CoughClassify: A Novel Mobile Application for Respiratory Disease Prediction

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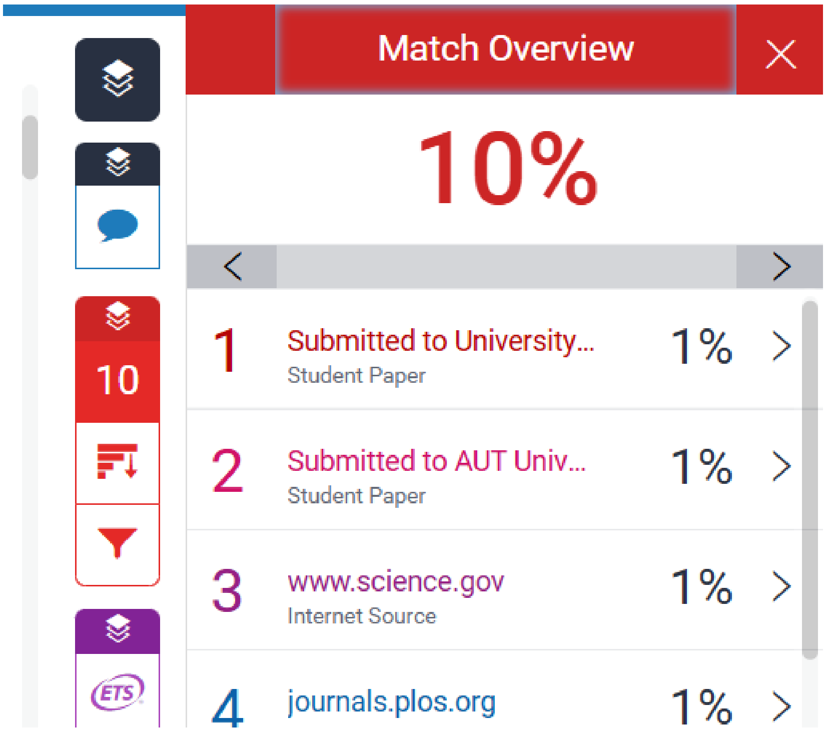

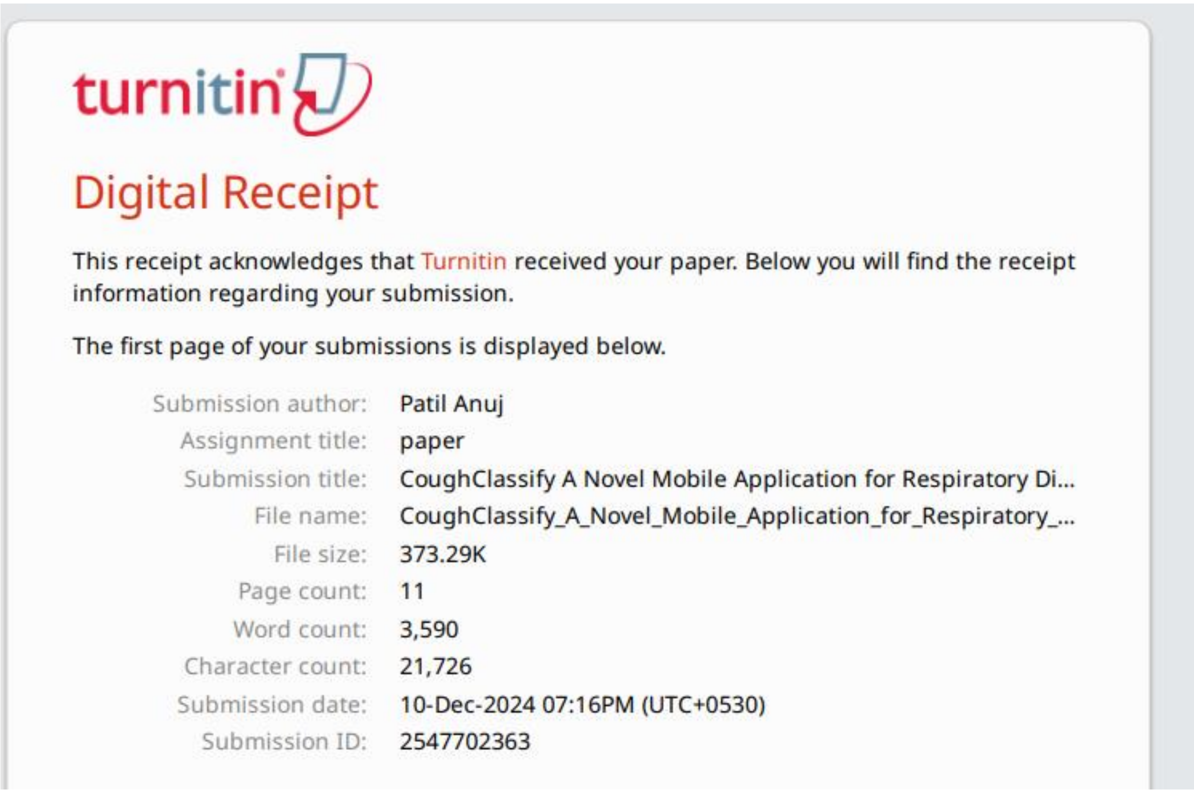
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CoughClassify: A Novel Mobile Application for Respiratory Disease Prediction

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***Abstract*— The early detection of respiratory diseases, such as Chronic Obstructive Pulmonary Disease (COPD), pneumonia, bronchiolitis, and upper respiratory tract infections (URTI), is crucial for improving patient outcomes, particularly in rural areas of third-world countries where healthcare resources are scarce. This project proposes the development of a mobile application that utilizes audio analysis to predict respiratory health. The application captures a patient's cough sound, which is then processed using a machine learning model hosted on a cloud server.**

Users can easily sign in using their Google accounts, grant microphone permissions, and record their coughs with a simple interface. The recorded audio is transmitted to the cloud for analysis, and the app provides immediate feedback on the likelihood of respiratory diseases based on the acoustic characteristics of the cough. By leveraging mobile technology and machine learning, this application aims to empower individuals in resource-limited settings to monitor their respiratory health proactively. This innovative solution not only addresses the gap in healthcare access but also fosters health awareness and encourages early medical consultation, ultimately aiming to improve public health outcomes in vulnerable populations.

Keywords—COPD, Mobile App, Pneumonia, Tuberculosis, Respiratory Diseases,

I. Introduction

Respiratory diseases, such as tuberculosis (TB), chronic obstructive pulmonary disease (COPD), pneumonia, and bronchiolitis, are significant global health challenges, often leading to severe morbidity and mortality. Early detection and accurate diagnosis are crucial for effective treatment and management of these conditions. Traditional diagnostic methods can be time-consuming, costly, and may require specialized equipment not readily available in many regions.

This paper presents a mobile application designed to enhance the early detection of respiratory diseases by leveraging the capabilities of deep learning and machine learning. The app records patients' cough audio and analyzes it to predict potential respiratory conditions. Developed using Flutter, the application offers a user-friendly interface for patients to easily record and submit cough samples. The backend is powered by a Flask API, which facilitates seamless communication between the app and the machine learning models hosted on a Google Cloud server.

By integrating advanced audio analysis with machine learning algorithms, this application aims to provide a quick, accessible, and non-invasive screening tool for respiratory diseases. The findings from this paper could significantly contribute to public health initiatives by enabling early diagnosis and promoting timely medical intervention. Through this report, we will detail the methodology, implementation, potential implications of our mobile application in the healthcare landscape.

Motivation

The motivation for this research stems from the global burden of respiratory diseases, which are among the leading causes of morbidity and mortality worldwide. Early detection is crucial for effective management, particularly for diseases like TB and COPD. The accessibility of mobile technology presents an opportunity to develop a tool that empowers users to monitor their respiratory health proactively, thereby potentially reducing the burden on healthcare systems.

II. Literature Review

1. Machine Learning and Deep Learning Models for Respiratory Disease Prediction

Recent advancements in machine learning (ML) and deep learning (DL) have led to the development of sophisticated models for predicting respiratory diseases based on audio data, primarily cough sounds. Studies such as those by Wang et al. (2021) and Kwon et al. (2022) have demonstrated high accuracy in identifying conditions like pneumonia and COVID-19 from cough recordings, achieving performance metrics exceeding 90% accuracy in controlled environments. However, despite these promising results, the practical application of these models in real-time settings remains limited. Many existing models require substantial computational resources, making on-device deployment challenging. This is particularly relevant for mobile applications, where the need for low latency and efficient processing is paramount. The lack of real-time testing capabilities on devices inhibits the potential for widespread use, especially in rural or underserved areas where access to healthcare professionals may be limited.

2. Limitations of Current Audio-Based Prediction Models

While many studies focus exclusively on cough sounds, there is a growing recognition that a broader range of respiratory sounds—such as wheezing and breath sounds—can significantly enhance predictive accuracy. Research by Goecke et al. (2020) highlights that wheezing can be an early indicator of conditions like asthma and chronic obstructive pulmonary disease (COPD), yet most ML/DL models do not incorporate this data. The emphasis on cough sounds alone neglects the multifaceted nature of respiratory conditions, where a combination of various sounds can provide a more comprehensive view of a patient's respiratory health. By integrating multiple audio inputs, future models could enhance diagnostic capabilities and improve early detection rates, offering a more holistic approach to patient assessment.

3. The Role of Patient Symptoms in Predictive Models

Another significant gap in the existing literature is the failure to incorporate patient-reported symptoms alongside audio data. Most predictive models rely solely on audio inputs without considering the subjective experiences of patients, such as shortness of breath, chest tightness, or fatigue. Research by Hurst et al. (2021) suggests that integrating symptomatology with audio analysis could yield more accurate predictions, as these symptoms often provide crucial context for interpreting respiratory sounds. By neglecting this aspect, current models may misclassify or overlook certain conditions, ultimately limiting their effectiveness. A mobile application that captures both audio data and symptom inputs could not only improve prediction accuracy but also empower patients to engage more actively in their health management.

III. Prototype Objectives

- **Goals of the Mobile Application**

The primary goal of this mobile application is to leverage advanced Deep Learning (DL) and Machine Learning (ML) algorithms to analyze patients' cough audio recordings and predict potential underlying respiratory conditions, such as tuberculosis (TB) and pneumonia. By integrating a cloud server for hosting the trained models, we aim to provide real-time, accessible diagnostics that can empower patients and healthcare providers alike. The application will focus on ease of use, allowing individuals with minimal technical skills to upload their cough recordings for analysis, thereby promoting proactive health management.

- **Target Audience**

Our target audience encompasses individuals residing in rural areas of third-world countries, particularly in regions of India where healthcare services are often limited. This demographic includes patients experiencing respiratory symptoms, caregivers, and healthcare workers who lack access to specialized diagnostic tools. By focusing on this underserved population, the application aims to bridge the gap in healthcare access, enabling timely interventions that can significantly impact public health.

- **Expected Outcomes**

The expected outcomes of this prototype are multifaceted:

1. **Early Detection**: By providing an accessible tool for cough analysis, we aim to facilitate early detection of serious respiratory diseases like TB and pneumonia. Early identification can lead to timely treatment, drastically improving patient outcomes and reducing mortality rates.

2. **Reduced Healthcare Burden**: By diagnosing conditions remotely, the application can alleviate the strain on local healthcare facilities, particularly in rural areas where resources are scarce. Patients can receive guidance on whether to seek further medical attention based on the application's predictions.

3. **Increased Awareness**: The application will also serve as an educational tool, informing users about common respiratory illnesses and the importance of early detection. This awareness can encourage individuals to seek medical advice sooner, further enhancing community health.

4. **Data Collection for Research**: The app will collect anonymized cough audio data, contributing to a growing dataset that can be used for further research on respiratory diseases, particularly in low-resource settings.

IV. System Architecture

The proposed mobile application leverages machine learning (ML) and deep learning (DL) techniques to analyze cough audio recordings and predict potential respiratory conditions. The architecture comprises three main components: the mobile front end, the cloud back end, and a database for storing user interactions and model data. The application employs a user-friendly interface for audio recording, processes the audio on a cloud server, and returns results to the user in real-time. Following are three major components of system architecture.

1) Front End

- **Mobile Application**: Built using a cross-platform framework Flutter to ensure compatibility with iOS and Android devices.
- **User Interface (UI)**:
  - Google Sign-In integration for user authentication.
  - Permission requests for voice recording access.
  - Instruction screens for cough recording protocol.
  - Audio recording interface with a "Start Recording" button.
  - Feedback screen displaying predicted cough type.

2) Back End

- **Cloud Server (Render)**:
  - Hosts the trained DL model for cough analysis.
  - Processes incoming audio data from the mobile app.
  - Implements RESTful API endpoints for communication between the mobile app and the server.
  - Utilizes the framework Flask for serving the model.
- **Machine Learning Model**:
  - Trained on labeled audio data including cough , wheezes to classify respiratory disease types.
  - Preprocessing pipeline for audio data such as noise reduction, feature extraction.
  - Model inference logic to predict respiratory disease types based on input audio.

3) Database

- **Database Management System**:
  - Google Firebase is used to store user data and interaction logs.
  - App Stores user profiles, audio recordings, and model prediction results.
  - Facilitates analytics for continuous improvement of the model and user experience.

V. Methodology

a) Application

The mobile application, developed using Flutter and Android Studio, serves as a user-friendly platform for recording cough audio to aid in the detection of respiratory diseases. The design prioritizes user experience while ensuring functionality and accessibility.

1. User Permission and Instructions:
Upon launching the app, users are prompted to grant microphone access to enable audio recording. This is essential for capturing cough sounds accurately.

2. Pre-Recording Guidelines:
After permission is granted, the app instructs users to wear a mask, if possible, and position their mobile phone a few inches away from their mouth. This helps to minimize interference and ensures the clarity of the cough audio.

3. Recording Process:
Once the user is ready, they press the record button, which initiates a countdown timer for a duration of 12 seconds. During this period, the app displays a "Cough Promoting" image to engage the user and provide visual feedback. This image serves to remind users to cough naturally and without hesitation.

4. Post-Recording Protocol:
After the recording ends, the app prompts users to sanitize their phone. This is a crucial step in promoting hygiene and reducing the risk of transmitting respiratory pathogens.

Through these features, the app not only captures the required audio data effectively but also emphasizes user safety and awareness, fostering responsible health practices. The recorded cough samples are then sent to the backend for analysis by the machine learning models, facilitating the predictive diagnosis of respiratory conditions.

b) Model Development

In this section, we detail the training of the deep learning model designed to classify respiratory diseases .The model leverages advanced signal processing techniques and a neural network architecture combining convolutional and recurrent layers. The training pipeline utilizes Python libraries such as NumPy, Pandas, Seaborn, TensorFlow, Matplotlib, and Resampy.

1) Data Preparation

The model is trained using two primary datasets:

1. Audio Files: .wav format cough audio recordings.
2. CSV File: Contains patient information and corresponding disease labels.

2) Data Augmentation

To enhance the robustness of the model, several audio augmentation techniques were applied to the cough recordings:

1. Add Noise: Random noise is added to the original audio to simulate various environmental conditions.
2. Shift: Temporal shifting of audio clips to mimic variations in cough timing.
3. Stretch: Time-stretching techniques are applied to alter the speed of the cough without changing the pitch.

These augmentations increase the variability of the training data, helping the model generalize better to unseen recordings.

3) Feature Extraction

From each audio recording, Mel-Frequency Cepstral Coefficients (MFCC) were extracted as features, which are widely used in audio classification tasks. A total of 50 MFCC features were extracted, resulting in a feature matrix for each audio sample. The final dataset is structured as a 2-dimensional array, with dimensions aligned to 5 disease classes:

4) Disease Classes:

COPD ,Bronchiolitis ,Pneumonia ,URTI (Upper Respiratory Tract Infection) ,Healthy

The resulting array has a shape of (n_samples, 5), where n_samples corresponds to the number of cough recordings processed.

5) Model Architecture

The deep learning model is implemented using Keras, with the following architecture:

1. **Input Layer**

- Accepts input sequences reshaped to (1, 52), where 52 represents the feature dimensions.

2. **Convolutional Layers:**

- Conv1D Layer 1: 256 filters with ReLU activation to capture local patterns in the MFCC features.
- MaxPooling1D: Reduces dimensionality and retains important features.

- BatchNormalization: Normalizes activations to improve training stability.
- Conv1D Layer 2: 512 filters with ReLU activation, further refining feature extraction.

3. GRU Layers:

- GRU Layer 1: 32 units capturing short-term dependencies.
- GRU Layer 2: 128 units for capturing longer-term temporal patterns.
- Outputs from both GRU branches are combined through addition, allowing the model to learn from multiple perspectives.

4. Dense Layers:

- Two parallel Dense layers with Leaky ReLU activations to process the combined features from GRU layers, facilitating non-linear transformation.
- Output Layer: A Dense layer with softmax activation, outputting class probabilities for the five respiratory disease categories.

Model Training and Evaluation

After defining the model architecture, the training process involved compiling the model with an appropriate optimizer and loss function suited for multi-class classification. The model was trained using the augmented feature set, with validation performed on a separate test dataset.

Performance Metrics

To evaluate model performance, class labels were predicted on the test dataset, and a confusion matrix was computed to visualize the classification results. This matrix provides insights into the model's accuracy, revealing how well the model distinguishes between different respiratory diseases.

VI. Results

Performance Metrics

To evaluate the effectiveness of our model, we employed several key metrics, including accuracy, precision, recall, and F1-score. The results, summarized in Table 1, indicate the performance of the model across different classes

Parametrs / Class	precision	recall	F1-score	Support
COPD	1.00	0.91	0.95	11
Bronchiolitis	0.88	0.78	0.82	9
Pneumonia	0.94	1.00	0.97	17
URTI	0.71	1.00	0.83	5
Healthy	0.94	0.89	0.91	18

Table 1 – Summary of results for all classes

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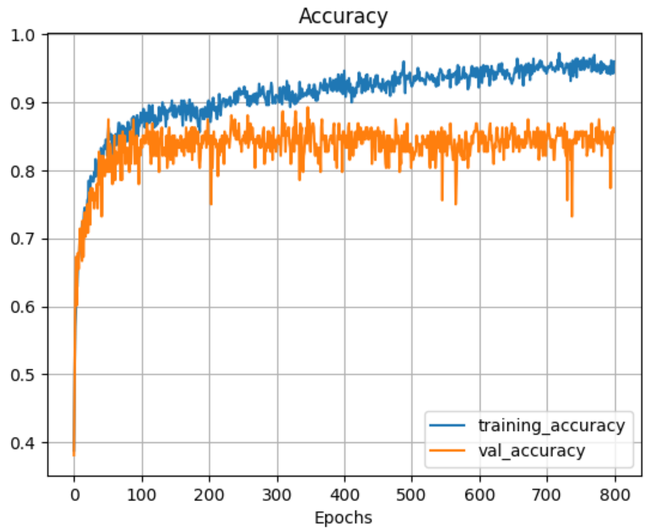

Fig. 1 – Accuracy Graph

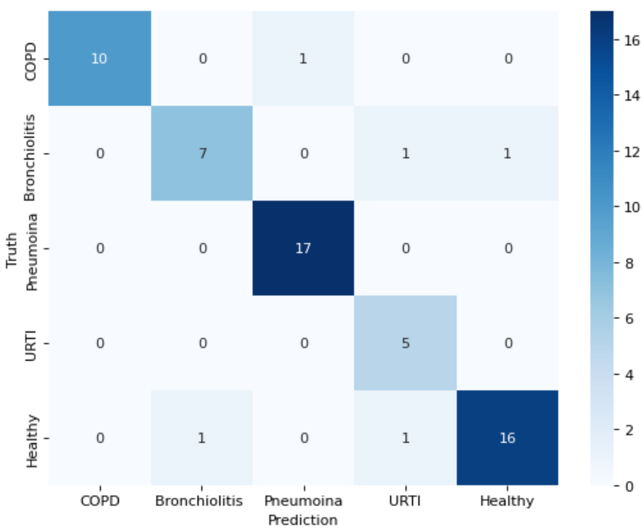

Fig 2 – Confusion Matrix of results.

User Interface :-

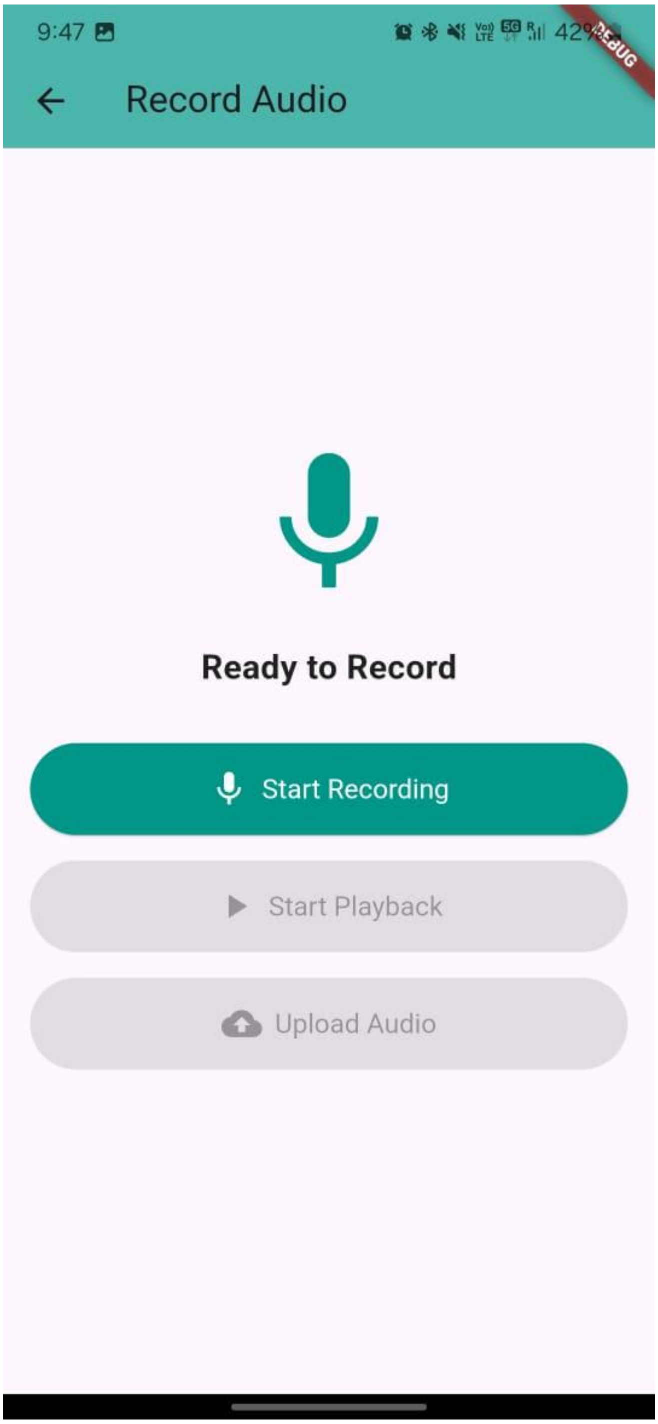

Image 1 :- UI for recording audio

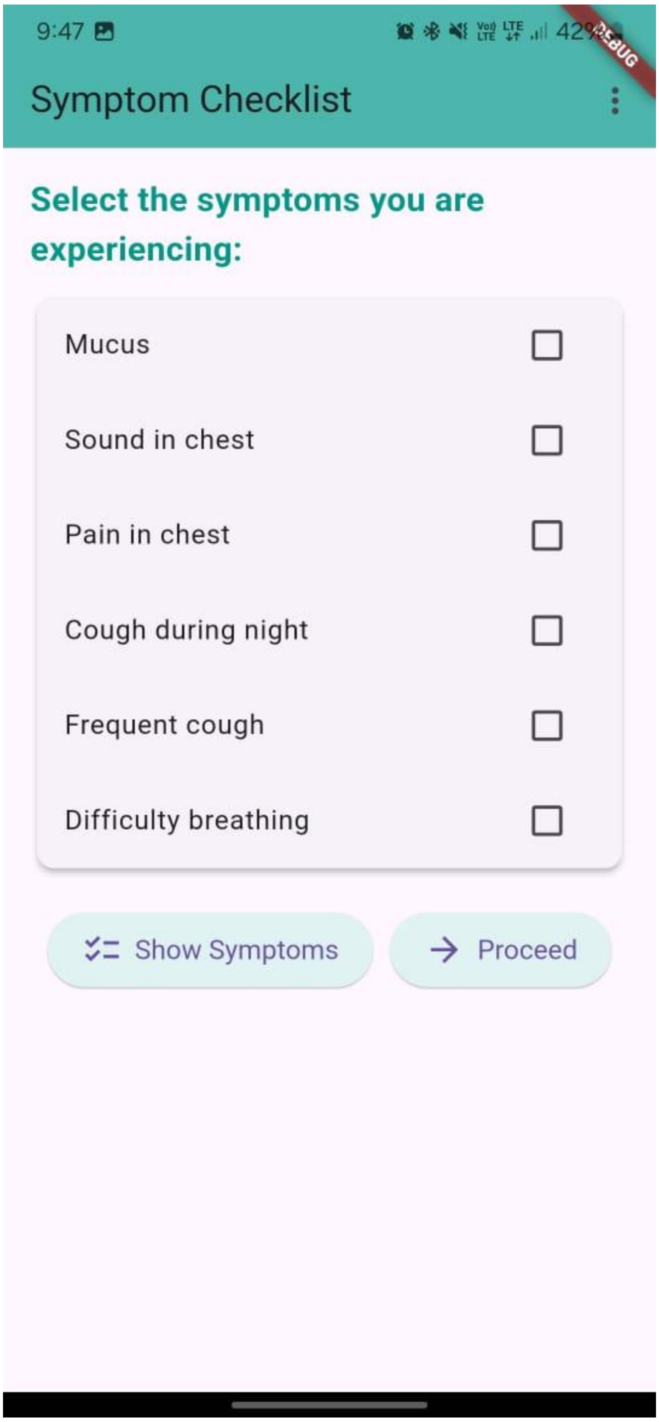

Image 2 :- Symptom checklist

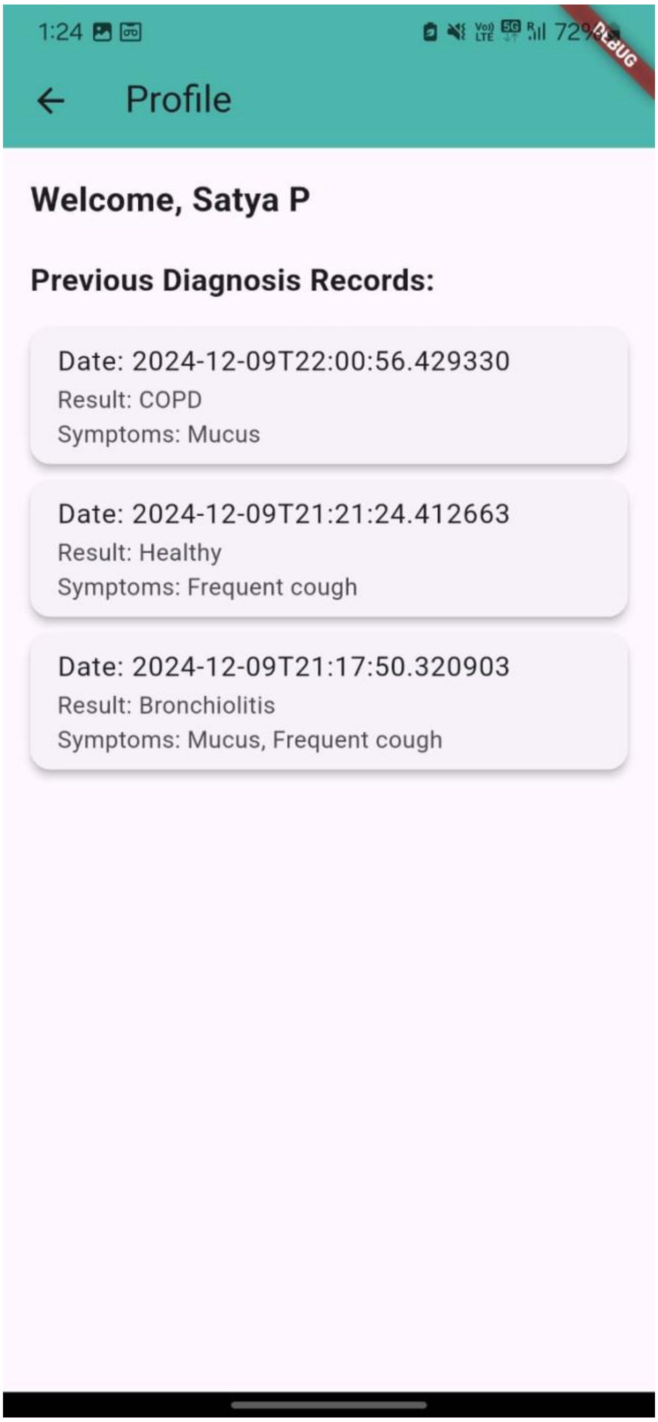

Image 3 :- User's diagnosis history

App Functionality

The application is designed to function seamlessly by recording cough audio directly on the device. Upon recording, the audio is transmitted to the server, where it is analyzed using the implemented ML/DL models. The predicted classification is then displayed to the user, providing immediate feedback on their respiratory health status.

VII. Discussion

Analysis of Results

Here, we developed a mobile application capable of capturing cough audio and predicting potential respiratory diseases using deep learning (DL) techniques. The primary diseases targeted by our model include Chronic Obstructive Pulmonary Disease (COPD), Bronchiolitis, Pneumonia, Upper Respiratory Tract Infections (URTI), and a healthy category

The model demonstrated varying levels of performance across the different classes. For instance, the precision and recall for COPD were notably higher than for Bronchiolitis, suggesting that the model was more adept at distinguishing between COPD and healthy patients. This could be attributed to the distinct acoustic characteristics of a COPD cough compared to other respiratory conditions.

On the other hand, the lower scores for Bronchiolitis indicate that further tuning of the model or enhancement of the dataset may be necessary to improve its predictive accuracy. The F1 score, which balances precision and recall, provides a comprehensive view of the model's effectiveness, especially in clinical applications where both false positives and negatives have significant implications.

Challenges Faced During Development

1. **Data Collection and Dataset Limitations**:

   One of the primary challenges encountered during the prototype was obtaining a sufficiently large and diverse dataset of cough audio samples. Respiratory diseases can manifest in various respiratory disease types influenced by numerous factors, including age, gender, and co-morbid conditions. As a result, acquiring a dataset that represents this variability was difficult. Initial attempts to use publicly available datasets were often insufficient in size or lacked the necessary labels for our specific diseases. Consequently, we had to seek collaborations with healthcare institutions to collect real-world cough audio samples, which introduced delays and logistical challenges.

2. **Cloud Hosting Limitations**:

   Another significant hurdle was finding a suitable, cost-effective cloud server to host our deep learning model. Many cloud services that offer machine learning capabilities charge based on resource consumption, making it challenging to sustain long-term operations without incurring high costs. While several free-tier options were available, they often lacked the computational power necessary for our model, leading to slow processing times and decreased user experience. We eventually opted for a tiered cloud service that offered some initial credits, allowing us to balance performance with cost while ensuring the application remained accessible to users.

Limitations :-

Despite the promising results of our mobile app for cough analysis, several limitations must be acknowledged:

1. **Exclusion of Tuberculosis Detection**: One significant limitation of the model is its inability to detect Tuberculosis (TB), a serious and potentially life-threatening respiratory disease. TB is known for its distinct cough characteristics; however, our model was not trained on cough samples from TB patients. As a result, it cannot identify this critical condition, which can lead to missed diagnoses in populations where TB prevalence is high.
2. **Lack of Symptom Consideration**: The model currently relies solely on cough audio for predictions, disregarding other important clinical symptoms that could enhance diagnostic accuracy. Respiratory diseases often present with a range of symptoms such as fever, fatigue, and shortness of breath. By not integrating these symptoms into the predictive framework, the model may produce inaccurate predictions or fail to capture the full clinical picture of a patient’s condition.
3. **Dataset Limitations**: As previously discussed, the dataset used for training the model was limited in size and diversity. This restriction may result in overfitting or a lack of generalizability to varied populations. Furthermore, the absence of rare or atypical cough patterns associated with certain diseases can hinder the model's performance in real-world settings.
4. **Variability in Cough Characteristics**: Cough sounds can be influenced by numerous factors, including age, gender, and underlying health conditions. The model's effectiveness may vary across different demographic groups, potentially leading to biased predictions if not adequately addressed.
5. **Environmental and Contextual Factors**: The model does not account for environmental variables such as pollution or allergens, which can exacerbate respiratory conditions. These factors can significantly influence cough characteristics and, by extension, diagnostic outcomes.
6. **User Dependency**: The effectiveness of the app is also dependent on user behavior. Factors such as the quality of the audio recording, background noise, and the user's understanding of how to use the app can impact the accuracy of the predictions.
7. **Real-time Analysis Limitations**: While the model can analyze cough audio, real-time processing might be limited by device capabilities or internet connectivity, potentially affecting user experience and engagement.

VIII. Future Work

To enhance the functionality and user experience of the mobile app for cough analysis, several key areas of future development are identified:

1. **Precautionary Measures and Advice**: Building on the symptom input feature, we propose providing users with personalized precautionary measures and health advice based on their reported symptoms and the model's predictions. This could include recommendations for home care, when to seek medical attention, and information about preventive measures relevant to specific respiratory diseases. This proactive approach could enhance user engagement and promote better health outcomes.
2. **Expansion of Disease Classification**: Future versions of the app could aim to include additional respiratory conditions, such as

Tuberculosis and asthma. This would broaden the app's utility and make it a more comprehensive tool for respiratory health management.

IX. Conclusion

Here, we have developed a mobile application designed to capture cough audio and predict potential respiratory diseases, including Chronic Obstructive Pulmonary Disease (COPD), Bronchiolitis, Pneumonia, Upper Respiratory Tract Infections (URTI), and a healthy classification. The app was built using Android Studio and Flutter, providing a user-friendly interface and cross-platform capabilities for broader accessibility.

To achieve accurate predictions, we employed advanced deep learning techniques, including Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs). These models were trained on cough audio samples, with features extracted using Mel-Frequency Cepstral Coefficients (MFCC) and a total of 52 relevant acoustic features. This feature extraction process was critical in enabling the model to distinguish between the different respiratory conditions based on the unique characteristics of each cough.

The deep learning model was hosted on Render's cloud server, ensuring efficient processing and scalable deployment, ensuring seamless app access and quick response times for cough analysis.

While the app demonstrates promising results in predicting respiratory diseases based on cough audio, several limitations have been identified, including the exclusion of Tuberculosis detection. Future work will focus on enhancing the app's capabilities by incorporating user-reported symptoms, providing precautionary health advice, adding functionality to classify respiratory disease types, and improving the overall user interface.

This prototype advances mobile technology and deep learning for respiratory health monitoring, aiming to improve early detection and management of conditions, ultimately leading to improved health outcomes.

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