Elderly Patient Monitoring System

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DECLARATION

I declare that this is my own work and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of our knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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The above candidate is carrying out research for the undergraduate Dissertation under my supervision.

Signature of the supervisor: Date:

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Mr. Yashas Mallawarachchi

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Table 1 List of Abbreviations

EPMS	Elderly Patient Monitoring System
GUI	Graphical User Interface
PC	Personal Computer
FFT	Fast Fourier Transformation
ANN	Artificial Neural Network
SVM	Server Vector Machines
IT	Information Technology

1 INTRODUCTION

Auscultation or the listening to the internal sounds using a stethoscope is an effective way of diagnosing the respiratory sounds and identify related diseases in the respiratory system such as Lung Diseases. But identification of respiratory sounds and separate them as normal and abnormal is not an easy task to perform as it requires a skill level of a well-trained physician. Trained physicians use stethoscopes to listen for changes in lung sounds to assess whether a patient has any obvious lung abnormalities. Despite many advances in medical equipment, the traditional analog stethoscope remains the main diagnostic tool used by physicians in lung auscultation. The purpose of this research component is to develop a system which can diagnose abnormal lung sounds along with severity level of respective lung sounds by using a modified stethoscope.

1.1 Background Context (Literature Survey)

1.1.1 Lung Sounds

Lung sounds can be divided roughly into normal and abnormal sounds. Normal breath sounds can be divided into bronchial, vesicular-bronchial, vesicular, and tracheal sounds, while abnormal breath sounds can be divided into crackles, rhonchi, and wheezes. Patients with lung disease have abnormal breath sounds, so abnormal breath sounds are an important component in the diagnosis of lung diseases. Different lung diseases cause different lung sounds. Pneumonia, chronic bronchitis, bronchiectasis, congestive heart failure, and obstructive pulmonary disease produce crackles. Obstructive pulmonary disease, asthma, and bronchial stenosis produce wheezes. Pneumonia, chronic bronchitis, and congestive heart failure produce rhonchi.

1.1.2 Machine Learning

Machine Learning allows computers to learn in order to achieve specific tasks without being programmed and it is evolving day by day. More information is fed in to existing algorithms to gain more accurate and the maximum outputs. There are so many applications of the Machine leaning techniques in various kinds of fields and the results are proven to be good. Many researches have been successfully implemented using machine learning in past few years and more researches are currently happening over the world. The development of computerized respiratory sound analysis has attracted many researchers in past years which has led to implementation of machine learning algorithms. Therefore respiratory sound analysis component of the EPMS has been implemented using machine learning.

Before beginning the design of the system, it is much required to conduct a literature survey to identify, analyze the existing solutions. This section will discuss related researches done in the same research area.

Mohammed Bahoura and Charles Pelletier have conducted a research to introduce a new parameter or an approach called cepstral analysis to classify respiratory sounds. The main objective of the research was to identify the wheeze sounds and the normal respiratory sounds of the patient. Mel-Frequency Cestrum Coefficient (MFCC) had been used to extract the features and Sound signal is divided in to segments and further will be characterized by a reduced number of cepstral coefficients. Classification method is Vector Quantification and two phases of the classification process was training and recognition of the respiratory sounds. In the training phase, an acoustical model (codebook) is constructed for each class of respiratory sound and the models are stored in a database. In the recognition phase, the unknown respiratory sound is analyzed and the best matching model is searched from the database. Higher classification rate was shown for the extracted features based on cepstral analysis but the researches have not done a comparison between other existing classification methods [1].

Rajkumar Palaniappan and K. Sundaraj have conducted a research on Respiratory Sound Classification using Cepstral Features and Support Vector Machine. Research is mainly based on distinguishing between normal, airway obstruction pathology and parenchymal pathology using respiratory sound recordings. Sound recordings had been gathered through RALE database which is having a respiratory sound database for research purposes. Preprocessing had been added to eliminate unwanted noises within the respiratory sounds. Mel frequency cepstral coefficient (MFCC) is used to extract the features in respiratory sounds with the normalization process. SVM one-against-one approach has been used to classify sounds and the MFCC feature vector feeds to the SVM classifier to distinguish normal, airway obstruction and parenchymal pathological condition. Confusion metrics is used to evaluate the performance of the algorithm. The mean classification accuracy has been shown as 90.77% which is very acceptable in respiratory sound analysis [2].

Group of researchers Khalid Badi-uz-zama, Abhishek Attal and Abhijit Verma presented a device capable of extracting, processing, displaying and storing sound data gathered from the patient's body with the help of chest piece diaphragm. Designed handheld device also has the capability of analyzing the sounds and give relevant warnings based on unhealthy situations of the patient. Raspberry pi single board computer is used to data collection, amplification and recording. Electronic noise made by the microphone and unwanted frequencies coming from outside has to be eliminated to amplify the captured sound. After the amplification, plotted signal can be displayed on the screen of the device in order to identify the pattern, frequency and the time differences between systolic and diastolic strokes. Fourier transformation function has been used to frequency matching as a technique along with some more techniques. None of the techniques are able to match the sample files with the data set. Sample dataset has been too small to compare the data set with the sample files. Research is mainly focused on identifying the anomalies in the heart sounds without considering about respiratory sound analysis. Device is feasible enough to for patients to get the warnings and doctors to identify the problem [3].

Sibghatuallah I. Khan, Naresh P. Jawarkar and Vasif Ahmed have investigated a research on Cell phone based Remote Early Detection of Respiratory Disorders for Rural Children using Modified Stethoscope. Lung sounds of children have been recorded at different chest locations by modified stethoscope and cell phone. Recorded lung sounds are sent to the relevant healthcare center for further analysis. The proposed method for lung sound analysis is based on MFCC analysis of lung sounds and classification using feed forward neural network using Error back propagation algorithm at the health care server. Results have been checked with two different set of features and accuracy rate of 92.5% have been shown. Proposed system need set of health workers, technical man power as well as volunteers to achieve the expected outcome [4].

A research paper presented by Achmad Rizal, Risanuri Hidayat and Hanung Adi Nugroho describe lung sound signal analysis using first order statistic texture analysis on the spectrogram. The spectrogram technique is used to convert the signal from time domain to time-frequency domain. Scaling process has been used to spread the value of the spectrogram to the range of 0-255 due to wide range of values in spectrogram. Texture analysis method is used by considering mean, variance, skewness, kurtosis, and entropy to extract the features properly. K- Nearest Neighbor method has been manipulated to classify the extracted features. Validation of the classification results are tested by three-fold validation method where data set is divides in to three parts. One data set is for testing data and other two data sets are for training module. Accuracy of 96.33 % has been achieved by the classification method after taking the average accuracy out of three. But the accuracy of the system is always depending on the parameters used by the spectrogram. Pre-processing techniques can be applied to increase the performance of the system [5].

R. Palaniappan, K. Sundaraj and C. K. Lam have proposed a method to classify respiratory pathology from breath sound signals. Data has been gathered as normal, wheeze, rhonchi, fine and coarse crackles. Pre-processing has been added to sample the breath sounds to 5 kHz range from 10 kHz original range. Breath sounds were filtered from noise and segmented into breath cycles followed by feature extraction. AR Coefficients and Mel Frequency Cepstral Coefficients (MFCC) features were extracted from breath sound cycles. Extracted features has been classified using SVM classifier. The SVM classifier was used to distinguish normal, wheeze, rhonchi, fine and coarse crackles. Reliability of the classification method has been evaluated using confusion matrix. The mean classification accuracy obtained using the proposed method was 88.72% and 89.68% for AR coefficients and MFCC features respectively. Since the number of features which was extracted is too high, feature reduction algorithm should be implemented to increase the rate of accuracy and reliability through high classification [6].

2 METHODOLOGY

2.1 Methodology

2.2 Testing and Implementation

2.2.1 Implementation

2.2.1.1 Preparation of data set

R.A.L.E. [7] repository along with a GitHub repository [8] were used to construct a proper dataset which was further separated in to Testing set and Training set. Dataset was divided in to four main classes; normal, wheezes, crackles and rhonchi. The sampling frequency of the acquired recordings was 11025 Hz.

2.2.1.2 Implementation of integrated stethoscope

A stethoscope and a condenser microphone are being used to directly capture the lung sounds of the patient. Y-shaped section of the stethoscope was removed and stethoscope head was integrated with the condenser microphone. Figure 1 shows the implementation of the stethoscope. Stethoscope collects the lung sounds and condenser microphone records the lung sounds which are transferred to the PC for further processing and analysis.

Figure 2.1 Modified Stethoscope

2.2.1.3 Filtration

Lung sounds used in this work were filtered with a band-pass filter to cover the major frequencies of lung sounds, 100 Hz and 2000 Hz cut-off frequencies, canceling out undesired frequencies such as those coming from heart sounds. Audacity software was used to compare the output signals with original signals of respiratory sounds. Wavelet technology is being used to de-noise the signal while preserving useful signals.

2.2.1.4 Feature extraction

Mel frequency cepstral coefficients are now being used as a highly effective algorithm in speech recognition. Furthermore promising results have been achieved by previous researches by applying MFCC to extract features in signal processing [9, 10]. MFCC is not highly robust with noise, but normalization process will eliminate the influence of noisy effects. Parameter capturing process of MFCC is started with framing. Framing is being performed to select sampling points of signal in order to observe signal characteristics. Energy of each frame will be calculated as the next step in MFCC. In the transferring process of the signal, high frequencies can be attenuated. Pre-emphasis method is utilized to reimburse the high frequencies by applying a high pass filter. Hamming window with overlapped is in use to prevent sudden changes of the signal. Triangular band pass filter is needed to calculate Mel frequency cepstral coefficients from the Fast Fourier Transform coefficients. Linear frequency can be converted to Mel- frequency by applying following equation.

$$Mel(f) = 2595 \log_{10}(1 + \frac{f}{700})$$

2.2.1.5 Classification

Classification is the next process follows after feature extraction. Classification is completely based on the representation of the extracted features. Artificial Neural Networks are used as classification method to achieve higher accuracy rate. ANN gives high performance for any given features, but requires fully optimized features for classification. Feed forward neural network was used as input layer was a matrix with size 1 x 39. There were 3 hidden layers and neuron of each are 13, 11 and 13. 80% of the dataset is used in the training phase while remaining as the test and validation data set.

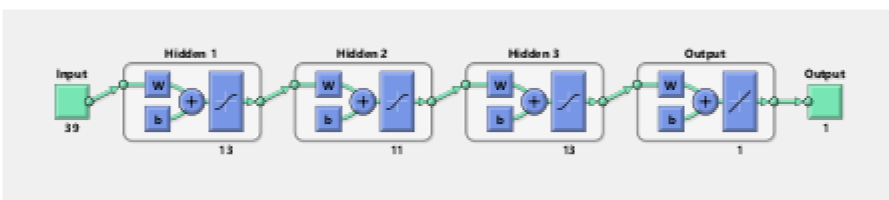

Figure 2.2 The structure of the neural network back-propagation used in this study

Immediately after the classification, lung sounds will be graded according to the health condition of the patient such as Good, Warning, Bad or Serious. Grading will be based on classification and segmentation. Sound frame will be segmented in to 10 frames and it will be categorized as normal and abnormal. Normal lung sounds are stated as 0 while 1 is assigned for abnormal lung sound. Proportion of the abnormal lung sounds in the recording will be taken in to a percentage. According to the percentage level, severity of the patient will be displayed in the system.

2.2.1.6 Design of the built system

Figure 3 shows the GUI for the Lung sound analysis system. Lung Sound Signal part of the GUI displays the lung sound waveform. Right side of the GUI will be used to record and analyze the lung sound in real time. Recorded lung sounds can also be evaluated using the right part of the GUI. Bottom part of the GUI contains the classification results of the lung sound.

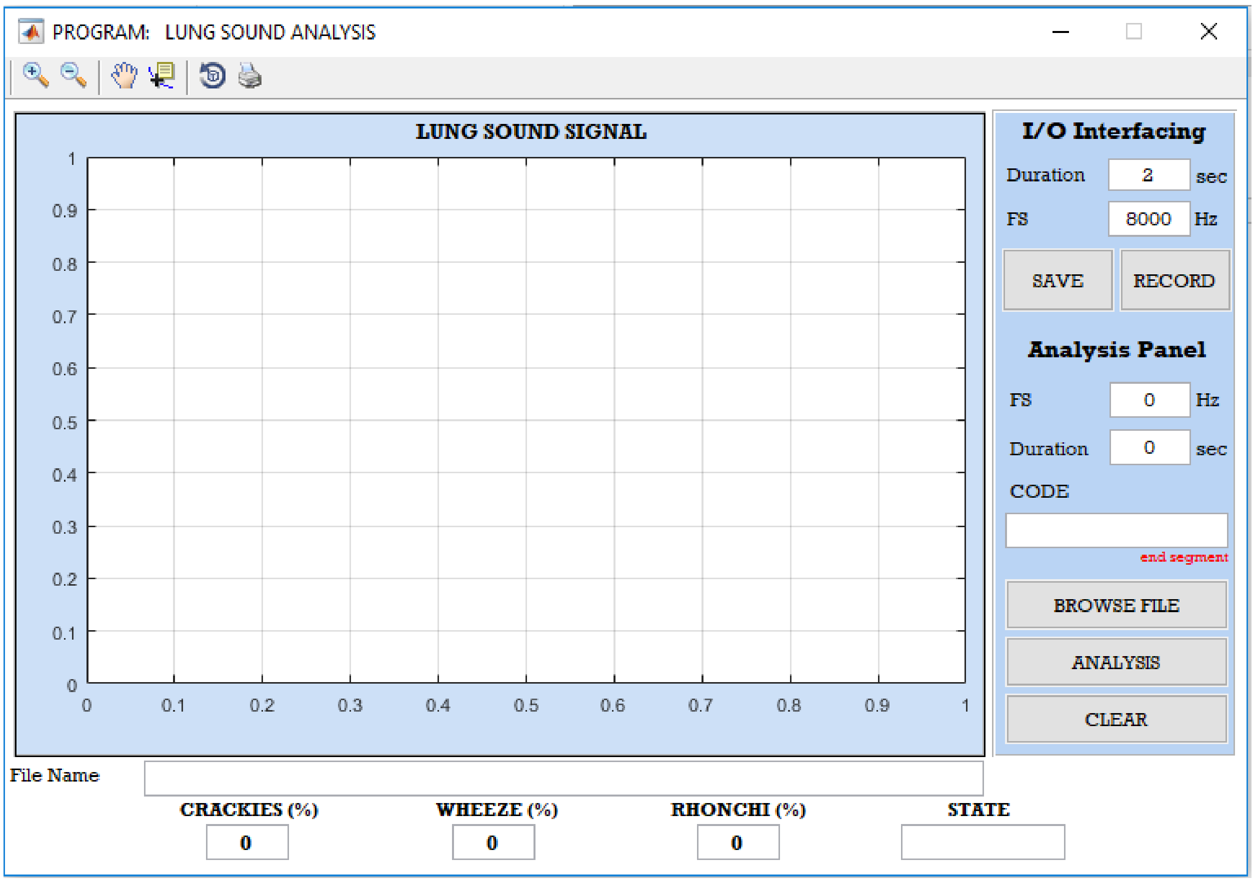

Figure 2.3 GUI design of the diagnosis system.

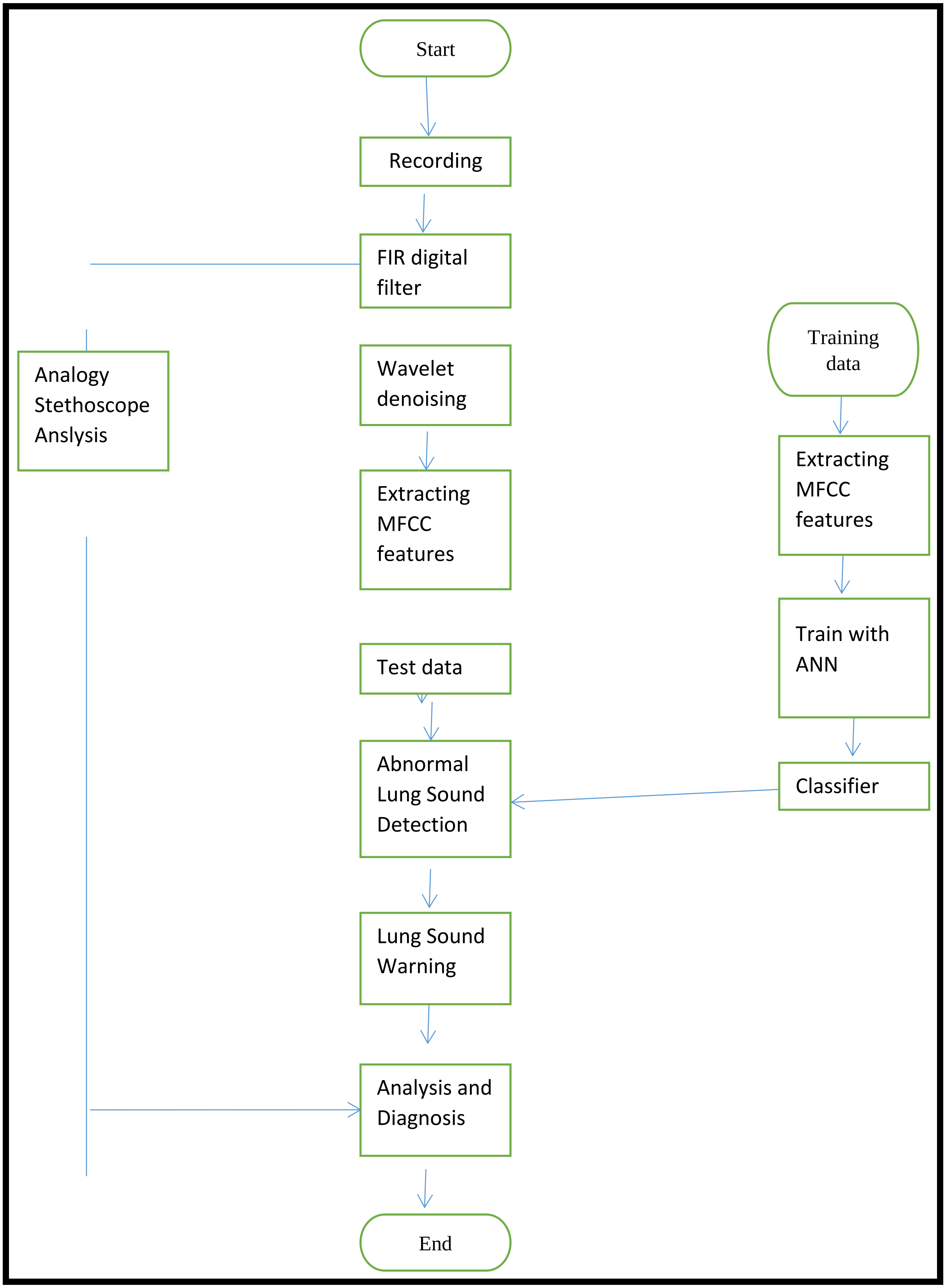

Figure 2.4 Flow chart of the implementation

2.2.2 Testing

2.2.2.1 Test Cases

Table 2 Test Case 01

Test Case ID	1
Test Case	Record lung sounds in real time with ‘Record’ and ‘Save’ Button
Input	Lung sound using the stethoscope
Expected Output	Return waveform and percentages of the lung sound with the severity level
Actual Output	Return waveform and percentages of the lung sound with the severity level
Test status	True

Table 3 Test Case 02

Test Case ID	2
Test Case	Press ‘Save’ button without recording
Input	Nothing
Expected Output	Return an error sound
Actual Output	Return an error sound
Test status	True

Table 4 Test Case 03

Test Case ID	3
Test Case	Record a sound which is not related to lungs
Input	Vocal Sound
Expected Output	Return the waveform of the sound but give an error sound after pressing ‘Analysis’ button
Actual Output	Return the waveform of the sound but give an error sound after pressing ‘Analysis’ button
Test status	True

Table 5 Test Case 04

Test Case ID	4
Test Case	Browsing a recorded lung sound from a directory of the PC.
Input	Lung sound
Expected Output	Return waveform, filename and percentages of the lung sound with the severity level
Actual Output	Return waveform, filename and percentages of the lung sound with the severity level
Test status	True

Table 6 Test Case 05

Test Case ID	5
Test Case	Changing the duration for the real time lung recording
Input	Real time lung recording
Expected Output	Return waveform, filename and percentages of the lung sounds with the severity level within new duration
Actual Output	Return waveform, filename and percentages of the lung sounds with the severity level within new duration
Test status	True

3 RESULTS AND DISCUSSION

The ANN was trained and tested using the conventional validation method in which 60% data was used in training and the remaining 40% data was used in testing the classifiers performance. 100% accuracy was achieved with the training data while testing data was gained 88.7% accuracy with 60 lung sound recordings.

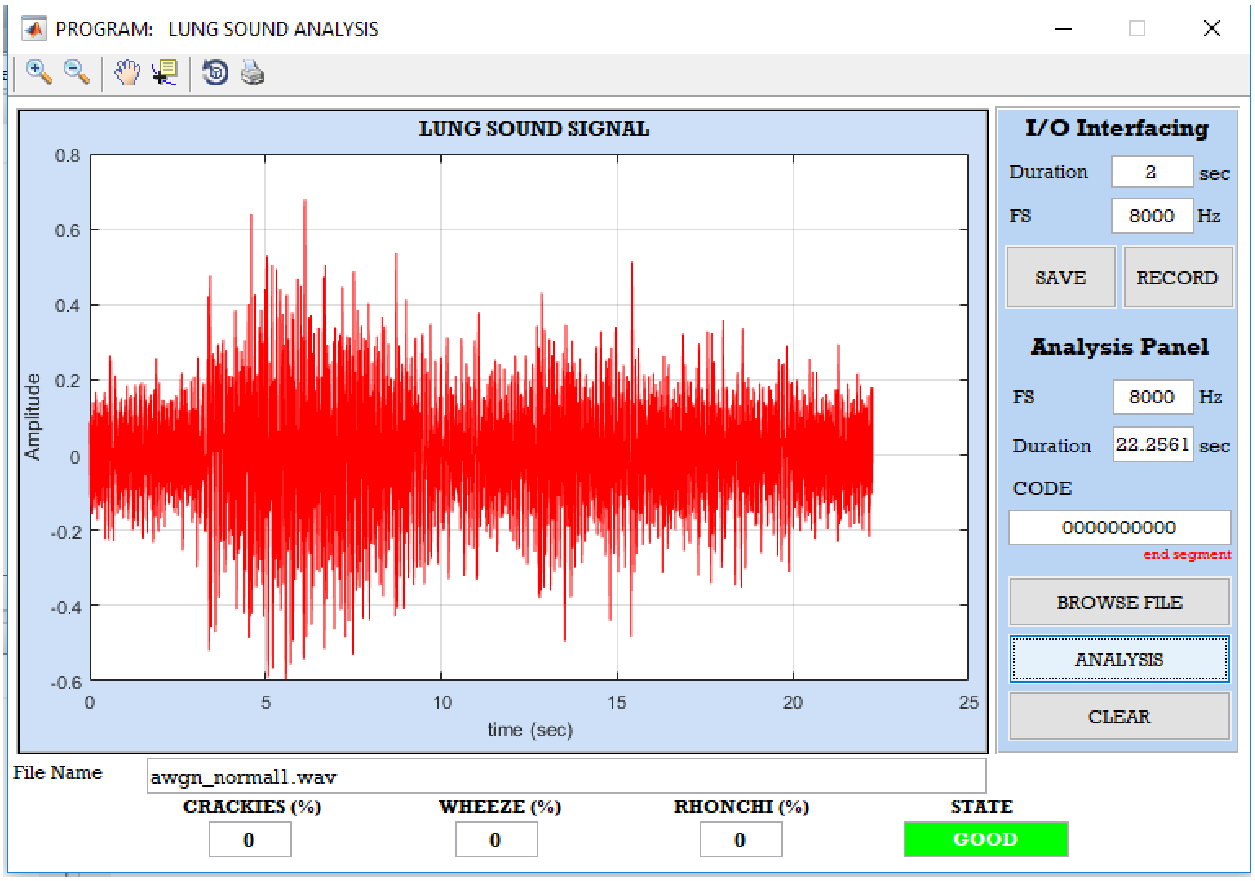

Figure 3.1 NN identified normal lung sound as normal

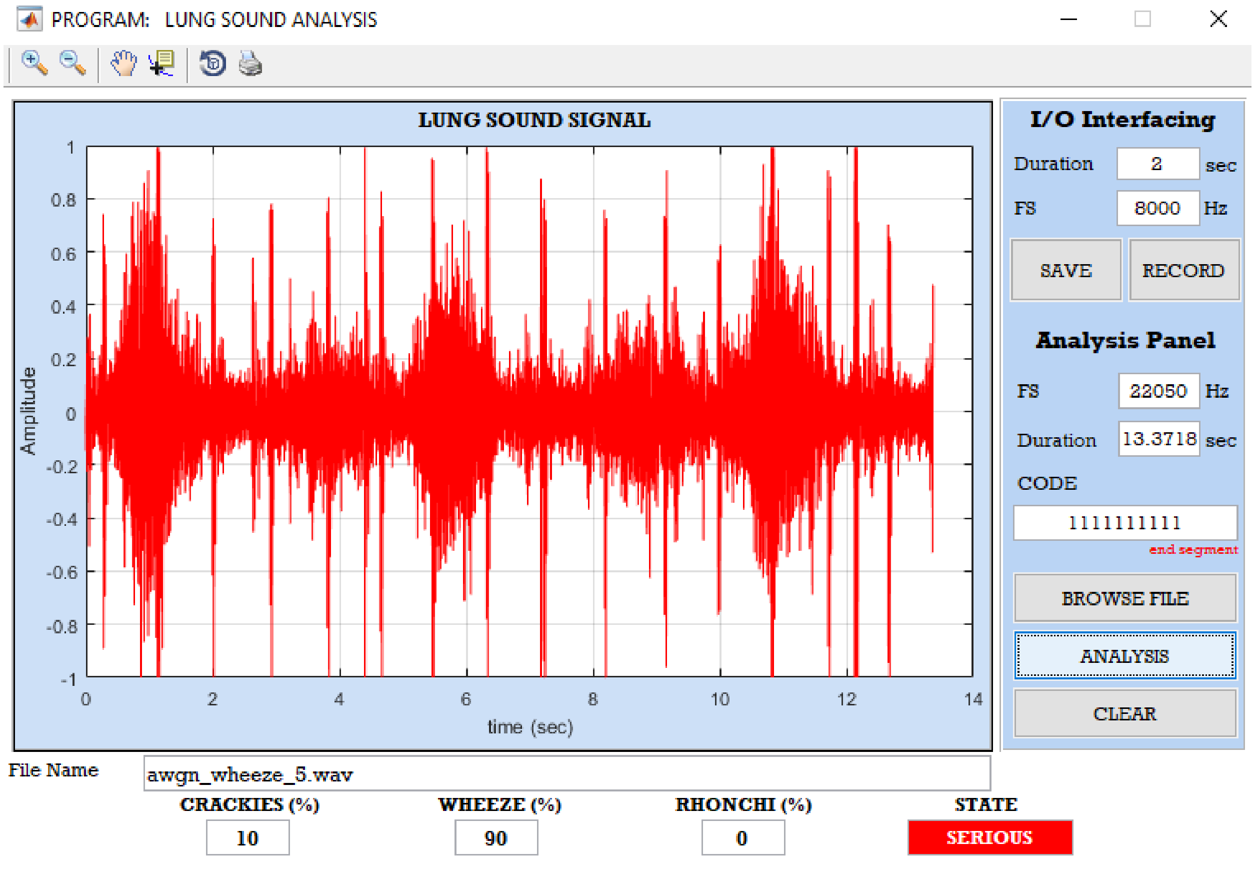

Figure 3.2 NN identified wheezing lung sound as wheezing

Training data set consisted with 80 lung sound recordings in which each class was having 20 lung recordings. All the trained lung sounds were able to get maximum accuracy while testing.

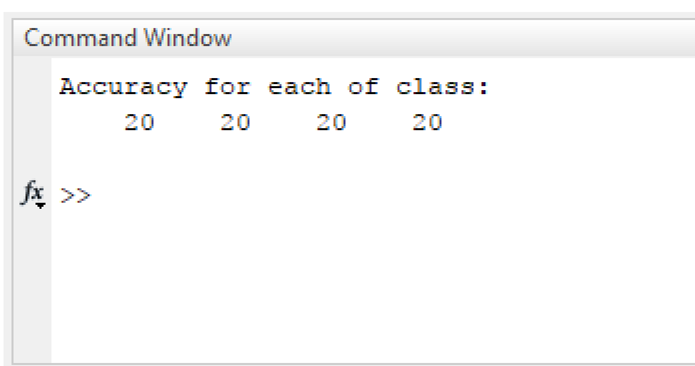

Figure 3.3 Accuracy of the Training data

Testing data set was created with 20 dB white Gaussian noise in order check whether built system can eliminate noise from lung sounds to ensure that results are accurate. Normal (20) and Wheezing (20) lung sounds with Gaussian noise were included in the training set while 10 each for crackles and rhonchi. Normal and wheezing classes achieved maximum accuracy while 5 and 8 lung sounds of crackles and rhonchi were identified successfully out of 10 recordings each.

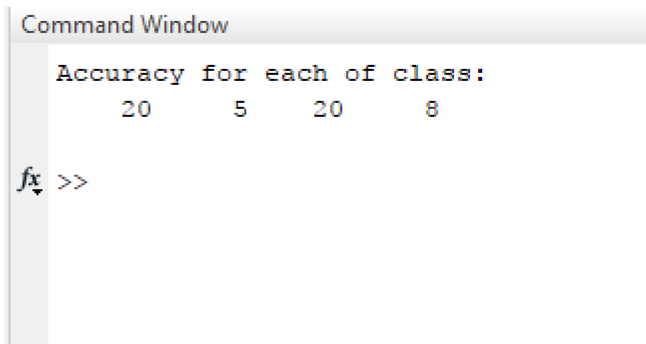

Figure 3.4 Accuracy of the Testing data

4 CONCLUSSION

In this study, Mel-frequency cepstral coefficients (MFCCs) was used to capture lung sound signal characteristic parameters, along with the ANN classification to establish a stethoscope system for detecting abnormal lung sounds (crackles, wheezes, and rhonchi). Based on the experimental results, MFCC combined with the ANN was successfully able to identify lung sounds. In an ideal noiseless environment, the proposed system’s training data identification rate can be as high as 100%. The average identification rate of lung sound signals mixed with 20 dB white Gaussian noise was 88.7%. Together, these results confirm that the proposed lung sound abnormal diagnosis system can help caregiver diagnose lung problems in patients.

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