International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 2s
DOI: https://doi.org/10.17762/ijritcc.v11i2s.6028
***Article Received**: 15 November 2022 **Revised**: 20 December 2022 **Accepted**: 29 December 2022*

A Detailed Analysis of Air Pollution Monitoring System and Prediction Using Machine Learning Methods

[1] Vinoth Thanagaraju, [2]Kothalam Krishnan Nagarajan
[1]Assistant Professor,Department of Mechatronics Engineering
Chennai Institute of Technology,Kundrathur, Chennai, Tamil Nadu 600069
Email :vino.eie07@gmail.com
[2]Associate Professor, Department of Electrical and ElectronicsEngineering
SSN College of Engineering, Kalavakkam,,Tamil Nadu 603110
Email: nagarajankk@ssn.edu.in

Abstract—Predicting air quality is a complex task due to the dynamic nature, volatility, and high variability in the time and space of pollutants and particulates.Due to the presence of governing factors, varying land uses, and many sources for the elaboration of pollution, the forecast and analysis of air pollution is a difficult procedure. At the same time, being able to model, predict, and monitor air quality is becoming more and more relevant, especially in urban areas, due to the observed critical impact of air pollution on citizens' health and the environment. In this paper, various air pollution monitoring and prediction models with respect to hardware interfacing modules and various classification approaches. The Air Quality Index (AQI) parameter is used in this paper to monitor the quality of air pollution in various regions of the world. The drawbacks of the conventional air pollution monitoring and prediction models have been stated in this paper with the methodologies used for air pollution prediction.

Keywords-Air Quality, Index, Pollution, Air Quality Index, Prediction

I. INTRODUCTION

At present, every human requires high sophisticated life which requires more consumable devices such as Mobile phones, two and four-wheeler. Moreover, so many industries are constructed from the past two decades. These things create air pollution which creates many life-threatening diseases to the human. The fuel incorporated two and four vehicles releases huge levels of gases which contains more harmful ingredients. These harmful ingredients are combined with the environmental good air and pollute them. These types of air pollution directly affect the human being, animals and also the growth of the plants on earth. The development and modernization of the urban area also is the main reason for air pollution. The air pollutant factors are the main reason behind the severe air pollution in world. These air pollutants are categorized into Carbon Oxide (CO_2), Nitrogen Oxide (CO_2) and sulphur oxide (SO). The sulphur oxide air pollutant is further categorized into type-1 SO (SO_2), type-2 SO (SO_3), and type-3 SO (SO_4). The forth important air pollutant is Particular Matter (PM) pollutant, which has the size less than 10 μm in environmental air. The air quality is measured based on the quantity of the air pollutants available in environmental air. Most of the countries in word allocated certain group of rules and guidelines to measure the air quality. Though these air quality measurements are available with defined guidelines, these are mainly dependant on the outdoor air pollution level. But, the actual air pollution is the accumulation of both outdoor and indoor air pollution levels. Also, the air pollution is either static or dynamic which based on the environmental changes in real world. The quality of the air is gradually changed or polluted in case of the static air pollution and the quality of the air is suddenly changed or polluted in case of the dynamic air pollution.

Fig. 1 shows the hardware interfacing of sensors for monitoring and predicting the air pollution. In Fig.1, all the sensor units or modules are connected to the data processing module where the preprocessing of sensed data has been processed here. The preprocessed data are now sent to processor or controller to predict the future air pollution results from the past trained sensed air pollution data.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 2s
DOI: https://doi.org/10.17762/ijritcc.v11i2s.6028
***Article Received**: 15 November 2022 **Revised**: 20 December 2022 **Accepted**: 29 December 2022*

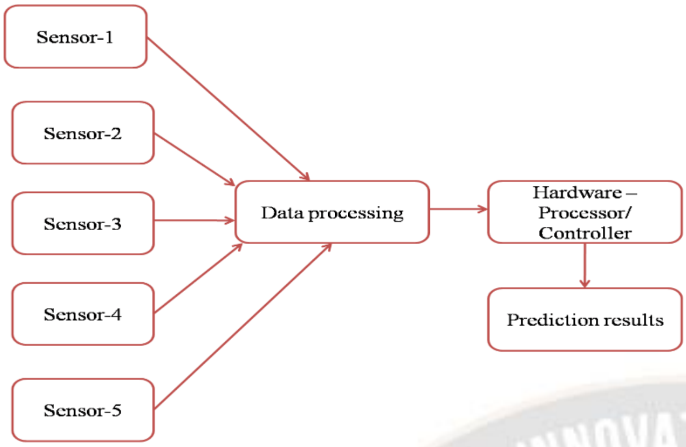

Figure 1 Hardware Interfacing of sensors for monitoring and predicting the air pollution

Fig. 2 shows the various classifiers for predicting the air pollution from the pre-trained classification modules in this section. The classifiers which are used to predict the future air pollution index level, are now categorized into machine and deep learning classification approaches.

In this paper, the air pollution monitoring and analyzing system is surveyed based on the hardware interfacing modules and classification approaches.

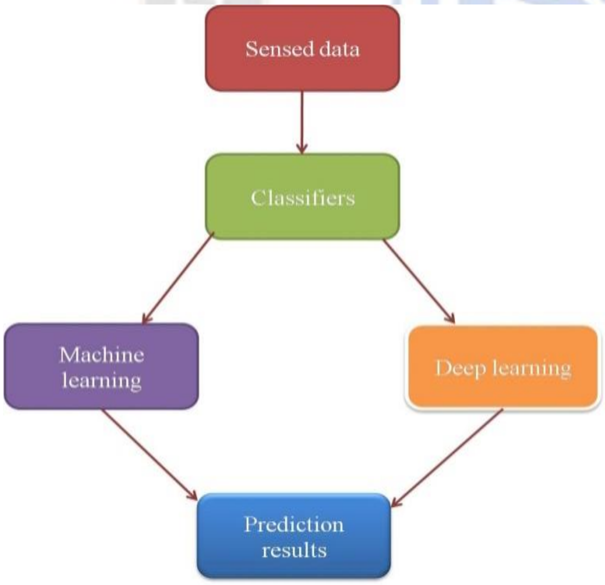

Figure 2 Classifiers for predicting the air pollution

II. LITERATURE SURVEY ON AIR POLLUTION MONITORING USING HARDWARE INTERFACING MODULES

In this section, the hardware interfacing modules and units which are used for monitoring the environmental air pollution are discussed with the experimental results and they are categorized into the following sub sections as stated below.

- IoT based air pollution monitoring;
- Embedded based air pollution monitoring;
- Cloud based air pollution monitoring;

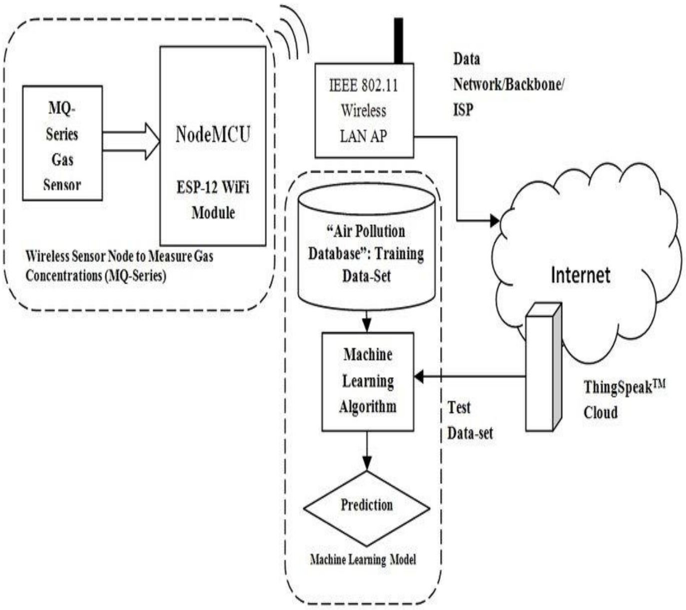

Figure 3 IoT based air pollution monitoring system

Figure 3 shows the IoT based air pollution monitoring system, which consist of various numbers of sensors and they are connected to the internet through the set of intermediate hardware modules. The prediction module in this work computes the air pollution ratio using machine learning algorithms such as Support Vector Machine (SVM), Neural Network (NN) and Adaptive Neuro Fuzzy Inference (ANFIS) classification approaches. The predicted air pollution details are sent to the internet through the web server module which is connected between the classification module and the internet as depicted in Fig. 3.

In case of Embedded based air pollution monitoring system, the systems used different number of air pollution measurement devices and they are connected with the embedded cores to effectively process the captured information to either cloud or internet. The embedded processors may have the Central processing units to process the captured information and the result of these embedded processors are filly dependent on the memory capacity of the entire air pollution monitoring system.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 2s
DOI: https://doi.org/10.17762/ijritcc.v11i2s.6028
***Article Received**: 15 November 2022 **Revised**: 20 December 2022 **Accepted**: 29 December 2022*

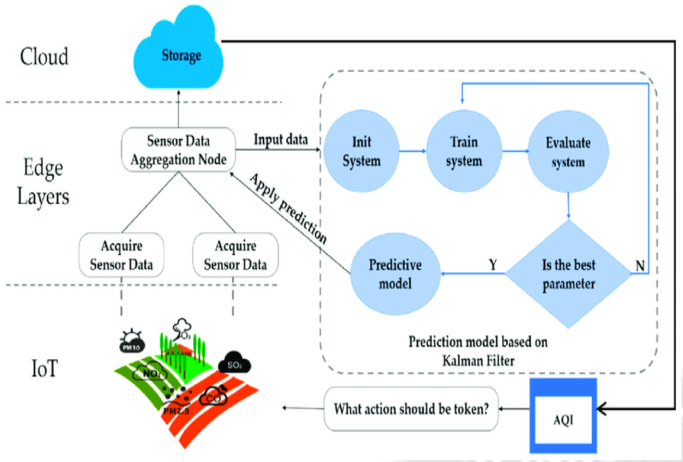

Figure 4 Cloud based air pollution monitoring system

Figure 4 shows the cloud-based air pollution monitoring system, which consist of prediction model and IoT devices to acquire the environmental air pollution data from the remote units. The measured data are processed through the edge layers which uses aggregation nodes to store this information to the cloud through the different cloud servers. In this cloud-based air pollution monitoring system, mostly private clouds are used than the public and hybrid clouds. The security level of the private cloud is higher than the security level of the public and hybrid clouds. Moreover, the data processing consumption is less in case of private clouds than the utilization of the public and hybrid clouds. In Fig.4, the kalman filter is used to predict the environmental air pollution and these preprocessed air pollution data are checked by the different sensing and modifying modules.

Abu El-Magd et al. (2022) observed the air pollution data in remote sensing method and these observed air pollution data were processed and analyzed using machine learning approach. The minimal number of hardware interfacing modules was involved in this work to observe the industrial air pollution data from the various regions of the countries. In this work, the authors checked and verified the efficiency of the developed air pollution monitoring system with respect to various machine learning algorithms. The experimental results were obtained for each machine learning algorithms individually and they were compared with respect to various distribution and performance estimation parameters in this work.

Tamas et al. (2016) used clustering approach to capture the air quality parameters to monitor them for hazard detection and prevention system. The authors identified the air pollutant peaks from the observed air pollution data from the various regions. This method was tested on various regions and the authors obtained 95.7% of air pollution detection accuracy and these experimental results were compared with various air pollution monitoring system in terms of the air pollution detection accuracy.

Ruiyun et al. (2016) developed air pollution monitoring and prediction system using Random Forest machine learning methodology or framework model. The developed Random Forest classification model were optimized using number of hyper parameters and their optimization was observed by varying its adjacent indexing parameters. This random forest based air pollution monitoring and predicting system used ARM board processing units and the power consumption and energy utilization of this developed model was significantly reduced in this paper.

Figure 5 shows the Random Forest classifications which are used for monitoring the environmental air pollution prediction. The collected data are split into various instances and from these instances, the tree diagram are constructed with number of nodes. The computation of voting is performed for individual tree diagram and finally the majority of voting is computed or determined using voting heuristic model. Then, the class is finalized with the maximum voting value in this work. The nodes and their instances used in random forest classification approach is clearly illustrated in Figure 5.

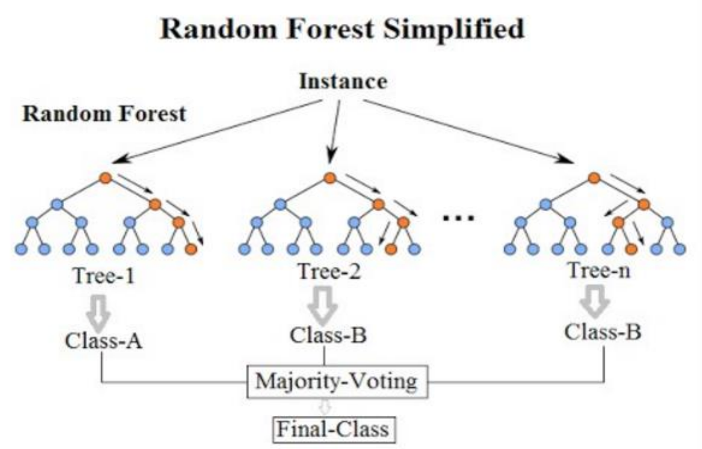

Figure 5 Random Forest classifications

Park et al. (2018) used artificial intelligence technique to monitor the real time parameters in Seoul metropolitan subway stations. The proposed artificial intelligence technique was constructed using three numbers of layers. The layer 1 which was called as input layer, was designed with 16 number of neurons. The layer 2 which was called as hidden layer, was designed with 67 number of neurons along with the unique output layer in the proposed artificial intelligence classifier design which was used in this paper to analyze and predict the air pollution in Seoul metropolitan subway stations.

Athanasiadis et al. (2003) constructed real time decision support system for observing and analyzing the air quality in various environmental regions in world. This proposed method

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 2s
DOI: https://doi.org/10.17762/ijritcc.v11i2s.6028
***Article Received**: 15 November 2022 **Revised**: 20 December 2022 **Accepted**: 29 December 2022*

used different machine learning models to observe and analyze the air quality parameters and these observed real time parameters were sent to the remote unit through the decision support system. This proposed system used computerized peripherals to capture or sense the real time on various environmental modes. This method was tested on various regions and the authors obtained 94.31% of air pollution detection accuracy and these experimental results were compared with various air pollution monitoring system in terms of the air pollution detection accuracy.

Ioannis et al. (2006) proposed and implemented number of classification methods for measuring and classification of the real time air pollution observing data. The authors validated these developed classification methods to check that which approach was best suitable for monitoring and analyzing the air quality in real time environment mode.

Caselli & L. Trizio et al. (2009) constructed Feed Forward Neural Networks (FFNN) to forecast PM10 data with the different power and energy optimized algorithms. The developed FFNN model was integrated with Radial Basis Function Network (RBFN) frame work to improve the air quality index rate on real time parameters. This method was tested on various regions and the authors obtained 92.10% of air pollution detection accuracy.

Table 2 is the analysis of different air pollution monitoring using hardware interfacing modules. In Table 2, the different methods which were used in conventional air pollution monitoring and prediction system model was stated and illustrated with their limitations. The architecture of FFNN which is used for measuring the environmental air pollution is depicted in Fig.6.

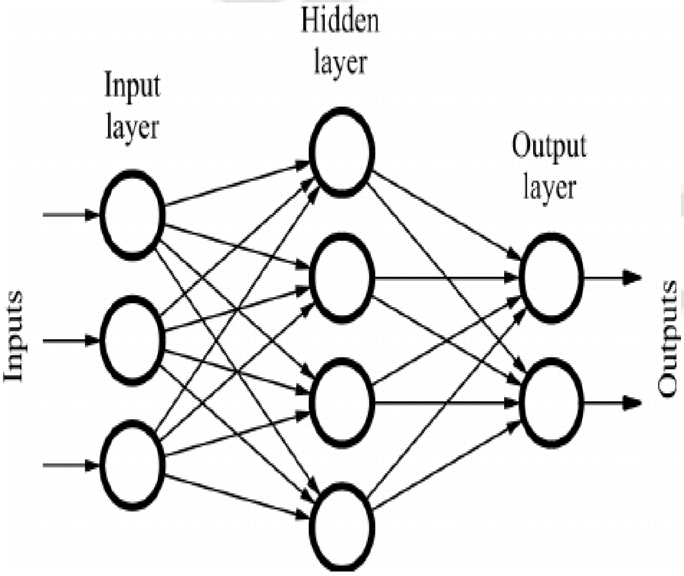

Figure 6 Architecture of FFNN

Table 2 Analysis of different air pollution monitoring using hardware interfacing modules

Authors	Methods	Limitations
Abu El-Magd et al. (2022)	Remote sensing method	High sensed time period
Tamas et al. (2016)	Pollutant peak algorithm	Low level of air prediction results
Ruiyun et al. (2016)	Random Forest machine learning methodology	No steady classifier
Park et al. (2018)	Artificial intelligence technique	Complex prediction architecture
Athanasiadis et al. (2003)	Real time decision support system	Poor stability
Ioannis et al. (2006)	Linear prediction model	No robustness of the developed classifier
Caselli & L. Trizio et al. (2009)	Feed Forward Neural Networks (FFNN)	Low level of air prediction results

III. Literature Survey On Air Pollution Monitoring Using Classification Algorithms

Pandey et al. (2013) predicted and analyzed sub-micron air pollutant in open air using machine learning mathematical model approach. This sub-micron air pollutant monitoring and measuring system using machine learning algorithms provided superior experimental results on various regions of environments in both open-air condition system and closed air condition system. The authors obtained 95.1% of sub-micron air pollutant detection rate on open air condition system and the authors obtained 97.3% of sub-micron air pollutant detection rate on closed air condition system.

Figure 7 shows the Recurrent Neural Networks modeling which is used for predicting the environmental air pollution. This network architecture consists of input layer, hidden layer along with the output layers as shown in Fig.7. The nodes in both hidden layer and output layer are recurrent with each other to obtain the maximum prediction results in this work.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 2s
DOI: https://doi.org/10.17762/ijritcc.v11i2s.6028
***Article Received**: 15 November 2022 **Revised**: 20 December 2022 **Accepted**: 29 December 2022*

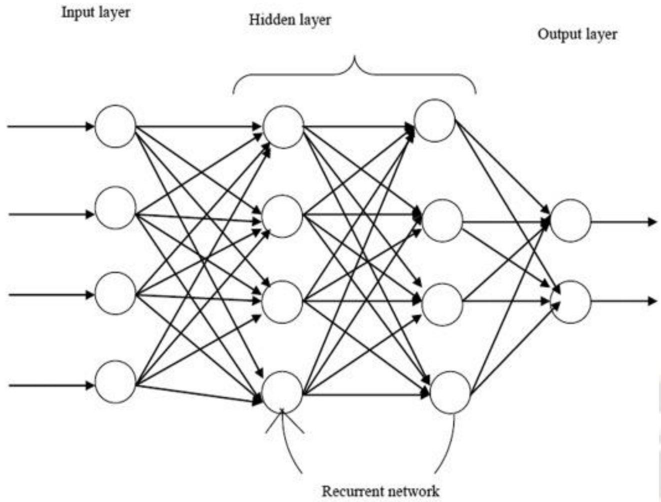

Figure 7 Recurrent Neural Networks

Barré et al. (2021) observed NO2 changes in real time environmental regions during lockdown stages in various countries to monitor the air pollution. This developed and proposed air quality observation and measuring models used in this paper applied their proposed linear regression algorithm on the parameters which were observed from the satellite and surface measuring sensors. The authors obtained 95.1% of sub-micron air pollutant detection rate on satellite condition system and the authors obtained 97.3% of sub-micron air pollutant detection rate on surface air condition system.

Athira et al. (2018) used recurrent networks modeling algorithm for observing and analyzing the air quality models. This proposed recurrent networks modeling algorithm on observed large amount of observing parameters were analyzed with respect to index rules which were stated in this paper.

Betancourt et al. (2021) analyzed different air quality prediction and observation models on bench mark air quality datasets. The proposed method was analyzed using air quality global index measurement system. The proposed air quality measurement models were tested on various kind on real time environment with respect to the air quality global index.

Fan et al. (2017) used Recurrent Neural Networks (RNN) modeling architecture for monitoring and predicting the air quality parameters under various environmental conditions in this paper. The authors obtained 93.2% of sub-micron air pollutant detection rate on satellite condition system and the authors obtained 95.3% of sub-micron air pollutant detection rate on surface air condition system.

Grange et al. (2018) used Random forest approach for observing and analyzing the black carbon particles in Swiss PM 10 trend environment.

Gidhagen et al. (2021) used machine learning algorithm Support vector Machine (SVM) for predicting the air pollution ratio under various environmental conditions.

Krishan et al. (2019) and Qin et al. (2020) designed air quality measurement system using long short-term memory (LSTM). This LSTM based air pollution monitoring system was applied and checked in NCT-Delhi, under various environmental regions to continuously monitor and observe the air quality parameters. The authors obtained 97.12% of sub-micron air pollutant detection rate on satellite condition system and the authors obtained 94.39% of sub-micron air pollutant detection rate on surface air condition system.

Kristiani et al. (2020) and Navares et al. (2020) proposed air quality monitoring system through dynamic training using deep learning algorithm.

Mauro Castelli et al. (2020) predicted and analyzed the quality of the air in free channel media using the integration of the machine learning classification algorithms Support Vector Regression (SVR) and Radial Basis Function (RBF). The hyper parameters of these integrated machine learning classifiers were varied by the node intermediate value and the authors obtained air quality index (AQI) of 94.1% in this work. This method for predicting the air pollution was worked well in terms of the AQI in real world environment in this work.

Wang et al. (2009) predicted the forecasting data from the different regions of the environment using the artificial intelligence technique in this work. The authors applied different artificial intelligence techniques on the forecasted data to predict the data in future for monitoring the real time data from the weather forecasting.

Lu et al. (2005) and Vong et al. (2012) used SVM classifier for observing and analyzing the real-world real-time parameters for predicting the weather report for future environment. These authors applied various SVM kernels for analyzing the performance of the proposed and developed multi class short term SVM classification approach in these research work for predicting the real time air pollution.

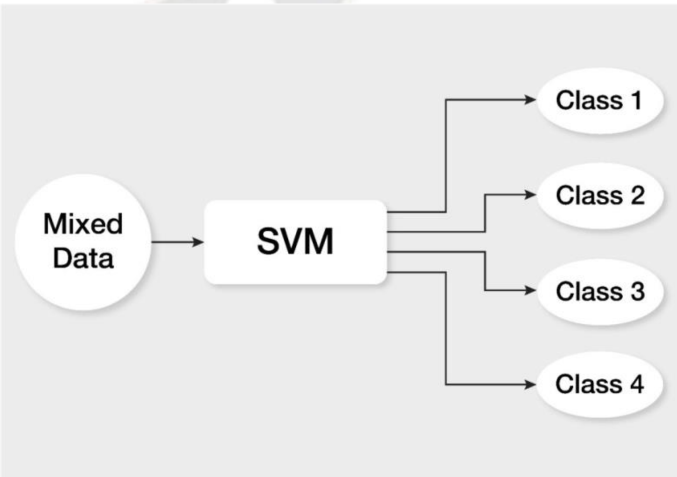

Figure 8 SVM classification model

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 2s
DOI: https://doi.org/10.17762/ijritcc.v11i2s.6028
***Article Received**: 15 November 2022 **Revised**: 20 December 2022 **Accepted**: 29 December 2022*

Figure 8 illustrates the SVM model which is used for environmental air pollution monitoring and prediction. The SVM architecture receives the mixed data or information and process this information into three or more number of output classes based on the levels of the kernels used in this work.

Sotomayor-Olmedo et al. (2013) and Kotsiantis et al. (2016) measured and analyzed the air pollutants from the different regions of country in mexico city using the robust machine learning kernel-based classifiers. The authors preprocessed the observed set of data for analyzing the micro kernel data for improving the performance of the machine learning classification models in this work.

Gocheva-Ilieva et al. (2014) and Cagliero et al. (2016) modeled time series analysis of the prediction of air pollution in various regions. The authors analyzed the time series network for comparing the modeled data with the other similar data from the same network environment. This method was tested on various regions and the authors obtained 92.1% of air pollution detection accuracy and these experimental results were compared with various air pollution monitoring system in terms of the air pollution detection accuracy.

Hajek et al. (2015) improved the AQI for observing and analyzing the various observational parameters for utilizing the air pollution monitoring system. Ma et al. (2020) analyzed the impact of the air pollution in human's health for the large population countries in various regions of the world. The severity of the human health issues has been addressed due to the impact of the air pollution.

Sharma et al. (2019) measured and detailed AQI parameters for various regions of the geographical network. The authors addressed various issues raised by the various regions in world due to the impact of the air pollution.

Kyrkilis et al. (2007), Sharma et al. (2017) and Idrees et al. (2018) designed and development of the air pollution monitoring and analyzing system for predicting the air quality of the various geographical network regions in world.

Table 3 is the analysis of different air pollution monitoring using classification methods. In Table 3, the different methods which were used in conventional air pollution monitoring and prediction system model was stated and illustrated with their limitations.

Table 3 Analysis of different air pollution monitoring using classification methods

Authors	Methods	Limitations
Pandey et al. (2013)	machine learning mathematical model approach	High sensed time period
Barré et al. (2021)	linear regression algorithm	Poor stability
Athira et al. (2018)	recurrent networks modeling algorithm	Low level of air prediction results
Betancourt et al. (2021)	air quality prediction and observation models	Complex prediction architecture
Fan et al. (2017)	Recurrent Neural Networks (RNN) modeling architecture	Low level of air prediction results
Grange et al. (2018)	Random forest approach	Failed to predict the future air pollution when large number of user's data available
Gidhagen et al. (2021)	machine learning algorithm Support vector Machine (SVM)	High sensed time period
Krishan et al. (2019) and Qin et al. (2020)	long short-term memory (LSTM).	Low level of air prediction results
Kristiani et al. (2020) and Navares et al. (2020)	dynamic training algorithm	Complex prediction architecture

IV. CONCLUSION

In this paper, various air pollution monitoring and prediction models with respect to hardware interfacing modules and various classification approaches. The following drawbacks of the various air pollution monitoring and prediction models have been identified and listed below.

- Low level of air prediction results
- High sensed time period
- Complex prediction architecture
- Poor stability
- No robustness of the developed classifier
- Failed to predict the future air pollution when large number of user's data available

Moreover, the following observations have been identified from the literature survey of the conventional air pollution monitoring and prediction system.

- Most of the conventional air pollution monitoring and prediction models used SVM classifier to predict the future air pollution.
- Mostly AQI parameters alone are used by the various conventional methods to predict the future air pollution.

- Feed Forward Neural Networks with various set of the layers and neuron patterns were used by the conventional methods for air pollution prediction.
- Most of the conventional air pollution monitoring and prediction models used ARM board processing units for air pollution prediction.

REFERENCES

[1] Abu El-Magd, S., Soliman, G., Morsy, M. Environmental hazard assessment and monitoring for air pollution using machine learning and remote sensing. Int. J. Environ. Sci. Technol. (2022).

[2] Tamas W, Notton G, Paoli C, Nivet ML, Voyant C (2016) Hybridization of air quality forecasting models using machine learning and clustering: An original approach to detect pollutant peaks. Aerosol AirQual Res 16(2):405–416.

[3] Ruiyun Y, Yang Y, Yang L, Guangjie H, Oguti AM (2016) RAQ–a random forest approach for predicting air quality in urban sensing systems. Sensors 16:86.

[4] Park S, Kim M, Kim M, Namgung HG, Kim KT, Cho KH, Kwon SB (2018) Predicting PM10 concentration in Seoul metropolitan subway stations using artificial neural network (ANN). J Hazard Mater 341:75–82.

[5] Athanasiadis, Ioannis N. "Applying machine learning techniques on air quality data for real-time decision support." First international NAISO symposium on information technologies in environmental engineering (ITEE`2003), Gdansk, Poland. 2003.

[6] Ioannis N. Athanasiadis, Kostas D. Karatzas and Pericles A. Mitkas. "Classification techniques for air quality forecasting." Fifth ECAI Workshop on Binding Environmental Sciences and Artificial Intelligence, 17th European Conference on Artificial Intelligence, Riva del Garda, Italy, August 2006.

[7] M. Caselli & L. Trizio & G. de Gennaro & P. Ielpo. "A Simple Feedforward Neural Network for the PM10 Forecasting: Comparison with a Radial Basis Function Network and a Multivariate Linear Regression Model." Water Air Soil Pollut (2009) 201:365–377.

[8] Pandey, Gaurav, Bin Zhang, and Le Jian. " Predicting sub-micron air pollution indicators: a machine learning approach.&quot ; Environmental Science: Processes & amp; Impacts 15.5 (2013): 996-1005.

[9] Barré, J., Petetin, H., Guevara, M., Pérez García-Pando, C., Bowdalo, D., and JorbaCasellas, O. (2021). Estimating lockdown-induced European NO2 changes using satellite and surface observations and air quality models. Atmos. Chem. Phys. 21, 7373–7394. doi: 10.5194/acp-21-7373-2021.

[10] Betancourt, C., Stomberg, T., Stadtler, S., Roscher, R., and Schultz, M. G. (2021). AQ-Bench: a benchmark dataset for machine learning on global air quality metrics. Earth Syst. Sci. Data Discuss. 13, 3013–3033.

[11] Athira, V., Geetha, P., Vinayakumar, R., and Soman, K. (2018). Deepairnet: applying recurrent networks for air quality prediction. Proc. Comput. Sci. 132, 1394–1403.

[12] Fan, J., Li, Q., Hou, J., Feng, X., Karimian, H., and Lin, S. (2017). A spatiotemporal prediction framework for air pollution based on deep RNN. ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci. 4, 15. doi: 10.5194/isprs-annals-IV-4-W2-15-2017.

[13] Gidhagen, L., Krecl, P., Targino, A. C., Polezer, G., Godoi, R. H. M., Felix, E., et al. (2021). An integrated assessment of the impacts of PM2.5 and black carbon particles on the air quality of a large Brazilian city. Air Qual. Atmos. Health. 14, 1455–1473.

[14] Grange, S. K., Carslaw, D. C., Lewis, A. C., Boleti, E., and Hueglin, C. (2018). Random forest meteorological normalisation models for Swiss PM 10 trend analysis. Atmos. Chem. Phys. 18, 6223–6239.

[15] Krishan, M., Jha, S., Das, J., Singh, A., Goyal, M. K., and Sekar, C. (2019). Air quality modelling using long short-term memory (LSTM) over NCT-Delhi, India. Air Qual. Atmos. Health 12, 899–908.

[16] Kristiani, E., Lee, C.-F., Yang, C.-T., Huang, C.-Y., Tsan, Y.-T., and Chan, W.-C. (2020). Air quality monitoring and analysis with dynamic training using deep learning. J. Supercomput. 77, 5586–5605.

[17] Navares, R., and Aznarte, J. L. (2020). Predicting air quality with deep learning LSTM: towards comprehensive models. Ecol. Inform. 55, 101019.

[18] Qin, D., Yu, J., Zou, G., Yong, R., Zhao, Q., and Zhang, B. (2019). A novel combined prediction scheme based on CNN and LSTM for urban PM 2.5 concentration. IEEE Access 7, 20050–20059.

[19] Mauro Castelli, Fabiana Martins Clemente, AlešPopovič, Sara Silva, Leonardo Vanneschi, "A Machine Learning Approach to Predict Air Quality in California", Complexity, vol. 2020, Article ID 8049504, 23 pages, 2020.

[20] W.-C. Wang, K.-W. Chau, C.-T. Cheng, and L. Qiu, "A comparison of performance of several artificial intelligence methods for forecasting monthly discharge time series," Journal of Hydrology, vol. 374, no. 3-4, pp. 294–306, 2009.

[21] W.-Z. Lu and W.-J. Wang, "Potential assessment of the "support vector machine" method in forecasting ambient air pollutant trends," Chemosphere, vol. 59, no. 5, pp. 693–701, 2005.

[22] C. M. Vong, W. F. Ip, P. K. Wong, and J. Y. Yang, "Short-term prediction of air pollution in Macau using support vector machines," Journal of Control Science and Engineering, vol. 2012, Article ID 518032, 11 pages, 2012.

[23] Sotomayor-Olmedo, M. A. Aceves-Fernández, E. Gorrostieta-Hurtado, C. Pedraza-Ortega, J. M. Ramos-Arreguín, and J. E. Vargas-Soto, "Forecast urban air pollution in Mexico City by using support vector machines: a kernel performance approach," International Journal of Intelligence Science, vol. 3, no. 3, pp. 126–135, 2013.

[24] S. B. Kotsiantis, P. E. Pintelas, and D. Kanellopoulos, "Data preprocessing for supervised leaning," International Journal of Computer Science, vol. 1, no. 1, 2006.

[25] S. G. Gocheva-Ilieva, A. V. Ivanov, D. S. Voynikova, and D. T. Boyadzhiev, "Time series analysis and forecasting for air pollution in small urban area: an SARIMA and factor analysis approach," Stochastic Environmental Research and Risk Assessment, vol. 28, no. 4, pp. 1045–1060, 2014.

[26] L. Cagliero, T. Cerquitelli, S. Chiusano, P. Garza, G. Ricupero, and X. Xiao, "Modeling correlations among air pollution-related data through generalized association rules," in Proceedings of the 2016 IEEE International Conference on Smart Computing, SMARTCOMP 2016, St. Louis, MO, USA, May 2016.

[27] P. Hajek and V. Olej, "Predicting common air quality index - the case of Czech microregions," Aerosol and Air Quality Research, vol. 15, no. 2, pp. 544–555, 2015.

[28] Ma, Q., et al.: Understanding the knowledge gaps between air pollution controls and health impacts including pathogen epidemic. Environ. Res. 189, 109949 (2020).

[29] Sharma, R., et al.: Inferring air pollution from air quality index by different geographical areas: case study in India. Air Quality, Atmosphere & Health. 12(11), 1347– 1357 (2019).

[30] Kyrkilis, G., Chaloulakou, A., Kassomenos, P.A.: Development of an aggregate Air Quality Index for an urban Mediterranean agglomeration: relation to potential health effects. Environ. Int. 33(5), 670– 676 (2007).

[31] Sharma, V., Kumar, R., Kaur, R.: UAV-assisted content-based sensor search in IoTs. Electron. Lett. 53(11), 724–726 (2017).

[32] Idrees, Z., Zou, Z., Zheng, L.: Edge computing based IoT architecture for low cost air pollution monitoring systems: a comprehensive system analysis, design considerations & development. Sensors. 18(9), 3021 (2018).