Performance Comparison of Machine Learning Techniques for Air Quality Index Prediction

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Abstract: *The AQI is essentially an important indicator that measures air and the potential effect that is can have on human health. The present work focuses on the AQI prediction using different machine learning approaches, supervised, unsupervised, and ensemble, for better accuracy and reliability of AQI forecast. The study focusses on implementing machine learning models like Support Vector Regression (SVR), Random Forest Regression (RFR), Cat Boost Regression (CR), and deep learning techniques like CNNs and RNNs. The SMOTE technique is used in this study to take care of imbalanced datasets, thus improving the prediction results. Some important discoveries from the study reveal that Random Forest Regression performs well for most cities across India, whereas Cat Boost Regression performs better for certain regions like New Delhi and Bangalore. Using SMOTE enhanced AQI forecasting accuracy markedly. The research points out the criticality of choosing the right machine learning model. It also suggests that hybrid and ensemble models showed promising results in the direction of improving AQI prediction.*
Keywords: *Air Quality Index (AQI), Machine Learning, Prediction, SMOTE, Random Forest Regression, Cat Boost Regression, Deep Learning, Ensemble Methods.*

I. INTRODUCTION

An index AQI standing Air Quality Index AQI is a listing used in contrast to evaluate and convey how good or unfavorable the air is in a given locality by taking into consideration some major pollutants, these include particulate matter (PM) 2.5, nitrogen dioxide (NO2), sulfur dioxide (SO2) ozone O3 and carbon monoxide (CO). It is traditionally looked upon as a health and environmental index because it defines the air condition in the community in terms of economic or health outcomes. An accurate prediction of the AQI is essential for the proper decision making and the implementation of policies [1]. Reasons such as these have made the issue of predicting AQI very topical in our time. In recent days' machine learning techniques are being widely employed on datasets for more accurate AQI predictions. These methods being adaptive and capable of constructing non-linear models and exploring data in multiple dimensions, provide a promising response to the issue of enhancement of model results. It is one of the primary aims of prediction incented environmental health models [2].

A. Common Air Pollutants and Their Impact on AQI

Particulate Matter (PM2.5 and PM10): Tiny particles form particulate matter in the air and can be breathed in. Particles less than 2.5 micrometers in size are called PM2.5, while particulate matter with the diameter below 10 micrometers is referred to as PM10. PM 2.5 can go deep into one's lungs and cause a lot of complications including breathing problems, heart disease and in some cases death. When inhaled, PM10 can cause sore throat and coughs mainly in people at risk [3].
Ozone (O3): Ground-level ozone is produced when sunlight reacts with hazardous chemicals emissions into the atmosphere such as nitrogen oxides and volatile organic compounds. This leads to health problems like shortness of breath or even deterioration of asthma among affected persons including persons in younger age brackets and the aged [4].
Nitrogen Dioxide (NO2): NO2 is mostly released in the atmosphere from the activities such as vehicles and industries. The continued breathing of NO2 for long periods by the individuals can irritate the lung, and also worsen asthma and aid in fog accumulation [5].
Sulfur Dioxide (SO2): Sulfur dioxide is predominantly discharged due to the burning of fossil fuels among other man-made activities. This chemical can result in breathing problems and aggravating situation such as dismissing bronchitis and asthma [6].
Carbon Monoxide (CO): CO is a colorless, odorless gas release from the burning of organic compounds. Carbon monoxide can cause poisoning at high doses and the signs can be as mild as headaches or as severe as death from inhaling it can in confined areas. There could be effects on persons over a long-term which include hypo tension and other heart diseases as well as other complications [7].
AQI is a method of comparing pollution levels within the air, and it is usually expressed as a numerical value derived from the specific concentration of several major air pollutants measured over a 24-hour period either using air sampling equipment/ air monitoring stations. The concentration of each pollutant is compared with the corresponding levels defined as quantile (breakpoint or threshold values) at which the air quality degrades from one AQI category to another as good, satisfactory, or under threatening level [8]. For each pollutant, the quantified amount of the pollutant is then transformed

into a sub-index using a specified formulae and the qualitative sub-index with the highest value among all such sub-index values in onto the scale is selected as the AQI for that area. With the majority of AQI reporting, ground-based sensors are the main source of data; although some additional help can be gotten from global satellite information. How often are these readings updated, and how are they accessible in the hands of the people? Many types of ground stations that are ground based depending on the observation themselves that measure and report air quality are usually equipped with the relevant equipment that can provide AQI information. Previously, optics furnished information only by passive observations of emissions, without direct measurements of air pollution or meteorological conditions [9].

II. Machine Learning in Air Quality Prediction

Machine learning acts in environmental surveillance, boosting accuracy and precision in forecasting by sifting through multiple datasets, including satellite imagery, weather signals, and past pollution data. Linear methods cannot handle complex environmental data; hence one uses machine learning techniques. The supervised methods range from linear regression, decision trees, and support vector machines. Neural networks-I would say RNNs and CNNs-are great at discerning patterns in time-series data and thus suit AQI prediction quite well. Random Forests and Gradient Boosting, on the other hand, are ensemble methods that take multiple views on a problem to achieve a better prediction. These are important in coordinating urban development, policymaking, and air quality interventions on the ground in real-time.

A. Role of Machine Learning in Environmental Monitoring

Machine learning has a significant impact in environmental monitoring through mechanizing the analysis of information and improving the accuracy of predictions, aside from enabling real-time feedback. Current approaches to air quality forecasting are usually based on simple linear models with limited historical data use [10]. However, all these models need environmental data that is too broad and varied, such as satellite imagery, and even weather patterns, and distribution of resources through sensor networks, as well as contamination data of the past. Such methods allow the computing of very flexible, dynamic models that change depending on the data at hand and the statistical relationships in the input data. This greatly improves the possibility of having real-time air pollution detection, as well as the ability to forecast such conditions [11].

Machine learning is a powerful tool that offers countless potential applications in all areas. From predicting the pollution levels in the air, to successful anomaly detection and prediction of public risks; up to supporting policy making and urban planning more efficiently especially for the environment by providing valuable insights [12]. Machine and other technologies can be put together in monitoring systems, thereby enhancing the ability to manage air quality and organizations failure of which will result in changes in air quality in reasonable time and compliment urbanization and the protect the environment movement [13].

B. Types of Machine Learning Techniques Used in AQI Prediction

The prediction of Air Quality Index (AQI) using various machine learning methods such as supervised learning, has difference advantages in terms of accuracy, efficiency, scale and the ability to learn complex environmental data challenges. One of the examples of a very useful technique is a supervised machine learning that employs a complete dataset, often termed models built on linear regression, decision trees and kernel methods, like support vector machines (SVM). These models use labelled historical data for training and this makes them efficient for cases when there is a structured internal dataset of the precise air quality measurements of the past and the respective AQI [14]. For instance, linear regression can forecast AQI using concentrations of pollutants, decision trees divide air quality into classes by taking into account various characteristics such as the types of pollutants, the climatic conditions and the physical features of a region. Moreover, Support vector machines which consume data into different predetermined AQI bounds even for more complicated and more non-linear data types. Advanced interpretation and automatic generation of results are aspects that favor supervised learning despite the error of overcoming the difficulty of the trained structure having practical strategies for decision making [15].

However, as the complexity of the data increases, more advanced techniques such as neural networks and deep learning algorithms come into play. These models have shown remarkable promise in AQI prediction because they excel at handling large, multi-dimensional datasets, which are common in environmental monitoring. Unlike traditional models, deep learning algorithms, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), can automatically learn features from the raw data, making them highly effective in extracting intricate patterns from complex datasets [16]. RNNs, especially those utilizing Long Short-Term Memory (LSTM) networks, are particularly adept at modeling time-series data, which is essential for forecasting AQI trends based on historical pollution data and temporal patterns. These models can capture the sequential dependencies in air quality data over time, making them ideal for predicting future AQI values and identifying long-term trends [17].

As an alternative, ensemble learning-based models such as Random Forests or Gradient Boosting are becoming popular with AQI predictions due to the fact that several models can be combined together to offer more accurate predictions and greater strength. The Power of Random Forests is that, a set of decision trees is generated and the predictions rendered, which in a sense reduces the chances of over fitting and at the same time enhances generalized learning. As for Gradient Boosting, it involves the hunt for a strong learner by improving the weights of miss-classified instances with weak learner's breeds in recurrent cycles [18]. This is not the case when dealing with ensemble type models, which are useful in cases of low level noise and poor model design. By putting together different machine learning models, ensemble methods in AQI forecasting provide a wider interpretation of the problem and thus improve the performance, ensuring less errors and biases. Concerning every particular machine learning tool, be it quite simple or very sophisticated, it may be clear that each of them has its own strengths and thus researchers, and environmental planners are free to select the most appropriate for the problem at hand based on features of the data set and the goals of predicting [19].

III. Machine Learning Techniques for AQI Prediction

Machine learning techniques have been gaining significant attention in the last decade or so for the prediction of the Air Quality Index (AQI), essentially the parameter used to measure air pollution. Generally, these approaches can be categorized into supervised learning, unsupervised learning, ensemble methods, and deep learning. Each of these approaches considers a different methodology to modeling and predicting the AQI based on several environmental and atmospheric parameters which might affect its value. The accurate prediction of the AQI from past experience and recognizing the complex patterns is an important decision support tool for planners, policymakers, and environmental scientists to understand pollution levels.

A. Supervised Learning Techniques

Supervised learning methods are among the most widely used approaches for AQI prediction, as they are trained on labeled data where the outcomes (AQI values) are known. Linear regression, one of the simplest supervised techniques, models the relationship between input variables, such as temperature, humidity, and particulate matter, and the AQI. This method assumes a linear relationship between these variables. Decision trees, on the other hand, split the data into subsets based on specific criteria, leading to a prediction at each leaf node [20]. Random forests improve on decision trees by aggregating multiple trees to reduce over fitting and improve accuracy. Support Vector Machines (SVM) find a hyper plane that best separates the data into different AQI classes (e.g., good, moderate, or hazardous), while neural networks, particularly deep neural networks, can capture complex, nonlinear relationships between variables, making them especially powerful in predicting AQI values that are influenced by multiple, interacting factors over time [21].

B. Unsupervised Learning Techniques

Unsupervised learning methods such as K-means clustering and Principal Component Analysis (PCA) are useful in situations where data are insufficiently labeled or are not labeled at all. K-means clustering clusters similar data points to help identify regions or time periods that exhibit similar air quality trends or behaviors. This proves particularly useful when various environmental factors cluster together and influence AQI levels [22]. On the contrary, PCA is a dimensionality reduction technique that attempts to reduce data complexity by concentrating on the most important variables, thus streamlining model construction. By converting high-dimensional data to a smaller set of features that capture most variance, PCA allows for the identification of hidden patterns within the data and helps to design better AQI prediction models [23].

C. Ensemble Methods

Assembling methods such as boosting and bagging have grown tremendously popular for the upliftment of an AQI prediction model. For boosting, the idea is to train models, often very weakly (weak model), typically decision trees: sequentially increasing the weight of those instances misclassified by previous models. Sequential consideration of errors produced by earlier models enables the construction of a highly accurate and robust prediction model. The bagging concept is on indirect contrast; it relies on building multiple models independently and in parallel and merges their prediction to minimize variance and prevent overfitting: averaging predictions from multiple models produces a more reliable and stable predictor for AQI [24]. Deep learning methods, mostly CNNs and RNNs, also provide some hope of an air quality forecast in cases of massive and complex datasets. CNNs work great in extracting spatial patterns within data and thus are appropriate for pollution spatial distribution; whereas, RNNs are made temporal data processors, making them somewhat primary for time series forecasting of AQI values. RNNs are great for characterizing air quality temporal evolution, capturing temporal relationships among data points, and predicting future AQI values from historical observations. These machine learning approaches, thus, provide a strong toolbox for precise air quality prediction, endowing us with much-needed insight toward effective policy and public health decisions [25].

IV. Challenges in AQI Prediction

Predicting the Air Quality Index (AQI) using those machine learning techniques poses a number of challenges. One challenge is that environment data are complex and highly variable--involving pollutants, weather patterns, and geographical conditions, and the tempo of change could literally be seconds. Melding data from diverse sources, such as satellite images, weather forecast data, and that of actual observatories, is vexing and could prove to be costly. Then, there are cases whereby these data could be incomplete, noisy, or inconsistent, which pose difficulty for accurate modeling. Another barrier is selecting appropriate supervised learning algorithms: choosing a certain method might work better for a dataset, whereas applying another algorithm to the same problem might work worse, so a large amount of trial and error is needed. Additionally, the training and inference of these sophisticated models require heavy computational resources, therefore proving to be practically impossible for applications needing real-time output or deployed in an environment with a low-level infrastructure.

The AQI is an air pollution parameter that evaluates influences on health during short-term exposure, making its accurate prediction essential for climate control and public health management. With respect to AQI prediction, several other machine learning methods were used, e.g., SVR, RFR, and CatBoost regression, with SMOTE used to enhance the performance of imbalanced datasets [26]. Another study that compared ML models for the prediction of AQI and AQG showed that stack models generally provided better performance vis-à-vis individual models, scoring very highly on R^2 and accuracy-based metrics [27]. Furthermore, a hybrid deep learning model based on ACNN, ARIMA, QPSO-LSTM, and XGBoost was proposed, which made great improvements on MSE and R^2 and hence performed better in AQI prediction [28]. Studies on dataset properties and model selection-based machine learning underline the importance of understanding these properties when clustering techniques are applied for personalization-oriented applications [29]. Furthermore, comparisons in machine-learning research, especially in the framework of supervised learning, are decisive for the best choice of method under different conditions of available data [30]. In the smart transportation context, demand for situational data has led to building safe and reliable models for road surface classification, with a CNN-based DNN achieving 93.17% accuracy [31]. A comparative study over deep learning architectures showed how CNNs performed well for specific tasks, whereas other architectures such as RNNs are shown to be more versatile across wide domains [32]. Finally, in credit scoring, Random Forest was shown to outperform other classifiers such as Naive Bayesian, Logistic Regression, and K-Nearest Neighbour with respect to precision, recall, and accuracy [33].

Table 2 Comparative Analysis of Machine Learning Models for AQI Prediction and Related Applications

Citation	Study	Models/Techniques Used	Datasets Used	Key Performance Metrics	Findings
[26]	Study 1 (AQI Prediction using SMOTE)	Support Vector Regression (SVR), Random Forest Regression (RFR), CatBoost Regression (CR)	AQI data from New Delhi, Bangalore, Kolkata, and Hyderabad	RMSE, Accuracy	RFR had the lowest RMSE in Bangalore, Kolkata, and Hyderabad. CatBoost had the highest accuracy for New Delhi and Bangalore. SMOTE improved accuracy in all cases.
[27]	Study 2 (AQI and AQG Prediction using Stack Models)	Random Forest (RF), Gradient Boosting (GB), Lasso Regression (LASSO), Stacked Regressor, K-Nearest Neighbors (KNN), SVM, Decision Tree (DT), MLP	Public AQI data from 2014-2019, six pollutants (PM10, PM2.5, NO2, SO2, CO, O3)	R2, RMSE, MAE, Accuracy (ACC), Matthew's Correlation Coefficient (MCC), F1 score	The Stacked Model outperformed all individual models, showing high R2 (0.973) and accuracy (90.970%).
[28]	Study 3 (Hybrid Deep Learning for AQI Prediction)	Attention Convolutional Neural Networks (ACNN), ARIMA, Quantum Particle Swarm Optimization (QPSO)-enhanced LSTM, XGBoost	Seoul Air Quality Data (2021-2022)	MSE, MAE, R2	The proposed hybrid model achieved 31.13% reduction in MSE, 19.03% reduction in MAE, and 2% improvement in R2 compared to conventional models.
[29]	Study 4 (Comparing Machine Learning Models for Personalized Data)	Simulated Human Data, Clustering Approaches	Simulated Human Data for clustering	Not provided	Focused on the relationship between dataset characteristics and classifier selection, but no explicit AQI prediction models.
[32]	Study 5 (Comparative Analysis of Deep Learning Models)	CNNs, RNNs, Transformers, GANs	Diverse real-world datasets (Healthcare, Autonomous Vehicles, NLP)	Accuracy, Precision, Recall, F1 Score, Computational Efficiency	Identified strengths and weaknesses of different deep learning models in various domains; CNNs excel in specific tasks, RNNs in time-series forecasting.
[31]	Study 6 (Road Surface Type Classification	CNN-based Deep Neural Network, Classical Machine Learning, Deep Learning	Road surface data collected from inertial sensors on	Validation Accuracy	CNN-based deep neural network achieved 93.17%

	Using Machine Learning)		various vehicles		accuracy for road surface classification.
[33]	Study 7 (Credit Scoring using Machine Learning)	Naive Bayesian Model, Logistic Regression, Random Forest, Decision Tree, K-Nearest Neighbor Classifier	Credit Information Dataset	Precision, Recall, AUC, Accuracy	Random Forest outperformed other classifiers in terms of precision, recall, AUC, and accuracy for credit scoring.

V. CONCLUSION

This study explored the application of machine learning techniques in AQI prediction, stressing that both traditional and advanced models should be used for accurate predictions. Techniques such as Random Forest Regression and CatBoost Regression, alongside SMOTE for dataset balancing, yield better prediction accuracy than simple linear models. Further, the study underlines the use of ensembles and hybrid modeling in tackling complex, dynamic environmental data. The knowledge generated through this study can direct future work in environmental monitoring and policymaking towards generating proper and quick AQI forecasts, which in turn would further public health outcomes and urban planning in efficient ways.

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