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Intelligent air pollution prediction algorithm-based optimized random forest regression for reducing asthmatic attacks

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ABSTRACT

Introduction: Air pollution can trigger the attack in asthmatic patients if uncontrolled. Previous works focused on controlling pollution by proposing algorithms to predict air pollution. While these prediction algorithms save patients from attack triggers, they have limitations such as prediction accuracy, mathematical complexity, and lack of adequate patient notification systems.
Materials and methods: This study proposed a novel Intelligent Air Pollution Prediction (IAPP) algorithm based on optimizing Random Forest Regression (RFR) to predict air pollution and send an alert message to the patient and hospital in real time. Meanwhile, IAPP utilized reliable data from Internet of Things (IoT)-based air pollution detection nodes. The performance of IAPP was evaluated in a real-world environment during the peak pollutant season to test the prediction accuracy of air pollution.
Results: Results showed that the proposed IAPP achieved a high prediction accuracy of 99.98% with an R-squared value of 0.99. This demonstrated that the IAPP algorithm based on the RFR model can effectively protect asthmatic patients from attack triggers.
Conclusion: As a result, the IAPP algorithm reduces hospital visits during high pollution and enables patients to complete their daily activities without obstacles or absence.

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Introduction

In recent years, the monitoring and prediction of air quality have become increasingly critical due to the adverse health effects of air pollution on asthmatic patients, especially in sensitive areas such as schools, universities, and nurseries [1]. According to specific health research and guidelines such as the World Health Organization (WHO) and the Environmental Protection Agency (EPA) standards guidelines on air quality [2], air pollution such as Temperature (T), humidity (H), Air Quality Index (AQI), and Particulate Matter (PM) play as a trigger for asthma exacerbations and lead to attacks [3]. Temperature variations outside the normal range and extremely cold or hot exposure lead to bronchoconstriction and increased asthma symptoms [4]. However, high humidity may encourage mold and dust mite growth, triggering asthma attacks. In addition, higher humidity can encourage mold growth and dust mites, common asthma triggers, while lower humidity can dry airways [5]. In contrast, AQI is a comprehensive indicator of air pollution's potential impact on asthmatic patients [6]. Conversely, PM is one of the most significant air pollutants that can reach deep into the lungs and exacerbate asthma symptoms [7].

Despite the other air pollution parameters, such as Carbon monoxide (CO) [8], Carbon dioxide (CO_2), Nitrogen dioxide (NO_2) [9], and Ozone (O_3), which may also slightly trigger asthma attacks [10]. Previous works focus on how to decrease the effectiveness of air pollution on asthmatic patients by proposing algorithms for predicting air pollution, such as Recurrent Neural Networks (RNN) [7], Support Vector Machines (SVM) [11], Back Propagation (BP) [12], Statistical Analysis Method (SAM) [13, 14], Kalman Filter (KF) with SWM for dynamic information evaluation [15], and Conditional Logistic Regression Models (CLRM) to evaluate risk concerning pollutants exposure [16-18]. In contrast, a related study used ready pollution data from National Ambient Monitoring Stations [19]. In contrast, other works adopted ready-home devices to collect data on pollution. Researchers in a study presented a new cloud platform that detects, analyses, and monitors the vital sign parameters and environmental parameters affecting asthma [11]. The author adopted different models and combinations of classifiers, such as SVM, Decision Trees (DT), and Random Forest Classifiers (RFC) algorithms, to predicate the attack. The results show that the proposed merging algorithms achieved 95.6% prediction accuracy.

In another study, it was provided an artificial neural network primarily based classifier to forecast height calls for days for emergency departments due to respiratory diseases like asthma [12]. The authors adopted the BP algorithm to predict height activities, and it appeared good performance of 8% accuracy in terms of air pollution prediction. Other researchers investigated the air quality that can affect asthma patients indoors based on on-air sensors [13]. They presented a Foobot validation study for measuring the personal indoor environmental measure-based health framework based on SAM. The proposed system revealed that the accuracy of the adopted algorithm-based SAM was 95.7% and can save patients from attack triggers.

On the other hand, researchers aimed to uncover how distinct pollutants affect respiratory health and increase hospital visits. By analyzing admission records, they sought to predict the relationship between pollution levels and the number of patients visiting healthcare facilities [20]. The findings highlighted that quick-term exposure to PM, AQI, and T with H considerably increases the likelihood of hospitalization for allergies. Despite the high performance of previous algorithms in predicting air pollution and reducing the triggers of asthma attacks, several limitations have been identified. These include the complexity of the algorithms, which involve intricate mathematical calculations [19]; the accuracy of predictions, which relies on air quality data from national stations that often have poor spatial and temporal resolution, making it difficult to detect an individual's accurate exposure to pollutants [20]; and the need to implement methods that connect with asthmatic patients to predict spatial air pollution exposure [21].

This work aims to address the gaps identified in previous studies by proposing a novel Intelligent Air Pollution Prediction (IAPP) algorithm to forecast the pollution levels around the asthmatic patient in real-time and spatially by using reliable data of air quality collected from Air Pollution Detection Nodes (APDNs) based on IoT technology. Additionally, it proposed the Air Pollution Index (API) method, which uses an optimized Random Forest Regression (RFR) algorithm to predict the risk level of air pollution. The proposed IAPP algorithm sends smartphone alert SMS messages to save patients from attack triggers.

The contribution of this work can be summarized below:

1. Proposed novel IAPP algorithm to predict pollution in real time and accurately to prevent asthma attacks.

2. In real-time, air quality and pollution levels were accurately monitored and predicted based on APDN through high-performance IoT technology.

3. Proposed new API method using machine learning based on optimized RFR algorithm to predicate the pollution risk and send SMS alerts to attention patients from attack triggers.

4. This work outperforms previous studies regarding prediction accuracy for air pollution, reduces mathematical complexity, and predicts the risk of pollution by sending alert SMS messages to patients.

Materials and methods

This section explains the structure of an air pollution monitoring system based on APDN and IAPP algorithms. In addition, it will discuss how to predicate the risk of pollution using the API and integrate physiological signals for a more integrated predictive model.

Air pollution data collections

An air pollution monitoring system was proposed to assess air quality by strategically placing four APDNs around critical locations such as schools [22], universities, and nurseries [23]. Using a calibrated Scientech 6205A device [24], it integrates IoT sensors designed to monitor air quality such as PM, AQI, T, and H, and is mounted on an APDNs. The air quality data collected by these sensors use to predicting air pollution levels using the proposed novel IAPP algorithms as illustrated in Fig. 1. This IoT-enabled approach ensures reliable, real-time air quality monitoring and a long monitoring distance for air pollution. APDNs is responsible for gathering and processing data from each sensor [25]. The collected air quality data is transmitted wirelessly to a central station powered by a Raspberry Pi processor, which centralizes the data for further analysis and prediction [26].

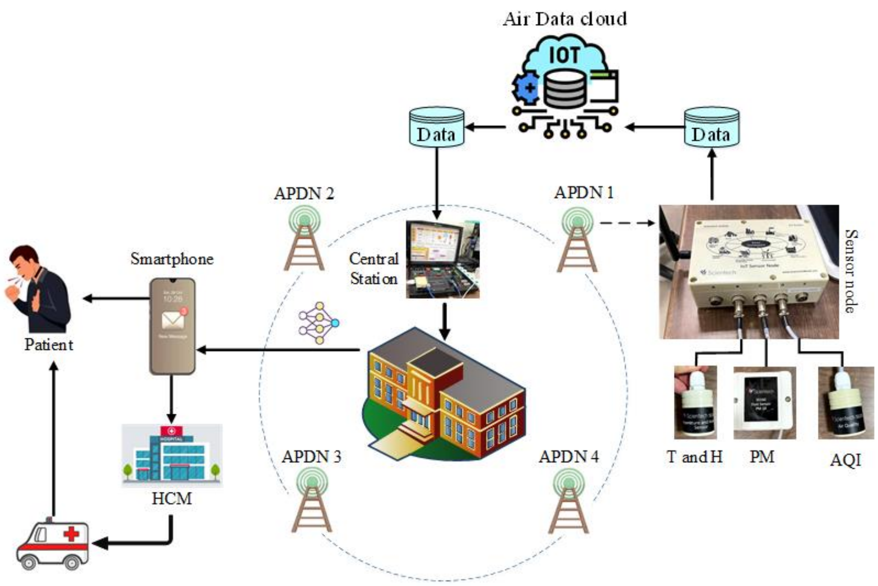

Fig. 1. Proposed air pollution monitoring architecture

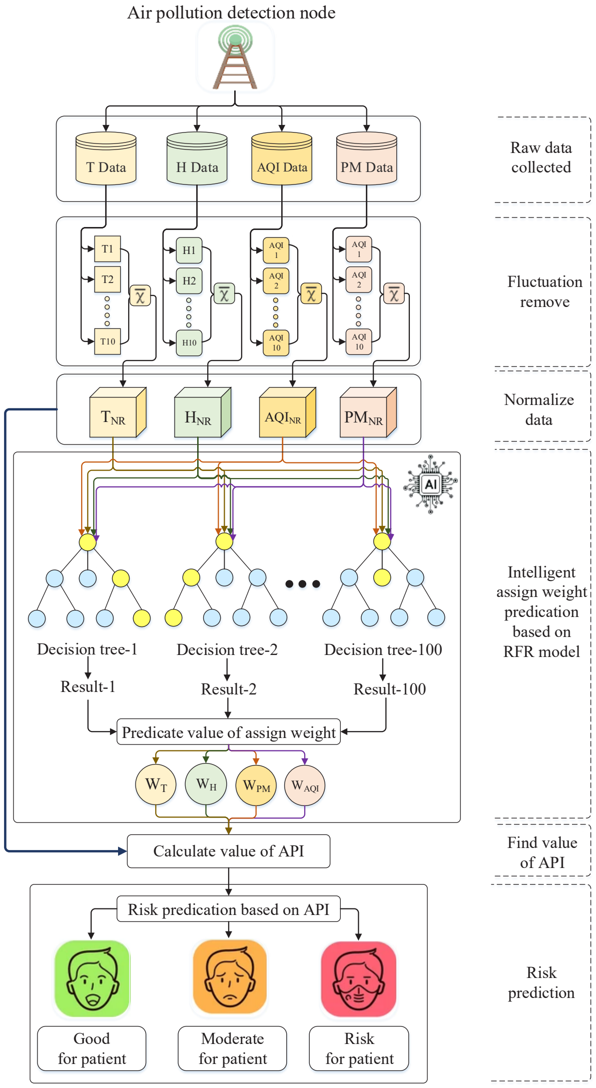

Fig. 2. Proposed IAPP algorithm-based RFR to predicate air pollution

Intelligent air pollution prediction algorithm

In this work, air quality data collected by APDNs is processed using the novel IAPP algorithm to accurately forecast pollution levels in real time. The algorithm filters noise and unstable measurements, then classifies pollution risk and notifying Personal Care Management (PCM) and Health Care Management (HCM) via SMS alerts, as shown in Fig. 2. Steps of IAPP are presented below:

Air quality data collecting

Air quality data was derived from geographically distributed APDNs. These nodes have sensors continuously monitoring environmental parameters. The collected data is transferred to the central station for further analysis and prediction.

Data fluctuaton cancellation method

IAPP algorithm is designed to remove any fluctuations, outliers, or unstable measurements that may have been introduced due to sensor errors, environmental disturbances, or other causes [27]. The average value method was adopted to simplify the data and ensure that only consistent and high-quality data was collected [28], by determined the average value of reading every ten seconds for each APDN measurement separately based on Eqs. 1 to 4 [29].

$$T_{AR} = \frac{\sum_{i=1}^{10} T_i}{10} \tag{1}$$

$$H_{AR} = \frac{\sum_{i=1}^{10} H_i}{10} \tag{2}$$

$$AQI_{AR} = \frac{\sum_{i=1}^{10} AQI_i}{10} \tag{3}$$

$$PM10_{AR} = \frac{\sum_{i=1}^{10} PM_i}{10} \tag{4}$$

Where T_{AR} represents the average T reading, where $\sum_{i=1}^{10} T_i$ is the summation of temperature readings from index i=1 to i=10. Similarly, H_{AR} is the average H reading, calculated as $\sum_{i=1}^{10} H_i$, which sums the humidity readings at each index i. The average AQI is denoted by AQI_{AR}, with $\sum_{i=1}^{10} AQI_i$ summing the AQI readings. Lastly, PM_{10AR} stands for the average PM_{10} reading, where $\sum_{i=1}^{10} PM10_i$ represents the sum of PM_{10} readings.

Air pollution index

API methods were proposed as part of the IAPP algorithm to classify the risk of pollution that triggers the attack. API is involving computing derived from a combination of individual air quality data based on average methods such as T_{AR}, H_{AR}, AQI_{AR}, and PM_{10AR}. This study proposed a novel API equation to evaluate the suitability of weather conditions for asthma patients, as delineated in Eq. 5. The API equation is developed in two steps: normalizing the average air quality data and assigning weights to each parameter based on its impact on the patient's condition.

$$API = T' * W_{T_{NR}} + H' * W_{H_{NR}} + AQI' * W_{AQI_{NR}} + PM10' * W_{PM10_{NR}} \tag{5}$$

The terms T',H',AQI', and PM' denote the normalized values of the air quality data parameters. Where W_{TNR}, W_{HNR}, W_{AQINR}, and W_{PM10NR} represent the weights assigned to normalizing T, H, AQI, and PM_{10}. To determine the normalized values of air quality data, this work adopted equations for normalizing data that can be derived as outlined in Eq. 6 through 9 [30].

$$T' = \frac{T - T_{min}}{T_{max} - T_{min}} \tag{6}$$

$$H' = \frac{H - H_{min}}{H_{max} - H_{min}} \tag{7}$$

$$AQI' = \frac{AQI - AQI_{min}}{AQI_{max} - AQI_{min}} \tag{8}$$

$$PM10' = \frac{PM10 - PM10_{min}}{PM10_{max} - PM10_{min}} \tag{9}$$

Where T_{min} and T_{max} represent the standard minimum and maximum values of T, respectively, which do not trigger asthma attacks in patients. Similarly, H_{min} and H_{max} denote the minimum and maximum H ranges considered safe for patients. AQI_{min} and AQI_{max} refer to the minimum and maximum values of the AQI that are within the safe range for preventing attacks. Additionally, PM_{10min} and PM_{10max} are represents the minimum and maximum values of PM_{10} which patients can remain in the environment without the risk of trigger. Table 1 presents the standard values for healthy and unhealthy air quality parameters specifically for asthma patients, defined by the WHO and EPA [31, 32].

Based on Table 1, the values of HAQ and UAQ can be used to determine the minimum and maximum values of the previous Eqs. 6 through 9. Subsequently, Table 2 presents air quality data's standardized, normalized values [32, 33].

Table 1. Standard values of air quality for asthmatic patients

Air quality data	Standard value of healthy air quality (HAQ)	Standard value of unhealthy air quality (UAQ)
T	20°C to 28°C	20°C > UAQ > 28°C
H	40% to 60%	40% > UAQ > 60%
		51 to 100 (moderates)
AQI	HAQ ≤ 50	101 to 150 (Unhealthy)
		UAQ > 150 (Increasingly harmful)
PM_{10}	HAQ ≤ 50 µg/m³	UAQ > 50 µg/m³

Table 2. Standard values of normalized air quality data

Air quality parameter	Minimum	Maximum
T	20°C	28°C
H	40%	60%
AQI	50	100
PM_{10}	0 µg/m³	50 µg/m³

Regarding weights assigned, this study adopted intelligent machine learning based on the optimized RFR model to assign weights by determining the average air quality data feature. Optimized RFR model used T', H', AQI', and PM_{10} as an input data feature (80% of the data used for training RFR and 20% for testing). Due to a slightly higher impact of the AQI' and PM_{10}' have compared to T' and H', boost factor scores were scaled accordingly: 1.5 for AQI' and PM', 1 for T' and H', as shown in Eq. 10 [34].

$$Adjusted_{F_i} = F_i * b_i \tag{10}$$

where $Adjusted_{Fi}$ is the adjusted normalized air quality data for each input feature i, F_i represented the normalized air quality data for each input feature i, and the b_i is the booster factor, which equals (1.5 for AQI' and PM', 1 for T' and H'). Furthermore, the RFR model adopted 100 trees to determine the weight values accurately W_{TNR}, W_{HNR}, W_{AQINR}, and W_{PM10NR} based on Equs. 11 and 12 [35, 36].

$$Total\_Adjusted_{F_i} = \sum_{i=1}^{4} Adjusted_{F_i} \tag{11}$$

$$W_i = \frac{Adjusted_{F_i}}{Total\_Adjusted_{F_i}} \tag{12}$$

Where W_i is the weight assigned to feature i, and $Total\_Adjusted_{Fi}$ is the sum of all adjusted normalized air quality data features. This approach allows for weight tuning, ensuring that the impact of air quality degradation is proportional to its predictive power [37].

Pollution risk classification

Last step of the IAAP algorithm use to classifies the risk of air pollution and sends alerts to PCM and HCM based on the API index values. This framework improves risk management by stratifying pollution levels, ensuring personalized monitoring and timely interventions. After normalizing air quality data and assigning weights, the API value ranges from 0 to 1. The API-based optimization with the RFR technique classifies pollution risk into three levels:

1. *Suitable for patients:* if the index value of API is less than 0.40, it indicates that the environment is safe and comfortable for asthma patients.

2. *Moderate for patients:* If the index value is ($0.40 \leq API \leq 0.80$), it indicates that some asthma patients may experience minor symptoms or discomfort. In this case, the IAPP sends an urgent SMS alert to the PCM, advising patients to stay indoors and remain safe.

3. *Risky for patients:* if the index value of API is more than 0.66, it signals a high risk for asthma patients. The IAPP sends an emergency SMS to PCM, advising patients to stay in a clean room and monitor symptoms. An alert is also sent to HCM for immediate response.

API's threshold index values can be adjusted based on further empirical data, expert recommendations specific to the population, and environmental conditions [38, 39].

Performance evaluation of IAPP algorithm

To evaluate the proposed IAPP algorithm, the School of Applied Science and Technology at Gujarat Technology University in Ahmedabad, India, was selected for air quality data collection. Ahmedabad's air quality worsens in late October which peaking in winter as cold air traps pollution and prevents it from dispersing. Pollution levels are higher in the morning and at night when winds are weaker. Research indicates high particulate matter concentrations between (7:00 to10:00 AM) and (9:00 to11:00 AM) [40, 41]. As shown in Fig. 3, ADPNs were placed at each corner of the building to monitor T, H, AQI, and PM. The data, collected between 7:00 to 10:00 AM in October, and then transmitted to the central station, stored in an Excel file, and processed using the IAPP algorithm.

Fig. 3. Adopted location to evaluate the proposed IAPP algorithm

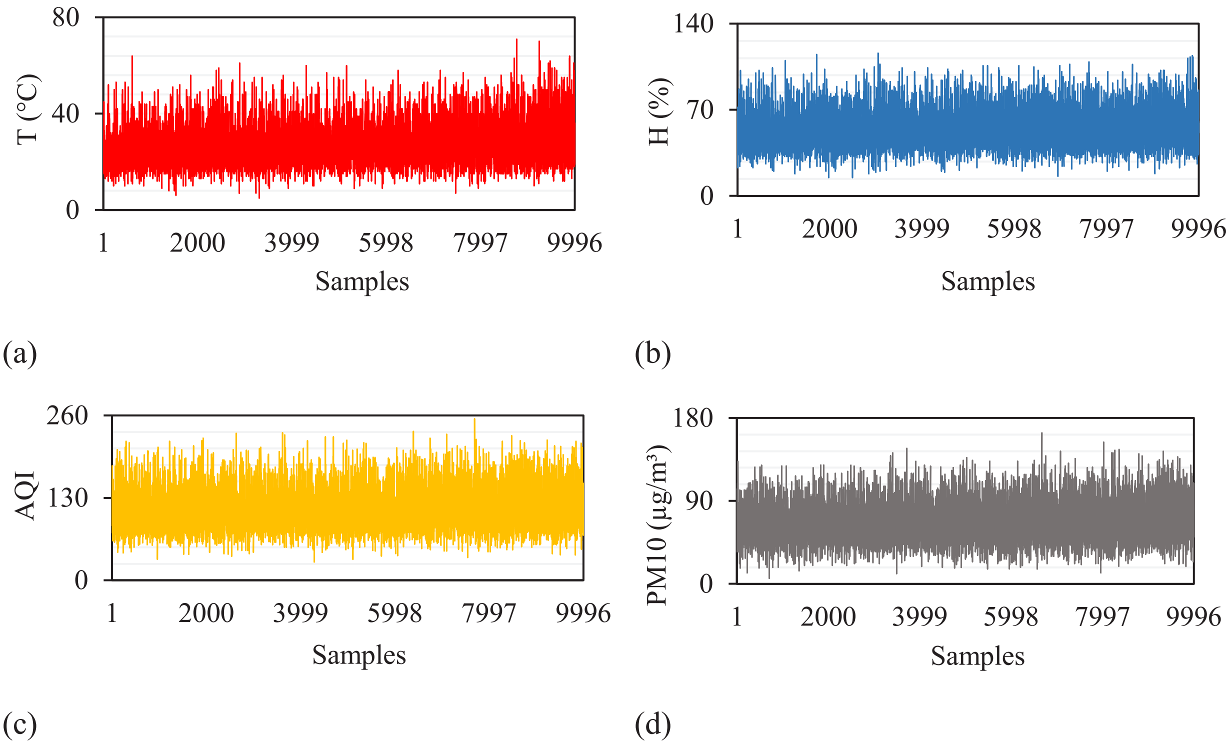

Fig. 4. Raw data of air quality data for (a) T, (b) H, (d) AQI, and (d) PM_{10}

Results and discussion

This section explains the result of the evaluation of the IAPP algorithm and compares the accuracy of the prediction with previous works as follows:

Raw data collecting results

The central station collected 10,000 samples (4 of APDN x 2500 samples) of the raw air quality data from the evaluation experiment of the IAPP algorithm based on APDNs. Fig. 4 presents the collected raw T, H, AQI, and PM10 data separately. The result appeared as the raw data of T, a variant between 5°C as the minimum value and 71°C as the maximum value. In contrast, H raw high and low measured values are 15% to 115%, respectively. On the other hand, the minimum value of AQI is 29, where 225 is the maximum value.

For the same, the values of PM10 are 164 μg/m³ to 6 μg/m³ as high to low detection raw data. As introduced, these collected data have many inaccurate values and need to remove the noises when applying the proposed algorithm.

Data fluctuation remove results

The average sample size was reduced from 10,000 to 1,000 samples for the raw air quality data when applying the average method, which reduced the fluctuation in the collected data. This reduction improved the accuracy of subsequent steps in the IAPP process. The AQD_{AR} results showed that the T_{AR} ranged from 19°C to 35°C, with temperature readings remaining stable and within the expected range despite the smaller sample size. The H_{AR} ranged between 41% and 69%, indicating a more reliable measurement. The AQI_{AR} values ranged from 82 to 143, consistent with the anticipated range based on earlier analyses with larger sample sizes. Additionally, the PM10AR results ranged from 46 to 86 μg/m². These findings demonstrate that the T_{AR}, H_{AR}, AQI_{AR}, and PM_{10AR} data quality and measurement reliability were well-maintained despite the reduction in sample size, highlighting the effectiveness of the filtering techniques, as illustrated in Fig. 5.

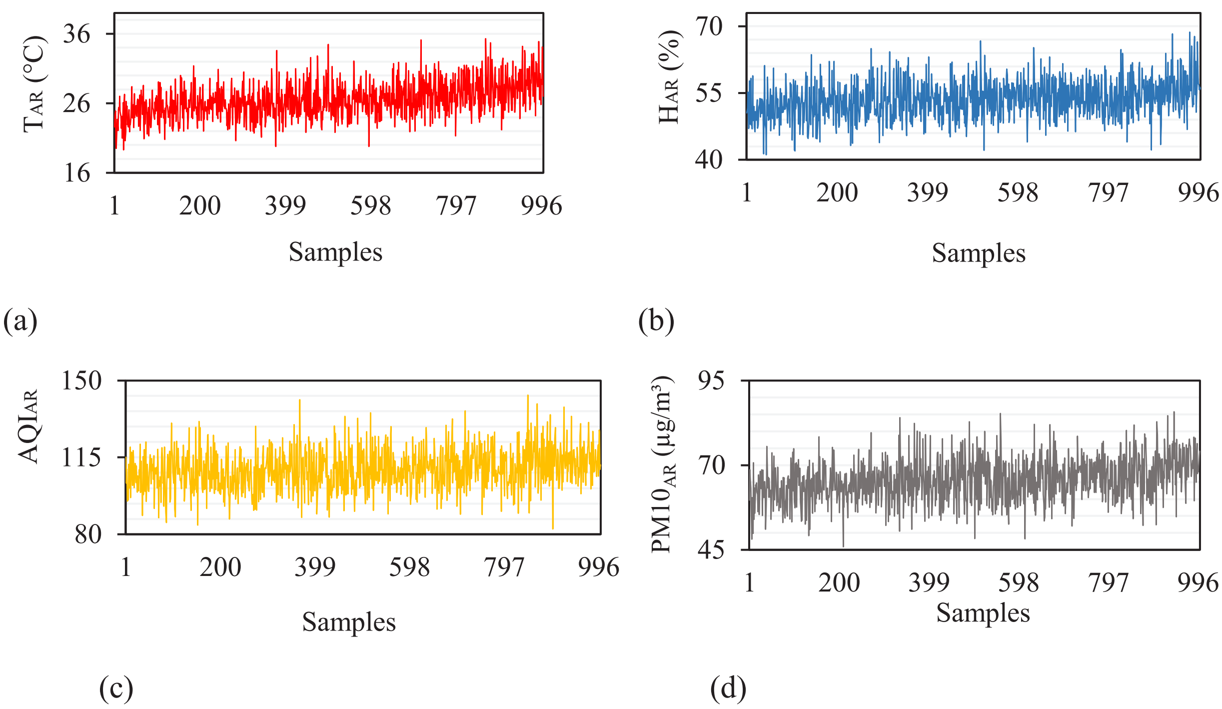

Fig. 5. Air quality data is based on an average method for (a) T, (b) H, (d) AQI, and (d) PM_{10}

Data normalizing results

The normalization of the AQD_{AR} data, such as T_{AR}, H_{AR}, AQI_{AR}, and PM_{10AR}, was executed according to the methodology outlined in Eqs. 6 through 9, as mentioned in chapter three. This process involved standardizing the values of and to a normalized range between 0 and 1, as shown in Fig. 6. The results show that the normalized AQD_{NR} value is 0 to 1 range, according to (Table 2) for T' and H' values closer to 1 are better for asthma patients. Whereas the lower values of AQI' and PM_{10} are more desirable. The normalized values thus provide a clear and comparative assessment of air quality conditions and their potential impact on asthma patients.

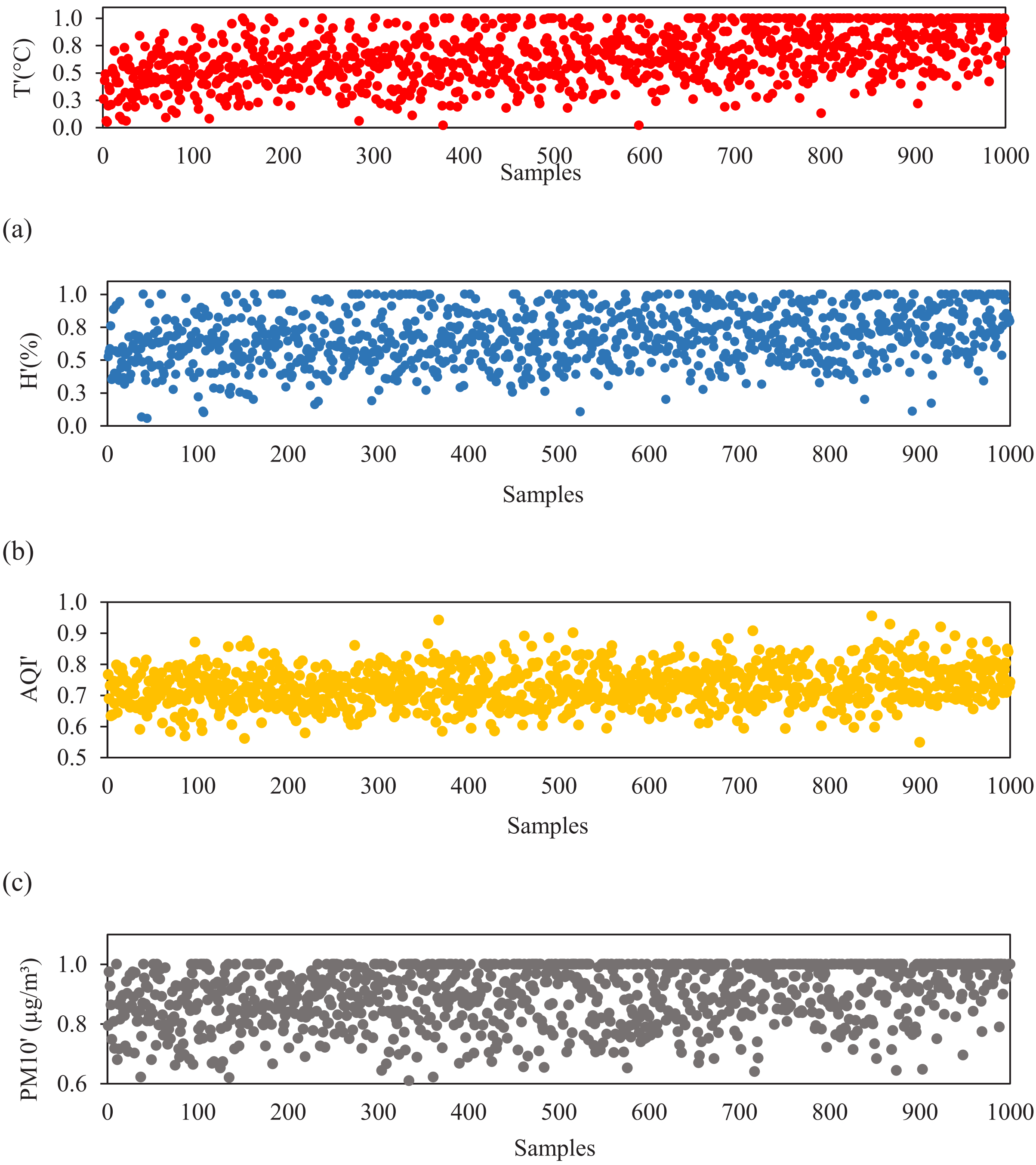

Fig. 6. Normalizing values for AQDNR data such as (a) T, (b) H, (c) AQI, and (d) PM_{10}

Result of assigning weight based on the RFR algorithm

Once the normalizing stage of AQD_{AR} is completed and then extract values of AQD_{NR} are, the proposed IAPP starts calculating the assigned W of the API, which is essential to determine the correct values of W_{TNR}, W_{HNR}, W_{AQINR}, and W_{PM10NR} based on the optimizing RFR method, as shown in Fig. 7. In this study, the optimizing RFR was trained on normalized air quality data, allowing for the evaluation of feature importance to determine their relative contributions to API prediction. After normalization, the results of W_{TNR}, W_{HNR}, W_{AQINR}, and W_{PM10NR} are 0.19, 0.20, 0.36, and 0.26, separately. These weights appeared to the critical roles of AQI_{NR} and PM_{NR} higher than T and H indicating its significant contribution. This analysis highlights the importance of AQI and PM in the API prediction model and provides a basis for further refinement of the prediction framework. Additionally, results concluded that the proposed optimizing RFR performs well in predicting the values of W for input normalized air quality data. Besides, the above results indicate that the optimizing RFR approach effectively forecasts the proper weight values for normalized air quality data, which helps it deal with other environmental factors and problems. Such problems are typical and the method helps the agency to achieve the quality and reliability of the air pollution risk predictions. This strongly indicates that the IAPP algorithm can process real-world data and its potential for real-time application in health risk assessment systems for asthmatic patients.

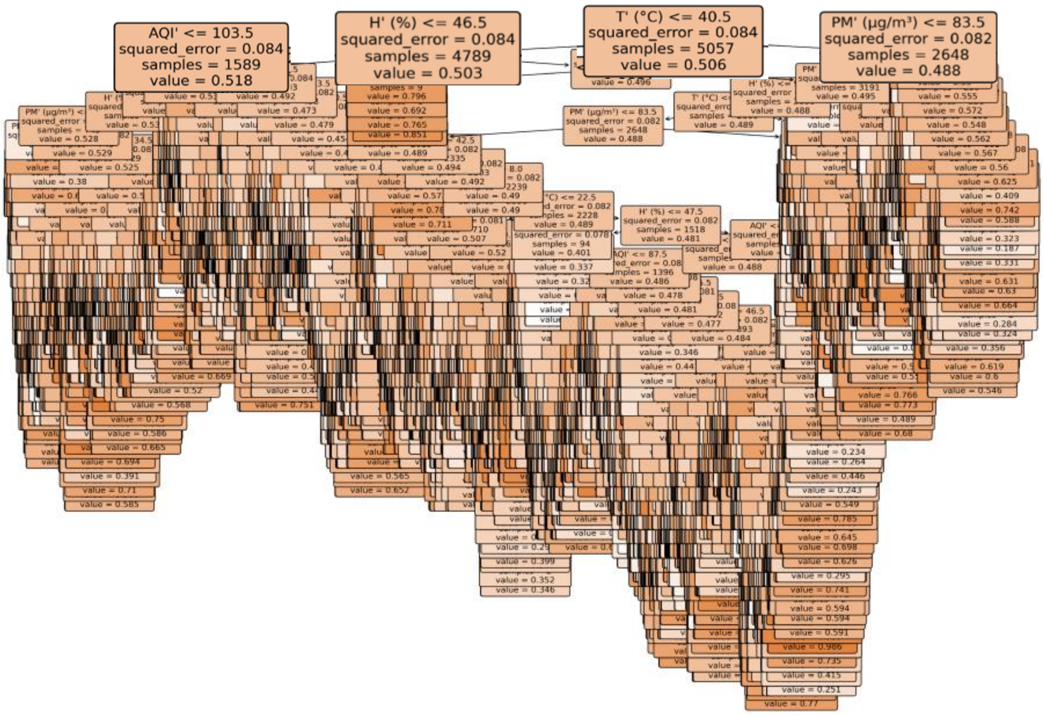

Fig. 7. Assigning weight prediction values based on the optimized RFR algorithm

Risk prediction accuracy calculations results

The proposed optimizing RFR technique was evaluated for its effectiveness in predicting risk levels based on API. The optimizing RFR model, trained on an AQD_{NR} dataset, is divided into training and testing subsets based on the confusion matrix, as shown in Fig. 8. Training and testing result of the normalizing air quality data shows that the API achieved a Mean Squared Error (MSE) of 0.002 for false predication of the polluted data. In addition, the low MSE indicates minimal deviation between the predicted and actual values, reflecting a high degree of accuracy, as illustrated in Fig. 9.

On the other hand, the optimizing RFR model's successful high value of R-squared, about 0.99, shows that it accounts for 99% of the variance in the target variable, demonstrating a near-perfect fit and close alignment with observed data of API, as mentioned in Fig. 10. This result revealed that the proposed API risk level prediction based on optimizing RFR achieved 99.98% accuracy, underscoring its ability to classify nearly all instances correctly. Finally, these results appeared in the validation experiment of the proposed IAPP based on the novel API method's robustness and high precision, establishing it as a reliable tool for accurately predicting air quality risk levels.

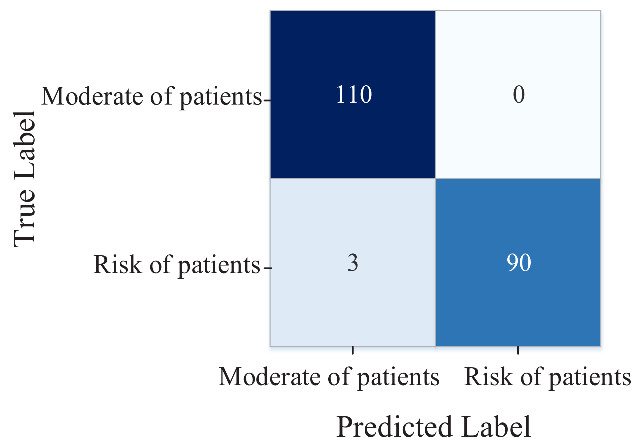

Fig. 8. Confusion matrix for proposed IAPP

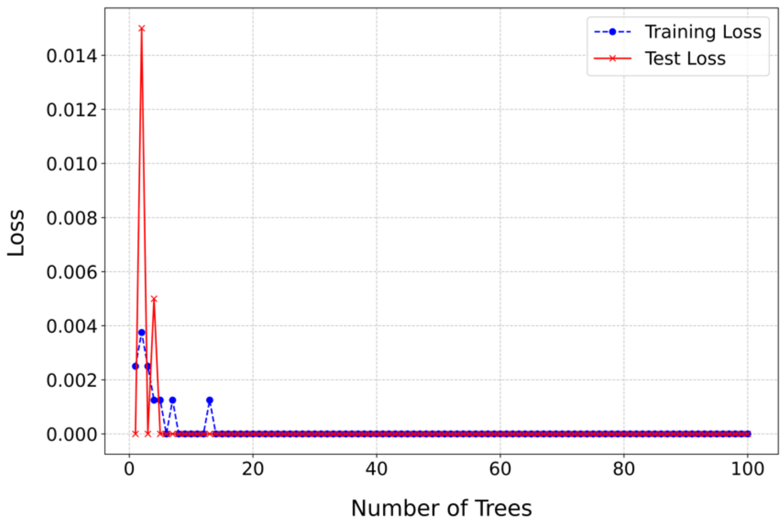

Fig. 9. MAE result of the proposed IAPP

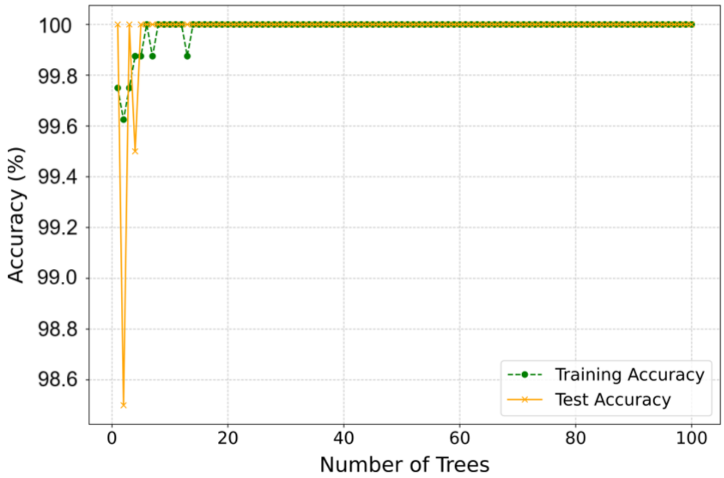

Fig. 10. Prediction risk accuracy for the proposed IAPP- RFR algorithm

Discussion

The IAPP algorithm effectively enhances air quality data accuracy and risk prediction. Initial raw data exhibited extreme variations which necessitating noise reduction and refined data trends and improved reliability. Normalization standardized air quality making assessments more interpretable, especially for asthma patients. Using the optimized RFR algorithm, assigned weights highlighted AQI and PM_{10} as dominant pollution factors. The model achieved exceptional 99.98% of accuracy, with an MSE of 0.002 and an R-squared value of 0.99 which confirming its predictive reliability. In contrast, Pollution Risk Classification enhances risk management by stratifying pollution levels and ensuring personalized monitoring. It sends timely alerts to PCM and HCM, helping asthma patients avoid exposure to harmful air quality. These findings underscore the model's robustness in handling environmental variability and ensuring precise air pollution risk assessment. The IAPP algorithm is a robust tool for real-time air quality monitoring and health risk assessment. Its capability to process vast data efficiently makes it valuable for environmental agencies and healthcare systems. Future work should integrate additional environmental factors, optimize computational efficiency, and explore deployment in various climatic and urban conditions to enhance adaptability and effectiveness.

Compression results

A comparative analysis of air pollution prediction algorithms to evaluate the efficacy of the proposed IAPP algorithm optimized with an API based totally on the optimizing RFR method. As illustrated in Fig. 11, the IAPP-optimizing RFR model executed a superior accuracy of 99.98%, appreciably outperforming different algorithms inside the observer. The closest contender, a hybrid model combining SVM+DT+RFC [11], had an accuracy of 95.7%. Other related algorithms, including RNN [7], BP [12], and SAM [14], exhibited lower accuracy prices, starting from 80.1% to 86.0%. These effects demonstrate the robustness of the IAPP algorithm in predicting the risk of air pollution, specifically while excessive accuracy is critical for powerful hazard management that affects asthmatic patients. The advanced optimization methods of the IAPP-optimizing RFR model, which enhance the predictive power of the random forest regressor through intelligent feature selection, are responsible for its exceptional performance. This finding is innovative in air pollution risk prediction to reduce triggers for asthma attacks. It highlights the standard-setting potential of the IAPP-optimizing RFR framework.

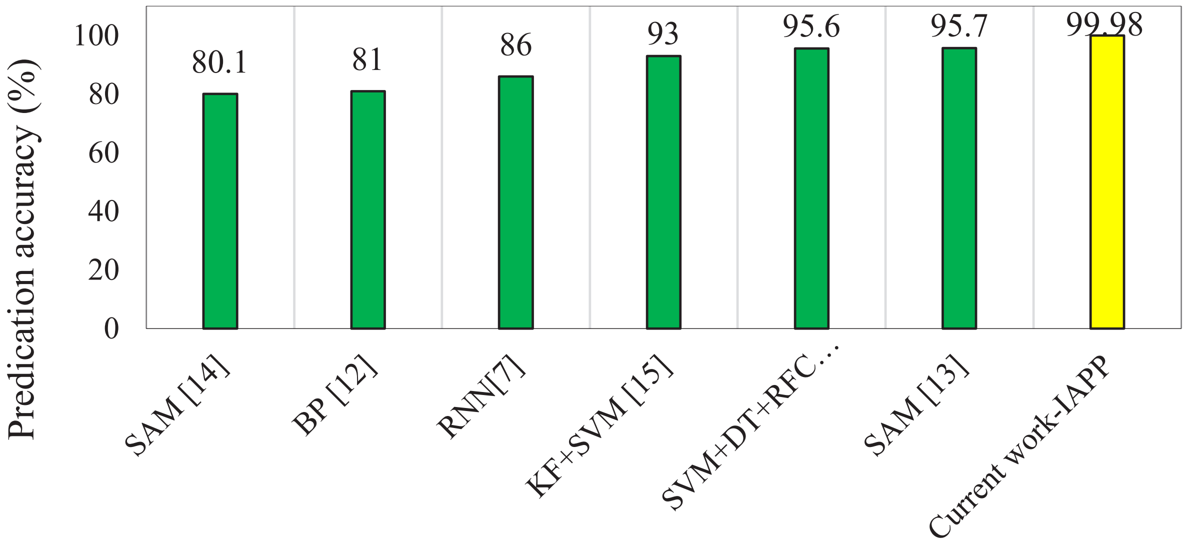

Fig. 11. Compression prediction accuracy between proposed IAPP and previous algorithms

Conclusion

This study presented an innovative air pollution monitoring system to protect asthmatic patients from pollution-trigger attacks. A novel IAPP algorithm was proposed to forecast the pollution around the patient in real-time and spatially by using IoT reliable air quality data collected based on APDNs. It proposes new classifications of the risk of pollution to save patients from attacks by pollution triggers (i.e., T, H, AQI, and PM) named the API method based on an optimized RFR algorithm. In addition, the IAPP algorithm sends alert SMS messages to personal care and health care management, informing them of the level of risk via smartphones to save patients from the trigger of attacks and send caregivers in emergency cases. The proposed IAPP algorithm achieved 99.98% accuracy in predicting pollution risk levels with an R-squared value of 0.99. This result revealed that the proposed IAPP algorithm by API method and Optimized RFR algorithm is reliability in providing real-time alerts to caregivers, effectively reducing the risk of asthma attacks caused by environmental triggers based on IoT technology. Besides this high performance of the IAPP algorithm, incomplete or inaccurate air quality data can impact model performance, especially in regions with limited monitoring stations, which leads to adopting their own APDN, which can increase the reliability of air data collection. Future work can consider the extension of the IAPP algorithm by including newer machine learning or deep learning models to support generalized predictions that can consider observations of disparate environmental conditions and various patient profiles.

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The authors declare no found.

Competing interests

The authors declare no conflicts of interest.

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Ethical considerations

This study did involve humans or animals as subjects, there was no harm anticipated to human or animal life. Ethical issues (Including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, etc) have been completely observed by the authors.

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