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Electric Vehicle Energy Demand Prediction: A Critical and Systematic Overview

B. RUPADEVI[1], SAMBAIAHPALEM ADIKESAVULU [2]

[1]Associate Professor, Dept of MCA, Annamacharya Institute of Technology & Sciences, Tirupati, AP, India, Email:*rupadevi.aitt@annamacharyagroup.org*

[2]Post Graduate, Dept of MCA, Annamacharya Institute of Technology & Sciences, Tirupati, AP, India, Email: *sambaiahpalemadikesavuvulu@gmail.com*

Abstract

Accurately predicting energy demand is crucial for managing charging infrastructure, maximising vehicle performance, and guaranteeing effective energy distribution as EV adoption picks up speed. This study offers a thorough and organised analysis of EV energy demand prediction methods, covering deep learning frameworks, machine learning models, and conventional statistical methods. It also presents a useful implementation using a web application built with Flask that forecasts EV energy use depending on variables like speed, temperature, battery capacity, and distance travelled. In order to provide real-time, easily navigable predictions, the system combines a learnt machine learning regressor with a data scaler. The entire pipeline—data preprocessing, model training, application design, and performance evaluation—is described in this paper, providing theoretical understanding and a practical solution for EV energy demand forecasting.

Keywords: *Electric Vehicle, Energy Demand Prediction, Machine Learning, Deep Learning, Data Preprocessing, Model Evaluation*

I. Introduction

A. Background

Electric vehicles, or EVs, are drastically changing how people travel across the world. EVs are viewed as a key element in lowering greenhouse gas emissions and reliance on fossil fuels as governments, businesses, and consumers shift towards sustainable and environmentally friendly mobility alternatives. However, one of the biggest barriers to EV adoption is accurately predicting energy consumption. Accurate forecasting enables the creation of charging infrastructure, extended vehicle range estimation, and optimal energy distribution. Demand forecasting and grid stability have become major concerns as the use of renewable energy sources increases. Inefficiencies, poorer vehicle performance, and even grid failures can result from an incorrect estimate of energy demand. As a result, putting in place trustworthy energy demand forecasting systems is both a technological and a socioeconomic necessity.

B. Problem Statement

Predicting an EV's energy needs is a difficult task. Road type, battery efficiency, driving speed, distance travelled, ambient temperature, and vehicle load are just a few of the dynamic factors that affect it. These dynamic dependencies cannot be adequately addressed by conventional methods that rely on static models. Therefore, it is crucial to investigate state-of-the-art data-driven techniques like machine learning and deep learning that can faithfully replicate these non-linear interactions.

C. Objectives

The primary objective of this research is to present a machine learning-based technique for reliably and precisely predicting the energy usage of electric cars. This entails a comprehensive analysis and categorisation of current methods for predicting energy demand, the identification of critical factors affecting EV energy consumption, and the development of a powerful machine learning model specifically designed for this use. The project also intends to use Flask to create and deploy a user-friendly, lightweight web application that offers real-time forecasts. To guarantee the model's efficacy and usefulness, its performance will be thoroughly assessed using the proper statistical measures.

II. Literature Review

Electric vehicle (EV) energy demand forecasting is essential for better fleet management, optimal charging infrastructure deployment, and effective grid management. By integrating EVs into current power systems and guaranteeing that charging stations are sufficiently stocked to meet peak demand, accurate energy forecasting makes this possible. Over time, numerous approaches have been used to solve the challenges of anticipating EV energy demand, ranging from advanced machine learning (ML) and deep learning (DL) techniques to traditional statistical models.

A. Traditional Statistical Models

Early methods for predicting EV energy consumption relied heavily on time-series forecasting models like ARIMA and traditional statistical techniques like linear regression. To predict the correlations between consumption and fundamental characteristics like speed and driving distance, linear regression was utilised in these models, which were based on historical data on energy consumption. These models, however, are unable to capture the dynamic and non-linear character of energy use, especially when it is impacted by environmental variables, traffic, and road conditions. Because of this, they frequently offer only a limited level of accuracy in real-world situations when these variables fluctuate wildly.

B. Machine Learning Approaches

Machine learning (ML) models have become more popular as problems become more complicated because of their capacity to identify complex patterns and connections in data. Random Forests (RF) and Support Vector Machines (SVM) are two of the most widely used models for predicting EV energy requirements. These models effectively capture non-linear relationships between factors including driving style, vehicle type, and weather. These methods work well on small to medium-sized datasets, but when used on huge datasets from an expanding fleet of EVs, they have problems with scalability and computing expense. By iteratively reducing prediction errors, more sophisticated machine learning approaches like gradient boosting (e.g., XGBoost, LightGBM) have demonstrated increased accuracy, making them appropriate for dynamic and heterogeneous data from various EV fleets. These models are challenging to implement on a broad scale due to their high computational requirements and meticulous tuning, even with their improved predictive capabilities.

C. Challenges and Future Directions

Despite significant advancements in the creation of models for predicting EV energy use, a number of difficulties still exist. Data quality is a major problem since real-world data on EV usage, including driving patterns, traffic patterns, and environmental conditions, are frequently noisy and sparse. High-quality, consistent data is necessary for accurate models, but it can be challenging to find, particularly in areas with low EV penetration. The interpretability of the model presents another difficulty. Because deep learning models, including ensemble methods and LSTMs, are sometimes viewed as "black boxes," it may be challenging to understand the logic underlying predictions. This lack of transparency could make it harder to trust the model's output, particularly in applications where energy forecast judgements have a direct influence on resource allocation decisions.

III. Methodology

The methodology for predicting the energy demand of electric vehicles (EVs) includes the following steps: data collection, preprocessing, feature selection, model creation, and evaluation. This section outlines the techniques for precisely

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predicting EV energy use, with a focus on fusing machine learning techniques with real data.

A. Data Collection

This study analysed data from both simulated and real-world driving scenarios to predict how much energy electric cars (EVs) would require. Speed (km/h), temperature (°C), battery capacity (kWh), distance (km), and energy consumption (kWh) are the dataset's five main characteristics. The selection of these traits was based on how well they predicted energy demand. Distance is directly proportional to the energy needed for travel, battery capacity determines the quantity of energy available, temperature affects battery performance, and speed influences energy consumption because of aerodynamic resistance. The data was carefully chosen to ensure that it accurately represents real-world driving conditions. To maintain the integrity of the data, outliers were removed using the interquartile range (IQR) approach, and missing values in the dataset were appropriately handled. This ensures that the model won't be distorted by erroneous data points, allowing it to generalise well in a variety of scenarios.

B. Data Preprocessing

Data pretreatment is necessary to ensure that the input data is suitable for training the machine learning model. Preprocessing began with addressing missing data. A mean imputation technique was used to impute any missing values, substituting the mean value of the corresponding feature for any missing entries. By eliminating rows with missing values, this method was chosen to prevent data loss. To make sure they are all on the same scale, all features were then normalised. The StandardScaler was used to change the data so that its mean was zero and its standard deviation was one. This enhances overall performance and speeds up the convergence of the machine learning model. Moreover, feature engineering was used to improve the dataset's capacity for prediction. For instance, in order to better reflect the relationship between driving circumstances and energy demand, interaction terms were incorporated, such as speed multiplied by distance.

C. Model Selection and Training

After experimenting with other algorithms, the Random Forest model was chosen to forecast how much energy electric vehicles would need. Because Random Forest can handle non-linear correlations in the data and has a high accuracy, it was selected. By building a forest of decision trees and producing the average prediction of each tree, this ensemble approach lowers variance and enhances generalisation. The dataset was divided into training and testing sets in an 80-20 ratio in order to train the model. The test set was utilised for validation, while the training set was used to fit the model. The Random Forest model's training hyperparameters were optimised via cross-validation to guarantee peak performance.

D. Model Deployment

The machine learning model was implemented for real-time predictions within the Flask application after it had been trained. Both the Random Forest model and the scaler were serialised using Python's pickle package in to make the trained model available in the web application. Through serialisation, the model can be stored in a manner that can be loaded for prediction later without requiring retraining. The Flask application loads the serialised model and scaler, applies the required transformations to the inputs, and generates a forecast based on the model when a user enters their parameters into the web form. To guarantee that the web application delivers prompt and precise forecasts, the outcome is then sent back to the user in the form of anticipated energy usage.

IV. Results and Implementation

A. Model Performance

To examine the model's accuracy in forecasting electric vehicle energy usage, its performance was assessed across several algorithms. The R2 Score, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) were used to train and evaluate the following models. These measures help evaluate how well the models match the data and extrapolate to new data. With comparable RMSE and MAE scores and an R2 value of roughly

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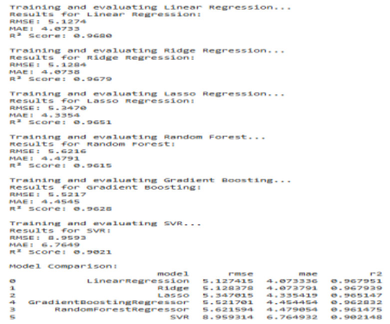
0.97, the data demonstrate that Ridge Regression and Linear Regression performed well. SVR, on the other hand, did the worst, having a lower R2 score and noticeably greater RMSE and MAE.



```
Training and evaluating Linear Regression...
Results for Linear Regression:
RMSE: 5.1274
MAE: 4.0733
R² Score: 0.9680

Training and evaluating Ridge Regression...
Results for Ridge Regression:
RMSE: 5.1284
MAE: 4.0738
R² Score: 0.9679

Training and evaluating Lasso Regression...
Results for Lasso Regression:
RMSE: 5.3470
MAE: 4.3354
R² Score: 0.9651

Training and evaluating Random Forest...
Results for Random Forest:
RMSE: 5.6216
MAE: 4.4791
R² Score: 0.9615

Training and evaluating Gradient Boosting...
Results for Gradient Boosting:
RMSE: 5.5217
MAE: 4.4545
R² Score: 0.9628

Training and evaluating SVR...
Results for SVR:
RMSE: 8.9593
MAE: 6.7649
R² Score: 0.9021

Model Comparison:
                        model      rmse       mae        r2
0            LinearRegression  5.127415  4.073336  0.967951
1                       Ridge  5.128378  4.073791  0.967939
2                       Lasso  5.347015  4.335419  0.965147
4   GradientBoostingRegressor  5.521701  4.454454  0.962832
3       RandomForestRegressor  5.621594  4.479054  0.961475
5                         SVR  8.959314  6.764932  0.902148
```

Figure 1: Model Evaluation Metrics

B. Web Application Interface

In order to forecast energy usage for electric vehicles, users can enter important factors like speed, temperature, battery capacity, and distance using the Flask-built web application. These inputs are gathered by the user-friendly form, and the trained Random Forest model uses them to produce predictions. Users are taken to a results page that shows the estimated energy use after submitting. It is a useful tool for EV owners to estimate energy use under different driving conditions because of its simple design, which guarantees that users can enter their data with ease and receive quick projections.

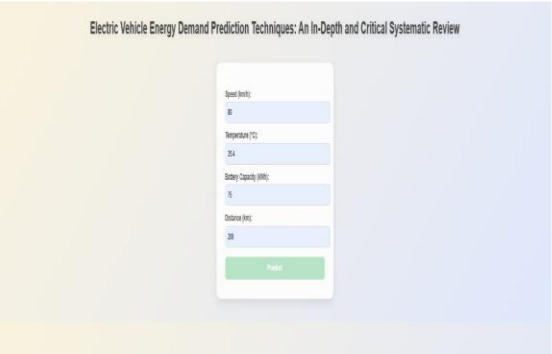


Figure 2: Web Application Input page

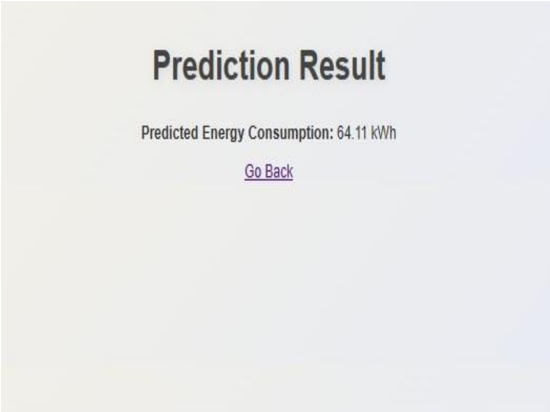


Figure 3: Prediction Results Page

V. Conclusion

This study successfully demonstrates how machine learning can be applied to predict how much energy electric vehicles would use based on factors like speed, distance travelled, temperature, and battery capacity. With low error rates and good accuracy, Ridge Regression and Linear Regression performed better than the other models in the examination. Because it can handle a variety of data sources, the Random Forest model was selected for implementation even if it is slightly less accurate. Flask was used to create an easy-to-use web application with an intuitive UI that allows real-time forecasts. The technology is a useful tool for EV owners and planners since it lets users enter driving circumstances and examine anticipated energy usage instantaneously. All things considered, this research demonstrates how data-driven strategies can encourage energy-efficient planning and driving in the expanding EV market, resulting in more intelligent and environmentally friendly transportation options.

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