Smart Air: A Novel Iot-Based Prediction Model for Air Pollution Forecasting and Monitoring

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Abstract
The internet of things, or IoT, is a network of interconnected computing devices, mechanical and digital machines, objects, animals, and people that are equipped with unique identifiers and the capability to transfer data over a network without the need for human-to-human or human-to-computer interaction. The internet of things enables enterprises to access real-time data and business insights that, when acted upon, can ultimately result in increased efficiency. The problem of air pollution is significant and severe because of human activity. Industrial growth is critical for the economic development of any country, as it maximises the utilisation of natural resources. In this paper the strategy identifies and present a broad framework called “Air Pollution Estimation Model (APEM)” for analyzing the role of pollution control boards in preventing and controlling industrial air pollution. The framework is to provide an overview of industrial air pollution prevention and control.
Keywords: Air pollution, Air Pollution Estimation Model (APEM), IoT

INTRODUCTION

Air quality prediction is mostly focused on these industrial locations. Industrial-scale use of this concept necessitates the use of pricey sensors and a massive quantity of power. The World Health Organization (WHO) classifies significant air pollutants as particle pollution, carbon monoxide (CO), sulphur dioxide (SO2), and nitrogen oxide (NO2). Along with the above-mentioned gases, PM or Particulate Matter and VOC or Volatile Organic Compounds constituents pose significant hazards. Long- and short-term exposure to toxicants floating in the air has varying toxicological effects on humans. Asthma, bronchitis, some cardiovascular disorders, and long-term chronic diseases such as cancer, lung damage, and in severe situations, diseases such as pulmonary fibrosis are among the diseases. Air pollutants are to blame for the thorough air pollution that wreaks havoc on human life. Air pollution can result in serious difficulties with the human respiratory system, skin illnesses, and eye irritation, among other things. The Air Quality Index, or AQI, is used to determine the level of pollution in the air. The AQI is a numerical figure that indicates the level of pollution in the air. The greater the AQI value, the more contaminated the location. The World Health Organization (WHO) lists Karachi, Pakistan; New Delhi, India; Beijing, China; Lima, Peru; and Cairo, Egypt as some of the world's most polluted cities. Smart cities can be constructed sustainably with reduced carbon footprints. Air pollution's long-term impacts can continue for years or even a lifetime. They can even result in death. As with humans, animals, and plants, entire ecosystems can be harmed by air pollution. The air quality in the majority of India's cities has deteriorated significantly in recent years. Apart from the ubiquitous Carbon Dioxide (CO2), various newer pollutants such as Nitrogen Dioxide (NO2), Sulfur Dioxide (SO2), and Carbon Monoxide (CO) have been introduced into the atmosphere. The majority of contaminants are hazardous to human health. However, CO is more dangerous. It is dubbed the Silent Killer due to the fact that it kills softly and fast. It enters the bloodstream immediately and substitutes oxygen molecules, depriving the brain and heart of vital oxygen. If it is in the air, it rapidly enters the bloodstream, causing symptoms such as headaches, flu, nausea, dizziness, and confusion. As the level grows, the individual may experience nausea, unconsciousness, and, if the exposure is prolonged, brain damage or death.

Individuals, like weather conditions, should become more concerned about air pollution in the future, so they can make better choices about their day/week. The sensor is capable of detecting variables such as air pressure, air composition, and water quality. WSNs are employed in a range of applications, including personal space, industrial floors, agricultural, home utility monitoring systems, factory automation, and automotive. WSNs are associated with the concept of the Internet of Things. The Internet of Things connects objects to transmit data via dispersed sensor networks. The Internet of Things has a number of beneficial uses in the medical area. Connecting devices such as cellphones and sensing systems enables the creation of an infrastructure for health care information and services. This strategy is dubbed "Mobile-Health." Air pollution is a significant environmental issue in many metropolitan areas. Local governments can examine the city's current traffic situation through real-time monitoring of pollution data and making suitable decisions. As a result, an early method for monitoring and determining the amount of AP utilising Air Quality (AQ) is required for accurately forecasting pollutant concentrations. The prediction of air quality can be enhanced by deploying Internet of Things (IoT)-based sensors that dynamically alter the prediction of air quality. The prediction and estimation of AP using a variety of existing methodologies is extremely expensive and has a very low accuracy. Machine Learning algorithms are rapidly advancing in terms of technology and are now being used in practically all industries and applications, although AP prediction is not restricted to those fields. This article discusses numerous research of machine learning algorithms for AP prediction and monitoring using IoT sensor data from various cities.

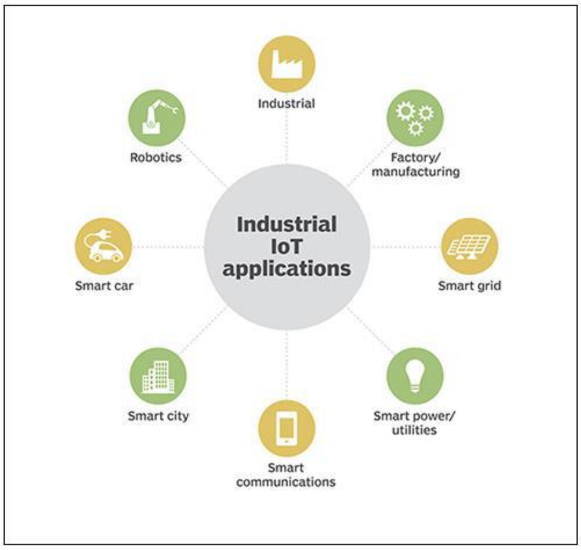

Figure 1: IOT Applications

Pollution has becoming more prevalent as industrialization and urbanisation progress. Air pollution is the presence of toxins or pollutant compounds in the atmosphere that have an adverse influence on human health. If we know the quantity of a pollutant, we can take appropriate steps to reduce air pollution. Recent studies demonstrate a strong link between air pollution and diseases such as asthma. Recent improvements in embedded electronics have enabled the monitoring of sensor data and air pollution using wireless network technology. The purpose of this study is to develop a model for forecasting and prediction of particular air pollutants and temperatures that are thought to be extremely dangerous. Two algorithms for machine learning have been implemented. These models offer a high predictive capacity, a high degree of generalisation, and a broad range of applications. In the subject of air pollution, much effort has been made to research chronic air pollution. Deep learning has been gaining traction in recent years, owing to considerable hardware advancements. Numerous publications have analysed current solutions for air pollution prediction that utilise artificial neural networks (ANNs) and asserted their capacity to efficiently extract representations of relevant functionalities and characteristics from massive volumes of data.

LITERATURE REVIEW

Ceci et al. (2020) highlighted the emergence of the Internet of Things (IoT) paradigm, which has empowered everyday objects with microcontrollers, digital communication transceivers, and suitable protocols for communication, thereby integrating them into the Internet. This has led to the generation of massive volumes of diverse data from devices such as home appliances, surveillance cameras, sensors, and cars, which can be processed to develop new applications. Advancements in IoT technology have facilitated the development of effective air pollution monitoring systems, comprising multiple sensors connected wirelessly via Bluetooth or WiFi for nearby locations, or through mobile networks and satellite for remote regions. To handle the large amount of data and enable near real-time monitoring, big data and cloud computing technologies may be employed. These monitoring systems provide high-quality data that can contribute to a better understanding of pollution trends.

Steininger et al. (2020) noted that while many deep learning algorithms for air pollution prediction rely on sequential sensor data, the use of camera pictures and convolutional neural networks (CNNs) is rare. Only two studies have explored this approach, which utilizes satellite photos and CNNs to build pollution maps. In contrast, the authors' models employ deep learning techniques trained on camera images, rather than satellite photos, for air pollution prediction.

Marques et al. (2019) highlighted that previous research has focused on incorporating IoT platforms for real-time outdoor air quality monitoring. However, combining these technologies can also be beneficial for improving indoor air quality. The authors presented an IoT-based indoor air quality monitoring platform that leverages cloud computing and IoT convergence. They designed an experimental wireless system that extends beyond hotspots to provide WiFi connectivity in remote locations at an affordable cost, utilizing Wireless Mesh Networks and Captive Portal technology. The system offers a diverse range of Internet-based communication services and applications. Experimental results demonstrated that the system is easily deployable in terms of coverage, management, and service provision.

METHODOLOGY

The proposed framework is called "Air Pollution Estimation Model (APEM)". The provided methodology for predicting the degree of air pollution is depicted below, along with the complete procedure for developing the model.

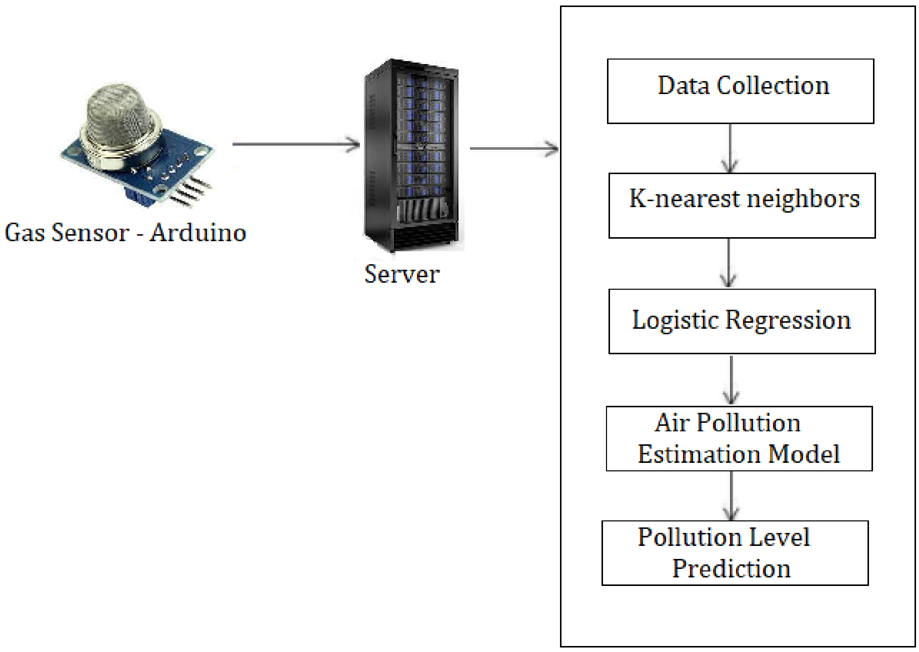

Figure 2: Proposed Framework Architecture

Data Collection

For pollution level estimation, vast volumes of data are required to improve the accuracy of machine learning algorithms. An Arduino microcontroller is used to collect data, coupled with gas sensors such as the MQ7 for carbon monoxide and the MQ135 for carbon dioxide. The sensor data obtained is then transmitted to the development machine via WiFi and the RF 433 network interface module. The collected data is labelled with the location of the Arduino. These data are then redistributed to the subsequent phase in order to perform the forecasts.

Prediction of Pollution Levels

This step completes the prediction of air pollution. This phase makes a prediction on the list of information gains received from the preceding list, based on the mean and standard deviation values. Each cluster is used to generate three probability lists. The probability list is then used for intercommunication in order to create the estimation model. This is accomplished by extracting the maximum and minimum values into a list. The lowest value is used to create the maximum list, and the highest value is then used to do predictions. The difference between the minimum and maximum values is calculated and then compared to the gathered data to provide an estimation of the pollution level. The server administrator is then notified of the estimated value.

Practical experience has shown that adhering to short-term air quality requirements for point sources significantly impacts their emission rates and release conditions, and their long-term impact on recipients is usually insignificant. This implies that adhering to short-term standards plays a crucial role in managing emissions from point sources. For area sources with minimal seasonal variation, adhering to long-term criteria or standards is typically sufficient to maintain short-term impacts within acceptable limits, excluding extremely variable sources and secondary pollutants. Adhering to long-term guidelines or regulations allows complex air quality problems to be effectively addressed by breaking them down into smaller, independent issues for each point source or category of area sources. Computational models can be used for quick assessment of point sources, which not only supports pollution control but also aids in designing effective air quality monitoring and exposure assessments. This approach limits the scope of direct measurement, which can be time-consuming and costly, to representative samples from key source groups, with computational models used to extend predictions to all sources under current and target conditions, with regular updates. This combined approach eliminates limitations of extensive waste measurement programs, which are costly, of limited management use, and temporary in impact.

Result and Discussion

The air quality monitoring node is installed in the laboratory, and data collection will take place from January to April 2020. The collected data included 36,388 recordings with eight characteristics each, including NH_3, CO, NO_2, CH_4, CO_2, PM 2.5, air temperature, and air humidity. Each of these air pollutants has a specific range relative to its quality class, as described in Table 5.1, where information about the range of each air pollutant, as well as its taxonomy, namely 'Good', 'Moderate', 'Un-Healthy for Sensitive People', 'Un-Healthy', 'Very Un-Healthy', 'Hazardous', and 'Highly Dangerous',.

Table 1: Air pollutants and quality spectrum

	Good	Moderate	Unhealthy	Very Unhealthy	Hazardous	Highly Dangerous
NH_2	<200	200-400	800-1200	1200-1800	1800+	
CO	<4.4	4.4 - 9.4	12.4-15.4	15.4-30.4	30.4-40.4	40.4+
NO_2	<0.053	0.053 - 0.1	0.36-0.65	0.65-1.24	1.24-1.64	1.64+
CH_2	<50	50-100	150-200	200-300	300-400	400+
CO_2	<1000	1000-2000	5000-10000	10000-20000	20000-40000	40000+
Dust	<12	12-35.4	55.4-150.4	150.4-250.4	250.4-350.4	350.4+

The designed IoT node for indoor air quality monitoring is installed inside the experimental facility to record readings of various air contaminants. Time series are created from the collected readings, which are then used to do predictive analysis. The APEM is applied to each air pollutant to forecast its values for subsequent time instances. To accomplish this, APEM with a single hidden layer containing ten hidden nodes is used. The loss function'mean squared error' is used in conjunction with the optimizer 'adam' to handle the sparse gradient and hence improve the performance of APEM. The following 50 air quality data are expected for prediction purposes.

The reason for choosing a short interval for air quality prediction is that changes in indoor air pollution in the near future are critical for decision-making about corrective measures, particularly in the event of a COVID-19 pandemic. The following sections discuss the prediction findings for the next 50 air quality events.

Prediction of CO2

CO2 is a poisonous gas that is commonly produced by fuel burning, industrial processes, and human respiration, among other things. The created IoT node for air quality monitoring was installed inside the lab, which is a confined setting where normally five to six people work from 9:30 a.m. to 5:00 p.m. Because there is no combustion mechanism in the lab, the primary source of CO2 is the lab's occupants. Although the quantity of CO2 breathed by an individual is negligible, if more than five persons are crammed into a small space with inadequate ventilation, the levels may surpass the acceptable limits.

Table 2: Performance Evaluation of APEM for every 5 min.

Gas	MAE	MSE	RMSE
CO2	0.05522181	0.00791775	0.08898173
CO	0.02109271	0.00187406	0.04329045
NO2	0.02131099	0.00075064	0.02739786
PM 2.5	0.11468725	0.01429022	0.11954172
Temperature	0.07548273	0.01136971	0.10662883
Humidity	0.07865122	0.01184788	0.10884799

The maximum CO2 concentration found in the recorded data set is 1506 ppm, which falls within the 'Moderate' class indicated in Table 5.1. The APEM model is used to forecast CO2 for future instances. Two types of forecasting are used for this purpose: time series forecasting of CO2 every 5 minutes and hourly forecasts, as seen in Figures 5.1 and 5.2, respectively. Scaling of features is conducted prior to APEM training, and after training the model, the original values are recovered using inverse mapping. The performance of the APEM model is summarised in Tables 5.2 and 5.3 for all performance indicators, including MAE, RMSE, and MSE.

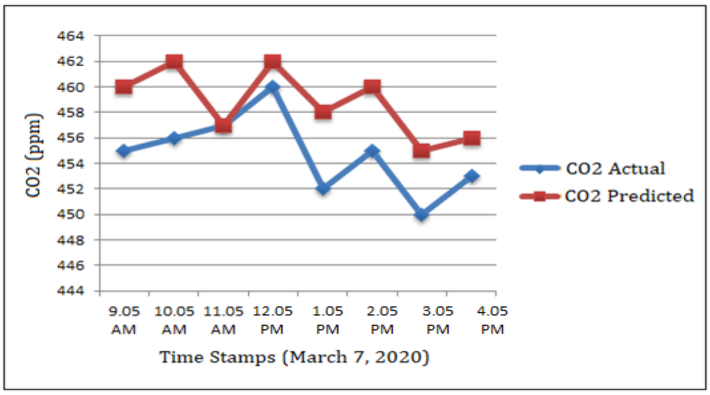

Figure 3: Hourly Predicted Values of CO2

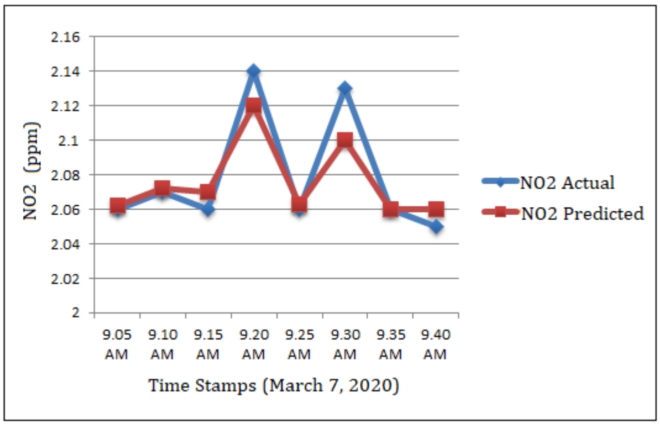

Figure 4: Predicted Values of NO2 for every 5 mins

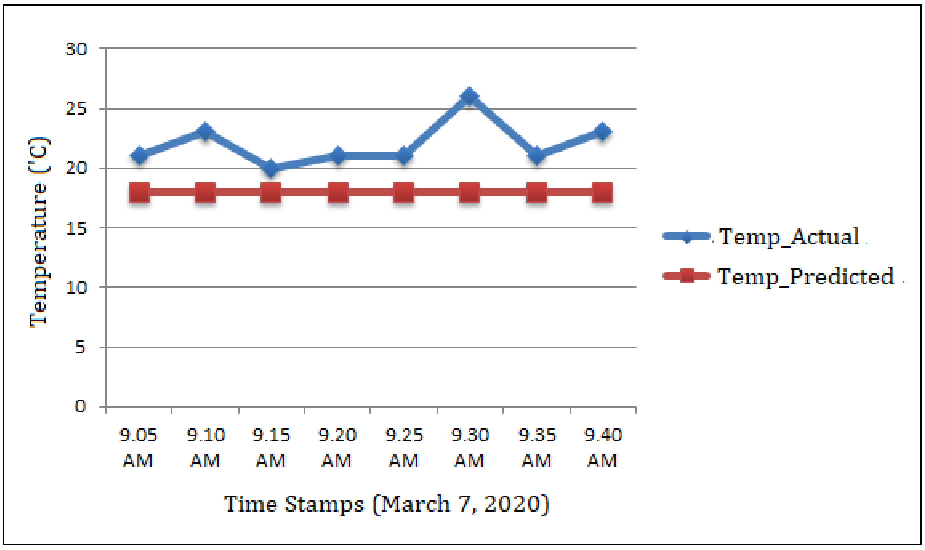

Figure 5: Predicted Values of Air Temperature for every 5 mins

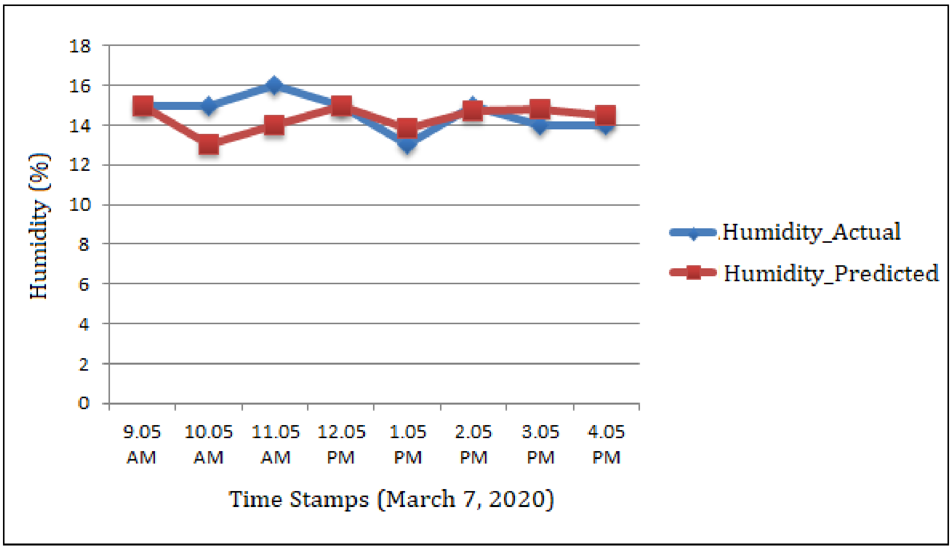

Figure 6: Hourly Predicted Values of Humidity

The APEM produced positive findings for the features studied for indoor air quality, with predicted values effective for delivering actionable insights and initiating corrective procedures.

Conclusion

The COVID-19 pandemic has highlighted the importance of indoor environment monitoring and prediction. With lockdown measures and work-from-home arrangements, indoor air quality has become a concern as public facilities prepare to reopen. Existing air quality monitoring solutions lack future air quality forecasting, which is crucial for COVID-19 patients and those with respiratory illnesses. To address this, we have developed an indoor air quality monitoring and prediction solution using IoT and machine learning, achieving high accuracy. Our online portal and mobile application generate notifications for poor air quality, providing users with awareness and understanding of the air they are breathing. Additionally, we have efficient machine learning approaches for predicting air pollution outside of vehicles, which can contribute to reducing air pollution and conserving natural resources.

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