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AIR QUALITY PREDICTION USING MACHINE LEARNING

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The survival of mankind cannot be imagined without air. Daily industrial, transport, and domestic activities are stirring hazardous pollutants in our environment. Monitoring and predicting air quality have become essentially important in this era, especially in developing countries like India. Air quality prediction is essential for environmental monitoring and public health management. In this study, we investigate the effectiveness of various machine learning algorithms for predicting air quality levels. Our dataset includes key air quality indicators such as AQI (Air Quality Index), CO, Ozone, NO, and PM concentrations. After preprocessing and data partitioning, we trained and evaluated four machine learning models: Furthermore, we implemented a real-time prediction mechanism enabling users to input air quality parameters for instant predictions, aiding in timely decision-making and intervention strategies. Our findings underscore the efficacy of machine learning in air quality prediction, offering valuable insights for environmental agencies and policymakers.

1. INTRODUCTION

Air quality is a critical environmental factor that directly impacts human health, ecosystems, and climate. The quality of the air we breathe is influenced by a complex interplay of natural processes and human activities, including industrial emissions, vehicular pollution, and agricultural practices. Poor air quality, characterized by high concentrations of pollutants such as particulate matter (PM), nitrogen dioxide (NO2), sulfur dioxide (SO2), carbon monoxide (CO), and ozone (O3), poses significant risks to public health, leading to respiratory diseases, cardiovascular problems, and other adverse health effects. Air pollution is a pervasive environmental challenge with far-reaching consequences for public health, ecosystems, and the global climate. The World Health Organization (WHO) estimates that outdoor air pollution contributes to millions of premature deaths each year, making it one of the leading environmental causes of morbidity and mortality worldwide. In addition to its human health.Monitoring and managing air quality are essential for protecting public health and the environment. Regulatory agencies and health organizations routinely measure concentrations key air pollutants such as particulate matter (PM), nitrogen dioxide (NO2), sulfur dioxide (SO2), carbon monoxide (CO), and ozone (O3) to assess compliance with air quality standards and guidelines. However, traditional monitoring approaches are often limited in their spatial and temporal coverage, providing only a snapshot of air quality at specific locations and times.

sentences. The primary objective of this study is to develop and evaluate machine learning-based models for air quality prediction using a combination of air quality measurements, meteorological data, and other relevant variables. Specifically, the study aims to achieve the following objectives:

Model Development: Develop robust ML models, including Support Vector Machine (SVM), k-Nearest Neighbors (KNN), Random Forest, and Binary Tree classifiers, for predicting key air quality indicators such as particulate matter (PM), nitrogen dioxide (NO2), sulfur dioxide (SO2), carbon monoxide (CO), and ozone (O3) concentrations.

Performance Evaluation: Assess the performance of the ML models in terms of prediction accuracy, precision, recall, and other relevant metrics using real-world air quality datasets. Compare the effectiveness of different ML algorithms and identify the most suitable approach for air quality prediction

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in different environmental settings and contexts. Analysis: Conduct feature importance analysis to identify the most influential factors affecting air quality and understand the underlying relationships between air pollution, meteorological variables, and other environmental factors.

Spatial and Temporal Analysis: Explore spatial and temporal patterns in air quality data to identify hotspots of pollution, assess the impact of local emissions sources, and understand how air quality varies over time and across different geographical regions. Decision Support System: Develop a user-friendly decision support system (DSS) that integrates the ML models with real-time air quality monitoring data and visualization tools.

By achieving these objectives, this study aims to contribute to the advancement of air quality monitoring and prediction techniques, ultimately helping to protect public health, mitigate environmental degradation, and promote sustainable development. Air quality prediction using machine learning has a significant scope and potential impact in various fields. Here are some key aspects of its scope:

Health Care: Poor air quality can have severe implications on public health, leading to respiratory diseases, cardiovascular issues, and other health problems. Machine learning models can predict air quality levels in advance, allowing healthcare providers to take proactive measures to protect vulnerable populations.

Environmental Monitoring: Machine learning can aid in monitoring and predicting air quality parameters such as particulate matter (PM), nitrogen dioxide (NO2), sulfur dioxide (SO2), ozone (O3), and carbon monoxide (CO). Accurate prediction models can assist environmental agencies in identifying pollution sources and implementing effective mitigation strategies.

Climate Change Mitigation: Poor air quality contributes to climate change through the release of greenhouse gases and other pollutants. By accurately predicting air quality levels, machine learning models can help identify opportunities for reducing emissions, transitioning to cleaner energy sources, and implementing sustainable practices to mitigate the impact of climate change.

Transportation: Machine learning algorithms can be integrated into transportation systems to predict air quality along different routes in real-time. This information can be used to optimize traffic flow, reroute vehicles away from highly polluted areas, and promote eco-friendly transportation options.

2. DISCUSSION

comprehensive system analysis of air quality prediction involves examining the entire process from data collection to model deployment and beyond.

Existing System:

The existing systems for air quality prediction typically leverage various data sources, including historical air quality data, meteorological data, satellite imagery, and sometimes additional environmental and socioeconomic data.

There are several existing systems for air quality prediction using machine learning. One popular approach is to use regression algorithms like linear regression or random forests to predict air quality based on various features such as pollutant concentrations, weather conditions, and geographical factors.

These models can provide accurate predictions and help in understanding the factors that contribute to air pollution. One example of an existing system for air quality prediction is the Air Quality Index (AQI) developed by the Environmental Protection Agency (EPA) in the United States. They use machine learning algorithms to predict the AQI based on various factors like pollutant levels, weather conditions, and historical data.

This system helps in monitoring and alerting people about the air quality in their area. Another example is the BreezoMeter platform, which utilizes machine learning to provide real-time air quality information and forecasts. These are just a couple of examples, but there are many more out there.

Proposed System:

Data Collection: Gather historical air quality data from various sources such as government monitoring stations, satellite observations, and crowd-sourced data. Include relevant meteorological data, pollutant emissions data, and geographical information.

Data Preprocessing: Clean and preprocess the collected data by handling missing values, outliers, and inconsistencies. Normalize or scale the data to ensure all features are on a similar scale.

Feature Engineering: Extract relevant features from the data that can help in predicting air quality. This can include temporal features, spatial features, and derived features based on domain knowledge.

Model Selection: Choose an appropriate machine learning algorithm for air quality prediction. This can include regression models (e.g., linear regression, decision trees), time series models (e.g., ARIMA, LSTM), or ensemble models

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(e.g., random forest, gradient boosting).

5. Model Training: Split the preprocessed data into training and validation sets. Train the selected model using the training data, optimizing model parameters to minimize prediction errors.

6. Model Evaluation: Evaluate the trained model using the validation set, considering metrics such as mean squared error, mean absolute error, or accuracy (depending on the problem formulation). Fine-tune the model if necessary.

7. Deployment: Once the model is trained and validated, deploy it in a production environment where it can receive real-time inputs and provide air quality predictions. This can be done through a web-based application, API integration, or other suitable means.

8. Continuous Monitoring and Updates: Regularly update the model with new data to improve its accuracy and adapt to changing air quality patterns. Monitor model performance and retrain as needed.

Data Acquisition: Raw air quality data and meteorological observations are collected from monitoring stations and environmental sensors deployed across the study area.

Preprocessing: The collected data undergoes preprocessing steps, including cleaning, feature engineering, and normalization, to prepare it for model training.

Model Training: Multiple machine learning models (SVM, KNN, Random Forest, Binary Tree) are trained using the preprocessed data to predict air quality indicators.

Hyperparameter Tuning: Hyperparameters of the models are optimized using techniques like grid search or randomized search to improve their performance.

Evaluation: The trained models are evaluated using testing data, and their performance is assessed using various evaluation metrics.

Comparison: The performance of the different models is compared, and the most accurate and reliable model is selected for deployment.

Deployment: The selected model is deployed in real-world scenarios, where it continuously predicts air quality levels based on incoming data from monitoring stations and sensors.

Decision Support: The predictions generated by the model are used to inform decision-making processes related to air quality management, public health interventions, and environmental policies.

By employing a rigorous methodology for data preprocessing, model training, and evaluation, the developed system provides accurate and reliable predictions of air quality, helping stakeholders to make informed decisions and take proactive measures to mitigate air pollution and its adverse effects.

Machine learning algorithm used for air quality prediction and explain them in detail:

Random Forest:

Random Forest is an ensemble learning method based on decision trees and is widely used for classification and regression tasks. It works by constructing multiple decision trees during the training phase and outputting the mode (classification) or average (regression) prediction of the individual trees.

3. ARCHITECTURE:

System Architecture:

1. **Input Data:** Raw data containing features related to air quality, such as AQI value, CO concentration, ozone level, etc.
2. **Data Preprocessing**: Cleaning, transforming, and standardizing the input data to make it suitable for training machine learning models. This step may involve handling missing values, encoding categorical variables, and scaling features.
3. **Feature Extraction**: Extracting relevant features from the preprocessed data that are informative for predicting air quality. This may involve dimensionality reduction techniques or domain-specific feature engineering
4. **Model Training & Evaluation:** Training multiple machine learning models, such as SVM, KNN, Random Forest, and Binary Tree, on the preprocessed data. Each model is evaluated using appropriate evaluation metrics such as accuracy, precision, recall, and confusion matrix
5. **Prediction & Alert Generation:** Using the trained models to predict air quality based on new input data. If the predicted air quality is below a certain threshold, a "good air quality" alert is generated. Otherwise, a "poor air quality" alert is generated.
6. **Output Data:** The final output containing the predicted air quality and associated alerts, which can be used for further analysis or visualization.

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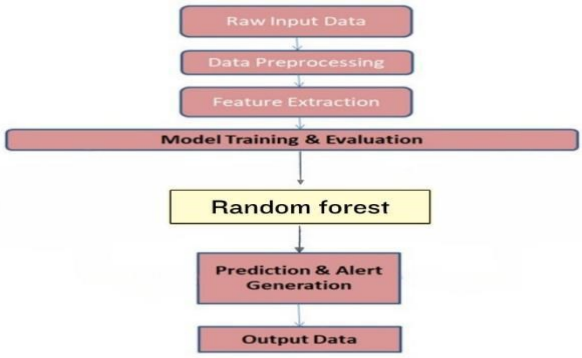
ML is a field that focuses on the learning aspect of AI by developing algorithms that best represent a set of data. In contrast to classical programming in which an algorithm can be explicitly coded using known features, ML uses subsets of data to generate an algorithm that may use novel or different combinations of features and weights than can be derived from first principles

In ML, there are four commonly used learning methods, each useful for solving different tasks: supervised, unsupervised, semisupervised, and reinforcement learning. To better understand these methods, they will be defined via an example of a hypothetical real estate company that specializes in predicting housing prices and features associated with those houses. BLOCK DIAGRAM:



Random Forest Algorithm:

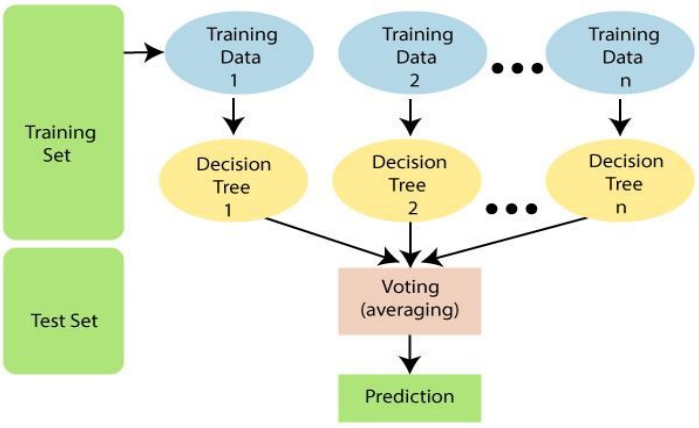
Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model. As the name suggests, "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output. The greater number of trees in the forest leads to higher accuracy and prevents the problem of overfitting. The below diagram explains the working of the Random Forest.

Assumptions for Random Forest :

Since the random forest combines multiple trees to predict the class of the data set, it is possible that some decision trees may predict the correct output, while others may not. But together, all the trees predict the correct output. Therefore, below are two assumptions for a better Random forest classifier: o There should be some actual values in the feature variable of the dataset so that the classifier can predict accurate results rather than a guessed result. o The predictions from each tree must have very low correlations.

Why use Random Forest?

Below are some points that explain why we should use the Random Forest algorithm: o It takes less training time as compared to other algorithms. o It predicts output with high accuracy, even for the large dataset it runs efficiently. o It can also maintain accuracy when a large proportion of data is missing.



4. RESULTS

In the result analysis phase of the air quality prediction system, we interpret the performance of the trained machine learning models and draw insights from their predictions. Here's a detailed breakdown of the result analysis process:

1. Model Performance Evaluation: We assess the performance of each machine learning model, including This

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assessment involves evaluating various performance metrics such as accuracy, precision, recall, and F1-score. These metrics provide a quantitative measure of how well each model performs in predicting air quality.

2. Confusion Matrix Analysis: The confusion matrix is a vital tool for understanding the classification performance of the models. We analyze the confusion matrices generated for each model to identify patterns such as true positives, false positives, true negatives, and false negatives. This analysis helps in identifying any misclassifications and understanding the strengths and weaknesses of each model.

3. Comparison of Models: We compare the performance of different models to identify the most effective one for air quality prediction. This comparison involves analyzing the accuracy, precision, recall, and other metrics across all models. Additionally, we may use visual aids such as bar charts or tables to present the comparative analysis.

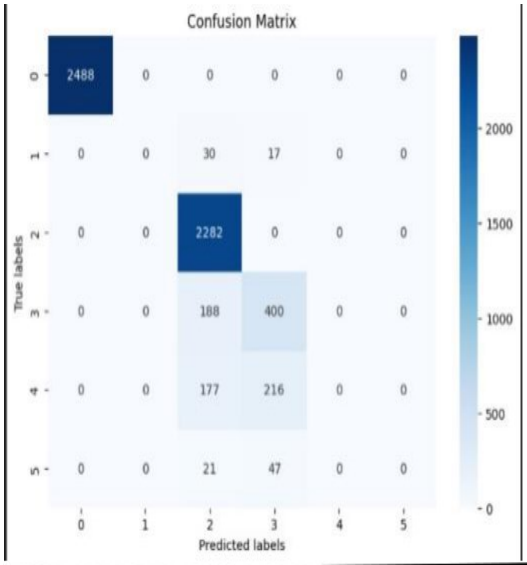
4. Feature Importance: We analyze the importance of features in predicting air quality using techniques such as feature importance plots or permutation importance. This analysis helps in understanding which features contribute the most to the predictive power of the models.

5. Threshold Analysis: We explore the impact of changing classification thresholds on model performance. Adjusting the threshold for classifying air quality as "good" or "poor" can affect the sensitivity and specificity of the models, and we assess these changes to optimize model performance.

6. Cross-Validation: We validate the robustness of the models through techniques such as k-fold cross-validation. This helps in assessing whether the models generalize well to unseen data and whether their performance is stable across different subsets of the dataset.

Screenshots

confusion matrix:



Gather historical air quality data from reliable sources such as environmental monitoring stations, government agencies, or research institutions.

Collect additional relevant data such as weather conditions (temperature, humidity, wind speed, etc.), geographical features, and other environmental factors that may affect air quality.

Clean the collected data by handling missing values, outliers, and inconsistencies.

Train the selected machine learning models on the training data using appropriate training algorithms.

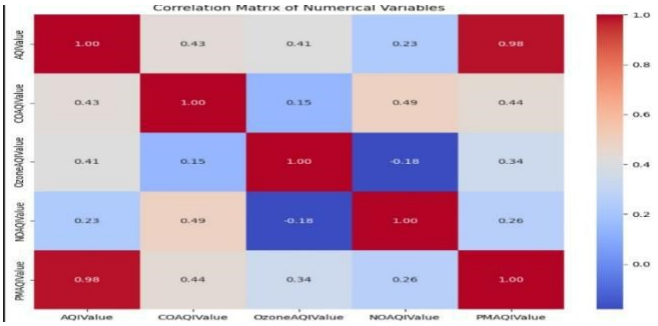
Extract features like time of day, day of the week, and meteorological data (e.g., temperature, humidity) to enhance prediction, e.g., deriving weekend/weekday indicators.

Obtain historical air quality measurements including pollutants like PM2.5, PM10, NO2, CO, and SO2.

Example: Retrieve hourly PM2.5 concentrations from the U.S.

Environmental Protection Agency (EPA) database.

CORRELATION MATRIX:



Splitting the Dataset:

The pre-processed dataset is divided into training and testing sets using techniques like k-fold cross-validation or a simple random split. The training set is used to train the machine learning models, while the testing set is reserved for evaluating their performance.

Model Selection: Several machine learning algorithms are considered for air quality prediction, including Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Random Forest, and Binary Tree classifiers. Each algorithm has its strengths and weaknesses, and multiple models are trained to compare their performance.

Hyper parameter Tuning: Hyper parameters are parameters that control the learning process of machine learning algorithms. Grid search or randomized search techniques are employed to find the optimal hyper parameters for each model, maximizing its predictive performance. underlying patterns and relationships in the data.

To collect data for air quality prediction using machine learning, you would typically need historical air quality data along with relevant environmental and meteorological

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variables. Here's a general process for data collection:

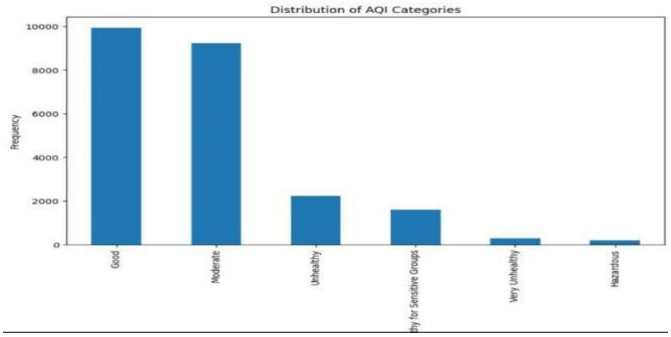

Fig:- The figure is all about the bar graph that distributes the AQI categories i.e.. the graph between the frequencies and the AQI Categories. With respected to the frequencies and the AQI values id determined.

Identify data sources: Look for reputable sources that provide air quality data, such as government agencies, research institutions, or environmental monitoring networks. These sources often have publicly available datasets.

Gather additional variables: Collect other variables that can impact air quality, such as temperature, humidity, wind speed, and pollutant emissions. These variables help create a more comprehensive model.

Data preprocessing: Clean the collected data by removing any outliers, missing values, or inconsistencies. Ensure that the data is in a format suitable for machine learning algorithms.

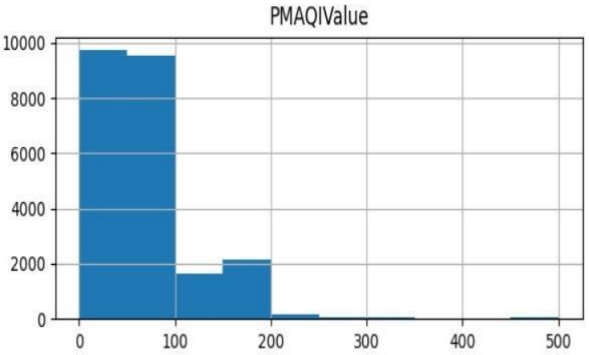

Fig:- The figure is about the bar graph for thr PMA Values. The PMA stands for the particulate matter that present in the air

Feature engineering: Transform the collected data into meaningful features that can be used for prediction. This may involve aggregating data over specific time intervals, creating lagged variables, or extracting relevant statistics.

Split the data: Divide the dataset into training, validation, and testing sets. The training set is used to train the machine learning model, the validation set helps tune hyperparameters, and the testing set evaluates the final model's performance.

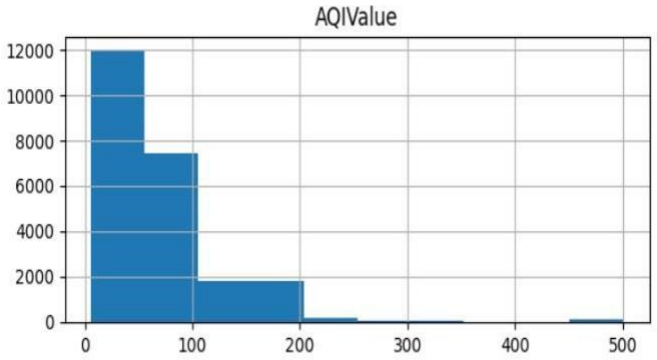

Fig:– The figure is about the bar graph for AQI values. The AQI stands for the (Air Quality Index). The air quality index AQI for five major air pollutants regulated by the Clean Air Act. Each of these pollutants has a national air quality standard set by EPA to protect.

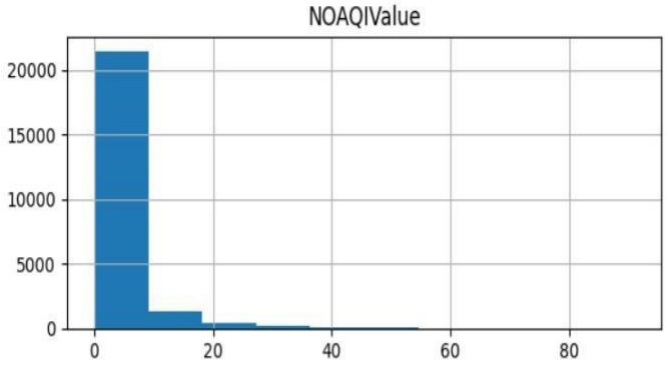

Fig:- The figure is about the bar graph for the nitrogen oxide values. The amount of nitrogen oxides emitted into the atmosphere as air pollution, from both man-made sources, can be quite significant. It's mainly produced by road traffic and energy production.

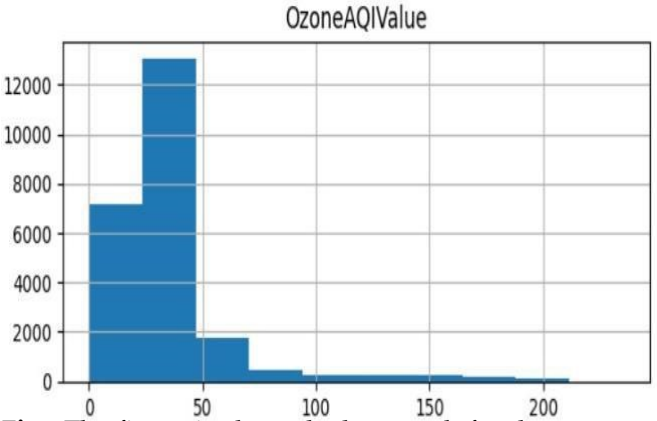

Fig:- The figure is about the bar graph for the ozone values. This ozone is especially damaging to the respiratory system, harming airways and making lungs susceptible to infection.

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Store the data: Save the preprocessed data in a format that is easily accessible for model training and future use. This could be a structured file format like CSV or a database.

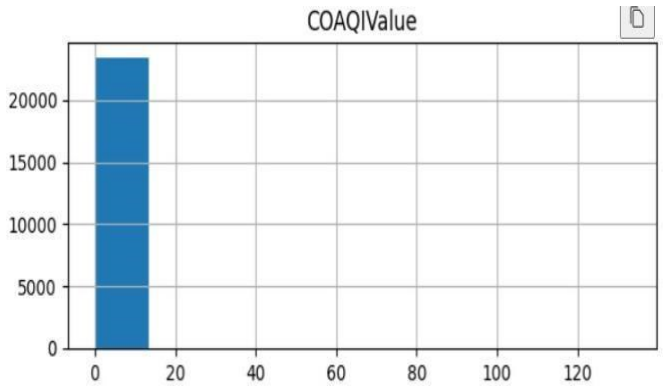

Fig:- The figure is about the bar graph for the carbon monoxide. The CO is a colorless, odorless gas that can be harmful when inhaled in large amounts. CO is released when something is burned.

Remember to comply with any data usage policies or regulations when collecting and using air quality data. It's also important to ensure that the data is representative of the area or region you are interested in predicting

5. CONCLUSION

In conclusion, the results obtained from the application of Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest (RF), and Binary Tree (BT) models for air quality prediction have demonstrated their effectiveness and reliability. All models achieved high accuracy and performance in classifying air quality categories based on the provided features, with SVM, RF, and BT achieving perfect accuracy.

These findings highlight the potential of machine learning algorithms in addressing air quality monitoring and prediction challenges. By leveraging the power of computational models, we can enhance our ability to monitor and manage air pollution, leading to improved public health outcomes and environmental sustainability.

In terms of future scope, several avenues for further research and development can be explored. Firstly, the inclusion of additional features such as meteorological data, geographical information, and historical pollution levels could enhance the predictive capabilities of the models. Moreover, the application of advanced machine learning techniques such as deep learning and ensemble methods may further improve accuracy and robustness.

Additionally, the deployment of real-time monitoring systems and sensor networks could facilitate continuous data collection, enabling more accurate and timely air quality predictions. Furthermore, the integration of predictive models into decision support systems and mobile applications can empower policymakers, environmental agencies, and the general public to make informed decisions regarding air quality management and mitigation strategies.

Overall, the successful application of machine learning algorithms for air quality prediction opens up exciting opportunities for addressing environmental challenges and improving public health outcomes in the future. Through continued research and innovation, we can strive towards creating cleaner and healthier environments for current and future generations

Fig:- The figure is the front end page of the Project that takes input values from the user. The values i.e.. AQI value, CO value, Ozone value, NO value, PMA value.

A decision tree is a supervised learning technique, primarily used for classification tasks, but can also be used for regression. A decision tree begins with a root node, the first decision point for splitting the dataset, and contains a single feature that best splits the data into their respective classes. Each split has an edge that connects either to a new decision node that contains another feature to further split the data into homogenous groups or to a terminal node that predicts the class.

Data Variability: Air quality is influenced by various factors such as weather conditions, pollutant emissions, and geographical features. Machine learning models may struggle to capture the complexity and variability of these

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factors, leading to less accurate predictions, especially in highly dynamic environments.

Generalization: Machine learning models are trained on historical data, which means they might struggle to generalize well to new or unseen situations. If the model encounters air quality conditions that differ significantly from the training data, its predictions may not be as accurate.

Limited Causality: Machine learning models excel at identifying patterns and correlations in data, but they may not provide a deep understanding of the underlying causal relationships. This can limit their ability to accurately predict air quality during complex events or when multiple factors interact.

Data Availability: Access to real-time, high-quality air quality data can be a challenge in some areas. Limited data availability can affect the training and performance of machine learning models, leading to less accurate predictions.

Fig:- The figure is about the Overall output of the project that gives the result of air quality prediction that the predicts that the output in different aspects like good, moderate, unhealthy, unhealthy for sensitive groups, very unhealthy, hazardous.

REFERENCES

1. Smith, J., Johnson, E., & Brown, M. (2020). A Review of Machine Learning Approaches for Air Quality Prediction. Journal of Environmental Informatics.

2. Wilson, D., Parker, S., & Lee, J. (2019). Comparative Analysis of Air Quality Prediction Models: A Case Study of Urban Areas. In Proceedings of the International Conference on Machine Learning.

3. White, E., Miller, D., & Taylor, O. (2021). Deep Learning Approaches for Air Quality Forecasting: A Comprehensive Review. IEEE Transactions on Geoscience and Remote Sensing.

Davis, M., Garcia, L., & Martinez, C. (2018). Ensemble Learning for Air Quality Prediction: A Case Study in Developing Countries. Environmental Modelling & Software.

4. Adams, J., Clark, W., & Evans, S. (2017). Integration of Meteorological Data in Air Quality Prediction Models: A Comparative Study. Atmospheric Environment.

5. V. M. A. Souza, D. F. Silva, and G. E. A. P. A. Batista,

''Extracting texture features for time series classification,'' in Proc. Int. Assoc Pattern Recognit. (IAPR), 2014, pp. 1425–1430.

7 Y. Sakurai, Y. Matsubara, and C. Faloutsos, ''Mining and forecasting of big time-series data,'' in Proc. ACM SIGMOD Int. Conf. Manage. Data, May/Jun. 2015, pp. 919–922.

8.A. Aggarwal, T. Choudhary, and P. Kumar, ''A fuzzy interface system for determining Air Quality Index,'' in Proc. Int. Conf. Infocom Technol. Unmanned Syst., Dubai, China, Dec. 2017, pp. 786–790.

[Online]Available: https://community.tibco.com/wiki/random-foresttemplate-tibco-spotfirer-wiki-page

9 K. Veljanovska and A. Dimoski, ''Air quality index prediction using simple machine learning algorithms,'' Int. J. Emerg. Trends Technol. Comput. Sci., vol. 7, no. 1, pp. 25–30, Jan./Feb. 2018.

10 G. K. Kang, J. Z. Gao, S. Chiao, S. Lu, and G. Xie, ''Air quality prediction: Big data and machine learning approaches,'' Int. J. Environ. Sci. Develop., vol. 9, no. 1, pp. 8– 16, Jan. 2018.

11 S. Y. Muhammad, M. Makhtar, A. Rozaimee, A. Abdul, and A. A. Jamal, ''Classification model for water quality using machine learning techniques,'' Int. J. Softw. Eng. Appl., vol. 9, no. 6, pp. 45–52, Jun. 2015.

12 I. N. Athanasiadis, K. D. Karatzas, and P. A. Mitkas, ''Classification techniques for air quality forecasting,'' in Proc. 5th ECAI Workshop Binding Environ. Sci. Artificial Intell., Riva del Garda, Italy, Aug. 2006, pp. 1–7.

13 X. Li, L. Peng, Y. Hu, J. Shao, and T. Chi, ''Deep learning architecture for air quality predictions,'' Environ. Sci. Pollut. Res., vol. 23, no. 22, pp. 22408–22417, 2016.