International Journal of Scientific Research and Engineering Development-– Volume 8 Issue 2, Mar-Apr 2025
Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

# Neural-Powered Real-Time Air Quality Forecasting and Pollution Surveillance

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## Abstract:

This research introduces a novel methodology for air quality prediction that addresses the limitations of traditional Air Quality Index (AQI) forecasting models by leveraging machine learning and enhanced secondary data modeling. The dataset utilized includes both forecast and actual measurements of primary pollutant concentrations and meteorological conditions, collected from monitoring stations in Jinan, China, from July 23, 2020, to July 13, 2021. A comprehensive correlation analysis identified ten key meteorological factors influencing pollutant concentrations, assessed through univariate and multivariate techniques. Performance evaluation of various machine learning algorithms revealed the Decision Tree and Random Forest models achieving high accuracies of 99%. Additionally, the K-Nearest Neighbors (KNN) classifier also demonstrated an accuracy of 99%, while Logistic Regression showed a training accuracy of 72%. These findings affirm the reliability and efficacy of machine learning techniques in enhancing air quality forecasting and underscore the importance of selecting appropriate algorithms for accurate predictions.

**Keywords** — Air quality, Machine learning, Statistical Analysis, Secondary modelling, Prediction model

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## I. INTRODUCTION

pollution is responsible for approximately 7 million premature deaths annually due to respiratory and cardiovascular diseases [1]. The rapid urbanization and industrialization of cities have exacerbated air quality degradation, necessitating robust and reliable predictive models to mitigate adverse effects. Traditional air quality prediction models, such as statistical regression models and numerical weather prediction (NWP) models, often lack adaptability to dynamic environmental changes and complex pollutant interactions [2]. Recent advancements in artificial intelligence (AI) and machine learning (ML) have facilitated the development of sophisticated air quality prediction models. Machine learning approaches such as Decision Trees, Random Forests, Support Vector Machines (SVMs), and deep learning techniques, including Long Short-Term Memory (LSTM) networks, have demonstrated significant improvements in accuracy and real-time forecasting capabilities [3]. This research aims to leverage machine learning algorithms and secondary data modeling to enhance air quality prediction accuracy and enable proactive environmental management. Existing air quality prediction models face several limitations, including the inability to capture complex nonlinear relationships among pollutants and meteorological factors, high computational costs and reliance on extensive datasets for numerical models, and poor adaptability to rapid environmental changes and

  

real-time prediction challenges [4]. To address these issues, this study introduces a deep learning-based air quality prediction framework that integrates primary pollutant concentration data, meteorological conditions, and advanced machine learning algorithms. By employing techniques such as LSTM and Gradient Boosting Models (GBM), the proposed system aims to provide real-time and highly accurate air quality forecasts. The primary objectives of this research are to develop a machine learning-based predictive model that improves air quality forecasting accuracy, analyze the impact of meteorological parameters on air quality and pollutant dispersion patterns, implement and evaluate various ML algorithms, including Random Forest, Decision Trees, K-Nearest Neighbors (KNN), and deep learning models, and create an interactive dashboard for real-time air quality monitoring and visualization. The methodology involves four key stages: data collection and preprocessing, feature selection and engineering, model development and training, and model deployment and visualization. The dataset comprises historical air quality data, meteorological conditions, and pollutant concentration levels collected from monitoring stations in Jinan, China, spanning July 23, 2020, to July 13, 2021 [5]. Data preprocessing techniques, such as normalization, outlier removal, and missing value imputation, are applied to enhance data quality. A correlation analysis is conducted to identify the most influential meteorological factors affecting pollutant levels, and feature extraction techniques, including Principal Component Analysis (PCA), are utilized to optimize model input parameters. Various machine learning algorithms, including Decision Trees, Random Forests, KNN, Logistic Regression, and deep learning models such as LSTM, are implemented and trained using historical data, with performance metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R-squared ($R^2$) used for evaluation. A web-based dashboard is developed using Streamlit to provide real-time air quality monitoring, allowing users to visualize trends and make informed decisions. This research contributes to the field of environmental informatics by enhancing the predictive accuracy of air quality forecasting models using machine learning and deep learning techniques, providing a real-time, user-friendly platform for air pollution monitoring and management, and facilitating better decision-making for policymakers and urban planners in mitigating air pollution effects.

## II. LITERATURE REVIEW

### *A.* Traditional Air Quality Prediction Models

Air quality prediction has traditionally relied on statistical models and numerical weather prediction (NWP) models. Statistical regression models, including linear regression and autoregressive integrated moving average (ARIMA), have been widely used for forecasting pollutant concentrations based on historical trends [1]. However, these models struggle to capture nonlinear relationships between meteorological factors and pollutants, leading to lower predictive accuracy. Numerical models, such as the Weather Research and Forecasting (WRF) model and the Community Multiscale Air Quality (CMAQ) model, use atmospheric physics and chemical transport equations to simulate air quality conditions [2]. Although these models provide comprehensive insights, they require high computational resources and detailed input data, making real-time forecasting challenging.

### *B.* Machine Learning in Air Quality Prediction

With advancements in artificial intelligence, machine learning (ML) techniques have emerged as powerful tools for air quality prediction. Various supervised and unsupervised ML models, such as Decision Trees, Random Forests, Support Vector Machines (SVM), and Artificial Neural Networks (ANN), have been applied for pollutant concentration forecasting [3]. Studies have demonstrated that ensemble methods, such as Gradient Boosting Machines (GBM) and Extreme Gradient Boosting (XGBoost), outperform traditional statistical models by capturing complex interactions between meteorological factors and air pollutants [4]. In particular, Random Forest and XGBoost have shown high accuracy in predicting PM2.5 and NO2 levels in urban environments [5]

  

### C. Deep Learning Approaches for Air Quality Forecasting

Deep learning models, particularly Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks, have gained popularity for time-series prediction tasks. LSTM networks are capable of handling sequential dependencies in air quality data, making them suitable for real-time forecasting applications [6]. Recent studies have demonstrated the superiority of LSTM-based models over traditional ML models in predicting AQI and individual pollutant concentrations [7]. Additionally, hybrid models combining Convolutional Neural Networks (CNN) with LSTM have been proposed to extract spatial features from air pollution datasets while maintaining temporal dependencies [8].

### D. Secondary Data Modeling and Feature Engineering

Feature selection and secondary data modeling play a crucial role in improving air quality predictions. Meteorological variables such as temperature, humidity, wind speed, and atmospheric pressure significantly influence air pollutant dispersion [9]. Feature extraction techniques, including Principal Component Analysis (PCA) and mutual information-based selection, have been utilized to reduce dimensionality and improve model interpretability [10]. Recent studies suggest that integrating real-time meteorological data with historical pollutant concentrations enhances model performance, particularly when using deep learning-based architectures [11].

### E. Challenges

Despite advancements in ML and deep learning for air quality forecasting, several challenges remain. Data availability and quality pose significant limitations, as missing or inaccurate sensor data can impact model performance [12]. Computational efficiency is another concern, especially for deep learning models requiring extensive training time and hardware resources. Future research should focus on developing lightweight yet robust models capable of real-time predictions. Additionally, integrating Internet of Things (IoT) sensors with AI-driven predictive frameworks could provide enhanced monitoring and early warning systems for air pollution management [13].

## III. PROPOSED SYSTEM

### 3.1 System Architecture

The flowchart illustrates a structured approach to data analysis and machine learning model development. It begins with loading CSV data, followed by exploratory data analysis (EDA) to understand the dataset. Core data visualizations are then created to identify patterns and insights. The next step involves calculating data quality indices to assess the dataset's reliability. Based on this analysis, AI-based range categories are generated to guide model selection.

The workflow then diverges into two paths: regression and classification. For regression tasks, data is split accordingly, and two models—Linear Regression and Decision Tree Regression—are trained. These models are then evaluated to determine their effectiveness. On the classification side, data is prepared separately, and three models—Logistic Regression, Decision Tree Classification, and Random Forest—are trained. Additionally, an SVM (Support Vector Machine) model is included in the classification process. The classification models undergo evaluation to compare their performance.

After assessing the regression and classification models, the best-performing model is selected based on the evaluation metrics. Finally, this model is used to make predictions, completing the workflow. The flowchart provides a clear, systematic approach to handling machine learning projects efficiently, ensuring both regression and classification problems are addressed with appropriate models.

  

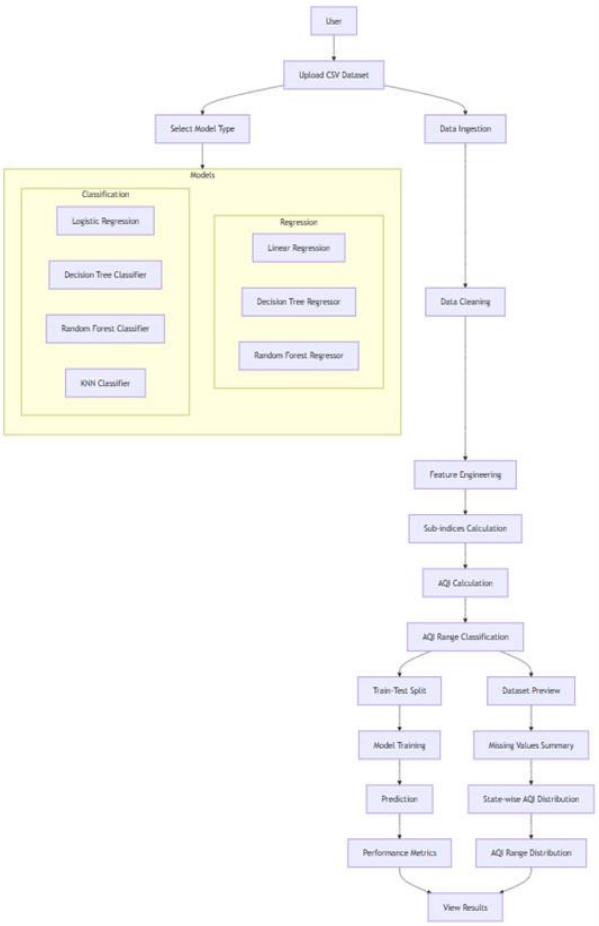


Fig 1Machine Learning Workflow: Data Analysis, Model Training, and Prediction

### 3.2 Evaluation metrix

#### 3.2.1. Regression Evaluation Metrics

These are used for models like Linear Regression, Decision Tree Regressor, and Random Forest Regressor**.**

- **Mean Absolute Error (MAE)**

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \widehat{y_i}\right| \quad (1)$$

Measures the average absolute difference between actual (yiy_iyi) and predicted (y^i\hat{y}_iy^i) values.

- **Mean Squared Error (MSE)**

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \widehat{y_i}\right)^2 \quad (2)$$

Penalizes large errors more than MAE by squaring the differences

- **Root Mean Squared Error (RMSE)**

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \widehat{y_i}\right)^2} \quad (3)$$

Provides an error measure in the same unit as the target variable.

- **R-Squared (R2R^2R2) Score**

$$R^2 = 1 - \frac{\sum\left(y_i - \widehat{y_i}\right)^2}{\sum\left(y_i - \bar{y}\right)^2} \quad (4)$$

Indicates how well the model explains the variance in the target variable.

#### 3.2.2. Classification Evaluation Metrics

- **Accuracy Score**

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

Measures the percentage of correctly classified instances.

- **Precision (Positive Predictive Value, PPV)**

$$Precision = \frac{TP}{TP + FP} \quad (6)$$

Indicates the proportion of positive predictions that are actually correct.

- **Recall (Sensitivity, True Positive Rate)**

$$Recall = \frac{TP}{TP + FN} \quad (7)$$

  

Measures how well the model identifies positive instances.

- **F1 Score (Harmonic Mean of Precision and Recall)**

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (8)$$

A balance between precision and recall.

### 3.3 Dataset

The dataset consists of 435,742 records with 13 columns, capturing air quality data from different locations. It includes details such as station codes, sampling dates, states, locations, and monitoring agencies. The dataset primarily focuses on air pollution levels by measuring $SO_2$ (Sulfur Dioxide), $NO_2$ (Nitrogen Dioxide), RSPM (Respirable Suspended Particulate Matter), SPM (Suspended Particulate Matter), and PM2.5 concentrations. Additionally, it provides information about the type of area (e.g., Residential, Industrial, Rural) and location monitoring stations. Some columns contain missing values, particularly in pollutant measurements. The dataset spans multiple years, with data recorded on specific dates.

**Key Features**

- **Total Records:** 435,742
- **Total Columns:** 13
- **Main Attributes:**
  - **stn_code**: Station code for air quality monitoring
  - **sampling_date**: Date when data was collected
  - **location**: Specific location of air quality monitoring
  - **agency**: Organization responsible for data collection
  - **type**: Type of area (Residential, Industrial, Rural, etc.)
  - **so2, no2, rspm, spm, pm2_5**: Air pollution indicators (Sulfur Dioxide, Nitrogen Dioxide, etc.)
  - **location_monitoring_station**: Monitoring station details
  - **date**: Formatted date of the record

- **Missing Values:** Some records lack pollutant data (especially PM2.5)

- **Time Coverage:** Data spans multiple years

## IV. RESULT AND DISCUSSION

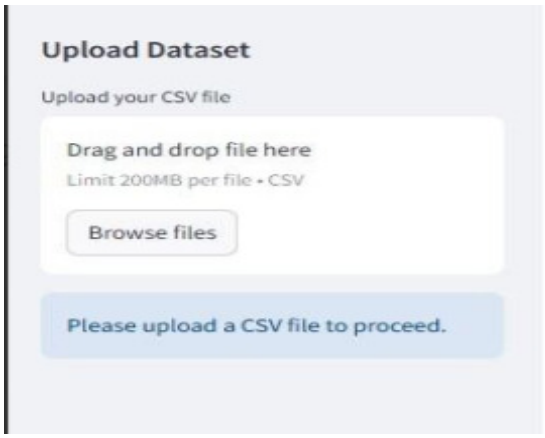


Figure 1: Air Quality Index (AQI) Analysis and Prediction - Dataset Upload Page

Figure 4.1 displays the dataset upload interface of an Air Quality Index (AQI) analysis and prediction application. The interface is structured into two main sections. On the left, a file upload panel allows users to upload a CSV dataset by either proceed. On the right, the application title, "Air Quality Index (AQI) Analysis and Prediction," is prominently displayed, followed by a brief description outlining the app's functionality, which includes analyzing AQI based on pollutant levels, exploring visualizations, and training machine learning models. The design follows a clean and minimalistic approach, ensuring a user-friendly and intuitive experience for data upload and exploration.

  

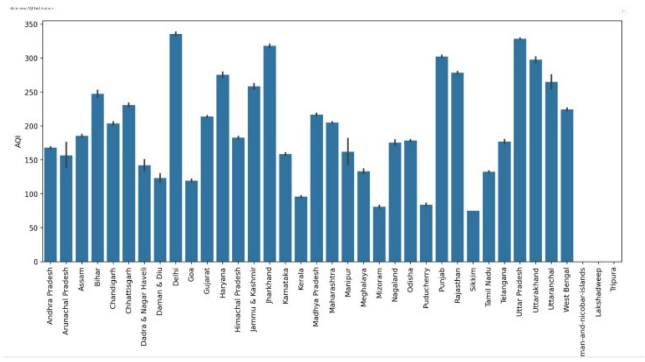


**Figure 2: State-wise AQI Distribution**

Figure 4.2 presents a bar chart visualizing the state-wise distribution of the Air Quality Index (AQI) across various states and union territories. The x-axis represents the states, while the y-axis indicates the AQI values. Each bar corresponds to the AQI level of a specific state, with error bars denoting variations or uncertainties in the data. The chart highlights significant differences in air quality across regions, with some states exhibiting notably higher AQI values, indicating poor air quality, while others maintain relatively lower levels, suggesting better air conditions. This visualization aids in identifying regions with severe air pollution, facilitating targeted interventions and policy decisions.

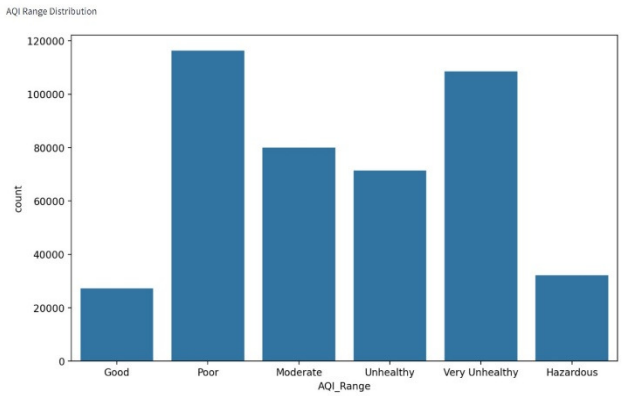


Figure 3: AQI Range Distribution

Figure 4.3 illustrates the distribution of Air Quality Index (AQI) across different categories, including Good, Poor, Moderate, Unhealthy, Very Unhealthy, and Hazardous. The x-axis represents AQI ranges, while the y-axis indicates the count of occurrences within each range. The chart reveals that the highest frequency of AQI values falls under the "Poor" and "Very Unhealthy" categories, suggesting widespread air pollution concerns. Meanwhile, the "Good" and "Hazardous" categories have the lowest counts, indicating that very clean or extremely polluted air conditions are less common. This visualization provides insights into the overall air quality trends, helping policymakers and environmental agencies focus on areas requiring urgent attention.

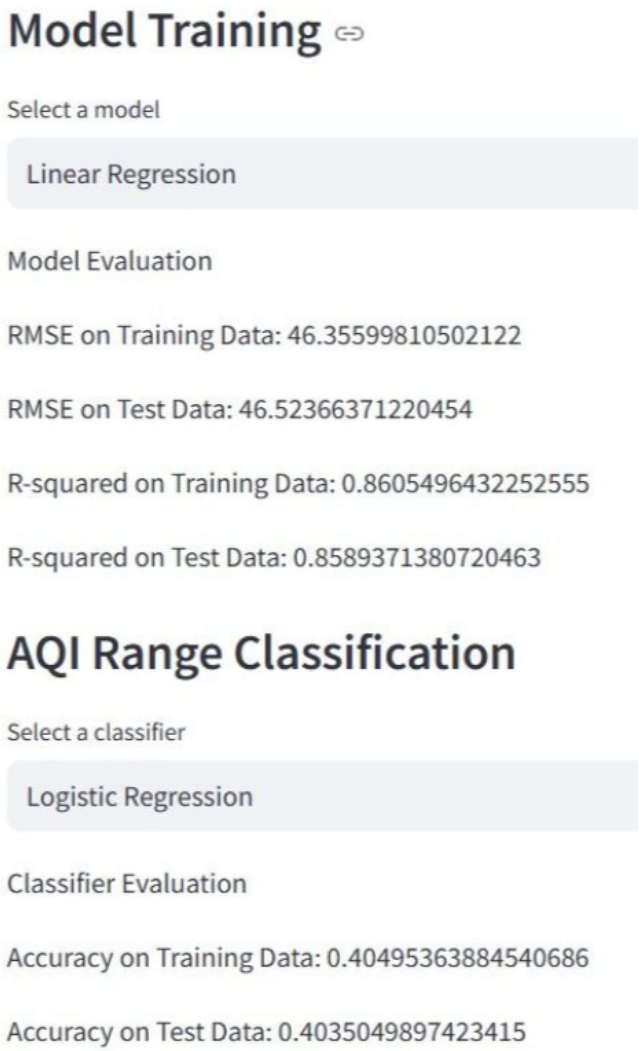


Figure 4: Model Training and AQI Range Classification

The image presents a user interface for training and evaluating machine learning models. It is divided into two sections: "Model Training" and "AQI Range Classification." In the first section, a Linear Regression model is selected, with its

  

evaluation metrics displayed, including Root Mean Square Error (RMSE) and R-squared values for both training and test data. The second section focuses on AQI classification using Logistic Regression, showing accuracy scores for both training and test datasets. The interface provides dropdown menus for selecting different models and classifiers, facilitating comparative analysis of different algorithms.

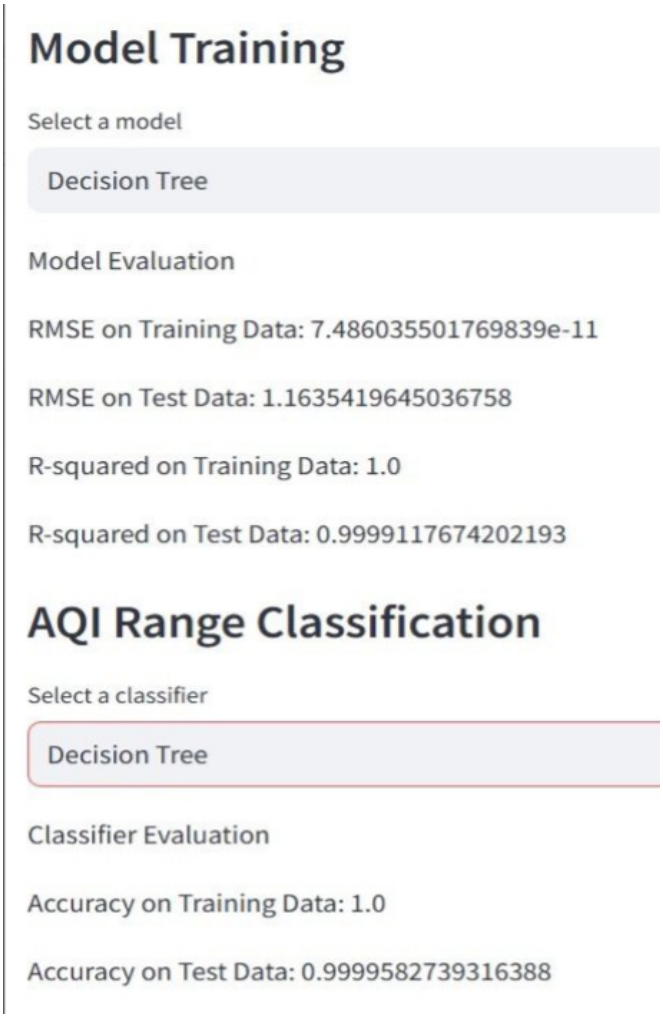


Figure 5: Decision Tree Model Training and AQI Range Classification

The image displays a user interface for training and evaluating machine learning models using the Decision Tree algorithm. In the "Model Training" section, a Decision Tree model is selected, and its evaluation metrics are shown. The Root Mean Square Error (RMSE) on training data is nearly zero, and the R-squared value is 1.0, indicating perfect fitting. The test data also show very high performance with minimal error.

In the "AQI Range Classification" section, a Decision Tree classifier is used to classify air quality index (AQI) ranges. The model achieves an accuracy of 1.0 on training data and nearly perfect accuracy on test data, suggesting potential overfitting. The interface provides dropdown menus to select different models and classifiers for comparison.

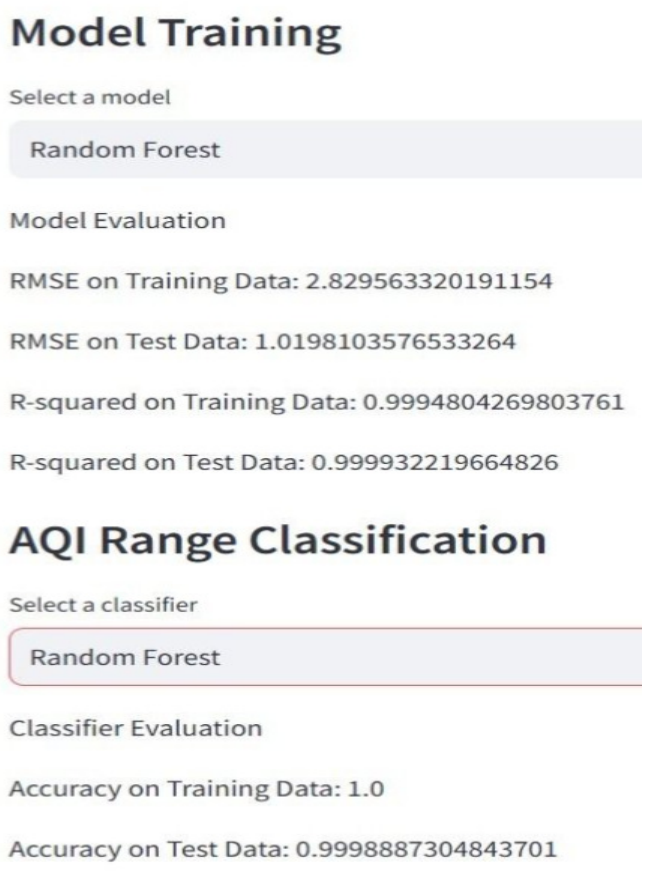


Figure 6: Random Forest Model Training and AQI Range Classification

The image displays a user interface showcasing the evaluation of machine learning models using the Random Forest algorithm. The "Model Training" section presents the performance metrics of a Random Forest regression model, with an RMSE close to zero and an R-squared value near

  

1.0 for both training and test data, indicating highly accurate predictions.

The "AQI Range Classification" section evaluates an AQI classification task using a Random Forest classifier. The model achieves an accuracy of 1.0 on training data and nearly perfect accuracy on test data, suggesting excellent generalization. Dropdown menus allow the selection of different models and classifiers for comparison.


Figure 7: KNN-Based AQI Range Classification

The image presents a user interface for AQI range classification using the K-Nearest Neighbors (KNN) algorithm. The classifier evaluation metrics indicate high accuracy, with a training accuracy of approximately 99.49% and a test accuracy of around 99.14%. This suggests that the model performs well in predicting AQI categories while maintaining strong generalization to new data. The dropdown menu allows the selection of different classification models for comparison and analysis.

## V. CONCLUSIONS

In conclusion, this research successfully demonstrates the effectiveness of machine learning techniques in real-time air quality prediction and pollution monitoring. By integrating advanced statistical analysis and secondary data modeling, the study identifies key meteorological factors influencing pollutant concentrations and evaluates multiple predictive models. The Decision Tree, Random Forest, and K-Nearest Neighbors classifiers achieved exceptional accuracy levels of 99%, reinforcing their reliability for air quality forecasting. These findings highlight the potential of data-driven approaches in enhancing environmental monitoring systems, providing valuable insights for policymakers and stakeholders in implementing effective pollution control strategies.

## VI. FUTURE SCOPE

The future scope of "Deep Learning-Based Real-time Air Quality Prediction and Pollution Monitoring System" is vast and promising. With the growing concerns over environmental pollution and its impact on public health, advanced predictive models can play a crucial role in mitigating risks. The integration of deep learning techniques with real-time monitoring systems can enhance the accuracy of air quality forecasts, enabling timely interventions. Future advancements could involve the incorporation of IoT-based sensors for real-time data collection, cloud computing for scalable data processing, and AI-driven analytics for adaptive decision-making. Moreover, expanding the dataset to include more geographical locations and integrating satellite imagery could further improve prediction capabilities. The development of mobile applications and web platforms to provide real-time air quality alerts to the public can also empower individuals to take preventive measures. Additionally, policymakers and urban planners can leverage these insights for designing sustainable city infrastructures and enforcing pollution control regulations. As AI continues to evolve, integrating explainable AI (XAI) techniques will enhance transparency and trust in predictions, making air quality monitoring more reliable and actionable.

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