CNN-LSTM Lung Sound Classification for Respiratory Diseases

B SIVA1, PANDITA AJAYA KUMAR2

#1Assistant Professor, Department of CSE-AIML, PBR Visvodaya Institute of Technology and Science, Kavali

#2 Assistant Professor, Department of CSE, PBR Visvodaya Institute of Technology and Science, Kavali

ABSTRACT_

As a major global health problem, respiratory illnesses need accurate diagnostic methods for effective treatment. When diagnosing pulmonary disorders, lung sound auscultation is a crucial tool. When diagnosing pulmonary disorders, auscultation of the lung sounds is crucial.Using convolutional neural network (CNN) architectures with gamma-tone cepstrum coefficients (GTCC) and convolutional neural network (CNN)-long short-term memory (LSTM) for respiratory sound analysis is presented in this study. We painstakingly picked four datasets that included various sorts of respiratory sounds in order to conduct a comprehensive illness categorization. An extensive investigation revealed that the algorithm outperformed the control group in identifying individual anomalies and differentiating between diseased and healthy conditions. Combining spectral and temporal data, it offers a potential tool for precise detection of respiratory disorders, and it might be widely used in clinical settings.

As a conclusion, our study demonstrates that CNN-LSTM algorithms can effectively categorize lung sounds as indicators of respiratory diseases. The proposed technique might find extensive use in clinical settings, offering a reliable tool for accurate and efficient respiratory diagnostics to healthcare providers.

1.INTRODUCTION

One of the most common causes of death and disability globally is respiratory disease.The disease burden was highest in the poorest regions of the world.According to the researchers, other important factors include aging, smoking, environmental pollution, and body weight.About 65 million people suffer from chronic obstructive pulmonary disease (COPD), and in 2017, an estimated 3.91 million people died from it, making it the third leading cause of death globally and a significant public health concern.From 3.32 million in 1990 to 3.91 million in 2017, there was an 18% increase in the number of deaths caused by chronic respiratory diseases.Asthma is the most common chronic childhood disease, affecting 14% of children worldwide. It affects approximately 334 million people.

The leading cause of death among children younger than five years old is respiratory diseases such as pneumonia, which kills millions of people every year.The most common and deadly infectious disease, tuberculosis (TB) affects over 10 million people annually and kills over 1.4 million.Cancer of the lung is the deadliest, claiming the lives of 1.6 million people annually.Worldwide, chronic respiratory disease claims the lives of four million people every year.Among the top 30 leading causes of death, five are respiratory diseases:The following are the ranks of the several types of lung cancer: tracheal, bronchial, and lung cancer (COPD), lower respiratory tract infection (TRTI), tuberculosis (TB), and asthma (28th).Acute or chronic respiratory problems affect about one billion individuals worldwide.The stark reality is that chronic respiratory disease is a leading cause of premature death for four million people every year.Particularly vulnerable are infants and young children.Pneumonia is the leading cause of death for children under the age of five, accounting for 9 million deaths annually [1].The lung is an organ susceptible to airborne infection and injury; people often take breathing and respiratory health for granted.People's social, economic, and health lives are significantly impacted by respiratory system diseases.Rates of death and disability were most affected by social deprivation, which was highest in the world's poorest regions.More affluent countries saw a decline in mortality as a result of better access to healthcare and more effective treatments. Lung diseases are the leading cause of death globally, making their treatment a top priority in the medical field.The importance of early diagnosis and intervention in respiratory diseases is being extensively studied for these reasons.It takes time and experience to accurately identify health problems using this information, but according to statistics from the World Health Organization (WHO) [3], 45 percent of WHO member states report having fewer than one doctor for every thousand people.advice from the World Health Organization (WHO).Taking these numbers into consideration, it is unrealistic to expect already-overbooked health specialists to examine and diagnose each patient individually.This is why it is crucial to find new ways to assist doctors in saving time.Therefore, more people can be diagnosed with the help of automated and dependable tools, and specialists can make fewer mistakes due to the work overload.

2.LITERATURE SURVEY

Previous works were categorized into Aykanataal in what follows.[25] Theprovided a convolutional network with a mel frequency spectral coefficient to aid in the classification of lung sounds using a vector machine.Two feature extraction methods exist: spectrogram generation using the short-time Fourier transform (STFT) and Melfrequencycepstralcoef✎cient (MFCC) feature extraction.As a widely accepted practice for audio classification, they utilized MFCC features in conjunction with SVM.The Melfrequency Spectral Unit (MFC) is a representation of a sound's short-term power spectrum in sound processing. It is based on the linear arc-sine transform of a log power spectrum on a non-linear frequency scale.An MFC is composed of MFCCs, which are efficiency factors.Their origin is a specific kind of cepstral representation of the audio clip.Clips are first preprocessed in the form of framing and windowing, followed by the extraction of MFCC features. MFCC features are also used in [26].Additionally, the second-level MFCC-2 feature values are computed to handle the uneven and large dimensionality problems mentioned in the following paragraphs.The frequency spectrum of a sound or other signal as it changes over time or with some other variable can be graphically represented by a spectrogram.The domains of music, sonar, radar, speech processing, and seismology make extensive use of them.These experiments were conducted using MFCC features, which allowed them to discover asensitivity, specificity, recall, accuracy, and precision as basal values.Audio detection also makes use of spectrogram images.Nonetheless, they were never evaluated using CNNs on respiratory audio.We used the SciPy package to build the MFCC datasets.They processed these datasets using support vector machines.A number of open-source image processing libraries and the free and open-source graph generation library Pyla were combined to create the spectrogram dataset.The original spectrum images were 800×600 RGBA, but they had to change the algorithm to generate 28×28 grayscale images so that CNN could process them, because the original size was too large for the computer's memory during the experiment.Using a dataset of 1,790,000 sounds recorded from 1,630 subjects, they tested four diverse scenarios, two of which included the proposed methods.By combining SVM and CNN, they were able to achieve a healthy-pathological classification accuracy of 86%.They came to the conclusion that, given the vast quantity of data, CNN and SVM machine learning algorithms can properly categorize and pre-diagnose respiratory sounds, and that spectrogram image classification using CNN works just as well as the SVM approach. Pramonoetal.tested dissimilar features for the purpose of identifying typical wheezes and other respiratory sounds.The dataset comprised of 38 recordings from diverse sources, and this research aimed to assess the discriminatory power of several feature types utilized in related studies.Of the 425 events, 223 were wheezes and the remaining ones were considered normal.They proved that several individual traits (MFCC, tonality index) are much better at identifying wheezes.Still, the computing demands of these characteristics are greater than those of simpler time-domain ones.It has also been demonstrated that there is a limit to how much improvement in performance there is after a certain number of features, even though using multiple features does improve classification accuracy in some cases.Lastly, they mentioned that although the classifier employed in this study is fairly basic, using more complicated classifiers like support vector machines or artificial neural networks might improve classification performance, but at the expense of computing complexity.Therefore, when choosing a feature for wheeze detection in various applications, it is important to consider all the competing requirements.In[27], they detail their experiments with various features and the outcomes.

The Acharyaetal brand.[28] ingave a presentation on a deep learning-based technique for lung sound classification.Due to its unparalleled success in a variety of applications, including clinical diagnostics and biomedical engineering, deep learning has gained a lot of attention in recent years.The network learns useful features and abstract representations from the data through training, so there's no need to manually craft them. This is a significant advantage of these deep learning paradigms.Due to the small dataset, numerous data augmentation techniques were employed to augment the size of the dataset and train a deep learning model.the collection.In addition to expanding the dataset, these data augmentation methods teach the network useful data representations despite issues like inter-patient variability of breathing rate, different recording conditions, different equipment, and patients' ages and genders.They have utilized a Mel-frequency spectrogram with a window size of 60 ms and 50% overlap for feature extraction.Next, each breathing cycle is transformed into a two-dimensional picture, with the rows representing frequencies on a Mel scale and the columns representing time (windows). Each value represents the logarithm of the signal's amplitude that corresponds to that frequency and window.They put forward a hybrid

3.PROPOSED SYSTEM

One of the main goals of this research is to provide an algorithmic strategy that can automatically classify lung sounds in different disease conditions. In addition to effectively classifying lung sounds, this study aims to provide a lightweight deeplearning architecture that does so with reduced computational complexity and parameter size. Due to the similarity in symptoms across most respiratory disorders, a spirometry test and a simple listening to the patient's lung sounds are often insufficient for a diagnosis.

Below is a list of the innovative contributions made by the proposed framework.

1) Developing an innovative, space-saving long short-term memory (LSTM) called CNN_LSTM for accurate lung sound classification while minimizing the amount of parameters that can be trained and the amount of data stored in the model.
2) Using three publicly accessible lung sound databases—the ICBHI 2017 challenge database, the chest wall lung sound database, and our own database—we classified seven respiratory disorders for the first time.

Because the DLM is trained with a broad range of lung sounds, engaging all the databases also guarantees the robustness of the classification process.
3) In order to conduct a comprehensive analysis of the proposed lightweight CNN_LSTM's performance and classification accuracy, statistics such as layers, parameters, accuracy, precision, recall, F1 score, and so on must be computed for the ablation study and classification report.

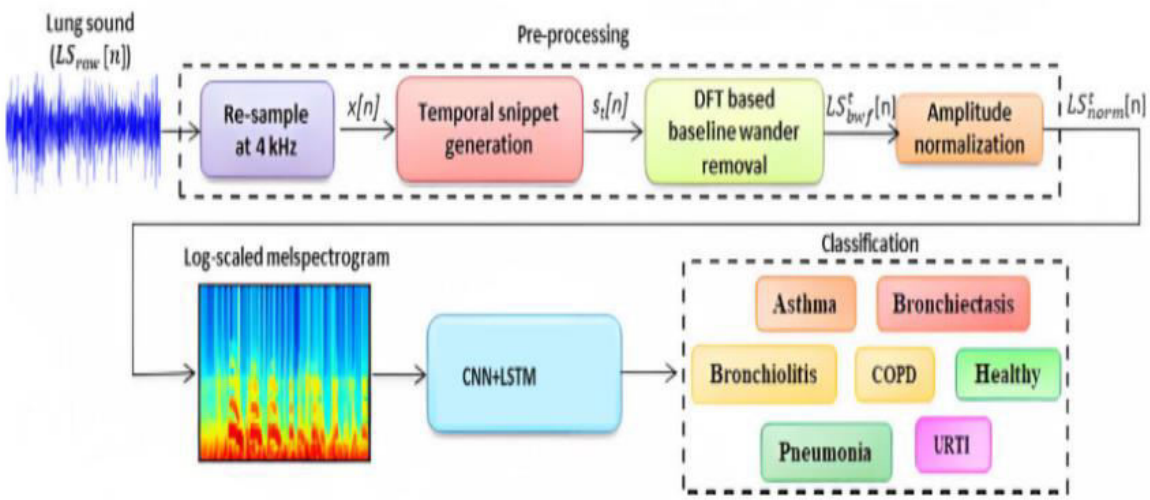

Fig 1:System Architecture

3.1 IMPLEMENTATION

3.1.1 Preprocessing

There are four submodules in the preprocessing stage:
1) dividing the input signal or time series into smaller subseries, known as snippets;
2) generating temporal snippets from the resampled signal; filtering based on the discrete Fourier transform (DFT) for baseline removal

3.1.2 Data Augmentation

Our major objective in this work is to classify a broad spectrum of respiratory illnesses, thus we have used three independent databases for that purpose.

If all three databases' audio signals are used, however, there will be an imbalance of power, with COPD being the dominant class and the others being the minority.

3.1.3 Extraction of TFR

Because of their highly varying amplitudes and variable frequency components, lung sound signals are notoriously difficult to analyze.

Hence, to fully comprehend them, it's required to convert the signal from one domain to another. With the help of transformation methods, it is possible to record both the time-domain and the frequency-domain information at the same time.

3.1.4 Lightweight CNN-LSTM Network

In order to distinguish between respiratory illnesses based on abnormal lung sounds, several CNN architectures have begun to use the time-frequency representation (TFR) of the lung sound signal as an input.

Here, we present a new lightweight CNN-LSTM that, using salient feature extraction from TFR pictures acquired from the lung sound signal, can identify seven different respiratory illnesses.

4.RESULTS AND DISCUSSION

Fig 4.1: Home screen

As a consolidated platform, the home screen page provides healthcare providers and researchers with critical information and tools for a complete study on respiratory illness categorization. The project's name and logo stand out on this page, making it easy to identify and understand its significance in the context of respiratory health. Accessing different parts, such as patient evaluation, diagnostic tests, treatment recommendations, resources, and project information, is made easy with a clear and simple navigation menu. Users are able to quickly find the precise information they need thanks to this simplified access, which guarantees effective navigation. In sum, the landing page establishes the groundwork for an intuitive interface that improves comprehension of respiratory illness categorization and treatment techniques, and that helps users make well-informed decisions.

LOGIN PAGE

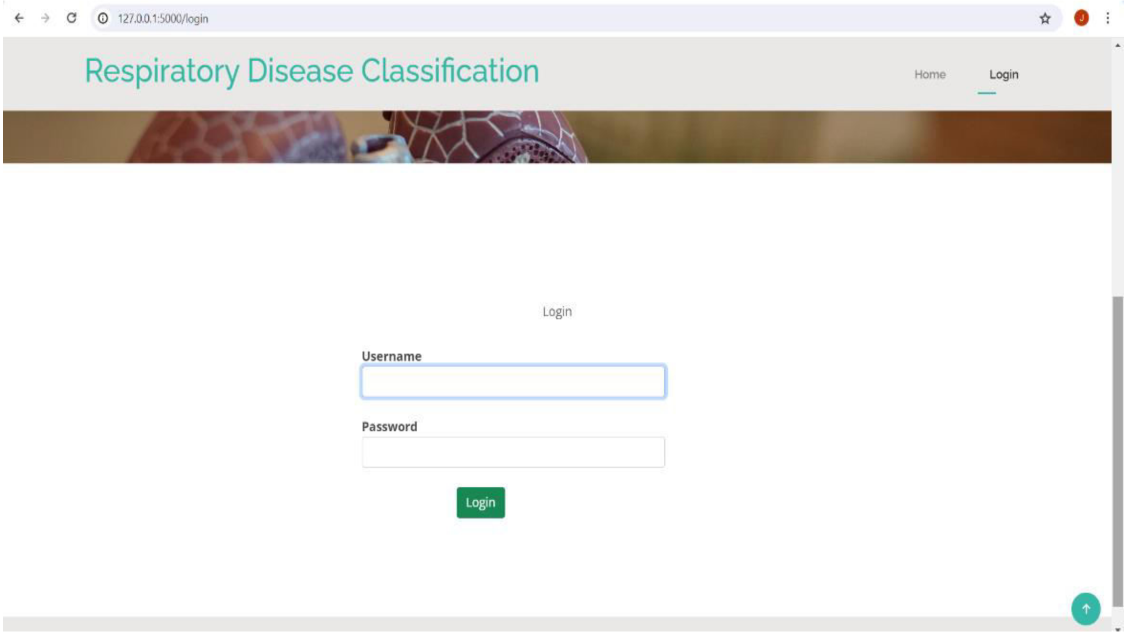

Fig 4.2: Login page

To ensure that only authorized users have secure access to respiratory illness categorization project materials and sensitive medical information, a login page has been created. This page serves as an initial safeguard by requesting credential authentication from users before allowing them to go further.

To ensure the security of the login process, users are asked to provide their username and password. If they forget their credentials, they may choose to recover or reset them.

To prevent data breaches and illegal access, advanced security measures like encryption protocols and multi-factor authentication may be put in place.

Users may access all of the project's features, such as patient assessment tools, diagnostic algorithms, treatment recommendations, and instructional materials, if they successfully authenticate.

In addition to securing sensitive patient information, this login method encourages responsibility and auditability among platform users.

PATIENT DETAILS

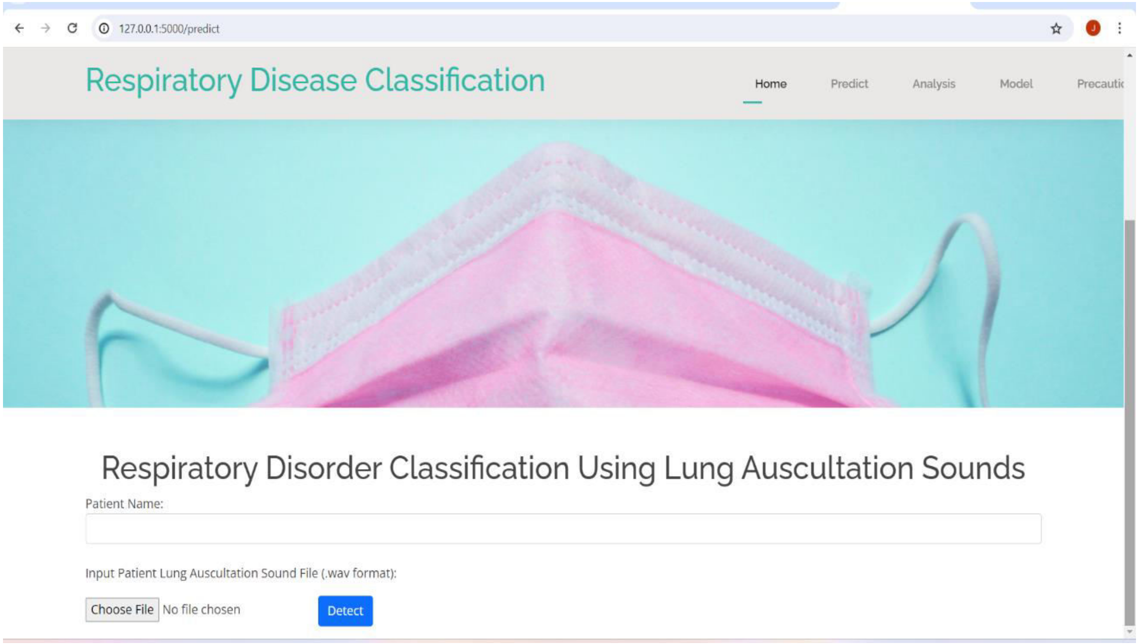

Fig 4.3: Patient Details

An essential part of the respiratory illness categorization project, the patient information page is the first destination for users when they log in. Here, medical staff may safely access and manage all of their patients' medical records in one convenient location.

When they arrive, visitors will see a user-friendly interface that is designed to make data input and retrieval as efficient as possible. Patient demographics, medical history, present symptoms, and pertinent test results are among the critical factors that they are asked to enter or evaluate. Users may accurately capture critical components of the patient's respiratory health using organized forms and dropdown menus, allowing for tailored treatment planning and precise diagnosis.

In addition, the patient details page follows all applicable regulations and industry standards for the protection of personal health information.

Healthcare providers are better able to provide timely, effective, and individualized treatment to patients with respiratory disorders when they can access all of their patient records in one safe location via the patient details page. As the project's foundation, it allows for thorough evaluation, categorization, and treatment of respiratory disorders, which improves patient outcomes and quality of life.

UPLOADING RAW LUNGS SOUND

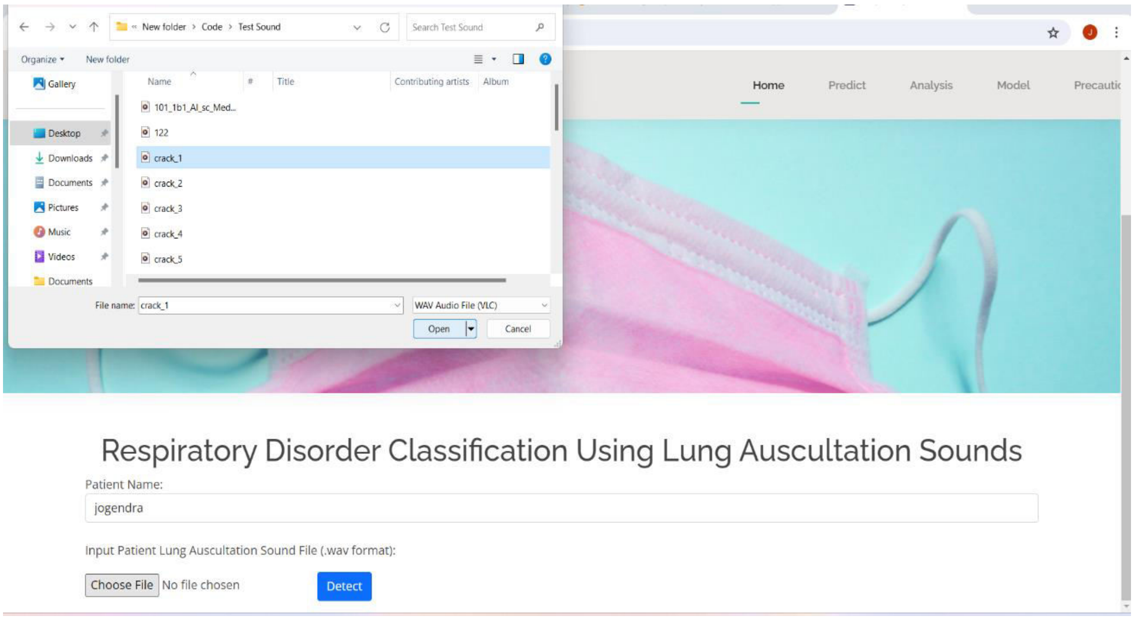

Fig4.4: Uploading Lungs Sound

Lung sound uploading is a critical component of the respiratory illness categorization project that allows for thorough evaluation and diagnosis of pulmonary disorders. Healthcare providers may easily add auscultatory data to a patient's electronic health record by using the specified upload interface. Recording lung sounds using specialized electronic stethoscopes or other recording equipment and then submitting the audio files to the website is an easy and straightforward procedure.

After uploading, the lung sound data undergoes a thorough analysis using state-of-the-art machine learning and signal processing methods. The existence of anomalous breath sounds, such as wheezes, crackles, or reduced breath sounds, may be automatically extracted from the audio recordings using these advanced techniques. Clinicians may quickly detect patterns suggestive of a variety of respiratory diseases, such as asthma, COPD, pneumonia, and pulmonary fibrosis, by using computational analysis.

In addition to augmenting conventional diagnostic tools like imaging and pulmonary function tests, the use of lung sound analysis improves the precision and timeliness of respiratory illness categorization. Together with other clinical data, auscultatory results may help clinicians acquire a better picture of their patients' respiratory health and decide how to best treat them.

DETECTED OUTPUT:

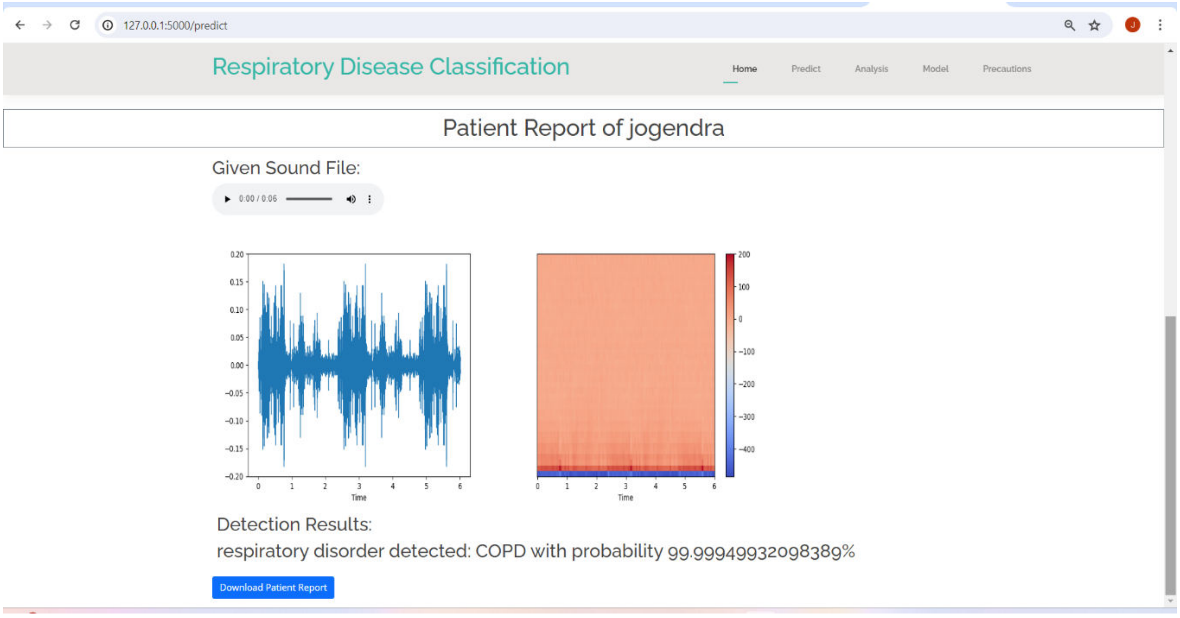

Fig 4.5: Output

A crucial interface for communicating diagnostic results and therapy suggestions to healthcare providers is the output page in the respiratory illness categorization project. The report compiles the findings of many evaluations, such as the patient's medical history, diagnostic testing, and an examination of lung sounds. In order to help doctors make informed decisions, this report summarizes the patient's respiratory state in a clear and concise manner, drawing attention to important results. Interactive elements may also be included on the output page, giving visitors the chance to delve further into data visualizations or find other resources to bolster their research. In pulmonary medicine, the output page is vital for enhancing patient care outcomes and promoting informed decision-making.

5.CONCLUSION

A machine learning-based method for identifying crackles in stethoscope-recorded sounds has been introduced as part of a comprehensive health survey.

Using a large number of audio recordings, we tested several feature extraction techniques and classifiers. Best results were achieved using a CNN-LSTM Kernel and a straightforward 5-dimensional layer. Thanks to its low-dimensional feature vector, CNN-LSTM is able to categorize lung sounds in real-time and is very fast.

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