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Development of a Web App for Asthmatic Wheeze Detection using Convolutional Neural Networks

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Abstract *– Asthma and chronic obstructive pulmonary diseases (COPD) are two lung conditions that frequently exhibit breathing problems. If you have asthma, your airways may become more constricted, enlarged, and mucus-producing. This could block your airways and result in wheezing, whining, coughing, and shortness of breath. As a result, wheezing can be a vital diagnostic tool for determining the presence of many disorders. An individual's respiratory rate increases when they wheeze, and as a result, their lungs are more likely to work harder than they normally would, and it will pose a significant health challenge and can lead to severe complications if not detected and managed early. In this research, we present a web application for asthmatic wheeze detection using Convolutional Neural Networks (CNNs) for the early identification of respiratory disorders in Sri Lanka. The system leverages a web application server to receive audio recordings from an electronic stethoscope and applies a CNN model to analyse the data and detect wheeze. Additionally, the system provides therapy recommendations and dosage prescriptions based on the detected respiratory disorder. The developed model achieves an accuracy of 74.68% in wheeze detection. This research aims to improve respiratory health monitoring in Sri Lanka and provide healthcare professionals with a reliable tool for early intervention.*

Keywords— Chronic obstructive pulmonary diseases, Asthma, Wheezing, Neural Networks

INTRODUCTION

As people's quality of life rises, monitoring health issues is getting more and more popular. Respiratory disorders, including asthma, pose a significant health challenge globally, affecting millions of individuals and impacting their quality of life. Timely detection and effective management of respiratory symptoms are crucial for improving patient outcomes and reducing healthcare burdens. However, current clinical practices often lack automated systems for the early detection of wheezing, a common symptom associated with respiratory disorders.

This research paper aims to address this gap by developing a web-based wheeze detection system using convolutional neural networks (CNNs). The system leverages advanced machine learning techniques to analyze audio recordings obtained from an electronic stethoscope, providing real-time wheeze detection and valuable insights for healthcare professionals.

The absence of an automated wheeze detection system in clinical settings hinders the early identification and timely intervention for patients with respiratory disorders. Healthcare professionals rely heavily on their clinical experience and auscultation skills to detect wheezing, which can be subjective and prone to errors. Consequently, there is a need for a reliable and efficient system that can accurately identify wheezing in audio recordings, enabling early diagnosis and appropriate management of respiratory conditions.

The primary aim of this research is to develop a web-based wheeze detection system that utilizes CNNs to analyze audio recordings and accurately identify wheezing. The specific objectives of this study include:

- To design and implement a web application server that can receive audio recordings from an electronic stethoscope and facilitate real-time data analysis.
- To develop a CNN model trained on a dataset of sound recordings of patients with respiratory disorders to accurately detect wheeze.
- To evaluate the performance and accuracy of the developed wheeze detection system through extensive testing and validation using diverse audio datasets.
- To provide therapy recommendations and dosage prescriptions based on the detected respiratory disorder, enhancing the clinical decision-making process.
- To assess the usability and user satisfaction of the web-based wheeze detection system among healthcare professionals, ensuring its practicality and effectiveness in real-world clinical settings.

By achieving these aims and objectives, this research intends to contribute to the advancement of respiratory care by providing a reliable and automated system for the early detection and management of wheezing in patients with respiratory disorders. This research has the potential to improve patient outcomes, reduce healthcare costs, and enhance the overall quality of respiratory healthcare delivery.

The rest of this paper is organized as follows. Section II includes a comprehensive literature review of the available applications for wheeze detection. Section III of the paper discusses the methodology used in this research. Section IV discusses the findings obtained through the research and the results obtained. Finally, section V concludes the overall research indicating the importance of this research, and section VI points out the further work that could be done in this research.

LITERATURE REVIEW

The research's chosen detecting applications include several asthmatic disease-based systems. Such systems, which use various types of methods to overcome this issue, have been discovered by numerous people. While some of this software was created just to identify wheezes, others also offer numerous other extra functionalities.

These applications have a variety of features that are necessary to meet both functional and non-functional criteria. These systems utilize a multitude of cutting-edge technologies for a variety of purposes, including frontend, and back-end frameworks, The technologies being employed, and the many features offered by the chosen systems are the main topics of this review.

Existing Systems for Asthmatic-Based Disease Detection

Researchers [1] have done a study that demonstrates a wearable microphone array system for health condition monitoring where they are monitoring the wheeze signals. The research provides a brand-new wheezing signal detection technique for wearable systems in particular. A Digital Signal Processing (DSP) based system has been used to implement the wheeze signal detector. The sampling rate of 1000Hz, which is much lower than the standard sample rate of 44kHz for audio signals, is what the detection method is intended to function at. The proposed approach runs at a sampling rate of 1000Hz, which is significantly lower than the standard sampling rate of 44 kHz for audio signals in order to comply with the low power consumption limitation under the wearable state. The findings demonstrate that the suggested wheeze detection method is resistant to power scaling issues and is capable of detecting wheezes with greater than 90% accuracy even when speech interference is present.

This study [2] introduces a brand-new technique for automatically detecting and classifying wheezes. The frequency spectrum of a wheezing signal is described by the proposed method by employing "entropy" and only either one or two entropy-based features can be used to identify wheezes. As a result, the computational complexity of the suggested solution has been significantly decreased, and it can operate under the wearable condition's low power consumption limitation. Lung sounds of patients and healthy persons were used to assess the effectiveness of the proposed approach at various Signal-to-Noise Ratios (SNR). The single step in this straightforward Entropy-Based Wheeze Detection (EBWD) approach is the estimation of signal entropy. A wearable sound-based respiratory monitoring system has been developed using the suggested methodology. The experimental findings demonstrate that, when the Signal-to-Noise Ratio (SNR) is 6dB, the suggested wheeze detection method is capable of detecting roughly 85% of wheezy samples and achieving its design aim.

This study demonstrated a flexible acoustic sensor that can monitor wheezing [3], which is a frequent asthma symptom, while attached to the chest of the patient. They have used air as the dielectric material in a parallel-plate capacitive arrangement. The upper diaphragm of the framework vibrates as a result of wheezing pressure (acoustic) waves\, modifying the output capacitance. The sensors are constructed in such a manner that something that resonates in the 100 to 1000 Hz wheezing frequency range, has two advantages. Resonance causes a significant diaphragm deflection, eliminating the need for signal amplifiers (used in microphones). In addition, the design itself functions as a lowpass filter to lessen the impact on background noise, which primarily occurs in the frequency band above 1000 Hz. Aluminum foil, a cheap sustainable material, is used in the sensor's construction, which significantly lowers the cost & complexity of the manufacturing process. When noisy signals coming from the chest that is in the same frequency band as wheezing are present, a reliable wheezing detection (matching filter) method is employed to distinguish between different forms of wheezing noises. The study further enhanced that the sensor may process signals and be further integrated into electronic healthcare electronic systems using the Internet of Things (IoT) as the result of the sensor's Bluetooth connection to a smartphone (IoT). The sensor is put through bending, cyclic pressure, heat, and perspiration testing to gauge how well it performs under a variety of realistically difficult situations.

This research [4] aims to present an Internet of Things (IoT) based early warning system for asthma patients. The suggested system, which measures the air quality, was created using a Raspberry Pi computer and accompanying sensors. The system uses various message-handling protocols, such as IBM's Message Queuing Telemetry Transport Server, to handle message transfers. It also uses various actuators, such as the SIM900A GSM Module, to notify patients and other relevant parties. The system is designed to notify the patients and the appropriate parties to take emergency precautions whenever the values of the said factors, which affect air quality, exceed a pre-identified threshold value. In conclusion, it could be said that the proposed, tested, and implemented IoT-based solution could early warn asthmatic situations to asthma patients by gathering sensor data (air quality, humidity, etc.), processing them, and issuing some warnings to the patients. Further, the IBM Watson IoT platform with some Artificial Intelligence (AI) techniques like deep learning models is also being used to make certain predictions against some input factors like patient's heart rate, blood pressure, etc.

The goal of this study [5] is to use Cepstral analysis in Gaussian Mixture Models to categorize normal and abnormal (wheezing) respiratory sounds. The sound stream is separated into overlapped segments, each of which is represented by Mel-Frequency Cepstral Coefficients-based reduced dimension feature vectors. The "speaker" in this investigation is a wheeze. Unknown audio is compared to all of the Gaussian Mixture Model (GMM) models during the test phase, and the classification choice is made using the Maximum Likelihood criterion. Identification in these processes is dependent on a threshold value. The audio is normal if the threshold exceeds zero. Wheeze otherwise can be heard. According to experimental findings, wheeze can be identified with up to 90% accuracy whenever the Gaussian mix number is 16.

The research study [6] suggests a brand-new automatic wheeze identification technique for automatically identifying wheezes by extracting time-frequency aspects of lung sounds. The suggested technique successfully locates wheezing features in a lung sound spectrogram using canonical correlation analysis. Additionally, a neural network technique is employed to distinguish between wheezing and healthy noises. The Canonical Correlation Analysis (CCA) methodology, when compared to previous wheezing analysis methods, could significantly lessen the impact of background breathing sounds and environmental noise. It could also detect wheezing features in a lung sound spectrogram. A majority of the lung sound characteristics for all asthma groups, including the respiratory rate, sound index, breathing cycle period, expiratory duration, maximum peak frequency, wheezing duration, and wheezing frequency, according to the experimental results, were significantly different from those of the healthy group, with the exception of the inspiratory duration. Additionally, the Radial Basis Function Neural Network (RBFNN) with extracted lung sound features performed superbly in differentiating between normal lung sounds and wheezing sounds (accuracy = 96.8%). As a result, the suggested method may effectively detect wheezing in children who have asthma and may one day be used to gauge the severity of wheezing.

In this study [7] they offer a brand-new, reliable algorithm created just for the Compressively Sensed (CS) recovered Short-Term Fourier Spectra (STFT), for wheeze detection. The suggested technique uses a hidden Markov model to detect the presence and monitor numerous distinct wheeze frequency lines (Hidden Markov Model). On Nyquist-rate sampled respiratory sounds STFT, the algorithm produces 89.34% sensitivity, 96.28% specificity, and 94.91% accuracy. When used with STFT that has been recovered by Orthogonal Matching Pursuit (OMP), it allows for a signal compression ratio of up to 4x (classification from only 25% of signal samples) with less than a 2% reduction in classification accuracy. It offers good parallelism prospects and has execution speeds comparable to equivalent methods.

Using MATLAB (Matrix Laboratory software), different lung sounds have been studied in this research [8] for wheeze identification and classification to Monophonic (one sound at a time) or Polyphonic (multiple sounds at a time). The American Thoracic Society (ATS) definition of wheeze and earlier studies are used to combine and analyze the set of factors in the provided algorithm. It has an overall sensitivity of 90% for wheezing episode detection and an accuracy of 91%. It is remarkably resilient, computationally simple, and accurate. The system has a sensibility of 91% and an accuracy of 70% for identifying monophonic and polyphonic wheezes. With a 90% specificity, the suggested method prevented other lung sounds from being mistakenly labeled as wheezes. This device can assist doctors in the early detection of lung obstructive disease and based on the analysis of lung sounds, may pinpoint the exact point of the obstruction in the lung. All they have to do is download the MATLAB compiler and launch the study program's executable file to detect respiratory wheeze sounds.

The invention of a quick and effective wheeze recognition system is described in this study [9]. The suggested wheeze detection system is based on back propagation neural networks (BPNN) and order truncate averages (OTA). The trained BPNN is then given some characteristics that were retrieved from the processed spectra. The trained BPNN eventually processes the fresh testing samples to determine whether they are asthmatic noises. The qualitative approach of wheeze recognition exhibits high responsivity of 0.946 and specificity of 1.0 according to experimental data. To address the shortcomings of Homs-Corbera et al’s study and to identify wheezes with great sensitivity, a novel modular approach to the OTA technique was created. The program provides doctors with processed data in addition to an automatic diagnosis. Prior to automatic recognition in this application, the processed spectrogram is displayed on a computer screen. The results of the trials show that this method can be highly helpful in clinical diagnostics, particularly when analysis can be performed continuously using a large number of patients' breathing cycles.

In this study [10], they created the first step in creating a computational model for respiratory phase-based wheeze identification, known as WheezeD [10]. First, they create an algorithm to identify the breathing phase from audio data. This is the first part of WheezeD [10]. They next turn the audio into a 2-D Spectro-temporal picture and create a model for wheeze identification based on a convolutional neural network (CNN). They assess model performance and contrast it with traditional methods. The results of experiments on a publicly available dataset demonstrate that their model can identify wheezing events with an accuracy of 96.99%, specificity of 97.96%, and sensitivity of 96.08%.

Since all these applications developed are not directly addressing the wheeze detection techniques the technologies, features, and concepts of them can be effectively used to improve the effectiveness in developing this kind of a system

Table 1: Comparison of Technologies, Equipment, Features, and Accuracy of the Revised Systems

Research Paper	A	B	C	D	E	F	G	H	I	J
Technology	DSP-based technology	Using LABVIEW	IOT	IOT & Deep learning models	Cepstral analysis in gaussian mixture models	Canonical correlation analysis & Neural networks	Hidden Markov model	DSP techniques	Order truncate average(OTA) and back-propagation neural network(BPNN)	Acoustic Data From Pulmonary Patients Under Attack
Equipment	Wearable microphone array system	Sensors, Signal conditioning circuits & PDA platform.	Acoustic sensors, filters	Raspberry Pi sensors, actuators	Sensor, amplifier and bandpass filters	Self assembled lung sound recorder	Wearable sensors	Collected from available databases	ECM wrapped inside the tube, filters, amplifiers	Collected from available databases
Feature	Sampling rate	Entropy-base features	Wheezing sounds	Air quality	Sound stream	Time frequency aspects of lung sounds	Wheeze signal frequencies	Monophonic wheezes and Polyphonic wheezes	OTA filtering of spectrogram	Breathing signal phase
Accuracy	In the presence of a speech interfering source, the accuracy is still above 90%	When SNR is 6dB 85% of accuracy	Low cost, low complexity design of the system	Early warning system to send warnings to authorities has a good accuracy	90% accuracy when gaussian mix number is 16	Accuracy 96.8%	89.34% sensitivity 96.28% sensitivity, 94.91% accuracy	90% sensitivity & 91% accuracy	High sensitivity of 0.946 and a specificity of 1.0 in qualitative analysis	accuracy of 96.99%, specificity of 97.96%, and sensitivity of 96.08%

METHODOLOGY

The methodology employed in this research encompasses several key steps to develop an accurate and reliable wheeze detection system using Convolutional Neural Networks (CNNs).

Gathering the dataset

Firstly, a comprehensive dataset of audio recordings from patients with respiratory disorders, including wheezing and non-wheezing instances, is used which is available in Kaggle. The audio data is then preprocessed by normalizing the recordings, segmenting them to focus on wheezing sounds, and converting them into spectrograms to visualize the frequency content over time.

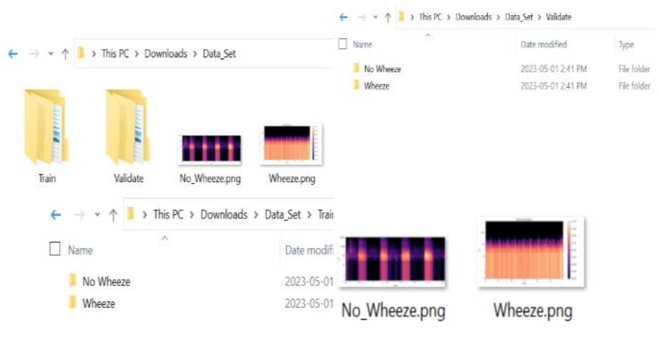

Figure 1: Data Set

Developing the model

Next, a CNN model tailored for wheeze detection is designed and implemented. The model is trained using the preprocessed spectrograms as input and the corresponding wheeze labels. Various hyperparameters are optimized through experimentation and validation to enhance the model's performance. Techniques such as transfer learning or feature extraction from pre-trained models may also be utilized to leverage existing knowledge and improve efficiency.

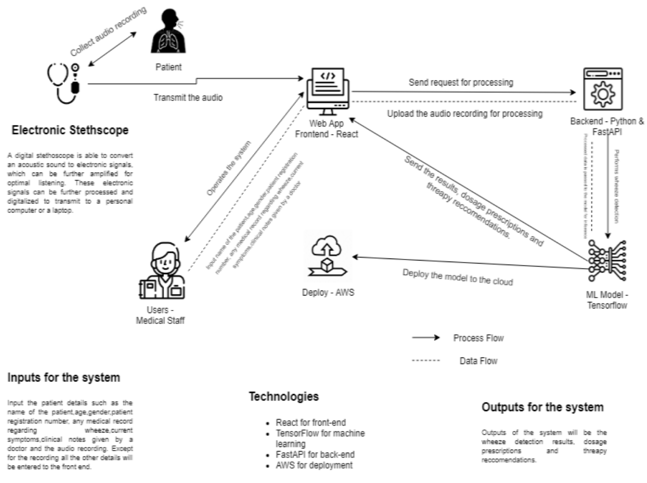

Figure 2: Overview of the system

Testing

The trained CNN model is evaluated using a testing dataset, with performance metrics such as accuracy, precision, recall, and F1 score calculated to assess its effectiveness. Cross-validation or additional validation techniques may be employed to ensure the model's robustness and generalizability.

Web Application Development

In parallel, a web-based wheeze detection system is to be developed to facilitate real-time analysis of audio recordings.

The system includes a user-friendly interface for clinical staff to upload recordings and receive wheeze detection results.

System Integration

The trained CNN model is integrated into the web application server to enable automated wheeze detection using API services. Additional features, such as therapy recommendations, dosage prescriptions, and the ability to send warning messages to doctors, are incorporated to enhance the system's functionality.

Evaluation

The performance of the developed system will be extensively evaluated, considering factors such as efficiency, reliability, and scalability. Feedback from clinical staff and domain experts is planned to be gathered to assess usability and effectiveness in real-world healthcare settings. The system's performance is compared to existing methods or alternative approaches for wheeze detection, highlighting its advantages and potential limitations. The clinical implications and potential benefits of implementing the wheeze detection system in healthcare settings are discussed.

The methodology presented in this research provides a comprehensive approach to developing a wheeze detection system using CNNs. The integration of machine learning techniques, web application development, and thorough performance evaluation contributes to the creation of an accurate and practical system for respiratory health monitoring.

RESULTS & DISCUSSION

The results & discussion section of this research paper focuses on interpreting and analyzing the findings and results obtained from the implementation and evaluation of the wheeze detection model using Convolutional Neural Networks (CNNs). The developed wheeze detection model demonstrated promising results in detecting respiratory disorders based on audio recordings. The system will successfully receive audio recordings from an electronic stethoscope via the web application server and passed them on to the machine learning platform for analysis using the trained CNN model.

```
In [32]:
train_datagen = ImageDataGenerator(rescale = 1./255,
shear_range = 0.2,
zoom_range = 0.2,
horizontal_flip = True)
test_datagen = ImageDataGenerator(rescale = 1./255)

training_set = train_datagen.flow_from_directory('C:/Users/Latitude/Downloads/Data_Set/Train',
target_size = (64,64),
batch_size = 32,
class_mode = 'binary')

test_set = test_datagen.flow_from_directory('C:/Users/Latitude/Downloads/Data_Set/Validate',
target_size = (64,64),
batch_size = 32,
class_mode = 'binary')

classifier.fit_generator(training_set,
steps_per_epoch = 160,
epochs = 10,
validation_data = test_set,
validation_steps = 46)

Found 79 images belonging to 2 classes.
Found 40 images belonging to 2 classes.

C:\Users\Latitude\AppData\Local\Temp\ipykernel_8452\2114581467.py:17: UserWarning: `Model.fit_generator` is deprecated and w
ill be removed in a future version. Please use `Model.fit`, which supports generators.
  classifier.fit_generator(training_set,

Epoch 1/10
  3/160 [..............................] - ETA: 1:06 - loss: 1.3573 - accuracy: 0.7468WARNING:tensorflow:Your input ran out
of data; interrupting training. Make sure that your dataset or generator can generate at least `steps_per_epoch * epochs` ba
tches (in this case, 1600 batches). You may need to use the repeat() function when building your dataset.
WARNING:tensorflow:Your input ran out of data; interrupting training. Make sure that your dataset or generator can generate
at least `steps_per_epoch * epochs` batches (in this case, 46 batches). You may need to use the repeat() function when build
ing your dataset.
160/160 [==============================] - 4s 13ms/step - loss: 1.3573 - accuracy: 0.7468 - val_loss: 2.0374 - val_accuracy:
0.7500

Out[32]: <keras.callbacks.History at 0x1da590d4280>
```

Figure 3: ML Model

```
In [48]:
import numpy as np
from tensorflow.keras.preprocessing import image
test_image = image.load_img('C:/Users/Latitude/Downloads/Data_Set/Wheeze.png', target_size=(64,64))
test_image = image.img_to_array(test_image)
test_image = np.expand_dims(test_image, axis = 0)
result = classifier.predict(test_image)
training_set.class_indices

if result[0][0] == 1:
    prediction = 'Wheeze is detected'
else:
    prediction = 'Wheeze is not detected'
print(prediction)

import numpy as np
from tensorflow.keras.preprocessing import image
test_image = image.load_img('C:/Users/Latitude/Downloads/Data_Set/No_Wheeze.png', target_size=(64,64))
test_image = image.img_to_array(test_image)
test_image = np.expand_dims(test_image, axis = 0)
result = classifier.predict(test_image)
training_set.class_indices

if result[0][0] == 1:
    prediction = 'Wheeze is not detected'
else:
    prediction = 'Wheeze is detected'
print(prediction)

1/1 [==============================] - 0s 47ms/step
Wheeze is detected
1/1 [==============================] - 0s 38ms/step
Wheeze is not detected
```

Figure 4: ML Model

The evaluation of the system's accuracy revealed a performance of 74.68%, indicating its capability to accurately detect wheeze in real-time. The dataset used for training and testing the model consisted of approximately 110 wheeze and non-wheeze recordings obtained from Kaggle. The dataset was divided into 70% for training and 30% for testing purposes, ensuring a comprehensive evaluation of the system's performance.

The results displayed by the system will include not only the detection of wheeze but also therapy recommendations and dosage prescriptions based on the identified respiratory disorder. This additional information will provide valuable insights for healthcare professionals in making informed decisions regarding patient care and treatment plans. The user-friendly interface of the web application allows clinical staff, such as nurses and doctors, to easily interpret and act upon the results provided by the system.

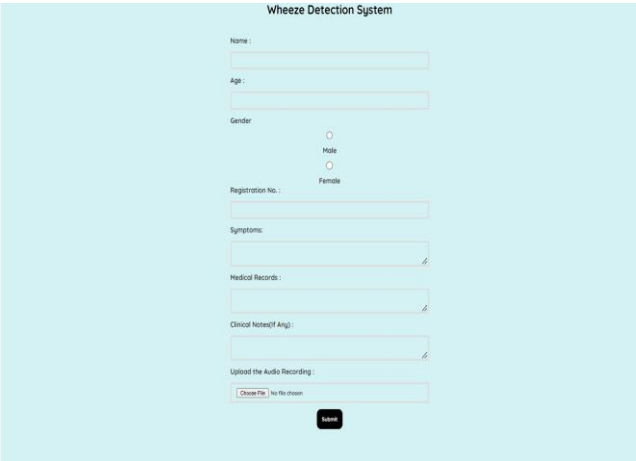

Figure 5: Main UI Design

Furthermore, the system will allow for sending warning messages to doctors if necessary. This feature will enable timely communication and intervention, ensuring that critical cases are promptly addressed, and appropriate medical attention is provided. The integration of such communication channels enhances the collaborative approach to patient care and facilitates efficient coordination among healthcare professionals.

Although the developed CNN model achieved a commendable accuracy of 74.68%, there is room for improvement. Future work should focus on fine-tuning the model to further enhance its performance and accuracy. This can be achieved through additional training iterations and optimization techniques to ensure the system's robustness in detecting wheeze across various scenarios and patient populations.

Moreover, deployment of the model on a cloud platform, such as the AWS Cloud Platform, would facilitate scalability and accessibility of the system, allowing it to cater to a larger user base and handle increased demands for wheeze detection services. Additionally, the development of the backend using FASTAPI and connecting it with the front-end React interface would further enhance the system's functionality and user experience.

In conclusion, the wheeze detection system to be developed in this research project shows promise in providing early detection of respiratory disorders through the analysis of audio recordings. The system's accuracy, therapy recommendations, dosage prescriptions, and warning message functionalities contribute to improving patient care and facilitating prompt interventions. Further enhancements and optimizations are recommended to increase the accuracy and scalability of the system, ensuring its effectiveness in real-time wheeze detection and clinical decision-making.

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CONCLUSION

In conclusion, this research project has successfully developed a wheeze detection model using Convolutional Neural Networks (CNNs) and integrated it into a web-based application. The system demonstrates promising results in accurately identifying wheezing sounds in audio recordings, with a commendable accuracy of 74.68%. The system's usability, efficiency, and additional functionalities, such as therapy recommendations and dosage prescriptions, make it a valuable tool for clinical staff in providing timely and effective respiratory care.

The integration of CNNs into the wheeze detection system allows for real-time analysis of audio recordings, providing prompt wheeze detection results. This can greatly assist in the early detection and management of respiratory disorders, leading to improved patient outcomes. The system's user-friendly interface ensures ease of use for clinical staff, enabling them to assess respiratory conditions and make informed decisions regarding patient care quickly and efficiently.

Overall, the wheeze detection system developed in this research has the potential to significantly improve the early detection and management of respiratory disorders. By leveraging the power of CNNs and web-based technology, the system offers a practical and efficient solution for healthcare professionals, empowering them to provide timely and effective respiratory care to patients.

VI. FURTHER WORKS

The wheeze detection system developed in this research project has demonstrated its effectiveness in early detection of respiratory disorders. However, to further enhance the system's performance and expand its capabilities, several areas warrant attention for future work. This section outlines the recommended avenues for further research and development of the wheeze detection system.

The wheeze detection system has tremendous potential for further advancements. By enhancing the dataset, improving system-level features and algorithms, and leveraging technological innovations, the system can be refined to achieve higher accuracy and broader applicability. These recommended works provide a roadmap for future research and development, aiming to enhance the early detection and management of respiratory disorders, ultimately benefiting patients, and improving their overall respiratory health.

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