IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, September 2026
Impact Factor: 8.2

A Survey On Deep Learning Based Asthma Detection Using Voice Signals

Dhruva A S[1], Anil[2], Lakshmi Priya G[3], Prof. Rachana D S[4]
Computer Science & Engineering
HKBK College of Engineering, Bangalore, India
1hk23cs043@hkbk.edu.in, 1hk23cs017@hkbk.edu.in, rachana.cs@hkbk.edu.in, 1hk23cs066@hkbk.edu.in

Abstract: *Asthma is a chronic respiratory disease affecting millions of people worldwide, characterized by inflammation and narrowing of the airways. Early detection and continuous monitoring are essential to prevent severe complications and improve patient outcomes. Traditional diagnostic techniques such as spirometry and pulmonary function tests require specialized equipment and trained professionals, making them less accessible in remote and resource-limited areas. With advancements in Artificial Intelligence (AI) and Deep Learning, voice-based diagnostic systems have emerged as a promising, noninvasive, and cost-effective alternative. This survey explores existing research on asthma detection using voice signals, cough sounds, and respiratory patterns. It highlights the role of digital signal processing, machine learning, and deep learning techniques such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and hybrid models. The paper analyzes various datasets, methodologies, challenges, and performance metrics used in current studies. Furthermore, it proposes an integrated deep learning-based framework for accurate and real-time asthma detection using voice signals. This system aims to enhance telemedicine, enable early diagnosis, and improve accessibility to healthcare. The proposed approach contributes to the advancement of intelligent healthcare solutions and supports the development of smart, AI-driven medical diagnostic systems*

Keywords: *Asthma Detection, Deep Learning, Voice Signals,* Artificial Intelligence, Respiratory Sound Analysis, CNN, LSTM, Digital Signal Processing, Healthcare Analytics, Telemedicine

I. INTRODUCTION

Asthma is a chronic respiratory disorder that affects over 300 million individuals globally. It is characterized by airway inflammation, wheezing, coughing, chest tightness, and shortness of breath. According to the World Health Organization (WHO), asthma is a significant public health concern, particularly in developing countries where access to healthcare facilities is limited. Early detection and continuous monitoring are essential for effective disease management and reduction of mortality rates.

Traditional diagnostic methods such as spirometry, peak flow measurement, and pulmonary function tests are accurate but require expensive medical equipment and trained professionals. These constraints limit their accessibility, especially in rural and underdeveloped regions. Consequently, there is a growing need for noninvasive, cost-effective, and easily accessible diagnostic solutions.

Recent advancements in Artificial Intelligence (AI) and Deep Learning have revolutionized the healthcare sector by enabling automated disease detection and diagnosis. Voice and respiratory sounds, including coughs, wheezes, and breathing patterns, contain valuable biomarkers that can be analyzed to identify respiratory disorders such as asthma.

With the widespread availability of smartphones and microphones, voice-based asthma detection systems offer a scalable and practical solution for remote healthcare and telemedicine.

DOI: 10.48175/IJARSCT-38234

This survey examines the current state of research in asthma detection using voice signals. It explores various signal processing techniques, machine learning algorithms, and deep learning models employed in the field. Additionally, it proposes a comprehensive framework for a deep learning-based asthma detection system using voice data.
The remainder of the paper is organized as follows: Section II presents the methodology of the survey. Section III reviews existing literature. Section IV describes the proposed system. Section V discusses the analysis and findings. Section VI concludes the paper, and Section VII outlines future research directions.

II. METHODOLOGY OF SURVEY

This survey was conducted to analyze existing research on asthma detection using voice signals and deep learning techniques. The primary objective was to identify advancements, methodologies, challenges, and research gaps in this domain.

A. Data sources

Relevant research papers were collected from:
• IEEE Xplore
• SpringerLink
• ScienceDirect
• Google Scholar
• PubMed
• ACM Digital Library

B. Search Keywords

The following keywords were used:
• "Asthma Detection Using Voice Signals"
• "Respiratory Sound Analysis"
• "Cough Sound Detection"
• "Deep Learning in Healthcare"
• "AI-Based Asthma Diagnosis"
• "Machine Learning for Respiratory Diseases"

C. Inclusion Criteria

• Studies focusing on asthma detection using audio signals.
• Research employing machine learning or deep learning techniques.
• Peer-reviewed journal and conference papers.
• Publications from 2015 to 2025.

D. Exclusion Criteria

• Studies unrelated to respiratory disease detection.
• Non-English publications.
• Research lacking experimental validation.

E. Survey Process

• Identification of relevant research papers.
• Screening based on relevance and quality.
• Comparative analysis of methodologies and results.
• Identification of research gaps and challenges.

IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429 Volume 6, Issue 1, September 2026 Impact Factor: 8.2

• Proposal of an improved deep learning-based framework.

This systematic approach ensured a comprehensive and unbiased review of the literature.

III. LITERATURE REVIEW

Significant research has been conducted on detecting respiratory diseases using artificial intelligence and audio signal processing.

Early studies utilized traditional machine learning algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Decision Trees, and Random Forests to classify respiratory sounds. These approaches relied heavily on handcrafted features such as Mel-Frequency Cepstral Coefficients (MFCCs), Zero Crossing Rate (ZCR), and spectral features.

With advancements in deep learning, Convolutional Neural Networks (CNNs) have been widely adopted for analyzing spectrogram images derived from respiratory sounds.

CNN-based models have demonstrated superior performance in identifying patterns associated with asthma and other respiratory diseases.

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have also been employed to capture temporal dependencies in voice signals. Hybrid CNN-LSTM models further enhance classification accuracy by combining spatial and temporal feature extraction.Several datasets, such as the ICBHI Respiratory Sound Database and the Coswara Dataset, have contributed significantly to research in this field. Despite notable progress, challenges such as limited datasets, environmental noise, and lack of standardization persist.

Historically, asthma diagnosis has relied on clinical evaluations such as spirometry, pulmonary function tests (PFTs), and peak expiratory flow measurements. While these techniques provide reliable results, they require specialized equipment and trained professionals. This dependency limits their accessibility in rural and resource- constrained regions. To overcome these limitations, researchers have explored computer-aided diagnostic systems based on respiratory sound analysis.

Early studies focused on digital signal processing techniques to analyze lung sounds. Features such as Mel-Frequency Cepstral Coefficients (MFCCs), Zero Crossing Rate (ZCR), spectral centroid, and spectral bandwidth were extracted to identify abnormal breathing patterns. These features laid the foundation for automated respiratory disease detection systems.

Table I: Comparison of Existing systems vs proposed system

Reference	Technique	Disease Detection	Limitations
[1]	SVM	Asthma	Limited accuracy
[2]	Random Forest	Respiratory Diseases	Feature Dependency
[3]	CNN	Asthma	Requires large datasets
[4]	LSTM	Wheeze Detection	High computation cost
[5]	CNN-LSTM	Asthma	Complex Architecture
Proposed System	Deep Learning	Asthma	Improved Accuracy

To better understand the evolution of asthma detection techniques using voice signals, a comparative analysis of existing systems is presented. This comparison evaluates various approaches based on methodologies, feature extraction techniques, performance, and limitations. It highlights the transition from traditional machine learning models to advanced deep learning architectures.

1. Traditional Machine Learning-Based Systems:Early research in respiratory disease detection relied heavily on classical machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, and Random Forests. These methods required manual extraction of acoustic features such as MFCCs and spectral parameters. Pramono et al. (2019): Demonstrated that cough sound analysis can be used to detect respiratory diseases using SVM classifiers. While effective for smaller datasets, the approach lacked scalability and deep feature learning capabilities. Rocha et al. (2019):

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, September 2026
Impact Factor: 8.2

Provided a standardized respiratory sound database that enabled the evaluation of machine learning algorithms. However, the system depended on handcrafted features, limiting its performance. Key Insight: Traditional methods are computationally efficient but rely heavily on manual feature engineering, which restricts accuracy and adaptability.

2. Deep Learning-Based Systems:The introduction of deep learning revolutionized respiratory disease detection by enabling automated feature extraction and improved classification accuracy.

ICBHI Challenge (2017): Encouraged the use of Convolutional Neural Networks (CNNs) for classifying respiratory sounds. CNNs demonstrated superior performance in detecting wheezes and crackles.

Brown et al. (2020): Developed an AI-based screening system using crowdsourced respiratory audio, proving the feasibility of remote diagnosis through digital platforms.

Coswara Project (2020): Initiated by the Indian Institute of Science (IISc), this project provided a valuable dataset of cough, breath, and speech sounds, facilitating research in voice-based disease detection.

IV. PROPOSED SYSTEM

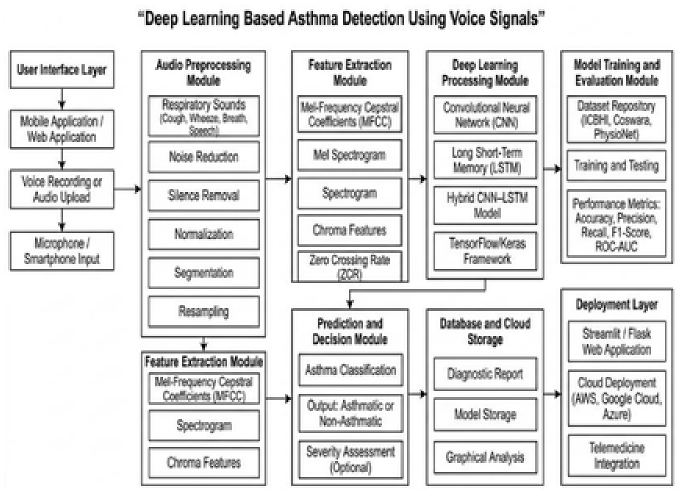

Fig 1 Architecture of a Deep Learning Based Asthma Detection Using Voice Signals.

A. Overview of the System

Given the limitations of traditional asthma diagnostic methods, the proposed system introduces a fully software-based, AI-driven framework for detecting asthma using voice signals. Conventional techniques such as spirometry and pulmonary function tests require specialized equipment and trained professionals, making them less accessible in remote and resource-constrained areas. To address these challenges, the proposed system leverages deep learning and digital signal processing to provide a non-invasive, cost-effective, and real-time diagnostic solution.

The system analyzes respiratory sounds such as cough, wheeze, breathing, and speech patterns to identify potential asthma conditions. By integrating audio processing with deep learning models, the platform enables early detection and continuous monitoring. Unlike conventional methods, the proposed solution is scalable, accessible through smartphones and web applications, and suitable for telemedicine.

The conceptual framework incorporates voice data acquisition, preprocessing, feature extraction, deep learning-based classification, prediction, and feedback mechanisms. The system ensures accurate diagnosis while continuously improving through data-driven learning.

B. Voice Data Input Layer

Before any analysis can take place, the system requires high-quality voice recordings. This layer is responsible for collecting and managing respiratory audio data. Users record or upload respiratory sounds using smartphones, microphones, or web-based applications. The input includes cough sounds, wheezing, breathing patterns, and spoken phrases that contain valuable acoustic biomarkers associated with asthma.

Sources of Data

• Smartphone microphones
• Digital stethoscopes
• Public datasets such as Coswara and ICBHI
• Telemedicine platforms

Therefore, preprocessing is essential to enhance audio quality and ensure accurate analysis.

C. Audio Preprocessing Techniques

• Noise Reduction
• Silence Removal
• Normalization
• Segmentation
• Resampling
• Filtering

After preprocessing, significant features are extracted using digital signal processing techniques.

Extracted Features

• Mel-Frequency Cepstral Coefficients (MFCC)
• Mel Spectrogram
• Spectrogram
• Chroma Features
• Zero Crossing Rate
• Spectral Centroid and Bandwidth

These features capture both frequency and temporal characteristics of respiratory sounds, enabling accurate detection of asthma-related abnormalities.

D. Deep Learning Processing Layer

The deep learning layer forms the core of the proposed system. It automatically learns patterns from audio signals and classifies them to detect asthma.

Models Used

• LongShort-TermMemoryNetworks(LSTM): Capture temporal dependencies in respiratory sounds.
• Convolutional Neural Networks (CNN): Extract spatial features from spectrogram images.
• HybridCNN–LSTMModel: Combines spatial and sequential analysis for improved accuracy.

Functions of the Input Layer

• Voice recording and uploading

Frameworks and Tools

• TensorFlow
• Audio labeling and storage
• Dataset management

ISSN: 2581-9429
Volume 6, Issue 1, September 2026
Impact Factor: 8.2

• Secure cloud storage

This layer serves as the foundation of the system, ensuring that reliable and high-quality data is available for further analysis.

C. Audio Preprocessing and Feature Extraction Layer

Raw audio signals often contain noise, distortions, and inconsistencies that can affect model performance.

• Keras
• PyTorch
• Scikit-learn

The models are trained using labeled datasets and optimized to achieve high accuracy in asthma detection. Continuous learning enables the system to adapt and improve over time.

E. Prediction and Decision Module

Once the features are processed by the deep learning model, the system generates predictions regarding the presence of asthma.

Outputs

• Asthmatic
• Non-Asthmatic
• Severity Level (Mild, Moderate, Severe – Optional)

Performance Metrics

• Accuracy
• Precision
• Recall
• F1-Score
• ROC-AUC

This module ensures reliable and interpretable results that assist users and healthcare professionals in decision-making.

F. Deployment and User Interface

The system is deployed as a web-based or mobile-based healthcare application, enabling accessibility and scalability.
Deployment Platforms

• Streamlit or Flask Web Applications
• Mobile Applications
• Cloud Platforms (AWS, Google Cloud, Azure)

User Interface Features

• Voice recording and uploading

Working Procedure of the Proposed System

• Real-time asthma detection
• Visual reports and analytics
• Secure patient data management

This layer ensures user-friendly interaction and seamless integration with telemedicine services.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429 Volume 6, Issue 1, September 2026 Impact Factor: 8.2

G. Feedback and Continuous Learning Module

To enhance system performance and reliability, a feedback mechanism is incorporated. This module collects user inputs and clinical validation data to refine model predictions.

Key Functions

• Collects feedback from users and healthcare professionals
• Updates datasets for retraining
• Improves prediction accuracy
• Enables continuous model optimization

This iterative learning approach ensures long-term efficiency and adaptability.

H. Components of the Proposed Asthma Detection System

Table: Components of the Proposed System

Module	Description
User Interface	Provides interaction through web and mobile platforms
Voice Data Collection	Captures respiratory sounds such as cough, wheeze, and breath
Audio Preprocessing	Removes noise and prepares audio for analysis
Feature Extraction	Extracts MFCC, spectrogram, and other acoustic features
Deep Learning Module	Uses CNN, LSTM, and hybrid CNN-LSTM models
Prediction Module	Classifies asthma presence and severity

• The user records or uploads a voice sample.
• The system preprocesses the audio signal.
• Relevant acoustic features are extracted.
• The deep learning model analyses the features.
• The system predicts the presence of asthma.
• Results are displayed through the user interface.
• Feedback is collected to improve future predictions.

V. ANALYSIS AND DISCUSSION

Analysis shows that numerous tools and technologies exist for diagnosing respiratory diseases, particularly asthma.
This is the most realistic starting point. AI-powered healthcare applications, digital stethoscopes, wearable sensors, and telemedicine platforms have significantly improved disease detection and patient monitoring.
Systems that analyze respiratory sounds, cough patterns, and breathing irregularities using machine learning and deep learning techniques have demonstrated promising results. Individually, most of these solutions perform effectively. Signal processing techniques have improved, classification algorithms have become more accurate, and digital health platforms have enhanced accessibility over the past decade.
However, despite these advancements, early and accurate detection of asthma remains a challenge, particularly in remote and resource-limited regions. This raises an important question: if advanced diagnostic tools already exist, why is asthma still underdiagnosed or misdiagnosed worldwide?
The primary reason is that most existing systems are designed to solve a single aspect of the problem rather than providing an integrated solution. Traditional diagnostic tools such as spirometry offer accurate measurements but require specialized equipment and trained professionals. Machine learning models often rely on handcrafted features, limiting their scalability and adaptability. Similarly, many deep learning-based solutions focus only on classification without incorporating

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, September 2026
Impact Factor: 8.2

real-time data acquisition, preprocessing, deployment, and feedback mechanisms. These fragmented approaches result in inefficiencies, reduced accessibility, and limited real-world applicability.

Another significant limitation is the reliance on manually collected clinical data and predefined rules. While these approaches may perform well under controlled laboratory conditions, they often fail in real-world environments where background noise, variations in recording devices, and patient diversity introduce complexity. As a result, many systems lack robustness, scalability, and adaptability.

The proposed system addresses these challenges by integrating voice data acquisition, preprocessing, feature extraction, deep learning-based classification, and

real-time deployment into a unified framework. Instead of functioning as isolated components, each module operates collaboratively within a continuous and intelligent pipeline. Voice signals are analyzed using advanced digital signal processing techniques, and deep learning models such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks extract meaningful spatial and temporal patterns associated with asthma.

VI. CONCLUSION

The challenge in early and accurate asthma detection lies not in the absence of technology, but in the lack of an integrated and accessible diagnostic system. Although advancements in artificial intelligence, digital signal processing, and deep learning have enabled significant progress in respiratory disease detection, existing approaches often address only isolated aspects of the problem. Traditional diagnostic methods require specialized equipment, while many AI-based systems operate as standalone solutions without real-time adaptability or scalability.

This study reviewed current methodologies and highlighted the need for a unified, non-invasive, and intelligent framework. The proposed system addresses these limitations by integrating voice signal acquisition, preprocessing, feature extraction, and deep learning models into a single cohesive platform. Utilizing advanced architectures such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, the system enables accurate and automated asthma detection using voice signals.

Furthermore, the inclusion of real-time analysis, cloud-based deployment, and a feedback-driven learning mechanism enhances adaptability and reliability. By enabling early diagnosis, remote monitoring, and telemedicine integration, the proposed approach contributes to the advancement of accessible and intelligent healthcare solutions. The effectiveness of the system will be validated through real-world testing, but its design is firmly grounded in identified research gaps, demonstrating its potential to transform respiratory disease diagnostics.

VII. FUTURE WORK

What has been outlined in this study serves as a strong foundation rather than a finished solution, and several areas remain open for further improvement. The predictive capabilities of the proposed system can be enhanced by training deep learning models on larger, more diverse, and clinically validated datasets. Currently, the models rely on available respiratory sound datasets, which, while useful, are limited in scope. Incorporating real-world clinical data, demographic variations, and environmental factors such as air quality, allergens, and weather conditions could significantly improve diagnostic accuracy and robustness.

One of the primary enhancements involves the integration of advanced noise cancellation and audio enhancement techniques. Since voice recordings may be captured in uncontrolled environments, implementing adaptive filtering, spectral subtraction, and deep learning-based denoising methods will improve signal quality and model reliability. These improvements will ensure accurate detection even in noisy real-world scenarios.

Trust and data security are equally important in digital healthcare systems. The integration of blockchain technology can provide a secure and transparent framework for managing patient records and medical data. This would ensure data integrity, privacy, and traceability, fostering trust among patients, healthcare providers, and institutions.

Additionally, explainable artificial intelligence (XAI) techniques can be incorporated to enhance the interpretability and transparency of diagnostic decisions.

Scalabilitypresents another critical area for future research.Asthesystem expands across different regions, variationsinlanguage, accent, age, and recording conditionsmayintroduce complexities. Developing multilingualandaccent-independent models will improve adaptabilityandglobal applicability. Deploying the system oncloud-basedplatforms and optimizing it for edge devicesandsmartphones will further enhance accessibility andreal-timeperformance

REFERENCES

[1] R. X. A. Pramono, S. A. Imtiaz, and E. Rodriguez-Villegas, "Automatic Identification of Respiratory Diseases from Cough Sounds Using Machine Learning Techniques," IEEE Access, vol. 7, pp. 97262–97276, 2019, doi: 10.1109/ACCESS.2019.2930594.

[2] B. M. Rocha, D. Filos, L. Mendes, G. Serbes, S. Ulukaya, I. Kahya, and N. Jakovljevic, "An Open Access Database for the Evaluation of Respiratory Sound Classification Algorithms," Physiological Measurement, vol. 40, no. 3, 2019, doi: 10.1088/1361-6579/ab03ea.

[3] G. Perna et al., "The INTERSPEECH 2017 Computational Paralinguistics Challenge: Respiratory Sound Classification," in Proc. INTERSPEECH, Stockholm, Sweden, 2017, pp. 3462–3466, doi: 10.21437/Interspeech.2017-43.

[4] A. Imran, I. Posokhova, H. N. Qureshi, U. Masood, M. S. Riaz, K. Ali, C. Nabeel, and I. Hussain, "AI4COVID-19: AI Enabled Preliminary Diagnosis for COVID-19 from Cough Samples," in Proc. IEEE Int. Conf. Engineering in Medicine and Biology Society (EMBC), 2020, pp. 1–5, doi: 10.1109/EMBC44109.2020.9175875.

[5]C. Brown, J. Chauhan, A. Grammenos, J. Han, A. Hasthanasombat, D. Spathis, T. Xia, P. Cicuta, and C. Mascolo, "Exploring Automatic Diagnosis of COVID-19 from Crowdsourced Respiratory Sound Data," Scientific Reports, vol. 10, no. 1, 2020, doi: 10.1038/s41598-020-73163-0.

[6] N. Sharma and P. Ghosh, "Deep Learning-Based Respiratory Sound Analysis for Detection of Chronic Respiratory Diseases," IEEE Reviews in Engineering, vol. 15, pp. 114–129, 2022, doi:Biomedical 10.1109/RBME.2021.3094481.

[7] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," in Proc. Advances in Neural Information Processing Systems (NIPS), Lake Tahoe, NV, USA, 2012, pp. 1097–1105, doi: 10.1145/3065386.

[8] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 2016, pp. 770–778, doi: 10.1109/CVPR.2016.90.

[9] A. Vaswani et al., "Attention Is All You Need," in Proc. Advances in Neural Information Processing Systems (NeurIPS), Long Beach, CA, USA, 2017, pp. 5998–6008, doi: 10.48550/arXiv.1706.03762.

[10] S. Orlandic, T. Teijeiro, and D. Atienza, "The COUGHVID Crowdsourcing Dataset: A Corpus for the Study of Large-Scale Cough Analysis Algorithms," Scientific Data, vol. 8, no. 156, 2021, doi: 10.1038/s41597-021-00937-4.

[11] A. Sharma, P. Krishnan, R. Kumar, and S. R. M. Prasanna, "Coswara: A Database of Breathing, Cough, and Voice Sounds for COVID-19 Diagnosis," in Proc. INTERSPEECH, Brno, Czech Republic, 2020, pp. 4811–4815, doi: 10.21437/Interspeech.2020-2768.

[12] World Health Organization, "Asthma Fact Sheets," Geneva, Switzerland, 2023. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/asthma

[13] P. Forgacs, "Lung Sounds," British Medical Journal, vol. 2, no. 5770, pp. 1351–1358, 1971, doi: 10.1136/bmj.2.5770.1351.

[14]D. Bahoura, "Pattern Recognition Methods Applied to Respiratory Sounds Classification into Normal and Wheeze Classes," Computers in Biology and Medicine, vol. 39, no. 9, pp. 824–843, 2009, doi: 10.1016/j.compbiomed.2009.06.005.

[15] T. N. Quatieri, Discrete-Time Speech Signal Processing: Principles and Practice. Upper Saddle River, NJ, USA: Prentice Hall, 2002