Cough Sound Based COVID-19 Detection System Using Machine Learning Algorithms

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Abstract

Due to the nature of the COVID-19 pandemic, the need for early detection is essential for a rapid recovery and limiting the spread of the virus. Ordinary and traditional methods of diagnosing COVID-19 depend on contact which is susceptible to transmission of the virus, as any misuse of traditional methods can lead to the spreading of the epidemic, increasing its severity and may lead to death. However, since the better methods and techniques are always required for diagnosis, this study is aimed at presenting a contactless approach to distinguish COVID-19 infection from other similar symptoms infections based on the cough sound. COVID-19 detection system has been implemented by using machine learning techniques; the Mel Frequency Cepstral Coefficients (MFCC) algorithm for extracting features from audio signals and Multilayer Perceptron Neural Network (MLP) for classification. The system has been implemented by using a sample of data downloaded from online provided COUGHVID dataset. The model has considerably shown a high performance as it achieved 96%, 92%, and 100% for average accuracy, sensitivity and specificity respectively.

Keywords— COVID-19, Cough Sound, MFCC, MLP, speech recognition

I. INTRODUCTION

At the end of 2019, a new virus emerged in China, spread rapidly and affected the whole world. The virus has caused a huge crisis worldwide as it leads to severe infections and eventually death in humans. Three months later, the World Health Organization (WHO) has announced that the virus outbreak has occurred[1]. The disease which is commonly known as covid-19 has converted into a global pandemic affecting all people's lifestyles. The disease is highly contagious, so it spreads rapidly. Since the time when the covid-19 epidemic has begun, health care teams around the world have been working to follow up on it in terms of diagnosis and knowledge to suggest appropriate solutions[2]. In addition to the fact that most researchers and interested people set out in their scientific career through programs and studies, the aim of which is to discover the disease in early time. Therefore, this topic has been interested for researcher and study based on the need of understanding the covid-19 problem for finding appropriate solutions as soon as possible. It is worth mentioning that, although the pandemic level has notably decreased in the beginning of the current year 2022, the international website “worldmeter.com” indicates that the daily new infected cases are still considerably high [3] as depicted by Fig. **1**.

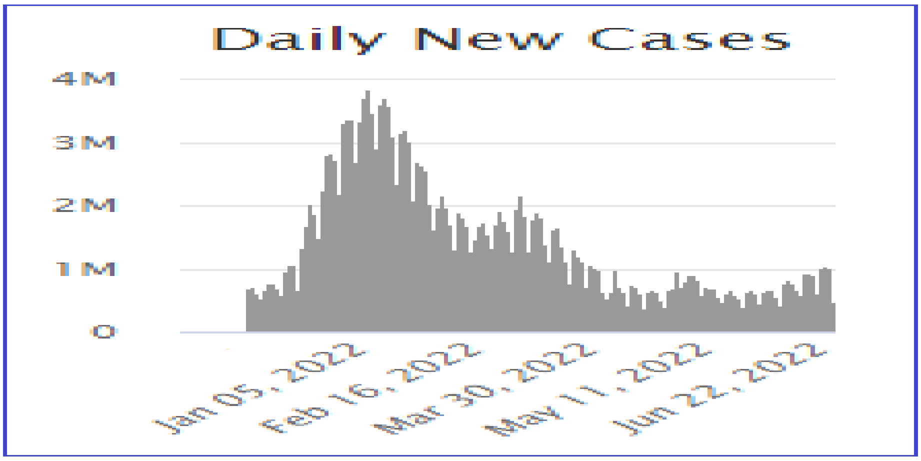

*Fig. 1: Daily new cases of COVID-19 in the world in 2022***.**

However, fever, cough and feeling tired are the most common symptoms of covid-19, in addition to shortness of breath, headache, and loss of sense of smell and taste, as these symptoms appear after a period ranging from two to fourteen days of infection with the virus[4]. Cough is one of the early recognizable symptoms of covid-19[5]. In fact, coughing is a sound, so it can be represented as a sound signal and thus can be investigated to help detecting the virus[4]. This study proposes an approach for detecting covid-19 based on cough sound analysis. That is, the system is designed to distinguish the cough of infected patients by covid-19 from the cough of those who are not infected with the virus.

The techniques of audio signal processing and machine learning algorithms are commonly used within the systems of voice recognition, speech synthesis, and speech/speaker recognition[4]. Therefore, they have been suggested to be applied on the cough sound signals for the purpose of infected patient detection. Generally, Speech recognition system consists of three stages; preprocessing, feature extraction, and classification as depicted in Fig. **2**.

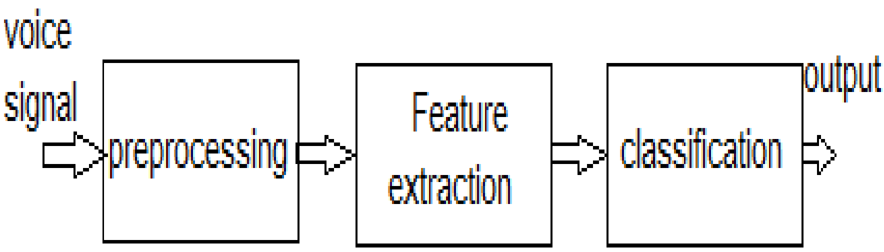

Fig. 2: General Speech recognition system

In voice and speech recognition systems, The Mel Frequency Cepstral Coefficients (MFCC) algorithm has shown a high performance for extracting features from sound signals[6], while Multi-Layer Perceptron (MLP) Neural Networks have been found as an effective method for classification[7]. Therefore, MFCC and MLP algorithms have been suggested to be used in this work for feature extraction and classification respectively.

II. RELATED WORK

The spread of covid-19 as an epidemic around the world pushes the researchers to show their interests and studies by discovering the disease at an early stage, and then they made their efforts to suggest advanced methods and techniques for discovering and diagnosing covid-19 based on the sound of coughing as it is one of the Early recognizable symptoms of covid-19. This section presents the relevant work that has been done for covid-19 detection based on cough sound.

In March 2021 K. Kumar et.al. in [8] reviewed the literature on COVID-19 diagnosis from respiratory sound data. They focused in their study mainly on how SARS-CoV-2 is spread and in-depth analysis of the diagnosis of COVID-19 from human respiratory sounds such as coughing, vocalization and breathing by analyzing respiratory sound parameters.

Paper [9] presented a study on COVID-19 Cough Analysis Using Automatic Speech Recognition System, in which they discussed cough changes in infected people based on a hidden Markov model (HMM) classification and analysis Speech recognition based on the formulation of cough sounds by exploiting spectrum technology. They have implemented an HMM-based cough recognition system with 5 HMM states, 8 Gaussian mixture distributions (GMMs) and 13 dimensions of Cepstral Fundamental Frequency Mel coefficients (MFCC) with 39 dimensions of the total feature vector. The overall accuracy of the cough recognition system was 93.33% for healthy coughs and 86.66% for COVID-19 cough sounds.

Tena et al. in [10] conducted a study for automated detection of COVID‑19 based on cough sounds. The have proposed an automated system for extracting features from time-frequency domain by using machine learning algorithms where they have used autoencoder and recursive features elimination (RFE) for features extraction and selection while they have used support vector machine (SVM) for classification. They have reported that their proposed model achieves a high performance with an average accuracy of 90%.

The paper [11] presented a study on identifying COVID-19 by using spectral analysis of cough recordings based on machine learning algorithms. They have used dataset of 16 individuals with suspected MERS-CoV infection with a particular patient demographic. In study, cough of patients infected by

COVID-19 could be distinguished from other coughs by applying effective feature extraction and classification techniques. The power spectrum density (PSD) was selected based on the Short Time Fourier transform (STFT) and Mel Frequency Cepstral coefficients (MFCC) as an effective feature extraction method and Support Vector Machine (SVM) algorithm for classification with accuracy of 95.86 and sensitivity of 91.7%.

Muzhir Shaban Al-Ani et al. in [4] presented a study on how to diagnose corona virus through patients' coughs. Accordingly, real samples were taken from people infected with the Corona virus and others who suffer from some respiratory diseases. The discrete wavelet transform is the adopted method to realize the detection process by approximation and analysis of the details of the coefficients. The obtained results show the acceptable detection accuracy of the studied samples.

In [2] researchers presented a study on detecting COVID-19 from non-COVID-19 patients by classifying just only a single cough sound. The study was able to distinguish the COVID-19 patients from the common cold or influenza patients by analyzing the sound of coughing via smart phones. A total of 328 cough sounds of four different types including COVID-19, asthma, bronchitis and healthy subjects were recorded from 150 people. The authors have used the MFCCs method for feature extraction stage and they have got average accuracy of 92.85%

III. COVID-19 DTECTION SYSTEM

This section describes an approach by using machine learning algorithms for designing a COVID-19 detection system based on patient coughing sound. The system has been adopted from speech recognition system[12] which illustrated by Fig. **2**. Patient cough is a sound signal that can be digitally acquired and recorded and generally it has the same characteristics of speech signal such as frequency and amplitude ranges [13]. Therefore, coughing signal features can be extracted with the same speech features extraction algorithms and then can be classified by common classifiers of speech.

A. Data set

Coughing sound data have been downloaded from publicly-available dataset called COUGHVID which has been collected by VIRUFY, the international non-profit organization and has been supported by several universities. The dataset were mainly collected for the purpose of building an international dataset of coughing sounds that can be used for detecting patterns of respiratory diseases, especially COVID-19. COUGHVID data is very accurate as it has been collected at a hospital and controlled by physicians. Data has also been labeled as positive COVID-19, negative COVID-19, along with other clinical information and metadata [14]. 4238 instances of the coughing sound data have been collected from 152 participants to be used in research. Among them, there are 80 participants were diagnosed with positive COVID-19. Data were divided into four participant groups; 65 positive COVID-19 for training, 15 positive for testing, 57 negative for training, and 15 negative for testing.

B. Data preprocessing

Coughing is a sound, so it can be recorded and represented as a sound signal and it is usually recorded in digital forms contaminated with environmental noises. Therefore, to obtain a noise-free signal, a filter is utilized for selecting only the desired frequencies and for removing noise frequencies and recordings that do not contain a cough signal, i.e. silent segments as depicted by Fig. 3 . Another issue worth mention is that data have been originally recorded at frequency sample 48000Hz and have been downsampled to 4.8 KHz.

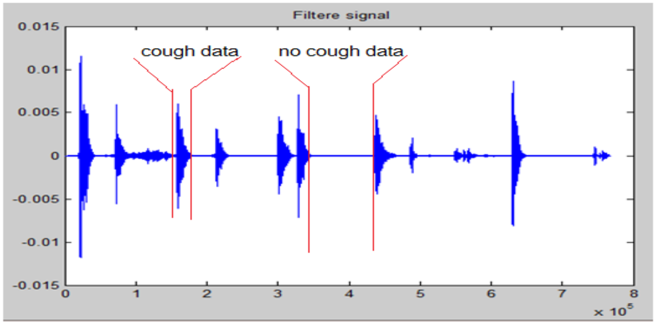

Fig. 3: cough signal including silent periods

C. Feature extraction

The second stage of recognition system is the feature extraction. There are several algorithms have been used for extracting features from signals. Mel Frequency Cepstral Coefficients (MFCC) in particular is frequently used with sound and voice signals. Therefore it has been suggested to be used in this work as it has shown high potential for extracting features from sound or voice signals. MFCC has been designed to perform the following steps as illustrated by Fig. **4**.

1- Frame blocking and windowing: coughing signal is a quasi-stationary signal. For best performance, cough signals have been analyzed in short time segments. 20 ms overlapped Hamming window technique has been applied for signal segmentation and thereby each segment has been analyzed as a stationary signal.

2- Fast Fourier transform: Discrete Fourier Transform (DFT) has been applied on each framing window to transform it from time domain into frequency domain in form of magnitude spectrum.

3- Mel-spectrum: The transformed signal for each segment is filtered by band-pass mel-frequency bank filter for computing the Mel-Spectrum. The mel scale utilizes the characteristics of human ears where it follows the linear frequency spacing below 1 kHz, and a logarithmic spacing above that[7].

4- Discrete Cosine Transform (DCT): DCT is applied to the transformed mel-frequency coefficients after representing it on a log scale to produce a set of cepstral coefficients. The system can be affective by extracting only the lower coefficients. Commonly, MFCC uses 13 cepstral coefficients but the zeroth coefficient is usually ignored

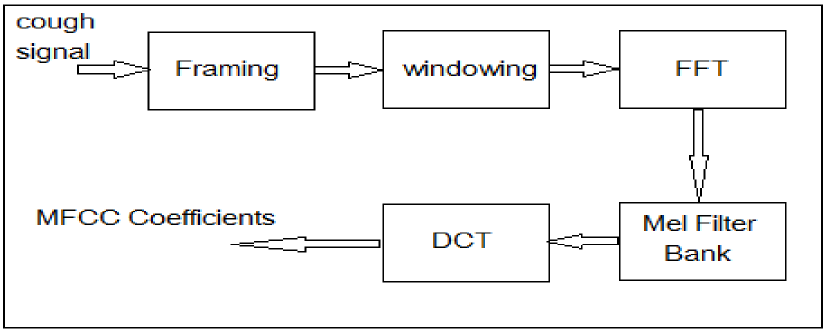

*Fig. 4: Mel Frequency Cepstral Coefficients components***.**

D. Coughing signal classification

Machine learning algorithms are frequently used for classifying voice and speech signals. Thus, a type of Artificial Neural Network; the Multi-Layer Perceptron (MLP) has been suggested to be used for classifying the patients cough sound in the proposed COVID-19 detection system. The used MLP classifier has a 12-neuron input layer, 20-neuron hidden layer, and one single-neuron output layer. It designed with 'tan-sigmoid' and 'purelin' activation functions for hidden and output layers respectively. The best training performance of MPL was 0.023 at epoch 9993. The results of the experiment are presented and discussed in details in the next section.

IV. RESULTS AND DISCUSSION

The output of the MLP classifier is a value ranged from -1 to +1 where the negative value indicates the negative infection of COVID-19 while the positive value indicates the positive infection of the virus. As a classifier, MLP has been given a set of instances from 122 patients for training and a set of instances from other 30 patients for testing. The 80 subjects who were diagnosed positively with COVID-19 infection have been divided into two groups; 65 for the training group and 15 of the test group. In the same manner, the rest subjects who were diagnosed negatively with COVID-19 have been divided into 57 for training group and 15 of the test group as presented by Table 1.

TABLE 1: DATA SAMPLE OF TRAINING AND TEST

Sample	Negative	Positive
Training (122)	1701 instances from 57 subjects	1560 instances from 65 subjects
Test (30)	390 instances from 15 subjects	587 instances from 15 subjects
Total (152)	2091 instances	2142 instances

System performance can be measured by the ability of classifying each instance whether it is correctly or wrongly classified. *Figure* ***5*** presents the results of classifying the positive status of 2 subjects from the same pool of data that were used in the training phase.

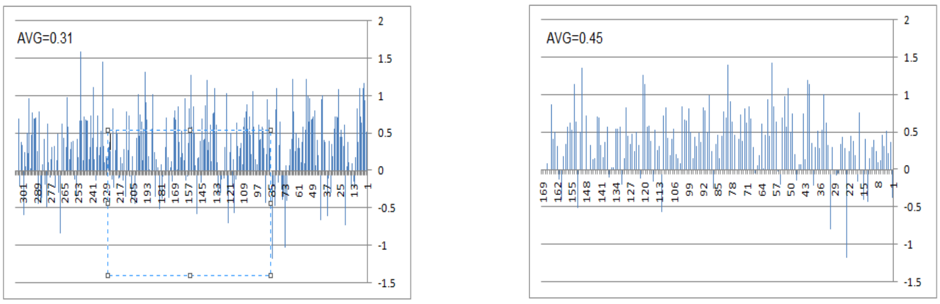

Figure 5: Classification result of positively infected subjects; S1 at left and S2 at right

Figure ***6*** presents the results of classifying the negative status of 2 subjects from the same pool of data that were used in the training phase.

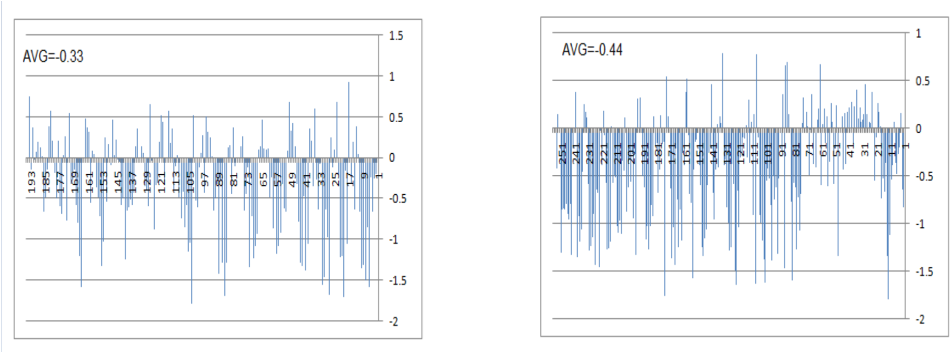

Figure 6: Classification result of negatively infected subjects; S1 at left and S2 at right

The final result of the subject classification can be calculated by taking the average of all instances for that subject. As it can be seen from the Figure 5, S1and S2 have been classified as positively infected with averages of +0.31 and +0.45 respectively, while it can be seen from Figure 6 that S1 and S2 from uninfected group have been classified as negatively infected with averages of -0.33 and -0.44 respectively.

The system performance is actually depends on the ability of the system on classifying data from outside training pool, which known as validation data. 977 instances from 15 infected and 15 uninfected subjects have been used for validation test. Figure 7 presents the classification results of 2 uninfected subjects while Figure 8 represents the classification results of 2 infected subjects.

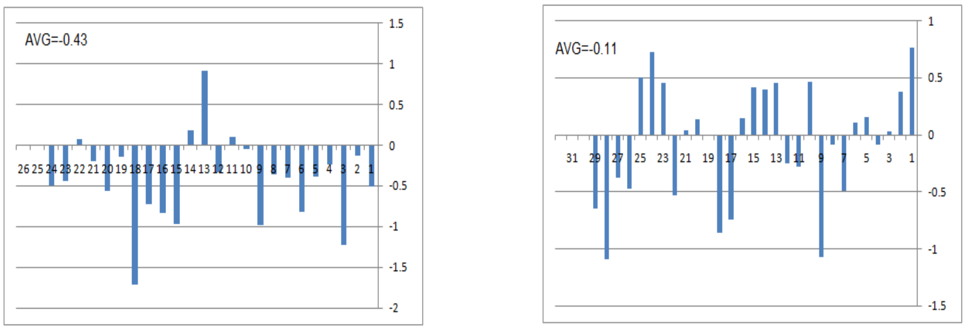

Figure 7: Classification result of negatively infected subjects; #S60 at left and #S61 at right

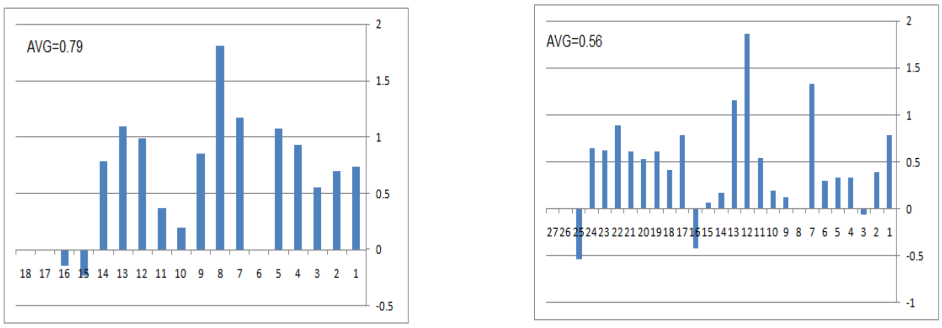

Figure 8: Classification result of positively infected subjects; #S70 at left and #S71 at right

Classification results of all 30 subjects of validation data are represented by Table 2: ***Classification results of all 30 subjects of validation data with their averages (Avg.)*** . The system was able to correctly classify positively infected data with accuracy of 100%, while it was able to correctly classify negatively infected data with accuracy of 93%.

Table 2: Classification results of all 30 subjects of validation data with their averages (Avg.)

S.#	Status	Predicted	Avg.	Subject number	status	predicted	Avg.
S66	POS	POS	0.20	S58	NEG	NEG	-0.04
S67	POS	POS	0.54	S59	NEG	POS	0.31
S68	POS	POS	0.22	S60	NEG	NEG	-0.43
S69	POS	POS	0.35	S61	NEG	NEG	-0.11
S70	POS	POS	0.79	S62	NEG	NEG	-0.19
S71	POS	POS	0.56	S63	NEG	NEG	-0.02
S72	POS	POS	0.43	S64	NEG	NEG	-0.01
S73	POS	POS	0.57	S65	NEG	NEG	-0.12
S74	POS	POS	1.02	S66	NEG	NEG	-0.39
S75	POS	POS	0.45	S67	NEG	NEG	-0.13
S76	POS	POS	0.54	S68	NEG	NEG	-0.22
S77	POS	POS	0.45	S69	NEG	NEG	-0.03
S78	POS	POS	0.66	S70	NEG	NEG	-0.12
S79	POS	POS	0.50	S71	NEG	NEG	-0.19
S80	POS	POS	0.40	S72	NEG	NEG	-0.13

The evaluation of the system performance can be carried out through the following parameters:

The accuracy: the Ratio of the correctly classified samples to the total number of samples and it can be calculated from the equation 1.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Sensitivity: the system ability to correctly classify the positively infected cough signal as positive from the total positive samples and it can be calculated from the equation 2.

$$Sensitifity = \frac{TP}{TP + FN} \quad (2)$$

Specificity: is the proportion of correctly classified negatively infected samples in relation to the total number of negatives and it can be calculated from the equation 3.

$$Specificity = \frac{TN}{TN + FP} \quad (3)$$

where P= Positive, N = Negative, TP = True Positive, FP =False Positive, TN = True Negative, and FN = False Negative. The accuracy, sensitivity, and specificity are illustrated by Table 3.

TABLE 3: THE SYSTEM ACCURACY, SENSITIVITY, AND SPECIFICITY

Parameters	Evaluation
Accuracy	97 %
Sensitivity	94%
Specificity	100%

Figure ***9*** shows our model's performance compared to other related work reviewed in this paper. The model average accuracy is the key of comparison. Even though, some work presents the accuracy of performance as well as the sensitivity, specificity, and F1 scoring. Some work shows also detailed accuracy such as [9], where the paper presents the accuracy of model for classifying positive cough as 93.33% while its accuracy for classifying negative accuracy was 86. For such models we have averaged the accuracy of both types.

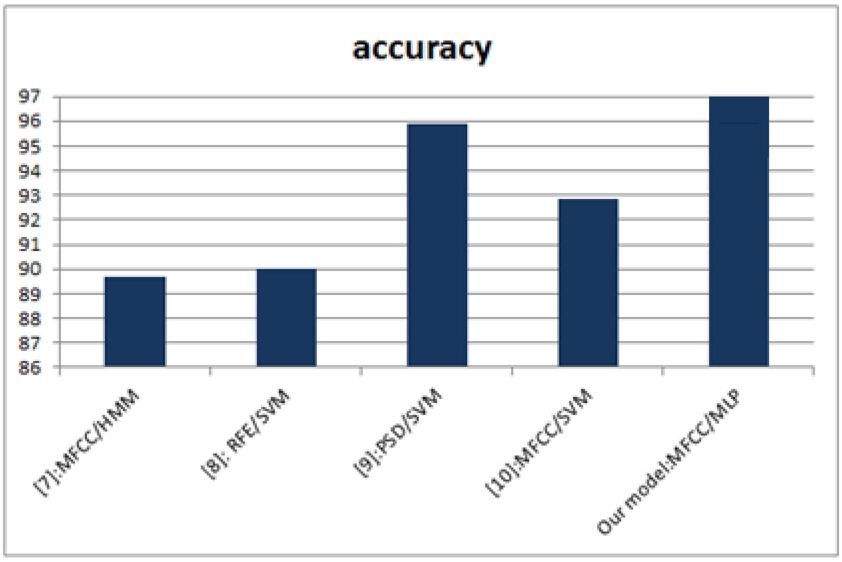

Figure 9: A comparison of our model to related work

V. CONCLUSION

This paper proposes a system for detecting and diagnosing people who are infected by covid-19 from those who are not based on cough sound analysis. Data of 152 (4238 instances) participants have been downloaded from online available COUGHVID dataset and have been used for the system design and test. The system manipulates the cough as a sound signal; thereby it has been built upon the idea of voice recognition system. It uses MFCC for extracting features from cough signal and uses MPL neural network to classify the signal to infected or non-infected. The system has shown a high performance with accuracy of 100% and 93% for detecting positive and negative cases of patients respectively.

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