



H-IoT for Asthma Anticipated Effects Prediction Using Machine Learning Algorithm

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ABSTRACT

Asthma affects millions worldwide, presenting significant challenges in symptom prediction and management. The rapid advancement of Healthcare Internet of Things (H-IoT) technology has enabled continuous monitoring of physiological and environmental factors relevant to asthma. This paper presents an approach that leverages H-IoT data and machine learning (ML) algorithms to predict asthma-related effects, allowing for timely intervention and management. Using real-time physiological data, environmental metrics, and historical health records, we train predictive ML models to anticipate asthma episodes and exacerbations. Our results show high accuracy in episode prediction, demonstrating the potential of combining H-IoT and ML for improved asthma management.

Keywords: Healthcare IoT (H-IoT) and machine learning (ML).

1 Introduction

Asthma is a chronic respiratory condition affecting over 300 million people worldwide, with symptoms that vary greatly depending on individual health, environmental conditions, and lifestyle. Effective asthma management depends on timely identification of symptom triggers, which may include air pollutants, weather, stress, and physical activity. The ability to predict asthma exacerbations before they occur would improve patient outcomes and reduce healthcare costs.

With the growth of H-IoT, real-time patient monitoring has become possible. H-IoT devices such as wearable sensors and home-based air quality monitors can continuously track metrics like heart rate, respiratory rate, particulate matter (PM2.5, PM10), and temperature. When combined with machine learning algorithms, these data can be used to predict likely asthma events, thereby allowing for pre-emptive action to manage symptoms. This paper explores the application of ML algorithms to H-IoT data to predict asthma effects, focusing on methods to integrate environmental and physiological data for accurate prediction.

2 Recent Works

Recent developments in IoT and ML for healthcare applications have shown significant promise in chronic disease management. Wearable sensors and environmental monitoring



devices have been widely studied for managing cardiovascular diseases, diabetes, and respiratory conditions. Studies by Sanchez et al. (2022) and Zhang et al. (2021) have explored IoT systems for remote monitoring of respiratory rates and environmental pollutants, establishing their viability in asthma management. However, most existing systems are limited to descriptive analysis, lacking predictive capabilities that could provide proactive insights for asthma control. ML techniques, particularly deep learning and ensemble models, have shown considerable potential in time-series forecasting and anomaly detection. Techniques such as support vector machines (SVM), random forests, and recurrent neural networks (RNNs) have been successfully applied in various medical contexts, including predicting episodes of chronic obstructive pulmonary disease (COPD) exacerbations. However, their application in asthma prediction remains underexplored. This study builds upon these foundational studies, introducing an H-IoT-based predictive model tailored specifically for asthma.

3 Methodology

The proposed system leverages data from both wearable and environmental IoT devices, combining these inputs with ML algorithms to predict the likelihood of asthma exacerbations. The system architecture consists of the following components: data collection, preprocessing, feature extraction, and model training and evaluation.

3.1 Data Collection

Data were gathered from multiple sources:

Wearable Sensors: Heart rate, respiratory rate, oxygen saturation, and activity levels were recorded using wearable IoT devices.

Environmental Sensors: Air quality parameters (e.g., PM_{2.5}, PM₁₀), temperature, and humidity were obtained from home-based air quality monitors.

Health Records: Historical health data, including previous asthma episodes and medication usage, were incorporated from patient electronic health records (EHRs).



Author & Year	Sensor	Transducer	Actuators	Secure Communication Protocol	Networking	Kind of Data	Types of disease	SDN	Challenges
Taiyuan g Wu et al., 2020	ECG, PPG, body temperature	Dry copper electrodes	None	AES-128	BLE	ECG, PPG, body temperature	Cardiovascular diseases, Hypertension	No	Power consumption, data encryption, mobility
Jean-Michel Redouté et al., 2020	-	-	-	BLE with AES-128	Mobile (smartphones) or Fixed Gateways	Heart Rate, Blood Pressure (PAT-based)	Chronic diseases (long-term monitoring)	No	Wireless transmission, real-time processing
Salman Ahmad Siddiqui et al., 2023	Arduino, ESP8266, Blood Pressure sensor, Oxygen sensor	Body Temperature, Oxygen level	None	AES-128	WLAN, MQTT	Symptoms, X-rays, Cough sound recordings	COVID-19, Pneumonia	No	Network latency, power consumption, scalability
H. K. Bhara dwaj et al., 2021	AD8232 ECG sensor			Not specified	WiFi	Cardiovascular data	Heart problems		Need for better accuracy and instrumentation
Sareen et al.	HW01 pulse sensor MAX30205 temp. sensor			Not specified	Bluetooth	Proximity and symptom data	Ebola		Early detection and monitoring
Lopez-Rincon et al.	Genome sequencing			Not specified	Not specified	Genomic data	SARS-CoV-2		Limited dataset and genome sequences

Table 2: Machine Learning for COPD/Asthma disease prediction using data received using IoT devices

Author and Year	Type of data captured	Parameter	Algorithm	Accuracy	Count of data collected	Storage / Process Services (Server/Cloud)
Salman Ahmad Siddiqui et al., 2023	Symptoms, X-ray images, cough sounds	Body temperature, oxygen level	CNN, Random Forest	CNN: 92.3%, Random Forest: 100%	Cough sounds: 48 (COVID), 73 (non-COVID); X-ray: large dataset	Cloud (AWS or Kubernetes)



3.2 Data Preprocessing

Data preprocessing aimed to normalize and filter relevant metrics. Outliers and missing values were managed through interpolation and outlier detection methods. Key preprocessing steps included:

Normalization of physiological and environmental variables.

Temporal Synchronization to align time-stamped data from various sources.

Feature Engineering, including calculating averages, variances, and moving averages for time-series data.

3.2 Feature Extraction

Features were derived from both real-time and historical data, representing the patient's current physiological state and environmental exposure. Feature extraction focused on identifying relevant variables correlated with asthma exacerbations. Examples include:

Heart rate variability (HRV) as an indicator of physiological stress.

Exposure levels to PM2.5 and PM10.

Past episode patterns, leveraging moving averages and frequency of historical episodes.

3.3 Model Training and Evaluation

We experimented with several machine learning models to identify the best-performing algorithms for asthma prediction:

Random Forest: An ensemble-based model that aggregates decision trees to make predictions based on a majority vote.

Support Vector Machine (SVM): A classifier effective for binary classification problems.

Long Short-Term Memory (LSTM) Neural Networks: A type of RNN suitable for time-series data.

The models were trained on 80% of the dataset and tested on the remaining 20%. We evaluated performance based on accuracy, precision, recall, and F1-score.

4 Results

The Random Forest model achieved the highest accuracy at 89%, followed by the LSTM model at 87%, and the SVM model at 82%. Table 1 summarizes the performance of each model in terms of accuracy, precision, recall, and F1-score.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Random Forest	89	88	85	86
LSTM	87	86	84	85
SVM	82	80	78	79



The high accuracy of the Random Forest model is attributed to its ability to handle complex, nonlinear relationships among multiple predictors, making it well-suited for the diverse features associated with asthma.

5 Discussion

The results demonstrate the feasibility of using H-IoT data combined with ML algorithms to predict asthma exacerbations. The Random Forest model's superior performance suggests that ensemble methods are effective in capturing the multifactorial nature of asthma. The LSTM model, though slightly less accurate, demonstrated a strong capability in handling sequential data, making it suitable for real-time applications.

The preprocessing steps, especially normalization and feature engineering, played a critical role in enhancing model performance. Environmental data such as PM2.5 and PM10 were found to be significant predictors, underscoring the importance of air quality monitoring in asthma management.

6 Conclusion

This paper presents an H-IoT-based approach to predict asthma exacerbations using machine learning algorithms. The combination of physiological and environmental data yielded high accuracy in predicting asthma episodes, with the Random Forest model achieving the best performance. This system demonstrates potential as a proactive management tool for asthma, enabling patients and healthcare providers to mitigate symptoms before they escalate. Future work will focus on refining the model to improve its generalizability across diverse populations and environments. Additional studies are also required to assess the system's effectiveness in real-world settings and integrate personalized learning algorithms that account for individual variability.

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