became a non-invasive model with real-time implications and less cost-effective. Initially, the collected signals were used to extract the MFCC features, which were fed into the Convolutional Neural Network (CNN). This model was structured with "one Poisson biomarker layer and 3 pre-trained ResNet50s in parallel". From the datasets, 4256 recordings were trained in the model as CNN, and 1064 signals were conducted for testing. Similarly, the transfer learning approach was employed to retrieve the biomarker features of the signal, which has also improved the detection performance. Finally, the simulation was carried out, and its corresponding value was validated by various metrics. Thus, the suggested method has scored the higher specificity as 98.5% and also the Area under the Curve (AUC) as 0.97, respectively.

In 2022, Ren et al. [19] have developed a model based on acoustic traits of cough to diagnose corona disease. The objective of this model was to analyze the test results as either positive or negative. With the admittance of traditional statistics, it could be used for analyzing the correlation among the signals that relied on ComParE set, which has comprised around 6,373 audio traits of cough. Subsequently, the machine learning approach was taken for classifying the features and explored the status of every affected individual. The simulated results were estimated by considering the multiple metrics as statistical value, MFCC features, root mean square energy, and so on for providing the outcome as negative and positive sample indications for COVID-19. Thus, the novel automated system has achieved an impressive value of 0.632 for Unweighted Average Recall (UAR) by considering the total samples as 1411 cough recordings.

In 2022, Pahar et al. [20] have used the transfer learning model and feature extraction process for identifying COVID-19 using the audio files of breath, cough, and speech. Since it could not be performed in a contact manner, the audio recordings were fetched from the benchmark online sources. It could be able to collect data of sneeze, cough, noise, or speech and could not have proper COVID-19 labels. To identify the sample labels, the deep learning models were pre-trained. Here, the three classifiers as, LSTM, CNN, and ResNet50, were taken. Further, these pre-trained networks were used to classify the features, whether it is in a state of normal or abnormal. Among the three models, the ResNet50 was used by concept inference of the transfer learning model. Finally, the results were computed by various metrics and provided comparative results. The simulation value of the model has been achieved as 0.94 for breath signals, 0.98 for cough recordings, and 0.92 for speech recordings, correspondingly.

In 2021, Sattar [21] has designed a fully automated based detection technique using cough audio for COVID-19 detection. This methodology was relied on the time domain characteristics of the signal to represent the cough recordings of the individual. Further, it has also considered the "plausible click sequences" for diagnosing the COVID19 affected patients. This type of sequence was determined from the slope functionalities of source signals. It was further utilized to estimate the "Scoring Index (SI) and Inter-Click Intervals (ICIs)". Also, it was done based on the Coefficient of Variation (CV) related to ICIs. Finally, the Probability Density Function (PDF) was acquired for output clicks. Here, the implementation was done by taking the real-time based audio from

Table 1
Advantages and limitations of cough detection in COVID-19.

Author [citation]	Techniques	Advantages	Limitations
Laguartaet al. [18]	CNN and ResNet50	• It effectively detects the COVID disorder with accurate results.	• It becomes fragile when it deals with a large-scale dimension of the dataset.
Ren et al. [19]	MFCC	• It increases performance as it extracts essential acoustic features. • It increases the training speed.	• Since it does not contain adequate symptom information, the performance gets degraded.
Pahar et al. [20]	CNN, LSTM, ResNet50	• The AUC value is increased to detect the cough in COVID patients. • It increases the robustness and reduces the load problem.	• While managing the enormous amount of data, the systems are falls with overfitting issues.
Sattar [21]	ICIs	• It enhances the entropy value that ensures to provide of the most essential features.	• It increases the time complexity, and overlapping occurs.
Hamdi et al. [22]	CNN-LSTM	• It improves the sensitivity and accuracy value. • It also increases the AUC score for cough sound.	• It degrades the overall performance as it restricts with class imbalance issues. • It has the constraints of binary class detection.
Soltanian and Borna [23]	CNN	• It reduces the computational burden • It enhances the F1-score and recall measures.	• Due to the scarcity of training samples, an inaccurate result is obtained.
Hemdanet al. [24]	GA-ML	• It helps to improve the performance regarding diverse validation measures. • It is applied for real-time applications.	• The scalability of the model gets mitigated by handling large datasets.
Klopper et al. [25]	KNN, SVM, LSTM, MLP	• It achieves better performance with respect to the higher value of AUC	• It does not support the huge amount of datasets.

the medical dataset as "Novel Coronavirus Cough Database (NoCoCoDa)". Finally, the performance was evaluated and analyzed on the time-domain features. Then, the analysis has demonstrated to attain precise results for detection.

In 2022, Hamdi et al. [22] have framed a novel detection model for diagnosing COVID-19 using a deep learning approach. This model was named as the augmentation process, where the data was applied in a pre-filtered format. The two steps were considered as (a) augment the pitch-shifting process of the source signal and (b) spectral-based augmentation as SpecAugment that has deployed mel-aided spectrogram features. The classification model was newly designed with CNN and LSTM networks, along with an attention mechanism to diagnose the disorder. The experimentation was carried out with CoughVid-type datasets and compared over classical methodologies. Based on the validation, the result has attained as 91.13% for accuracy and AUC 90.93% for sensitivity, which has ensured to exhibit better detection performance.

In 2022, Soltanian and Borna [23] have explored a novel lightweight deep-learning technique for providing the classified result as Non-COVID and COVID patients. Here, the analysis was made using the Virufy database, which was then compared with other existing approaches. Hence, the outstanding results regarding accuracy has been improved when compared with the other conventional methods. In 2022, Hemdan et al. [24] have introduced the machine learning-assisted detection model using cough audio. It has also inferred the Genetic Algorithm (GA) to exploit the optimal value. The performance was computed based on recall, precision, and F-measure. In contrast with other conventional models, the proposed GA-aided machine learning has obtained outperformed outcomes to diagnose the COVID-19. The suggested method has achieved a better accuracy value. Hence, from the analysis, the recommended method has ensured that it has exploited better outcomes to improve the detection performance.

In 2021, Pahar et al. [25] have introduced machine learning-based models for detecting COVID-19 positive or negative using cough audio samples. To experiment with the model, it has considered publicly available online sources such as the Coswara dataset, which was comprised of 92 positive cases and 1079 negative reports. Similarly, the second dataset was taken from the region of South Africa, where it has included 18 and 26 cases of positive and negative. Subsequently, it has employed the "Synthetic Minority Oversampling Technique (SMOTE)". Here, the training was done by seven distinct classifiers as K-Nearest Neighbour (KNN), CNN, Multi-Layer Perceptron (MLP), Support Vector Machine (SVM), LSTM, ResNet50 and Logistic Regression (LR). Finally, the validation of the designed method was estimated with different metrics. In the designed method, the recommended technique has achieved an AUC of 98%. Through the extensive results, the suggested approach has enhanced efficiency, reduced the cost functions, and become flexible to implement in such medical institutions.

2.2. Research gaps and challenges

Amongst all other syndromes for COVID-19, the cough becomes the predominant symptom that immensely affects the respiratory of the individual. Several studies have concentrated on cough detection in Covid 19 disease, and its advantages and disadvantages are discussed in Table 1. CNN and ResNet50 [18] effectively detect COVID disorder with accurate results. But, it becomes fragile when it deals with large-scale dimensions of the dataset. MFCC [19] increases the performance as it extracts the essential acoustic features and also increases the training speed. Since it does not contain adequate symptom information, the performance gets degraded.CNN, LSTM, and ResNet50 [20] increase the AUC value to detect the cough in COVID patients and also increases the robustness and reduce the load problem. Yet, while managing the enormous amount of data, the systems fall into the overfitting issue. ICIs [21] enhance the entropy value that provides essential features. On the other hand, it increases the time complexity, and overlapping occurs. CNN-LSTM [22] improves the sensitivity and accuracy value and increases the AUC score for cough sounds. However, it degrades the overall performance as it restricts class imbalance issues and has the constraints of binary class detection. CNN [23] reduces the computational burden and enhances the F1-score and recall measures. Due to the scarcity of training samples, an inaccurate result is obtained. GA-ML [24] enhances the performance of diverse validation measures and is applied for real-time applications. But, the scalability of the model gets mitigated by handling large datasets. KNN, SVM, LSTM, and MLP [25] achieve better performance concerning the higher value of AUC. However, it does not support the huge amount of datasets. With the aim of overcoming these challenging problems, it is suggested to design an efficient framework for cough detection.

3. Intelligent model with cough detection for COVID diagnosis using optimized DEC

3.1. Proposed cough detection framework

By 2021 February, COVID-19 affects millions of individuals in the

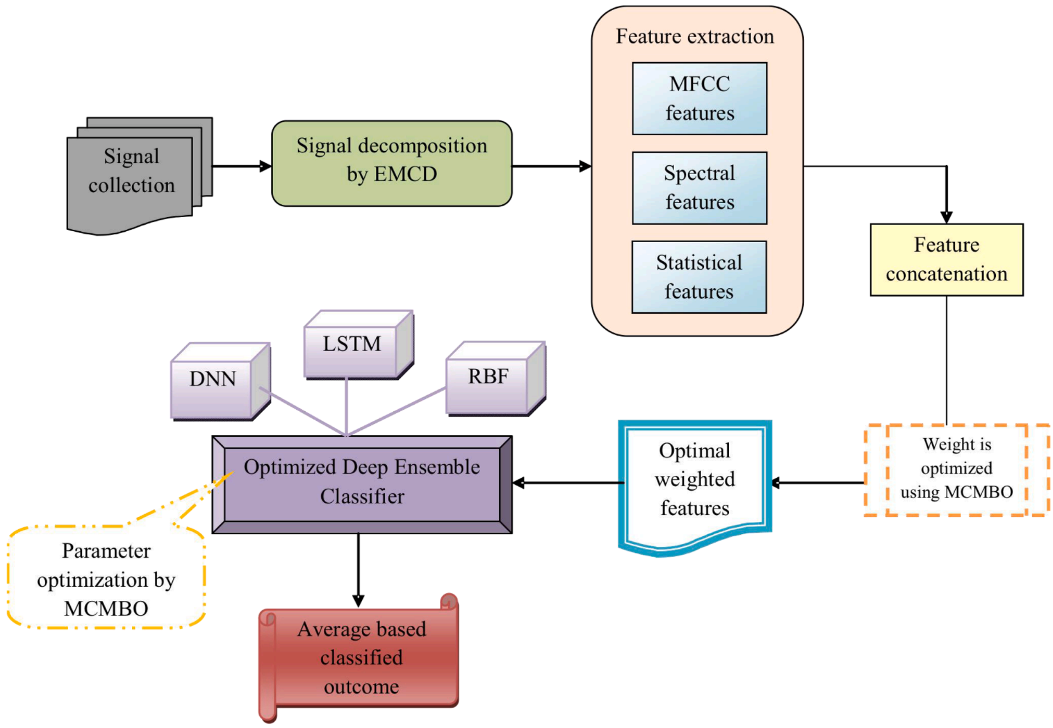

Fig. 1. The architecture of the developed cough detection model by ensemble deep learning model with cough audio signal.

world, it still continues the pandemic situation in some regions. Due to its variant nature, it cannot be able to suppress. Therefore, the recent attention is to diagnose the ailments significantly. Since the vaccination is progressed, it exists to affect the persons with less immunity power. Owing to the contagious nature of the virus, the diagnosis becomes a challenging issue. This disorder is identified by such symptoms as cough, fever, and lack of smell or taste. Rather than other syndrome, the cough plays a vital role in detection techniques. The acoustic nature of cough aids to rapidly detect COVID-19 [40 41]. Since the cough audio signals render key information, it exhibits the respiratory state of each individual. Thus, some experts plan to use the audio signals to perform the detection performance. For the past few years, various machine-learning methods have been adopted to diagnose the disease. Since, it contains some limitations, such as time and structural complexity. Several feature extraction techniques have been used as the signal entails with peculiar traits like frequency and time domain in the signal samples. Yet, it faces the issue of dimensional problems that degrades performance. Recently, a deep learning approach has been performed to improve the detection results. Being with the diverse characteristics of deep learning classifier, it also exploits the promising results to ensure the effectiveness of the system. Nevertheless, it faces some shortcomings as complexity occurrence of ensemble deep classifiers also becomes infeasible, as well as more consumption of training time. Sometimes, data acquisition also comes under motivational factors as it does not contain real-time signals. Thus, it increases the overfitting problem. To combat all the aforementioned challenges, a new heuristic-aided deep ensemble classifier is proposed which is represented in Fig. 1.

The suggested methods comprise with distinct phases as (a) Audio signal acquisition, (b) Decomposing the signal, (c) Feature Extraction, (d) Optimal Weighted Feature Extraction, (e) Detection. Firstly, the source cough audio signals are fetched from the online data sources. It is further deployed for signal decomposition, where the decomposed signal is attained by EMCD. Subsequently, the feature extraction is carried out with three techniques as MFCC features, spectral features, and statistical features. Here, the relevant features are identified from the decomposed signal that is further combined with each other. Based on the acquired features, the optimal weighted features are chosen, where the weight is optimally evaluated by the MCMBO algorithm. Owing to this, it solves the dimensional issue and mitigates the false rate. Finally, the novel ODEC is developed with LSTM, DNN, and RBF, respectively, which is employed to provide the classified results as either the presence of COVID-19 or the absence of COVID-19. It has a complexity problem that is to be overcome by optimizing the parameters as epochs and hidden neuron counts by the MCMBO algorithm. The performance and comparative analysis are conducted over existing works of cough detection. Hence, the findings of the recommended method demonstrate to achieve impressive results, thereby ensuring an effective detection model.

3.2. Cough detection dataset description

The cough detection is performed by considering two different datasets explained below.

Dataset 1: The first dataset is named as "Covid-19 Cough Audio Classification", where the required audio signals are fetched. The collected signals are taken from "https://www.kaggle.com/datasets/andrewmvd/covid19-cough-audio-classification: Access Date: 2022–10–10". It constitutes almost 25,000 recordings of cough audio, which is used for classification and regression. It also contains 2800 subsets of audio files examined by four clinicians to identify the disorder.

Dataset 2: For the second dataset, the cough audio signals are collected from "https://www.kaggle.com/code/himanshu007121/covid-19-cough-classification/data: Access Date: 2022-10-10". The source files are extracted via the Kaggle website for performing the detection task.

Here, the gathered input audio signals for both datasets are represented as C_s where $s = 1, 2, 3, \ldots, S$. Here, the variable S defines the total cough audio signals used for subsequent sections.

3.3. EMCD-based signal decomposition

Once the required signal is taken, it is further fed to the process of signal decomposition. The novel method utilizes EMCD [26] for

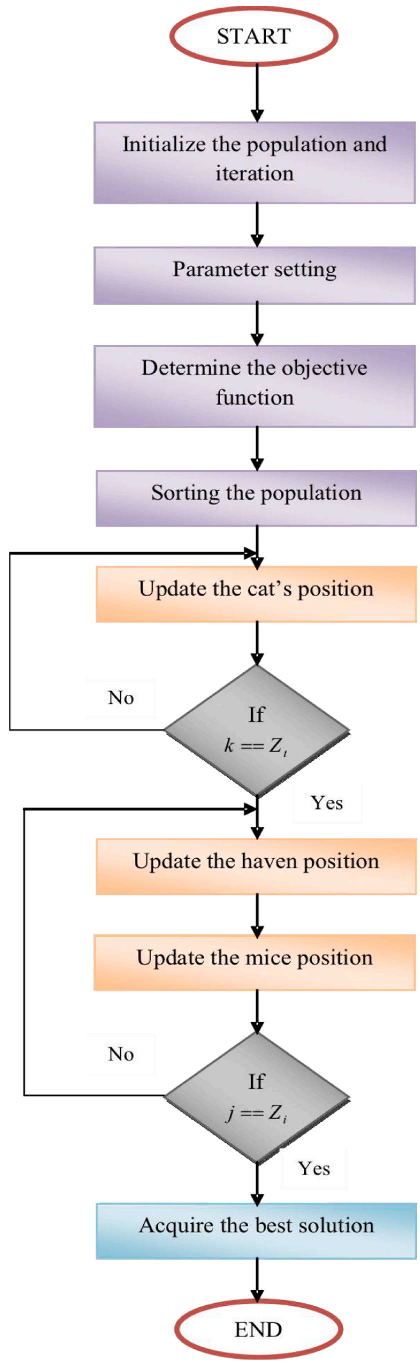

Fig. 2. The diagrammatic visualization of the designed method of the MCMBO algorithm.

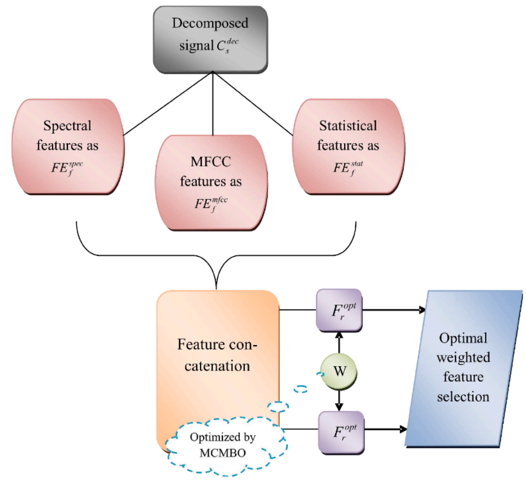

Fig. 3. Diagrammatic illustration of optimal weighted feature selection using MCMBO algorithm.

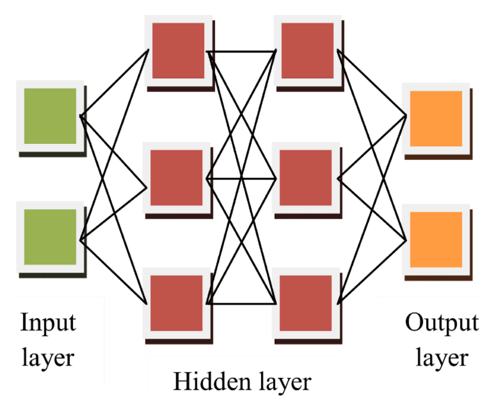

Fig. 4. General architecture of the DNN model.

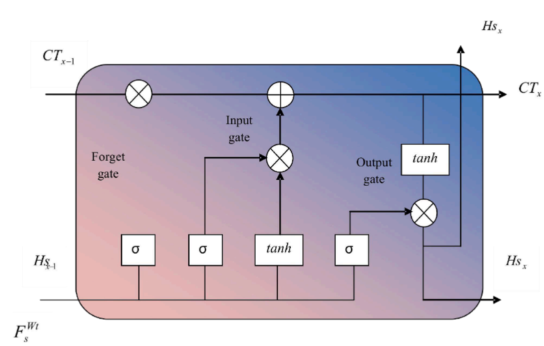

Fig. 5. The basic architecture of the LSTM model.

decomposing the signal. The signal as C_s is given as input for decomposition. The core function of this decomposition method is to decompose the time-series-based input signal in the manner of data-driven. Further, it is processed with a maxima and minima approach. Finally, the inferior and superior envelope and mean curves are considered for achieving the decomposed signal. The mathematical expression of EMCD is explained as follows.

Maxima and Minima: In the input signal as $C_s(a)$, where $a = 1,2,3, \ldots, A$. Thus, the maximal series of the input signal is represented by $\{(g, C[g]), g = 1, 2, \ldots, A_g\}$. Here, the number of maxima and their time indices is denoted by g and A_g, correspondingly. Similarly, the minimal series of the input signal is declared as $\{(h, C[h]), h = 1, 2, \ldots, A_h\}$. Here, the total number of minima and their time indices is noted as h and A_h, respectively.

Superior Envelope: It encompasses the entire maxima time series signal on the basis of the upper curve. In order to interpolate all the maxima series signals, it uses B-Spline (BS) interpolation technique. It is referred using Eq. (1).

$$C^{sp}[a] = bs\{(g, C[g]),\ C_s(a)\} \tag{1}$$

Inferior Envelope: It consists of all minima time series signal that relies on a lower curve. For interpolating all the series, it employs the BS interpolation approach, and which is given in Eq. (2).

$$C^{in}[a] = bs\{(h, C[h]),\ C_s(a)\} \tag{2}$$

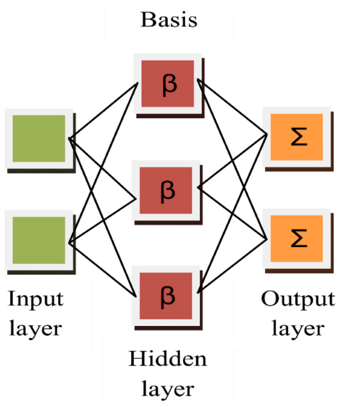

Fig. 6. The general structure of the RBF model.

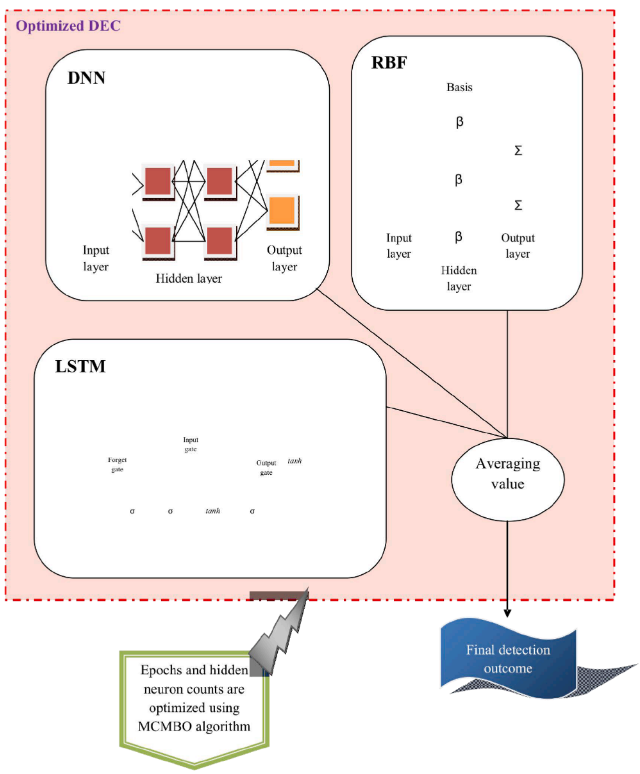

Fig. 7. The structure of ODEC with parameter optimization of MCMBO algorithm.

Mean Curve: It is computed by taking the average value of inferior and superior envelopes. It is given in Eq. (3).

$$C^{mc}[a] = \frac{C^{sp}[a] + C^{in}[a]}{2} \tag{3}$$

Mode: The mode characteristic of the signal is estimated by taking the average value of maxima and minima. It is expressed using Eq. (4).

$$md[C_s(a)] = \frac{A_g + A_h}{2} \tag{4}$$

Empirical waveform: During the mean curve time of determination, it generates a new signal as extrema and alters the maxima and minima. It is derived in Eq. (5).

$$ew[C_s(a)] = \{(g, C[g]),\ (h, C[h])\} \tag{5}$$

In addition to this, the empirical period and empirical frequency are evaluated using Eq. (6) and Eq. (7).

$$e^{pd} = A/md(C_s(a)) \tag{6}$$

$$e^{fy} = md(C_s(a))A \tag{7}$$

Finally, concerning waveform representation and maxima and minima mode, the decomposed signal is attained that is denoted by C_s^{dec}. It is further used for extracting the relevant features in the following section.

4. Modified CMBO-based optimal weighted feature selection for enhanced cough detection

4.1. Feature extraction

With the admittance of the resultant decomposed signal, then the process of feature extraction is outperformed. Here, the three distinct types of features are determined. Those techniques are illustrated as given below.

MFCC [27]***:*** The MFCC feature is commonly used to extract information related to the signals. It is mainly focussing on Mel-coefficients and Mel-filters to obtain the resultant features. The objective behind MFCC is to process the extraction as a signal windowing method, "Discrete Fourier Transform (DFT)". It computes the logarithmic value of mel-coefficient magnitudes and mel-frequency scales on the functionality of "Discrete Cosine Transform (DCT)".

Thus, the features are identified by mel-spectrum trait of the signal, which is acquired using the Fourier transform and fed into the band pass filter series. Here, the decomposed signal C_s^{dec} is taken as input. It is formulated using Eq. (8).

$$MFCC(ff) = 2595\log_{10}\left(1 + \frac{ff}{700}\right) \tag{8}$$

The term ff signifies the length of the decomposed signal frame. Therefore, the acquired MFCC feature is indicated by FE_f^{mfcc}.

Spectral Features [28]***:*** It represents the activities on the cough audio signals. For spectral feature analysis, the decomposed signal C_s^{dec} acts as an input. Some of the strategies used for choosing the spectral features that are explained as follows.

Power Spectrum: It is identified by computing the frequency magnitude value of decomposed signal. Every spectral peak is used here to retrieve the feature information regarding amplitude, frequency, and width.

Cross-Spectral Density (CSD: The CSD is used to determine the graphical characteristics of the decomposed signal to fuse the power-based features. It is extracted on the basis of frequency domain irrespective of the time domain. With the help of power measure, features of CSD are acquired.

Magnitude-Squared Coherence: It is retrieved by considering the two stationary features of decomposed signals correspondingly. It is represented in real number value.

$$SQ_{i,j}^2(C) = \frac{|MG_{ij}(C)|^2}{MG_{ii}(C)MG_{jj}(C)} \tag{9}$$

Spectrogram: As the name itself, the spectrogram features are to be calculated by both frequency and time characteristics of the decomposed signal. Thus, the required features are obtained.

Short-Time Fourier Transform: The STFT features are determined using the spectral features of the decomposed audio signal. It is evaluated by accounting for the decomposed audio signal and window as C_s^{dec} and window as N, as shown in Eq. (10).

$$stft = \sum_{t=0}^{T-1} C_t^{dec} + fN_t e^{-j2\pi ft} \tag{10}$$

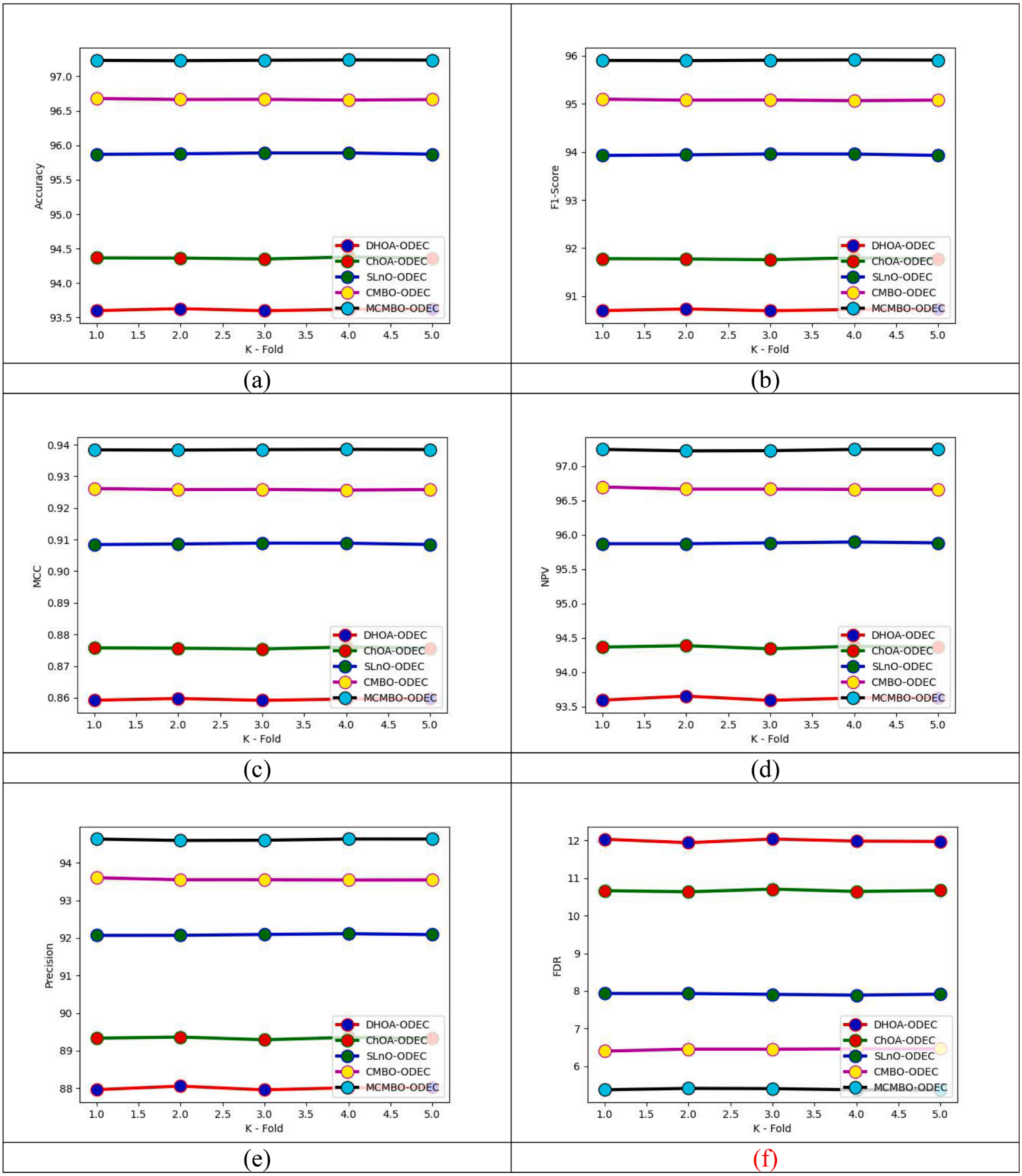

Fig. 8. K-fold validation of the designed cough detection model concerning "(a) Accuracy, (b) F1-score, (c) MCC, (d) NPV, (e) Precision, (f) FDR, (g) FNR, (h) FPR, (i) Sensitivity, and (j) Specificity".

Thus, the spectral related features are acquired and represented by FE_f^{spec}.

Statistical features [29]***:*** The statistical based features are estimated on the basis of five distinct factors as "Mean, Median, Standard Deviation, Variance, Minimum, and Maximum". Here, the features are computed from the decomposed signal as C_s^{dec}. Thus, it describes as below.

Mean: It is the process of finding "the sum of a collection of samples in decomposed signal is divided from the total samples of signal" is given in Eq. (11).

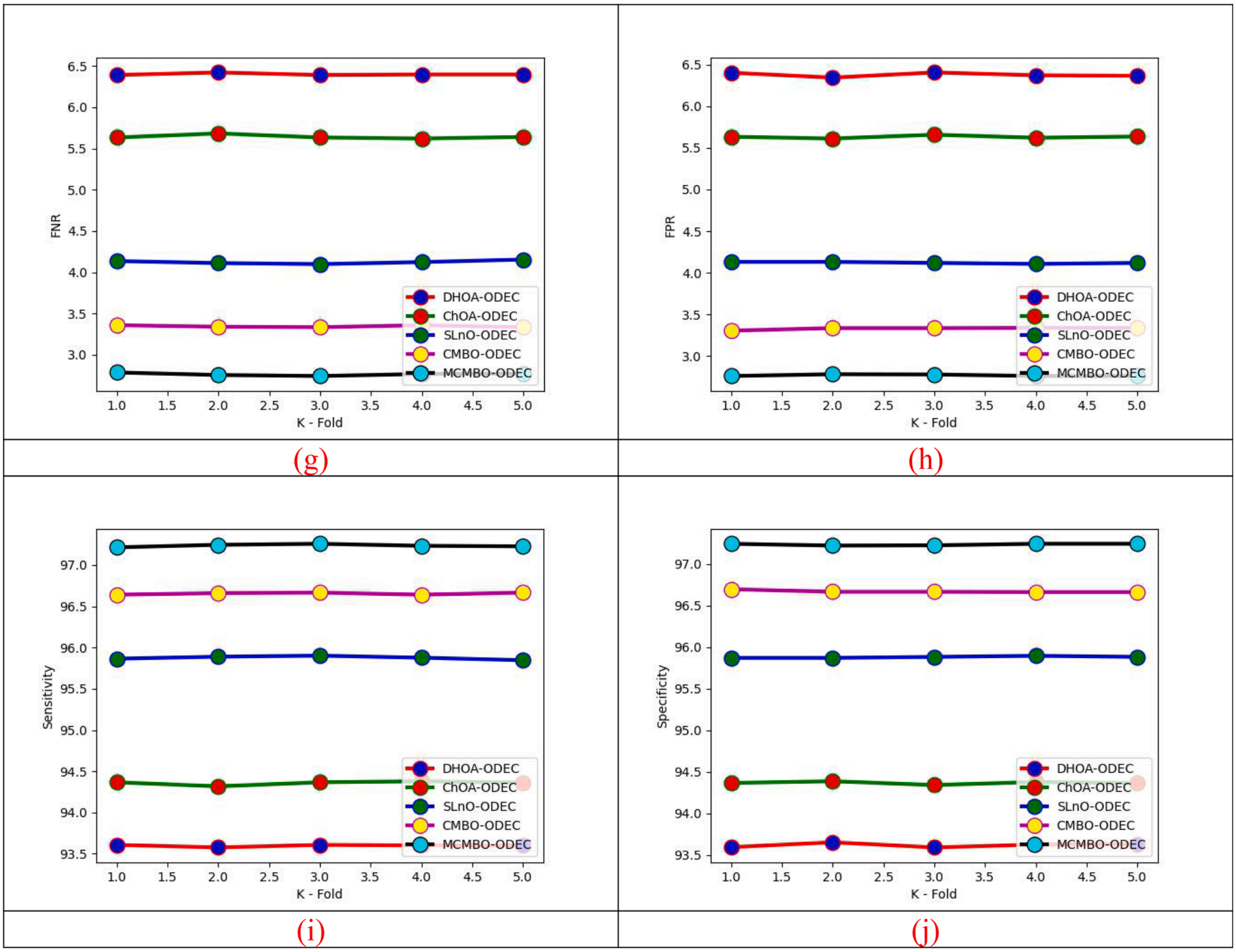

Fig. 8. (*continued*).

$$Mn = \frac{1}{S}\sum_{s=1}^{S} C_s^{dec} \tag{11}$$

Median: The median value is computed by the centre samples of the decomposed signal as C_s^{dec}. It represents both the upper and lower half of signal samples, which is derived by Eq. (12).

$$Mdn = \frac{S+1}{2} \tag{12}$$

Standard Deviation: SD uses to determine "how much the signal samples are different from the mean". The value is acquired via Eq. (13).

$$SD = \frac{\sqrt{\sum_{a=1}^{A}\sum_{b=1}^{B} |T(a,b) - Mn|^2}}{AB} \tag{13}$$

Variance: It refers by the "measure of how samples of decomposed signal that is completely varying from the mean value. It shows the given sample is spread towards from the average value" is given in Eq. (14).

$$Vnc = \sum_{s=1}^{S} \left(C_s^{dec} - Mn\right)^2 \tag{14}$$

Minimum: The value that annotates the minimum number of samples that exist in decomposed signal. It also estimates by considering the less feature and minimal samples.

Maximum: It defines the highest sample representation of the decomposed signal. Here, also, it considers the maximal signal samples along with more number of features.

Hence, the statistical related features are obtained on the basis of statistical measurement of the decomposed signal and indicated by FE_f^{stat}. Further, the feature concatenation process is used to combine all the acquired three features. It is noted by $FC_f = \left\{FE_f^{mfcc}, FE_f^{spec}, FE_f^{stat}\right\}$ that is used for selecting the optimal features.

4.2. Modified CMBO

The proposed MCMBO algorithm is developed with the objective of the conventional CMBO [30] algorithm. Some advantages are achieving good generalization capability and convergence measure and also solving the local optima issue. Since, it is not utilized in the real-time data, multi-objective constraints, etc. To overcome with all challenging problems, a new MCMBO algorithm is developed.

As the name implies, this optimization algorithm is developed by cats and mouse. It mimics the chasing behaviour of cat to attack the mouse that escapes from the searching region. Here, the search agents are categorized into two elements as cats and mice. The optimization process is accomplished using two different ways. In a first way, the cat movements are explained, while at the second way, the mice make a move to escape and reach the haven place. The mathematical expression of the new MCMBO algorithm is explored as given here.

Initialization: Initiate the population that is taken from the matrix format. It is shown in Eq. (15).

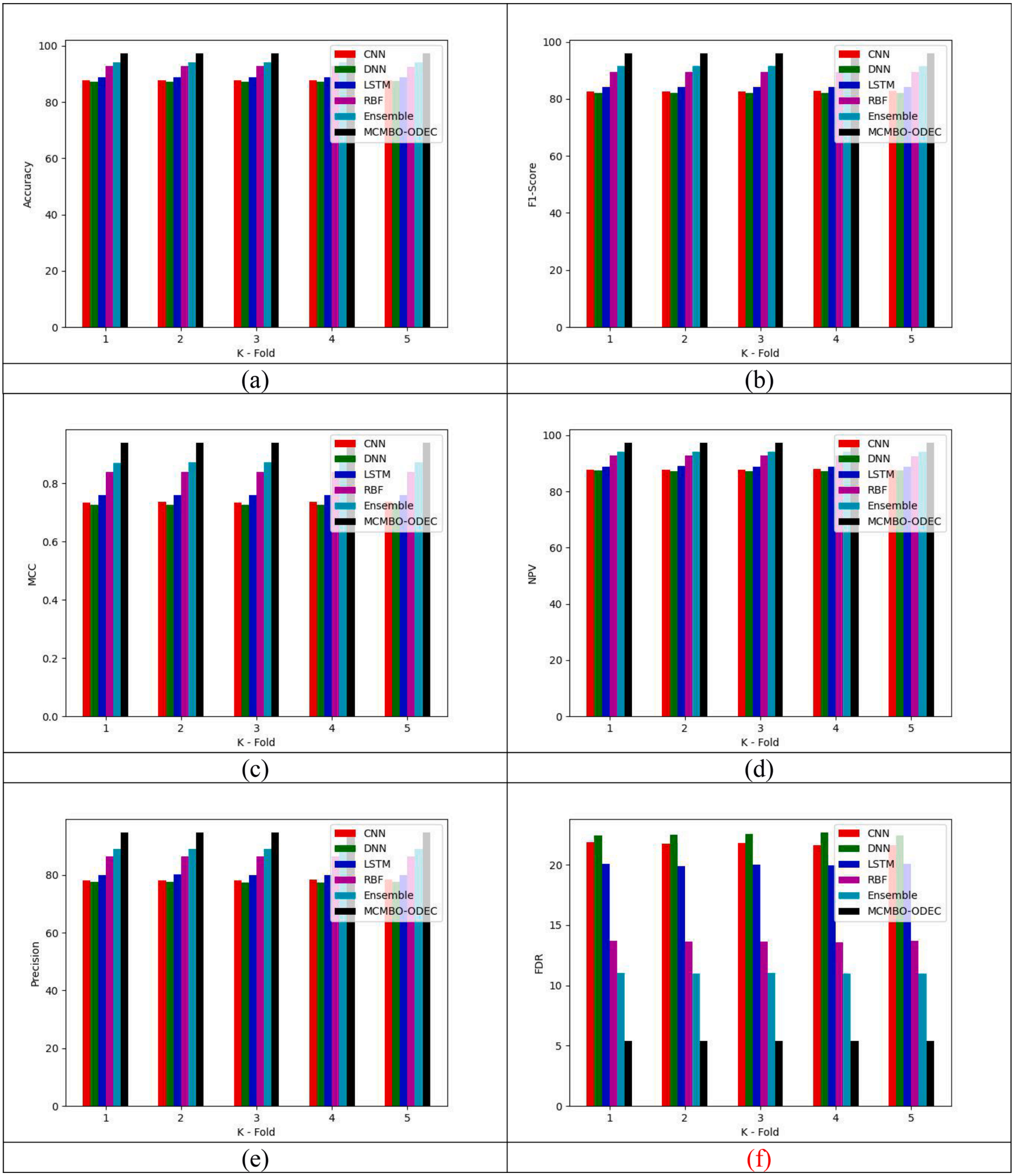

Fig. 9. K-fold analysis of developed cough detection model concerning“(a) Accuracy, (b) F1-score, (c) MCC, (d) NPV, (e) Precision, (f) FDR, (g) FNR, (h) FPR, (i) Sensitivity, and (j) Specificity”.

$$Y = \begin{bmatrix} Y_1 \\ \vdots \\ Y_j \\ \vdots \\ Y_Z \end{bmatrix}_{Z\times n} = \begin{bmatrix} y_{1,1} & \cdots & y_{1,x} & \cdots & y_{1,n} \\ \vdots & \ddots & \vdots & \dots & \vdots \\ y_{j,1} & \cdots & y_{j,x} & \cdots & y_{j,n} \\ \vdots & \dots & \vdots & \ddots & \vdots \\ y_{Z,1} & \cdots & y_{Z,x} & \cdots & y_{Z,n} \end{bmatrix}_{Z\times n} \tag{15}$$

Here, Y_j represents the j^{th} agents for searching, the number of population and problem variables is declared by Z and n, correspondingly. Then, the value of x^{th} problem variable, along with j^{th} search agents, is noted by $y_{j,x}$. With respect to the total population, the fitness value is estimated and given in matrix format as Eq. (16).

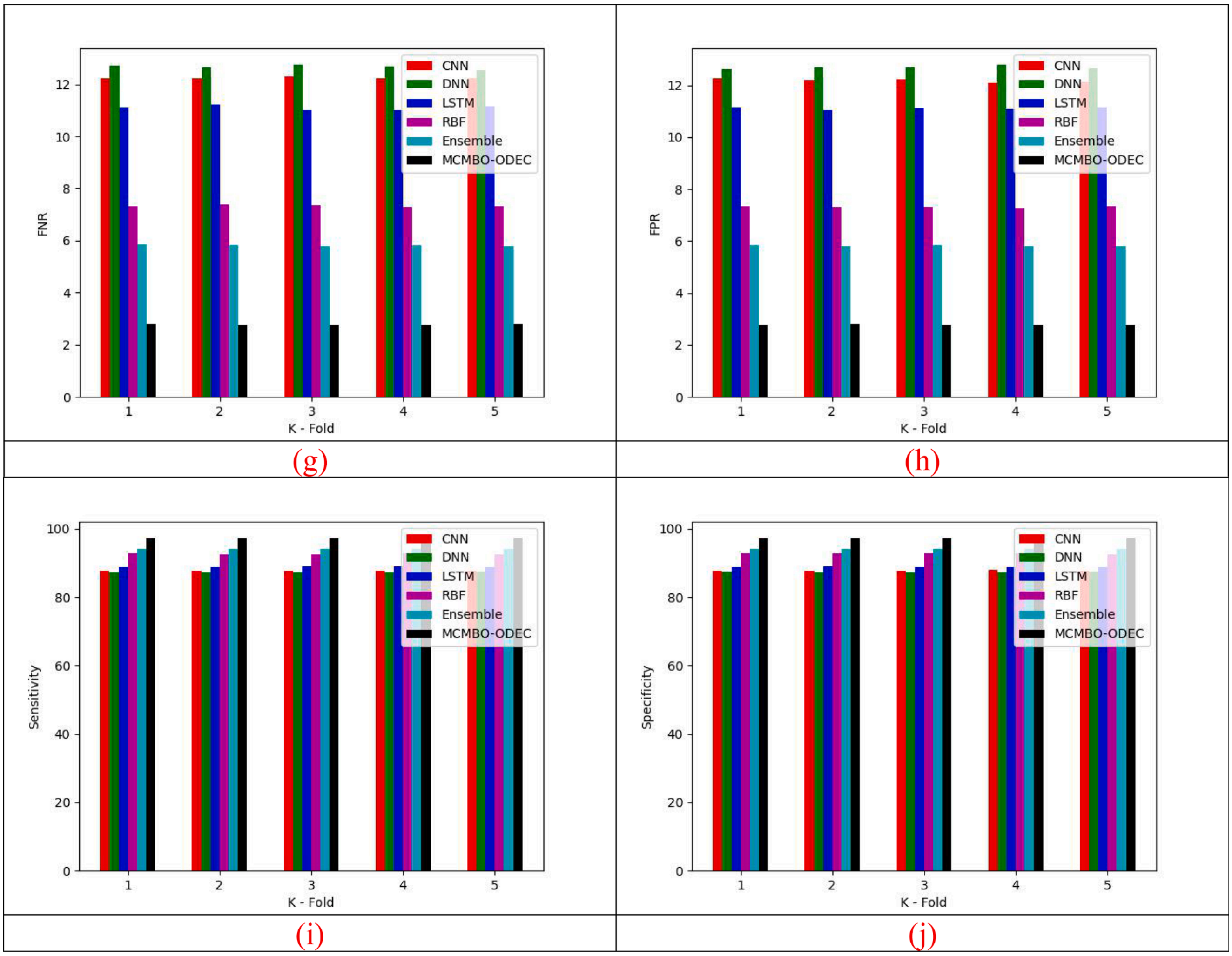

Fig. 9. (*continued*).

$$Ft = \begin{bmatrix} Ft_1 \\ \vdots \\ Ft_j \\ \vdots \\ Ft_Z \end{bmatrix}_{Z\times 1} \tag{16}$$

The term Ft_j signifies the fitness function of j^{th} the search population.

Sorting the population: In this phase, it is performed by the fitness objective function of the search agents is sorted. The sorting is happened from the best population of lower fitness value to the worst population of higher fitness value. The sorting operation is expressed via Eq. (17) and Eq. (18).

$$Y^A = \begin{bmatrix} Y_1^A \\ \vdots \\ Y_j^A \\ \vdots \\ Y_Z^A \end{bmatrix}_{Z\times n} = \begin{bmatrix} y_{1,1}^a & \cdots & y_{1,x}^a & \cdots & y_{1,n}^a \\ \vdots & \ddots & \vdots & \dots & \vdots \\ y_{j,1}^a & \cdots & y_{j,x}^a & \cdots & y_{j,n}^a \\ \vdots & \dots & \vdots & \ddots & \vdots \\ y_{Z,1}^a & \cdots & y_{Z,x}^a & \cdots & y_{Z,n}^a \end{bmatrix}_{Z\times n} \tag{17}$$

$$Ft^A = \begin{bmatrix} Ft_1^A & mn(Ft) \\ \vdots & \vdots \\ Ft_Z^A & mx(Ft) \end{bmatrix}_{Z\times 1} \tag{18}$$

In the aforementioned two equations, the sorted population based on the matrix is defined as Y^A. Similarly, the j^{th} member of sorted search agents is defined using Y_j^A. Further, the term Ft^A annotates the sorted fitness function.

Population matrix of cats and mice: The initial population matrix comprised of cats and mice. Here, the members are differentiated with the better and lower values of the objective population. Therefore, the members of lower values contain a cat population, whereas the member with higher function entails mice population. Thus, the population of mice is given in Eq. (19), and the cat population matrix is shown in Eq. (20).

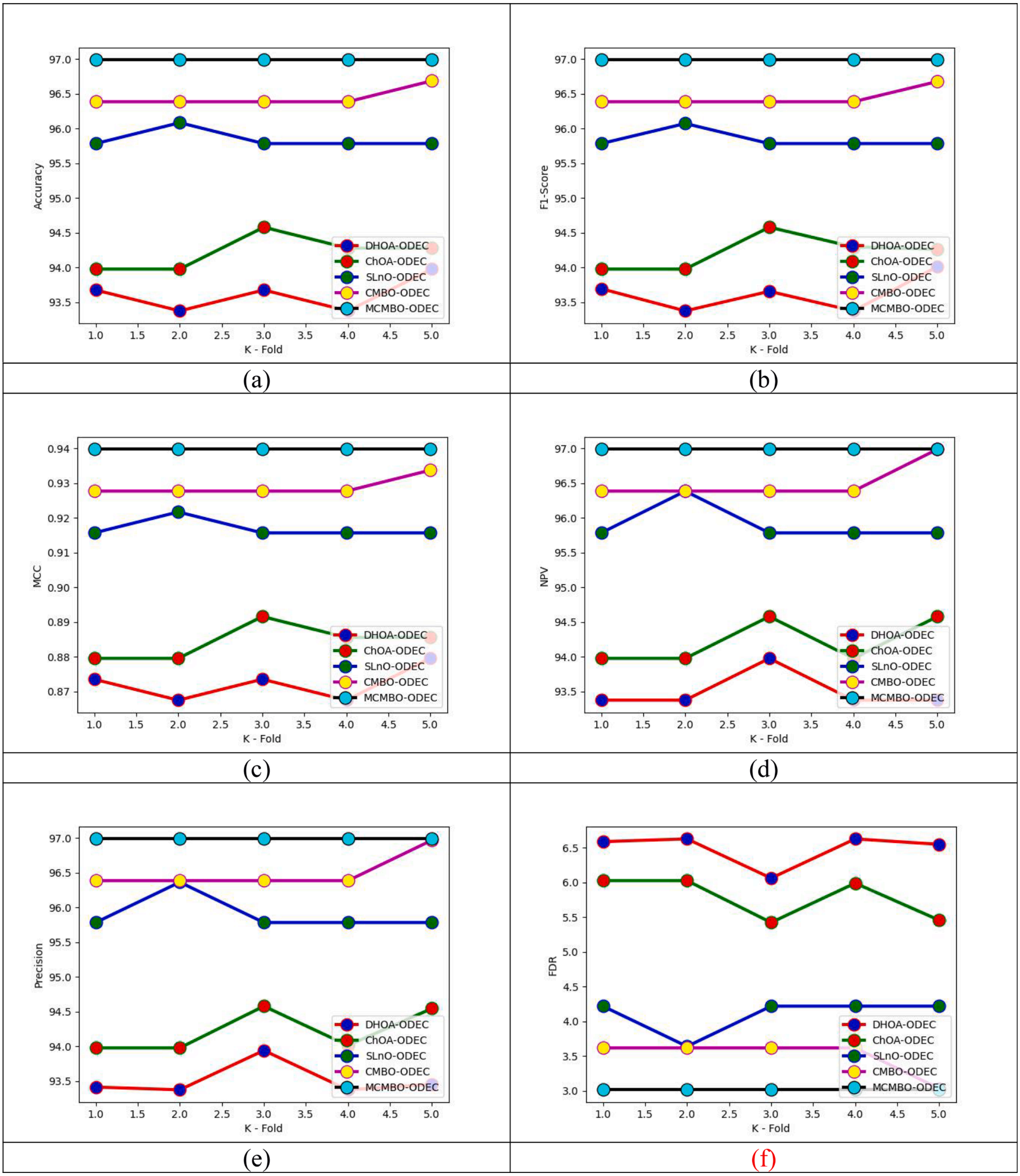

Fig. 10. K-fold validation of the cough detection model concerning (a) Accuracy, (b) F1-score, (c) MCC, (d) NPV, (e) Precision, (f) FDR, (g) FNR, (h) FPR, (i) Sensitivity, and (j) Specificity".

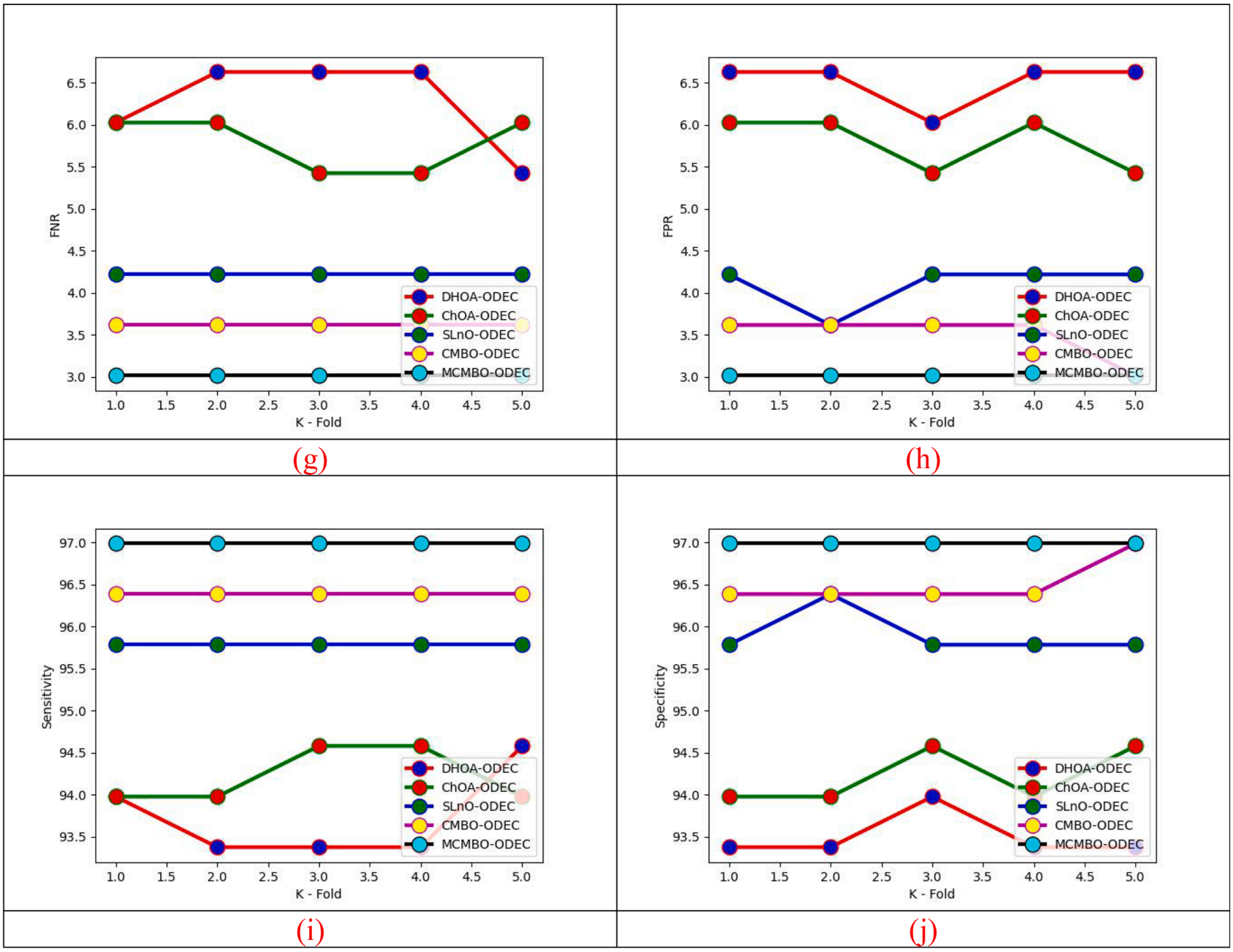

Fig. 10. (*continued*).

$$I = \begin{bmatrix} I_1 = Y_1^A \\ \vdots \\ I_j = Y_j^A \\ \vdots \\ I_{Z_i} = Y_{Z_i}^A \end{bmatrix}_{Z_i \times n} = \begin{bmatrix} y_{1,1}^a & \cdots & y_{1,x}^a & \cdots & y_{1,n}^a \\ \vdots & \ddots & \vdots & \ldots & \vdots \\ y_{j,1}^a & \cdots & y_{j,x}^a & \cdots & y_{j,n}^a \\ \vdots & \ldots & \vdots & \ddots & \vdots \\ y_{Z_i,1}^a & \cdots & y_{Z_i,x}^a & \cdots & y_{Z_i,n}^a \end{bmatrix}_{Z_i \times n} \tag{19}$$

$$T = \begin{bmatrix} T_1 = Y_{Z_i+1}^A \\ \vdots \\ T_k = Y_{Z_i+k}^A \\ \vdots \\ T_{Z_t} = Y_{Z_i+Z_t}^A \end{bmatrix}_{Z_t \times n} = \begin{bmatrix} y_{Z_i+1,1}^a & \cdots & y_{Z_i+1,x}^a & \cdots & y_{Z_i+1,n}^a \\ \vdots & \ddots & \vdots & \ldots & \vdots \\ y_{Z_i+k,1}^a & \cdots & y_{Z_i+k,x}^a & \cdots & y_{Z_i+k,n}^a \\ \vdots & \ldots & \vdots & \ddots & \vdots \\ y_{Z_i+Z_t,1}^a & \cdots & y_{Z_i+Z_t,x}^a & \cdots & y_{Z_i+Z_t,n}^a \end{bmatrix}_{Z_t \times n} \tag{20}$$

In both equations, the population matrix for mice and cat is denoted by I and T, respectively. The number of cats and mice is represented by Z_t and Z_i, correspondingly.

Updating the cat's position: In this first phase, the cats usually changed their position to chase the mouse. The updating process for cats is modelled in Eq. (21).

$$T_k^{nw} : t_{k,a}^{nw} = t_{k,a} + rd \times \left(i_{l,a} - N \times t_{k,a}\right), \quad where,\ k = 1 : Z_t,\ a = 1 : n,\ l = 1 : Z_i \tag{21}$$

Here, the random value lies where the ranges between [0, 1] is denoted by rd, $i_{l,a}$ refers the a^{th} dimension with l^{th} mouse agents. As the utilization of random value, the conventional CMBO is not satisfying the optimal values. It also leads to cause the overall performance degradation in terms of detection. It also provides the fluctuation in results to optimize the required parameters. To overcome this issue, the new MCMBO algorithm is developed by deriving a new formulation. Hence, in Eq. (21), the term N is estimated with novel expression in the MCMBO algorithm is given in Eq. (22).

$$N = round\left[Y \cdot \left(\frac{mn(Ft) + mx(Ft)}{2}\right)^2\right] \tag{22}$$

The total population as Y, maximum and minimum fitness value is declared by $mn(Ft)$ and $mx(Ft)$, respectively. Thus, the new position is obtained using the below equation as Eq. (23).

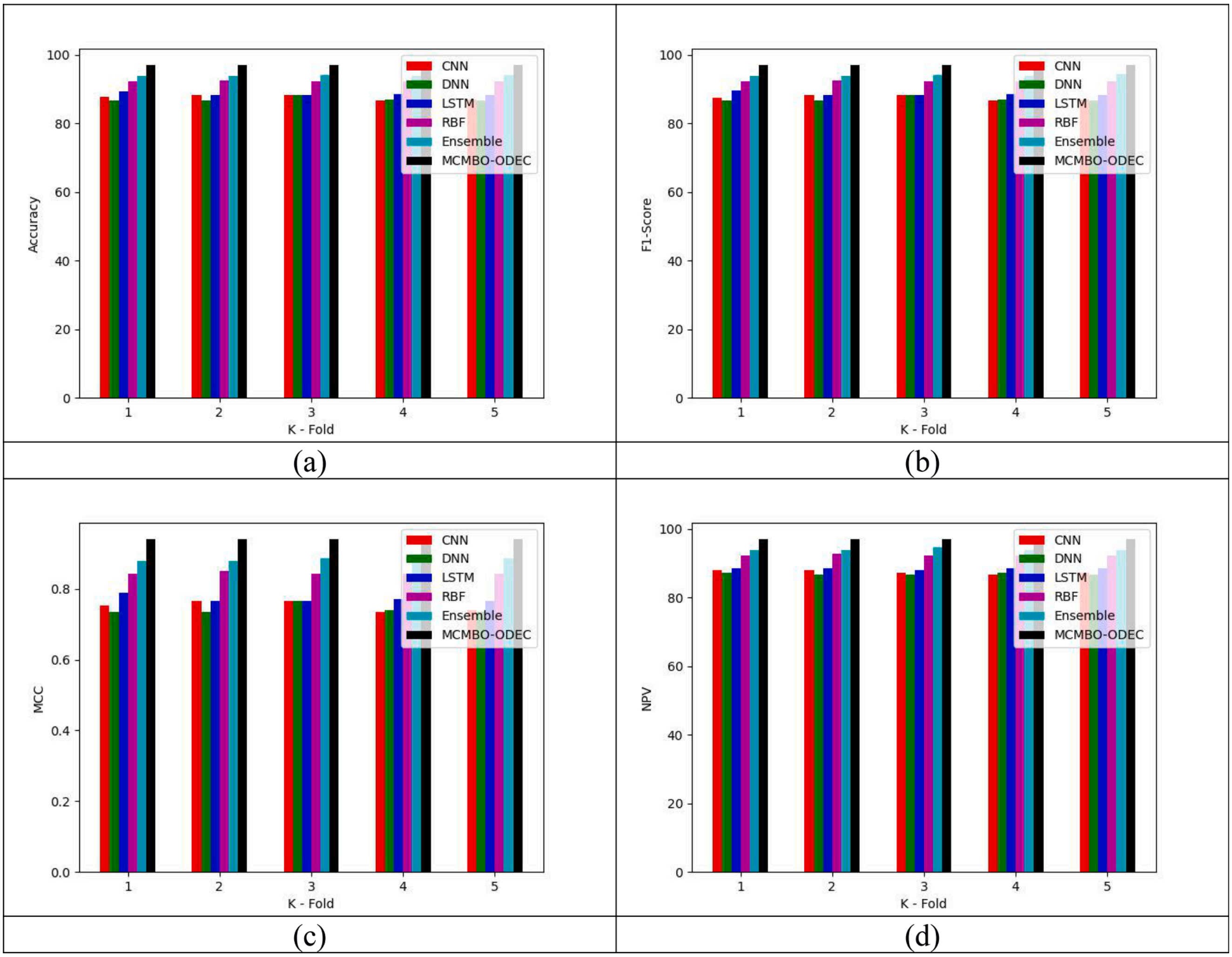

Fig. 11. The K-fold using developed cough detection model for dataset 2 regarding "(a) Accuracy, (b) F1-score, (c) MCC, (d) NPV, (e) Precision, (f) FDR, (g) FNR, (h) FPR, (i) Sensitivity, and (j) Specificity".

$$T_k = \begin{cases} T_k^{nw}, & Ft_k^{t,nw} < Ft_k^t, \\ T_k, & otherwise \end{cases} \tag{23}$$

The new position for cat search agent is referred by T_k^{nw}. Moreover, the new fitness value is estimated based on the new position of cat, it is expressed as $Ft_k^{t,nw}$.

Updating the mice position: In the second phase, the mice are planning to escape from the cats that enter into a haven. Assume each mouse takes the haven for hiding purpose as in a random manner. Thus, in the search space, the haven positions are arbitrarily selected, and it is given in Eq. (24).

$$V_b : v_{b,a} = y_{c,a}, \ where, \ b = 1 : Z_i, \ a = 1 : n, \ c = 1 : Y \tag{24}$$

Then, the new position is acquired for mice that it derived using Eq. (25) and Eq. (26).

$$I_j^{nw} : i_{j,a}^{nw} = i_{j,a} + rd \times \left(v_{b,a} - N \times i_{j,a}\right) \times sign\left(Ft_j^i - Ft_j^V\right) \tag{25}$$

$$I_j = \begin{cases} I_j^{nw}, & Ft_j^{i,nw} < Ft_j^i, \\ I_j, & otherwise \end{cases} \tag{26}$$

Term, I_j^{nw} defines the new location for the mouse. Also, the new fitness function is computed for mice denoted by $Ft_j^{i,nw}$. The pseudo-code of the MCMBO algorithm is summarized as below.

Algorithm 1: Suggested MCMBO algorithm

Initiate population and maximum iteration
Determine the fitness value for all search agents
Evaluate the term N with new formulation is shown in Eq. (22)
For every iteration
  Sorting all the population by Eq. (17) and Eq. (18)
  Initialize mice population using Eq. (19) and cat population by Eq. (20)
  For every cat agent
    Position is upgraded with Eq. (21), Eq. (22), and Eq. (23)
  End for
  For every mice agents
    Haven position is revised in Eq. (24)
    New solution is created for mice using Eq. (25) and Eq. (26)
  End for
  Acquires the finest solution
End for
Return the best solution

Simultaneously, the flow diagram of the proposed MCMBO is illustrated in Fig. 2.

4.3. Optimal weighted feature selection

The fused feature FC_f is given as input to get the optimal weighted features. Owing to the concatenated feature, the dimension problem

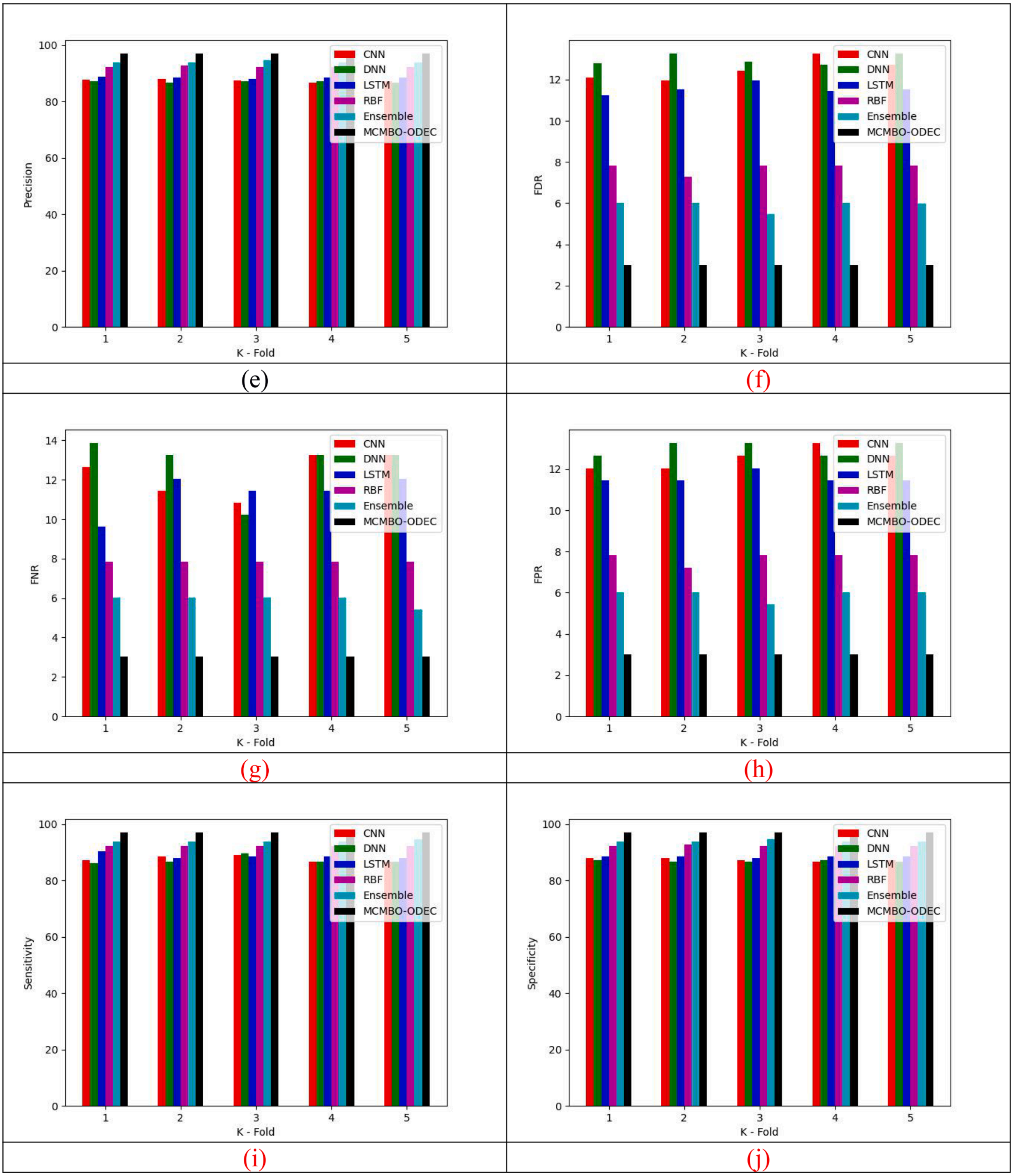

Fig. 11. (*continued*).

occurs that degrades the detection performance. In order to avoid the dimensional curse and inefficient performance, the MCMBO algorithm is utilized to select the optimal features denoted by F_r^{opt}. It aims to choose the optimal weighted features to improve the performance of the designed method. Here, the weight factor is determined optimally by influencing the MCMBO algorithm. It is mathematically modelled using Eq. (27).

$$F_s^{Wt} = Wt^* F_r^{opt} + (1 - Wt)^* F_r^{opt} \tag{27}$$

Term, Wt defines the weight factor that is optimally evaluated by the MCMBO algorithm. The range of weight is varied from 0.01 to 0.99. This resultant optimal weighted feature is fed into the deep ensemble learning model. Thus, the schematic representation of optimal weighted feature selection by the novel MCMBO algorithm is shown in Fig. 3.

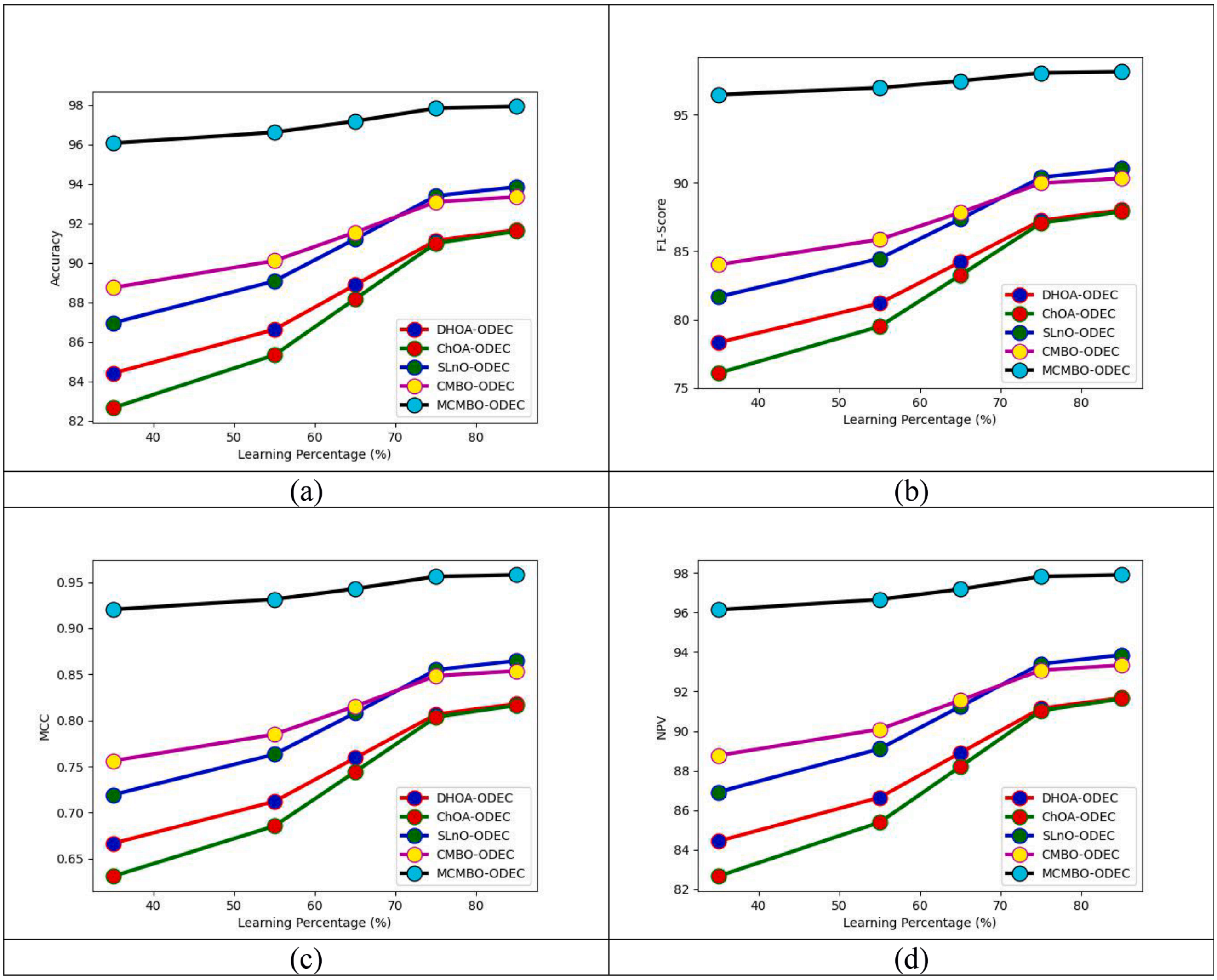

Fig. 12. Comparative analysis of the developed cough detection model for dataset 1 concerning "(a) Accuracy, (b) F1-score, (c) MCC, (d) NPV, (e) Precision, (f) FDR, (g) FNR, (h) FPR, (i) Sensitivity, and (j) Specificity".

5. Novel model for COVID cough detection using optimized deep Ensemble classifier

5.1. DNN model

DNN [31] assists to classify the features into positive or negative indication for COVID-19 disorder. Rather than other models [42], it constitutes multiple hidden neurons connected between the "input and output layer". In the input layer, it contains many nodes to get the input and passes to the hidden layer. Meanwhile, the binary decision is obtained from the output layer. Here, the "softmax activation function" whereas the hidden nodes employ the "sigmoid function". Other than the presence of layer, some of the notable components are present in the network to do the classification task. Such nodes are bias, weight, and function. Finally, the DNN model exhibits the effectively classified result as either presence or absence of COVID-19. Fig. 4 shows the general architecture of the DNN model.

5.2. LSTM model

Nowadays, LSTM [20] has become the trendsetting techniques to perform the detection using cough audio. Here, F_s^{Wt} it is given as input to LSTM, where the features are classified as either COVID-19 or non–COVID-19. LSTM is defined as an extended version of the Recurrent Neural Network (RNN) model that processes in long-term dependency nature. The beneficial traits of this model are resolving the gradient vanishing issues and improving the classification accuracy. Unlike other deep classifiers, the LSTM constitutes various gates such as "input as *IG*, forget as *FG* , and output as *OG*".

The input gate is used to consider the required features from the preceding layer. The forget gate as the name implies, it forgets or ignores such irrelevant features. Finally, the output gate takes responsibility for providing the classified result. Hence, the derivation for the LSTM model is given in the below equations.

$$IG = \sigma\left(W_{IG}\cdot\left[Hs_{x-1}, F_s^{Wt}\right] + Bs_{IG}\right) \tag{28}$$

$$OG = \sigma\left(W_{OG}\cdot\left[Hs_{x-1}, F_s^{Wt}\right] + Bs_{OG}\right) \tag{29}$$

$$FG = \sigma\left(W_{FG}\cdot\left[Hs_{x-1}, F_s^{Wt}\right] + Bs_{FG}\right) \tag{30}$$

$$CT_x^{'} = \tanh\left(W_{CS}\cdot\left[Hs_{x-1}, F_s^{Wt}\right] + Bs_{CG}\right) \tag{31}$$

$$CT_x = FG_x\cdot CT_{x-1} + IG_x\cdot CT_x^{'} \tag{32}$$

$$Hs_x = OG_x{}^{*}\tanh(CT_x) \tag{33}$$

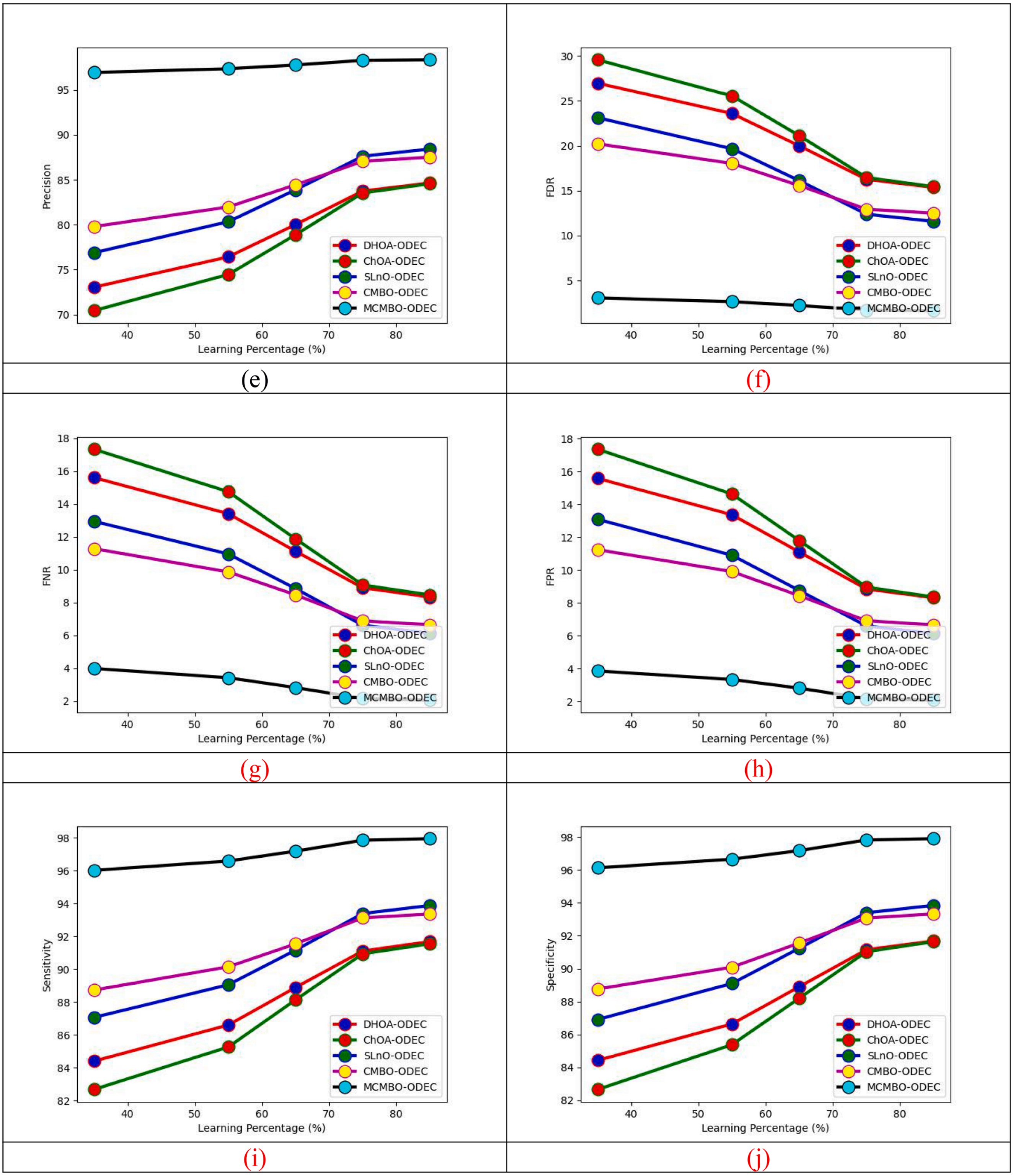

Fig. 12. (*continued*).

In the above all equations, the term F_s^{Wt} defines the input vector CT_x and denotes the cell state of LSTM, the hidden state, and the bias term is declared by Hs_{x-1} and Bs, accordingly. Finally, the activation functions are marked by σ and tanh, respectively. The structural diagram of the LSTM model is depicted in Fig. 5.

5.3. RBF model

RBF [32] is mostly used for the signal-based classification model. As the nature of high-speed learning process, it enhances the COVID-19 detection performance. It is processed as non-linear based kernel function to classify the features. It consists of three major layers as input, hidden, and output layer as well. Here, the weighted feature F_s^{Wt} acts as a model input. The input layer fetches the weighted feature and forwards

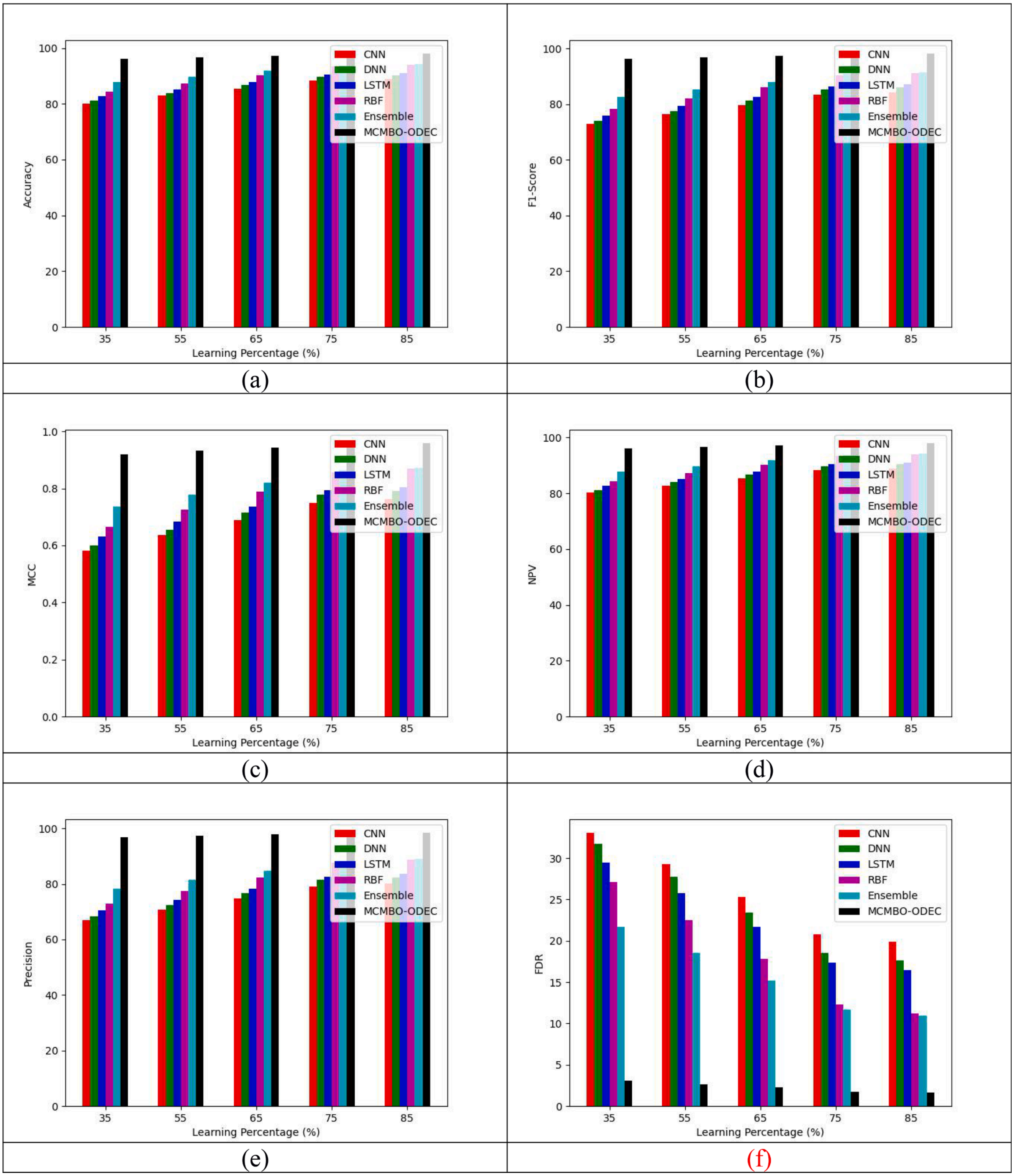

Fig. 13. Comparative analysis of designed cough detection model in terms of "(a) Accuracy, (b) F1-score, (c) MCC, (d) NPV, (e) Precision, (f) FDR, (g) FNR, (h) FPR, (i) Sensitivity, and (j) Specificity".

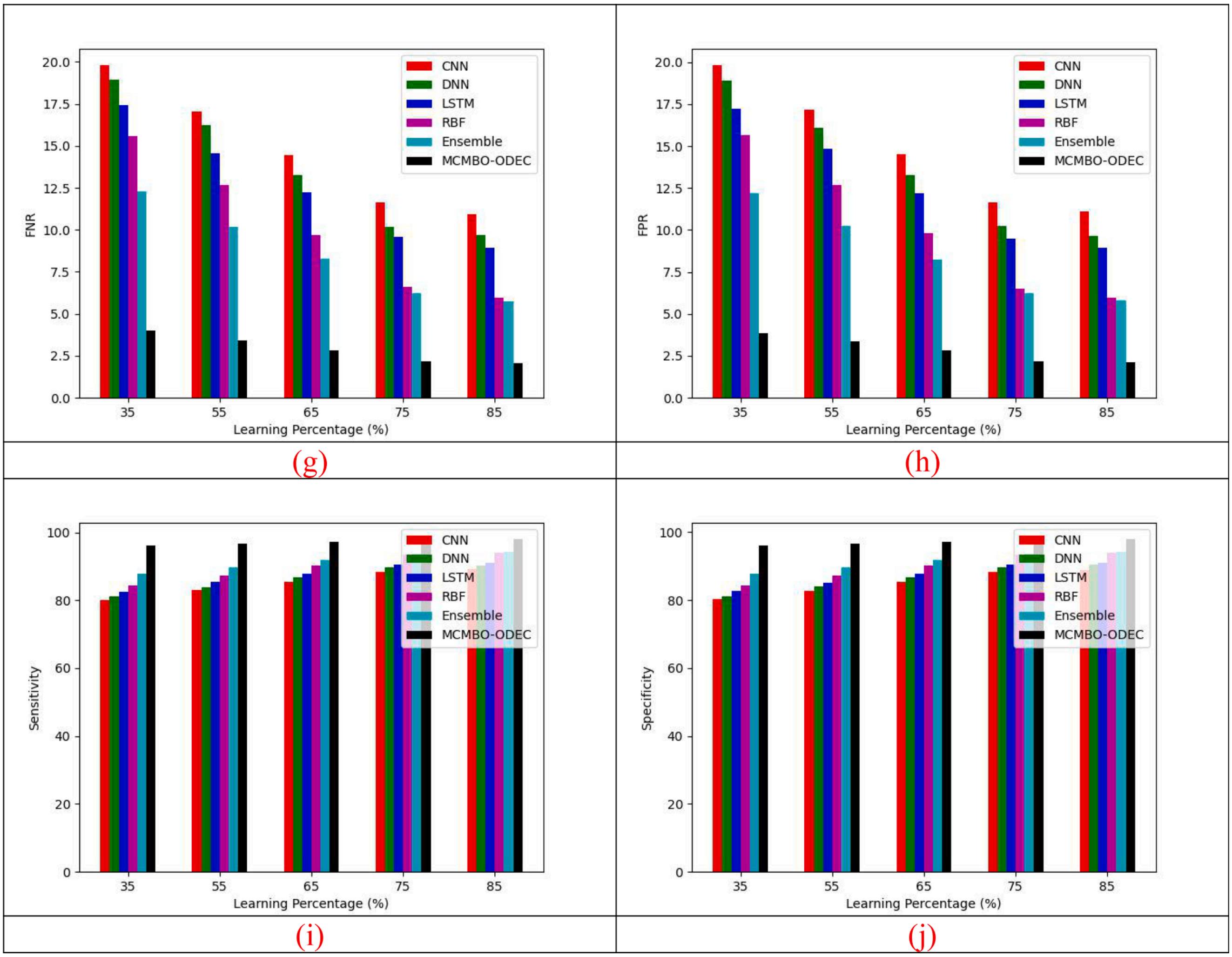

Fig. 13. (*continued*).

to the hidden layer. The activation function and weight factor are used to process the features. Finally, the output layer exploits the outcome by performing the linear relationship of all hidden units.

Let us consider F_s^{Wt} the given input and wg refers the weight vector and basis term. It is derived using Eq. (34).

$$RBF = \sum_{z=1}^{Z} wg_z \varphi_z \left(F_z^{Wt}\right) \tag{34}$$

Here $\varphi_z = Gn(\|x - \mu_z\|)$, which indicates the Gaussian function to do the cough detection task. The basic structure of the RBF model is depicted in Fig. 6.

5.4. Optimized deep Ensemble classifier

The three classifier models as, DNN, LSTM, and RBF, play a vital role in the cough detection framework. Though, it provides certain advantages for improving performance. However, it still subsists with certain shortcomings. Due to the presence of enormous hidden neurons of DNN and LSTM, it easily becomes vulnerable to the overfitting problem. On the other hand, the LSTM and RBF is processed on the preceding layer function, thus it requires more epoch counts. This count value causes an impact on computational complexity. To overcoming these issues, these parameters like hidden neuron counts and epochs are optimally chosen with the objective of novel MCMBO algorithm. The objective function of ODEC is expressed by Eq. (35).

$$OF = \underset{\left\{F_r^{opt}, Wt, Ep^{LSTM}, Hn^{LSTM}, Ep^{RBF}, Hn^{DNN}\right\}}{\operatorname{argmax}} [ARY] \tag{35}$$

The term F_r^{opt} refers to the optimal selected features that lie between 1 and 10. The optimized weight as Wt lies in the range of [0.01, 0.99], and the epochs in LSTM and RBF are declared by Ep^{LSTM} and Ep^{RBF}, which ranges from 50 to 100. Finally, the hidden neuron in DNN and LSTM is noted by Hn^{DNN}, and Hn^{LSTM} that contains the range of [5, 255]. In addition to this, ARY specifies the accuracy, it is the state or quality to represent the appropriate value is given in Eq. (36).

$$ARY = \frac{TrP + TrN}{TrP + TrN + FaP + FaN} \tag{36}$$

In Eq. (36), the true as well as false positive value is mentioned by TrP and FaP, and also, a true and false negative value is defined by TrN and FaN. Once the parameter is optimized, the three classifier models are performed and provide the results. Further, the ODEC model computes the average value with three outcomes to attain the final detection results. The process of ODEC using the MCMBO algorithm is demonstrated in Fig. 7.

6. Results

6.1. Simulation settings

The improved cough detection framework was implemented using

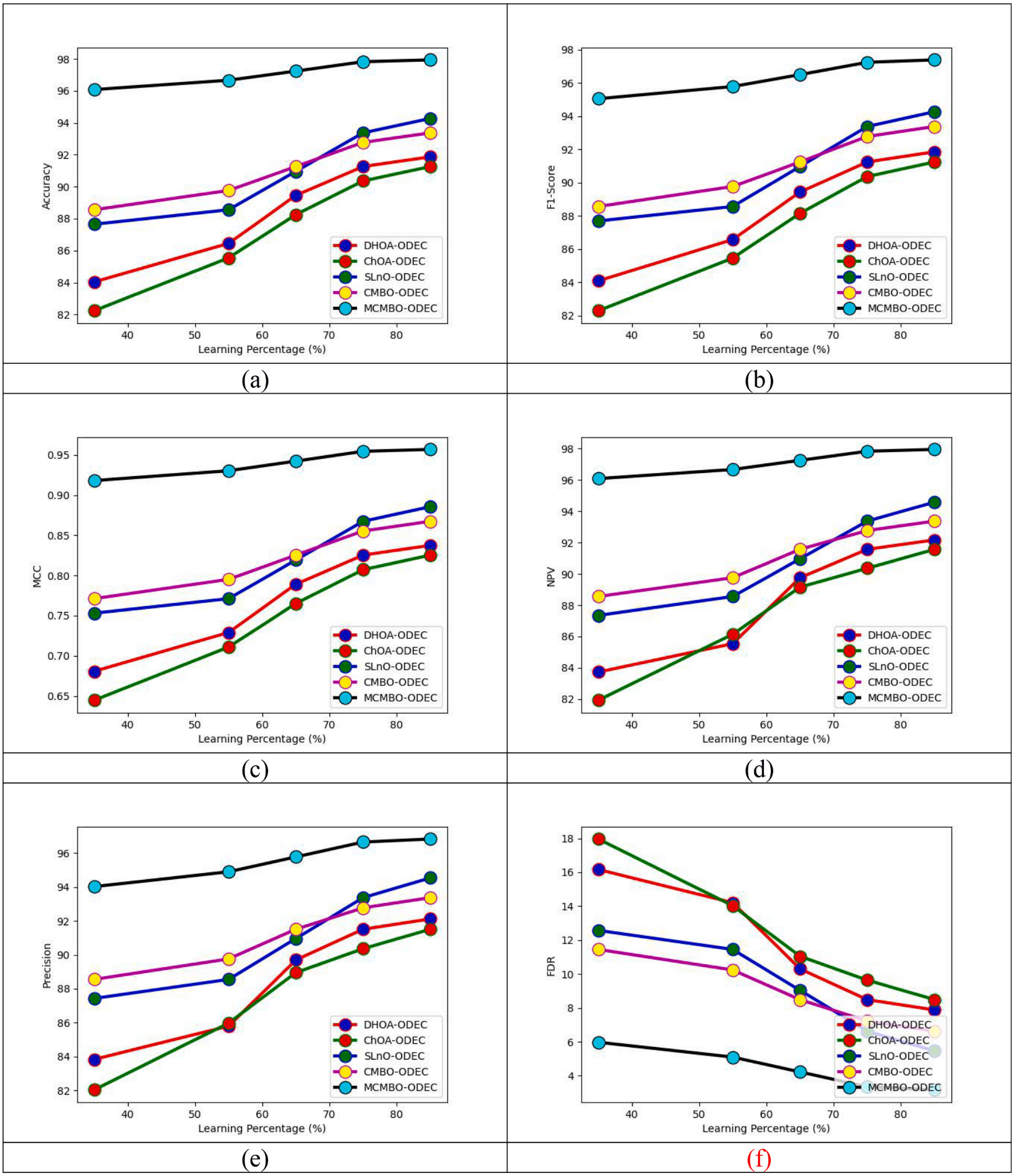

Fig. 14. Comparative analysis of the designed cough detection model for dataset 2 regarding "(a) Accuracy, (b) F1-score, (c) MCC, (d) NPV, (e) Precision, (f) FDR, (g) FNR, (h) FPR, (i) Sensitivity, and (j) Specificity".

Python, and its simulated value was measured. Here, the number of population is considered as 10, maximum iteration counts as 25, and chromosome length as 15. Heterogeneous metrics were considered as Negative Predictive Value (NPV), Sensitivity, Specificity, Precision, Accuracy, False Negative Rate (FNR), F1Score and Mathews Correlation Coefficient (MCC), False Positive Rate (FPR), and False Discovery Rate (FDR). The analysis of the proposed model was compared with (Deer Hunting Optimization Algorithm) DHOA-ODEC [33], (Chimp Optimization Algorithm) ChOA-ODEC [34], (Sea Lion Optimization) SLnO-ODEC [35], and CMBO-ODEC [30]. On the second hand, different classifiers like CNN [18], DNN [31], LSTM [20], RBF [32], and Ensemble [36] were taken.

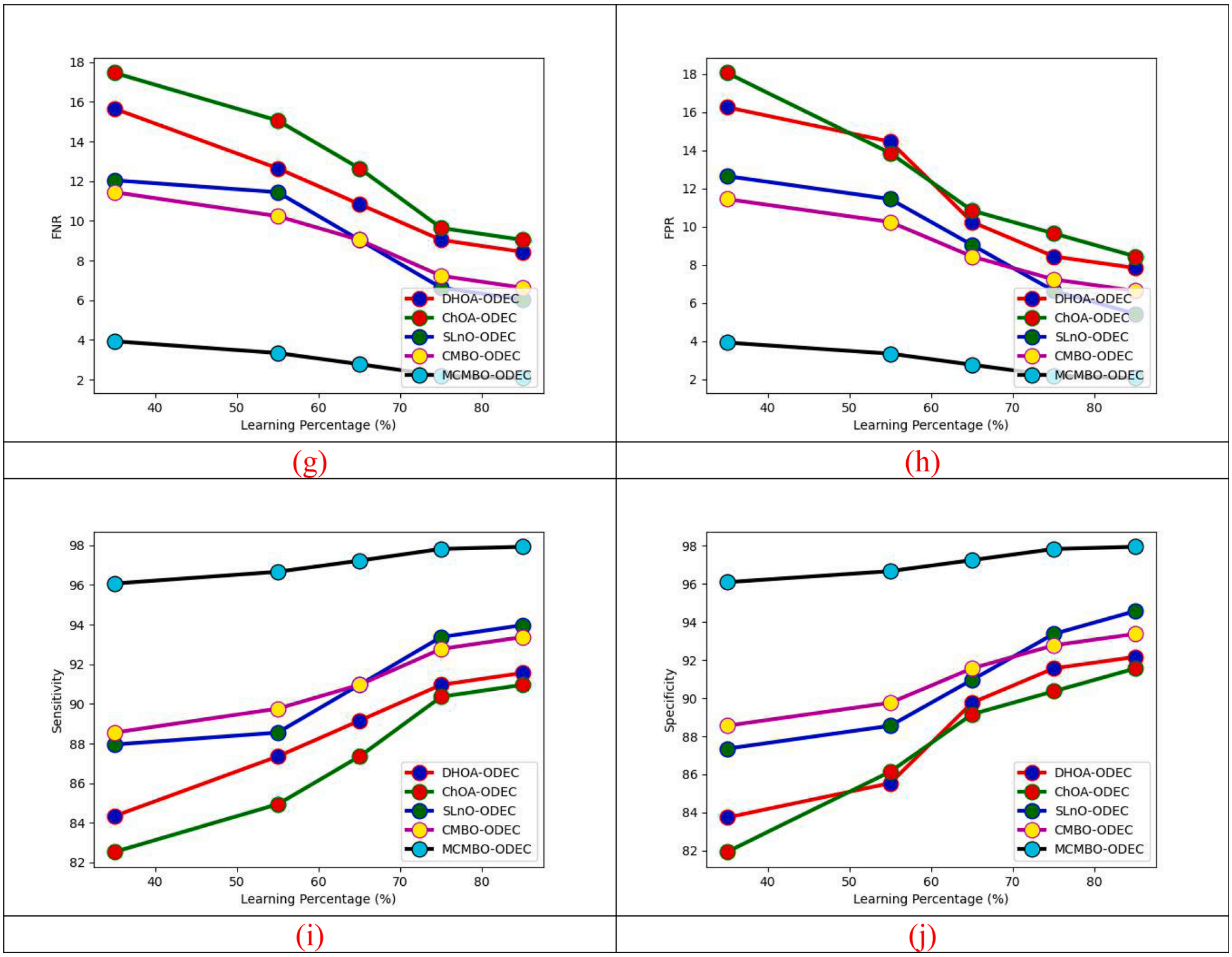

Fig. 14. (*continued*).

6.2. Evaluating parameters

Various parameters are considered for proving the effectiveness of the system which is explained as below [37].

Accuracy: It is given in Eq. (36).

Precision: It estimates the very close values of the cough audio signal.

$$Pn = \frac{TrP}{TrP + FaP} \tag{37}$$

FPR and FNR: "The false positive rate results are not estimated accurately in the presence of audio signals. The false negative is used to determine the incorrect samples of cough signal when the signal is present".

$$FPR = \frac{FaP}{FaP + TrN} \tag{38}$$

$$FNR = \frac{FaN}{FaN + TrP} \tag{39}$$

Sensitivity and Specificity: "The actual positive test is termed as sensitivity, and also the probability of negative test is taken as specificity".

$$Sensitivity = \frac{TrP}{TrP + FaN} \tag{40}$$

$$Specificity = \frac{TrN}{TrN + FaP} \tag{41}$$

F1-Score: "It is the mean value of recall and precision".

$$F1Score = 2^{*}\frac{Pn^{*}Re}{Pn + Re} \tag{42}$$

FDR: "It is the ratio among the false positive values by the total of true and false positive values".

$$FDR = \frac{FaP}{TrP + FaP} \tag{43}$$

NPV: "The ratio of true negative by the total value of true and false negative".

$$NPV = \frac{TrN}{TrN + FaN} \tag{44}$$

MCC: It is evaluated by "difference among the classified as well as the actual value".

$$MCC = \frac{TrP \times TrN - FaP \times FaN}{\sqrt{(TrP + FaP)(TrP + FaN)(TrN + FaP)(TrN + FaN)}} \tag{46}$$

6.3. K-fold Analysis of the recommended cough detection model for dataset 1

Figs. 8 and 9 depict the k-fold validation of the cough detection

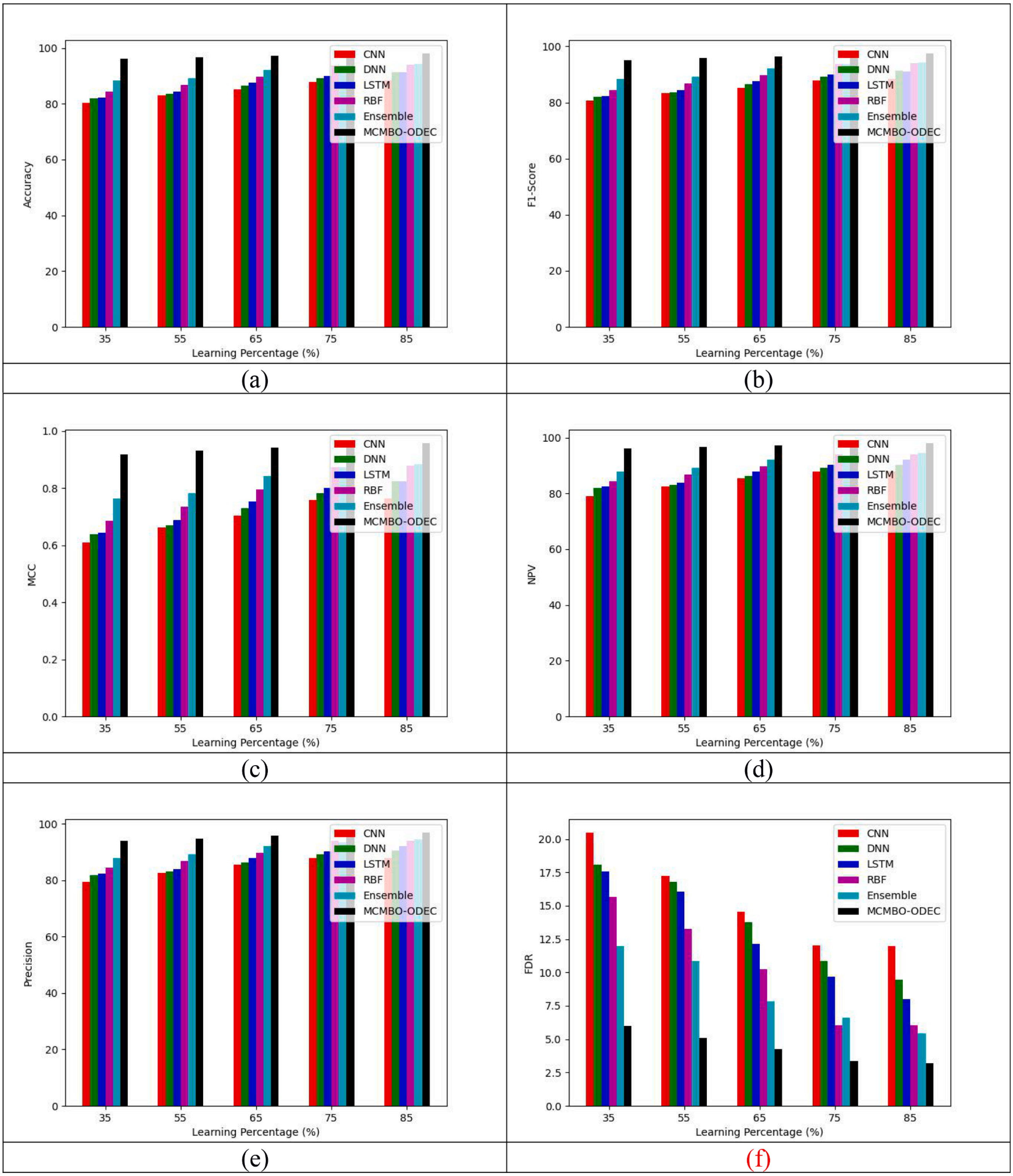

Fig. 15. Comparative analysis of offered cough detection model compared with traditional deep learning classifiers for dataset 2 concerning “(a) Accuracy, (b) F1-score, (c) MCC, (d) NPV, (e) Precision, (f) FDR, (g) FNR, (h) FPR, (i) Sensitivity, and (j) Specificity”.

model over different optimization algorithms and classifiers while using dataset 1. The analysis of the F1-score measure is given in Fig. 8 (b) with respect to different k-folds. When the k-fold is 3, the proposed MCMBO-ODEC achieves better performance rather than a lesser value of 6% of DHOA-ODEC, 4.3% of ChOA-ODEC, 2.08% of SLnO-ODEC and 1.04% of CMBO-ODEC, correspondingly. Hence, the higher value tends to achieve the higher efficiency of the detection model.

6.4. K-fold Evaluation of the recommended detection model for dataset 2

The k-fold results of the developed model are depicted in Fig. 10 over various algorithms and Fig. 11 with existing classifiers for dataset 2.

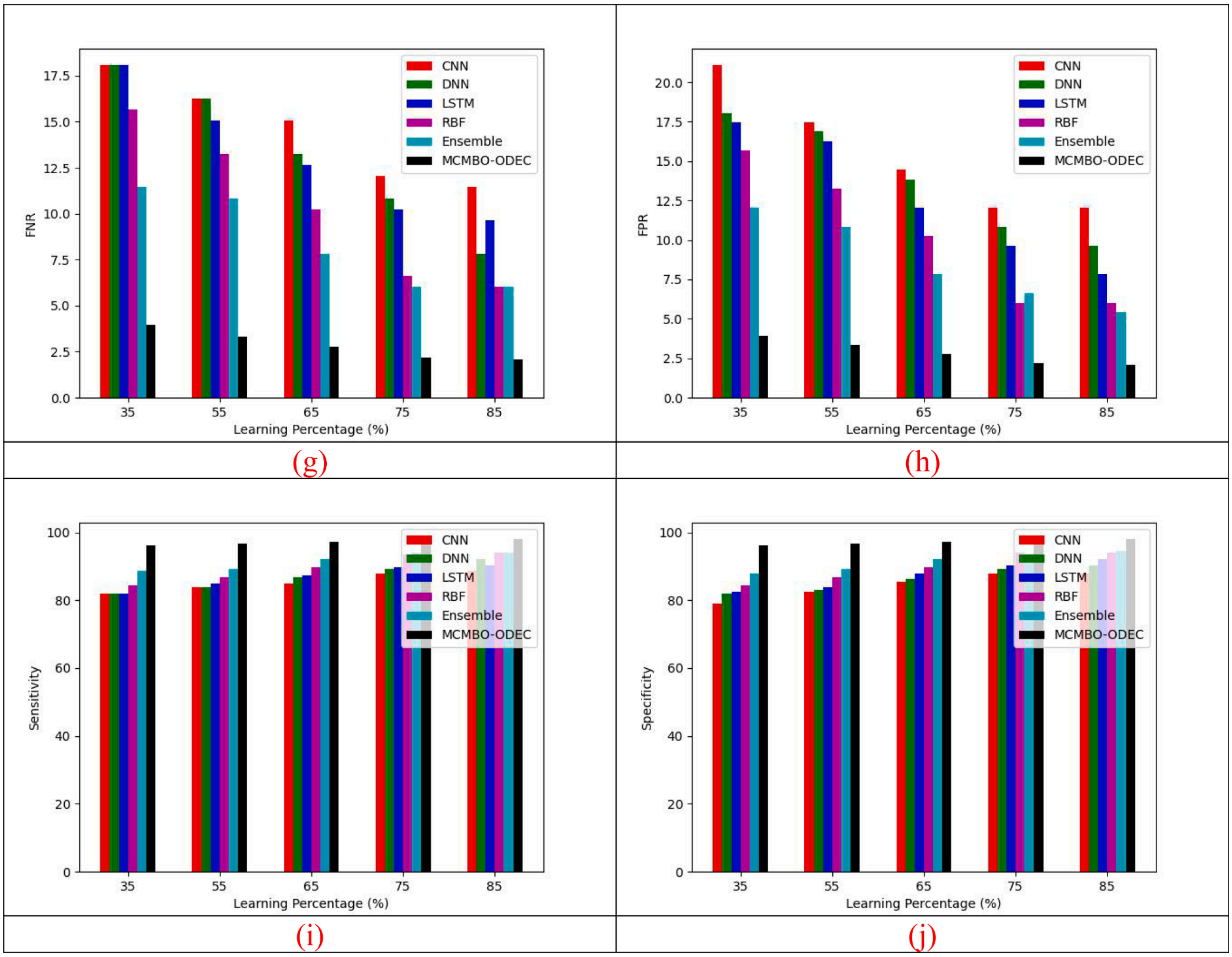

Fig. 15. (*continued*).

Table 2
Analysis of optimal weighted feature selection over tradition extraction techniques for two datasets.

Metrics	MFCC [27]	Spectral [28]	Statistical [29]	Fused Features [27 28 29]	Optimal Weighted Features
Dataset 1					
"Accuracy"	90.99071	90.99893	91.87007	93.95957	97.9292
"Sensitivity"	91.0318	91.07495	91.87007	93.94107	97.94694
"Specificity"	90.97017	90.96092	91.87007	93.96881	97.9066
"Precision"	83.44539	83.4378	84.96266	88.62077	98.35078
"FPR"	9.02983	9.03907	8.12993	6.03118	2.093398
"FNR"	8.968195	8.925049	8.129931	6.058925	2.053064
"NPV"	90.97017	90.96092	91.87007	93.96881	97.9066
"FDR"	16.55461	16.5622	15.03734	11.37923	1.649223
"F1-Score"	87.07367	87.08926	88.28146	91.2034	98.14844
"MCC"	0.803584	0.803819	0.82219	0.866953	0.958006
Dataset 2					
"Accuracy"	91.26506	90.66265	91.86747	93.9759	97.93761
"Sensitivity"	91.56627	90.36145	92.16867	93.9759	97.92566
"Specificity"	90.96386	90.96386	91.56627	93.9759	97.94528
"Precision"	91.01796	90.90909	91.61677	93.9759	96.83348
"FPR"	9.03614	9.03614	8.43373	6.024096	2.054719
"FNR"	8.433735	9.638554	7.831325	6.024096	2.074343
"NPV"	90.96386	90.96386	91.56627	93.9759	97.94528
"FDR"	8.982036	9.090909	8.383234	6.024096	3.166521
"F1-Score"	91.29129	90.63444	91.89189	93.9759	97.37651
"MCC"	0.825316	0.813268	0.837365	0.879518	0.956817

Table 3
Tabulation results of proposed cough detection model over former algorithms for two various datasets.

Metrics	DHOA-ODEC [33]	ChOA-ODEC [34]	SLnO-ODEC [35]	CMBO-ODEC [30]	MCMBO-ODEC
Dataset 1					
"Accuracy"	91.6831	91.61119	93.86095	93.3432	97.9292
"Sensitivity"	91.67899	91.54956	93.87944	93.36169	97.94694
"Specificity"	91.68516	91.64201	93.8517	93.33395	97.9066
"Precision"	84.64603	84.5602	88.41867	87.50433	98.35078
"FPR"	8.31484	8.35798	6.14829	6.6660	2.093398
"FNR"	8.321006	8.450444	6.120562	6.638314	2.053064
"NPV"	91.68516	91.64201	93.8517	93.33395	97.9066
"FDR"	15.35397	15.4398	11.58133	12.49567	1.649223
"F1-Score"	88.02225	87.91619	91.06726	90.33816	98.14844
"MCC"	0.818204	0.816581	0.864872	0.853728	0.958006
Dataset 2					
"Specificity"	92.16867	91.56627	94.57831	93.37349	97.94528
"Accuracy"	91.86747	91.26506	94.27711	93.37349	97.93761
"Sensitivity"	91.56627	90.96386	93.9759	93.37349	97.92566
"Precision"	92.12121	91.51515	94.54545	93.37349	96.83348
"FPR"	7.83132	8.43373	5.42168	6.626506	2.054719
"FNR"	8.433735	9.036145	6.024096	6.626506	2.074343
"NPV"	92.16867	91.56627	94.57831	93.37349	97.94528
"FDR"	7.878788	8.484848	5.454545	6.626506	3.166521
"F1-Score"	91.8429	91.23867	94.25982	93.37349	97.37651
"MCC"	0.837365	0.825316	0.885558	0.86747	0.956817

Table 4
Tabulation results of proposed cough detection model over former classifiers for two various datasets.

Metrics	CNN [18]	DNN [31]	LSTM [20]	RBF [32]	Ensemble [36]	MCMBO-ODEC
Dataset 1						
"Accuracy"	88.97313	90.34763	91.05646	94.05408	94.21022	97.9292
"Sensitivity"	89.07791	90.31681	91.05646	94.03353	94.24926	97.94694
"Specificity"	88.92073	90.36304	91.05646	94.06435	94.19071	97.9066
"Precision"	80.0797	82.4128	83.58132	88.79059	89.02538	98.35078
"FPR"	11.07927	9.636958	8.94354	5.935651	5.809295	2.093398
"FNR"	10.92209	9.683185	8.94354	5.966469	5.75074	2.053064
"NPV"	88.92073	90.36304	91.05646	94.06435	94.19071	97.9066
"FDR"	19.92021	17.58718	16.41867	11.20941	10.97462	1.649223
"F1-Score"	84.33953	86.18398	87.15891	91.33689	91.56287	98.14844
"MCC"	0.761236	0.789858	0.804905	0.868991	0.872434	0.958006
Dataset 2						
"Accuracy"	88.25301	91.26506	91.26506	93.9759	94.27711	97.93761
"Sensitivity"	88.55422	92.16867	90.36145	93.9759	93.9759	97.92566
"Specificity"	87.95181	90.36145	92.16867	93.9759	94.57831	97.94528
"Precision"	88.0239	90.53254	92.0245	93.9759	94.54545	96.83348
"FPR"	12.04819	9.638554	7.831325	6.024096	5.421687	2.054719
"FNR"	11.44578	7.831325	9.638554	6.024096	6.024096	2.074343
"NPV"	87.95181	90.36145	92.16867	93.9759	94.57831	97.94528
"FDR"	11.97605	9.467456	7.97546	6.024096	5.454545	3.166521
"F1-Score"	88.28829	91.34328	91.18541	93.9759	94.25982	97.37651
"MCC"	0.765074	0.825436	0.825436	0.879518	0.885558	0.956817

Table 5
Computational complexity of the developed cough detection model.

Proposed	Computational complexity
MCMBO-ODEC	$O(Iter^*((N_c + N_c{}^*chlen)) + (N_m + (N_m{}^*chlen))))$

Table 6
Computational analysis of the suggested cough detection model.

Methods	MCDM [8]	GMM-UBM [38]	HMM [39]	MCMBO-ODEC
Dataset 1				
Time (sec)	55.5484	55.3257	58.4865	50.5337
Dataset 2				
Time (sec)	59.5367	58.6844	61.6432	53.0563

Fig. 11 (c) visualizes the MCC values is enhanced by varying the k-fold numbers. At 2nd k-fold, the value is acquired as 21%, 26%, 22%, 11%, and 8% for CNN, DNN, LSTM, RBF, and Ensemble, which is lesser than the novel MCMBO-ODEC method, accordingly. Thus, the findings reveal that it obtains the desired outcome for diagnosing the disease.

6.5. Comparative evaluation for dataset 1

Fig. 12 elucidates the performance analysis of the suggested model is validated with different algorithms. Similarly, Fig. 13 demonstrates the performance analysis over various classifier networks for dataset 1. In Fig. 12 (a), it explains the accuracy of the model. The accuracy of the proposed MCMBO-ODEC acquires 8.7% higher than DHOA-ODEC, 10.4% more than ChOA-ODEC, 6.4% more than SLnO-ODEC, and 5.6% higher than CMBO-ODEC. Therefore, the more accurate value helps clinicians to diagnose the disease appropriately.

Table 7
Comparative analysis of the given offered cough detection model.

TERMS	MCDM [8]	GMM-UBM [38]	HMM [39]	MCMBO-ODEC
Dataset 1				
Accuracy	93.69369	94.77477	95.67568	97.83784
Sensitivity	93.51351	94.59459	95.67568	97.83784
Specificity	93.78378	94.86486	95.67568	97.83784
Precision	88.26531	90.20619	91.70984	95.7672
FPR	6.216216	5.135135	4.324324	2.162162
FNR	6.486486	5.405405	4.324324	2.162162
NPV	93.78378	94.86486	95.67568	97.83784
FDR	11.73469	9.793814	8.290155	4.232804
F1-Score	90.81365	92.34828	93.65079	96.79144
MCC	0.861018	0.88442	0.904209	0.951737
Dataset 2				
Accuracy	93.6747	94.57831	95.18072	98.19277
Sensitivity	93.9759	94.57831	95.18072	98.19277
Specificity	93.37349	94.57831	95.18072	98.19277
Precision	93.41317	94.57831	95.18072	98.19277
FPR	6.626506	5.421687	4.819277	1.807229
FNR	6.024096	5.421687	4.819277	1.807229
NPV	93.37349	94.57831	95.18072	98.19277
FDR	6.586826	5.421687	4.819277	1.807229
F1-Score	93.69369	94.57831	95.18072	98.19277
MCC	0.87351	0.891566	0.903614	0.963855

Table 8
Configuration of the recommended cough detection model.

CONFIGURATIONS	DHOA [33]	ChOA [34]	SLOA [35]	CMBO [30]	MCMBO
Dataset 1					
Configuration 1	1.00327	1.00011	1.00202	1.00241	1.00482
Configuration 2	1.00003	1.00086	1.00277	1.0045	1.0055
Configuration 3	1.00008	1.00231	1.00543	1.00672	1.01524
Configuration 4	–	–	1.00526	1.01733	1.03052
Configuration 5	–	–	1.00270	–	–
Dataset 2					
Configuration 1	1.00543	1.00171	1.00324	1.00435	1.00743
Configuration 2	1.00015	1.00251	1.00547	1.00578	1.00854
Configuration 3	1.00020	1.00287	1.00831	1.00853	1.03425
Configuration 4	–	–	1.00743	1.02897	1.04045
Configuration 5	–	–	1.00433	–	–

6.6. *Comparative analysis of dataset 2*

The performance analysis of the novel detection model is compared over conventional algorithms and classifiers, as shown in Figs. 14 and 15 for dataset 2. Fig. 15 (e) provides the precision measure of the designed method. At the learning percentage of 35, the better performance is achieved for the suggested MCMBO-ODEC that is compared with 14% less value of CNN, 13.4% less value of DNN, 13% less value of LSTM, 10.7% less value of RBF and 7.52% less value of Ensemble, accordingly. Due to more precision value, it improves the efficiency level for detecting the disease.

6.7. *Analysis of optimal weight feature selection with classical extraction techniques*

Table 2 provides the result analysis for optimal weighted feature selection. By using the optimal features, the divergent metrics are estimated to validate the efficiency. The FPR value of optimal features obtain as 1.43% of MFCC and spectral, 1.2% of statistical, and 0.62% of fused features, which is higher than the proposed optimal weighted features. Hence, less error aids to increase the detection accuracy. (SeeTable 3.).

6.8. *Overall evaluation of suggested detection model with different algorithms*

The overall validation of the novel method compared with conventional algorithms for two datasets. This table analysis is based on the learning percentage. The sensitivity is yielded as 4.76% of DHOA-ODEC, 4.9% of ChOA-ODEC, 2.5% of SLnO-ODEC, and 3.05% of CMBO-ODEC is lesser than the suggested MCMBO-ODEC while using dataset 1. Thus, the acquired results enhance the detection performance.

6.9. *Overall evaluation of the suggested detection model with distinct classifiers*

Table 4 demonstrates the overall evaluation of the novel method by validating for two datasets compared over diverse classifiers. When implementing dataset 2, the specificity is acquired as 8.74%, 6.24%, 4.37%, 2.5%, and 1.87% for CNN, DNN, LSTM, RBF, and Ensemble, which is lesser than offered work. This proves the system efficiency of the detection performance.

6.10. *Analysis of computational complexity of the cough detection model*

The analysis of the computational complexity of the designed cough detection model is given in Table 5. The variable *chlen* defines the chromosome length, and also the term *Iter* defines the total number of iterations. The term N_c and N_m is represented the number of mice and a number of cats, respectively.

6.11. *Computation time of the designed cough detection model*

The detecting the cough has been analyzed based on the computational time is shown in Table 6. Thus, the developed MCMBO-ODEC method attains better performance when compared with other existing approaches.

6.12. *Comparative analysis of the given offered method for the cough detection model*

The validation of the given offered model for various existing methods is depicted in Table 7. The recommended MCMBO-ODEC method achieves 10.5%, 7.6%, and 5.2% enriched performance than MCDM, GMM-UBM, and HMM. Thus, the empirical outcome of the designed MCMBO-ODEC method attains enhanced performance.

6.13. *Configuration of the developed method for cough detection model*

The configuration of the offered MCMBO-ODEC method for the cough detection model is shown in Table 8. Here, the DHOA and ChOA algorithm contains three configurations. Additionally, the SLOA algorithm contains totally five configurations. The CMBO and the developed MCMBO algorithm have four configurations. Based on the result analysis, the developed MCMBO algorithm obtains an enriched performance than other heuristic algorithms.

6.14. *Discussion*

In this research work, standard evaluation measures like specificity, precision, sensitivity, FPR, accuracy, FNR, FDR, F1-score, MCC, and NPV were evaluated to improve efficiency and system performance. Thus, the experimental result analysis of the designed method has attained 96% regarding accuracy. Hence, the designed method can be applied in subsequent real-time applications like health monitoring and mobile application. In recent times, the mobile application can be utilized to detect cough and snoring sound based on the audio spectrograms. In a practical scenario, it helps to speed up the cough diagnosis process so; it can be easily detecting the disease at an early stage. Hence, it provides the precautions from the disease. Nevertheless, we will definitely try to put into practice the developed model for any one of the above mentioned real time applications.

7. Conclusion

This work has presented a new cough detection framework by using the optimized ensemble learning approach. To experiment the model, the input audio signals were gathered from the datasets. Further, the input signal was decomposed by using the EMCD, which was further fed into the feature extraction process. Here, the MFCC features, spectral and statistical features were used to determine the informative features and fused together. Consequently, the fused features were upgraded into optimal weighted feature selection, where the weight was optimized by using the MCMBO algorithm. Then, these weighted features were given into the novel ODEC model, where the three classifiers as, LSTM, DNN, and RBF, were utilized to determine the average value of the final classified outcome. The parameters were optimally tuned by the MCMBO algorithm to provide optimal results. The analysis was made with various metrics and compared over classical approaches. While using dataset 2, the accuracy of the proposed model has achieved at 8.7% for CNN, 5.6% for DNN and LSTM, 2.8% for RBF, and 2.5% for Ensemble, which was inferior to the novel methodology. Thus, the empirical results have declared that it has improved the detection performance regarding diverse parameters.

Declaration of Competing 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.

Data availability

Data will be made available on request.

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