

A Survey of Air Quality Index (AQI) Prediction Models and their use in Making Predictions

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Abstract: The review explores the current state of Air Quality Index (AQI) prediction models and their applications, highlighting both traditional and modern approaches to forecasting air quality. The importance of AQI forecasting is underscored by its role in mitigating the impacts of air pollution on public health, urban planning, and environmental sustainability. The paper discusses various prediction models, ranging from traditional methods like statistical regression and time-series forecasting to more advanced data-driven techniques utilizing machine learning (ML) and deep learning (DL). Notably, machine learning models, including Random Forests, Support Vector Machines (SVM), and deep learning methods like Long Short-Term Memory (LSTM) networks, have shown significant improvements in prediction accuracy, particularly in capturing complex, non-linear relationships in air quality data. Hybrid models, which integrate traditional statistical techniques with advanced machine learning and deep learning algorithms, have gained prominence for their ability to improve predictive accuracy and handle the complexities of real-time air quality data. The review emphasizes the importance of high-quality, real-time data from air quality monitoring stations, weather models, and other environmental data sources for enhancing AQI forecasting. Additionally, it identifies key challenges in AQI prediction, including spatial and temporal variability, model overfitting, and the dynamic nature of pollution sources. Looking forward, the paper suggests that future advancements in AQI prediction will be driven by enhanced machine learning techniques, the integration of real-time data from IoT devices, and the development of more localized models that offer granular, hyperlocal predictions. Furthermore, the potential for integrating AQI prediction systems with public health applications, urban planning, and policy-making is explored, with an emphasis on improving public awareness and response to air quality risks. The review concludes by highlighting the growing sophistication of AQI prediction models and their potential in guiding effective environmental and public health strategies.

Keywords: Air Quality Index (AQI), Machine Learning (ML), Deep Learning (DL), Long Short-Term Memory (LSTM).

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I. INTRODUCTION

Importance of Air Quality

Environmental sustainability, economic growth, and public health are all significantly impacted by air quality. Chronic health issues and socioeconomic

consequences, including millions of early deaths and neurodevelopmental impairments, may result from exposure to air pollutants such PM_{2.5}, NO₂, SO₂, and ozone. Because pollutants like ozone and black carbon warm the atmosphere and harm ecosystems, poor air quality also makes climate change and biodiversity

loss worse [1]. Policy frameworks that acknowledge the need to mitigate both climate change and the decline of air quality have emerged as a result of the interaction between air pollution and climate change. Increased air pollution emissions are another problem for urban regions, especially in low- and middle-income nations. High-income nations have put policies into place that, via increased public awareness, tougher laws, and technological advancements, have resulted in significant reductions in pollution emissions [2].

Integrative strategies that put public health and environmental sustainability first are crucial for addressing the complex issues surrounding air quality. This calls for a multidisciplinary strategy that incorporates policy studies, urban planning, environmental science, and public health research [3]. Green infrastructure, low-emission technology, and air pollution monitoring networks are examples of emerging tactics and technologies that show promise for improving air quality in both developed and developing nations. By providing the public with information about local air pollution levels, real-time air quality monitoring may encourage community action and well-informed decision-making [4].

Need for AQI Prediction

Predicting the Air Quality Index (AQI) is essential for combating air pollution, reducing its negative impacts, and advancing environmental sustainability [5]. To completely address the health concerns linked with air pollution, real-time monitoring is not enough. Stakeholders can anticipate high-risk times and carry out early actions thanks to the great accuracy with which advanced forecasting technologies can estimate air quality levels. These tools also provide useful information on pollution patterns [6]. Long-term planning of urban infrastructure to lessen air pollution sources and enhance air quality generally is also made possible by predictive models. Personalized health advice is also supported by AQI prediction, which helps those with cardiovascular or respiratory illnesses stay away from dangerous air quality situations [7]. Additionally, it facilitates the customization of public health initiatives by focusing medical resources on regions where the quality of the air is rapidly declining. AQI prediction may be used as a direct tool to alert people to dangerous air quality conditions and promote exposure-reducing behavior

adjustments by combining predictive capabilities with mobile health apps [8].

The accuracy and dependability of AQI forecasts have been shown to increase using a multidisciplinary strategy that incorporates data from air quality monitoring stations, weather models, and machine learning algorithms. It has been discovered that deep learning methods, such neural networks, perform better in predicting air quality than conventional statistical models [9]. To model air quality data and forecast future trends, machine learning methods like support vector machines and random forests are also used. In addition to being a scientific breakthrough, the creation of precise and effective AQI prediction systems is also a public health need. By accurately forecasting air quality, people, groups, and governments may lower exposure to dangerous pollutants, safeguard vulnerable groups, and put sustainable environmental strategies into place [10].

II. AQI PREDICTION MODELS

Traditional Methods

Because of their ease of use, interpretability, and comparatively low processing needs, traditional approaches to Air Quality Index (AQI) prediction models—such as statistical regression, physical modelling, time-series forecasting, and empirical methods—remain applicable in a variety of contexts. These conventional methods are based on physical models, statistical techniques, and empirical correlations between meteorological variables and air pollution concentrations. Assuming that past trends in pollutant behavior may be used to forecast future air quality levels, statistical regression models, such multiple linear regression (MLR), create correlations between pollutant levels and meteorological factors. Nevertheless, these models often fall short in capturing the intricate relationships and non-linearities among the many factors affecting air quality [11]. To overcome some of these drawbacks, more sophisticated types of regression have been created, including polynomial regression and generalized additive models (GAMs). The mechanisms controlling the dynamics of air pollution are simulated using physical and chemical models, such as the Gaussian dispersion model. These models are very helpful in forecasting the quality of the air close to particular sources of pollutants, but they have trouble forecasting the quality of the air in intricate

urban settings or areas with many, scattered sources of pollution [12]. For AQI prediction, time-series models such as autoregressive integrated moving average (ARIMA) models are also often used, particularly where predicting short-term pollutant concentrations from previous data is the main objective.

In the conventional paradigm for AQI prediction, artificial neural networks, or ANNs, have also been used. In order to estimate pollutant levels based on input factors including historical concentrations, meteorological data, and time of day, early ANN implementations in air quality forecasting usually used simpler, backpropagation neural networks. Without the complex deep learning architectures used in contemporary prediction models, ANNs may still be regarded as a classical method [13]. Another significant conventional technique for AQI prediction is empirical forecasting, which is based on observational data and recognized air quality metrics. These models perform better in regions with relatively stable pollutant types and sources, while they perform worse in regions with high pollution variability or quickly changing environments [14].

In summary, our knowledge of the dynamics of air quality has been greatly influenced by conventional techniques for AQI prediction, such as statistical regression, physical modelling, time-series forecasting, and empirical approaches. In order to increase accuracy, adaptability, and resilience in a variety of environmental scenarios, future developments in AQI prediction are probably going to need combining conventional and current methods, using their respective advantages [15].

Data-Driven Approaches

Because data-driven methods to Air Quality Index (AQI) prediction models can manage complicated, large-scale data and provide very accurate predictions of air quality conditions, they have attracted a lot of interest. These approaches have shown significant promise in enhancing the precision, scalability, and adaptability of AQI predictions, especially those that use machine learning (ML) and deep learning (DL) techniques. Supervised machine learning, which involves training models on past air quality data to forecast future pollutant concentrations or AQI levels, is one of the most popular data-driven methods for AQI prediction [16]. Well-known machine learning techniques, including random forests, support vector

machines (SVM), and decision trees, have been successfully used to forecast air quality. Because SVM models can handle high-dimensional data and non-linear connections, they have gained popularity as AQI prediction models. In data-driven AQI prediction, artificial neural networks (ANNs), particularly their more sophisticated variations like deep neural networks (DNNs), have emerged as essential instruments. Complex, non-linear interactions between input variables, like weather, time of day, and pollution levels, may be modelled using DNNs [17]. Because they may reduce mistakes and increase prediction resilience, ensemble learning approaches like AdaBoost and Gradient Boosting Machines (GBM) are often utilized in air quality forecasting. By combining predictions from several separate models, ensemble models lower the chance of overfitting and improve the model's capacity for generalization [18].

Principal component analysis (PCA) and k-means clustering are two examples of unsupervised learning approaches that have been used to cluster air quality data and find patterns without the use of predetermined labels. With convolutional neural networks (CNNs) and recurrent neural networks (RNNs), especially Long Short-Term Memory (LSTM) networks, being used more and more in air quality forecasting, the emergence of deep learning has further transformed the area of AQI prediction [19]. Combining many machine learning methods, hybrid models have become a potent method for AQI prediction. Hybrid models may leverage the advantages of each approach by combining models such as ANN and SVM with statistical or ensemble methodologies, producing predictions that are more reliable and accurate. To sum up, data-driven methods for AQI prediction provide notable gains in terms of flexibility, scalability, and prediction accuracy. These models provide insights that go much beyond the scope of conventional techniques by learning from vast amounts of historical and real-time data, allowing for more precise and useful air quality predictions [19].

Machine Learning Models

Because machine learning algorithms can evaluate vast amounts of environmental data, find intricate correlations, and forecast air quality with high accuracy, they are crucial for current Air Quality Index (AQI) prediction. Although Decision Trees and

Random Forests are popular models, they may overfit when used to data that is noisy or extremely variable. Another useful strategy is Support Vector Machines (SVM), especially in high-dimensional and non-linear situations. Because of their ability to represent intricate, non-linear interactions, artificial neural networks, or ANNs, are often used in AQI prediction [20].

Specialized recurrent neural networks (RNNs) called Long Short-Term Memory (LSTM) networks are perfect for time-series forecasting in dynamic urban settings because they can identify long-term dependencies in sequential data. By concentrating on data points that are more difficult to predict, gradient boosting machines (GBM), an ensemble learning technology, gradually develop many weak learners and increase prediction accuracy [21]. A simple but powerful machine learning approach for classification and regression problems is K-Nearest Neighbours (KNN). Hybrid models are very helpful in predicting AQI under different environmental circumstances because they incorporate several machine learning approaches to increase AQI prediction accuracy. These models capture both linear and non-linear correlations in the data [22].

Deep Learning Models

Because deep learning models can learn intricate patterns from large-scale, high-dimensional datasets, they have emerged as the gold standard for forecasting the Air Quality Index (AQI). These models include deep neural networks (DNNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs). Non-linear correlations between environmental elements, including pollution concentrations, meteorological variables, and geographical features, are especially well-captured by DNNs. CNNs evaluate regionally dispersed air quality measurements to detect localized air quality anomalies or high pollution levels, which makes them effective for AQI prediction, especially when spatial data is included [23]. Because of their exceptional ability to handle sequential data, recurrent neural networks (RNNs) are especially well-suited for time-series forecasting problems. Because of its capacity to manage the temporal structure of air quality data and retain long-term relationships, linear support vector machines, or LSTMs, have become more prominent in the field of AQI prediction. Because they use fewer parameters and solve the vanishing gradient issue with

conventional RNNs, Gated Recurrent Units (GRUs) are a more straightforward and effective option for AQI prediction than Linear Support Vector Machines (LSTMs) [24].

For AQI prediction, hybrid deep learning models—which blend several neural network types or integrate deep learning with conventional statistical methods—have gained popularity because they use the benefits of many models to achieve improved accuracy and resilience. For AQI forecasting, autoencoders—an unsupervised deep learning model—have also been used. Deep learning models will continue to be essential in enhancing AQI prediction, facilitating improved air quality management, and facilitating prompt health interventions as more data from real-time monitoring networks and sensor systems becomes accessible [25].

Hybrid Models

A potent strategy to improve the efficiency and precision of air quality forecasting is the use of hybrid models for Air Quality Index (AQI) prediction. These models integrate classic statistical models with contemporary artificial intelligence approaches, or they combine the advantages of many algorithms or frameworks, such as deep learning and machine learning. Hybrid methods may identify both simple and intricate patterns in air quality data by using the complementing qualities of many models, producing forecasts that are more accurate and dependable. Combining machine learning methods (like support vector machines (SVM) or random forests) with deep learning techniques (like deep neural networks and LSTMs) is one popular strategy. Combining Convolutional Neural Networks (CNNs) with Recurrent Neural Networks (RNNs), especially Long Short-Term Memory (LSTM) networks, is another well-known hybrid model. Large cities with intricate pollution dynamics benefit greatly from these models [26].

In order to manage huge, complicated datasets, hybrid statistical and machine learning models—which combine statistical approaches with machine learning or deep learning techniques—are being employed more and more in AQI prediction. Another well-liked hybrid strategy is genetic algorithms (GAs), which optimize machine learning model parameters for increased precision and generalizability. To provide more precise forecasts, data fusion models integrate

data from several sources, including satellite images, meteorological data, and air quality sensors. Hybrid models will probably be essential to enhancing air quality forecasting and reducing the negative effects of air pollution on the environment and human health as AQI forecasting systems develop [27].

III. FEATURE SELECTION AND DATA PROCESSING

To create a precise model for forecasting the Air Quality Index (AQI), feature selection and data processing are essential steps. Weather, satellite data, air quality monitoring stations, and other environmental factors are the main sources used to estimate the AQI. The AQI values, which are determined using a variety of pollutants such PM_{2.5}, PM₁₀, NO₂, SO₂, O₃, and CO, are the goal variable. Managing missing data, identifying outliers, and converting data types are all part of data cleaning. To enhance model performance, feature engineering entails developing new features or altering preexisting ones. Rolling averages, delayed features, temporal features, and interaction features are a few examples [7].

Reducing redundant or unnecessary features is the goal of feature selection in order to enhance model performance and minimize overfitting. Finding the most significant features may be aided by methods such as Principal Component Analysis, recursive feature removal, univariate feature selection, correlation analysis, and feature significance rankings [11]. Machine learning models, particularly those that use distance metrics like k-NN, SVM, or gradient-based models, need data scaling and normalization. For features that include outliers, standardization, min-max scaling, and robust scaling are used. Log transformation and categorical encoding are two data transformation methods that may assist normalize data and enhance model performance. Train-test split is the process of dividing a dataset into subsets for testing and training, usually in an 80/20 or 70/30 ratio. Cross-validation, like K-fold cross-validation, helps prevent overfitting and assess model performance further [17].

IV. EVALUATION METRICS FOR AQI PREDICTION MODELS

When evaluating Air Quality Index (AQI) prediction models, it is important to select appropriate evaluation metrics that reflect the model's

performance, particularly for regression tasks, since predicting AQI is typically a continuous value. Here are some commonly used evaluation metrics for AQI prediction models:

Mean Absolute Error (MAE)

MAE calculates the average of the absolute differences between the predicted and actual AQI values. It gives an idea of how far off the predictions are from the actual values on average.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

Where:

y_i = Actual AQI value

\hat{y}_i = Predicted AQI value

n = Number of predictions

MAE gives the error in the same units as AQI, which is easier to interpret. However, it does not take into account large errors as much as other metrics like MSE.

Mean Squared Error (MSE)

MSE computes the average of the squared differences between the predicted and actual values. This metric penalizes large errors more than MAE.

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

MSE is sensitive to outliers since larger errors are squared, meaning a single large error can disproportionately affect the MSE. While this could be a disadvantage, it can also help highlight cases where the model is making extreme errors.

Root Mean Squared Error (RMSE)

RMSE is simply the square root of MSE. It is commonly used when the model's errors are normally distributed, and it's more interpretable since it returns the error in the same units as the target variable (AQI).

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

RMSE is sensitive to large errors and is useful when large deviations are particularly undesirable. It can be more informative than MAE when the cost of large errors is high.

V. APPLICATIONS OF AQI PREDICTION MODELS

For the purpose of assessing air pollution levels and supporting decision-making in the areas of public health, environmental protection, urban planning, energy management, agriculture, mobility, and transportation, predictive models for the Air Quality Index (AQI) are essential. Public health management uses AQI data to assess health risks, develop early warning systems, and improve urban design. Agricultural companies may use it to evaluate pollution levels and put crop protection measures in place. By using AQI prediction algorithms to estimate pollution levels based on traffic patterns, traffic management enables cities to restrict certain vehicles during periods of high pollution. In regions where high pollution events occur often, the implementation of electric cars is driven by AQI prediction. Through smartphone apps, consumer applications—like wearable technology—offer personalized health information and real-time air quality forecasts.

The management of indoor air quality, tourism, the energy and power sector, disaster relief, research, and education all make use of AQI prediction models. They notify travelers of air quality conditions, assist homeowners in planning outside activities, and predict days with poor air quality. Additionally, they facilitate the integration of renewable energy sources, improve disaster management and emergency response, and help environmental researchers comprehend how pollutants interact with weather patterns. Governments and non-governmental organizations may use these models to promote pollution reduction programs and run public awareness campaigns about the health risks linked to poor air quality.

VI. CHALLENGES IN AQI PREDICTION

Because of its intricacy, environmental factors, and data limitations, the Air Quality Index (AQI) is an

essential instrument for measuring air pollution levels. Missing data, sparse sensor networks, unreliable data formats, and real-time data availability are some of its problems, however. Modelling the impacts of air pollution is challenging due to its complexity, which includes pollutants and their interactions. Human activity, land use changes, urbanization, microclimates, seasonal impacts, weather unpredictability, and industrial pollution are some of the factors that affect the prediction of the AQI.

The main problems with AQI prediction models are overfitting and model complexity, which lead to poor predictions over extended time horizons. Pollutant dispersal is also influenced by geography and geographical variety, which makes precise prediction challenging. Models perform best in short-term forecasting, but their accuracy decreases with longer time horizons. Socioeconomic and policy factors also influence AQI, and by comprehending how various factors impact air pollution and enacting reasonable restrictions, these factors may be remedied. However, it is challenging to predict these changes due to human behavior and timely implementation. Rapid changes in air quality might make real-world validation impractical, and differences between expected and actual results can be caused by variations in the accuracy of measurement devices or monitoring stations. People's resistance to altering their behavior may make it challenging for the public to understand and perceive AQI projections.

VII. FUTURE DIRECTIONS

It is anticipated that developments in data science, environmental science, and technology will lead to major improvements in the prediction of the Air Quality Index (AQI) in the future. These advancements will increase the precision, timeliness, and applicability of AQI predictions, strengthening their impact on public health, environmental management, and policy-making. It will be essential to include cutting-edge machine learning and artificial intelligence techniques including deep learning models, ensemble models, and transfer learning procedures. More precise and dense air quality monitoring networks will be made possible by IoT-enabled devices and big data, which will provide hyper-local, real-time data. Instantaneous AQI forecasting, microclimate modelling, personalized air quality alerts, and hyperlocal air quality prediction will all be made possible by real-time predictive

technology. Accurate fine-scale air quality predictions and more targeted actions will be made possible by urban microclimates and granular spatial resolution.

When there are high-impact, low-frequency events that cause sudden rises in the AQI, event-driven forecasting will be essential. Using policy impact modelling, policymakers will be able to predict the long-term benefits of legislation and develop effective ones. The relationship between AQI and public health data will inform health recommendations. In order to evaluate future changes in air quality and facilitate mitigation efforts, long-term AQI forecasting will take climate change projections into account. Better data interchange and collaboration will result from increased collaboration between governments, academic institutions, and the private sector.

VIII. CONCLUSION

An analysis of prediction models for the air quality index (AQI) offers important new information on the level of air quality forecasting today. It draws attention to the variety of models and methodologies, the significance of data integration and quality, and the difficulties in making predictions in terms of time and space. The availability of high-quality data from monitoring stations, weather predictions, traffic data, and other sources is crucial for accurate AQI prediction. For AQI predictions to be more accurate, data fusion and multi-source integration are essential. Since air quality varies greatly over time, substantial temporal variability is necessary for precise short-term predictions. To provide accurate short-term predictions, seasonal variations, daily traffic patterns, and weather fluctuations must be precisely modelled. Long-term projections, such as seasonal or yearly AQI forecasts, are still difficult to make, however, because of the impact of erratic occurrences like traffic jams or wildfires.

Because air pollution sources and dispersion patterns vary widely, spatial variability is a problem. High-density sensor networks in conjunction with more localized models are becoming crucial instruments for enhancing the spatial accuracy of AQI forecasts. Public health requires real-time and predictive skills, especially for vulnerable populations. Numerous models now in use are capable of short-term AQI prediction, providing useful hourly or daily predictions. Effective AQI prediction models, which may act as early warning systems for pollution events

and enable authorities and the public to take preventative action, depend on predictive capacity. For evaluating the effectiveness of AQI prediction models, evaluation measures including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R2 are crucial. By offering practical insights for environmental management, AQI prediction models may help legislators create rules that effectively enhance air quality. By knowing which regions and demographic groups are at danger, they may also help with the design of public health initiatives. Real-time data integration, AI-powered systems, and integration with climate change models are some future approaches. By automating AQI forecasting, model calibration, and real-time warning creation, these developments may improve the effectiveness and accessibility of forecasts. The study concludes by highlighting the growing sophistication of AQI prediction models and the potential for boosting prediction accuracy via the use of machine learning and data fusion methods.

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