AI Based Diagnosis of Pneumonia

B. Vidhya1 · M. Nikhil Madhav2 · M. Suresh Kumar1 · S. Kalanandini1

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Abstract

Pneumonia is a lung infection caused by bacteria, viruses and fungi. In this infection, the air sac (alveoli) of the lungs gets inflamed and breathing becomes difficult which causes mild to severe illness among people. They are diagnosed by performing chest X-ray, blood test, pulse oximetry. Pneumonia can also be identified using lung sounds that are recorded in the digital stethoscope. In this proposed work, a software is developed to diagnose pneumonia from the lung sound using gradient boosting algorithm. Lung sounds give enough symptoms for pneumonia identification. Lung sounds are recorded by doctors using Electronic Stethoscope. The recorded lung sounds are processed using audacity software. This software separates the required sound from unwanted noises. The healthy individual’s audio files are labelled as 0 and the pneumonia patient’s audio files are labelled as 1 for training the algorithm. During diagnosis study and the performance evaluation with various machine learning algorithms like support vector machine and k-nearest neighbours (KNN) algorithms, it was observed that the gradient boosting algorithm exhibits good identification property with 97 percent accuracy. This proposed method also reveals excellent diagnoses of pneumonia over other artificial intelligence and deep learning techniques. This method can also be used to predict Covid affected lungs sounds.

Keywords  Gradient boosting algorithm · KNN · Pneumonia · Lungs · Stethoscope

1 Introduction

Pneumonia is an infection that occurs in one or both lungs. It is caused by bacteria, viruses, and fungi. The infection leads to inflammation in the air sacs of the lung called as alveoli. The pus or fluid filled alveoli makes breathing difficult for the patients. Pneumonia is a contagious disease which can spread from one person to another. This infection is mostly observed in the elderly people and children below 5 years. Every year, pneumonia attack
about 450 million people in the world and results in 4 million deaths. These are due to the late diagnosis of pneumonia [1].

The physical examination of pneumonia [2] by the physicians will observe the following
(a) With the fluid movement, bubbling noises and crackling sounds will arise in the tiny air sacs of the lung. (b) When tapping the chest, dull thuds are heard (Percussion dullness) that shows that there would be fluid in the lung or collapsing a part of a lung. (c) In the course of rubbing the swollen lung tissue (inflamed) on the lung cavity’s lining (pleural friction rub), sounds are made. (d) In some areas of the chest, there will be a lack of breath sounds, which leads to knowing that air is not entering the area of the lung.

Mendes et al. [3] proposed a technique for the identification of wheezes dependent on their distinct mark in the spectrogram space. In this component, 29 musical features were processed utilizing the MIR Toolbox which gave a performance of 91% sensitivity.

In bronchial tubes, wheezing is present. In the lungs, “E” to “A” changes occurred (ego phony). When the letter “E” is pronounced, the doctor listens to chest. When the doctor will hear through a stethoscope, if pneumonia is affected then, “E” may sound like “A” [3–6].

Pneumonia can be diagnosed by performing some tests such as blood test, sputum test, pulse oximetry, chest X-ray [7, 8]. Metaphors of tissues and internal structures of the body such as teeth, chest and bones etc., can be produced through X-rays which is a convenient means for predicting fractures, pneumonia, dental problems for about hundred years. With the technology improvements, Computed Tomography generates 3D X-ray images for detecting the diseases with the help of the computer.

Wavelet transform and interpolation techniques may also be employed for the detection of audio signals of pneumonia patients effectively that is similar to image classification methods [9, 10]. Another way of diagnosing pneumonia is by using machine learning algorithms. In this method, the lung sounds of the patient are taken and diagnosed. Machine learning plays an important role in healthcare sector. Some of the recent application of machine learning in healthcare sector are disease identification, medical imaging diagnosis, drug discovery and robotic surgery tools.

Morten Grønnesby [11] detected pulmonary crackle through signal processing and machine learning. He further extracted features for machine learning based crackle detection in lung sounds from healthy survey [12] which was an initiative to propose our work using machine learning algorithms.

The main objectives of this work are as follows:

- To design an application tool for the diagnosing pneumonia that is easier, cheaper with minimized harmfulness than X-ray and CT scan
- To develop a software for diagnosing pneumonia with the help of gradient boosting algorithm
- To reduce the time consumption for diagnosing pneumonia
- To process the recorded lung sound using machine learning algorithms and deep learning for performance evaluation

Instead of traditional tests, the proposed software will be better in diagnosing pneumonia with the help of lung sound that are recorded using the digital stethoscope and will be analysed using machining learning algorithms after training the audio datasets.
2 Materials and Methods

Respiratory sounds are significant markers of respiratory wellbeing and respiratory issues. The sound produced when an individual inhales is straightforwardly identified with air development, changes inside lung tissue and the situation of emissions inside the lung. A wheezing sound, for instance, is a typical sign that a patient has an obstructive aviation route illness like asthma or persistent obstructive pneumonic infection (COPD).

These sounds can be recorded utilizing computerized stethoscopes and other account strategies. This computerized information opens up the chance of utilizing Artificial Intelligence to consequently analyse respiratory issues like asthma, pneumonia and bronchiolitis and so on.

2.1 Audio Database

The Respiratory Sound Database was made by two examination groups in Portugal and Greece. It incorporates 920 explained accounts of varying length from 10 to 90 s. The 126 patients are taken into account. There is a collection of 5.5 long stretches of accounts containing 6898 respiratory cycles—1864 contain snaps, 886 contain wheezes and 506 contain the two pops and wheezes. The information incorporates both clean respiratory sounds and uproarious accounts that reproduce genuine conditions. The patients range all ages—kids, grown-ups and the old. The database can be download from kaggle platform [13].

2.2 Kaggle Dataset

Kaggle is a customizable Jupyter Notebooks domain where GPUs and an enormous source of community published data and code are available for free access with registration. Out of this, 920 wav sound records and 920 comment txt documents were considered. The sound database contained lot of background noise, which will affect the accuracy score, so it needs to be pre-processed to reduce noise.

2.3 Audacity

Audacity is a free, open source, cross platform software for recording and editing audio files that are supported for Windows, Linux and Mac operating systems. Audacity was built by Dominic and Roger in 1999 and Version 0.8 was launched on May 2000. Audacity is a digital audio editor and is available in 38 languages and is capable of processing two files simultaneously. Audacity software has various features including, recording sounds and playback, editing via cut, copy, paste with unlimited trials, amplitude envelope editing, a large array of digital effects and plugin, noise reduction function, change in sound pitch, saving and stacking of client presets for impact settings across meetings. It uses Fourier transform algorithm for audio spectrum analysis, filters available for audio signal processing and so on.

2.4 Role of Audacity in Pneumonia Diagnosis

Audacity reduces the background noise like doctor’s communication noise and patient voice noise and other external sounds during recording. In pneumonia diagnosis, some
unwanted low volume background noise can be neglected using HPF and LPF. If the high pass filtration was not satisfied, HPF can be applied again on the same file repeatedly and vice versa for LPF. At the same time, if the noise is found in certain area in audio, then that particular area can be chosen for filtering to reduce the noise instead of applying as a whole. Data preprocessing flow diagram is illustrated in Fig. 1.

A crackle, bubbling noises and fluid movement will arises in the tiny air sacs of the lung during pneumonia that is illustrated in spectrogram view as shown in Fig. 2.

2.5 Machine Learning

Machine learning is the method of data analysis that automates analytical model building. Machine learning is the branch of artificial intelligence based on the idea that systems can learn data, identify patterns and can make decisions with minimal human intervention. Machine learning is developing fast and it is the trend in health care industry and with the help of wearable devices and sensors, data can be used to assess a patient’s health effectively [14–16]. WHO reported that pneumonia is such a kind of disease that should be predicted as early as possible because it causes death of more than 15% in children who are below 5 years [17]. Public with no or very little medical knowledge and even patients will
also be able to operate the artificial intelligence-based tool with easy for medical assistance at remote places [18].

2.6 Deep Learning

The process of using huge volume of information for performing advanced computation with the help of artificial neural networks is referred to as deep learning. It is considered as a branch of machine learning that recreates the working of the human brain. The algorithms for the deep learning can be trained from the samples from various firms. Chest X-rays was used for predicting pneumonia through computer-aided diagnosis system [19]. A significant technique of artificial intelligence that is used in providing solutions to wide variety of issues of critical computer vision are termed as deep learning [20]. Spreading of Covid'19 can be also predicted using deep learning method. Several years of unsolved mystery is detecting pneumonia with the help of chest X-rays [21] due to the fact that the data is not available for analysis purposes publicly. When AI is incorporated in the medical field, we can obtain many benefits such as disease prediction and even assistance in remote places where doctors are not available [22].

3 Result and Discussion

The Fig. 3 illustrates the working flowchart of the prediction model. The steps involved in this algorithm are

![Flow of the pneumonia diagnosis](image-url)
• Fit the model
• Tune the model’s parameters and hyperparameters
• Make predictions
• Interpret the results

3.1 Mel Frequency Cepstral Coefficients

A spectrum is the Fourier transform of a signal that converts a time domain signal to frequency domain signal. As such, a spectrum is the frequency area portrayal of the input audio’s time–space signal. A spectrum is passed through the mel filter bank, to produce the mel cepstrum log magnitude to obtain a discrete cosine transform. DCT extracts the main information and peaks in the signal and the block diagram for the generation of the mel frequency cepstral cooefficients is illustrated in the Fig. 4. JPEG and MPEG compressions are widely used. The first 13 co-efficient holds the information about the audio (Fig. 4).

3.2 Feature Extraction

The lung sounds of both healthy and pneumonia patients are recorded using electronic stethoscope and are in.wav format. These sounds have heart sounds and external noises which affect the accuracy. In order to remove these unwanted sounds, audacity software is used. This software is used to separate the lung sounds from the unwanted sounds by using noise reduction and high and low pass filter. In this work, 13 columns of MFCC feature were extracted from audacity processed respiratory database by using the librosa module in python and it was converted into data frame, then the data was cleaned and preprocessed by min–max scalar functions for better result. The target value for healthy sound was assigned as 0 and pneumonia audio files are named as 1. Then the dataset is classified as training and test data. These audio files are checked for accuracy using SVM classifier, gradient boosting algorithm and KNN classifier.

3.3 Support Vector Machine (SVM)

SVM is one of the supervised learning methods that helps to solve both linear and non-linear problems and be used for two group classifications. Nowadays SVM are used for healthcare purposes. In this work, SVM is used for classifying of pneumonia and healthy

![Fig. 4 Mel frequency cepstral co-efficient](image-url)
sounds. Here, plotting is done for each and every data item as a point in n-dimension space (n = Number of features) with the value of each feature being the value of a particular coordinate. Then, the classification was performed by finding the hyperplane that differentiates the classes. When the data are in four or more dimensions, the Support Vector Classifier (SVC) will be a hyperplane. In order to make the mathematical possible, SVM uses kernel functions to systematically find SVC in higher dimensions.

3.3.1 Radial Basis Function (RBF)

Radial Basis Function is one of the kernel functions to deal with overlapping data. It will work similar to nearest neighbour algorithm. RBF is used to find SVC in infinite dimensions.

The mathematical representation of RBF is

$$K(a, b) = \exp[-\gamma (a-b)^2]$$

(1)

where a, b- different observations and \(\gamma\)-slope determined by cross validation. When the values are plugged into the radial kernel, the high dimensional relationship is obtained. A large dot product terms that define infinite planes is obtained by taking the Taylor series of Eq. (1).

3.3.2 Model Fitting and Prediction

The classifier is trained with the 80% from complete input dataset using SVM. Then, the model is tested using 20% of the complete dataset by SVM prediction function, which produces the prediction data like [0 0 0 1 1 1]. For finding the performance of the classifier, the corresponding target of test data and prediction data are compared. The prediction rate may be increased with parameter tuning that can be varied depending upon the input data-sets. The truthful parameter will only give a better accuracy else it may cause performance degradation of classification. Parameter tuning can be achieved in both classifier and feature extraction functions for increasing the performance of the predicting model. The most tuneable parameter in SVM was kernel function because it systematically finds the SVC dimension effectively.

3.4 KNN Classifier

K nearest neighbours or KNN Algorithm is a simple algorithm that uses the entire dataset in its training phase. Whenever a prediction is required for an unseen data instance, it searches through the entire training dataset for k most similar instances and the data with the most similar instance is finally returned as the prediction. KNN is the non-parametric algorithm that does not make any assumptions based on underlying data.

3.5 Gradient Boosting

Gradient Boosting is a powerful machine learning algorithm that can be used to perform regression, classification and ranking. This algorithm gives prediction in the form of ensemble weak prediction models like decision trees. In gradient boosting, shortcomings
are identified by gradients. This is used in healthcare classifications. In the proposed work, gradient boosting is proposed for the diagnosis of pneumonia.

Gradient boosting involves three major elements namely (1) A loss function to be optimised, (2) A weak learner to make predictions and (3) An additive model to add weak learners to minimise the loss function. Gradient boosting is a greedy algorithm and can overfit a training dataset quickly. The gradient boosting algorithm is mainly selected for this work because it provides predictive accuracy than the other methods, more flexible, works great with categorical and numerical values and it can optimise on different loss functions.

3.5.1 Model Fitting and Prediction

In a python programming language, ensemble gradient boosting classifier was imported from Sci-kit Learn library.

The Algorithm that is proposed in gradient boosting classifier is given.

- Initialize $F_0(x) = \arg\min \sum_{i=1}^{N} L(y_i, \rho)$
- For $m = 1$ to $M$ do:
  - Step 1: Compute the negative gradient
    \[ \hat{y} = -\left[ \frac{\partial L(y_i, F(x_i))}{\partial F_{xi}} \right] \]
  - Step 2: Fit a model
    \[ \alpha_m = \arg\min_{\alpha, \beta} \sum_{i=1}^{N} [\hat{y}_i - \beta h(x_i; \alpha_m)]^2 \]
  - Step 3: Choose a gradient descent step size as
    \[ \rho_m = \arg\min_{\rho} \sum_{i=1}^{N} L(y_i, F_{m-1}(x_i) + \rho h(x_i; \alpha) \]
  - Step 4: Update the elimination of $F(x)$
    \[ F_m(x) = F_{m-1}(x) + \rho_m h(x; \alpha_m) \]
- End for
- Output the final regression function $F_m(x)$

In the above algorithm, $y_i$ is the observed values, $L$ is the loss function, and $\rho$ is the value for log (odds). The loss function for each observed value is added. The argmin over $\rho$ represents the need to identify a log (odds) value that reduces this sum. Then, the derivative of each loss function is performed to calculate the residual values hence one predicted probability. The new predicted value must be getting little closer to the original value. Gradient Boosting algorithm builds a lot of trees and $M$ could be as large as 100 or more for more accuracy.
3.5.2 Parameter Tuning

Parameter tuning plays an important role in the accuracy rate. In this pneumonia diagnosis research, learning_rate and max_depth parameters affect the accuracy, so these parameters were tuned to 0.1(learning_rate) and 3 (max_depth) respectively for increased accuracy after several experiments. In the librosa MFCC extracting function, dct_type parameter value is made equal to 2 which increased the accuracy rate.

3.6 Accuracy Results

Each of the classifiers in the machine learning algorithm, produces the prediction value, which are compared with known test target values to generate the accuracy score for finding the performance of the classifier.

Experiments were performed for the diagnosis of pneumonia sounds among healthy sounds for accuracy prediction with three classifiers. Many simulations were performed with various audio datasets among which only five simulations are illustrated in Table 1 as samples.

Pneumonia audio files are diagnosed and the percentage of prediction is given by the Eq. (2)

\[
Pneumonia\ prediction\ (%) = \frac{\text{Number of pneumonia sounds identified}}{\text{Total number of pneumonia files present}} \times 100\quad (2)
\]

Healthy sounds and pneumonia sound within the datasets are projected and each classifier is designed to predict the pneumonia sounds. Figure 5 illustrates the accuracy of prediction among various Artificial Intelligence techniques such as SVM classifiers, KNN classifiers and gradient boosting algorithm.

Figure 6 represents the performance analysis of SVM classifier. From the results, it was observed that the diagnosis percentage of SVM classifier is approximately 67%. Figure 7 shows the performance analysis of KNN classifier and it gave the diagnosis of 89%.

Figure 8 demonstrates the accuracy of diagnosis of pneumonia for gradient boosting algorithm.

The proposed gradient boosting algorithm outperformed the other machine learning algorithm and provided a greater accuracy of 97% in predicting the pneumonia successfully.
The comparison of gradient boosting model with deep learning models like Convolutional Neural Network (CNN) and Multilayer Perceptron (MLP) are also being performed to estimate the accuracy and the performance of the proposed algorithm. Convolutional Neural Networks (CNNs) used many layers to perform the feature extraction of the lung sound. Multilayer Perceptron (MLP) also has several layers of perceptron for audio
processing with the connected input and output layer. For analysis purpose, the sigmoid functions are used as an activation function for identifying the nodes for firing.

Figure 9 illustrates the training loss and accuracy of models of deep learning algorithm such as CNN, MLP with gradient boosting algorithm. And also, the accuracy of pneumonia detection percentage of the above three algorithms are also shown in Fig. 10. Gradient boosting algorithm experienced a training loss of 0.1271 which is less compared to CNN and MLP. More than 20% of training accuracy is achieved than the other models in training phase. When pneumonia prediction is performed using deep learning-based algorithm, it was found that CNN produced 86% accuracy and MLP produced 91.6% accuracy. 97% of accuracy of pneumonia detection is achieved in the proposed gradient boosting algorithm. With these results, it can be concluded that the proposed algorithm outperforms all the other algorithms in terms of predicting the pneumonia accurately.
3.7 Applications in COVID Prediction

COVID’19 is really infectious and there is a lack in healthcare provider worldwide. It is alarming the normal life cycle of every individual in the society and all the countries face the economic decline. The world is looking for an innovation in this field to help the mankind. During this pandemic situation, telemedicine is expected to play a major role where the doctors can work remotely to diagnose people with respiratory issues.

Normally with the help of stethoscope, every doctor will diagnose symptoms of the patients for lung related diseases. The digital stethoscopes as illustrated in Fig. 11 will be an excellent tool in the field of telemedicine.

When Artificial Intelligence is embedded along the digital stethoscope, definitely a revolution in telemedicine field will emerge. Though individuals cannot afford, proper implementation in public centres will help to predict early to prevent the spreading of such diseases. Initially, we tried to predict the sound of pneumonia patients among thousands of recorded respiratory audio files and found successful in simulation. But

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![Fig. 10](image1.png) Comparison of gradient boosting algorithm with CNN and MLP

![Fig. 11](image2.png) Digital stethoscope
now extending our work to predict COVID infected people using lung sound that are recorded to predict at an early stage, so that spreading of infections from one person to another is prevented. Real time application with people is planned with hospitals in future for execution to serve our society.

4 Conclusion

In this study, an application tool is developed to diagnosis pneumonia using gradient boosting algorithm. This proposed method will help the medical practitioners to predict the pneumonia patients easily at an early stage. Pneumonia is identified using lung sounds that are recorded using a digital stethoscope and we report that there is no need to perform chest X-ray, blood test and pulse oximetry tests. To estimate the accuracy score of the proposed method, the performance analysis is done with various training sets in numerous simulations under two more Artificial Intelligence classifiers namely SVM and KNN. During the analysis for performance evaluation with the deep learning-based algorithm, it was found that CNN produced 86% accuracy and MLP produced 91.6% accuracy. On comparing all the above classifiers, the gradient boosting algorithm was found to give a higher accuracy of 97% of predicting the pneumonia patients exactly. In future, this application tool can be connected directly with the digital stethoscope and can be used to predict the pneumonia affected people directly than recording it separately and then processing it further for prediction. Hence time taken to diagnosis pneumonia will be greatly reduced and instantaneous. The proposed method can also be used to predict the lungs that are affected due to Covid by analysing the audio sounds of lungs using digital stethoscope. With these experimental results, it can be concluded that the proposed algorithm outperforms all the other algorithms in terms of predicting the pneumonia accurately and is faster, safer and economical.

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Declarations

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B. Vidhya received her Bachelor Degree in Electronics and Communication Engineering from Madras University and Masters in Applied Electronics from Anna University, Chennai. She is awarded Ph.D. from Anna University, Chennai for her research in the field of Image Compression. She is having 16 years of teaching experience and currently working as an Assistant Professor at Dr. N. G. P. Institute of Technology, Coimbatore.

M. Nikhil Madhav is currently pursuing B.E. Computer Science at Sri Shakthi Institute of Engineering and Technology, Coimbatore, Tamil Nadu, India. His areas of interests are Business, Marketing, Information Technology.

M. Suresh Kumar completed his UG in Bio Medical Engineering and his areas of interests are medical electronics, instrumentation, medical device service, Machine learning and python.
S. Kalanandini completed her UG in Bio Medical Engineering and her areas of interest are Machine learning, python, biomedical instrumentation and biomaterials.