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SRC: Superior Robustness of COVID-19 Detection from Noisy Cough Data Using GFCC

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Abstract: This research is focused on a highly effective and untapped feature called gammatone frequency cepstral coefficients (GFCC) for the detection of COVID-19 by using the nature-inspired meta-heuristic algorithm of deer hunting optimization and artificial neural network (DHO-ANN). The noisy crowdsourced cough datasets were collected from the public domain. This research work claimed that the GFCC yielded better results in terms of COVID-19 detection as compared to the widely used Mel-frequency cepstral coefficient in noisy crowdsourced speech corpora. The proposed algorithm's performance for detecting COVID-19 disease is rigorously validated using statistical measures, F1 score, confusion matrix, specificity, and sensitivity parameters. Besides, it is found that the proposed algorithm using GFCC performs well in terms of detecting the COVID-19 disease from the noisy crowdsourced cough dataset, COUGHVID. Moreover, the proposed algorithm and undertaken feature parameters have improved the detection of COVID-19 by 5% compared to the existing methods.

Keywords: COVID-19; GFCC; DHO-ANN; cough data

1 Introduction

COVID-19 disease had spread like wildfire around the world after December 2019. This life-threatening COVID-19 disease was declared a global pandemic, and many researchers have carried out the detection of coronavirus from the infected people by using Artificial Intelligence (AI) based Machine Learning (ML) techniques [1–6]. In the current market, the reverse transcription polymerase chain reaction (RT-PCR) is a gold standard testing strategy for detecting the COVID-19 virus. However, RT-PCR processing is time-consuming and more expensive [7]. COVID-19 infected people have an array of symptoms such as fever, cough, shortness of breath, fatigue, body aches, headache, loss of test, loss of smell, sore throat, runny nose, congestion, vomiting, diarrhea etc. It has been reported by the World Health Organization (WHO) that 67.7% of COVID-19 patients have dry cough symptoms [8]. Recent researchers worldwide carry out dry cough symptom analysis to identify COVID-19 at the early stage of the coronavirus before the deadly virus becomes fatal [9]. The COVID-19 infection identification from cough data set using AI and ML paves the way to discover an affordable, simple, quick, and accurate mechanism.

Grant et al. [10] applied Mel-frequency cepstral coefficients (MFCCs), and Relative spectral-perceptual linear prediction (RASTA-PLP) features from the crowdsourced database with two different classification techniques, random forests (RF) and deep neural networks (DNN) to detect COVID-19 [8]. Using machine learning, Stasak et al. [11] used glottal, prosodic, spectral from short-duration speech segments for automatic COVID-19 classification. Dash et al. [12] improved the efficiency of COVID-19 detection by using the COVID-19 Coefficient (C-19CC). Sharma et al. [13] applied temporal and spectral acoustic features such as MFCCs (13-D), spectral roll-off, spectral centroid, mean square energy zero crossing rate, spectral bandwidth, etc., from respiratory sounds using random forest classifiers for point-of-care diagnosis of respiratory infection. Schuller et al. [14] used COMPARE acoustic feature set for the binary classification of COVID-19 infection.

Miranda et al. [15] used Short Time Fourier Transform (STFT), MFCC, Mel-filter Bank (MFB) using Deep Neural Network (DNN), convolutional Neural Network (CNN), and Long-Short Term Memory (LSTM) for acoustic cough detection. Monge-Alvarez et al. [16] applied local Hu moments Robust detection of audio-cough events with 88.51% sensitivity and 99.7% specificity in various noise conditions. Quatieri et al. [17] established a framework for vocal biomarkers of COVID-19 based on respiration, phonation, and articulation. Schuller et al. [18] provided an overview of the contribution towards the sars-cov-2 corona crisis using speech and sound analysis.

This proposed work emphasized on detection of COVID-19 in a noisy crowdsource cough dataset. Noise is an integral and unavoidable unit during the collection of crowdsource speech data for future usage in COVID-19 analysis through AI and ML techniques. However, the performance of the AI-based machine learning techniques reduces greatly in the presence of a noisy data set. The focus was on noise robustness speech features called Gammatone Cepstral Coefficients (GFCCs), which are untapped feature parameters for detecting COVID-19 infection. The untouched meta-heuristic-based machine learning algorithms were applied to detect COVID-19 infection using GFCCs feature vectors in the noisy public domain crowdsource cough dataset.

The research objectives are:

- To analyze the GFCC features to detect COVID-19 infection in a noisy cough dataset and compare the results with most features applied in COVID-19 detection.
- To apply different untouched metaheuristic algorithms for the detection of COVID-19 from noisy crowdsourced cough data and compare their performances.
- To propose a hybrid algorithm combining nature-inspired metaheuristic algorithms based on DHO and neural networks.
- To perform a rigorous validation of the proposed method and undertaken feature vectors.

The remaining manuscript is designed: Section 2 discusses the crowdsourced cough data set and feature parameters selection. Section 3 emphasizes nature-inspired meta-heuristic-based ANN. Section 4 analyses the findings of this research work, and Section 5 focuses on the conclusion and future work.

2 Crowdsourced Cough Data Set and Feature Parameter Selection

$\gamma_2(\mathrm{v_i}, \mathrm{v_j}) \leq \max\,[\gamma_1(\mathrm{v_i}), \gamma_1(\mathrm{v_j})]$ The publicly-available largest dataset of cough recordings, i.e., the COUGHVID crowdsourcing dataset, was used in this research work. The COUGHVID dataset was collected from different regions of the world. The COUGHVID dataset was recorded from Apr 1, 2020, in a Web application and deployed on a private server at the École Polytechnique Fédérale de Lausanne

(EPFL), Switzerland [19]. The quality of the COUGHVID dataset has been enhanced with clinically validated information by four expert physicians and provided publicly 2800 labeled cough data. The cough recordings are stored in WEBM or OGG formats with a sampling frequency of 48 kHz. COUGHVID crowdsource dataset also contained a text file in the .json extension for each cough recording. The description of each text file (.json) is shown in Fig. 1.

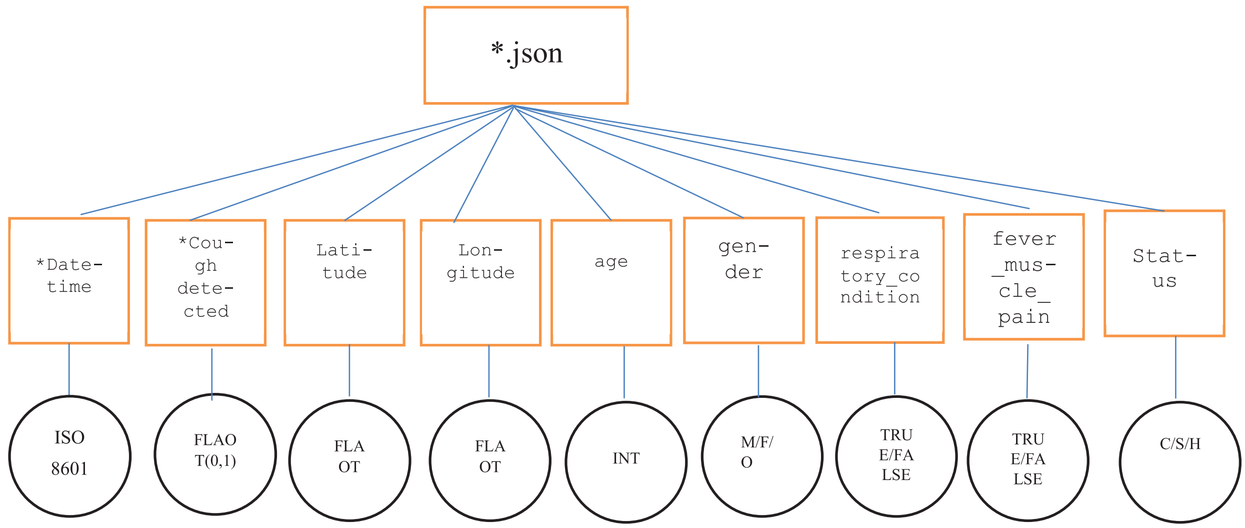

Figure 1: Description of each coughs dataset in COUGHVID crowdsource dataset

Each WEBM OR OGG file of the COUGHVID crowdsourced dataset was converted into WAV files, resampled into 16 kHz, and set into monotype. Figs. 2 and 3 describe the distribution of age and gender information found in the COUGHVID crowdsourcing dataset. It is found in the Fig. 3 that more male persons have participated than female candidates in COUGHVID crowdsourced dataset collection.

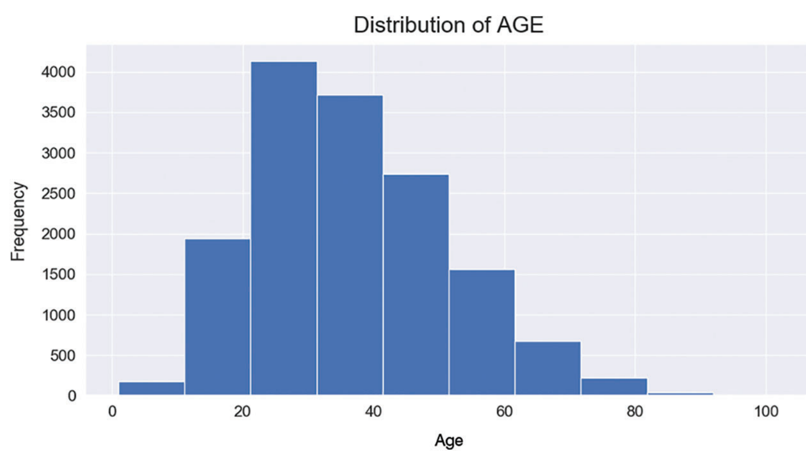

Figure 2: Distribution of ages in the COUGHVID crowdsourcing dataset

Feature extraction plays a crucial role in detecting COVID-19 infection from noisy cough data using AI-based machine learning techniques. It is found in a survey made by Deshpande et al. [20] that 50% of the total efforts made for COVID-19 infection detection are based on MFCCs as feature vectors. Furthermore, it is also observed by Bader et al. [21] that MFCCs from the speech are not reliable features for segregating COVID-19-infected individuals and healthy individuals. Therefore, it was emphasized on two crucial parameters during feature extraction from COUGHVID crowdsource cough dataset, i.e., first, the noise robustness feature vector as the undertaken problem is dependent on the public crowdsource dataset, and second, the feature vector should be highly correlated in nature. Consequently, Gammatone Frequency Cepstral Coefficients (GFCCs) were considered feature vectors during the extraction stage that will fulfill noise robustness and correlate to the objectives [22]. The detailed process of GFCC extraction from the COUGHVID crowdsource cough data set is as follows [23]. GFCC Extraction algorithm is listed below:

a) Pass each COUGHVID crowdsource cough sound as an input signal through a 64-channel gammatone filterbank.
b) At each channel, the filter response is rectified and decimated to 100 Hz as a way of time windowing. Absolute value is taken afterward, creating a variant of the cochleagram in terms of time-frequency (T-F) representation.
c) Apply the cubic root on the output of the previous step, i.e., T-F representation.
d) Finally, DCT is applied to derive the cepstral features.

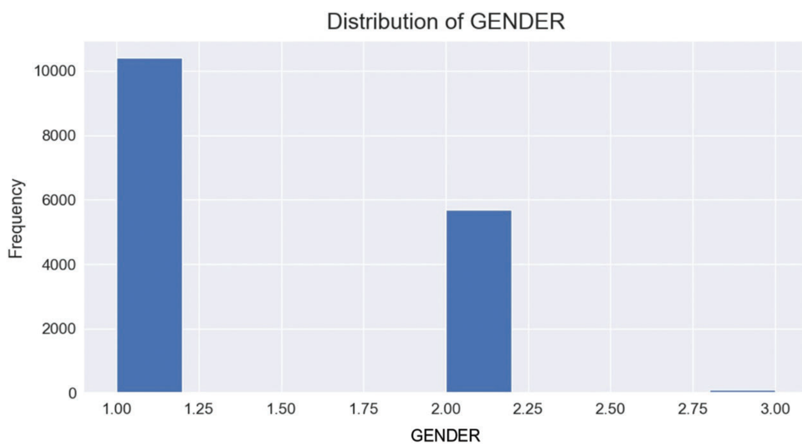

Figure 3: Male and female gender participants in the COUGHVID crowdsourcing dataset

The filter is defined in the time domain by using impulse response, h(t), as in Eq. (1):

$$h(t) = t^{a-1}\exp(-2\pi bt)\cos(2\pi f_c t + \varphi) \quad (1)$$

where a and b indicate the filter, t is time, f_c It is the filter's center frequency, and φ is the phase.

GFCCs are based on equivalent rectangular bandwidth (ERB) frequency scale and human data on ERB of the auditory filter with a function as in Eq. (2):

$$\mathrm{ERB}\,(f_c) = f_c/Q + B_0, \quad (2)$$

Glasburg et al. [24] suggested the following value to simulate auditory response of human hearers

B_0= 24 .7, Q = 9 .64498.

where B_0 is minimum bandwidth, and Q is the asymptotic filter quality at large frequencies [24–26].

3 Nature Inspired Meta-Heuristic-Based ANN

The main purpose of deer hunting, a nature-inspired meta-heuristic algorithm, is to find the optimal position for the hunters to attack the deer by studying the behavior of the deer [27]. Algorithm determines the first best solution as leader position, Hlead using fitness function and the Hlead, is treated as the first best position of the hunter and successor position, Hsuccessor, which is the position of the succeeding hunter [28–29]. The population of the hunter is represented as H1, H2, …. Hn.

Each individual in the population attempts to reach the goal point (best position) by updating the position in any random location within the space as the following Eqs. (3)–(5).

$$H_{i+1} = H^L - X * s * \left| L * H^L - H_i \right| \tag{3}$$

$$X = \frac{1}{4}\log\left(i + \frac{1}{i_{max}}\right)\mu \tag{4}$$

$$L = 2 * \epsilon \tag{5}$$

where i_{max} is the maximum iteration, μ is a parameter that has a value between −1 and 1, and ϵ is a random number within the interval [0, 1].

The search space of the hunter is enhanced by incorporating the visualization angle of deer for a highly effective attack on the prey as Eq. (6):

$$\alpha_i = \frac{\pi}{8} * r \tag{6}$$

The position angle, φ is updated by making the difference between the wind angle, ω and visual angle as Eq. (7):

$$\varphi_{i+1} = \varphi_i + d_i \tag{7}$$

where, $d_i = \omega_i - \alpha_i$

Now, the position is updated by using the position angle as Eq. (8):

$$H_{i+1} = H^L - s * \left| \cos(\varphi_{i+1}) * H^L - H_i \right| \tag{8}$$

The position is also updated on the successor position instead of the leader position as per the following Eq. (9):

$$H_{i+1} = H^S - X * s * \left| L * H^S - H_i \right| \tag{9}$$

The above equation is suitable for the vector L value greater than 1.

The algorithm for deer hunting optimization works as follows:

Algorithm 1:

Step 1: Initialization of the population of hunters:$\{H1,\ H2,\ \ldots.\ Hn\ \}$

  Initialize μ, ϵ, α_i, d, s, φ, ω, X, L

Step 2: Evaluate the fitness of each solution in the search space as:

  H^L: leader position, which is the first best position of the hunter

  H^S: successor position, which is the position of the succeeding hunter

Step 3: While (i < Max no of iteration)

   For each search agent

   Compute the fitness of each solution

   Update μ, ϵ, α_i, d, s, φ, ω, X, L

(Continued)

Algorithm 1: (continued)

if (s < 1)
  if (|L >= 1)
    Update the position of the individual using Eq. (3)
  Else
    Update the position of the individual using Eq. (8)
  End if
Else
  Update the position of the individual using Eq. (9)
End if
End for
  Compute the filter of each solution
  Update H^L and H^S
  i=i+1
End While
  Return H^L
DHO-ANN Crowd-source Cough Classifier

Now, it was focused on the blending of nature-inspired meta-heuristic DHO algorithm with neural network algorithm for better accuracy in COVID-19 detection instead of traditional approaches [30–31]

The values of weights and biases in artificial neural networks play a key role in the training phase of networks [32–35]. The performance of the artificial neural network is measured in terms of the average mean square error (MSE) as follows Eq. (10) [36–37].

$$MSE = \frac{1}{N}\sum_{1}^{N}\frac{1}{N}\sum_{1}^{M}\left(T_i^k - P_i^k\right)^2 \tag{10}$$

where "M" represents the number of outputs, "N" represents the number of training samples, and $T_i^k - P_i^k$ is the error between the target and predicted output of the i^{th} input unit when the k^{th} training sample is used. The lower value of MSE represents a better model.

The particle swarm optimization (PSO) technique is categorized in bio-inspired algorithms, which are used to search for an optimal solution in the solution space [38]. This algorithm aims to approximate the global optimum by observing all particles during the run. Another optimization technique is Multi-Verse Optimizer (MVO) [39]. The MVO algorithm is categorized into white, black, and wormholes. These three concepts are correspondingly known for performing exploration, exploitation, and local search. One more optimization algorithm we hybridized with ANN is Cuckoo Search (CS) meta-heuristic optimization algorithm [40]. The CS optimization algorithm is based on the brood parasitism of selected cuckoo species considering Levy flight's random walks.

DHO-ANN algorithm to detect the COVID-19 infection is shown in flowchart Fig. 4.

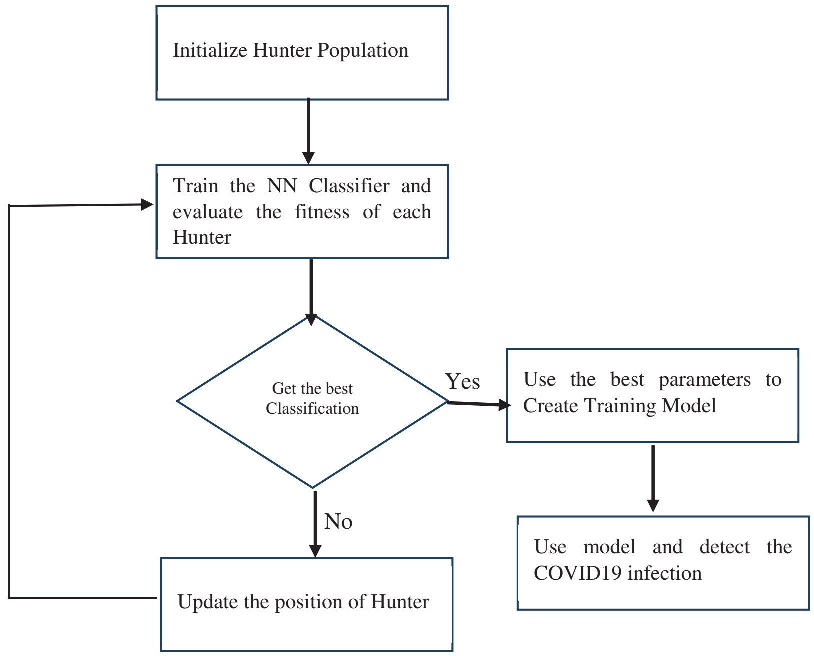

Figure 4: Flowchart of DHO-ANN algorithm to detect the COVID-19 infection

4 Application of HFG's Laplacian Energy in Decision-Making

DHO-ANN, nature-inspired algorithm is having dependent parameters and those parameters are set to values that can improve the performance of detection of COVID-19 infection in noisy crowd sourced cough data set. Moreover, the dependent parameters also play crucial role in the stability, convergence, and robustness of DHO-ANN algorithm.

The performance of modified ANN based on deer hunting optimization, a nature-inspired meta-heuristic algorithm in terms of statistical analysis, F1 score over widely used feature parameter, MFCC, and noise-robust feature parameters, GFCC. Further, the proposed approach was compared with other existing models. Table 1 represents the performance of DHO-ANN over MFCC features generated from COUGHVID crowdsource cough data. Table 2 represents the performance of DHO-ANN over GFCC features generated from COUGHVID crowdsource cough data.

Table 1: Performance of DHO-ANN and other models over MFCC features

Feature	MFCC			
Model	DHO-ANN	PSO-ANN	MVO-ANN	CS-ANN
F1 SCORE	0.80	0.66	0.56	0.46

Table 2: Performance of DHO-NN and other models over GFCC features

Feature	GFCC			
Model	DHO-ANN	PSO-ANN	MVO-ANN	CS-ANN
F1 SCORE	0.91	0.77	0.72	0.69

It is observed from Tables 1 and 2 that DHO-ANN performs comparatively better for other models and also found that DHO-ANN yielded pretty good performance in GFCC feature vectors as compared to MFCC feature vectors.

Further, the performance of the proposed algorithm is also analyzed over MFCC, and GFCC features in terms of confusion matrices are represented in Tables 3 and 4. It is found in Table 3 that the average accuracy of the proposed algorithm over MFCC features is 81.22%. The proposed algorithm yielded pretty better result over GFCC at 91.05 % as per Table 4.

Table 3: Confusion matrix representation of DHO-ANN using MFCC as features

PREDICTED → ACTUAL ↓	Negative	Positive
Negative (900)	TN = 736	FP = 164
Positive (810)	FN = 157	TP = 653

Table 4: Confusion matrix representation of DHO-ANN using GFCC as features

PREDICTED → ACTUAL ↓	Negative	Positive
Negative (900)	TN = 816	FP = 84
Positive (810)	FN = 69	TP = 741

The strength of undertaken cepstral coefficients was measured in MFCC and GFCC by using a statistical measure called correlation. The correlation graph of MFCC and GFCC is shown in Figs. 5 and 6, respectively.

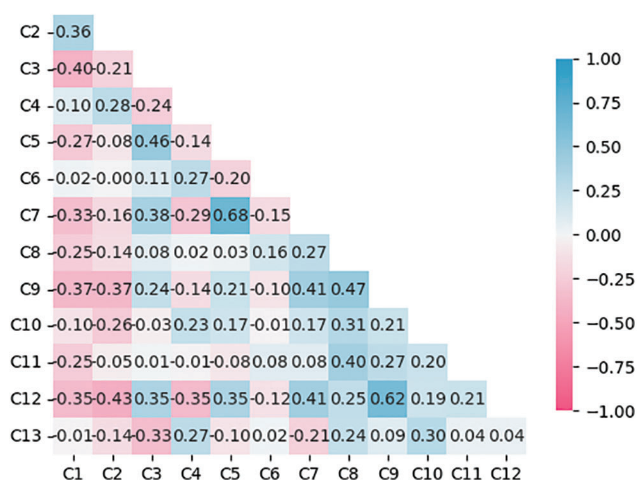

Figure 5: Correlation values over cepstral coefficients of MFCC in noisy crowd source cough data

It is observed from Figs. 5 and 6 that the cepstral coefficients of GFCC are high strength of the relationship as compared to MFCC.

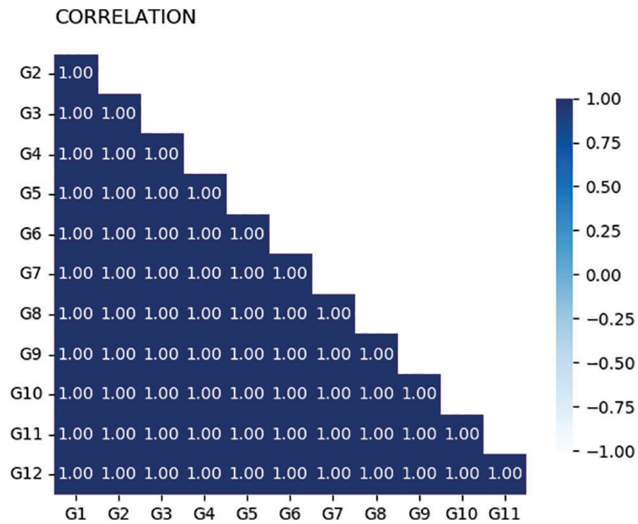

Figure 6: Correlation values over cepstral coefficients of GFCC in noisy crowdsource cough data

The DHO-ANN algorithm was tested over highly correlated GFCC features from the noisy cough dataset using different iteration ranges. It is observed that the DHO-ANN algorithm results in smoother convergences between 60 to 100 iteration value ranges, as shown in Fig. 7.

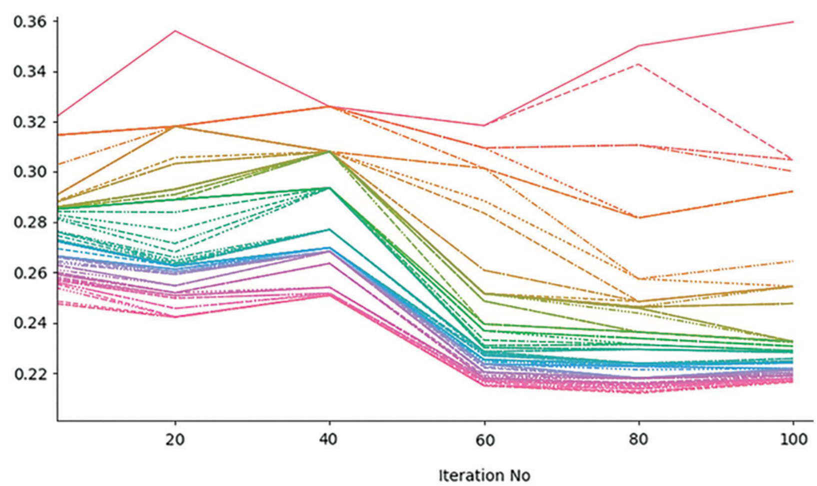

Figure 7: Smoother convergence of DHO-ANN algorithm

Fig. 8 represents DHO-ANN algorithm performance for detecting COVID-19 disease from noisy cough data in terms Area under Curve (AUC) of Receiver Characteristic Operator (ROC) using GFCC feature parameters.

Further, the evaluation explored the ability of DHO-ANN to detect COVID-19 from noisy cough data set in terms of specificity and sensitivity parameters over two different feature parameters shown in Table 5.

A comparison was made of the proposed algorithm for detecting COVID-19 with other existing models for the same purpose, shown in Table 6.

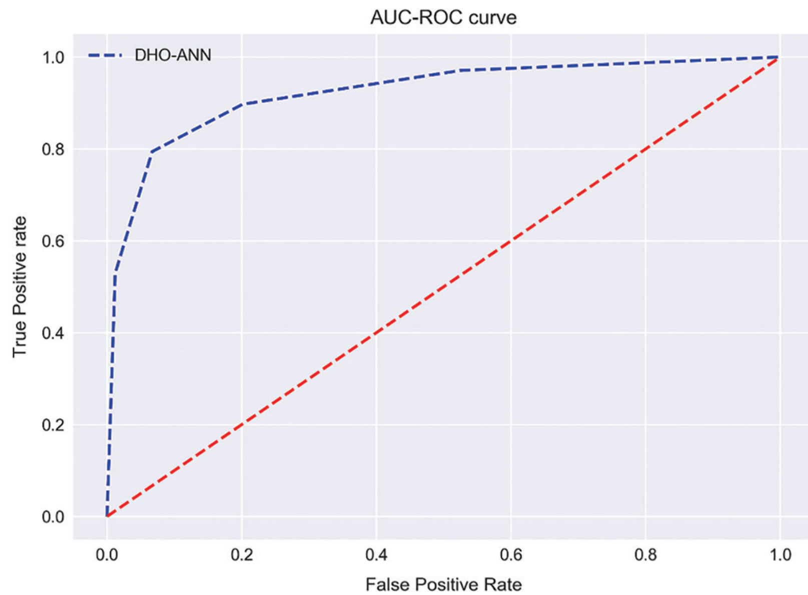

Figure 8: AUC-ROC of DHO-ANN algorithm

Table 5: DHO-ANN model ability test

Feature parameters	Specificity	Sensitivity
MFCC	0.82	0.81
GFCC	0.90	0.91

Table 6: AUC-ROC comparing the proposed method to other methods in the literature

Reference	Sound Type	Features	No. of features	Classifier	AUC-ROC (%)
Grant [8]	Cough	MFCC + Deltas	60	DNN	68.36
Stasak [9]	Vowel sound	Prosodic	6	Decision tree	80
Dash [10]	Cough	C-19CC	13	SVM	85.57
Sharma [11]	Heavy cough	Temporal and spectral acoustic features	9	Random forest	76
Proposed technique	Crowd source cough	GFCC	13	DHO-ANN	91

5 Conclusion

It is observed in this research work that GFCCs performed better results as compared to MFCCs feature parameters for detecting COVID-19 in noisy crowdsourced cough data. Furthermore, it was obvious from the experimental results that the GFCCs were highly correlated feature parameters for COVID-19 detection rather than MFCCs. The proposed algorithm, DHO-ANN, yielded better results than other Machine

Learning models such as PSO-ANN, MVO-ANN, and CS-ANN. Moreover, DHO-ANN performed comparatively superior by using GFCC features from noisy crowdsourced cough data set for the detection of COVID-19 and yielded 0.914 AUC-ROC values. It was found from the confusion matrix that the proposed algorithm yielded pretty better result over GFCC feature parameters as 91.05%. The proposed algorithm's performance for detecting COVID-19 disease was rigorously validated using statistical measures, F1 score, confusion matrix, specificity, and sensitivity parameters. The specificity and sensitivity of DHO-ANN algorithm were found as 0.90 and 0.91 respectively for detection of COVID-19 from noisy cough data set over GFCC feature parameters. Moreover, it was evident that the proposed algorithm using GFCC performed superiorly in detecting the COVID-19 disease from the noisy crowdsourced cough dataset, COUGHVID. The proposed technique with undertaken feature parameters improved the detection of COVID-19 by at least 5% compared to other existing methods and feature parameters. As a future work direction, the focus may be on the impact of GFCC on detecting the COVID-19 disease under the noisy crowdsourced cough dataset using the nature-inspired meta-heuristic based Deep Neural Network (DNN) and convolutional auto-encoder neural network.

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Conflicts of Interest: The authors declare they have no conflicts of interest to report regarding the present study.

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