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Implementation of Real-Time Respiratory Disease Classification with Improved Convolutional Neural Networks (ICNN)

R. Rampriya [1]*, Dr. N. Suguna [2], Dr. R.G. Suresh Kumar[3]

Research Scholar, Department of Computer Science and Engineering, Faculty of Engineering and Technology, Annamalai University.
Associate Professor, Department of Computer Science and Engineering, Faculty of Engineering and Technology, Annamalai University.
Professor & Head, Department of Computer Science and Engineering, Rajiv Gandhi College of Engineering and Technology, Pondicherry.
* Corresponding author's Email: javarampriya@gmail.com

Abstract

Automatic detection of respiratory diseases plays a crucial role in modern healthcare, offering several benefits in terms of efficiency, accuracy, and timely intervention. With the integration of advanced technologies such as machine learning and deep learning, automated systems can analyze respiratory data and swiftly identify various respiratory conditions. This approach eliminates the need for manual analysis, reducing the time required for diagnosis and allowing for prompt medical attention. This paper presents an Automatic Respiratory Data Classification System utilizing an Improved Convolutional Neural Network (CNN) and wavelet transform applied to real-time clinical data. The Respiratory Classification System (RCS) demonstrates robust performance with impressive Normal Respiratory Detection Rates (NRDR) of 98% for normal male data and 95% for normal female data. High accuracy is also achieved in classifying abnormal respiratory data, with NRDRs of 96.67% for abnormal male data and 96% for abnormal female data. The comprehensive evaluation on a substantial dataset results in an outstanding Respiratory Detection Rate (RDR) of 98.8%. The proposed Improved CNN algorithm attains a remarkable RDR with low computational time, showcasing its potential for respiratory disease classification.

Keywords: Convolutional Neural Network, Internet of Things, Wavelet transform, Mean, Data Augmentation.

1. INTRODUCTION

Respiratory diseases present a complex and diverse spectrum of disorders that profoundly impact the complex process of human respiration. These conditions affect various structures responsible for breathing, including the nasal cavities, pharynx, larynx, trachea, bronchi, bronchioles, lung tissues, and respiratory muscles within the chest cage. Understanding respiratory diseases requires a comprehensive exploration of their multifaceted causes, which range from infectious agents to environmental factors, genetic predispositions, occupational exposures, and lifestyle choices. Infections, caused by both viral and bacterial agents, play a pivotal role in respiratory diseases. Influenza, common cold viruses, pneumonia, bronchitis, and tuberculosis exemplify the diverse nature of respiratory infections, showcasing the range of symptoms and complications associated with these conditions. Environmental factors contribute significantly to respiratory diseases, exposing individuals to various pollutants and irritants. Tobacco smoke, air pollution, occupational dust or chemicals, and indoor pollutants like mold or asbestos pose substantial risks to respiratory health. Recognizing the impact of these environmental factors is crucial for effective prevention and management strategies. Allergens, including airborne particles such as pollen, pet dander, mold spores, and certain foods, can trigger allergic reactions, leading to conditions like allergic rhinitis, asthma, and hypersensitivity pneumonitis. The immune system's exaggerated response to these allergens can result in inflammation and constriction of the airways, affecting normal respiratory function. Genetic factors also play a significant role in respiratory diseases, with certain conditions having a hereditary component. Cystic fibrosis and alpha-1 antitrypsin deficiency serve as examples of inherited disorders that impact the respiratory system, highlighting the genetic complexities associated with these diseases. Occupational exposures in specific industries can lead to respiratory diseases. Miners exposed to coal dust may develop pneumoconiosis, while workers in asbestos mining face the risk of developing asbestosis. The occupational hazards underscore the importance of workplace safety and monitoring to prevent respiratory health issues. Tobacco smoking stands out as a major risk factor for respiratory diseases, contributing to a range of conditions, including chronic obstructive pulmonary disease (COPD), lung cancer, and emphysema. The harmful chemicals in cigarette smoke can cause inflammation, damage to lung tissues, and a decline in overall respiratory function. Autoimmune diseases, such as rheumatoid arthritis and systemic lupus erythematosus, have the potential to affect the respiratory system, inducing inflammation and lung damage. The complex behavior between autoimmune conditions and respiratory health necessitates a thorough understanding for accurate diagnosis and targeted management. Advancing age increases susceptibility to respiratory diseases, with older individuals being more prone to conditions like pneumonia and COPD. Age-related changes in the respiratory system, coupled with a potential decline in immune function, contribute to the heightened vulnerability observed in the elderly population. Pre-existing medical conditions, such as heart disease or diabetes, can heighten vulnerability to respiratory infections and complications. Imaging studies, such as chest X-rays and computed tomography (CT) scans, offer detailed visuals of the chest, aiding in the identification of abnormalities like infections, tumors, or fluid accumulation. Pulmonary function tests (PFTs), including spirometry, assess lung capacity and function. These tests provide valuable information about the extent of respiratory impairment and aid in the classification of respiratory diseases. Blood tests are conducted to identify markers of inflammation, infection, or specific antibodies related to autoimmune or allergic conditions. Arterial blood gas (ABG) tests measure oxygen and carbon dioxide levels in the blood, providing insights into respiratory efficiency. Microbiological tests, such as sputum cultures and blood cultures, assist in identifying the presence of pathogens. Allergy testing, through skin prick tests or blood tests, helps pinpoint allergens contributing to respiratory symptoms. Invasive procedures like bronchoscopy allow for direct visualization of the airways, sample collection, and assessment of abnormalities. Biopsies may be conducted for microscopic examination, providing crucial information for diagnosis. Additional diagnostic tools include electrocardiograms (ECGs) to rule out cardiac issues, sleep studies to evaluate sleep-related respiratory disorders, and exercise testing to assess respiratory function under increased demand. Genetic testing may be employed when there is suspicion of genetic respiratory diseases, aiding in the identification of specific mutations. A comprehensive diagnosis and management of respiratory diseases often require a collaborative effort from various specialists, including pulmonologists and allergists. Recognizing the complex functioning of contributing factors and implementing a thorough diagnostic strategy are crucial for effective treatment and prevention.

In the existing systems, the machine learning (ML) model has shown promising results in respiratory disease detection and classification, it is essential to acknowledge certain drawbacks associated with its application in this domain. One significant limitation is the dependence on the availability and quality of labeled datasets for training algorithms. Obtaining large and diverse datasets that accurately represent the complexity of respiratory diseases can be challenging, potentially leading to biased models or limited generalizability. Moreover, the interpretability of ML models in the context of respiratory diseases remains a concern. Many machine learning algorithms operate as black-box systems, making it challenging for healthcare professionals to understand the underlying reasoning behind a particular classification. Interpretability is crucial in the medical field, where decisions impact patient well-being, and clinicians need to trust and comprehend the basis of algorithmic predictions. Another drawback is the potential for overfitting, especially when dealing with imbalanced datasets or noisy input data. Overfitting occurs when a model learns to perform well on the training data but fails to generalize to new, unseen data. In the context of respiratory diseases, where individual variability is significant, overfitting can compromise the robustness of the model in real-world scenarios. Furthermore, the ethical considerations surrounding patient privacy and data security are paramount. ML models trained on sensitive health data may inadvertently reveal personal information or contribute to discriminatory outcomes. Ensuring the responsible and ethical use of machine learning in healthcare settings is crucial to building trust among patients and healthcare providers. Deep learning, a subset of machine learning, has demonstrated advantages over traditional ML methods in respiratory disease detection. Deep learning models, particularly neural networks, can automatically learn hierarchical representations of data, allowing them to capture complex patterns and features from complex respiratory signals. This capability is particularly beneficial in handling the nuanced nature of respiratory diseases, where subtle variations in signal patterns may hold diagnostic significance. Moreover, deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), excel in feature extraction and sequential data processing, making them well-suited for analyzing time-series respiratory signals. Their ability to automatically learn relevant features from raw data reduces the need for manual feature engineering, making the modeling process more efficient and adaptable to various respiratory conditions.

The paper's structure includes Section 2, which details the current respiratory data classification process with simulated values. This section serves as the foundation for understanding existing methodologies and sets the stage for the introduction of the proposed RCS. Section 3 introduces the Respiratory Classification System and outlines its real-time hardware interfacing modules. This section describes the technical details of the proposed system and explains the possible uses that can be made in comparison to traditional ways. Experimental results obtained by the proposed RCS find a detailed explanation in Section 4. Comparative analyses with other classical systems shed light on the system's effectiveness and reliability in respiratory signal classification. Section 5 offers concluding remarks, summarizing the research findings and emphasizing the potential impact of the proposed respiratory signal classification system on the diagnosis and management of respiratory diseases. The multidisciplinary approach, involving specialists from various fields, remains integral in addressing the diverse challenges posed by respiratory diseases.

2. LITERATURE SURVEY

Asatani *et al.* (2021) introduced a novel automatic classification method for respiratory sounds using deep learning algorithms to support the diagnosis of respiratory diseases. The proposed method involves generating spectrograms through a short-time Fourier transform and classifying respiratory sounds into normal and abnormal categories, including crackle, wheeze, or both. The results demonstrated sensitivity of 0.63, specificity of 0.83, an average score of 0.73, and a harmonic score of 0.72, outperforming other methods. Zhang *et al.* (2023) focused on training deep learning algorithms, including Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), CNN ensembled with unidirectional LSTM (CNN-LSTM), and CNN ensembled with bidirectional LSTM (CNN-BLSTM), on a dataset of 920 patient respiratory audio files from the Respiratory Sound Database. The study aimed at exploring the effectiveness of different deep learning architectures in respiratory sound classification. Kim *et al.* (2021) addressed the challenges of accurate interpretation of respiratory sounds during auscultation by developing an automated classification system. They utilized a deep learning convolutional neural network (CNN) to categorize 1918 respiratory sounds recorded in clinical settings, achieving an accuracy of 86.5% and demonstrating the potential to complement clinicians' auscultation. Li *et al.* (2022) presented a method combining convolutional neural network (CNN) and long-short-term memory network (LSTM) for the prediction and diagnosis of respiratory diseases. Their approach involved preprocessing clinical records, word vectorization using the Bidirectional Encoder Representation from Transformers (BERT) model and encoding and decoding of information using CNN and LSTM layers. Gang *et al.* (2021) proposed a pediatric fine-grained diagnosis-assistant system for prompt and precise diagnosis of respiratory diseases using clinical notes. The system involved two stages: test result structuralization and disease identification. They developed a deep learning algorithm incorporating adaptive feature infusion and multi-modal attentive fusion, achieving high average precisions for pneumonia, upper respiratory tract infection (RTI), bronchitis, and asthma. Qasim *et al.* (2023) conducted a systematic literature review on the detection and classification of respiratory diseases using deep learning methods. They analyzed 47 articles published between 2015 and 2021, emphasizing the prevalence of supervised learning with deep convolutional neural networks in this domain. The review highlighted a shortage of tools, hindering the transition from academic research to industrial applications. Chip Lynch *et al.* (2017) applied various supervised learning techniques, including linear regression, Decision Trees, Gradient Boosting Machines (GBM), Support Vector Machines (SVM), and a custom ensemble, to classify lung cancer patients based on survival using the SEER database. Their study explored the predictive power of different techniques and identified key data attributes influencing survival prediction. Jayalakshmy *et al.* (2020) proposed a pre-trained optimized Alexnet Convolutional Neural Network (CNN) architecture for predicting respiratory disorders. Their approach involved empirical mode decomposition (EMD) to segment respiratory sound signals and achieved improved accuracy compared to traditional wavelet transform methods. Brunese *et al.* (2022) presented a machine learning-based method for respiratory sound analysis to detect and characterize lung diseases. Their approach involved gathering a feature vector directly from breath audio, and using supervised machine learning techniques, they achieved high accuracy in lung disease detection and characterization, particularly with a neural network model. Jasmine *et al.* (2022) focused on the detection and classification of lung diseases, including pneumonia, tuberculosis, and lung cancer, using deep learning models trained on X-ray and CT scan images. They implemented three deep learning models and compared their performance, demonstrating high accuracy and effectiveness for faster disease detection. Israa *et al.* (2022) aimed at predicting the readmission of COPD patients using machine learning algorithms. They evaluated models based on Area Under Curve (AUC) and Accuracy (ACC), identifying important variables for each outcome and achieving high accuracy (91%) in predicting readmission. Stavros *et al.* (2018) introduced an integrated mHealth system for real-time personalized feedback to patients for proper inhaler use in asthma and chronic obstructive pulmonary disease. Their system achieved a high classification accuracy of 98%, outperforming existing approaches and providing intuitive feedback interfaces for patient engagement. Palaniappan *et al.* (2013) provided a comprehensive review of computer-based respiratory sound analysis techniques used by various researchers. The methodologies, sensor types, signal processing, and classification methods employed in previous works were examined, offering insights into the evolution and possibilities for further improvements in the field.

3. PROPOSED METHODOLOGY

Breathing signal analysis plays a vital role in various domains, including healthcare and wellness monitoring. The process of utilizing Convolutional Neural Networks (CNNs) in conjunction with wavelet transform features for breathing signal classification is a sophisticated approach that enhances the interpretation of physiological data.

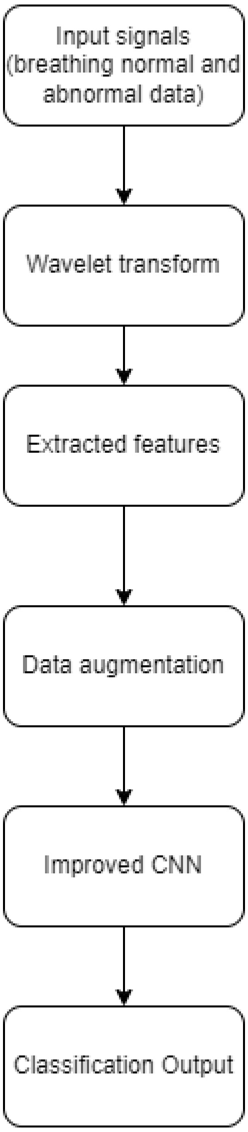

Figure 1. Block diagram of Respiratory Classification system

3.1 Signal Acquisition

The initial step involves the acquisition of breathing signals through sensors. These signals, inherently analog, undergo Analog-to-Digital (A/D) converter and Micro controller unit (Arduino) along with RS232 interfacing module to facilitate subsequent digital processing. This crucial conversion allows for the manipulation and analysis of the signals in a digital environment.

Figure 2. Constructed breathing sensor

3.2 Wavelet Transform:

Upon digitization, the breathing signals enter the realm of wavelet transform. This mathematical tool excels in breaking down signals into distinct frequency components, offering a multiresolution analysis. The result is a set of coefficients that encapsulate the signal's characteristics at different scales and frequencies. Features extracted from this process include mean values, energy, standard deviation, kurtosis, skewness, peak max indices, peak min indices, and linear indices, each corresponding to different levels of decomposition.

3.3 Extracted Features

The features derived from the wavelet transform act as descriptors, encapsulating essential information about the breathing signal. These features serve as the foundation for subsequent analysis and classification. Mean values provide insights into the central tendencies of the signal, while energy values convey the overall power or intensity of signal variations. Standard deviation measures signal variability, while kurtosis and skewness offer insights into the distribution's shape and asymmetry. Peak max and min indices pinpoint the locations of significant signal peaks and troughs, while linear indices provide a linear representation of the signal's progression.

The extraction of essential features from wavelet-transformed signals involves several key procedures. The Mean (μ) is computed as the average of the wavelet coefficients (x_i) at a specific decomposition level, involving the summation of where N represents the number of coefficients. The Energy (E) is determined by summing the squared values of the coefficients, given by Standard Deviation (σ) is calculated using the square root of the mean squared deviation from the mean, expressed as Kurtosis and Skewness, measures of distribution shape, involve higher-order statistical calculations based on the coefficients' deviations from the mean. The Peak Max Index is derived by identifying the index corresponding to the maximum coefficient value using the argmax operation. Similarly, the Peak Min Index is obtained by finding the index corresponding to the minimum coefficient value through the argmin operation. Finally, the Linear Index is computed by generating a linear representation of the signal's progression, where each index (i) is normalized within the range [0, 1], allowing for a comprehensive understanding of the signal's evolution. These procedures collectively enable the extraction of valuable information from wavelet-transformed signals, providing a detailed characterization of breathing patterns and states.

3.4 Data augmentation

Data augmentation for features extracted from wavelet transform involves introducing variations to the existing dataset to enhance the robustness and generalization capability of a classification model, such as a Convolutional Neural Network (CNN). Specifically, for features like Mean, Energy, Standard Deviation, Kurtosis, Skewness, Peak Max Index, Peak Min Index, and Linear Index obtained from wavelet transform, augmentation can be applied.

For features like Mean, Energy, Standard Deviation, Kurtosis, and Skewness, variations can be introduced by perturbing the magnitude and distribution of these statistical measures. This may include altering the mean value, adjusting energy levels, introducing random noise to mimic fluctuations, or skewing and transforming the distribution of kurtosis and skewness to simulate diverse scenarios.

Peak Max and Min Indices, indicating significant points in the signal, can undergo augmentation by introducing slight variations in the positions of these peaks and troughs. This may involve shifting the indices, adding or removing peaks, or adjusting the amplitude of existing peaks.

Linear Index Feature, representing the linear progression of the signal, can be augmented by applying transformations such as rotation or scaling. These variations mimic potential distortions in the signal's temporal progression and contribute to a more comprehensive dataset.

It's important to note that the goal of data augmentation is to expose the model to a diverse range of scenarios that it might encounter during real-world applications. By introducing controlled variations in the dataset, the model becomes more adaptable and less prone to overfitting. The augmented dataset, enriched with these variations, is then used for training the CNN, allowing it to learn from a broader set of examples and improving its ability to generalize to unseen data. Overall, data augmentation is a crucial step in the pipeline to ensure the model's effectiveness in handling the complexities and variations present in real-world physiological signals.

3.5 Convolutional Neural Network (CNN)

The extracted features become the input for a Convolutional Neural Network (CNN). The architecture of the CNN is designed to utilize the hierarchical learning capabilities of convolutional layers, pooling layers, and fully connected layers. Convolutional layers automatically learn spatial features and patterns at different levels of abstraction. Pooling layers reduce spatial dimensions, focusing on critical features. Fully connected layers amalgamate the learned features to facilitate the final classification. This combination of layers ensures that the CNN can discern complex patterns within the wavelet-transformed features.

3.5.1 Classification Output:

The ultimate goal of this process is classification. The CNN, having processed the extracted features, generates a classification output. This output assigns labels to the input signals based on the learned hierarchical representations. For instance, the CNN might categorize signals as indicative of normal or abnormal breathing patterns. This classification output is a tangible result of the model's ability to discern patterns and relationships within the complex, multiresolution features obtained through wavelet transform.

The extracted features form the foundation for subsequent data augmentation, a pivotal step that broadens the diversity of the training dataset. Data augmentation introduces controlled variations to the feature set, simulating real-world scenarios and contributing to the model's adaptability. These variations may include adjusting statistical measures, introducing noise, or perturbing peak indices, among other transformations. This augmented dataset becomes a robust training ground for an improved CNN designed for breathing signal classification.

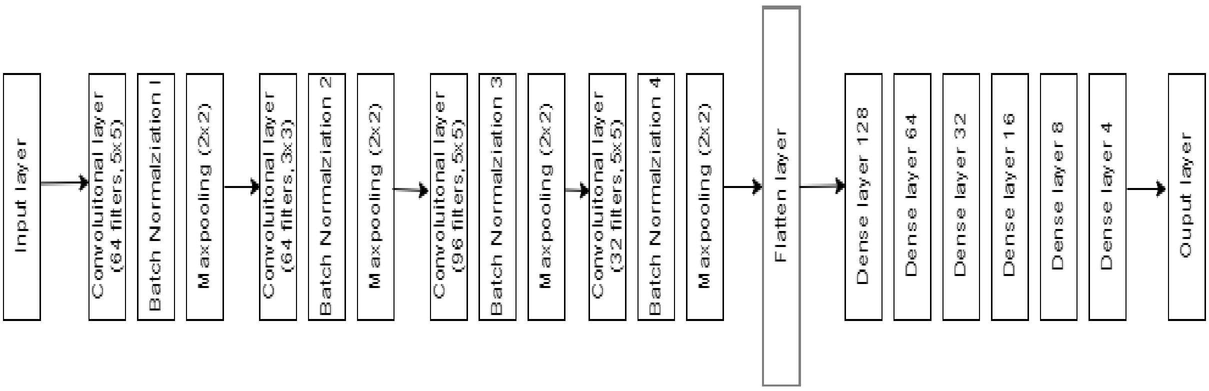

Figure 3. Improved CNN architecture

The architecture of the CNN unfolds with a first convolutional layer employing 64 output filters and a 5x5-pixel size kernel, coupled with a subsequent 2x2-pixel max-pooling layer for down-sampling. The subsequent three convolutional layers continue the hierarchy, each featuring a 3x3-pixel size kernel and 64, 96, and 96 filters sequentially. Batch-normalization layers are strategically interleaved with these convolutional layers, serving to stabilize and accelerate the training process. Corresponding 2x2 max-pooling layers follow, contributing to the hierarchical learning of the network. A new convolutional layer, characterized by a 3x3-pixel size kernel and 32 output filters, introduces additional complexity to the model. Post this layer, batch-normalization and max-pooling layers follow suit, contributing to the normalization of extracted features and the reduction of spatial dimensionality in the feature maps.

The incorporation of batch-normalization is pivotal, acting as a regularizer during training and stabilizing the learning process by reducing internal covariate shift. This allows for smoother convergence and facilitates the training of deeper networks. The max-pooling layers, on the other hand, contribute to spatial down-sampling, retaining critical features while reducing the computational load.

This complex architecture is designed to capture hierarchical representations and spatial relationships within the wavelet-transformed features. The convolutional layers automatically learn patterns at different levels of abstraction, while batch-normalization ensures stable training dynamics. The ensuing max-pooling layers focus on preserving essential features and down-sampling the spatial dimensions for efficiency. Collectively, this CNN architecture serves as a potent tool for the classification of breathing signals, leveraging the enhanced feature set obtained through wavelet transform and data augmentation. In conclusion, the entire process encapsulates a synergistic integration of signal processing techniques, advanced feature extraction, and deep learning methodologies, contributing to the development of a robust and effective model for breathing signal classification.

3.6 Integration and Interpretation:

The integration of wavelet transforms and CNNs offers a comprehensive approach to breathing signal analysis. Wavelet transform, with its ability to provide detailed insights into different scales of the signal, serves as a robust feature extraction method. CNNs, with their capacity for hierarchical learning, thrive in analyzing these features, automatically discerning complex patterns that might signify specific breathing states.

The utilization of wavelet transform features in conjunction with Convolutional Neural Networks represents a sophisticated methodology for breathing signal analysis. The integration of these two powerful techniques allows for a nuanced understanding of physiological data, offering valuable insights into breathing patterns and states. As technology advances, the synergy between signal processing and machine learning continues to pave the way for innovative approaches in healthcare and well-being monitoring. The interaction between the wavelet-transformed features and the hierarchical learning of CNNs encapsulates the essence of a robust and advanced analytical process.

4. RESULTS AND DISCUSSION

The proposed Respiratory Classification System (RCS) outlined in this study was simulated using the Python environment on a system with 8 GB RAM and a 1TB Hard disk. To validate the efficacy of the system, a real-time dataset was meticulously constructed. This dataset encompasses both normal and abnormal respiratory data obtained from individuals at the Upgraded Govt. Primary Health Centre in Srimushnam. The dataset collection involved 550 male participants and 475 female participants. Among the 550 male individuals, 400 displayed normal respiratory patterns, exhibiting no symptoms of any respiratory issues according to clinician reports. The remaining 150 males exhibited abnormal respiratory data, showcasing symptoms of respiratory problems as per clinician assessments. Similarly, among the 475 female participants, 300 demonstrated normal respiratory patterns, and clinician reports indicated the absence of respiratory issues. The remaining 175 females presented abnormal respiratory data, displaying symptoms of respiratory problems according to clinician evaluations. This meticulous dataset compilation ensures a diverse and representative sample for comprehensive evaluation and testing of the proposed RCS.

Table 1. Evaluation and estimation of Respiratory Detection Rate

Sex category	**Number of normal persons (without any respiratory problems)**	**Number of abnormal persons (with any kind of respiratory problems)**	**Number of normal persons correctly detected**	**Number of abnormal persons correctly detected**	**Normal Respiratory Detection Rate (NRDR) in %**	**Abnormal Respiratory Detection Rate (ARDR) in %**
Male	400	150	392	145	98	96.67
Female	300	175	285	168	95	96
	700	325	675	311	96.43	95.69

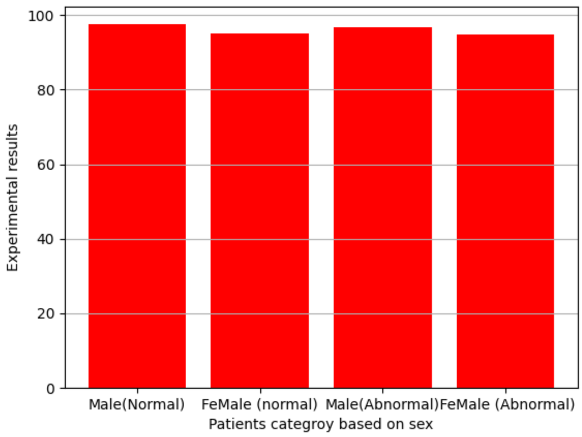

Figure 4. Graphical estimation of Respiratory Detection Rate

Table 1 presents the assessment and estimation results for the Respiratory Detection Rate (RDR) in the evaluated Respiratory Classification System (RCS). The system achieves a commendable performance, accurately identifying 392 out of 400 normal male data, resulting in a 98% Normal Respiratory Detection Rate (NRDR). Similarly, for normal female data, the RCS correctly identifies 285 instances out of 300, yielding a 95% NRDR.

In the case of abnormal respiratory data, the RCS exhibits robust performance, detecting 145 out of 150 abnormal male data and achieving a 96.67% NRDR. For abnormal female data, the system correctly identifies 168 instances out of 175, resulting in a 96% NRDR. These results underscore the effectiveness of the RCS in accurately classifying both normal and abnormal respiratory patterns, showcasing its high detection rates across gender-specific datasets.

Table 2. Sample collections for RCS

Day order	**Male persons**	**Female persons**	**Number of samples**	**Number of samples**	**Number of samples**	**Number of samples**
1	550	475	10	10	5500	4750
2	550	475	20	20	11000	9500
3	550	475	30	30	16500	14250
4	550	475	40	40	22000	19000
5	550	475	50	50	27500	23750
6	550	475	40	40	22000	19000
7	550	475	30	30	16500	14250
8	550	475	20	20	11000	9500
9	550	475	10	10	5500	4750
10	550	475	10	10	5500	4750
			260	**260**	**132000**	**123500**

In this real-time dataset, each individual contributes 10 samples collected at various time intervals on the same day. Consequently, a total of 5,500 data samples are collected for the 550 male participants, and 4,750 data samples are gathered for the 475 female participants in this experimental study. Therefore, a cumulative total of 10,250 data samples are collected at different time intervals on the same day from the combined group of 550 male participants and 475 female participants. Table 3 details the sample collections conducted for the Respiratory Classification System (RCS). The study involves the collection of a substantial dataset, totalling 132,000 data samples from male participants and 123,500 data samples from female participants. These data samples are collected from individuals who undergo testing continuously for 10 days, with samples collected at various time intervals. This comprehensive data collection approach ensures a rich and diverse dataset for the evaluation and validation of the RCS over an extended period.

Table 3. Computation of RDR for the proposed RCS

Category	**Total samples collected**	**Number of samples classified correctly**	**Respiratory Detection Rate (RDR) in %**
Male case	**132000**	130416	98.8
Female case	**123500**	122018	98.8

The computation of Respiratory Detection Rate (RDR) for the proposed Respiratory Classification System (RCS) demonstrates a remarkable accuracy in both male and female cases. For male cases, out of a total of 132,000 samples collected, the RCS correctly classifies 130,416 samples, yielding an impressive RDR of 98.8%. Similarly, in female cases, where 123,500 samples were collected, the RCS accurately identifies 122,018 samples, resulting in an equivalent 98.8% RDR. These consistent and high RDR values underscore the reliability and effectiveness of the RCS in accurately classifying respiratory patterns across gender-specific datasets. The balanced performance in both male and female cases highlight the system's robustness and suitability for diverse respiratory data sets.

Table 4. Performance analysis using metrics

Metrics	**Experimental results in %**
Sensitivity	98.87
Specificity	98.86
Accuracy	98.87

The experimental results showcase a highly robust performance of the proposed respiratory data classification system, with a sensitivity of 98.87%, specificity of 98.86%, and an overall accuracy of 98.87%. These metrics reflect the system's exceptional ability to correctly identify positive cases (sensitivity) and negative cases (specificity), resulting in an impressive accuracy level. The well-balanced values across sensitivity and specificity indicate the model's effectiveness in both detecting abnormalities and accurately classifying normal cases. The consistently high metrics underscore the reliability and accuracy of the proposed classification system, making it a promising tool for respiratory data analysis.

Table 5. Performance comparisons of RCS using different classifiers

Classifier category	**Classifiers**	**Total samples**	**RDR in %**	**Computational time for per sample (ms)**
Deep learning	Proposed improved CNN	254500	98.8	0.24
	Existing LeNet	254500	92.8	0.92
Machine learning	SVM	254500	91.7	1.65
	NN	254500	90.6	1.74
	ANFIS	254500	87.5	1.98

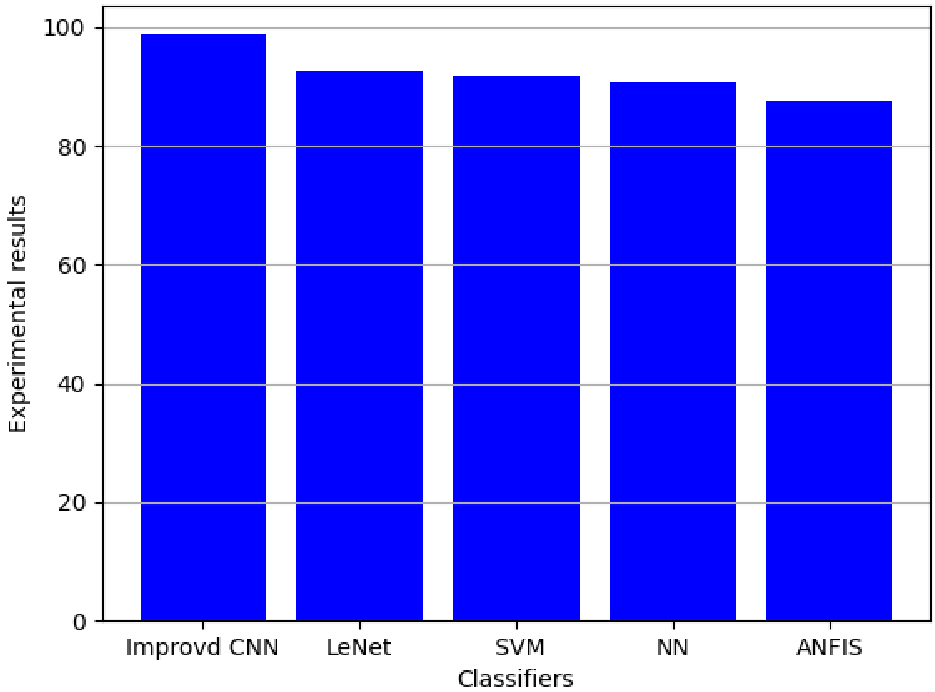

Figure 5. Graphical performance comparisons using different classifiers

In this comparative analysis of classifiers, the proposed Improved CNN stands out as a powerful deep learning model, achieving an impressive 98.8% Respiratory Detection Rate (RDR) with a remarkably low computational time of 0.24 ms per sample. In contrast, the existing LeNet, another deep learning model, demonstrates a lower RDR of 92.8% with a comparatively higher computational time of 0.92 ms per sample. Among the machine learning classifiers, Support Vector Machine (SVM) leads with a respectable 91.7% RDR, while Neural Network (NN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) achieve RDRs of 90.6% and 87.5%, respectively, with varying computational times ranging from 1.65 to 1.98 ms per sample. The proposed Improved CNN emerges as an efficient and accurate choice for respiratory data classification with notable advantages in both RDR and computational efficiency.

5. CONCLUSION

In this Automatic Respiratory Data Classification System utilizing an Improved Convolutional Neural Network (CNN) classification algorithm applied to real-time clinical data. The Respiratory Classification System (RCS) demonstrates robust performance, accurately identifying 392 out of 400 normal male data with a commendable 98% Normal Respiratory Detection Rate (NRDR). Similarly, for normal female data, the RCS correctly detects 285 instances out of 300, resulting in a 95% NRDR. In the case of abnormal respiratory data, the RCS achieves high accuracy, detecting 145 out of 150 abnormal male data (96.67% NRDR) and 168 out of 175 abnormal female data (96% NRDR). The comprehensive evaluation involves a substantial dataset, including 130,416 male case samples acquired at different time intervals from a total of 132,000 samples, achieving an impressive 98.8% Respiratory Detection Rate (RDR). Additionally, 122,018 female case samples, obtained from various time intervals out of 123,500 samples, also attain a notable 98.8% RDR. Consequently, the mean RDR across both male and female datasets is approximately 98.8%. The proposed Improved CNN deep learning algorithm attains the remarkable RDR of 98.8% with a computational time of 0.24 ms. Looking ahead, the future direction of this research involves storing and processing acquired respiratory data, along with diagnosing classified respiratory data, in a public cloud with a heightened level of security using Internet of Things (IoT) techniques.

Conflicts of Interest

The authors declare no conflict of interest.

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