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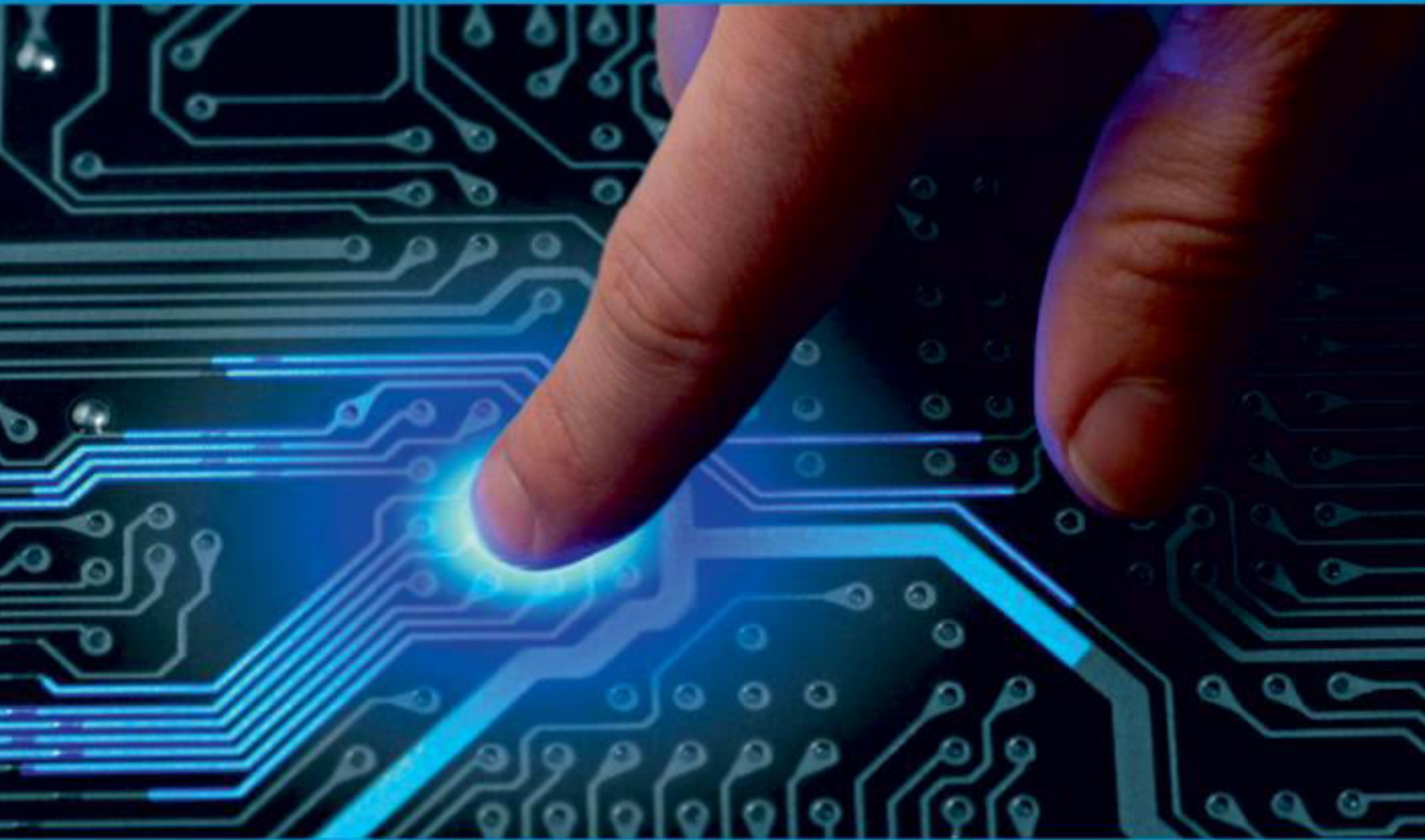

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Machine Learning Based Predictive Modelling of Vehicle CO2 Emissions: An Extensive Examination of Automobile Features

Jahnavi Shetty[1], Haripriya V[2]

PG Student, School of CS & IT, Jain(Deemed-to-be-University), Bengaluru, India[1]

Assistant Professor, Department of School of CS & IT, Jain (Deemed-to-be-University), Bengaluru, India[2]

ABSTRACT*:* There is a growing interest in discovering novel and inventive methods to decrease the emission of carbon dioxide (CO2) from diverse sources, mostly due to concerns about safeguarding the environment and mitigating the adverse effects of greenhouse gas emissions, especially in the automotive sector. This study article explores the fascinating potential of predicting the quantity of CO2 generated by autos using machine learning (ML) based methodologies. In order to create a system that can predict carbon dioxide emissions depending on a number of factors, we are investigating machine learning. Significant details about the car, such as its construction, kind, number of cylindrical objects, horsepower, gearbox type, fuel type, and fuel consumption, are included in the dataset that forms the basis of our investigation.

This project's main objective is to create accurate and dependable prediction models for calculating vehicle-generated CO2 emissions. Legislators that deal with the environment, corporations, and consumers could find great value in these models. We use a range of machine learning (ML) techniques, such as ensemble techniques, neural networks, decision trees, and regression algorithms, to accomplish this goal. This study assesses the prediction accuracy, adaptability to different situations, and data utilisation of several techniques.

To determine which predictive models are most suited for predicting CO2 emissions within the limitations of the given information, we employ a comprehensive evaluation process. Additionally, we look at how different feature subsets affect prediction accuracy, providing an indication of the relative significance of different vehicle parameters in relation to CO2 emissions. Our results advance the field of predictive emissions models and provide insight on the primary drivers of vehicle-related greenhouse gas emissions.

KEYWORDS*:* Climate, Automobiles, Artificial Intelligence, Machine Learning, CO2 Emissions, Environment

I. INTRODUCTION

Reducing greenhouse gas emissions is becoming increasingly important as concern over climate change and its effects on the environment grows worldwide. One of the main causes of the ongoing problems associated with climate change is carbon dioxide (CO2). Transportation, especially road vehicles, is a major source of CO2 emissions. Consequently, developing efficient plans for tracking, reducing, and controlling vehicle emissions is becoming increasingly important.

Environmental issues have gained prominence as they tackle one of the most serious problems facing contemporary society. Emissions of greenhouse gases (CO2) are a primary cause of global warming. Due to these emissions, which are mostly caused by human activities such as combustion processes (Mitić et al., 2017), there have been noticeable global climate impacts.

Burning fossil fuels has been the primary source of approximately 75 percent of carbon dioxide (CO2) emissions driven via people during last 20 years. Fossil fuels are essential for numerous activities that are closely related to economic growth, including transportation, manufacturing, electricity production, and consumption of goods and services. As such, when developing climate policies and making plans for energy requirements, it is imperative to consider CO2

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pollutants in the context of energy use (Rehan et al., 2018). Estimating CO2 emissions is crucial for projecting future energy needs because of the close relationship between GDP and energy consumption. Many researchers have carefully read through and evaluated the literature regarding CO2 emissions, how they affect the environment, and the factors that influence them and other energy uses.

Advances in data science, especially machine learning (ML), have created new avenues for tackling challenging problems such as CO2 emission prediction. Using machine learning techniques, it is possible to find complex relationships in large datasets, which can lead to the development of predictive models that calculate CO2 emissions depending on different vehicle attributes. Accurate emission prediction models can be developed because of the availability of extensive datasets that include specific vehicle information such as make, model, engine specs, and fuel consumption.

The purpose of this study is to examine how different machine learning techniques can be applied to predict CO2 emissions from automobiles using a dataset that includes a broad range of vehicle attributes. These attributes include specifics such as Vehicle Category, Engine Size, Number of Cylinders, Car Brand, Car Model, Gearbox Type, Fuel Variety, Fuel Efficiency in Various Driving Conditions, Urban and Highway Contexts, and CO2 Emission Values. This study aims to use machine learning (ML) to help develop instruments and insights that will enable consumers, automakers, and environmental policymakers to make better decisions.

There are two main objectives of this study:

1. Forecasting through modelling: Develop accurate and reliable predictive models that can analyse vehicle characteristics to estimate CO2 emissions. These models will be useful in assessing how various vehicle configurations and design choices affect emissions.

2. Analyse the relative significance of different vehicle attributes in influencing CO2 emissions using attribute importance analysis. By identifying the most impactful attributes, targeted initiatives to reduce emissions through technological and design interventions can be guided by this analysis. Several different ML techniques will be applied to attain these objectives.

The final half of this essay is organised as follows: In Section 2, we will look at previous research on CO2 emission prediction and the use of machine learning in environmental modelling. Section 3 describes the methodology, as well as the dataset, machine learning algorithms, and assessment standards used to assess model performance. Section 4 discusses the findings of the experiment and explains the link between vehicle features and CO2 emissions. The report concludes with Section 6, which summarises the contributions, considers the implications of the findings, and suggests potential avenues for further research in this area.

II. RELATED RESEARCH

Reducing global carbon dioxide emissions is crucial for sustainable social development and has been highlighted as a global issue. Carbon emissions present different challenges in many countries and regions. In a study covering the years 1970-2010, Bouzenita and Pablo-Romero (2016) examined the link among Algeria's GDP and CO2 emissions, revealing a significant relationship, as Aftab et al. (2021). Looking at Pakistan from 1971 to 2019, the link between carbon dioxide emissions and energy consumption was examined using the Auto Regressive Distributed Lag (ARDL) and Johansen Cointegration techniques, which included the influence of rapid economic expansion on power usage and CO2 emissions. Khobai et al. (2017) investigated the vital relationship in GDP and energy use in South Africa, while Vasif Gokmenoglu and Taspnar (2016) identified economic factors as determinants of development and energy use. Ghosh et al. (2014) investigated the relationship in economic development, CO2 emissions and the impact of energy consumption on the economy of Bangladesh.[5],[7]

Mirza and Kaval (2017), using Johansen and modified generalized least squares (GLS) discovered that population growth and demand for energy are substantial contributors to ecological deterioration in Pakistan. In Bangladesh,

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Sarkar et al. (2018) analyzed government policies related to energy intake and carbon dioxide emissions, which highlighted the faster growth of carbon dioxide emissions compared to GDP and energy absorption. Çak et al. (2018) conducted a study using the ARDL limits test to examine the relationships in green power utilization and economical development and CO2 emissions in the G7 nations. The outcomes show the integration of carbon dioxide emissions and energy consumption, which is particularly evident when calculating carbon dioxide emissions per capita with the integrated vector.[8]

Salari et al. (2021) used both fixed and dynamic models to investigate the connection among emissions, demand for energy and total domestic output in US. In a similar vein, Wasti and Zaidi (2020) investigated the connection in energy use and CO2 emissions. Their investigation revealed a positive correlation. Khan et al. (2017) looked at CO2 emissions, energy use, exports, economic development and population density in Asian countries from 1960 to 2014. According to the literature, there are many factors that can affect CO2 emissions; therefore, it is important to predict their impact.[11],[12]

New models such as Li et al. (2020), mainly centered on China's CO2 emissions, have been developed in recent studies to forecast CO2 emissions. These researches demonstrate China's committed to minimizing CO2 magnitude. Yuan et al. (2012) presented a modeling approach that predicts that if China maintains economic growth of 7 percent and 6 percent during the twelve and thirteenth schemes for five years, it will reduce carbon dioxide emissions by 45 percent for 2040.

Heydari et al. (2019) used a generalized regression neural network (GRNN) and Gray Wolf optimization (GWO) to predict long-term trends in CO2 emissions. The proposed method showed higher accuracy in predicting long-term trends in CO2 emissions in Iran, Canada and Italy. Fang et al. (2018) used an advanced Gaussian process simulation system for forecasting CO2 emissions, which showed that China's total CO2 emissions will continue to grow more slowly, while the United States and Japan should better control their emissions. Hosseini et al. (2019) utilized chronology. and persistence inspection to project Iran and CO2 emissions until 2030. Their findings indicate that Iran is unlikely to achieve the targets. and assumptions of the Paris Contract under business-as-usual (BAU) scenarios is not justified.[16],[17],[18]

III. METHODOLOGY

1. Data Gathering

Our extensive research is backed by a large database containing information on 7500 diverse vehicles, each with its own set of distinguishing characteristics. This dataset contains a variety of properties, including core elements that provide information on the vehicle's company, structure, and type, such as Car Make, Car Model, and Vehicle Category. Detailed data such as engine size, cylinders, gearbox, and fuel type provide insight into the mechanical aspects of these vehicles. We have added fuel consumption measurements for city and highway driving circumstances, measured in L/100 km units, to better understand fuel economy in these vehicles. These extra details enable a more detailed understanding of the fuel economy profiles demonstrated by these vehicles.

2. Experimental Analysis of Data:

To acquire a full picture of the spread and diversity of cars in our dataset, we thoroughly examine each variable during the exploratory data analysis (EDA) process. This starts with an examination into the car's manufacturer, model, and class. By investigating these variables, we can find probable connections among engine size, cylinder measure, gearbox type, fuel type, and greenhouse gases. Furthermore, by visually portraying fuel consumption measurements under both urban and highway circumstances, we can determine the differences in fuel efficiency across different types of automobiles. Furthermore, by carefully examining the distribution of emissions of CO2 in our dataset, we can detect any potential outliers and evaluate the total environmental impact of these vehicles. The information gathered during this exploratory phase will be critical in guiding our attribute engineering decisions and guiding our model selection

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approach. Ultimately, it will improve both accuracy and understandability for predicting the release of carbon dioxide using future models.

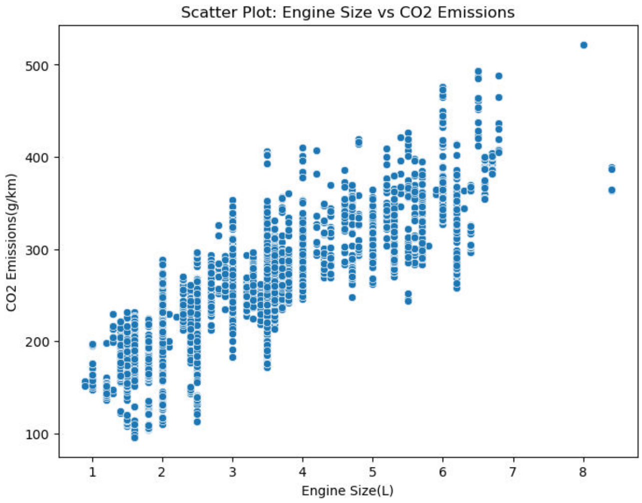

Fig .1 Engine Size versus CO2 Emission in a Scatter Plot

We can identify any possible changes, structures, or anomalies in data by looking at the scatter plot that shows Engine Size on the x-axis and CO2 emission on the y-axis. We hope to determine whether there is a relationship between a car's engine size and CO2 emissions through this graphic representation.

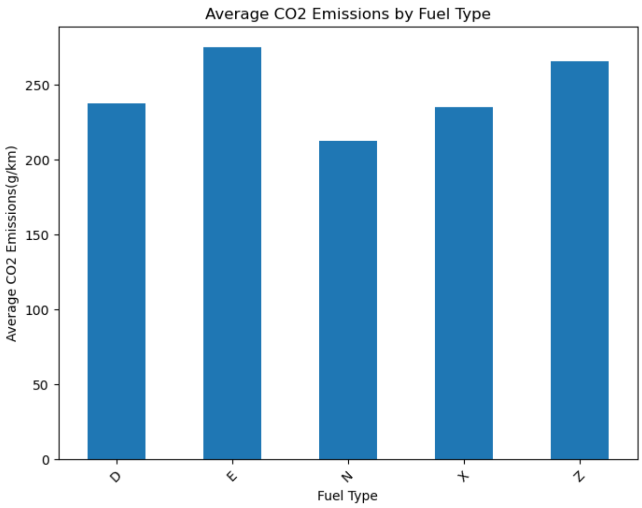

Fig.2 CO2 Emission Average by Fuel Type

In collection of 7,500 vehicles, the bar chart gives an obvious and concise ratio of average CO2 emissions for different fuel classes, explore how different types of fuel affect the ecology mapping fuel types on the x-axis and average CO2 emissions on the y-axis. Thanks to this graphical representation, we can determine which type of fuel causes on average lower or higher CO2 emissions.

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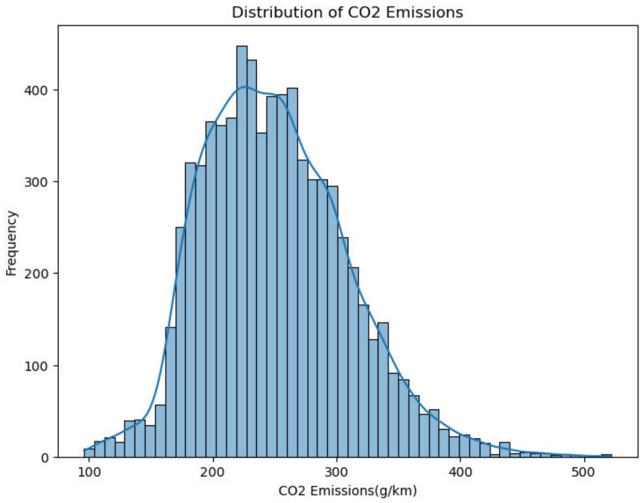

Figure 3: Distribution of Emissons in CO2

Provides a visual representation of the the chance dense equation of CO2 emissions, allowing us to understand the underlying distribution pattern. Considering both the shape of the curve and its peaks, we can get an idea of the most common CO2 emission areas of the vehicles in our dataset.

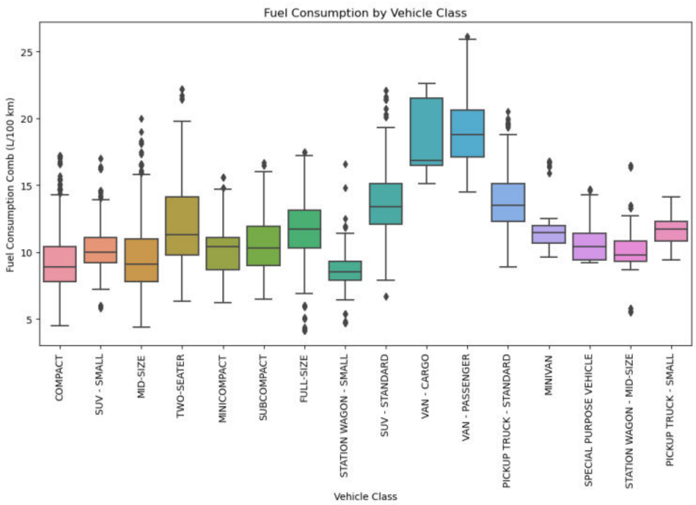

Figure 4: Fuel Usage by Class of Vehicle

The box plot visualizes the distribution of fuel usage across vehicle classes. It describes the central trend, variability, and potential outliers in the data. The height of each box represents the interquartile range (IQR) of fuel consumption values for a certain vehicle class, and its position on the plot indicates the median fuel consumption. Individual data points outside the box's "whiskers" are outliers.

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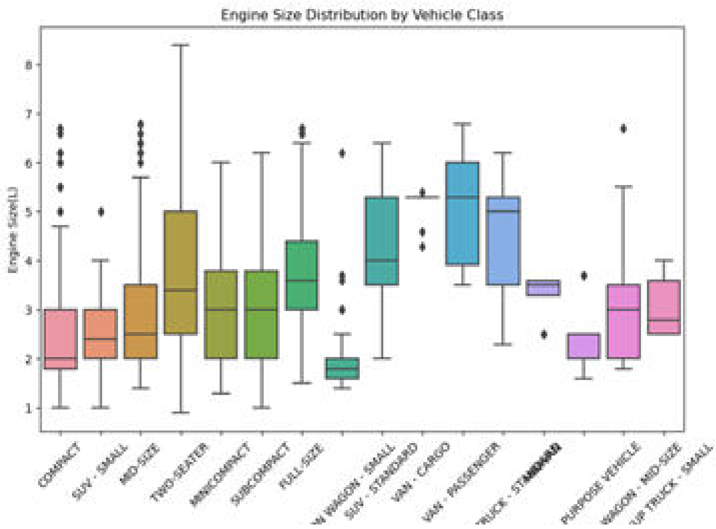

Fig. 5 Engine Capacity Variation by Type of Automobile

Box plot concisely illustrates how engine sizes vary across different vehicle classes, revealing trends, scattering, and possible outliers.

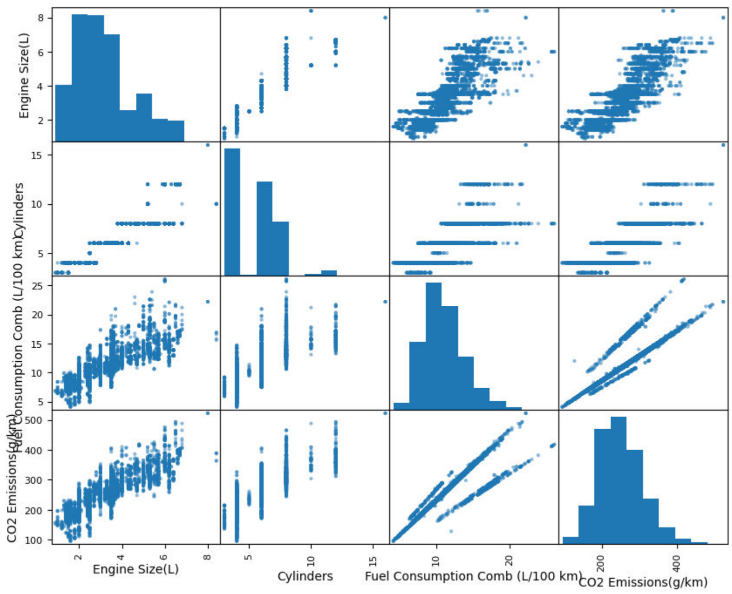

Fig: 6 Multivariable Analysis

This examines several variables at once to find patterns and relationships that may not be visible with univariable analysis. We were able to see how various characteristics, such as engine capacity, fuel consumption, class, and more, are interdependent with respect to CO2 emissions by making graphs . This method offers a comprehensive understanding of the ways in which these factors together affect CO2 emissions.

3. Utilised machine learning algorithms

a) Linear Regression: Within our research paper, which focuses on utilizing Machine Learning techniques for predicting CO2 emissions, we incorporated the Linear Regression algorithm as a fundamental tool for predictive modelling. A supervised learning algorithm called linear regression is used to find a linear relationship in the the reliant

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on factor is in this example CO2 emissions, and separate variables such as engine size and fuel consumption, and vehicle class. With the goal of minimising the discrepancy between the actual and predicted CO2 emissions, the algorithm determines the value of the coefficients of the equation of linearity that best suits the dataset that is provided. By leveraging the learned relationships from the training data, the Linear Regression model can predict CO2 emissions for new, unseen data points. In our study, we applied this algorithm to construct a predictive model that takes into account the impact of various vehicle attributes on CO2 emissions. This allows us to make accurate forecasts of emissions based on the characteristics of different cars within the dataset containing 7500 entries.

1. Input: Training dataset with features (independent variables) X and target variable (CO2 emissions) Y.

2. Initialize coefficients (weights) and bias.

3. Calculate predictions using the linear equation: Y_pred = (X * coefficients) + bias.

4. Compute the Mean Squared Error (MSE) between Y_pred and actual Y.

5. Use gradient descent to minimize the MSE by updating coefficients and bias.

6. Repeat steps 3-5 until convergence or a specified number of iterations.

7. Output: Trained Linear Regression model with optimized coefficients and bias.

b) Decision Tree Algorithm: The problem of predicting CO2 emissions through machine learning techniques was tackled in our research paper, which employed the Decision Tree algorithm as a dependable tool for prediction model. The Decision Tree algorithm [23] is a versatile supervised learning method that partitions the dataset into members depending on feature values with the aim of building a hierarchical decision structure. By assessing each feature's capacity to distinguish and forecast CO2 emissions most accurately, it recursively determines the most important ones. The algorithm builds a tree-like structure that is capable of making precise predictions for data points that have not yet been seen by repeatedly branching into sub-nodes and formulating decision rules. Using this algorithm, we created a Decision Tree model that captures the complex relationships between different vehicle characteristics and CO2 emissions, such as engine size, fuel consumption, and vehicle class. With our dataset comprising 7500 car entries, this allowed us to develop a predictive model that could offer insights into emission trends across various car types and help with decision-making in the context of environmental concerns and regulatory standards.

1. Input: A training dataset containing the target variable Y and features X.

2. Select the most advantageous feature to divide the dataset according to a standard (such as information gain or Gini impurity).

3. Using the selected feature, divide the dataset into subsets.

4. Recursively apply steps 2–3 to each subset until a stopping condition, like the maximum depth or the bare minimum of samples per leaf, is met.

5. Give each leaf node a predicted value (such as the leaf's mean Y values).

6. Output: Decision Tree model after training.

c) Random Forest: We used the Random Forest algorithm in our attempt to predict CO2 emissions using machine learning techniques [20][22]. Random Forest, an ensemble learning technique, combines multiple decision trees in order to improve prediction accuracy and address a problem of overfitting. Using feature randomization and bootstrap aggregating (bagging), the algorithm produces a large number of decision trees. Each decision tree is trained with a subset of the dataset were algorithm combines the results of all the trees to produce a final prediction during prediction. By using an ensemble approach, the model becomes more resilient and can capture complex interactions and nonlinearities in the data. Using data from our extensive dataset of 7500 cars, including size, consumption, groups,

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model, and more we used the Random Forest algorithm in our study to create a predictive model for CO2 emissions. Our objective was to develop a highly accurate prediction tool that provides insights into emission trends across a variety of vehicle attributes, utilising Random Forest's capabilities to help with environmental management and educated decision-making.

1. Input: A training dataset containing the target variable Y and features X.

2. Create several Decision Trees by bagging, or selecting random portions of the dataset.

3. Randomly choose features for every tree at every split (feature randomization).

4. To create an ensemble prediction, combine the predictions from each tree.

5. Result: Multiple Decision Trees and a trained Random Forest model.

d) Support Vector Machines: Here utilized the Support Vector Machines (SVM) algorithm to address the challenging issue of predicting CO2 emissions through machine learning approaches [21], [24]. An especially successful method for supervised learning in classification and regression problems is support vector machines. SVM aims to identify a hyperplane that effectively separates data points while maximizing the distance between different classes of CO2 emissions, aligning with our objective. To capture intricate relationships that may not be linearly separable in the initial feature space, this algorithm employs kernel functions to convert input features into a higher-dimensional space. Support Vector Machines (SVM) can generate precise predictions for novel, unseen data by determining the ideal hyperplane that reduces prediction errors. Utilising our large dataset of 7500 cars, we used the SVM algorithm's capabilities to create a predictive model for CO2 emissions in our study. This model included features like car make, type of car, classification of vehicle, size of the engine. Due to its versatility in dealing with both linear and non-linear connections within the data, SVM enabled us to create a dependable forecasting tool that offers valuable insights into the complex patterns of CO2 emissions across various vehicle characteristics.

1. Input: A training dataset containing the target variable Y and features X.

2. Choose a kernel function to translate characteristics input into a higher-dimensional region.

3. Locate the hyperplane (or regression value predictor) that maximally divides the classes.

4. To reduce errors and increase margin, optimise the hyperplane.

5. Output: Trained SVM model with the ideal hyperplane

IV. RESULTS AND DISCUSSION

Model	Mean Squared Error	Mean Absolute Error	Comments
Linear regression	30.00	3.24	Assumes a linear relationship; higher error metrics suggest limitations in capturing dataset complexities.
Decision tree	14.27	1.86	Captures non-linear relationships; improved performance compared to linear regression.
Random Forest	12.32	1.83	Ensemble technique, reduces overfitting risk; further improvement in prediction accuracy.
Support Vector Machine (SVM)	406.86	9.54	Searches for effective hyperplane; somewhat worse performance compared to other models.

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Discussion: The assessments of these ML models reveals the varying levels of success in predicting CO2 emissions based on the vehicle attribute dataset. While providing a straightforward baseline, Linear Regression's accuracy falls short of capturing all the subtleties present in the data. Decision Trees and Random Forests both exhibit improved accuracy; Random Forest's ensemble technique reduces overfitting. Even though it works well in some circumstances, the Support Vector Machine appears to be having issues in this instance.

The Random Forest and Decision Tree models outperformed the Linear Regression and Support Vector Machine models in CO2 emission prediction.

V. CONCLUSION

During this work, looked at the application of machine learning algorithms to predict CO2 emissions utilizing a Set of Data containing more than 7,500 car characteristics. By conducting thorough analysis and experiments, we gained important insight into how well different models perform in accurately predicting CO2 emissions. This work contributes to the the field of ecological responsibility is showing and machine learning may be used to anticipate greenhouse gases from cars. The effectiveness of such strategies in optimizing automotive design and drive emission reduction decisions is a testament to the successful application of predictive models. Accurate estimates of CO2 emissions might be vital in assisting the automotive industry to give choices about meeting strict environmental standards. Together, the research shows how promising machine learning methods can be for solving practical environmental problems.

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