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DETECTION OF ABNORMAL LUNG SOUNDS USING REMOTE STETHOSCOPE VEST COAT WITH DEEP CONVOLUTION NEURAL NETWORKS

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ABSTRACT

Much healthcare data is collected from various hospitals to analyze and diagnose specific diseases in the medical field. Diagnosing the specific diseases based on the disease patterns and sample analysis is complex. This paper proposes a novel approach to remotely detecting and analyzing lung sounds using a vest coat stethoscope with deep learning algorithms. The proposed system addresses the limitations of traditional stethoscopes, which require physical contact with the patient and can be difficult to use in remote or noisy environments. The proposed system consists of a vest coat stethoscope equipped with a microphone array to capture lung sounds and a deep learning algorithm to process and analyze the data. The system is designed to be lightweight and portable, making it ideal for use in remote or field settings. The experiments were conducted with volunteers in various settings, including a hospital environment and a noisy construction site. The results showed that the proposed system 2dCNN could accurately detect and classify lung sounds in quiet and noisy environments, with a high level of accuracy compared with the 1D-CNN Model and LSTM. Overall, the proposed system shows great promise for remote diagnosis and monitoring of lung conditions, particularly in settings where traditional stethoscopes may not be effective. Future work will focus on refining the deep learning algorithms and expanding the system to include additional physiological signals for a more comprehensive analysis of lung health.
Keywords: *1D-CNN Model, LSTM, 2D-CNN, Lung Sounds*.

1. INTRODUCTION

Respiratory disorders have a large global impact, impacting millions of individuals annually. These disorders can be acute or chronic, with symptoms ranging from mild to severe. The most prevalent respiratory disorders include asthma, chronic obstructive pulmonary disease (COPD), pneumonia, tuberculosis (TB), and lung cancer. According to the World Health Organization (WHO), respiratory disorders account for 10% of all fatalities globally, making them one of the main causes of death [1].In 2019, it was estimated that 3.9 million deaths were attributed to respiratory diseases globally. In addition to the human toll, respiratory diseases also have a significant economic impact. They can lead to reduced productivity, higher healthcare costs, and lower quality of life. According to a survey published by the Forum of International Respiratory Societies, the global economic burden of respiratory disease is projected to be $2.1 trillion USD [2]. Respiratory diseases also have a disproportionate impact on vulnerable populations, including children, the elderly, and those living in low- and middle-income countries [3]. Factors such as air pollution, tobacco use, and poor living conditions can increase the risk of developing respiratory diseases [4]. Prevention and early detection are key to reducing the global impact of respiratory disease. Strategies such as reducing exposure to environmental pollutants, promoting healthy behaviors, and increasing access to healthcare can help to prevent respiratory diseases and improve outcomes for those affected by them [5].

Machine learning (ML) algorithms have the potential to revolutionize the diagnosis of lung problems, such as respiratory illnesses and lung cancer [6]. These algorithms can analyze vast amounts of data and uncover patterns that would be impossible for human experts to spot. Machine learning algorithms can help in the diagnosis of lung diseases by analyzing medical images such as X-rays, CT scans, and MRI scans [7]. These algorithms can be trained to identify anomalies in images, such as nodules or tumors, and classify them as cancerous or non-cancerous.

This can help physicians to make more accurate diagnoses and develop more effective treatment plans. ML algorithms can also be used to analyze other types of data, such as patient health records, genetic information, and environmental factors. By recognizing trends in this data, algorithms can help forecast which individuals are more likely to develop specific lung disorders and generate personalized treatment regimens. One of the primary benefits of machine learning algorithms is their capacity to continuously learn and improve over time. As more data becomes available, algorithms can be trained on this data to improve their accuracy and effectiveness. However, there are also some challenges associated with the use of machine learning algorithms in the diagnosis of lung issues. These algorithms, for example, may be biassed if the training data does not accurately represent the population being diagnosed. Furthermore, some may be concerned about the interpretability of these algorithms, as it might be difficult to grasp how they arrive at their diagnoses. Overall, ML algorithms have the potential to be a powerful tool in the diagnosis of lung issues, but their use must be carefully evaluated and monitored to ensure that they are providing accurate and reliable results.

CNN algorithms can play a crucial role in diagnosing lung issues based on lung sounds recorded using a vest coat stethoscope. The primary advantage of using a vest coat stethoscope is that it can capture lung sounds from multiple locations on the chest, providing a comprehensive view of the patient's respiratory health. The use of CNN algorithms can help to automate the analysis of these lung sounds, reducing the reliance on human expertise and potentially increasing the accuracy of diagnoses. The algorithm can be trained using a large dataset of lung sounds, with each sound labeled as belonging to a particular category, such as normal breathing or wheezing. Once trained, the CNN algorithm can automatically classify new lung sounds into these categories, providing a quick and accurate diagnosis of any potential issues. This can be particularly useful in situations where trained medical professionals are not readily available, such as in remote or rural areas. Overall, the use of CNN algorithms in conjunction with a vest coat stethoscope has the potential to greatly improve the diagnosis of lung issues based on lung sounds. However, it is important to note that these algorithms should be used as a tool to assist medical professionals and not as a replacement for their expertise.

2. REVIEW RELATED WORK

Chen H et al. [8] proposed a novel technique that finds the different types of sounds from the respiratory system with the help of OST and ResNets. The input respiratory sound is processed by using the OST. The respiratory sounds are recognized based on the classification feature learning methods. The proposed model extracts the features like a wheeze, crackling, and respiratory sounds, which is used to improve the performance. Finally, the proposed model achieved accuracy, sensitivity, and specificity up to 98.79%, 96.27%, and 100%. These results are more than 2.34% and 4.87% compared with existing models. Demir F et al. [9] proposed the pre-trained model, which is used to recognize several lung sounds collected using electronic stethoscopes to check various respiratory diseases. The in-depth features are extracted using the middle and max-pooling layers, improving the classification performance. To analyze the features of the LDA and RSE applied on given samples and achieve better results. Fraiwan M et al. [10] discussed various datasets that belong to several lung-based diseases. All these datasets contain different audio recordings collected from several hospitals in the world. Fraiwan L et al. [11] proposed various hybrid techniques with the multi-class classification of respiratory diseases. The experiments are analyzed from multiple lung sound recordings from ICBHI datasets. All these recordings have diseases belonging to the health conditions of patients. The features are extracted from input lung sounds from the selected dataset. The proposed technique achieved an accuracy of 98.89%, a sensitivity (of 91.5%), and a specificity (of 98.55%). These suggested model results are far better compared with existing models, and it is more suitable for finding accurate results based on given input sounds. Jacome C et al. [12] proposed a new DL model that detects lung sounds based on the stage of lung diseases. The proposed approach extracts the features by deleting the particular features explicitly. From the experimental results, the proposed model is more suitable for detecting the abnormalities from breathing stages in input lung sounds.

Anavati F et al. [13] proposed the DL model that finds the abnormal tissues from the lungs. The model combined with CNN and EfficientNet-B3 architecture classifies the affected and not-effected lungs from the input datasets. C.H. Chen et al. [14] designed the dynamic stethoscope that helps doctors to find abnormal sounds from input lung images. The proposed model is connected to various hardware devices to get accurate sounds from the lungs. KNN is used to classify sample inputs based on usual and abnormal. Bardou D et al. [15] compare three varieties of ML models to find the strange sounds from lungs. All these models combined with various feature extraction techniques to extract the features from the given samples.

Finally, the proposed model achieved the best accuracy based on the classification of samples. Petmezas et al. [16] proposed a hybrid approach for recognizing abnormal lung sounds. The feature extraction models extract the deep features using the STFT spectrograms with the help of CNN and LSTM. Four components are removed from the ICBHI 2017 dataset based on various sounds. Padilla-Ortiz et al. [17] proposed a new model that analyzes the lung and heart sounds collected from multiple sensors and datasets belonging to several hospitals. The lung sounds are used for experimental analysis to diagnose the medical assessment. Rocha et al. [18] proposed an automated technique to classify the adventitious respiratory sounds (ARS) collected from various hospitals. The proposed model overcomes different classification models that perform better than existing techniques. Chamberlain et al. [19] developed the dynamic classification of lung sounds from various types of patients. The proposed model focused on detecting and recognizing the lung sounds collected from several regions from multiple patients based on pulmonary disease. The proposed model achieved better ROC

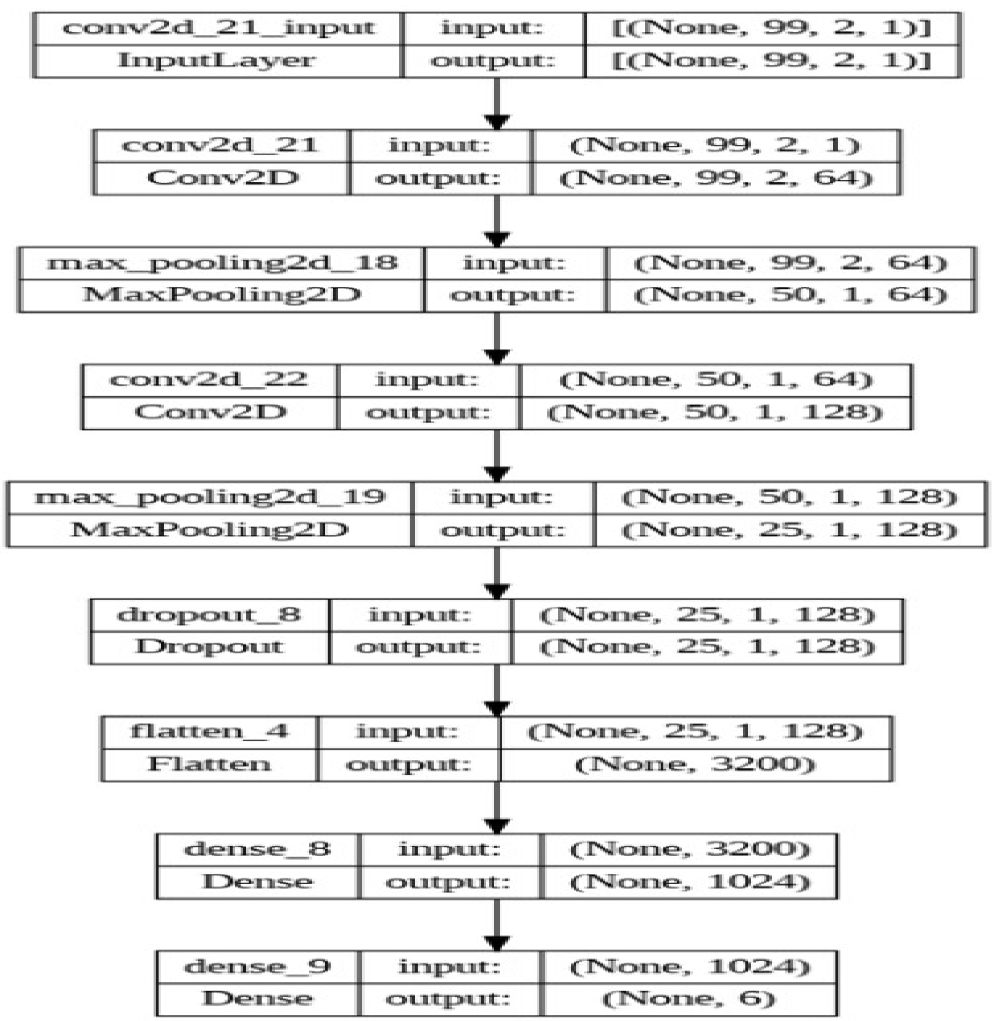

Figure 1: Architecture of the Proposed 2D CNN Model

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curves, with 86% for wheeze and 74% for crackle. B. V. Vardhan and M. K. Geetha, et al. [20] proposed an automated system for detecting abnormal lung sounds using a vest-coat stethoscope equipped with multiple sensors and deep learning algorithms

3. PROPOSED METHOD

In this study, we propose a novel method for classifying lung sounds using a 2D Convolutional Neural Network (CNN) illustrated in Figure 1 trained on a comprehensive set of audio features.

From each respiratory cycle in the ICBHI 2017 dataset, we extracted features such as Mel-Frequency Cepstral Coefficients (MFCCs), chroma features, mel spectrogram, spectral contrast, tonnetz, poly features, spectral flatness, spectral rolloff, and bandwidth. These features were organized into feature vectors and fed into the 2D CNN.

The proposed CNN model consists of two convolutional layers with 64 and 128 filters, respectively, each employing a 3x3 kernel size and a stride of 1. Max pooling layers with a pool size of 2x2 were applied after each convolutional layer to down sample the feature maps. To prevent overfitting, a dropout layer with a rate of 0.5 was incorporated. The flattened output from the convolutional layers was then passed to two fully connected layers with 1024 and 6 neurons, respectively. Finally, a softmax activation function was applied to the output layer to produce the classification probabilities for the six lung sound classes.

This feature-based approach aims to improve classification accuracy and efficiency compared to conventional methods that rely on spectrogram images.

Steps involved in the proposed model are:

Figure 2 represents the steps involved in designing the remote stethoscope vest coat on edge device (Raspberry pi 4). Figure 3 represents the prototype.

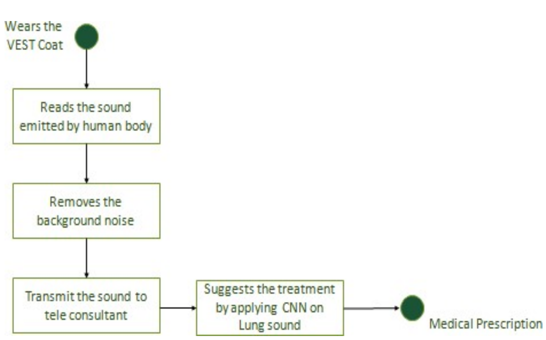

Figure 2: Procedure involved in Remote Stethoscope Vest Coat

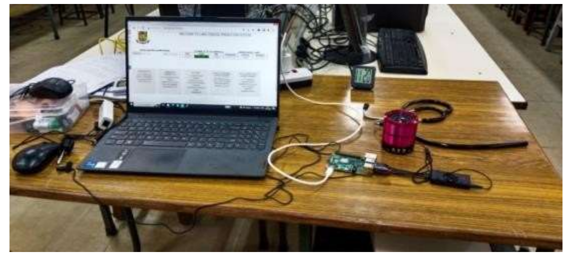

Figure 3: Remote Stethoscope Vest Coat for Lung Sound Classification prototype

Data collection: Lung sounds can be recorded using a vest coat stethoscope equipped with a microphone. The recordings can be made while the patient is breathing normally or during specific breathing maneuvers, such as deep breaths, coughs, or sustained phonation. A dataset of lung sound recordings should be collected, with each recording labeled as normal or abnormal.

Preprocessing: The raw lung sound recordings should be preprocessed to remove noise and artifacts, and to enhance the relevant features. This can involve filtering, denoising, and feature extraction techniques.

Feature extraction: The preprocessed lung sound recordings can then be transformed into a feature space that can be used as input to the CNN model. Several feature extraction techniques can be used, such as short-time Fourier transforms (STFT) which is represented by using equation (1):

$$\mathrm{STFT}\{x(t)\} = X(\tau, W) = \int_{-\infty}^{\infty} x(t) w(t-\tau) e^{-jwt}\, dt \qquad (1)$$

Data augmentation: The dataset can be expanded by adding noise, adjusting the time axis, or altering the pitch of the recordings. This can increase the dataset's variability while also improving model performance.

Model architecture: To extract spatial characteristics from lung sound recordings, the CNN model should have many convolutional layers. The output of the convolutional layers can then be passed into fully connected layers for classification. Several design choices need to be made, such as the number of layers, filter sizes, pooling strategies, and activation functions.

Training: The model can be trained using a supervised learning method, with the labeled dataset utilized to optimize the model parameters. The training method consists of minimizing a loss function that assesses the difference between predicted and real labels. The optimization can be carried out using gradient descent techniques, such as stochastic gradient descent (SGD).

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SGD is a famous optimization technique that is widely used in machine learning to train models. The purpose of SGD is to minimize the loss function by iteratively updating the model parameters using a random subset of the training data. To use SGD to detect anomalous lung sounds in recordings, we must first build an appropriate loss function that captures the difference between the expected and true labels of the lung sounds. This loss function could be binary cross-entropy, since we are trying to predict whether a sound is abnormal or not. Next, we need to preprocess the lung sound recordings to extract relevant features that can be fed into our model. This could involve applying Fourier transforms to convert the audio signals into the frequency domain. Once we have defined our loss function and extracted the relevant features, we can train our model using SGD. At each iteration of the algorithm, we randomly select a batch of lung sound recordings and labels and use them to update the model parameters. The learning rate, which defines the amount of each parameter update, is a crucial hyper parameter that must be carefully controlled to guarantee that the algorithm converges to a good solution.. The parameter update for every training sample $a^{(k)}$ and label $b^{(k)}$:

$$\theta = \theta - \eta . \nabla_{\theta} J\,(\theta;\ a^{(k)};\ b^{(k)}) \qquad (2)$$

Evaluation: To measure performance, the trained model should be evaluated on a separate test set. Several metrics can be employed, including accuracy and loss. The model can also be visualized to better understand its underlying representations and suggest opportunities for development.

Deployment: The final stage is to test the model in a real-world environment. This can include incorporating the model into a software application or medical gadget that healthcare providers can use to diagnose lung diseases based on recorded lung sounds.

4. PERFORMANCE METRICS

A confusion matrix for a 2D convolutional neural network (2DCNN) is a table commonly used to assess the performance of classification models. The square matrix contrasts the expected and actual class labels.

Assuming we have two classes, the confusion matrix for a 2DCNN typically looks like this:

True Positive (TP)	**False Positive (FP)**
False Negative (FN)	**True Negative (TN)**

In this matrix, the rows represent the predicted class labels and the columns represent the actual class labels. The elements of the matrix represent the number of samples that were classified into each category.

The accuracy and loss can be calculated using the values in the confusion matrix.

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

$$\text{Loss} = 1 - \text{Accuracy}$$

Table 1: Comparative Analysis of DL algorithms

Algorithms	Accuracy	Loss
1D-CNN	93%	0.9167
LSTM	95%	0.1866
2D-CNN	96%	0.2544

Figure 4 (a) (b) & Figure 5 (a) (b) denotes the visualization representation for 1D-CNN , 2D-CNN Accuracy and Loss.

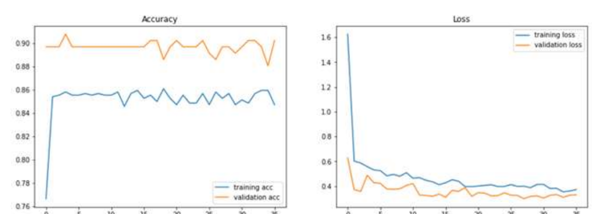

Figure 4 (a) (b): Visualization representation for 1D-CNN based on Accuracy and Loss

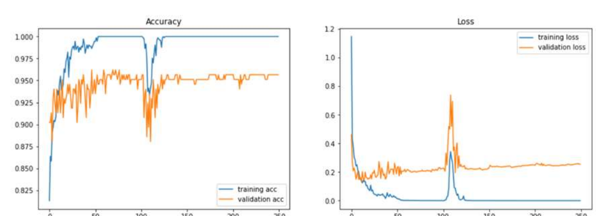

Figure 5 (a) (b): Visualization representation for 2D-CNN based on Accuracy and Loss

5. CONCLUSION

In conclusion, a 2D-CNN (convolutional neural network) can be an effective approach for detecting abnormal sounds from lung recordings. The use of a 2D-CNN allows for the identification of patterns and features in the recorded audio data, which can be used to distinguish between normal and abnormal lung sounds. To develop a 2D-CNN for this task, a dataset of lung recordings must first be collected and labeled to train the network. The network can then be optimized using techniques such as transfer learning or data augmentation to improve performance. Once trained, the 2D-CNN can be used to classify new recordings as either normal or abnormal based on the patterns and features identified in the training data. This can be a useful tool for medical professionals in diagnosing respiratory conditions and improving patient outcomes. Overall, the use of a 2D-CNN for detecting abnormal sounds from lung recordings has the potential to improve the accuracy and efficiency of respiratory disease diagnosis, ultimately leading to better patient care.

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