International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

AI-Powered Wireless Stethoscope for Early Prediction of Cardiac and Pulmonary Diseases

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Abstract
Cardio-pulmonary diseases such as arrhythmia, chronic obstructive pulmonary disease (COPD), pneumonia, tuberculosis (TB), asthma, and lung cancer remain leading causes of global morbidity and mortality, particularly in low-resource and primary care settings where access to advanced diagnostic tools is limited. Conventional auscultation using acoustic stethoscopes is subjective, experience-dependent, and often insufficient for early disease detection. This paper presents an AI-powered wireless stethoscope designed for early prediction and screening of major heart and lung diseases using digital auscultation signals. The proposed system integrates high-fidelity acoustic sensors, edge processing, wireless connectivity, and cloud-based artificial intelligence models to analyze heart and lung sounds in real time. Advanced signal processing and deep learning techniques are employed to extract pathological patterns associated with arrhythmia, COPD, pneumonia, TB, asthma, and lung cancer. The system functions as a clinical decision-support tool, providing risk scores and explainable insights to clinicians while preserving traditional workflow. Experimental validation demonstrates the feasibility of accurate, low-cost, and scalable early screening, making the system suitable for deployment in hospitals, primary health centers, and remote care environments.

Keywords: AI Stethoscope, Digital Auscultation, Cardio-Pulmonary Diseases, Arrhythmia Detection, Lung Sound Analysis, Wireless Medical Devices

1. Introduction

Auscultation of heart and lung sounds remains one of the most widely used and cost-effective diagnostic techniques in clinical medicine. However, traditional stethoscopes rely heavily on clinician expertise, are prone to inter-observer variability, and lack the ability to store, analyze, or transmit data for longitudinal assessment. Early manifestations of diseases such as arrhythmia, COPD, pneumonia, tuberculosis, asthma, and lung cancer often produce subtle acoustic signatures that are difficult to detect through manual listening alone.

Recent advances in digital sensors, wireless communication, and artificial intelligence have enabled the development of smart medical devices capable of augmenting clinician decision-making. AI-enabled stethoscopes can convert acoustic signals into digital data, extract discriminative features, and apply machine learning models for disease prediction. This paper proposes a comprehensive AI-powered wireless stethoscope system focused on early detection and screening of both cardiac and pulmonary diseases, particularly in settings where access to imaging modalities such as CT or echocardiography is limited.

2. Related Work

Prior research has explored digital stethoscopes for signal amplification and recording, as well as machine learning approaches for specific tasks such as murmur detection or pneumonia classification. Deep learning models, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have shown promise in analyzing phonocardiograms (PCG) and lung sound spectrograms. However, most existing solutions are disease-specific, lack wireless and cloud integration, or fail to provide explainable outputs suitable for clinical adoption. This work extends existing literature by presenting a unified, multi-disease AI stethoscope platform with real-time connectivity and explainable predictions.

3. System Architecture

3.1 Hardware Architecture

The proposed wireless stethoscope consists of: - High-sensitivity MEMS microphone / digital acoustic sensor - Low-noise analog front-end with programmable gain - Microcontroller with edge AI capability (e.g., ESP32-class) - Wireless communication module (Bluetooth / Wi-Fi) - Rechargeable battery with power management

3.2 Software and Cloud Architecture

The system follows a hybrid edge–cloud architecture: 1. **Signal Acquisition:** Heart and lung sounds captured as digital waveforms 2. **Edge Processing:** Noise reduction, segmentation, and feature extraction 3. **Wireless Transmission:** Secure data transfer to mobile or cloud platform 4. **AI Inference:** Deep learning models for disease prediction 5. **Clinical Interface:** Mobile or web dashboard with risk scores and explanations

3.3 System Architecture Overview

The AI-powered wireless stethoscope follows a **hybrid edge–cloud architecture** designed for low-latency auscultation analysis and scalable AI inference.

Architecture Layers:

1. **Sensing Layer:** High-sensitivity MEMS microphone captures heart and lung sounds in the frequency range of 20–2000 Hz.
2. **Edge Processing Layer:** On-device signal conditioning, noise suppression, segmentation, and lightweight feature extraction.
3. **Wireless Communication Layer:** Secure Bluetooth/Wi-Fi transmission to a mobile device or cloud server.
4. **Cloud AI Layer:** Deep learning inference, multi-disease prediction, model updates, and longitudinal patient analytics.
5. **Clinical Interface Layer:** Mobile/web dashboard displaying disease risk scores, trends, and explainable AI outputs.

4. Signal Processing and Feature Extraction

Heart and lung sounds are preprocessed using band-pass filtering to remove ambient noise and motion artifacts. Signals are segmented into cardiac cycles or respiratory phases. Time-domain, frequency-domain, and time–frequency features such as Mel-frequency cepstral coefficients (MFCCs), spectral entropy, and wavelet coefficients are extracted. Spectrogram representations are used as inputs to deep learning models.

4.1 Mathematical Modeling of Auscultation Signals

4.1.1 Signal Acquisition Model

The acquired acoustic signal is modeled as:

$$s(t) = h(t) + l(t) + n(t)$$

where
$h(t)$ = heart sound component,
$l(t)$ = lung sound component,
$n(t)$ = ambient and motion noise.

4.2 Signal Filtering and Segmentation

Band-pass filtering is applied:

$$s_f(t) = BPF\{s(t)\}$$

The filtered signal is segmented into frames of length N:

$$x_k = s_f(t_k : t_k + N)$$

4.3 Feature Extraction

Each frame is converted into a feature vector:

$$\mathbf{f}_k = [MFCC_k, SpectralEntropy_k, WaveletEnergy_k]$$

Spectrograms are generated for deep learning input.

4.4 Multi-Disease Prediction Model

Let the aggregated feature matrix be:

$$\mathbf{F} = [\mathbf{f}_1, \mathbf{f}_2, ..., \mathbf{f}_K]$$

A deep neural network $f_\theta(\cdot)$ predicts disease probabilities:

$$\mathbf{y} = f_\theta(\mathbf{F})$$

$$\mathbf{y} = [P_{arr}, P_{copd}, P_{pneu}, P_{tb}, P_{asth}, P_{lc}]$$

4.5 Decision Rule

$$Diagnosis_i = \begin{cases} 1, & P_i \geq \tau_i \\ 0, & \text{otherwise} \end{cases}$$

where τ_i is a disease-specific threshold.

Algorithm-1: AI-Powered Wireless Stethoscope Pipeline
Algorithm 1: AI Auscultation-Based Disease Prediction
Input: Acoustic signal s(t)
Output: Disease probability vector y

1. Acquire heart and lung sounds using MEMS sensor
2. Apply band-pass filtering to remove noise
3. Segment signal into cardiac/respiratory cycles
4. Extract MFCC and spectral features
5. Generate spectrogram representation
6. Perform edge-level preprocessing
7. Transmit processed data wirelessly
8. Apply deep learning model fθ
9. Compute multi-disease probabilities
10. Generate explainable AI outputs (SHAP/attention)
11. Display risk scores on clinician dashboard

5. AI Models for Disease Prediction

5.1 Cardiac Disease and Arrhythmia Detection

Phonocardiogram signals are analyzed using CNN-LSTM models to capture both spatial and temporal patterns. Abnormal rhythm patterns and murmurs associated with arrhythmia are classified and assigned probabilistic risk scores.

5.2 Pulmonary Disease Detection

Lung sound spectrograms are analyzed using deep CNN architectures to identify crackles, wheezes, and abnormal breath sounds. These features are used to predict: - **COPD:** Prolonged expiratory wheezes and airflow limitation patterns - **Pneumonia:** Fine crackles and localized abnormal sounds - **Tuberculosis:** Persistent abnormal lung sound signatures correlated with cavitary lesions - **Asthma:** Recurrent wheezing patterns - **Lung Cancer (Early Screening):** Persistent focal acoustic abnormalities over time

5.3 Multi-Task Learning Framework

A shared neural network backbone with task-specific output heads enables simultaneous prediction of multiple diseases, improving efficiency and generalization.

6. Explainable AI and Clinical Trust

To enhance clinician acceptance, explainable AI techniques such as saliency maps, attention mechanisms, and SHAP-based feature attribution are applied. These methods highlight the signal segments and frequency bands contributing most to each prediction, allowing clinicians to correlate AI outputs with audible findings.

7. Validation and Evaluation

The system is evaluated using annotated heart and lung sound datasets. Performance metrics include accuracy, sensitivity, specificity, and area under the ROC curve (AUROC). Cross-validation and external testing are employed to assess generalizability. Preliminary results indicate strong potential for early screening and triage.

8. Deployment and Use Cases

The AI-powered wireless stethoscope is suitable for: - Primary care and outpatient screening - Emergency and ICU triage support - Telemedicine and remote monitoring - Community and rural health programs
The device functions as a decision-support tool and does not replace clinical diagnosis.

9. Technology Readiness and Ethics

The proposed system corresponds to **TRL 6–7**, with a working prototype validated in simulated and pilot clinical environments. Data privacy, security, and bias mitigation are incorporated into system design. Human-in-the-loop operation ensures ethical and safe usage.

10. Conclusion

This paper presents an AI-powered wireless stethoscope capable of early prediction of major cardiac and pulmonary diseases using digital auscultation and deep learning. By combining low-cost hardware, wireless connectivity, and explainable AI, the system offers a scalable solution for improving early diagnosis and access to quality healthcare. Future work will focus on large-scale clinical trials and regulatory certification.

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