**Journal of Global Research in Electronics and Communication (JGREC)**
Volume 2 | Issue 7 | July 2026 | Pages 01–07
DOI: https://doi.org/xxxxxxxxxxxxx
e-ISSN: 2321-3175
REVIEW ARTICLE OPEN ACCESS Available online: https://jgrec.info/index.php/jgrec/index

# Deep Learning-Based Prediction of Air Pollutant Concentrations Across Seasonal and Environmental Conditions

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**Received:** 1 July 2026 | **Revised:** 5 July 2026 | **Accepted:** 25 July 2026

***Abstract*—Air pollution has become a major environmental concern because of its harmful effects on human health, ecosystems, and climate. Accurate prediction of pollutant concentrations is therefore essential for effective air-quality management and timely preventive action. This review examines air pollutant concentration prediction using conventional approaches and deep learning-based techniques. It discusses major pollutants, including $PM_{2.5}$, $PM_{10}$, $NO_2$, $SO_2$, CO, and $O_3$, together with their spatial and temporal variability and monitoring approaches. The study further explores multi-pollutant prediction, pollutant interactions, and the influence of seasonal and environmental factors such as temperature, humidity, wind speed, rainfall, atmospheric pressure, and solar radiation. Particular emphasis is placed on deep learning-based prediction across varying atmospheric and environmental conditions, including AQI prediction and global air-quality studies. The review also highlights the adverse effects of air pollution on respiratory, cardiovascular, neurological health and ecosystems. Finally, major challenges associated with pollution mitigation, rapid urbanization, technological limitations, infrastructure, public awareness, regulatory barriers, and climate change are discussed. Overall, the study provides a comprehensive perspective on air pollution prediction and supports the development of reliable forecasting strategies for sustainable environmental management and improved public health.**

***Keywords*—Deep Learning, Air Pollution, Pollutant Concentration Prediction, Air Quality Index, Healthcare.***

## I. INTRODUCTION

Air pollution is a major environmental concern that adversely affects human health, ecosystems, and overall environmental quality. Understanding and predicting air pollutant levels is essential for effective environmental management, public health protection, and the development of appropriate pollution-control measures. The Air Quality Index (AQI) is an important tool for representing the overall level of air pollution in a simple and understandable form by integrating the concentrations of major pollutants into a standardized index [1]. It helps assess air quality, communicate health risks to the public, support timely preventive actions, and guide authorities in developing effective air-quality management strategies. The World Health Organization (WHO) reports on six major air pollutants, namely particle pollution, ground-level ozone, carbon monoxide, sulfur oxides, nitrogen oxides, and lead. Air pollution can have a disastrous effect on all components of the environment, including groundwater, soil, and air. Additionally, it poses a serious threat to living organisms. In this vein, interest is mainly to focus on these pollutants, as they are related to more extensive and severe problems in human health and environmental impact. Acid rain, global warming, the greenhouse effect, and climate changes have an important ecological impact on air pollution [2]. Methods for predicting air pollutant concentrations can be broadly classified into numerical simulation models, statistical models, traditional machine-learning algorithms, and deep-learning approaches. Numerical simulation models are grounded in atmospheric dynamics and pollutant dispersion theory and represent the transport, diffusion, and deposition of pollutants through coupled physical and mathematical equations [3]. These models, however, depend heavily on high-accuracy emission inventories, are computationally demanding, and are difficult to calibrate dynamically [4]. Statistical models infer concentration dynamics from historical observations; common approaches include autoregressive integrated moving average (ARIMA) model, multiple linear regression (MLR) model, and geographically weighted regression model. Such methods have relatively low data requirements and are computationally efficient, making them well suited for short-term predictions.

The estimation that countries with similar geographical latitude and continental climates, may exhibit similar trends in seasonal variations in particulate concentrations and air quality; (b) the assessment of health risks associated with prolonged exposure to PM10 and PAH pollutants, considering the seasonal variability in their concentrations, which offers a new perspective on health risks related to different times of the year; (c) the analysis of the relationships and correlations

DOI: https://doi.org/xxxxxxxxxxxxx

between PM10 and PAH concentrations and other environmental and meteorological parameters, which enabled a deeper understanding of the interactions between these substances, as well as the identification of factors that may intensify or mitigate their impact on health [5]. Deep learning (DL) techniques have emerged as powerful tools for AQI forecasting. The power of automatic feature extraction and modeling of complex temporal and spatial dependencies are the key driving mechanisms behind these growths. Time-series data is particularly assayed as a measure of success in these models and the much-imported capture for long-term of gets of pollutant concentrations [6]. Successful hybrid models which are comprised of distinct deep learning designs or which integrate more traditional machine learning and statistical techniques have shown superior forecasting performance.

### A. Structure of the Paper

The structure of the paper: Section II introduces air pollutant concentration prediction, monitoring, and conventional methods. Section III discusses seasonal and environmental factors affecting prediction. Section IV presents deep learning-based pollutant prediction and AQI forecasting. Section V reviews recent studies and research gaps, while Section VI concludes the paper and outlines future research directions.

## II. Air Pollutant Concentration Prediction

Air pollutant concentration prediction estimates future levels of pollutants such as $PM_{2.5}$, $PM_{10}$, $NO_2$, $SO_2$, CO, and $O_3$ using historical observations, meteorological conditions, emission patterns, and environmental variables. Statistical, machine learning, and deep learning models can capture complex temporal and nonlinear relationships, supporting effective air-quality management and early-warning systems. Air pollutants are the root cause of air pollution. The things that create pollution are called pollutants. There are essentially two categories of air pollutants:

### A. Spatial and Temporal Variability of Urban Air Pollution

An important component of personal exposure assessment is a better understanding of spatial and temporal variability in pollutant concentrations [7]. The dynamics in emissions namely from road transport (e.g., activity patterns such as the morning rush hour leading to peaks in traffic-related pollution) are one of the factors leading to the significant variation of air pollutants concentrations in cities.

### B. Air Pollution Monitoring Equipment

Conventional air pollution monitoring systems are mainly based on sophisticated and well-established instruments. In order to guarantee data accuracy and quality, these instruments use complex measurement methods and a lot of assisting tools including temperature controller (cooler and heater), relative humidity controller, air filter (for PM), and build-in calibrator [8].

- **Ground-Based Monitoring Stations:** Ground-based monitoring stations employ standardized analyzers and sampling systems to record pollutant levels at fixed locations, enabling long-term observation of concentration patterns and local pollution episodes[9].
- **IoT-enabled low-cost sensors facilitate:** Decentralized air-quality surveillance through connected sensing devices, offering affordable, real-time observations across dense networks while facing challenges related to calibration, humidity interference, drift, and accuracy [10].
- **Satellite-based monitoring:** Employs remote-sensing observations to characterize pollutant distributions across large areas, revealing regional patterns, emission hotspots, and temporal changes where conventional ground monitoring networks remain limited.

### C. Conventional Air Pollution Prediction Methods

The numerical simulation and statistical approaches. Numerical models represent pollutant transport, dispersion, and chemical reactions through atmospheric equations, whereas statistical models analyze historical concentration patterns using regression and time-series techniques. However, their effectiveness is limited by nonlinear pollutant behavior, changing meteorological conditions, and complex environmental interactions.

#### 1) Particulate Matter (PM10 and PM2.5)

Particulate matter (PM) originates from primary emissions (e.g., soot from combustion sources (such as construction sites, unpaved roads, fields, and smokestacks), sea salt, and soil from wind-driven resuspension) and the formation of secondary particles in the atmospheree [11]. Particulate matter (PM) is a term used for physical and chemical substances that exist as discrete particles, either as liquid droplets or solids over a wide range of sizes Figure 1 illustrates the relative sizes of $PM_{2.5}$ and $PM_{10}$ particles compared with common airborne particles and materials, highlighting their small dimensions and potential to penetrate the respiratory system.

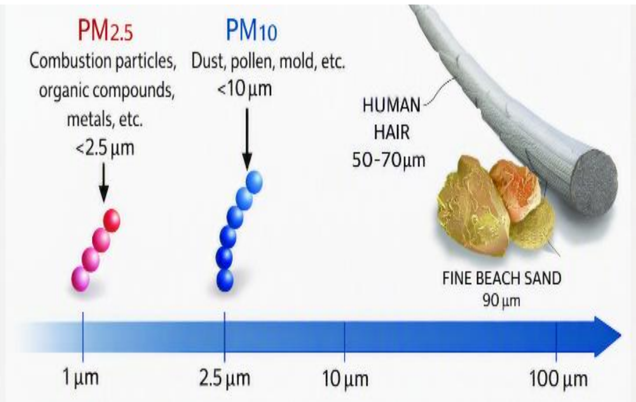


Fig. 1. Comparisons of Particulate Matter Size (PM)

#### 2) Ozone (O3)

Ozone (O3) is an important secondary pollutant that forms photochemically when organic compounds react with nitrogen oxides (NOx) [48]. For instance, this occurs when pollutants emitted by cars, refineries, chemical plants, power plants, industrial boilers, and other sources chemically react in the presence of sunlight. Hence, the presence of heat and sunlight is highly important for its formation, as shown in Figure 2 formation of ground-level ozone through the interaction of nitrogen oxides (NOx) and volatile organic compounds (VOCs) in the presence of heat and sunlight, primarily from vehicular and industrial emissions [12].

DOI: https://doi.org/xxxxxxxxxxxxx

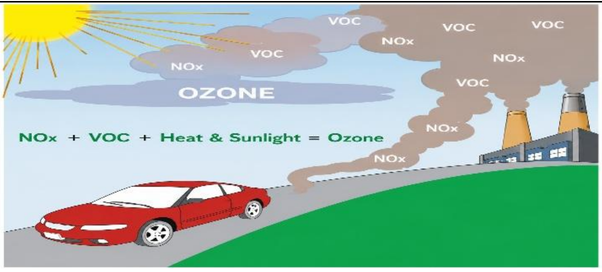

Fig. 2. Formation of Ozone

*3) Carbon Monoxide (CO)*

A colorless, odorless, and tasteless gas that is slightly lighter than air [49]. It is a by-product of combustion, present whenever fuel is burned in a limited supply of air (oxygen) [13]. CO is formed by the incomplete combustion of natural gas and any other material containing carbon, such as gasoline from vehicles, kerosene, oil, propane, coal, and wood, among others. The health risks associated with CO vary with its concentration and duration of exposure.

*4) Sulphur Dioxide (SO2)*

An acidic, colorless, and poisonous gas that may remain in the atmosphere for periods of up to several weeks [14]. It can be detected by taste and odour in a concentration that ranges between 0.38–1.15 ppm and above 3 ppm, with an irritating odour. It is estimated that 65 million tonnes of SO2 per year enter the atmosphere because of human activities, primarily from the combustion of fossil fuels. Other possible sources include fuel-based industry, vehicle emissions, smelting of mineral ores, and refinery.

*5) Nitrogen Dioxide (NO2)*

A suffocating, brownish gas, one of a family of highly reactive gases, the nitrogen oxides (NOx). They are formed when fuel is burned at high temperatures. Nitrogen dioxide is also an irritant to humans and corrosive to metals. Scientists in the United States have observed the adverse effects of photochemical contaminants on human health, especially in urban areas [15]. However, the US EPA only regulates NO2 because it is the most prevalent form of NOx in the atmosphere that is generated by anthropogenic activities.

### *D. Multi-Pollutant Concentration Prediction*

Multi-pollutant concentration prediction focuses on forecasting multiple air pollutants, including $PM_{2.5}$, $PM_{10}$, $NO_2$, $SO_2$, $O_3$, and CO, simultaneously. Deep learning models can capture complex temporal and nonlinear relationships among pollutants and meteorological variables. This approach provides comprehensive air quality information and improves the reliability of pollution assessment and forecasting across different environmental conditions.

*1) Evidence for the Relationship Between Air Pollution and Climate Change*

The scientific community knows the link between air pollution and climate change. Climate change was deemed “the single most significant threat to human health facing humanity” by the World Health Organization in 2021. Greenhouse gases are compounds that create the phenomenon known as the greenhouse effect, which entails an inability for the sun's heat to escape to outer space and remain trapped within the earth's atmosphere. Among these gases is carbon dioxide, this gas stems from human activities ranging from industrialization, fossil fuel burning, and mineral extractions [16].

*2) Multivariate Analysis*

The statistical methods used in this study were Pearson’s correlation coefficients, principal component analysis (PCA), and hierarchical cluster analysis (CA) [17]. The correlation coefficient is a statistic tool used to measure the extent of the relationship between variables, when compared in pairs. There are several types of correlation coefficients, Pearson’s correlation is commonly used in linear regression and has been used to measure the strength of relationships among the four air pollutants.

*3) Interaction Among Pollutants*

Air pollutants exhibit complex interactions influenced by common emission sources, atmospheric transport, and chemical transformation processes [18]. Primary pollutants such as $NO_2$, $SO_2$, and CO can interact with particulate matter and atmospheric oxidants, altering pollutant concentrations over time. Understanding these relationships is essential for identifying pollution patterns and improving comprehensive air quality assessment.

## III. Seasonal and Environmental Factors Affecting Air Pollution Prediction

Seasonal and environmental conditions strongly influence pollutant concentrations and prediction accuracy. Temperature, humidity, wind speed, rainfall, atmospheric pressure, and solar radiation affect pollutant dispersion, accumulation, and chemical transformation. Seasonal changes further modify emission patterns and atmospheric behavior, making air quality prediction challenging across different weather conditions and geographical environments.

### *A. Seasonal Variation in Air Pollutants*

The seasonal variations of PM10 and PM2.5 with other air pollutants (NO2, SO2, O3 and CO) respectively. Additionally, an analysis of variance was conducted to examine the differences in the AQI of different pollutants across different seasons. The assessment reveals significant variations for most pollutants [19]. The results suggest that various air pollutants are significantly affected by seasonal variations, emphasizing the significance of ongoing monitoring of air quality and policy development tailored to each season.

*1) Influence of Temperature on Concentration of Pollutants*

Temperature influences pollutant concentrations by affecting atmospheric stability, chemical reactions, and dispersion processes [20]. Higher temperatures can accelerate photochemical reactions and ozone formation, whereas temperature inversions suppress vertical air movement, causing pollutants to accumulate near the ground. Consequently, temperature variability contributes significantly to seasonal and regional differences in air pollution levels.

*2) Seasonal Dynamics in Urban Pollution*

Seasonal variation in pollutant concentrations arises from the interplay of emission source variability, atmospheric chemistry, and meteorological conditions. Winter-elevated PM and NO2 concentrations reflect increased residential and industrial heating demand combined with atmospheric temperature inversions that trap pollutants near the surface [21]. Summer ozone elevation reflects photochemical production driven by intensified solar radiation—a mechanism contrarian to most primary pollutant patterns.

J. Glob. Res. Elec. Comm., 2 (7):01-07
DOI: https://doi.org/xxxxxxxxxxxxx

### B. Environmental Factors Affecting Air Pollution Prediction

Environmental factors strongly influence air pollutant concentrations and prediction accuracy. Temperature, humidity, rainfall, wind speed, atmospheric pressure, and solar radiation regulate pollutant dispersion, accumulation, and chemical transformation. Urbanization, industrial activities, traffic density, and land-use patterns further modify emission levels, creating complex spatial and temporal variations in atmospheric pollution across regions.

#### 1) Correlations Observed Between Meteorological Factors and Air Pollutants.

Air quality is directly influenced by the interaction of meteorological factors that impact the dispersion transformation and removal of pollutants in the atmosphere.

- **Temperature:** A meteorological factor that influences the dispersion of air pollutants. Notably, it influences pollutants that are of great harm to the human population: Ozone(O3), Particulate Matter(PMx), and Nitrogen Dioxide(NO2) [22].
- **Humidity:** The amount of water vapor in the air. Low humidity decreases the stomatal uptake of air pollutants. Stomatal uptake is a process where the stomata of a plant take in CO2 and O3, effectively removing it from the environment [23].
- **Wind Speed:** The natural flow of air from zones of high to low atmospheric pressure, resulting from the rotation of the earth and the sun's uneven heating of the earth's surface. Wind has a major influence on meteorological conditions, influencing storm formation, temperature, and more.
- **Atmospheric Pressure:** The amount of pressure exerted by molecules of gas in the atmosphere on objects that are on Earth's surface. Atmospheric Pressure plays a key role in the dispersion of air pollutants [24].

## IV. Deep Learning-Based Prediction of Air Pollutant Concentrations Across

Deep learning enables accurate prediction of air pollutant concentrations by learning complex patterns from historical, meteorological, and environmental data. Its ability to capture nonlinear relationships supports forecasting across varying seasonal, spatial, and atmospheric conditions. Such approaches improve prediction reliability, facilitate multi-pollutant assessment, and support timely air quality management.

### A. Deep Learning for AQI Prediction

Deep learning for AQI prediction captures complex nonlinear relationships between pollutant concentrations and environmental conditions. By learning patterns from historical air-quality and meteorological data, these approaches provide accurate AQI estimation, pollution forecasting, early warnings, and improved decision-making for effective urban air-quality management.

#### 1) Global Air Quality Studies

The geographical distribution of published articles about air quality prediction in different countries with DL approaches the performance of state of the art models in DL for individual air pollutants the models used, the target pollutants, the geographical regions considered, the evaluation measures used and the main results reported in each work [25]. The D. Rajan covers many DL architectures from sequence-based model such as Long Short-Term Memory (LSTM) & Gated Recurrent Unit (GRU) to hybrid frameworks, CNN-LSTM. advanced architectures such as spatiotemporal architectures such as GCN-ConvLSTM.

### B. Impact of Air Pollution on Human Health

Air pollution can be harmful to the health of humans and living organisms. The impacts of air pollution are multifaceted and significant and have long been known to have a hostile impact [26]. The impacts can include respiratory diseases, cardiovascular issues, aggravation of existing health conditions, reduced air quality, damage to crops and ecosystems and climate change.

- **Respiratory problems:** Air with high concentrations of PM10 and PM2.5 can lead to respiratory issues such as asthma, bronchitis, reduced lung function and chronic obstructive pulmonary disease (COPD). The presence of NO2 in the air also causes respiratory disease.
- **Cardiovascular issues:** Long-term exposure to air pollution has been connected to heart disease and the risk of heart attacks
- **Cancer risk:** Air contaminants like formaldehyde (CH2O) and benzene (C6H6) are known carcinogens and long-time exposure to them can increase the risk of cancers.
- **Neurological effects:** Some studies reported the link between air pollution and neurological disorders. High levels of pollutants have been associated with cognitive decline and increased risk of conditions like Alzheimer's and Parkinson's disease. Ingested high concentrations of Pb can damage the brain.

### C. Challenges in the Mitigation of Air Pollution

Several challenges persist in addressing and mitigating air pollution worldwide [27]. Some of the key challenges include:

- **Complexity of sources:** The sources of air pollution are diverse. The coordination efforts to control toxic gases generated from the different sources are complex.
- **Urbanization and population growth:** Rapid urbanization and population growth lead to increased vehicular traffic, industrial activities, and energy consumption, resulting in higher emissions and exacerbating air pollution problems.
- **Lack of awareness and education:** Many people are not fully aware of the health impacts of air pollution or the measures that can be taken to reduce it. Awareness and education campaigns are necessary to engage and inform the public.
- **Technological and infrastructural challenges:** Upgrading infrastructure and implementing cleaner technologies require substantial investment and time. This transition often faces resistance due to cost implications and technological limitations.
- **Political and regulatory hurdles:** Implementing effective policies and regulations to control emissions often faces political and economic challenges. Balancing environmental concerns with economic interests can be a significant obstacle.

DOI: https://doi.org/xxxxxxxxxxxxx

- **Climate change and air quality:** Climate change and air quality are closely linked [28]. Some measures to reduce greenhouse gas emissions might inadvertently increase air pollution, necessitating a balanced approach to tackle both issues simultaneously.

## V. Literature Review

Recent research highlights the growing use of ML, DL, and IoT technologies for air quality prediction and environmental monitoring. Studies using Transformer, CNN-LSTM, LSTM, and GRU models demonstrate improved forecasting performance, while IoT frameworks enable real-time monitoring. However, limitations remain regarding model generalization, scalability, and long-term prediction accuracy.

S. Han, et al. (2026) proposed a deep learning-based air quality prediction model aimed at accurately forecasting key air quality indicators, PM2.5 and PM10. The study innovatively replaces the multi-head attention mechanism in the encoder of the Transformer model with a Patch-wise Attention mechanism, while also incorporating the SCI-Block module and the Feature Mixing MLP module to construct an efficient and precise prediction model. The encoder extracts time-series features through multiple layers of Patch-wise Attention, and the decoder utilizes the Transformer architecture to make accurate predictions of future air quality [29].

H. Zhen, et al. (2026) proposed a deep learning-based peanut yield prediction model called PeanutYieldNet, which integrates the advantages of convolutional neural networks and long short-term memory networks to automatically extract spatiotemporal features from multi-source environmental data. Experimental results show that PeanutYieldNet demonstrates excellent predictive performance under various environmental stress conditions, with an average prediction accuracy of 92.847%, root mean square error of 0.236t/ha, and R2 coefficient of 0.891, significantly outperforming traditional machine learning methods and single deep learning models [30].

A. Borah (2025) presents a deep learning based anomaly detection approach to identify anomalous concentrations of five different air pollutants: Carbon Monoxide (CO), Ozone (O3), Nitogen Oxide (NOX) and Particulate Matters (PM2.5, PM10) in a real-life environmental dataset. The collected data is multivariate in nature containing hourly generated information about several air pollutants and atmospheric parameters from a non-polluted city in India [31].

A. Chakraborty, et al. (2025) presents an IoT framework for air quality monitoring utilizing NodeMCU ESP8266 microcontroller, DHT11 humidity and temperature sensor, and MQ-135 gas sensor to capture real-time environmental parameters. The collected data is transferred to the Thing Speak cloud platform, allowing for continuous remote monitoring. To overcome the restrictions of a single-location deployment and allow for reliable future prediction, machine learning and deep learning models were trained using a publicly available Kaggle air quality dataset [32].

D. Rajan and V. Rohini (2024) offer insights into recent advances in algorithms using deep learning and machine learning for anticipating AQI and forecasting pollutant concentrations by combining current research in this topic. In order to inform policy decisions and measures aimed at reducing air pollution and its adverse effects on public health, trend analysis integration affords a more thorough comprehension of the dynamics of air quality [33].

F. Naz et al. (2023) comparative analysis of various deep learning-based single-step forecasting models such as long short-term memory (LSTM), gated recurrent unit (GRU), and a statistical model to predict five air pollutants namely Nitrogen Dioxide (NO2), Ozone (O3), Sulphur Dioxide (SO2), and Particulate Matter (PM2.5, and PM10). For empirical evaluation, used a publicly available dataset collected in Northern Ireland, using an air quality monitoring station situated in Belfast city centre. It measures the concentration of air pollutants [34].

G. Kunwar and R. Jha (2023) research on the application of deep learning architectures to the UCI machine learning-compiled Beijing PM2.5 dataset. It have suggested a CNN and LSTM model with deep learning capabilities. Root Mean Square Error (RMSE) as well as Mean Absolute Error (MAE) were used to assess the performance of these models (MAE). Experimental findings reveal that technique “CNN-LSTM” provides more precise predictions than the classic models stated and has superior predictive performance [35].

Existing studies mainly focus on individual pollutants such as $PM_{2.5}$ and $PM_{10}$, limiting comprehensive AQI forecasting. Transformer-based approaches demonstrate improved temporal feature extraction, while CNN-LSTM and recurrent models effectively capture spatial and temporal dependencies, but their performance may vary across datasets and geographical regions. IoT-based frameworks provide real-time monitoring capabilities, yet many systems remain restricted to single-location deployments and face challenges related to sensor reliability, scalability, and data quality. Anomaly detection approaches identify abnormal pollutant concentrations but do not directly provide reliable future AQI forecasts. Furthermore, comparative studies evaluate individual models without establishing a unified framework integrating meteorological variables, pollutant concentrations, temporal patterns, and real-time sensor data. Limited attention has also been given to explainability, cross-regional generalization, and robust long-term forecasting. Therefore, a comprehensive, scalable, and intelligent AQI prediction framework integrating heterogeneous environmental data, advanced deep learning, real-time monitoring, and explainable forecasting is required. The literature review summarized in Table I indicates substantial progress in machine learning, deep learning, and IoT-based air quality prediction; however, several research gaps remain.

TABLE I. Summary of Key Studies on Air Pollutant Concentrations Across Seasonal and Environmental Conditions Using DL

| Author & Year | Research Objective | Dataset / Input Parameters | Proposed Method / Model | Performance / Key Results | Limitations / Research Gap |
|---|---|---|---|---|---|
| S. Han et al. (2026) | To forecast $PM_{2.5}$ and $PM_{10}$ concentrations accurately. | Time-series air quality data including $PM_{2.5}$ and $PM_{10}$ | Transformer with Patch-wise Attention, SCI-Block, and Feature Mixing MLP | Efficient temporal feature extraction and accurate future air quality prediction. | Model complexity and dependence on quality time-series data may affect generalization. |

DOI: https://doi.org/xxxxxxxxxxxxx

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|---|---|---|---|---|---|
| H. Zhen et al. (2026) | To predict environmental-dependent peanut yield under different stress conditions. | Multi-source environmental data | PeanutYieldNet integrating CNN and LSTM | 92.847% average accuracy, RMSE = 0.236 t/ha, $R^2 = 0.891$. | Focuses on agricultural prediction rather than direct AQI forecasting. |
| A. Borah (2025) | To identify anomalous concentrations of major air pollutants. | Hourly multivariate environmental data; CO, $O_3$, $NO_x$, $PM_{2.5}$, $PM_{10}$ and atmospheric parameters | Deep learning-based anomaly detection | Effectively detected abnormal pollutant concentration patterns. | Primarily addresses anomaly detection rather than long-term AQI forecasting. |
| A. Chakraborty et al. (2025) | To develop a real-time air quality monitoring and prediction framework. | Temperature, humidity, gas concentration and public air quality data | IoT, NodeMCU ESP8266, DHT11, MQ-135, ThingSpeak, ML/DL | Enabled continuous remote monitoring and future air quality prediction. | Single-location sensing and sensor limitations may restrict scalability and generalization. |
| D. Rajan & V. Rohini (2024) | To analyze recent ML/DL approaches for AQI and pollutant forecasting. | AQI and pollutant concentration data | Machine learning, deep learning and trend analysis | Demonstrated the value of combining forecasting with trend analysis for air pollution management. | Review-based study; lacks a unified predictive framework. |
| F. Naz et al. (2023) | To compare single-step models for forecasting multiple air pollutants. | Belfast monitoring station; $NO_2$, $O_3$, $SO_2$, $PM_{2.5}$ and $PM_{10}$ | LSTM, GRU and statistical models | Provided comparative evaluation of deep learning and statistical forecasting models. | Single-step forecasting may not adequately capture complex long-term dependencies. |
| G. Kunwar & R. Jha (2023) | To improve $PM_{2.5}$ prediction using deep learning. | UCI Beijing $PM_{2.5}$ dataset | CNN-LSTM | CNN-LSTM achieved better prediction performance based on RMSE and MAE. | Dataset-specific evaluation may limit applicability to different geographical regions. |

## VI. Conclusion and Future Work

Air pollution prediction is essential for understanding changing environmental conditions and supporting effective air-quality management. This review examined the prediction of major pollutants, including $PM_{2.5}$, $PM_{10}$, $NO_2$, $SO_2$, CO, and $O_3$, considering their spatial and temporal variability. Conventional prediction approaches provide useful information but face limitations in representing nonlinear relationships and complex atmospheric interactions. Deep learning-based approaches offer greater potential for learning patterns from historical, meteorological, and environmental data, supporting pollutant concentration and AQI prediction across diverse conditions. Multi-pollutant prediction further provides a comprehensive representation of air-quality behavior. Seasonal variations, temperature, humidity, wind speed, rainfall, atmospheric pressure, and other environmental factors substantially influence pollutant concentrations and prediction reliability. Air pollution also presents serious risks to human health and ecosystems. Therefore, reliable monitoring, advanced prediction, public awareness, technological development, and effective regulatory strategies are required. Integrating deep learning with diverse air-quality observations can strengthen forecasting capabilities and contribute to timely warnings, informed environmental decisions, and sustainable air-quality management.

Future research should focus on improving deep learning-based air pollution prediction across diverse regions and environmental conditions. Integrating real-time sensor, satellite, meteorological, and emission data can enhance prediction reliability. Further studies should address data scarcity, changing pollution patterns, uncertainty, model generalization, and early-warning capabilities to support sustainable air-quality management.


- **Funding:** This research received no external funding.
- **Institutional Review Board Statement:** Not applicable.
- **Informed Consent Statement:** Not applicable.
- **Data Availability Statement:** The data supporting the findings of this study are available from the corresponding author upon reasonable request.
- **Conflicts of Interest:** The author declares no conflict of interest.


**How to cite this article:**

B. K. Sharma, “Deep Learning-Based Prediction of Air Pollutant Concentrations Across Seasonal and Environmental Conditions,” *Journal of Global Research in Electronics and Communication*, vol. 2, no. 7, pp. 01–07, Jul. 2026, Doi: xxxxx.

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