ASEAN
Journal of Scientific and Technological Reports
Online ISSN:2773-8752

Research article

An AIoT-based Air Quality Monitoring System for Real-time $PM_{2.5}$ Prediction in Urban Environments

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Citation:
Otanasap, N. ; Tadsuan, S.; Chalermsuk, C. An AIoT based air quality monitoring and forecasting system for real-time $PM_{2.5}$ prediction in urban environments. *ASEAN J. Sci. Tech. Report.* **2025**, *28*(1), e255168. https://doi.org/10.55164/ajstr.v28i1.255168

Article history:
Received: July 24, 2024
Revised: October 20, 2024
Accepted: October 25, 2024
Available online: December 14, 2024

Abstract: This study aimed to develop an air quality monitoring and forecasting system focusing on $PM_{2.5}$ using a combination of AI of Things (AIoT) technology. The system was designed to provide warnings of $PM_{2.5}$ levels through a mobile application. Air pollution, particularly $PM_{2.5}$, is a significant health concern globally, with Southeast Asia being heavily affected. Bangkok, Thailand, experiences high $PM_{2.5}$ concentrations during cool weather. Existing research explores short-term $PM_{2.5}$ prediction using AIoT. Still, there is a need for improved software, hardware, and ML algorithms for user-friendly mobile applications with real-time data access and health advisories. The system was installed on a building next to a main road in Bangkok. It collected data on $PM_{2.5}$. The Air Quality Index (AQI) was used to categorize $PM_{2.5}$ levels and their health impacts. Time series analysis with moving averages and the Random Forest algorithm were employed in advance for $PM_{2.5}$ forecasting. A mobile application was developed to provide a user interface and data visualization. The MARF (Moving Average and Random Forest) model emerged as a success, achieving higher accuracy (average of 92.59%) for 1-hour advance forecasts compared to the Moving Average (MA) model (average of 84.16%). The developed system demonstrates the potential of AIoT for accurate $PM_{2.5}$ monitoring and forecasting. Future research could explore more advanced ML algorithms and integrate additional environmental factors for enhanced forecasting accuracy.

Keywords: AIoT; $PM_{2.5}$; Random Forest; Moving Average; Forecasting; AQI

1. Introduction

Research worldwide shows that air pollution, known as $PM_{2.5}$, refers to fine particles with an aerodynamic diameter smaller than 2.5 microns. Populations around the world, especially in Southeast Asia, are greatly affected. According to research reports [1-2], deaths occurred in the highest proportion due to $PM_{2.5}$ worldwide in 2015. Thailand is one of the regions heavily affected by $PM_{2.5}$, especially Bangkok, the capital [3]. During the cold weather of the year, various districts in Bangkok will have $PM_{2.5}$ concentrations exceeding the standard level compared to the 24-hour air quality average of more than 50 $\mu g/m^3$ [4]. The Nong Khaem district has the highest average $PM_{2.5}$ concentration out of the 50 districts [5], especially along Phet Kasem Road. $PM_{2.5}$ data from the $PM_{2.5}$ monitoring system from satellite and geoinformatics technology [6] of Geo-Informatics and Space Technology Development Agency (Public Organization) or GISTDA found that the density value of $PM_{2.5}$ in the Nong Khaem district of

Bangkok in the first quarter of 2024, when Bangkok was still influenced by cool air from the north, was 38.48 μg/m^3. When compared to the Krung Thonburi area, which is on the west side of Bangkok and has similar characteristics, it was found that the average $PM_{2.5}$ density was 35.61 μg/m^3 or an average rate of 8.06 percent. On the day that Nong Khaem District had the highest $PM_{2.5}$ density at 104.59 μg/m^3, it was 193.74 percent higher than the average in the entire Krung Thonburi area. Therefore, monitoring $PM_{2.5}$ density and air quality is essential and helps affected people understand the situation [7-9]. In addition, developing a system that can predict air quality and $PM_{2.5}$ in advance is an important issue that will help them deal with problems better, such as managing time for outdoor activities and protecting themselves with dust masks. Several researchers [10-12] are interested in developing short-term $PM_{2.5}$ predictions using IoT technology combined with AI, which has shown that this technology can predict $PM_{2.5}$ levels in advance. However, this research area still needs to be improved in terms of software, hardware, and even better AI algorithms, such as notification of $PM_{2.5}$ forecast results in advance through a mobile app system. Make it easy for users to understand the meaning of AQI, accurate forecasts with less complex algorithms, etc. For example, researchers [13] have developed a machine learning algorithm to predict $PM_{2.5}$, which tends to increase in the short term, 60 minutes in advance. $PM_{2.5}$ forecasting has also been studied using current ground-level meteorological data to estimate $PM_{2.5}$ concentrations 1-5 hours in advance [14, 15]. Even though Nong Khaem District is a suburb of Bangkok, there are few high-rise buildings, and most of the area is still green. The design and development of this air quality measurement and forecasting system aims to apply IoT technology and artificial intelligence to measure and forecast air quality [16], especially $PM_{2.5}$, to provide warnings in advance via mobile application.

This research developed an air quality monitoring station. It was installed on the 6th floor of the Polakrit Building, Southeast Asia University, next to Phet Kasem Road in the Nong Khaem District, Bangkok. This measurement station is approximately 40 meters above ground level, providing comprehensive air quality measurements. This research aims to develop a $PM_{2.5}$ monitoring and forecasting system with the AQI index using IoT technology and artificial intelligence to notify users of forecast results in advance through mobile applications. The station includes sensors measuring $PM_{2.5}$, temperature, humidity, air pressure, wind speed, and wind direction.

2. Related Works

This section represents several research papers relevant to developing a $PM_{2.5}$ monitoring and forecasting system using a mixed model of IoT and Machine Learning (ML) accessible through a mobile application. Data Collection and Sensor Technology: Balogun, Alaka, & Egwim (2021) [17] demonstrate the use of IoT sensors to collect air quality data, including NO_2, alongside weather and traffic data. This highlights the potential of IoT for $PM_{2.5}$ data collection in the proposed method.

Machine Learning for $PM_{2.5}$ Prediction: Many researchers are interested in presenting their research papers [18-23], which examine various machine learning algorithms for air quality prediction, including NO_2 (similar to $PM_{2.5}$) prediction [17]. These reports showcase the effectiveness of Artificial Neural Networks (ANN) [22], Long Short-Term Memory (LSTM) [20, 21], Fuzzy Time Series (FTS) [18], Multilinear Regression (MLR) [19], ARIMA models [B6], and CEEMDAN-ARMA-LSTM model [23]. These findings suggest we explore a combination of these algorithms to find the optimal model for $PM_{2.5}$ prediction in the proposed research.

Factors Affecting $PM_{2.5}$ Concentration: Baharfar et al. [24] examine factors influencing indoor $PM_{2.5}$ concentration, including outdoor $PM_{2.5}$ levels, number of occupants, ambient temperature, wind speed, and wind direction. While this paper focuses on indoor settings, open doors, and windows highlight the importance of considering various environmental factors alongside $PM_{2.5}$ sensor data for improved prediction accuracy.

Mobile Application Integration: The papers above focus on data collection and prediction models. However, recent advancements in mobile cloud computing and secure data transmission protocols must be considered for mobile application integration to ensure user privacy and real-time data access.

Novelty and Contribution: While existing research provides a strong foundation, this project offers a novel contribution focusing on $PM_{2.5}$ prediction using a combination of the most effective ML algorithms and integrating a user-friendly mobile application for real-time data access, visualization, and potential health advisories based on $PM_{2.5}$ levels. Furthermore, to enhance prediction accuracy, especially for outdoor environments, consider a more comprehensive range of environmental factors beyond those explored in [24].

3. Materials and Methods

3.1 Air Quality Index

The Air Quality Index is an easy-to-understand air quality report for the public. To make the public aware of the level of air pollution in each area, how much does it affect health? One air quality index represents the concentration of 6 air pollutants: Particulate matter no larger than 2.5 microns in size ($PM_{2.5}$) that arises from combustion from vehicles, agricultural materials, forest fires, and industrial processes. It causes respiratory disease.

In addition, if accumulated for a long time or received in large amounts, it will accumulate in the lung membranes, reducing the efficiency of the lungs and causing bronchitis and asthma symptoms. Particulate matter no larger than 10 microns (PM_{10}) is dust with a diameter of no more than 10 microns. Burning fuel, open burning, industrial processes, grinding, milling, or pulverization from construction produce it. It affects health because when inhaled, it can accumulate in the respiratory system. Ozone gas (O_3) is a colorless or light blue gas with a pungent odor, is slightly soluble in water, and occurs both in the atmosphere high above the Earth's surface and near the ground. Ozone gas, an air pollutant, is ozone gas in the Earth's surface atmosphere. It is caused by a reaction between nitrogen oxides and volatile organic compounds, with sunlight acting as a catalyst. It affects health by causing eye irritation and irritation of the respiratory system and various mucous membranes, decreased lung capacity, and early fatigue, especially in children, the elderly, and people with diabetes cystic fibrosis. Nitrogen dioxide (NO_2) is a colorless and odorless gas slightly soluble in water. It is commonly found in nature or caused by human actions, such as burning various fuels, some industries, etc. This gas affects the visual system and people with asthma or other respiratory diseases. Sulfur dioxide (SO_2) is a colorless to pale yellow gas with a taste and odor at high concentrations. It is caused by nature and the combustion of fuels that contain sulfur. It is highly soluble in water and can combine with other pollutants to form small dust particles. This gas directly impacts health, irritating the mucous membranes of the eyes, skin, and respiratory system. If you take it for a long time, it can cause chronic bronchitis.

Thailand's Air Quality Index (AQI) [5] is divided into five levels, from 0 to 201 and above. Each level uses a color to symbolize the level of impact on health. An air quality index of 100 is equivalent to air quality standards in the general atmosphere. If the air quality index exceeds 100, the air pollution concentration exceeds the standard, and that day's air quality will begin to affect public health. The air quality index is between 0 and 25, represented by blue, which means the air quality level is excellent, and all citizens can lead everyday lives. The air quality index value is between 26 and 50, represented by green, meaning the air quality level is good, and the public can do outdoor activities as usual. People in at-risk groups should monitor themselves for unusual symptoms such as coughing, chest tightness, fatigue, or dizziness. Air quality index values between 51 and 100, represented by yellow, indicate moderate air quality. The public should reduce activity time or exercise outdoors. People in high-risk groups should wear protective equipment, such as masks, to prevent $PM_{2.5}$ exposure every time they go outside the building. In addition, they need to reduce the time they spend doing activities or exercising outdoors and consult a doctor if they encounter any irregular symptoms. An AQI value between 101 and 200, represented by orange, means the air quality level is starting to impact health. The public should use personal protective equipment such as a $PM_{2.5}$ mask outside the building. Limit your time in outdoor activities or exercise and watch for unusual symptoms such as coughing, sneezing, or eye irritation. People in at-risk groups should wear personal protective equipment, such as masks, to prevent $PM_{2.5}$ exposure every time they go outside the building. Avoid doing activities or exercising outdoors, and follow your doctor's advice. If you have any unusual symptoms, consult your doctor immediately. Air quality index values greater than 201, represented by red, mean air quality levels affect health. To prevent $PM_{2.5}$, all citizens must avoid outdoor activities and always wear personal protective equipment, such as masks. If you have any abnormal symptoms, please consult a doctor immediately. For patients with chronic diseases, stay in areas safe from air pollution. Prepare necessary medicines and equipment and strictly follow the doctor's instructions.

Calculation of the daily air quality index of each type of air pollutant. It is calculated from air pollutant concentration values and air quality measurement results. The air pollutant concentration values are equivalent to the air quality index values at various levels. Calculating the air quality index within a level range is a linear equation.

$$1 = \frac{I_j - I_i}{X_j - X_i}\ (X - X_i) + I_i \tag{1}$$

I = Air quality sub-index value,
X = concentration of air pollutants from measurement,
X_i, X_j = minimum, maximum values of the pollutant concentration range with values of X,
I_i, I_j = minimum, maximum values of the air quality index range corresponding to the concentration range X from the calculated sub-index values.

Which air pollutant has the highest index value was used as the Air Quality Index (AQI) at that time.

3.2 Time Series Analysis and Moving Average

According to the emergence of $PM_{2.5}$, the values measured by sensors are time series data. Time series analysis [25] is the prediction of future values of a dependent variable by using data on that variable to study various patterns of relationships. Time series analysis involves separating the various components in the data and analyzing their interrelationship patterns to predict their future value. Time series data can be separated into four movement patterns: Secular Trend, Seasonal Movement, Cyclical Movement, and Irregular Movement [26]. The Moving Average (MA) model is one of four used for time series forecasting. It is a mathematical technique for finding the average value changing over time. It replaces the oldest data set with the most recent dataset, then re-averages it over periods such as 3, 6, 12, and 24 hours in advance, as used in this study. There are two methods of calculating the moving average: Simple Moving Average and Weighted Moving Average.

This research uses the Simple Moving Average model to forecast $PM_{2.5}$ air quality because the system collects data hourly, with 24 items per day and 168 items per week. To forecast from historical data throughout the week, which has different data characteristics each day, this research uses 168 historical data items for calculation, as shown in the following equation.

$$F_t = \frac{A_{t-1} + A_{t-2} + \cdots + A_{t-168}}{n} \tag{2}$$

$$F_3 = \frac{A_{t-1} + A_{t-1} + \cdots + A_{t-166} + F_{t-1} + F_{t-2}}{n} \tag{3}$$

$$F_6 = \frac{A_{t-1} + A_{t-1} + \cdots + A_{t-163} + F_{t-1} + \cdots + F_{t-5}}{n} \tag{4}$$

$$F_{12} = \frac{A_{t-1} + A_{t-1} + \cdots + A_{t-157} + F_{t-1} + \cdots + F_{t-11}}{n} \tag{5}$$

$$F_{24} = \frac{A_{t-1} + A_{t-1} + \cdots + A_{t-143} + F_{t-1} + \cdots + F_{t-23}}{n} \tag{6}$$

Where
F_t = the forecast value for the period t.
$A_{t\text{-}n}$ = actual value in period t-n
n = number of data sets to find the moving average.

Forecasting 1 hour ahead, using 168 past actual $PM_{2.5}$ values (2), 3-hour advance forecast (3), 166 past actual $PM_{2.5}$ values, and 1-and 2-hour advance forecasts (4). Forecasting 6 hours, using 163 past actual $PM_{2.5}$ values along with forecast values 1-5 hours ahead (5); forecast 12 hours in advance, using 157 past actual $PM_{2.5}$ values together with forecast values from 1-11 hours in advance and 24-hour advance forecast (6), using 143 past actual $PM_{2.5}$ values along with 1 – 23-hour advance forecast values.

3.3 Random Forest

The research team proposed a method for integrating forecasting techniques with machine learning to improve the accuracy of $PM_{2.5}$ air quality forecasts. Due to the conditions of the developed system are designed to be adaptable, ensuring that the forecast results can be displayed 1, 3, 6, 12, and 24 hours in advance at any given time. Using historical data, including $PM_{2.5}$, temperature, humidity, air pressure, wind speed, and wind direction, to train the system according to the principles of supervised machine learning, we have chosen a method that balances processing time with accuracy and reliability, ensuring dependable performance. Therefore, the research team proposes using the random forest technique, a widespread algorithm used in regression and classification forecasting without needing hyperparameter tuning to get better results.

Random Forest is a popular model developed from a decision tree. The principle of random forest is to create a model from many decision trees. Each model receives a different subset of the data set. Then, forecasting is assigned to each decision tree model to calculate its forecast results. In the case of classification, the vote output is obtained from each forecast that the decision tree selects the most. This improves the prediction results from the decision tree, which are more accurate and control over-fitting.

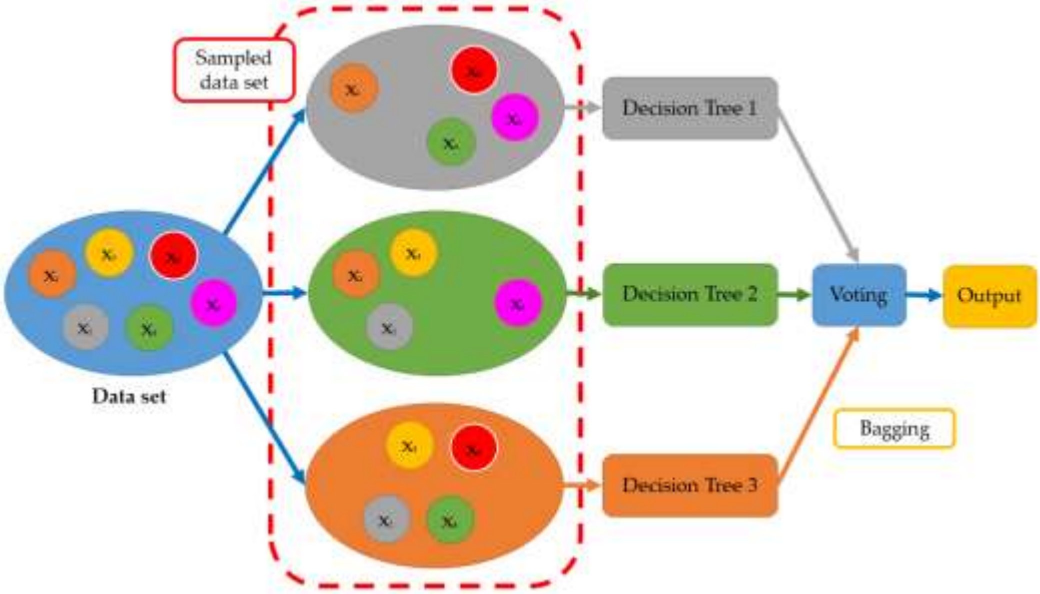

Figure 1. Random forest process

In this research, Bootstrapping from all data sets is used to get *n* data sets that differ according to the number of decision trees in random forests from a total of 6 features, including wind speed, wind direction, humidity, air pressure, temperature, and $PM_{2.5}$ (X_1, X_2, ..., and X_6), to create a model decision tree for each dataset. Then, the results are aggregated from each model or bagged with voting. The *RandomForestClassifier* of Scikit-learn ensemble methods for classification is used in forecasting processing, with the *n_estimators* parameter set to 100 trees. The supported criteria are the *Gini impurity, log_loss*, and *entropy* for the Shannon information gain [27]. The developed system will take the forecast values obtained from the moving average process, separate them, and specify $PM_{2.5}$ levels from 1, the lowest, to 5, which is a very high $PM_{2.5}$ value, as input and use them. All data from the database is used to train the system every hour. Then, the obtained model with moving average (MA) and random forest (RF) forecasting (MARF) will be used to forecast $PM_{2.5}$ air quality 1, 3, 6, 12, and 24 hours in advance.

3.4 System Framework

Figure 2 shows an overview of the system's operation. The sensors measure temperature, humidity, air pressure, wind speed, wind direction, and the amount of $PM_{2.5}$ dust in the air. All collected information is stored in a database, which can display $PM_{2.5}$ air quality values at the current time and label each frame according to the five class $PM_{2.5}$ values with rule-based classification. The system then processes air quality forecasts 1, 3, 6, 12, and 24 hours in advance. The research team has chosen two comparative methods to compare the forecasts: A moving average (MA) and a mixed method with a moving average and a Random Forest (MARF). Moving Average processing uses 168 historical data frames (24 hours, seven days) to forecast the future. In addition, the system will take the forecast values obtained from the six moving averages in advance as input data to create a forecast model with MARF. Forecasts are processed with an impurified random forest of 100 trees every 1-hour using Scikit-learn's Python library, and the forecast results are divided into five classes stored in the database. While mobile applications are developed in Dart, a programming language developed by Google, it is designed to create mobile and web applications. It is developed on the Flutter framework to work cross-platform, and it can be used on Windows, Mac OS, Linux, iOS, or Android.

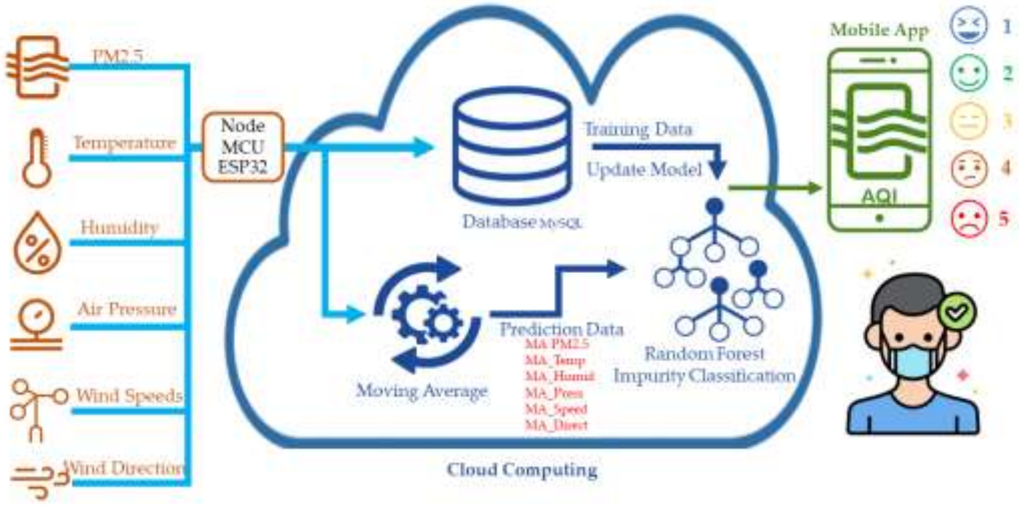

Figure 2. Framework of the AQI $PM_{2.5}$ monitoring and forecasting system

Forecast data is divided into five classes: Class 1 means very good air quality with an average $PM_{2.5}$ not exceeding 15 ug/m^3; Class 2 means good air quality with an average $PM_{2.5}$ between 15.1-25.0 μg/m^3; Class 3 means that the air quality is moderate with an average $PM_{2.5}$ between 25.1 - 37.5 μg/m^3; Class 4 means that the air quality is starting to have an impact on health, with an average $PM_{2.5}$ between 37.6 – 75.0, and Class 5 means Air quality affects health, the average $PM_{2.5}$ is more than 75.1 μg/m^3.

3.5 Hardware Design and Development

The hardware development of this air quality monitoring and forecasting system consists of the following hardware: BME280 Temperature Humidity Barometric Pressure Sensor [28] is a sensor device for measuring temperature, air humidity, and barometric pressure. It is connected via Inter-Integrated Circuit (I2C) and uses a current of 1.7 - 3.6V. It can measure temperature from -40 to 85 degrees Celsius, humidity from 0 to 100%, and barometric pressure from 300 to 1,100 hPA. Temperature accuracy class ± 0.5 degrees Celsius (at 25 degrees Celsius). The Laser Dust Sensor PM 2.5 PMS7003 [29] measures the amount of dust in the air by detecting dust particles with laser light. It can detect small particles ranging from 0 to 500 micrograms per cubic meter. The particles it can detect are $PM_{1.0}$, $PM_{2.5}$, and PM_{10}.

The smallest particle that can be detected is 0.3 micrometers. This sensor's output is qualitative and quantitative information on individual particles of different sizes per unit volume. The particle count volume unit is 0.1 liter, and the mass concentration unit is μg/m^3. Wind Direction Sensor Signal 0-5V [30] measures wind direction. Its output voltage is 0-5 volts, input power is 10-30 volts, it can rotate 360 degrees, measure in eight directions, and works at temperatures from 20 to 60 degrees Celsius. In addition, Wind Speed Sensor Signal 0-5V [31] is used to measure wind speed. It is a 3-cup wind-measuring device with an output voltage of 0-5 volts and an input voltage of 7-24 volts. It measures wind speed in the 0-30 m/s range, with a value accuracy of 0.1 m/s. It works at a temperature of -20 to 60 degrees Celsius.

According to Figure 3 (a) and (b), an ESP32 board [32] is used as an embedded processing unit to receive sensor values, process them, and forward the data to cloud computing. The ESP32 Board uses an Xtensa single-core 32-bit, LX6 microprocessor, running at 160 or 240 MHz. It has 520 KB SRAM, Wi-Fi: 802.11 b/g/n, and Bluetooth: v4.2 BR/EDR and BLE. It operates at temperatures of -40ºC to 125ºC. The private server used for processing is a Dell PowerEdge T150 Server with an Intel Xeon E-2314 2.8 GHz, 8M Cache, 4C/4T 16GB UDIMM, 3200M/Ts, and ECC 3*2TB HDD SATA 6Gbps, installed at the IT Center, Polakrit Building, Southeast Asia University, Bangkok.

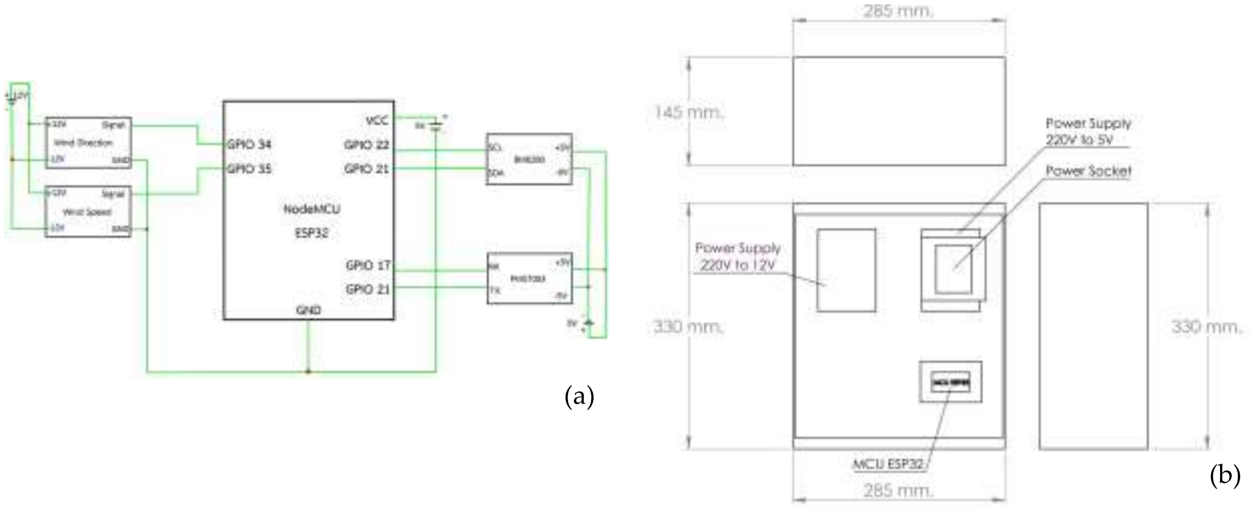

Figure 3. Electronic circuit diagram of the AQI $PM_{2.5}$ monitoring and forecasting system.

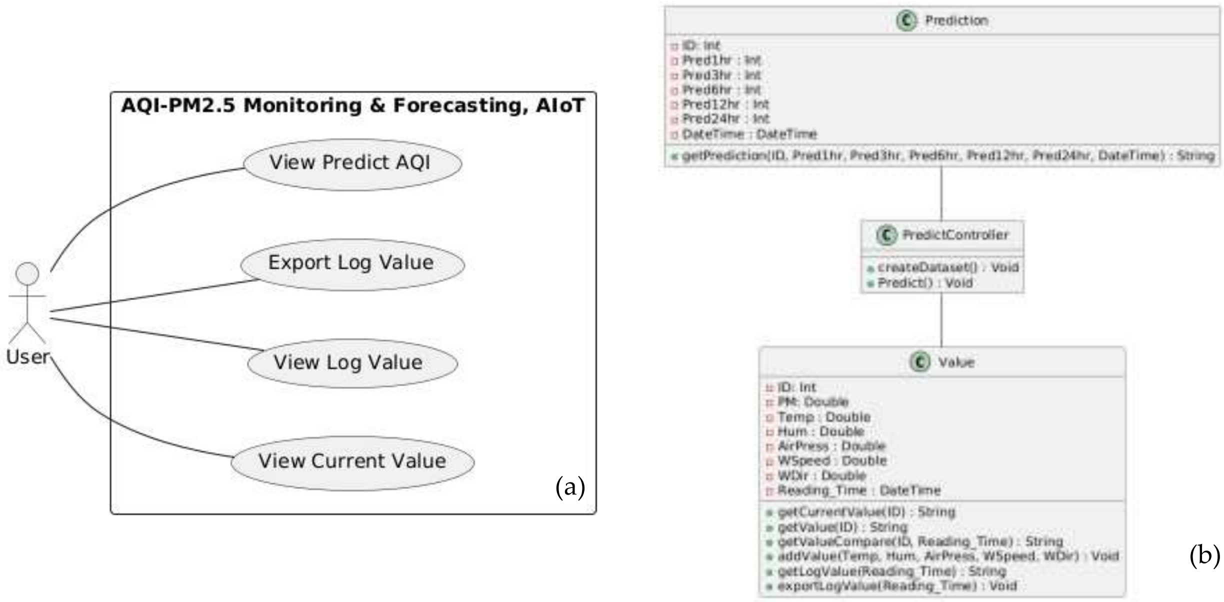

Figure 4. Use case and class diagram of AQI $PM_{2.5}$ monitoring and forecasting system

3.6 Software Design and Development

System Analysis and Design (SAD) for this research include: 1. Functional Requirements consist of (1) being able to track wind speed, wind direction, humidity, air pressure, temperature, and $PM_{2.5}$ at the current time and historical data and (2) being able to follow the future air quality index forecast AQI $PM_{2.5}$. 2. Non-functional requirements consist of (1) $PM_{2.5}$ data and other values that can be tracked 24 hours a day and (2) can be used by both web and mobile applications. The basic working principles of the $PM_{2.5}$ air quality monitoring and forecasting system using artificial intelligence are as follows. PMS7003 measures the amount of $PM_{2.5}$ in the air. The BME280 measures temperature, air pressure, and humidity in the air. Meanwhile, turbines measure the speed and direction of the wind, as shown in Figure 4.

All sensors are connected to a Node MCU ESP32 to collect data and then forward it to the MySQL Database at 1 hour per frame. The code program was developed with PHP to communicate with the Node MCU ESP32, and the MySQL database system, which manages both current and historical data, was installed on the private server. Examining past dust values, processing current data to forecast future air quality indexes, and storing the processed forecast data in a database system. Users can choose to use it through web applications or mobile applications. The display of $PM_{2.5}$ values is divided into five levels according to Thailand's air quality index classification, as shown in Figures 5 and 6. By using only the density of $PM_{2.5}$ in the air, each level uses color to symbolize the level of impact on health. When measured, the $PM_{2.5}$ value is between 0 – 15.00 μg/m^3, meaning that the $PM_{2.5}$ density is very low, represented by a blue color. If the value is measured between 15.10 – 25.00 μg/m^3, the $PM_{2.5}$ density is low and represented by a green color. If the value is measured between 25.1 and 37.5 μg/m^3, the $PM_{2.5}$ density is moderate and starting to impact health, represented by a yellow value. If the value is measured between 37.6 – 75.0 μg/m^3, the $PM_{2.5}$ density is high and dramatically impacts health, represented by orange. If the value is more than 75.1 μg/m^3 or more, the $PM_{2.5}$ density is very high and has a very high impact on health, represented in red.

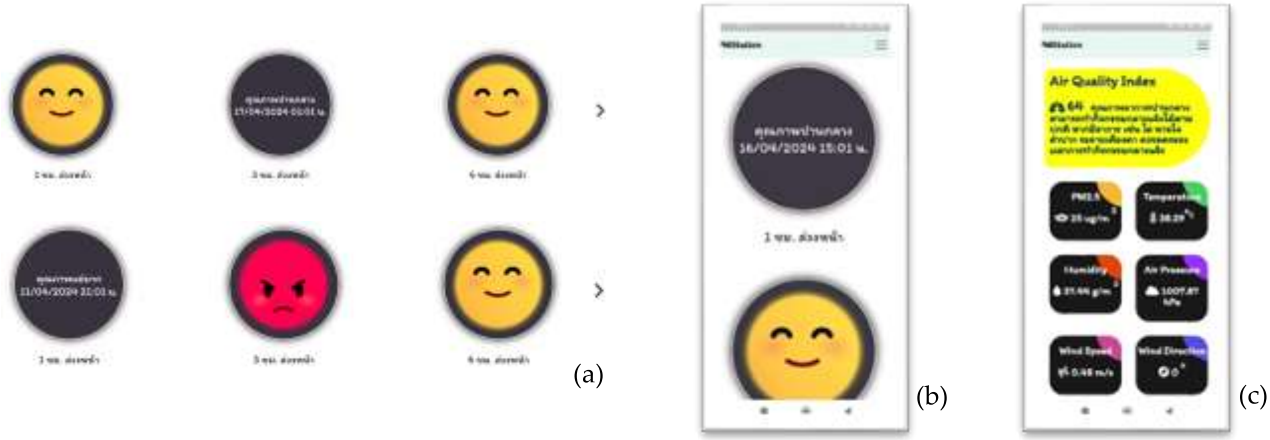

Figure 5. Example of User Interface of AQI $PM_{2.5}$ monitoring and forecasting system

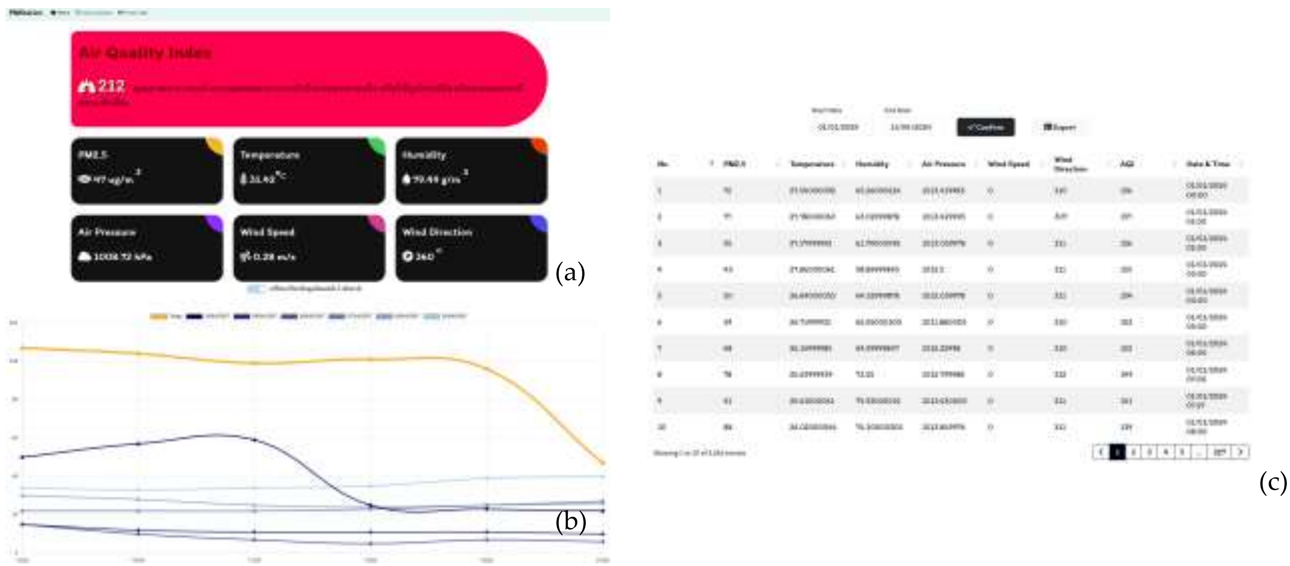

Figure 6. Example of user interface showing notifications and historical data

4. Results and Discussion

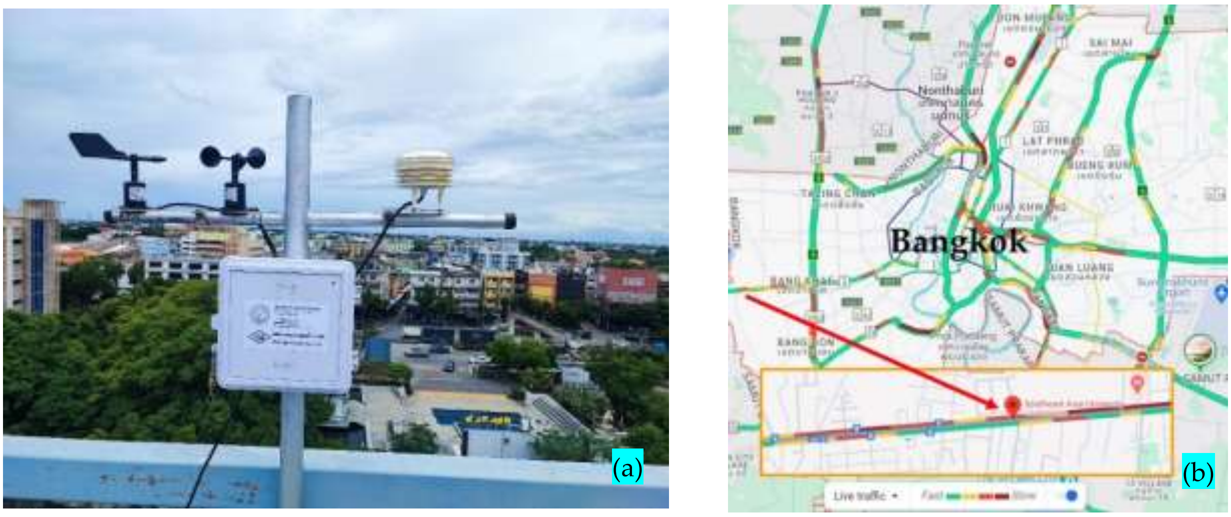

Figure 7. The acquisition station is installed on the Polakrit Building, Southeast Asia University, and the location of the installation point

This research installed equipment to measure $PM_{2.5}$ dust, temperature, humidity, air pressure, wind speed, and wind direction on the 5th floor of the Polakrit Building, approximately 40 meters above ground level. The Polakrit Building, situated on Petchkasem Road, Figure 7, a major thoroughfare with heavy daily traffic, especially during the morning and evening rush hour, provides a significant context for this research Figure 7. Data collection lasted 175 days, from Saturday, November 25, 2023, to Thursday, May 30, 2024. From December to February, Bangkok is significantly affected by high pressure from China, which causes cool weather and a substantial increase in $PM_{2.5}$ dust yearly. Therefore, Thailand enters summer from March to May every year. Low air pressure influences Bangkok, which is less affected by $PM_{2.5}$ dust [6]. This allows the experiment of this air quality monitoring and forecasting system to compare different weather conditions. The system collects data from various sensors once an hour and records it in the MySQL database, with 24 daily records and 4,209 records. Random forest prediction requires a dataset to train the system. Therefore, the forecast runs from March 4, 2024, to May 31, 2024, a total of 88 days and 2,112 records for forecasting and analysis.

Confusion matrix, also known as error matrix, and cross-entropy loss, also known as log loss, are used in machine learning to evaluate the performance of classification models. In this specific study, these two techniques were used to evaluate the performance of MA and MARF for classification purposes. A confusion matrix is a summary table showing how well a model predicts different class samples. When optimizing the classification model, calculate the difference between the predicted and actual responses. Cross-entropy can be used as a loss function [33].

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

$$Specificity = \frac{TN}{FP + TN} \tag{8}$$

$$Precision = \frac{TP}{TP + FP} \tag{9}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{10}$$

$$F1\,Score = 2 * \frac{Recall * Precision}{Recall + Precision} \tag{11}$$

TP, TN, FP, and FN are True Positive, True Negative, False Positive, and False Negative, respectively [34].

After analyzing the confusion matrix, various performance parameters, including Sensitivity or Recall, Specificity, F1 score, Accuracy, and Precision, are calculated to evaluate the model's performance. Accuracy is defined as the proportion of correct predictions out of all predictions. Recall, also known as true positive rate, is calculated as the proportion of correctly predicted positive instances to the total number of positive instances. Specificity, also known as true negative rate, refers to the proportion of predicted negative instances that are accurate relative to the total number of negative instances. Accuracy, also known as positive prediction value, refers to the proportion of positive instances correctly predicted compared to the total number of cases predicted to be positive. The F1 score can be defined as the harmonic average of Recall and Accuracy, two crucial data analysis parameters [34]. Equations (1-5) can be used to calculate these parameters.

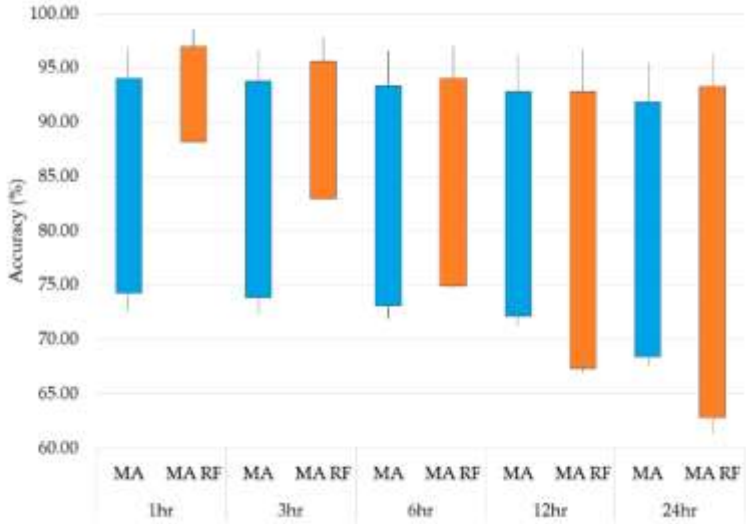

Figure 8. Comparison of the accuracy of forecasts 1, 3, 6, 12, and 24 hours in advance using the MA and MARF methods.

Figure 8 shows the results of comparing the average percentage accuracy of the 1-hour advance forecast results, including all classes; it was found that the MA model had a total average of 84.16 percent (±9.87), which was less than the MARF model, which had an average total of 92.59 percent (±4.39). When comparing the average percentage accuracy of the 3-hour advance forecast results for all classes, it was found that the MA model had an overall average of 83.80 percent (±9.96), which was less than the MARF model, which had an overall average of 89.29 percent (±6.33). When comparing the average percentage accuracy of the 6-hour forecast results for all classes, it was found that the MA model had an overall average of 83.23 percent (±10.14), which was less than the MARF model, which had an overall average of 84.50 percent (±9.54). When comparing the average percentage accuracy of the 12-hour forecast results for all classes, it was found that the MA model had an overall average of 82.49 percent (±10.34), which was higher than the MARF model, which had an overall average of 80.12 percent (±12.74). When comparing the average percentage accuracy of the 24-hour forecast results for all classes, it was found that the MA model had an overall average of 80.18 percent (±11.71), which was higher than the MARF model, which had an overall average of 78.06 percent (±15.26). The above comparison results show that in the 1, 3, and 6-hour forecasts, the MARF model is more accurate than the MA model. Still, when the estimates are extended 12 and 24 hours in advance, the MA model is more accurate than the MARF model. Moreover, the candlestick chart also shows that the MA forecast has an average standard deviation between 9.87 and 11.71, which mostly stays the same compared to the MARF model; the average standard deviation has increased accordingly. More extended forecast periods are 4.39, 6.33, 9.54, 12.74, and 15.26.

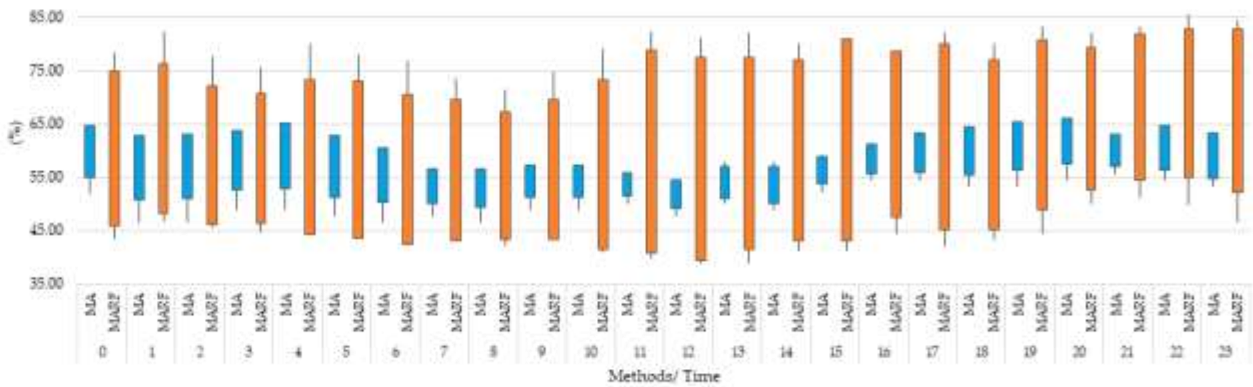

Figure 9. Average accuracy (%) of MA and MARF methods, distributed hourly.

Figure 9 reveals a significant finding in our comparative analysis. The MARF forecast, when compared to the MA forecast, demonstrated a higher average percentage accuracy from 11:00 AM to 11:00 PM. This was particularly articulated during the period 00:00 AM to 10:00 AM of the day. Meanwhile, the average percentage accuracy of MA forecasts remained constant throughout the day. One notable difference we observed was in the variability of the forecasts. The candlestick chart shows that the MARF forecasts have a more spread-out mean standard deviation than the MA forecasts.

Table 1. A comparison of the data analysis results of the MA and MARF methods on an hourly basis.

Methods		Acc.	Precis.	Recall	F1	Spec.
1hr	MA	84.16	50.57	59.78	52.81	89.26
	MARF	92.59	76.10	8.27	79.18	95.19
3hr	MA	83.80	49.67	18.93	51.79	89.03
	MARF	89.29	65.20	11.05	68.81	93.01
6hr	MA	83.23	48.09	55.29	49.98	88.66
	MARF	84.50	51.45	64.42	54.44	89.73
12hr	MA	82.49	46.14	21.28	47.61	88.17
	MARF	80.12	37.68	54.08	38.60	86.70
24hr	MA	80.18	41.47	43.78	42.34	86.53
	MARF	78.06	30.60	43.47	28.90	85.07

Refer to Table 1 and Figure 10, showing the results of the comparative analysis of Accuracy, Precision, Recall, F1 Score, and Specificity of forecasts using MA and MARF methods 1, 3, 6, 12, and 24 hours in advance. Accuracy's comparative analysis found that the MARF one-hour forecast is accurate at 92.59 percent, more than the MA model, which has an average accuracy of 84.16 percent. It is in the same direction as the 3-hour and 6-hour forecasts, which found that the MARF model had an average percent accuracy of 89.29 and 84.50, more than the MA model, which had an average percent accuracy of 83.80 and 83.23, respectively. However, when considering the 12-hour and 24-hour forward forecasts, the MA model had an average accuracy percentage of 82.49 and 80.18, respectively, compared to the MARF model, which had an average accuracy percentage of 80.12 and 78.06, respectively. This is consistent with the hourly average accuracy percentage analysis. One key takeaway from our results is the noticeable impact of more extended advance forecasts on accuracy. As the forecast duration increases, the accuracy of the forecasts is affected.

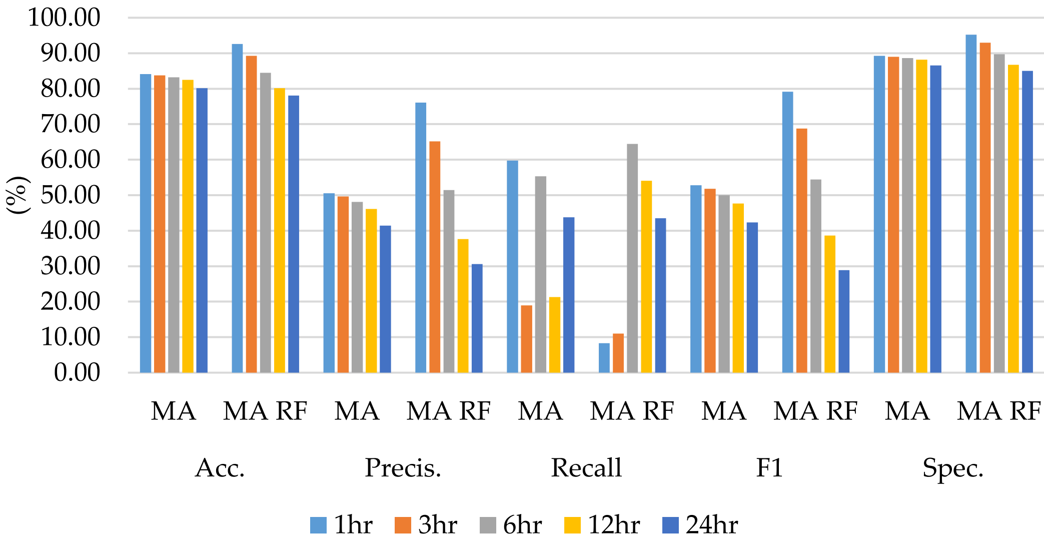

Figure 10. A comparison of the data analysis results of the MA and MARF methods on a 1, 3, 6, 12, and 24 hours in advance.

When considering the Precision, it is also found to correspond to the Accuracy value. The 1, 3, and 6-hour forecasts using the MARF method have averages of 76.10, 65.20, and 51.45 percent, respectively, higher than those of the MA method, with averages of 50.57, 49.67, and 48.09 percent. On the other hand, when forecasting 12 and 24 hours in advance, MARF had an average precision percentage of 37.68 and 30.60, less than MA, which had an average of 46.14 and 41.47 percent, respectively. When considering recall, it was found that the 1-and 3-hour forecasts using the MARF method had an average of 8.27 percent and 11.05 percent, less than the MA method, which had an average of 59.78 percent and 18.93 percent, respectively. On the other hand, when forecasting 6, 12, and 24 hours in advance, it was found that MARF had average recall percentages of 64.42, 54.08, and 43.47, higher than MA, which had average percentages of 55.29, 21.28, and 43.78, respectively. This shows that MARF forecasting can recall long-term forecasts better than MA forecasting. On the other hand, MA forecasts have better short-term recall ability.

In addition, when considering the F1-Score, which shows the model's performance by taking Precision and Recall values to calculate the Harmonic Mean, it was found that MA forecasts have average percentages of 1, 3, 6, 12, and 24 percent, with forecasts of 52.81, 51.79, 49.98, 47.61, and 42.34 percent. The trend decreases with longer forecast periods. While the MARF forecasts had average percentages of 1, 3, 6, 12, and 24 percent of forecasts at 79.18, 68.81, 54.44, 38.60, and 28.90, the trend decreased with more extended forecasts. When comparing the F1-Score, it was found that the MA forecast was 48.91 percent, lower than the MARF's 53.98, indicating that the MARF was more effective.

Finally, considering the Specificity, it was found that the MA forecasts are 1, 3, 6, 12, and 24 hours ahead. The results were 89.26, 89.03, 88.66, 88.17, and 86.53 percent, with a slightly decreasing trend. The MARF forecast is 1, 3, 6, 12, and 24 hours ahead. The results were 95.19, 93.01, 89.73, 86.70, and 85.07 percent, with a slight decrease in trend.

Table 2 compares the average Accuracy, Precision, Recall, F1, and Specificity percentage, separated by class. It was found that class 5, the MARF model, has the highest Accuracy at 97.28, and the MA model is next at 96.34 in the same class, respectively, as shown in Figure 11 (a). Meanwhile, MARF and MA in class 3 have the highest precision values, 82.07 and 69.48, respectively, as shown in Figure 11 (b). For Recall, the MARF and MA models in Class 1 had the highest values of 94.16 and 83.47, respectively, as shown in Figure 11 (c). The MA model of class 1 and the MARF model of class 3 have the highest F1 values of 71.44 and 70.13, respectively, as shown in Figure 11 (d). For Specificity, it was found that MARF and MA models in class 5 had the highest values of 97.78 and 97.21, respectively, as shown in Figure 11 (e).

Table 2. A comparison of the data analysis results of the MA and MARF methods on a Class basis.

	Class									
	1		2		3		4		5	
	MA	**MARF**	**MA**	**MARF**	**MA**	**MARF**	**MA**	**MARF**	**MA**	**MARF**
Accuracy	90.54	89.87	79.54	86.92	71.13	75.11	76.31	75.39	96.34	97.28
Precision	62.56	49.15	36.91	30.85	69.48	82.07	53.86	67.93	13.13	31.04
Recall	83.47	94.16	35.05	58.18	56.47	61.66	58.32	55.90	34.69	52.37
F1	71.44	61.95	35.94	38.28	62.29	70.13	56.00	61.24	18.86	38.32
Specificity	91.77	89.55	88.22	88.50	81.87	87.80	82.60	86.06	97.21	97.78

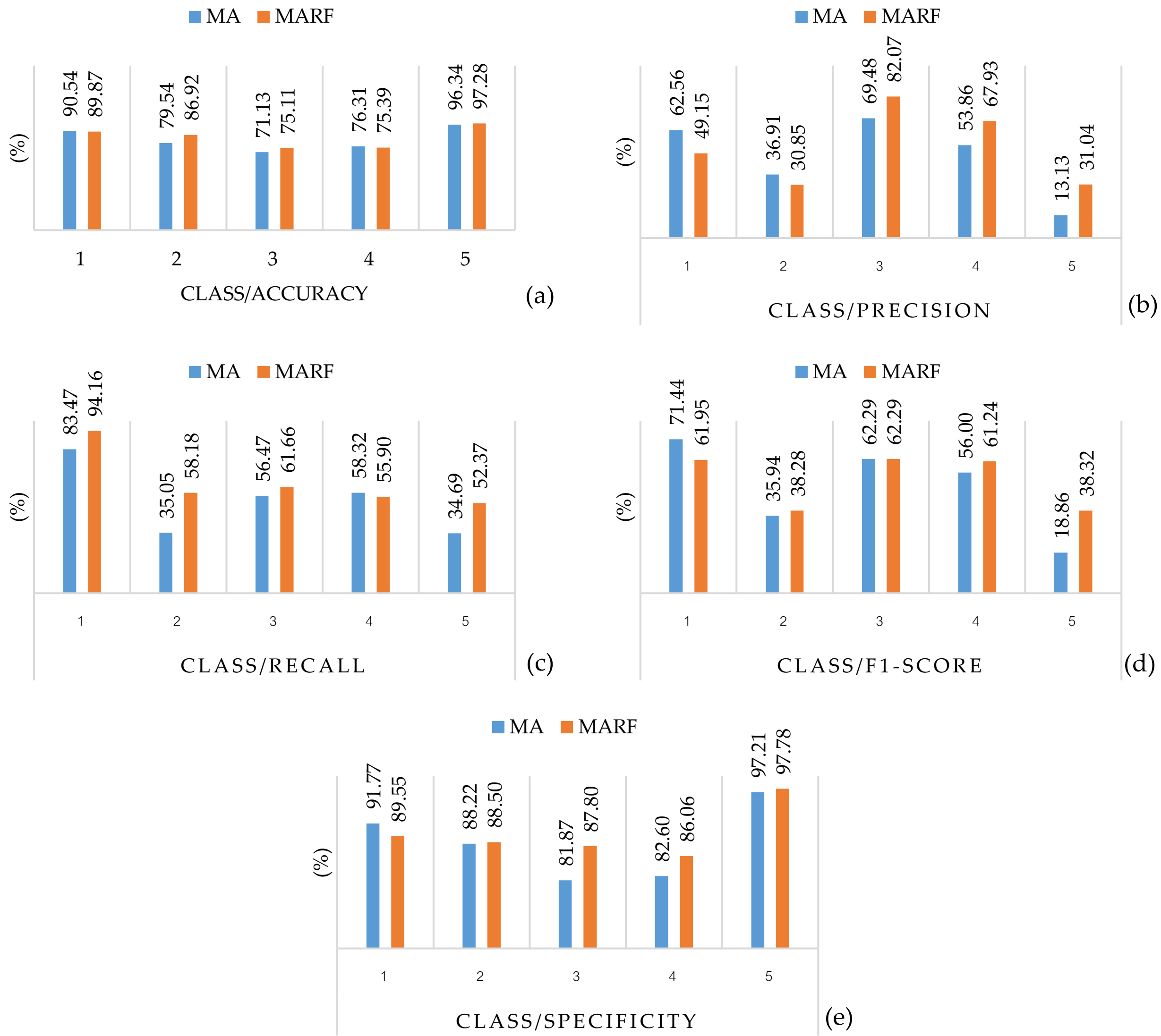

Figure 11. A comparison of the data analysis results of the MA and MARF methods on a Class basis.

4. Conclusions

The AQI $PM_{2.5}$ monitoring and forecasting system was developed, and the experimental results show that it can monitor and forecast $PM_{2.5}$ according to the objective. Moreover, the system has a user-friendly interface. It displays $PM_{2.5}$ concentration status notifications in a 5-color level visual symbol that is easily recognizable according to Thailand's AQI-$PM_{2.5}$ measurement standard. This feature ensures that users can navigate the system with ease and comfort. Unlike most similar studies, which focus solely on machine learning forecasting algorithms, our system stands out as a more comprehensive framework. It begins with sensors for data collection, aggregates the data, and sends it to a MySQL database and cloud computing using an ESP32 board. This comprehensive approach instills confidence in the system's capabilities. It then demonstrates the processing of time-series forecasts with moving averages compared to a combination of moving averages and random forest, a popular machine learning model. It also showcases current and historical data, especially the five-level notification symbols, making it easy for users to understand through mobile and web applications. While the current system is effective, there is always room for improvement.

The system's future looks promising, with the potential to conduct more extended experiments covering all seasons and expand the station installations for more data collection. This information will make the audience feel optimistic about the system's development. Considering the cloud's processing load, it may also integrate other machine learning models, such as ANN, XGBoost, Gradient Descent, and LSTM. The cloud must train the model every hour using all the available data in the database, which can be a heavy workload. The researcher may adjust the time to teach the system to be less suitable for the model.

When comparing the effectiveness and accuracy of the prediction results with similar research that forecasts only time-series $PM_{2.5}$ and is a forward prediction class, it is found that the prediction results of this research using MARF have a Total average accuracy of 84.91%. That is slightly better than Masinde, Gitahi, & Hahn (2020) [35, 36], which achieved an average of 82.00% using a Stochastic gradient descent model with a Gated Recurrent Unit (GRU), which has a more complex computation.

5. Acknowledgements

The authors thank the Thai Pipe Industry Co., Ltd. for the financial support. Thank you, Mr. Natthaphon Yuyuenyong, Mr. Thanakrit Phrompong, and Mr. Ekkanut Prasitthiyannawong, who assisted in installing and maintaining both hardware and software. We also want to thank Dr. Panuwat Taerakul, Dean of Engineering Faculty at Southeast Asia University, for his significant support and guidance throughout the project.

Author Contributions: Conceptualization, N.O. and S.T.; methodology, N.O. S.T.; software, N.O. and C.C.; validation, N.O. and S.T.; formal analysis, N.O.; investigation, N.O.; resources, N.O., S.T., and C.C.; data curation, N.O. and S.T.; writing-original draft preparation, N.O.; writing-review and editing, N.O.; visualization, N.O.; supervision, N.O. and S.T.; project administration, N.O.; funding acquisition, N.O.

Funding: This research was funded by Thai Pipe Industry Co., Ltd.

Conflicts of Interest: The authors declare no conflict of interest.

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MA

1hr: Predict \ Actual (Class)	1	2	3	4	5	Sum
1	250	30	0	0	0	280
2	108	149	66	32	0	355
3	40	120	529	210	12	911
4	0	31	131	337	45	544
5	0	0	0	11	10	21
Sum	398	330	726	590	67	2111

3hr: Predict \ Actual (Class)	1	2	3	4	5	Sum
1	249	36	0	0	0	285
2	106	139	67	41	0	353
3	43	123	525	205	13	909
4	0	32	132	333	44	541
5	0	0	2	11	10	23
Sum	398	330	726	590	67	2111

6hr: Predict \ Actual (Class)	1	2	3	4	5	Sum
1	246	42	0	0	0	288
2	107	128	67	52	3	357
3	45	126	519	203	12	905
4	0	34	136	324	43	537
5	0	0	4	11	9	24
Sum	398	330	726	590	67	2111

12hr: Predict \ Actual (Class)	1	2	3	4	5	Sum
1	249	49	3	8	0	309
2	96	110	63	64	8	341
3	53	130	508	195	10	896
4	0	41	143	312	41	537
5	0	0	9	11	8	28
Sum	398	330	726	590	67	2111

24hr: Predict \ Actual (Class)	1	2	3	4	5	Sum
1	251	54	2	22	7	336
2	81	83	67	82	9	322
3	65	140	441	192	2	840
4	1	53	191	283	42	570
5	0	0	25	11	7	43
Sum	398	330	726	590	67	2111

MARF

1hr: Predict \ Actual (Class)	1	2	3	4	5	Sum
1	311	8	0	0	0	319
2	31	206	17	0	0	254
3	8	75	657	80	12	832
4	48	41	52	503	12	656
5	0	0	0	7	43	50
Sum	398	330	726	590	67	2111

3hr: Predict \ Actual (Class)	1	2	3	4	5	Sum
1	267	11	1	1	0	280
2	40	158	21	1	0	220
3	19	104	630	118	20	891
4	72	57	74	460	16	679
5	0	0	0	10	31	41
Sum	398	330	726	590	67	2111

6hr: Predict \ Actual (Class)	1	2	3	4	5	Sum
1	194	14	3	3	0	214
2	34	97	22	4	0	157
3	39	142	582	167	32	962
4	131	77	119	399	14	740
5	0	0	0	17	21	38
Sum	398	330	726	590	67	2111

12hr: Predict \ Actual (Class)	1	2	3	4	5	Sum
1	110	11	0	5	0	126
2	28	39	20	4	0	91
3	60	176	557	227	53	1073
4	200	100	149	347	5	801
5	0	4	0	7	9	20
Sum	398	330	726	590	67	2111

24hr: Predict \ Actual (Class)	1	2	3	4	5	Sum
1	96	0	0	0	0	96
2	8	9	0	9	1	27
3	88	207	553	283	66	1197
4	206	110	169	295	0	780
5	0	4	4	3	0	11
Sum	398	330	726	590	67	2111

MA			Class						
1hr (%)	1	2	3	4	5	X	SD	Min	Max
Accuracy	91.57	81.67	72.57	78.21	96.78	84.16	9.87	72.57	96.78
Precision	62.81	45.15	72.87	57.12	14.93	50.57	22.30	14.93	72.87
Recall	89.29	41.97	58.07	61.95	47.62	59.78	18.33	41.97	89.29
F1	73.75	43.50	64.63	59.44	22.73	52.81	20.08	22.73	73.75
Specificity	91.92	89.69	83.58	83.85	97.27	89.26	5.76	83.58	97.27

MA RF			Class						
1hr (%)	1	2	3	4	5	X	SD	Min	Max
Accuracy	95.50	91.85	88.44	88.63	98.53	92.59	4.39	88.44	98.53
Precision	78.14	62.42	90.50	85.25	64.18	76.10	12.49	62.42	90.50
Recall	97.49	81.10	78.97	76.68	86.00	84.05	8.27	76.68	97.49
F1	86.75	70.55	84.34	80.74	73.50	79.18	6.95	70.55	86.75
Specificity	95.15	93.32	94.61	94.02	98.84	95.19	2.15	93.32	98.84

MA			Class						
3hr (%)	1	2	3	4	5	X	SD	Min	Max
Accuracy	91.24	80.81	72.29	77.97	96.68	83.80	9.96	72.29	96.68
Precision	62.56	42.12	72.31	56.44	14.93	49.67	22.30	14.93	72.31
Recall	87.37	39.38	57.76	61.55	43.48	57.91	18.93	39.38	87.37
F1	72.91	40.70	64.22	58.89	22.22	51.79	20.30	22.22	72.91
Specificity	91.84	89.14	83.28	83.63	97.27	89.03	5.87	83.28	97.27

MA RF			Class						
3hr (%)	1	2	3	4	5	X	SD	Min	Max
Accuracy	93.18	88.92	83.09	83.47	97.82	89.29	6.33	83.09	97.82
Precision	67.09	47.88	86.78	77.97	46.27	65.20	17.96	46.27	86.78
Recall	95.36	71.82	70.71	67.75	75.61	76.25	11.05	67.75	95.36
F1	78.76	57.45	77.92	72.50	57.41	68.81	10.66	57.41	78.76
Specificity	92.85	90.90	92.13	90.92	98.26	93.01	3.05	90.90	98.26

MA			Class						
6hr (%)	1	2	3	4	5	X	SD	Min	Max
Accuracy	90.81	79.58	71.91	77.31	96.54	83.23	10.14	71.91	96.54
Precision	61.81	38.79	71.49	54.92	13.43	48.09	22.75	13.43	71.49
Recall	85.42	35.85	57.35	60.34	37.50	55.29	20.20	35.85	85.42
F1	71.72	37.26	63.64	57.50	19.78	49.98	21.15	19.78	71.72
Specificity	91.66	88.48	82.84	83.10	97.22	88.66	6.07	82.84	97.22

MA RF			Class						
6hr (%)	1	2	3	4	5	X	SD	Min	Max
Accuracy	89.39	86.12	75.18	74.80	97.02	84.50	9.54	74.80	97.02
Precision	48.74	29.39	80.17	67.63	31.34	51.45	22.27	29.39	80.17
Recall	90.65	61.78	60.50	53.92	55.26	64.42	15.04	53.92	90.65
F1	63.40	39.84	68.96	60.00	40.00	54.44	13.64	39.84	68.96
Specificity	89.25	88.08	87.47	86.07	97.78	89.73	4.65	86.07	97.78

MA			Class						
12hr (%)	1	2	3	4	5	X	SD	Min	Max
Accuracy	90.10	78.64	71.29	76.17	96.26	82.49	10.34	71.29	96.26
Precision	62.56	33.33	69.97	52.88	11.94	46.14	23.54	11.94	69.97
Recall	80.58	32.26	56.70	58.10	28.57	51.24	21.28	28.57	80.58
F1	70.44	32.79	62.64	55.37	16.84	47.61	22.21	16.84	70.44
Specificity	91.73	87.57	82.06	82.34	97.17	88.17	6.43	82.06	97.17

MA RF			Class						
12hr (%)	1	2	3	4	5	X	SD	Min	Max
Accuracy	85.60	83.75	67.55	66.98	96.73	80.12	12.74	66.98	96.73
Precision	27.64	11.82	76.72	58.81	13.43	37.68	28.85	11.82	76.72
Recall	87.30	42.86	51.91	43.32	45.00	54.08	18.92	42.86	87.30
F1	41.98	18.53	61.92	49.89	20.69	38.60	18.75	18.53	61.92
Specificity	85.49	85.59	83.72	81.45	97.23	86.70	6.12	81.45	97.23

MA			Class						
24hr (%)	1	2	3	4	5	X	SD	Min	Max
Accuracy	89.01	76.98	67.60	71.86	95.45	80.18	11.71	67.60	95.45
Precision	63.07	25.15	60.74	47.97	10.45	41.47	22.96	10.45	63.07
Recall	74.70	25.78	52.50	49.65	16.28	43.78	23.17	16.28	74.70
F1	68.39	25.46	56.32	48.79	12.73	42.34	22.79	12.73	68.39
Specificity	91.72	86.19	77.58	80.08	97.10	86.53	8.07	77.58	97.10

MA RF			Class						
24hr (%)	1	2	3	4	5	X	SD	Min	Max
Accuracy	85.69	83.94	61.30	63.05	96.31	78.06	15.26	61.30	96.31
Precision	24.12	2.73	76.17	50.00	0.00	30.60	32.44	0.00	76.17
Recall	#####	33.33	46.20	37.82	0.00	43.47	36.15	0.00	#####
F1	38.87	5.04	57.51	43.07	0.00	28.90	25.12	0.00	57.51
Specificity	85.01	84.60	81.07	77.84	96.81	85.07	7.18	77.84	96.81