2025 International Conference on Quantum Photonics, Artificial Intelligence, and Networking (QPAIN)
31 July – 2 August 2025, Rangpur, Bangladesh

2025 International Conference on Quantum Photonics, Artificial Intelligence, and Networking (QPAIN) | 979-8-3315-9694-1/25/$31.00 ©2025 IEEE | DOI: 10.1109/QPAIN66474.2025.11171716

Enhancing COPD Detection with WaveNet: Assessing the Efficacy of Deep Learning Model

Md. Habibul Islam[1], Md. Rashed[2], Nitun Kumar Podder[3],
Md. Imran Hossain[4] and Ankur Kumar Mondol[5]
[1,3,5]Department of CSE, Pabna University of Science and Technology
Pabna, 6600, Bangladesh
[2,4]Department of ICE, Pabna University of Science and Technology
Pabna, 6600, Bangladesh
Email: [1]habibulislamruddro@gmail.com, [2]rashedulislam.ice.pust@gmail.com, [3]nituncse@gmail.com,
[4]imran05ice@pust.ac.bd, [5]ankurmondol2109@gmail.com

***Abstract*—Chronic Obstructive Pulmonary Disease (COPD) is a progressive respiratory disorder that causes airflow obstruction and breathing difficulties, making early diagnosis essential for effective treatment and management. Traditional diagnostic methods, such as auscultation and pulmonary function tests, rely on expert interpretation, leading to variability and potential delays in detection. To address these challenges, this study introduces a hybrid deep-learning framework that leverages multiple models for accurate respiratory sound classification. We explore several deep learning techniques, including 1D-CNN + LSTM, spectrogram-based CNNs such as VGG19, ResNet101, and EfficientNet, CBAM, DenseNet, and waveform-based models like WaveNet and SoundNet. Among these models, WaveNet demonstrates superior performance, achieving 95% accuracy, 99% precision, 99% recall, 99% F1-score, 75.38% G-mean, 66.57% MCC, and an RMSE of 14.74%, outperforming traditional and other deep learning-based approaches. Our experimental results highlight the effectiveness of deep learning in respiratory sound analysis, with WaveNet proving to be a highly reliable model for early COPD detection. This framework enhances diagnostic accuracy, providing a promising solution for automated respiratory disease classification and early medical intervention.**

***Index Terms*—COPD, Respiratory Disease Classification, Deep Learning, WaveNet, Diagnostic Support.**

I. Introduction

COPD is a prominent pulmonary disease characterized by breathing difficulties and reduced airflow. It is also known as chronic bronchitis or emphysema. Approximately 80 million individuals are affected by moderate to severe chronic obstructive pulmonary disease (COPD), and the illness was responsible for over 3 million fatalities in 2005, or 5% of all deaths. Chronic obstructive pulmonary disease, which includes emphysema and chronic bronchitis, is a term used to describe progressive lung conditions that make breathing more difficult [1]. Due to bronchial inflammation and lung tissue damage, airflow is reduced. A reliable diagnostic tool is necessary to mitigate COPD's impact on individuals and society, especially with its rising prevalence, severity, and healthcare strain. ML and DL technologies have the potential to transform traditional diagnostic methods, including for COPD [2]. Current research in Machine Learning (ML) and Deep Learning (DL) emphasizes healthcare and disease diagnosis, enhancing diagnostic precision, medical imaging, and early detection using ML or DL advanced methods such as CNNs [3]. ML and DL are used to identify complex patterns, improve diagnostic accuracy, and enable non-invasive, real-time detection. They also automate feature extraction, enhancing efficiency and early intervention [4]. Using advanced DL models, this work aims to advance our understanding of COPD identification [5]. To provide more precise and effective COPD diagnosis tools, this concept is based on respiratory sound analysis and is improved by utilizing cutting-edge feature extraction and classification approaches [6]. In this study we propose a deep learning framework based on WaveNet for respiratory sound classification. By analyzing raw waveforms, WaveNet captures fine-grained temporal details and long-range dependencies, providing superior performance for COPD detection. This approach enhances feature extraction, improves diagnostic accuracy, and supports early intervention for automated respiratory disease classification The main contributions of the developed framework can be highlighted as follows:

- **WaveNet-Based Model:** Our proposed model, based on WaveNet, analyzes raw audio waveforms to capture fine-grained temporal details, improving COPD detection.
- **Handcrafted Acoustic Features:** A set of acoustic features, including MFCCs and Tonnetz, enhances model robustness by capturing key sound characteristics.
- **CBAM for Improved Feature Selection:** The use of CBAM refines feature extraction by focusing on the most relevant areas in spectrograms.
- **Early COPD Detection:** CBAM for Improved Feature Selection:The model supports automated and accurate early detection of COPD, reducing the reliance on expert interpretation.

The study introduces a deep learning framework for COPD detection using respiratory sounds. It compares various models, with WaveNet achieving superior performance.

II. Problem Statement

Chronic Obstructive Pulmonary Disease (COPD) comprises a serious worldwide health issue, resulting in significant deaths and disabilities. It is characterized by growing obstruction in airflow and breathing difficulties, making early identification crucial to proper treatment and counseling. Traditional diagnostic techniques, including ultrasound and pulmonary function tests, depend significantly on expert interpretation, resulting in unpredictability, subjectivity, and delays in diagnosis. Advancements in deep learning and machine learning generated interest in creating automated, non-invasive, and real-time systems for respiratory sound analysis to enhance COPD identification. However, current machine learning and deep learning methodologies for respiratory sound classification frequently encounter obstacles, including reduced accuracy, problems with collecting subtle temporal features, and difficulties in feature extraction. The selection of an optimum model for COPD prediction is challenging due to the complexity of respiratory sounds and dataset variability. Consequently, a necessity exists for a flexible, high-precision deep learning framework capable of properly analyzing respiratory sounds, identifying long-range interactions and enhancing early COPD identification. This study seeks to overcome these limitations by providing a deep learning model utilizing WaveNet, which employs sophisticated feature extraction methods and attention processes to improve the accuracy and reliability of COPD diagnosis.

III. Literate Review

A significant quantity of studies has been published with a particular common objective: efficiently separating at-risk individuals from healthy populations by recognizing early risk factors and symptoms associated with Chronic Obstructive Pulmonary Disease (COPD). By identifying comparable risk profiles in new individuals, this categorization seeks to reveal important trends for early diagnosis. Matoog et al. [7] suggest conventional methods by achieving 94% accuracy in diagnosing COPD early using an SVM-KNN fusion model with MFCC feature extraction. However, its limitation lies in computational complexity and dimensionality issues. Albadr et al. [8] uses traditional methods by using EMD and spectral analysis for respiratory disease classification and biometric analysis, achieving high accuracy. Limitations include lower accuracy in BINARY classification (94.43%) and potential model generalization challenges. Taloba et al. [9] presented results on lung sound classification using pre-trained CNNs for feature extraction combined with SVM classification. Their approach achieved moderate accuracy (65.5% and 63.09%), with limitations primarily attributed to the use of noise-affected datasets (ICBHI 2017). Chambres et al. [10] achieved 85% prediction accuracy by using a patient-level model. However, limitations include a reliance on prior models' predictions and the modest accuracy of initial classifications (50%) for adventitious sound detection. Srivastava et al. [11] apply traditional methods by utilizing the Fr-WCSO-based DRN for detecting pulmonary abnormalities with high accuracy (94.8%). Limitations include reliance on pre-processing, feature extraction, and potential data quality issues. Rocha et al. [12] elaborate best system in the challenge achieved 52.5% accuracy with respiratory cycle annotations and 91.2% with event annotations. Limitations include the relatively low performance on cycle annotations and the need for more diverse data for broader applicability. Perna et al. [13] focuses on applying CNNs to respiratory sound data using MFCC features for identifying unhealthy indicators. While promising, potential limitations could include the need for large datasets and real-time applicability for clinical settings. Arpan Srivastava et al. [14] apply CNN based deep learning model and Librosa features to enhances COPD detection accuracy to an ICBHI score of 93% its limitations include dependency on respiratory audio quality and dataset diversity. Siddiqui et al. [15] suggest LSTM, CNN, and other machine learning models for non-invasive COPD detection using UWB radar. LSTM achieves 93% accuracy, outperforming other models. However, additional features (age, gender, smoking history) are needed for robust detection, and high computational demand limits real-time use.

IV. Methodology

This study presents (in Fig. 1) a novel, multi-step analytical framework for detecting COPD using the Wavenet model trained on respiratory disease datasets. The framework integrates binary classification to identify COPD. The methodology is described step-by-step below:

A. Data Collection and Description

The dataset employed in this study was obtained from the Respiratory Sound Database, available on the Kaggle platform. It comprises 920 annotated audio recordings with durations ranging from 10 to 90 seconds. In total, the dataset spans approximately 5.5 hours of recordings, covering 6,898 respiratory cycles. Among these cycles, 1,864 exhibit crackles, 886 exhibit wheezes, and 506 contain both crackles and wheezes. The data were collected from 126 patients by collaborative research teams based in Portugal and Greece. This dataset had both clean sound and also have noisy recording respiratory that represent real-life environments. All age categories are represented among the patients: children, adults, and senior citizens [16].

B. Data Preprocessing

Class Exclusion: There were initially eight diagnostic categories in the dataset. To enhance classification performance and preserve class balance, however, cases classified as LRTI and asthma were eliminated.

Z-Score Normalization: Z-score normalization was applied on the retrieved features to ensure numerical stability and improve model convergence. By subtracting the mean and dividing by the standard deviation, this transformation provides a mean of zero and unit variance, normalizing the features.

$$Z\_score = \frac{x - \mu}{\sigma} \tag{1}$$

Feature Encoding: To make classification easier for the deep learning model, diagnosis labels were transformed into a categorical format using one-hot encoding.

Dataset Splitting: For the train model, splitting the dataset into two different parts train data (80 percent) and testing data (20 percent) with the help of Scikit Learn Library.

Dataset balancing: To address class imbalance in the training set, SMOTE was applied to synthetically generate samples for the minority class. This resulted in a balanced training dataset consisted of 644 COPD Positive and 644 COPD Negative samples, reducing bias and improving model generalization.

C. Feature Extraction

Mel-Frequency Cepstral Coefficients (MFCCs): A collection of 40 MFCCs was recovered to depict the spectral properties of the audio signals to record phonetic changes in respiratory sounds.

Chroma Features: The chroma energy distribution was computed using a short-time Fourier transform (STFT), emphasizing the periodicity and tonal quality of the sound stream. Mel Spectrogram: The power spectrum has been transformed into the Mel scale to represent sound characteristics in a manner that is comparable to human auditory perception.

Spectral Contrast: The differentiation between both high and low frequencies in the spectral energy distribution was measured for the reason of differentiating individual sound textures.

Tonnetz Features: Tonal centroid characteristics have been computed from the signal's harmonic component to represent the timbral properties of respiratory sounds.

D. Network Architecture

In this architecture, we try to improve the categorization accuracy of respiratory sounds, we use a variety of deep-learning models. Our hybrid framework integrates spectrogram-based CNNs, waveform-based models, and 1D-CNN + LSTM, each of which contributes to a distinct facet of feature extraction and classification. The spatial and temporal patterns in respiratory sounds are captured by 1D-CNN + LSTM, which makes it especially well-suited for sequential signal processing. While the LSTM layers maintain long-term dependencies, the CNN layers enhance classification performance by extracting local frequency patterns. To enhance the architecture, we integrate spectrogram-based models like VGG19, ResNet101, and EfficientNet. To enable convolutional networks to extract rich spectral characteristics, these models convert respiratory sounds into spectrograms. While EfficientNet maximizes accuracy with the least amount of computing expense, ResNet101 tackles vanishing gradient problems with its deep residual connections. The Convolutional Block Attention Module, or CBAM, is incorporated into these models to improve feature representation through the application of spatial and channel attention, guaranteeing that the network concentrates on the most pertinent spectrogram areas. By recycling features across layers and enhancing gradient propagation, DenseNet significantly enhances performance. We also use models that analyze raw audio signals directly, such as WaveNet and SoundNet, which are based on waveforms. These models, in contrast to spectrogram-based CNNs, capture small respiratory abnormalities and fine-grained temporal relationships while maintaining the integrity of the original waveform. With its dilated causal convolutions, WaveNet is especially good at analyzing respiratory sounds because it can learn long-range relationships. Important audio features that are frequently lost in spectrogram conversions are preserved by autoregressively modelling raw waveforms. Improved diagnosis accuracy results from the system's ability to generalize better across a variety of respiratory diseases thanks to the integration of various models. When this method is applied methodically, it improves robustness and provides a dependable option for early intervention and COPD identification. Table I represent of the hyperparameters of WaveNet architecture.

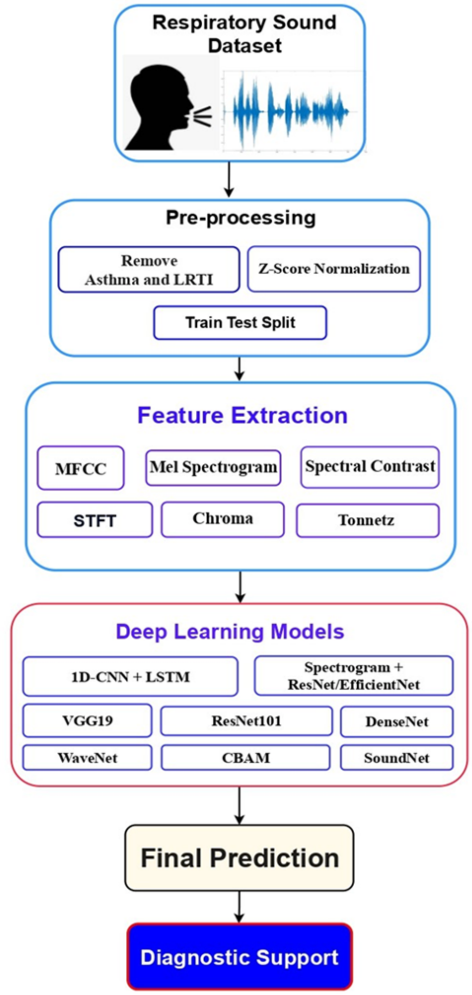

Fig. 1: Suggested architecture for COPD Detection

V. Results and Discussions

Table II presents a comparative analysis of various deep learning models for respiratory sound classification. The evaluated models include 1D-CNN + LSTM, spectrogram-based architectures (ResNet101, EfficientNet, VGG19, CBAM), waveform-based models (WaveNet, SoundNet), and DenseNet.

Algorithm 1 Training WaveNet-Style CNN for Multiclass Classification

Require: Training data $X_{\text{train}}, y_{\text{train}}$; Testing data $X_{\text{test}}, y_{\text{test}}$
Ensure: Trained WaveNet-style model M_{WaveNet}

if X has multiple channels **then**
  Convert X to single-channel by averaging across the channel dimension
end if
Define input shape (T, C) from X_{train}
$inputs \leftarrow \text{Input}(shape = (T, C))$
$x \leftarrow \text{Conv1D}(64, \text{kernel} = 2, \text{padding} = \text{“same”}, \text{activation} = \text{“relu”})(inputs)$
Define dilation rates $D \leftarrow \{1, 2, 4, 8, 16, 32\}$
for each $d \in D$ **do**
  $res \leftarrow x$
  $x \leftarrow \text{Conv1D}(64, \text{kernel} = 2, \text{padding} = \text{“causal”}, \text{dilation} = d, \text{activation} = \text{“relu”})(x)$
  $x \leftarrow \text{Conv1D}(64, \text{kernel} = 2, \text{padding} = \text{“causal”}, \text{dilation} = d)(x)$
  $x \leftarrow \text{Add}([x, res])$
  $x \leftarrow \text{Activation}(\text{“relu”})(x)$
end for
$x \leftarrow \text{Flatten}(x)$
$x \leftarrow \text{Dense}(512, \text{activation} = \text{“relu”})(x)$
$outputs \leftarrow \text{Dense}(2, \text{activation} = \text{“sigmoid”})(x)$
$M_{\text{WaveNet}} \leftarrow \text{Model}(inputs, outputs)$
Compile model using binary cross-entropy, Adam optimizer, and accuracy metric
Train for 100 epochs with batch size 200
Validate on $(X_{\text{test}}, y_{\text{test}})$
return M_{WaveNet}

Among them, WaveNet and ResNet101 achieved the highest accuracy (95%), followed by CBAM (94%) and DenseNet (93%). Other models, such as VGG19 and 1D-CNN + LSTM, recorded 90%, while EfficientNet ranged between 88% and 89%. In terms of precision, WaveNet and SoundNet outperformed with 99%, while CBAM, ResNet101, and VGG19 followed with 97%. Recall was highest for 1D-CNN + LSTM (100%), while WaveNet, ResNet101, and other spectrogram-based models ranged from 97% to 99%. WaveNet also achieved the highest F1 Score (99%), surpassing ResNet101 (98%) and CBAM (97%), reflecting strong classification performance. Regarding robustness, ResNet101 had the highest Geometric Mean (99.15%), while WaveNet led in MCC (89.57%). The lowest RMSE was recorded by CBAM (10.43%), followed by WaveNet (12.74%) and ResNet101 (12.77%) indicating minimal classification errors. While ResNet101 and CBAM performed well, WaveNet demonstrated the best overall performance, offering the highest precision, F1 score, and recall, making it the most reliable model for respiratory sound classification.

The experimental results depicted in Fig. 2 compare the performance of various deep learning models (1D-CNN + LSTM, Spectrogram + ResNet/EfficientNet, CBAM, VGG19, ResNet101, EfficientNet, DenseNet, WaveNet, and SoundNet) for COPD detection using the Respiratory Sound Database. ResNet101 and WaveNet showing the highest acuracy store 95.0%. CBAM accuracy is slightly lower at 94.0%. DenseNet, SoundNet also showed good accuracy at 93.0%, 92.% and.VGG-19 and 1D-CNN + LSTM showing accuracy 90%. The lowest accuracy showing by Spectrogram + ResNet/EfficientNet and EfficientNet respectively 89.0% and 88.0%. ResNet101 may be affected by biasing toward a specific class because of a low MCC score and still have a tendency to favour the dominant class in the dataset. Among all models, WaveNet consistently provided the best accuracy and other classification scores, demonstrating its robust predictive performance.

TABLE I: Proposed WaveNet Architecture Hyperparameter

Layer (type)	Output Shape	Param
InputLayer (input_3)	(None, 193, 1)	0
Conv1D (conv1d_26)	(None, 193, 64)	192
Conv1D (conv1d_27)	(None, 193, 64)	8,256
Conv1D (conv1d_28)	(None, 193, 64)	8,256
Add (add_12)	(None, 193, 64)	0
Activation (activation_12)	(None, 193, 64)	0
Conv1D (conv1d_29)	(None, 193, 64)	8,256
Conv1D (conv1d_30)	(None, 193, 64)	8,256
Add (add_13)	(None, 193, 64)	0
Activation (activation_13)	(None, 193, 64)	0
Conv1D (conv1d_31)	(None, 193, 64)	8,256
Conv1D (conv1d_32)	(None, 193, 64)	8,256
Add (add_14)	(None, 193, 64)	0
Activation (activation_14)	(None, 193, 64)	0
Conv1D (conv1d_33)	(None, 193, 64)	8,256
Conv1D (conv1d_34)	(None, 193, 64)	8,256
Add (add_15)	(None, 193, 64)	0
Activation (activation_15)	(None, 193, 64)	0
Conv1D (conv1d_35)	(None, 193, 64)	8,256
Conv1D (conv1d_36)	(None, 193, 64)	8,256
Add (add_16)	(None, 193, 64)	0
Activation (activation_16)	(None, 193, 64)	0
Conv1D (conv1d_37)	(None, 193, 64)	8,256
Conv1D (conv1d_38)	(None, 193, 64)	8,256
Add (add_17)	(None, 193, 64)	0
Activation (activation_17)	(None, 193, 64)	0
Flatten (flatten_2)	(None, 12352)	0
Dense (dense_4)	(None, 512)	6,324,736
Dropout (dropout_2)	(None, 512)	0
Dense (dense_5)	(None, 2)	3,078
Total Parameters		**6,427,078**
Trainable Parameters		**6,427,078**
Non-trainable Parameters		**0**

Fig. 3 presents the ROC curves comparing different deep learning models for COPD detection. The models include 1D-CNN + LSTM, EfficientNetB0, CBAM, VGG19, ResNet101, DenseNet169, WaveNet, and SoundNet. The curves illustrate the true positive rate versus the false positive rate, showcasing each model's classification ability. WaveNet, SoundNet, DenseNet169, and CBAM achieved perfect classification with an AUC of 1.00, indicating superior predictive performance. VGG19, ResNet101, and EfficientNet performed slightly lower but remained highly competitive with AUC values of 0.99 and 0.97. The attention-based CBAM and deep feature extractors demonstrated the most robust results, closely following the

TABLE II: Performance Evaluation of Different DL Models

Evaluation Indexes	1D-CNN + LSTM	Spectrogram + ResNet/EffNet	CBAM	VGG19	ResNet101	EffNet	DenseNet	WaveNet	SoundNet
Accuracy (%)	90.0	89.0	94.0	90.0	95.0	88.0	93.0	95.0	92.0
Precision (%)	90.0	90.0	97.0	94.0	97.0	92.0	96.0	99.0	99.0
Recall (%)	100.0	99.0	98.0	98.0	99.0	97.0	98.0	99.0	97.0
F1 Score (%)	95.0	94.0	97.0	96.0	98.0	95.0	97.0	99.0	98.0
G-Mean (%)	52.5	34.5	84.25	53.3	99.15	53.3	74.73	95.38	53.3
MCC (%)	47.8	51.3	84.04	42.31	82.95	47.7	51.48	89.57	42.31
RMSE	19.5	19.5	10.43	18.06	12.77	19.5	19.5	12.74	18.06

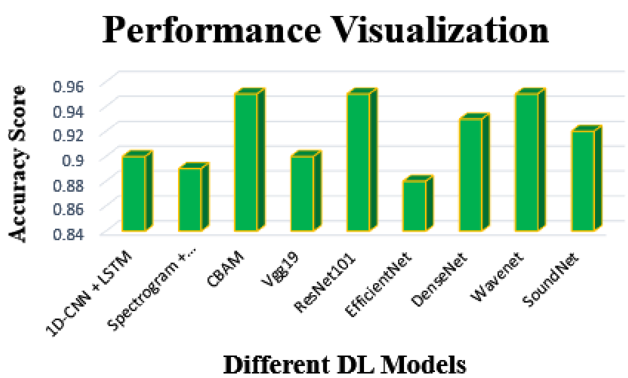

Fig. 2: Comparison of accuracies of Different DL model

ideal classification line, ensuring minimal false positives and high sensitivity. These findings highlight the effectiveness of WaveNet and attention-based models in respiratory sound classification, confirming their reliability for early COPD detection.

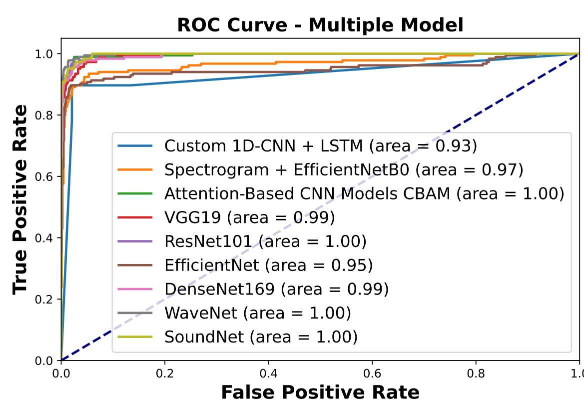

Fig. 3: Receiver Operating Characteristic (ROC) curve of Different DL model

Figure 4 illustrates the learning progression of the models during the training and validation phases, as indicated by the accuracy and loss curves for WaveNet. The curve demonstrates a robust learning pattern within this dataset and demonstrates model stability.

Figure 5 shows the COPD classification confusion matrix

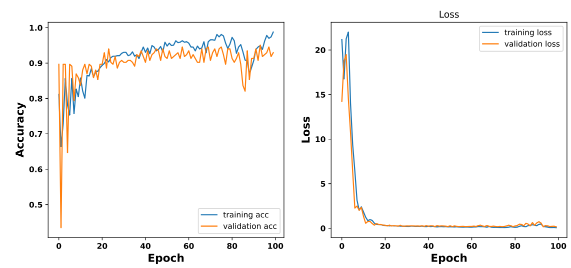

Fig. 4: Accuracy and Loss curves of proposed WaveNet model

in WaveNet. 94.6% of the COPD-positive and 96.3% of the COPD-negative were correctly classified, showing excellent discriminative performance. The misclassifications were small, with only 5.4% COPD-positive as negative and 3.7% COPD-negative as positive. These are indicative of the model's robustness and consistency to differentiate COPD or not.

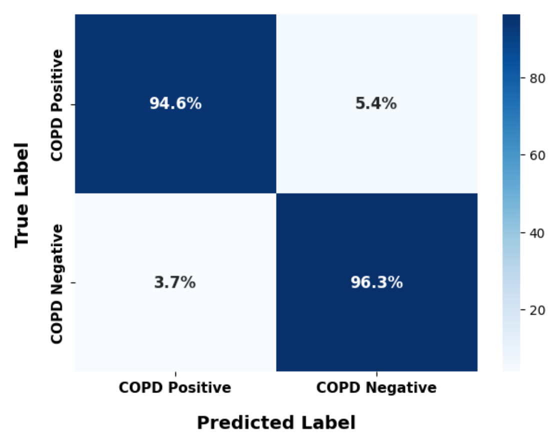

Fig. 5: Confusion Matrix of proposed WavNet model

Table III presents a comparative analysis of various models used for COPD prediction and lung disease identification, highlighting their accuracy levels. Traditional machine learning models, such as the SVM-KNN approach used in COPD prediction [7], achieved a high accuracy of 94%, whereas the MLP Classifier [8] performed significantly lower at 72%, indicating its limitations in handling complex medical data. Deep learning models like CNN [14] and LSTM [15] demonstrated their effectiveness in feature extraction and sequential learning, both achieving an accuracy of 93%. However, hybrid models like CNN-SVM [9], designed for automatic lung disease identification, exhibited a much lower accuracy of 65.5%, suggesting potential challenges in optimizing the integration of CNN with SVM for medical diagnosis. Additionally, the Boosted Decisional Tree model [10] used for distinguishing between sick and healthy individuals performed moderately well, reaching 85% accuracy. Another advanced approach, the Fr-WCSO-based DRN [11], achieved a slightly higher accuracy of 94.4%, indicating its effectiveness in lung disease detection. Despite these advancements, our proposed WaveNet model surpasses all previous models by achieving the highest accuracy of 95%, demonstrating its superior ability to capture temporal dependencies in COPD prediction. Compared to CNN [14] and LSTM [15], which both reached 93%, WaveNet provides better feature extraction and sequential pattern recognition. Moreover, it outperforms SVM-KNN [7] and Fr-WCSO-based DRN [11], showcasing its robustness in handling complex medical data. In comparison, our proposed WaveNet-based COPD prediction model demonstrates superior performance over all previous approaches.

TABLE III: Comparison Table with State of the Art Works

Ref.	Work	Model	Accuracy (%)
[7]	COPD Prediction	SVM-KNN	94%
[8]	COPD Prediction	MLP Classifier	72%
[9]	Automatic Lung Disease Identification	CNN-SVM	65.5%
[10]	Sick or Healthy	Boosted Decisional Tree	85%
[11]	Lung Disease Detection	Fr-WCISO-based DRN	94.4%
[14]	COPD Prediction	CNN	93%
[15]	COPD Prediction	LSTM	93%
Proposed Model	**COPD Prediction**	**WaveNet**	**95%**

VI. Conclusion

This study compared various machine learning and deep learning models for COPD prediction, highlighting their performance in terms of accuracy. Traditional models such as SVM-KNN and Boosted Decision Trees demonstrated moderate success, while deep learning models like CNN and LSTM provided improved results. However, our proposed WaveNet-based COPD prediction model achieved the highest accuracy of 95%, surpassing all previous approaches. This superior performance can be attributed to WaveNet's ability to capture long-range dependencies in respiratory sound signals using dilated causal convolutions. The results indicate that WaveNet is a highly effective and reliable model for COPD detection, offering a promising solution for early diagnosis and clinical decision-making.

Future research will focus on further optimizing the WaveNet architecture to enhance its robustness and generalizability across diverse datasets. Also, integrating multimodal data sources, such as spirometry readings and patient medical histories, could improve predictive accuracy. Additionally, a smaller TinyWaveNet model will be employed by using knowledge distillation. The TinyWaveNet will replicate the behaviour of the larger WaveNet model, hence maintaining accuracy while minimizing computation overhead.

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