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CNN+SVM+KNN: An Ensemble Framework for Predictive Analysis of Respiratory Sounds

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ABSTRACT: Vital information about a patient's lungs can be gathered through their respiratory sounds. The, the examination of lung sounds is a tedious process that needs a lot of time and results of this depends on the medical knowledge and diagnostic expertise of the doctors. This research introduces an ensemble framework to identify lung sounds for disease identification. The framework is an integration of convolutional neural network (CNN), support vector machine (SVM) and K-nearest neighbor (KNN). Initially, pulmonary acoustic features are extracted from recorded breathing sounds which are used for identification of respiratory disorders. Pulmonary sound signals are subjectively classified as normal, parenchymal, or obstruction of the airway's pathology. CNN is used for its high specificity, dynamic result generation, high sensitivity, and model uniformity which predict the same values on a single input sample. SVM is trained on lung acoustic signals waveforms and spectrogram pictures without providing lesion-based criteria thus resulting with greater accuracy and specificity for detecting lung conditions in patients. KNN classifies sounds through an instance-based learning method that utilizes the feature space's closest training examples. The performance results of this proposed ensemble model is validated and compared with conventional classifiers such as Naïve Bayes (NB), Random Forest (RF), Gradient boosting (GB), Logistic regression (LR) and state-of-art works based on accuracy (%) metrics. The results notify that the proposed model attains the highest accuracy of 98.76% so it is enhancing patient results and the effectiveness of healthcare in the field of respiratory diseases.

1. INTRODUCTION

According to WHO epidemiological data , 210 million people are suffering from Chronic Obstructive Pulmonary Disease (COPD) world-wide and more than 30 million have asthma. From studies it shows that 15 to 25 million people in India suffering from asthma [1-2]. The auscultatory method is an inexpensive, non-invasive way to assess lung and heart health [3][4]. It really offers details on how the lungs function, and as consequently, it is crucial to determine pulmonary diseases [3]. LS are commonly classified as either abnormal, normal, or incidental. Usually, normal LS adopt cyclic patterns that represent the respiratory system's air passage process. It is defined in pulmonary disease events as by continuously restricting lung airflow, which interferes with usual breathing that is not entirely reversible [5]. The diagnosis and classification of pulmonary conditions using acoustic patterns is an important obstacle in modern healthcare to get accurate and quick identification is very important for effective treatment and care. Still conventional diagnostic techniques frequently come short in capturing all aspects of lung disease symptoms.

Healthcare field of respiratory diseases having emerged model of machine learning (ML) and deep learning (DL) . Support Vector Machines (SVMs), Random Forests and KNN advanced classification algorithms that learn from data to recognize patterns. On the other hand, Deep Learning architectures as Recurrent Neural Networks (RNN) and Convolutional Neural

Networks (CNN) are effective at identifying intricate patterns in sound data that might offer particular data on a selection of lung diseases. By learning characteristics straight from raw or spectrogram data, these deep learning models boost accuracy and eliminate away with the need for manual processing. Machine learning traditional models as SVM and Random Forest rely on handcrafted features like MFCCs, STFTs, and wavelet transforms as mel-frequency cepstral coefficient (MFCC) feature that extracted by the pre-processed lung sounds signals. These features further analysed for the features extraction, categorization, and preprocessing are all part of the standard procedure. Even while DL makes end-to-end systems possible and improves performance for illnesses like pneumonia and COPD, there are still issues, mainly with data scarcity, recording variability, and model interpretability. A potential framework is offered by combining MFCCs with ML/DL; still further study is required before clinical application is possible. Crackles effective identification done by time frequency distribution characteristics in the lung sounds' peaks following the Hilbert Huang transform in [6].

Lung sounds wave are categories using the self-organizing map (SOM)[7] and feature vectors were constructed using their spectral representation through Fast Fourier transform (FFT). Many research of lung auscultation done by Support vector machines and used Short-Time Fourier transform (STFT) to extract feature characteristics for wheeze recognition and classification [8] and from lung sounds Lung sound waves differentiated into frequency sub bands by applying wavelet transform. For classifying the lung sound statistical features were collected through sub bands which represented in the wavelet coefficients distribution.

Applying an artificial neural network, lung sounds are divided into six groups as normal, wheeze, crackle, rhonchi, stridor, other abnormal lung sounds patterns [9]. This study summarizes and compares lung sound measurement and classification methods proposed in the last five years. It uses feature extraction and models to identify the most accurate and effective methods. To ensure the accuracy and length of the review articles, we adopted an exacting literature screening process.

1.1 Lung Sound Waveforms

1.1.1 The Regular Lung Sounds There are basically three kinds of main regular lung sounds. Vesicular breath sounds are low-pitched, rustling and soft in nature, louder during inhalation than exhalation, and can be heard across the lung. Bronchial breath sounds are hollow, high-pitched and loud when heard over the trachea. if heard these elsewhere, they may indicate disease. Tracheal breath sounds are loud, harsh, and high-pitched in nature and usually heard over the trachea. These sounds help assess normal and abnormal lung function. In Table 1 shows in abnormal lung sounds containing Lung Sound as wheezing, rhonchi, stridor and pleural rub. Wheezing is a continuous high-pitched sound caused by the narrowing of the airway. Squawks are brief inspiratory wheezes; polyphonic wheezes are multiple tones during exhalation with growing pitch into the end; and monophonic wheezes are single-toned sounds that can occur during either or both respiratory phases with fixed or variable frequency. Crackles are discontinuous sounds usually heard during inhalation and may resemble bubbling, bursting, or clicking having types Coarse crackles: Loud, low-pitched, and longer-lasting; often heard in larger bronchi. Medium crackles: Produced by mucus in medium-sized bronchi. Fine crackles: Soft, high-pitched sounds from small airways, more frequent during inspiration.

Table 1. Abnormal Lung sound Classification

Adventitious Sound	**Underlying Mechanism**	**Location**	**Key Characteristics**	**Acoustic Features**	**Associated Conditions**
Fine Crackles	Intermittent opening of small airways; not related to secretions	Peripheral lung zones	Discontinuous, high-pitched, predominantly inspiratory	Rapidly dampened waveform; ~650 Hz; duration ~5 ms	Interstitial lung disease, early pneumonia, heart failure
Coarse Crackles	Rupture of fluid films resulting accumulated secretions.	Peripheral lung zones	Not continuous, low-pitched, inspiratory	Rapidly dampened waveform; ~350 Hz; duration ~15 ms	Advanced pulmonary edema, pneumonia
Wheezes	Airflow through narrowed airways	Bronchial tree	Continuous, high-pitched; more	Sinusoidal waveform with frequency ranging	Asthma, COPD, airway obstruction

			prominent during expiration	100–5000 Hz and as duration >80 ms	by mass or foreign body
Rhonchi	Vibration of airway walls due to obstruction	Large bronchi	Continuous, low-pitched; more prominent during expiration	Sinusoidal waveform; ~150 Hz; duration >80 ms	Chronic bronchitis, pneumonia
Stridor	Turbulent airflow caused by upper airway obstruction.	Larynx and trachea	High-pitched, initially inspiratory and continuous	Sinusoidal waveform; frequency >500 Hz	Obstruction of the airway, Epiglottitis, foreign body post-extubation events
Pleural Friction Rub	Inflammation of pleural surfaces	Chest wall region	Grating, low-pitched; occurs during both respiratory phases	Sequence of short, musical short sounds having frequency <350 Hz; duration >15 ms	Pleural friction associated with Pleurisy, pericarditis, pleural neoplasms

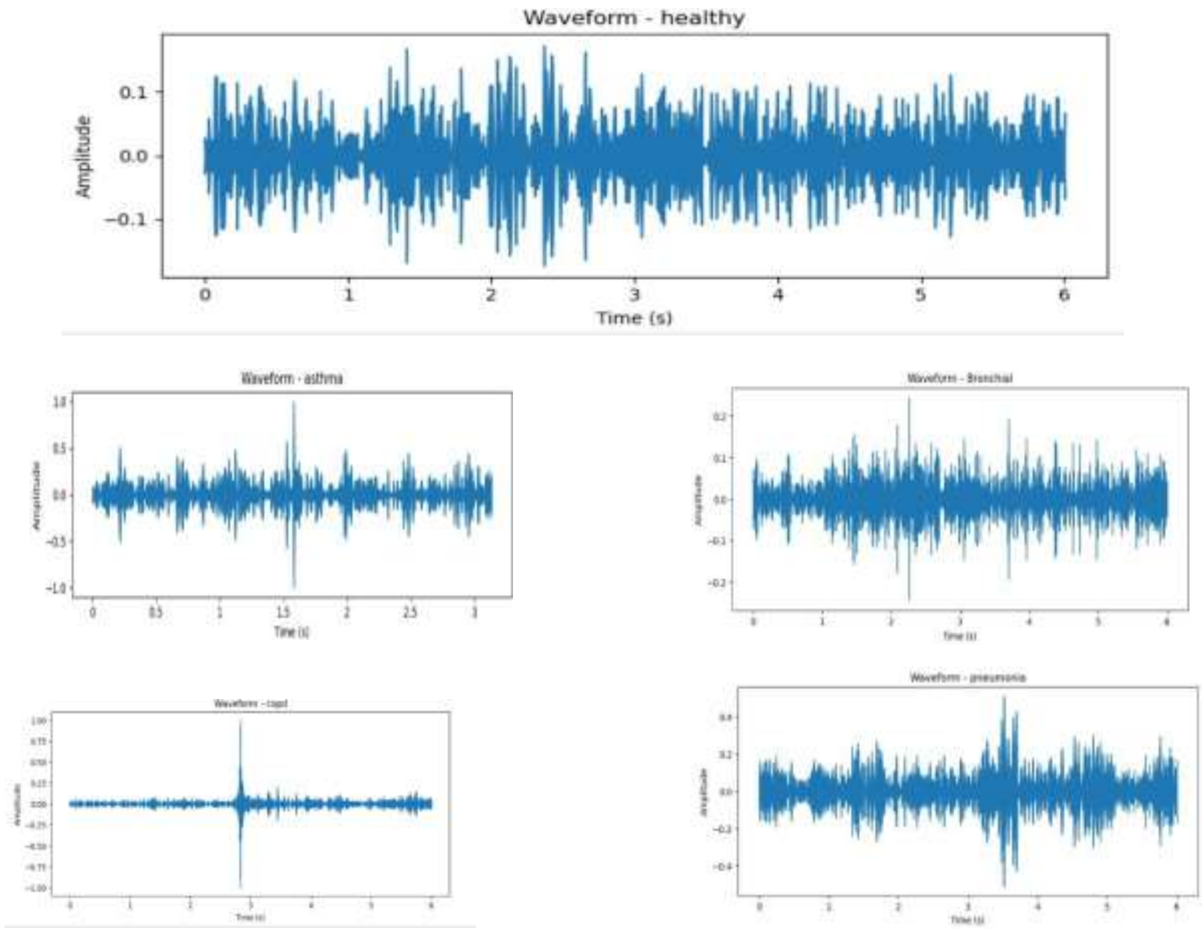

Figure 1. Some wave form of Lung sounds :(a) Normal lung wave (b)Asthma (c) Bronchial (d) COPD (e) Pneumonia (self)

Rhonchi are low-pitched, continuous, snoring-like sounds typically heard during exhalation or both respiratory phases. They result from secretions or fluid in the major airways. Stridor is high-pitched inspiratory lung sound that occurs in the upper airway obstruction. Pleural rub is occurring inflamed pleural surfaces by rubbing surface together is course during respiration. In the above Fig 3 showing various abnormal sound. Asthma is for wheeze. Fig 3:b is for Bronchial breath sounds are usually associated with lobar pneumonia, but they can also be seen in fibrosis, tumors, atelectasis, and pleural effusion when lung tissue is consolidated or compressed. Another fig d showing the COPD and Fig e Showing Phenomonia.

2. RELATED WORKS

Lung sound analysis's non-invasiveness and cost have generated much attention on early identification of respiratory conditions. Meaningful characteristics have been obtained from lung sound recordings employing traditional signal processing methods as Mel Frequency Cepstral Coefficients (MFCCs), Discrete Wavelet Transform (DWT), and Short-Time Fourier Transform (STFT) [44]. However, in noisy contexts, these approaches frequently have insufficient robustness. Recent studies have explored machine learning algorithms as Random Forests (RF),Support Vector Machines (SVM), and k-Nearest Neighbours (k-NN) for classification of lung sounds [45]. These models, although interpretable, rely heavily on hand-crafted features and lack scalability for large-scale datasets. In advancement in deep learning, Convolutional Neural Networks (CNNs) have been recently used for automatic feature extraction from spectrograms of lung sounds. For instance, Perna and Tagarelli [46] proposed a CNN model trained on MFCC-based representations, achieving improved classification accuracy. Similarly, Demir et al. [47] utilized spectrograms with a VGG-based CNN, highlighting the potential of visual-based audio learning. However, most CNN-only architectures fail to capture temporal dependencies within lung sound sequences Shi et al. [10] recommended a VGGish-BiGRU based algorithm for lung sound identification, effectively addressing temporal and spatial features in binary classification, though it lacked multi-class capability. The beneficial effects of neural networks in clinical practice has been established by Brunese et al. [11], who created a supervised DL system that demonstrated great performance in lung disease detection (F-measure of 0.983) and classification (0.923).

Kim et al. [12] used CNNs to differentiate respiratory sounds into crackles, wheezes, rhonchi, and normal, giving a solution to clinician variability in auscultation with an AUC of 0.92. According to a study published in IEEE Transactions on Biomedical Engineering, a ResNet CoTuning technique was effective in 2-class classification but lacked scalability for multi-class applications [13]. An additional investigation published in MDPI Bioengineering proposed RBF-Net, which attempted to minimize demographic bias but encountered difficulties due to sparse and skewed datasets [14].

In a study a hybrid model is studied. In this CNN-LSTM model with focal loss was created in [15], which performed well on the ICBHI 2017 dataset but lacked generalizability across databases. In a similar vein, [16] integrated CNN and ML techniques for lung sound analysis, emphasized the need for balanced datasets and improved noise management, and suggested spectrogram-based features. Srivastava et al. [17] provided a method based on deep learning using respiratory sounds to detect chronic obstructive pulmonary disease (COPD). This approach, when tested on a custom dataset, produced promising output that showed the feasibility of deep models in real-time COPD detection. Using spectrogram pictures, Demir et al. [18] designed an efficient CNN architecture for lung disease classification that utilized automatic feature extraction to perform better than conventional ML techniques. Azam et al. [19] created a breath analysis system that runs on a smartphone, enabling portable diagnostics through the use of respiratory sound recordings. This method made lung health monitoring simpler to perform, but it had limitations that included real-world noise fluctuations and apparatus dependency. Analysis of respiratory sounds can be carried out in a number of ways. Common approaches for analyzing audio signals include machine learning with MFCC (Mel Frequency Cepstrum Coefficient) and deep learning with spectrum images. In accordance to the literature, a wide area for research has been done with positive outcomes. In this study, a suggested deep learning model with an LU-based autoencoder kernel produced remarkable performance in classification, with rates of 95.00%, 93.33%, and 93.54% for precision, specificity, and sensitivity, effectively identified between healthy participants and patient with COPD. (chronic obstructive pulmonary disease) [20], [21].

2.1 The dataset mostly frequently used in the literature

The ICBHI 2017 lung sound database is used in this study for classification of lung sounds employing a deep convolutional neural network. Table 2 provides the list of datasets used in this research field. Different respiratory sound datasets (Table 2) provided research in automated pulmonary diagnostics. The database (77 samples, >17 s) includes frequent respiratory diseases but lacks detailed sound annotations to add. In addition, large but undocumented datasets (920-14,138). The ICBHI 2017 dataset (126 samples, 10-90 s) contains crackles and wheezes associated with COPD. Fraiwan et al. (112 samples, 5-30 s) investigate a variety of conditions, including asthma and pneumonia. HF_Lung_V1 and V2 (261 and 303 samples, 15 s) provide specific sound types for diseases such as heart failure and ARDS. Respiratory(samples) exist, but their scope is limited by unclear metadata. Regardless of their importance, standardization across datasets remains a major challenge. They used the time-frequency approach to transform the lung sounds to spectrogram images, despite the accuracy was only roughly 65% [22].

Table 2. Respiratory Sound Datasets Overview

Dataset	**Ref** **Reff**	**No. of Samples**	**Recording Duration**	**Sound Types**	**Related Conditions**
ICBHI 2017	[39]	126	10–90 s	Normal, wheeze, crackle and combined crackle and wheeze pattern	COPD 0–5, wheezing, crackle
Fraiwan et al.	[40]	112	5–30 s	Normal respiration includes wheezes, crackles, and expiratory	Lower/Upper respiratory infections commonly associated with COPD, pneumonia, asthma, bronchiolitis, bronchiectasis, cystic fibrosis disease.
Respiratory Database@TR	[43]	77	>17 s	Not clearly specified	Asthma, COPD, bronchitis, healthy
HF_Lung_V1	[41]	261	15 s	Inhalation, exhalation, stridor, rhonchus, crackle	Respiratory sound as normal; asthma, pneumonia, COPD, bronchitis, heart failure, lung fibrosis, pleural effusion.
HF_Lung_V2	[42]	303	15 s	Inspiration, expiration, stridor, rhonchus, crackle	With acute/chronic respiratory failure, keen exacerbation of COPD, pneumonia, ARDS, emphysema
R.A.L.E. repository	[44]	Not explicitly specified	5 to 60 seconds	Normal, wheezes, crackles, other adventitious sounds	This collection contains the digital recordings of normal and diseased respiratory sounds.

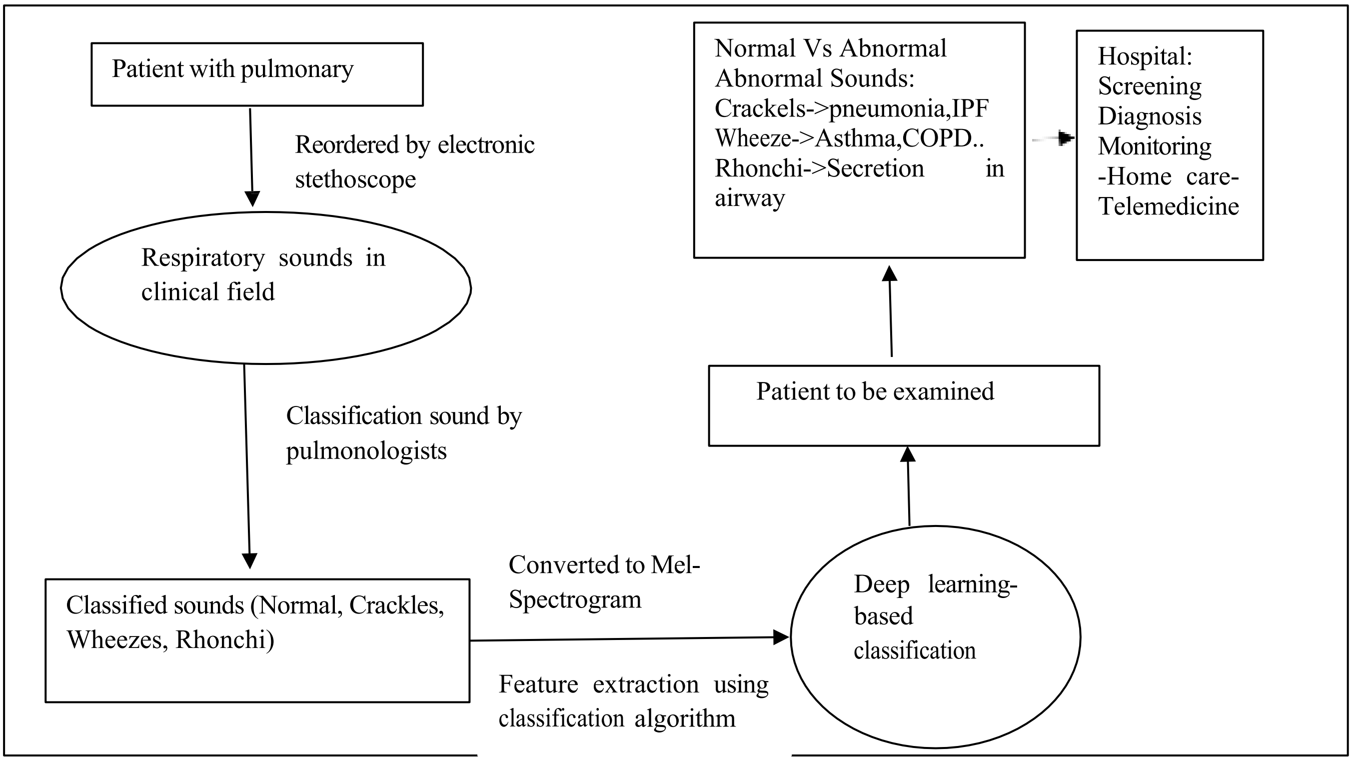

Figure 2. Flow chart of diagnosis of respiratory sounds

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3. PROPOSED FRAMEWORK

Figure 2 depicts the workflow of diagnosis of respiratory sounds which are converted to Mel-spectrograms and processed through ensemble classifiers (CNN+SVM+KNN) for feature extraction. Pulmonary acoustic features extracted from recorded breathing sounds used for identification of respiratory disorders. Pulmonary sound signals were subjectively classified as

normal, parenchymal, or obstruction of the airways pathology. Mel-frequency cepstral coefficients (MFCCs) were extracted from the pre-processed signals so need an instrument for patients and medical professionals to use for self-management, education, and differential diagnosis.

3.1. Convolution Neural Network

Deep neural networks can be trained on large databases of lung acoustic signals and spectrogram pictures without providing lesion-based criteria, resulting with greater accuracy and specificity for detecting lung conditions in patients. The main advantages of using this automated disease detection technique are achieving specificity, robust result generation, high sensitivity, and model uniformity—a model consistently predicts the same values on a single input sample. In Fig 3, convolution layer is where the received image is processed using filters and an activation function.

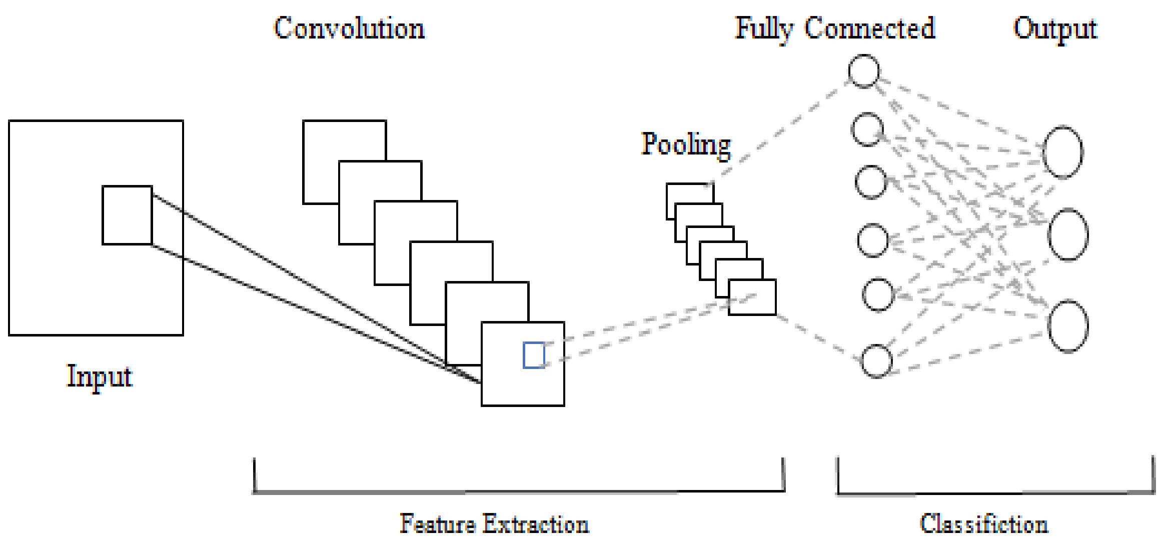

Figure 3. Transferring learning in CNN [32].

In neural network model, where the back propagation approach is used to carry out the learning process and the weights are continuously updated. The multidimensional discrete convolution is defined as a linear operation given by:

$$y(n_1, n_2) * w(n_1, n_2) = \sum_{k_1=-\infty}^{\infty} \sum_{k_2=-\infty}^{\infty} x(n_1, n_2) w(n_1 - k_1, n_2 - k_2)$$

In this x (n1, n2) shows the input image and w(n1, n2) gives filter impulse outcome having the y(n1, n2) as give output as an image.

This layer allows for the adjustment of filter number and size. Either the pooling layer and also called the convolution layer receives the output. The Pooling layer brings together important features from the preceding layers. The data size decreases in this tier. Convolution and pooling layers can be used in any number and extent, with adjustable output. Data that has passed by each of these layers is sent to the flatten layer to train the full connected layer of a neural network [32].

3.2 K-Nearest Neighbour

The KNN algorithm is a widely used simple learning technique. The distance between each data point in the test set and the training set is computed. To identify the K samples from the training set which lie closest to each data point in the test set.

$$\boldsymbol{d}_{(x,y)} = \sqrt{\sum_{i=1}^{n}((\boldsymbol{x}^2 - \boldsymbol{y}^2)}$$

The k-nn algorithm in pattern recognition classifies objects through an instance-based learning method that utilizes the feature space's closest training examples. The mostly vote of its neighbours defines how an objects are classified. It means that the object is attributed to the most common class within its k-nearest neighbours, where k represents a positive integer [22].

3.3 Support Vector Machine (SVM)

SVM is a supervised machine learning algorithm that is employed in regression and classification. SVM trains a model by classifying data points using a hyperplane.

The hyperplane's position varies based on data distance. Hyperplanes are definition based on the various of classes formed. As adding new data, it is labelled to the appropriate class based on its position in space and plane. SVM enables effective nonlinear classification[34] [29].A linear support vector classifier is represented by this Equation

$$f(x)=\beta_0 + \sum_{i=1}^{n} \alpha_i \,(x, x_i)$$

where $\alpha_1 \ldots\ldots \alpha_n$ and β_0 are parameters which are evaluated by $\binom{n}{2}$ inner multiplication between pairs of training measurements. By solving the inner product with $K(x_i, x_i')$ is known as the kernel represented as

$$K(x_i, x_i') = \sum_{j=1}^{p} x_{ij}\, x_{ij}'$$

A polynomial kernel having degree d (where d is positive) can be represented as

$$K(x_i, x_i') = (1 + \sum_{j=1}^{p} x_{ij} x_{ij}')^d$$

Combining a non-linear kernel and a support vector classifier produced classification results for the SVM classifier, which was created specifically for binary classification.

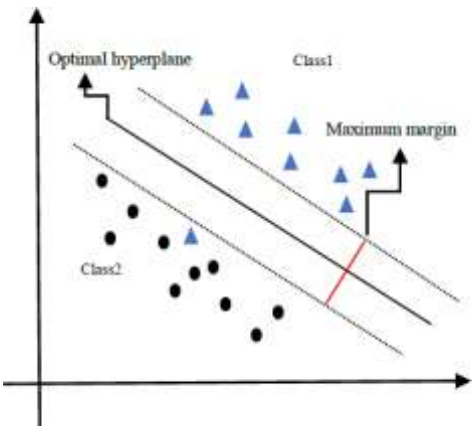

Figure 4. Hyperplane in Support Vector Machine(self)

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4. RESULTS

Using the ICBHI dataset [39], this study compares the proposed ensemble model with existing models such as random forest (RF), Naïve Bayes (NB) Logistic regression (LR) and Gradient boosting (GB). The results show that the proposed model achieves the highest accuracy (98.76%) and is useful for audio-based respiratory diagnosis as shown in table 3. Figure 5 shows PCA Scatterplot of MFCC Features for Respiratory Sound Classification. Figure 6 shows analysis.

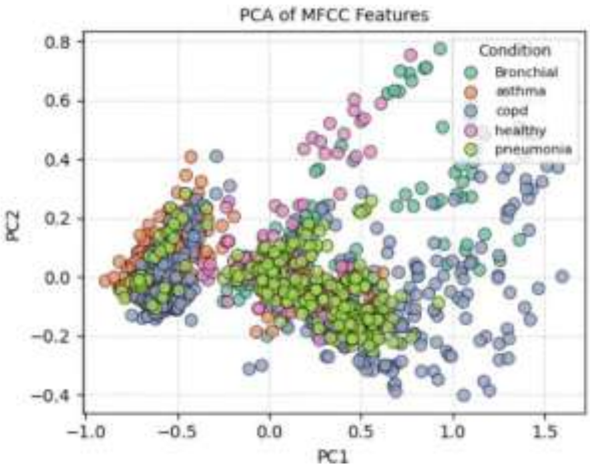

Figure 5. PCA Scatterplot of MFCC Features for Respiratory Sound Classification

Table 3. Validation of the proposed model

Models/classifiers	Accuracy (%)
RF	88.11
NB	86.77
LR	83.45
GB	92.45
[39]	91.34
[40]	88.23
[41]	86.12
[42]	78.67
[43]	87.98
Proposed	98.76

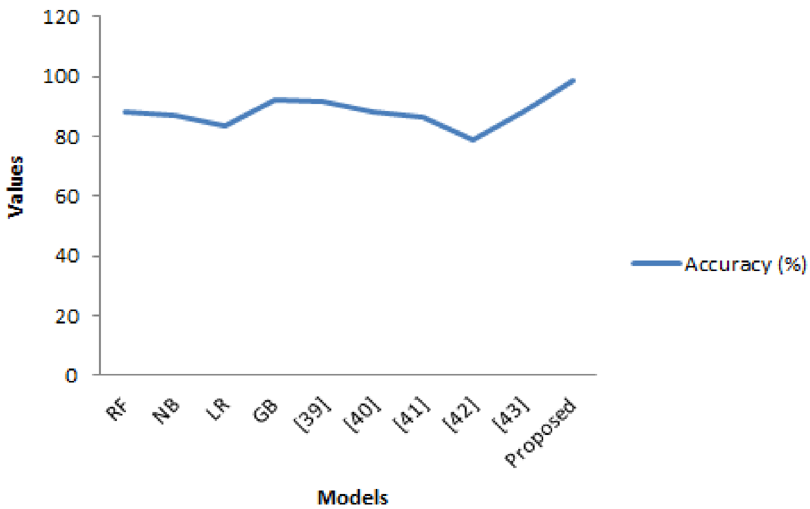

Figure 6. Comparative analysis

5. CONCLUSION AND FUTURE SCOPE

Respiratory Sound Database (ICBHI 2017) is used in this work to examine lung sound classification and respiratory diseases prediction. This dataset has 920 annotated recordings from 126 individuals, encompassing both healthy and pathological respiratory states. The dataset was divided into two parts as training and validation sets. First, the audio files were normalised than four feature extraction methods were used to transform audio into forms that are adaptable for machine learning: MFCC, Chroma, ZCR, and Spectral Centroid. The tests represent the efficacy of the proposed model for respiratory sound classification when used alongside proper feature extraction methods. With consistently better performance across all classifiers, (CNN+SVM+KNN) proved to be the best discriminative feature set among the features that were tested, including Chroma, Spectral Centroid, Zero Crossing Rate (ZCR), and MFCC. The proposed model attains the highest accuracy of 98.76% thereby surpassing few conventional classifiers.

AUTHOR CONTRIBUTIONS

Jaspreet Kaur: Conceptualization, Investigation, Methodology, Laboratory Analysis, Data Curation, Formal Analysis.

Brijesh Kumar: Supervision, Writing—Review & Editing.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

ETHICS STATEMENT

Ethical approval was not required for this study.

DATA AVAILABILITY STATEMENT

Data supporting the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

[1] J. L. M. Amaral, A. J. Lopes, J. M. Jansen, A. C. D. Faria, and P. L. Melo, *Machine learning algorithms and forced oscillation measurements applied to the automatic identification of chronic obstructive pulmonary disease,* Computer Methods and Programs in Biomedicine, vol. 105, pp. 183-193, 2012

[2] Aykanat, Ö. Kılıç, B. Kurt, and S. Saryal, *Classification of lung sounds using convolutional neural networks, EURASIP* Journal on Image and Video Processing, vol. 65, pp. 1-9, 2017. DOI: 10.1186/s13640-017-0213-2.

[3] B. Sang, H. Wen, G. Junek, W. Neveu, L. Di Francesco, and F. *Ayazi, An Accelerometer Based Wearable Patch for Robust Respiratory Rate and Wheeze Detection Using Deep Learning*, Biosensors-14-00118-V2 (3), 2024.

[4] A. H. Sabry, O. I. Dallal Bashi, N. H. Nik Ali, and Y. Mahmood Al Kubaisi, *Lung disease recognition methods using audio-based analysis with machine learning*, Heliyon, vol. 10, no. 4, p. e26218, 2024, 10.1016/j.heliyon.2024.e26218.

[5] S. Abbasi, R. Derakhshanfar, A. Abbasi, and Y. Sarbaz, *Classification of normal and abnormal lung sounds using neural network and support vector machines*, in Proc. 21st Iranian Conf. Elect. Eng. (ICEE), May 2013,pp. 14.

[6] Z.LiandM.Du, *HHT based lung sound crackle detection and classification*, in Proc. Int. Symp. Intell. Signal Process. Commun. Syst., Dec. 2006, pp. 385388.

[7] L. P. Malmberg, K. Kallio, S. Haltsonen, T. Katila, and A. R. A. Sovijärvi,*Classification of lung sounds inpatients with asthma ,emphysema, rosing alveolitis and healthy lungs by using self-organizing maps*, Clin. Physiol., vol. 16, no. 2, pp. 115129, 1996.

[8] P. Bokov, B. Mahut, P. Flaud, and C. Delclaux, *Wheezing recognition algorithm using recordings of respiratory sounds at the mouth in a pediatric population*, Comput. Biol. Med., vol. 70, pp. 4050, Mar. 2016.

[9] A. Kandaswamy, C. S. Kumar, R. P. Ramanathan, S. Jayaraman, and N. Malmurugan, *Neural classification of lung sounds using wavelet coefficients*, Comput. Biol. Med., vol. 34, no. 6, pp. 523537, 2004.

[10] L. Shi, K. Du, C. Zhang, H. Ma, and W. Yan, *Lung Sound Recognition Algorithm Based on VGGish-BiGRU*, IEEE Access, vol. 7, pp.

[11] L. Brunese, F. Mercaldo, A. Reginelli, and A. Santone, *A Neural Network-Based Method for Respiratory Sound Analysis and Lung Disease Detection, Applied Sciences*, vol. 12, no. 8, p. 3877, Apr. 2022, doi: 10.3390/app12083877.

[12] Y. Kim, Y. Hyon, S. S. Jung, S. Lee, G. Yoo, C. Chung, and T. Ha, *Respiratory sound classification for crackles, wheezes, and rhonchi in the clinical field using deep learning*, Scientific Reports, vol. 11, no. 1, p. 17192, Aug. 2021, doi: 10.1038/s41598-021-96676-8.

[13] Nguyen, T., & Pernkopf, F. (2022). *Lung Sound Classification Using Co-Tuning and Stochastic Normalization.* IEEE Transactions on Biomedical Engineering, 69(9), 2872–2882. DOI: 10.1109/TBME.2022.3156293.

[14] F. Mercaldo, L. Brunese, A. Reginelli, and A. Santone, *Bias-Free Network (RBF-Net): An AI-Enabled Model for Diagnosing Respiratory Diseases Using Cough Aud*io, Bioengineering, vol. 11, no. 1, 2024.

[15] G. Petmezas, G.-A. Cheimariotis, L. Stefanopoulos, et al., *Automated Lung Sound Classification Using a Hybrid CNN-LSTM Network and Focal Loss Function*, *Sensors*, vol. 22, no. 3, p. 1232, 2022, doi: 10.3390/s22031232.

[16] Prabhakar, S. K., & Won, D.-O. (2023). *HISET: Hybrid interpretable strategies with ensemble techniques for respiratory sound classification*. *Heliyon*, 9(8), e18466. DOI: 10.1016/j.heliyon.2023.e18466.

[17] A. Srivastava, S. Pandya, S. Jain, S. Patil, K. Kotecha, and R. Miranda, *Deep learning based respiratory sound analysis for detection of chronic obstructive pulmonary disease*, PeerJ Computer Science, vol. 7, p. e369, 2021, doi: 10.7717/peerj-cs.369.

[18] F. Demir, A. Sengur, and V. Bajaj, *Convolutional neural networks based efficient approach for classification of lung diseases*, Health Information Science and Systems, vol. 8, no. 1, 2019, doi: 10.1007/s13755-019-0091-3.

[19] M. A. Azam, A. Khalid, A. Shahzadi, U. Naeem, and S. M. Anwar, *Smartphone Based Human Breath Analysis from Respiratory Sounds*, in Proc. IEEE EMBC, 2018, pp. 445–448, doi: 10.1109/EMBC.2018.8512452.

[20] Altan, G., Kutlu, Y., Pekmezci, A. & Yayık, A. (2018). *Diagnosis of Chronic Obstructive Pulmonary Disease using Deep Extreme Learning Machines with LU Autoencoder Kernel*. 7th International Conference on Advanced Technologies (ICAT'18). 618-622.

[21] Altan, G., Kutlu, Y., Garbi, Y., Pekmezci, A.Ö. & Nural, S., (2017). *Multimedia Respiratory Database (RespiratoryDatabase@TR): Auscultation Sounds and Chest X-rays*. NE Sciences, 2017, 2 (3): 5972.

[22] Demir, F., Sengur, A. & Bajaj, V. *Convolutional neural networks based efficient approach for classification of lung diseases. Health Inform.* Sci. Syst. 8, 4. https://doi.org/10.1007/s13755-019-0091-3 (2020).

[23] Zheng, L. et al. *Artificial intelligence in digital cariology: A new tool for the diagnosis of deep caries and pulpitis using convolutional neural networks*. Ann. Transl. Med. 9, 763. https://doi.org/10.21037/atm-21-119 (2021).

[24] J. L. M. Amaral, A. J. Lopes, J. M. Jansen, A. C. D. Faria, and P. L. Melo, *Machine learning algorithms and forced oscillation measurements applied to the automatic identification of chronic obstructive pulmonary disease*, Computer Methods and Programs in Biomedicine, vol. 105, pp. 183-193, 2012.

[25] L.P. Malmberg, K. Kallio, S. Haltsonen, T. Katila &A.R.A Sovijärvi, *Classification of lung sounds in patients with asthma, emphysema, fibrosing alveolitis and healthy lungs by using self-organizing maps*, Clinical Physiology, 1996, pp. 115-129.

[26] Ma,Y.; Xu, X.; Yu, Q.; Zhang, Y.; Li, Y.; Zhao, J.; Wang, G. *LungBRN: A smart digital stethoscope for detecting respiratory disease using bi-resnet deep learning algorithm*. In Proceedings of the 2019 IEEE Biomedical Circuits and Systems Conference (BioCAS), Nara, Japan, 17–19 October 2019; pp. 1–4.

[27] Runze Yang 1, Kexin Lv ,Yizhang Huang, Mingxia Sun, Jianxun Li, and Jie Yang *Respiratory Sound Classification by Applying Deep Neural Network with a Blocking Variable* Appl. Sci. 2023, 13, 6956. https://doi.org/10.3390/ app13126956 Academic Editors: Qingyu Zhao, Daniel Moyer and Magdalini Paschal , Appl. Sci. 2023, 13, 6956. https://doi.org/10.3390/app13126956

[28] Gairola, S.; Tom, F.; Kwatra, N.; Jain, M. *Respirenet: A deep neural network for accurately detecting abnormal lung sounds in limited data setting.* In Proceedings of the 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Virtual, 1–5 November 2021; pp. 527–530

[29] Srivastava, A., Jain, S., Miranda, R., Patil, S., Pandya, S., & Kotecha, K. (2021). *Deep learning based respiratory sound analysis for detection of chronic obstructive pulmonary disease*. PeerJ Computer Science, 7, e369

[30] T. Saeed, A. Ijaz, I. Sadiq, H. N. Qureshi, A. Rizwan, and A. Imran, *An AI-Enabled BiasFree Respiratory Disease Diagnosis Model Using Cough Audio, Bioengineering*, vol. 11, no. 1, 2024, doi: 10.3390/bioengineering11010055

[31] McFee, B. librosa. librosa 0.8.0. https://doi.org/10.5281/zenodo.3955228 (2020).

[32] O. Balli and Y. Kutlu, *Effect of Deep Learning Feature Inference Techniques on Respiratory Sounds*, Akıllı Sistemler ve Uygulamaları Dergisi, vol. 3, no. 2, pp. 134–137, 2020.

[33] R. Palaniappan, K. Sundaraj, and S. Sundaraj, *A comparative study of the SVM and K-NN machine learning algorithms for the diagnosis of respiratory pathologies using pulmonary acoustic signals, BMC Bioinformatics*, vol. 15, no. 223, pp. 1–11, 2014. [Online]. Available: http://www.biomedcentral.com/1471-

[34] Paweł Stasiakiewicz, Andrzej P. Dobrowolski, Tomasz Targowaski, Natalia Gałązka, Swiderek, Teresa Sadura-Sieklucka, Katarzyna Majka, Agnieszka Skoczylas, Wojciech Lejkowski, Robert Olszewski *Automatic classification of normal and sick patients with crackles using wavelet packet decomposition and support vector machine* Biomedical Signal Processing and Control 67 (2021) 102521.

[35] S. Maji, A. C. Berg, and J. Malik, *Classification using intersection kernel support vector machines is efficient*, in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Anchorage, AK, USA, Jun. 2008, pp. 1–8. doi: 10.1109/CVPR.2008.4587630.

[36] D. Lavanya and K. U. Rani, *Performance evaluation of decision tree classifiers on medical datasets*, International Journal of Computer Applications, vol. 26, no. 4, pp. 1–4, 2011.

[37] Zhu,Q.; Wang, Z.; Dou, Y.; Zhou, J. *Whispered Speech Conversion Based on the Inversion of Mel Frequency Cepstral Coefficient Features*. Algorithms 2022, 15, 68. [CrossRef]

[38] T. Grzywalski, M. Piecuch, M. Szajek, A. Bręborowicz, H. Hafke-Dys, J. Kociński, A. Pastusiak, and R. Belluzzo, *Practical implementation of artificial intelligence algorithms in pulmonary auscultation examination*, European Journal of Pediatrics, vol. 178, pp. 883–890, 2019, doi: 10.1007/s00431-019-03363-2. PMID: 30927097; PMCID: PMC6511356.

[39] ICBHI 2017 Challenge | ICBHI Challenge. (n.d.). Retrieved. https://bhichallenge.med.auth.gr/ICBHI_2017_Challenge 2022.

[40] Fraiwan M, Fraiwan L, Khassawneh B, Ibnian A. *A dataset of lung sounds recorded from the chest wall using an electronic stethoscope*. Data Brief. 2021;35:106913.

[41] Hsu FS, Huang SR, Huang CW, Huang CJ, Cheng YR, Chen CC, et al. *Benchmarking of eight recurrent neural network variants for breath phase and adventitious sound detection on a self-developed open-access lung sound database-HF_Lung_V1*. PLoS One. 2021;16(7):e0254134

[42] The R.A.L.E. Repository. (n.d.). Retrieved June 24, 2022, from http://www.rale.ca/.

[43] J. L. Rodríguez, P. R. López, and M. G. García, *Feature extraction techniques for classification of lung sounds*, Biomedical Signal Processing and Control, vol. 43, pp. 1–10, 2018.

[44] A. K. Gupta, H. Kim, and D. Park, *Hybrid CNN-RNN for respiratory disease classification*, IEEE Access, vol. 9, pp. 39457–39469, 2021.

[45] M. Chen, L. Wang, and A. N. Johnson, *Deep learning with audio spectrograms for respiratory sound classification*, Pattern Recognition Letters, vol. 156, pp. 142–149, 2022.

[46] F. Demir, A. Şengür, V. Bajaj, and K. Polat, *Transfer learning-based respiratory sound analysis*, Sensors, vol. 21, no. 19, p. 6370, Sep. 2021.