ARTIFICIAL INTELLIGENCE MODEL FOR AIR QUALITY INDEX PREDICTION AND ANALYSIS

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ABSTRACT

Over the years, predicting and analyzing air quality has undergone significant advancements. In the past, we heavily relied on traditional methods like statistical models and simplified equations. However, these approaches struggled to capture the complex and dynamic nature of air pollution. As technology evolved, scientists and researchers turned to AI, machine learning, and big data analytics to improve air quality predictions. On the other hand, air pollution is a critical global issue that affects not only our environment but also our health and well-being. It is also linked to respiratory and cardiovascular diseases, leading to an increase in illnesses and deaths. Accurate air quality predictions empower governments, local authorities, and individuals to take timely actions to combat pollution, safeguard public health, and optimize urban planning. To tackle this pressing problem, we need accurate air quality prediction and analysis. Our motivation behind developing this AI model stems from the limitations of traditional air quality prediction methods. We've seen that these methods often lack accuracy and struggle to account for the intricate factors influencing air pollution. The potential of AI, with its ability to process vast amounts of real-time data and identify complex patterns, offers a promising solution to enhance the accuracy and reliability of air quality predictions. Therefore, this work introduces an innovative Artificial Intelligence (AI) model designed to predict and analyze air quality with exceptional precision and efficiency. By incorporating cutting-edge AI algorithms and data analytics techniques, this model aims to meet the growing demand for reliable real-time air quality information.

Keywords: Air Quality Index, Flask, Random Forest, Health Care.

1.INTRODUCTION

Energy consumption and its consequences are inevitable in modern age human activities. The anthropogenic sources of air pollution include emissions from industrial plants; automobiles; planes; burning of straw, coal, and kerosene; aerosol cans, etc. Various dangerous pollutants like CO, CO_2, Particulate Matter (PM), NO_2, SO_2, O_3, NH_3, Pb, etc. are being released into our environment every day. Chemicals and particles constituting air pollution affect the health of humans, animals, and even plants. Air pollution can cause a multitude of serious diseases in humans, from bronchitis to heart disease, from pneumonia to lung cancer, etc. Poor air conditions lead to other contemporary environmental issues like global warming, acid rain, reduced visibility, smog, aerosol formation, climate change, and premature deaths.

Scientists have realized that air pollution bears the potential to affect historical monuments adversely [1]. Vehicle emissions, atmospheric releases of power plants and factories, agriculture exhausts, etc. are responsible for increased greenhouse gases. The greenhouse gases adversely affect climate conditions and consequently, the growth of plants [2]. Emissions of inorganic carbons and greenhouse gases also affect plant-soil interactions [3]. Climatic fluctuations not only affect humans and animals, but agricultural factors and productivity are also greatly influenced [4]. Economic losses are the allied consequences too.

The Air Quality Index (AQI), an assessment parameter is related to public health directly. higher level of AQI indicates more dangerous exposure for the human population. Therefore, the urge to predict the AQI in advance motivated the scientists to monitor and model air quality. Monitoring and predicting AQI, especially in urban areas has become a vital and challenging task with increasing motor and industrial developments. Mostly, the air quality-based studies and research works target the developing countries, although the concentration of the deadliest pollutant like PM2.5 is found to be in multiple folds in developing countries [5]. A few researchers endeavoured to undertake the study of air quality prediction for Indian cities. After going through the available literature, a strong need had been felt to fill this gap by attempting analysis and prediction of AQI for India.

Various models have been exercised in the literature to predict AQI, like statistical, deterministic, physical, and Machine Learning (ML) models. The traditional techniques based on probability, and statistics are very complex and less efficient. The ML-based AQI prediction models have been proved to be more reliable and consistent. Advanced technologies and sensors made data collection easy and precise. The accurate and reliable predictions through such huge environmental data require rigorous analysis which only ML algorithms can deal with efficiently.

2.LITERATURE SURVEY

In [6], Gopalakrishnan (2021) combined Google's Street view data and ML to predict air quality at different places in Oakland city, California. He targeted the places where the data were unavailable. The author developed a web application to predict air quality for any location in the city neighborhood. Sanjeev [7] studied a dataset that included the concentration of pollutants and meteorological factors. The author analyzed and predicted the air quality and claimed that the Random Forest (RF) classifier performed the best as it is less prone to over-fitting. Castelli et al. [8] endeavoured to forecast air quality in California in terms of pollutants and particulate levels through the Support Vector Regression (SVR) ML algorithm. The authors claimed to develop a novel method to model hourly atmospheric pollution. Doreswamy et al. [9] investigated ML predictive models for forecasting PM concentration in the air. The authors studied six years of air quality monitoring data in Taiwan and applied existing models. They claimed that predicted values and actual values were very close to each other.

In [10], Liang et al. studied the performances of six ML classifiers to predict the AQI of Taiwan based on 11 years of data. The authors reported that Adaptive Boosting (AdaBoost) and Stacking Ensemble are most suitable for air quality prediction, but the forecasting performance varies over different geographical regions. Madan et al. [11] compared twenty different literary works over pollutants studied, ML algorithms applied, and their respective performances. The authors found that many works incorporated meteorological data such as humidity, wind speed, and temperature to predict pollution levels more accurately. They found that the Neural Network (NN) and boosting models outperformed the other eminent ML algorithms. Madhuri et al. [12] mentioned that wind speed, wind direction, humidity, and temperature played a significant role in the concentration of air pollutants. The authors employed supervised ML techniques to predict the AQI and found that the RF algorithm exhibited the least classification errors. Monisri et al. [13] collected air pollution data from various sources and endeavoured to develop a mixed model for predicting air quality. The authors claimed that the proposed model aims to help people in small towns to analyze and predict air quality.

3.PROPOSED METHOD

3.1 Overview

Air quality prediction using IoT sensor data is a critical application that leverages technology to monitor, assess, and forecast air quality conditions in various environments. This process involves collecting real-time data from a network of IoT sensors deployed in different locations, analyzing this data, and using it to make predictions about air quality. In the process of collecting and managing data from IoT sensors, the information gathered is carefully stored within a centralized database or cloud-based platform. This data is marked with timestamps, providing details about the location of the sensors, the specific type of sensors used, and the actual measurements recorded. This meticulous record-keeping ensures that we have a comprehensive dataset to work with. Prior to delving into data analysis, there is a crucial step known as data preprocessing. During this phase, the data undergoes a series of operations aimed at refining it for further analysis. These operations include addressing missing data points, handling outliers, and, if necessary, converting data into standardized formats. This step ensures that the data is in its best possible condition for accurate analysis. Once the data is preprocessed, the next step involves feature engineering. Here, we extract and create relevant features from the raw sensor data.

Moving forward, this research employs machine learning and statistical models to scrutinize the data and construct predictive models. These models draw insights from historical data, which is often used to train them. A range of algorithms, such as regression, time series analysis, or neural networks, can be applied in this context. The primary objective is to build models capable of forecasting future air quality conditions based on both historical patterns and the latest sensor readings. With the trained models in place, the proposed model equipped to make real-time predictions about upcoming air quality conditions, leveraging the most recent sensor readings. These predictions encompass a variety of valuable information, including AQI values, pollutant concentrations, and air quality forecasts tailored to specific time intervals, such as hourly or daily periods.

To ensure that the air quality information is accessible and comprehensible, it is often visualized through intuitive mediums like dashboards, maps, or graphs. This facilitates easy understanding for the general public, environmental agencies, and policymakers. Additionally, mechanisms are put in place to issue alerts and warnings in cases where air quality levels exceed safety thresholds. The insights drawn from air quality predictions can guide important actions and mitigation strategies. For instance, these predictions can inform decisions related to traffic management, industrial emissions control, and the issuance of health advisories to safeguard public well-being.

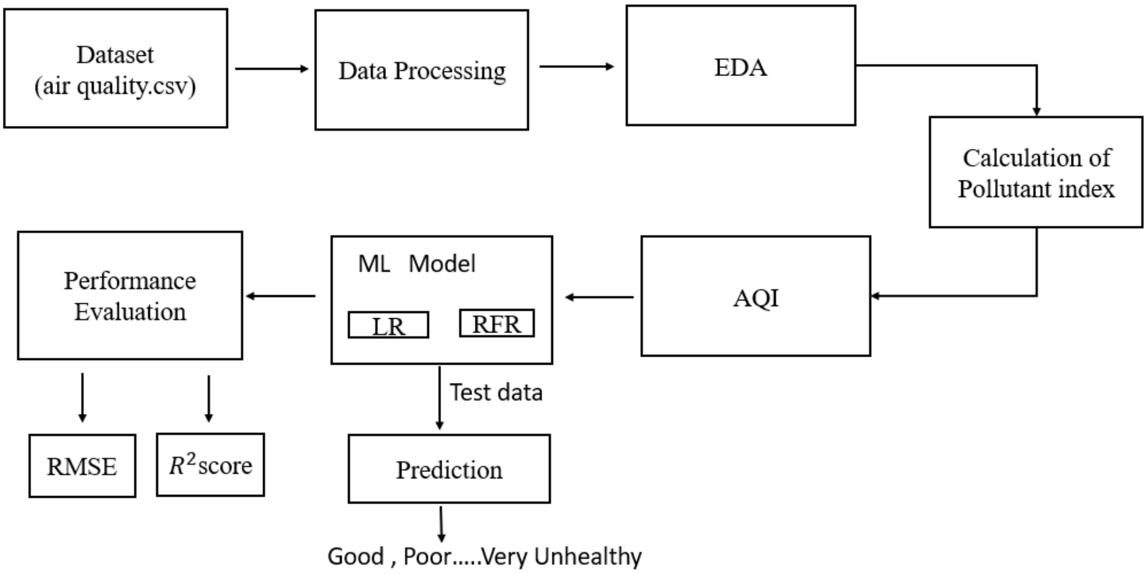

Figure 3.1: Overall design of proposed air quality prediction.

- By deleting the particular row: The first way is used to commonly deal with null values. In this way, we just delete the specific row or column which consists of null values. But this way is not so efficient and removing data may lead to loss of information which will not give the accurate output.
- By calculating the mean: In this way, we will calculate the mean of that column or row which contains any missing value and will put it on the place of missing value. This strategy is useful for the features which have numeric data such as age, salary, year, etc.

Encoding Categorical data: Categorical data is data which has some categories such as, in our dataset; there are two categorical variables, Country, and Purchased. Since machine learning model completely works on mathematics and numbers, but if our dataset would have a categorical variable, then it may create trouble while building the model. So, it is necessary to encode these categorical variables into numbers.

3.2 RFR Model

The RFR model is a powerful machine learning algorithm employed for tasks. It is a versatile and robust algorithm, well-suited for air quality prediction. Its ensemble nature, coupled with randomization in data sampling and feature selection, makes it effective at capturing complex relationships and delivering accurate predictions based on historical and environmental data.

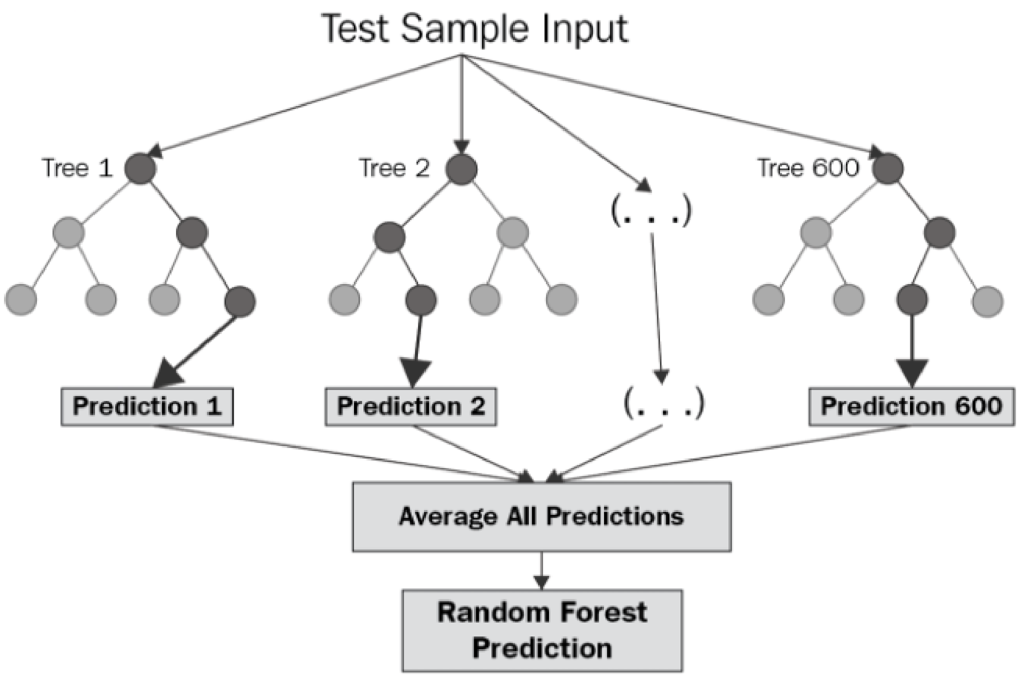

Figure 4.4: Working of RFR model.

It operates by constructing an ensemble of decision trees, and its functionality can be comprehensively explained as follows:

Ensemble of Decision Trees: It assembles a collection of decision trees during the training phase. Each decision tree, resembling a hierarchical structure, learns to make predictions based on input data.

Bootstrapped Training Data: To train this ensemble, the algorithm employs a technique known as bootstrapping. It creates multiple subsets, or samples, of the original training data. This means that each decision tree is trained on a slightly different version of the data, fostering diversity among the trees.

Random Feature Selection: In addition to data sampling, the Random Forest introduces randomness in feature selection. At each node of each decision tree, only a random subset of the available features is considered for making split decisions. This randomness helps prevent overfitting and promotes decorrelation among the individual trees.

Individual Tree Training: Each decision tree is trained independently using its unique bootstrapped sample of data. This training process employs recursive binary splitting, where the tree repeatedly divides the data into subsets based on the selected features. It continues this process until reaching a stopping criterion, such as a predefined maximum depth or a minimum number of data points in a leaf node.

Predictions by Individual Trees: Once the decision trees are trained, each tree can independently make predictions for new data points. In the context of air quality prediction, each tree predicts a continuous target value, such as concentrations of pollutants like PM2.5 or NO2.

Aggregation of Predictions: The strength of the RF lies in its ensemble approach. To make a final prediction, it aggregates the predictions from all individual decision trees. In regression tasks like air quality prediction, this aggregation is typically done by computing the average (mean) of the predictions from all trees.

Reducing Overfitting: The ensemble nature of RFs is instrumental in mitigating overfitting. While individual trees may overfit the training data, the aggregation process tends to balance out the errors and allows the model to generalize effectively to new, unseen data.

Feature Importance: It provide a measure of feature importance, indicating which features had the most significant influence on the predictions across all trees. This information is valuable for understanding the critical factors affecting air quality predictions.

Hyperparameter Tuning: To optimize the performance, hyperparameters such as the number of trees, maximum tree depth, and the number of features considered at each split can be fine-tuned through techniques like cross-validation.

Prediction and Evaluation: Once trained and optimized, it can be used for air quality prediction. It takes input data containing relevant features (e.g., historical air quality data, weather conditions) and produces predictions for air quality indices or pollutant concentrations.

Advantages

- Ensemble Learning: It is an ensemble of decision trees, which helps reduce overfitting and makes it robust against noise in the data.
- Non-Linearity: It can capture non-linear relationships and interactions between features more effectively compared to linear regression.
- Robustness: It is less sensitive to outliers and noise in the data due to the aggregation of multiple trees.
- Feature Importance: It provides a measure of feature importance, allowing you to understand which features contribute the most to the predictions.

4.RESULTS

4.1 Results Description

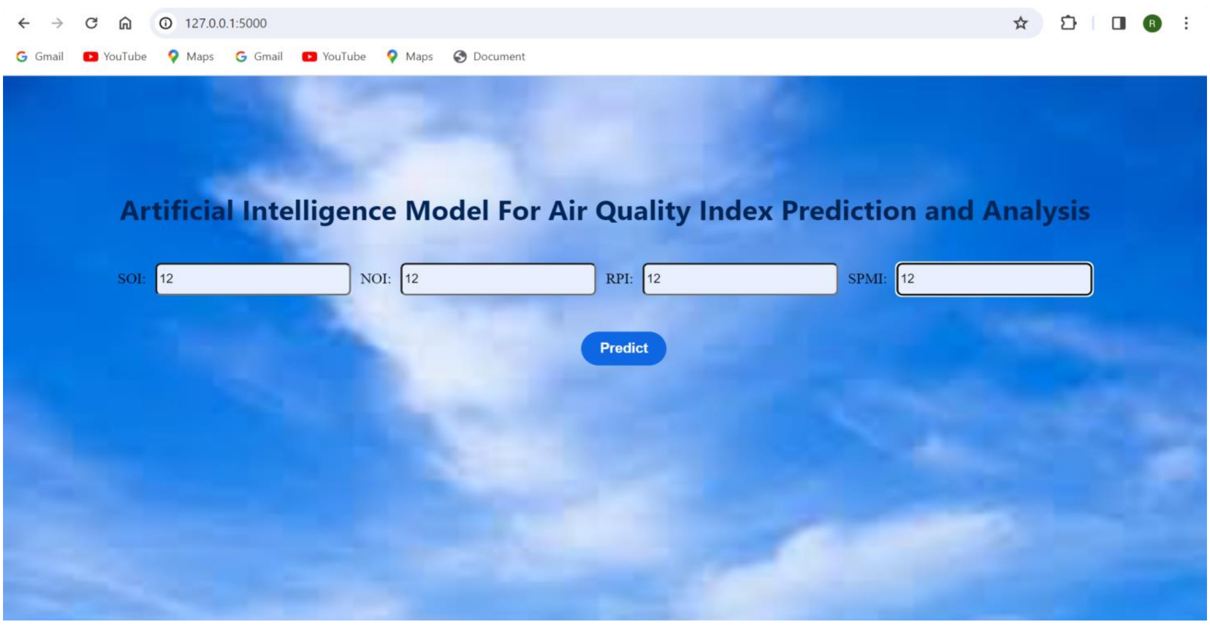

Figure 1: Presents the Web page development using Flask for AQI Prediction.

Figure 1 Shows an user interface for predicting air quality based on four input parameters: SOI (Sulfur Oxide Index), NOI (Nitrogen Oxide Index), RPI (Respirable Particulate Index), and SPMI (Suspended Particulate Matter Index). The form is styled using CSS to ensure proper alignment and spacing of input fields. A background image is set to enhance the visual appeal of the form.

Figure 2 shows the representation of a dataset containing air quality measurements, where ach row corresponds to a specific measurement taken at a particular point in time and location. The columns include various attributes discussed in dataset description.

	stn_code	sampling_date	state	location	agency	type	so2	no2	rspm	spm	location_monitoring_station	pm2_5	date
0	150	February - M021990	Andhra Pradesh	Hyderabad	NaN	Residential, Rural and other Areas	4.8	17.4	NaN	NaN	NaN	NaN	1990-02-01
1	151	February - M021990	Andhra Pradesh	Hyderabad	NaN	Industrial Area	3.1	7.0	NaN	NaN	NaN	NaN	1990-02-01
2	152	February - M021990	Andhra Pradesh	Hyderabad	NaN	Residential, Rural and other Areas	6.2	28.5	NaN	NaN	NaN	NaN	1990-02-01
3	150	March - M031990	Andhra Pradesh	Hyderabad	NaN	Residential, Rural and other Areas	6.3	14.7	NaN	NaN	NaN	NaN	1990-03-01
4	151	March - M031990	Andhra Pradesh	Hyderabad	NaN	Industrial Area	4.7	7.5	NaN	NaN	NaN	NaN	1990-03-01

Figure 2: Sample dataset of air quality measurements taken at a particular location and time.

Figure 3 displays a list of features that are considered important for training ML model to classify air quality. The features are variables or attributes that will be used by the ML model to make predictions or classification. These features are selected based on their potential impact on air quality and their relevance to the prediction task.

	state	location	type	so2	no2	rspm	spm	pm2_5
0	Andhra Pradesh	Hyderabad	Residential, Rural and other Areas	4.8	17.4	0.0	0.0	0.0
1	Andhra Pradesh	Hyderabad	Industrial Area	3.1	7.0	0.0	0.0	0.0
2	Andhra Pradesh	Hyderabad	Residential, Rural and other Areas	6.2	28.5	0.0	0.0	0.0
3	Andhra Pradesh	Hyderabad	Residential, Rural and other Areas	6.3	14.7	0.0	0.0	0.0
4	Andhra Pradesh	Hyderabad	Industrial Area	4.7	7.5	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...
435737	West Bengal	ULUBERIA	RIRUO	22.0	50.0	143.0	0.0	0.0
435738	West Bengal	ULUBERIA	RIRUO	20.0	46.0	171.0	0.0	0.0
435739	andaman-and-nicobar-islands	Guwahati	Residential, Rural and other Areas	0.0	0.0	0.0	0.0	0.0
435740	Lakshadweep	Guwahati	Residential, Rural and other Areas	0.0	0.0	0.0	0.0	0.0
435741	Tripura	Guwahati	Residential, Rural and other Areas	0.0	0.0	0.0	0.0	0.0

435742 rows × 8 columns

Figure 3: Important features for the proposed ML model.

Figure 4 showing the header information for an index that quantifies the pollution levels of individual pollutants, specifically sulphur dioxide (SO2) and nitrogen dioxide (NO2). Figure 4 displays the header information for an overall Air Quality Index (AQI) calculated using the data values from the Figure 3. AQI is a composite index that provides a simplified way to understand air quality by condensing multiple pollutants into a single value. The header includes details about the AQI scale, for different air quality levels, and the categories used to classify air quality (e.g., good, moderate, unhealthy, etc.).

	so2	SOi
0	4.8	6.000
1	3.1	3.875
2	6.2	7.750
3	6.3	7.875
4	4.7	5.875

	no2	Noi
0	17.4	21.750
1	7.0	8.750
2	28.5	35.625
3	14.7	18.375
4	7.5	9.375

Figure 4: Header of individual pollutant index for SO2 and NO2.

Figure 5 is a visualization for the classification of air quality based on the calculated AQI values. The classification likely involves different categories such as "good," "moderate," "poor," "unhealthy," "very unhealthy," and "hazardous." These categories indicate the level of pollution and associated health risks.

	state	SOi	Noi	Rpi	SPMi	AQI
0	Andhra Pradesh	6.000	21.750	0.0	0.0	21.750
1	Andhra Pradesh	3.875	8.750	0.0	0.0	8.750
2	Andhra Pradesh	7.750	35.625	0.0	0.0	35.625
3	Andhra Pradesh	7.875	18.375	0.0	0.0	18.375
4	Andhra Pradesh	5.875	9.375	0.0	0.0	9.375

Figure 5: Header of Air Quality Index calculated from every data value.

	state	location	type	so2	no2	rspm	spm	pm2_5	SOi	Noi	Rpi	SPMi	AQI	AQI_Range
0	Andhra Pradesh	Hyderabad	Residential, Rural and other Areas	4.8	17.4	0.0	0.0	0.0	6.000	21.750	0.0	0.0	21.750	Good
1	Andhra Pradesh	Hyderabad	Industrial Area	3.1	7.0	0.0	0.0	0.0	3.875	8.750	0.0	0.0	8.750	Good
2	Andhra Pradesh	Hyderabad	Residential, Rural and other Areas	6.2	28.5	0.0	0.0	0.0	7.750	35.625	0.0	0.0	35.625	Good
3	Andhra Pradesh	Hyderabad	Residential, Rural and other Areas	6.3	14.7	0.0	0.0	0.0	7.875	18.375	0.0	0.0	18.375	Good
4	Andhra Pradesh	Hyderabad	Industrial Area	4.7	7.5	0.0	0.0	0.0	5.875	9.375	0.0	0.0	9.375	Good

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Good              219643
Poor               93272
Moderate           56571
Unhealthy          31733
Hazardous          18700
Very unhealthy     15823
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Figure 6: Obtained classification of air quality as good, moderate, poor, unhealthy, very unhealthy, and Hazardous.

Table 1 provides a comparison of two different machine learning models used for air quality prediction based on two evaluation metrics: Root Mean Squared Error (RMSE) and R-squared (R^2) score.

RMSE (Root Mean Squared Error): The RMSE is a metric used to measure the average magnitude of the errors between predicted values and actual (observed) values. It quantifies how well the predictions align with the actual data. A lower RMSE value indicates better predictive performance, as it means the model's predictions are closer to the actual values. From Table 1:

- For the "LR" model, the RMSE is 13.67.
- For the "Random Forest Regressor" model, the RMSE is 1.16.

A lower RMSE for the Random Forest Regressor suggests that it has smaller prediction errors compared to the LR model.

R^2-score (Coefficient of Determination): The R^2 score is a statistical measure that represents the proportion of the variance in the dependent variable that's explained by the independent variables in a regression model. It ranges from 0 to 1, where higher values indicate that the model's predictions closely match the actual data. An R^2 score of 1 indicates a perfect fit. From Table 1:

- For the "LR" model, the R^2 score is 0.9847.
- For the "Random Forest Regressor" model, the R^2 score is 0.999.

The R^2 scores for both models are quite high, indicating that they both provide excellent fits to the data. However, the Random Forest Regressor's score of 0.999 suggests an almost perfect fit, meaning that it captures the variability in the data extremely well. Finally, the Random Forest Regressor outperforms the LR model in terms of both RMSE and R^2 score, indicating its superior predictive capability and ability to explain the variance in air quality data.

Table 1: Comparison of ML models.

Model name	RMSE	R^2-score
LR	13.67	0.9847
Random Forest Regressor	1.16	0.999

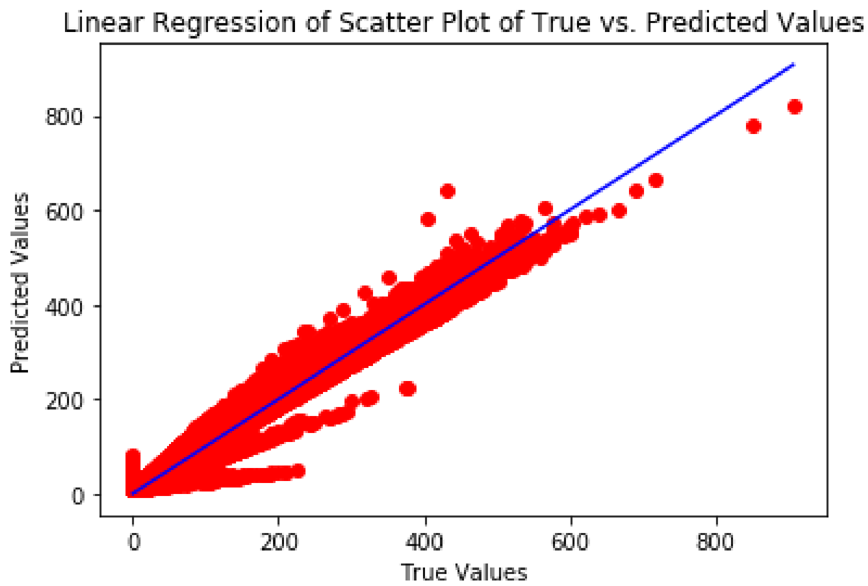

Figure 7: Scatter plot of true and predicted values obtained using LR model.

Figure 7 is a scatter plot visualizes the performance of a LR model. In this plot, each point represents a data instance. The x-axis represents the true values (actual observations) of the target variable, while the y-axis represents the predicted values of the target variable made by the LR model. Each point on the plot corresponds to a data instance, where its position relative to the diagonal line (which represents a perfect prediction) indicates how well the model's predictions align with the actual data. If the points are close to the diagonal line, it suggests that the model's predictions are accurate. In Figure 8, the scatter plot illustrates the performance of a Random Forest regressor model. Each point on the plot represents a data instance, where the x-axis shows the true values of the target variable, and the y-axis shows the predicted values made by the Random Forest model. The positioning of points relative to the diagonal line helps assess the accuracy of the model's predictions. From Figure 8, it indicates that the points cluster around the diagonal line are closely matches the actual values.

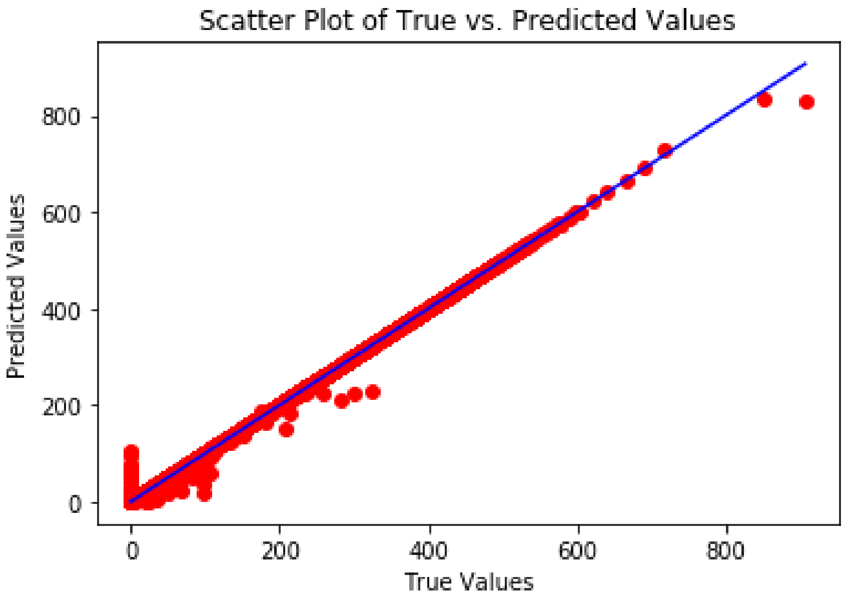

Figure 8: Scatter plot of true and predicted values obtained using Random Forest regressor model.

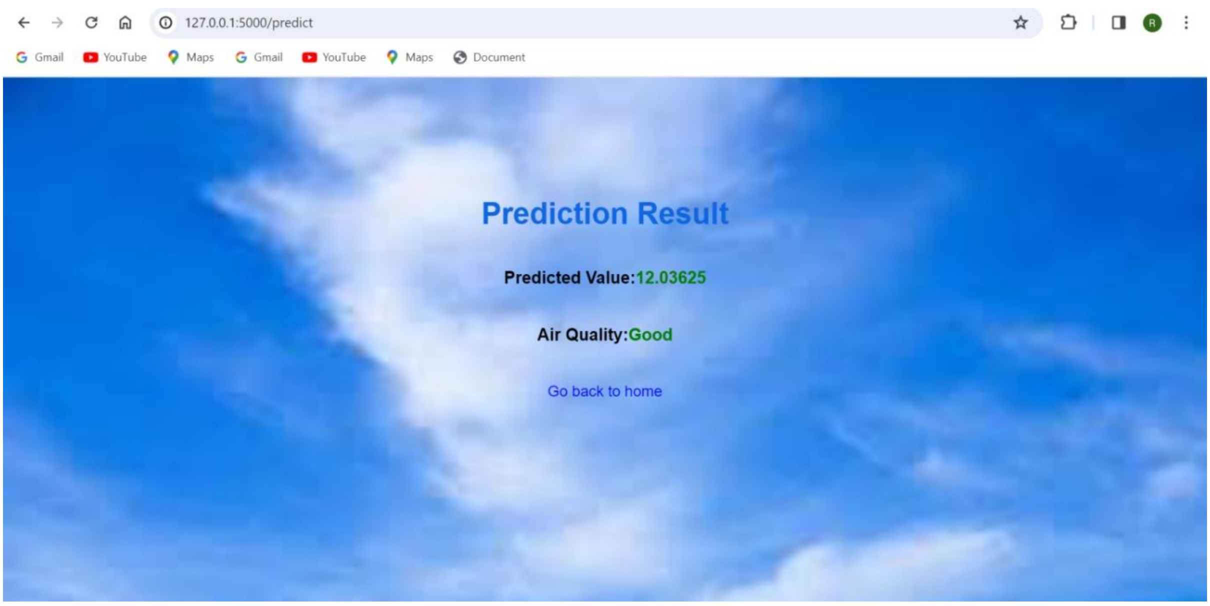

Figure 9: Prediction output using Random Forest Regression

Figure 9 Displaying the results of a RFC Model Prediction, specifically related to air quality. It consists of a header titled "Prediction Result" followed by two paragraphs. The first paragraph displays the predicted value, while the second one shows the air quality. Both values are displayed in green font color.

The template includes a hyperlink labeled "Go back to home," which allows users to navigate back to the home page. The background of the page is styled with a fixed background image using CSS, enhancing the overall visual appeal of the template.

Overall, this HTML template is designed to provide a clear and visually appealing presentation of prediction results related to air quality.

5.CONCLUSIONS

In the realm of air quality prediction, both LR and RFR models have been pivotal in providing valuable insights and forecasts. However, when assessing their performance, it becomes evident that the RFR consistently outshines LR due to its capacity to handle complex relationships and mitigate overfitting. LR, while a straightforward and interpretable model, tends to perform optimally when air quality data exhibits linear relationships. It may not capture the nuances of complex, non-linear interactions within the data, which are often present in real-world air quality scenarios. On the other hand, the RFR demonstrates superior performance by leveraging an ensemble of decision trees. This ensemble approach excels in capturing intricate relationships and interactions between various air quality parameters. Moreover, it is more robust against outliers and tends to generalize well to new data.

While the RFR model has proven to be a formidable choice for air quality prediction, the field of air quality forecasting continues to evolve. Further exploration of feature engineering techniques, including the creation of novel features and the incorporation of additional environmental and meteorological data, can lead to more robust models. Combining the strengths of different models, such as combining RF with deep learning techniques like neural networks, can lead to hybrid models that leverage both accuracy and interpretability.

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