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Jaya Honey Badger optimization-based deep neuro-fuzzy network structure for detection of (SARS-CoV) Covid-19 disease by using respiratory sound signals

Received 1 March 2022
Revised 18 March 2022
1 April 2022
22 April 2022
Accepted 28 April 2022

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Abstract

Purpose – The Covid-19 prediction process is more indispensable to handle the spread and death occurred rate because of Covid-19. However early and precise prediction of Covid-19 is more difficult because of different sizes and resolutions of input image. Thus these challenges and problems experienced by traditional Covid-19 detection methods are considered as major motivation to develop JHBO-based DNFN.

Design/methodology/approach – 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), 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 JHBO algorithm. Accordingly, the developed JHBO method is newly designed by incorporating Honey Badger optimization Algorithm (HBA) and Jaya algorithm.

Findings – The performance of proposed hybrid optimization-based deep learning algorithm is estimated by means of two performance metrics, namely testing accuracy, sensitivity and specificity of 0.9176, 0.9218 and 0.9219.

Research limitations/implications – The JHBO-based DNFN approach is developed for Covid-19 detection. 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.

Practical implications – The proposed Covid-19 detection method is useful in various applications, like medical and so on.

Originality/value – Developed JHBO-enabled DNFN for Covid-19 detection: An effective Covid-19 detection technique is introduced based on hybrid optimization–driven deep learning model. The DNFN is used for detecting Covid-19, which classifies the feature vector as Covid-19 or non-Covid-19. Moreover, the DNFN is trained by devised JHBO approach, which is introduced by combining HBA and Jaya algorithm.

Keywords Deep neuro fuzzy network, Covid-19 detection, Spectral centroid, Honey Badger optimization algorithm, Zero crossing rate

Paper type Research paper

1. Introduction

Covid-19 is respiratory disease, which is usually produced by Severe Acute Respiratory Syndrome Coronavirus-2 (SARS-CoV-2). Originally, 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 accounted 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,

International Journal of Intelligent Computing and Cybernetics

1756-378X
DOI 10.1108/IJICC-03-2022-0062

since no vaccines are available in medical area (Waheed *et al.*, 2020). The precise and fast detection of disease is progressively vibrant because 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, especially for patients offering early-onset of indicators (Tahamtan and Ardebili, 2020). 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 (Horry *et al.*, 2020).

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 (Lella and PJA, 2021). 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 (Brown *et al.*, 2020).

The deep learning approach is widely utilized in various domains (Achampetkar, 2021; Srinivas, 2020). 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. Various researchers normally designed classification methods, which adopts the general network structure in deep learning area without particular strategies for respiratory pattern classification (Manapure *et al.*, 2020). 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 depend on the exclusive audio features (Brown *et al.*, 2020). There has been various modern researches 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. 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, namely Support Vector Machine (SVM) and logistic regression schemes.

The analysis of pulmonary abnormalities may depend on the diagnostic experience and the medical skills of the physicians and is a time-consuming practice. 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's signals (Dar *et al.*, 2021a). The developed WCSO-based HAN obtained efficient performance using True Positive Rate (TPR), True Negative Rate (TNR) and accuracy with the values of 0.943, 0.913 and 0.923 using dataset 1, respectively (Dar *et al.*, 2021a). Also, an efficient Fractional Water Cycle Swarm Optimizer-based Deep Residual Network (Fr-WCSO-based DRN) is developed in another research for detecting the pulmonary abnormalities using respiratory sounds signals. In this research the proposed Fr-WCSO is newly designed by the incorporation of Fractional Calculus (FC) and Water Cycle Swarm Optimizer WCSO (Dar *et al.*, 2021b). Meanwhile, WCSO is the combination of Water Cycle Algorithm (WCA) with Competitive Swarm Optimizer (CSO). The developed method achieved superior performance by considering the evaluation measures, namely True Positive Rate (TPR), True Negative Rate (TNR) and testing accuracy with the values of 0.963, 0.932 and 0.948 (Dar *et al.*, 2021b).

Furthermore, these methods are effective for identifying Covid-19 from cough and breath sounds (Glangetas *et al.*, 2021; Lapteva *et al.*, 2021). Moreover, GSA and GA algorithms are embedded together by feeding the genetic operators into the GSA algorithm. For it, firstly GSA algorithm has been applied to find the solution of the problem and then during each epoch, the best solution is modified with the help of genetic operators to balance between the exploration and exploitation process (Garg, 2019). Furthermore, a new TLNNABC hybrid algorithm to solve reliability and engineering design optimization problems. In this algorithm, the structure of the artificial bee colony (ABC) algorithm has been improved by incorporating the features of the neural network algorithm (NNA) and teaching-learning based optimization (TLBO) (Kundu and Garg, 2022).

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) (Kumar *et al.*, 2018), spectral flatness, zero crossing rate, spectral centroid, mean square energy and spectral contract are extracted for further processing. Finally, DNFN (Javaid *et al.*, 2019) is applied for detecting Covid-19 and the deep leaning model is trained by designed JHBO algorithm. Accordingly, the developed JHBO method is newly designed by incorporating Honey Badger optimization algorithm (HBA) (Hashim *et al.*, 2022) and Jaya algorithm (Rao, 2016).

Research limitations: The JHBO-based DNFN approach is developed for Covid-19 detection. 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.

Practical implications: The proposed Covid-19 detection method is useful in various applications, like medical and so on.

The foremost contribution of this research is elucidated as below:

(1) *Developed JHBO-enabled DNFN for Covid-19 detection*: An effective Covid-19 detection technique is introduced based on hybrid optimization–driven deep learning model. The DNFN is used for detecting Covid-19, which classifies the feature vector as Covid-19 or non-Covid-19. Moreover, the DNFN is trained by devised JHBO approach, which is introduced by combining HBA and Jaya algorithm.

The residual section of this paper is ordered as follows: Section 2 deliberates literature survey of existing Covid-19 detection techniques with their limitations and benefits. The developed Covid-19 detection approach is specified in section 3. The results and discussion of introduced JHBO-based DNFN is shown in section 4, and section 5 elucidates conclusion of paper.

2. Motivation

The Covid-19 prediction process is more indispensable to handle the spread and death occurred rate because of Covid-19. However, early and precise prediction of Covid-19 is more difficult, because of different sizes and resolutions of input image. Thus, these challenges, and problems experienced by traditional Covid-19 detection methods are considered as major motivation to develop JHBO-based DNFN.

2.1 Literature survey

The traditional Covid-19 prediction techniques based on respiratory sounds are explicated as follows with advantages and limitations. Sharma *et al.*, (2020) 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 and Pja (2022) 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 *et al.* (2021) 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 *et al.* (2020) 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 *et al.* (2021) 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 *et al.* (2021) 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 *et al.* (2022) 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 *et al.* (2021) 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.

2.2 Challenges

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

(1) Most of non-contact monitoring approaches needs fixed, making it problematic to employ them in ambulances, which are practised to trembling in transportation.

Moreover, thermal imaging cameras do not afford precise measurements, while nose and mouth portions are not observable in an image.

(2) For detecting accurate measurements, Coswara model was developed in Sharma *et al.* (2020) for Covid-19 detection, but this Coswara data was not effective for classifying dissimilar health conditions with better accuracy.

(3) To improve the detection accuracy, DCNN is developed in Lella and Pja (2022) for Covid-19 detection. This approach effectively classifies the sound although this model failed to include infrequent regularization for better performance.

(4) For considering infrequent regularization, XGBoost classification approach was introduced in Purnomo *et al.* (2021), even though this model failed to analyse other classification techniques for improving detection performance.

(5) To enhance the detection performance, A RS-TENG was designed with facemask in Lu *et al.* (2022), which awards latter with respiratory monitoring model, even though when wearer respires deeply or shocks to mask directly, respiratory signal trigger over the threshold value, which affects detection performance (Lu *et al.*, 2022).

2.2.1 Structured definition's.

(1) Background/Introduction: The problem of respiratory sound categorization has attained more significant consideration from clinical scientists as well as medical researcher's community in previous recent years for detecting Covid-19 disease. However, it is more indispensable to detect the positive cases for reducing further spread of virus, and former treatment of affected patients.

(2) Purpose/hypothesis: The Covid-19 prediction process is more indispensable to handle the spread and death occurred rate because of Covid-19. However, early and precise prediction of Covid-19 is more difficult, because of different sizes and resolutions of input image. Thus, these challenges, and problems experienced by traditional Covid-19 detection methods are considered as major motivation to develop JHBO-based DNFN.

(3) Population/subjects/phantom/specimen/animal model (type and numbers): The database employed for detecting Covid-19 using designed JHBO-based DNFN is Coswara-data. The data is utilized for Covid-19 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) Field strength/sequence/design/methodology/approach/Methods: 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), 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 JHBO algorithm. Accordingly, the developed JHBO method is newly designed by incorporating HBA and Jaya algorithm.

(5) Objectives: To design and develop hybrid optimization-based deep learning technique for Covid-19 detection.

(6) Assessment: The implementation of developed Covid-19 detection approach using hybrid optimization-based deep learning is performed using Coswara dataset.

(7) Statistical tests: Statistical analysis is performed to analyse the performance of the proposed method based on testing accuracy, sensitivity and specificity.

(8) Results/Findings: The performance of proposed hybrid optimization-based deep learning algorithm is estimated by means of two performance metrics, namely testing accuracy, sensitivity and specificity of 0.9176, 0.9218 and 0.9219.

(9) Research limitations: The JHBO-based DNFN approach is developed for Covid-19 detection. 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.

(10) Practical implications: The proposed Covid-19 detection method is useful in various applications, like medical and so on.

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

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 artefacts 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 (Kumar *et al.*, 2018), spectral roll-off, mean square energy, spectral centroid, zero-crossing rate, spectral bandwidth and spectral flatness are extracted. Finally, classification is done using DNFN (Javaid *et al.*, 2019) wherein the training of DNFN is done using JHBO algorithm. The proposed JHBO algorithm is newly devised by combining Jaya algorithm (Rao, 2016) and HBA (Hashim *et al.*, 2022). The block diagram of Covid-19 detection model using designed JHBO-based DNFN is exposed in Figure 1.

3.1 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 rth records in a dataset, and it is used for further pre-processing stage.

3.2 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,

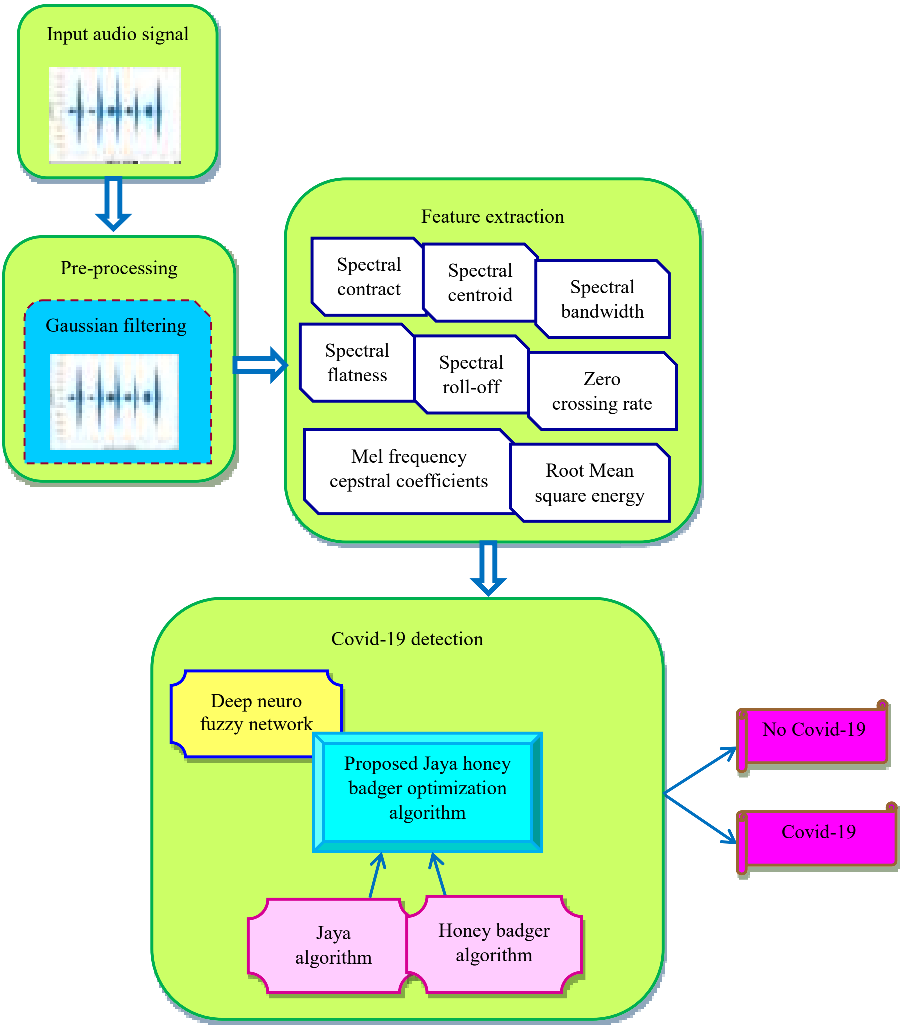

Figure 1.
Block diagram of devised Covid-19 detection process using hybrid optimization-based DNFN

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

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.

3.3 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 (Kumar *et al.*, 2018), spectral centroid, zero-crossing rate, spectral bandwidth, mean square energy and spectral flatness are extracted.

3.3.1 MFCC. MFCC (Kumar *et al.*, 2018) 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,

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

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

3.3.2 Spectral contract. Spectral contract (Jiang *et al.*, 2002) is represented as decibel difference amongst valleys and peaks in a spectrum, which is denoted as d_2.

3.3.3 Spectral roll-off. This feature is used for calculating spectral shape, like spectral centroid (Choudhury *et al.*, 2018). 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,

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

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.

3.3.4 Spectral centroid. Spectral centroid (Choudhury *et al.*, 2018) 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,

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

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.

3.3.5 Root mean square energy. This feature (Sandhya *et al.*, 2020) is referred as global energy of audio signal, which is estimated by,

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

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

3.3.6 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 (Sandhya *et al.*, 2020). The zero-crossing rate feature is denoted as d_6.

3.3.7 Spectral bandwidth. Spectral bandwidth (Xie, 2017) is utilized for signifying the difference among lower and upper cut-off frequencies, which is given by,

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

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

3.3.8 Spectral flatness. This feature (Sandhya *et al.*, 2020) 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 are combined together in order to generate feature vector, which is expressed as,

$$D_r = \{d_1, d_2, \ldots, d_8\} \tag{8}$$

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

3.4 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.

3.4.1 DNFN. The DNFN (Javaid *et al.*, 2019) 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 Figure 2.

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 are followed by output.

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

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

where d and m refer input to every ϖth 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,

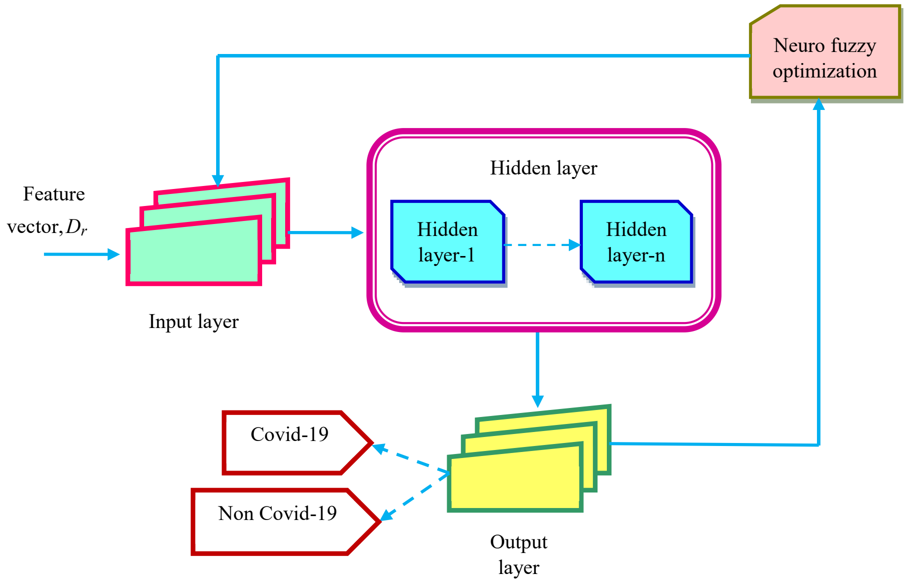

Figure 2.
Architecture of DNFN

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

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

(2) *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.

(3) *Normalization layer*: Here, each entity estimates the firing strength ratio of ϖth 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,

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

(4) *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,

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

where, X, L and F depict consequent parameter set.

(5) *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.

3.4.2 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 (Hashim *et al.*, 2022) with Jaya algorithm (Rao, 2016). 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,

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

$$R_r = P_r + w_1 \times (Q_r - P_r) \tag{15}$$

where R_r denotes rth 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.

3.4.2.2 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,

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

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

3.4.2.3 Defining intensity. Intensity is corresponding to concentration strength of prey as well as distance among rth 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,

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

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

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

$$v_r = R_{prey} - R_k \tag{19}$$

3.4.2.4 Update density factor. The density factor handles the time fluctuating randomization for ensuring smooth transition from exploitation to exploration. The density 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 number of iterations.

3.4.2.5 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.

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

(1) *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, $\varepsilon \geq 1$, 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,

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

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.

(2) *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,

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

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),

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

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

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

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

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

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

3.4.2.7 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.

3.4.2.8 Termination. The directly above steps are executed continually until greatest solution is achieved. The pseudo-code of introduced JHBO algorithm is specified in Table 1.

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.

S.No.	Pseudo-code of introduced JHBO algorithm
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

Table 1. Pseudo-code of introduced JHBO method

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. The goal is to create a dataset of sound samples from healthy and unhealthy individuals, including those identified as COVID-19. For sound data, we focus on nine different categories, namely, breathing (two kinds: shallow and deep), cough (two kinds: shallow and heavy), sustained vowel phonation (three kinds:/ey/as in made,/i/as in beet,/u:/as in cool) and one to twenty digits counting (two kinds: normal and fast paced). We also collect some metadata information, namely, age, gender, location (country, state/province), current health status (healthy/exposed/cured/infected) and the presence of co-morbidity (pre-existing medical conditions). No personally identifiable information is collected. The data is also anonymised during storage.

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 (Coswara-data taken from, 2022). The data is utilized for Covid-19 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.

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

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

(2) *Sensitivity*: Sensitivity is estimated to correctly categorise Covid-19 disease, and it is represented by,

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

(3) *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, ρ_f specifies true negative, σ_t is a false positive and σ_f denotes false negative.

4.4 Experimental results

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

4.5 Performance analysis

Figure 4 specifies the performance analysis of introduced JHBO-based DNFN based on various performance metrics by varying training data. Figure 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 Figure 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. Figure 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.

4.6 Comparative techniques

The existing Covid-19 detection techniques, such as DCNN (Lella and Pja, 2022), BI-AT-GRU (Wang *et al.*, 2020) and XGBoost (Purnomo *et al.*, 2021), are considered for comparing the performance of developed approach. Moreover, several optimization methods, like Aquila Optimizer (AO) (Abualigah *et al.*, 2021), SailFish Optimizer (SFO) (Shadravan *et al.*, 2019), Horse herd Optimization (HHO) (MiarNaeimi *et al.*, 2021) algorithm, Jaya algorithm (Rao, 2016), HBA (Hashim *et al.*, 2022) and developed JHBO are considered with DNFN 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 metrics.

4.7.1 Comparative analysis using k*-fold value.* Figure 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 Figure 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. Figure 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%. Figure 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 Figure 6. Figure 6(a) portrays analysis of JHBO-based DNFN for testing accuracy by altering training data. The testing

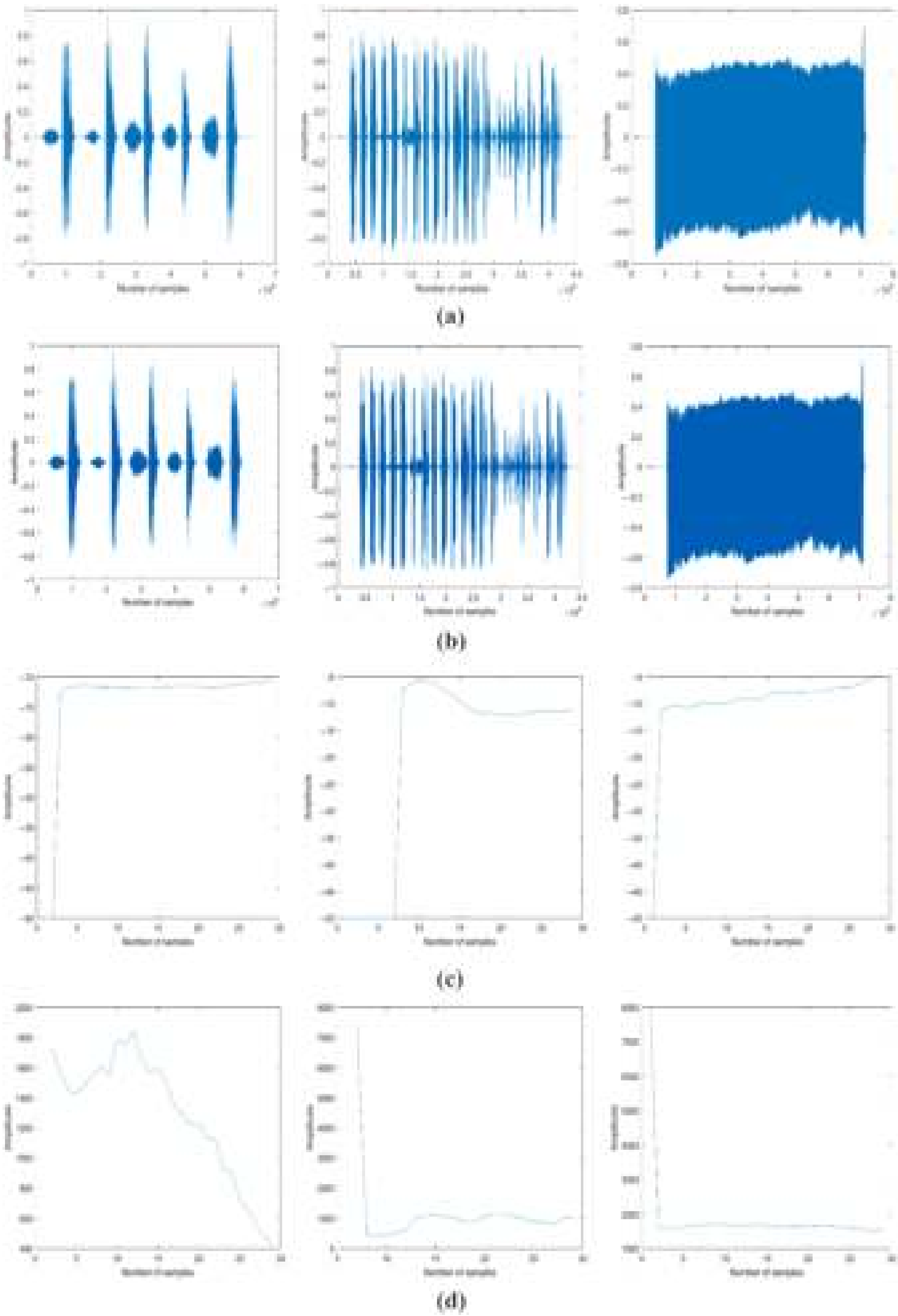

Figure 3.
Experimental results of developed Covid-19 detection method (a) input signal-1, 2 and 3, (b) pre-processing signal-1, 2 and 3, (c) MKFCC for signal-1, 2 and 3, (d) spectral centroid for signal-1, 2 and 3, (e) spectral flatness for signal-1, 2 and 3, (f) spectral roll-off for signal-1, 2 and 3

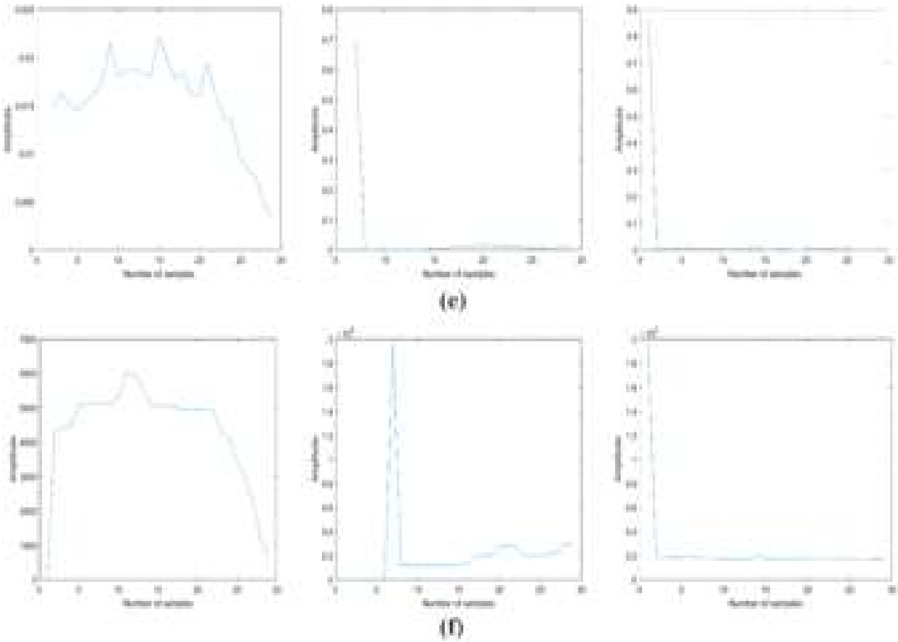

Figure 3.

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%. Figure 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 Figure 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

Figure 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 population size is exposed in Figure 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. Figure 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%

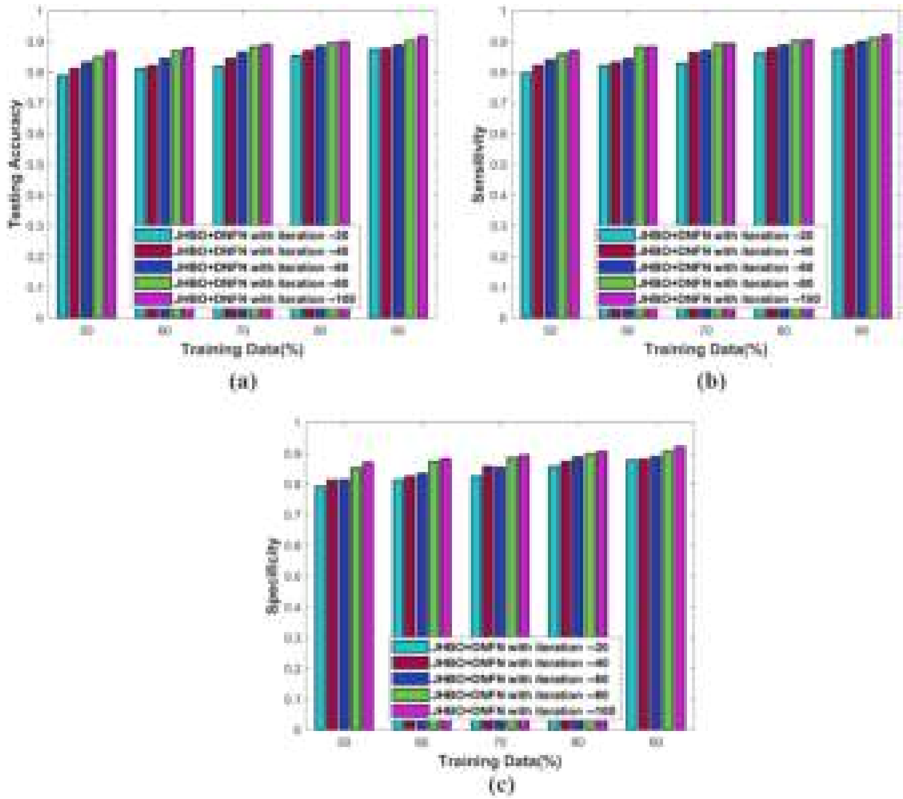

Figure 4.
Performance analysis of introduced JHBO-based DNFN (a) training accuracy, (b) sensitivity and (c) specificity

with other existing methods. Figure 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 2 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.

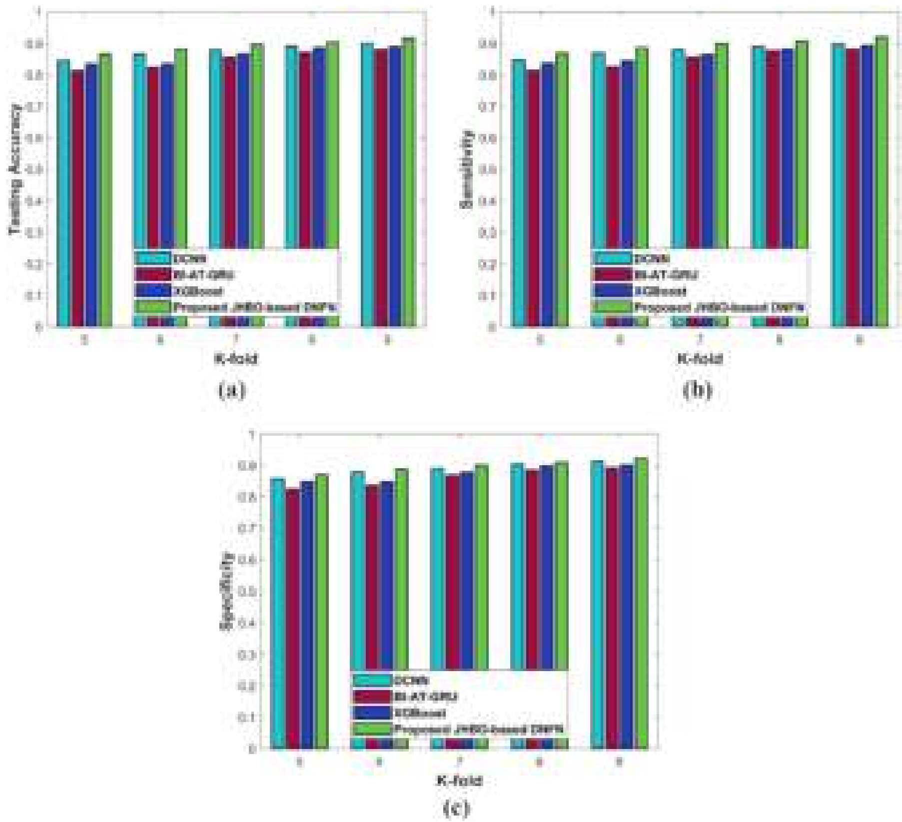

Figure 5. Comparative analysis of introduced JHBO-based DNFN with *k*-fold value (a) training accuracy, (b) sensitivity and (c) specificity

4.9.2 Comparative discussion for algorithm analysis. The comparative discussion of developed JHBO-based DNFN for various performance metrics is illustrated in Table 3. 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 The key highlights of the paper are as follows.

(1) The JHBO-based DNFN is introduced for Covid-19 prediction by audio signal.

(2) The pre-processing process is employed for eliminating the noises present in input sample. The extraction of unique features is done in developed Covid-19 detection model for obtaining better performance.

(3) Here, Covid-19 prediction is done using DNFN, and it is trained by developed JHBO algorithm.

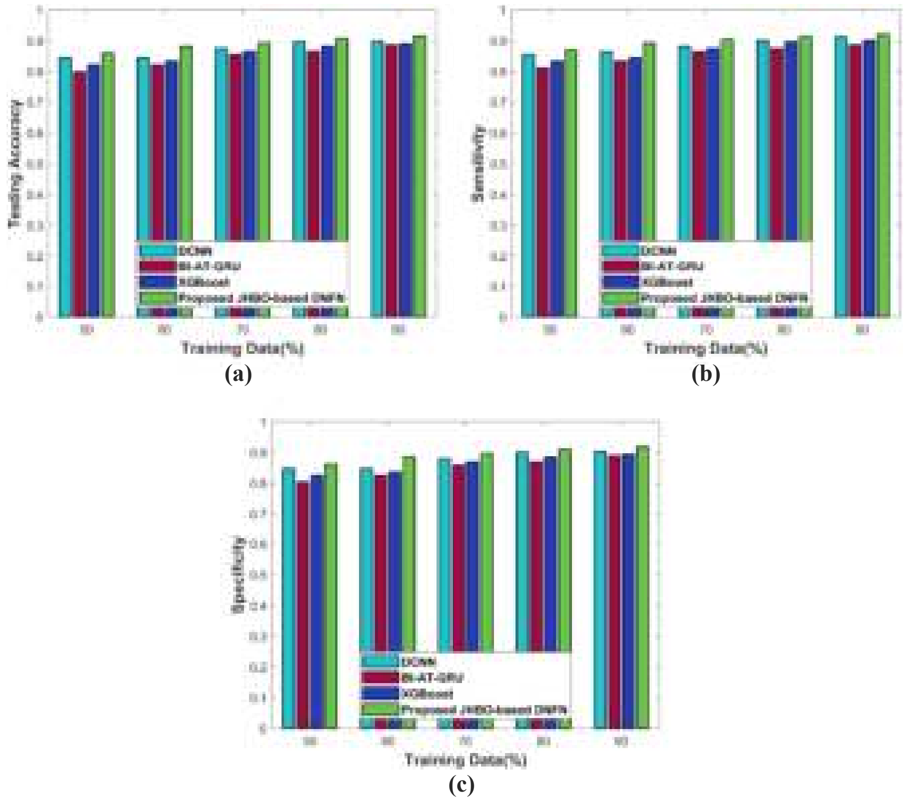

Figure 6.
Analysis of designed JHBO-based DNFN with training data (a) training accuracy, (b) sensitivity and (c) specificity

(4) The paper may gain high interest from the readers and experts of

- Deep neuro-fuzzy network
- Covid-19 detection
- Spectral centroid
- Honey Badger optimization algorithm
- Zero-crossing rate

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

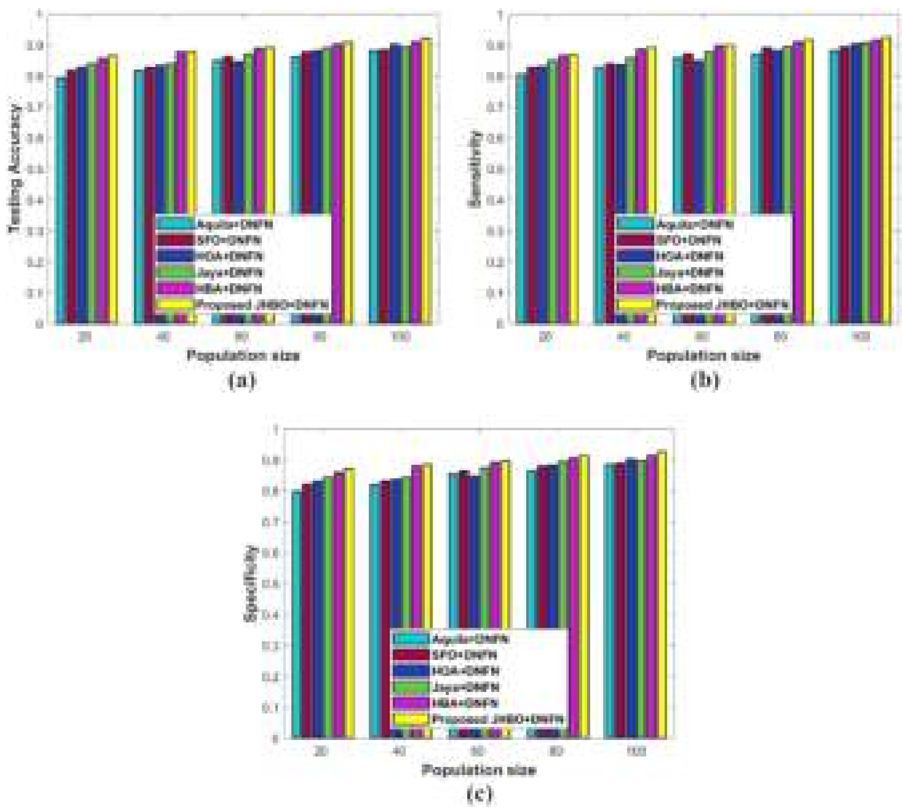

Figure 7. Algorithm analysis of designed JHBO-based DNFN (a) training accuracy, (b) sensitivity and (c) specificity

Table 2. 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*

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. Statistical analysis is performed to analyse the performance of the proposed method based on testing accuracy, sensitivity and specificity. Future work, 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.

Table 3.
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

Acknowledgments

The authors are obliged for the helpful comments by the Anonymous reviewers that helped us to improve the quality of the manuscript. All persons who have made substantial contributions to the work reported in the manuscript (e.g. technical help, writing and editing assistance, general support).

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 The datasets used and/or analysed during the current study are available as, *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 code of current model is available at https://github.com/Jawad-Dar/Jaya-Honey-Badger-Optimization-based-Deep-Neuro-Fuzzy-Network-structure-for-detection-of-Covid-19-.

Competing interests: No conflict of interest exists. We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

Authors' contributions: (1) Conception and design of study: all authors contributed, (2) Acquisition of data: all authors, contributed, (3) Analysis and interpretation of data: all authors contributed, (4) Drafting of manuscript: all authors contributed, (5) Approval of the version of the manuscript to be published: all authors consent

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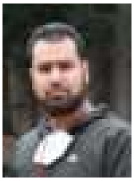

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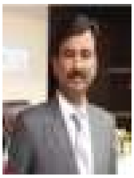

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