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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

Jawad Ahmad Dar a,*, Kamal Kr Srivastava a, Sajaad Ahmed Lone b

a Department of Computer Science and Engineering, Mansarovar Global University, Madhya Pradesh, India
b Department of Computer Science and Engineering, Islamic University of Science and Technology, Kashmir, India

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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

* Corresponding author.
E-mail addresses: jawad sirphysics@gmail.com (J.A. Dar), kamalsrivastava0001@gmail.com (K.K. Srivastava), sajaad.lone@islamicuniversity.edu.in (S. Ahmed Lone).

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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-contact 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 [24]. 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
Here, the audio signal is considered as input for detecting Covid-19. The abnormalities from the respiratory sound signals. However, the developed optimization technique named WCSO is devised by incorporating Empirical Mode Decomposition (EMD) for detecting the pulmonary infection with enhanced accuracy.

Table 1

| 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 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 movement 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 contrast are extracted for further processing. Finally, DNFN [11] is applied for detecting Covid-19 and the deep leaning model is trained by designed JHBO method. 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-channeled 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 trials, 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 anywhere, 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
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 degree of every parameter of DNN is premises and consequences in which premises are base of membership function in fuzzification layer, which is termed as occurrence level. Likewise, consequent is mostly classifier. Furthermore, output layer is also denoted as defuzzification layer. Fuzzy Interference System (FIS) for rule base evaluation and it is the outcome of each rule is formed function, which is assigned with maximal 1 and minimal 0 value, which is given by,

\[ \beta = \beta_{w}(X_{\omega}, m + F_{\omega}) \land \forall \omega = 1, 2 \]  

where, \( X \), \( Land \) \( F \) 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,

\[ N_{m} = \sum_{\omega} \beta_{w} \rightarrow N_{m} = \sum_{\omega} \beta_{w} / \sum_{\omega} \beta_{w} \]  

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,

\[ H = \{ S_{1}, S_{2}, ..., S_{r}, ..., S_{q} \} \]  

where, \( S_{q} \) denotes total amount of sound recordings, and \( S_{r} \) specifies \( m^{th} \) 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 smoother transition elimination of redundant data from audio sample. The Gaussian filter is specified as,

\[ B(S_{r}) = \frac{1}{\sqrt{2\pi\psi^{2}}} \exp \left( \frac{S_{r}^{2}}{2\psi^{2}} \right) \]  

where, \( \psi \) 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 ofcoefficients 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,

\[ N_{m} = \bar{p}_{w} = \bar{p}_{w}(X_{\omega}, m + F_{\omega}) \land \forall \omega = 1, 2 \]
\[ \mu_g = 2595 \log_{10}\left(1 + \frac{f}{700}\right) \]  
\[ \text{where, } g \text{ represents physical frequency in hertz, and } \mu_g \text{ implies perceived frequency. The MFCC feature is denoted as } d_i. \]

3.5.2. Spectral contrast

Spectral contrast [22] is represented as decibel difference amongst valleys and peaks in a spectrum, which is denoted as \( d_z \).

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:

\[ d_i = \frac{\sum_{j=1}^{K} |A_j(j)|}{k^2} \text{ with } (4) \]

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

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:

\[ d_i = \frac{\sum_{j=1}^{X} b(j)|n(b)|}{\sum_{b=0}^{X} |n(b)|} \text{ with } (5) \]

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

3.5.5. Root mean square energy

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

\[ d_i = \sqrt{\frac{1}{T} \sum_{t=1}^{T} U_t^2} \text{ with } (6) \]

where, \( U_t \) defines signal amplitude at \( t \)th amplitude, \( z \) symbolizes quantity of frames in sample length, and \( d_i \) 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 \( d_z \).

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:

\[ d_i = \sqrt{\frac{\sum_{m=1}^{z} (y(m) - d_i)^2 |y(m)|}{\sum_{m=0}^{z} |n(b)|}} \text{ with } (7) \]

where, \( d_i \) represents spectral centroid and spectral bandwidth is signified as \( d_i \).

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 \( d_s \).

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:

\[ R_t = P_t + w_1 \times (Q_t - P_t) \text{ with } (15) \]

where, \( R_t \) denotes \( T \)th honey badger location in total population, \( P_t \) refers lower bounds, \( Q_t \) 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 denoted as best solution for Covid-19 detection. The fitness function is estimated by:

\[ \delta = \frac{1}{T} \sum_{t=1}^{T} (G_t - G_s)^2 \text{ with } (16) \]

where, \( r \) indicates total amount of data, \( G_t \) specifies target output, \( G_s \) classified output from DNFN, and \( \delta \) denotes fitness function.

3.6.3. Defining intensity

Intensity is corresponding to concentration strength of prey as well as distance among \( i \)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,

\[ I_p = w_2 \times \frac{E}{4 \pi r^2} \text{ with } (17) \]

where, \( w_2 \) denotes random value amongst 0 and 1, \( E \) implies concentration strength, and \( v_i \) implies distance amongst \( i \)th honey badger and prey. Moreover, the term \( E \) and \( v_i \) is illustrated in following expression.

\[ E = (R_i - R_{i+1})^2 \text{ with } (18) \]

\[ v_i = R_{prey} - R_i \text{ with } (19) \]

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 $y_{max}$, $T$, $r$, and $E$ |
| 4     | Compute the fitness measure using equation (16) |
| 5     | while $y \leq y_{max}$ do |
| 6     | Update the decreasing factor $v$ 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 $f_{new} \leq f_r$ then |
| 16    | Set $R = R_{best}$ and $f_r = f_{new}$ |
| 17    | else |
| 18    | if $f_{new} \leq f_{prey}$ 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 DFNF structure effectively detects the Covid-19 disease with minimal time and error. In addition, developed JHBO scheme is employed for training process of DFNF in order increase the detection performance.

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

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

(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

$$R_{new}(1 - w_1 + w_2 + 1) = \left( R_{prey} + N \times w_3 \times 0 \times 0 + R_c \right)(1 - w_1 + w_2) + w_1R_{best} - w_2R_{worst}$$

(32)

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,

$$R_{new} = R_{prey} + N \times \epsilon \times r \times R_{prey} + N \times w_5 \times 0 \times 0 + w_5 \times \cos(2\pi w_5) \times [1 - \cos(2\pi w_5)]$$

(21)

where, $R_{prey}$ refers location of prey, $\epsilon \geq 1$, $w_5$, $w_4$ and $w_6$ are random number among 0 and 1. Moreover $N$ operates as flag, which varies search direction and it is identified by,

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

(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,

$$R_{new} = R_{prey} + N \times w_3 \times 0 \times 0 + w_5$$

(23)

The standard expression of Jaya algorithm is given by,

$$R_{i,tf} = R_{i,tf} + w_{ljf}(R_{i,best,f} - |R_{i,tf} - |R_{i,best,f}|)$$

(24)

Let assume, $R_{i,best,f}$ is positive, $R_{i,tf} = R_{new}$, $R_{i,best,f} = R_f$, $w_{ljf} = w_1$, $R_{i,best,f} = R_{best}$, $R_{i,worst} = R_{worst}$, $w_{ljf} = w_2$, thus above expression is re-written as,

$$R_{new} = R_f + w_1(R_{best} - R_f) - w_2(R_{worst} - R_f)$$

(25)

$$R_{new} = R_f(1 - w_1 + w_2) + w_1R_{best} - w_2R_{worst}$$

(26)

$$R_f = R_{new} - w_1R_{best} + w_2R_{worst}$$

(27)

Substitute $R_f$ on both sides in equation (23),

$$R_{new} - R_f = R_{prey} + N \times w_3 \times 0 \times 0 + w_5 - R_f$$

(28)

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

$$R_{new} - R_f = R_{prey} + N \times w_3 \times 0 \times 0 - \left( R_{new} - w_1R_{best} + w_2R_{worst} \right)$$

(29)

$$R_{new} = R_{prey} + N \times w_3 \times 0 \times 0 - \left( R_{new} - w_1R_{best} + w_2R_{worst} \right) + R_f$$

(30)

$$R_{new} + \frac{R_{new}}{1 - w_1 + w_2} = R_{prey} + N \times w_3 \times 0 \times 0 + w_1R_{best} - w_2R_{worst} + R_f$$

(31)

$$R_{new} = \frac{R_{prey} + N \times w_3 \times 0 \times 0 + R_f(1 - w_1 + w_2) + w_1R_{best} - w_2R_{worst}}{2 - w_1 + w_2}$$

(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.
4. Results and discussion

This section exposes results and discussion of devised JHBO driven DNFN for Covid-19 detection. Furthermore, experimental results, data-set 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,

\[ A = \frac{\rho_t + \rho_f}{\rho_t + \rho_f + \sigma_t + \sigma_f} \]  

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

\[ S_e = \frac{\rho_f}{\rho_f + \sigma_t} \]  

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

\[ S_p = \frac{\rho_t}{\rho_t + \sigma_f} \]  

where, \( \rho_t \) indicates true positive, \( \rho_f \) specifies true negative, \( \sigma_t \) 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
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.
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.

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. The results are summarized in Table 4 and Table 5.

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                   |

Table 5
Comparative discussion for algorithm analysis.

| Metrics       | Aquila + DNFN | SFO + DNFN | HHO + DNFN | Jaya + DNFN | HBA + DNFN | Proposed JHBO + DNFN |
|---------------|---------------|------------|------------|-------------|------------|-----------------------|
| K-fold 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. 7. Algorithm analysis of designed JHBO-based DNFN (a) Training accuracy, (b) Sensitivity and (c) Specificity.

Fig. 8. Comparative discussion for comparative analysis.

Fig. 9. Comparative discussion for algorithm analysis.
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 enhancement of designed 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, 0.8925, and XGBoost 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 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 a) portrays 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.
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, 0.8959, 0.9107, and 0.9189 for 80 population size. 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.
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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(b). Acquisition of data: all authors contributed
(c). Analysis and interpretation of data: all authors contributed
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Jawad ahmad dar (Graduate student, received B.Tech degree in CSE from IUST Kashmir and M.Tech degree in CSE from Kurukshetra University Kurukshetra india, he is currently pursuing the Ph.D. degree in engineering(CSE) from Mansarovar Global University (MGU) india.He has been involved in varying roles as a research analyst and an Assistant Pro- fessor. His current research interests include artificial intelligence, Machine Learning and Deep Learning), designing of cryptographic algorithms. Email Id: jawadhairphysics@gmail. com

Dr kamal Kr.Srivastava is working as a Professor in faculty of Computer Science and Engineering, Department in Mansarovar Global University Madhya Pradesh.He was also associate with Dr APJ abdul Kalam Technical University Uttar Pradesh. Dr kamal Kr.Srivastava received his Phd degree in field of computer science and Engineering for increasing the efficiency of cloud computing.He has also presented and published many papers at several reputed national and international conferences and journal. Dr kamal Kr. Srivastava is also Reviewer and member of many reputed journal and international conferences.His research activities are currently related with artificial Intelligence, Deep Learning and Machine Learning Email Id: 2007.srivastava@gmail.com

Dr Sajaad Ahmed Lone received the M.Tech in Information Technology from Guru Gobind Singh Indraprastha University New Delhi and PhD from National Institute of Technology, Srinagar Jammu and Kashmir India. His current research interests include Biometrics, Image Processing, Network Security. He has received numerous awards, including the young scientist award, throughout his academic journey. Email Id: sajaad.lone@islamicuniversity.edu.in