

VEHICLE EMISSION DETECTION USING MACHINE LEARNING AND ALERT DETECTION

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ABSTRACT

This project proposes a revolutionary solution to combat air pollution caused by vehicle emissions on roads. The system utilizes Air Quality Detection technology to continuously monitor car emissions, identifying vehicles that exceed emission limits. Through Instant Owner Notification, car owners are promptly informed when their emissions surpass the set limit, encouraging responsible action to reduce their carbon footprint. A Progressive Warning System with escalating consequences incentivizes compliance, and an upcoming Automated Engine Stop mechanism aims to enforce adherence to emission standards. The goal is to create a healthier tomorrow with cleaner air, leading to improved societal well-being.

INTRODUCTION

The popularization of vehicles in our daily life has been continuously enhanced with the expansion of urbanization around the world. Gasoline-engine vehicles are the most popular and widely used type compared with new energy ones, and the pollution gases, such as carbon dioxide, carbon oxide, hydrocarbon, and oxynitride, from vehicles have become the main contaminants in urban atmospheric pollution [1]. Efficient vehicle pollution detection therefore turns to be an emergency task which attracts more and more attention. Exhaust emission detection methods have evolved from periodic detection in the environmental monitoring station to daily road detection with remote sensing technology. This paper studies the vehicle emission detection in cities of China which is one of the largest developing countries.

In the USA, EPA (Environmental Protection Administration) proposed MOVES algorithm [2] to calculate the vehicle emission ratio in some fixed locations and periods of time. The Japanese government enforces the vehicle exhaust emission monitoring system in their country, and the emission behaviour of each vehicle in Japan can be checked on the official website of Japanese national transportation [3]. In order to rapidly capture the emission detection results, a French transport agency collects the emission pollution-related information from different places and puts them together to realize the sharing network for vehicle emission detection [4]. Related researches and works on this area started a bit later in China. In 2011, Cheng et al. [5] made systematic analysis for the harm caused by vehicle emission, verifying the necessities of exhaust emission controlling. Next year, Wu [6] collected the values of CO₂, HC, CO, and NO exhausted by 1092 vehicles in the Xian Yang city using simplified loaded mode. They established regression equations between the emission value and vehicle information and found that the average emission value was highly related with the vehicle acceptability and the age of the vehicle. Referring to the local standards, they further gave a systematic explanation for the rationalization of the local standard mean emission value based on their research. With the development of remote sensing technology, a large amount of practical exhaust emission data can be obtained by environmental protection agencies in China. This paper introduces data mining technology to these valuable data to explore efficient information in vehicle

exhaust emission detection. This research has a huge potential contribution in promoting the environmental protection department's accurate assessment of unqualified vehicles and providing a theoretical basis for policymakers to learn from.

The first successful vehicle emissions demonstration system was probably an across-road vehicle emissions remote sensing system (VERSS) proposed by Gary Bishop and colleagues in the University of Denver in the late 1980s [7, 8]. A liquid nitrogen cooled nondispersive infrared was the first instrument that can only measure CO and CO₂. In the next two decades, their team continuously refined the system: added hydrocarbon, H₂O, and NO channels to their NDIR system [9, 10], integrated an ultraviolet spectrophotometer and improved it to enhance NO measurement, and removed the dependence on the liquid nitrogen cooling [10]. The Denver group designed another commonly used remote sensing device, known as fuel efficiency automobile test, providing some of the inchoate comments on across-road particulate measurement. There are also many other sensing systems typically based on multiple spectrometric approaches proposed for detection of passing vehicle emissions. More recently, Hager Environmental and Atmospheric Technologies introduced an infrared laser-based VERSS named Emission Detection and Reporting (EDAR) system, which incorporated several new functions, making it a particularly interesting system for vehicle emission detection.

Important information is buried in the vehicle emission remote sensing data. This paper exploits data mining methods to deal with the data and obtain valuable knowledge from them. There are three main directions in data mining: the improvements of classical data mining algorithms, ensemble learning algorithms, and data mining with deep learning. The improvements on classical algorithms are usually performed and employed in multiple application scenarios taking additional information into consideration. Ensemble learning is actually the integration of multiple learners with a certain structure which completes learning tasks by constructing and combining different learners. Its general structure can be concluded as follows: firstly, generate a set of individual learners and then combine them with some strategies. The combining strategies mainly include average method, voting method, and learning method. Bagging and boosting [10] are the most commonly used ensemble learning algorithms which improve the accuracy and robustness of prediction models. As the rapid development and popularization of deep learning, it plays more and more important roles in data learning with the support of big data and high-performance computing. Many traffic engineering-related researches mainly focus on analyzing relevant data such as traffic diversion [9], traffic safety monitoring [10], engine diagnosis, road safety [2] and traffic accident [2], and remote sensing image processing, extracting useful information and digging out valuable knowledge. A few works are proposed in vehicle emission evaluation in data mining ways which is the key study subject in this paper. Xu et al. used XgBoost to develop prediction models for CO₂eq and PM_{2.5} emissions at a trip level. In, Ferreira et al. applied online analytical processing (OLAP) and knowledge discovery (KD) techniques to deal with the high volume of this dataset and to determine the major factors that influence the average fuel consumption and then classify the drivers involved according to their driving efficiency. Chen et al. proposed a driving-events-based ecodriving behaviour evaluation model and the model was proved to be highly accurate (96.72%).

Relevant environmental policies have been introduced to define difficult limitation standards based on the vehicle fuel type and registration time in China. The vehicle license plate number, plate color, speed, acceleration, and VSP (vehicle specific power), etc., will be captured by the surveillance system when vehicles pass by the remote survey stations. The analysis for the smoke plume generated by gas emission is simultaneously conducted by laser gears at the stations, where the exhaust emission value can be calculated. With the fuel type and registration time information learned from vehicle plate numbers, it is able to obtain the gas emission standard value to judge whether the vehicle emission is eligible. However, register information of nonlocal vehicles and partial local vehicles is not recorded in the official database due to the limitation of environmental policies, which leads to the failure to provide the fuel type and registration time information for

vehicle emission detection. According to the National Telemetry Standard in China, relevant departments will treat the information-missing vehicles as the diesel consumption ones, and this situation keeps the limitation criteria of the emission value of partial vehicles unknown, resulting in the evaluation for these vehicles being unable to carry on. Therefore, the precise information upon fuel types and registration time of vehicles is an essential prerequisite for finding out the pollution-exceeding vehicles. This paper adopts multiple data mining methods to learn the fuel type and registration information of vehicles from remote sensing data and further utilize cascaded classified framework to make accurate prediction on vehicle emission-related information, providing valuable reference standards on evaluation of different vehicles.

LITERATURE

SURVEY

The advanced diesel emission control catalyst Pt-Pd-MnOx-Al₂O₃ has been developed on the basis of the synergetic effect of Pt with Pd and manganese oxides observed in hydrocarbon and carbon monoxide oxidation reactions. This effect allows a decrease in the total loadings of Pt and Pd down to 0.52g/L in the monolithic catalyst, providing high activity in low temperature oxidation of light hydrocarbons and high thermal stability. The catalytic [2] activity of Pt-Pd-MnOx-Al₂O₃ monolithic catalysts in butane oxidation and DIESEL tests depends on the Pt and Pd precursors, their individual loadings and their ratio (Pt/Pd). For a selected Pt precursor at its content 0.17g/L, the catalytic performance of Pt-Pd-MnOx-Al₂O₃ catalyst improves with an increase in Pd loading from 0 to 0.35g/L and is nearly constant at a higher Pd loading (0.70g/L). The most active monolithic Pt-Pd-MnOx-Al₂O₃ catalyst is prepared by using platinum-dinitrodiamine and palladium nitrate solutions as noble metal precursors. The catalytic activity in light hydrocarbon oxidation is shown to correlate with the RedOx properties of PdPt-MnOx-Al₂O₃ catalysts and the Pt-Pd particle size. The non-additive increase in the catalytic activity of bimetallic catalyst is suggested to connect with a formation of nanoscale PdO-PtOx particles on the surface of Mn₃O₄ and a modification of alumina structure by Mn³⁺ and PtPd cluster.

Optimization of Catalyst Composition:

Despite advancements in diesel emission control catalysts, there's a need to optimize the composition of Pt-Pd-MnOx-Al₂O₃ [5] catalysts to achieve maximum efficiency in reducing emissions. This includes investigating the influence of Pt and Pd precursors, their individual loadings, and their ratio on catalytic performance, especially in low-temperature oxidation of hydrocarbons

Enhancing Catalytic Activity: Understanding the mechanisms behind the synergetic effect of Pt with Pd and manganese oxides is crucial for enhancing catalytic activity in diesel vehicle emission control. Further research is needed to elucidate how the formation of nanoscale PdO-PtOx particles on the surface of Mn₃O₄ and the modification of alumina structure by Mn³⁺ and PtPd clusters contribute to catalytic performance?

Improving Stability and Efficiency:

While the developed Pt-Pd-MnOx-Al₂O₃ catalyst shows high thermal stability and activity in low-temperature oxidation of light hydrocarbons, there's a need to improve its stability under various operating conditions encountered in diesel engines. Additionally, efforts should focus on maximizing catalytic efficiency while minimizing the total loadings of Pt and Pd to reduce costs and environmental impact

The Desert Research Institute conducted an on-road mobile source emission study at a traffic tunnel in Van Nuys, California,[7] in August 2010 to measure fleet-averaged, fuel-based emission factors. The study also included remote sensing device (RSD) measurements by the University of Denver of 13,000 vehicles near the tunnel. The tunnel and RSD fleet-averaged emission factors were compared in blind fashion with the corresponding modeled factors calculated by ENVIRON International

Corporation using U.S. Environmental Protection Agency's (EPA's) MOVES2010a (Motor Vehicle Emissions Simulator) and MOBILE6.2 mobile source emission models, and California Air Resources Board's (CARB's) EMFAC2007 (EMission FACTors) emission model. With some exceptions, the fleet-averaged tunnel, RSD, and modeled carbon monoxide (CO) and oxide of nitrogen (NO_x) emission factors were in reasonable agreement ($\pm 25\%$). The nonmethane hydrocarbon (NMHC) emission factors (specifically the running evaporative emissions) predicted by MOVES [9] were insensitive to ambient temperature as compared with the tunnel measurements and the MOBILE- and EMFAC-predicted emission factors, resulting in underestimation of the measured NMHC/NO_x ratios at higher ambient temperatures. Although predicted NMHC/NO_x ratios are in good agreement with the measured ratios during cooler sampling periods, the measured NMHC/NO_x ratios are 3.1, 1.7, and times higher than those predicted by the MOVES, MOBILE, and EMFAC models, respectively, during high-temperature periods. Although the MOVES NO_x emission factors were generally higher than the measured factors, most differences were not significant considering the variations in the modeled factors using alternative vehicle operating cycles to represent the driving conditions in the tunnel. The three models predicted large differences in NO_x and particle emissions and in the relative contributions of diesel and gasoline vehicles to total NO_x and particulate carbon (TC) emissions in the tunnel

Assessment of Mobile Source Emission Models:

This study aims to evaluate the performance of three prominent mobile source emission models, MOVES2010a, MOBILE6.2, and EMFAC2007, by comparing their predicted fleet-averaged emission factors with measurements obtained from on-road traffic tunnel and remote sensing devices

Accuracy of Predictive Models for On-Road Emissions:

Investigating the accuracy of emission predictions from MOVES2010a, MOBILE6.2, and EMFAC2007 models against real-world measurements, this study highlights discrepancies and areas of improvement in estimating carbon monoxide (CO), oxide of nitrogen (NO_x), and nonmethane hydrocarbon (NMHC) emissions under different ambient temperature conditions

Challenges in Modeling On-Road Vehicle Emissions:

By analyzing the performance of emission models against tunnel and remote sensing measurements, this study addresses challenges such as insensitivity to ambient temperature, underestimation of NMHC/NO_x ratios, and significant differences in NO_x and particle emissions predictions, providing insights for refining mobile source emission modeling methodologies.

In this study, ozone (O₃) sensitivity and linearity over East Asia (EA) and seven urban areas are examined with an integrated air quality modeling system under two categories of scenarios: (1) The effects of domestic emission are estimated under local emission reduction scenarios, as anthropogenic NO(x) and volatile organic compounds (VOC) emissions are reduced by 20%, 50%, and 100%, respectively and independently; and (2) the influence of intercontinental transport is evaluated under Task Force on Hemispheric Transport of Air Pollution (TF HTAP) emission reduction scenarios, as anthropogenic NO(x) emission is reduced by 20% in Europe (EU), North America (NA), and South Asia (SA), respectively. Simulations are conducted for January and July 2001 to examine seasonal variation. Through the domestic O₃ sensitivity investigation, we find O₃ sensitivity varies dynamically depending on both time and location: North EA is VOC limited in January and NO(x) [9] limited in July, except for the urban areas Beijing, Shanghai, Tokyo, and Seoul, which are VOC limited in both months; south EA is NO(x) limited in both January and July, except for the urban areas Taipei, which is VOC-limited in both months, and Pearl River Delta, which is VOC limited in January. Surface O₃ change is found to be affected more by NO(x) than by VOC over EA in both January and July. We also find different O₃ linearity characteristics among urban areas in EA: O₃ at Beijing, Tokyo, and Seoul shows a strong negative linear response to

NO(x) emission in January; O₃ at Shanghai, Pearl River Delta, and Taipei shows a strong positive response to VOC emission in both January and July. Through the long-range transport investigation, monthly O₃ changes over EA resulting from different source regions indicate the largest source contribution comes from NA (0.23 ppb), followed by SA (0.11 ppb) and EU (0.10 ppb). All of the three regions show higher impacts in January than in July.

Assessing Ozone Sensitivity and Linearity in East Asia:

This study investigates the sensitivity and linearity of ozone (O₃) levels across East Asia and urban areas within the region. By analyzing [10] the effects of domestic emissions and intercontinental transport on O₃ concentrations, the research aims to understand the dynamic variations in O₃ sensitivity over time and location, providing insights into the key drivers of O₃ formation and distribution in East Asia

Impact of Local Emission Reduction Scenarios on Ozone Sensitivity:

By examining the effects of local emission reduction scenarios on O₃ sensitivity, this study evaluates the response of O₃ levels to reductions in anthropogenic NO(x) and volatile organic compounds (VOC) emissions in East Asia. The research aims to identify the dominant factors influencing O₃ concentrations in different regions and seasons, facilitating targeted emission control strategies to mitigate O₃ pollution

Evaluation of Intercontinental Transport Effects on Ozone Concentrations:

Focusing on the influence of intercontinental transport on O₃ levels in East Asia, this study assesses the impact of emission reductions in Europe, North America, and South Asia on O₃ concentrations. By quantifying the contributions of different source regions to O₃ variability, the research aims to elucidate the significance of long-range transport in shaping O₃ pollution patterns in East Asia, particularly during different seasons

The constrained weighted-non-negative matrix factorization (CW-NMF) hybrid receptor model was applied to study the influence of steelmaking activities on PM_{2.5} (particulate matter with equivalent aerodynamic diameter less than 2.5 μm) composition in Dunkerque, Northern France. Semi-diurnal PM_{2.5} samples were collected using a high volume sampler in winter 2010 and spring 2011 and were analyzed for trace metals, water-soluble ions, and total carbon using inductively coupled plasma – atomic emission spectrometry (ICP-AES), ICP – mass spectrometry (ICP-MS), ionic chromatography and micro elemental carbon analyzer. The elemental composition shows that NO₃⁻, SO₄²⁻, NH₄⁺ and total carbon are the main PM_{2.5} constituents. Trace metals data were interpreted using concentration roses and both influences of integrated steelworks and electric steel plant were evidenced. The distinction between the two sources is made possible by the use Zn/Fe and Zn/Mn diagnostic ratios. Moreover Rb/Cr, Pb/Cr and Cu/Cd combination ratio are proposed to distinguish the ISW-sintering stack from the ISW-fugitive emissions. The a priori knowledge on the influencing source was introduced in the CW-NMF to guide the calculation. Eleven source profiles with various contributions were identified: 8 are characteristics of coastal urban background site profiles and 3 are related to the steelmaking activities. Between them, secondary nitrates, secondary sulfates and combustion profiles give the highest contributions and account for 93% of the PM_{2.5} concentration. The steelwork facilities contribute in about 2% of the total PM_{2.5} concentration and appear to be the main source of Cr, Cu, Fe, Mn, Zn.

Investigating PM_{2.5} Composition in a French Urban Coastal Site:

This study aims to assess the composition of PM_{2.5} in Dunkerque, Northern France, under the influence of steelmaking activities. By employing the constrained weighted-non-negative matrix factorization (CW-NMF) receptor model, the research seeks to identify the main constituents of

PM2.5 and distinguish the contributions from steelworks emissions using trace metal analysis and diagnostic ratios ?

Characterizing Steelworks Emission Influences on PM2.5:

Focusing on the impact of steelmaking activities on PM2.5 composition, this study utilizes advanced analytical techniques to analyze PM2.5 samples collected during winter 2010 and spring 2011. By interpreting trace metal data and employing diagnostic ratios, the research aims to differentiate between integrated steelworks and electric steel plant emissions and quantify their contributions to PM2.5 levels ?

Application of CW-NMF Receptor Model for Source Apportionment:

This research applies the constrained weighted-non-negative matrix factorization (CW-NMF) receptor model to identify and quantify the sources contributing to PM2.5 in Dunkerque, Northern France. By integrating a priori knowledge of influencing sources, such as steelmaking activities, the study aims to delineate distinct source profiles and assess their relative contributions to PM2.5 concentrations, providing insights into pollution sources in urban coastal environments.

3. EXISTING SYSTEM

Environmental protection is a fundamental policy in many countries, where the vehicle emission pollution turns to be outstanding as a main component of pollutions in environmental monitoring. Remote sensing technology has been widely used on vehicle emission detection recently and this is mainly due to the fast speed, reality, and large scale of the detection data retrieved from remote sensing methods. In the remote sensing process, the information about the fuel type and registration time of new cars and nonlocal registered vehicles usually cannot be accessed, leading to the failure in assessing vehicle pollution situations directly by analyzing emission pollutants.

A system for vehicle emission detection using machine learning typically involves collecting real-time data from sensors installed in vehicles or roadside monitoring stations. Machine learning algorithms can then analyze this data to detect patterns indicative of excessive emissions. Alert detection can be implemented to notify authorities or vehicle owners when emissions exceed predefined thresholds, helping to enforce regulations and reduce environmental impact.

Disadvantages

- Manual analysis will not give better prediction
- No machine learning algorithm were used

4. PROPOSED SYSTEM

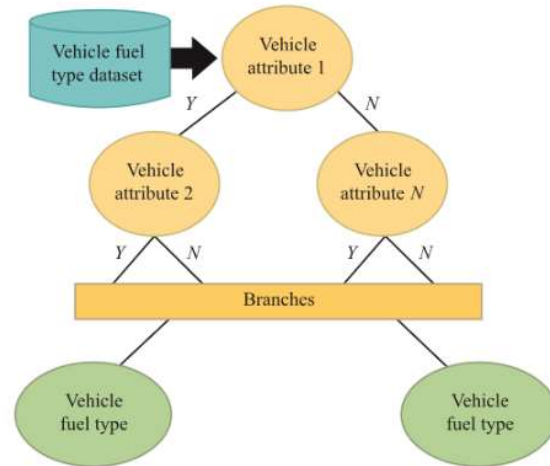
This paper adopts data mining methods to analyze the Vehicle emission data to vehicle emission. This paper takes full use of linear regression, random forest, KNN, XgBoost, to successfully make precise prediction for essential information and further employ them to an essential application: vehicle emission evaluation.

A proposed system for vehicle emission detection integrates machine learning algorithms with real-time data collection and alert detection mechanisms. This system involves the installation of sensors in vehicles or roadside stations to collect emission-related data, including CO₂, NO_x, and particulate matter levels. Upon data collection, preprocessing techniques are applied to handle noise and missing values, followed by feature engineering to extract relevant information such as engine type and vehicle speed. Machine learning models, such as decision trees or neural networks, are then trained on this preprocessed data to detect patterns indicative of excessive emissions. When emissions exceed predefined thresholds or abnormal patterns are detected, the system triggers alerts to notify authorities or vehicle owners. Additionally, the system incorporates a feedback loop to continuously improve model accuracy and effectiveness over time

Advantages

- We are using machine learning algorithms to analysis the data
- Analyzing with multiple ML algorithms
- Gives better prediction

SYSTEM ARCHITECTURE



6. IMPLEMENTATION

ADMIN

Here admin is a module should login into the account after successful login admin can perform some operations such as

LOAD DATASET: here loading dataset from dataset folder available in project

PREPROCESS: in this step we are going to clean dataset and defining predictor and target variables and splitting data into training and testing.

RUN LINEAR REGRESSION: here training this algorithm with training dataset which is split in preprocess stage

RUN RANDOM FOREST REGRESSION: here training this algorithm with training dataset which is split in preprocess stage

RUN KN: here training this algorithm with training dataset which is split in preprocess stage

RUN XGBOOST: here training this algorithm with training dataset which is split in preprocess stage

COMPARISION: showing comparison graph with all algorithm generated accuracy

PREDICT VEHICLE EMMISION: in this step we need to predict vehicle emission by passing test data to the algorithm

LOGOUT: this operation for coming out from admin accout

EXPECTED OUTCOMES



Fig 7.1 Index Page

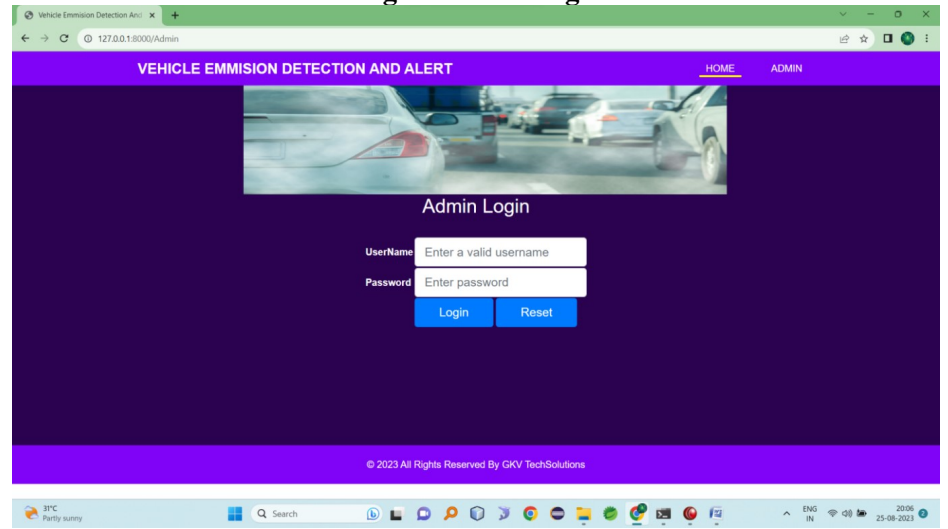


Fig 7.4 Home Page

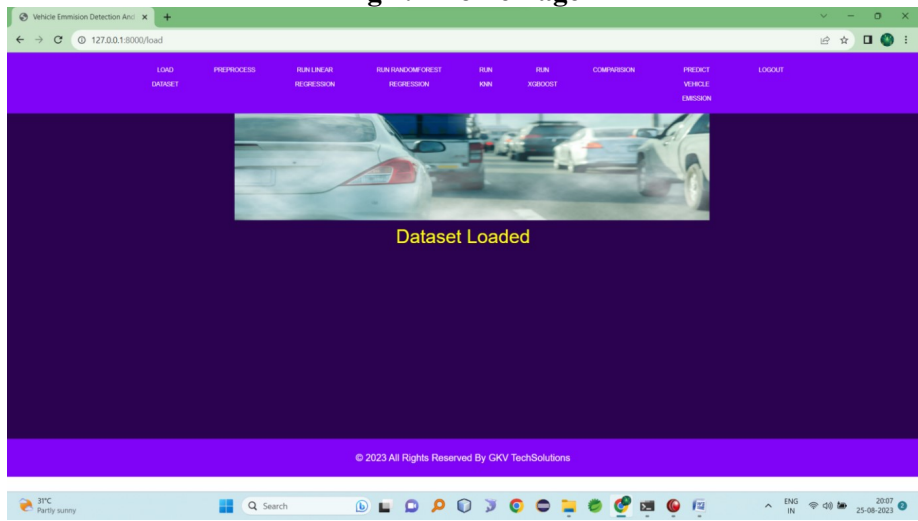


Fig 7.5 Dataset Loaded

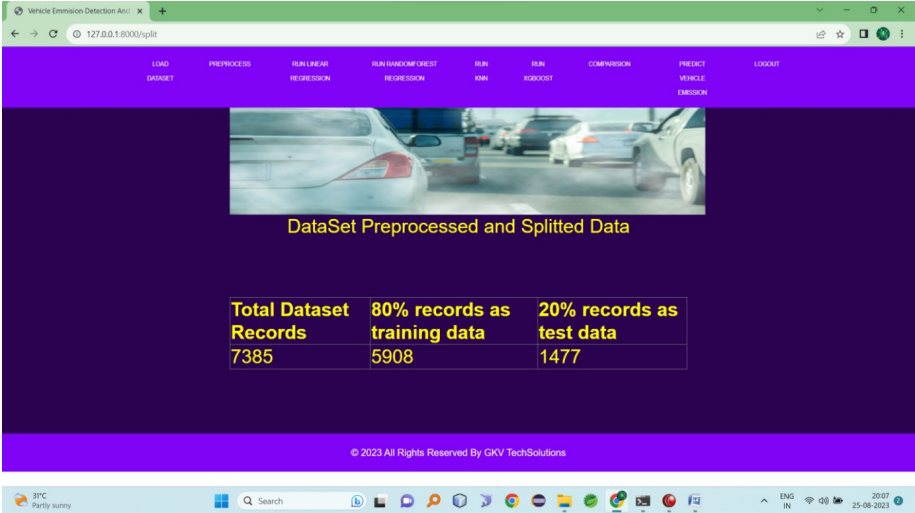


Fig 7.6 Preprocessor Completes

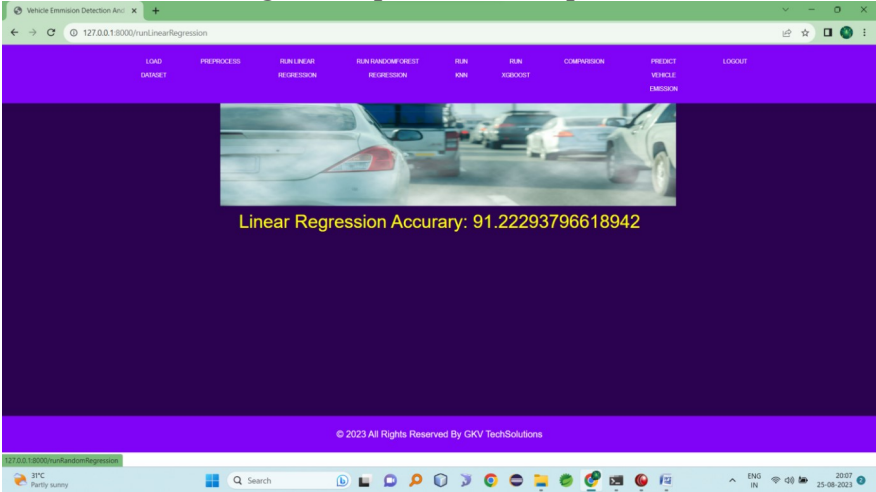


Fig 7.7 Linear Regression

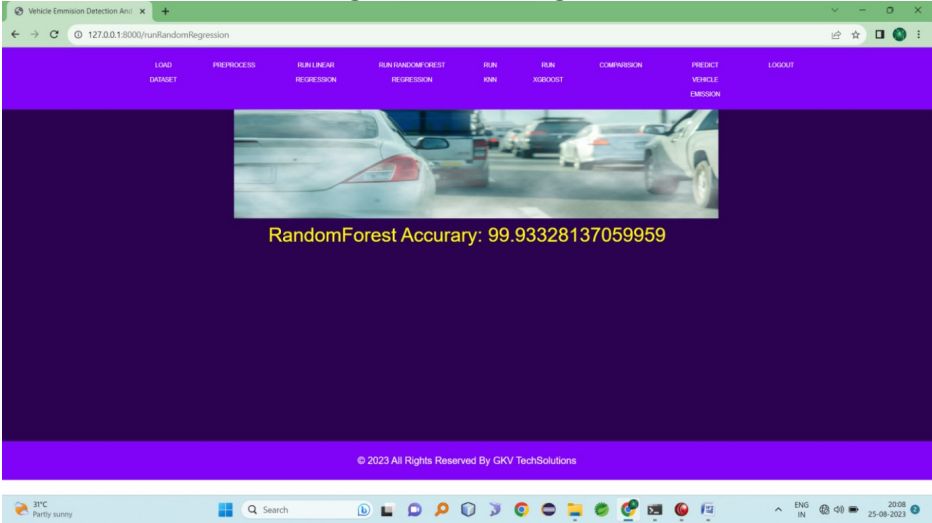


Fig 7.8 Random Forest Regression

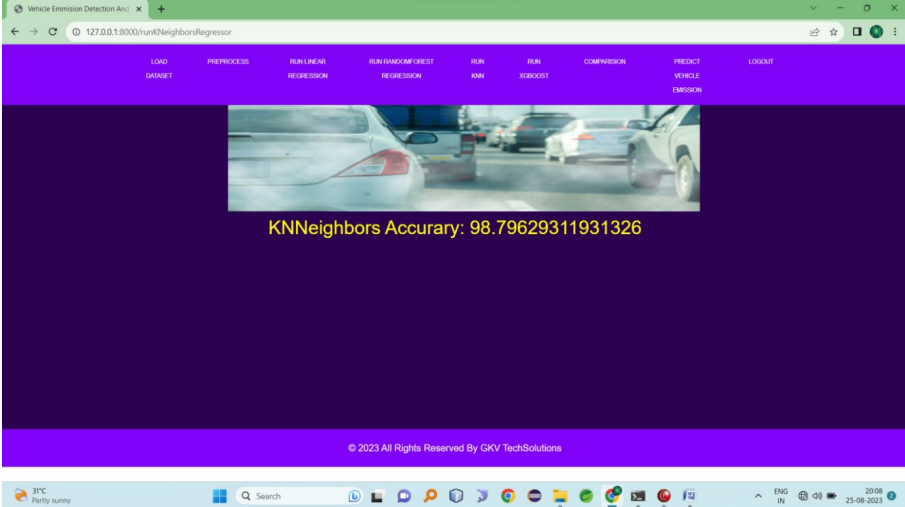


Fig 7.9 KNNNeighbors accuracy

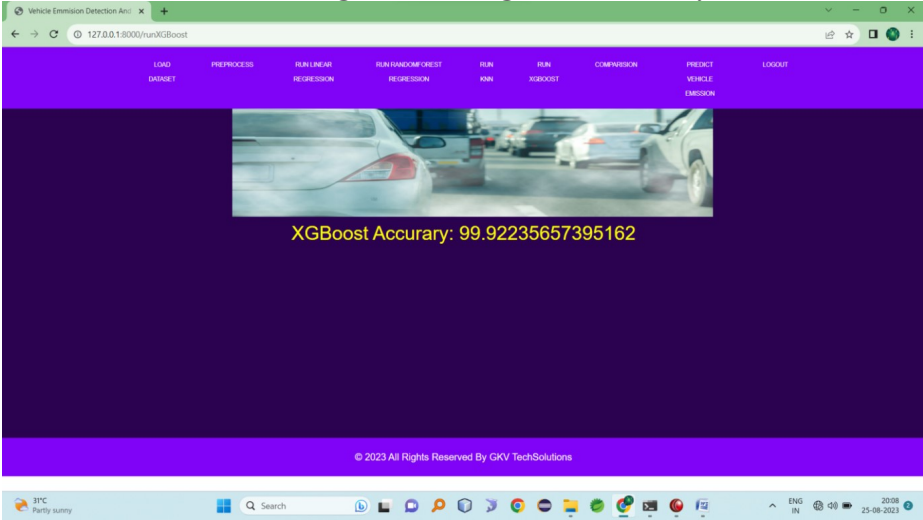


Fig 7.10 Run xgboost algorithm

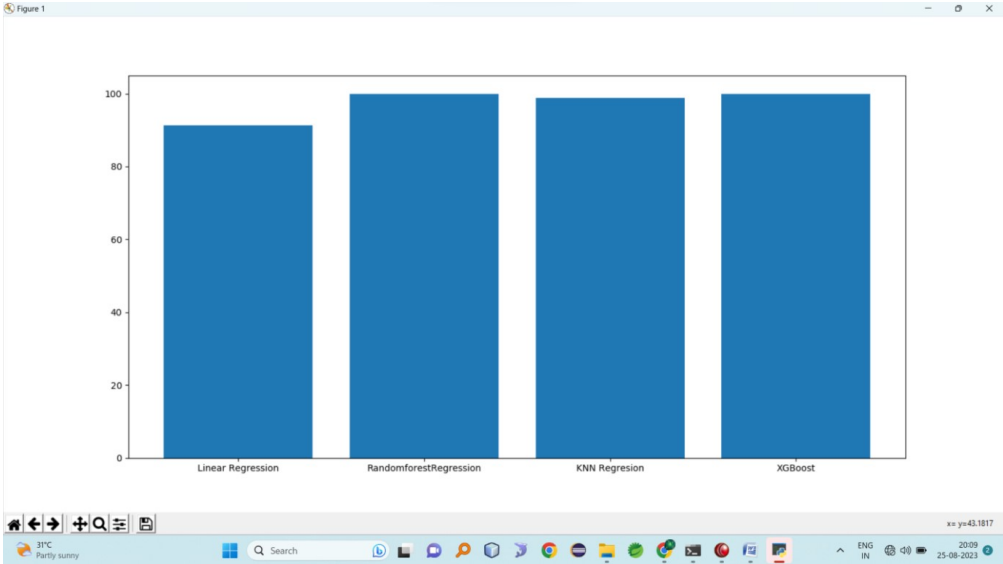


Fig 7. 11 Comparison graph

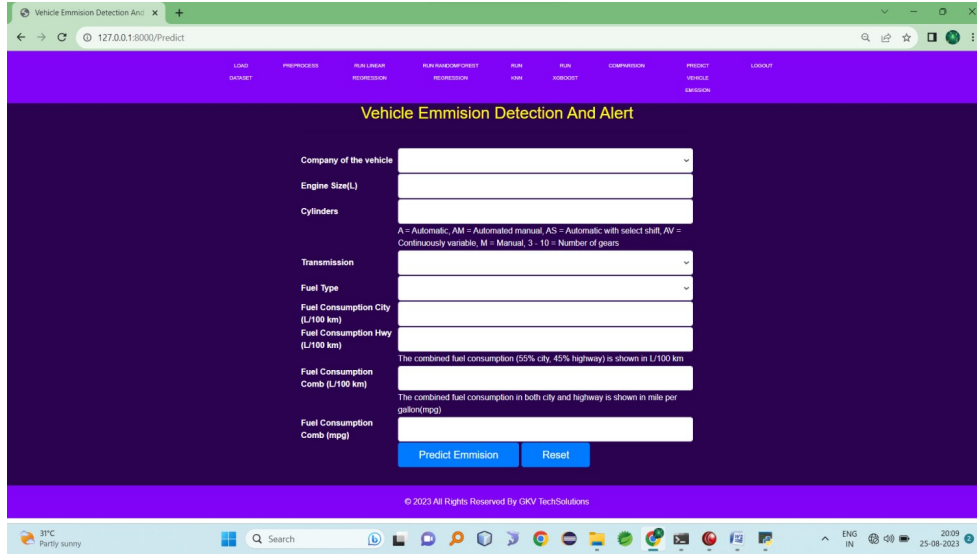


Fig 7.12 vehicle Details

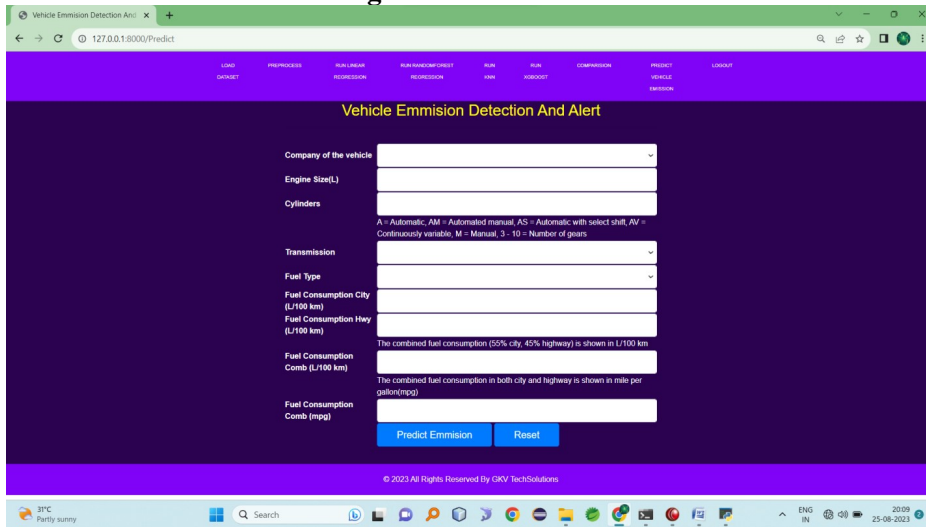


Fig 7.13 Vehicle Details

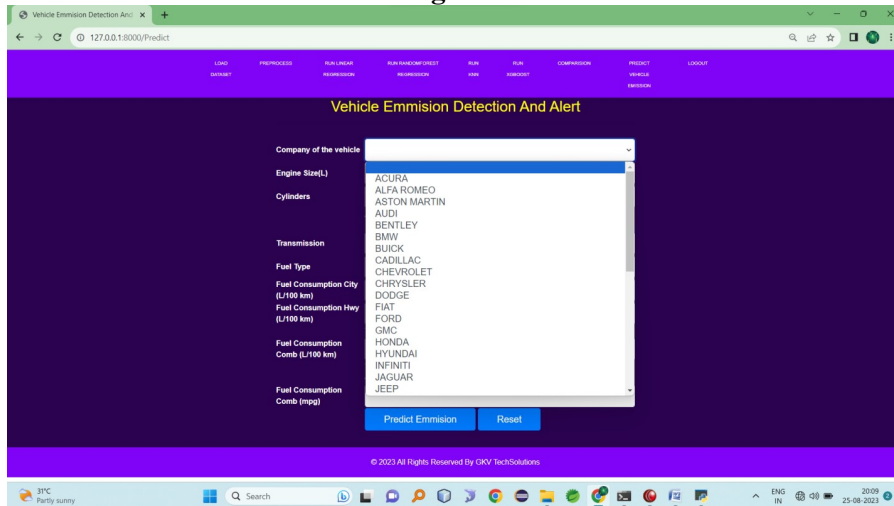


Fig 7. 14 Vehicle company

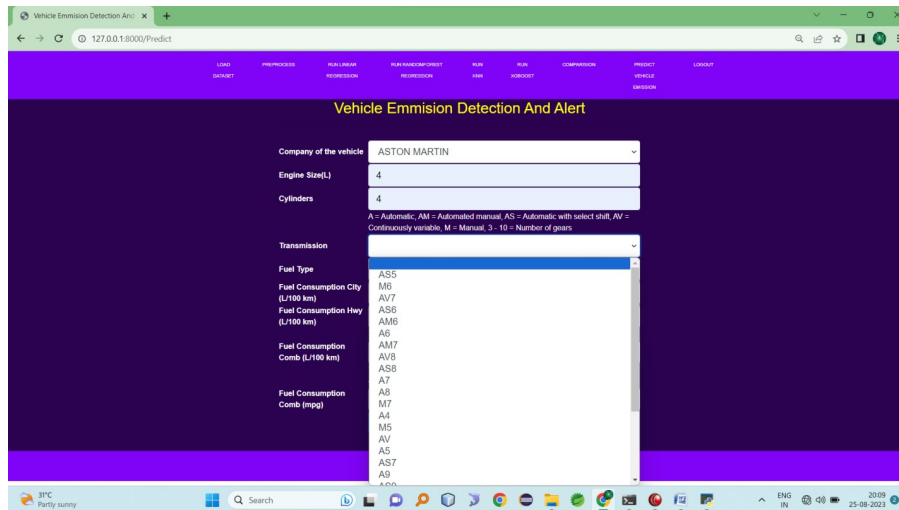


Fig 7.15 Vehicle Transmission

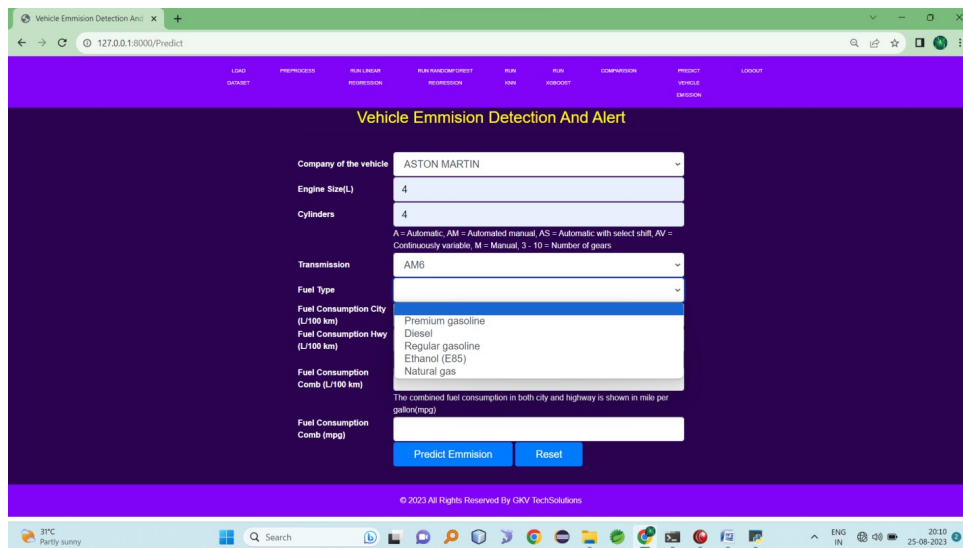


Fig 7. 16 Vehicle Fuel Type

CONCLUSION

Environmental protection has been a hot topic in academic and industrial communities. This paper focuses on predicting the missing basic information of vehicles from telemetry data to monitor the vehicle emission. A variety of data mining methods are adopted to perform predictions based on the vehicle telemetry data provided by an environmental protection agency in a certain city and successfully made precise inferences on fuel type and gasoline-powered vehicle registration time. In the prediction for the registration time of diesel vehicles, the prediction accuracy rate just reaches about 70% due to the fact that the division of registration time is artificially controlled and the status of different vehicles varies a lot for different users. Further work will be carried out on the basis of more related data and improved algorithms to make more precise prediction on the vehicle emission-related information

FUTURE SCOPE

The future scope for vehicle emission detection using machine learning and alert detection is promising. With advancements in AI and IoT, there's potential for real-time monitoring of emissions, enabling authorities to enforce stricter regulations and individuals to make informed decisions about vehicle usage. Additionally, integrating such systems into smart cities could lead to more efficient traffic management and reduced environmental impact.

Moreover, machine learning algorithms can optimize fleet management operations, minimizing emissions while maintaining operational efficiency. These systems can also assess the health impacts of emissions on local populations, informing public health interventions and policy decisions. As autonomous vehicles become more prevalent, integration of emission detection systems directly into vehicle control systems will further enhance efficiency and reduce environmental impact.

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