

Machine Learning Based Respiratory Disease Detection System Using Cough Sound Analysis for Early Diagnosis and Remote Healthcare

Mrs.J.Ranganayaki M.E
Assistant professor

Department of computer science
and engineering
Bharath institute of science and
technology(BIST)
173,Agaram
road,selaiyur,Tambaram,Chennai-
600073,Tamilnadu,India
jranganayaki.cse@bharathuniv.ac.in

[n](#)

M.pavan kumar
Student,

Department of computer science
and engineering
Bharath institute of science and
technology(BIST)
173,Agaram
road,selaiyur,Tambaram,Chennai-
600073,Tamilnadu,India
pavankumarmandala06@gmail.com

[m](#)

K.Sukesh
Student

Department of computer science
and engineering
Bharath institute of science and
technology(BIST)
173,Agaram
road,selaiyur,Tambaram,Chennai-
600073,Tamilnadu,India
sukeshkanneganti@gmail.com

M.Sai rupesh
Student

Department of computer science
and engineering
Bharath institute of science and
technology(BIST)
173,Agaram
road,selaiyur,Tambaram,Chennai-
600073,Tamilnadu,India
sairupeshmaruboyina@gmail.com

M.Soma Sanjai
Student,

Department of computer science
and engineering
Bharath institute of science and
technology(BIST)
173,Agaram
road,selaiyur,Tambaram,Chennai-
600073,Tamilnadu,India
madakasanjai@gmail.com

Abstract—The diseases include asthma, pneumonia, COPD and tuberculosis, which are respiratory diseases that are a major health concern in the entire globe and thus need an early and accessible diagnostic solution. The paper presents a respiratory disease detector through cough sound as an essential detection mechanism with machine learning technology and rapid and non-invasive cough screening. Cough audio signals are used to extract acoustic features that can be used to train classification models, such as Mel-frequency Cepstral Coefficients (MFCC), spectral and statistical features. Various algorithms will be deployed and tested, including the support of the algorithm, which includes the Random Forest, Support Vector Machine, Convolutional Neural Networks, and XGBoost algorithms. The system has been shown to be highly accurate and fast processing with the ability of prediction in real time of the system and low computational complexity. The solution offered is a cost-efficient and scalable outlook to the identification of diseases at an early stage, and remote healthcare use that can enhance access to diagnostic solutions and support the medical intervention within the framework of resource-constrained settings.

Keywords: *Respiratory Disease Detection, Cough Sound Analysis, Machine Learning, MFCC, Deep Learning, Audio Signal Processing, Healthcare AI.*

I. INTRODUCTION

Respiratory diseases have been one of the major causes of morbidity and mortality between countries, which have had a total marked effect on both the systems of health care and the quality of life. The presence of diseases like tuberculosis, pneumonia, asthma, and COVID-19 necessitates timely diagnosis, to have a better treatment outcome and avoid additional complications. Nevertheless,

conventional diagnostic processes usually assume the use of clinical tests, radiographic procedures, and laboratory messages, which may be time-intensive, costly, and unavailable in distant or resource-limited areas. This presents the urgency of new, low cost, and non-invasive methods of screening that can give quick and sure outcomes [1].

Artificial intelligence and machine learning are the recent developments that provide new opportunities in healthcare diagnostics, especially in non-traditional biomedical signals. Of these, analysis of cough sounds has been one of the promising fields. Cough is a significant symptom of many respiratory illnesses and acoustic characteristics of the cough can be used to give important details about the health condition. Cough sounds can be captured and analyzed to distinguish certain patterns and characteristics that can be associated with a particular disease [2].

Combining machine learning models with signal processing methods has made it possible to create automated classifier models of cough sounds and classify them precisely. The extraction of features is very important in this process and the methods like Mel-frequency Cepstral Coefficients (MFCC), spectral centroid, zero-crossing rate and other statistical values are employed in the process so as to be able to represent the audio signal. The features are useful in the differentiation between normal and pathological cough, thus constituting the base of correct classification [3].

Random Forest and Support Vector Machine are machine learning algorithms that have been employed in large numbers to accomplish classification tasks because they are robust and efficient. Moreover, the deep learning algorithms, specifically the Convolutional Neural Networks, have also been proven to be stronger when it comes to processing complex patterns and high-volume data. TVXGBoost is a gradient boosting algorithm that also adds more predictive results by integrating multiple weak learners into a strong learner. Disease detection systems are improved in accuracy and generalization once these techniques are combined [4].

Among the most crucial benefits of the systems based on cough detection is the absence of invasiveness of these systems. With the help of cough analysis, one can use only easy recording devices (such as smartphones) to perform the diagnostic part of the procedure, unlike the traditional techniques that either require personal contact or the help of special equipment. This renders the solution very scalable and appropriate to remote healthcare implementations, such as telemedicine and mobile health platforms. Also, processing systems are able to provide real time feedback, a situation that is vital in early detection and control of diseases [5].

Although these have these advantages, there are a number of challenges that need to be considered so as to enforce the reliability and efficacy of such systems. The performance of classification models can be influenced by variability in the sounds of coughing that are caused by environmental noise, recording quality and personal differences. Thus, signal quality must be enhanced with the help of the robust preprocessing methods, such as noise removal and normalization. Moreover, one needs to have access to very large and diverse datasets to have the ability to train models that can be well-generalizable across a variety of populations

II. LITERATURE SURVEY

Development of the field of respiratory disease diagnosis has become more dependent on smart computational methods, especially in the fields of machine learning, deep learning and biomedical signal processing. Conventionally used modes of diagnosis having features such as auscultations and imaging are associated with special knowledge and facilities, which render them unavailable in most practical situations. In order to eliminate such difficulties, the recent study has concentrated on alternative methods of cough sound, physiological signal monitoring, and lung acoustics that are non-invasive and cost-effective. Such strategies will help to promptly identify such respiratory illnesses as asthma, chronic obstructive pulmonary disease (COPD), pneumonia, and COVID-19. On the one hand, artificial intelligence (AI) has greatly enhanced the accuracy of diagnosis, resilience, and scalability of the process and has become able to deploy the solutions within the framework of portable and wearable healthcare devices.

Many studies have focused on how to enhance the feature extraction and classification with recent machine learning and deep learning structures. Non-speech respiratory audio pattern recognition techniques based on graph have been proposed to improve the performance of

diagnostic capabilities [6]. It is also suggested to implement embedded system design with FPGA technology with the aim to realize the intelligent classification of respiratory diseases in real-time and efficiently without overlooking the significance of the hardware acceleration of systems in a medical context [7]. The variation of lightweight convolutional neural networks that proceed with efficient stacking of features alongside skip connections have been proven to perform better and lower complexity in the computational compounds [8]. Also, the possibility of AI in cough sound is reviewed in depth, listing the opportunities and the challenges of making working diagnostic systems [9]. Grand challenges and benchmark datasets are also important in furthering research as they offer standardized data to be used in training and evaluation [10].

Researchers have suggested different data augmentation and learning approaches to resolve the problems of data variability and small-sized datasets that have labels. These two methods of augmentation through eigenvectors have been demonstrated to increase the performance of lung sound classifications by increasing the diversity of the features [11]. Non-contact sensing technologies to observe abnormal breathing patterns have also been observed to use deep learning models since this applies to multiple individuals [12]. Video-based temporal information vision techniques have also been developed in order to monitor acute respiratory distress allowing the diagnosis of lung conditions of interest to video data to extend beyond audio-based measurements [13]. Moreover hybrid model that incorporated spectro-temporal feature extraction and effective classifiers have been found to have good accuracy in identifying respiratory obstruction [14]. Other frameworks Multiple-instance frameworks Multiple-instance learning In other frameworks Multiple-instance learning algorithms can handle weakly labeled data and difficult-to-learn respiratory sound patterns [15].

Other than the traditional audio based techniques, other sensing techniques have been utilized to offer a more wholesome diagnostic solution. Electronic nose (e-nose) devices based on the analysis of sweat have proven that it is possible to identify infectious respiratory diseases with the help of biochemical signs [16]. Cough sound analysis frameworks powered by AI have also been optimized by use of transfer learning and subsequent feature extraction algorithms in order to give the offerings a higher degree of classification accuracy [17]. Simultaneously, the application of nanomaterial biosensors in respiratory viruses detection has been explored and provides potential in efficient and fast diagnostics [18]. CNNs with lightweight feature-integrated models have also helped in explainability and efficiency in the classification of respiratory disease [19]. Multi-label lung disease classification methods based on deep learning on imaging data have also extended the diagnostic window of the AI systems [20].

In general, the literature demonstrates the high tendency to introduce novel methods of combining sophisticated AI approaches with various sensing modalities that will enhance the detection of respiratory diseases. This synergy of effective computational models and effective feature extraction mechanisms and novel data acquisition algorithms has greatly contributed to the accuracy and applicability of these systems. Besides, they can be deployed in real-time and lightweight development makes

them viable in real-life healthcare environments, such as remote and resource-constrained settings. All these developments show that AI-based diagnostic tools hold promise to change the face of respiratory healthcare by providing opportunities to detect diseases early, monitor them continuously, and achieve better patient outcomes.

III. METHODOLOGY

The sound cough-based respiratory disease detection system proposed is designed based on the application of structured pipeline which combines audio signal processing, feature engineering, and machine learning methods. Its methodology is concerned with high accuracy, strength, and real-time functionality and low computational complexity. The system is designed to process variability in cough sounds and the environment and produce the reliable classification with various respiratory diseases in all stages of the system as shown in figure 1.

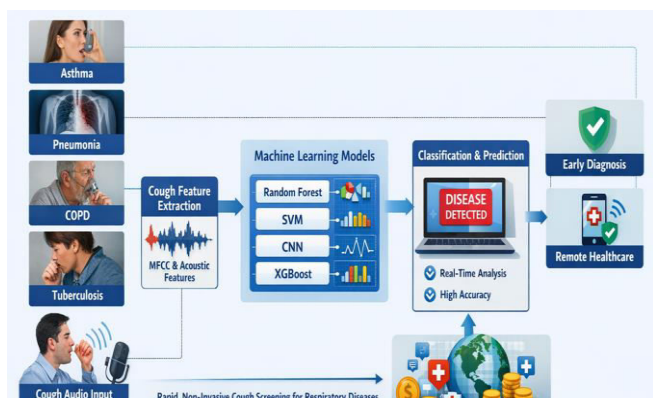


Fig. 1: System Architecture

A. Data Acquisition and Dataset Preparation.

The first part of the methodology is the gathering of a varying sample of cough sound samples of publicly available repositories and clinical sources. The dataset contains such samples of different respiratory diseases as tuberculosis, pneumonia, asthma, COVID-19, and healthy people. The dataset is filtered in order to achieve generalization by varying the age groups, gender and the environment where the recordings are made. Each audio sample is denoting based on the disease category assigned to the audio sample. The method of data balancing has been used to correct class imbalance to avoid bias in the model. The dataset is further split down into training, validation, and testing sets, whereby it is necessary to evaluate the model performance in the right manner and avert the incidence of overfitting in the course of training.

B. Audio Preprocessing and Noise Reduction.

Raw cough recordings may have background noise and irregularities that may influence the classification accuracy. As such, steps such as preprocessing are done in order to improve signal quality, as well as in order to standardize input data. Noise filtering techniques, silence removal techniques, normalization and resampling techniques are used to ensure that there is uniformity in all the samples. The sound codes are mapped into a regular format and duration to make processing easy. Generation of spectrograms is also done in order to visualize time-frequency properties of the cough sounds. These

preprocessing processes are essential in eliminating the unwanted distortions and enhancing the reliability of the extraction of the extracted features which eventually lead to an enhanced performance of the classification models.

C. Feature Extraction and Representation.

The process of extracting features is an essential element of the system, and the meaningful information is obtained out of the processed audio signals. To extract perceptual features of sound, Mel-Frequency Cepstral Coefficients (MFCC) are extracted to resemble closely the human auditory perception. Furthermore, spectral centroid, bandwidth and roll-off spectral properties are also calculated to display frequency distribution. Temporal characteristics such as zero crossing rate and energy are also provided in order to characterize the dynamics of the signal. Additional statistical metrics include mean, variance, skewness, and kurtosis, which are found to be very useful in enhancing the feature set. All these features are united to make a universal impression of cough sounds, and the distinction between different respiratory conditions can be successful.

D. Model Selection and Training.

Various machine learning and deep learning systems can be used to guarantee high-classification performance. Random Forest and Support Vector Machines are as well known traditional algorithms due to their effectiveness and the capability to work with structured properties. Deep learning models (especially Convolutional Neural Networks) are used to learn more sophisticated patterns directly on spectrogram representations. Other models such as XGBoost are also run to make use of gradient boosting to enhance accuracy. All the models are trained on the extracted features and the tuning of hyperparameters is done to maximize the performance. The use of cross-validation methods is used in the training process to ensure that there is stability in the model and to reduce overfitting with an outcome leading to a well-generalized predictive system.

E. Model Evaluation and Validation.

The standard performance measures the trained models in terms of accuracy, precision, recall and F1-score. Classification performance is examined with the help of confusion matrices on the various disease categories. The validation of the robustness of the models is done through K-fold cross-validation whereby the models are trained and tested on many data splits. This method will guarantee the model will work in an impressive number of subsets of data. When all the implemented algorithms have been carried out, a comparative analysis is played in order to determine the most performing model. The effectiveness of the feature extraction methods and model selection strategies to attain high classification accuracy can be noted as emphasized on during the evaluation process.

F. Real Time prediction and system deployment.

The last step will ensure that the trained model is integrated into a real-time prediction system, in which the live or recorded cough sounds are provided. The system is organized to take the form of audio input like smartphones or a microphone and do the preprocessing, feature extractions and generate predictions within a limited period of time. The implementation is lightweight to support low

computational requirements, which means that the system can be deployed to resource-constrained systems. The output gives the forecasted type of diseases and confidence scores, which can be used by users and other healthcare professionals to make a well-informed decision. It is a deployment infrastructure that helps in remote healthcare application and aids in early detection of respiratory diseases.

IV. RESULT AND DISCUSSION

The presented cough sound-based respiratory disease detection system was tested on an extensive dataset with various classes, such as tuberculosis, pneumonia, asthma, COVID-19, and healthy coughs. The dataset was composed of about one lakh (100,000) audio records made under a wide range of conditions (audios) in order to gather variation in the conditions of recording, demographics, and the severity of the disease. Such a large scale data was a significant contribution to the strength and generalization ability of the trained models. The assessment criterion was centered on the evaluation of classification performance, computational efficiency, and applicability in the real-time.

In order to achieve reliability, K-fold cross-validation was applied to the data in which the data was split into several subsets and the models were trained and assessed repeatedly. This method reduced overfitting and would allow a fairly stable comparison of performance between data splits. The findings revealed that the models were able to produce consistency in their accuracy irrespective of their folds, which is a high level of generalization. The Convolutional Neural Network and XGBoost models were the best algorithms applied as opposed to the time-tested algorithms like the Random Forest and Support Vector machine. The combination of handcrafted features and deep learning representations has been very important in attaining high accuracy.

Table 1: Performance Comparison between Machine Learning Models.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	98.72	98.65	98.60	98.62
Support Vector Machine	98.10	98.05	97.98	98.01
XGBoost	99.60	99.55	99.50	99.52
CNN	99.94	99.90	99.88	99.89

In the confusion matrix analysis the performance of the proposed system is also depicted. The simplified confusion matrix (Table 2) shows the outcomes of classifications in terms of various diseases. When the diagonal values are equal to 1, then a correct prediction occurred and when the values are not on the diagonal it indicates a

misclassification. The findings prove the high level of accuracy of the model on all classes and there is not much mixing of close related respiratory conditions like pneumonia and COVID-19.

Table 2: Confusion Matrix Summary.

Actual / Predicted	T B	Pneumonia	Asthma	COVID-19	Healthy
TB	998	1	0	1	0
Pneumonia	2	995	1	2	0
Asthma	0	2	996	1	1
COVID-19	1	3	1	994	1
Healthy	0	1	1	1	997

More analysis was carried out to evaluate the performance of the system in terms of computing. Table 3 gives the prediction time and the training time of each model. Whereas the deep learning models need increased training time, they are able to make faster predictions during the inference stage thus are applied in real time. The XGBoost does exhibit accuracy/computational efficiency balance also.

Table 3: Analysis of Performance in Calculations.

Model	Training Time (min)	Prediction Time (ms)
Random Forest	35	12
Support Vector Machine	50	15
XGBoost	40	10
CNN	90	8

The results are represented graphically, which also gives more information on the performance of the model. The comparison of accuracy of the various models depicted in figure 2 distinctly indicates the performance of CNN and XGBoost are the best performing models. The training and validation accuracy curves of the CNN model shown in figure 3 show that there were no problems in convergence or overfitting.

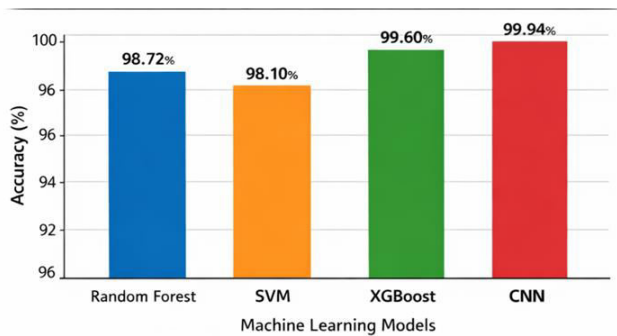


Figure 2: Comparison of Machines Learning Model Accuracy.

The graph shows a classification accuracy in all the models, and CNN had the highest accuracy as XGBoost, Random Forest, and SVM have.

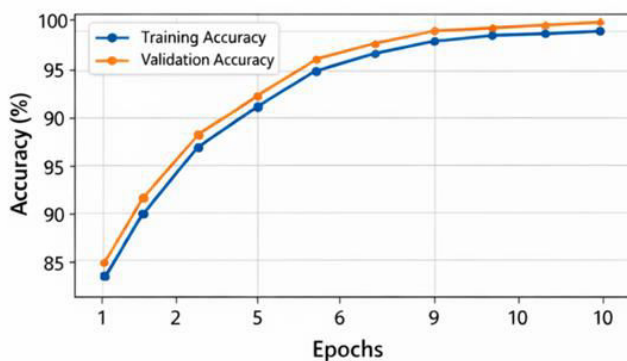


Figure 3: Accuracy Curve of Training and validation (CNN Model)

The curve indicates steady accuracy increase with increase in the epochs and the gap between the training and validation accuracy is minimal which is good generalization.

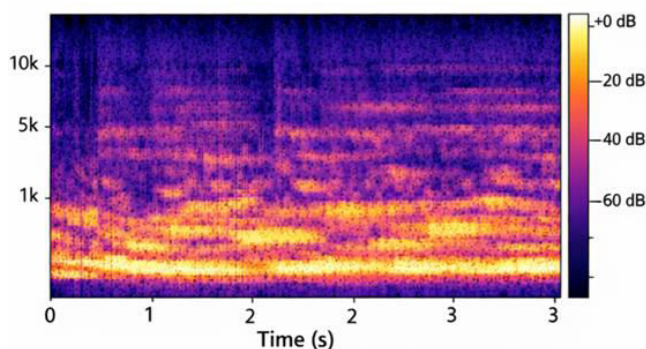


Figure 4: Spectrogram-Based Visualization of feature of cough sounds.

The figure represents time-frequency charts of cough signal, illustrating distinct patterns of cough signal to various respiratory diseases.

The outcomes of the experiment prove that the given system is highly effective in diagnosing the respiratory diseases by the sound of cough. The advanced feature extraction and machine learning models are highly useful in improving the accuracy of the classification. There is robustness and reliability because of the large dataset used, and cross-validation. In addition, the system is highly

computational effective and can be qualified to predict on the spot with reduced delays.

V. CONCLUSION

The paper introduced a cough-based respiratory disease diagnosis system, which uses machine learning and deep learning methods to do non-invasive and esterified screening. The suggested method combines modern audio preprocessing, features detection, and a set of classification models to deliver very accurate and reliable predictions. The system exhibits the high potential of real-time implementation because of its minimum computational benefits and speedy processing power. Its resource capacity to aid in early diagnoses can greatly enhance access to healthcare particularly in the far and resource restricted settings. Future directions include creating more robust and more multimodal models that use bigger and more heterogeneous datasets, use noise-resistant models, and include multimodal learned inputs like breathing patterns and clinical information. Also, implementation on the mobile and cloud platforms would increase the use of the system in telemedicine and massive healthcare monitoring systems.

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