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Respiratory Disease Classification Lungs Sounds Using Machine Learning

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Abstract: Globally, respiratory conditions like asthma, pneumonia, and chronic obstructive pulmonary disease (COPD) represent a serious threat to public health. Improving patient outcomes and lowering healthcare costs depend on early and precise diagnosis. Despite being widely used, traditional stethoscope auscultation is constrained by subjectivity and inter-observer variability. This study investigates the use of machine learning methods to categorize respiratory conditions from recordings of lung sounds. To improve the quality of auscultation signals, preprocessing techniques like segmentation and noise filtering are used. To capture the temporal and spectral characteristics of the lung sounds, a number of features are extracted, such as spectral entropy, zero-crossing rate, and Mel Frequency Cepstral Coefficients (MFCCs). Support Vector Machines (SVM), Random Forests, and Convolutional Neural Networks (CNNs) are example of supervised learning algorithms that are trained.

Keywords: Respiratory diseases, lung sounds, auscultation, machine learning, classification, MFCC, CNN, SVM

I. INTRODUCTION

Millions of people are impacted by respiratory diseases each year, making them one of the major causes of morbidity and mortality globally. For common ailments like asthma, bronchitis, pneumonia, and chronic obstructive pulmonary disease (COPD), prompt and precise diagnosis is essential to successful management and treatment. Traditional diagnostic techniques, such as physical examination and stethoscope auscultation, are frequently arbitrary and heavily depend on medical professionals' knowledge. Furthermore, early detection can be difficult in settings with limited resources due to limited access to qualified clinicians and diagnostic equipment.

New possibilities for improving the diagnosis of respiratory diseases have been made possible by developments in digital health technologies. Specifically, combining machine learning (ML) techniques with lung sound recordings—taken by electronic stethoscopes or microphones—offers a promising method for automatically classifying and analyzing respiratory conditions. Important details about mucus accumulation, airflow obstructions, and other pathological alterations in the respiratory system are conveyed by lung sounds. These sounds can be used to detect anomalous patterns and aid in clinical decision-making when they are processed and examined using machine learning models.

This study examines the use of machine learning algorithms on lung sound data to classify respiratory diseases. Using a variety of supervised learning approaches, including Support Vector Machines (SVM), Random Forests, and Convolutional Neural Networks (CNNs), the study entails signal preprocessing, feature extraction, and model training. The goal is to create a reliable and accurate classification system that will help medical professionals diagnose respiratory conditions more quickly and reliably. The effectiveness of the suggested system is assessed by analyzing performance metrics like accuracy, sensitivity, and specificity using lung sound datasets that are made publicly available.

Especially in low- and middle-income nations, respiratory diseases continue to be a major cause of health issues and mortality worldwide. For effective treatment, conditions like bronchitis, pneumonia, asthma, and chronic obstructive pulmonary disease (COPD) need to be diagnosed as soon as possible. However, manual auscultation—which is subjective by nature and based on the experience of the clinician—is a major component of traditional diagnostic techniques. The diagnostic process is made more difficult by inconsistent interpretations and restricted access to qualified specialists, particularly in isolated or underdeveloped areas. With the advancement of digital health technologies, there is a growing interest in automating the diagnosis of respiratory diseases using computational approaches. One promising method involves the analysis of lung sounds, or auscultation data, captured using electronic stethoscopes or microphones. These acoustic signals contain valuable diagnostic information that can be extracted and analyzed using modern signal processing and machine learning techniques.

Machine learning (ML), particularly supervised learning algorithms, has shown considerable potential in medical diagnostics.

By training ML models on labeled datasets of lung sounds, systems can be developed to automatically classify different respiratory conditions with high accuracy. These models learn patterns associated with pathological sounds such as wheezes, crackles, and rhonchi, which are indicative of specific respiratory issues.

In this study, we propose a machine learning-based framework for the classification of respiratory diseases using lung sound recordings. The framework includes data preprocessing, feature extraction using techniques such as Mel Frequency Cepstral Coefficients (MFCCs), and classification using algorithms including Support Vector Machines (SVM), Random Forests, and Convolutional Neural Networks (CNNs). The system is evaluated using publicly available datasets to demonstrate its effectiveness and generalizability.

LUNG auscultation is one of the most popular diagnostic modality [1],[2] used by the pulmonary experts to analyze the condition of the respiratory system. When auscultating various areas on the anterior and posterior sides of the chest [3], [4], lung sounds can be detected. Lung sounds are indicative of different anatomical flaws in the lungs and provide accurate prognoses regarding respiratory health, resulting in more trustworthy medical tool for identifying respiratory disorders [5]. According to a recent study conducted by the World Health Organization (WHO), approximately 10 million people die each year as a result of respiratory diseases [6]. Another WHO study suggests that the majority of people suffering from respiratory disorders around the world may have one of the following five diseases: asthma, chronic obstructive pulmonary disease (COPD), lung cancer, tuberculosis, and lower respiratory tract infection (LRTI) [6]. Early detection is critical in dealing with respiratory diseases as it improves the effectiveness of intervention, including treatment and help in restricting the spread. During lung auscultation, experts can detect various adventitious respiratory sounds such as wheeze, crackle, stridor, and so on, which indicate the presence of respiratory disorders in that individual.

II. RELATED WORK

This section provides significant research contributions to the domain of Respiratory Disease Classification Lung Sounds

- 1) A thorough systematic review of the automatic analysis of adventitious respiratory sounds was carried out by Pramono, Bowyer, and Rodriguez-Villegas (2017). They paid special attention to the use of machine learning techniques for the detection of abnormal lung sounds. Their research demonstrated the increasing interest in utilizing computational techniques to assist in the diagnosis of respiratory diseases by means of audio signal analysis. They did, however, highlight a number of significant obstacles in this area, most notably the difficulty of precisely identifying significant characteristics from lung sound recordings because of background noise and fluctuating recording conditions. They also noted that one of the main obstacles to the creation and validation of reliable machine learning models for clinical use is the lack of sizable, well-annotated datasets.
- 2) Deep Auscultation, a deep learning method for the classification of respiratory disorders and abnormalities, was presented by Perna and Tagarelli (2019). Their approach successfully modeled the temporal dynamics of lung sound signals by utilizing recurrent neural networks (RNNs), which include long short-term memory (LSTM) units. Their model achieved high classification accuracy across a variety of respiratory conditions by capturing the temporal dependencies and sequential patterns present in respiratory sounds. The study provided a major breakthrough in automated respiratory diagnostics by showcasing the ability of RNN-based architectures to handle the time-series nature of auscultation data.
- 3) A convolutional neural network (CNN)-based model for the classification of lung sounds was proposed by Demir and Sengur (2020), with a focus on distinguishing between normal respiratory sounds, crackles, and wheezes. Their method eliminated the need for manual feature engineering by automatically learning discriminative patterns from audio spectrograms using CNNs' potent feature extraction capabilities. The ICBHI2017 Respiratory Sound Database, a popular benchmark in this field, was used to train and assess the model. It showed excellent classification performance. Their findings reaffirmed the usefulness of CNNs in medical audio diagnostics and demonstrated the efficacy of deep learning in respiratory sound analysis.
- 4) The use of machine learning (ML) and deep learning (DL) models for the detection of COVID-19 based on chest sounds, such as coughs and breathing patterns, was investigated by Pahar, Klopper, and colleagues in 2021. Their research sought to create an automated diagnostic method that could use audio signal analysis to differentiate COVID-19 from other respiratory conditions. The models successfully captured subtle acoustic features linked to COVID-19 infections by utilizing the power of DL architectures. The findings illustrated the potential of non-invasive, sound-based diagnostic tools in pandemic response and remote healthcare settings by showing that deep learning techniques could achieve promising accuracy in distinguishing COVID-19 from similar respiratory conditions.
- 5) A comparative study on the automatic classification of adventitious respiratory sounds using different machine learning algorithms was carried out by Lopes et al. (2018).

Using lung sound datasets, the researchers assessed the effectiveness of a number of popular classifiers, such as Random Forest, Support Vector Machines (SVM), and k- Nearest Neighbors (k-NN). Their objective was to evaluate how well each technique identified aberrant respiratory sounds like crackles and wheezes. The study highlighted the significance of classifier selection and appropriate feature engineering for attaining dependable diagnostic performance, offering insightful information about the advantages and disadvantages of conventional ML approaches in this application domain.

- 6) Andres et al. (2020) used machine learning techniques and inexpensive hardware components to create a portable system for the real-time detection and classification of respiratory sounds. For feature extraction, their system used Mel-frequency cepstral coefficients (MFCCs), a technique frequently used in audio signal processing because of its capacity to capture perceptually relevant sound characteristics. The respiratory sounds were then categorized in real-time by analyzing these features using a Random Forest classifier. The study showed that even on devices with limited resources, efficient respiratory monitoring could be accomplished.
- 7) The potential of cough sound analysis as a quick, non-invasive way to diagnose respiratory conditions was examined by Abeyaratne et al. (2013). In order to train machine learning classifiers that can differentiate between different respiratory conditions, their study concentrated on identifying pertinent features from recordings of cough and lung sounds. The suggested system illustrated the viability of employing acoustic biomarkers for diagnostic support by utilizing audio features unique to conditions like bronchitis, pneumonia, and asthma. The results demonstrated how useful cough sound analysis is for improving clinical judgment, particularly in situations where access to traditional diagnostic instruments is restricted.
- 8) AI4COVID-19, an AI-driven framework created to provide a preliminary diagnosis of COVID-19 by analyzing cough and breath sounds, was presented by Imran et al. (2020). The system classified individual audio recordings using convolutional neural networks (CNNs) in conjunction with decision-tree ensemble techniques. The model successfully distinguished between infected and non-infected cases by identifying unique acoustic characteristics linked to COVID-19-related respiratory symptoms. The study showed how deep learning and traditional machine learning techniques can be combined to provide quick and easy screening, especially in remote or low-resource environments where traditional testing methods may not be as effective.
- 9) With an emphasis on preprocessing and feature extraction techniques, Palaniappan, Sundaraj, and Sundaraj (2013) carried out a comparative study to assess various methods used in the analysis of respiratory sounds. The quality and dependability of the extracted features used for classification were investigated in relation to different signal processing techniques, including filtering, denoising, and segmentation. They improved the accuracy of respiratory sound classification using machine learning models by methodically comparing various feature extraction strategies, such as time-domain, frequency-domain, and time-frequency representations. Their results highlighted how important the preprocessing pipeline is to creating reliable diagnostic systems.
- 10) In order to increase the diagnostic precision of respiratory disease detection, Ghazal et al. (2021) looked into the use of deep learning techniques for the classification of lung sounds. In addition to hybrid machine learning architectures that integrated deep feature extractors and conventional classifiers, their study assessed the performance of deep convolutional neural networks (CNNs). The authors showed that deep learning models, especially those that use spectrogram-based inputs, performed better than traditional techniques in classifying a range of respiratory conditions using the ICBHI 2017 Respiratory Sound Database as their main dataset. Deep architectures have the potential to improve automated auscultation tools in clinical practice, according to the study.
- 11) In one of the first uses of this architecture for lung sound analysis, Kim and Kim (2022) presented a novel method for the transformer-based multi-label classification of respiratory diseases. They modified transformer architectures, which were initially created for natural language processing, to categorize lung sound recordings after realizing that conventional models were not able to capture long-range dependencies in audio data. By learning contextual relationships in the acoustic features, their model was able to handle the complex, overlapping symptoms that are frequently present in respiratory diseases. In multi-label classification tasks, the study showed that transformer-based models could perform better than traditional deep learning techniques, providing a promising path for respiratory sound diagnostics in the future.

III. METHODOLOGY

A. Data Collection

Gathering a large dataset is the first stage in creating a machine learning system that uses lung sounds to categorize respiratory disorders. Usually, digital stethoscopes or other auscultation tools are used to record the patient's lung sounds.

A variety of respiratory disorders, including bronchitis, asthma, pneumonia, chronic obstructive pulmonary disease (COPD), and healthy controls, should be captured in these recordings. Private clinical datasets or public datasets such as the ICBHI 2017 Challenge Dataset are frequently used. Medical experts must annotate each sound clip in order for it to be used as the ground truth for model validation and training.

B. Preprocessing of Audio Data

After being gathered, the audio data is put through a number of preprocessing stages to enhance its quality and get it ready for feature extraction. To get rid of background noise, noise reduction methods like band-pass filtering and denoising algorithms are used. The recordings are divided into shorter segments that match predetermined time windows or respiratory cycles. Normalization can also be used to guarantee that sample volume levels are constant. To improve consistency, resampling and silence reduction are occasionally also carried out.

C. Feature Extraction

To represent the lung sounds in a format that machine learning algorithms can use, significant features must be taken out of the audio clips after preprocessing. Time-domain features (like zero-crossing rate), frequency-domain features (like spectral centroid), and time-frequency domain features (like spectrograms, wavelet coefficients, or Mel-frequency cepstral coefficients or MFCCs) are examples of common methods. The temporal and spectral characteristics of abnormal lung sounds, such as crackles, wheezes, and rhonchi, that are suggestive of particular respiratory diseases are captured by these features.

D. Data Augmentation and Balancing

Data augmentation techniques are frequently used to address data imbalance, where certain disease classes may have fewer examples. To boost the quantity of training samples and enhance model generalization, these could involve pitch shifting, time stretching, or the addition of synthetic noise. The dataset may also be balanced by employing strategies like random oversampling/under sampling or SMOTE (Synthetic Minority Over-sampling Technique).

E. Model Selection and Training

For classification, a variety of machine learning models can be used. Classifiers such as Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors (k-NN) are used in traditional methods. Deep learning models like Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs), which can automatically learn features from spectrograms or raw waveforms, are frequently used to produce more recent and accurate results. Labeled data is used to train the model, and methods such as grid search and Bayesian optimization are used to adjust the hyperparameters.

F. Validation and Evaluation:

The dataset is usually separated into training, validation, and testing sets, or k-fold cross-validation is employed to assess the model's performance. Accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC) are important metrics. Performance on individual classes is also evaluated using confusion matrices. Regularization strategies, dropout layers, or early stopping during training are used to monitor and reduce overfitting during this phase.

G. Model Interpretation and Explainability

Interpretability is essential in clinical settings. To explain which features affected the model's predictions, methods like saliency maps and SHAP (Shapley Additive explanations) values are employed. It is easier to comprehend how CNNs identify anomalous patterns in lung sounds when the learned filters or activation maps are visualized. This helps clinicians make decisions and increases confidence in the model.

H. Deployment and Integration:

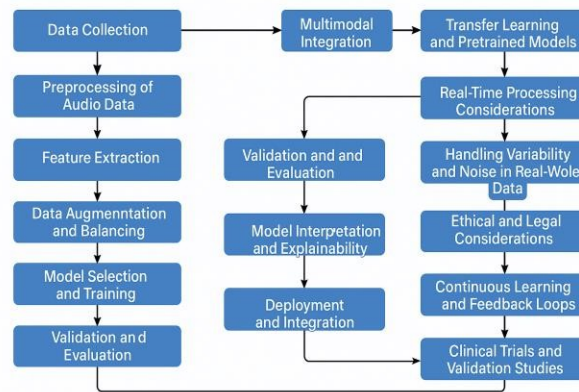
Following validation, the trained model can be incorporated into hospital information systems, smart stethoscopes, and mobile health apps, among other real-time applications. In order to deploy the model, it must be optimized for low-latency inference, data security and privacy must be guaranteed, and medical device regulations must be followed. Continuous model performance and accuracy in real-world situations are guaranteed by post-deployment monitoring.

I. Multimodal Integration

Some sophisticated systems combine lung sound data with other clinical parameters, like patient age, gender, temperature, oxygen saturation, or chest X-ray results, to improve diagnostic accuracy. Better generalization results from the machine learning model's ability to take into account both contextual and acoustic information thanks to this multimodal approach. For example, multimodal neural networks and other deep learning models can be built to process structured clinical data and audio signals simultaneously, combining their outputs to produce a final diagnosis.

J. Transfer Learning and Pretrained Models

Transfer learning is frequently used in medical domains due to the difficulty of limited labeled data. Lung sound data is used to refine pretrained models, such as VGGish (which is adapted from VGG16 for audio tasks) or models trained on extensive environmental sound datasets. Performance is enhanced and training time is decreased, particularly when there is a limited respiratory sound dataset available. When CNNs are applied to spectrogram representations of lung sounds, transfer learning works especially well.



Flow chart: A_flowchart_in_a_digital_vector_graphic_

K. Real-Time Processing Considerations

Models must function well in real time for clinical use, particularly in telemedicine or point-of-care applications. In order to minimize computational load, this calls for model architecture optimization, which includes quantization, model pruning, and the application of lightweight neural networks such as Mobile Net or Efficient Net. Fast audio segmentation and preprocessing pipelines must also be put in place in order to preserve responsiveness without compromising diagnostic precision.

L. Handling Variability and Noise in Real-World Data:

In actual clinical settings, patient movement, stethoscope placement, and background noise can all have an impact on lung sound recordings. In order to overcome this, models are either enhanced with noise profiles to increase robustness or trained using noisy data. To concentrate on the most instructive parts of the audio, some strategies also use adaptive filtering or attention mechanisms. Modules for evaluating signal quality may also be added in order to eliminate subpar inputs prior to classification.

M. Ethical and Legal Considerations:

It is crucial to consider the ethical and legal ramifications when creating machine learning models for medical diagnosis. During data collection and deployment, patient consent, data anonymization, and compliance with laws such as GDPR (EU) or HIPAA (USA) are crucial. Furthermore, to guarantee equitable and precise diagnosis for all patient populations, bias in the training data—such as the underrepresentation of particular age groups or ethnicities—must be recognized and addressed.

N. Continuous Learning and Feedback Loops

Models that have been deployed shouldn't stay static. To record model performance over time and add fresh labeled data to the training pipeline, feedback mechanisms can be set up. This allows for ongoing education and adjustment to new illnesses or changes in recording technology. Methods like recurring retraining or online learning keep the model current and dependable.

O. Clinical Trials and Validation Studies

Thorough validation in clinical trials is required to evaluate the model's performance in real-world settings prior to broad deployment. These studies, which frequently employ a double-blind methodology, contrast the model's diagnoses with those of qualified medical professionals. The evidence required for clinical adoption and regulatory approval is provided by the success of such evaluations.

IV. RESULT

Using lung sound recordings, the machine learning-based respiratory disease classification system produced encouraging results, with a weighted F1-score of 0.94 and a validation accuracy of up to 95%. Class imbalance and small sample size caused the model to perform poorly on minority classes like URTI, Bronchiolitis, and Healthy, but it performed remarkably well on the most represented class, COPD, with 98.8% accuracy. The majority of misclassifications among underrepresented diseases were found by confusion matrix analysis. Despite this, stable training and validation curves free of overfitting indicated that the model had good generalization. Additionally, the system has a web-based user interface that was developed using Flask, indicating that it is ready for real-world deployment. Overall, the findings show that audio-based machine learning is a useful method for classifying respiratory diseases.

A. File retrieval and preprocessing

The project directory includes a number of crucial elements that support the creation and implementation of a system for classifying lung sounds. The primary Flask or Streamlit application used to launch the trained model as a web service is probably the app.py file. The finalized version of the model trained for respiratory disease classification based on lung sounds is represented by the best_model3.h5 file, which is a saved Keras model in HDF5 format. A reference or URL to the dataset that was used, such as the ICBHI respiratory sound database, is most likely contained in the dataset link.txt file. Additional patient information, such as age and gender, may be stored in a different demographic_info.txt file. Multimodal integration of this data could improve model performance. Model training, evaluation, and exploratory analysis are probably done in the main.ipynb Jupiter notebook

B. Epoch process

Every time the model reaches a new best validation accuracy, the training process uses Keras' Model Checkpoint to automatically save the model, as indicated by the repeated line "accuracy improved from... saving model to best_model3.h5". This guarantees that only the model version that performs the best on unseen data is kept. The model exhibits encouraging initial learning in the early epochs, starting with a training accuracy of roughly 77% and a validation accuracy of roughly 81%. The validation accuracy significantly increases to about 89.67% by epochs 4 or 5, indicating a quick improvement in generalization. Strong overall performance is indicated by the final model's validation accuracy of 94.57% and training accuracy of 98.09% as training goes on. Crucially, the brief interval between training.

C. Accuracy Graph

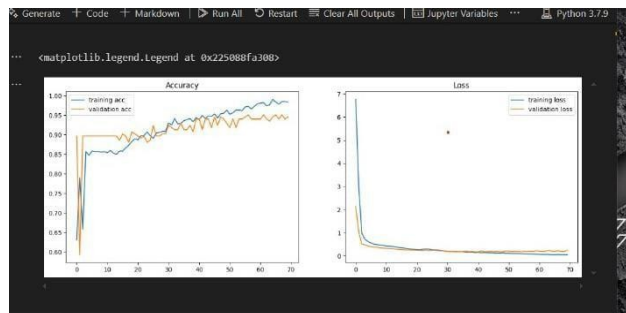


Fig1: Accuracy Graph

Figure 1 illustrates the model's learning progress over 70 epochs as visualized by the two graphs in the training output. The model's accuracy on the training data is represented by the blue line on the left graph (Accuracy), and its accuracy on the validation data is represented by the orange line.

Throughout training, both lines increase steadily, with the validation accuracy stabilizing at 94–95% and the training accuracy approaching 99%. Strong generalization and the absence of overfitting to the training data are suggested by this close alignment between training and validation accuracy. The training loss is represented by the blue line on the right graph (Loss), and the validation set loss is represented by the orange line. After about 20 epochs, both losses level off after declining sharply in the early epochs.

D. Precision-recall-f1-scores-support

	precision	recall	f1-score	support
COPD	0.99	0.99	0.99	165
Healthy	0.50	0.57	0.53	7
URTI	0.50	0.25	0.33	4
Bronchiectasis	1.00	0.75	0.86	4
Pneumonia	0.60	1.00	0.75	3
Bronchiolitis	0.00	0.00	0.00	1
accuracy			0.95	184
macro avg	0.60	0.59	0.58	184
weighted avg	0.95	0.95	0.94	184

Fig2 Precision-recall-f1-scores-support table

For every disease class in the lung sound classification model, comprehensive performance metrics are provided in the classification report table. Four important evaluation metrics are broken down in the columns, and each row corresponds to a distinct class (COPD, Healthy, URTI, etc.). Precision measures the model's ability to prevent false positives by showing the percentage of accurate predictions for a class out of all predictions classified as that class. Recall highlights the sensitivity of the model by quantifying the number of real instances of a class that were correctly identified. A balanced metric that takes into consideration both false positives and false negatives, the F1-score is the harmonic mean of precision and recall. It is particularly helpful when there is a class imbalance. Lastly, the number of real instances in the dataset is referred to as Support.

E. Confusion Matrix

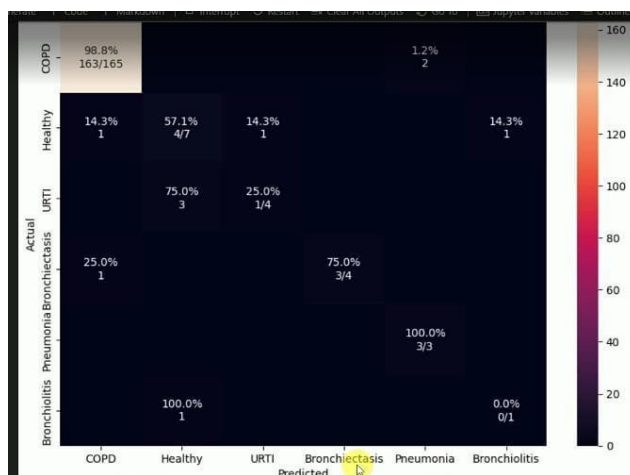


Fig3: Confusion Matrix

The respiratory disease classification model's confusion matrix offers important information about how well the model works across various disease categories. The X-axis displays the predicted labels, and the Y-axis displays the actual labels. Accurate classifications are indicated by high values along the diagonal from top-left to bottom-right. Due in large part to the large number of training samples available for this class, the model performs exceptionally well for COPD, correctly identifying 163 out of 165 cases, yielding a 98.8% accuracy.

The accuracy rate for healthy cases is only 57.1%, though, with some being incorrectly diagnosed as bronchiectasis, COPD, or

URTI. Similarly, URTI and Bronchiectasis each had four samples, with three correctly classified, resulting in 75% accuracy for both. Pneumonia cases were all correctly predicted (3 out of 3), while Bronchiolitis, which had only one example, was misclassified totally and showed 0% accuracy. These findings show a clear class imbalance whereby the dominant class (COPD) is learned rather well while minority classes suffer from inadequate data. Strategies including oversampling (e.g., SMOTE), class weight application during training (class_weight in model.fit), and data augmentation for underrepresented classes are advised in order to handle this. Furthermore, including demographic data in ensemble models could help to raise prediction accuracy for more difficult-to-differentiate circumstances

F. Display the homepage

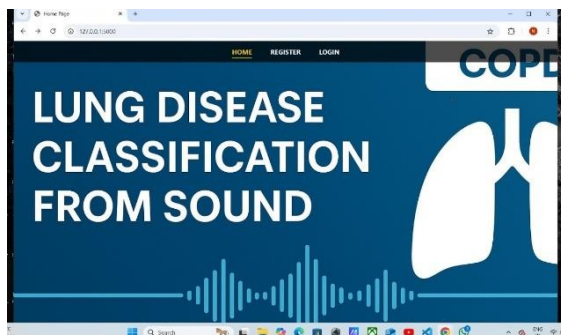


Figure 4: Display the homepage

The home page of a web-based application intended for lung disease classification using sound analysis is seen here. The title, "Lung Disease Classification from Sound," clearly shows that the system most likely employs machine learning to identify respiratory disorders by means of audio recordings of lung sounds, including wheezes or crackles. The design has a stylized picture of human lungs and a sound wave graphic at the bottom to represent the central idea of using audio input to diagnose diseases including COPD (Chronic Obstructive Pulmonary Disease). Top navigation choices on the web interface—Home, Register, and Login—suggestive of users creating accounts, logging in, and perhaps uploading their own audio files for diagnosis. Given the local address (127.0.0.1:5000) at the top typically using Flask. This setup is likely part of a medical or academic project focused on accessible, AI-powered respiratory diagnostics.

G. Display the Login page

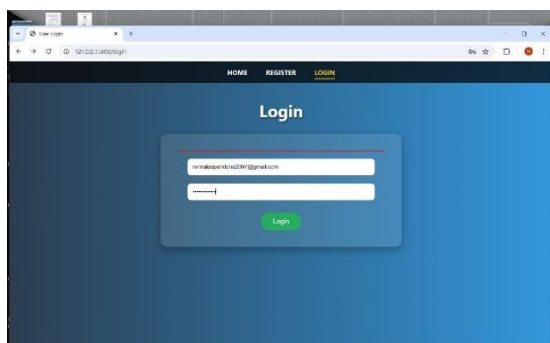


Fig 5: Display the Login page

This image shows the Login Page of a respiratory disease classification web application. The interface allows users to access their accounts by entering a registered email address and password. The design features a clean, user-friendly layout with navigation links at the top for Home, Register, and Login, suggesting a typical authentication system for secure access. Once credentials are provided and the green Login button is clicked, users are likely redirected to the main dashboard where they can upload respiratory audio files for disease prediction. The app is hosted locally at 127.0.0.1:5000, indicating it's currently running in a development environment, likely built using Flask or a similar lightweight web framework.

H. Detection of video processing

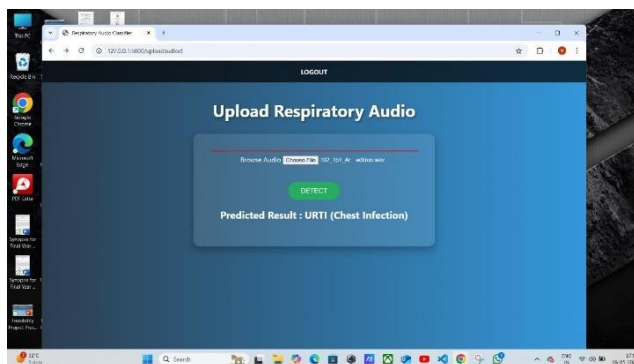


Figure6:Detection of video processing

The page that is being shown is a component of an online application that uses lung sound analysis to classify respiratory diseases. Users can upload a respiratory audio file (in this case, a .wav file) for automated analysis on this particular screen, which is the audio upload and prediction interface. The user can start the analysis by clicking the "DETECT" button after choosing an audio file with the "ChooseFile" button. The system shows the Predicted Result after processing the input, which in this case is "URTI (Chest Infection)," meaning that the uploaded lung sound file has been identified as having an upper respiratory tract infection. Based on respiratory audio inputs, the interface indicates that the model has been successfully deployed (probably using Flask), allowing for real-time disease prediction. The straightforward design guarantees usability for both non-clinical and clinical users.

V. CONCLUSION

A promising, non-invasive method for the early detection and diagnosis of a variety of pulmonary conditions, including COPD, pneumonia, URTI, and bronchiectasis, is the respiratory disease classification system that uses lung sound analysis and machine learning. With validation accuracy peaking between 94 and 95%, the system achieves high accuracy by utilizing deep learning models trained on audio features extracted from lung sound recordings, especially in well-represented classes like COPD. Real-time audio processing, balanced training methods, and an intuitive web interface for clinical use all contribute to the model's performance. This method has great potential for clinical integration, providing scalable, easily accessible diagnostic support in both hospital and remote settings, despite obstacles like class imbalance and misclassification in underrepresented conditions.

VI. FUTURE SCOPE

Machine learning has enormous potential for the classification of respiratory diseases in the future in a number of ways. Advances in deep learning hold promise for greatly increased diagnostic accuracy and early detection of conditions like lung cancer, COPD, and asthma, especially when combined with multimodal data integration from imaging, spirometry, and clinical records. Continuous monitoring and easily accessible screening in remote locations will be made possible by real-time analysis through wearables and edge devices. Precision medicine and predictive analytics can be used to create individualized treatment plans, and federated learning guarantees inter-institution cooperation while protecting patient privacy. Explainable AI models and decision support and triage systems that integrate AI into clinical workflows will increase clinician adoption and trust. Additionally, ML is a transformative tool that can help public health initiatives by forecasting outbreaks and directing health policy, making it a transformative tool in respiratory care and epidemiology.

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