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AI-Powered Smart Fuel Level Indicator and Prediction of Mileage for Two-Wheelers

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Abstract

Most two-wheelers in India use analog fuel meters, which lack accuracy. Traditional fleet management relies on fixed conditions for fuel estimation, but real-world mileage varies due to factors like driving style, speed, and road conditions. To address this, our work develops a digital fuel measurement system using sensors and a microcontroller to accurately display the exact fuel inlet. This cost-effective solution ensures transparency and prevents fraud. Along with this it uses machine learning-based regression to predict the distance a two-wheeler can travel with available fuel. Sensors on the vehicle and fuel tank provide real-time data, enhancing accuracy in mileage prediction for efficient fleet management. The study evaluates various fuel sensors, identifies limitations in existing systems, and introduces an improved digital sensing technology for precise fuel measurement.

Major Findings: *The regression model achieved an R-squared of 0.94, explaining 94% of the variance in mileage, with RMSE 2.72 and MSE of 5.44 indicating high accuracy. Road conditions, traffic, and weather were the most influential factors, and residual plots confirmed model reliability, predicting mileage at 26.65 kmpl for a given input.*

Keywords: *Digital Fuel, Machine Learning, Mileage, Regression Model, R-Squared*

1.0 Introduction

Accurate fuel measurement is crucial for both economic and performance-based considerations in two-wheelers. Traditional digital fuel meters commonly display fuel levels using bar indicators rather than providing precise numerical values, leading to inaccurate estimations of the fuel present in the tank. This lack of precision makes it difficult for riders to gauge the exact amount of fuel available, potentially causing inconvenience or unexpected fuel shortages[1]. Fuel consumption prediction is essential for optimizing fuel economy, preventing fuel theft, and improving the efficiency of two-wheelers. With the rising cost of fuel and increasing concerns about resource conservation, accurately estimating fuel usage has become a crucial aspect of modern vehicle management[2]. However, traditional fuel monitoring systems often provide only basic estimations, failing to consider real-world variables that significantly impact fuel efficiency. Fuel consumption is influenced by both internal factors

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and external conditions[3]. Internal factors include the type of vehicle, engine efficiency, load capacity, and the distance travelled. On the other hand, external factors such as road conditions, traffic congestion, driving behavior, and weather play a major role in determining how efficiently fuel is utilized. In real-world scenarios, fuel consumption varies dynamically due to these influences, making traditional estimation methods less reliable. In a dynamic transportation sector marked by constant innovations and a growing emphasis on efficiency, sustainability, and user experience, the role of two-wheelers has become increasingly important[4]. Kussl S, *et al.,* presents a privacy-focused vehicle classification system using MEMS magnetic sensors and machine learning to identify type, model, and fuel without visual data, offering a non-intrusive, accurate alternative for traffic monitoring[5]. Ajdadi F, *et al.,* presents, a Motorcycles and scooters are quick and convenient ways of urban transportation, negotiating congested streets and providing an alternative to traditional four-wheeled vehicles[6]. Recognizing the importance of these two-wheelers in the modern transportation environment, this work seeks to accelerate their progress through the creation of a new solution: Real-time monitoring of engine oil and fuel levels. Jaimon Chacko Varghese[7] investigated Low-Cost Intelligent Real-Time Fuel Mileage Indicator for Motorcycles. In this competitive arena, everyone aspires for higher accuracy than previously presented methods. To improve accuracy, we combined ultrasonic and flow sensors to provide fuel level indicator findings. This experimental study produced satisfactory findings when compared to conventional methods.

Deep Gupta, Brajesh Kr. Singh, and Kuldeep Panwar[8] present research of a prototype model for a fuel level detector and optimizer. There are numerous sensor-based systems available in the market for detecting liquid levels, which provide a general indication of liquid quantity. However, none can provide an exact approximation of quantity, such as gasoline meters in cars, which display whether the tank is full, empty, or half full. Sarath T.M, Subha H P, and Danial Furtado[9] did a study on level measurement with pressure sensors. The LED's purpose is to display and indicate the current fuel tank level. A sensor is used to detect and monitor fuel levels in the fuel tank. This notion is primarily advantageous to the car sector. S. A. Gandhi[10] did research on the Smart Fuel Level Indication system. Until now, the precision of fuel level measurement has not been particularly critical.

The objective of measuring the gasoline level is to display the information on the dashboard via a fuel level meter. The primary considerations, rather than accuracy, are to prevent abrupt fluctuations in the displayed fuel level and to ensure the meter indicates an empty tank when the gasoline level falls below a certain threshold.

This work seeks to provide an intelligent digital fuel gauge and a fuel consumption forecasting system for motorcycles. Through the incorporation of sensor-based fuel measurement, the system delivers precise real-time fuel levels in litters or millilitres, thereby removing the uncertainty associated with conventional bar-based meters. A machine learning-based mileage prediction model employing linear regression determines the distance a motorcycle can go depending on available fuel, considering parameters such as traffic, speed, weather and road conditions. This novel method promotes fuel transparency, enhances trip planning, and maximizes fuel efficiency, benefiting both individual riders and fleet operators.

2.0 Methodology

The technique for the smart fuel level indicator and prediction of mileage for two-wheelers entails the integration of sensor-based fuel monitoring technology with machine learning algorithms to optimize fuel management. The smart fuel level indicator use high-precision sensors to accurately detect real-time fuel levels in litters or millilitres, thereby removing the inaccuracies

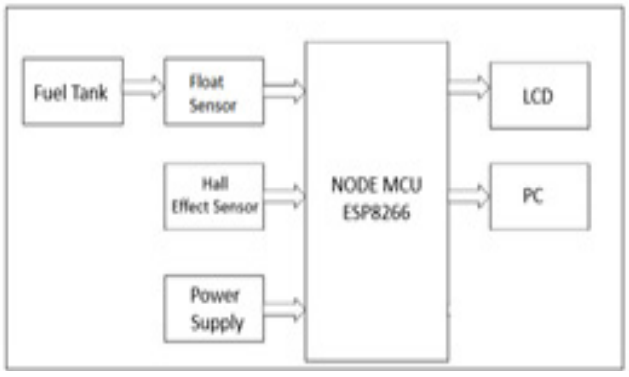


Figure 1. Smart fuel level indicator.

associated with traditional bar-based indications. A regression-based model for mileage prediction is constructed utilizing real-time sensor inputs, accounting for variables like as speed, load, road conditions, traffic, and weather. The system analyzes these factors to calculate the distance a two-wheeler can traverse with the available fuel, facilitating precise fuel consumption assessment, improved trip planning, and increased efficiency. A standard smart fuel level indicator system has been designed and implemented, as illustrated in Figure 1.

2.1 Tank

In this case, the fuel tank will contain a flow meter, and a sensor will count the revolutions when the rotor begins to rotate as mentioned in Figure 2. As a result, it will display the fuel level in the tank[11].



Figure 2. Tank for smart fuel level indicator.

2.2 Float Sensor

One tool used to measure and show the amount of fuel in a tank is a float sensor for fuel level monitoring[12]. Usually, a mechanical arm is attached to a buoyant float.

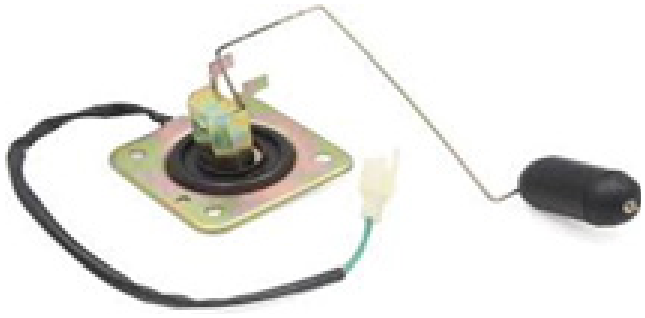


Figure 3. Float sensor for fuel level.

The float rises or falls in proportion to variations in the tank's gasoline level. To ascertain the current fuel level, the float's movement is converted into electrical signals that can be deciphered[13]. The picture of float is displayed in Figure 3.

2.3 Hall Effect Sensor

A Hall Effect sensor is a transducer used for current sensing, speed detection, proximity switching, and positioning that changes its output voltage in reaction to a magnetic field as mentioned in Figure 4. It functions as an analog transducer, producing voltage in response to the strength of the magnetic field. Often integrated with threshold detection, it functions as a switch in industrial and consumer applications, such as pneumatic cylinders, printers, and high-reliability keyboards. Hall sensors are widely used in timing engine ignition, tachometers, anti-lock braking systems, and brushless DC motors to detect magnet positions. They also regulate disk drive speeds by sensing rotational motion.

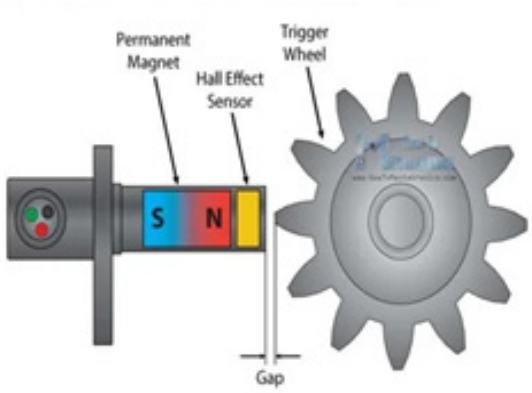


Figure 4. Hall effect sensor.

2.4 ESP-8266 Node MCU

The Node-MCU (Node Micro Controller Unit), built around the ESP8266, is an open-source development platform featuring built-in Wi-Fi connectivity, low power consumption, compact design, multiple GPIO pins, IoT[14] compatibility, fast processing, and easy programming, making it ideal for real-time fuel level indication by enabling seamless sensor integration, data processing, and remote monitoring for efficient fuel management. The ESP8266 Node-MCU development

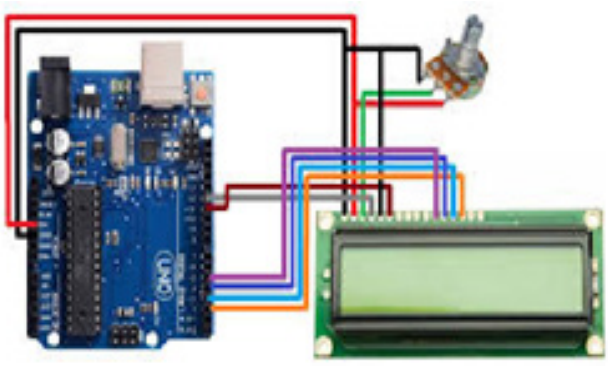


Figure 5. Node MCU with LCD interface.

board plays a crucial role in a smart fuel indicator by enabling real-time fuel level monitoring and data transmission.

With built-in Wi-Fi capabilities, it offers easy connecting to cloud platforms or mobile applications[15], enabling remote access to fuel data. The board processes sensor inputs, such as those from ultrasonic or hall effect sensors, to measure fuel levels accurately and transmit the data wirelessly. It also supports IoT integration for tracking historical fuel consumption, predictive analytics, and automated alerts. Its low power consumption, affordability, and ease of programming make it perfect for integrating smart fuel monitoring systems in two-wheelers. The arduino uno controls the AI-powered fuel indicator, collecting GPS and fuel sensor data, processing it, and predicting mileage. A 16x2 LCD with I2C displays fuel levels, estimated range, and alerts, ensuring efficient and cost-effective fuel monitoring.

2.5 AI-Powered Prediction of Mileage

The flowchart depicts an iterative method for creating and testing a regression model to ensure correct predictions.

Table 1. Structured data for the model

Speed (km/h)	Load (kg)	Road Condition	Traffic Level	Weather Condition	Mileage kmpl
58	89	3	2	1	19.60
71	131	1	4	3	10.91
48	160	4	1	1	18.47
34	102	1	4	1	30.76
62	73	1	4	3	24.37
27	173	3	3	1	22.55
40	90	2	1	3	30.81
58	64	2	4	2	21.27
77	94	1	4	1	17.67
38	114	4	2	2	21.01
42	138	2	4	3	16.24
30	120	4	4	2	20.47
30	58	2	2	2	33.64
43	137	4	3	3	13.69
72	178	3	4	2	3.50
55	185	4	2	2	12.19
59	112	3	1	3	21.83
43	188	3	3	2	12.80
41	185	3	1	2	24.25
22	130	4	1	3	24.25

Table 2. Conditions for the set value

Value	Road Condition	Traffic Level	Weather Condition
1	Smooth (Highway or Well-Maintained)	Low (Free flowing, No Congestion)	Clear (Sunny, No Adverse Weather)
2	Normal (City Roads with Minimal Potholes)	Moderate (Some Traffic, No Major Delays)	Cloudy (Overcast, But No Rain)
3	Rough (Uneven Roads, Minor Potholes)	High (Heavy Traffic, Slow movement)	Rainy (Light to Moderate Rain)
4	Very Rough (Heavy Potholes, Dirt Roads)	Severe (Traffic Jams, Stop-and-Go)	Extreme (Heavy Rain, Fog, or Snow)

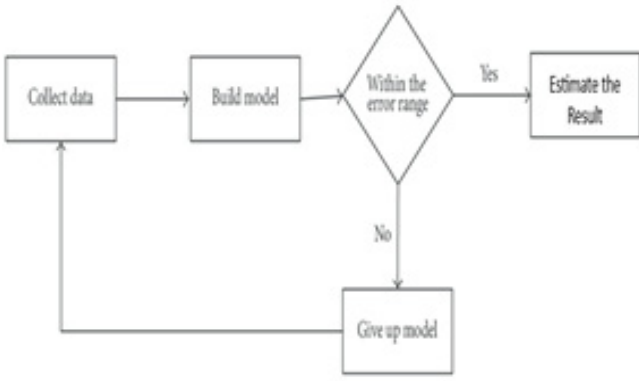


Figure 6. AI Model for prediction of mileage.

It starts with data collection, which gathers essential input variables as in Table 1. A regression model is then constructed and evaluated based on prediction error. If the error is within the acceptable range typically 5% to 10% deviation from actual values.

The model is considered valid, and the results are estimated. If the error exceeds this threshold, the model is rejected, and the procedure is repeated to collect further data to refine and enhance the model as in Figure 6. This iterative strategy assures the creation of a reliable regression model capable of producing precise predictions for informed decision-making.

2.5.1 Data Set

The dataset is structured to develop a regression model for predicting the mileage (kmpl) of a two-wheeler based on key influencing factors. It includes Speed (km/h), Load (kg), Road Condition, Traffic Level, and Weather Condition, all which impact fuel consumption. Speed determines fuel efficiency, while higher loads generally reduce mileage. Road conditions, categorized from smooth (1) to rough (4), influence rolling resistance and energy loss. Traffic levels, ranging from free flow (1) to heavy congestion (4), affect frequent acceleration and braking, impacting fuel usage as mentioned in Table 2. Weather conditions, from clear (1) to extreme (4), also play a role, with harsh weather increasing fuel consumption. The model aims to analyse these variables using linear regression to establish relationships and accurately predict the vehicle's mileage under different driving conditions.

2.5.2 Regression

A regression model is a statistical approach used to establish a relationship between a dependent variable (Mileage in kmpl) and one or more independent variables (Speed, Load, Road Condition, Traffic Level, and Weather Condition). In this case, we use a multiple linear regression model, which can be mathematically expressed as in Equation (1).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \epsilon \quad (1)$$

where:

- Y= Mileage (kmpl) (Dependent Variable)
- X_1=Speed(km/h)
- X_2= Load (kg)
- X_3= Road Condition (1-4)

- X_4= Traffic Level (1-4)
- X_5= Weather Condition (1-4)
- β_0= Intercept (Mileage when all predictors are zero)
- $\beta_1, \beta_2, \ldots, \beta_5$ = Coefficients representing the impact of each factor on mileage
- ϵ = Error term (accounts for randomness and unobserved factors)

The regression model is trained using least squares estimation, which minimizes the sum of squared residuals as in Equation (2).

$$mileage = \min \sum \left(Y_i - \hat{Y}_i\right)^2 \quad (2)$$

Where are the actual and predicted mileage respectively. Model performance is evaluated using R-squared (R2), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) to determine the accuracy of predictions. By analyzing this model, we can predict mileage based on different road and driving conditions, optimizing fuel efficiency for two-wheelers.

3.0 Results and Discussions

Predicting fuel levels and estimating a two-wheeler's mileage using a regression model are the main goals of the proposed work.

3.1 Smart Fuel Level Indicator

Implementing the real-time engine oil monitoring and fuel level monitoring system has shown in Figure 7 provides promising results in enhancing two-wheeler performance, longevity, and safety. The system includes precision sensors that continuously monitor fuel levels and engine oil in real time, giving riders with precise and trustworthy data under a variety of operating circumstances.

In the circuit schematic, a arduino uno serves as the core controller, communicating with a hall effect magnetic sensor, LCD display, buzzer, potentiometer, and other components. The fuel level monitoring system operates via sensor-based detection, which measures fuel levels and transmits real-time data to the LCD screen

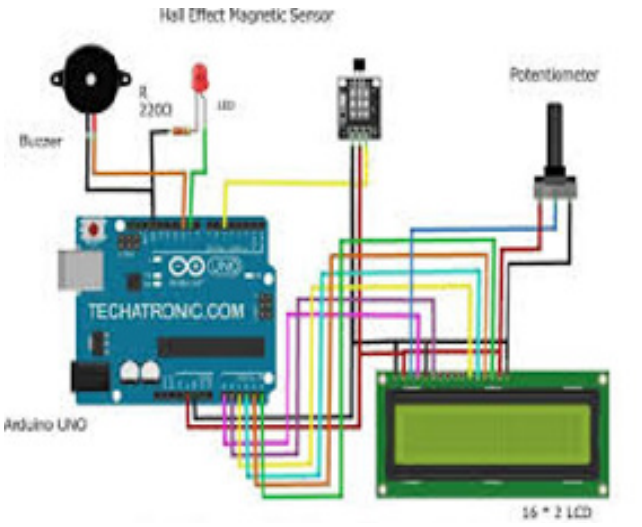


Figure 7. Arduino based fuel level indicator.

for immediate visibility. When gasoline hits a critical level, the buzzer can serve as an alert system, ensuring that riders act quickly. The potentiometer in the circuit is most likely used as a control element to change display parameters or sensor sensitivity.

Integrating this technology into two-wheelers improves urban mobility, decreases emissions, and ensures proactive vehicle maintenance. By offering real-time insights into fuel and oil levels, riders may make more educated refuelling and servicing decisions, eventually enhancing vehicle economy and sustainability. The seamless data collecting and processing through a CPU allows for efficient monitoring, making this technology a significant leap in intelligent vehicle management.

3.2 AI-Powered Prediction of Mileage using Linear Regression

The dataset is structured to develop a regression model for predicting the mileage (kmpl) of a two-wheeler based on key influencing factors. It includes essential variables such as Speed (km/h), Load (kg), Road Condition, Traffic Level, and Weather Condition, all of which significantly impact fuel consumption. By analyzing these parameters, the model aims to establish relationships between the independent variables and mileage, ensuring accurate predictions.

A total of 100 data points were collected to build and validate the regression model. The dataset was split into training and testing sets using an 80-20 approach,

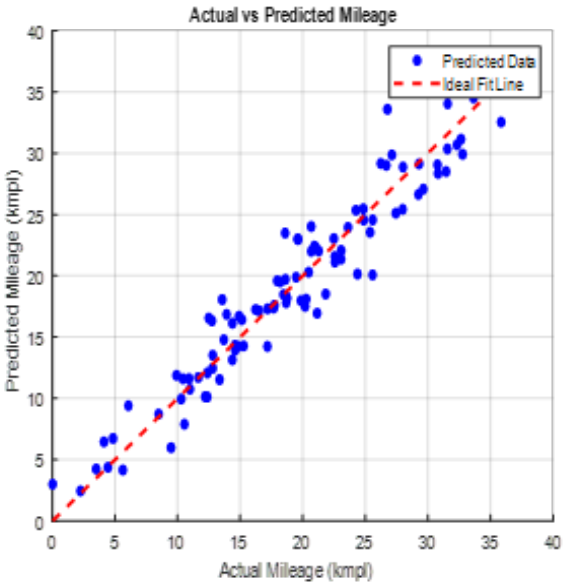


Figure 8. Scatter plot for the data.

where 80% of the data was utilized for training the model, and the remaining 20% was reserved for testing its accuracy. Various regression techniques were applied, and statistical analyses were conducted to evaluate model performance. Key performance metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2), were used to assess the model's effectiveness in predicting mileage. The results provided insights into how different factors influence fuel efficiency and helped refine the model for better accuracy and reliability. The scatter plot compares actual vs. predicted mileage, where blue dots represent predictions, and the red dashed line indicates perfect accuracy as in Figure 8. The close alignment of points to the line suggests good model performance, with minimal errors, though some deviations exist.

The residual plot in Figure 9 displays the difference between actual and predicted mileage values. The black dots represent residuals, while the red dashed line indicates zero error. Ideally, residuals should be randomly distributed around this line, signifying that the model does not show bias in predictions. The scattered nature Figure suggests the model captures trends well but may have minor errors across different mileage ranges.

The distribution of residuals histogram in Figure 10 shows how the errors (differences between actual and predicted mileage) are spread. The bell-shaped pattern suggests a roughly normal distribution, indicating that the regression model makes unbiased predictions. Most residuals are centred around zero, meaning the model is accurate, with only a few large errors. This confirms the model's effectiveness in predicting mileage with minimal deviation.

According to Table 3, the coefficient values, the factors that have the biggest effects on the system are weather1.8, traffic -2.0, and road condition 2.3, suggesting that they are crucial in determining results or performance. In

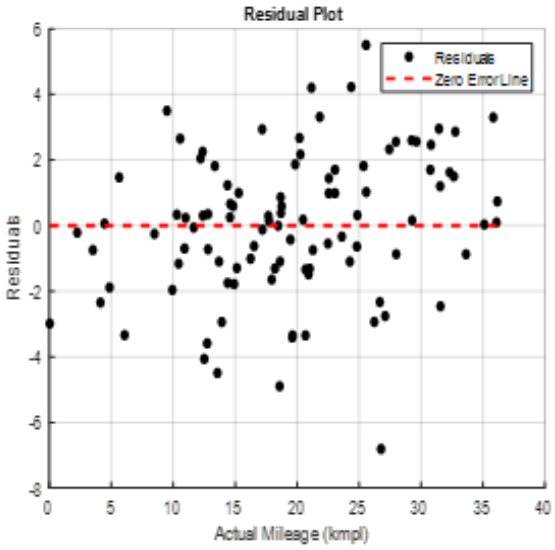


Figure 9. Residual plot for mileage values.

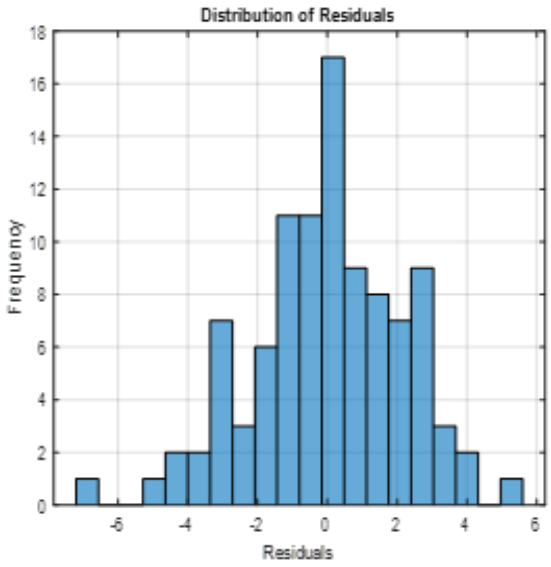


Figure 10. Distribution of residuals.

contrast, the effects of load at 0.1 and speed at 0.3 are negligible.

Table 3. Analysis of regression model

Sl. No.	Features	Coefficient Value
1	Road Cond	2.3
2	Traffic	2.0
3	Weather	1.8
4	Speed	0.3
5	Load	0.1

Similarly, Figure 11 depicts, feature Importance bar chart shows the impact of different factors on mileage prediction. The road condition has the highest influence, followed by traffic level and weather conditions, indicating that environmental factors significantly affect fuel efficiency. Speed and load have a lower impact, suggesting that while they contribute to mileage variation, their effect is relatively minor compared to road and traffic conditions. This insight helps prioritize key factors for improving mileage prediction accuracy.

The heatmap in Figure 12 illustrates the correlation between features affecting two-wheeler mileage. Speed

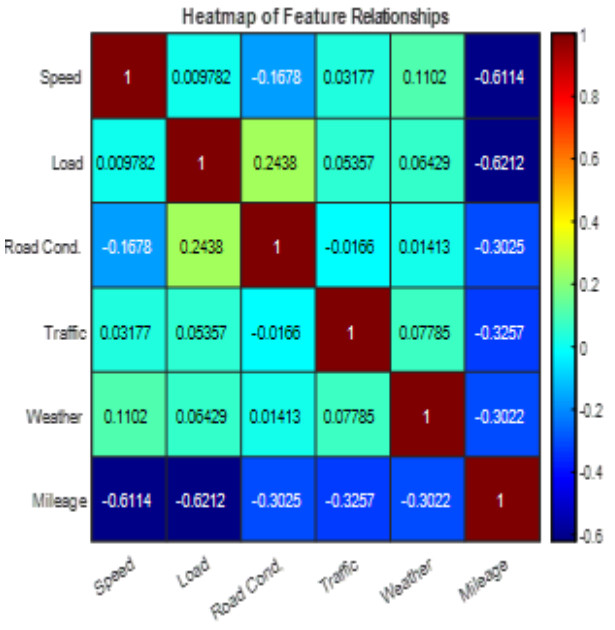


Figure 11. Feature importance.

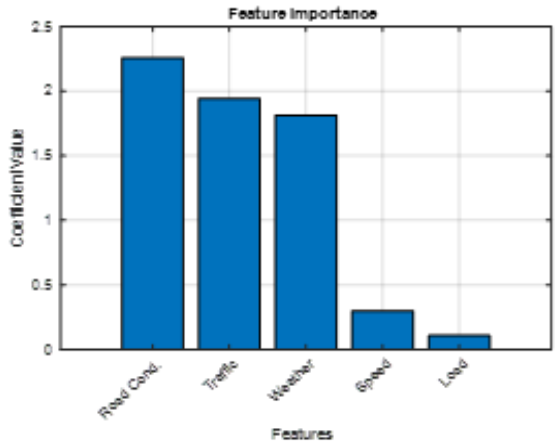


Figure 12. Heat map.

and Load show a strong negative correlation with Mileage (-0.6114 and -0.6212, respectively), indicating that higher speed and load reduce fuel efficiency. Road Condition, Traffic, and Weather also negatively impact Mileage but to a lesser extent. The diagonal values are 1, representing self-correlation. This analysis helps identify key factors influencing mileage and their relationships, aiding in optimizing fuel efficiency.

3.3 Model Performance

Table 4 and Table 5 highlights the overall analysis of the regression model for a two-wheeler system. The regression model for predicting two-wheeler mileage demonstrates high accuracy, with an R-squared value of 0.94, indicating that 94% of the variance in mileage is explained by the input features. The RMSE (2.72) and average RMSE (2.33) suggest minimal prediction error, while the MSE (5.44) confirms consistency. The model predicts a mileage of 26.65 kmpl based on given input parameters, making it a reliable tool for estimating fuel efficiency.

Table 4. Error analysis of the model

Sl. No.	MSE	RMSE	RMSE
1	5.1	2.6	2.2
2	5.5	2.8	2.6
3	5.8	2.9	2.4
4	5.2	2.6	2.2
5	5.6	2.9	2.5
Average	5.44	2.72	2.33

Table 5. Mileage analysis of the model

Sl. No.	R-squared	Avg. RSQ	Predicted Mileage
1	0.92	0.91	26.40
2	0.93	0.93	26.80
3	0.95	0.94	26.50
4	0.94	0.93	26.60
5	0.94	0.94	26.70
Average	**0.94**	**0.932**	26.65 kmpl

4.0 Conclusions

The purpose of this study is to develop a regression model for accurately predicting the mileage (kmpl) of a two-wheeler based on key influencing factors such as Speed (km/h), Load (kg), Road Condition, Traffic Level, and Weather Condition. Understanding these relationships can help optimize fuel efficiency and enhance vehicle performance. The dataset consists of 100 records, with 80% used for training and 20% for testing. A regression analysis was applied to establish the relationship between these variables and mileage. The model performed well, achieving an R-squared value of 0.94, meaning it explains 94% of the variance in mileage. The low RMSE (2.72) and MSE (5.44) indicate high accuracy. Feature importance analysis highlights that road conditions, traffic, and weather are the most influential factors, followed by speed and load. Residual plots show a normal error distribution, confirming model reliability. The model successfully predicts mileage, with a predicted value of 26.65 kmpl for a given input.

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