Remaining Range Prediction for Electric Vehicle Using Machine Learning

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***Abstract*—Electric vehicles are one of the most rapidly growing technologies in the modern world. However, a major issue with electric vehicles is their limited driving range. The limited driving range of electric vehicles often causes anxiety among drivers about the distance these vehicles can cover. Despite various technological developments, accurately predicting the remaining range of electric vehicles remains a significant challenge.**

In this paper, a machine learning model is proposed to predict the range of electric vehicles based on real-world data. The system utilizes a Linear Regression model in conjunction with Ridge Regression and Lasso Regression models for the prediction of electric vehicle ranges. The system is trained to learn the relationship between driving distance and the various features of electric vehicles in real-world scenarios.

Keywords-Range Prediction, Electric Vehicles, EVs, Machine Learning, Linear Regression Model

I. INTRODUCTION

Overcoming the challenge of limited driving range stands as a pivotal step for the widespread adoption of electric vehicles (EVs). A key aspect in alleviating drivers' concerns about range anxiety is the accurate prediction of the remaining driving range. This research introduces a novel machine learning model that blends various techniques to predict the remaining driving range of EVs, leveraging insights from real-world historical driving data. The model is intricately trained to decipher the relationship between driving distance and crucial features, including the cumulative output energy of the motor and battery, diverse driving patterns, and battery temperature. Furthermore, we propose a strategy based on an 'anchor (baseline) approach' to effectively address the imbalanced distribution within the dataset, demonstrating its success in rectifying disparities. This introductory exploration lays the foundation for a comprehensive investigation into enhancing the practical application of electric vehicles.

II. RELATED WORKS

There are two ways to reduce the anxiety of the driver and to find the remaining range of the electric vehicle. They are 1) Finding the energy consumption rate and 2) Directly determining the remaining range.

A. Energy Consumption Rate

There are many studies and many researches have been established in the area of the determining the energy consumption rate in that area of research Witvoet et al.[19] established an efficient system for acquiring the energy consumption rate of the battery of electric vehicles with which the remaining charge of the battery is found with that state of charge the remaining range of the vehicle will also be determined. He et al.[12] also carried out the energy consumption rate finding and also produced the same result of determining the remaining range of the vehicle.

B. Determining Remaining Range

1) Model Based Works: The model based Range prediction system have high precision and more efficient way of finding the remaining range of the electric vehicle and reducing the drivers anxiety. Eissa et al.[6] proposed a model based system with the batteries, motors and vehicle drive system to determine the remaining range of the EV. The Oliva et al.[15] establishes real time range prediction mechanism with the model based data driven system.

2) Simulation Based Works: The simulation based prediction system provide ranges with its own defect because the in simulation environments many real time factors are not considered but for research purposes the simulation based systems helps a lot. Birrell et al.[2] establishes simulation based range prediction for electric vehicles using the lithium ion batteries and their specifications. Dokgoz et al.[5] also publishes the simulation based work but it is different from other works as it uses the State of Charge but also directly predicts the remaining range of the E-vehicles. Some other authors [4], [17], [18] are also purposed new systems in the simulation environment to predict the remaining range.

III. OBJECTIVES

The two main objectives of the paper is A)Enhance Prediction Accuracy: Employ advanced machine learning techniques to refine the accuracy of the model for predicting the remaining driving range of electric vehicles. B)Implement ’Fusion-Based’ Strategy: Integrate a ’fusion-based’ strategy into the prediction process to effectively eliminate imbalance issues within the training label dataset.

IV. Remaining Range Prediction Framework

The remaining range prediction in this module is done through the three basic and most efficient machine learning algorithm.

1) Linear Regression Algorithm
2) Ridge Regression Algorithm
3) Lasso Regression Algorithm

With those three algorithm models have been made to determine the fitting values to find the remaining range of the electric vehicles.

A. Linear Regression Model

The goal of linear regression is to fit a linear equation to observed data to model the relationship between a dependent variable (target) and one or more independent variables (features). The equation for a simple linear regression (with one independent variable) is:

$$y = mx + by = mx + b \tag{1}$$

where yy is the dependent variable (target),xx is the independent variable (feature), mm is the slope of the line, bb is the y-intercept.The model learns the coefficients (mm and bb) that minimize the difference between the predicted and actual values in the training data during training. The model is trained by minimizing a cost function, which is typically the Mean Squared Error (MSE), which measures the average squared difference between predicted and actual values.

1) Assumptions to make in Linear Regression Algorithm: :

- Linear Regression assumes that the features and the target have a linear relationship.
- It assumes error (residual) independence, which means that the errors should not follow a pattern.
- It is based on the assumption of homoscedasticity, which means that the variance of residuals is constant across all levels of the independent variable.

B. Ridge regression Model

Ridge Regression is a linear regression technique that adds a regularization term to the ordinary least squares (OLS) objective function. It is also known as Tikhonov regularization or L2 regularization. The regularization term is added to the sum of squared residuals and is proportional to the square of the magnitude of the coefficients. Ridge Regression's goal is to prevent overfitting by discouraging the model from fitting large coefficients. The following are some key points about Ridge Regression:

- Regularization Term: The Ridge Regression objective function is as follows:

$$Objective = OLSLoss + \alpha \sum_{i=1}^{n} \beta_i^2 \quad (2)$$

- Regularization parameter (α): The regularization parameter controls the degree of regularization.Greater values of result in stronger regularization, which can cause coefficients to shrink.

Ridge Regression is implemented in scikit-learn using the Ridge class. It is used to find the optimal value, the regularization strength (α) can be tuned using techniques such as cross-validation.

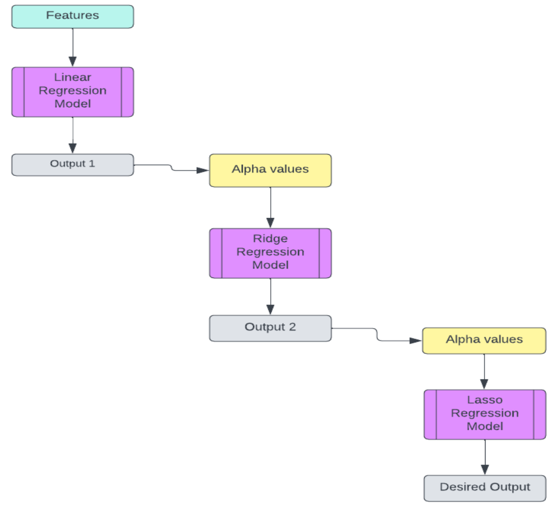


Figure 1: Block Diagram

C. Lasso Regression Model

Lasso regression, also known as L1 regularization, is a linear regression technique that adds a regularization term to the cost function of the linear regression. The goal of lasso regression, like that of ridge regression, is to prevent overfitting and improve model generalization. Lasso regression, on the other hand, employs a different regularization term, which is the absolute value of the coefficients. The goal of standard linear regression is to minimize the sum of squared differences between predicted and actual values. Lasso regression augments this objective function with a regularization term that penalizes large coefficients based on their absolute values. The use of this term encourages the use of sparse models with some coefficients that are exactly zero, effectively performing feature selection. The Lasso Regression Model is formulated as follows:

$$\sum_{i=1} \left(y_i - \beta_0 - \sum_{j=1} \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1} \beta_j$$

(3)

The regularization term is defined as $\lambda \sum_{j=1}^{p} \beta_j$,and it is scaled by the regularization parameter. The parameter is an optional hyperparameter that determines the trade-off between fitting the data well and keeping the coefficients sparse. The Lasso regression model is available in scikit-learn, and it includes cross-validated methods for determining the best value. When dealing with datasets with a large number of features, Lasso regression is especially useful because it tends to set some coefficients to exactly zero, effectively performing feature selection.

V. RESULTS

The dataset of the brands we have used in the project with the range is shown in the figure 2.

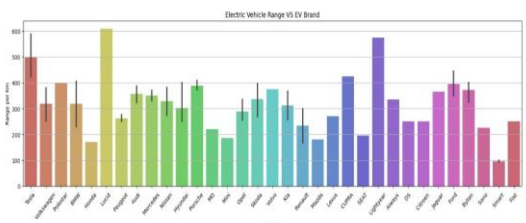


Figure 2: EV Brand Vs Range

The results of the Linear Regression Module is shown in the figure 3.

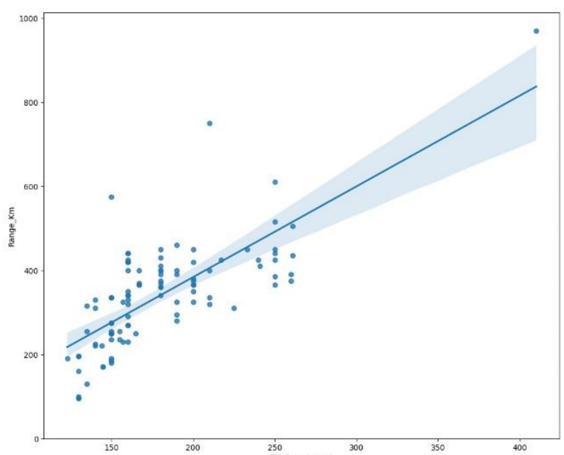


Figure 3: The Range predicted by the Linear Model

The figure 4 shows the actual value and the fitted value's difference which is found by the linear regression model.

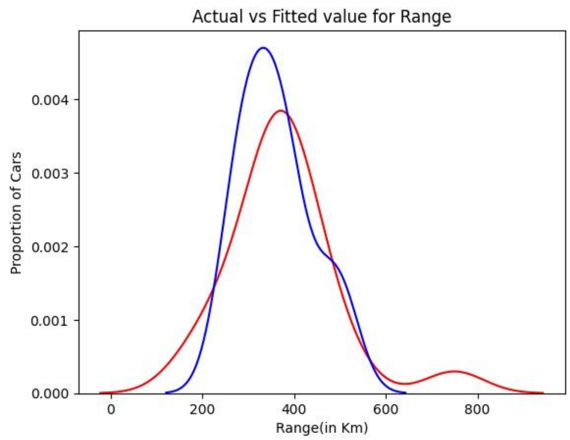
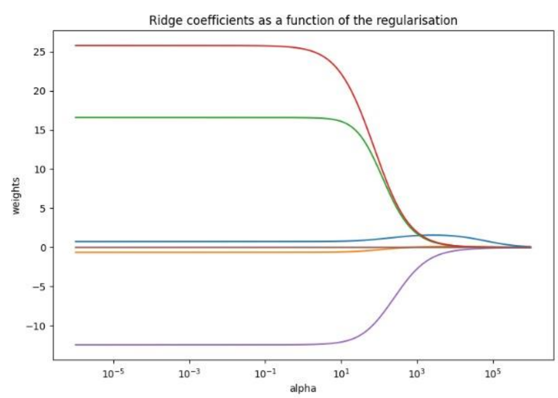


Figure 4: Actual Vs Fitted Value

The figure 5 shows the output which is closer to the accurate one but it not that accurate. This output is produced by Ridge Regression Model.



The figure 6 shows the final result of remaining range by the Lasso Regression Model.

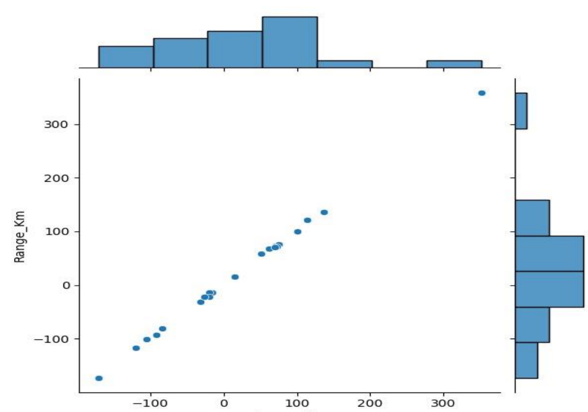


Figure 6: The Remaining Range predicted by the Lasso Regression Model

VI. CONCLUSION

In brief, the goal of this research was to reduce range anxiety in electric vehicle (EV) drivers by developing a resilient machine learning model for forecasting remaining driving range. The model demonstrated tremendous potential in offering precise and timely insights into EV range expectations by including advanced algorithms, a ’fusion-based’ technique to address data inconsistencies, and careful feature selection. Our approach contributes to broader acceptance of sustainable transportation by lowering uncertainty related with electric car capabilities. The accomplishment of this program not only enhances the driving experience of EV users, but it also represents a step forward in the ongoing efforts to establish electric vehicles as a reliable and viable option for environmentally aware transportation.

VII. FUTURE SCOPE

In the future, this project will use cutting-edge technology and approaches to improve the accuracy of estimating the remaining driving range of electric cars (EVs). Integration of real-time data streams and IoT sen- sors for continuous monitoring and adaption to dynamic driving situations is an attractive option. Furthermore, the project’s future scope includes the creation of machine learning models capable of not only anticipating but also detecting probable anomalies or difficulties that could influence an EV’s overall range capacity. This all- encompassing approach aims to reduce uncertainties, im- prove prediction accuracy, and contribute to the contin- ued advancement of intelligent and user-centric electric car technology. Collaboration with industry stakeholders and the use of developing technology place this project at the forefront of its advancements in sustainable and efficient transportation solutions.

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