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Air Pollution Hazard Assessment Using Decision Tree

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ABSTRACT:

The quality of air of a given region can be utilised as a primary determinant of air pollutants, as well as how well that the city's industry and population are controlled. With the development of industrialisation, monitoring urban air quality has become a persistent issue. All around the world, air quality has remained a severe concern for the government and the public. Air pollution has a notable impact on both the human health and the environment, culminating in acid rain, global climate change, heart problems, and melanoma. Utilizing two Machine Learning Algorithms, this study tackles the problem of forecasting the Air Quality Index (AQI) with the goal of reducing pollution before it becomes a problem.: Random Forest, Decision Tree, and Logistic Regression The Central Pollution Control Board (CPCB), Ministry of Environment, Forest and Climate Change, Government of India, provided the air pollution database. The proposed Machine Learning (ML) approach for predicting the Delhi AQI is impressive. The findings show an increase in predictive performance and imply that the model might be applied to other smart grids.

Keywords: Air pollution, Air Quality index, Machine Learning Algorithms, Neural Network, Support Vector Machine

I. Introduction

When dangerous or excessive quantities of things, such as gases, particles, and organic macromolecules, are injected into the Earth's atmosphere, this is known as air pollution. It has the potential to cause infections, allergies, and even death in humans; and also has the potential to affect other living species such as animals and food crops, as well as degrade the natural or constructed surroundings. Either human influence and geological cycles have the potential to cause harm[1-2].

Throughout the 2008 Blacksmith Institute World's Worst Tainted Places report, indoor air pollution and urban poor interior environmental impact are recognised as two of the world's worst hazardous pollution problems. According to a report published by the World Health Organization in 2014, pollution killed nearly 7 million individuals worldwide in 2012, a figure substantially confirmed by the International Energy Agency [3-5].

Air Pollutants:

An pollution is a substance in the atmosphere that can harm people and the environment. Solid particles, water vapour, or gases can all be used as the material. Pollutants can be either natural or man-made. Pollutants are divided into two categories: main and secondary. Primary pollution is commonly produced by natural activities, including such volcanic activity. Other examples include carbon monoxide emitted by automobiles or sulphur dioxide emitted by industry. Secondary pollutants are not directly emitted. Rather, they develop in the air as a result of the reaction or interaction of primary pollutants. Ozone at ground level is a good informal fallacy pollutant. It's possible that certain contaminants are both descriptive and inferential: They are released both immediately and through the formation of other primary pollutants.

Major Air Pollutants:

- Carbon dioxide (CO_2)
- Sulfur Oxides (Sox)
- Nitrogen Oxides (NOx)
- Carbon Monoxide (MOx)
- Volatile Organic Compounds (VOC)
- PM 2.5 & PM 10

Carbon dioxide (CO_2) –It has been dubbed "the leading pollutant" and "the greatest climate pollution" because to its activity as just a greenhouse gas. Carbon dioxide is a natural lightest element that is required for plant life and is emitted by the respiratory system of humans. This language debate has real-world implications, such as assessing wether the US Clean Air Act is considered to control emissions of co2. CO_2 now makes up around 410 parts per million (PPM) of the earth's atmosphere, opposed to about 280 ppm in post periods, and the burning fossil fuels emits billions of metric tonnes of CO_2 each year. CO_2 levels in the atmosphere have been steadily rising [6-8].

Sulfur oxides (SOx) – specifically, sulphur dioxide (SO_2), a molecular molecule having the formula SO_2. Volcanoes and different industrial activities both produce SO_2. Sulphur molecules are common in coal and petroleum, and their combustion produces Sulfur. H_2SO_4 is formed through further oxidation of SO_2, typically in the presence of catalysts like NO_2. One of the reasons for worry about the impact on the environment of using these fuel as a power supply was that.

Nitrogen oxides (NOx) – Nitrogen oxides, notably nitrogen dioxide, are ejected from elevated burning and created by electric discharge during storms. They appear as a brown hazy dome over cities or as a plume downwind. The chemical molecule nitrogen dioxide has the formula NO_2. It was one of a group of nitrogen oxides. This reddish-brown poisonous gas has a distinctive sharp, biting stench and is one of the most common air contaminants

Carbon monoxide (CO) – CO is a colourless, odourless gas that is both poisonous and non-irritating. It is a byproduct of the flue gas, coal, or wood as a fuel. The bulk of carbon monoxide released into our environment comes from vehicle exhaust. It causes a smog-like buildup in the air, which has been related to a variety of pulmonary ailments as well as environmental and animal problems. In 2013, automobile traffic generated upwards of half of a carbon monoxide discharged into the air, and one tank of gas can often release more than ten pounds of carbon dioxide into the environment.

Volatile organic compounds (VOC) – Volatile organic compounds (VOCs) are a well-known outdoor air contaminant. They are classified as methane (CH_4) or non-methane (NH_3) (NMVOCs). Methane is a highly effective greenhouse gas that contributes to rising global temperatures. Because of their involvement in producing ozone and extending the life of methane, other hydrocarbon VOCs are also substantial greenhouse gas emissions.. This effect varies depending on the quality of the air in the area. The aromatic NMVOCs benzene, toluene, and xylene are suspected carcinogens that can cause leukaemia in those who are exposed to them for a long time. Another hazardous chemical connected with commercial use is 1,3-butadiene.

Fine Particles (PM 2.5)– PM 2.5 are particles having a diameter of 2.5 micrometers or less that can only be detected under an electron microscope. All sorts of combustion, including automobiles, power plants, domestic wood burning, wild fires, agricultural burning, and also some industrial activities, produce small dust. While PM10's narrative finishes at the airways, PM2.5 can enter our bloodstream and go throughout our body, earning him the moniker "invisible killer." PM10 (Coarse Dust Particles) have a diameter of 2.5 to 10 micrometres. Crushing and grinding processes, as well as dust provoked by vehicles, are all causes. These microscopic particles, nearly 30 times thinner than that of the diameter of a human hair, are tiny enough to get through our protective ear lobes and then into our lung.

II. BACKGROUND STUDY (LITERATURE)

[A] MACHINE LEARNING

AI includes PCs finding how they can perform undertakings without being expressly customized to do as such. AI and information mining regularly utilize similar strategies and cover fundamentally, however while AI centers around expectation, in light of realized properties gained from the preparation information, information mining centers around the revelation of (already) obscure properties in the information (this is the examination step of information disclosure in data sets). Information mining utilizes many AI techniques, however with various objectives; then again, AI additionally utilizes information mining strategies as "solo learning" or as a pre-handling step to improve student exactness. Performing AI includes making a model, which is prepared on some preparation information and afterward can handle extra information to make forecasts. Different kinds of models have been utilized and investigated for AI frameworks.

[B]KEY FINDINGS

Number of papers have been distributed the works which centers around controlling air contamination and following air quality.Insights from not many of the papers refered [9-10].

This paper is inspired to address every one of these difficulties by using the data contained in the unlabeled information and the spatio-worldly information, and performing highlight determination and affiliation investigation for the metropolitan air related information. In spite of the fact that named information are troublesome or costly to get, a lot of unlabeled models can frequently be assembled inexpensively. By and large, unlabeled information can help in giving data to all the more likely endeavor the mathematical design of the information. Additionally, a large portion of the metropolitan air related information contain both existence data. The proposed highlight determination and investigation strategy uncovers the significance of various information highlights to the forecasts of the neural organizations, consequently can uncover some internal instrument of the discovery profound models, which doesn't restrict to air contamination counteraction and control, however can likewise be applied to numerous different applications, like clinical analysis and psychological oppression identification.

[C]GAPS IDENTIFIED

- Time consuming more
- Accuracy is high
- Not user friendly : The existing system is not user friendly because the retrieval of data is very slow and data is not maintained efficiently.
- Time consuming: Every work is done manually so we cannot generate report in the middle of the session or as per the requirement because it is very time consuming.

- Managing a very large

III. METHODOLOGY

The entire hypermedia framework for the Wasp is determined by the System Architecture design. The objectives for a WebApp, the material to be delivered, the users who will visit, and the navigational methodology that has been developed all influence design documentation. The structure of content items for appearance and navigation is referred to as content architectural. The way the app is structured to manage interactivity, manage embedded sensor duties, effect movement, and display content is referred to as WebApp structure. The structure of a WebApp is specified in terms of the application development in which it will be developed [11-15].

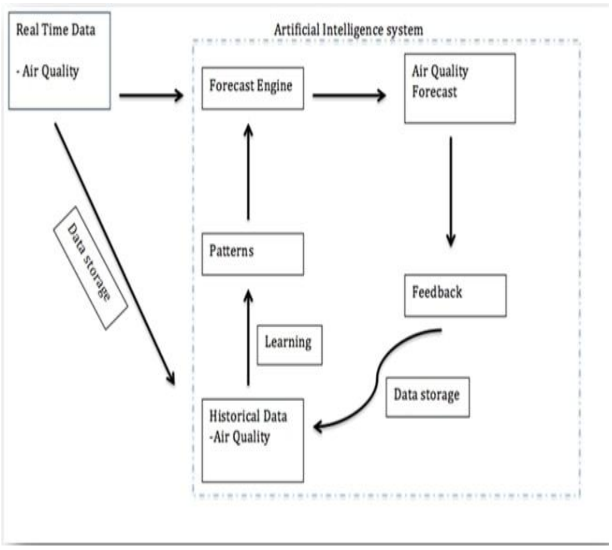

Fig 3.1 System Architecture

IV. IMPLEMENTATION

The implementation in this study consists of the following procedures: data collection and preprocessing, feature selection, time windowing, and model building. All the machine learning models exploited in this study will be constructed on the open-source data mining platform, a software programmed under the python script. In this section, the details of procedures will be discussed respectively.

Data Collection: The main pollutant emissions are due to energy production industry, traffic, waste incineration and agriculture. Six pollutants (O3, PM2.5, PM10, CO, SO2, and NO2) are monitored and controlled based on their concentration time-series. Types of data used as predictors to perform analysis involve AQ: air quality data, MET: meteorological data, and TIME: the day of the month, day of the week, and the hour of the day. From 1 January 2008 to 31 December 2018, air quality data are collected from several monitoring stations across India. The datasets represent different environmental conditions related to air pollutant concentration [16-19].

Data Pre-Processing :The number of raw data points for monitoring stations includes 91,672, 94,453, and 94,145, respectively. The analysis of these readings begins with a crucial phase – data preprocessing. Various preprocessing operations precede the learning phase. At any particular time, one invalid variable will not affect the whole data group, and thus it will just be either marked blank or, where available, replaced by a value sourced from the dataset, without eliminating the full row. The missing values are treated by imputation to recover the corresponding values. Given the lack of spatial proximity of the readings to the original monitoring stations, the missing values are imputed for relative humidity, temperature, and rainfall, without using wind speed or wind direction. Then, input and target data are normalized to eliminate potential biases; thus, variable significance won't be affected by their ranges or their units. All raw data values are normalized to the range of [0, 1].Inputs with a higher scale than others will tend to dominate the measurement and are consequently given greater priority [20-24].

Feature Engineering :In regard to selecting features in the predictive models, the hourly AQI readings with the highest index out of 6 pollutants: O3, PM2.5, PM10, CO, SO2, and NO2 are selected. To convert the time-window-specific concentration of 6 pollutants, the AQI [18] are adopted and the AQI is manually calculated using the following Equations (1) and (2), where index values of O3, PM2.5, and PM10 are needed to define AQI and the lack of one or more of these values will significantly reduce the accurate assessment of current air quality [25-26].

$$AQI = \begin{cases} max\{I_{O3}, I_{PM2.5}, I_{PM10}, I_{CO}, I_{SO2}, I_{NO2}\}, I_{O3}, I_{PM2.5}, I_{PM10} \neq \varnothing \\ \varnothing, otherwise \end{cases} \quad (1)$$

Pollutant concentration ($value_i$) is converted to pollutant index (I_i) by the following formula:

$$I_i = LB_j + \frac{value_i - lb_i}{ub_i - lb_i} \times \left(UB_j - LB_j\right) \quad (2)$$

where i = O3, PM2.5, PM10, CO, SO2, NO2; j denotes which level in AQI system occupied by the concentration of the specific pollutant using categories of good, moderate, unhealthy which includes specific groups, unhealthy, very unhealthy, and hazardous [27-29]. The data transformation defines the time-window-specific concentration to calculate Ii values. For example, based on the AQI, the concentration valueO3 = 0.06 ppm will fall in the interval with lbO3 = 0.055 ppm and ubO3 = 0.070 ppm corresponding to the "moderate" pollutant level with LBmoderate = 51 and UBmoderate= 100. The valueO3 is defined by matching either of two conditions: if the 8-h average concentration is more precautionary for a specific site and is also below 0.2 ppm, then this value is used; otherwise, the 1-h average concentration will be considered. Both valuePM2.5 and valuePM10 are the moving average values which consider two time-windows. Other variables, such as valueCO and valueNO2 only account for a single time window, i.e., last 8 h and 1 h, respectively. Meanwhile, valueSO2 emphasizes the 24-h average concentration if the 1-h average concentration exceeds 185 ppb; otherwise, the 1-h average value will be used. The AQI mechanism introduces several new variables to train the prediction model. For several pollutants, time windows other than hourly are more sensitive in determining AQI; therefore, the prediction interval related to the accuracy of long-term predictions is under investigation to clarify the time dependency between consecutive data points [30-33].

Performance Evaluation: The most used metrics are RMSE (root mean squared error) and MAE (mean average error), calculated based on the difference between the prediction result and the true value, while another metric, R 2 (R-squared) is essential to explain the strength of the relationship between predictive models and target variables [34]. These three metrics provide a baseline for comparative analysis across different parameter settings for each model and across different methods. However, performance validation leads to a bias when the data set is split, trained, and tested only one time. This also means the result drawn from the testing dataset may no longer be valid after the testing subset is changed. To overcome this problem, each model is re-built 20 times using different random subsets of training and testing samples. The splitting proportion remains the same (80:20).All metrics report only a single value from the average performance of 20 identical models validated into 20 different subsets of testing instances [35-40].

V. RESULT

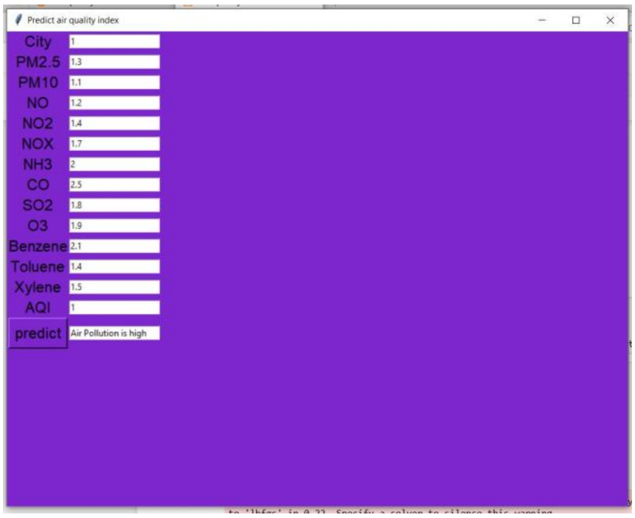

Fig 5.1 Sample Result

It predicts the nature of the air by discovering the level of carbon dioxide, sulfur oxide, nitrogen oxide etc in air. Therefore it find the air pollution is high or low in the preferred city.

VI. CONCLUSION

In view of the bar plots plotted we reach the resolution that a few urban communities are exceptionally contaminated and need critical consideration. Likewise for urban areas like Pune ,Mumbai where convergence of so2 is expanding, we can take measures from now to not deal with issues later. We utilized AR model and ARIMA model for foreseeing upsides of so2. Highlights, for example, area checking station or station code were of no utilization as they don't have anything to do with so2 expectations request to anticipate air quality, pm2_5 is additionally a significant property. The upsides of this should be recorded in future as this particulates are answerable for different wellbeing impacts including cardiovascular impacts, for example, cardiovascular arrhythmias and coronary episodes, and respiratory impacts, for example, asthma assaults and bronchitis. This model can't show expected yield as the information isn't in arrangement according to date section .The equivalent is the issue for urban communities. On the off chance that we anticipate for the whole state, it wont be useful So we will be currently computing AQI and use order models further.

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