Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606
Volume 06 Issue 02
2024

Research Article
https://doi.org/10.56979/602/2024

IoT based Intelligent Pollution Monitoring System using Machine Learning Technique

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Received: November 09, 2023 **Accepted:** February 26, 2024 **Published:** March 01, 2024

Abstract: In recent rising environmental concerns, the need for efficient pollution monitoring systems has grown critical. This is because traditional methods face substantial hurdles such as restricted spatial analysis, elevated costs, as well as delayed data processing, impeding their effectiveness in addressing the escalating pollution crisis. Moreover, the traditional statistical models may fall short in apprehending the complicated and non-linear relationships inherent in pollution data, thereby regulating their predictive abilities. The Machine Learning (ML) based Artificial Neural Network (ANN) is an efficient approach that is a promising solution for IoT based intelligent pollution monitoring system to address the limitations of traditional pollution monitoring systems. By harnessing the potential of ANN, the proposed approach empowers decision-makers with an intelligent and efficient pollution monitoring system, thereby paving the way for proactive pollution control strategies. This proposed approach has the potential to revolutionize pollution monitoring with its scalable solution, as simulations are demonstrating accuracy 91.3% compared to the previous published approaches.

Keywords: Machine Learning; Sensor Networks; Air Quality Monitoring; Smart Cities; Artificial Neural Networks.

1. Introduction

In the realm of conventional urban policy, the implementation of technology-focused smart city initiatives has stirred numerous debates and recommendations. These smart cities, powered by advanced technologies, have been criticized for overlooking the multi-faceted variables surrounding them. Smart city strategies integrate essential infrastructure elements and align city plans to achieve multiple goals simultaneously, fostering appreci-ation through "challenge" competitions that inspire innovative projects showcasing the benefits of smart city solutions [1,2].

When planning a smart city, it is essential to consider five key human factors: social, tech-nological, economic, environmental, and political. This involves understanding and ad-dressing the needs of a diverse population, integrating cutting-edge technologies, fostering a thriving economy, prioritizing sustainability, and ensuring effective governance and col-laboration with stakeholders [3, 4].

In recent decades, the increasing issue of environmental pollution has become a major global concern, affecting significant challenges to human health, ecosystems, and sus-tainable development. As industries expand, urbanization intensifies, and energy con-sumption rises, conventional methods of monitoring pollution have proven inadequate in providing real-time, accurate, and comprehensive data [5]. To tackle this pressing chal-lenge, researchers and engineers have turned to cutting-edge technologies such as the In-ternet of Things (IoT) and Machine Learning (ML) to develop innovative pollution moni-toring systems that can revolutionize environmental management.

The Internet of Things (IoT) represents an interconnected network of physical devices, ve-hicles, appliances, and other objects, embedded with sensors and software, that enables them to collect and exchange data autonomously. By leveraging the power of IoT, the tra-ditional pollution monitoring can be transformed into a dynamic, interconnected, and in-telligent system, having the capacity to capture diverse data points across various geo-graphical locations in real time [6-8,40,41].

Machine Learning (ML) [9-12], a subset of Artificial Intelligence (AI), offers the ability to recognize patterns, learn from historical data, and make informed decisions autonomous-ly. By integrating ML techniques, including powerful algorithms like Support Vector Ma-chine (SVM), into the IoT-based pollution monitoring system, it can achieve data-driven insights and predictive models that aid in identifying pollution sources, understanding emission patterns, and devising effective mitigation strategies [13]. SVM, known for its proficiency in handling high-dimensional data, is particularly well-suited for classifica-tion tasks and can assist in accurately categorizing pollution sources based on complex environmental factors. Its ability to find optimal hyperplanes that separate different clas-ses allows the system to detect patterns and correlations in the data, contributing to more precise pollution source identification. Furthermore, leveraging Support Vector Machine within the pollution monitoring system allows us to process and analyze vast amounts of real-time data from various sensors and sources. By employing SVM's powerful classifica-tion capabilities, the system can predict pollution events and potential sources, aiding in proactive decision-making and prompt responses to environmental challenges. The com-bination of Machine Learning and Support Vector Machine within the IoT-based pollution monitoring system empowers us to build a comprehensive, adaptable, and effective solu-tion that helps create cleaner and healthier environments for communities worldwide.

2. Literature Review

Most of the researchers have widely focused on pollution monitoring, highlighting its vital role in environmental studies and sustainable growth efforts, and emphasizing its impli-cation in addressing environmental challenges.

The researchers in [14,15] have emphasized pollution source types (point, line, field, vol-ume), stationary (e.g., flue gas piles), mobile sources (e.g., vehicles), and the reliance on network stations for air quality monitoring. Stations were categorized based on major emission sources, including traffic, industrial, as well as background stations. Air quality modeling was applied to estimate pollution, particularly in areas lacking dimension sta-tions. Research focused on sensor networks, energy consumption reduction, and data transfer to sources for knowledge analysis in the literature.

The performance of low-cost sensors embedded in the network links varied depending on the service area, with air quality sensors being one of the regions where their efficacy was tested [16]. Manufacturer calibration of "NO2, NO, Ozone (O3), and particle matter (PM2.5, PM5)" sensors was irregular and often inadequate for precise measurement data. This quality control absence has led to negative perceptions of regulations and vigilant utiliza-tion within the scientific community, driving a strong demand for strategies to validate sensor data for air pollution monitoring [17-19].

There has been an increasing interest in comparing and evaluating several calibration al-gorithms, such as Multiple Linear Regression (MLR) [20,21], K-Nearest Neighbors (KNN), Support Vector Regression (SVR) [22,23], and Random Forest (RF) [24], for air pollution monitoring. Many studies have utilized sensor nodes to mount arrays, as certain air con-taminants demonstrated direct or inverse correlations with other pollutants (e.g., "ozone was negatively proportional to nitrogen oxide due to titration") or meteorological condi-tions (temperature and relative humidity).

In [25], an "Air Quality Monitoring (AQM) system based on fog computing and IoT was employed to collect air quality data over a specific period, transferring it to fog nodes for processing. Non-actionable data was refined and sent to the cloud for long-term storage, facilitating global analytics on shared equipment data. Developed with microprocessors and IoT-cloud platforms, experimental findings demonstrated the system's capability to sense air quality, enabling long-term monitoring for a deeper understanding of air pollu-tion and identifying strategies for its reduction. The installation of this system was unre-stricted, and the IoT cloud was utilized for evaluating air quality data and creating visual-izations for end-users.

According to [26], the researchers have devised an IoT-based air pollution monitoring sys-tem comprising an Arduino, gas sensors for hazardous gas detection, a mobile unit, a temporary memory buffer, and an internet-connected web server. The system collects data from different locations and timestamps the information accordingly.

Table 1. Comparison of the existing approaches

Sr.	Challenge	Method	Strength	Limitations
1	Predictive air quality for next 24 hr. inTehran by effective way.	Naïve Bayes (NB), Logistic regression (LR) [27].	They find LR to bestestimator.	LR can perform well to explain find continuous outcomes in predicting.
2	Analyzing air quality utilizing ML.	Regularization as well as Optimization [28].	Reduces the error rate utilizing closed regularization.	Amount of data is small. Accuracy is discussed but processing time is not stated.
3	ML for classification of air quality.	Decision tree (DT) and NB algorithm [29].	91% accuracy for DT.	Short data amount. DT is not good classifier for time series.
4	IoT sensors AQI forecast.	K-Means [30].	Upsurge the accuracy as compared to PFCM.	Data size is incomplete. K-mean poor classifier for time-series.
5	Low cost AQI Measuring sensors placement and utilizing ML analysis.	Radio frequency (RF) [31].	They decreased the cost.	No data handling and no processing time.
6	A hybrid computational intelligence system for mutual ML.	Un-supervised clustering Ensemble ANN [32].	This method upsurges the computational accuracy.	No computational cost and processing time.
7	Air pollution forecast for short era.	Co-relation and Neural Network [33].	Recover the accuracy of air pollutant forecast.	Sampling station is measured only on; thus, the dataset is very small containing of few hours.

Table 1 is showing a comprehensive comparison, emphasizing the strengths and limita-tions of various air pollution monitoring systems. It offers valuable insights for research-ers and decision-makers in selecting the most suitable approach for their specific monitor-ing needs. The table provides a summary of research works using ML for air quality or pollution prediction. Different methods like), Logistic regression (LR), Decision tree (DT), K-Means, and Radio frequency (RF)are employed, showing varying steps of success in ac-curacy development. However, limitations comprise small data size, unsuitable classifiers for time series, and lack of dispensation time info.

3. Methodology

The critical concern of air quality or pollution in smart cities directly impacts residents' quality of life, necessitating the monitoring of environmental factors and detection of pollution sources to ensure a safe and healthy atmosphere. To address these challenges, this research proposes an intelligent system leveraging machine learning to predict pollution nodes and tracking corrective actions that can be taken to enhance environmental health. The proposed IOT based approach empowers authorities to make data-driven infrastructure and policy planning decisions, contributing to a cleaner, healthier, and more sustainable urban environment. The proposed system is given in Figure 1.

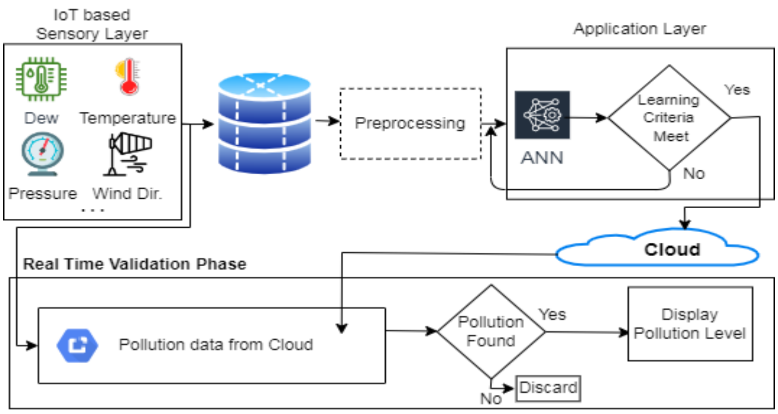

Figure 1. Proposed pollution monitoring model

Figure 1 illustrates the proposed pollution monitoring system, featuring three interconnected layers: The IoT based sensory layer containing input parameters, the preprocessing, and the application layer. These layers cooperatively form the methodology for pollution monitoring, enabling efficient data acquisition, processing, and application of the system. The sensory layer receives input parameters, acquires data through IoT sensors including (dew, temperature, pressure, wind dir., etc.), and stores in a database. The data stored in database is considered raw data due to wireless communication, which may include missing values or noisy data. To address this, the preprocessing in figure 2, is responsible for purifying the raw data, handling missing values, and mitigating noise to ensure the data reliability for further analysis.

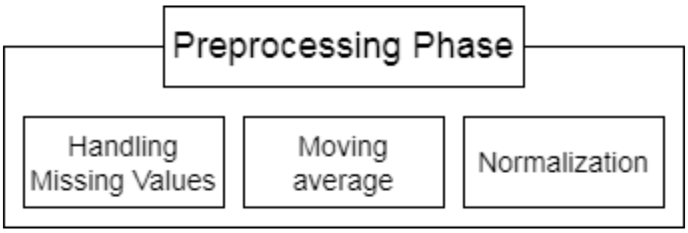

Figure 2. Preprocess phase

After preprocessing, the output is sent to the application layer, where an ML-based ANN algorithm is applied to predict the pollution. In prediction, the input, hidden, and output layers are applied

Let's adapt the generic feedforward neural network representation for pollution monitoring. In this context, we can consider features related to pollution levels as inputs, and the network aims to predict pollution levels.

Table 2. Proposed system validation using ANN

	Proposed Model Validation		
	Samples (13,140)	**Result**	
	Expected output	**Predicted Positive**	**Predicted Negative**
Input	11,000 Positive	True Positive (TP) 10,000	False Positive (FP) 1000
	1140 Negative	False Negative (FN) 140	True Negative (TN) 1000

The trained ANN's outcome then be utilized for pollution predicting, as accuracy and miss rate, regardless of whether the learning criteria are met or not. If the outcome specifies 'NO', the training layer will be retrained, while 'YES' will lead to saving the output in a cloud database. The in validation phase the input is collected from input layer features, and trained pollution patterns are imported from cloud to determine whether the prediction is found or not. If the pollution is found, the message will be shown that pollution is predicted, whereas, in the case of no, the process will be discarded.

It is shown in table 2 that the proposed model predicts the drug during the training period using ANN. During training, 13,140 samples are divided into 11,000, 1140 positive, and negative samples. 10,000 true positives are successfully forecast, and no pollution is recognized, but 1000 records are mistakenly predicted as negatives, indicating the drug is recognized. Likewise, 1140 samples are obtained, with negative showing pollution is identified and positive indicating no pollution. With 1000 samples correctly identified as negative, showing the pollution is recognized, and 140 samples inaccurately foreseen as positive, representing no pollution is identified despite the presence of the drug.

4. Results and Discussions

In the domain of pollution monitoring, modern technological advancements are increasingly employed to implement complicated structures that capture environmental specifics across various regions. Artificial Neural Networks (ANN) prove to be a promising approach for early-stage prediction of pollution, offering potential time and cost savings. This research introduces an intelligent system that empowers pollution monitoring through the python-based ANN which is applied to a dataset [42] gathered from a reliable Kaggle repository. The ANN model is trained on a substantial number of instances (43,800) to effectively analyze pollution patterns. The dataset is divided into training (70%) and validation (30%) sets, consisting of 30,660 and 13,140 samples, respectively, to ensure robust performance evaluation. Various performance metrics are employed to assess the model's accuracy and efficiency in predicting pollution levels and identifying trends.

Sensitivity is determined by dividing the total number of true positive cases by the total number of actual positive cases.

$$Sensitivity = \frac{\sum True\ Positive}{\sum Condition\ Positive} \tag{1}$$

The line calculates Specificity, a performance metric in binary classification, by dividing the sum of true negative instances by the sum of actual negative instances.

$$Specificity = \frac{\sum True\ Negative}{\sum Condition\ Negative} \tag{2}$$

Accuracy is a measure of the proportion of correctly identified instances, calculated by summing true positives and dividing by the total population.

$$Accuracy = \frac{\sum True\ Positive + \sum True\ Positive}{\sum Total\ Population} \tag{3}$$

The miss rate quantifies the proportion of false negatives relative to the total condition positive instances.

$$Miss - Rate = \frac{\sum False\ Negative}{\sum Condition\ Positive} \tag{4}$$

The fallout represents the proportion of false positives relative to the total instances in the condition negative group.

$$Fallout = \frac{\sum False\ Positive}{\sum Condition\ Negative} \tag{5}$$

The likelihood positive ratio measures the ratio of true positive rate to false positive rate across the dataset.

$$Likelihood\ Positive\ Ratio = \frac{\sum True\ Positive\ Ratio}{\sum False\ Positive\ Ratio} \tag{6}$$

The likelihood negative ratio evaluates the ratio of true positive rate to false positive rate across the dataset, specifically focusing on negative outcomes.

$$Likelihood\ Negative\ Ratio = \frac{\sum True\ Positive\ Ratio}{\sum False\ Positive\ Ratio} \tag{7}$$

Positive Predictive Value (PPV) reflects the proportion of correctly predicted condition positive instances relative to the total predicted condition positive

instances.

$$Positive\ Predictive\ Value = \frac{\sum True\ Positive}{\sum\ Predicted\ Condition\ Positive} \tag{8}$$

Negative Predictive Value (NPV) denotes the proportion of correctly predicted condition negative instances relative to the total predicted condition negative instances.

$$Negative\ Predictive\ Value = \frac{\sum True\ Negative}{\sum\ Predicted\ Condition\ Negative} \tag{9}$$

It is shown in table 3 that the proposed model predicts the pollution during the training period using ANN. During training, 30,660 samples are divided into 21,660, 9000 positive, and negative samples.

Table 3. Proposed system trainnig using ANN

Proposed Model Training			
	Result (output)		
Total number of Training samples (30,660)	**Expected output**	**Predicted Positive**	**Predicted Negative**
	21,660 Positive	True Positive (TP) 20,660	False Positive (FP) 1,000
	9,000 Negative	False Negative (FN) 1,000	True Negative (TN) 8,000

It is shown in table 3 that the proposed model predicts the pollution during the training period using ANN. During training, 30,660 samples are divided into 21,660, 9000 positive, and negative samples. 20,660 true positives are successfully forecast, and no pollution is recognized, but 1000 records are mistakenly predicted as negatives, indicating the pollution is recognized. Likewise, 9000 samples are obtained, with negative showing pollution is identified and positive indicating no pollution. 8000 samples correctly identified as negative, showing the pollution is recognized, and 1000 samples inaccurately foreseen as positive, representing no pollution is identified despite the presence of the pollution.

Table 4. Proposed system performance in training and validation

ANN	Accuracy	Sensitivity TPR	Specificity TNR	Miss-Rate (%) FNR	Fall-out FPR	LR+	LR-	PPV (Precision)	NPV
Training	0.934	0.953	0.888	0.066	0.111	8.58	0.074	0.953	0.888
Validation	0.913	0.987	0.50	0.087	0.50	1.97	0.174	0.916	0.877

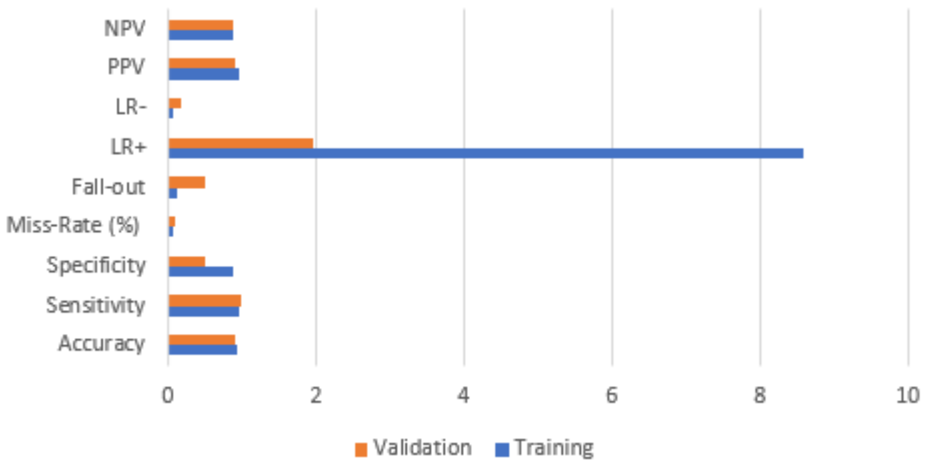

Figure 3. Graphical representation of proposed system performance in training and validation

Table 4, and Figure 3 presents that in the training dataset, the ANN is achieving an accuracy of 93.4%, sensitivity (True Positive Rate) of 95.3%, and specificity (True Negative Rate) of 88.8%. However, in the validation dataset, the ANN maintains an accuracy of 91.3%. Its sensitivity is 98.7%, and the specificity is 50%. It is clearly shown that the accuracy of the proposed pollution monitoring system is 91.3%.

Table 5, and Figure 4 represent the comparison of the performance of proposed system to predict pollution monitoring, which compares the ANN approach with the previous approaches [34]. It is clearly shown that the proposed system is better than the previous results in terms of accuracy and miss rate.

Table 5. Comparing the proposed system with previous research work.

Technique	Accuracy	Miss-rate
Support Vector Regression [34]	84.83	15.17
Random Forest Regression [34]	84.72	15.28
Cat Boost [34]	85.48	14.16
Recurrent Neural Network RNN [35]	80.27	19.73
Random Forest [36]	70	30
Extra trees [37]	85.3	14.7
Extreme Learning Machine [38]	75.5	24.5
Random forest [39]	79	21
Proposed system	91.3	8.7

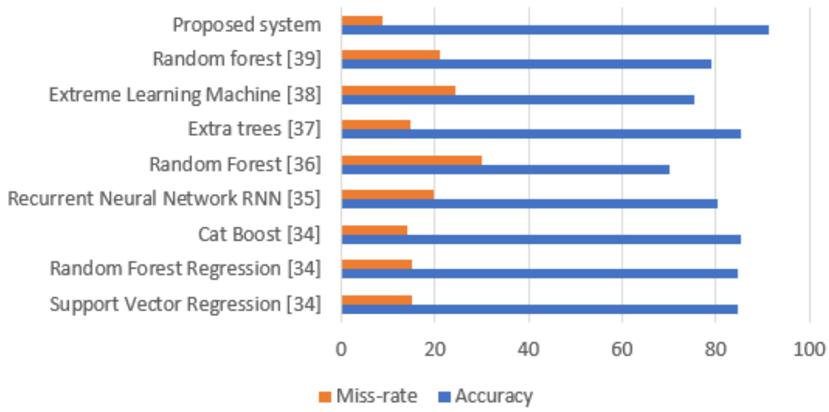

Figure 4. Graphical representation of proposed system performance comparison with previous research work

5. Conclusions

The intensifying array of environmental challenges has underscored the imperative for the development and implementation of efficient pollution monitoring systems. However, conventional methodologies have established limitations in comprehensively capturing the intricate and non-linear dynamics characteristic within pollution data, thus hindering their predictive capabilities. Considering these constraints, a promising avenue for advancement involves the utilization of Artificial Neural Networks (ANN) within an Internet of Things (IoT)-based intelligent pollution monitoring system. The simulation of the proposed approach is demonstrating an impressive 91.3% accuracy rate and 8.7% miss-rate. The proposed approach revolutionizes pollution monitoring, offering better accuracy compared to previous methods, empowering practical pollution control strategies in mounting environmental concerns.

References

1. T. Quynh Anh, D. Quang Hung, L. Tung, N. Huy Tien, and L. Tan Duy, “Air quality monitoring and forecasting system using iot and machine learning techniques,” https://github.com/tranquynhanh/air-qualitymonitoring-and-forecasting-system, 2022.
2. Zygiaris, S., 2013. Smart city reference model: Assisting planners to conceptualize the building of smart city innovation ecosystems. Journal of the knowledge economy, 4, pp.217-231.
3. Sahoo, S., Kumar, A. and Upadhyay, A., 2023. How do green knowledge management and green technology innovation impact corporate environmental performance? Understanding the role of green knowledge acquisition. Business Strategy and the Environment, 32(1), pp.551-569.
4. Salim, N., Ab Rahman, M.N., Abd Wahab, D. and Muhamed, A.A., 2020. Influence of social media usage on the green product innovation of manufacturing firms through environmental collaboration. Sustainability, 12(20), p.8685.
5. Özkara, A., Akyıl, D. and Konuk, M., 2016. Pesticides, environmental pollution, and health. In Environmental health risk-hazardous factors to living species. IntechOpen.
6. Al-Dmour, N.A., Salahat, M., Nair, H.K., Kanwal, N., Saleem, M. and Aziz, N., 2022, October. Intelligence Skin Cancer Detection using IoT with a Fuzzy Expert System. In 2022 International Conference on Cyber Resilience (ICCR) (pp. 1-6). IEEE.
7. Chang, C., Srirama, S.N. and Buyya, R., 2019. Internet of Things (IoT) and new computing paradigms. Fog and edge computing: principles and paradigms, 6, pp.1-23.
8. Fatima, S.A., Hussain, N., Balouch, A., Rustam, I., Saleem, M. and Asif, M., 2020. IoT enabled smart monitoring of coronavirus empowered with fuzzy inference system. International journal of advance research, ideas and innovations in technology, 6(1), pp.188-194.
9. Saleem, M., Abbas, S., Ghazal, T.M., Khan, M.A., Sahawneh, N. and Ahmad, M., 2022. Smart cities: Fusion-based intelligent traffic congestion control system for vehicular networks using machine learning techniques. Egyptian Informatics Journal, 23(3), pp.417-426.
10. Saleem, M., Khan, M.S., Issa, G.F., Khadim, A., Asif, M., Akram, A.S. and Nair, H.K., 2023, March. Smart Spaces: Occupancy Detection using Adaptive Back-Propagation Neural Network. In 2023 International Conference on Business Analytics for Technology and Security (ICBATS) (pp. 1-6). IEEE.
11. Athar, A., Asif, R.N., Saleem, M., Munir, S., Al Nasar, M.R. and Momani, A.M., 2023, March. Improving Pneumonia Detection in chest X-rays using Transfer Learning Approach (AlexNet) and Adversarial Training. In 2023 International Conference on Business Analytics for Technology and Security (ICBATS) (pp. 1-7). IEEE.
12. Sajjad, G., Khan, M.B.S., Ghazal, T.M., Saleem, M., Khan, M.F. and Wannous, M., 2023, March. An Early Diagnosis of Brain Tumor Using Fused Transfer Learning. In 2023 International Conference on Business Analytics for Technology and Security (ICBATS) (pp. 1-5). IEEE.
13. Srivastava, H., Mishra, S., Das, S.K. and Sarkar, S., 2020. An IoT-Based Pollution Monitoring System Using Data Analytics Approach. In Electronic Systems and Intelligent Computing: Proceedings of ESIC 2020 (pp. 187-198). Springer Singapore.
14. P. Huang, L. Xiao, S. Soltani, M. W. Mutka, and N. Xi, "The evolution of mac protocols in wireless sensor networks: A survey," IEEE communications surveys & tutorials, vol. 15, no. 1, pp. 101–120, 2013.
15. VYANKAT, Y., 2014. Air Pollution Tolerance Index nanded city, MA. Journal of Applied Phytotechnology in Environmental Sanitation, 3(1), pp.23-28.
16. A. Lewis, W. R. Peltier, and E. von Schneidemesser, "Low-cost sensors for the measurement of atmospheric composition: overview of topic and future applications," World Meteorological Organization, 2018.
17. L. Spinelle, M. Gerboles, M. G. Villani, M. Aleixandre, and F. Bonavitacola, "Field calibration of a cluster of low-cost commercially available sensors for air quality monitoring. part b: NO, CO and CO2," Sensors and Actuators B: Chemical, vol. 238, pp. 706–715, 2017.
18. Cortina-Januchs, M.G, SO2 classification for air quality levels estimation using artificial intelligent techniques, Multiconference on Electronics and photonics,pp:158- 162, 2008.
19. N. Li, G. Calis, B. Becerik-Gerber, Measuring and monitoring occupancy with an RFID based system for demand-driven HVAC operations, Autom. Constr. 24 (2012) 89–99, https://doi.org/10.1016/j.autcon.2012.02.013.
20. J. M. Barcelo-Ordinas, J. Garcia-Vidal, M. Doudou, S. Rodrigo-Munoz, ˜ and A. Cerezo-Llavero, "Calibrating low-cost air quality sensors using multiple arrays of sensors," in Wireless Communications and Networking Conference (WCNC). IEEE, 2018, pp. 1–6.
21. D. Hagan, G. Isaacman-VanWertz, J. Franklin, L. Wallace, B. Kocar, C. Heald, and J. Kroll, "Calibration and assessment of electrochemical air quality sensors by colocation with regulatory-grade instruments," Atmosph. Measurement Tech., vol. 11, no. 1, pp. 315–328, 2018.
22. N. Zimmerman, A. A. Presto, S. P. Kumar, J. Gu, A. Hauryliuk, E. S. Robinson, A. l. L. Robinson, and R. Subramanian, "A machine learning calibration model using random forests to improve sensor performance for lower-cost air quality monitoring." Atmospheric Measurement Techniques, vol. 11, no. 1, 2018.
23. H. Wu, Z. Zhang, C. Jiao, C. Li, and T. Q. Quek, "Learn to sense: a meta-learning based sensing and fusion framework for wireless sensor networks," IEEE Internet of Things Journal, 2019.
24. Yannawar Vyankatesh, Bhosle Arjun, Yannawar Sonali, —Prediction of Air Pollution Concentration Using a Fixed Box Model, May,2014.
25. Senthilkumar, R. P. (2020). "Intelligent based novel embedded system based IoT enabled air pollution monitoring system". Microprocessors and Microsystems 77, 103172.

26. Pal, P. e. (2017). "IoT based air pollution monitoring system using Arduino". International Research Journal of Engineering and Technology (IRJET) 4.10, 1137-1140.
27. Kim, Ki-Hyun, Ehsanul Kabir, and Shamin Kabir. "A review on the human health impact of airborne particulate matter." Environment international 74 (2015): 136-143.
28. Hvidtfeldt, Ulla Arthur, Matthias Ketzel, Mette S_rensen, Ole Hertel, Jibran Khan, J_rgen Brandt, and Ole Raaschou-Nielsen. "Evaluation of the Danish AirGIS air pollution modeling system against measured concentrations of PM2.5, PM10, and black carbon." Environmental Epidemiology 2, no. 2 (2018): e014.
29. A. J. Cohen et al., \Articles Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015," Lancet, vol. 6736, no. 17, pp. 1{12,2017.
30. En:wikipedia:org:(2018):Airqualityindex:[online]Availableat : https:==en:wikipedia:org=wiki=Airqualityindex[Accessed2Dec:2018].
31. Yi, Wei, Kin Lo, Terrence Mak, Kwong Leung, Yee Leung, and Mei Meng. "A survey of wireless sensor network based air pollution monitoring systems." Sensors 15, no. 12 (2015): 31392-31427.
32. Y. Xing, Y. Xu, M. Shi, and Y. Lian, \The impact of PM2 . 5 on the human respiratory system," vol. 8, no. I, pp. 69{74, 2016.
33. M. M. Rathore, A. Paul, A. Ahmad, and S. Rho, \US CR," Comput. Networks, no. 2016, 2015.
34. Gupta, N.S., Mohta, Y., Heda, K., Armaan, R., Valarmathi, B. and Arulkumaran, G., 2023. Prediction of Air Quality Index Using Machine Learning Techniques: A Comparative Analysis. Journal of Environmental and Public Health, 2023.
35. Xiaosong Zhao , Rui Zhang, Jheng-Long Wu, Pei-Chann Chang and Yuan Ze University, A Deep Recurrent Neural Network for Air Quality Classification, 2018, Journal of Information Hiding and Multimedia Signal Processing
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. Soubhik Mahanta, T. Ramakrishnudu, Rajat Raj Jha and Niraj Tailor, Urban Air Quality Prediction Using Regression Analysis,2019, IEEE
38. Burhan BARAN, Prediction of Air Quality Index by Extreme Learning Machines,2019, IEEE
39. Venkat Rao Pasupuleti , Uhasri , Pavan Kalyan , Srikanth and Hari Kiran Reddy, Air Quality Prediction Of Data Log By Machine Learning,2020,IEEE
40. Saleem, M., Khan, M.A., Abbas, S., Asif, M., Hassan, M. and Malik, J.A., 2019, July. Intelligent FSO link for communication in natural disasters empowered with fuzzy inference system. In 2019 International Conference on Electrical, Communication, and Computer Engineering (ICECCE) (pp. 1-6). IEEE.