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A Review of ICBHI 2017 Respiratory Sounds Analysis using Deep Learning

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Abstract. *Death rates across the globe are often linked to respiratory illnesses, with severe conditions like- chronic obstructive pulmonary disease (COPD) and asthma being the primary culprits. Early detection of the-se diseases in their initial stages is more crucial than we may realize. The ancient diagnostic technique of lung auscultation, where a stethoscope is placed on the lungs, is renowned but also has inherent limitations and susceptibility to data distortion due to environmental variables. This led to the deve-lopment of modern solutions, born out of necessity, to address these challenges innovative methods that harness the power of deep learning algorithms to capture respiratory sounds more accurately. The International Conference on Biomedical and Health Informatics (ICBHI) dataset, containing lung sound recordings, is available to the machine learning community for research and development. Leveraging machine learning and deep learning techniques, with the latter being a subset of machine learning, such as convolutional neural networks, has enabled more accurate diagnoses compared to traditional auscultation methods. These advanced algorithms have achieved impre-ssive voice classification accuracy rates, outperforming conventional approaches. The fusion of cutting-edge technology and medical expertise has the potential to revolutionize respiratory disease detection and management. Scientific investigations and research have demonstrated that when utilizing (ICBHI 2017) data set, its precision varies from 42% to 90%.*

The goal of this article is to review articles related to the use of deep learning algorithms, which are combined in some articles with other machine learning algorithms, and the way they deal with the ICBHI 2017 dataset.

Keywords: *ICBHI 2017, Respiratory Sounds, CNN, Machine learning, Deep learning, SVM, KNN, RNN*

1. INTRODUCTION

Lung sounds come from the back and chest when air passes in and out through the lungs during breathing. In which they are considered as a critical sign of lung health of every person and may be an instrument for diagnosing a range of problems related to the lungs.[1] AI, proves to be a cutting edge technology making it easy and correct to analyze and classify lung sounds rather than the usual methods which are traditional ones and may often be less accurate compared to them.[2]
The adoption AI technology in this area entails within it novel points of concerns and opportunities.
We might say, promotion of exact algorithms that would help us in the extraction of the diverse characteristics (lung sounds) is a great challenge[3].

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Also for new and more realistic data to be collected, for these models to be effectively trained, it demands many collecting reliable data.[4]
In addition to main opportunities, one should remember the potential of creation of smart diagnostic tools with clear and straight diagnostic capabilities that could help doctors in an early diagnosis of lung issues. These technological tools are likely to be used to keep track of the progress of disease condition and to get a more precise estimate of the possible drug effects.[5][6]
The ICBHI (International Conference on Biomedical and Health Informatics) dataset is a worldwide known dataset. It encloses the audio recordings of lung sounds with reference classifications. The object of interest to the tracking group of pathologists and the Artificial Intelligence technologists in the field of lung sound classification is a great. This model is very helpful in lung sound classification using AI.[7][8]
Other feature that needs more study and the development is the research of the opportunity to use the other data like demographic and clinical overviews for better diagnosis and prognosis through the lung sounds discussions.[9]

2. MATERIALS AND METHODS

2.1. Machine learning

Machine Learning is a newer area of Artificial Intelligence. It allows computers and systems to learn, grow, and improve their functioning through experience without human coding. It is a captivating subcategory of computer science that takes advantage of algorithms and statistical models, resulting in the budding of intelligent robots that can function properly, that is, they can operate correctly without the rules of the past. At the core of Machine Learning is the fact that it transfers to machines the ability to learn, accumulate knowledge, and predict or even make decisions by themselves, thus, the labor of humans gets excluded from the process.[10] This is achieved through the use of a wide range of algorithms and techniques that weave through the data meticulously in search of being able to consistently discover the sequences of correlations and even draw cen-tral knowledge that is hidden in the interrelations of parameters. Mathematical approaches developed through deep data analysis can therefore utilize these new ideas to create machine learning algorithms that can learn the volumes of empirical data obtained making them automate themselves further and adapt to new situations with such e-xquisite accuracy.[11][31]

2.1.1 Supervised Learning

Firstly, the machine learning model in this approach is used on the labeled data that helps Ml system defining the input data and the expected output through a target variable. The model learns the dataset, the relationships, dependencies, and thus the function, and later is used on the new, never seen, but strongly similar data to make predictions. Some examples are naming of the condition, say, lung sounds as the case may be, elevation of the level of the condition, etc.[10][11]

2.1.2 Unsupervised Learning

In this approach, the machine learning model is trained on unlabeled data, without any predetermined output variables. The goal is to discover hidden patterns, structures, or groupings within the data. Unsupervised learning techniques include clustering (e.g., grouping similar lung sound patterns) and association rule mining (e.g., finding relationships between patient attributes and lung sound characteristics).[12]

Machine learning is a type of computing that allows computers to identify patterns in data. It can be applied in numerous areas of life including health care, finance, languages, and vision. It can diagnose such conditions as poor breathing and pneumonia very early, if the right lung sounds are out of the norm. Further it has been seen that the patient's details, such as his or her characteristics are what are influencing the sounds. This whole process of modernization moves together with the millennial generation and the

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consequent higher accuracy of the data collection. It is a result of the increase in the quantity of lung sound analysis. Thus it gets clearer to physicians what the problem with breathing is and also, they are able to give the solution to the patients.[12][13]

2.2 Deep learning

A subfield of machine learning, has been increasingly utilized to significantly improve the accuracy of lung sound detection and classification systems. Convolutional Neural Networks (CNNs) are a prominent category of deep learning models that have demonstrated highly developed performance in various domains, including computer vision, brain activity prediction, and human behavior analysis. The typical CNN architecture is composed of several fundamental layers, such as convolutional layers, max pooling layers, fully connected layers, and finally, a SoftMax or output layer. Well known CNN models like LeNet, Alex Net, and VGG Net exemplify this standard structure. More advanced CNN architectures have been developed to further enhance the performance of these models. These include Residual Networks (Res Net), GoogLe Net with Inception units, and Densely Connected Convolutional Networks (Dense Net). While these advanced architectures share many of the same basic elements like convolution and pooling, they differ in their connectivity, computational complexity, and the specific operations executed within the different layers.[14][15]

The application of these sophisticated deep learning techniques, especially CNN models, has shown great promise in improving the accuracy and reliability of automated lung sound analysis systems. The ability of deep learning to extract and learn relevant features from the data, without the need for extensive manual feature engineering, has been a key factor in its successful adoption in the field of lung sound classification and respiratory disease detection.[16]

3. Literature Review

- J. Woo Kim, et L 2024 [17] was used pretrained speech models to classify lung sounds. Lung sounds may be more like spe-ech than other data used for this task. But the authors found a gap between speech and lung sound samples. They say data changes are needed to bridge this gap. SpecAugment is often used to change data, but it needs 2D spectrogram input. It can't be used on spe-ech wave models. So the- authors made RepAugment. RepAugment changes the data's form, not just the input. It can be used on any pre traine-d model, no matter the input type. Tests show RepAugment works better than SpecAugment. It improved accuracy for rare lung diseases by up to 7.14%. This shows RepAugment could help diagnose abnormal lung sounds better. That's a key challenge in this area.
- J. Trivedi, et al 2024 [18] examined various machine- learning (ML) and deep le-arning (DL) models for recognizing lung disease- sounds. It analyzed the performance of algorithms like Support Vector Machines (SVM), Random Forests, K Nearest Neighbours (KNN), Convolutional Ne-ural Networks (CNN), and Recurrent Ne-ural Networks (RNN). These models classified different lung disease sounds from respiratory sound and audio recordings. The ML models, such as SVM, Random Forests, and KNN, showed strong classification abilities. The DL models, especially CNNs, excelled at extracting complex features from audio data. Their performance was evaluated using metrics like accuracy, sensitivity, specificity, and area under the curve (AUC). The DL models, notably CNNs, achieve-d high accuracy rates, often exceeding 90%, in identifying lung disease sounds. The ML models also performed well, with accuracies in the 80 90% range. This thorough review can contribute to developing more accurate diagnostic tools for respiratory disorders, potentially improving patient outcomes and healthcare efficiency.
- R. Khan,et al 2024 [19], have combined deep learning and signal processing methods. They changed the sounds into two types of graphs: wavelet transform and Mel spectrogram. They then used autoencoders to extract key features from these graphs. Next, they combined these features and used a long short-term memory (LSTM) model to classify the lung conditions. The method worked well

on the dataset. For identifying eight lung diseases, it had accuracy, 89.56% for normal vs. abnormal lung sounds.

- C. Wu, et al 2024 [20] have improved version of the Bi-ResNet deep learning model for classifying lung sounds. This enhanced model combines convolutional neural networks (CNNs) and residual networks (ResNets). It uses two types of lung sound features short time Fourier transform (STFT) and wavelet transform to train and analyze the model. The goal is to improve lung sound classification accuracy by enhancing feature extraction and integration. Compared to the- standard Bi-ResNet model, the improved version achieves 77.81% classification accuracy on the ICBHI 2017 dataset, a remarkable 25.02% improvement. The model's F1 score is 71.05%. The enhanced Bi-ResNet model demonstrates significantly better lung sound classification accuracy than the standard version. This highlights the proposed approach's effectiveness in fully utilizing extracted features and enhancing model performance for respiratory disease diagnosis.
- W. Song, et al 2024 [21] have simulated the quasiperiodic characteristics of respiratory sounds through a self-supervised approach. Using a sparse self-relation matrix, the method extracts segment representations and evaluates similarity between periodic dependent parts. It defines a periodic consistency loss to bring these matrices closer for randomly clipped samples of the same audio. When evaluated on the ICBHI 2017 respiratory sound classification benchmark, this approach outperformed base-line methods by 7.67%. This demonstrates improved performance compared to existing self-supervised techniques. Overall, the paper proposes an interesting deep learning method that captures the quasi-periodic copatterning of respiratory sounds through self-supervision. This explicit modelling leads to strong results on a standard classification task. This clear modelling leads to strong results on the standard classification task. Indeed, the methodology used the student-teacher framework, resulting in a performance score of 59.32.
- W. Zhang et al 2024 [22]. They have tried Support Vector Machines (SVM), Convolutional Neural Networks (CNN) like parallel pooling CNN and Bi-ResNet. They extracted features from lung sounds using Mel Frequency Spectrum (MS) and Mel Frequency Cepstral Coefficient (MFCC). Current algorithms struggle to get key info from these features. With SVM and feature fusion, they got an ICBHI score of 67.29%. With parallel pooling CNN and short time Fourier spectrum features, they achieved 70.45% ICBHI score. The Bi-ResNet CNN with the same features got 69.30% ICBHI score. More research is needed to enhance machine learning for accurate lung sound analysis. This could help diagnose lung diseases better.
- Z. Wang et al 2024 [23] They have tested a CNN model on the ICBHI 2017 lung sound dataset with normal and abnormal recordings. Instead of traditional methods like SVMs, they used a CNN. The authors looked at how classification performance changed with different parameters: the length of lung sound frames, how much frames overlapped, and the type of features (spectrogram or Mel frequency Cepstral Coefficients). The dataset was balanced by adding white noise, stretching sounds, and shifting pitch. The results showed that classification performance varied a lot depe-nding on the parameter settings. The overlap percentage of frames was especially important, with higher overlap leading to better results. The best settings were 128 frame length, 75% overlap, and using spectrogram features. This gave relatively good performance without needing extra computing power or storage.
- J. Woo Kim, et al 2024 [24]. Have focused on enhancing the accuracy of respiratory sound classification using advanced techniques called cross domain adaptation. The study utilizes the ICBHI dataset, which contains respiratory sound samples collected from various electronic stethoscopes, making it a sound-based dataset. The researchers proposed deep learning methods for cross domain adaptation in respiratory sound classification. They introduce two key techniques: Domain adversarial training, which helps reduce disparities caused by different domains or sources,

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and Stethoscope guided supervised contrastive learning, which combines domain adversarial training and supervised contrastive learning for more effective cross domain adaptation. The experiments conducted on the ICBHI dataset demonstrate the effectiveness of these proposed methods. The stethoscope guided supervised contrastive learning approach achieved an impressive ICBHI score of 61.71%, a significant 2.16% improvement over the baseline method. In summary, this research addresses the challenge of respiratory sound classification, where data scarcity and biases introduced by different electronic stethoscopes can impact accuracy. The proposed cross domain adaptation techniques, particularly the stethoscope guided supervised contrastive learning approach, aim to mitigate domain related disparities and enhance classification performance.

- L. Daria Mang, et al. 2024 [25] have explored new ways to detect breathing issues early. It looks at sounds from the lungs found in the ICBHI dataset. The authors fed a visual model called Vision Transformers (ViT) with Cochleogram visual maps of sound signals. ViT was first made for image analysis, but the authors tested it on lung sound classification. ViT took the cochleograms as input to identify wheezing, crackles, and other breathing noises. The authors compared ViT's results to other smart models using different input types like sound spectrograms and Mel frequency data. Remarkably, the ViT with cochleograms outperformed the other methods, correctly classifying over 90% of breathing sounds. This research shows Vision Transformers could be a powerful tool for automatically detecting lung issues from audio recordings. It's an exciting advancement that may allow for earlier diagnosis and treatment of respiratory diseases.
- S. Kumar et al, 2023 [26]. Have proposed five automated respiratory sound classification methods in "HISET: Hybrid interpretable strategies with ensemble techniques for respiratory sound classification". Machine Learning classifiers, L2 Granger Analysis, Supportive Ensemble Empirical Mode Decomposition, and SVM based Recursive Feature Elimination are recommended. Accuracy, F score, and confusion matrices evaluate authors' methods. Manhattan distance based VMD ELM performed best for 2 class (95.39%), 3 class (90.61%), and 4 class (89.27%) classification. The authors note that their study's single dataset and need for validation on larger datasets are limitations.
- D. Ngo, L. Pham, et al 2021 [27], there system has two main parts. First, it uses a Gammatone filter to make a special image called a Gammatone gram. This image shows the sound's pitch and time details. Next, it uses two deep learning models: a Convolutional Ne-ural Network (CNN) and an Autoencoder. Together, they sort the breathing cycles into the four groups. The authors say the-ir system works well on the ICBHI dataset. It has an average score of 0.49 and a harmonic score of 0.42. These scores demonstrate that the deep learning approach can detect breathing problems based on sound data.
- R. Zulfiqar, et al. 2021 [28] have used two deep learning algorithms for spectrogram categorization. This investigation concentrated on ICBHI databasing different frequencies and noise. One of the systems used deep CNN for feature extraction and SVM for classification as the primary method and then it used spectrogram for the other system. The first method scored the lowest accuracy but still at an acceptable level of 65.5%, and the other 63.09%. Unnamed researchers examined the subject. The study, however, failed to include the majority of the sounds/recordings which can be justified as a limitation in the corresponding study. Additional work on the topic of sound spectrum and synthetic noise can improve the recognition of patterns.
- F. Demir, et al., et al. 2020 [29] This study has used neural networks to classify lung illnesses from the ICBHI 2017 database. The data had lung sounds with different frequencies, noise, and background noise. The sounds were changed into images with the Short Time- Fourier Transform. Two approaches using neural networks were tested the CNN. One used a pre trained network to find features, then a support vector machine classified them. The other fine-tuned a pre trained network on the- images. Using cross validation, the network support vector machine approach got 65.5%

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accuracy. The fine-tuned network (VGG-16 CNN model with SoftMax classifier) got 63.09% accuracy. The authors say these results beat some past techniques for classifying lung illnesses.

- Saraiva's et al 2020 [30] have advocated a deep learning based convolutional neural network (CNN) technique for respiratory sound tagging. In this idea, they were talking about data preprocessing, CNN training and testing and performance analysis. The Mel Frequency Cepstral Coefficients (MFCCs) method is a technique that analyses the audio samples that are transformed into a visual representation. By using visual representation after learning and testing with these picture representations, the CNN's performance is evaluated over some metrics. The proposed strategy of the CNN succeeded in the classification of the respiratory sounds from the four dataset classifications over 74%. Nonetheless, the dataset of this study was found to be imbalanced that affected the CNN's performance negatively. Thus, a further study is needed to verify the proposed strategy by using a more balanced dataset.

TABLE 1.1 Overview of ICBHI 2017 studies using machine and deep learning to analyze respiratory sounds.

Ref. and year	Dataset and its Types	Machine/ Deep learning	Methods	Performance
J. Woo Kim, et al. 2024	ICBHI 2017 Challenge dataset	ML , DL	SpecAugment	7.14%
J. Trivedi , et al. 2024	ICBHI 2017 Challenge dataset	DL	CNNs, SVM, RNN,KNN	80-90% range
R. Khan , et al. 2024	ICBHI 2017 Challenge dataset	DL	LSTM	0.8956
C. Wu , et al. 2024	ICBHI 2017 Challenge dataset	DL	Bi-ResNet CNN	F1- score 77.81% 71.05%
W. Song,et al 2024	ICBHI 2017 Challenge dataset	DL	teacher-student framework	F1- score 59.32%
W. Zhang et al 2024	ICBHI 2017 Challenge dataset	ML, DL	CNN +Bi-ResNet SVM	60.3% 75.73%
Z. Wang et al 2024	ICBHI 2017 Challenge dataset	DL	CNN	0.75
J. Woo Kim, et al 2024	ICBHI 2017 Challenge dataset	DL	cross domain adaptation	61.71%,
L. Daria Mang, et al. 2024	ICBHI 2017 Challenge dataset	DL	Vision Transformers (ViT) with Cochleogram visual maps	0.9
S. Kumar et al, 2023	ICBHI 2017 Challenge dataset	ML	SVM	2 class (95.39%) 3 class (90.61%) 4 class (89.27%)
D. Ngo, L. Pham, et al 2021	ICBHI 2017 Challenge dataset	DL	ELM	49% 42%
R. Zulfiqar, et al. 2021	ICBHI 2017 Challenge dataset	DL	CNN.SVM	65.5%,

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3. DISCUSSION

With the control and guidance of these new technologies like artificial intelligence and deep learning, that the human race has ever imagined, Artificial Intelligence (AI) can now do unmanned flight, get to Mars, or simply just determination the most challenging diseases for humans. The problem to be solved by the AI researchers is a task that has to be both found and implemented for the AI software that will be able to autonomously explore the production values of a new material. Therefore, finding and optimizing these parameters in the deep learning process are truly tough tasks since the problem has not fully been solved and has not been fully resolved even with the help of numerous new researchers. The teaching of deep learning models is a way of learning which is mainly dealing with solving optimization problems that are NP hard and at the same time posed by various theorical and computational restrictions. The list of documents that were reviewed showed that many different algorithms are used to train the different models with varying degrees of accuracy. Moreover, there is the frequent use of the ICBHI 2017 dataset, which has been used by various researchers in the field, as well as considered the most common and widely used dataset. However, persisting in the problem is the first step that is finding the best algorithm to yield the highest possible accuracy. The proper utilization of the Newly Developed Algorithms together with Evolutionary Algorithms will result in a comparison and contrast of the situation that will help the quick alignment in this very important field. It is the era of discovery and newer research and research experiments are being carried out in the field of artificial intelligence and machine learning as a result of the inclusion of evolutionary algorithms and deep learning technologies. More and more studies dealing with deep learning optimization using diverse evolutionary algorithms are being first on the market in the world. Scientists from nearly all around the world are engaged in a relentless struggle to find/come up with the best techniques and algorithms that will improve the quality and hence will make efficiency of the deep learning algorithms for chest voice detection and also for many other applications better. Today we have touched the levels which were invisible to us until now. And now we have entered the era of a world which is technically advanced to such an extent that unbelievable things are already here. We are on the verge of a technological revolution, which will certainly change the whole scene of occupational life and industrialization, the other issues are to be seen.

4. CONCLUSIONS

Numerous studies and scientific research have relied on automated lung sound classification, utilizing the widely used ICBHI 2017 data set. It is various machine learning classifiers, deep learning based convolutional neural networks, and deep learning algorithms that have been the mainstay of this development. Many different models such as SVM, CNN, and LSTM have been used for lung diseases with slippage ranging from 63.09% to 90.16%. Moreover, studies have proposed some models such as Bi ResNet which on the ICBHI 2017 dataset achieved a classification accuracy of 77.81%. These studies indicate a high level of reliability of lung sound analysis results. The main purpose is to solve two difficulties in diagnosing the disease and the correct way to treat respiratory diseases by using correct/positive lung sound analysis. After noticing the topic of lung sound classification, as well as reading some recent scientific articles, the consistent theme I have is where I used the popular ICBHI 2017 database, I will create a model using the CNN algorithm and then enhance it with one of the Python optimization algorithms and then prove the optimization.

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