Journal of Management & Entrepreneurship
ISSN 2229-5348
UGC Care Group I Journal
Vol-14 Issue-01 June 2025

PREDICTION OF AIR POLLUTION THROUGH MACHINE LEARNING

Prof. D. V. Varaprasad, M.Tech, (Ph.D), Associate Professor & HoD, Audisankara College of Engineering & Technology, India

Mrs M.Narmada, Assistant Professor, Department of CSE, Audisankara College of Engineering & Technology ,India

Bommalata Komala, Department of CSE, Audisankara College of Engineering & Technology, India

Abstract: In many growing and metropolitan regions, keeping the air clean and safe is a big problem. Electricity, electrical, and automobile pollution are hurting artefacts. The economy is rising, which is causing the air and water in cities to become polluted. Our country's population is growing swiftly.

Burning thermal fuel makes nitrogen oxide (NO), which is bad for people's health and pollutes the air. It also makes sulphur dioxide (SO2), which is bad for the environment. The benefits of air are overestimated because of how it changes with location, time, and fog. This study looks at ways to use artificial intelligence to predict air quality.

INDEX TERMS: Air Pollution, Machine Learning, Air Quality Prediction, Sulphur Dioxide (SO_2), Nitrogen Oxide (NO), Urban Pollution, Environmental Monitoring, Artificial Intelligence, Predictive Modeling, Smart Cities

1. INTRODUCTION

The fast growth of cities and industries in recent years has led to a big rise in air pollution levels. Air pollution is a big problem, especially in developing countries where car emissions, industrial discharges, and burning fossil fuels release a lot of dangerous chemicals including Sulphur Dioxide (SO_2) and Nitrogen Oxide (NO). These pollutants are bad for the environment and may also be very bad for people's health, causing problems with their hearts and lungs. To protect public health and prevent long-term harm to the environment, it is now important to keep an eye on and anticipate air quality.

A lot of research is being done on machine learning techniques to see how well they can anticipate things. Machine learning algorithms can predict future air quality indices (AQI) by looking at past pollution data. This lets the government and the public take action before problems happen. This project is all about utilising Linear Regression and Stepwise Multiple Linear Regression to figure out how much air pollution there will be depending on different environmental factors. It also contains preprocessing chores like dealing with missing information and checking how well the model works by using metrics like Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) to make sure the predictions are correct.

2. LITERATURE SURVEY

2.1 Variational Bayesian Network with Information Interpretability Filtering for Air Quality Forecasting:

[Mathematics | Free Full-Text | Variational Bayesian

Network with Information Interpretability Filtering for Air Quality Forecasting (mdpi.com)

Forecasting helps governments plan and grow in a way that is good for the environment and people's health. Multi-step forecasting is nonlinear and difficult because of time and space issues, which makes it hard to make predictions. Deep models are the best way to guess what the air quality will be like, and they can also simulate crucial nonlinearities. Forecasting that can't be understood leads to risky conclusions, especially for governments, if there isn't a mechanism-based research. This paper shows a reasonable variational Bayesian deep learning model for predicting PM2.5 via information self-screening. depends on things like temperature, humidity, wind speed, how far apart things are, and the amount of PM2.5 in the air.

A good way to screen multivariate data that gets as much relevant data as feasible for predicting PM2.5. Second, the self-screening layer of the deep learning network made it possible to choose the best input variables. We created a variational Bayesian gated recurrent unit (GRU) network to deal with the complicated distribution of PM2.5 and provide reliable multi-step forecasts after adding the screening layer.

PM2.5 data from Beijing, China, shows that the recommended strategy, which employs deep learning technology to predict PM2.5 levels based on various parameters, is quite accurate.

2.2 Spatiotemporal air quality forecasting and health risk assessment over smart city of NEOM:

Spatiotemporal air quality forecasting and health risk assessment over smart city of NEOM - ScienceDirect

Predicting and forecasting levels of air pollution can help alert people about harmful pollutants. It is hard to anticipate air quality because dynamic processes are hard to predict and there isn't enough data on chemical components and emissions sources.

This post suggested using deep learning to get a lot of abstraction from data and capture spatiotemporal characteristics every hour and every day in NEOM City, Saudi Arabia. The suggested method used both ConvLSTM and ResNet. A ResNet model improved the ConvLSTM method by dramatically extracting spatial information and cutting down on feature loss from pollution and weather data. Health risk assessment was then used to look at the risk sensitivity of PM10 and PM2.5 in five NEOM City zones. The recommended method with successful feature extraction made spatiotemporal air quality forecasts better than the best algorithms available. MASE said that PM2.5 and PM10 will be 13.57 and 9.13, respectively, during the next hour. The recommended strategy makes it easier to predict air pollution and is available all across the world.

2.3 Development and evaluation of an advanced National Air Quality Forecasting Capability using the NOAA Global Forecast System version 16:

(PDF) Development and evaluation of an advanced National Air Quality Forecasting Capability using the NOAA Global Forecast System version 16 (researchgate.net)

NASA and NOAA produced the Finite-Volume Cubed-Sphere (FV3) dynamical core, which powers the GFS and other limited-area models that NOAA uses to predict local weather and air pollution. NOAA upgraded the operational FV3GFS to GFSv16, which improved the physics of the model, how it takes in data, and how it is built up. It was easy to see how much better the weather feedback was because of the change in the atmosphere. We add the GFSv16 update to the Community Multiscale Air Quality (CMAQ) model to make the National Air Quality Forecasting Capability (NAQFC) better and keep people and the environment healthy in the US. It is shown how FV3GFSv16 and CMAQ 5.3.1, a "state-of-the-science" model, are related. The NOAA-EPA Atmosphere-Chemistry Coupler (NACC), which was the first of its kind, was a big part of the next operational NAQFC system (NACC-CMAQ), which made GFS-CMAQ coupling possible. NACC-CMAQ uses satellite data to enhance land cover and soil properties. It also uses projections of dust and smoke from wildfires to estimate PM2.5 levels during dangerous events that might harm people, ecosystems, and society. The GFS-driven NACC-CMAQ model does a better job of predicting near-surface ozone and PM2.5 levels and 72-hour diurnal patterns (3 d) than the operational NAQFC model.

2.4 Deep Air Using Hybrid Quality Forecasting Deep Learning Framework:

Deep Air Quality Forecasting Using Hybrid Deep Learning Framework | IEEE Journals & Magazine | IEEE Xplore

NASA and NOAA built the Finite-Volume Cubed-Sphere (FV3) dynamical core, which is what the GFS and other limited-area models that NOAA uses to predict local weather and air pollution run on. NOAA updated the operational FV3GFS to GFSv16. This made the model's physics better, how it gathers data, and how it is put together. The shift in the atmosphere made it clear how much superior the weather feedback was. We incorporate the GFSv16 update to the Community Multiscale Air Quality (CMAQ) model to improve the National Air Quality Forecasting Capability (NAQFC) and keep people and the environment healthy in the US. It is illustrated how FV3GFSv16 and CMAQ 5.3.1, which is a "state-of-the-science" model, are connected. The NOAA-EPA Atmosphere-Chemistry Coupler (NACC) was the first of its kind and was a key element of the next operational NAQFC system (NACC-CMAQ), which made GFS-CMAQ coupling possible. NACC-CMAQ uses data from satellites to improve the attributes of land cover and soil. It also utilises forecasts of smoke and dust from wildfires to guess PM2.5 levels during dangerous events that might hurt people, ecosystems, and society. The operational NAQFC model doesn't do as well at predicting near-surface ozone and PM2.5 levels and 72-hour diurnal patterns (3 d) as the GFS-driven NACC-CMAQ model does.

- **LSTMs** excel in modeling sequential data, such as time series (important for air quality, which often shows clear temporal patterns).
- **CNNs** can capture spatial features, like geographical influences on pollution, in cases where multiple monitoring stations are used.
- Combining the two might also handle the noisy and complex nature of real-world air quality data.

2.5 "Multivariate regression analysis of air quality index for Hyderabad city: Forecasting model with hourly frequency:

Multivariate regression analysis of air quality index for Hyderabad city: Forecasting model with hourly frequency (allresearchjournal.com)

This article talks about the air quality index (AQI) for the city of Hyderabad in India. The primary AQI factors include benzene, toluene, xylene, PM2.5, ambient temperature, relative humidity, bar pressure, solar radiation, wind speed, wind direction, NO, NO2, NOx, SO2, and rack temperature. An Air Quality Index (AQI) is used in a multivariate regression model to quantify and show the air quality in Hyderabad. This model might assist predict air quality indices in big cities where there is a lot of industrial, commercial, and residential activity in the short and long term.

To make the index more useful, air quality is divided into five groups: Clean, Moderate, Poor, Bad, and Dangerous. Long-term air quality indices are made using hourly data from Hyderabad, a large Indian city with a climate that is changing quickly. This official research includes air quality models that look at emissions to ambient concentrations, atmospheric processes, ambient measurements, emissions characterisation, and how humans and ecosystems respond to being exposed to ambient contaminants. New management strategies based on standards and criteria are needed to make people more responsible for improving air quality and cutting down on emissions. Being responsible would include setting goals for lowering the risk of contamination.

3. METHODOLOGY

a) Proposed Work:

The suggested system's goal is to use reputable data sources, including the official datasets from the Delhi Government, to estimate levels of air pollution. The first step of the project is to do an exploratory data analysis, which means finding outliers, checking for consistency, and dealing with missing results. To deal with missing data, we fill in the average (mean) values for each characteristic. This makes sure that the dataset is comprehensive and correct for training and testing the machine learning models.

The system uses Linear Regression and Stepwise Multiple Linear Regression to make predictions. These algorithms assist predict the Air Quality Index (AQI) by looking at different locations and times and using the features that are available. We check the model's correctness with measures like the Root Mean Squared Error (RMSE) and the Mean Absolute Percentage Error (MAPE). The technology can help with real-time pollution monitoring and forecasting by properly estimating the levels of pollutants like PM2.5. This will help people make better choices for public health and environmental safety.

b) System Architecture:

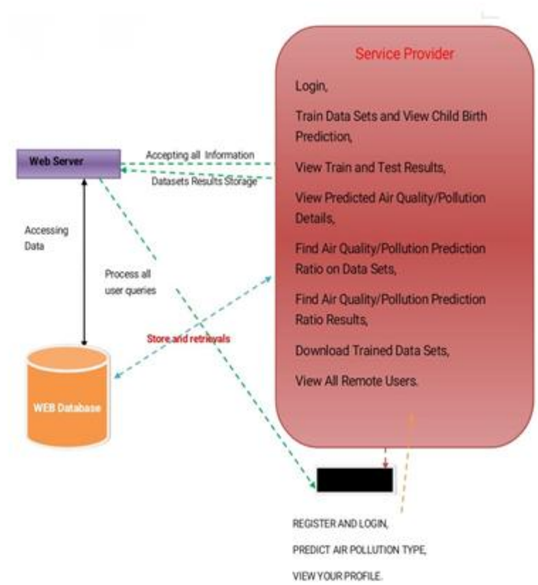

Fig 1 Proposed Architecture

There are four primary parts to the system architecture: collecting data, preparing data, training and predicting models, and the user interface. To start, data on air pollution is gathered from reliable government sources. This data includes things like PM2.5, NOx, SO_2, temperature, and humidity. This data goes through preparation, which involves cleaning it, dealing with missing values by utilising mean imputation, and normalising the dataset. After cleaning, the data is used to train machine learning models, especially Linear Regression and Stepwise Multiple Linear Regression, to guess what the future air quality index (AQI) values will be. Finally, a simple Android app shows users the projected findings, including real-time AQI values and hourly pollution projections, so that people may be aware of and take action on them.

c) Modules:

1. User Interaction

This module gives end users important features including registration, logging in, and managing their profiles. Users may enter certain information about the weather and get forecasts about the kind and amount of air pollution. This is the system's entry point, which makes sure that users can easily utilise the prediction interface and keep their accounts safe.

2. Service Provider Functionality

The service provider module takes care of the system's analytical backbone and administrative operations. Once they have logged in, service providers may upload and train datasets for air pollution analysis, keep an eye on the results of training and testing, and get to the expected output data. They can also figure out and compare prediction ratios and download training datasets to use later. This module also lets the provider see information about all remote users who are using the system, which helps in keeping the system running smoothly and updating the model.

3. Web Server

The web server is the main processor of the system. It is in charge of handling and sending all requests and data between users, service providers, and the database. It takes care of session restrictions, handles prediction requests, and makes sure that data is safely saved or retrieved from the online database. The server's main job is to make sure that information flows smoothly across the system.

4. Web Database

The web database is where the whole program stores and retrieves data. It has datasets, user profiles, outputs from trained models, and outcomes from predictions. It makes sure that you can obtain the data you need in real time by making it easier for the web server to run queries. This module is very important for keeping the data needed for prediction, reporting, and historical analysis safe and accessible.

e) Algorithms:

1. Linear Regression

- Used to predict the Air Quality Index (AQI) based on multiple environmental input features like PM2.5, NOx, temperature, and humidity.
- It identifies the linear relationship between input features and the output (AQI) to make accurate predictions.

2. Stepwise Multiple Linear Regression

- An extension of linear regression that selects the most relevant input features step-by-step by adding or removing variables based on statistical significance.
- Helps in improving model accuracy by eliminating less significant or redundant features.

3. Mean Imputation (for Preprocessing)

- A simple statistical technique used to handle missing values in the dataset.
- It replaces missing values with the mean of the respective feature to maintain data consistency.

4. EXPERIMENTAL RESULTS

The experimental findings show that the machine learning models that were used were able to properly estimate levels of air pollution. We trained and evaluated the system with Linear Regression and Stepwise Multiple Linear Regression algorithms using historical data from trustworthy sources. The model's performance was measured using measures like Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). These indicated low error rates, which means the predictions were quite accurate. The Android interface showed both current and predicted AQI levels, giving consumers real-time information. These results show that the model may be trusted to work in real-life situations when air quality has to be checked.

Accuracy: How well a test can differentiate between healthy and sick individuals is a good indicator of its reliability. Compare the number of true positives and negatives to get the reliability of the test. Following mathematical:

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: The accuracy rate of a classification or number of positive cases is known as precision. The formula is used to calculate precision:

Precision = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Recall: The ability of a model to identify all pertinent instances of a class is assessed by machine learning recall. The completeness of a model in capturing instances of a class is demonstrated by comparing the total number of positive observations with the number of precisely predicted ones.

$$Recall = \frac{TP}{(FN + TP)}$$

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic.

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

mAP: Assessing the level of quality Precision on Average (MAP). The position on the list and the number of pertinent recommendations are taken into account. The Mean Absolute Precision (MAP) at K is the sum of all users' or enquiries' Average Precision (AP) at K.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{the AP of class } k$$

$$n = \text{the number of classes}$$

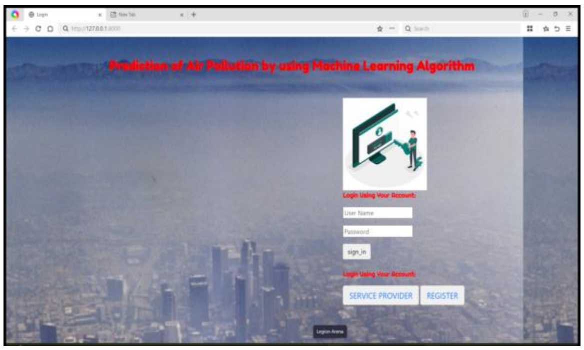

Fig 3 REMOTE USER

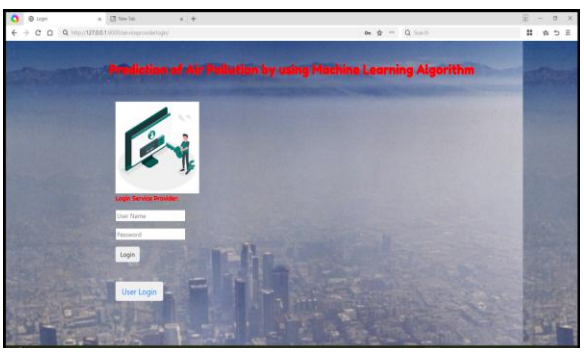

Fig 4. SERVICE PROVIDER

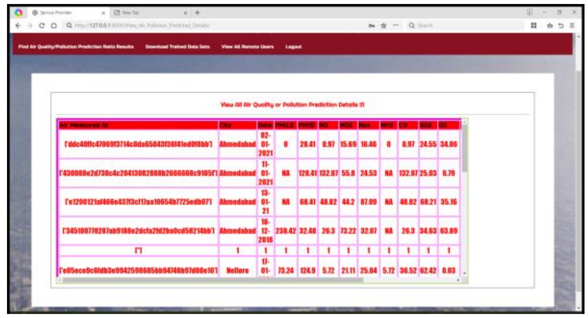

Fig 5 POLLUTION DETAILS

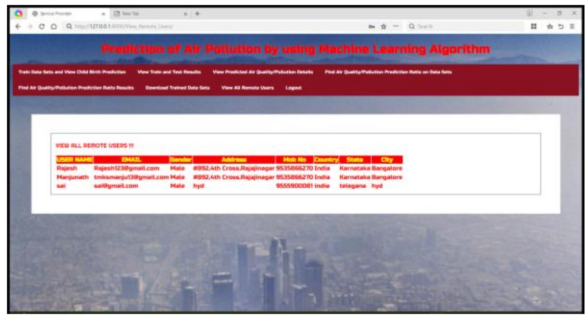

Fig 6 USER DETAILS

5. CONCLUSION

The suggested approach uses machine learning methods like Linear Regression and Stepwise Multiple Linear Regression to make accurate predictions about levels of air pollution. The technology helps increase awareness and promotes proactive steps for public health by analysing environmental data and accurately predicting AQI levels. Adding a user-friendly Android app makes it possible to get pollution data in real time, which makes the system useful and easy to use in cities every day.

6. FUTURE SCOPE

In the future, the system might be made better by adding more powerful machine learning models, such as Random Forest, XGBoost, or deep learning networks, to make predictions more accurate. You may use real-time data from IoT-based air quality monitors to keep an eye on things that change. The app may be expanded to include new locations and contaminants. It can also send pollution alarms, provide health recommendations, and show data in charts. Adding satellite data and weather forecasts can also make the predictions more complete and precise to a certain area.

REFERENCES

[1] X. Li, L. Jin, and H. Kan, ''Air pollution: A global problem needs local fixes,'' Nature, vol. 570, no. 7762, pp. 437–439, Jun. 2019.

[2] Y. Han, J. C. K. Lam, and V. O. K. Li, ''A Bayesian LSTM model to evaluate the effects of air pollution control regulations in China,'' in Proc. IEEE Big Data Workshop (Big Data), Dec. 2018, pp. 4465–4468.

[3] L. Bai, J. Wang, X. Ma, and H. Lu, ''Air pollution forecasts: An overview,'' Int. J. Environ. Res. Public Health, vol. 15, no. 4, p. 780, 2018.

[4] Y. Ding and Y. Xue, ''A deep learning approach to writer identification using inertial sensor data of air-handwriting,'' IEICE Trans. Inf. Syst., vol. E102-D, no. 10, pp. 2059–2063, 2019.

[5] S.-Q. Dotse, M. I. Petra, L. Dagar, and L. C. De Silva, ''Application of computational intelligence techniques to forecast daily PM10 exceedances in Brunei Darussalam,'' Atmos. Pollut. Res., vol. 9, no. 2, pp. 358–368, Mar. 2018.

[6] M. Jia, A. Komeily, Y. Wang, and R. S. Srinivasan, ''Adopting Internet of Things for the development of smart buildings: A review of enabling technologies and applications,'' Automat. Construct., vol. 101, pp. 111–126, May 2019.

[7] S. Abirami, P. Chitra, R. Madhumitha, and S. R. Kesavan, ''Hybrid spatio-temporal deep learning framework for particulate matter (PM2.5) concentration forecasting,'' in Proc. Int. Conf. Innov. Trends Inf. Technol. (ICITIIT), Feb. 2020, pp. 1–6.

[8] Y. Cheng, S. Zhang, C. Huan, M. O. Oladokun, and Z. Lin, ''Optimization on fresh outdoor air ratio of air conditioning system with stratum ventilation for both targeted indoor air quality and maximal energy saving,'' Building Environ., vol. 147, pp. 11–22, Jan. 2019.

[9] A. C. Cosma and R. Simha, ''Machine learning method for real-time non-invasive

prediction of individual thermal preference in transient conditions,'' Building Environ., vol. 148, pp. 372–383, Jan. 2019.

[10] M. Bhowmik, K. Deb, A. Debnath, and B. Saha, ''Mixed phase Fe2O3/Mn3O4 magnetic nanocomposite for enhanced adsorption of methyl orange dye: Neural network modeling and response surface methodology optimization,'' Appl. Organometallic Chem., vol. 32, no. 3, p. e4186, Mar. 2018.

[11] V. Chaudhary, A. Deshbhratar, V. Kumar, and D. Paul, ''Time series based LSTM model to predict air pollutant's concentration for prominent cities in India,'' in Proc. Int. Workshop Utility-Driven Mining (UDM), Aug. 2018, pp. 1–9.

[12] M. Chen, J. Yang, L. Hu, M. S. Hossain, and G. Muhammad, ‘‘Urban healthcare big data system based on crowdsourced and cloud-based air quality indicators,’’ IEEE Commun. Mag., vol. 56, no. 11, pp. 14–20, Nov. 2018.

[13] R. Chen, X. Wang, W. Zhang, X. Zhu, A. Li, and C. Yang, ‘‘A hybrid CNN-LSTM model for typhoon formation forecasting,’’ GeoInformatica, vol. 23, no. 3, pp. 375–396, Jul. 2019.

[14] S. Du, T. Li, Y. Yang, and S. Horng, ‘‘Deep air quality forecasting using hybrid deep learning framework,’’ IEEE Trans. Knowl. Data Eng., vol. 33, no. 6, pp. 2412–2424, Jun. 2021.

[15] R. Feng, H.-J. Zheng, H. Gao, A.-R. Zhang, C. Huang, J.-X. Zhang, K. Luo, and J.-R. Fan, ‘‘Recurrent neural network and random forest for analysis and accurate forecast of atmospheric pollutants: A case study in Hangzhou, China,’’ J. Cleaner Prod., vol. 231, pp. 1005–1015, Sep. 2019.

[16] B. S. Freeman, G. Taylor, B. Gharabaghi, and J. Thé, ‘‘Forecasting air quality time series using deep learning,’’ J. Air Waste Manage. Assoc., vol. 68, no. 8, pp. 866–886, Aug. 2018.

[17] S. Mahajan, H.-M. Liu, T.-C. Tsai, and L.-J. Chen, ‘‘Improving the accuracy and efficiency of PM2.5 forecast service using cluster-based hybrid neural network model,’’

IEEE Access, vol. 6, pp. 19193–19204, 2018.

[18] J. Jin, J. Gubbi, S. Marusic, and M. Palaniswami, ‘‘An information framework for creating a smart city through Internet of Things,’’ IEEE Internet Things J., vol. 1, no. 2, pp. 112–121, Apr. 2014.

[19] A. Grover, A. Kapoor, and E. Horvitz, ‘‘A deep hybrid model for weather forecasting,’’ in Proc. 21st ACM SIGKDD Int. Conf. Knowl. DiscoveryData Mining, Aug. 2015, p. 379–386.

[20] A. Agarwal and M. Sahu, ‘‘Forecasting PM2.5 concentrations using statistical modeling for Bengaluru and Delhi regions,’’ Environ. Monit. Assessment, vol. 195, p. 502, Mar. 2023.

[21] D. J. Lary, T. Lary, and B. Sattler, ‘‘Using machine learning to estimate global PM2.5 for environmental health studies,’’ Environ. Health Insights, vol. 9, no. 1, pp. 41–52, 2015.

[22] Y. Zheng, X. Yi, M. Li, R. Li, Z. Shan, E. Chang, and T. Li, ‘‘Forecasting fine-grained air quality based on big data,’’ in Proc. 21th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, New York, NY, USA, Aug. 2015, pp. 2267–2276.

[23] Y. Zheng, L. Capra, O. Wolfson, and H. Yang, ‘‘Urban computing: Concepts, methodologies, and applications,’’ ACM Trans. Intell. Syst. Technol., vol. 5, no. 3, p. 38, Sep. 2014.

[24] T. S. Rajput and N. Sharma, ‘‘Multivariate regression analysis of air quality index for Hyderabad city: Forecasting model with hourly frequency,’’ Int. J. Appl. Res., vol. 3, no. 8, pp. 443–447, 2017.

[25] Z. Kang and Z. Qu, ‘‘Application of BP neural network optimized by genetic simulated annealing algorithm to prediction of air quality index in Lanzhou,’’ in Proc. IEEE Comput. Intell. Appl. (ICCIA), Sep. 2017, pp. 155–160, doi: 10.1109/CIAPP.2017.8167199.

[26] B. Liu, S. Yan, J. Li, G. Qu, Y. Li, J. Lang, and R. Gu, ''A sequence-tosequence air quality predictor based on the n-step recurrent prediction,'' IEEE Access, vol. 7, pp. 43331–43345, 2019.

[27] K. Elbaz, I. Hoteit, W. M. Shaban, and S.-L. Shen, ''Spatiotemporal air quality forecasting and health risk assessment over smart city of NEOM,'' Chemosphere, vol. 313, Feb. 2022, Art. no. 137636.

[28] P. C. Campbell, Y. Tang, P. Lee, B. Baker, D. Tong, R. Saylor, A. Stein, J. Huang, H.-C. Huang, E. Strobach, J. McQueen, L. Pan, I. Stajner, J. Sims, J. Tirado-Delgado, Y. Jung, F. Yang, T. L. Spero, and R. C. Gilliam, ''Development and evaluation of an advanced national air quality forecasting capability using the NOAA Global Forecast System version 16,'' Geosci. Model Develop., vol. 15, no. 8, pp. 3281–3313, Apr. 2022.

[29] X.-B. Jin, Z.-Y. Wang, W.-T. Gong, J.-L. Kong, Y.-T. Bai, T.-L. Su, H.-J. Ma, and P. Chakrabarti, ''Variational Bayesian network with information interpretability filtering for air quality forecasting,'' Mathematics, vol. 11, no. 4, p. 837, Feb. 2023.

[30] J. Li, W. Shi, and D. Yang, ''Color difference classification of dyed fabrics via a kernel extreme learning machine based on an improved grasshopper optimization algorithm,'' Color Res. Appl., vol. 46, no. 2, pp. 388–401, Apr. 2021.

Authors profile:

Ms.K.Pavani working as Assistant professor in the department of MCA in SRK Institute of technology, Enikepadu, NTR District,Vijayawada. She has done M.tech and MCA from JNTUK and BCA from Andhra University . She has 9 years of teaching experience in SRK Institute of technology. Her area of interest includes Machine Learning with Python, DWDM.

Ms.M.Anitha Working as Assistant & Head of Department of MCA ,in SRK Institute of technology in Vijayawada. She done with B .tech, MCA ,M. Tech in Computer Science .She has 14 years of Teaching experience in SRK Institute of technology, Enikepadu, Vijayawada, NTR District. Her area of interest includes Machine Learning with Python and DBMS.

Ms.B.Maithili is an MCA Student in the department of Computer Application at SRK Institute of technology, Enikepadu, NTR District, Vijayawada. She has Completed Degree in B.Sc.(Computers) from Ch.s.d.st.Theresa's college,Eluru. Her area of interest are DBMS and Machine Learning with Python.