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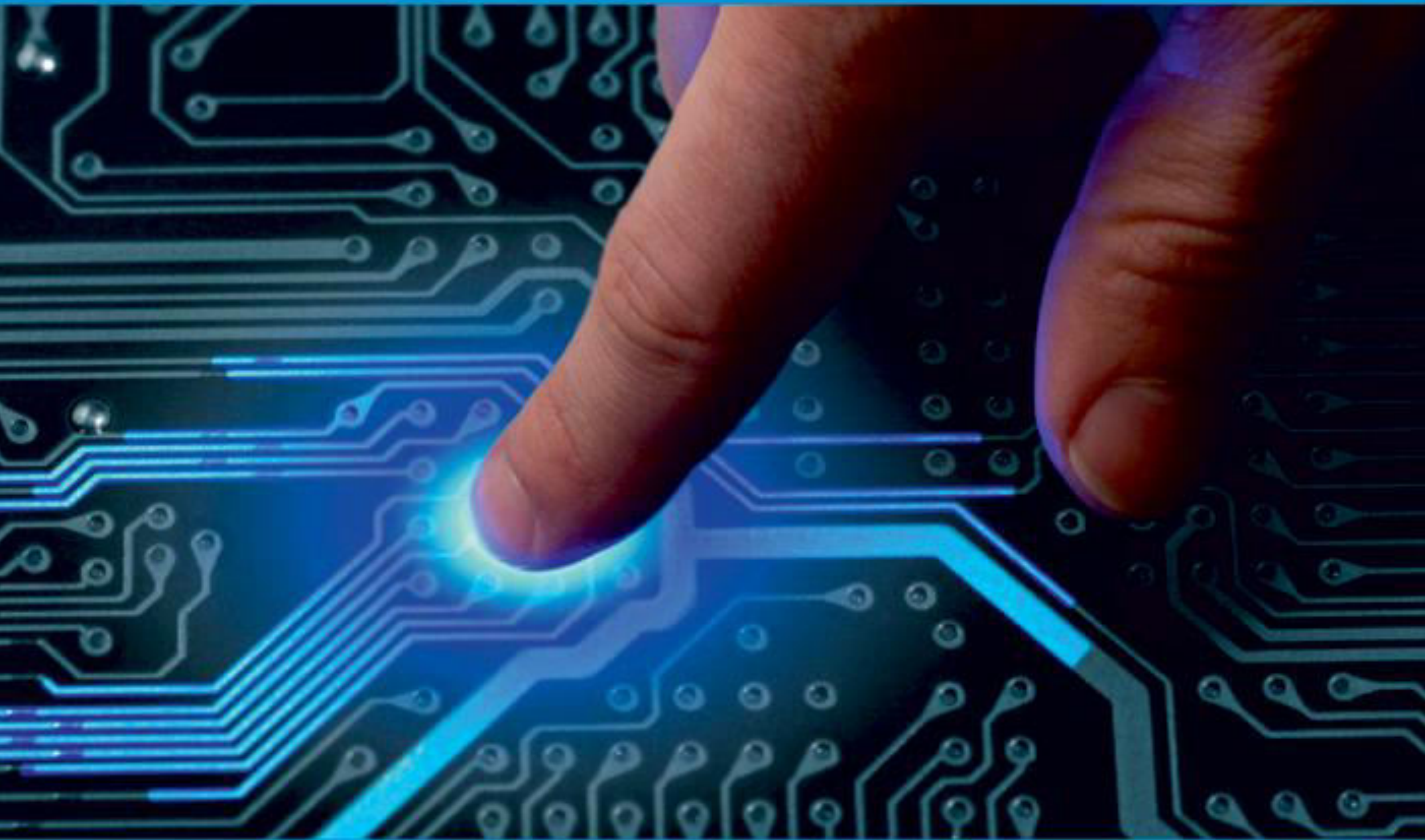

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Detection and Prediction of Air Pollution Using Machine Learning Models

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ABSTRACT - The regulation of the air is seen as a major responsibility by governments in developed and densely populated nations. The consuming of petroleum derivatives, traffic designs, and modern elements like power plant outflows all altogether affect air contamination. Among all the particles that have an impact on air quality, particulate matter (PM 2.5) requires more attention. People's health suffers greatly when its concentration in the air is high. As a result, regularly monitoring its level in the atmosphere is essential for controlling it. In this study, we use logistic regression to see if a data sample is polluted. In light of the past PM2.5 readings, autoregression is utilized to gauge future PM2.5 levels. We can lower the level of PM2.5 below the dangerous range if we know what it will be in the coming months, weeks, or years. This system tries to predict PM2.5 levels and determine air quality using a data set that includes daily atmospheric conditions in a particular city.

KEYWORDS*:* Pollution detection, Pollution Prediction, RF Regression, RF Classifier, Autoregression

I. INTRODUCTION

Both naturally occurring and man-made particles can exist. Examples include ash, sea spray, and dust. When solid or liquid fuels are burned for power production, home heating, or in car engines, particulate matter (including soot) is released into the air. The size of the particles varies (i.e. the diameter or width of the particle). PM2.5 is the term used to describe the mass of airborne particles with a diameter of less than 2.5 micro-meters (m) per cubic meter of air[13]. PM2.5, or fine particulate matter, is another name for it (2.5 micro-meters is one 400th of a millimeter). Because fine particulate matter (PM2.5) poses a serious threat to public health when airborne levels are elevated, it is an important component of the pollutant index. When levels are high, PM2.5, or particulate matter 2.5, reduces visibility and gives the air a hazy appearance. On the basis of a data set made up of daily atmospheric conditions, various machine learning models have been used to identify air pollution and forecast PM2.5 levels.

Modern human activities inevitably involve energy usage and its effects. The burning of straw, coal, and kerosene are only a few examples of the anthropogenic sources of air pollution, along with emissions from factories, cars, planes, and aerosol cans. Every day, a wide range of harmful pollutants, including CO, CO2, Particulate Matter (PM), NO2, SO2, O3, NH3, and Pb, are discharged into our environment.

The health of people, animals, and even plants is impacted by the chemicals and particles that make up air pollution. Humans are susceptible to a wide range of dangerous illnesses brought on by air pollution, including pneumonia, lung cancer, heart disease, and bronchitis.

Smog, aerosol production, impaired vision, global warming, acid rain, early mortality, and other current environmental problems are all caused by poor air quality. Scientists have recognized that air pollution has the potential to negatively impact historic sites. The atmospheric emissions from factories and power plants, as well as exhausts from agricultural and other sources, are to blame for the rise in greenhouse gases. The greenhouse gases have a negative impact on the climate, which in turn affects how quickly plants develop. Plant-soil interactions are also impacted by emissions of greenhouse gases and inorganic carbons. In addition to having an impact on people and animals, climatic changes also have a significant impact on agricultural factors and productivity.

The related repercussions also include financial losses. A measurement metric known as the Air Quality Index (AQI) has a direct connection to public health. An International Journal of Environmental Science and Technology 1 3 higher AQI level denotes a population at risk of more exposure. Therefore, the desire to accurately anticipate the AQI drove scientists to track and model air quality. With an increase in industrial and motorized activity, monitoring and forecasting AQI, particularly in metropolitan areas, has become an essential and difficult undertaking. Though the concentration of the deadliest pollutant, PM2.5, is shown to be multiplied in developing countries, the majority of air

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quality studies and research efforts focus on these nations. A few researchers attempted to do the study of Indian city air quality prediction. Following a review of the research, it was decided that study and prediction of the AQI for India would be a good way to close this gap.

1.1 Work Related to This:

The idea of using machine learning algorithms to forecasts of air quality has been explored in a great number of earlier research. Researchers from time to time have attempted to predict objectives by breaking them down into discrete tiers. Elaborated effects on air pollution only from meteorological features such as temperature, wind, precipitation, solar radiation, and humidity; also classified air pollution into different levels (low, med, high, and alarm) by using a lazy learning approach, the case-based reasoning (CBR) system. This system is a type of inductive learning.
On the basis of meteorological characteristics and other pollutants such as SO2, NO, NO2, and so on, used the -fuzzy lattice neuro-computing classifier to predict and categorize O 3 concentrations into three levels: low, mid, and high. These levels were determined by the classification of O 3 concentrations.

Problem Statement

Air contamination is one such structure that alludes to the pollution of the air, regardless of inside or outside. It occurs when pollutants enter the atmosphere and pollute the air, making it difficult for humans, animals, and plants to survive. The atmosphere is made up of a collection of gases that help all living things survive. Changes in these gases can cause an imbalance that can be detrimental to survival.

II. LITERATURE REVIEW

Application of an SVM-based regression model to the air quality study at local scale in the Avilés urban area (Spain) A. Suárez Sánchez, Elsevier 2021
A support vector machine (SVM) technique-based regression model of air quality for the Spanish city of Avilés will be locally scaled in this study. A hazardous air pollutant or toxic air contaminant is a substance that poses a current or potential risk to human health or that has the potential to increase mortality or serious illness. An exceptionally nonlinear model of the air quality in the Avilés metropolitan core (Spain) in view of SVM methods is created utilizing exploratory information of nitrogen oxides (NOx), carbon monoxide (CO), sulfur dioxide (SO2), ozone (O3), and dust (PM10) for the years 2006-2008. One of the objectives of this model is to estimate at the local scale the relationship between primary and secondary pollutants in the Avilés metropolitan area. The second objective is to identify the factors that have the greatest impact on air quality so that lifestyle and health modifications can be suggested. The major air pollutants' limit values are set by the United States' National Ambient Air Quality Standards (NAAQS) to safeguard healthy individuals' health. The expression "measures contaminations" applies to them. The fundamental concepts of statistical learning theory are incorporated into this support vector regression model in order to accurately anticipate the connections that exist between the primary pollutants in the urban area of Avilés. On the basis of these numerical calculations, the work's conclusions are then drawn using the support vector regression (SVR) method.

An LSTM-based aggregated model for air pollution forecasting Yue-Shan Changa, Hsin-Ta Chiao, Atmospheric Pollution Research, Elsevier 2020

Due to its negative effects on people's health and wellbeing, severe air pollution has recently attracted attention on a global scale. As a result, there is a lot of interest among researchers in the analysis and forecasting of air pollution. Deep learning, neural networks, and conventional machine learning are among the research fields. It becomes crucial to determine how to effectively and properly predict air pollution.

We suggest an Aggregated LSTM (Long Short-Term Memory) model (ALSTM) in this research that is based on the LSTM deep learning technique. In this new model, we incorporate the stations for regional pollution sources, surrounding industrial regions, and local air quality monitoring stations. We combine three LSTM models into a predictive model for early forecasts based on information from adjacent industrial air quality stations and other sources of pollution in order to increase prediction accuracy. Then used the Taiwan Environmental Protection Agency's data with 17 attributes from 2012 to 2017 as the training data to create the ALSTM forecasting model, and we tested the model using the data from 2018. We tested our new ALSTM model in comparison to SVR (Support Vector Machine based Regression), GBTR (Gradient Boosted Tree Regression), LSTM, etc., in the prediction of PM2.5 over 1–8 hours,

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and we assessed them using a variety of assessment approaches, including MAE, RMSE, and MAPE. The outcomes show that the suggested aggregated model can significantly increase prediction accuracy.

Spatiotemporal prediction of air quality based on LSTM neural network Dewen Seng, Qiyan Zhang, Alexandria Engineering Journal, and Elsevier 19 December 2020

For our daily lives, accurate air quality monitoring is crucial. We can limit the hazard to human life by issuing prompt warnings and taking other precautions by anticipating the air quality. The deep learning-based air quality prediction is thoroughly investigated using a vast amount of environmental data. A comprehensive prediction model with multi-output and multi-index of supervised learning (MMSL) was presented based on long short-term memory (LSTM). The meteorological data, the gaseous pollutant data in the air (mostly CO, NO2, O3, SO2), the particle concentration data (primarily PM2.5, meaning particles with aerodynamic dimension 2.5 mm) of the current monitoring station, as well as that of the closest neighbor stations, were merged. All data were standardized and translated to the supervised learning format. To forecast the values of the air quality pollution indicators (PM2.5, CO, NO2, O3, SO2), the LSTM was trained.

In the current study, the representative stations from among the 35 monitoring stations in Beijing were chosen. The representative stations' air quality sequences, which had various data characteristics, were then input into the model to obtain the predicted concentration values of the representative stations' air quality indicators. The average value was then calculated as the result of Beijing's overall air quality prediction. The performance of the model in comparison to other baseline models and the two most advanced models was validated using the air quality time series datasets gathered from 35 air quality monitoring stations in Beijing between January 1, 2016, and December 31, 2017. The performance of the current model is often superior to other baseline models, according to experimental findings.

Artificial neural networks forecasting of PM2.5 pollution using air mass trajectory based geographic model and wavelet transformation Xiao Feng, Atmospheric Environment, Elsevier 11Feb2015

In order to increase the artificial neural networks (ANN) forecast accuracy of daily average PM2.5 concentrations two days in advance, an unique hybrid model incorporating air mass trajectory analysis and wavelet processing is proposed. 13 separate air quality monitoring stations in Beijing, Tianjin, and the province were used to create the model (Jing-Jin-Ji area). In order to identify discrete pathways for the transportation of "dirty" air and "clean" air to chosen stations, the air mass trajectory was used. Based on air mass trajectories and the distances between nearby sites, a triangular station net was built for each corridor.

This trajectory-based air pollution indicator value was calculated taking into account the wind speed and direction. A few sub-series with lower variability were created via wavelet processing from the original time series of PM2.5 concentration. Each of them was subjected to the prediction approach, which then combined the outcomes of each forecast. A multi-layer perceptron (MLP) type back-propagation neural network was utilized as the input, and the variables used to predict the daily weather as well as the corresponding pollutant predictors were employed as output. Between September 2013 and October 2014, the experimental verification of the suggested model was carried out over a period of more than a year. It has been discovered that the wavelet transformation and trajectory-based geographic model can both be useful techniques for increasing the precision of PM2.5 forecasts. The hybrid model's root mean squared error (RMSE) can typically be decreased by up to 40%. Wavelet decomposition is used in particular to almost predict high PM2.5 days, and the detection rate (DR) for a given warning level of a hybrid model can reach 90% on average. This method demonstrates the potential for use in the air quality forecasting systems of other nations.

Improving the prediction of air pollution peak episodes generated by urban transport networks Mario Catalano, Environmental Science & Policy, Elsevier 2015

The study of the results shows that combining the two models into an ensemble is the most effective way to anticipate extreme concentrations. The ARIMAX model predicts peaks better than the neural network, but it more accurately depicts how the concentration depends on the features of the wind. In order to strengthen the ARIMAX model specification and emphasize the relevant functional forms, the Neural Network can be used. In the end, the study demonstrates that requiring traffic management measures when the expected concentration surpasses a lower threshold than the normative one can improve the ability to foresee exceedances of legal pollution limits.

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A time series forecasting based multi-criteria methodology for air quality prediction Raquel Espinosa, Applied Soft Computing, Elsevier 7 September 2021

A lot has been written about how to create and assess models of environmental pollution, particularly in the atmosphere. The focus of current and recent models, however, is on elucidating the causes and their temporal linkages rather than thoroughly examining the performances of pure predicting models. We take into account three years' worth of data that show hourly nitrogen oxide levels in the air because it has been shown that exposure to excessive levels of these pollutants may contribute to a number of respiratory, circulatory, and even nervous illnesses. For each measurement, nitrogen oxide concentrations are combined with weather information and statistics on vehicle traffic. We suggest an approach based on exactness and robustness standards to contrast various pollutant forecasting models and their features. Different window sizes are examined for 1DCNN, GRU, and LSTM deep learning models, as well as regression models for Random Forest, Lasso Regression, and Support Vector Machines. As a result, our most accurate models provide a highly accurate prediction of the concentration of pollutants in the air in the area under consideration 24 hours in advance. This prediction may be used to plan and carry out various interventions and steps to lessen the effects on the population.

A machine learning-based model to estimate PM2.5 concentration levels in Delhi's atmosphere Saurabh Kumar, Shweta Mishra, and Science Direct 2020

The air quality in Delhi, the capital of India, has been dangerous for a number of years. Asthma and other breathing-related issues have been identified in many persons. The main cause of this has been the atmosphere's high concentration of potentially fatal PM2.5 particles. In order to protect the locals from numerous health-related disorders, a decent model that can predict the concentration level of these dissolved particles may help to better equip the people with prevention and safety measures. By using time series analysis and regression using a variety of atmospheric and surface parameters, including wind speed, air temperature, pressure, and others, this work intends to forecast the PM2.5 concentration levels in various parts of Delhi on an hourly basis. The Indian Meteorological Department has put up several weather monitoring stations throughout the city to provide the data for the analysis (IMD). It is suggested to utilize Extra-Trees regression and AdaBoost for further boosting in a regression model. Experimental work is conducted to compare with recent efforts, and the findings show that the suggested model is effective.

Regional air quality forecasting using spatiotemporal deep learning S Abirami, P Chitra, Journal of Cleaner Production, Elsevier 2021

Accelerated urbanization and industrialization have led to poor air quality, threatening lung health. Monitoring, modeling, and forecasting air quality can raise awareness and protect people from air pollution. Various air quality monitoring stations monitor a region's air quality. These stations' air quality data are highly dynamic, nonlinear, and stochastic. Deep learning methods that can abstract data well capture its spatiotemporal properties. DL-Air is a hierarchical deep learning model that forecasts air quality. The encoder encodes geographical data relationships. The second component, STAA-LSTM, identifies temporal relations and the amount of relationship between detected spatiotemporal relation and forecast. The STAA-LSTM predicts latent space spatiotemporal linkages. Decoder decodes these relations to get the actual forecast. The proposed methodology was used to anticipate Delhi's air quality. DL-Air has 30% lower RMSE and MAE, 37% lower AAD, 11% higher R2 and 8% greater AQI category prediction accuracy than baseline techniques. DL-predicted Air's performance is stable across Delhi's seasons.

A model for particulate matter (PM2.5) prediction for Delhi based on machine learning a approaches, Adil Masooda , Kafeel Ahmad, Science Direct 2020

The exposures have caused significant negative effects on people's health. As a result, it is essential to be able to make precise predictions regarding the magnitude of PM2.5 concentrations in order to formulate emission reduction plans for the control of air quality. In light of this, just a handful of machine learning strategies have been utilized to attempt to forecast the daily concentrations of PM2.5 in Delhi. On the basis of the inputs of a wide variety of meteorological and pollutant parameters corresponding to the period of two years spanning 2016-2018, two distinct models, namely SVM and ANN, were constructed. The performance evaluation of the models for predicting PM2.5 has been carried out, and the results have been talked about.

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Potential of machine learning for prediction of traffic related air pollution An Wang, Junshi Xu, Transportation Research Part D, Science Direct 2020

The land use regression (LUR) method has been extensively utilized in the investigation of the spatial distribution of air pollution. However, addressing non-straight communications and provincial foundations with direct strategies may be challenging. Machine learning methods have recently been used to predict air quality. Utilizing information from a versatile mission of fine particulate matter and dark carbon in Toronto, Canada, this study examines the restrictions of LUR approaches as well as the capability of two unmistakable AI models — Counterfeit Brain Organizations (ANN) and slope support.
The data was collected during the course of the study. In addition to that, a moving camera was utilized to record the traffic in real time. The performance of the models that were built for fine particulate matter was superior to those that were developed for black carbon. Machine learning demonstrated higher performance compared to LUR for the same pollutants, suggesting that LUR performance may benefit from an understanding of how explanatory factors were portrayed in machine learning models. This study investigates the performance of various models in the context of how they capture the relationship between air quality and various predictors in order to shed light on the black-box nature of machine learning algorithms. Specifically, this research looks at how well these models capture the relationship between air quality and various predictors.

Objectives

- The primary objective is to develop a machine learning model that predict and detect air pollution or quality.
- This system attempts to predict PM2.5 level and detect air quality based on a data set consisting of daily atmospheric conditions in a specific city.
- The outcomes demonstrate the way that AI models (calculated relapse and straight relapse) can be effectively used to distinguish the nature of air and anticipate the degree of PM2.5 later on.
- The proposed system will help common people as well as those in the meteorological department to detect and predict pollution levels and take the necessary action in accordance with that.

III. SYSTEM DESIGN

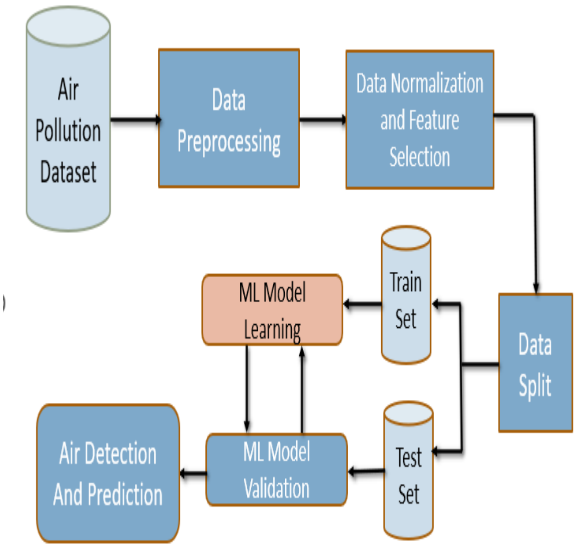

Figure1.1: System Design Diagram

Algorithm steps

- Step 1: Read the dataset.
- Step 2: Data pre-processing and remove Nan values From dataset.
- Step 3: Divide the dataset into two parts i.e., Train dataset and Test dataset.

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- Step 4: Feature selection are applied for the proposed models.
- Step 5: Accuracy and performance metrics has been calculated to know the efficiency for algorithms.
- Step6: Then retrieve the best algorithm based on efficiency for the given dataset

IV. RESEARCH METHODOLOGY

The term "machine learning" refers to an automated procedure for extracting patterns from a dataset. Predictive data analytics is the science of creating and applying models that use patterns found in historical data to make predictions.

Algorithm:

A. Random Forest Algorithm

The supervised learning method includes the well-known Random Forest machine learning algorithm. In ML, it can be used for both problems involving classification and regression..

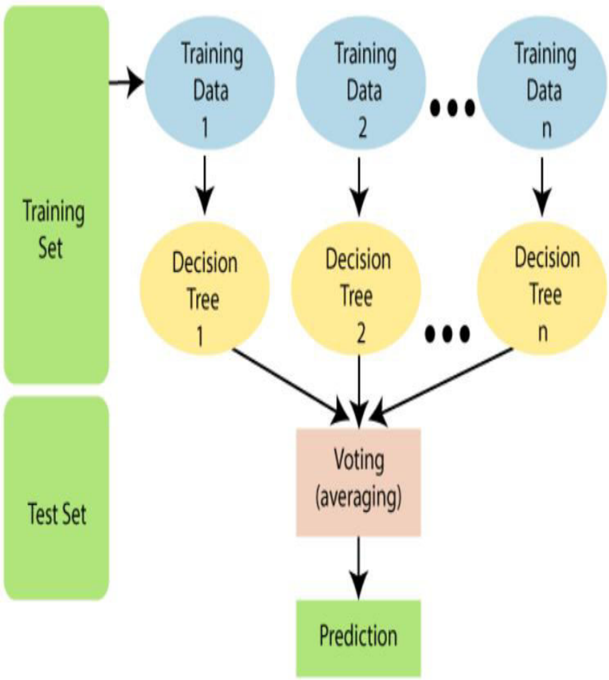

Figure1.2: Random Forest Algorithm

Assumptions for Random Forest:

It's possible that some decision trees will correctly predict the output, while others won't because the random forest combines multiple trees to predict the dataset's class. However, together, every one of the trees foresee the right result. As a result, a better Random forest classifier is based on the following two assumptions:

The classifier will be able to come up with accurate predictions rather than guesses if there are some actual values in the dataset's feature variable. There must be very low correlations between each tree's predictions.

Working of Random Forest Algorithm:

We need to investigate the ensemble learning method before we can comprehend how the random forest algorithm in machine learning works.
Ensemble implymeans combining multiple models; thus a collection of models is used to make predictions rather than an individual model.

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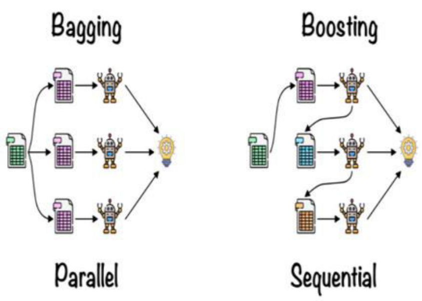
Ensemble uses two types of methods:



1. **Bagging**– It makes an alternate preparation subset from test preparing information with substitution and the last result depends on greater part casting a ballot. Random Forest, for instance
2. **Boosting**– It creates sequential models that combine weak learners with strong learners to produce the most accurate final model. For instance, ADA Lifts, XG Lift.

Training algorithm

For Air prediction, there are several different optimization algorithms used models development.

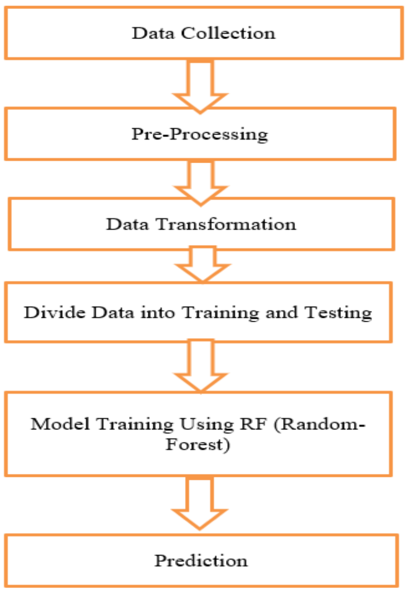


Fig 1.3: The Training Architecture

Construction of models

I) **Data Preprocessing**
1) Noise Removal

Due to the potential for inaccurate results from noisy data, this is crucial for making the data useful. The telecom dataset contains numerous imbalance attributes, incorrect values such as "Null," and missing values.

2) Feature selection

Feature Selection is a crucial step for selecting the relevant features from a dataset based on domain knowledge. A number of techniques exist in the literature for feature selection in the context of churn predictions.

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Ii) Training the Network

The primary goal of training is to minimize an error using error techniques. In this Project We will training machine learning model using random forest algorithm. this is classifier and regression algorithm .

Iii) Testing

Through this process, the RF fined the predicted and compares it with the input values using data that was not used in training or validation process. At this stage no adjustment occurs to weights.

Performance Evaluation Matrix:

In this study, the proposed churn prediction model is evaluated using accuracy, precision, and recall, f-measure, and ROC area. Equation 1 calculates the accuracy metric. It identifies a number of instances that were correctly classified.

Accuracy = (TP + TN) (TP + TN + FP + FN) …….(1)

Here ‘‘TN’’ stands for True Negative,
‘‘TP’’ stands for True Positive,
“FN’’ stands for False Negative and
‘‘FP’’ stands for False Positive.
TP Rate is also known as sensitivity. It tells us what portion of the data is correctly classified as positive.

For any classifier, the TP rate must be high. TP rate is calculated by using Equation 2.

TP Rate = True Positives Actual Positives……….. (2)

FP Rate tells us which part of the data is incorrectly classified as positive. The result of the FP rate must be low for any classifier. It is calculated by using Equation3.

FP Rate = False Positives Actual Negatives……… (3)

Accuracy, also known as Positive Predictive Value (PPV), indicates which part of the prediction data is positive. It is calculated by using Equation 4.

Precision = True Positive (True Positive + False Positive)…………………………………………… (4)

The recall is another measure for completeness i.e. the true hit of the algorithm. It is the probability that all the relevant instances are selected by the system. The low value of recall means many false negatives. It is calculated by using Equation 5.

Recall = (True Positive) (True Positive + False Negative)………………………………………… (5)

The F-measure value is a trade-off between correctly classifying all the data points and ensuring that each class contains points of only one class. It is calculated by using Equation 6.

F − measure = 2 ∗ Precision ∗ Recall Precision + Recall ……………………………………………(6)

The average performance against all possible cost ratios between FP and FN is represented by the ROC area. This is a flawless prediction if the ROC area value is 1.0. Also, the qualities 0.5, 0.6, 0.7, 0.8 and 0.9 address arbitrary forecast, awful, moderate, great and unrivaled separately. Any values in ROC areas other than these point to a problem.

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V. RESULT

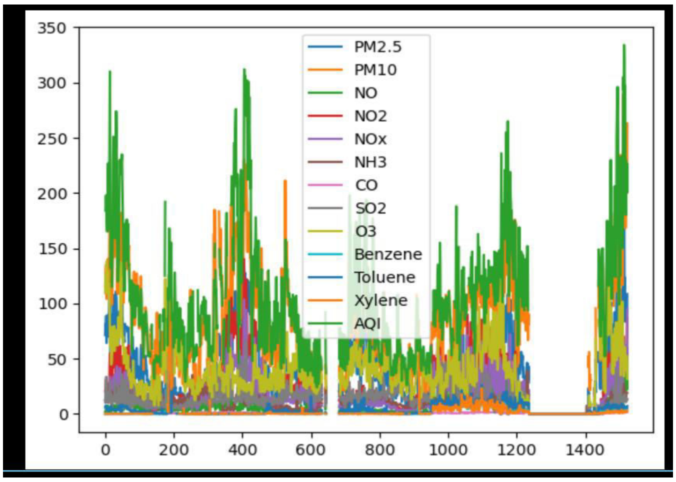

Figure1.4: Over All Data

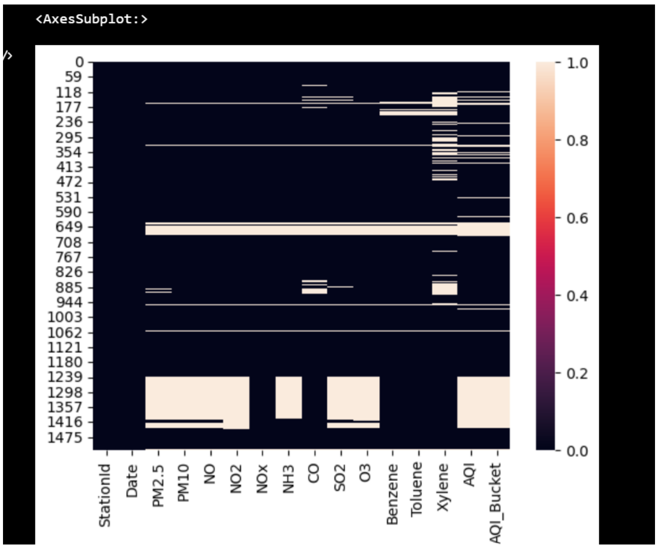

Figure1.5: Noisy Data

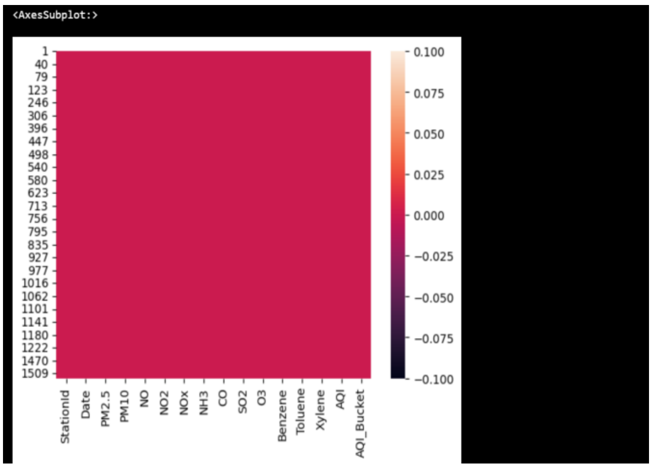

Figure1.6: Clean Data

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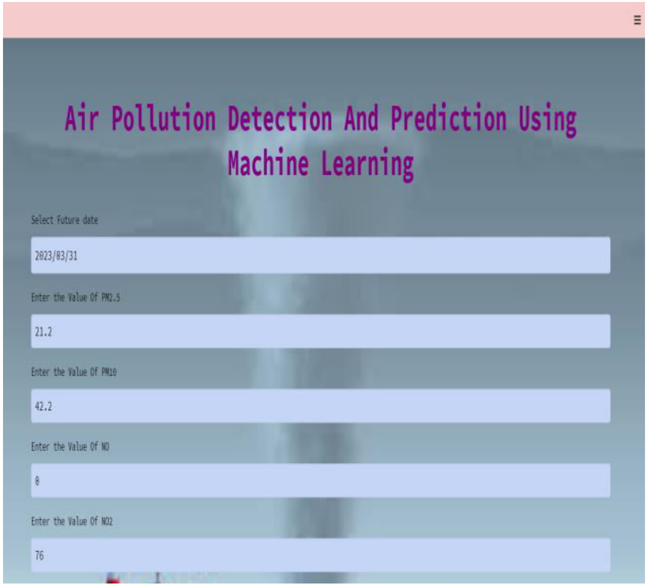
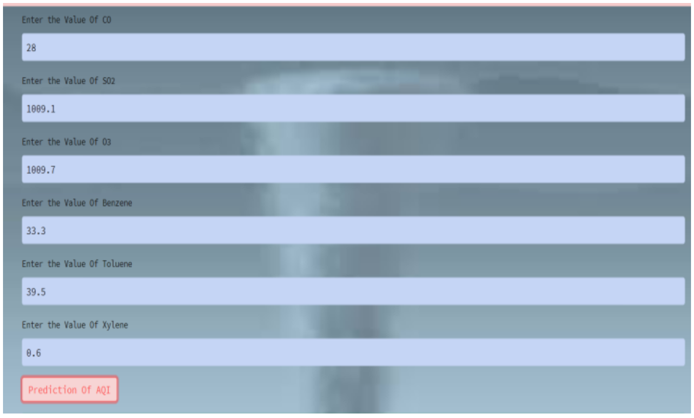
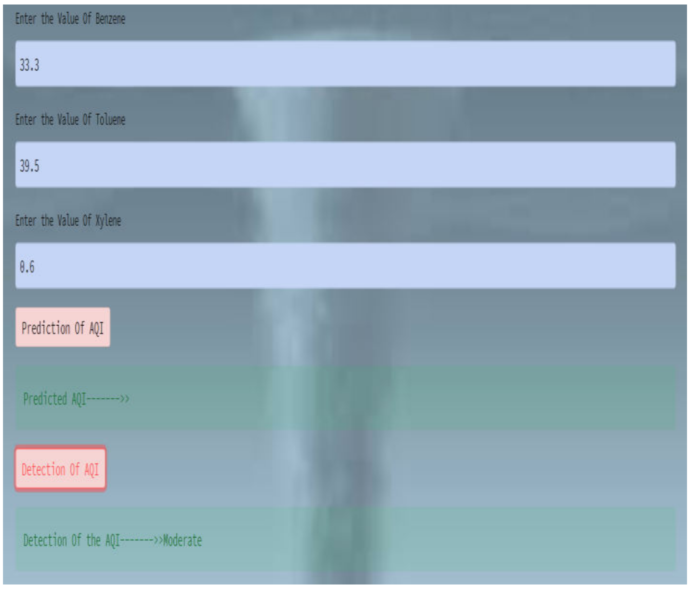
GUI







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