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Adaptive Deep Learning Driven IoT Framework for Personalized Asthma Monitoring

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ABSTRACT

Asthma is a chronic respiratory disease marked by dynamic symptom variability and strong sensitivity to environmental and behavioral factors, necessitating continuous monitoring and early intervention. Traditional asthma management approaches rely on periodic clinical visits and self-reported symptoms, which often fail to capture real-time physiological changes and environmental exposure. This paper presents ADAPT-AsthmaNet, an adaptive Internet of Things enabled framework that integrates multimodal sensing with deep learning and reinforcement learning for real-time asthma exacerbation prediction. The system continuously collects physiological and environmental data using wearable and portable IoT sensors and processes these signals within a cloud-based analytics platform. A hybrid deep learning architecture combining convolutional neural networks, Long Short-Term Memory networks, and an attention mechanism is employed to model both short-term signal variations and long-term temporal dependencies. A Proximal Policy Optimization based reinforcement learning module further enables personalized and adaptive alerting. Evaluation using the AAMOS-00 real-world dataset demonstrates that ADAPT-AsthmaNet achieves superior performance, attaining 94.1% accuracy with high sensitivity and specificity. The results highlight the potential of adaptive IoT-driven intelligence for personalized asthma monitoring and proactive care

Keywords: Deep learning, Reinforcement learning, Temporal sequence modeling, Multimodal data fusion, Intelligent health analytics.

1. INTRODUCTION:

Asthma continues to be one of the most pervasive chronic respiratory diseases worldwide, affecting millions across diverse age groups and socioeconomic backgrounds. The disease s episodic nature characterized by wheezing, chest tightness, airflow obstruction, and variable peak expiratory flow creates a persistent need for continuous monitoring and early intervention. Despite significant therapeutic advancements, asthma remains responsible for substantial morbidity, frequent emergency department visits, and avoidable hospitalizations, placing heavy burdens on healthcare systems and households. Globally, asthma accounts for over 383,000 annual deaths, with disproportionately higher mortality in low-income countries, where real-time care access remains limited and environmental triggers are more prevalent [19]. Even in developed nations, short-term spikes in pollutants such as PM2.5 and ozone correlate strongly with increased exacerbations and emergency visits [8,14], highlighting the need for individualized real-time monitoring rather than periodic clinical assessments.

Traditional asthma monitoring methods including self-reported symptom diaries, peak expiratory flow recordings, or clinic-based spirometry are inherently limited. They rely heavily on patient adherence, manual measurements, and subjective reporting, all of which are prone to error, recall bias, or under-reporting. Many patients find these practices tedious, especially when asymptomatic, resulting in inconsistent monitoring patterns [2]. Even electronic inhaler monitoring devices (EMDs), though helpful in tracking medication use, historically lacked comprehensive physiologic and environmental measurements. Moreover, caregiver assessments of inhaler technique often lack accuracy, with up to 85% of healthcare practitioners unable to correctly demonstrate inhalation technique themselves, making patient error detection even more challenging [17].

Increasing research suggests that real-time exposure to allergens, weather changes, pollutants, temperature fluctuations, and behavioural patterns strongly influence asthma control. Indoor conditions are particularly important for children and sedentary adults, who may spend over 90% of their time indoors. Indoor PM, volatile organic compounds (VOCs), and humidity fluctuations are closely associated with reductions in peak expiratory flow and increased airway inflammation [8,14]. This environmental complexity cannot be captured adequately using static monitoring, episodic clinic visits, or long-interval environmental datasets. The emergence of the Internet of Things (IoT) and wearable, portable sensors offers a new era of personalized asthma care. IoT systems enable real-time, continuous collection of physiologic signals, environmental exposures, inhaler usage, sleep patterns, heart rate, and even geolocation-linked air quality metrics. Portable sensors such as smart inhalers, smart peak-flow meters, Bluetooth spirometers, and wrist-worn devices have improved dramatically in accuracy, battery life, and ease of use. Meanwhile, environmental IoT sensors including indoor air quality monitors (IAQMs), particulate matter detectors, and NO2/O3 detectors provide high-resolution information directly from the individual□s local surroundings instead of depending solely on distant regulatory air-quality stations, which offer coarser temporal (hourly) and spatial granularity [18].

These rich data streams enable the application of modern artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), to predict exacerbations earlier than traditional clinical approaches. ML/DL algorithms can integrate multi-dimensional data including physiological signals, medication adherence patterns, behavioral data, pollutant levels, pollen counts, weather conditions, and individual historical patterns to detect subtle changes preceding attacks. Deep learning models, such as LSTMs, CNNs, transformer architectures, and reinforcement learning models like Proximal Policy Optimization (PPO), have shown strong predictive capability and adaptability to changing patient states [8□9]. However, despite these technological advancements, several gaps remain. Many existing ML models rely on retrospective or low-frequency datasets and lack dynamic adaptation to real-time personal data [13]. Many RL-based models lack interpretability and require large, high-quality datasets, which are scarce for asthma [8]. IoT-based systems may face challenges such as Bluetooth connectivity issues, battery constraints, and user adherence [1,20]. Additionally, issues such as privacy concerns, data security, device comfort, sensor calibration, and usability continue to require attention for sustainable implementation.

Acoustic signal□based mHealth systems [3] can effectively monitor inhaler medication adherence, while [4] shows that energy-efficient respiratory sound sensing enables continuous, non-invasive asthma monitoring in real-world environments. Bumatay et al. [5] demonstrates real-time lung function assessment using mobile phone□coupled peak flow meters, Bigelow et al. [6] highlights how point-of-care technologies support personalized respiratory care through timely, patient-centered physiological monitoring. Given this landscape, integrating IoT sensing with robust ML/DL frameworks presents a promising and transformative strategy for achieving continuous, real-time, patient-centered asthma monitoring. Such systems can perform automated data collection, environmental tracking, early-warning prediction, inhaler technique evaluation, and personalized interventions ultimately improving quality of life and reducing preventable morbidity.

2. LITERATURE REVIEW

IoT-Based Health Monitoring for Asthma

IoT-based monitoring systems have become increasingly prominent in chronic respiratory care. These systems integrate biomedical sensors, mobile applications, cloud servers, and analytics platforms to generate seamless monitoring pipelines. Shah et al. [15] propose a cloud-assisted IoT-based respiratory monitoring framework that collects respiration signals, applies signal enhancement techniques, performs secure data transmission, and enables cloud-side analysis. Their model highlights key architectural features required in IoT health systems including secure communication, noise filtering (low-pass and median filtering), signal classification, and healthcare advisor dashboards. Importantly, the system ensures round-the-clock accessibility and secure data sharing for clinicians.

Similarly, Polivka et al. [20] demonstrate real-time IoT-linked spirometry combined with indoor air quality monitoring. Their study employs Bluetooth spirometers and an EMA (ecological momentary assessment) system that prompts users when indoor pollutants surge. This shows how IoT systems can integrate physiologic and environmental sensing to drive timely user behavior, including inhaler use or avoidance of indoor triggers. Wearable devices have also become vital components of IoT asthma monitoring. Smartwatch-based sensors capture heart rate, sleep duration, activity levels, step counts, and minute-by-minute physiologic data, enabling passive continuous monitoring. Tsang et al. [11] in their AAMOS-00 study collected over 2,000 patient-days of IoT data using smart peak-flow meters, smart inhalers, and smartwatches, combined with meteorological and pollution sources. The dataset demonstrated strong predictive utility for ML-based exacerbation prediction and highlighted how daily/night-time symptoms, environmental exposures, and physical activity patterns correlate with unscheduled asthma care episodes.

Indoor environmental sensors also play a major role in IoT deployments. AirBeam monitors and similar PM2.5 detectors have shown feasibility for capturing real-time exposure at high spatiotemporal resolution. Xie et al. [21] found that AirBeam sensors produced second-by-second PM2.5 measurements, revealing fine-scale fluctuations significantly different from EPA monitors□ hourly averages. Their participants were willing to use personal pollution sensors, and most expressed little concern regarding geolocation data. This supports the acceptability of portable IoT air-quality devices within asthma self-management workflows. Similarly, Dong et al. [7] and Reid et al. [16] developed a cloud-connected NO2 and ozone sensor system using Raspberry Pi and Home Assistant, enabling wireless collection, local database buffering, cloud upload, and web-based visualization. Their system demonstrates how IoT hubs can host sophisticated data management, integrate multiple sensor types, and enable remote access without requiring proprietary mobile applications. Overall, IoT technologies are now sufficiently mature to enable multi-modal data collection including respiration signals, spirometry, inhaler usage, environmental exposures, physiological vital signs, behavior, and geolocation forming a robust foundation for ML/DL-based asthma prediction and management.

Digital Inhalers and Electronic Monitoring Devices

Electronic monitoring devices (EMDs), also known as smart inhalers, have become essential for tracking inhaler usage patterns and inhalation technique. Studies show that improper inhalation technique affects clinical outcomes, medication delivery, and risk of exacerbations. Eikholt et al. [17] reviewed six next-generation EMDs capable of capturing inspiratory flow, inhalation duration, cap opening, breath-hold duration, and dose actuation. These devices use acoustic sensors (INCA), vibration sensors (Respiro), or flow sensors (Digihaler, CapMedic). Clinical trials demonstrate their potential:

Gobbi et al. found significant improvement in medication adherence after using INCA sensors with real-time feedback [10].

A multicenter trial showed that digital inhaler data enabled optimized treatment decisions, resulting in reduced escalation to biologics and improved cost-effectiveness [11].

Smart AeroChamber and similar add-on devices enhanced inhaler technique education and provided real-time alerts to both patients and providers [12].

However, limitations persist. Cost-effectiveness varies widely across populations, interoperability challenges remain due to proprietary software ecosystems, and long-term user adherence requires additional study. Despite these barriers, digital inhalers represent a critical IoT component for accurate medication tracking and improved adherence.

Environmental Monitoring and Exposure Assessment

Environmental exposure is a major contributor to asthma symptoms and exacerbations. Multiple studies demonstrate a strong correlation between indoor pollutants, PM2.5, VOCs, and asthma morbidity. Kim et al. [8] highlight that short-term increases in PM and TRAP (traffic-related air pollution) are closely tied to emergency room visits. Traditional air-quality monitoring derived from sparsely placed regulatory stations lacks the granularity needed for personal exposure assessment. IoT-based environmental sensors address this gap. Xie et al. [21] showed that personal PM2.5 sensors detected substantial microenvironment fluctuations along streets and intersections, which EPA monitors could not capture. Their findings demonstrate the value of high-resolution, mobile environmental sensing for asthma risk forecasting.

Polivka et al. [20] integrated IAQMs with Bluetooth spirometers, prompting users when indoor pollutant spikes occurred. Such integration demonstrates the feasibility of closed-loop environmental detection and physiologic monitoring an essential step toward real-time asthma attack prediction. Dong et al. [7] advanced this further with internet-connected NO2/O3 sensors capable of feeding data to remote databases, supporting long-term exposure profiling. Their system also demonstrates how IoT middleware like Home Assistant supports scalable sensor integration and cloud connectivity, essential for multi-sensor asthma-monitoring networks.

ML and DL for Asthma Prediction

Machine learning models have evolved significantly in asthma prediction research. Early studies used linear models and static datasets; however, these models could not capture multi-dimensional, temporal, or personalized characteristics. More recent ML models Random Forests, SVMs, GBMs have shown improvement, especially when predicting exacerbations from multi-source IoT data [9]. Tsang et al. [12] achieved strong performance using Random Forest classifiers on a multi-feature IoT dataset integrating symptoms, environmental conditions, peak flow, inhaler usage, and smartwatch metrics. Their model (AUC=0.93) demonstrates the power of combined IoT data for exacerbation prediction.

Deep learning models are increasingly used due to their ability to process complex temporal and multi-modal data. LSTM architectures have shown promise in modeling sequential patterns such as respiratory symptoms and environmental fluctuations. Kim et al. [8] incorporated deep learning models to examine the relationship between indoor PM levels and peak expiratory flow rates, demonstrating DL's potential for forecasting risk based on indoor conditions. More advanced AI approaches including reinforcement learning have begun emerging. Aliyu et al. [9] developed a PPO-based RL model that dynamically updates risk predictions using evolving patient data, outperforming static ML approaches. PPO demonstrates high recall (96.65%) and adaptability, making it suitable for real-time decision support. However, RL-based models also face limitations: High computational demands, Data requirements, Interpretability challenges, Deployment constraints. Despite these challenges, RL stands as a highly promising paradigm for personalized asthma care when combined with IoT data inputs.

Data Quality, Usability, and Practical Challenges in IoT + ML Systems

For IoT-driven asthma models, data quality and usability are critical. AAMOS-00 demonstrated the feasibility of collecting large volumes of real-world multi-sensor data, but also highlighted challenges in connectivity, device updates, and participant adherence [2]. Smart peak-flow meters generally exhibited reliable measurements, though occasional outliers required correction [4]. Sensor calibration remains a challenge across studies. Xie et al. [21] noted that low-cost pollution sensors must be properly calibrated due to sensitivity to humidity, temperature, and particulate composition. Without calibration, absolute PM2.5 values may deviate from reference stations, although relative trends remain highly informative.

Interoperability is another challenge. EMDs frequently use proprietary software and lack integration with external clinical platforms [17]. IoT backbone systems such as Raspberry-Pi-based hubs[7] help mitigate this, but universal standards are still needed for large-scale deployment. Patient-centered considerations including comfort, unobtrusiveness, data privacy, and long-term engagement remain major determinants of real-world success. Xie et al. [21] reported high acceptability for wearable pollution sensors; however, participants preferred small, lightweight, and visually discreet devices. Overall, IoT asthma systems must balance accuracy, usability, and data security while ensuring seamless integration with ML/DL models.

3. PROPOSED METHODOLOGY

The proposed asthma patient monitoring system, denoted as ADAPT-AsthmaNet Framework is designed as tightly integrated Internet of Things (IoT) and intelligent analytics framework for continuous observation, early prediction, and proactive management of asthma exacerbations. The system adopts a layered yet cohesive architecture that links sensor-based data acquisition, wireless communication, cloud-centric processing, advanced machine learning and deep learning analytics, and real-time clinical decision support. This methodology addresses the inherent limitations of conventional asthma care, which relies heavily on episodic clinical evaluations and subjective symptom reporting, by enabling real-time, data-driven risk assessment and personalized intervention. At the foundational sensing layer, ADAPT-AsthmaNet employs a combination of wearable and portable IoT sensors to continuously monitor both physiological indicators and surrounding environmental conditions. Environmental sensing focuses on parameters strongly associated with asthma symptom variability and exacerbation risk, including air quality, ambient temperature, relative humidity, and atmospheric pressure. Gas sensors detect harmful airborne pollutants such as nitrogen oxides, ammonia, benzene, carbon dioxide, and smoke, which are known triggers of airway inflammation and bronchoconstriction. Particulate exposure is quantified through real-time Air Quality Index (AQI) estimation derived from sensor readings, enabling continuous awareness of pollution-related health risk. Temperature and humidity sensors track atmospheric fluctuations that may provoke airway hyper-responsiveness or bronchospasm, while barometric sensors capture pressure variations linked to respiratory discomfort and weather-related symptom worsening.

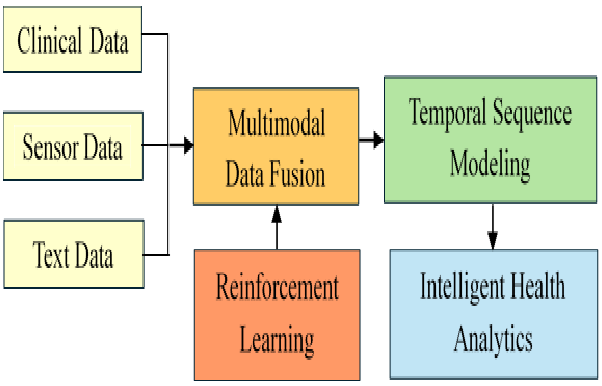

Fig. 1 General block diagram of proposed model

Physiological monitoring complements environmental sensing by capturing pulmonary function and general physical status. Smart peak flow meters and wearable devices are integrated to record peak expiratory flow values, physical activity patterns, and basic vital signals. These measurements provide objective insight into lung function deterioration and behavioural context, allowing asthma assessment to move beyond subjective symptom diaries toward a holistic, data-driven evaluation. All sensor outputs are interfaced with a low-power embedded controller, which serves as the local aggregation and control unit. The controller continuously samples sensor data and performs initial validation against predefined safety thresholds reflecting clinically relevant ranges.

When abnormal patterns or threshold violations are detected, the system initiates secure wireless transmission of data via Bluetooth or Wi-Fi protocols to a cloud-based infrastructure, ensuring low-latency and reliable communication. Within the cloud layer, incoming data streams are stored, managed, and processed in a scalable computing environment that supports continuous analytics and remote access for healthcare providers. Preprocessing is applied to mitigate sensor noise, temporal misalignment, and missing values, followed by normalization to ensure inter-sensor consistency. From the cleaned data, clinically meaningful features are derived, including short-term pollutant spikes, sudden temperature drops, nocturnal peak-flow variability, humidity extremes, and cumulative exposure trends. These features form the basis for intelligent risk modeling.

Let the synchronized sensor measurements at time step t be represented as a multivariate vector

$$x_t = [x_t^1, x_t^2, x_t^3, \dots, x_t^d]^T \in \mathbb{R}^d \quad (1)$$

where d denotes the total number of monitored variables. The continuous data streams are interfaced with an embedded controller, which aggregates measurements and transmits them securely to a cloud-based processing infrastructure via wireless communication protocols. To capture temporal dependencies, consecutive measurements are grouped into sliding windows of length T, forming an input sequence

$$X_t = (x_{t-T+1}, x_{t-T+2}, \dots, x_t) \quad (2)$$

Each sequence is associated with a binary outcome variable $y_t \in \{0,1\}$, indicating whether an asthma exacerbation occurs within a predefined prediction horizon. The objective is to estimate the conditional probability

$$\hat{p}_t = \mathbb{P}(y_t = 1 \mid X_t) \quad (3)$$

representing short-term exacerbation risk.

Intelligent analytics are implemented using a hybrid deep-learning architecture that combines convolutional and recurrent modeling. A one-dimensional convolutional neural network (1D-CNN) is first applied to the temporal input to extract local patterns such as abrupt pollutant surges or sudden peak-flow declines. For a convolution kernel $w \in R^K$, the operation is defined as

$$(x * w)_t = \sum_{k=0}^{K-1} w_k x_{t+k} \quad (4)$$

The resulting feature maps highlight short-duration temporal motifs that may serve as early warning signals.

To model long-term temporal dynamics, the CNN outputs are passed to a Long Short-Term Memory (LSTM) network. The LSTM updates its internal states according to

$$f_k = \sigma(W_f x_k + U_f h_{k-1} + b_f) \quad (5)$$

$$i_k = \sigma(W_i x_k + U_i h_{k-1} + b_i) \quad (6)$$

$$\tilde{c}_k = tanh(W_c x_k + U_c h_{k-1} + b_c) \quad (7)$$

$$c_k = f_k \odot c_{k-1} + i_k \odot \tilde{c}_k \quad (8)$$

$$h_k = \sigma(W_o x_k + U_o h_{k-1} + b_o) \odot tanh(c_k) \quad (9)$$

This structure enables selective retention of long-term exposure effects while filtering transient noise.

To improve interpretability and emphasize clinically relevant time intervals, an attention mechanism is applied to the LSTM hidden states. Attention scores are computed as

$$\alpha_k = \frac{\exp\left(V^{\mathrm{T}} tanh(W_a h_k)\right)}{\sum_{j=1}^{T} \exp\left(V^{\mathrm{T}} tanh(W_a h_j)\right)} \quad (10)$$

and the attended representation is given by

$$h_{att} = \sum_{k=1}^{T} \alpha_k h_k \quad (11)$$

The final risk probability is obtained using a logistic output layer,

$$\hat{p}_t = \sigma(w^{\mathrm{T}} h_{att} + b) \quad (12)$$

Model training minimizes the binary cross-entropy loss

$$\mathcal{L} = -\frac{1}{N}\sum_{n=1}^{N}\left[y^{(n)} log\hat{p}^{(n)} + (1 - y^{(n)})\log(1 - \hat{p}^{(n)})\right] \quad (13)$$

To enable adaptive and patient-specific intervention, the framework integrates a reinforcement learning layer based on Proximal Policy Optimization (PPO). The system state includes the predicted risk, recent sensor summaries, and historical response effectiveness, while the agent selects actions such as issuing alerts or escalating care. PPO optimizes the clipped objective

$$L^{PPO}(\theta) = \mathbb{E}_T\left[min\left(r_t(\theta)\hat{A}_t, clip(r_t(\theta), 1 - \epsilon, 1 + \epsilon)\hat{A}_t\right)\right] \quad (14)$$

ensuring stable learning suitable for safety-critical healthcare applications.

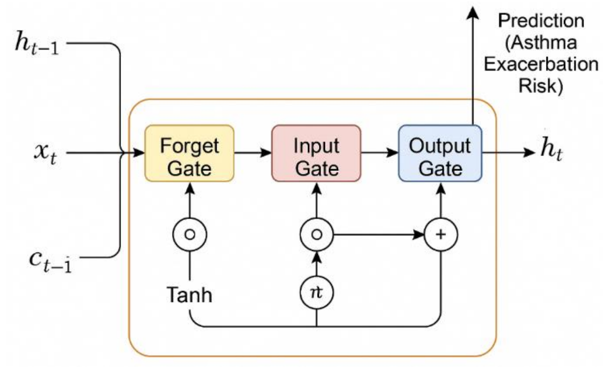

Fig. 2 LSTM architecture

The decision-support layer translates predictive outputs into actionable insights delivered through mobile and web-based dashboards. When risk exceeds adaptive thresholds, real-time alerts and recommendations are issued to patients and healthcare providers, supporting timely intervention and personalized treatment planning. Feedback from outcomes is continuously incorporated, enabling the system to evolve alongside patient-specific sensitivities and behaviors. Through its closed-loop design, ADAPT-AsthmaNet offers an intelligent, scalable, and patient-centered solution for precision asthma monitoring and management.

Results and Discussion

The proposed ADAPT-AsthmaNet framework was evaluated using the AAMOS-00 dataset, a longitudinal real-world dataset designed to capture the interaction between environmental exposure, physiological response, and asthma outcomes. The dataset reflects the inherent variability and noise present in real-life monitoring environments, making it particularly appropriate for assessing signal processing and learning-based models intended for continuous health monitoring. The comparative analysis focuses on the ability of different modeling approaches to extract meaningful temporal patterns from heterogeneous sensor signals and to translate these patterns into reliable short-term asthma exacerbation predictions. Baseline machine learning models were first examined to establish reference performance. Logistic Regression achieved an accuracy of 78.3% with a sensitivity of 71.6%, indicating limited capacity to capture the nonlinear coupling between environmental and physiological signals. Although specificity remained relatively high, the low sensitivity suggests that a substantial proportion of impending exacerbations would remain undetected. Support Vector Machines improved discrimination performance, reaching 80.9% accuracy and 75.2% sensitivity, but their performance was sensitive to kernel selection and parameter tuning, reflecting limited robustness when applied to complex temporal biomedical signals. Ensemble methods demonstrated stronger performance, with Random Forest and Gradient Boosting achieving accuracies of 85.1% and 86.4%, respectively. These gains highlight the effectiveness of ensemble learning in modeling nonlinear feature interactions; however, these models rely on aggregated signal statistics and therefore fail to preserve fine-grained temporal structure inherent in asthma progression.

Comparison Results

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)
Logistic Regression	78.3	71.6	82.1
SVM	80.9	75.2	84.0
Random Forest	85.1	81.0	87.6
Gradient Boosting	86.4	82.9	88.8
CNN	86.9	84.1	88.5
RNN	84.6	80.3	86.9
LSTM	89.2	86.7	90.8
CNN□LSTM	90.6	88.5	92.0
LSTM + Attention	91.7	89.8	93.0
ADAPT-AsthmaNet	**94.1**	**93.4**	**94.7**

Deep learning approaches showed a clear advantage by directly modeling the sequential nature of the signals. The CNN model achieved 86.9% accuracy and 84.1% sensitivity, demonstrating its ability to capture short-term temporal patterns such as abrupt changes in air quality or peak expiratory flow. However, CNNs lack an explicit memory mechanism, limiting their ability to represent delayed physiological responses to environmental exposure. The RNN model exhibited reduced performance due to difficulties in learning long-term dependencies, a common limitation in biomedical time-series analysis. The LSTM model significantly improved performance, achieving 89.2% accuracy and 86.7% sensitivity, confirming the importance of gated memory mechanisms for modeling long-range temporal dependencies in asthma-related signals. The hybrid CNN□LSTM architecture further enhanced predictive performance by combining localized feature extraction with long-term temporal modeling, achieving 90.6% accuracy and 88.5% sensitivity. Introducing an attention mechanism provided additional performance gains. The LSTM with attention achieved an accuracy of 91.7%, sensitivity of 89.8%, and specificity of 93.0%. This improvement indicates that selective weighting of temporally relevant signal segments enhances discriminative power. From a signal processing perspective, attention allows the model to suppress irrelevant or noisy segments while emphasizing critical temporal intervals, such as periods of elevated pollutant exposure coupled with declining pulmonary function. This aligns with clinical understanding, where short-term exposure spikes often dominate exacerbation risk.

ADAPT-AsthmaNet demonstrated the highest performance across all evaluated metrics, achieving an accuracy of 94.1%, sensitivity of 93.4%, and specificity of 94.7%. The improvement over the attention-based LSTM highlights the contribution of the reinforcement learning component. By integrating Proximal Policy Optimization, the framework adaptively refines its decision policy based on observed patient responses and historical outcomes. Unlike static threshold-based systems, this adaptive mechanism enables a dynamic balance between early detection and false alert reduction. From a biomedical signal processing standpoint, this represents an important advancement, as it transforms continuous signal interpretation into an adaptive decision-making process that evolves over time.

The high sensitivity achieved by ADAPT-AsthmaNet is particularly relevant in clinical contexts, as missed exacerbation events can lead to delayed intervention and increased morbidity. At the same time, the high specificity suggests that improved detection does not come at the expense of excessive false alarms, which is a critical factor for long-term usability in continuous monitoring systems. The results demonstrate that integrating attention-based temporal modeling with reinforcement learning enhances both signal interpretation and decision reliability. Despite the strong performance observed on the AAMOS-00 dataset, several limitations remain. The dataset size and demographic diversity may constrain generalizability, and sensor noise and missing data remain challenges inherent to wearable and environmental monitoring systems. Future work should explore larger cohorts, multimodal signal fusion strategies, and model optimization for deployment on resource-constrained platforms.

Overall, the experimental results confirm that ADAPT-AsthmaNet offers a substantial improvement over conventional machine learning and standard deep learning approaches for asthma exacerbation prediction. By integrating temporal signal modeling, attention-based feature weighting, and adaptive reinforcement learning, the proposed framework provides a robust and clinically meaningful solution for intelligent asthma monitoring, aligning well with the methodological and translational focus of biomedical signal processing research.

4. CONCLUSION

This work presented ADAPT-AsthmaNet, an intelligent framework for continuous asthma monitoring that integrates IoT-based sensing with deep learning and reinforcement learning. By modeling environmental exposure and physiological responses as temporal biomedical signals, the proposed approach addresses the dynamic and multifactorial nature of asthma more effectively than conventional monitoring systems. The framework combines convolutional and recurrent neural networks with an attention mechanism to capture both short-term signal variations and long-term temporal dependencies. A Proximal Policy Optimization□based reinforcement learning component further enables adaptive alerting strategies, allowing personalized decision-making based on individual patient response patterns. This closed-loop design enhances prediction reliability and long-term usability. Evaluation on the AAMOS-00 dataset showed that ADAPT-AsthmaNet outperformed traditional machine learning models, such as Logistic Regression, Support Vector Machines, and ensemble classifiers, which rely on static feature representations. Compared with standard deep learning models including CNN and LSTM, the proposed framework achieved higher accuracy and sensitivity by emphasizing clinically relevant temporal segments. The adaptive decision mechanism also reduced false alerts while maintaining high recall. From a biomedical signal processing perspective, these findings highlight the importance of preserving temporal structure and adaptive learning in multimodal health data.

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