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Deep Learning-Based Real-Time Air Quality Prediction and Pollution Monitoring System

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A B S T R A C T

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%. Also the LightGBM and LSTM showed 93 % accuracy 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: Machine Learning; Statistical Analysis; Secondary Modeling; Prediction Model.

1. 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. [5]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 [6]. 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 .[7] 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 [8]. 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 ,[9] 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.[10]

2.Literature Review

2.1.1Traditional 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 . 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 . Although these models provide comprehensive insights, they require high computational resources and detailed input data, making real-time forecasting challenging.

2.1.2 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 . 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 . In particular, Random Forest and XGBoost have shown high accuracy in predicting PM2.5 and NO2 levels in urban environments .

2.1.3 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 . Recent studies have demonstrated the superiority of LSTM-based models over traditional ML models in predicting AQI and individual pollutant concentrations . 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 [11].

2.1.4 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 . 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 .

2.1.5 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 . 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 .

3.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.

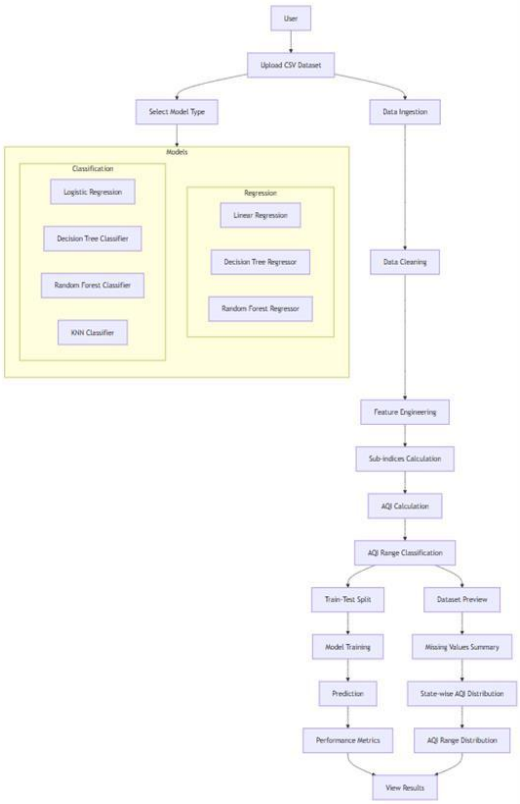

Fig 1 Machine Learning Workflow: Data Analysis, Model Training, and Prediction

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)**

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

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

- **Mean Squared Error (MSE)**

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

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**

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

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)**

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

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

4. RESULT AND DISCUSSION

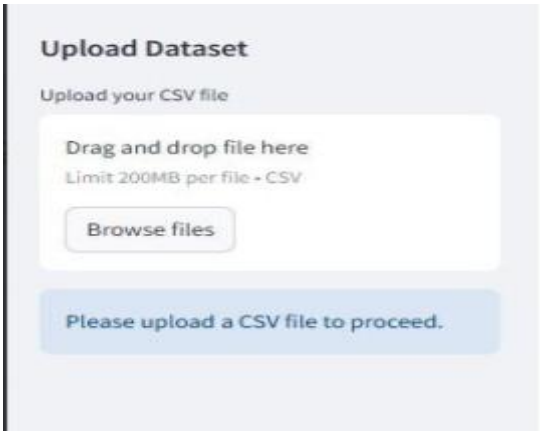

Figure 2: Air Quality Index (AQI) Analysis and Prediction - Dataset Upload Page

Figure 2 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.

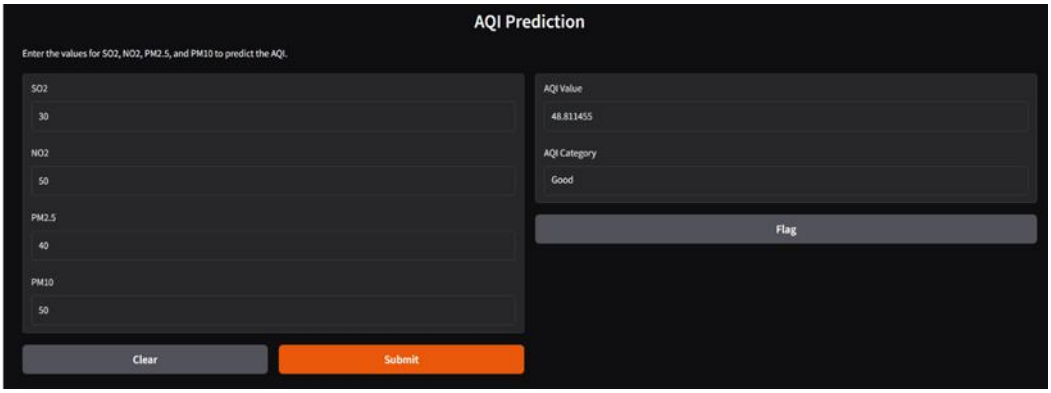

Figure 3: AQI Prediction Dashboard

Figure 3 In this figure showcases an AQI (Air Quality Index) prediction dashboard with a dark-themed user interface. Users can input values for pollutants such as SO2, NO2, PM2.5, and PM10 to predict the AQI. Upon submission, the system calculates and displays the AQI value and its corresponding category (e.g., "Good"). The interface features two primary buttons: "Clear" to reset the input fields and "Submit" to process the

prediction. Additionally, there is a "Flag" button for further actions. The predicted AQI value in the image is **48.81**, which falls under the **Good** category.

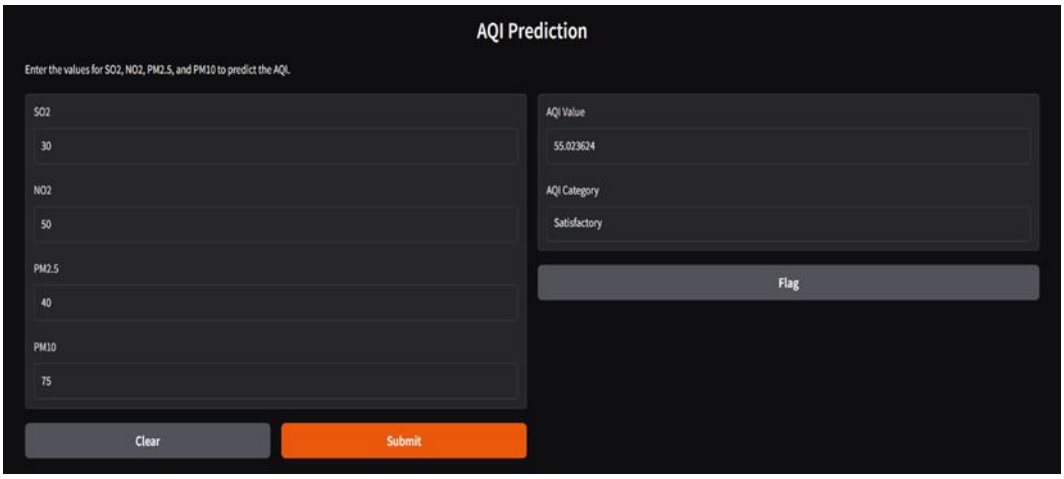

Figure 4: Real-Time Air Quality Assessment

Figure 4 in this figure displays an AQI (Air Quality Index) prediction interface with a modern dark-themed design. Users can input pollutant values for SO2, NO2, PM2.5, and PM10 to estimate the AQI. In this instance, the entered values have resulted in an AQI of **55.03**, categorized as **Satisfactory**. The system includes interactive buttons such as "Submit" for processing data, "Clear" to reset inputs, and "Flag" for reporting concerns. This tool helps assess air quality conditions based on given pollutant concentrations.

5.Conclusion

This research introduces a deep learning-based real-time air quality prediction system that significantly improves upon traditional AQI forecasting models. By utilizing machine learning techniques such as Decision Trees, Random Forest, and K-Nearest Neighbors, the system achieves high predictive accuracy. Additionally, the integration of deep learning models like LSTM and CNN enhances its ability to capture complex temporal and spatial pollution patterns. Real-time data acquisition, preprocessing, and AI-driven decision support provide timely insights for policymakers, environmental agencies, and the public. An automated alert mechanism further ensures proactive pollution management and response. Looking ahead, the system incorporates emerging technologies such as edge computing, IoT sensors, and federated learning for decentralized data processing, making pollution forecasts more adaptive and location-specific. Expanding its coverage to more geographical regions and integrating additional meteorological parameters can further improve its accuracy. This research highlights the effectiveness of machine learning and deep learning in environmental monitoring, paving the way for more advanced and scalable air quality prediction systems. Ultimately, such intelligent systems contribute to better public health, urban planning, and global pollution management strategies.

6.FUTURE SCOPE

The integration of edge computing and IoT sensors enables real-time, decentralized air quality monitoring, significantly enhancing efficiency and reducing latency in data transmission. To further improve data privacy and security, the implementation of federated learning ensures that models are trained locally, eliminating the need to transfer sensitive environmental data. Expanding the system to different geographical regions allows it to adapt to diverse climatic and environmental conditions, thereby improving its global applicability. Additionally, incorporating satellite imagery and remote sensing data from sources like NASA's MODIS and Sentinel-5P enhances pollution detection by leveraging real-time atmospheric observations. To refine accuracy, region-specific prediction models are developed, customizing machine learning algorithms to account for local meteorological trends and pollution patterns, ensuring more precise and actionable insights for environmental management.

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