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Design and development of hybrid optimization enabled deep learning model for COVID-19 detection with comparative analysis with DCNN, BIAT-GRU, XGBoost

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ABSTRACT

The recent investigation has started for evaluating the human respiratory sounds, like voice recorded, cough, and breathing from hospital confirmed Covid-19 tools, which differs from healthy person's sound. The cough-based detection of Covid-19 also considered with non-respiratory and respiratory sounds data related with all declared situations. Covid-19 is respiratory disease, which is usually produced by Severe Acute Respiratory Syndrome Coronavirus-2 (SARS-CoV-2). However, it is more indispensable to detect the positive cases for reducing further spread of virus, and former treatment of affected patients. With constant rise in the COVID-19 cases, there has been a constant rise in the need of efficient and safe ways to detect an infected individual. With the cases multiplying constantly, the current detecting devices like RT-PCR and fast testing kits have become short in supply. An effectual Covid-19 detection model using devised hybrid Honey Badger Optimization-based Deep Neuro Fuzzy Network (HBO-DNFN) is developed in this paper. Here, the audio signal is considered as input for detecting Covid-19. The gaussian filter is applied to input signal for removing the noises and then feature extraction is performed. The substantial features, like spectral roll-off, spectral bandwidth, Mel frequency cepstral coefficients (MFCC), spectral flatness, zero crossing rate, spectral centroid, mean square energy and spectral contract are extracted for further processing. Finally, DNFN is applied for detecting Covid-19 and the deep leaning model is trained by designed hybrid HBO algorithm. Accordingly, the developed Hybrid HBO method is newly designed by incorporating Honey Badger optimization Algorithm (HBA) and Jaya algorithm. The performance of developed Covid-19 detection model is evaluated using three metrics, like testing accuracy, sensitivity and specificity. The developed Hybrid HBO-based DNFN is outpaced than other existing approaches in terms of testing accuracy, sensitivity and specificity of "0.9176, 0.9218 and 0. 9219". All the test results are validated with the k-fold cross validation method in order to make an assessment of the generalizability of these results. When k-fold value is 9, sensitivity of existing techniques and developed JHBO-based DNFN is 0.8982, 0.8816, 0.8938, and 0.9207. The sensitivity of developed approach is improved by means of gaussian filtering model. The specificity of DCNN is 0.9125, BI-AT-GRU is 0.8926, and XGBoost is 0.9014, while developed JHBO-based DNFN is 0.9219 in k-fold value 9.

1. Introduction

(SARS-CoV-2) Covid-19 is breathing ailment, which is frequently formed by Severe Acute Respiratory Syndrome Coronavirus-2 (SARS-CoV-2). COVID-19 (also known as coronavirus) pandemic is an ongoing infectious disease caused by severe acute respiratory syndrome (SARS) coronavirus [3]. Initially, Covid-19 was identified in Wuhan, China in December 2019 and it spreads globally, thus it is leading to ongoing 2020 coronavirus epidemic. It is reported that more than 4.18 million cases and 286,000 deaths in more than 2000 countries. The only effectual mode of human protection against Covid-19 is to decrease disease spread through rapid evaluation of populace as well as isolation of diseased persons, since no vaccines are available in medical area [13]. The precise and fast detection of disease is progressively vibrant because

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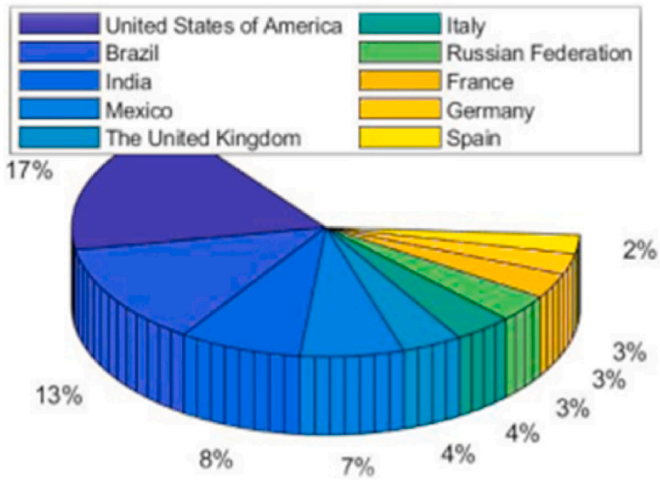


Fig. 1. Top 10 countries in terms of cumulative deaths (13/May/2021).

of fast spread and increasing amount of Covid-19 produced by SARS-CoV-2 for managing the infection source as well as it assists the patients for preventing progression of illness. Moreover, there are substantial challenges with regards to the utilization of nucleic acid assessment or clinical behaviours of affected patients as reference standard for making decisive detection of Covid-19 patients, since 2019. Since the early identification of Covid-19 is more essential for preventing and managing the Covid-19 pandemic. In addition, clinical behaviours cannot alone express the identification of Covid-19, specially for patients offering early-onset of indicators [14]. Furthermore, early identification of Covid-19 may assist for developing a suitable treatment purpose and disease containment decisions. The premature detection, isolation and treatment for patients are key approach for improved management of Covid-19 disease. The acquisition of adequately huge, publicly accessible quantity of medical image data for wholly trained deep learning techniques is challenging process for novel medical circumstances, namely Covid-19, since assortment and classification of images needs substantial period and resources to compile [15].

As of 13/May/2021, there are over 161.14 m confirmed cases and over 3.34 m deaths attributed to COVID-19. The cumulative deaths of the top 10 countries are shown in Fig. 1 [36]. The main symptoms of COVID-19 are a low fever, a new and ongoing cough, a loss or change to taste and smell. In UK, the vaccines approved were developed by Pfizer/BioNTech, Oxford/AstraZeneca, and Moderna. The joint committee on vaccination and immunization (JCVI) [35] determines the order in which people will be offered the vaccine. Numerous countries have to take solemn containment measures such as nation-wide lockdowns and mounting up of the isolation facilities in hospitals. The lockdown is useful as it gives time for large scale testing of individuals. The gold standard for COVID-19 diagnosis is the reverse transcription polymerase chain reaction (RT-PCR) of infected secretions (from nasal or throat cavity). The results of a RT-PCR test are available in 2–48 h [1]. The limitations of the testing include: (i) violation of social distancing which increases the chance of infection spread, (ii) expenses involved in the chemical reagents and devices, (iii) testing time in hours and needs expertise, and (iv) difficulty in large scale deployment [1].

The recent investigation has started for evaluating the human respiratory sounds, like voice recorded, cough, and breathing from hospital confirmed Covid-19 tools, which differs from healthy person's sound. The cough-based detection of Covid-19 also considered with non-respiratory and respiratory sounds data related with all declared situations. Moreover, data review of huge crowd sourced respiratory sounds or speech dataset are obtained for precise detection of Covid cases. Besides, medical clinicians and researchers are utilized the audio recording generated by humans, namely respiratory sound, swallow breathing, pulmonary sounds, heart sound, breath, and pulse sound for detecting and tracking human illness. Generally, these symptoms are collected through physical auscultation before current patient visits. Various scientists and researchers are utilized digital technologies for capturing sounds from human body by means of stethoscope and also operate automatic investigation on data for identifying illness [16]. Moreover, audio signals created by human body for example, breathing, digestion, sighs, vibration sounds, and heart have normally utilized by clinicians as indicators for detecting disease or progression. In recent days, various signals are gathered by manual auscultation at planned visits. Furthermore, several works demonstrate the capacity in detection indicative signals of Covid-19 from coughs and voices. The utilization of human engendered audio as biomarker for different illnesses affords massive possible for premature analysis [17].

The deep learning approach is widely utilized in various domains [26]. Moreover, Convolutional Neural network (CNN) obtained the identification of deep breathing in terms of respiratory pattern identification. Therefore, labelling of respiratory signals extracted by non-contract measurement systems with the service of deep learning approach is more significant. Every database needed for the process is acquired by assessing the respiratory events of test subject in deep learning approaches [27]. Various researchers normally designed classification methods, which adopts the general network structure in deep learning area without particular strategies for respiratory pattern classification [18]. Furthermore, machine learning techniques are also utilized for classifying and detecting the respiratory diseases from sounds particularly coughs as well as it utilizes CNN for detecting cough in ambient audio. Moreover, machine learning schemes detect three potential illnesses depends on the exclusive audio features [17]. There has been various modern research in digitizing respiratory sound acquisition based on electronic stethoscopes for improving the identification of abnormal lung sounds. After that, the obtained sounds are analysed by means of Artificial Intelligence (AI) techniques with deep learning schemes. An automatic architecture design method based on monarch butterfly optimization (MBO). Specifically, an expressive Neural Function Unit (NFU) based architecture representation is designed, which integrates promising architectures in GoogLeNet, ResNet and DenseNet to facilitate the joint search of macro-architecture and depth of CNNs [38]. Additionally, AI approaches has explored clear patterns in radiological performance for Covid-19 produced by SARS-CoV-2 as well as some of preliminary indication on predictive measurements of respiratory sound is emergent because of the application of simple methods [19], namely Support Vector Machine (SVM) and logistic regression schemes. Furthermore, these methods are effective for identifying Covid-19 from cough and breath sounds [20]. A self-adaptive mechanism is introduced into the ELM. Herein, a new variant of ELM, called self-adaptive extreme learning machine (SaELM), is proposed. SaELM is a self-adaptive learning algorithm that can always select the best neuron number in hidden layer to form the neural networks [37].

Traditional artificial intelligence (AI) and modern deep learning (DL) methods have achieved excellent results in analysing medical images. e. g., Lu [32] proposed a radial basis-function neural network (RBFNN) to detect pathological brains. A novel deep learning model that can diagnose COVID-19 on chest CT more accurately and swiftly. Based on traditional deep convolutional neural network (DCNN) model, is effective in detecting COVID-19 based on chest CT images [31]. A novel multiple input deep convolutional attention network (MIDCAN) model is proposed for diagnosis of COVID-19 [34]. One input of this model receives 3D chest CT image, and other input receives 2D X-ray image. There is a lot of detailed and essential information on chest radiographs, but manual processing is not as efficient or accurate. As a result, how efficiently analysing and processing chest radiography of COVID-19 patients is an important research direction to promote COVID-19 diagnosis. To improve the processing efficiency of COVID-19 chest films, a multilevel thresholding image segmentation (MTIS) method based on an enhanced multiverse optimizer (CCMVO) is proposed [39]. CCMVO is

Table 1
Classical techniques for COVID-19 diagnosis using respiratory sounds.

Authors	Methods	Advantages	Disadvantages
Sharma, N et al. [1]	Coswara tool	Shows good accuracy for detecting respiratory disorders.	Not able to identify sound-based biomarkers for Covid-19.
Lella, K.K. and Pja, A [2]	Multi-channeled Deep Convolutional Neural Network (DCNN)	Efficiently classifies COVID-19 sounds to detect COVID-19 positive symptoms.	Unable to deal with large-scale trials with more labelled results.
Andreu-Perez, J et al. [3]	Empirical Mode Decomposition (EMD)	Facilitates rapid detection of the infection with enhanced accuracy.	Did not consider parameter tuning of the sonograph representations and complementary analysis of coughing behaviours.
Wang, Y et al. [4]	Bidirectional and attentional mechanisms with gated recurrent unit neural network (BI-AT-GRU)	Provides enhanced accuracy.	Not suitable in real-life platforms.
Purnomo, A.T et al. [5]	Xtreme Gradient Boosting (XGBoost) classification model	Allows monitoring the breathing waveform with enhanced accuracy.	Monitoring and measuring the breathing pattern in a noisy environment is a challenge.
Tuncer, T et al. [6]	Present-Substitution Box-Pattern (present S-Box pattern)	Can run on a basic system with straightforward configurations.	Did not include feature selectors to select optimal number of features.
Lu, Q. et al. [7]	Triboelectric nanogenerator for respiratory sensing (RS-TENG)	Can achieve self-powered respiratory sensing anytime and anywhere.	Suffered from computation complexity.
Takahashi, Y et al. [8]	Respiratory Quality Index	Provides good accuracy	Measurement cannot be performed when body movements other than breathing occur.

improved from the original Multi-Verse Optimizer by introducing horizontal and vertical search mechanisms. A new multilevel image segmentation method based on the swarm intelligence algorithm (SIA) to enhance the image segmentation of COVID-19 X-rays is developed [40]. This paper first introduces an improved ant colony optimization algorithm, and later details the directional crossover (DX) and directional mutation (DM) strategy, XMACO.. In order to solve such issues, an efficient Water Cycle Swarm Optimizer-based Hierarchical Attention Network (WCSO-based HAN) is developed for detecting the pulmonary abnormalities from the respiratory sound signals. However, the developed optimization technique named WCSO is devised by incorporating the Water Cycle Algorithm (WCA) with Competitive Swarm Optimizer (CSO) [35]. The major contribution of this research is to design an effectual Covid-19 detection model using devised JHBO-based DNFN. Here, the audio signal is considered as input for detecting Covid-19. The gaussian filter is applied to input signal for removing the noises and then feature extraction is performed. The substantial features, like spectral roll-off, spectral bandwidth, Mel frequency cepstral coefficients (MFCC) [21], spectral flatness, zero crossing rate, spectral centroid, mean square energy and spectral contract are extracted for further processing. Finally, DNFN [11] is applied for detecting Covid-19 and the deep leaning model is trained by designed JHBO algorithm. Accordingly, the developed hybrid JHBO method is newly designed by incorporating Honey Badger optimization Algorithm (HBA) [10] and Jaya algorithm [12].

2. Literature survey

The traditional Covid-19 prediction techniques based on respiratory sounds are explicated as follows with advantages and limitations. Sharma, N et al. [1] presented Coswara tool for detecting Covid-19 from voice sounds. This approach obtained better detection accuracy for respiratory disorders. However, this approach was not effective for identifying sound-based biomarkers in Covid-19.

To detect sound-based biomarkers, Lella, K.K. et al. A [2] introduced multi-channelled Deep CNN (DCNN) for Covid-19 detection using sounds. This method proficiently classifies the Covid-19 affected sounds to find the positive symptoms. Although, this technique was not able to manage huge-scale trials with additional labelled outcomes.

For handling large scale trails, Andreu-Perez, J et al. [3] devised Empirical Mode Decomposition (EMD) mode for covid-19 detection process. This model highly increased the detection accuracy, but still failed to consider parameter tuning of sonograph depictions as well as balancing analysis of coughing characteristics.

In order to perform parameter tuning, Wang, Y et al. [4] developed Bidirectional and Attentional mechanisms with Gated Recurrent Unit neural network (BI-AT-GRU) for Covid-19 recognition. This algorithm obtained enhanced accuracy, even though it is not appropriate in real-life stands.

For considering real-life standards, Purnomo, A.T et al. [5] introduced Xtreme Gradient Boosting (XGBoost) classification approach for detecting Covid-19. This technique permits observation of breathing waveform with improved accuracy. However, monitoring and also determining of breathing form in noisy atmosphere is more challenge process.

To monitor and measure the breathing pattern even in noisy surroundings, Tuncer, T et al. [6] devised Present-Substitution Box-Pattern for Covid-19 identification using lung breathing sounds. This technique was operated even on basic system with straightforward formations. Although, it failed to comprise feature selectors for choosing optimal quantity of features.

For selecting better number of features, Lu, Q. et al. [7] presented Triboelectric nanogenerator for respiratory sensing (RS-TENG) for respiratory monitoring. This method obtained self-powered respiratory sensing anytime and anyplace, but computational complexity was not decreased.

In order to solve computational complexity issues, Takahashi, Y et al. [8] developed respiratory likelihood index for computing respiratory rate in Covid-19. The detection accuracy was increased, even though this approach was evaluated in actual emergency situations.

The eight classical techniques for COVID-19 diagnosis using respiratory sounds are listed along with its merits and demerits are also listed in Table 1.

2.1. Challenges

The challenges faced by classical techniques for COVID-19 diagnosis using respiratory sounds are listed.

- The COVID-19 pandemic presents global challenges transcending boundaries of country, race, religion, and economy. The current gold standard method for COVID-19 detection is the reverse transcription polymerase chain reaction (RT-PCR) testing. However, this method is expensive, time-consuming, and violates social distancing [1].
- In this regard, studies concurrent in time with ours have investigated different respiratory sounds, including cough, to recognise potential Covid-19 carriers. However, these studies lack clinical control and rely on Internet users confirming their test results in a web questionnaire or crowdsourcing and thus rendering their analysis inadequate [3].
- Several studies have been conducted to obtain an accurate respiration rate from chest displacement information. However, patients

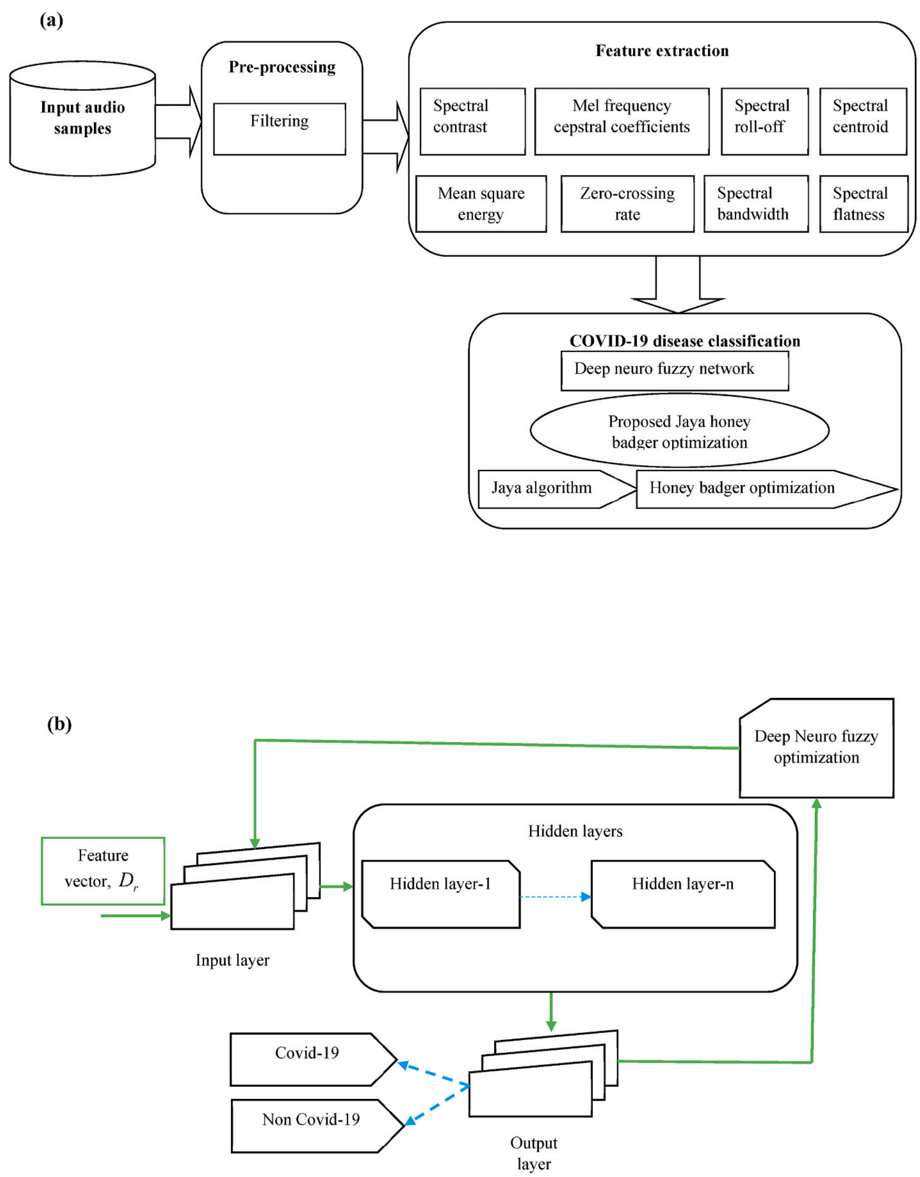


Fig. 2. (a). Block diagram of devised covid-19 detection model using hybrid optimization. Fig. 2(b). Architecture of DNFN.

with a respiration disorder or COVID-19 have an unusual respiration characteristic pattern that cannot be represented by using the respiration rate [5].

- Although current technologies may detect illnesses symptoms, such as temperature, heart rate, and even stress and other physiological conditions, most of them suffer the declination of precision from a social distancing in performing the health screening on masked participants [7].
- Most of the non-contact monitoring methods require the subject to remain stationary, making it difficult to apply them to ambulances, which are subject to shaking during transport. In addition, thermal imaging cameras do not provide accurate measurements when the nose and mouth regions are not visible in the image.

3. Developed Covid-19 detection model based on hybrid optimization

This section deliberates about the Covid-19 detection method using developed JHBO-based DNFN. The series of steps followed for introduced Covid-19 diagnosis model are pre-processing, feature extraction, and classification. Originally, input audio signals are passed into the pre-processing module wherein the noise and artifacts contained in audio samples is discarded using gaussian filtering technique. Then, the pre-processed audio samples are passed into the feature extraction module. Here, significant features, such as spectral contrast, MFCC [21], spectral roll-off, mean square energy, spectral centroid, zero-crossing rate, spectral bandwidth, and spectral flatness are extracted. Finally, classification is done using DNFN [11] wherein the training of DNFN is done using JHBO algorithm. The proposed JHBO algorithm is newly devised by combining Jaya algorithm [12] and HBA [10]. The block diagram of Covid-19 detection model using designed JHBO-based DNFN is exposed in Fig. 2(a).

3.1. Covid-19 detection

The covid-19 detection process using designed hybrid optimization-based DNFN is explicated in this section. The DNFN classifier is applied for detecting Covid-19, and the weights and bias of DNFN is trained by devised JHBO algorithm for improving the detection performance.

3.2. DNFN

The DNFN [11] structure is hybridization of fuzzy logic system and Deep Neural Network (DNN). The validation error and training time is highly reduced, thereby DNFN is utilized for developed Covid-19 detection method. In DNFN, major two procedures are done wherein initial process is executed with DNN, whereas second one is accomplished with fuzzy logic to evaluate system objective. Moreover, DNFN mainly encompasses three layers, such as input, hidden and output layer. The input layer is considered by means of various input parameters as well as fuzzification system value. Moreover, three layers, namely normalization, rule and also defuzzification layers are employed in this classifier. Furthermore, output layer is also denoted as defuzzification layer. The essential parameter of DNN is premises and consequents in which premises are base of membership function in fuzzification layer, which is termed as occurrence level. Likewise, consequent is mostly depending on defuzzification process. The neuro fuzzy model comprises Fuzzy Interference System (FIS) for rule base evaluation and it is the essential process in neuro fuzzy scheme. The structural diagram of DNFN for Covid-19 detect is depicted in Fig. 2(b).

Here, every input and output are mapped for defining the information processing component in neuro fuzzy system. The degree of every input is assigned amongst 0 *and* 1, which is elucidated by fuzzy system. Moreover, all entities of first layer is followed by output.

i) **Input layer:** Let us include two premises n and a with one consequent O, which is illustrated as,

$$N_{1,\varpi}(d) = \lambda J_{\varpi}(d) \ or \ N_{1,\varpi} = \lambda W_{\varpi-2}(m), \forall \varpi = 1,2,3 \tag{9}$$

where, d and m refers input to every ϖ^{th} entity, λJ_{ϖ} and $\lambda W_{\varpi-2}$ symbolizes precursor membership function, and $N_{1,\varpi}$ implies membership degree function. Additionally, membership function is designed as bell formed function, which is assigned with maximal 1 and minimal 0 values, which is given by,

$$\lambda J_{\varpi}(d) = \frac{1}{1 + \left|\frac{d = B_{\varpi}}{C_{\varpi}}\right|^{2U_{\varpi}}} \tag{10}$$

where, U_{ϖ}, C_{ϖ} and B_{ϖ} symbolizes membership function of premise parameter, which is enhanced through training procedure.

ii) **Rule base layer:** The second layer is named as rule base layer, which is utilized for explicating the rule groups. Every single entity in this layer is multiplied through linguistic variable in order to fulfil membership degree. Furthermore, multiplication of membership variable value indicates firing strength of rule.

$$N_{2,\varpi} = \beta_{\varpi} = \lambda J_{\varpi}(d) \lambda W_{\varpi-2}(m) \quad , \forall \varpi = 1,2 \tag{11}$$

where, β_{ϖ} represents weight of generic network factor.

iii) **Normalization layer:** Here, each entity estimates the firing strength ratio of ϖ^{th} rule associated to summation of firing strength of every rule. Therefore, outcome of each rule is normalized along with firing strength of rule, which is expressed as,

$$N_{3,\varpi} = \overline{\beta}_{\varpi} = \frac{\beta_{\varpi}}{\beta_1 + \beta_2} \quad , \forall \varpi = 1,2 \tag{12}$$

iv) **Defuzzification layer:** The consequent of each rule is computed for designating the overall output and output generated at this layer is denoted in below equation,

$$N_{4,\varpi} = \overline{\beta}_{\varpi} I_{\varpi} = \overline{\beta}_{\varpi}(X_{\varpi} d + L_{\varpi} m + F_{\varpi}) \quad , \forall \varpi = 1,2 \tag{13}$$

where, X, $L$and F depicts consequent parameter set.

v) **Output layer:** The concluding layer is named as summation layer, where summation of prior layer results is estimated. The output of this layer is specified by,

$$N_{5,\varpi} = \sum_{\varpi} \overline{\beta}_{\varpi} I_{\varpi} = \frac{\sum_{\varpi} \beta_{\varpi} C_{\varpi}}{\sum_{\varpi} \beta_{\varpi}} \tag{14}$$

Furthermore, number of hidden layers is used for producing effectual training process even in large data. The output of DNFN classifier is represented as G_r, where the feature vector is classified as Covid-19 or non-Covid. Furthermore, the weights and bias of DNFN is trained by designed JHBO technique.

3.3. Input audio sample

Let us consider the dataset with different audio recordings for Covid-19 detection, which is specified as,

$$H = \{S_1, S_2, ..., S_r, ..., S_q\} \tag{1}$$

where, S_q denotes total amount of sound recordings, and S_r specifies r^{th} records in a dataset, and it is used for further pre-processing stage.

3.4. Pre-processing

Here, input data S_r is considered and Gaussian filter is applied in order to remove the noises from input audio sample. Gaussian filter has better capacity to afford similar transition in frequency domain, thus it is used for Covid-19 detection process. Generally, Gaussian filter is effectual since, it makes smother transition elimination of redundant data from audio sample. The Gaussian filter is specified as,

$$B(S_r) = \frac{1}{\sqrt{2\pi\psi^2}} \exp\left(S_r^2 / 2\psi^2\right) \tag{2}$$

where, ψ indicates standard deviation of distribution, S_r symbolizes input audio sample and output of pre-processing phase using gaussian filter is represented as K_r.

3.5. Feature extraction

The pre-processed audio sample K_r is further applied in feature extraction phase in which significant features, including spectral roll-off, spectral contrast, MFCC [21], spectral centroid, zero-crossing rate, spectral bandwidth, mean square energy and spectral flatness are extracted.

3.5.1. MFCC

MFCC [21] is a most employed spectral features in audio sample, which are group of coefficients and it affords significant information about the audio. This feature mainly includes, four phases namely pre-emphasis, windowing, and mel frequency wrapping and calculation of cepstral coefficients. The pre-emphasis process increases the high-frequency segments energy of audio sample. The discontinuities of edge effect are decreased through windowing process and the obtained frequency spectrum is passed to Mel filter, which finds the number of energy present in every frame. Mel spectrum is estimated through passing Fourier transformed signal with a group of band pass filters, termed Mel filter bank. The filter banks are executed in frequency domain for MFCC estimation. Finally, all the cepstral coefficients are attained through transforming logarithmic Mel Spectrum to time domain by means of Discrete Cosine Transform (DCT). The MFCC is computed by,

$$\mu_g = 2595 \log_{10}\left(1 + \frac{g}{700}\right) \quad (3)$$

where, g represents physical frequency in hertz, and μ_g implies perceived frequency. The MFCC feature is denoted as d_1.

3.5.2. Spectral contract

Spectral contract [22] is represented as decibel difference amongst valleys and peaks in a spectrum, which is denoted as d_2.

3.5.3. Spectral roll-off

This feature is used for calculating spectral shape, like spectral centroid [23]. It affords coarse idea of high frequency as well as frequency in which specific quantity of energy is limited. The spectral roll-off is estimated by,

$$\sum_{j=1}^{K} |A_f(j)| = 0.85 \sum_{j=1}^{X/2} |A_f(j)| \quad (4)$$

where, X implies frame length, j implies frequency coefficient of frame, $A_f(j)$ refers Short Time Fourier Transform (STFT) of frame and K denotes highest value of j. The spectral roll-off feature is represented as d_3.

3.5.4. Spectral centroid

Spectral centroid [23] displays the centre of mass or geometric centre of pre-processed signal. Moreover, centroid of every frame is specified by amplitude of frame multiplied by average frequency of signal divided by sum of frame amplitudes. The spectral centroid is given by,

$$d_4 = \frac{\sum_{b=0}^{B} h(b)|n(b)|}{\sum_{b=0}^{B} |n(b)|} \quad (5)$$

where, $h(b)$ signifies amplitude of frame multiplied by average frequency, $n(b)$ is sum of frame amplitudes and spectral centroid feature is denoted as d_4.

3.5.5. Root mean square energy

This feature [24] is referred as global energy of audio signal, which is estimated by,

$$d_5 = \sqrt{\frac{1}{z} \sum_{j=1}^{z} U_z^2} \quad (6)$$

where, U_z defines signal amplitude at z^{th} amplitude, z symbolizes quantity of frames in sample length, and d_5 specifies root mean square feature.

3.5.6. Zero crossing rate

This feature defines the ratio of quantity of times the audio sample alters the value from negative to positive or else positive to negative to frame dimension [24]. The zero-crossing rate feature is denoted as d_6.

3.5.7. Spectral bandwidth

Spectral bandwidth [25] is utilized for signifying the difference among lower and upper cut-off frequencies, which is given by,

$$d_7 = \sqrt{\frac{\sum_{b=0}^{B-1} (b - d_4)^2 |y(m)|}{\sum_{b=0}^{B-1} n(b)}} \quad (7)$$

where, d_4 represents spectral centroid and spectral bandwidth is signified as d_7.

3.5.8. Spectral flatness

This feature [24] refers amount of uniformly distributed frequency in power spectrum, which is estimated by ratio of geometric and arithmetic mean of sub band. The spectral flatness feature is indicated as d_8.

Meanwhile, the extracted features from pre-processed output is combined together in order to generate feature vector, which is expressed as,

$$D_r = \{d_1, d_2, \ldots, d_8\} \quad (8)$$

The formulated feature vector D_r is further passed to DNFN for Covid-19 recognition process.

3.6. Developed Jaya honey badger optimization algorithm for training process of DNFN

The DNFN is trained by introduced optimization technique, named JHBO model for improving the detection performance. Accordingly, the devised JHBO approach is newly developed by incorporating HBA [10] with Jaya algorithm [12]. Jaya algorithm is devised based on the candidate solutions, which operates independent of any parameters. This method is functioned in single phase and the operation is simple. Alternatively, HBA is designed by means of intelligent foraging features of honey badger. The energetic search nature of honey badger along with honey and digging discovery methods are employed. The HBA effectively solves the optimization issues by means of search policy. Hence, the Jaya algorithm is combined with HBA for improving the performance with better convergence speed. The algorithmic process of devised JHBO model is illustrated as.

3.6.1. Initialization

Originally, amount of honey badger is initialized with population size T along with corresponding positions, which is specified as,

$$R_r = P_r + w_1 \times (Q_r - P_r) \quad (15)$$

where, R_r denotes r^{th} honey badger location in total population, P_r refers lower bounds, Q_r implies upper bound, and w_1 represents random number among 0 and 1.

3.6.2. Fitness function computation

The fitness measure is estimated in order to find the ideal solution and the fitness value with least value is dented as best solution for Covid-19 detection. The fitness function is estimated by,

$$\delta = \frac{1}{r} \sum_{\sigma=1}^{r} \left(G_r^* - G_r\right)^2 \quad (16)$$

where, r indicates total amount of data, G_r^*specifies target output, G_r is classified output from DNFN, and δ denotes fitness function.

3.6.3. Defining intensity

Intensity is corresponding to concentration strength of prey as well as distance among r^{th} honey badger and prey. The movement is fast if the smell is high and vice versa, which is expressed by means of inverse square law. The intensity is defined as,

$$T_r = w_2 \times \frac{E}{4\pi v_r^2} \quad (17)$$

where, w_2 denotes random value amongst 0 *and* 1, E implies concentration strength, and v_r implies distance amongst r^{th} honey badger and prey. Moreover, the term E and v_r is illustrated in following expression.

$$E = (R_k - R_{k+1})^2 \quad (18)$$

$$v_r = R_{prey} - R_k \quad (19)$$

3.6.4. Update density factor

The density factor handles the time fluctuating randomization for ensuring smooth transition from exploitation to exploration. The density

Table 2
Pseudo-code of introduced JHBO method.

S.No.	Pseudo-code
1	**Input:** Total population
2	**Output:** Best solution
3	Set the parameters $y_{\max}$, T ε, and E
4	Compute the fitness measure using equation (16)
5	**while** $y \le y_{\max}$ do
6	Update the decreasing factor υ based on equation (20)
7	**for** $r = 1$ *to* T do
8	Estimate the intensity T_r by equation (17)
9	**if** $w < 0.5$ then
10	Update the location by means of expression (21)
11	**Else**
12	Update the location using equation (33)
13	**end if**
14	Estimate the new position and allocate to f_{new}
15	**if** $f_{new} \le f_r$ then
16	Set $R_r = R_{new}$ and $f_r = f_{new}$
17	**end if**
18	**if** $f_{new} \le f_{prey}$ then
19	Set $R_{prey} = R_{new}$ and $f_{prey} = f_{new}$
20	**end if**
21	**end for**
22	**end while**
23	Check feasibility of solution
24	Return best solution

Thus, the DNFN structure effectively detects the Covid-19 disease with minimal time and error. In addition, developed JHBO scheme is employed for training process of DNFN in order increase the detection performance.

factor decreases along with iterations for reducing randomization with time by below equation.

$$\upsilon = V \times \exp\left(\frac{-y}{y_{\max}}\right) \tag{20}$$

where, V denotes constant, and $y_{\max}$ is maximum amount of iterations.

3.6.5. *Escaping from local optimum*

This method utilizes flag N, which modifies search direction for rewarding high prospects for agents in order to scan search space severely.

3.6.6. *Updating position of agents*

The position updation process of HBA mainly includes two phases, namely digging and honey phase, which are explicated as follows.

a) **Digging stage:** The honey badger executes the action similar to Cardioid shape and the Cardioid movement is motivated by,

$$R_{new} = R_{prey} + N \times \varepsilon \times T \times R_{prey} + N \times w_3 \times \upsilon \times v_r \times |\cos(2\pi w_4) \times [1 - \cos(2\pi w_5)]| \tag{21}$$

where, R_{prey} refers location of prey, $\varepsilon \ge 1$, w_3, w_4 and w_5 are random number among 0 *and* 1. Moreover N operates as flag, which varies search direction and it is identified by,

$$N = \begin{cases} 1 & , if\ w_6 \le 0.5 \\ -1 & , else \end{cases} \tag{22}$$

where, w_6 implies random integer among 0 *and* 1. A honey badger mainly depends on small intensity T of prey R_{prey}. Additionally, badger may obtain any trouble N in digging activity, which permits to identify optimal prey position.

b) **Honey stage:** The source while a honey badger follows honey guide bird for reaching beehive can be stimulated by,

$$R_{new} = R_{prey} + N \times w_7 \times \upsilon \times v_r \tag{23}$$

The standard expression of Jaya algorithm is given by,

$$R'_{t,u,r} = R_{t,u,r} + w_{1,t,r}\left(R_{t,best,r} - \left|R_{t,u,r}\right|\right) - w_{2,t,r}\left(R_{t,worst,r} - \left|R_{t,u,r}\right|\right) \tag{24}$$

Let assume, $R_{t,u,r}$ is positive, $R'_{t,u,r} = R_{new}$, $R_{t,u,r} = R_r$, $w_{1,t,r} = w_1$, $R_{t,best,r} = R_{best}$, $R_{t,worst} = R_{worst}$, $w_{2,t,r} = w_2$, thus above expression is re-written as,

$$R_{new} = R_r + w_1(R_{best} - R_r) - w_2(R_{worst} - R_r) \tag{25}$$

$$R_{new} = R_r(1 - w_1 + w_2) + w_1 R_{best} - w_2 R_{worst} \tag{26}$$

$$R_r = \frac{R_{new} - w_1 R_{best} + w_2 R_{worst}}{1 - w_1 + w_2} \tag{27}$$

Substitute R_r on both sides in equation (23),

$$R_{new} - R_r = R_{prey} + N \times w_7 \times \upsilon \times v_r - R_r \tag{28}$$

Substitute equation (27) in RHS of (28),

$$R_{new} - R_r = R_{prey} + N \times w_7 \times \upsilon \times v_r - \left(\frac{R_{new} - w_1 R_{best} + w_2 R_{worst}}{1 - w_1 + w_2}\right) \tag{29}$$

$$R_{new} = R_{prey} + N \times w_7 \times \upsilon \times v_r - \left(\frac{R_{new} - w_1 R_{best} + w_2 R_{worst}}{1 - w_1 + w_2}\right) + R_r \tag{30}$$

$$R_{new} + \frac{R_{new}}{1 - w_1 + w_2} = R_{prey} + N \times w_7 \times \upsilon \times v_r + \frac{w_1 R_{best} - w_2 R_{worst}}{1 - w_1 + w_2} + R_r \tag{31}$$

$$\frac{R_{new}(1 - w_1 + w_2 + 1)}{1 - w_1 + w_2} = \frac{\left(R_{prey} + N \times w_7 \times \upsilon \times v_r + R_r\right)(1 - w_1 + w_2) + w_1 R_{best} - w_2 R_{worst}}{1 - w_1 + w_2} \tag{32}$$

$$R_{new} = \frac{\left(R_{prey} + N \times w_7 \times \upsilon \times v_r + R_r\right)(1 - w_1 + w_2) + w_1 R_{best} - w_2 R_{worst}}{2 - w_1 + w_2} \tag{33}$$

where, R_{new} indicates new location of honey badger, and w_7 defines random integer among 0 *and* 1.

3.6.7. *Evaluating feasibility of solution*

The best optimal solution is attained by means of fitness function, which defined in equation (16), and fitness function with minimal value is considered as optimum solution.

3.6.8. *Termination*

The directly above steps are executed continually until greatest solution is achieved. The pseudo-code of introduced JHBO algorithm is specified in Table 2.

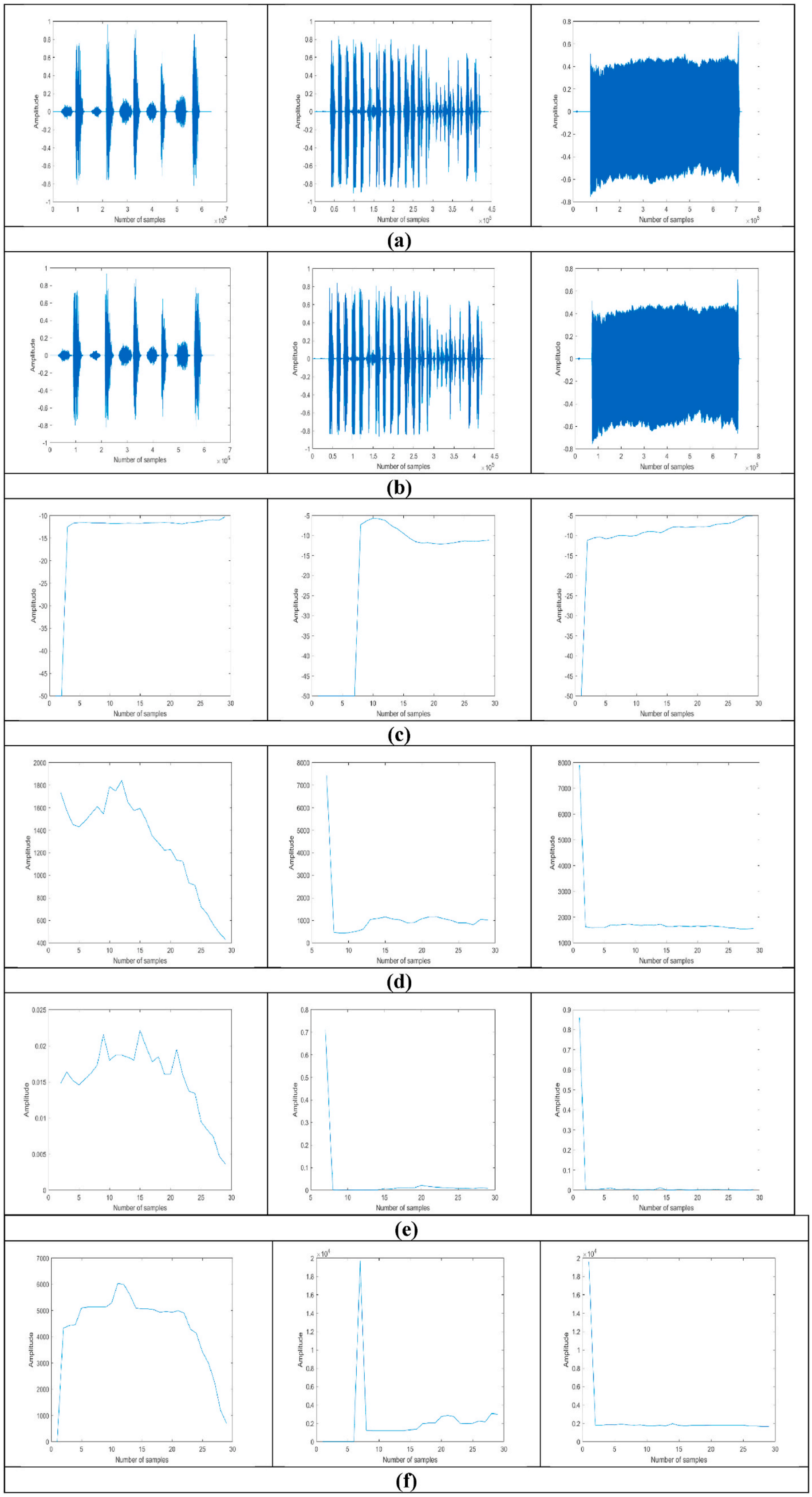


Fig. 3. Experimental results of developed Covid-19 detection method a) Input signal-1,2, and 3, (b) Pre-processing signal-1,2, and 3, (c) MKFCC for signal-1,2, and 3, (d) Spectral centroid for signal-1,2, and 3, (e) Spectral flatness for signal-1,2 and 3, (f) Spectral roll-off for signal-1,2 and 3.

Table 3
Performance analysis of introduced JHBO-based DNFN (a) Training accuracy, (b) Sensitivity and (c) Specificity.

Training Data/Iteration	Accuracy	Sensitivity	Specificity
90%/20	0.8747	0.875	0.8774
90%/40	0.8783	0.8883	0.881
90%/60	0.8871	0.9005	0.8898
90%/80	0.904	0.9107	0.9067
90%/100	0.9176	0.9207	0.9207

4. Results and discussion

This section exposes results and discussion of devised JHBO driven DNFN for Covid-19 detection. Furthermore, experimental results, dataset description, experimental setup, performance metrics, comparative techniques as well as various analysis, including algorithm, performance and comparative analysis is shown in this section.

4.1. Experimental setup

The devised Covid-19 detection method using JHBO-based DNFN is executed in MATLAB with Windows 10 OS having Intel i3 processor and 8 GB RAM.

4.2. Dataset description

The database employed for detecting Covid-19 using designed JHBO-based DNFN is Coswara-data [9]. The data is utilized for Covid19 detection process along with various audio recordings like cough, breathing, and speech sounds of an individual. Moreover, this data is introduced by Indian Institute of Science (IISc) Bangalore. The voice samples are gathered, like phonation of sustained vowels, cough sounds, breathing sounds, and counting numbers at fast and slow pace. In addition, the metadata information includes participant's gender, age, location, current health status and the presence of comorbidities.

4.3. Performance metrics

The performance of designed Covid-19 detection model using JHBO-based DNFN is evaluated based on three various metrics, including testing accuracy, specificity, and sensitivity.

i) **Testing accuracy:** Accuracy is utilized for computing the true negative, and true positive proportions of all audio samples, which is specified as,

$$A_c = \frac{\rho_t + \rho_f}{\rho_t + \rho_f + \sigma_t + \sigma_f} \tag{34}$$

ii) **Sensitivity:** Sensitivity is estimated to correctly categorize Covid-19 disease, and it is represented by,

$$S_e = \frac{\rho_f}{\rho_f + \sigma_t} \tag{35}$$

iii) **Specificity:** Specificity is calculated for predicting the precise classification of Covid-19, and it is denoted by,

$$S_p = \frac{\rho_t}{\rho_t + \sigma_f} \tag{36}$$

where, ρ_t indicates true positive, $\rho_f$specifies true negative, σ_t is a false positive, and $\sigma_f$denotes false negative.

4.4. Experimental results

This section exposes experimental outcomes of introduced JHBO enabled DNFN for Covid-19 prediction. Here, Fig. 3 a) depicts the original input signal-1,2 and, pre-processed signal-1, 2 and 3 is illustrated in Fig. 3 b). In addition, MFCC for input signal-1, 2 and 3 is

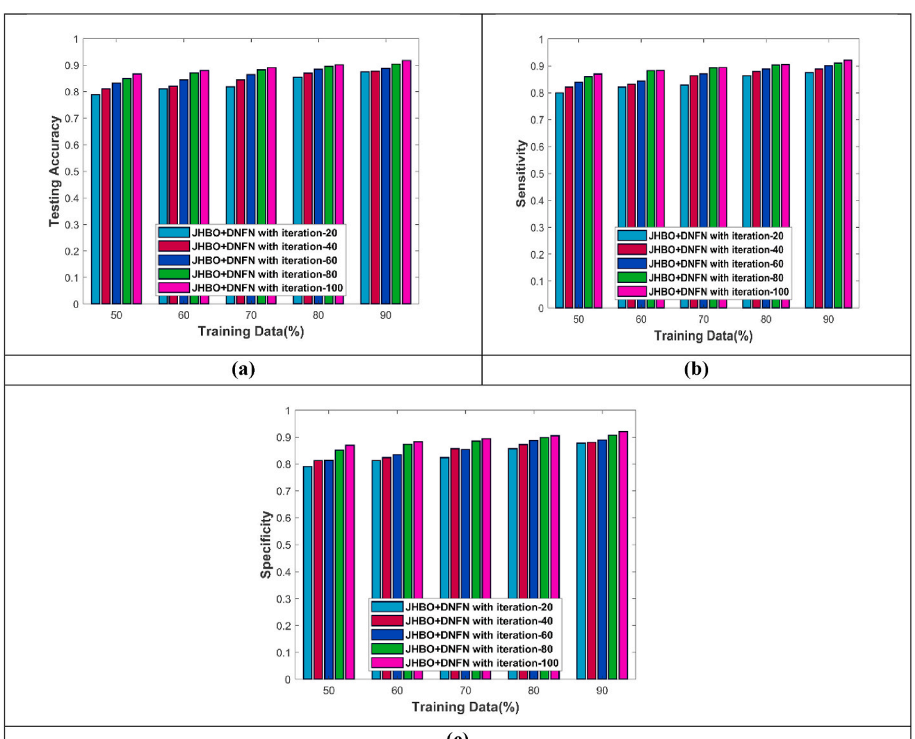


Fig. 4. Performance analysis of introduced JHBO-based DNFN (a) Training accuracy, (b) Sensitivity and (c) Specificity.

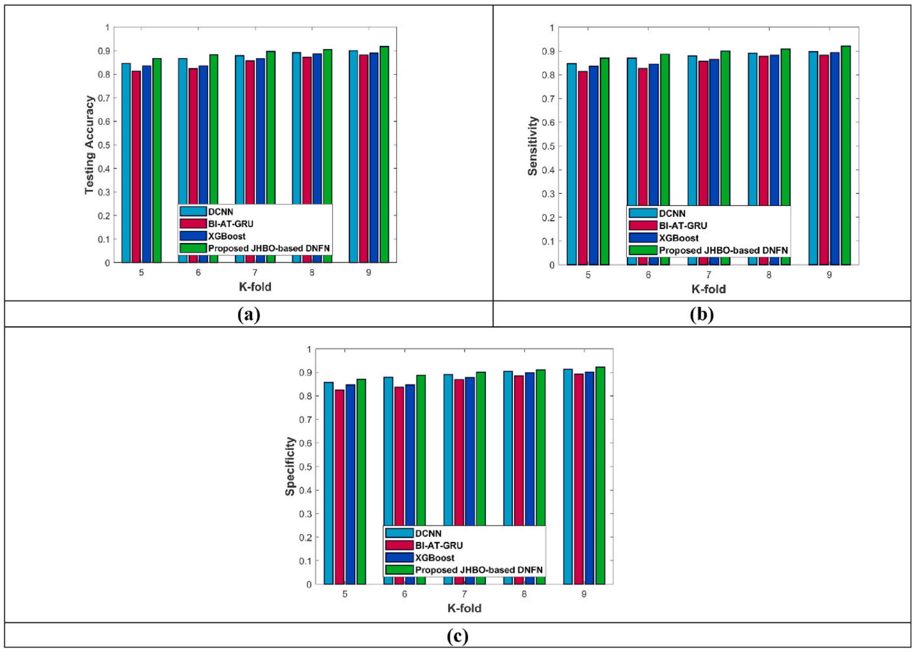


Fig. 5. Comparative analysis of introduced JHBO-based DNFN with k-fold value (a) Training accuracy, (b) Sensitivity and (c) Specificity.

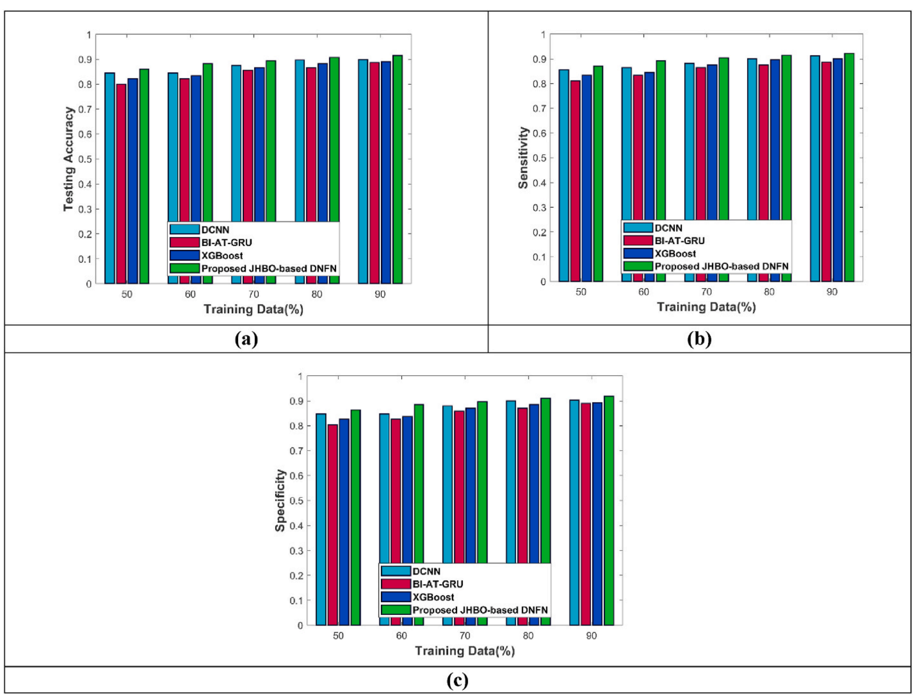


Fig. 6. Analysis of designed JHBO-based DNFN with training data (a) Training accuracy, (b) Sensitivity and (c) Specificity.

deliberated in Fig. 3 c). Fig. 3 d) exposes the spectral centroid for input signal-1, 2 and 3. The spectral flatness and roll-off for input signal-1, 2 and 3 is represented in Fig. 3 e) and f).

4.5. Performance analysis

Table 3 and Fig. 4 specifies the performance analysis of introduced hybrid JHBO-based DNFN based on various performance metrics by varying training data. Fig. 4 a) depicts analysis of devised JHBO-based DNFN for accuracy with various iterations. The testing accuracy of developed JHBO-based DNFN with iteration 20, 40, 60, 80 and 100 is 0.8747, 0.8783, 0.8871, 0.904, and 0.9176, while training data is 90%. The analysis of devised JHBO-based DNFN for sensitivity with different iterations is plotted in Fig. 4 b). The sensitivity of introduced JHBO-based DNFN with iteration 20 is 0.875, 40 is 0.8883, 60 is 0.9005, 80 is 0.9107, and 100 is 0.9207. Fig. 4 c) represents the performance analysis of designed JHBO-based DNFN for specificity with various iterations. When the training data is 90%, specificity of designed JHBO-based DNFN is 0.8774, 0.881, 0.8898, 0.9067, and 0.9207 for iteration 20, 40, 60, 80, and 100.

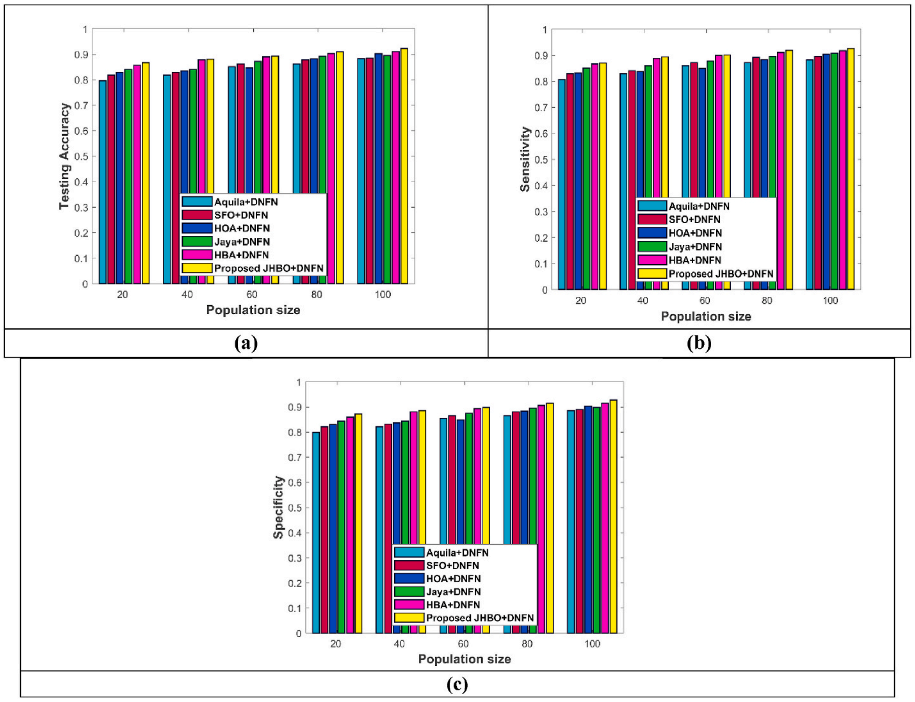


Fig. 7. Algorithm analysis of designed JHBO-based DNFN (a) Training accuracy, (b) Sensitivity and (c) Specificity.

Table 4
Comparative discussion for comparative analysis.

Based on	Metrics	DCNN	BI-AT-GRU	XGBoost	Proposed JHBO-based DNFN
K-fold	Testing accuracy	0.9005	0.8806	0.8894	**0.9176**
	Sensitivity	0.8982	0.8816	0.8938	0.9207
	Specificity	0.9125	0.8926	0.9014	**0.9219**
Training data	Testing accuracy	0.8989	0.8865	0.8901	0.9151
	Sensitivity	0.9123	0.8868	0.9001	**0.9218**
	Specificity	0.902	0.8896	0.8932	0.9182

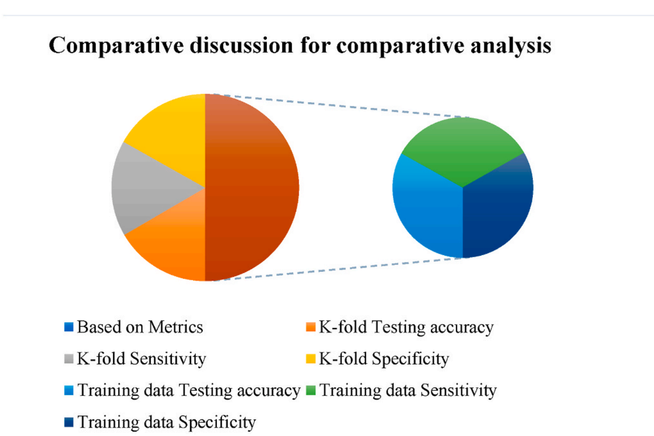


Fig. 8. Comparative discussion for comparative analysis.

4.6. Comparative techniques

The existing Covid-19 detection techniques, such as DCNN [2], BI-AT-GRU [4], and XGBoost [5] are considered for comparing the performance of developed approach. Moreover, several optimization methods, like Aquila Optimizer (AO) [28], SailFish Optimizer (SFO) [29], Horse herd Optimization (HHO) [30] algorithm, Jaya algorithm [12], HBA [10] and developed JHBO are considered with DNFN for algorithm analysis.

Table 5
Comparative discussion for algorithm analysis.

Metrics	Aquila + DNFN	SFO + DNFN	HOA + DNFN	Jaya + DNFN	HBA + DNFN	Proposed JHBO + DNFN
Testing accuracy	0.8823	0.8859	0.9021	0.8947	0.9110	0.9234
Sensitivity	0.8826	0.8959	0.9044	0.9081	0.9177	0.9265
Specificity	0.8854	0.8890	0.9032	0.8978	0.9141	0.9277

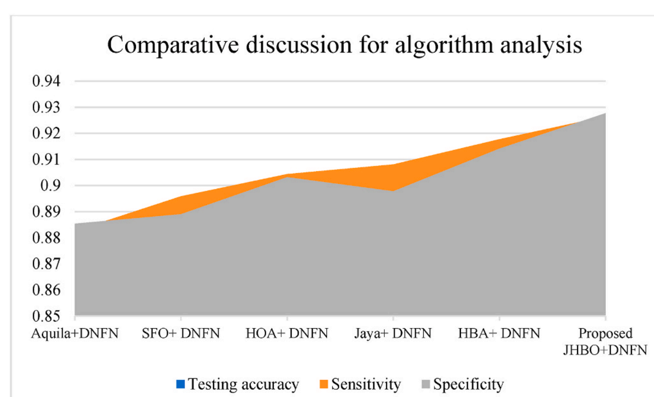


Fig. 9. Comparative discussion for algorithm analysis.

4.7. Comparative analysis

This section illustrates comparative analysis of devised JHBO driven DNFN using training data and k-fold value for various performance

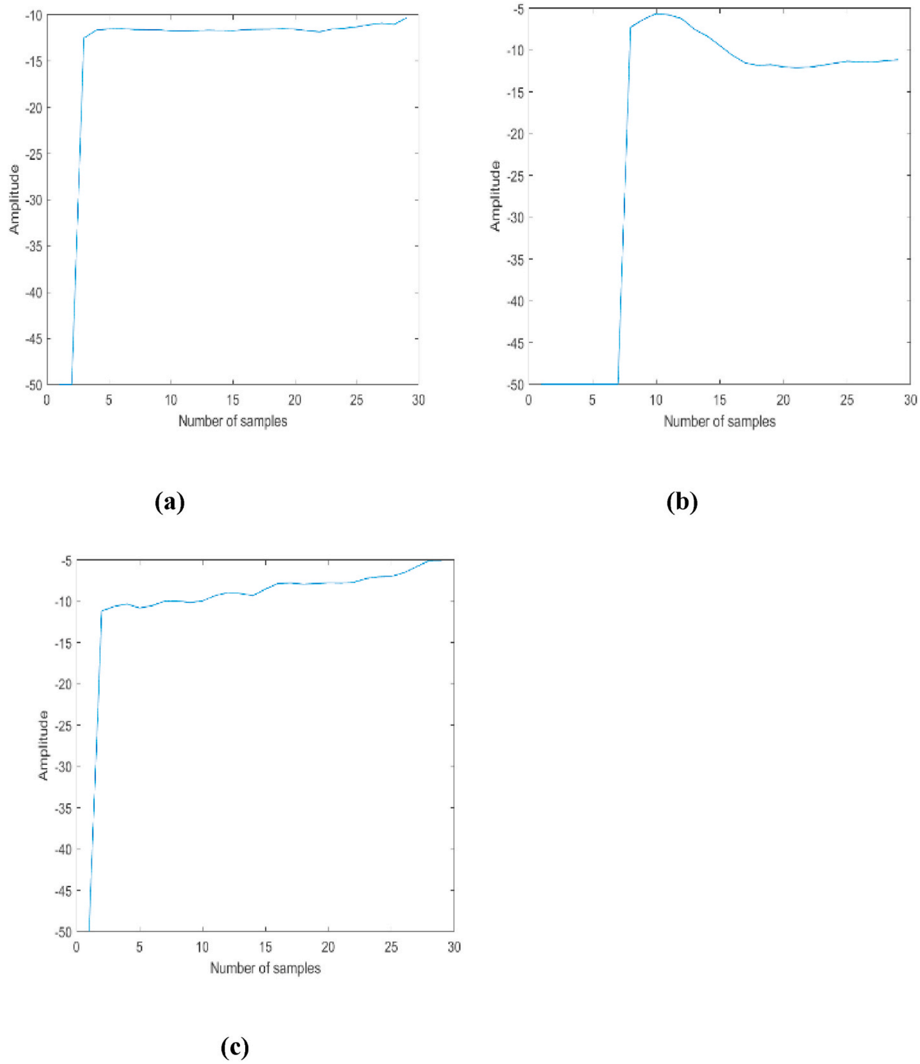


Fig. 10. “MKFCC for input signals during processing”.

metrics.

4.7.1. Comparative analysis using k-fold value

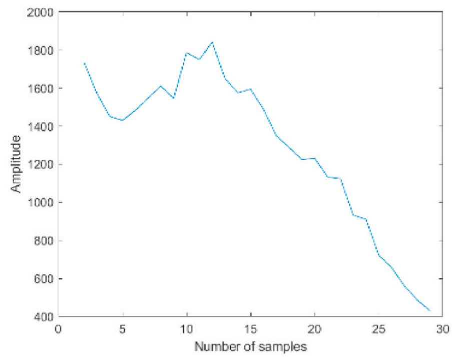
Fig. 5 represents comparative analysis of devised JHBO-based DNFN with performance metrics. The comparative analysis of introduced JHBO driven DNFN for testing accuracy by altering k-fold is exposed in Fig. 5 a). The testing accuracy of DCNN is 0.8925, BI-AT-GRU is 0.8725, and XGBoost is 0.887, while developed JHBO-based DNFN is 0.9054 in k-fold value 8. The performance improvement of designed JHBO-based DNFN is 1.42%, 3.63%, and 2.03%, while compared with existing techniques. Fig. 5 b) portrays the comparative analysis of JHBO-based DNFN for sensitivity with various k-fold value. The sensitivity of developed JHBO-based DNFN is 0.9085, whereas DCNN, BI-AT-GRU, and XGBoost is 0.8912, 0.878, and 0.8816 for k-fold value 8. The performance improvement of developed JHBO-based DNFN with DCNN is 1.90%, BI-AT-GRU is 3.35%, and XGBoost is 2.96%. Fig. 5 c) explicates comparative analysis of JHBO-based DNFN for specificity by changing k-fold. When the k-fold is 8, specificity of existing methods and developed JHBO-based DNFN is 0.9045, 0.8845, 0.899, and 0.9097. The performance improvement of introduced JHBO-based DNFN is 0.57%, 2.77%, and 1.17%, while compared with existing Covid-19 detection methods.

4.7.2. Comparative analysis by means of training data

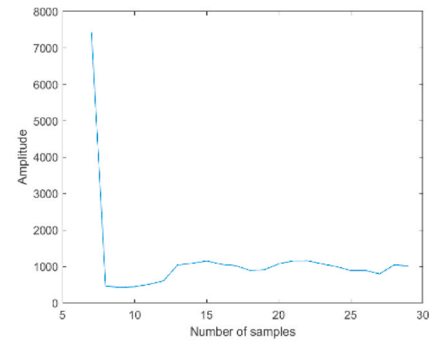
The analysis of introduced JHBO driven DNFN with various performance metrics is exposed in Fig. 6. Fig. 6 a) portrays analysis of JHBO-based DNFN for testing accuracy by altering training data. The testing accuracy of developed JHBO-based DNFN is 0.9071, whereas DCNN, BI-AT-GRU, and XGBoost is 0.8965, 0.8664, and 0.882 for 80% training data. The performance enhancement of designed JHBO-based DNFN with DCNN is 1.17%, BI-AT-GRU is 4.49%, and XGBoost is 2.77%. Fig. 6 b) represents analysis of devised JHBO-based DNFN for sensitivity by changing training data. When training data is 80%, sensitivity of existing approaches and developed JHBO-based DNFN is 0.9001, 0.8754, 0.8965, and 0.9148. The performance improvement of introduced JHBO-based DNFN is 1.61%, 4.31%, and 2%, while compared with existing Covid-19 detection methods. The analysis of devised JHBO-based DNFN for specificity by altering training data is exposed in Fig. 6 c). The specificity of DCNN is 0.8996, BI-AT-GRU is 0.8695, and XGBoost is 0.8851, while developed JHBO-based DNFN is 0.9102 in 80% of training data. The performance improvement of designed JHBO-based DNFN is 1.17%, 4.47%, and 2.76%, while compared with present schemes.

4.8. Algorithm analysis

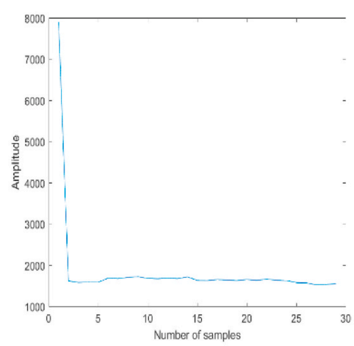
Fig. 7 denotes the algorithm analysis for devised JHBO-based DNFN with performance metrics by varying population size. The algorithm analysis of devised JHBO-based DNFN for testing accuracy with various



(a)



(b)



(c)

Fig. 11. "Spectral centroid for input signals".

population size is exposed in Fig. 7 a). The testing accuracy of Aquila + DNFN is 0.8622, SFO + DNFN is 0.8778, HOA + DNFN is 0.8815, Jaya + DNFN is 0.8923, and HBA + DNFN is 0.9030, while developed JHBO-based DNFN is 0.9098 in 80 population size. The performance improvement attained by devised approach is 5.22%, 3.51%, 3.11%, 1.91%, and 0.74%, while compared with existing algorithm analysis techniques. Fig. 7 b) reveals algorithm analysis of JHBO driven DNFN for sensitivity with different population size. The sensitivity of developed JHBO-based DNFN is 0.9265, whereas Aquila + DNFN, SFO + DNFN, HOA + DNFN, Jaya + DNFN, and HBA + DNFN is 0.8712, 0.8923, 0.8838, 0.8959, 0.9107, and 0.9189 for 80 population size. The performance improvement of developed JHBO-based DNFN is 5.18%, 2.88%, 3.81%, 2.49%, and 0.88% with other existing methods. Fig. 7 c) explicates algorithm analysis of JHBO-based DNFN for specificity by changing population size. When the population size is 80, specificity of Aquila + DNFN is 0.8653, SFO + DNFN is 0.8809, HOA + DNFN is 0.8826, Jaya + DNFN is 0.8954, HBA + DNFN is 0.9061 and developed JHBO-based DNFN is 0.9141. The performance improvement of introduced approach with Aquila + DNFN is 5.33%, SFO + DNFN is 3.62%, HOA + DNFN is 3.44%, Jaya + DNFN is 2.03%, HBA + DNFN is 0.87%.

4.9. Comparative discussion

This section explicates comparative discussion for comparative analysis and algorithm analysis with various performance metrics.

4.9.1. Comparative discussion for comparative analysis

Table 4 and Fig. 8 specifies comparative discussion of introduced JHBO driven DNFN based on training data and k-fold value for different performance metrics. The testing accuracy of developed JHBO-based DNFN is 0.9176, whereas DCNN, BI-AT-GRU, and XGBoost is 0.9005, 0.8806, and 0.8894 for k-fold value 9. The testing accuracy of developed Covid-19 detection approach is highly increased because of the hybrid optimization model. When k-fold value is 9, sensitivity of existing techniques and developed JHBO-based DNFN is 0.8982, 0.8816, 0.8938, and 0.9207. The sensitivity of developed approach is improved by means of gaussian filtering model. The specificity of DCNN is 0.9125, BI-AT-GRU is 0.8926, and XGBoost is 0.9014, while developed JHBO-based DNFN is 0.9219 in k-fold value 9. Due to the extraction of spectral features, the specificity of developed method is highly increased.

4.9.2. Comparative discussion for algorithm analysis

The comparative discussion of developed JHBO-based DNFN for various performance metrics is illustrated in Table 5 and Fig. 9. The testing accuracy of Aquila + DNFN is 0.8823, SFO + DNFN is 0.8859, HOA + DNFN is 0.9021, Jaya + DNFN is 0.8947, and HBA + DNFN is 0.9110, while developed JHBO-based DNFN is 0.9234 in 100 population size. The sensitivity of developed JHBO-based DNFN is 0.9265, whereas Aquila + DNFN, SFO + DNFN, HOA + DNFN, Jaya + DNFN, and HBA + DNFN is 0.8826, 0.8959, 0.9044, 0.9081, and 0.9177 for 100 population size. When the population size is 100, specificity of Aquila + DNFN is 0.8854, SFO + DNFN is 0.8890, HOA + DNFN is 0.9032, Jaya + DNFN is 0.8978, HBA + DNFN is 0.9141 and developed JHBO-based DNFN is 0.9277.

4.9.3. Investigational conclusions

Investigational conclusions of introduced Hybrid JHBO enabled DNFN for Covid-19 detection and Prediction are shown as in Fig. 10, Fig. 11, Fig. 12.

4.9.4. Convergence assessment

The convergence assessment of the developed technique for both testing and training phase for dataset 1 and dataset-2 are depicted in Fig. 13 given below.

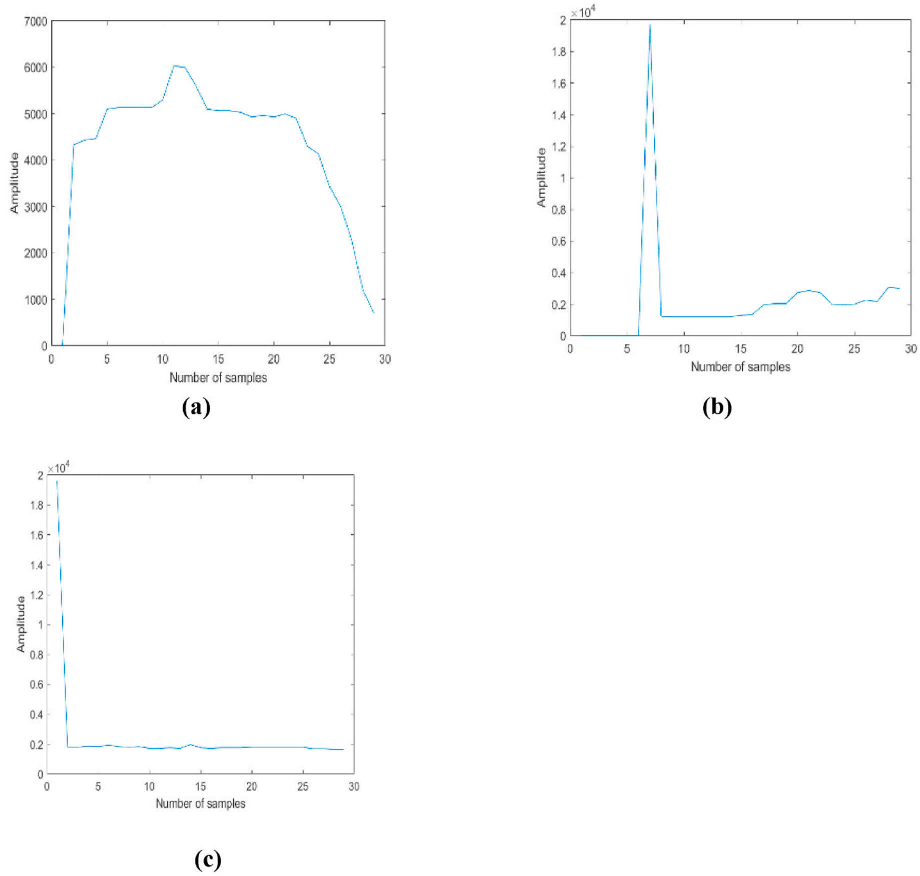


Fig. 12. "Spectral roll-off for input signals".

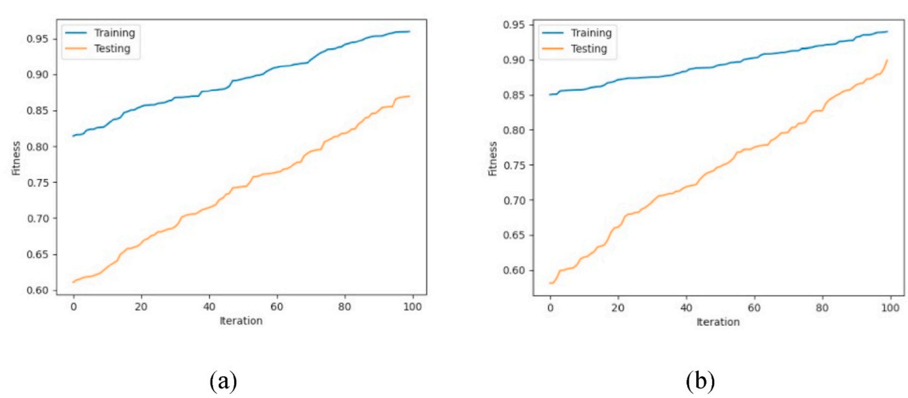


Fig. 13. Convergence analysis of proposed method with a) dataset-1 and b) dataset-2.

5. Conclusion

This paper explicates the Covid-19 detection approach using designed JHBO-based DNFN with audio sample. The input audio sample is acquired from a Coswara dataset and gaussian filter is applied. The gaussian filter effectively reduces the salt and pepper noise with minimal duration. Feature extraction process is most significant for precise detection of Covid-19, where spectral bandwidth, spectral roll off, Spectral flatness, MFCC, spectral centroid, root mean square energy, spectral contract, and zero crossing rate are extracted. The Deep learning approach is effectual for disease detection and classification process in medical field. Here, DNFN is utilized for detecting the Covid-19 disease. Moreover, DNFN is trained by developed JHBO approach for obtaining better performance. The Jaya algorithm is incorporated with HBA for obtaining improved performance with better convergence speed. The performance of DNFN is estimated with three performance metrics, namely specificity, testing accuracy and sensitivity. The proposed JHBO-based DNFN achieved improved performance testing accuracy, sensitivity and specificity of 0.9176, 0.9218 and 0.9219. The developed approach can be extended by including other hybrid optimization algorithms as well as other features can be extracted for further improving the detection performance.

Ethics approval and consent to participate

Approved by RDC of mansarovar Global University Madhya Pradesh India.

Consent for publication

Yes.

Data availability statement

Availability of data and materials.

In case of benchmark data:

The data underlying this article are available in Coswara-data taken from, "https://github.com/iiscleap/Coswara-Data".

In case of real data:

The data (Real database) underlying this article cannot be shared publicly due to the privacy.

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Authors' contributions

(a). Conception and design of study: all authors contributed
(b). acquisition of data: all authors contributed
(c). analysis and interpretation of data: all authors contributed
(d). drafting of manuscript: all authors contributed
(e). Approval of the version of the manuscript to be published: all authors consent

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.

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