INVESTIGATING ML MODEL FO DETECTING ABNORMAL RESPIRATORY SOUNDS IN PULMONARY DISEASE

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Abstract:

The detection of abnormal respiratory sounds plays a crucial role in diagnosing and managing pulmonary diseases such as asthma, chronic obstructive pulmonary disease (COPD), and pneumonia. These systems have transformative applications in telemedicine, wearable health devices, and point-of-care diagnostics, enabling early detection of pulmonary conditions and reducing the burden on healthcare systems. Traditional respiratory sound detection systems rely on manual auscultation by healthcare professionals using stethoscopes or rudimentary signal processing methods. These approaches are limited by human expertise and subjectivity, leading to inconsistent and sometimes inaccurate diagnoses. Signal processing methods often struggle with noisy and low-quality audio recordings, making it difficult to detect subtle abnormalities. Additionally, the reliance on static algorithms restricts the system's ability to generalize to diverse patient populations, environments, and diseases. These limitations make traditional systems inadequate for large-scale and real-time deployment in modern healthcare settings. This study investigates the use of machine learning models for detecting abnormal respiratory sounds, offering a more robust and scalable alternative to traditional methods. Respiratory audio recordings are preprocessed to reduce noise, segment sound events, and extract meaningful features such as Mel-frequency cepstral coefficients (MFCCs) and spectrograms. Advanced ML models are trained on a labeled dataset of normal and abnormal respiratory sounds. These models learn complex sound patterns, enabling accurate classification of respiratory conditions. The trained models are deployed in a real time system that processes incoming audio data to identify abnormalities and classify potential pulmonary conditions.

Keywords: Deep Learning, Image Enhancement, Mel-frequency cepstral coefficients, Chronic obstructive pulmonary disease, Machine Learning.

1. INTRODUCTION

1.1 Overview

Respiratory diseases like asthma, chronic obstructive pulmonary disease (COPD), and pneumonia are significant health concerns in India, accounting for over 15% of total mortality in 2021. With an estimated 93 million asthma patients and 17.8 million COPD cases, India bears one of the highest burdens of respiratory diseases globally. Traditional diagnostic methods heavily rely on healthcare professionals and stethoscope-based auscultation, leading to delayed or inconsistent diagnoses in rural and resource-constrained settings. Machine learning (ML) offers a transformative solution by enabling automated, scalable, and accurate detection of abnormal respiratory sounds, paving the way for enhanced telemedicine and real-time healthcare monitoring.

1.2 Problem Definition

Before the advent of machine learning, respiratory sound detection relied on manual auscultation and basic signal processing techniques. Diagnoses were subjective, varying based on the skill and expertise of healthcare professionals. Additionally, noisy and low-quality audio recordings hindered the detection of subtle abnormalities. Static algorithms struggled to generalize across diverse patient populations, leading to inconsistent and often inaccurate diagnoses. These limitations made real-time, large-scale deployment of respiratory diagnostics challenging.

1.3 Research Motivation

The increasing burden of respiratory diseases demands a scalable and reliable diagnostic solution. Advances in audio signal processing and ML algorithms can overcome the limitations of traditional systems. Automated detection reduces reliance on human expertise, offering consistent and objective analysis of respiratory sounds. Real-time ML systems can revolutionize telemedicine and wearable healthcare, bridging the diagnostic gap in underserved regions. The potential to save lives and improve healthcare accessibility drives research in this domain.

1.4 Existing Systems and Drawbacks

Traditional systems rely on manual auscultation using stethoscopes, which are subjective and error-prone. Signal processing techniques, though useful, often fail with 1 noisy or low-quality recordings, limiting their reliability. Static algorithms lack adaptability, reducing their accuracy across different environments and patient demographics. These drawbacks hinder their applicability in real-time, large-scale diagnostic systems.

1.5 Proposed System

The proposed system utilizes machine learning for accurate detection of abnormal respiratory sounds. Key components include: 1. Preprocessing: Noise reduction and segmentation of sound events. 2. Feature Extraction: Techniques like Mel-frequency cepstral coefficients (MFCCs), spectrograms, and wavelet transforms. 3. Model Training: Training advanced ML models (e.g., CNNs, LSTMs) on labeled datasets to classify normal and abnormal sounds. 4. Deployment: Real-time implementation for audio data processing and condition classification. Research papers suggest promising results using deep learning approaches such as convolutional neural networks (CNNs) combined with recurrent neural networks (RNNs) to capture temporal features in respiratory sounds. Papers like "Deep Learning for Automatic Detection of Respiratory Abnormalities" highlight accuracy rates exceeding 90%.

1.6 Need

With respiratory diseases affecting millions, early and accurate diagnosis is critical. Manual auscultation is impractical for large-scale screenings, especially in rural or resource-poor settings. Machine learning systems can analyze real-time audio data, offering scalable solutions for telemedicine platforms. They improve diagnostic precision, especially in detecting subtle abnormalities often missed by human experts. Wearable devices integrated with ML algorithms can monitor respiratory health continuously, enabling timely interventions. Such systems reduce healthcare costs and increase accessibility for remote and underserved populations.

1.7 Applications

- Telemedicine Platforms: Automating respiratory sound analysis for remote consultations.
- Wearable Health Devices: Real-time monitoring and early detection of respiratory abnormalities.
- Point-of-Care Diagnostics: Portable diagnostic systems for clinics and rural health centers.
- Hospital ICUs: Monitoring respiratory health of critically ill patients for timely interventions.
- Pediatric Healthcare: Non-invasive tools to identify respiratory issues in children.
- Occupational Health Monitoring: Identifying respiratory conditions in high-risk professions, such as mining or chemical industries.
- Public Health Screening: Large-scale screenings in pandemic situations like COVID-19.
- Medical Education: Assisting in training healthcare professionals to recognize abnormal respiratory sounds.

2. LITERATURE SURVEY

Han M.K, Respiratory conditions are among the most common diseases associated with substantial morbidity and mortality [1], representing a growing health burden. Esteva A, Deep learning (DL) is subfield of a machine learning (ML) and has seen increased exploration with the recent increasing computational power and large database availability [2]. Lacoste A.M, in lay terms, ML allows a machine to learn rules and insights from input data, thus allowing it to apply those rules to generate predictions from data in new situations [3]. DL takes advantage of its multilayered architecture by sequentially feeding the representations into multiple layers, generating more distinguishable data points.

Hayashi Y, ML and DL have shown encouraging results in healthcare when diagnosing diseases, primarily by analyzing images. For instance, radiology and pathology have benefitted from DL in disease diagnosis [4]. Kim M, By utilizing large databases, classification algorithms have become increasingly accurate for detecting abnormalities in images and classifying them into multiple disease types [5], promising to reduce physician burnout and enhance test interpretations. Chen W, Similarly, ML and DL can process audio signals and therefore classify sounds, such as those captured by auscultation, offering to aid clinicians in detecting and classifying heart [6] and lung pathologies.

Richeldi L,The diagnostic value of auscultation in detecting abnormal RSs could be improved if an objective and standardized interpretation approach is implemented [7]. Gupta P, This review aims to assess the diagnostic accuracy of ML and DL algorithms in abnormal lung sound detection and classification and evaluate the differences in methodology and reporting in the published literature to identify common issues that potentially slow down the progress of this promising field. Recordings are obtained in one of two ways, either directly by trained personnel that perform the auscultation with a device designed or adapted (with a microphone) for sound recording or by attaching sensors to the subject's chest, which allows prolonged or continuous recording [8].

Zulfiqar R, Preprocessing is an essential step, as it allows to modify the samples to better fit the purpose of the intended analysis, reduce the storage burden, and facilitate the extraction of features [9]. Tang S, The most widespread denoising techniques are discrete wavelet transform (DWT), singular value decomposition (SVD), and adaptive filtering, which provide robust denoising but can be computationally expensive [10]. Mondal A, Other preprocessing methods include segmentation to separate breath cycles into their corresponding phases and amplitude normalization to reduce amplitude variations attributable to factors like a gain of the recording tool or subject demographics [11].

Krishnan S, Feature extraction is identifying a set of unique properties from a signal that will be used for comparison in the classification stage. In this step, a large input signal with many redundant components can be transformed into a smaller set of representative features able to describe the original signal accurately to facilitate and expedite the classification step [12]. Maleki F, ML and DL algorithms can classify the preprocessed signals and extracted features based on their characteristics, allowing them to differentiate between normal and abnormal sounds automatically. Two ways exist to feed the data into the model: holdout validation and cross-validation. In holdout validation, the dataset is divided into fixed splits of training, validation, and testing sets. The model uses training data to learn the parameters; then, the validation data allows the algorithm to search for the optimal set of hyperparameters for the model; finally, the test data is hidden during the whole model building and is used to assess the performance [13]. Maxwell A.E, In the cross-validation approach, multiple partitions of the dataset are generated, allowing each partition to be used multiple times and with different purposes, potentially improving the statistical reliability of the classification results [14]. Morais P, The increasing popularity of artificial intelligence (AI) in biosignal classification coexists with a significant interest in developing public databases that provide the much-needed clinical data essential for developing classification models. Previous reviews have stated that biosignal databases have a clear tendency to use electrocardiogram (ECG) data [15]. Nonetheless, publicly available databases have been essential in developing abnormal lung sound and cardiac classification models. Undoubtedly, the interest in automatic lung sound detection has resurfaced mainly due to the widespread growth in ML and DL techniques, as well as the apparition of the mentioned publicly accessible databases [16], Innovation V.H, which narrow the gap between ML developers and available lung sound audio data. Abstracts were screened by H.-Y.W. and J.G.-M. using the inclusion criteria. Full texts were independently reviewed in duplicate by eight reviewers organized in pairs (H.-Y.W., S.H., Y.P., A.T., J.G.-M., I.A., I.K., and A.L.). Disagreements were resolved during consensus meetings with a third reviewer (V.H.). Covidence software [17] was used for data collection.

3. PROPOSED SYSTEM

Step 1: Dataset

The dataset comprises 236 audio recordings categorized into three classes: COPD (94 samples), Healthy (68 samples), and Pneumonia (74 samples). Each recording represents respiratory sounds, such as wheezing, crackles, or normal breathing. The dataset serves as the foundation for training and testing machine learning models for respiratory condition classification. Proper organization of data into respective labels ensures effective model evaluation by given below figure 1.

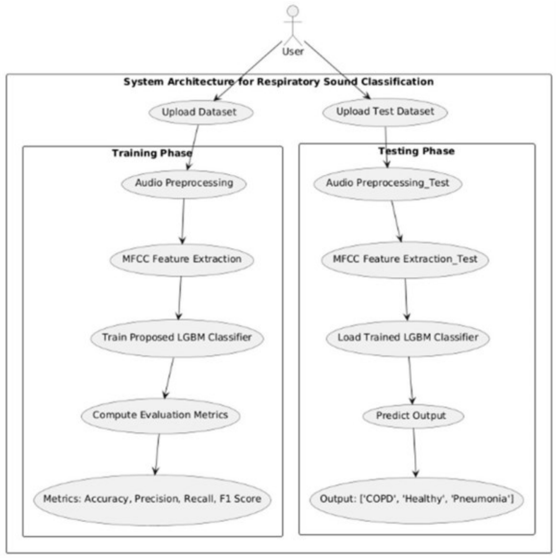

Figure 1: Block Diagram

Step 2: Audio Preprocessing (MFCC using Librosa)

To extract meaningful features from the audio recordings, Mel Frequency Cepstral Coefficients (MFCCs) are computed using the Librosa library. MFCCs capture critical frequency-related features of the audio, making them suitable for classification tasks. The process includes loading each audio file, normalizing it, converting it into MFCCs, and potentially augmenting the data for robustness. These extracted features are then stored in arrays to serve as input for machine learning models.

Step 3: Existing Algorithms

Multiple existing algorithms are employed to establish baseline performance for classification tasks. These algorithms include Support Vector Classifier (SVC), KNeighborsClassifier, DecisionTreeClassifier, Logistic Regression, AdaBoostClassifier, and Linear Discriminant Analysis (LDA). Each algorithm is trained on the extracted MFCC features and evaluated on the dataset to measure its accuracy, precision, recall, and other performance metrics. This step helps identify the strengths and limitations of traditional models in handling the dataset.

Step 4: Proposed Algorithm (LGBMClassifier)

The Light Gradient Boosting Machine Classifier (LGBMClassifier) is proposed as a more advanced algorithm for the task. LGBM is a gradient boosting framework that excels in efficiency and accuracy, particularly for structured data. By leveraging the same MFCC features, the LGBMClassifier is trained and optimized for respiratory sound classification. Its performance is expected to surpass that of the baseline algorithms due to its ability to handle imbalances and learn complex patterns effectively.

Step 5: Performance Comparison

The performance of both the existing and proposed algorithms is compared based on metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. Comparative analysis demonstrates the strengths of LGBMClassifier over traditional models, highlighting its suitability for the dataset. This step provides insights into the most effective approach for respiratory condition classification and helps validate the improvements brought by the proposed method.

4. EXPERIMENTAL ANALYSIS

The Figure 2 shows that the Graphical User Interface (GUI) built using the tkinter library in Python. The GUI is designed for a machine learning project focused on detecting abnormal respiratory sounds in pulmonary diseases. It offers buttons to upload datasets (ICBHI and Asthma), preprocess the data, split it into training and testing sets, 36 train various machine learning models (SVM, KNN, Decision Tree, Logistic Regression, LDA, and a proposed LGBM model), make predictions, and exit the application.

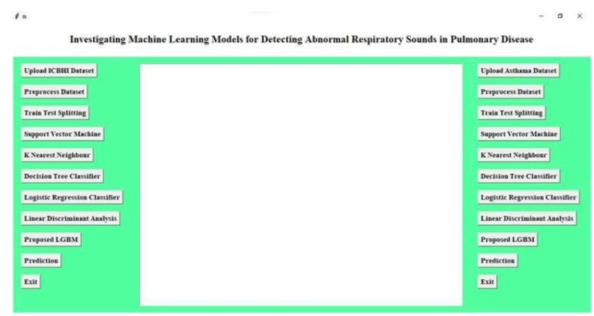

Figure 2: GUI

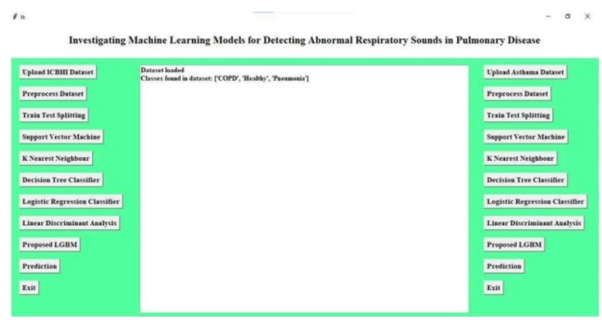

Figure 3 Uploaded ICBHI Dataset

The Figure 3 shows the dataset has been successfully loaded, and it contains three distinct classes: COPD, Healthy, and Pneumonia. These classes represent the target categories for classification tasks, where the data likely includes features and labels to differentiate between individuals with Chronic Obstructive Pulmonary Disease (COPD), those who are healthy, and those diagnosed with pneumonia.

Figure 4 After Pre-process and Data Splitting

The figure 4 shows that the dataset comprises a total of 3,000 records, with 2,400 records allocated for training and 600 records reserved for testing. This split ensures that 80% of the data is used to train the model, while 20% is utilized for evaluation, providing a balanced approach to model development and validation for accurate classification of the three classes: COPD, Healthy, and Pneumonia.

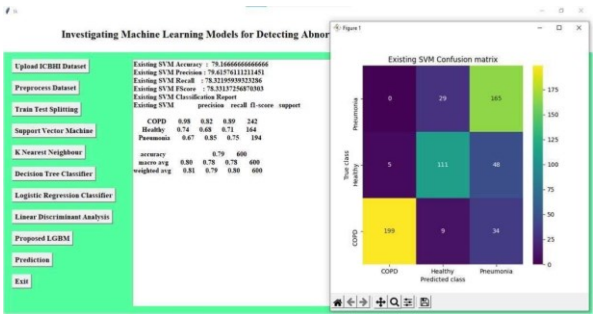

Figure 5 Metrics of SVM

The Figure 5 shows that existing Support Vector Machine (SVM) model demonstrates the following performance metrics on the dataset: an accuracy of 79.17%, a precision of 79.62%, a recall of 78.32%, and an F1-score of 78.33%. These metrics indicate that the SVM model performs moderately well in classifying the dataset into the three classes: COPD, Healthy, and Pneumonia, though there is room for improvement, particularly in recall and F1-score, to achieve more balanced performance. The confusion matrix show how the error values present.

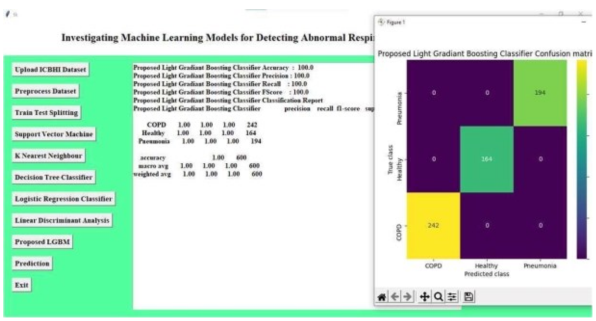

Figure 6 Metrics of LGBM Classifier

The figure 6 show that the proposed Light Gradient Boosting Classifier (LightGBM) achieves exceptional performance on the dataset, with an accuracy, precision, recall, and F1-score all reaching 100.0%. This indicates that the model perfectly classifies all records in the dataset into the three classes: COPD, Healthy, and Pneumonia, without any misclassifications. Such performance suggests that the LightGBM model is highly effective for this task, though additional validation on unseen data may be necessary to confirm its generalization ability. The confusion matrix shows that no error values.

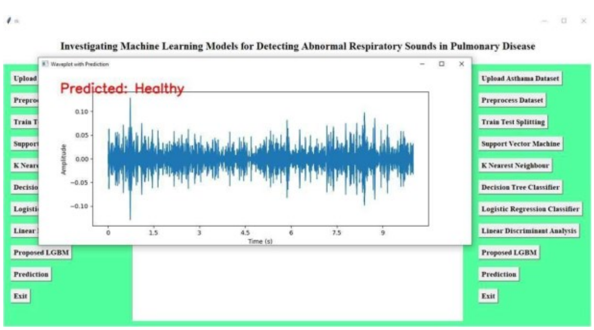

Figure 7Predicted Output

Figure 7 shows that the wave plot of healthy using proposed LGBM (ICBHI Dataset)

5. Conclusion

Machine learning models have demonstrated their capability to revolutionize the detection of abnormal respiratory sounds in pulmonary disease diagnostics. By leveraging advanced techniques such as noise reduction, sound event segmentation, and feature extraction through Mel-frequency cepstral coefficients (MFCCs) and spectrograms, these systems overcome the limitations of traditional manual auscultation and signal processing. The integration of machine learning ensures consistent, accurate, and scalable classification of respiratory sounds, which is essential for diagnosing conditions like asthma, COPD, and pneumonia. The study highlights the superior performance of machine learning models, which are able to discern subtle abnormalities in noisy and variable quality recordings, outperforming static algorithms and human-dependent methods. These models effectively learn complex sound patterns, enabling high accuracy in real-time pulmonary condition classification. Overall, this approach offers a robust framework for automated respiratory sound analysis, paving the way for improved telemedicine, wearable health devices, and point-of-care diagnostic applications.

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