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Air Quality Monitoring and Prediction systems: A Review

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Abstract: Our nation's economic, industrial, power creation, and automotive all have grown enormously in the recent period, resulting in more significant pollutant emissions. Countries like India, China, and Iran have a severe effect of air pollution on overall health and work productivity. Air pollution figures are warning everyone. People spend 80-90 percent of their waking moments in vehicles, offices, and households. Society needs clean air to breathe. The hazards of living toxins from the air are emphasized, mandating an efficient ambient Monitoring and alerting System. Artificial Intelligence (AI) based solutions can be a solution to tackle this difficult situation. The integration of AI to the Air Quality Monitoring (AQM) systems makes it possible to assess the Air Quality (AQ) and alert people about their susceptibility to pollutant gases. The main scope of this research is to examine how air pollutants (AP) affect human health, and different Machine Algorithms can be used to estimate them and alert individuals

Keywords: Air Pollutants, Air Quality Monitoring, Machine Learning.

I. INTRODUCTION

In 2021, new guidelines from World Health Organization (WHO) provided a clear picture of air pollution's impact on public health. The new guidelines are recommended for critical AP, affecting climate change. According to WHO, the significant gases that are considered pollutants are Carbon Dioxide (CO2), Sulphur Dioxide (SO2), suspended Particulate Matter (PM) of size lesser than 10(PM10) and 2.5 microns (PM2.5), Ozone (O3), Carbon Monoxide (CO), and Nitrogen Dioxide (NO2) [1]. In a report, WHO mentioned that approximately 3 million deaths in a year are connected to exposure to outdoor air contamination. And 92% of the people on the globe lived in an ambient where air pollution exceeded the WHO 2005 standards [2].

Traditionally, governmental agencies have monitored air contaminants at fixed locations using expensive high-end sensing technologies. These stations are widely spaced and only estimate average pollution levels impacting significant populations. On the other hand, air pollution is a becoming complicated process with complex geographical and short-term variations [3]. For example, pollution concentrations in main streets might change by meters in distance and minutes in time [4].

As a result, increasing the spatiotemporal resolution of available AQ data is required to assess health risks and take preventive measures. Asia has the most severe air pollution, having China and India top in the list [5]. Air pollution worsens at an alarming rate. Massive smog covered Delhi following Diwali, India's most celebrated event, in 2016, indicating a case of contaminated air [6]. Due to horrific pollution in Beijing and neighbouring cities, the Government of China issued an alert in December 2016, advising the public to stay indoors [7]. Several other countries have experienced a similar situation [8], explaining the unavoidable need for air quality monitoring (AQM).

II. AIR QUALITY INDEX(AQI)

Many countries have developed the AQI concept and using it at present [9], [10], [11] to evaluate the quality of air. So in our country, a program called National Air Quality Index was initiated by the Ministry of Environment, Forests, and Climate, India, in 2015. Central Pollution Control Board (CPCB), India, released new values of Indian National Air Quality Standards (INAQS) (2009) for twelve air pollutants [CO, SO2, NO2, O3, PM2.5, PM10, Ammonia (NH3), Lead (Pb), Benzo (a) Pyrene (BaP), Arsenic (As), Benzene (C6H6), and Nickel (Ni)]. The current state of the AQ and its impact on health have led to the adoption of the IND-AQI detail categories listed in Table I. These AQI ranges should be mapped to critical pollutants breakpoints using a segmented linear or nonlinear function. For calculating the practical AQI at least, three key pollutants are essential, out of which one must be either PM2.5 or PM10, to which short-term standards are recommended and must be measured continuously [12].

Table I[13]: IND-AQI Category and Range

AQI Range	AQI Category
500 – 401	Severe
400 – 301	Very Poor
300 – 201	Poor
200 – 101	Moderate
100 – 51	Satisfactory
50 – 0	Good

The WHO guided standards and India air quality standards for critical pollutants are tabulated in Table II [1], [12] it shows that there is a need to revise the air quality standards by CPCB.

Table II: WHO Recommended 2021 AQG levels and India AQ standards

Air Pollutant in µg/m3	Averaging time	2021 AQG level	Indian National Air Quality Standards
PM2.5	24-hour*	15	60
PM10	24-hour*	45	100
NO2	24-hour*	25	80
SO2	24-hour*	40	80
O3	8-hour*	100	180
NH3	24-hour*	-	400
CO, mg/m3	**8- hour**	**7**	**2**

*99th percentile (i.e., 3–4 exceedance days per year).

Table III: WHO Recommended levels for a short time

Pollutant	Air quality guidelines that remain valid	Averaging time
NO2, µg/m3	200	1-hour
SO2, µg/m3	500	10-minute
CO, mg/m3	10	8-hour
	35	1-hour
	100	15-minute

Table III[1] lists the air quality standards for NO2, SO2, and CO (short averaging times), which were not re-evaluated by WHO but are still in effect.

III. AIR POLLUTANTS AND THEIR EFFECT ON PUBLIC HEALTH

The AP was identified in the global expert consultation, and several varieties of health problems were included in the summary report. In the following discussion, the Guideline Development Group (GDG) resolved to produce Air Quality Guideline (AQG) thresholds for PM10, PM2.5, SO2, NO2, O3, and CO concerning health outcomes critical for decision-making and for relevant averaging times. The primary sources of AP are listed in Table IV.

a. Effects due to CO2

It quickly accumulates in poorly ventilated areas and is a high-density greenhouse gas with an atmospheric concentration of 300-400 ppm. People generate CO2 with every exhalation they take, but since CO2 is non-toxic, it can cause health problems such as hypoxia if its concentration exceeds the recommended level. In addition, If people stay much time in an overly crowded environment or a place with poor ventilation, the exceeded CO2 concentrations standard can cause discomfort. Therefore, CO2 is used as a health index by the Government to measure indoor air pollution [14].

b. **Effects due to CO**
CO, like a compound, is a colorless, tasteless, non-irritating, and odorless gas that is the most common toxic gas in everyday life. In general, the activities like a wood fire, engine exhaust, and incomplete gas combustion produce CO [14]. Because the heme-binding capacity of the blood is 200 times greater than those of Oxygen, it is tough for the heme to handle Oxygen after absorption. As a result, after inhaling CO, people experience symptoms such as dizziness, headaches, chest pains, and vomiting [15].

c. **Effects due to NO2**
NO2 is released due to heating, transport, and power generation. NO2 can irritate human airways and aggravate respiratory symptoms. NO2 is a critical ozone precursor and a pollutant linked to asthma and other respiratory diseases [16].

d. **Effects due to SO2**
SO2 is soluble in aqueous media and affects the nose and upper respiratory tract mucous membranes. Outdoor air is the source of fossil fuel combustion, including petroleum, coal, and natural gas. Acute exposure leads to bronchial activity [17].

e. **Effects due to PM**
Fine particles of 2.5 microns (PM2.5) diameter can reach deep into the lungs producing severe respiratory issues. PM exposure has long-term and short-term impacts on health and is linked to cardiovascular, respiratory disease, morbidity, and mortality. Long-term exposure has also been linked to poor baby outcomes and lung cancer. The International Agency for Research on Cancer (IARC) [18] identified PM as a cause of lung cancer in 2013.

f. **Effects due to NH3**
Ammonia is a corrosive chemical. The seriousness of health effects is dependent on parameters like the route of exposure, dose, and duration. Acute burning in the eyes, nose, throat, and lungs is observed when ammonia concentrations are high in the air. Sometimes it causes blindness or death. Coughing and nose discomfort are also caused by inhaling smaller amounts [19].

Table IV: Major Sources of AP

Pollutants	Major Sources of Emission
CO2	motor vehicle in garages, Combustion activities and metabolic activity
CO	Tobacco smoke, stoves, water-boilers, kerosene or gas heaters, fuel-burning
NO2	Garaged automobiles, fuel combustion, and outdoor air
SO2	Combustion of fossil fuels such as oil, coal, and natural gas, as well as outdoor air pollution
PM2.5 & PM10	Tobacco smoke, re-suspension, combustion products
NH3	Main sources of ammonia comprise organic waste decomposition or breakdown, gas reactions with the atmosphere, forest fires, animal and human waste, and nitrogen fixation processes.

IV. METHODS TO COLLECT AIR POLLUTION DATA

As illustrated in the figure, we can divide data collection into two broad categories:

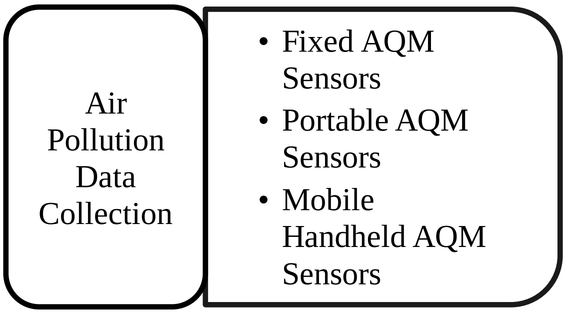

Figure I: Air quality Data collection methods

a. **Fixed AQM Sensors:** Air pollution data is obtained through sensors fixed in a specific location. Unlike mobile monitoring stations, selected wireless devices can be grouped nearby to produce absolute data values rather than aggregated. Fixed AQM guarantees that data quality is best. Wireless connectivity, such as Bluetooth, Global System for Mobiles (GSM), Zigbee, General Packet Radio Service (GPRS), gateways, routers, e.t.c., are being used to transfer the gathered data to a central server. Sensors vary in terms of functionality, size, and storage capabilities.

The authors of the papers [20], [21], [22], [23], and [24] mention a variety of fixed AQM sensors for AQ data collection. Although fixed sensors are easier to install and maintain. This device has a downside: short battery life, frequent calibration, and short operational life. Because the sites are immobile, the results could be less precise. Quality, sophistication, and memory all contribute to the cost. When location-specific pollutants are not strictly required, low cost may be advantageous.

b. **Portable AQM Sensors:** Portable sensors can collect more detailed data on AQ because they are not tied to a specific geographic area and can be moved from one location to another by mounting sensors on vehicles. This device can monitor broad areas and offer Spatio-temporal data. As a way, trends in AQ data gathered by wireless portable devices can be observed more precisely. [25], [26], [27] describes a choice of portable AQM sensors for collecting data on AQ. The portable devices increase battery consumption and price.

c. **Mobile handheld AQM Sensor:** Because of technological advancements, manufacturers can now introduce low-cost mobile sensors that do not need any external aid for deployment. They could be used as personal handsets that people carry with them when they go out in public or stored in a backpack or private vehicle. Because these sensors are taken anywhere, a user can navigate multiple paths and collect fine-grained data. This original data, also known as crowdsourced data, is uploaded to a cloud service for analysis, and the outcomes can be used to make a variety of personal health recommendations. A mobile app or a web application controls the mobile sensors.

The authors of [28], [29], [30], [31], [32], [33], and [34] mention various Mobile handheld AQM sensors for collecting AQ data. Maybe this is the more adaptable of the three approaches, persuading persons to bring sensors and participate in participatory sensing. Mobile handheld sensing devices consume more power because they are mobile, which quickly depletes smartphone batteries when making frequent cellular and Bluetooth connections. Increasing battery life in this type of device is still difficult. These sensors are also more expensive than other types of sensors. Another difficulty with using such sensors is their accuracy, requiring periodic calibration.

Although AQ observation is location-dependent, it is critical to double-data spatial resolution. Although these methods can predict AQ, the results are inaccurate due to a lack of high-quality data. Furthermore, because each technique has disadvantages, it was impossible to compare them. Table V contains a summary of the Indoor AQM devices.

V. VARIOUS AIR QUALITY PREDICTION STUDIES

The Benzene concentration is determined using an Artificial Neural Network (ANN) and a Support Vector Machine (SVM). However, they could not estimate the gap between the actual effect and predicted values and the correlation approach used to determine their relationship with CO [34].

An investigation [35] Based on a neural network (NN) with an integrated sensor may produce correct AP values in their study. However, it is slow since it requires all the training data and cannot work with incomplete data.

Random Forest (RF) was the best method for determining PM10 levels. Although RF cannot estimate the level of harmful contaminants with accuracy, it can operate with partial data sets [36].

Decision trees and Multinominal Logistic regression are employed to estimate AQ pollutant levels. First, correlation is performed, followed by feature analysis and prediction. The researcher should preferably use K-means clustering to create 3 clusters and categorize them as severe, moderate, and less air pollution. The dataset is then separated into two parts: training and testing. Multinominal Logistic regression and decision trees are utilized after k means clustering to forecast future values. Original values are substantially nearer to expected values in multinominal logistic regression, and using multinominal logic regression yields a more exact result [37].

Raspberry Pi platform and a machine learning (ML) algorithm called Multilayer Perceptron (MLP) to predict AQ accurately. The MLP addresses the classification problem, which is utilized for discrete values, regression, and continuous data. Since the author used discrete values and MLP with backpropagation, the input did not reach the activation

Table V: Different Fixed AQM monitoring devices

Manufacturer	Type of Sensor	Communication Channel	Pollutants Monitored
Alphasense	Gas And Infrared sensors[20]	GPRS using Constrained Application Protocol(CoAP)	CO,O3,CO2,NO2,NO
Libelium	Waspmote wireless Gas sensors[21]	Meshlium Gateways	NO2, O3, CO, CO2, and PM10
Alphasense	Gas Sensors[22]	ZigBee-GSM and GSM Ethernet Gateways	CO, CO2, SO2, NO2, H2S,O3,PM2.5 and PM10
e2v	Semi conductor[23]	Gateways and GSM	CO
uHoo	Metal Oxide and Electro Chemical[24]	Not Mentioned	CO2, NO2, CO, O3, TVOC, PM2.5

Table VI: List of AQM with AI-based papers included in this study

AI Method Used	Prediction Performance	Air Pollutant	Metrological Parameter
Artificial Neural Networks[34]	MRE:-0.16	Benzene	-
Neural Networks[35]	Accuracy:99.56%	Smoke(MQ2), NH3, S, Benzene, CO2(MQ135), LPG(MQ5)	Air temperature, Relative humidity.
Random Forest[36]	Accuracy: Between 70% and 90%	PM10	Wind speed & direction, Temperature
Regression model[37]	Error rate:0.428	SO, NOx	General
MLP Regressor[38]	Coefficient of determination R2:0.65	NO, NO2, O3 and PM10	-
Extra trees[39]	Accuracy:85.3%	SO2, NO2,CO, CO2, NH3, PM2.5 and PM10	Pressure, wind direction, temperature, humidity
Extreme Learning Machine[40]	Accuracy:75.5%	PM10 and SO2	Temperature, humidity, pressure, wind speed
Random Forest[41]	Accuracy: O3 (79%), NO2 (70.1%), CO (79%), SO2 (85.6%), PM2.5 (86%), PM10 (79%)	CO, O3, NO2, SO2, PM10 and PM2.5	-
Support Vector Regression[42]	R2=0.9890 MSE=6.4513 RMSE= 2.5410 MAE= 0.97194	CO2, PM10, PM2.5,	Speed, Humidity, Temperature
CNN & GRU[43]	MAE= 7.75 RMSE= 13.80	PM2.5,NO2,SO2, CO,O3, PM10	-

Function, resulting in a 0 or 1 showing the size of the discrepancy between the expected and actual value. The obtained R2 is better [38].

Many strategies were investigated to forecast air quality monitoring, including linear regression (LR), neural network regression, Decision Forest, Lasso regression, Extra trees, elastic net regression, Boosted decision tree, XGBoost, and kth Nearest Algorithm (KNN), and Ridge regression. Extra trees increase accuracy by organizing features in decreasing order of relevance to forecasting the next value. [39].

An extreme learning machine (ELM) is proposed to predict Air quality. The ELM- ANN is a single-layer, feed-forward neural network. ELM employs a faster rate of learning. The activation methods used are sigmoidal –hard limit, and sine, with sigmoidal function providing better accuracy. The AP level is measured using ELM with more hidden neurons and ten cross-validate [40].

Comparison of decision trees, LR and RF is done in this research. Using the Arduino Platform, primary AP and meteorological conditions are measured. Because of overfitting, which reduces errors, the random forest provides more accurate results. Moreover, RF has more memory and high cost [41].

Multilayer linear regression is developed to predict the values, and the outcomes obtained are compared with the SVM, LR & MLP. The SVR-radial basis function-based estimation model showed better accuracy and generalization [42].

GRU, 1DCNN and LSTM deep learning models are analysed, along with RF, Lasso Regression and SVM regression models. And the results showed that the deep-learning approach of GRU and LSTM allows 24-hours ahead prediction [43].

In Table VI, various ML algorithms used in predicting AQ data are listed with the performance parameters.

VI. CONCLUSION

The parameters often used to measure AQI are decided by the information available, avg duration, observing frequency, and measurement techniques. It was also discovered that all of the research employed different data sets, and pollutant data is more location-dependent, making significant comparison hard. Furthermore, the pollutants under investigation are uncommon. As a result, an effective AI algorithm for predicting AQI must be developed to consider all critical AP. More research is also needed to design low-cost, simple, and robust AQM devices.

REFERENCES

1. "New WHO Global Air Quality Guidelines aim to save millions of lives from air pollution," World Health Organization. [Online]. Available: https://www.who.int/news/item/22-09-2021-new-who-global-air-quality-guidelines-aim-to-save-millions-of-lives-from-air-pollution. [Accessed: 11-Oct-2021].
2. World-Health-Organization, "WHO releases country estimates on air pollution exposure and health impact," https://goo.gl/G4uqFE, 2016.
3. C. Monn, "Exposure assessment of air pollutants: a review on spatial heterogeneity and indoor/outdoor/personal exposure to suspended PM, nitrogen dioxide and ozone," Atmospheric Environment, vol. 35, no. 1, pp. 1–32, 2001.
4. A. Dobre, S. Arnold, R. Smalley, J. Boddy, J. Barlow, A. Tomlin, and S. Belcher, "Flow field measurements in the proximity of an urban intersection in London, UK," Atmospheric Environment, vol. 39, no. 26, pp. 4647–4657, 2005.
5. A. Bhattacharya, "At last, India is on track to beat China at something-air pollution," Quartz. [Online]. Available: https://qz.com/india/910597/at-last-india-is-on-track-to-beat-china-at-something-air-pollution/. [Accessed: 11-Oct-2021].
6. "Delhi News, Latest Delhi News, New Delhi News Today and Headlines," Hindustan Times. [Online].Available:https://www.hindustantimes.com/cities/delhi-news. [Accessed: 11-Oct-2021].
7. https://www.theguardian.com/world/2016/dec/17/beijing-smog-pollution-red-alert-declared-in-china-capital-and-21-other-cities
8. https://www.theguardian.com/global-evelopment/2016/nov/22/cloud-filth-envelope-asian-cities-urban-smog-air-pollution-india-china
9. "System Alerts," *AirNow.gov*. [Online]. Available: https://www.airnow.gov/. [Accessed: 01-Nov-2021].
10. "Review of Air Quality Index and Air Quality Health Index." [Online]. Available: https://www.publichealthontario.ca/-/media/documents/A/2013/air-quality-health-index.pdf?la=en. [Accessed: 01-Nov-2021].
11. "Ontario's Air Pollution Index and Alert System," Taylor & Francis. [Online]. Available:https://www.tandfonline.com/doi/abs/10.1080/00022470.1970.10469451. [Accessed: 01-Nov-2021].
12. National Air Quality Index (AQI) launched by the Environment Minister AQI is a huge initiative under Swachh Bharat. [Online]. Available: https://pib.gov.in/newsite/PrintRelease.aspx?relid=110654. [Accessed: 11-Oct-2021].
13. S. Pandya, H. Ghayvat, A. Sur, M. Awais, K. Kotecha, S. Saxena, N. Jassal, and G. Pingale,

"Pollution Weather Prediction System: Smart Outdoor Pollution Monitoring and Prediction for Healthy Breathing and Living," *Sensors*, vol. 20, no. 18, p. 5448, 2020.

14. https://apps.who.int/iris/handle/10665/345329

15. D. Zhang and S. S. Woo, "Real Time Localized Air Quality Monitoring and Prediction Through Mobile and Fixed IoT Sensing Network," IEEE Access, vol. 8, pp. 89584–89594, 2020.
16. S. Mcgrath, C. Flanagan, L. Zeng, and C. Oleary, "IoT Personal Air Quality Monitor," 2020 31st Irish Signals and Systems Conference (ISSC), 2020.
17. K. Zheng, S. Zhao, Z. Yang, X. Xiong, and W. Xiang, "Design and Implementation of LPWA-Based Air Quality Monitoring System," IEEE Access, vol. 4, pp. 3238–3245, 2016.
18. "Types of pollutants," World Health Organization. [Online]. Available: https://www.who.int/teams/environment-climate-change-and-health/air-quality-and-health/health-impacts/types-of-pollutants. [Accessed: 11-Oct-2021].
19. "Department of Health," The Facts About Ammonia. [Online]. Available: https://www.health.ny.gov/environmental/emergency/chemical_terrorism/ammonia_general.htm. [Accessed: 11-Oct-2021].
20. Boris Pokric, Srdan Kreo, Dejan Drajic, Maja Pokric, Ivan Jokic, and Milena Jovaevic Stojanovic. ekonet-environmental monitoring using low-cost sensors for detecting gases, particulate matter, and meteorological parameters. In *Innovative Mobile and Internet Services in Ubiquitous Computing (IMIS), 2014 Eighth International Conference on*, pages 421–426. IEEE, 2014.
21. Theofylaktos Pieri and Michalis P Michaelides. Air pollution monitoring in lemesos using a wireless sensor network. In *Electrotechnical Conference (MELECON), 2016 18th Mediterranean*, pages 1–6. IEEE, 2016.
22. Chavez M David, Quispe T River, Rojas M Jorge, Jacoby K Andres, and Garayar L Guillermo. A low-cost, rapid-deployment and energyautonomous wireless sensor network for air quality monitoring. In *Sensing Technology (ICST), 2015 9th International Conference on*, pages 122–127. IEEE, 2015.
23. Jen-Hao Liu, Yu-Fan Chen, Tzu-Shiang Lin, Da-Wei Lai, Tzai-Hung Wen, Chih-Hong Sun, Jehn-Yih Juang, and Joe-Air Jiang. Developed urban air quality monitoring system based on wireless sensor networks. In *Sensing technology (icst), 2011 fififth international conference on*, pages 549–554. IEEE, 2011
24. A. Baldelli, "Evaluation of a low-cost multi-channel monitor for indoor air quality through a novel, low-cost, and reproducible platform," Measurement: Sensors, vol. 17, p. 100059, 2021.
25. Srinivas Devarakonda, Parveen Sevusu, Hongzhang Liu, Ruilin Liu, Liviu Iftode, and Badri Nath. Real-time air quality monitoring through mobile sensing in metropolitan areas. In *Proceedings of the 2nd ACM SIGKDD international workshop on urban computing*, page 15. ACM, 2013.
26. David Hasenfratz, Olga Saukh, Silvan Sturzenegger, and Lothar Thiele. Participatory air pollution monitoring using smartphones. *Mobile Sensing*, pages 1–5, 2012.
27. Xiaofeng Liu, Chaosheng Xiang, Bin Li, and Aimin Jiang,"Collaborative bicycle sensing for air pollution on roadway", *2015 IEEE 12th Intl Conf on Scalable Computing and Communications and Its Associated Workshops*, pp 316–319, 2015.
28. Min Mun, Sasank Reddy, Katie Shilton, Nathan Yau, Jeff Burke, Deborah Estrin, Mark Hansen, Eric Howard, Ruth West, and Peter Boda. Peir, the personal environmental impact report, as a platform for participatory sensing systems research. In *Proceedings of the 7th international conference on Mobile systems, applications, and services*, pages 55–68. ACM, 2009.
29. Bratislav Predic, Zhixian Yan, Julien Eberle, Dragan Stojanovic, and Karl Aberer. Exposuresense: Integrating daily activities with air quality using mobile participatory sensing. In *Pervasive Computing and Communications Workshops (PERCOM Workshops), 2013 IEEE International Conference on*, pages 303–305. IEEE, 2013.
30. Ke Hu, Vijay Sivaraman, Blanca Gallego Luxan, and Ashfaqur Rahman. Design and evaluation of a metropolitan air pollution sensing system. *IEEE Sensors Journal*, 16(5):1448–1459, 2016.
31. Peter Volgyesi, Andras Nadas, Xenofon Koutsoukos, and Akos Ledeczi. Air quality monitoring with sensormap. In *Information Processing in Sensor Networks, 2008. IPSN'08. International Conference on*, pages 529–530. IEEE, 2008.

32. Celal Ziftci, Nima Nikzad, Nakul Verma, Piero Zappi, Elizabeth Bales, Ingolf Krueger, and William Griswold. Citisense: mobile air quality sensing for individuals and communities. In *Proceedings of the 3rd annual conference on Systems, programming, and applications: software for humanity*, pages 23–24. ACM, 2012.
33. Savina Singla and Archan Misra. Indoor location error-detection via crowdsourced multi-dimensional mobile data. In *Proceedings of the First Workshop on Mobile Data*, pages 19–24. ACM, 2016.
34. Timothy M. Amado & Jennifer C. Dela Cruz, Development of Machine Learning-based Predictive Models for Air Quality Monitoring and Characterization, 2018, IEEE
35. Arwa Shawabkeh , Feda Al-Beqain , Ali Rodan, Maher Salem, Benzene Air Pollution Monitoring Model using ANN and SVM,2018, IEEE
36. Nicolás Mejía Martínez, Laura Melissa Montes, Ivan Mura and Juan Felipe Franco, Machine Learning Techniques for PM10 Levels Forecast in Bogotá,2018,IEEE
37. Nandini K & G Fathima, Urban Air Quality Analysis and Prediction Using Machine Learning,2019,IEEE
38. Desislava Ivanova and Angel Elenkov, Intelligent System for Air Quality Monitoring Assessment using the Raspberry Pi Platform,2019, IEEE
39. Soubhik Mahanta, T. Ramakrishnudu, Rajat Raj Jha and Niraj Tailor, Urban Air Quality Prediction Using Regression Analysis,2019, IEEE
40. Burhan BARAN, Prediction of Air Quality Index by Extreme Learning Machines,2019, IEEE
41. Venkat Rao Pasupuleti, Uhasri, Pavan Kalyan, Srikanth and Hari Kiran Reddy, Air Quality Prediction Of Data Log By Machine Learning,2020,IEEE
42. C. C. Goh, L. M. Kamarudin, A. Zakaria, H. Nishizaki, N. Ramli, X. Mao, S. M. M. S. Zakaria, E. Kanagaraj, A. S. A. Sukor, and M. F. Elham, "Real-Time In-Vehicle Air Quality Monitoring System Using Machine Learning Prediction Algorithm," *Sensors*, vol. 21, no. 15, p. 4956, 2021.
43. R. Espinosa, J. Palma, F. Jiménez, J. Kamińska, G. Sciavicco, and E. Lucena-Sánchez, "A time series forecasting based multi-criteria methodology for air quality prediction," Applied Soft Computing, vol. 113, p. 107850, 2021.