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Smart Framework for Personal Fuel Expense Tracking and Carbon Emission Assessment

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Abstract

This study presents a smart system that is intended to assist individuals and administrators in tracking their fuel costs and keeping an eye on their daily carbon emissions. It makes it simpler to make decisions by examining fuel consumption and its effects on the environment. The technology gathers real-time emissions data from vehicles equipped with Internet of Things devices. It can predict future trends of emissions by utilizing AI-based predictive modeling. Users can proactively monitor and lessen their environmental impact with this creative technique. The findings demonstrate that the system offers insightful data on fuel usage and carbon footprints, promoting more environmentally friendly behavior. To maximize fuel efficiency, lower emissions, and support users and administrators in making educated decisions about vehicle maintenance and driving practices, the system offers real-time feedback and alarms. Through the promotion of more environmentally friendly driving practices and improved fuel management, this proactive approach fosters cost savings and sustainability. This framework is a progressive approach that makes use of state-of-the-art technology to tackle the mounting issue of vehicle emissions and fuel management, promoting more environmentally friendly transportation and economical fuel use.

Keywords: Carbon dioxide (CO_2), CariQ, internet of things (IoT), probability distribution function (PDF), cumulative distribution function (CDF), global positioning system (GPS), mean square error (MSE), intelligent transportation system (ITM)

INTRODUCTION

The world is being impacted by the effects of climate change, including drought, storms, and extreme weather. Greenhouse gas emissions are the main cause of climate change, with carbon dioxide (CO_2) accounting for most of these emissions [1, 2]. With the increased focus on sustainability and environmental consciousness in today's world, both individuals and companies are looking for more and more ways to monitor and reduce their carbon footprint. Personal transportation is a major source of carbon emissions, with gasoline and diesel being the main fossil fuels used in it [3, 4]. Thus, there is an urgent need for efficient instruments and processes to monitor personal fuel costs and evaluate related carbon emissions in detail. The creation of a thorough framework for tracking personal fuel expenses and calculating carbon emissions is a key component of initiatives aimed at enabling people to make knowledgeable decisions about their mode of transportation.

By providing users with insights into their fuel consumption patterns and carbon emissions, such a framework can facilitate behavior change towards more sustainable modes of transportation and fuel usage. The comparative analysis will consider factors such as ease of use, accuracy of carbon emission calculations, data privacy and security,

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integration with existing systems and scalability to accommodate diverse user needs and preferences [5–7].

LITERATURE SURVEY

The history of researching car navigation systems is extensive. Most of the early navigation technology was based on physics. The Honda Electro Gyrocator, the world's first commercially marketed automobile navigation system, was a significant development. Roads were displayed on several advanced map cards, and gyroscope sensing was employed to detect the direction of driving in the absence of GPS (Global Positioning System) satellite support [8]. Navigation systems have gotten more and more data driven in recent years due to the emergence of mobile computing devices and the widespread use of GPS technology. It suggested a navigation system that alerted users about traffic accidents [9]. Numerous base stations, communication networks, and sensors make up the system. Traffic management, vehicle monitoring, driver and time management were all maintained and controlled via the Internet of Things. The Intelligent Transportation System (ITM) was utilized to determine the conditions of the roads and climate. There was talk about GPS, car tracking systems, and collision avoidance techniques [10]. The Internet of Things concept based on global navigation satellite systems and advanced driver assistance systems has been considered [11]. ARM process controllers in the Internet of Things have been used to determine the driver's intoxication level and vehicle speed. Different approaches were used to discuss IoT intelligent transport systems and smart car technology [12]. Automated vehicles employed distinct protocols and network structures [13]. Wireless sensor networks allowed for efficient communication. The internet was used to conduct automated car tracking and routing [14]. The vehicle's position and speed were estimated using the GPS. The engine performance was tracked using the cloud database management system for data analysis and storage. An Internet of Things-based system has been used to measure the amount of air pollution [15]. Wireless sensor networks and a variety of sensors improved pollution monitoring. Cloud computing technology has been used to store and evaluate the pollution related data. The amount of pollution produced by the car was tracked, and corrective action was taken to lower the pollution levels [16]. There has been discussion on the research and development of IoT applications across several disciplines for contemporary society [17]. The machine learning algorithms were used to forecast vehicle carbon emissions based on variables including vehicle type, fuel type, road conditions, and traffic patterns. Many studies were examined on the use of learning techniques in the analysis of automobile emissions. Emission estimating and modeling were used to predict emissions from vehicle attributes, driving habits, and environmental factors using learning approaches, but individual vehicle-based estimation has not yet detected by the work. Emissions optimization and control were used for creating control strategies based on machine learning to minimize emissions in real time or by managing a fleet of vehicles. Emission hotspot detection process utilizes learning techniques to identify geographic locations or traffic patterns linked to elevated amounts of emissions but failed to detect individual vehicle emissions. The LSTM and BiLSTM models were built [18] and experiment on Canada emission dataset collected through repositories, no other dataset available for individual vehicle. The BiLSTM model outperformed, by achieving high MSE and RMSE prediction values.

METHODOLOGY

Here, the Figure 1 shows the proposed architecture of the system. The OBD2 port is connected to the CariQ device. After registration of the CariQ device, the CariQ application also works on user mobile, through this work, real-time screenshots of the application were used to create the real time dataset, through the CariQ device that is connected to the On-Board Device port [19–21], of the vehicles. By using an IoT interface system, vehicle's performance metrics such as speed, tires and engine oil condition, mileage, mechanism, and air pressure are tracked. Inadequate vehicle maintenance and monitoring is the primary source of vehicle pollution. All these conditions are detected by CariQ device and application. The CariQ device is used to collect the real-time dataset and captured the real-time screenshots of different windows of the CariQ application. The application first shows the profile window in Figure 2, this window contains the details like Name, email-id, and Mobile number.

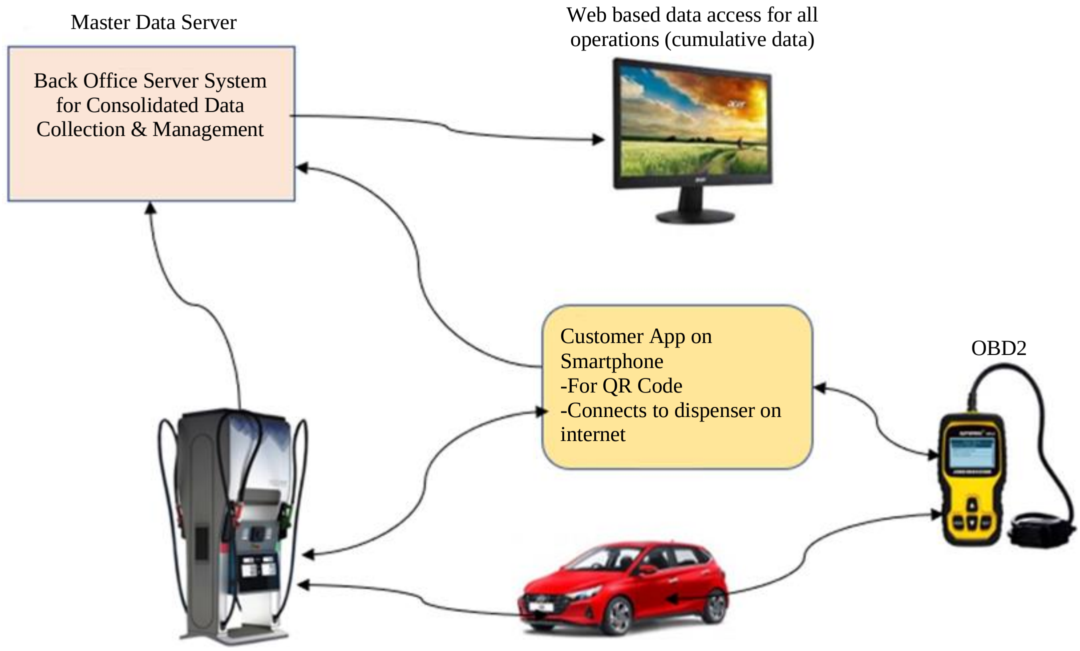


Figure 1. System Architecture.

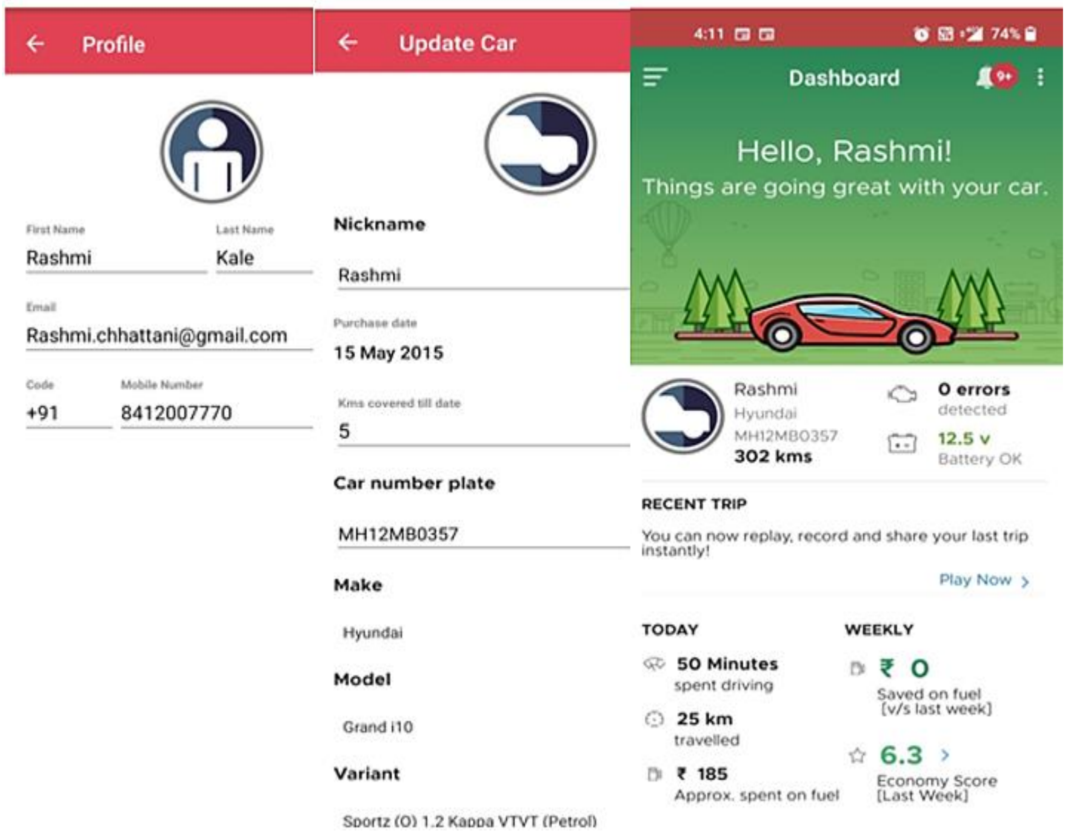


Figure 2. Application Profile, Vehicle Registration and Dashboard window.

After filling these details, the profile gets created. In Vehicle registration window, all vehicle details need to be filled to get the correct parameters related to the vehicle. It contains the details regarding the vehicle like vehicle number plate, Owner name, Purchase Date, Make, Model, Fuel type, etc. After entering all the correct details regarding the vehicle, the registration becomes successful. Based on the entered details, when owner drives the car, the mobile application displays the individual vehicle per trip fuel expenses on dashboard, kilometers travelled, and minutes required for the trip. Through this, the system can detect the individual fuel expenses per trip as well. By using this CariQ device collected all the readings on different vehicles for almost 2 years. Based on these readings, the dataset is created. By using this collected and created dataset, carbon emission model is created, different machine learning and deep learning algorithms are applied on this dataset to define the dashboard of individual vehicle carbon emission to define the dashboard of individual vehicle carbon emission.

Mathematical Formulation

A mathematical model utilizing the cumulative distribution function and probability distribution function to predict carbon emissions is as follows:

In predicting carbon emission probability theory and statistics, a Probability Distribution Function (PDF) and Cumulative Distribution Function (CDF) play important role. Mathematical modelling works as follows:

Probability Distribution Function

The probability that a continuous random variable, X, will fall inside a specific range of values is expressed by the probability distribution function, f(x). In mathematical terms, the integral of the PDF across any given interval (a, b) yields the probability P (a≤X≤b):

$$P\ (a \leq X \leq b) = \int_a^b f\ (x)dx \tag{1}$$

Principal attributes of a PDF:

1. f(x)≥0 for all x.
2. The total area under the PDF curve over the entire range of possible values of x is equal to 1:

$$\int_{-\infty}^{\infty} f\ (x)dx = 1$$

Cumulative Distribution Function

Given a random variable X, the probability that its value would be less than or equal to x is given by the cumulative distribution function F(x). In mathematical terms, it can be expressed as the integral of the PDF between x and the lower limit of integration, which is typically negative infinity.

$$F(x) = \int_{-\infty}^{x} f\ (t)dt \tag{2}$$

Principal attributes of a CDF:

1. 0≤F(x)≤1 for all x.
2. The CDF is non-decreasing: F(x1)≤F(x2) if x1≤x2.
3. F(x) approaches 0 as x approaches negative infinity while F(x) approaches 1 as x approaches positive infinity.

The behavior of random variables in numerous probability distributions, including the normal distribution and exponential distribution, can be understood and analyzed using these mathematical models as a foundation.

MODEL IMPLEMENTATION

After collecting the dataset, data is sent to the administrator; after that, actual implementation of the model starts. Firstly, created the dashboard for the module. Vehicle numbers from the dataset separated through the clustering methodology. Each cluster defines the separate data of the car emissions. Select the Vehicle number from the dashboard and click on submit button. Figure 3 shows these details.

After clicking on the submit button, next window appears that shows vehicle details like vehicle type, company, model, engine size, number of cylinders, fuel type and carbon emission till date. It shows total emissions of the vehicle on dashboard. Figure 4 shows all the details.

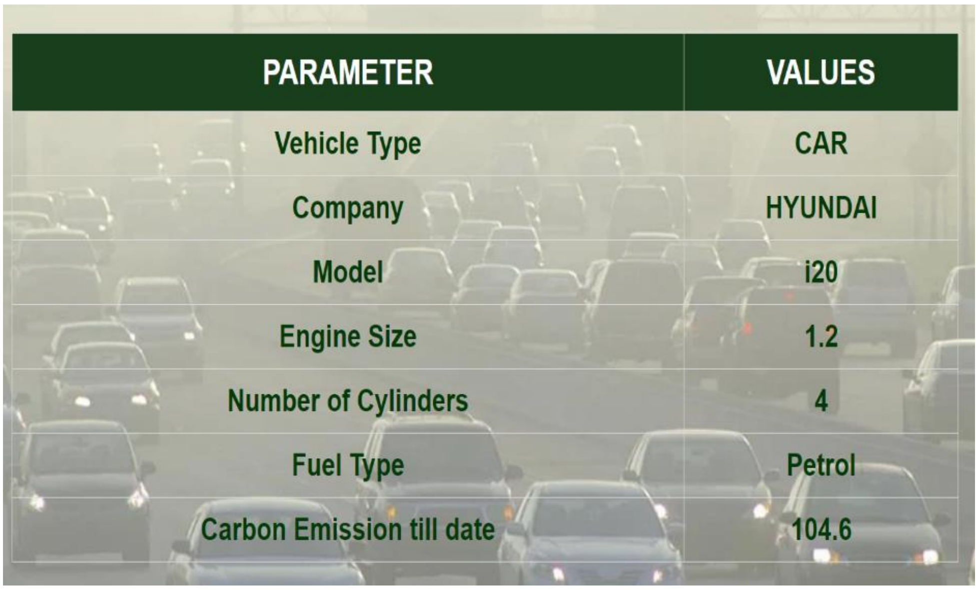
Emission graphs of selected vehicle number get generated. Figure 5 shows the Day wise emissions of the vehicle in the graph through probability distribution function. This graph represents day wise emission as well as the overall yearly chart of the emission. If you click any date on the graph, it will show the cumulative emission till that date.

Figure 6 shows the cumulative distribution graph of carbon emission. If clicked on any point on the graph it shows the carbon emission till that day cumulatively since the starting date.

RESULTS AND DISCUSSION

Collected data from the device has been applied to the model to test the accuracy of different algorithms. 10 machine learning algorithms were applied to build idling emission models, including ABML, SVM, Decision Making, Random Forest, Linear Regression, KNN, Logistic Regression, Ridge Regression, Gradient Boosting and Proposed system algorithm that is advanced LSTM. Accuracy results of all the algorithms are showed in Figure 7.

Figure 3. Select vehicle number from dashboard.



PARAMETER	VALUES
Vehicle Type	CAR
Company	HYUNDAI
Model	i20
Engine Size	1.2
Number of Cylinders	4
Fuel Type	Petrol
Carbon Emission till date	104.6

Figure 4. Dashboard window displays the emission and other details of the vehicle.

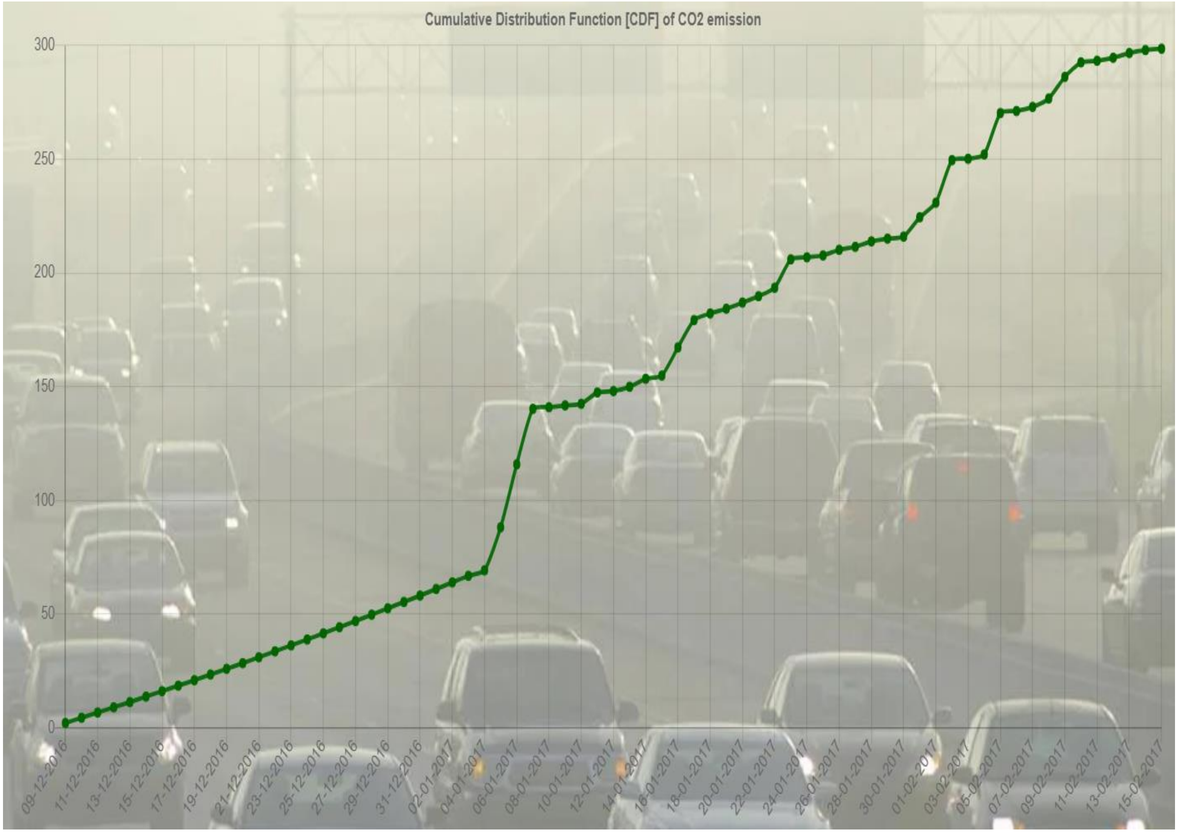


Figure 5. Day WISE EMISSION GRAPHS of vehicle.

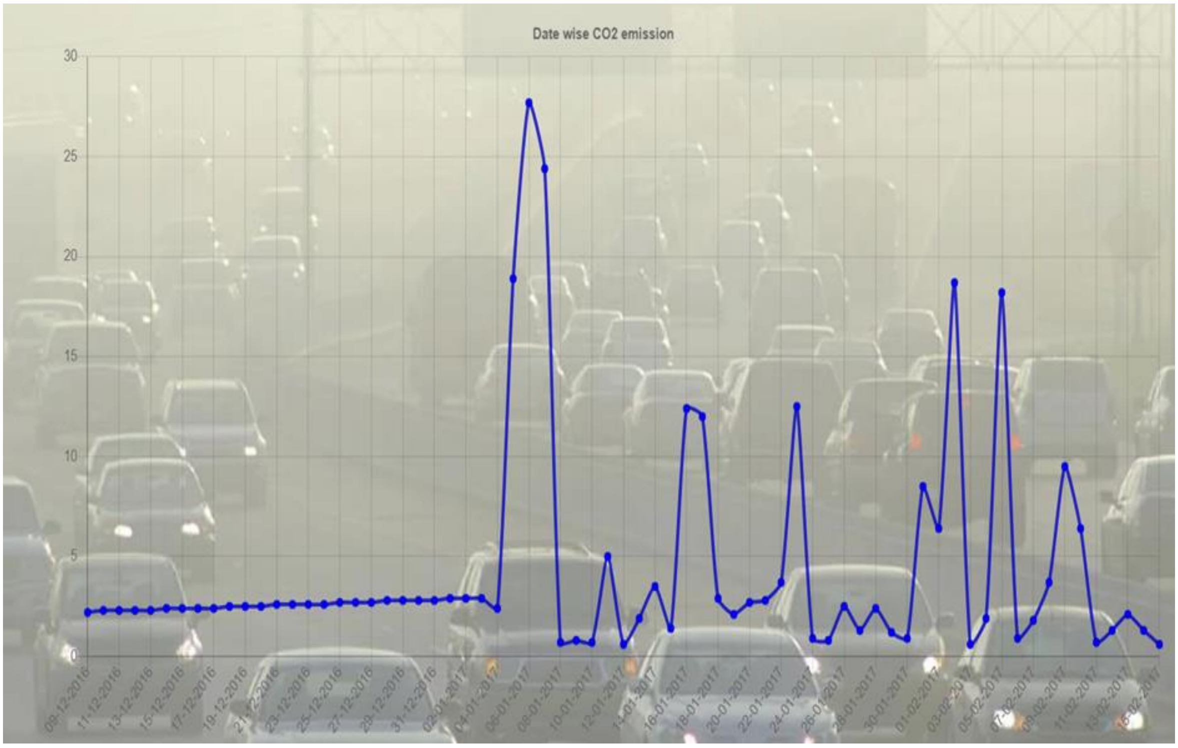


Figure 6. Cumulative emission graphs of vehicle.

Mean squared Error values are calculated for each applied algorithm. These values are showed in Figure 8. Based on it the proposed advanced LSTM gives better accuracy and less Mean Square Error.

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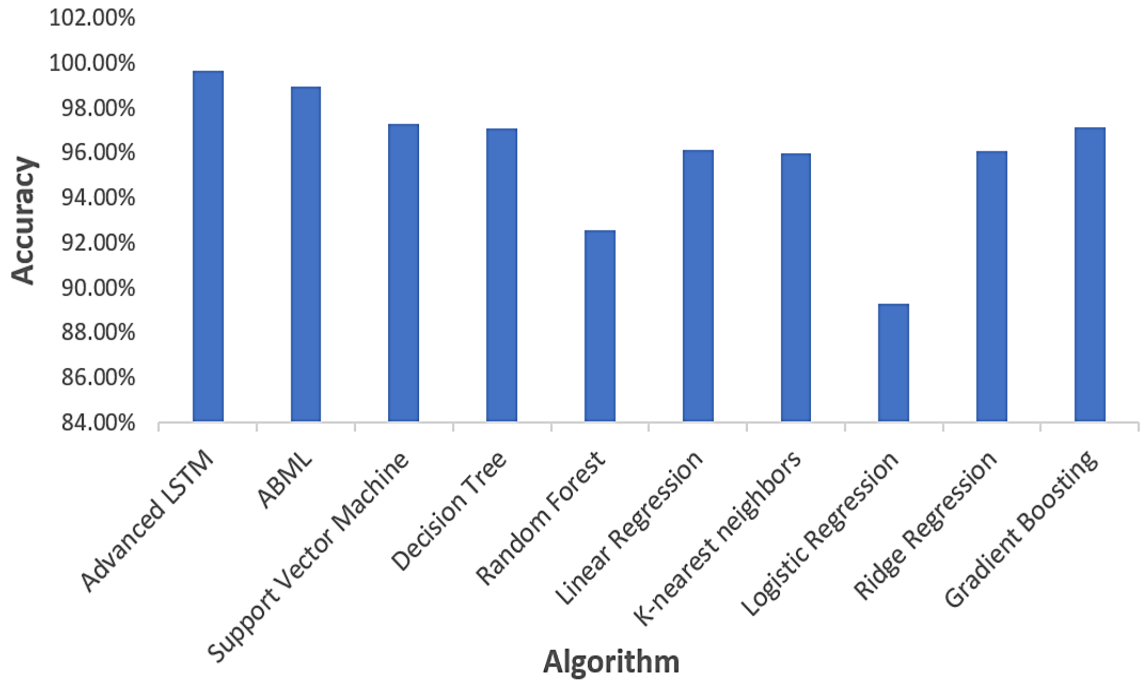

Figure 7. Accuracy results of applied algorithms.

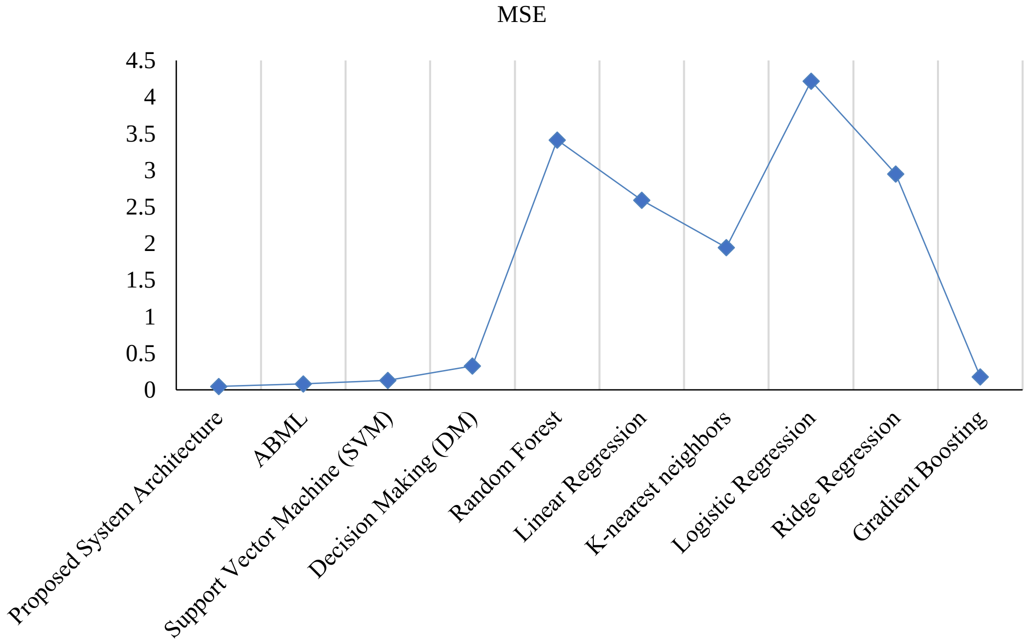

Figure 8. MSE values of the applied algorithms.

CONCLUSION

This study explains the creation of a strong system for tracking personal fuel costs and calculating carbon emissions by combining IoT technology and machine learning. It uses predictive algorithms along with real-time data from cars, collected through IoT devices, to forecast fuel use and emissions. The technology encourages people to adopt greener commuting habits and makes better decisions for them. It is a valuable tool for both individuals and organizations aiming to reduce their carbon footprint by offering insights into fuel consumption and emissions, ultimately supporting environmental sustainability. The research confirms the framework's effectiveness in promoting more sustainable practices.

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