COUDE - MACHINE LEARNING BASED COUGH DETECTION SYSTEM FOR RESPIRATORY ABNORMALITIES

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***Abstract*— Cough is a forceful expiratory act where air from the alveoli to the airways, trachea, pharynx, and mouth. It contains valuable information and reflects different signal characteristics, making the collection of cough sounds crucial for primitive screening and examination of respiratory disorders. The Proposed Work aims to identify the location of the irritant and diagnose the underlying cause of cough. The Edge Impulse platform is utilized for Data Acquisition, Pre-Processing, and Training the model. The main features from the audio signal are extracted using MFCC technique. The algorithm is trained using Convolutional Neural Networks (CNN), achieving an accuracy of 96%. The trained model is then deployed on a Raspberry Pi 4 device, allowing real-time cough data to be captured through a microphone. A responsive web application is developed, providing doctors with access to instantaneous data for remote monitoring. This approach enables doctors to remotely monitor patients and make informed decisions. Furthermore, the patient records are stored in a database for future reference.**

Keywords*— *Cough, MFCC technique, Raspberry Pi, Edge Impulse, Web Application, Remote Monitoring, Convolutional Neural Network

I. Introduction

Cough is a natural reaction that helps remove irritants and foreign objects from the respiratory tract. A doctor can locate the underlying reason with the help of a cough's distinctive characteristics. For instance, a cough that produces mucus and suggests a respiratory illness may also be an allergy or asthma attack. A intermittent cough is a normal and healthy biological function. Throat and airways' nerves pick up on irritants and work to eliminate them, producing a quick and effective reaction. Usually, a tiny amount of mucus is produced by the throat and lungs to keep the airways wet and provide a thin barrier that protects against allergens and bacteria that are inhaled. The occasional coughing does not hurt your body and helps to move the mucus. Coughing also makes it easier to quickly expel any unwanted particles you may intake.

Different types of coughs are:

- **Productive Cough:** A cough that produces mucus or phlegm is referred to be productive. It may be a sign of the flu, bronchitis, or pneumonia. The underlying disease can be deduced from the mucus' colour. For instance, mucus that is yellowish-green or has blood in it may point to a more serious problem.
- **Non-Productive Cough:** A cough that doesn't produce mucus is called a dry or non-productive cough.
- **Acute Cough:** A slight cough that normally lasts up to three weeks is considered acute. Typically, it is not serious and doesn't need medical treatment. It is recommended to get medical help if your cough is accompanied by additional symptoms such a fever, headache, sleepiness, or breathing difficulties. Furthermore, it is important to pay attention to coughs that make particular noises, such as whooping, wheezing, or barking, since they may point to a more serious underlying problem.
- **Chronic Cough:** Coughs that continue longer than eight weeks may indicate a more serious or long-lasting lung condition.

A. Respiratory Abnormalities

A variety of diseases and disorders that affect the lungs and airways and impair people's ability to breathe collectively are referred to as respiratory abnormalities. Any part of the respiratory system can be impacted by illnesses or infections, which can cause a variety of difficulties. When the immune system becomes contaminated, it reacts similarly to other sections of the body by causing an inflammatory response. As a result, the mucous lining swells and the blood flow is increased, which in turn affects ventilation and can make it difficult to breathe. Fibrosis, which causes a loss of elasticity and possibly a permanent decrease in ventilation, may develop if the illness progresses to a chronic stage. As a result, there is a reduction in oxygen absorption and a rise in carbon dioxide levels. As a result, the tissues become less functioning, which has an impact on general health and makes the patient easily fatigued.

In addition to the inflammatory reaction, there is an increase in mucus production, which blocks the airways and causes the lung tissue to collapse beyond the obstruction. It is essential to quickly restore the expansion of this area since the collapsed tissue experiences fibrosis, which permanently reduces lung ventilation capacity. Asthma, COPD, pulmonary fibrosis, pneumonia, and lung cancer are a few common pulmonary disorders. Soliński, M et al [2] showed that cough events in spirometry curves can be detected using airflow signals. Many AioCare-collected signals were used. The classification algorithm developed in this study is a robust tool for detecting cough events during spirometry measurements.

Types of Respiratory Abnormalities:

- **COPD:** Chronic obstructive pulmonary disease (COPD) is a chronic inflammatory lung illness that causes the lungs' airflow which mainly affects the deeper portion of the lungs to become blocked. Symptoms include trouble breathing, coughing, mucus (sputum) production, and wheezing. Long-term exposure to irritating chemicals or particulate particles, most often cigarette smoke, is a common cause. COPD patients are more prone to develop heart disease, lung cancer, and a range of other problems. Although COPD is a progressive condition that worsens with time, it is curable. With effective therapy, most persons with COPD can achieve good symptom control and quality of life. If macular edema impairs vision, therapy is necessary to to avoid irreversible vision loss.
- **Asthma:** Asthma is a chronic lung illness that may afflict anyone at any age. Breathing becomes difficult due to inflammation and muscular tightness around the medium sized airways. Misdiagnosis and inadequate treatment are prevalent, especially in low- and middle-income nations. Untreated asthma can cause sleep disruption, fatigue during the day, and difficulties concentrating. Coughing, wheezing, shortness of breath, and chest tightness are all symptoms. These symptoms might be moderate or severe, and they can appear and disappear over time.
- **Pneumonia:** Pneumonia is an illness that causes the air sacs (deeper portion of the lungs) in one or both lungs to become inflamed. The air sacs may become clogged with fluid or pus (purulent material), resulting in phlegm or pus cough, fever, chills, and trouble breathing. Pneumonia can be caused by a number of species, including bacteria, viruses, and fungus. Coughing up phlegm or pus, fever, chills, and trouble breathing are all symptoms.
- **Covid:** Coronaviruses are viruses that can cause the common cold, severe acute respiratory syndrome (SARS), and Middle East respiratory syndrome (MERS). It mainly affects the deeper portion of the lungs. A new coronavirus has been identified as the root of a disease outbreak that began in China in 2019.SARS-CoV-2 (severe acute respiratory syndrome coronavirus) is the name of the virus. Coronavirus disease 2019 (COVID-19) is the virus that causes it. Early COVID-19 symptoms may include a loss of taste or smell. Other signs and symptoms may include: Breathing difficulties or shortness of breath, muscle pains, chills, sore throat, runny nose, headache, chest discomfort.
- **Pharyngitis:** Pharyngitis is an inflammation of the mucous membranes of the oropharynx (upper portion of the lungs). It is usually caused by a bacterial or viral infection. Other less common causes of pharyngitis include allergies, trauma, cancer, reflux, and certain toxins. According to the World Health Organisation (WHO), over 3 million people each year die from chronic obstructive pulmonary disease (COPD), or about 6% of all mortality worldwide. It is crucial to emphasise that 90% of lung-related deaths occur in low- and middle-income nations.

In India, respiratory illnesses are thought to have contributed to 1.16 million deaths in 2019. Furthermore, about 10% of all fatalities in the nation have been linked to respiratory illnesses. Air pollution, workplace dangers, smoking, and a lack of access to healthcare services are some of the factors that contribute to the high rate of respiratory-related mortality in India. Fig.1 shows clinical burden due to Respiratory Diseases in India in 2022 where most of the patients needed hospitalization due to the pandemic. These figures demonstrate the urgent need for efficient solutions and all-encompassing plans to deal with the problems associated with respiratory health and lessen their negative effects on India's general health.

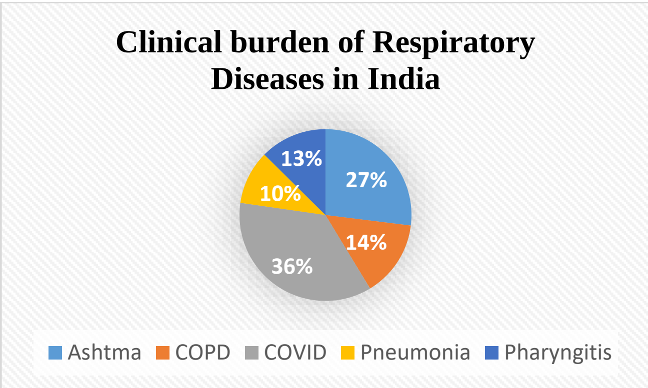


Fig.1 Clinical Burden due to Respiratory Diseases in India

The proposed study incorporated five different respiratory disorders, categorizing them based on the location of the irritant within the lungs. Conditions such as COPD, COVID, and Pneumonia were linked to the deeper regions of the lungs, while Asthma was associated with the medium-sized airways. Pharyngitis, on the other hand, was connected to the upper part of the lungs. Cough audio samples were collected for each disease and classified using the power spectrum of the signals. In addition, the classification process involved including audio samples of normal coughs and background noise as supplementary features. The comprehensive approach aimed to effectively distinguish and categorize different respiratory disorders by analyzing the distinctive characteristics present in the cough audio samples

II. Related Work

This discussion covers wide range of topics, including the approach for automatically classifying asthma and pneumonia and identifying the two diseases was presented. It makes use of sound analysis of coughs. Factors like Mel frequency, cepstrum coefficient, and short-term energy are incorporated into the classification system for cough sounds [3]. A novel sensor fusion strategy to address the issue of unidentified classes was presented. The strategy includes matching algorithms for templates and classification algorithms. It made use of the head motion information gathered from an inertial measurement unit (IMU) as well as the audio signal recorded from an in-ear sensor [4]. To recognize and extract cough sounds from audio signal Support Vector Machine was used as the classification model to divide the audio segment into cough sounds and non-cough sounds [5]. The performance of a small wearable cough detector (SIVA-P3) that uses deep neural networks for the automatic counting of coughs was examined in an outpatient setting where the cough epochs with SIVA-P3 were recorded over eight consecutive days in patients with chronic cough [6]. A method which aims to ascertain if the new coughing manners promoted by public health agencies have considerably altered the sound of a cough was studied. They did this by examining the auditory features of coughs that were captured using various cough etiquettes. To determine whether there is a noticeable difference between the cough noises, they compared the characteristics using statistical techniques [7]. A cough detection system was created using information on cough noises collected from an Arduino 33 BLE Sense and Edge Impulse. To distinguish between cough noises and other noises, the system was created. This was accomplished by employing a cough detection neural network (NN) classifier, which was trained and assessed [8] [10][14] and an automated cough detection has significant applications for the surveillance of diseases and supports medical decisions, as cough sounds can be a useful biomarker. Using the dataset, different Convolutional Neural Network architectures for classifying short audio segments as Cough or Non-Cough are evaluated [9]. A method for COVID-19 identification based on smartphone recordings of coughing was suggested. Using raw audio data, coughing noises are segmented, and COVID-19 was then identified based on these segments. The method made use of long-term short memory (LSTM), which is well-known for its efficiency in analysing time series signals, to store raw coughing noises and their properties [11]. A long-term, remote COPD patient monitoring was presented. The information gathered over the period of 90 days in the patients' homes lead to two difficulties. In the first, scientists examined how effectively different machine learning methods handled cough occurrences that were captured in the environment. In the second, they looked at how patients' coughs were the only ones that the identical learning paradigms could recognize [12]. A mathematical model was constructed to analyze noises and recognize coughs where there were no tests or trials involving human subjects included in the study. A smartphone application was developed and tested to capture the necessary acoustic data, ensuring that its technological specs met the necessary parameters [13]. CoughWatch is a compact cough detection system designed for smartwatches, utilizing audio and motion information to identify coughing incidents in real-world scenarios [15]. The effective early detection and treatment of lung disorders was recommended using a portable cough monitoring device. The system makes use of sensors that are placed on the thoracic, tracheal, and abdominal areas, as well as an amplification system, to process cough signals in real time in both the temporal and frequency domains. As a result, several pulmonary disorders may be analyzed. It is possible to distinguish between common coughs and contagious ones by looking at the signal patterns. As a result, those with lung conditions receive immediate medical care, providing respite to the rural population and lowering the number of COPD-related fatalities [16]. A novel system that includes a prototype (hardware) for data gathering as well as software for analyzing the collected data for cough detection, visualization, and classification was proposed. Sensors such as ECG, thermistor, chest belt, accelerometer, oximeter, contact and audio microphones were included in the prototype using which they were able to distinguish cough from other event categories, and ability to detect cough events [17]. As the primary programming block in the Cough Detection method, a system using a convolutional neural network as a feature extraction technique and classification system was provided. This system could recognize a cough sound based only on the patient's vocalizations [18]. In this method, the basic principle, hardware composition, and experimental results of a cough monitoring instrument are analyzed in detail. This paper also analyzes objective assessment algorithms of cough and their advantages and disadvantages [19]. Cough signals' acoustic aspects include knowledge of the respiratory system's condition. These attributes may be utilized to develop a powerful illness prediction system using deep learning or signal processing. So, a whole machine learning model was suggested in this [20].

The proposed work focuses on locating the irritant and determining the origin of the cough. The system acquires, pre-processes, and trains the model using MFCC features and CNN algorithms, attaining a noteworthy 96% accuracy utilising the Edge Impulse platform. Real-time cough data can be recorded using a microphone by deploying on a Raspberry Pi 4. With immediate access to data for remote monitoring provided by a responsive web application, doctors are better equipped to make wise decisions. To ensure thorough care and follow-up, patient records are safely kept in a database for future use.

III. METHODOLOGY

This project aims to create a Low-Cost, Portable, Smart Cough Detection System to find Respiratory Abnormalities. Analysing audio signal patterns will be used to achieve this. To reduce the risk of pulmonary disorders-related mortality, the main objective is to identify the source of irritation and the origin of the cough. The purpose if the study is to create a system that efficiently recognises coughs in their early stages, helping to manage and prevent respiratory illnesses. The system offers remote monitoring through a Web Application, allowing clinicians to access and treat patients remotely. Patient records are consistently updated and kept in the database for future use.

As shown in below Fig.2 the proposed system involves the integration of both software and hardware components. The process begins with data acquisition, where cough audio samples data are collected. This data is then pre-processed using the Mel Frequency Cepstral Coefficients (MFCC) technique, which extracts mel coefficients from the audio signal. The collected data is then divided into training (70%), testing (20%), and validation (10%) sets. Convolutional Neural Network (CNN) is used to train the model. The final accuracy obtained were 96%. All of these steps are performed within the Edge Impulse platform. Once the data is classified, the trained model is deployed onto a Raspberry Pi device. By utilizing the microphone, real-time cough data can be captured and displayed in a Web Application. This Web Application is accessible to doctors, enabling remote monitoring and allowing them to make informed decisions remotely.

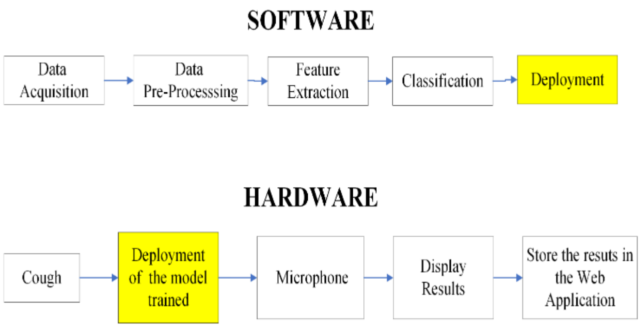


Fig.2 Proposed Methodology

A total of 93 cough audio samples from hospitals, clinics, and diagnostic facilities were collected; these samples represented different respiratory illnesses. For data classification, the Edge Impulse platform was used. To identify the ailment in real-time, the trained model was deployed on a Raspberry Pi 4. Firebase was used to store the databases for Web Development and for quick access and retrieval.

A. *Software Implementation*

A dataset of 93 cough audio samples, obtained from hospitals, clinics, and diagnostic facilities, encompassed various respiratory illnesses. The dataset obtained were converted into .wav format. The Edge Impulse platform was employed for data classification purposes.

Table1 shows the information of the dataset.

Dataset Name	COUDE Dataset
Dataset Source	Clinics, Hospitals & Diagnostic Centers
Dataset Format	.wav
Training Set	70%
Testing Set	20%
Validation	10%

B. *Feature Extraction*

MFCC technique is employed to extract the features from the Cough audio sample. MFCCs are an effective feature extraction method that may be used to represent the spectral content of a sound. They are frequently employed in speech recognition, speaker identification, and music information retrieval systems.

Steps Involved:

- Apply the Fast Fourier Transform (FFT) to the signal to get its power spectrum
- Use triangle overlapping windows or, as an alternative, cosine overlapping windows to map the powers of the spectrum produced above onto the mel scale.
- Take a look at the power loggings for each of the mel frequencies.
- Consider the discrete cosine transform of the list of mel log powers as a signal.

Additional details about each steps:

Calculating the power spectrum: A graph that depicts the distribution of energy (or power) across various frequencies is called the power spectrum. The FFT, a mathematical procedure that may be used to quickly compute the Fourier transform of a signal, can be used to calculate it. A mathematical procedure called the Fourier transform breaks down a signal into its constituent frequencies.

Mapping the powers to the mel scale: A nonlinear frequency scale called the mel scale is more perceptually significant than a linear frequency scale. This indicates that the mel scale takes into account how sound frequencies are perceived by people. You can use a triangle or cosine overlapping window to map the spectral powers to the mel scale. It is given by the formula:

$$m = 1127.\log\left(1 + \frac{f}{100}\right) \qquad (1)$$

Taking the logs of the powers: Taking the logs of the powers at each of the mel frequencies aids in lowering the dynamic range of the data and facilitates the extraction of characteristics from the data.

Taking the discrete cosine transform: A signal can be transformed mathematically from the time domain to the frequency domain using the discrete cosine transform (DCT). When it comes to MFCCs, the DCT is employed to transform the mel log powers into a collection of coefficients that stand in for the signal's frequency components. Depending on the application, several MFCC coefficients may be computed. 12 to 20 MFCC coefficients are frequently employed in voice recognition systems. More MFCC coefficients could be used in applications for music information retrieval.

$$F(u) = \left(\frac{2}{N}\right)^{\frac{1}{2}} \sum_{i=0}^{N-1} \Lambda(i).\cos\left[\frac{\pi.u}{2.N}(2i+1)\right] f(i) \qquad (2)$$

The spectral content of a sound can be represented using the potent feature extraction method known as MFCCs. They are frequently employed in systems for music information retrieval, speaker identification, and speech recognition.
The advantages are that they can withstand distortion and noise. They are easy to compute effectively. They are capable of representing a variety of sounds.
Fig. 3 shows the steps involved extracting the features in the proposed work.

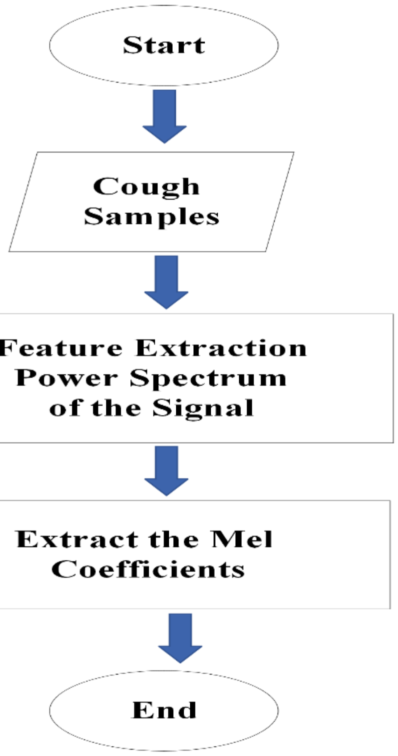


Fig. 3 Feature Extraction Steps

Fig.4 shows the raw data of the cough signal and Fig.5 shows the MFCC visualization with processed features (Mel Coefficients)

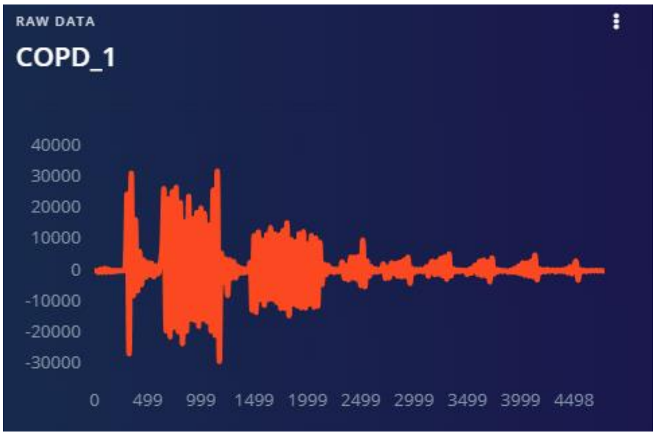


Fig.4 Raw data of the cough signal

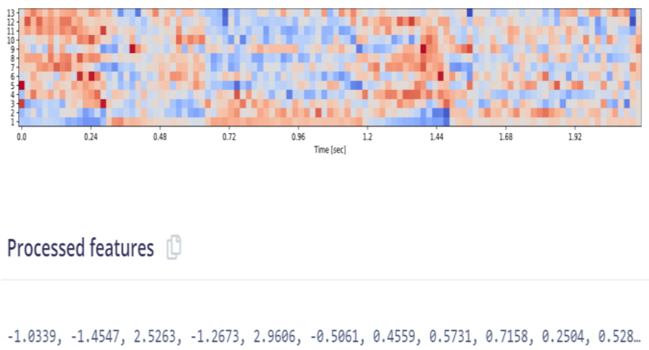


Fig.5 MFCC visualization with processed features (Mel Coefficients)

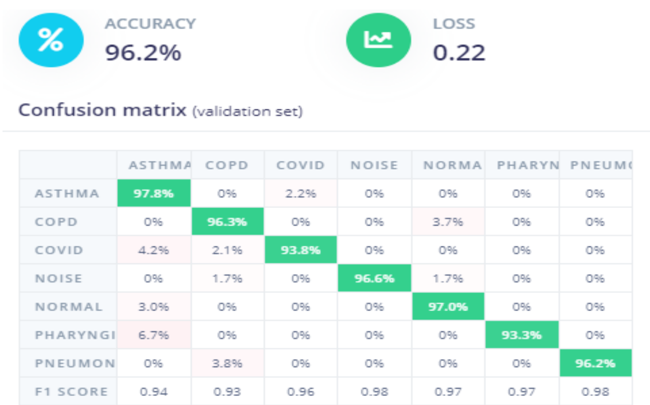
C. *Edge Impulse*

The model was trained using the Edge Impulse platform, which takes raw data and applies signal processing techniques to extract relevant features. A Convolutional Neural Network (CNN) algorithm was employed to classify the data into different categories. The labels for classification included Asthma, COPD, Covid, Noise, Normal, Pharyngitis, and Pneumonia. The dataset was split into 70% for training, 20% for testing, and 10% for validation.

Convolutional Neural Network:
Convolutional neural networks are a form of artificial neural network that uses the mathematical operation convolution instead of ordinary matrix multiplication in at least one of its layers. They are employed in image recognition, audio processing and processing and are especially built to handle the data. CNNs are effective for audio classification as the concept of dimensionality reduction suits the huge number of parameters in an audio. CNNs are very effective in reducing the number of parameters without losing on the quality of the audio.

IV. Results & Discussion

The Edge Impulse platform, which uses signal processing methods to extract important features from raw data, was used for the model's training. For feature extraction, the Mel Frequency Cepstral Coefficients (MFCC) method was used particularly. The data, after feature extraction, was then classified into various categories using the Convolutional Neural Network (CNN) algorithm. This approach improved the model's performance by accurately classifying the data.
The final accuracy obtained was 96%.
Fig. 6 shows the confusion matrix of the trained model. Fig.7 shows the data that are correctly predicted in the training set.



ACCURACY
96.2%

LOSS
0.22

Confusion matrix (validation set)

	ASTHMA	COPD	COVID	NOISE	NORMA	PHARYN	PNEUM(
ASTHMA	97.8%	0%	2.2%	0%	0%	0%	0%
COPD	0%	96.3%	0%	0%	3.7%	0%	0%
COVID	4.2%	2.1%	93.8%	0%	0%	0%	0%
NOISE	0%	1.7%	0%	96.6%	1.7%	0%	0%
NORMAL	3.0%	0%	0%	0%	97.0%	0%	0%
PHARYNGI	6.7%	0%	0%	0%	0%	93.3%	0%
PNEUMON	0%	3.8%	0%	0%	0%	0%	96.2%
F1 SCORE	0.94	0.93	0.96	0.98	0.97	0.97	0.98

Fig.6 Confusion Matrix

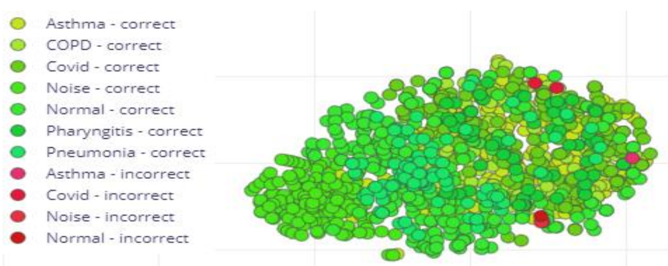


Fig.7 Data classified in the Training Set

A. Evaluation Criteria

A table known as a confusion matrix is widely used to test a classification model or classifier on a test dataset with known actual values.

Important terms:

- **Precision:** The ratio between the overall number of positive cases that a model correctly categorises and the overall number of instances that belong to the positive class is given.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{3}$$

- **Recall:** This can be defined as the portion of patterns or instances that, irrespective of their class label, are correctly classified by a model.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{4}$$

- **F1 Score**: The Harmonic mean between Recall and Precision values is known as F1 Score

$$\text{F1 Score} = 2 * \frac{\text{Recall} * \text{Precision}}{\text{Recall} + \text{Precision}} \tag{5}$$

- **Accuracy Score:** A model's accuracy is measured as a percentage of its true or accurate forecasts in relation to all of its predictions.

$$\text{Accuracy} = \frac{TN + TP}{TN + TP + FP + FN} \tag{6}$$

The performance parameters are plotted on the graph which is shown in the Fig.8 below for the Proposed Work.

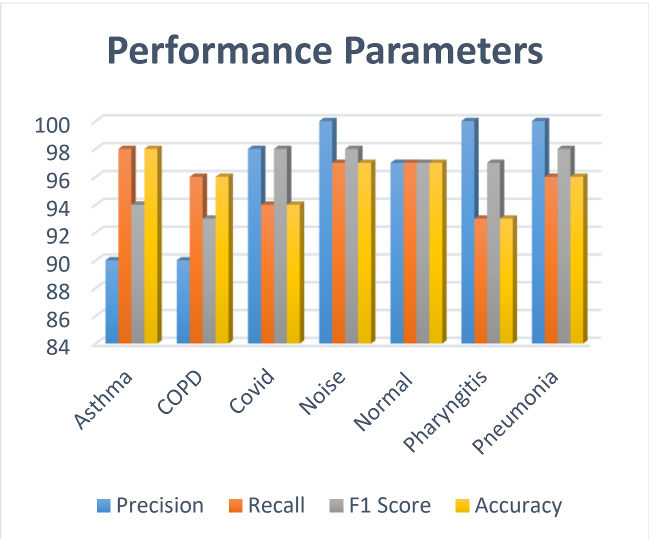


Fig. 8 Performance Parameters

B. Web Application

In order to help clinicians remotely monitor and treat patients, a web application utilising Firebase has been developed. It enables physicians to remotely update and access patient records, assisting in the early diagnosis of respiratory problems and preventing mortality connected to pulmonary conditions. Due to the responsiveness of the application and its interface with Firebase, patient data are stored securely and effectively, enabling the provision of remote healthcare

Fig.9 shows the login portal of the Web Application. The login portal utilizes role-based access for authentication and authorization purposes.

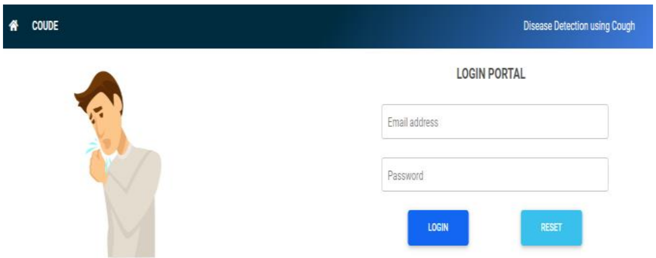


Fig.9 Login Portal

Fig.10 shows the Dashboard for Viewing or Adding or Updating the Patient Records. The dashboard makes it easier for physicians to access, add, and update patient records, ensuring that the database is kept up to date for future use.

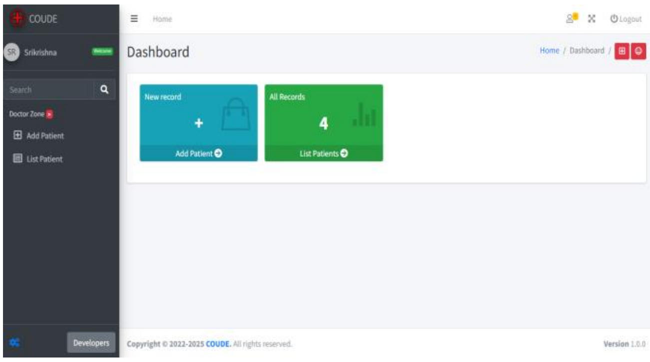


Fig.10 Dashboard for Viewing or Adding or Updating the Patient Records

Fig.5.2.3 shows the Dashboard for Adding the Patient Records. In order to maintain patient records, the clinicians enter the patient's information, which is in turn stored in the database.

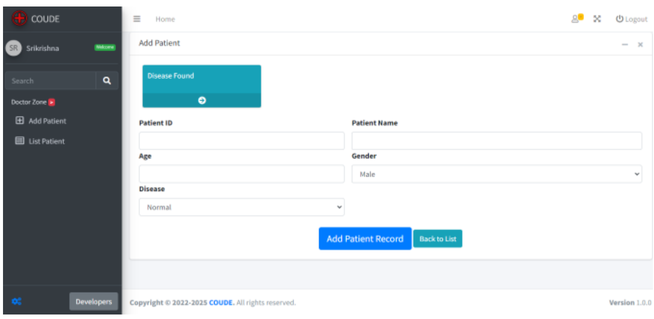


Fig.10 Dashboard for Adding the Patient Records

Fig.11 shows the Dashboard for Adding the Patient Records. This functionality allows clinicians to access the patient's past history and update the database as needed. It enables them to have a comprehensive view of the patient's medical records and make informed decisions.

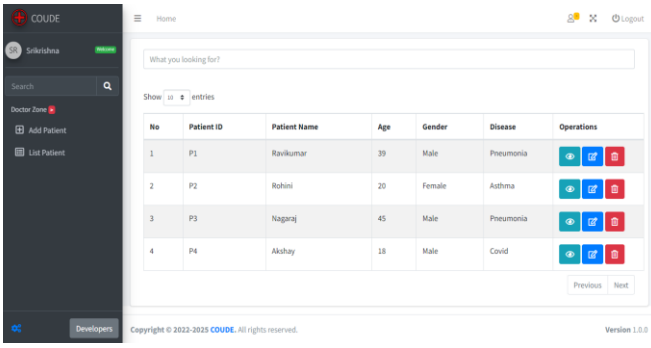


Fig.11 Dashboard for Viewing or Updating the Patient Records

C. Integration with Raspberry Pi

The Edge Impulse platform provides the deployment of the model to various devices, such as Raspberry Pi 4, Arduino BLE Sense 33 allowing it to run offline without relying on an internet connection. This deployment capability reduces minimizes power consumption, and ensures efficient performance. In the context of this proposed work, the trained data can be deployed on a Raspberry Pi 4, which is compatible with the Edge Impulse platform for seamless integration and execution.

The patient can utilize a microphone to cough, and the real-time data will be presented on a web application accessible to the doctor. This approach facilitates remote monitoring, allowing doctors to monitor and analyze the patient's coughing patterns and symptoms in real-time from a remote location.

D. Comparisons with the Recent Works

The Proposed Work is compared to recent studies that aim to identify Respiratory Abnormalities based on Cough audio samples. The comparison focuses on accuracy levels and the number of labels utilized in the classification process. Table1 shows the comparison of the Proposed work with Recent Works.

Table2. Comparisons of the Proposed works with Recent Works.

Reference No	No. of Labels used	Accuracy (%)
[1]	2	97
[2]	-	91
[3]	2	77
[5]	2	91.4
[8]	4	84.5
[18]	2	73.6
Proposed Work	7	96

From the above table2. It can be concluded that the proposed Work gives better accuracy in terms of Cough Detection System.

V. CONCLUSION

Cough sound analysis is a valuable approach for detecting and diagnosing Respiratory Disorders as coughing is a prevalent symptom in such conditions. The unique characteristics of cough sounds can offer valuable insights into the root cause of the cough. By examining the power spectrum of the cough sound patterns, it becomes possible to determine the location of the irritant or the affected area in the respiratory system. This analysis provides crucial information for identifying and understanding different Respiratory Disorders. In the proposed study, five Respiratory Disorders were used based on the location of the irritant within the lungs. The Deeper Regions of the Lungs were linked to COPD, COVID, and Pneumonia, whereas Asthma is connected to the Medium-Sized airways. The upper part of the lungs is associated with Pharyngitis. For each disease, Cough audio samples were collected and categorised using the Signal's Power Spectrum. Additionally, audio samples of Normal Coughs and Background Noise were included as additional features in the classification process.

The Edge Impulse platform is used for Data Acquisition, Data Pre-Processing using MFCC, and Data Classification through a Convolutional Neural Network (CNN) algorithm. The resulting model achieved a final accuracy rate of 96%, indicating its effectiveness in accurately classifying the data. The development of a Responsive Web Application using Firebase has showcased its immense potential in aiding doctors enabling Remote Monitoring, allowing doctors to treat patients remotely, thereby enhancing accessibility and improving patient care. The efficiency of the Proposed Solution is increased by deploying the learned data on hardware like the Raspberry Pi 4 model utilising the Edge Impulse platform. This feature enables Remote Monitoring in areas with scarce resources or poor connectivity.

The distinguishing aspect of the Proposed Work is its ability to identify the location of the irritant in the respiratory system based on Cough sound. By integrating remote monitoring, patient record management, and primitive screening features, it offers a comprehensive solution for doctors in addressing respiratory health concerns.

The Proposed Work includes many advantages facilitating early detection of respiratory illnesses by providing faster basic screening through cough sound analysis. The web application makes it easier for doctors and clinicians to update patient information remotely and provides a user-friendly interface.

The Proposed Work has some drawbacks, such as a small dataset, the requirement for collecting cough samples without making noise, and dependence on a steady internet connection. To get beyond these restrictions, you'll need a bigger dataset, better noise reduction methods, and workarounds for places with erratic internet access.

VI. FUTURE SCOPE

The proposed approach has the potential to evolve into marketable product for primitive screening of respiratory problems. It can give medical professionals a more complete tool for diagnosis and therapy by extending the spectrum of observable respiratory illnesses. Additionally, patients could easily access their medical records with the creation of a special mobile application for them that is compatible with both the Android and iOS platforms. Further enhancements could include incorporating additional diagnostic tools, refining the classification algorithms, and integrating telemedicine features for real-time consultations between doctors and patients. Such advancements would contribute to the future growth and effectiveness of the system, improving respiratory healthcare and patient outcomes.

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