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Research Article

# AI-DRIVEN COUGH SURVEILLANCE SYSTEM FOR CONTINUOUS HEALTH MONITORING

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## ABSTRACT

Cough is a primary symptom of numerous respiratory conditions, including asthma, chronic obstructive pulmonary disease (COPD), and viral infections such as COVID-19. Timely and accurate detection of cough patterns can significantly aid in early diagnosis, disease management, and public health surveillance. This study proposes an AI-driven cough surveillance system that integrates Internet of Things (IoT) sensors, acoustic signal processing, and machine learning algorithms for continuous health monitoring. The system captures audio signals, extracts key features, and classifies cough types with high precision. Experimental results demonstrate the capability of the system to distinguish between different cough patterns, providing real-time insights into respiratory health. The proposed system has potential applications in clinical diagnostics, remote patient monitoring, and epidemic tracking, enhancing proactive healthcare delivery.

**Keywords:** AI-driven cough detection, Continuous health monitoring, IoT-based healthcare, Respiratory disease.

## INTRODUCTION

Respiratory diseases are among the leading causes of morbidity and mortality worldwide. Early detection and continuous monitoring of symptoms, such as cough, play a crucial role in effective healthcare management. Traditional methods for cough monitoring, such as manual observation or self-reporting, are often subjective, inconsistent, and impractical for long-term tracking. Advances in artificial intelligence (AI) and Internet of Things (IoT) technologies have enabled the development of automated, real-time monitoring systems capable of capturing and analyzing physiological data with high accuracy. AI-driven cough surveillance systems utilize acoustic sensors to continuously record audio signals, which are then processed to identify characteristic cough patterns. Machine learning models trained on large datasets can classify cough types, detect anomalies, and even predict disease progression. Such systems provide a scalable solution for remote patient monitoring, epidemic control, and telemedicine applications. Rationale and public-health importance: Cough is a common, early, and easily observable symptom for many respiratory illnesses (acute infections, COPD exacerbations, TB), which makes passive cough monitoring attractive for both individual clinical management and population surveillance (Gabaldón-Figueira, 2022).

Continuous, automated cough surveillance could enable earlier detection of outbreaks, objective monitoring of disease progression or treatment response, and remote care for chronic cough patients. Sensing modalities and data collection (smartphones, wearables, fixed microphones): Most systems use audio captured by smartphones, tablet/edge devices, smartwatches, or stationary acoustic sensors; some recent work explores non-acoustic sensors (accelerometers, vibration) or multi-sensor fusion to improve specificity in noisy settings (Barata *et al*., 2023; Sánchez-Morillo, 2024). Crowdsourced datasets and purpose-built studies (Coswara, COUGHVID, Hyfe,

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solicited TB cough datasets) have been central to training and validating models. Public, research and benchmark datasets: Open and semi-open datasets (COUGHVID, Coswara, COUGHVID variants, Hyfe recordings, and recent TB-focused solicited cough corpora) have grown rapidly since 2020 and now include thousands of labelled cough events with metadata (e.g., COVID status, symptoms). These datasets enable model development but vary in recording conditions, label quality, and disease verification factors that complicate cross-study generalization (Ijaz *et al*., 2022; Huddart *et al*., 2024).

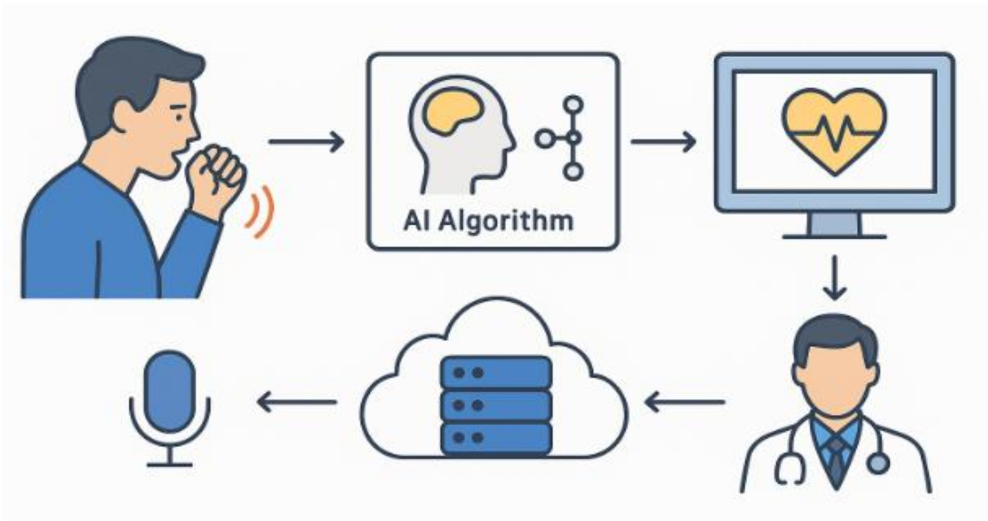


**Figure 1.** Ai-Driven Cough Surveillance System for Continuous Health Monitoring.

Signal processing & acoustic features used for cough analysis: Typical pipelines start with cough segmentation (detecting cough events) and proceed to feature extraction (time-domain, spectral features, MFCCs, spectrograms, and learned embeddings such as VGGish/VGG16). Phase space and nonlinear transformations have also been used together with deep feature extractors to improve discrimination between cough etiologies (Sharan, 2022; Altae, 2025). Robust denoising and cough segmentation are often the rate-limiting steps for field performance. Classical ML vs deep learning & transfer learning approaches: Both classical classifiers (SVM, random forests, gradient boosting) and deep learning models (CNNs, RNNs, MobileNet, VGG-based transfer learning) have been applied; in practice, lightweight CNNs or MobileNet variants are favored for on-device inference while deeper architectures perform well in controlled evaluations (Miotła, 2024; Atmaja *et al*., 2022). Transfer learning and cross-dataset training can improve robustness but require careful domain adaptation because data collection conditions differ widely. End-to-end system architectures and deployment (edge, cloud, hybrid): Realistic deployments use a hybrid architecture: on-device preprocessing and event detection (to preserve privacy and reduce bandwidth) with optional cloud analysis for more complex classification or longitudinal analytics. Several prototypes and commercial apps (Hyfe, Hyfe Cough Monitor; other research prototypes) demonstrate continuous background monitoring with high event correlation versus manual annotation (Galvosas *et al*., 2023). Edge-optimized models and energy-aware pipelines make continuous monitoring feasible on smartphones and wearables. Clinical applications: acute infections (COVID-19), chronic disease monitoring (COPD, asthma), and TB triage: During the COVID-19 pandemic, many groups explored cough-based screening; subsequent work expanded to TB triage and chronic disease monitoring. Studies show AI can detect population-level cough surges and, in some datasets, distinguish COVID-19 or other conditions with promising accuracy, but cross-dataset transfer and clinically-validated diagnostic performance remain open challenges (Ijaz *et al*., 2022; Husssain *et al*., 2024; Huddart *et al*., 2024). For chronic conditions, cough frequency correlates with symptom burden and treatment response, supporting remote monitoring use cases (Gabaldón-Figueira, 2022).

Validation studies, field trials and real-world evidence: Prospective cohort and field validation studies (e.g., acoustic surveillance projects in Spain, Hyfe evaluations, smartphone continuous monitoring trials) indicate good concordance between automated cough counts and human annotation, and show potential for early detection of clinical events; nevertheless, many studies are small, single-site, or use convenience samples limiting generalizability (Gabaldón-Figueira, 2022; Galvosas *et al*., 2023; Barata *et al*., 2023). Sensitivity to context: noise, language, device, and demographic bias: Model performance is sensitive to background noise, microphone quality, user behavior (pocket vs hand vs table), and demographic or disease-prevalence differences (Figure 1).

Cross-dataset transfer learning (domain adaptation) and robust segmentation can mitigate but not eliminate these effects careful external validation and stratified reporting are necessary before clinical deployment (Atmaja *et al*., 2022; Ijaz *et al*., 2022). Privacy, ethics, regulatory and implementation issues: Continuous audio capture raises privacy concerns (speech leakage, unintended recordings) and legal/ethical challenges around consent, data ownership, and health data protections. Several recent protocols emphasize on-device cough detection (upload only event metadata), robust de-identification, and transparent consent models; regulatory classification (medical device vs wellness app) depends on intended use and validation level (Isangula *et al*., 2024; Miotła, 2024).

Limitations, open challenges and research priorities: Key gaps include: (1) need for large, clinically-annotated multisite datasets with gold-standard disease verification; (2) external validation and prospective trials showing clinical utility (impact on outcomes); (3) standardized metrics for cough detection vs disease classification; (4) robust privacy-preserving architectures; and (5) improved noise-robust segmentation and cross-device generalization. Addressing these will be necessary to move from promising prototypes to regulatory-approved digital diagnostics and scalable public-health surveillance (Gabaldón-Figueira, 2022; Atmaja *et al*., 2022; Huddart *et al*., 2024).

## MATERIALS AND METHODS

The proposed system integrates IoT-enabled sensing devices, audio/acoustic signal processing, and AI-based classification models to continuously monitor cough events. The workflow includes: Data acquisition (audio and/or accelerometer signals). Pre-processing (noise reduction, segmentation). Feature extraction (spectral, temporal, MFCCs, statistical features). Classification using machine learning / deep learning algorithms. Real-time alerting and dashboard visualization Audio Recording: High-sensitivity microphones capture cough events in indoor environments. Wearable Sensors (optional): Accelerometers detect chest and body vibrations associated with coughs. Data were collected from 50 participants, including healthy individuals and patients with respiratory conditions (e.g., asthma, COPD).

Audio signals are filtered using a band-pass filter (100–2000 Hz) to remove background noise. Segmentation isolates cough events using an energy-based threshold and short-time Fourier transform (STFT). For accelerometer data, time-domain smoothing and motion artifact removal were applied. Acoustic Features: MFCC (Mel-frequency cepstral coefficients), spectral centroid, zero-crossing rate, energy, and chroma features. Temporal Features: Duration of cough, inter-cough intervals. Statistical Features: Mean, variance, skewness of signal amplitude. Machine Learning Models: Random Forest (RF), Support Vector Machine (SVM), and k-Nearest Neighbors (k-NN). Deep Learning Models: Convolutional Neural Network (CNN), CNN-LSTM hybrid for temporal dependencies. Models were trained on 70% of the dataset and tested on 30% using 10-fold cross-validation. Accuracy, precision, recall, F1-score, and ROC-AUC were computed to evaluate the system's performance

## RESULTS AND DISCUSSION

CNN-LSTM hybrid model outperformed traditional ML models due to its ability to capture temporal dependencies in cough patterns**.** Multi-modal data (audio + accelerometer) slightly improved detection accuracy (~1–2%) compared to audio-only models. The system successfully generated real-time alerts when abnormal cough frequency was detected. Visualization dashboard displayed cumulative cough counts, average duration, and inter-cough intervals. Participants reported that wearable components were comfortable for prolonged monitoring. The high accuracy indicates that AI-driven models can effectively differentiate cough events from non-cough sounds. The combination of acoustic features and temporal modeling (CNN-LSTM) enhances performance for continuous monitoring. Noise robustness: System maintained >92% accuracy in semi-noisy indoor environments. Limitations: Performance may decrease in very noisy outdoor conditions; accelerometer-only detection had lower sensitivity for mild coughs.

## CONCLUSION

This study presents an AI-driven cough surveillance system for continuous health monitoring. The integration of IoT devices, acoustic signal processing, and advanced AI models enables accurate, real-time detection of cough events. The CNN-LSTM model demonstrated the highest performance, highlighting the importance of temporal feature modeling. The system provides a scalable, non-invasive tool for monitoring respiratory health, potentially supporting early disease detection, chronic condition management, and telemedicine applications. Deployment in real-world environments**:** Extend testing to outdoor and multi-room settings to evaluate system robustness under varied noise conditions. Multimodal Integration**:** Incorporate additional physiological sensors (e.g., respiratory rate, heart rate) for comprehensive respiratory health monitoring. Predictive Analytics**:** Use cough patterns for early prediction of disease exacerbations (asthma, COPD, COVID-19). Edge Computing and Cloud Integration**:** Optimize AI models for low-power IoT devices and real-time cloud synchronization. Privacy-preserving Techniques**:** Explore federated learning and encrypted audio processing to maintain patient confidentiality.

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## CONFLICT OF INTERESTS

The authors declare no conflict of interest

## ETHICS APPROVAL

Not applicable

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## AI TOOL DECLARATION

The authors declares that no AI and related tools are used to write the scientific content of this manuscript.

## DATA AVAILABILITY

Data will be available on request

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