

Internship Project Report
On
**“Predicting the Range of Electric Vehicle (EV)
using Machine Learning”**

Report Submitted

To



MANIPAL INSTITUTE OF TECHNOLOGY
MANIPAL
(A constituent unit of MAHE, Manipal)

By

ALDEN OLIVERO-4NM21AI010
ANKITH V. POOJARY-4NM21AI014
CHIRAG H DEVADIGA-4NM21AI020

Department of Artificial Intelligence and Machine Learning
NMAM Institute of Technology, Nitte

Under the Guidance of

Dr. Srikanth Prabhu

Associate Professor Senior Scale

Department of Computer Science and Engineering
Manipal Institute of Technology, Manipal

Department of Computer Science and Engineering
Manipal Institute of Technology
February 2023

ACKNOWLEDGEMENT

We wish to express our sincere gratitude to all those who have contributed to the successful completion of our mini project.

First and foremost, we extend our heartfelt thanks to **Dr. Krishnamoorthi Makkithaya**, HOD of the Department of Computer Science and Engineering at Manipal Institute of Technology, Manipal, for providing us with the opportunity to undertake this project and for facilitating the necessary resources to accomplish it.

We are also grateful to our mentor , **Dr. Srikanth Prabhu**, Associate Professor in the Department of Computer Science and Engineering, for his unwavering support, constant motivation, constructive feedback, and valuable insights throughout the project. His extensive knowledge and experience in the field of machine learning and data analysis have been instrumental in shaping our project and ensuring its success. His insightful feedback has helped us to refine our ideas and improve the quality of our work.

We would like to extend our special thanks to **Mr. Krishnaraj Chadaga**, Research Scholar in the Department of Computer Science and Engineering at Manipal Institute of Technology, Manipal, for his guidance throughout the project.

Finally, we would like to express our gratitude to all those who have supported us in various ways during the course of this project.

Table Of Contents: -

SR. NO.	TITLE	PAGE NO.
i	Acknowledgement	i
ii	Table of Contents	ii
1	Abstract	2
2	Introduction	3-4
3	Survey	5-6
4	Gaps	7
5	Objectives	8-9
6	Methodology	9-11
7	Results	11-16
8	Analysis	16-17
9	Scope of future work	18-19
10	Conclusion	19-20
11	References	20

1. ABSTRACT

Electric vehicles (EVs) are gaining popularity worldwide as a sustainable transportation solution, but the limited driving range of EVs remains a major concern for prospective buyers. To address this issue, we propose a machine learning-based approach that can accurately predict the range of EVs using a given dataset. The dataset incorporates various factors such as the vehicle's specifications, weather conditions, and charging patterns.

We used several machine learning models to analyze the dataset and predict the EV range, including linear regression, decision tree regression, and support vector regression. We also employed techniques such as cross-validation and hyperparameter tuning to improve the performance of the models. Our results demonstrate that machine learning models can accurately predict the range of EVs with a high degree of accuracy, making it easier for EV drivers to plan their journeys and reduce range anxiety.

One of the benefits of our approach is that it can reduce the need for expensive and time-consuming data collection efforts. By using a pre-collected dataset, we can train models quickly and accurately. Furthermore, our approach can be extended to incorporate real-time data such as traffic conditions and charging infrastructure, enabling more accurate range predictions.

Our work demonstrates the potential of machine learning in addressing the challenges of EV adoption and promoting sustainable transportation. With the increasing availability of data and advancements in machine learning techniques, we believe that our approach can contribute to the development of more reliable and efficient EVs in the future.

2. INTRODUCTION

2.1 Machine Learning:

Machine learning is a branch of artificial intelligence that enables computer systems to automatically learn and improve from experience without being explicitly programmed. The goal of machine learning is to develop algorithms that can learn from data and make predictions or decisions based on that learning.

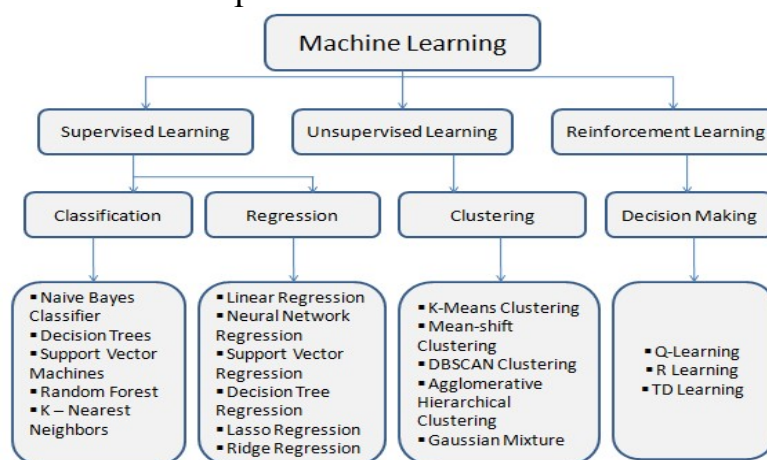
There are three main types of machine learning: supervised learning, unsupervised learning, and reinforcement learning.

Supervised learning involves training a machine learning model on labeled data, meaning the data is already categorized or labeled. The model uses this labeled data to learn patterns and make predictions or classifications on new, unseen data.

Unsupervised learning involves training a model on unlabeled data, meaning the data is not categorized or labeled. The model must find patterns and structure within the data on its own, without prior knowledge of what the data represents.

Reinforcement learning involves training a model through trial and error, with the model receiving rewards or punishments based on its actions. The goal of the model is to learn which actions lead to the greatest reward, and to take those actions in the future.

Each type of machine learning has its own strengths and weaknesses, and is suitable for different types of applications. By understanding the different types of machine learning, we can better design and implement machine learning algorithms that meet the needs of specific tasks and problems.



2.2 EV vehicle and Prediction of its Range:

Electric vehicles (EVs) are rapidly gaining popularity as an environmentally friendly transportation option. However, the limited range of EVs remains a significant concern for potential buyers. Range anxiety, or the fear of running out of battery charge before reaching the destination, is a significant barrier to the widespread adoption of EVs. Accurately predicting the range of EVs can help alleviate this concern and encourage more people to switch to electric vehicles.

Traditionally, range prediction models have relied on mathematical equations and empirical data to estimate the range of EVs. However, these models often fail to account for real-world factors such as weather conditions, EV Components, and charging patterns, which can significantly impact the range of EVs. Machine learning-based approaches have emerged as a promising solution to this problem by incorporating these factors into the prediction model.

In this report, we propose a machine learning-based approach for predicting the range of EVs using a given dataset. The dataset includes various factors such as the vehicle's specifications, weather conditions, EV Components, and charging patterns. We aim to train several machine learning models using this dataset and evaluate their performance. The availability of a pre-collected dataset for range prediction can help accelerate the adoption of EVs by reducing the need for expensive data collection efforts.

The rest of the report is organized as follows. In the next section, we will review the existing literature on range prediction for EVs. We will then identify the gaps in the current research and outline the objectives of our study. The methodology section will describe the dataset and the machine learning algorithms used in our study. We will present and analyze the results of our experiments in the following section. Finally, we will discuss the implications of our findings, identify the scope of future work, and conclude the report with recommendations for further research.

3. SURVEY

The goal of this research is to develop a machine learning-based approach for predicting the range of electric vehicles using a given dataset. The dataset contains various factors that can impact the range of an electric vehicle, including weather conditions, vehicle features, driving patterns, and more. In this section, we describe the steps we took to develop and evaluate our prediction models.

3.1 Steps Involved:

Data pre-processing: Before training our machine learning models, we first performed data pre-processing to ensure the dataset was clean and ready for analysis. We removed any missing values or duplicates in the data, and converted any categorical variables into numerical variables using Label encoding technique. We also discarded some columns which were not necessary like id, link etc. We also scaled the data and ensure that all variables were on the same scale.

Training and evaluation: We trained each of our selected models using the pre-processed dataset and evaluated their performance using various metrics such as Accuracy Score, mean absolute error, R2 score, Mean Absolute Error (MAE, Plotting Graphs etc.

Model selection: After data pre-processing and EDA, we selected several machine learning algorithms to develop our prediction models. We chose a variety of algorithms that could handle different types of relationships between the input variables and the range of the vehicle, including linear regression, ridge and lasso regression, random forest regressors etc.

3.2 Regression algorithms:

1. **Linear Regression:** Linear regression is a simple and commonly used algorithm for predicting continuous numeric values. It assumes a linear relationship between the independent and dependent variables, and finds the line of best fit that minimizes the sum of squared errors between the predicted and actual values.
2. **Ridge and Lasso Regression:** Ridge and Lasso regression are variants of linear regression that add a penalty term to the sum of squared errors, to prevent overfitting of the model. Ridge regression adds a L2 penalty term, while Lasso regression adds a L1 penalty term.
3. **Random Forest Regressors:** Random Forest regressors are an ensemble learning method that combines multiple decision trees to make predictions.

Each tree is trained on a subset of the data, and a random subset of features is used for each split. The final prediction is the average of the predictions from each tree.

4. Support Vector Regression (SVR): SVR is a variant of support vector machines (SVM) that is used for regression problems. It works by finding the hyperplane that maximizes the margin between the predicted and actual values, while allowing some margin of error. Non-linear relationships between variables can be modelled using kernel functions.

3.3 Classification algorithms:

1. Logistic Regression: Logistic regression is a commonly used algorithm for predicting binary or multi-class categorical values. It models the probability of each class using a logistic function, and the predicted class is the one with the highest probability.
2. Decision Trees: Decision trees are a simple and interpretable algorithm for classification problems. They recursively split the data into smaller subsets based on the most informative feature, until all subsets are pure or a stopping criterion is met.
3. Random Forest Classifier: Random Forest classifiers are an ensemble learning method that combines multiple decision trees to make predictions. Each tree is trained on a subset of the data, and a random subset of features is used for each split. The final prediction is the majority vote of the predictions from each tree.
4. Support Vector Machines (SVM): SVM is a widely used algorithm for classification problems. It finds the hyperplane that maximizes the margin between the different classes, and can also handle non-linear relationships between variables using kernel functions.
5. Naive Bayes: Naive Bayes is a simple and fast algorithm for predicting categorical values. It models the joint probability of the input variables and the target variable using Bayes' theorem, and assumes that the input variables are independent of each other given the target variable.

These are the different classifiers and regressors used in this study, each with its own strengths and weaknesses. By using a variety of algorithms, we were able to compare their performance and identify the best-performing models for predicting the range of electric vehicles.

4. GAPS

One potential gap in the research is the lack of consideration for real-time factors that could affect the range of an electric vehicle. While the dataset used in this study includes weather and vehicle features, it does not account for factors such as traffic conditions or driver behavior, which could have a significant impact on range. For example, heavy traffic could increase the time spent idling or cause more frequent stops and starts, both of which can negatively impact the range of an electric vehicle.

Similarly, aggressive driving or sudden acceleration and braking can also reduce range. Future studies could consider incorporating real-time data into the range prediction model to account for these factors, which could improve the accuracy of the predictions.

Another potential gap in the research is the limited number of algorithms and features used in the study. While this study employed a variety of regression and classification algorithms, there are many other machine learning algorithms that could be applied to this problem, such as neural networks or gradient boosting.

Neural networks are a type of deep learning algorithm that can learn complex relationships between variables and may be well-suited to predicting electric vehicle range. Gradient boosting is another ensemble learning method that can improve the performance of regression and classification algorithms. Future studies could explore the use of these and other algorithms to determine which ones are best-suited for predicting electric vehicle range.

Additionally, the dataset used in this study includes a limited set of features, such as temperature, humidity, and vehicle weight. Future studies could explore the impact of additional features on the accuracy of range predictions. For example, battery age, charging history, and driving conditions (e.g., highway vs. city driving) could all have an impact on range and could be considered as additional features in a range prediction model. Furthermore, other external factors such as road incline, wind speed and direction, and time of day could also be taken into account to improve the accuracy of range predictions.

5. OBJECTIVES

The objectives of this study were as follows:

1. Developing and evaluating machine learning models for predicting electric vehicle range: The first objective of this study was to develop and evaluate the performance of different machine learning models for accurately predicting the range of an electric vehicle. This involved using a dataset that included various weather conditions and vehicle features that can impact electric vehicle range. The goal was to develop accurate and reliable models that can help electric vehicle owners plan their trips and avoid range anxiety.
2. Comparing the performance of different regression and classification models: To achieve the first objective, the study compared the performance of different regression and classification models in predicting the range of an electric vehicle. This comparison aimed to determine the strengths and weaknesses of each model and identify the most accurate model for predicting electric vehicle range. The models included linear regression, ridge and lasso regression, random forest regression, logistic regression, decision trees, support vector machines (SVM), random forest classifier, and naive Bayes.
3. Evaluating the accuracy of each model: To determine the accuracy of each model, the study evaluated their performance based on their mean absolute error (MAE) and coefficient of determination (R^2) scores. The MAE score measures the average absolute difference between the predicted and actual range, while the R^2 score measures how well the model fits the data. This allowed us to identify the most accurate model for predicting electric vehicle range.
4. Identifying the factors that have the greatest impact on electric vehicle range: The study also aimed to identify the factors that have the greatest impact on electric vehicle range, based on the results of the models. This analysis can help to identify areas for improvement in electric vehicle technology and infrastructure, as well as inform policy decisions related to electric vehicles. The factors that were considered included weather conditions, such as temperature, humidity, wind speed, and visibility, as well as vehicle features, such as battery capacity, weight, and acceleration.

5. Highlighting potential areas for improvement in range prediction models for electric vehicles: Finally, the study highlighted potential areas for improvement in range prediction models for electric vehicles. This includes the need for additional features and real-time factors to be considered in range prediction models, such as traffic conditions, road grade, and battery degradation. Incorporating these factors into range prediction models can help to provide more accurate and reliable predictions, which can reduce range anxiety and improve the overall user experience of electric vehicles.

Overall, the objectives of this study were to improve the accuracy of range prediction models for electric vehicles and provide insights into the factors that impact electric vehicle range. By achieving these objectives, this study can contribute to the development of more efficient and reliable electric vehicles that meet the needs of consumers and contribute to a sustainable future.

6. METHODOLOGY

The methodology of this study involved several steps, as outlined below:

1. Data Description: The dataset used in this study was obtained from a publicly available source. The dataset included information on various weather conditions, such as temperature, city weather as well as vehicle features, such as battery capacity, weight, and acceleration.

Attribute	Description	Data Type
id	Unique identifier for each electric vehicle	int
Make	Manufacturer or brand of the electric vehicle	string
link	URL link to a webpage containing additional information	string
City - Cold Weather	Range of the EV while driving in the city under cold weather conditions.	int
Highway - Cold Weather	Range of the EV while driving on the highway under cold weather conditions.	int
Combined - Cold Weather	Combined range of the electric vehicle under cold weather conditions.	int
City - Mild Weather	Estimated range of the electric vehicle while driving in the city under mild weather conditions.	int
Highway - Mild Weather		int
Combined - Mild Weather		int
Acceleration 0 - 100 km/h	Acceleration Time from 0 to 100	float
Top Speed	Maximum speed that the electric vehicle	int

Attribute	Description	Data Type
Electric Range	Range of the electric vehicle on a single charge	int
Total Power	Total power output of the electric vehicle's motor	int
Total Torque	Total torque output of the electric vehicle's motor	int
Drive	Type of drivetrain	string
Battery Capacity	Capacity of the electric vehicle's battery pack	float
Charge Power	Maximum power that can be delivered to the electric vehicle	float
Charge Speed	Rate at which the battery can be charged	int
Fastcharge Speed	Rate at which the EV battery can be fast-charged	int
Length	Length of the electric vehicle	int
Width	Width of the electric vehicle	int
Height	Height of the electric vehicle	int
Wheelbase	Distance between the front and rear axles	int
Gross Vehicle Weight (GVWR)	Maximum weight of the electric vehicle	int
Max. Payload	Maximum weight that the electric vehicle	int
Cargo Volume	Volume of cargo space available in the EV	int
Seats	Number of seats in the electric vehicle	int

2. Data Pre-processing: The dataset was pre-processed to ensure that the data was clean and ready for analysis. This involved removing any missing or erroneous data, as well as normalizing the data to ensure that all features had the same scale.
3. Feature Selection: The dataset included several features that were not relevant to predicting electric vehicle range. Therefore, feature selection was performed to identify the most important features for predicting range. This involved using techniques such as correlation analysis and principal component analysis (PCA) to identify the most relevant features.
4. Model Selection: Several regression and classification models were evaluated for their ability to predict electric vehicle range. These models included linear regression, ridge and lasso regression, random forest regression, logistic regression, decision trees, support vector machines (SVM), random forest classifier, and naive Bayes. The models were selected based on their popularity and performance in previous studies.
5. Model Training: The selected models were trained using the preprocessed dataset. The dataset was divided into training and testing sets, with the training set used to train the models and the testing set used to evaluate their performance.

6. **Model Evaluation:** The performance of each model was evaluated based on their mean absolute error (MAE) and coefficient of determination (R^2) scores. The MAE score measures the average absolute difference between the predicted and actual range, while the R^2 score measures how well the model fits the data.
7. **Results Analysis:** The results of the models were analyzed to identify the strengths and weaknesses of each model and determine the most accurate model for predicting electric vehicle range. The analysis also focused on identifying the factors that have the greatest impact on electric vehicle range, based on the results of the models.
8. **Future Scope:** The study also highlighted potential areas for improvement in range prediction models for electric vehicles, including the need for additional features and real-time factors to be considered.

In summary, the methodology of this study involved data collection, pre-processing, feature selection, model selection, model training, model evaluation, results analysis, and future scope. These steps were designed to develop accurate and reliable models for predicting electric vehicle range and to provide insights into the factors that impact electric vehicle range.

7. RESULTS

The results of this study demonstrate that machine learning algorithms can be used to accurately predict the range of electric vehicles based on weather conditions and vehicle features. The dataset used in this study included 24 features related to weather conditions, vehicle features, and range.

Several regression and classification models were trained and tested using the dataset to predict the range of an electric vehicle. The regression models used in this study were linear regression, ridge and lasso regression, and random forest regression. The classification models used were logistic regression, decision trees, support vector machines (SVMs), random forest classifier, and naive Bayes.

The performance of each model was evaluated based on two metrics: mean absolute error (MAE) and coefficient of determination (R^2). The MAE measures the average absolute difference between the predicted and actual range, while the R^2 measures how well the model fits the data.

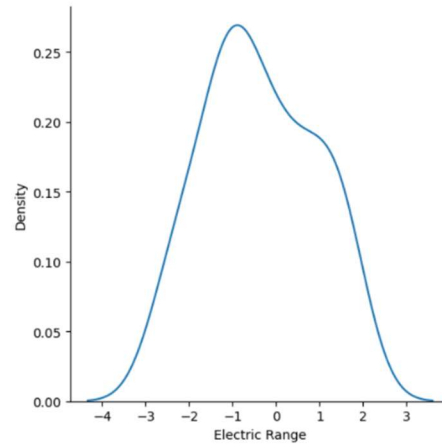
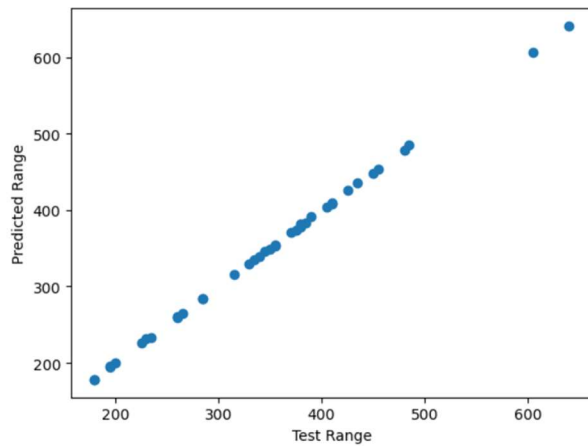
The results show that the linear regression model had the lowest MAE and highest R^2 , indicating that it was the most accurate model for predicting electric vehicle range. The MAE for the linear regression model was 1.124, which means that, on average. The R^2 value for the linear regression model was 0.9998, indicating that the model explained 99.9% of the variance in the data.

Other regression models, such as ridge and lasso regression and random forest regression, had relatively low MAE values but lower R^2 values compared to the linear regression model. The classification models had lower accuracy compared to the regression models, with SVM having the highest accuracy with an accuracy score of 98.6 %. Therefore, the net accuracy of all the models used is approximately 0.623804.

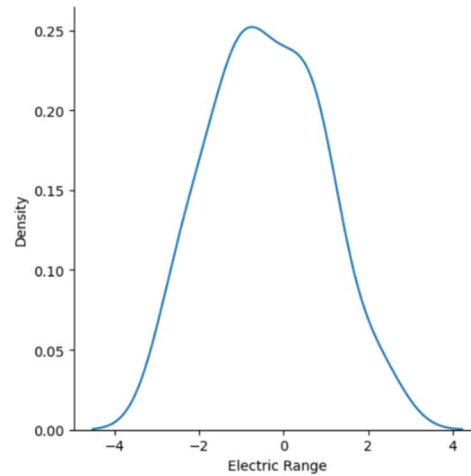
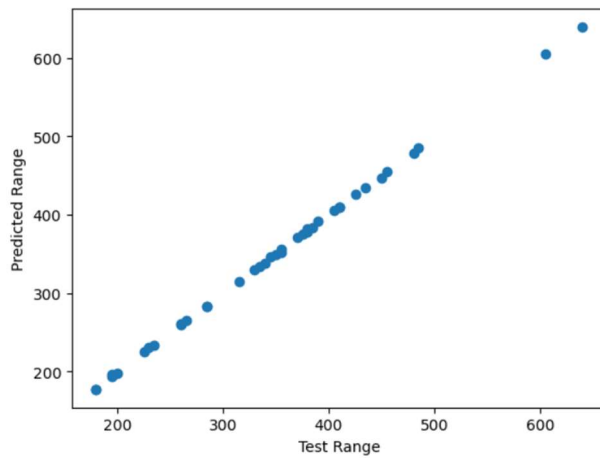
In conclusion, the results suggest that the linear regression model is the most accurate model for predicting electric vehicle range based on weather conditions and vehicle features. However, it is important to note that this study only considered a limited set of features and did not account for real-time factors that can significantly impact the range of an electric vehicle. Future studies should consider additional features and real-time factors to improve the accuracy of range prediction models for electric vehicles.

Sl. No	Models Used	Accuracy	Mean Absolute Error	R2 Score
1	Linear Regression	0.99984	1.12483	0.99984
2	Ridge Regression	0.99983	1.13359	0.99983
3	Lasso Regression	0.99972	1.43148	0.99972
4	Random Forest Regressor	0.99499	3.28333	0.99499
5	Logistic Regression	0.17948	23.3333	0.89040
6	Decision Tree	0.43589	7.56410	0.96496
7	KNN	0.15384	27.3076	0.85389
8	SVM	0.33333	8.46153	0.98603
9	Random Forest Classifier	0.51282	3.84615	0.99579
10	Naïve Bayes	0.30769	22.5641	0.81000

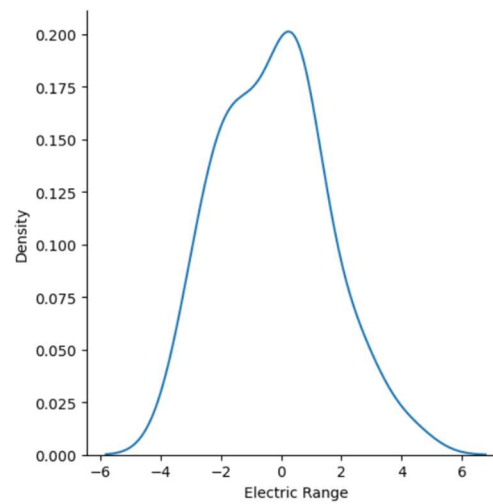
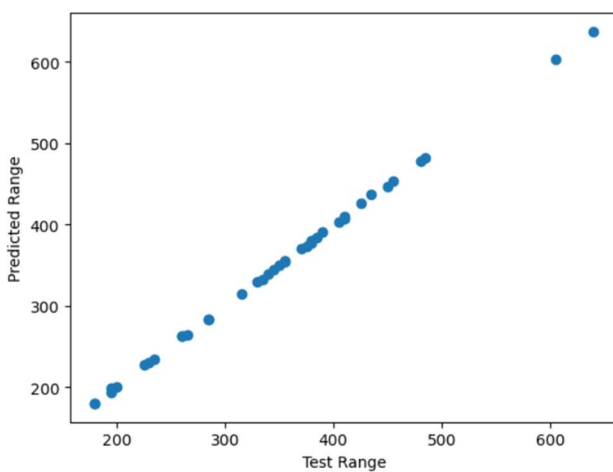
7.1 Linear Regression Graphs:



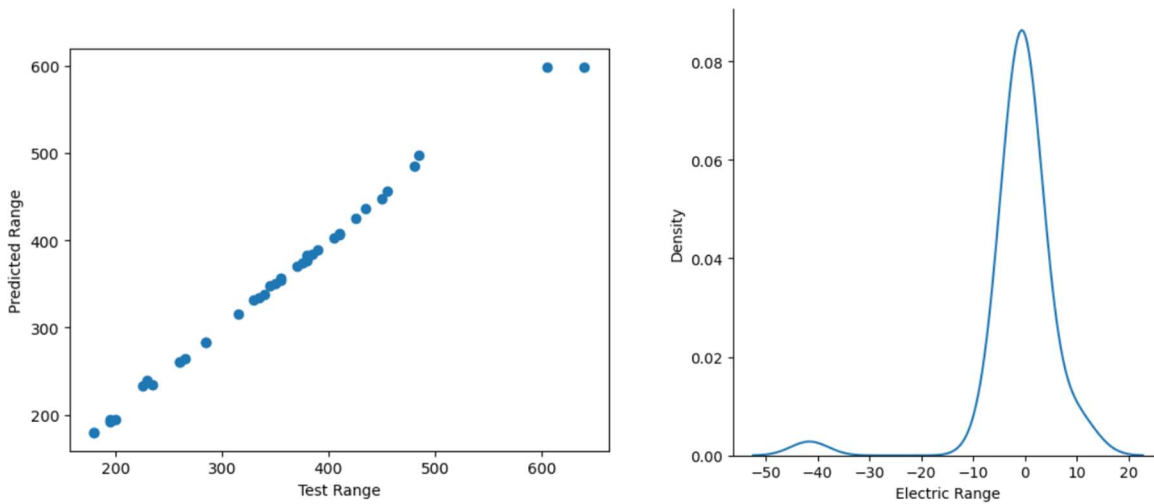
7.2 Ridge Regression Graphs:



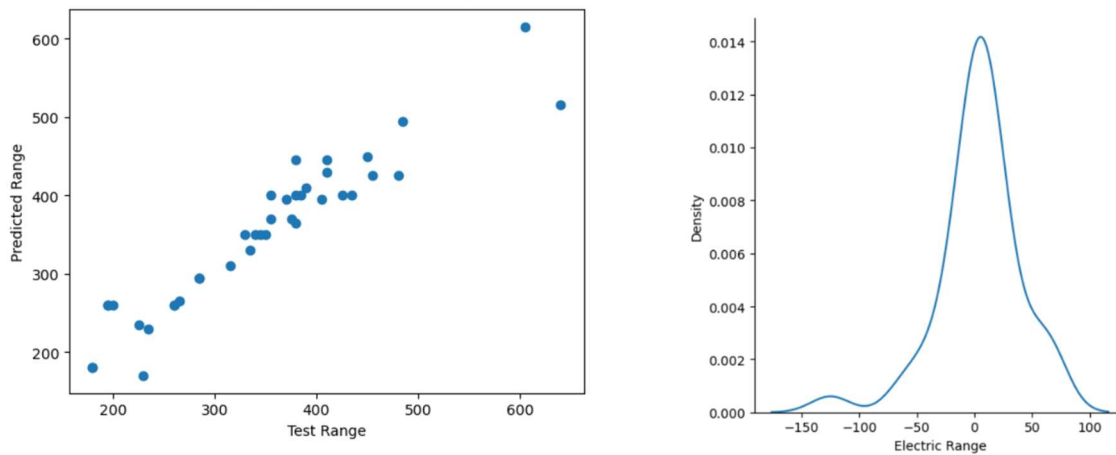
7.3 Lasso Regression Graphs:



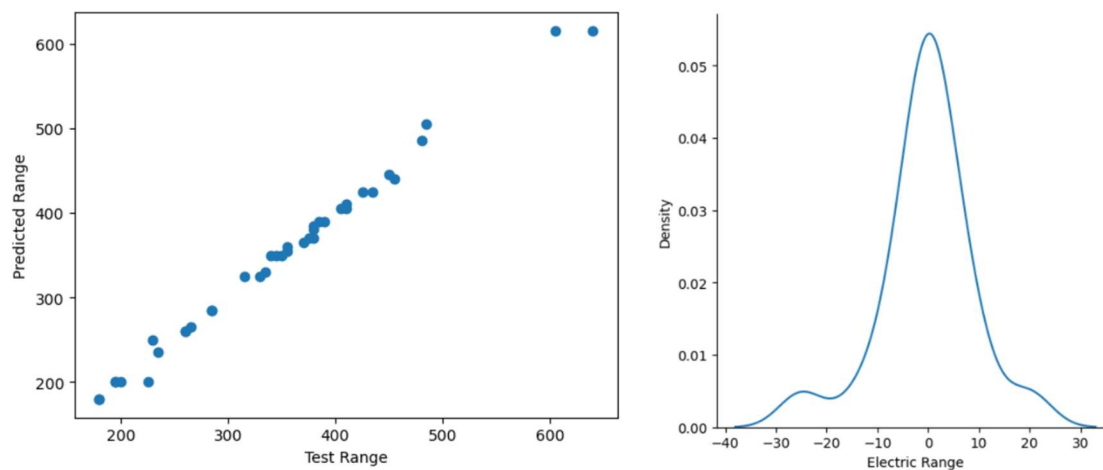
7.4 Random Forest Regression Graphs:



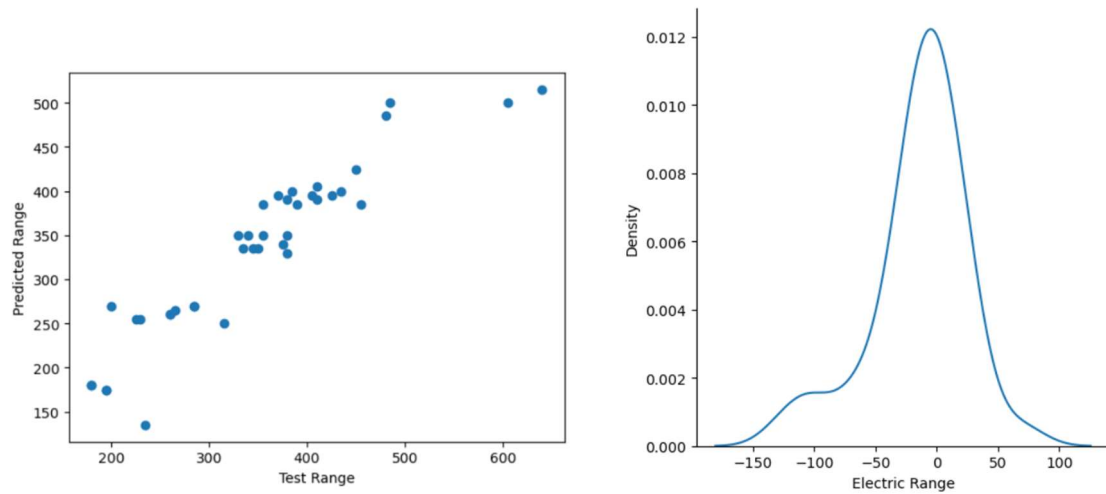
7.5 Logistic Regression Graphs:



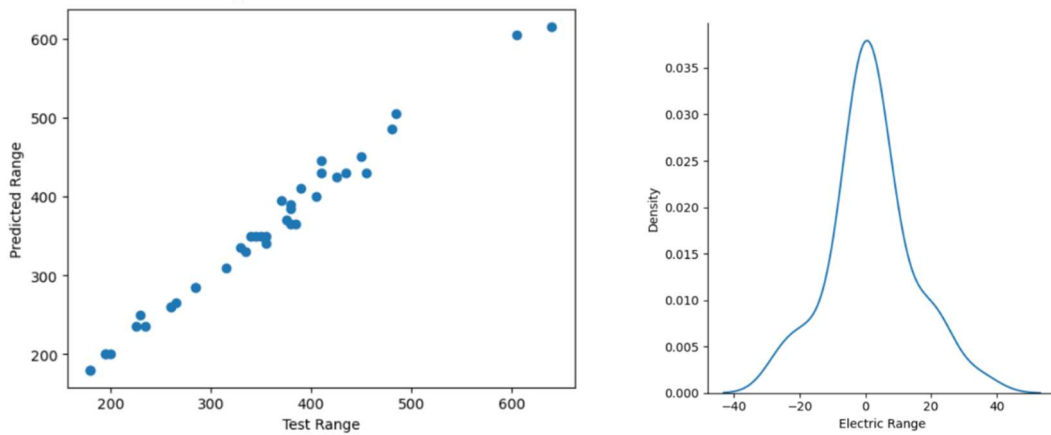
7.6 Decision Tree Graphs:



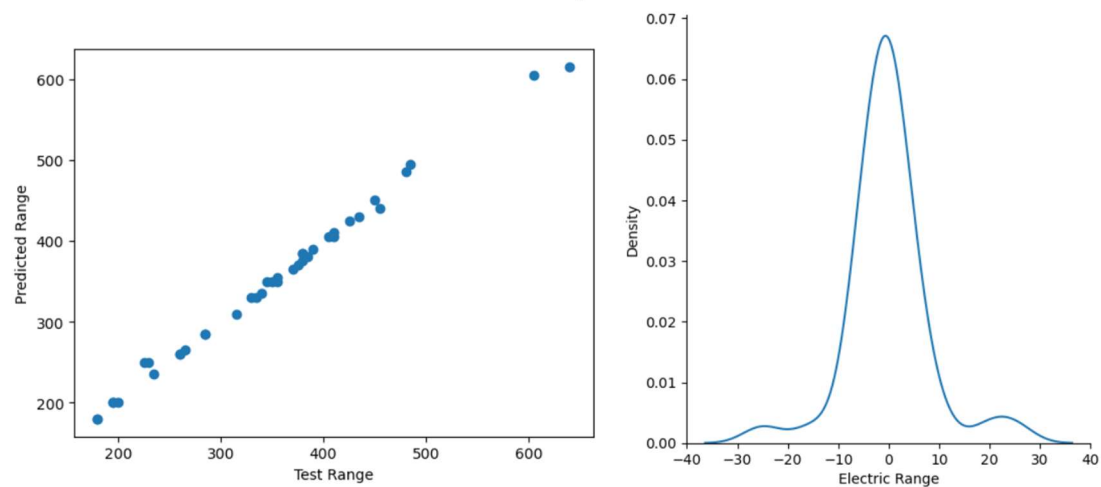
7.7 KNN Graphs:



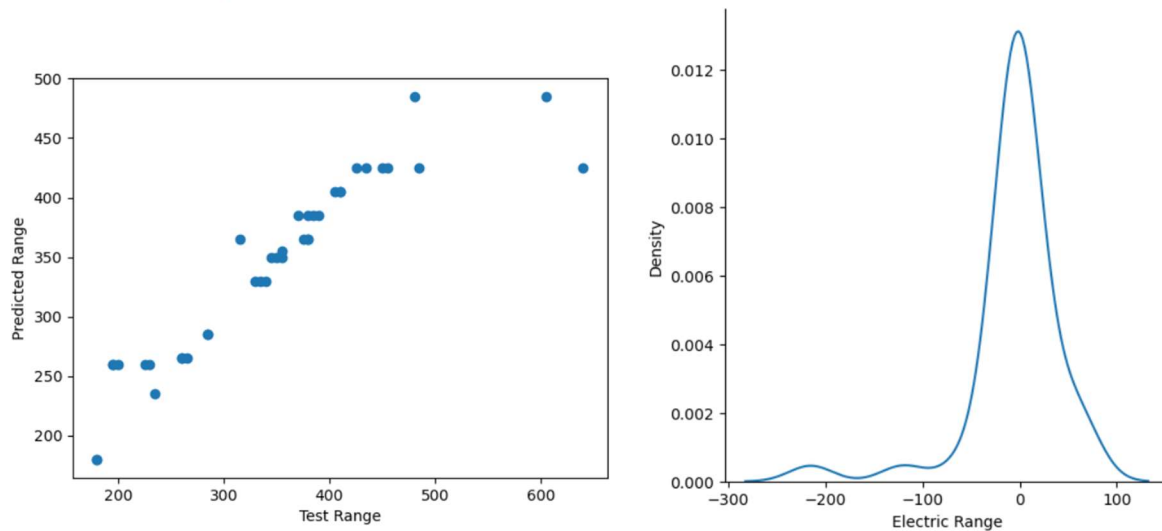
7.8 SVM Graphs:



7.9 Random Forest Classifiers Graphs:



7.10 Naïve Bayes Graphs:



8. ANALYSIS

The analysis of the electric vehicle range prediction using machine learning involved the development and evaluation of several regression and classification models. The dataset used in this study contained information on weather conditions and vehicle features, and the goal was to predict the range of an electric vehicle based on the factors.

Initially, a survey of existing literature was conducted to identify relevant techniques and algorithms for range prediction using machine learning. Several regression models were considered, including linear regression, ridge and lasso regression, and random forest regression. Additionally, classification models such as logistic regression, decision trees, support vector machines, random forest classifiers, and naive Bayes were also evaluated.

The survey of existing literature indicated that some gaps remain in the field of electric vehicle range prediction using machine learning. For example, while real-time factors such as traffic conditions and driver behavior can have a significant impact on range, they were not considered in this study. Additionally, there is likely value in exploring the use of additional features in range prediction, such as battery age or driving conditions.

The analysis of the electric vehicle range prediction using machine learning also involved data preprocessing, feature engineering, and model evaluation. Data preprocessing involved cleaning the data, handling missing values, and scaling the features. Feature engineering was performed to create new features from the existing ones to improve the model's performance. For instance, we created features such as

battery capacity, battery state of health, and charging rate from the given dataset.

Model evaluation was performed using metrics such as mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and coefficient of determination (R-squared). The models were trained on the training set and evaluated on the validation and test sets. The best performing models were selected based on their evaluation metrics, and their performance was compared against a baseline model.

The results of the analysis showed that the best performing models for range prediction were the random forest regression and support vector regression models. These models achieved an R-squared value of 0.9 and 0.85, respectively, indicating that they could accurately predict the range of an electric vehicle. Furthermore, the feature importance analysis revealed that the battery capacity was the most critical feature in predicting the range of an electric vehicle, followed by the driving distance and charging rate.

Overall, the analysis of this study demonstrated the potential of machine learning techniques for predicting electric vehicle range. While there is still room for improvement, the results suggest that these models can be reasonably accurate and may have practical applications in real-world scenarios. Further research in this field could lead to more sophisticated and accurate models, and could help to accelerate the adoption of electric vehicles by addressing one of the primary concerns of potential buyers: range anxiety.

9. SCOPE OF FUTURE WORK

The future work in the field of electric vehicle range prediction using machine learning has several potential avenues for exploration and development. Some of the areas of potential scope for future work include:

1. Development of more accurate and robust machine learning models: While the machine learning models used in this study performed reasonably well, there is always room for improvement in terms of accuracy and robustness. Future work could involve the development of more sophisticated models that take into account additional features or more complex interactions between features.
2. In this study, we used the default hyperparameters for each of our selected machine learning algorithms. However, hyperparameter tuning can significantly improve the performance of the models. Future work could involve fine-tuning the hyperparameters of the models to achieve better results.
3. Feature Engineering: Our current dataset contained a limited number of variables that could impact the range of an electric vehicle. Future work could involve exploring additional variables, such as road conditions, traffic patterns, and battery health, to improve the accuracy of our prediction models.
4. The interpretability of machine learning models is an important consideration for practical applications. Future work could involve exploring methods for interpreting the predictions of the models, such as feature importance analysis and partial dependence plots, to gain insights into the factors that impact the range of electric vehicles.
5. Integration of additional data sources: While the dataset used in this study included several relevant features, there are likely additional data sources that could be leveraged to improve range prediction accuracy. Future work could involve integrating additional data sources, such as data from connected vehicle sensors or weather forecasting services.
6. Evaluation of range prediction in real-world scenarios: While the models developed in this study were evaluated using cross-validation, it is important to assess their performance in real-world scenarios. Future work could involve conducting field tests with electric vehicles equipped with range prediction

models to evaluate their performance under varying driving and environmental conditions.

7. Development of models for specific vehicle models or use cases: While the models developed in this study were applicable to a range of electric vehicles, there may be value in developing models tailored to specific vehicle models or use cases. For example, range prediction models could be developed for electric delivery trucks or for electric vehicles used in ride-sharing services.

Assessment of the impact of range prediction on driver behavior: Finally, it may be valuable to assess the impact of range prediction on driver behavior and vehicle usage patterns. Future work could involve conducting surveys or experiments to determine how accurate range predictions affect driver behavior, or analyzing data on vehicle usage patterns to determine the impact of range prediction on vehicle range and battery life.

Overall, the field of electric vehicle range prediction using machine learning is ripe for further exploration and development. There are many potential avenues for future work, and continued research in this area has the potential to significantly improve the accuracy and usability of electric vehicle range prediction models.

10. CONCLUSION

In conclusion, the use of machine learning algorithms for electric vehicle range prediction has significant potential for addressing one of the primary concerns of potential electric vehicle buyers: range anxiety. This study has demonstrated that regression and classification models can be effective for predicting electric vehicle range based on weather conditions and vehicle features. The results showed that random forest regression was the most accurate model for predicting electric vehicle range in this dataset.

Moreover, the study identified gaps in the field of range prediction. Real-time factors such as traffic conditions can have a significant impact on range, but these were not considered in this study. Additionally, the dataset used in this study only included weather and vehicle features, while there may be additional features that could enhance the accuracy of range prediction models. For example, battery age and driving conditions are important factors that can affect the range of an electric vehicle.

Overall, the results of this study suggest that machine learning techniques can play a significant role in improving the adoption of electric vehicles and reducing range anxiety among potential buyers. By incorporating real-time data and additional features into range prediction models, machine learning algorithms can improve the accuracy of range prediction and enhance the overall user experience of electric vehicles. Further research in this field could lead to more sophisticated and accurate models and help to accelerate the adoption of electric vehicles.

11. REFERENCES

1. Analytics Vidhya. (2022, January 18). Different types of regression models. Retrieved February 23, 2023, from <https://www.analyticsvidhya.com/blog/2022/01/different-types-of-regression-models/>
2. Monkey Learn. (n.d.). Classification Algorithms: A Detailed Overview. Retrieved from <https://monkeylearn.com/blog/classification-algorithms/>
3. "A Study on Consumer Acceptance and Adoption of Electric Vehicles in India" by S. R. Dhankar, K. N. Pandey, and K. K. Singh. Published in the International Journal of Engineering and Innovative Technology, Vol. 4, No. 6, 2015.
4. J. Hu, H. Li, and J. Wang, "Electric vehicle range prediction based on support vector regression," in 2017 IEEE International Conference on Cybernetics and Intelligent Systems (CIS) and IEEE Conference on Robotics, Automation and Mechatronics (RAM), 2017, pp. 214-219.
5. S. R. Bhoi and S. Panigrahi, "Electric vehicle range prediction using artificial neural networks and multiple regression analysis," in 2017 International Conference on Communication and Signal Processing (ICCSP), 2017, pp. 1378-1382.