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An Analysis of Market Size Trends Forecasting and Range Prediction in Electric Vehicles Using Machine Learning Algorithms

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Abstract

Electric vehicles face fundamental challenges primarily related to battery and charging systems. Conducting a market size analysis is an essential component of market research as it provides insights into the potential sales volume within a specific market. This study focuses on conducting a comprehensive analysis of market size within an electric vehicles industry segment, alongside predictions for the range. By leveraging data-driven approaches and predictive modelling techniques, insights into market dynamics and future trends are explored. The article contains 177866 data the task of performing a market size analysis for the electric vehicles sector using Python. Range estimation of the electric vehicle has been conducted using Linear, Random Forest, Ridge, Lasso, and Elastic Net Regression model types. When predicting range, performance metrics such as R-Squared, Adjusted R-Squared, Mean Squared Error, Root Mean Squared Error, and Mean Absolute Error are used, while Compound Annual Growth Rate is utilized for current and estimated electric vehicles market size. Based on the findings, the Tesla brand is predominantly preferred. A consistent annual growth rate of 51% has been noted. Random Forest Regression is identified as the premier model for predicting electric vehicle range due to its superior performance metrics, such as a higher R-Squared value and lower mean squared error in comparison to other regression methods.

Keywords: Compound Annual Growth Rate, Machine Learning, Market Size Analysis, Range Prediction, Regression

1. Introduction

Electric vehicle (EV) that are powered entirely or partially by electricity, using electric motors instead of traditional internal combustion engines. The automotive industry is undergoing a transformative shift towards sustainable mobility solutions, with electric vehicles (EVs) emerging as a key driver of this transition. As market demand for EVs continues to rise, the accurate forecasting of market size trends and precise range prediction play pivotal roles in shaping strategic decisions for manufacturers, policymakers, and consumers alike.

In recent years, the EVs market has witnessed substantial growth. In 2020, the global market size for EVs was assessed at $163.01 billion, with a forecast to hit $823.75 billion by 2030, showcasing a Compound Annual Growth Rate (CAGR) of 18.2% from 2021 to 2030. The EVs market's expansion is bolstered by factors like rising demand for fuel-efficient, high-performance, and low-emission vehicles, strict government mandates on vehicle emissions, decreasing costs of EV batteries, rental and escalating fuel prices [3, 11].

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In a literature review focusing on market size forecasting, consumer behaviour, and range prediction within the realm of EVs; the studies offer an empirical approach with a substantial sample size of over 2,000 responses, indicating a robust methodology to analyse factors influencing EVs adoption. Factors like mileage, battery, charge station availability, price, maintenance, government policy, promotion, and brand perception are analysed to understand consumer adoption of EVs, with Structural Equation Models demonstrating a strong fit of the model [22].

[14] Consumer behaviour studies on New Energy Vehicles reveal key factors influencing consumer decision-making, aiding enterprises and governments in understanding consumer needs. [10] Conduct a comprehensive review on consumer preferences for EVs, outlining influential factors categorized into socio-economic, psychological, mobility, and social influence aspects. Their research agenda proposes future directions for studying EVs consumer preferences, guiding policymakers and researchers in this domain. [18] Delve into the pricing and consumer characteristics affecting EV purchases in Europe. By analysing feature importance and utilizing Boosted decision tree models, they identify factors like car size, battery durability, and acceleration as crucial considerations for consumers when choosing EVs. [4] Analyse factors influencing consumer preferences for EVs, highlighting age, gender, parenthood, education, urban living, and past EV experience as positive influencers of EV preference. Their study underscores the significance of reputation and sociodemographic factors in shaping consumer attitudes towards EV adoption.

The concept of "Green Premiums" in the EV industry is discussed, with China leading in commercializing EVs and predicting cost parity with Internal Combustion Engine Vehicles by 2030 [9]. [21] Investigates consumer brand preferences for environmentally friendly products, specifically EVs in Bangkok, Thailand. The study reveals the impact of social influence on environmental concern, attitude, fuel efficiency perception, and brand preference, highlighting the interconnectedness of these variables.

Evaluation of machine learning and deep learning algorithms to predict daily charging demands of EVs shows similar levels of performance across all models, indicating their effectiveness for seasonal effects analysis [19]. Machine learning techniques are utilized to estimate the Driving Range of EVs, providing precise and consistent estimations for both short and long trips, enhancing trip planning for EV users [2]. [17] Demonstrate the efficacy of the gradient boosting decision tree algorithm in predicting driving range for EVs, showcasing improved accuracy compared to conventional regression models. The method yields minimal prediction errors, providing more reliable estimations for users to plan their journeys effectively. [6] Propose leveraging past driving data and real-time EV parameters to estimate vehicle range autonomy accurately. By developing regression models based on driver profiles and external factors, the approach aims to optimize trip planning and navigation for EV users. [12] Introduce an EV range estimation method that clusters driving patterns to predict future energy consumption per kilometer. By utilizing features like average speed and power, the model accurately estimates EV range based on driving behaviour, demonstrating a low error rate in predicting energy consumption. [5] Aims to build a machine learning model to predict individuals' likelihood to purchase or not purchase an EV in India. This model considers factors such as age, gender, income, environmental awareness, vehicle cost, performance, driving range, and social behaviour as key predictors of EV purchases. Surprisingly, factors like education level, employment status, and government subsidies do not significantly influence EV adoption in the Indian market, indicating unique consumer dynamics. A novel deep learning LSTM model is introduced by [15] for forecasting EV charging demand. By optimizing parameters and utilizing empirical mode decomposition, the EMD-AOA-DLSTM model overcomes challenges in recurrent neural networks. Tested on an EV charging dataset, the model achieves impressive results with high prediction accuracy and low errors, showcasing its efficacy in predicting EV charging demand accurately. [1] Studies analyse factors influencing EV range using data-driven approaches and regression techniques. Correlations between range and battery capacity, top speed, curb weight, and acceleration are identified. Regression techniques like support vector machine regression achieve low Root Mean Square Error (RMSE), providing consumers with accurate estimations of EV range based on key parameters.

The motivation for this study stems from the rapid growth and evolution of the EV market, which presents both significant opportunities and challenges. As the demand for sustainable transportation solutions increases, understanding the factors influencing EV adoption becomes crucial. This study aims to provide valuable insights into market size trends, consumer behaviour, and range prediction using machine learning algorithms. By leveraging data-driven approaches, study seeks to inform stakeholders—including policymakers, manufacturers, and consumers—about the dynamics of the EV market, ultimately contributing to the development of effective strategies that promote the adoption of EVs and enhance sustainable transportation initiatives. This research not only addresses existing gaps in the literature but also aims to guide future studies and practical applications in the EV sector.

2. Material and Method

Data was collected through the on 16.03.2024, Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs) specified in “https://catalog.data.gov/dataset/electric-vehicle-population-data” that are currently registered through Washington State Department of Licensing constitutes. In the research, trying to find a regression model using Forward Feature Selection by iteratively including one feature at a time until no further enhancements were observed on the prediction metrics used and scope of 177866 data in total, which are split 142292 test (%80) and 35574 train (%20). It is defined as independent variable (X) Model Year, dependent variable (Y) Electric Range.

The process of conducting market size analysis, consumer behaviours, and range prediction for EVs entails several key steps, including defining the market scope, gathering and preparing data, conducting analytical modelling, and communicating findings through visualization and reporting. Figure 1 shows the steps involved in performing a market size analysis and range prediction for EVs.

Figure 1. Data Analysis Process

The provided Figure 1, a comprehensive approach to analysing the EV market and range prediction. It suggests defining the geographical scope of analysis, collecting data from various sources, utilizing historical data to identify trends, analysing market size and growth rates, and formulating strategic recommendations based on the insights gained.

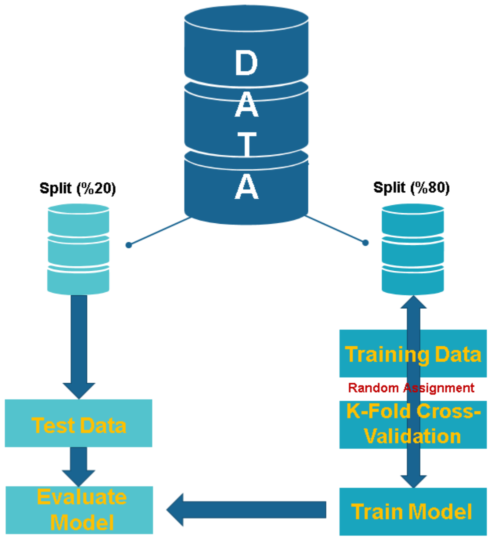

Figure 2. Machine Learning Core Specification of Model

As indicated in Figure 2, the data set is divided into training, validation, and test sets (80/20). In detail and sequentially, the training data set is randomly divided into K equal parts. Each part is used sequentially as validation data, while the other parts are used as the training data set. The model is trained on each training data set, and its performance is measured with the validation data. This process is repeated K times, with a different part chosen as validation each time (K=15). Consequently, K different accuracy values or other performance metrics are obtained. The average of K accuracy values or performance metrics is calculated to evaluate the overall performance of the model. Finally, the model's measured actual performance with the test data set.

K-Fold Cross Validation is a common validation technique used to evaluate model performance and measure its generalization ability. K-Fold Cross Validation divides the training data set into K equal parts and then uses one part for validation within itself while using the other parts as the training data set. This process is repeated K times, with a different part selected as the validation data each time. As a result, K different accuracy values are obtained, and the average of these values is used to evaluate the model's performance [7]. Within this article, taking the value we processed as K=15, Cross-Validation accuracy scores are as follows [0.68227669 0.68464763 0.68172713 0.68270844 0.70298469 0.68140145 0.69685267 0.69104403 0.67333821 0.68094892 0.69363645 0.68723196 0.68079699 0.67370363 0.6826772]. Sklearn.model_selection method cross_val_score used for K-fold Cross-Validation accuracy is 0.685 +/- 0.008 observed.

2.1. Used Metrics

In the context of this article, is a financial metric which is CAGR, and five key metrics used for evaluating regression models: R-Squared, Adjusted R-Squared, Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE).

The CAGR serves as a frequently utilized metric for measuring growth over a specific period, commonly employed in the assessment of investments or business performance. It offers a consistent rate of growth that reflects the average annual growth rate over a specified period, assuming a steady progression throughout the timeframe [16]. The formula for CAGR is:

CAGR = (Ending Value / Beginning Value)^(1/n) – 1 (1)

Where represents to Ending Value: The value at the end of the period, Beginning Value: The value at the beginning of the period, and n: Number of years.

R-Squared quantifies the proportion of variation in the dependent variable explained by the regression model, while Adjusted R-Squared adjusts for the number of predictors, improving only with significant model enhancements. MSE averages squared differences between predicted and actual values, emphasizing larger discrepancies, beneficial for addressing unexpected values. RMSE is the square root of MSE, aligning the error metric with the target variable's unit for easier interpretation. MAE averages absolute differences between predicted and actual values, treating all differences equally and showing less sensitivity to outliers [20].

2.2. Used Algorithms

Regularization is one of the types of linear regression used to prevent over fitting and improve the generalization performance of model. Regularization works by adding a penalty term to the model’s loss function.

$$\text{Regularization} = \text{Loss Function} + \text{Penalty} \tag{2}$$

This penalty discourages the model from fitting the noise and discourages large coeeffient weights, making it more robust and simple of making accurate prediction on new data.

In the domain of regression analysis, several techniques like linear regression, ridge regression, lasso regression, and elastic net regression play vital roles in modelling and predicting relationships between variables. A concise overview of each technique: Linear regression is a fundamental statistical method that establishes a linear relationship between dependent and independent variables. Ridge regression or L2 Regularization adds a penalty term with the loss function, which keeps the magnitude of the model’s weights (coefficients) as small as possible. It is particularly useful when multicollinearity exists in the data, helping to stabilize and improve the performance of the model. Lasso regression or L1 Regularization, short for Least Absolute Shrinkage and Selection Operator, is another variant of the regularization technique used to reduce the complexity of the model and feature selection. Same like Ridge it adds Penalty term which tends to shrink some of the weight coefficients to zero, meaning the model will ignore those features and only selects important features. By combining features of ridge and lasso regression, elastic net regression offers an optimal solution for managing multicollinearity and addressing challenges related to feature selection. Both of the L1 and L2 terms are added to the cost function. This method is particularly effective in scenarios with high levels of multicollinearity and where variable selection is critical [13]. Random Forest Regression is a machine learning technique that uses an ensemble of decision trees to perform regression tasks. It works by constructing multiple decision trees during training and outputting the average prediction of the individual trees for regression tasks [8].

3. Results and Discussions

In the market size analysis of EVs, the focus areas include EV adoption over time, geographical distribution, EV types, electric ranges, estimated growth in market sizes, make and model popularities.

The dataset encompasses the number of EVs registered each year from 1997 through 2024. However, the data for 2024 is incomplete as it only includes information up to March. In 2021, there were 19,132 EVs registered. This number increased to 27,776 EVs in 2022. A significant surge to 57,587 EVs was observed in 2023. As for 2024, the current data indicates that 7,080 EVs are registered, suggesting that the data is partial due to the timeframe.

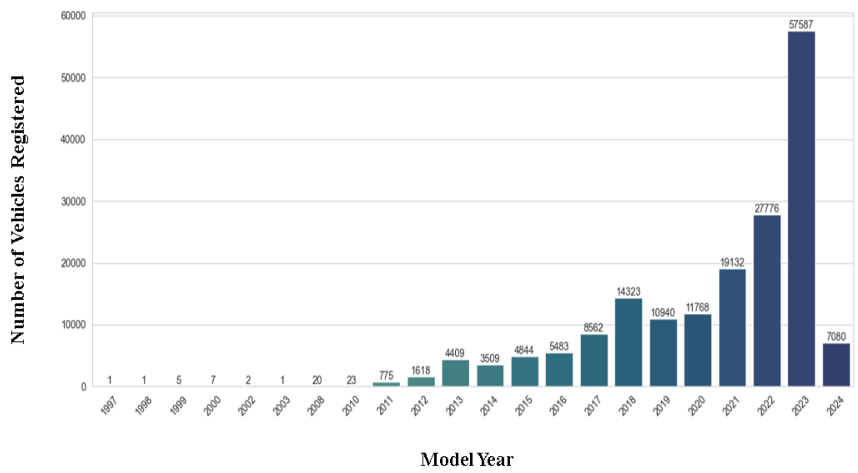

Figure 3. EV Adoption Over Time

Based on the Figure 3, it is evident that the adoption of EVs has been steadily increasing over time, notably showing a significant upward trend from around 2016 onwards. The registered vehicle count demonstrates modest growth leading up to this period, followed by a more pronounced rise starting from 2017. Notably, the year 2023 exhibits a particularly sharp surge in registered EVs, with the bar for 2023 being the highest on the graph, signifying a peak in EV adoption.

In Figure 4, shows the top 5 counties based on EV registrations and then analyse the distribution of EVs within the cities of those counties.

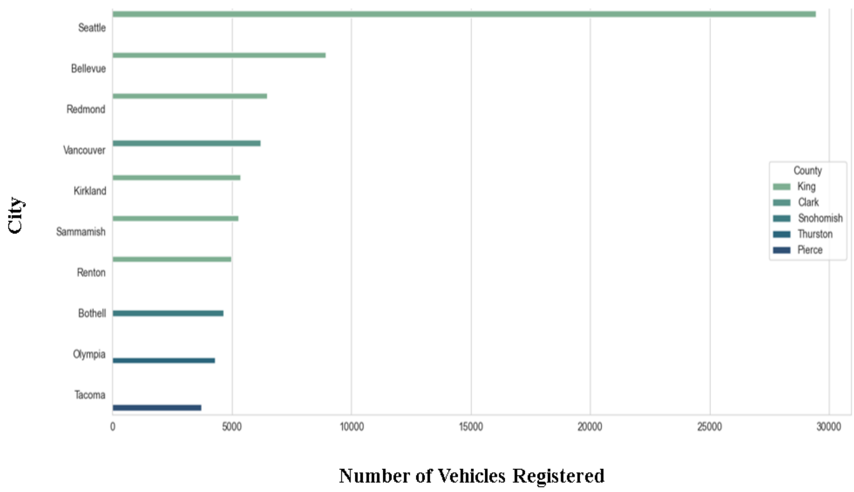

Figure 4. Top Cities in Top Counties by EV Registrations

The Figure 4 provides a comparison of the number of EVs registered in cities across five counties: King, Clark, Snohomish, Thurston, and Pierce. The horizontal bars represent the cities, with their length reflecting the number of registered vehicles, color-coded by county.

Seattle, located in King County, stands out with the highest number of EV registrations by a significant margin, surpassing all other listed cities. Bellevue and Redmond, also in King County, follow Seattle with the next highest registrations, albeit at a considerably lower level. Vancouver leads in Clark County and ranks fourth overall. Cities in King County, such as Kirkland and Sammamish, exhibit moderate EV registrations. Among the King County cities, Renton has the lowest number of registrations. Bothell in Snohomish County and Olympia in Thurston County have lower rankings. Tacoma, representing Pierce County, shows the fewest EV registrations among the listed cities. The majority of the cities depicted are from King County, indicating its dominance in EV registrations across the five counties.

Overall, the graph illustrates that EV adoption is not evenly distributed across the cities and is more concentrated in specific areas, particularly within King County.

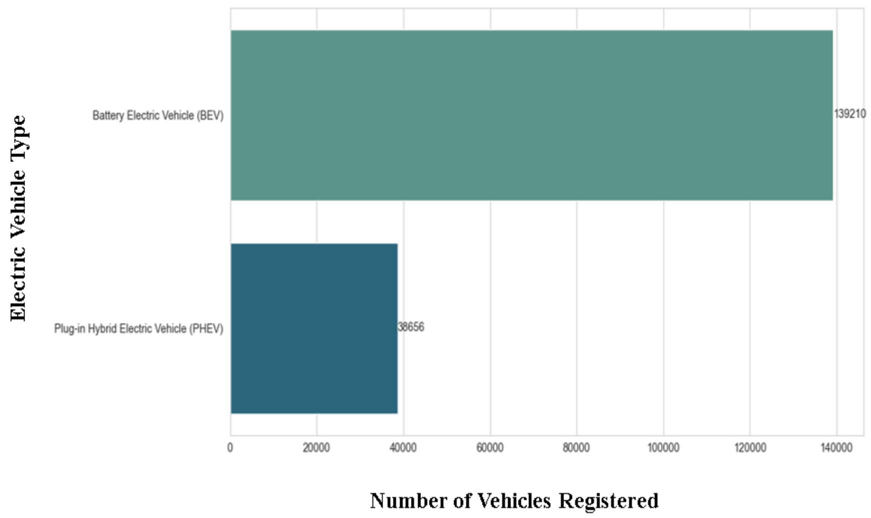

Figure 5. Distribution of EV Types

According to Figure 5, BEVs are the more popular choice over PHEVs among the registered EVs in the United States.

In Figure 6, the emphasis is on the prevalence of EV manufacturers and models among the registered vehicles. This analysis aims to uncover the leading manufacturers and specific models that hold sway in the EV market, potentially shedding light on consumer preferences, brand loyalty, and the efficacy of manufacturers' strategies in promoting electric mobility.

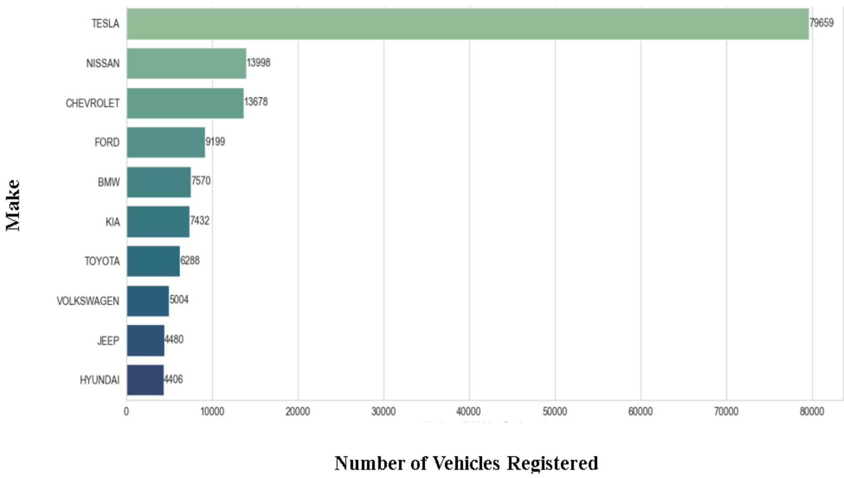

Figure 6. Top 10 Popular EV Makes

Based on Figure 6, TESLA holds a commanding lead with the highest number of registered vehicles, followed by NISSAN as the second most popular manufacturer, and CHEVROLET in third place, although both have notably fewer registrations than TESLA. Following in descending order of registered vehicles are FORD, BMW, KIA, TOYOTA, VOLKSWAGEN, JEEP, and HYUNDAI.

In Figure 7, the distribution of EV registrations among different models from the top five manufacturers—TESLA, NISSAN, CHEVROLET, FORD, and BMW—is depicted.

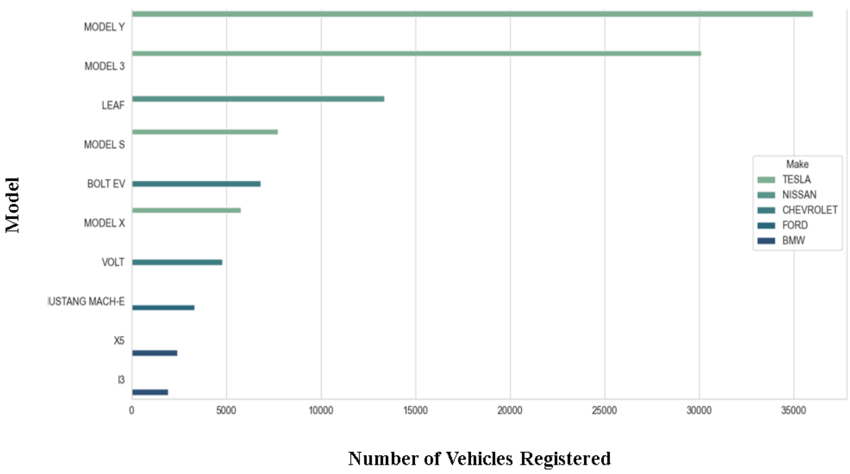

Figure 7. Top Models in Top 5 Makes by EV Registrations

TESLA's MODEL Y and MODEL 3 lead as the most registered vehicles, with MODEL Y boasting the highest number of registrations. NISSAN's LEAF ranks as the third most registered model and holds the distinction of being the most registered non-TESLA vehicle. TESLA's MODEL S and MODEL X also exhibit a significant number of registrations. Following in the ranking are CHEVROLET's BOLT EV and VOLT. FORD's MUSTANG MACH-E, BMW's X5 and i3 have the fewest number of registrations among the models showcased.

In Figure 8, the electric range of vehicles is explored, a critical factor for analysing the market size of EVs. The electric range indicates how far an EV can travel on a single charge, and advancements in battery technology have steadily increased these ranges over the years.

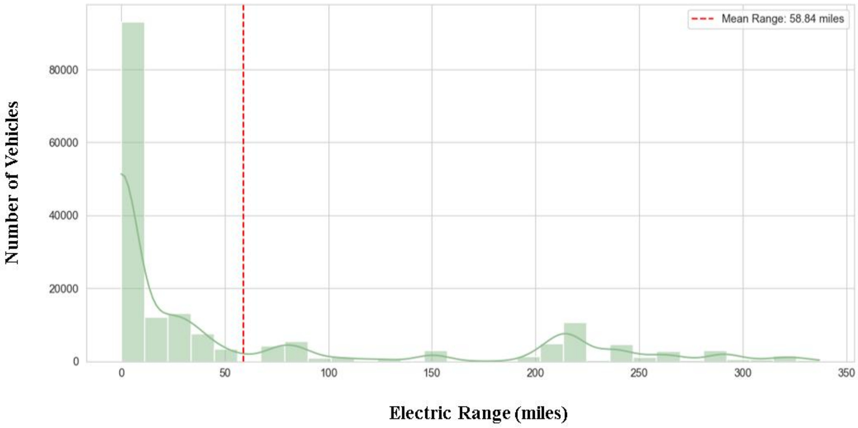

Figure 8. Distribution of EV Ranges

The figure 8 depicts the mean electric range, with several key observations: There is a high frequency of vehicles with a low electric range, featuring a significant peak just before the 50-mile mark. The distribution skews to the right, with a long tail extending towards higher ranges, although the occurrence of vehicles with higher ranges is less frequent. The mean electric range for this set of vehicles is approximately 58.84 miles, relatively low compared to the highest ranges shown in the graph. Despite the presence of EVs with ranges extending up to around 350 miles, the majority of the vehicles have a range below the mean. This suggests that while EVs with high electric ranges are available, the average range is skewed lower due to a substantial number of vehicles with shorter ranges.

In Figure 9 shows the trend of electric ranges over model years.

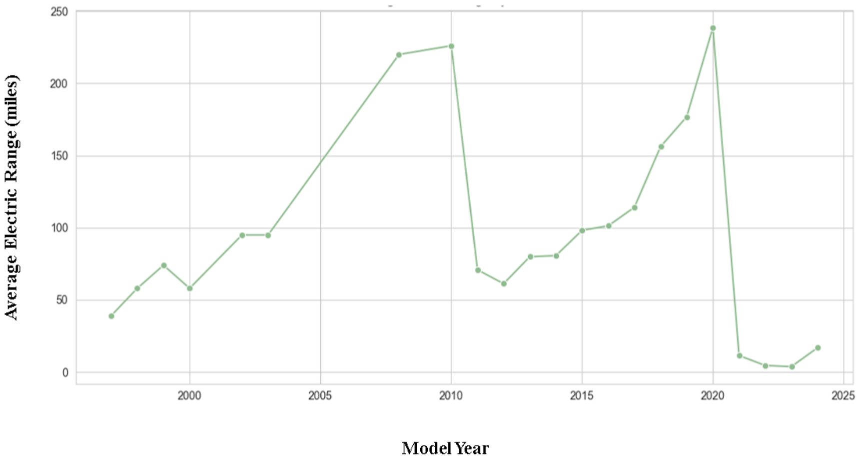

Figure 9. Average Electric Range by Model Year

The Figure 9 illustrates the progression of the average electric range of vehicles from around the year 2000 to 2024, yielding several key findings: There is a consistent upward trend in the average electric range of EVs over the years, signifying advancements in technology and battery efficiency. A notable peak is observed around the year 2020, when the average range reaches its highest point. Subsequent to 2020, there is a marked decline in the average range, potentially indicating incomplete data or the introduction of several lower-range models. Following the sharp decline, there is a slight recovery in the average range in the most recent year depicted on the graph.

The data suggests that despite fluctuations, the overall trend over the last two decades has been towards an increase in the electric range of EVs.

In Figure 10 shows the electric ranges vary among the top manufacturers and models.

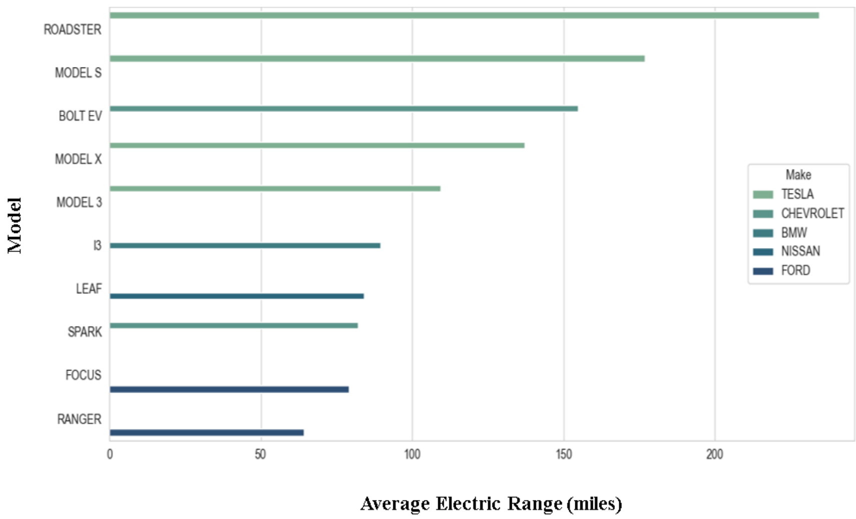

Figure 10. Top 10 Models by Average Electric Range in Top Makes

The TESLA ROADSTER boasts the highest average electric range among the listed models. TESLA's models (ROADSTER, MODEL S, MODEL X, and MODEL 3) dominate the majority of the top positions, indicating that, on average, TESLA's vehicles have higher electric ranges. BMW’s i3 is located in the midrange. The SPARK stands out among the CHEVROLET models, exhibiting a significantly same range than the NISSAN’S LEAF. In contrast, FORD's FOCUS and RANGER occupy the lower half of the chart, pointing towards more modest average ranges.

The CAGR is calculated by comparing the data from a recent year with complete data 2023 to an earlier year in order to project the 2024 figures. Furthermore, it helps in estimating the market size for the next five years. An average increase of 51% per year has been observed.

Table 1. Estimated Market Size

Year	Number of EV Registrations
2024	79092
2025	119565
2026	180748
2027	273240
2028	413061
2029	624431

Based on Figure 11, the following observations can be made: The actual EV registrations remained relatively low and stable until around 2010, after which a consistent and steep upward trend emerged, indicating a significant increase in EV adoption. The forecasted EV registrations predict an even more dramatic increase in the near future, with the number of registrations expected to rise sharply in the coming years. Considering the growing trend in actual EV registrations and the projected acceleration as per the forecast data, it can be inferred that the EV market size is anticipated to expand considerably. The sharp increase in forecasted registrations suggests an increasing consumer adoption of EVs, likely to persist in the future. Overall, the data points towards a promising future for the EV industry, signalling a significant shift in consumer preferences and a potential rise in related investment and business opportunities.

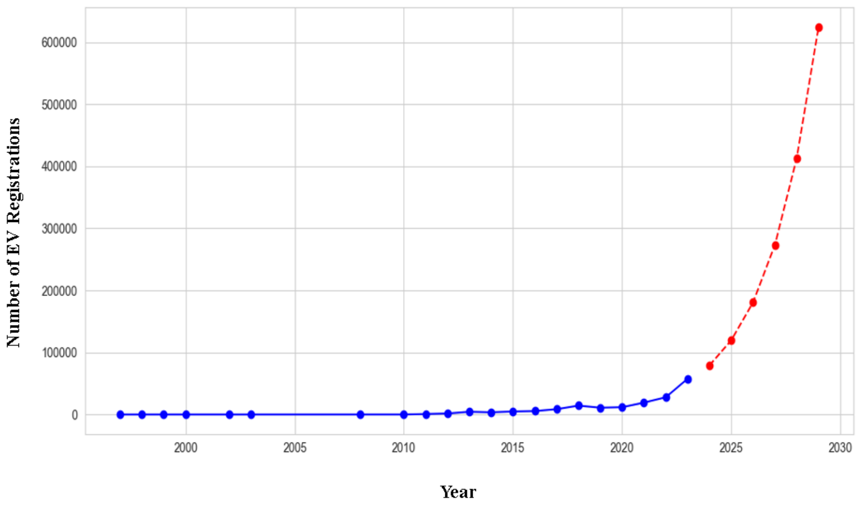

Figure 11. Current & Estimated EV Market

Table 2 shows the results of the specified performance metrics for each machine learning algorithm.

Table 2. Results of the performance metrics for the mentioned machine learning algorithms

	R-Square	Adjusted R-Squared	MSE	RMSE	MAE
Ridge	0.23	0.23	6517.48	80.73	58.82
Lasso	0.22	0.22	6564.52	81.02	60.22
Elastic Net	0.23	0.23	6524.40	80.77	59.31
Linear	0.23	0.23	6517.48	80.73	58.82
Random Forest	0.68	0.68	2709.96	52.06	30.59

After a thorough evaluation of the discussed models, it is clear that Random Forest Regression stands out as the preferred option. This decision is supported by its superior R-Squared value of 0.68 and lower MSE of 2709.96 when compared to alternative models.

This underscores Random Forest Regression's strength as a dependable and precise tool for estimating the distance an electric vehicle can cover on a full charge. Leveraging this advanced machine learning technique can significantly enhance decision-making processes and optimize the development and implementation of EV technologies.

Consequently, Random Forest Regression emerges as the top-performing model for accurately predicting the range of an EV.

4. Conclusions and Recommendations

This study explores the EV industry segment, offering insights into market dynamics and upcoming trends using real-world examples abound where data-driven methodologies and predictive modelling techniques.

The combination of market size analysis and range prediction offers valuable strategic insights for decision-makers aiming to understand market potential and optimize product positioning within competitive landscapes. This analysis helps businesses in comprehending the level of demand, evaluating market saturation, and pinpointing growth prospects.

The calculation of the CAGR provides a valuable method for projecting future market figures by analysing data from a comprehensive year 2023 and comparing it to an earlier year. This comparison enables the estimation of market size trends and growth rates, facilitating informed decision-making and strategic planning for the upcoming years, specifically up to 2024 and beyond. Observations reveal a consistent annual growth rate of 51%, highlighting a substantial upward trend in the data analysed. This significant increase signifies a notable progression or expansion within the context under consideration, showcasing a robust and sustained pattern of growth over time.

Upon reviewing the models discussed, it becomes clear that Random Forest Regression stands out as the optimal choice for predicting the range of an EV. This conclusion is drawn from its superior performance metrics, including a higher R-Squared value and lower MSE when compared to alternative models like Linear Regression, Ridge Regression, Lasso Regression, and

Elastic Net Regression. The robustness and accuracy exhibited by Random Forest Regression make it the most effective model for estimating the range of EVs, offering valuable insights for decision-making in the realm of electric vehicle development and optimization.

Market size analysis is a critical component of market research that assesses the potential sales volume within a given market. It helps businesses in comprehending the scale of demand, evaluating market saturation levels, and identifying growth opportunities. Our analysis of the market size for EVs reveals a promising future for the EVs industry, signalling a noteworthy shift in consumer preferences and a potential uptick in related investment and business opportunities.

The trends driving growth in the electric vehicle market can be Advancements in Battery Technology, Government Support and Regulations, Infrastructure Development, Consumer Awareness and Demand, Rise of Electric SUVs and Trucks.

Continuous progress in battery technology is resulting in enhanced energy density, increased range, and reduced charging times, making EVs more practical and attractive to consumers. Numerous governments are enacting policies to incentivize the adoption of EVs, such as tax incentives, rebates, and emissions regulations, thereby contributing to the expansion of the market. The ongoing expansion of charging infrastructure, including the implementation of fast-charging stations, is alleviating concerns related to range anxiety and facilitating the widespread adoption of EVs. The escalating environmental consciousness among consumers, combined with a growing preference for sustainable transportation, is propelling the demand for EVs. The emergence of electric SUVs and trucks by major automakers is broadening the appeal of EVs beyond sedans, consequently fostering market growth.

Given the rapid growth and evolution of the EV market, it would be beneficial to explore the consumer behaviour and preferences regarding EV adoption. Understanding the factors influencing consumer decision-making, potential barriers to adoption, and the impact of marketing efforts on consumer perceptions can provide valuable insights for businesses looking to enter or expand within the EV market.

Referring to Consumer Behaviour and Preferences in the EV Market, it shows that Consumer Perception, Barriers to Adoption, Purchase Decision Factors, Brand Preference and Marketing Effectiveness.

Understanding how consumers perceive EVs in terms of affordability, performance, environmental impact, and overall value proposition is vital for shaping marketing strategies and product positioning. Identifying and addressing the primary concerns and obstacles that inhibit consumers from embracing EVs, such as range anxiety, charging infrastructure, initial cost, or perceived inconvenience, can lead to targeted solutions and educational campaigns to alleviate these barriers. Analysing the key factors that influence consumers' decisions to purchase or lease EVs, including incentives, total cost of ownership, environmental considerations, and technological features, can reveal opportunities for differentiation and value proposition enhancement. Examining which brands and models resonate most with consumers and the factors driving these preferences, such as reputation, design, or technological innovation, can inform branding strategies, partnerships, and product development efforts. Assessing the impact of marketing initiatives, including awareness campaigns, educational efforts, and targeted promotions, on shaping consumer attitudes and willingness to consider EVs is essential for optimizing marketing strategies and messaging.

There are a number of factors that also affect EV range on Driving Behaviour, Weather Conditions, Terrain, Vehicle Weight, Tire Pressure and Accessories in Use.

Aggressive acceleration, high speeds, traffic, frequent braking can reduce an EV's range. Extreme temperatures, both hot and cold, can affect battery performance and decrease range. Also, heating and air conditioning an addition. Driving uphill or on rough terrain can require more energy, reducing the range of an EV. Heavier vehicles typically have shorter ranges due to increased energy consumption. Underinflated tires can create higher rolling resistance, leading to decreased range. Using features like heating, air conditioning, and entertainment systems can drain the battery faster.

Building on the foundation of real data analysis showcased in the article, future studies can explore EV market segmented by type across various geographic entities such as counties, cities, and regions. This approach can provide valuable insights into the adoption trends, preferences, and challenges associated with EVs at a more granular level, and the way for innovative strategies to promote sustainable transportation initiatives. Additionally, studies can be done according to EV Type.

In conclusion, the study on market size trends forecasting and range prediction in EVs using machine learning algorithms represents a significant contribution to the literature on data-driven approaches in the transportation sector. By referencing this research, scholars can gain valuable insights into the methodologies, findings, and implications of leveraging machine learning for informed decision-making in the EV industry.

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Declaration of competing interest

There is no conflict of interest the author.

Author Contributions

The author has contributed to be valid in all study.

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