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Air Quality Prediction in Urban Environment Using IoT Sensor Data

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Abstract:- The increasing concern for environmental health has led to a heightened need for accurate air quality monitoring and prediction. This study presents a framework for predicting the Air Quality Index (AQI) using existing datasets rather than relying on real-time data from IoT sensors. The proposed system incorporates various machine learning algorithms, including Linear Regression, Neural Networks, and XGBoost, to analyze the relationships between air pollution indicators and AQI values. The methodology encompasses essential steps such as data preprocessing, normalization, and dividing the dataset into training and testing sets. Although the system has not yet been implemented, preliminary analyses indicate that the use of these models has the potential to yield reliable AQI predictions, which can significantly assist policymakers and public health officials in implementing effective air quality management strategies.

Keywords:- *IoT Sensors, Air Quality Index (AQI), Machine Learning, Deep Learning, Random Forest, Linear Regression, Neural Networks, XGBoost, Logistic Regression, Voting Classifier, AQI Values, Min-Max Scaling.*

I. INTRODUCTION

Air quality has become a critical concern in urban environments due to increasing levels of pollution caused by rapid industrialization, vehicular emissions, and urbanization. Poor air quality directly impacts human health, leading to respiratory illnesses, cardiovascular diseases, and even premature deaths. According to the World Health Organization (WHO), air pollution contributes to over 4 million deaths annually, with a significant proportion occurring in urban areas. Hence prediction of air quality is essential to mitigate these health risks, inform policy decisions, and enable early warnings for vulnerable populations [1].

Urban air pollution is a major global problem caused by rapid city growth, rising population, and increased industrial activity. Recently, more people have become aware of how population growth and human activities impact the environment [2]. The United Nations estimates that the world has about 7.6 billion people and around 4.2 billion (or 55%) of them live in cities. By 2050, the number of people living in cities is expected to double. As cities grow quickly, industries are expanding to keep up with the needs of more people [3].

Effective urban development planning requires collaboration from different fields, such as politics, environmental engineering, and spatial planning. People's happiness is influenced by how well policymakers do their jobs, living conditions, access to education, and a healthy environment [4]. At first, the metallurgical industry was the biggest cause of pollution, but heating with fossil fuels has become a more important source over time [5].

Even though using solid fuels for heating is completely banned, it is still the main cause of pollution during the winter [6,7]. Air pollution from outside the city is moving into the city, especially during the colder months [8]. Krakow's position, surrounded by small hills and the Carpathian Mountains to the south [9], makes this worse. As a UNESCO World Heritage site, Krakow deals with issues that impact both locals and visitors. The COVID-19 pandemic caused a drop in tourism, which led to initiatives aimed at rebuilding the tourism industry in a more sustainable way [10].

The advent of Internet of Things (IoT) technology has opened new possibilities for high-resolution air quality monitoring. Low-cost sensors can now be deployed at a scale, providing real-time data on various pollutants across urban areas [11]. This wealth of data, combined with advances in machine learning (ML) techniques, presents an opportunity to develop more accurate and localized air quality prediction models. Recent advancements in air quality prediction systems have increasingly focused on the integration of Internet of Things (IoT) sensor data with machine learning (ML) techniques. A variety of models, including time-series approaches like SARIMA and LSTM, are being used to improve accuracy in forecasting Air Quality Index (AQI) levels. One notable approach is the Bayesian optimization of hybrid time-series models, which has been shown to outperform traditional methods in urban environments [12]. Machine learning algorithms like XGBoost, and Random Forest, and deep learning models such as LSTM are particularly effective in handling the non-linear and complex nature of air pollution data. These models are also frequently evaluated using error metrics like RMSE and MAE to ensure robust predictions [13].

This paper explores the integration of IoT sensor data with machine learning algorithms to predict air quality in urban environments. By leveraging the spatial and temporal resolution of IoT sensor networks and the predictive power of ML models, we aim to develop a system that can provide accurate, real-time air quality forecasts at a neighborhood level. Such a system has the potential to inform public health policies, guide urban planning decisions, and empower citizens to make informed choices about their daily activities [14].

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➢ *Our Research Addresses Several Key Challenges in this Domain, Including:*

- The integration and preprocessing of heterogeneous data from IoT sensor networks.
- The selection and optimization of appropriate machine learning algorithms for air quality prediction.
- The incorporation of contextual factors such as weather conditions, traffic patterns, and urban morphology into the predictive models.
- The validation and interpretation of model outputs in the context of existing air quality standards and health guidelines.

By addressing these challenges, we aim to contribute to the growing body of work on smart city technologies and environmental informatics, while providing practical tools for improving air quality management in urban areas.

II. LITERATURE REVIEW

Feng et al. [15] proposed an ensemble learning approach that combined multiple ML algorithms, including gradient boosting and neural networks. Their hybrid model demonstrated improved performance in predicting air quality index (AQI) values compared to individual models.

Xu et al. [16] developed an edge computing-based air quality prediction system that utilized IoT sensors and deep learning models. Their approach reduced data transmission latency and improved the real-time prediction capabilities of the system. As scientific and technological advancements accelerate, predictive technologies have permeated numerous domains. These range from everyday applications like forecasting individual movement patterns, traffic conditions, and air quality, to more specialized fields. The reach of predictive techniques extends beyond simple forecasting, finding utility in complex optimization challenges [17, 18], anticipating service quality levels [19], and enhancing user recommendation systems [20, 21]. This widespread adoption underscores the versatility and growing importance of predictive technologies across diverse sectors.

Genc et al. [22] used a multiple linear regression model to predict Ankara's air pollution index. Moisan et al. [23] proposed a method based on dynamic multivariate linear equations to predict PM2.5 pollution concentrations at different monitoring stations. The abovementioned studies are all based on linear model prediction methods. However, the relationships between air quality and its related factors are mostly nonlinear. The linear models mentioned above do not represent their complex interrelationships well.

Ge et al. [24] emphasized the importance of considering both temporal and non-temporal factors in forecasting air quality. They recognized that a comprehensive approach, considering time-dependent patterns as well as static influences, could lead to more accurate predictions. In a related effort to improve prediction accuracy, Qi et al. [25] developed an innovative hybrid model called GC-LSTM. This model cleverly combined two distinct neural network architectures: graph convolutional networks (GCN) and Long Short-Term Memory (LSTM) networks. The GCN component was employed to analyze and leverage the spatial relationships between different monitoring locations, while the LSTM network was utilized to identify and model the temporal patterns in the air quality data across various time points.

Nahar et al. [26] developed a model that applies machine learning classifiers to forecast the Air Quality Index (AQI). The authors examined data provided by the Jordanian Ministry of Environment, covering a span of 28 months, and observed pollutant levels. Their model successfully identified the regions with the highest pollution levels. Castelli et al. [27] conducted a study aimed at forecasting air quality in California, USA, by estimating pollutant concentrations using the support vector regressor (SVR) algorithm. The authors introduced a novel method to predict atmospheric pollution levels on an hourly timescale. Soundari et al. [28] developed a neural network model for forecasting the Indian Air Quality Index (AQI). Their research demonstrated that, with access to relevant data on air pollutant concentrations, it is possible to accurately predict the AQI for the entire nation or specific regions using their proposed model.

Table 1 Air Quality Index (AQI)

Ref.	Findings	Methods used	Dataset	Limitations
[29]	Machine learning models, like back propagation neural networks, can analyze IoT sensor data to predict air quality by considering pollutant concentrations, street geometry, emission sources, and meteorological factors.	ANN approach used for air quality prediction. Back propagation neural network model implemented for prediction	Measured data for a street in Chennai. Particulate pollutants of size 2.5 and 10 microns	Seasonal changes showed no similar profiles among street geometries. The concentration of pollutants varied at different heights in street canyons.
[30]	Integrating IoT sensor data with machine learning models, such as LSTM variants, enables accurate air quality predictions by analyzing environmental factors and traffic density, addressing data inconsistencies effectively.	A multi-modal framework integrating sensor data and traffic density. LSTM model variants: Bi-LSTM, CNN-LSTM, ConvLSTM for prediction	Real-time data from environmental sensors. Traffic density from Closed Circuit Television footage	Data inconsistencies from sensor and camera malfunctions. Challenges in predicting air quality at locations with no sensors

[31]	Make use of IoT sensors to capture air quality data, apply pre-processing techniques to filter out noise, perform feature selection, and utilize machine learning models like BTBSR-QWEBC for accurate prediction outcomes.	Bilateral Transformative Broken-Stick Regression-based Quadratic Weighted Emphasis Boost Classification (BTBSR-QWEBC) technique.	Air quality sample data ranges from 10,000 to 100,000. IoT devices collect air quality data.	Existing models struggle with accurate pollutant forecasting. Noisy data increases time and space complexity.
[32]	Utilizing IoT sensor data, machine learning algorithms can analyze real-time pollution metrics to predict air quality by identifying patterns and correlations in pollutant concentrations across urban environments.	ML research projects using IoT sensor data. Historical and current data on AQ prediction models and methods	Historical and current data based on AQ prediction models. IoT sensor data in the context of diverse cities.	Low accuracy and cost in AP prediction. Challenges in real-time AQ monitoring and prediction.
[33]	By using IoT sensor data, machine learning algorithms like neural networks and support vector machines can analyze contamination patterns to predict air quality indices in urban environments.	Neural networks for air quality prediction. Support vector machines for air quality prediction.	Air contamination datasets from the Central Pollution Control Board (CPCB). Used for predicting Delhi Air Quality Index (AQI).	Comparison of processing time for multiple datasets needed. Need for closer examination of different AI learning tools.
[34]	By applying IoT sensor data, deep learning models such as Graph Convolutional Networks (GCNs) and Long Short-Term Memory (LSTM) networks can be used to extract spatial-temporal features, resulting in accurate air quality predictions.	Spatial interpolation method for optimizing the sample data set. Improved graph convolutional network and improved long short-term memory for feature extraction.	1520 groups of air quality data from Beijing, China. Sample database constructed from January 2019 to January 2021	Number of hidden layer units affects prediction accuracy.
[35]	By applying IoT sensor data, machine learning algorithms such as DBSCAN and Linear Regression can efficiently analyze air quality, detect pollution trends, and forecast contamination levels in urban areas.	Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm. Linear Regression.	Air quality monitoring data. Physicochemical processes data.	Limited attributes result in less accuracy. Real-time monitoring is unsuitable due to performance constraints.
[36]	Air quality can be predicted in urban environments by utilizing IoT sensors to collect data, which is then analyzed using machine learning models like Artificial Neural Networks for accurate forecasting.	Artificial Neural Network (ANN) machine learning model. TensorFlow lite library for air quality prediction and weather monitoring	Dataset from IQAir website for one region. Real-time sensory data from multiple sensors.	Limited to one region's dataset for training the ANN model. Future work includes training model with data from multiple regions.
[37]	Air quality can be forecasted by analyzing data from IoT sensors with the help of machine learning models like Linear Regression and Random Forest Regression, providing accurate predictions of pollution levels.	Machine learning algorithms: Linear Regression and Random Forest Regression. Sensors to measure the concentration of air pollution-causing gases	Training data set for air quality prediction. Collected data stored in Firebase.	Limited to predicting air quality using specific machine learning algorithms. The notification feature only indicates very severe pollution levels
[38]	Machine learning models, like Artificial Neural Networks, can utilize IoT sensor data on meteorological parameters and pollutant concentrations to accurately predict urban air quality.	Artificial Neural Network (ANN) model Computational Fluid Dynamics (CFD) model	Meteorological parameters and PM10 concentrations In situ diurnal traffic profile	The ANN model is a "black box" and has limited contribution to knowledge development of physical processes and interaction of driving mechanisms related to dispersion within urban street canyons.

[39]	Air quality in urban environments can be predicted using IoT sensor data by applying machine learning algorithms like Random Forest, which analyzes pollutant levels and meteorological data for accurate forecasting.	Machine learning techniques for pollution forecasting. Comparative study to determine the best model	Pollutant data: CO, SO2, O3 for 74 Chinese cities. Meteorological data: Temp, Wind, and Humidity for 74 cities.	Linear Regression over-simplifies real-world issues. Decision Trees are complex and do not generalize well.

III. PROPOSED SYSTEM

The proposed approach uses strong machine learning techniques and data from IoT devices to estimate mental air quality. The system operates according to a well-organized workflow, which starts with the preparation, training, testing, and evaluation of data utilizing machine learning and model validation. Figure 1. depicts the system architecture of the proposed model.

This architecture is intended for predicting the Air Quality Index (AQI) using machine learning models based on pre-existing datasets, rather than real-time data collected from sensors. The process can be outlined in the following stages:

➢ *Data Preprocessing:*

Data collected from the IoT devices are clubbed together and processed which includes the following activities:

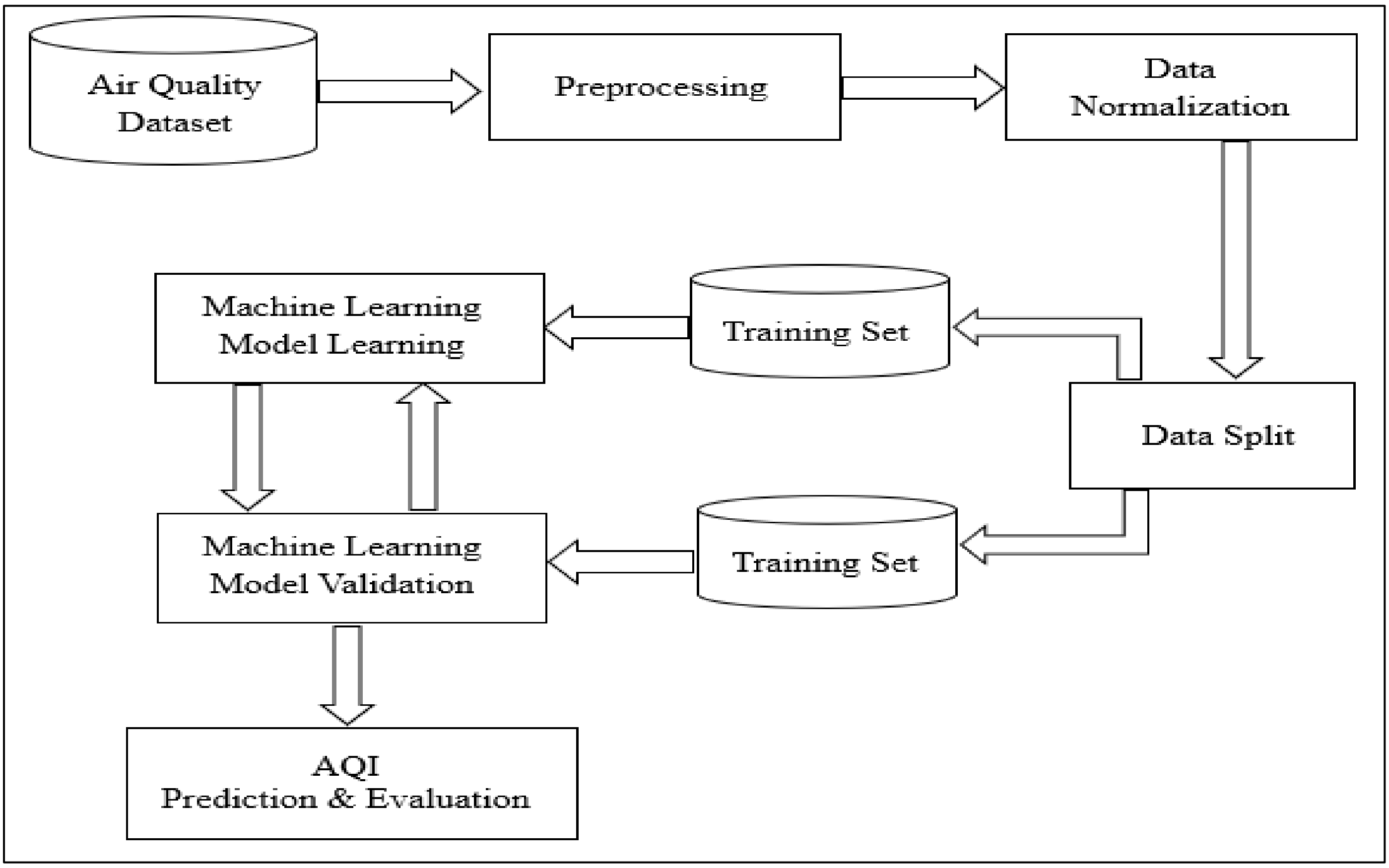

Fig 1 Proposed System Architecture

- Handle missing data (e.g., fill with mean or median).
- Remove outliers (if necessary).
- Feature selection (e.g., based on correlation or PCA).

➢ *Data Normalization:*

Data normalization is required to clean data and apply Min-Max scaling or standardization to bring features to a comparable scale.

➢ *Splitting Data:*

80% of the dataset is used for training, while 20% is used for testing. Several classification models are trained on the training dataset to identify trends and correlations that may point to problems with the quality of the air.

➢ *Model Training:*

- Train the Linear Regression model to predict AQI as a continuous target.
- Train the Neural Network with a multi-layered structure for capturing nonlinear patterns in the data.
- Train XGBoost for high-accuracy prediction, with hyperparameter tuning to optimize performance.

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➢ *Model Validation:*

- Validate each model using the testing set.
- Calculate performance metrics: MAE, RMSE, R-squared.

➢ *AQI Prediction:*

- Use the trained models to predict AQI for new data points.
- Evaluate the results and compare model performances.

This system architecture provides a streamlined and efficient approach to predicting air quality using machine learning models on pre-existing datasets.

IV. EXPECTED RESULTS

The proposed system for predicting air quality in urban environments using pre-existing IoT sensor data aims to achieve high accuracy in Air Quality Index (AQI) predictions. By employing machine learning models such as Linear Regression (LR), Neural Networks (NN), and XGBoost, we expect to obtain reliable predictions. The integration of these models will facilitate a comprehensive analysis, with neural networks effectively capturing complex non-linear relationships among pollutants, while XGBoost excels in handling large datasets and enhancing prediction accuracy. We anticipate that XGBoost will demonstrate superior performance compared to the other models, particularly due to its robust mechanisms for managing overfitting and effectively processing intricate data patterns. Although Linear Regression offers a straightforward approach, its performance is expected to be reasonable, especially for datasets exhibiting strong linear correlations between pollutant levels and AQI.

In terms of model evaluation metrics, we aim to achieve low Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), along with a high R-squared value, ideally exceeding 0.85. This will indicate the models' effectiveness in explaining the variance in AQI data. Additionally, we expect the models to generalize well when applied to unseen datasets, demonstrating reliable performance with minimal overfitting. The computational efficiency of each model will also be analyzed; while XGBoost is anticipated to provide high accuracy, Linear Regression may be favored for its simplicity and lower computational demands. Neural Networks, while potentially requiring more resources, will be evaluated for their capability to identify complex patterns within the data. This analysis will offer valuable insights into the trade-offs between accuracy, complexity, and efficiency across the different modeling approaches.

V. CONCLUSION & FUTURE SCOPE

This research outlines a systematic approach for predicting the Air Quality Index using machine learning techniques and pre-existing datasets. By employing multiple algorithms, including Linear Regression, Neural Networks, and XGBoost, the proposed framework demonstrates the capability to provide accurate AQI forecasts. While the implementation is still pending, the expected results suggest that these models could effectively generalize to unseen data, contributing valuable insights for air quality management. The findings highlight the importance of utilizing existing datasets to enhance environmental health, ultimately aiding in the development of actionable policies for improving air quality.

Future research can build upon this work by integrating more diverse datasets that include additional environmental factors and pollutant indicators, thereby improving the accuracy of AQI predictions. Additionally, exploring advanced machine learning techniques, such as ensemble learning and deep learning approaches, could provide deeper insights into the complex relationships among air quality variables. Furthermore, once the system is implemented, real-time data collection from IoT sensors could facilitate dynamic AQI monitoring and prediction, allowing for timely responses to air quality fluctuations. Ultimately, the integration of these methodologies will significantly contribute to advancing air quality management and promoting public health initiatives.

REFERENCES

[1]. World Health Organization. "Health aspects of air pollution: results from the WHO project" Systematic review of health aspects of air pollution in Europe"." (2004).

[2]. Rybarczyk, Yves, and Rasa Zalakeviciute. "Machine learning approaches for outdoor air quality modelling: A systematic review." Applied Sciences 8.12 (2018): 2570.

[3]. Van Bavel, Jan. "The world population explosion: causes, backgrounds and projections for the future." Facts, views & vision in ObGyn 5.4 (2013): 281.

[4]. Chang, Daniel Lage, et al. "Knowledge-based, smart and sustainable cities: A provocation for a conceptual framework." Journal of Open Innovation: Technology, Market, and Complexity 4.1 (2018): 1-17.

[5]. Bokwa, A. Environmental impacts of long-term air pollution changes in Krakow, Poland. Pol. J. Environ. Stud. 2008, 17, 673–686.

[6]. Podstawczyńska, A., & Chambers, S. D. (2019). Improved method for characterising temporal variability in urban air quality part I: Traffic emissions in central Poland. Atmospheric Environment, 219, 117038.

[7]. Rajagopalan, Sanjay, Sadeer G. Al-Kindi, and Robert D. Brook. "Air pollution and cardiovascular disease: JACC state-of-the-art review." Journal of the American College of Cardiology 72.17 (2018): 2054-2070.

[8]. Li, Rui, et al. "Air pollution characteristics in China during 2015–2016: Spatiotemporal variations and key meteorological factors." Science of the total environment 648 (2019): 902-915.

[9]. Pasierb, Bernadetta, Michał Grodecki, and Rafał Gwóźdź. "Geophysical and geotechnical approach to a landslide stability assessment: a case study." Acta Geophysica 67.6 (2019): 1823-1834.

[10]. Kapera, I. (2018). Sustainable tourism development efforts by local governments in Poland. Sustainable cities and society, 40, 581-588.

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/IJISRT20MAY999

[11]. Lidia Morawska, Phong K. Thai et al., Applications of low-cost sensing technologies for air quality monitoring and exposure assessment: How far have they gone?,Environment International,Volume 116, 2018, Pages 286-299, ISSN 0160-4120, https://doi.org/10.1016/j.envint.2018.04.018.

[12]. Islam, Md Shaedul. "An intelligent system on environment quality remote monitoring and cloud data logging using Internet of Things (IoT)." 2018 International Conference on Computer, Communication, Chemical, Material and Electronic Engineering (IC4ME2). IEEE, 2018.

[13]. Kodali, Ravi Kishore, and Sasweth C. Rajanarayanan. "IoT based indoor air quality monitoring system." 2019 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET). IEEE, 2019.

[14]. Zheng, Yu, Furui Liu, and Hsun-Ping Hsieh. "U-air: When urban air quality inference meets big data." Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining. 2013.

[15]. Rui Feng, Hui-jun Zheng et al.," Recurrent Neural Network and random forest for analysis and accurate forecast of atmospheric pollutants: A case study in Hangzhou, China, Journal of Cleaner Production, Volume 231, 2019, Pages 1005-1015, ISSN 0959-6526, https://doi.org/10.1016/j.jclepro.2019.05.319.

[16]. Li, Xiang, et al. "Deep learning architecture for air quality predictions." Environmental Science and Pollution Research 23 (2016): 22408-22417.

[17]. Wang, Xiufeng, et al. "Eldp: Extended link duration prediction model for vehicular networks." International Journal of Distributed Sensor Networks 12.4 (2016): 5767569.

[18]. Na, Woongsoo, et al. "Frequency resource allocation and interference management in mobile edge computing for an Internet of Things system." IEEE Internet of Things Journal 6.3 (2018): 4910-4920.

[19]. Wang, Shangguang, et al. "Multi-dimensional QoS prediction for service recommendations." IEEE Transactions on Services Computing 12.1 (2016): 47-57..

[20]. Ghezzi, Carlo, et al. "Mining behavior models from user-intensive web applications." Proceedings of the 36th international conference on software engineering. 2014.

[21]. Yang X., Zhou S., and Cao M., An approach to alleviate the sparsity problem of hybrid collaborative filtering-based recommendations: the product-attribute perspective from user reviews, Mobile Networks and Applications. (2019) 25, 1–15.

[22]. Genc D. D., Yesilyurt C., and Tuncel G., Air pollution forecasting in Ankara, Turkey using air pollution index and its relation to assimilative capacity of the atmosphere, Environmental Monitoring and Assessment. (2010) 166, no. 1–4, 11–27, https://doi.org/10.1007/s10661-009-0981-y, 2-s2.0-77954144269.

[23]. Moisan S., Herrera R., and Clements A., A dynamic multiple equation approach for forecasting PM2.5 pollution in Santiago, Chile, International Journal of Forecasting. (2018) 34, no. 4, 566–581, https://doi.org/10.1016/j.ijforecast.2018.03.007, 2-s2.0-85048258541.

[24]. Ge L., Zhou A., Li H. et al., Spatially fine-grained air quality prediction based on DBU-LSTM, Proceedings of the 16th ACM International Conference on Computing Frontiers, 2019, Ischia, Italy, 202–205.

[25]. Qi Y., Li Q., Karimian H., and Liu D., A hybrid model for spatiotemporal forecasting of PM2.5 based on graph convolutional neural network and long short-term memory, Science of the Total Environment. (2019) 664, 1–10, https://doi.org/10.1016/j.scitotenv.2019.01.333, 2-s2.0-85061200096.

[26]. Kumar, Anikender, and P. Goyal. "Forecasting of daily air quality index in Delhi." Science of the Total Environment 409.24 (2011): 5517-5523.

[27]. Wei, Wenjuan, et al. "Machine learning and statistical models for predicting indoor air quality." Indoor Air 29.5 (2019): 704-726.

[28]. Soundari A. Gnana, Jeslin J. Gnana, Akshaya A.C.,"Indian air quality prediction and analysis using machine learning", Int J Appl Eng Res, 14 (11) (2019), pp. 181-186

[29]. Li, Xiang, et al. "Deep learning architecture for air quality predictions." Environmental Science and Pollution Research 23 (2016): 22408-22417.

[30]. Zhang, Chuang, et al. "Weather visibility prediction based on multimodal fusion." IEEE Access 7 (2019): 74776-74786.

[31]. Huang, Chiou-Jye, and Ping-Huan Kuo. "A deep CNN-LSTM model for particulate matter (PM2. 5) forecasting in smart cities." Sensors 18.7 (2018): 2220.

[32]. Perera, Charith, et al. "A survey on internet of things from industrial market perspective." IEEE Access 2 (2014): 1660-1679.

[33]. Kang, Gaganjot Kaur, et al. "Air quality prediction: Big data and machine learning approaches." Int. J. Environ. Sci. Dev 9.1 (2018): 8-16

[34]. Du, Shengdong, et al. "Deep air quality forecasting using hybrid deep learning framework." IEEE Transactions on Knowledge and Data Engineering 33.6 (2019): 2412-2424.

[35]. Wei, Wenjuan, et al. "Machine learning and statistical models for predicting indoor air quality." Indoor Air 29.5 (2019): 704-726.

[36]. Shaban, Khaled Bashir, Abdullah Kadri, and Eman Rezk. "Urban air pollution monitoring system with forecasting models." IEEE Sensors Journal 16.8 (2016): 2598-2606.

[37]. Kennedy Okokpujie, Etinosa Noma-Osaghae et al., "A SMART AIR POLLUTION MONITORING SYSTEM", International Journal of Civil Engineering and Technology (IJCIET) Volume 9, Issue 9, September 2018, pp. 799–809, Article ID: IJCIET_09_09_077

[38]. Zhao, Junhan, et al. "Deep CNN-based methods to evaluate neighborhood-scale urban valuation through street scenes perception." 2018 ieee third international conference on data science in cyberspace (dsc). IEEE, 2018
[39]. S. Ameer et al., "Comparative Analysis of Machine Learning Techniques for Predicting Air Quality in Smart Cities," in IEEE Access, vol. 7, pp. 128325-128338, 2019, doi: 10.1109/ACCESS.2019.2925082.