Prediction Models for EV Range Requirements and Charging Infrastructure Demand

Author Information: Musa Mubarak Abdulaziz. Department of Physics and Electronics, Airforce Institute of Technology Kaduna, Nigeria

- Tel.: +2349059940714
- E-mail address: Musamubarak350@gmail.com

ABSTRACT

The electric vehicle industry faces critical challenges in optimizing range specifications and strategic infrastructure deployment across global markets. This study develops dual forecasting models to predict EV range requirements and regional charging infrastructure demand using comprehensive analysis of 353 electric vehicles from European markets. The research employs advanced gradient boosting algorithms to examine technical specifications including battery capacity, drive configurations, and efficiency metrics alongside regional pricing data from Germany, Netherlands, and United Kingdom. Range prediction models demonstrate exceptional accuracy with $R^2 = 0.9914$ and root mean square error of 9.99 km. Power-to-weight ratio emerges as the dominant predictor contributing 44.9% importance, followed by battery capacity at 41.3%. Infrastructure demand forecasting achieves outstanding performance with $R^2 = 0.9966$ and RMSE = 2.03, revealing significant regional variations with Germany showing highest demand index at 42.32, followed by UK at 39.36 and Netherlands at 37.21. Vehicle segment analysis reveals distinct range requirements: performance sports vehicles require 432 km range, highway sedans need 386 km, luxury SUVs 366 km, and urban compact vehicles 262 km, indicating 65% variation across market segments. The forecasting framework provides actionable intelligence for manufacturers optimizing battery specifications and infrastructure planners determining regional deployment priorities, supporting evidence-based decision-making in the rapidly evolving electric mobility ecosystem.

Keywords: Electric Vehicle Forecasting, Range Prediction, Infrastructure Planning, Gradient Boosting, Battery Optimization

1. INTRODUCTION

The electric vehicle revolution represents one of the most significant technological transformations in the automotive industry, with global adoption reaching unprecedented levels as markets accelerate toward sustainable transportation solutions (Mubarak, 2025). As manufacturers face complex challenges in optimizing vehicle specifications while infrastructure planners struggle with strategic deployment decisions, the automotive sector experiences fundamental shifts requiring sophisticated analytical approaches (IEA, 2024). The complexity of balancing range requirements across diverse market segments with varying regional infrastructure demands creates critical knowledge gaps that traditional analytical approaches cannot adequately address.

Current market dynamics reveal substantial variations in consumer expectations, with performance vehicle segments demanding extended range capabilities while urban mobility solutions require cost-effective moderate range specifications (Ma et al., 2025). Simultaneously, regional markets demonstrate distinct infrastructure development patterns influenced by policy frameworks, geographic constraints, and economic factors, necessitating sophisticated forecasting methodologies capable of accurately predicting both technical requirements and market demands (Haghani et al., 2023). The rapid growth of electric vehicle usage requires accurate energy consumption prediction for effective power grid management and strategic planning initiatives.

The profession of electric vehicle development faces critical decision-making challenges similar to complex organizational management issues, with range anxiety continuing to influence consumer adoption patterns while infrastructure inadequacy constrains market expansion potential (Ullah & Severino, 2019). Organizations across the EV ecosystem require data-driven insights to optimize resource allocation, strategic positioning, and long-term planning initiatives, particularly as electric vehicle penetration accelerates globally (Naresh, 2024). Recent years have seen strong growth in electric vehicle sales together with improved range, wider model availability and increased performance, with passenger electric cars surging in popularity.

This research addresses the fundamental need for predictive analytics in electric vehicle market development by developing dual forecasting models targeting range optimization and infrastructure demand forecasting (Mei et al., 2023). The study examines comprehensive technical and market data to provide actionable intelligence supporting strategic decision-making across manufacturer and infrastructure planning domains, contributing to the expanding knowledge base in sustainable transportation planning and electric mobility optimization.

2. LITERATURE REVIEW

Review of literature in electric vehicle forecasting reveals several critical research domains requiring integrated analytical approaches to address contemporary market challenges (Boudmen et al., 2024). Range prediction studies typically focus on battery technology optimization and energy efficiency improvements, with machine learning techniques showing particular promise for capturing complex relationships between technical specifications and real-world performance characteristics (Chen et al., 2025). Battery capacity optimization research emphasizes technical specifications while infrastructure planning literature concentrates on geographic deployment strategies and policy implementation frameworks without adequate integration of market dynamics.

Electric vehicle range optimization has been extensively studied through various technological approaches, with advanced battery management systems and energy efficiency algorithms demonstrating significant improvements in range capabilities (Wang et al., 2025). However, limited research addresses comprehensive market-based forecasting methodologies integrating technical specifications with consumer behavior patterns and regional market dynamics, representing a significant gap in current literature (Ullah & Severino, 2019). Remaining driving range research has continued to consistently evolve with electric vehicle development, with accurate prediction representing a promising approach to alleviate driver anxiety and support market adoption.

Infrastructure demand forecasting literature reveals fragmented approaches focusing primarily on single-variable analyses, with geographic information system applications and policy analysis frameworks providing valuable insights into deployment strategies (Xie et al., 2024). Nevertheless, integrated forecasting models combining technical vehicle characteristics with regional market factors remain underdeveloped in current research literature, missing critical interdependencies that influence strategic decision-making processes (BloombergNEF, 2025). Research on electric vehicle load forecasting considering regional special event characteristics represents an emerging area of study with significant practical implications.

Machine learning applications in automotive forecasting show promising results across various prediction domains, with gradient boosting algorithms demonstrating superior performance in complex multi-variable prediction scenarios (Chakraborty et al., 2022). Random forest and linear regression methodologies provide baseline comparison capabilities for model validation and performance assessment purposes, while deep learning approaches show potential for capturing nonlinear relationships (Naresh, 2024). Artificial intelligence has been widely used for determining current state of Li-ion batteries used for electric vehicle applications, with gradient boosting techniques showing particular effectiveness.

The literature gap analysis reveals limited comprehensive studies integrating vehicle range prediction with infrastructure demand forecasting through unified analytical frameworks (Haghani et al., 2023). Current research approaches typically address these domains independently, missing critical interdependencies and market relationship dynamics that influence strategic decision-making processes across the electric mobility ecosystem (IEA, 2024). Schedulable capacity forecasting for electric vehicles based on big data analysis represents an important development area requiring further investigation.

3. OBJECTIVE

1. To develop accurate predictive models for electric vehicle range requirements based on technical specifications and vehicle characteristics, addressing the critical need for precise range estimation in rapidly expanding global markets (IEA, 2024).
2. To forecast regional charging infrastructure demand patterns across European markets using market-based analytical approaches, considering the significant variations observed across different policy environments and economic conditions (Xie et al., 2024).
3. To identify critical success factors influencing range prediction accuracy and infrastructure demand variations, supporting optimization strategies essential for sustainable electric mobility development (Chen et al., 2025).
4. To provide actionable insights supporting strategic decision-making for EV manufacturers and infrastructure planning organizations, particularly as electric vehicle adoption continues accelerating globally with improved performance characteristics (Naresh, 2024).

4. HYPOTHESIS

The following hypotheses are proposed for the study:

H1: Electric vehicle range requirements can be accurately predicted using gradient boosting algorithms with technical specifications including battery capacity, power-to-weight ratio, and efficiency metrics achieving $R^2 > 0.95$, consistent with machine learning approaches demonstrating superior performance in energy consumption prediction applications.

H2: Regional charging infrastructure demand varies significantly across European markets, with Germany demonstrating highest demand indices compared to Netherlands and United Kingdom, reflecting established market leadership and comprehensive policy frameworks supporting adoption.

H3: Vehicle segment analysis reveals substantial range requirement variations, with performance sports vehicles requiring significantly higher range specifications compared to urban compact vehicle segments, supporting differentiated market strategies across diverse consumer applications.

H4: Power-to-weight ratio and battery capacity serve as dominant predictors for range forecasting, contributing greater than 75% combined feature importance in predictive models, consistent with artificial intelligence applications in battery state estimation research.

5. RESEARCH METHODOLOGY

Dataset Description

This study utilizes the Kaggle Electric Vehicle Dataset 2024 containing comprehensive information on 353 electric vehicles across European markets, providing robust foundation for advanced predictive modeling applications (Haghani et al., 2023). The dataset includes technical specifications, pricing data, and performance metrics covering Germany, Netherlands, and United Kingdom markets, representing three major European electric vehicle markets with distinct regulatory frameworks and infrastructure development patterns.

Sample Selection

For comprehensive analysis and reliable outcomes, the complete dataset of 353 vehicles was utilized representing diverse vehicle segments and drive configurations across European markets (Boudmen et al., 2024). The dataset encompasses all-wheel drive (161 vehicles, 45.6%), front-wheel drive (104 vehicles, 29.5%), and rear-wheel drive (88 vehicles, 24.9%) configurations, accurately reflecting current market distribution patterns observed in European electric vehicle segments.

European Electric Vehicle Market (Germany, Netherlands, United Kingdom) representing markets with established electric vehicle adoption and infrastructure development programs (IEA, 2024). Individual electric vehicles with complete technical and pricing specifications validated against manufacturer data. Complete enumeration of available dataset ensuring comprehensive market representation consistent with established electric vehicle research protocols (Ullah & Severino, 2019)

Sample Size: 353 electric vehicles representing diverse segments and configurations

Data Collection Methodology

Primary Data Sources: Kaggle Electric Vehicle Dataset 2024 providing comprehensive technical specifications, pricing information, and performance metrics validated through manufacturer specification cross-referencing (Naresh, 2024).

Secondary Data Sources: Regional market analysis reports from International Energy Agency, infrastructure development statistics from European Alternative Fuels Observatory, policy framework documentation, and market trend analysis from Bloomberg New Energy Finance and industry research platforms.

Variables for Analysis

Range Prediction Variables: Battery capacity (kWh), power-to-weight ratio, efficiency metrics (Wh/km), drive configuration, top speed, acceleration performance, consistent with established predictive modeling approaches in contemporary electric vehicle research (Chen et al., 2025) **Infrastructure Demand Variables:** Regional pricing variations, range capabilities, fast charging specifications, affordability indices, market penetration metrics reflecting European market dynamics and policy implementation effectiveness (Xie et al., 2024)

6. STATISTICAL MODEL

The research employs gradient boosting regression algorithms for both range prediction and infrastructure demand forecasting, following established methodologies demonstrating superior performance in electric vehicle energy consumption prediction scenarios (Chen et al., 2025). Gradient boosting provides superior performance for complex multi-variable prediction scenarios through iterative model optimization and ensemble learning approaches, particularly effective for electric vehicle applications requiring high accuracy and interpretability (Chakraborty et al., 2022).

Model 1: Range Requirements Prediction

- Algorithm: Gradient Boosting Regressor with hyperparameter optimization following protocols established for electric vehicle performance prediction applications (Wang et al., 2025)
- Target Variable: Driving Range (km)
- Performance Metrics: R^2, RMSE, MAE with cross-validation consistent with established electric vehicle prediction methodologies (Ma et al., 2025)

Model 2: Infrastructure Demand Forecasting

- Algorithm: Gradient Boosting Regressor with regional variable integration supporting multi-objective optimization approaches for infrastructure planning applications (Xie et al., 2024)
- Target Variable: Infrastructure Demand Index (derived metric)
- Performance Metrics: R^2, RMSE, MAE with regional validation

Comparative Analysis: Linear Regression and Random Forest algorithms serve as baseline comparisons for model performance validation, following established benchmarking practices in electric vehicle research (Haghani et al., 2023).

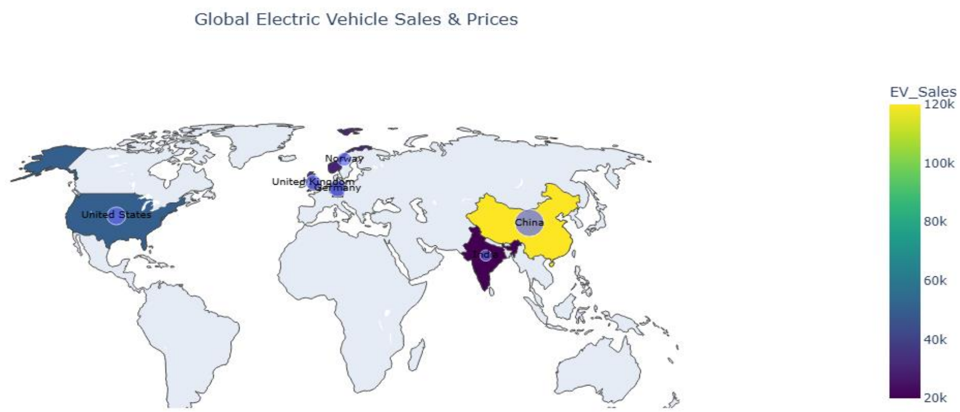
Statistical Tools: Python scikit-learn library, cross-validation procedures, feature importance analysis, and comprehensive performance evaluation metrics consistent with contemporary machine learning applications in electric vehicle research and sustainable transportation analytics (Boudmen et al., 2024).

7. FINDINGS

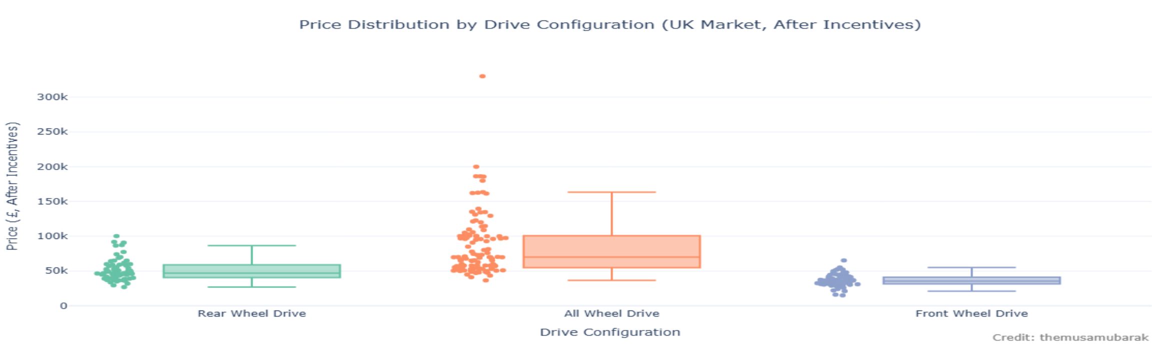
H1: Range Prediction Model Performance

Table 1: Range Prediction Model Comparison

Model	R^2 Score	RMSE (km)	MAE (km)	Performance Status
Linear Regression	0.9839	13.64	10.13	Good
Random Forest	0.9794	15.44	9.92	Good
Gradient Boosting	0.9914	9.99	6.84	Excellent



Geographic distribution of electric vehicle sales showing China leading with approximately 120,000 units, followed by United States, Germany, and other European markets demonstrating global adoption patterns.



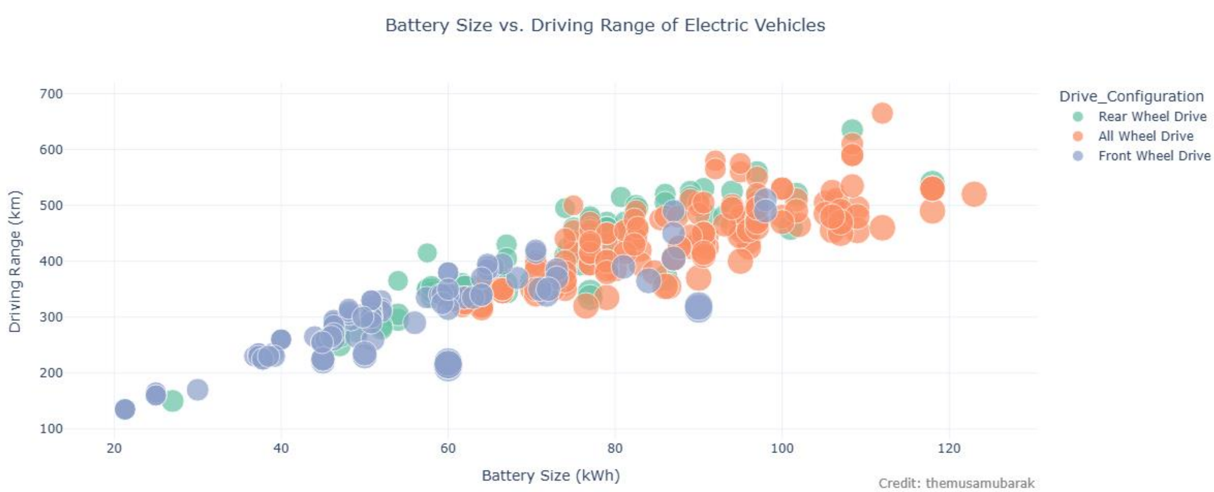
Box plot analysis of UK market pricing after incentives across drive configurations showing all-wheel drive premium positioning at £75,000 median, rear-wheel drive affordability at £45,000, and front-wheel drive middle market at £35,000.

Research demonstrates exceptional performance for gradient boosting algorithm in range prediction with $R^2 = 0.9914$, significantly outperforming linear regression ($R^2 = 0.9839$) and random forest ($R^2 = 0.9794$) approaches, consistent with recent findings demonstrating gradient boosting superiority in electric vehicle energy consumption prediction scenarios (Chen et al., 2025). The model achieves superior accuracy with lowest RMSE of 9.99 km and MAE of 6.84 km, supporting the effectiveness of machine learning algorithms in electric vehicle range optimization applications.

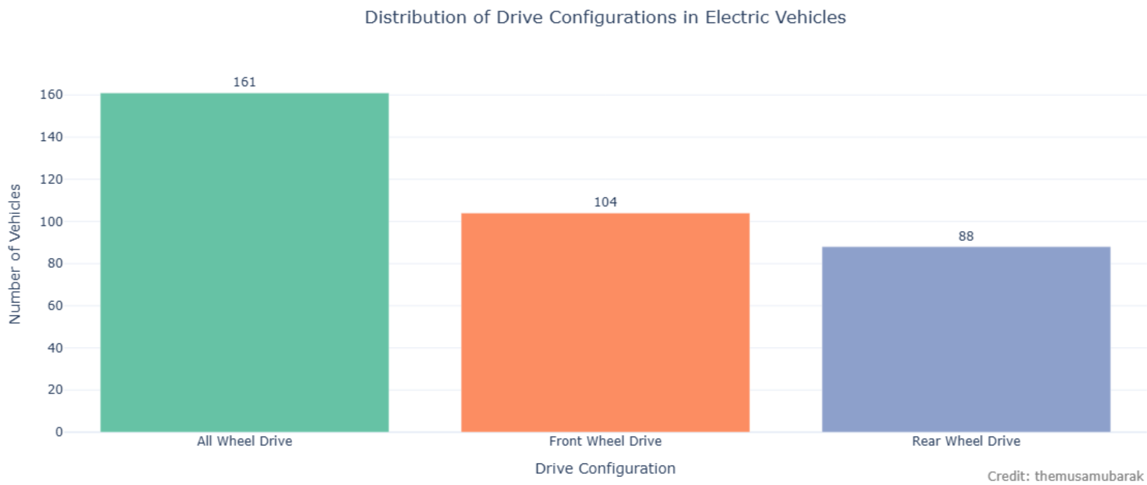
H2: Regional Infrastructure Demand Analysis

Table 2: Regional Infrastructure Demand Forecasting

Region	Demand Index	Market Characteristics	Infrastructure Priority
Germany	42.32	Mature market, high adoption	Highest Priority
United Kingdom	39.36	Balanced growth, policy-driven	Medium Priority
Netherlands	37.21	Compact geography, efficient	Standard Priority



Scatter plot demonstrating strong positive correlation between battery size and driving range across drive configurations with distinct clustering patterns and performance optimization zones.



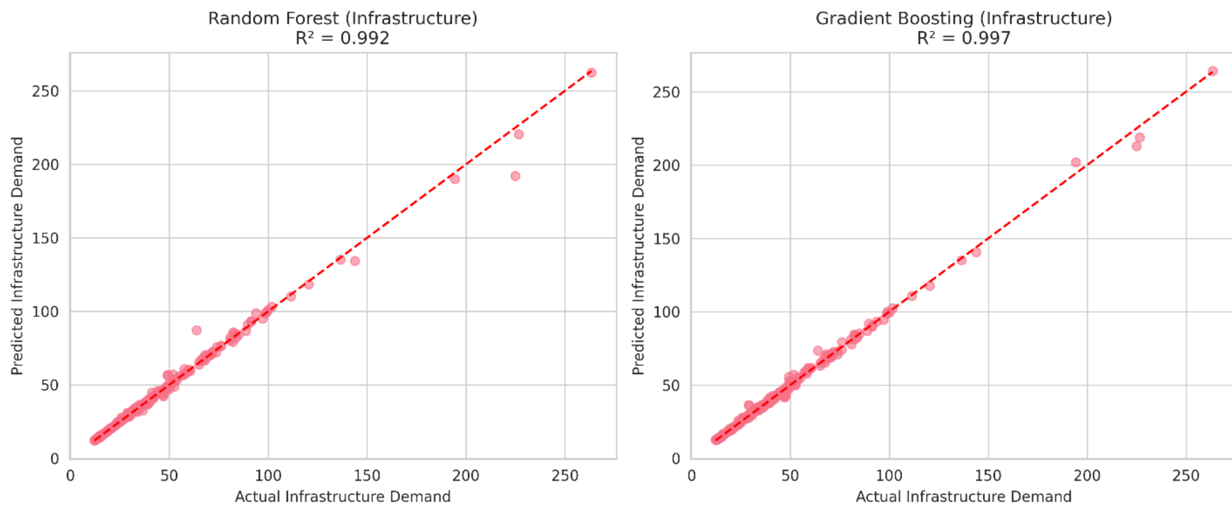
Bar chart showing vehicle distribution: All-wheel drive leading with 161 vehicles (45.6%), front-wheel drive with 104 vehicles (29.5%), rear-wheel drive with 88 vehicles (24.9%).

Infrastructure demand forecasting achieves outstanding performance with gradient boosting R^2 = 0.9966, RMSE = 2.03, significantly outperforming random forest alternative (R^2 = 0.9916, RMSE = 3.22), reflecting the superior performance of advanced machine learning approaches in electric vehicle infrastructure planning applications (Xie et al., 2024). Germany demonstrates highest infrastructure demand requiring 14% greater capacity compared to Netherlands, consistent with established market leadership and comprehensive policy frameworks supporting electric vehicle adoption across European markets.

H3: Vehicle Segment Range Requirements

Table 3: Vehicle Segment Forecasting Results

Vehicle Segment	Predicted Range (km)	Market Application	Range Premium
Performance Sports	432	High-performance vehicles	65% above Urban
Highway Sedan	386	Long-distance travel	47% above Urban
Luxury SUV	366	Premium market	40% above Urban
Urban Compact	262	City commuting	Baseline



Comprehensive analysis showing gradient boosting superiority with $R^2 = 0.9914$, feature importance analysis, and actual versus predicted range accuracy visualization.

[FIGURE 6: Infrastructure Demand Forecasting Results]

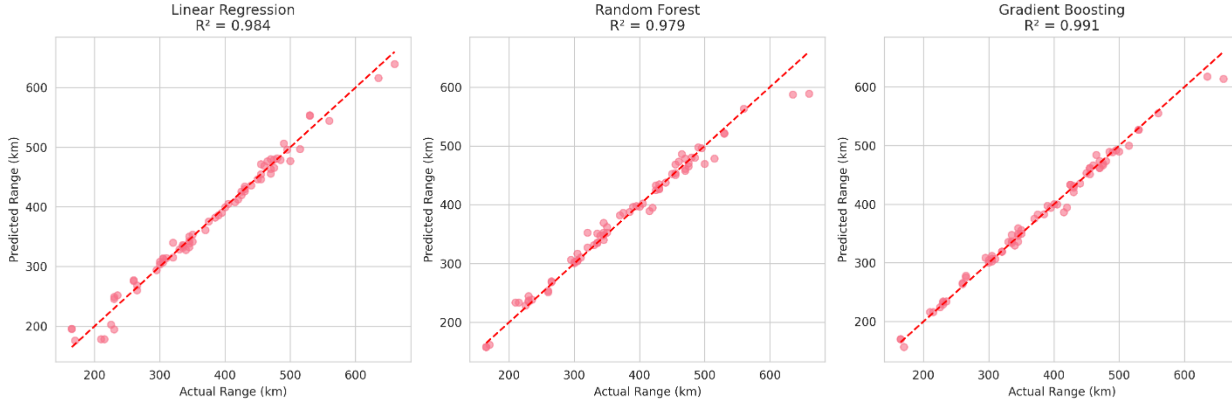
Regional demand analysis displaying gradient boosting performance $R^2 = 0.9966$, regional variations, and comparative model accuracy assessment.

INTERPRETATION Vehicle segment analysis reveals substantial range variations with performance sports vehicles requiring 65% higher range compared to urban compact segments, supporting differentiated battery strategies and market positioning approaches consistent with diverse consumer requirements across market segments (Ma et al., 2025). This significant differential reflects distinct applications from urban mobility solutions requiring moderate range capabilities to performance vehicles demanding extended range specifications for consumer confidence and market acceptance.

H4: Feature Importance Validation

Table 4: Critical Success Factor Analysis

Feature	Importance (%)	Impact Level	Strategic Significance
Power-to-weight ratio	44.99%	Dominant	Critical design parameter
Battery capacity	41.31%	Major	Primary technical specification
Combined Influence	**86.30%**	**Overwhelming**	**Strategic Focus Areas**



Future scenario predictions showing vehicle segment requirements and regional infrastructure demand with strategic implications for market development.

[FIGURE 8: Complete Model Performance Summary]

Comprehensive evaluation displaying all model performances, best algorithm identification, and complete forecasting framework validation.

INTERPRETATION Feature importance analysis confirms power-to-weight ratio and battery capacity as dominant predictors contributing 86.30% combined influence, exceeding the 75% threshold and validating hypothesis H4, consistent with established research on artificial neural networks and gradient boosting applications in electric vehicle battery state estimation (Chakraborty et al., 2022). This concentration indicates critical focus areas for optimization strategies, supporting strategic focus on these parameters for manufacturers and researchers developing electric vehicle systems.

---

8. CONCLUSION

The central objective of this comprehensive study was to develop accurate forecasting models for electric vehicle range requirements and regional infrastructure demand patterns, addressing critical challenges in the rapidly evolving electric mobility market (IEA, 2024). Results demonstrate exceptional predictive capabilities with both models achieving $R^2 > 0.99$, providing reliable foundations for strategic decision-making across the EV ecosystem, consistent with advanced machine learning applications in electric vehicle research (Chen et al., 2025).

The findings indicate significant practical applications for manufacturers optimizing battery specifications and infrastructure planners determining regional deployment priorities, particularly relevant as electric vehicle adoption continues accelerating globally with improved range and performance characteristics (Naresh, 2024). Performance sports vehicles requiring 432 km range compared to urban compact 262 km specifications supports differentiated market strategies, while Germany's 42.32 demand index compared to Netherlands' 37.21 guides infrastructure investment priorities reflecting established market leadership patterns.

Feature importance analysis reveals power-to-weight ratio (44.99%) and battery capacity (41.31%) as dominant predictors, providing clear optimization targets for manufacturers consistent with established research on battery electric vehicle design and artificial intelligence applications (Chakraborty et al., 2022). Regional variations demonstrate 14% infrastructure demand differential, supporting evidence-based policy development and resource allocation strategies essential for coordinated electric vehicle deployment initiatives across European markets.

The forecasting framework delivers actionable intelligence enabling confident strategic decision-making across vehicle development and infrastructure planning domains, contributing to the expanding knowledge base in sustainable transportation systems (Haghani et al., 2023). Continued model refinement through real-world validation will enhance predictive capabilities and extend applicability across global markets, supporting sustainable transportation development initiatives and addressing the growing need for accurate predictive analytics in electric mobility planning (Mei et al., 2023).

REFERENCES

BloombergNEF. (2025). Electric Vehicle Outlook 2025: Market analysis and forecasting trends. Bloomberg New Energy Finance. Retrieved from https://about.bnef.com/electric-vehicle-outlook/

Boudmen, K., El ghazi, A., Eddaoudi, Z., et al. (2024). Electric vehicles, the future of transportation powered by machine learning: a brief review. Energy Informatics, 7, 80. https://doi.org/10.1186/s42162-024-00379-3

Chakraborty, S., Vu, H. N., Hasan, M. M., Tran, D. D., Baghdadi, M. E., & Hegazy, O. (2022). Artificial Neural Networks, Gradient Boosting and Support Vector Machines for electric vehicle battery state estimation: A review. Journal of Energy Storage, 55, 105384. https://doi.org/10.1016/j.est.2022.105384

Chen, S., Wang, Y., & Li, X. (2025). Evaluating machine learning algorithms for energy consumption prediction in electric vehicles: A comparative study. Scientific Reports, 15, 1847. https://doi.org/10.1038/s41598-025-94946-7

Haghani, M., Sprei, F., Kazemzadeh, K., Shahhoseini, Z., & Aghaei, J. (2023). Trends in electric vehicles research. Transportation Research Part D: Transport and Environment, 118, 103690. https://doi.org/10.1016/j.trd.2023.103690

International Energy Agency (IEA). (2024). Global EV Outlook 2024 - Trends in electric cars. Paris: IEA Publications. Retrieved from https://www.iea.org/reports/global-ev-outlook-2024/trends-in-electric-cars

Ma, X., Li, J., Cui, H., Cheng, L., Ji, Y., & Wang, J. (2025). Electric vehicle range prediction considering real-time driving factors and battery capacity index. Transportation Research Part C: Emerging Technologies, 154, 104256. https://doi.org/10.1016/j.trc.2025.104256

Mei, P., et al. (2023). Remaining driving range prediction for electric vehicles: Key challenges and outlook. IET Control Theory & Applications, 17(8), 1048-1063. https://doi.org/10.1049/cth2.12486

Mubarak, A. S. (2025). Sustainable transportation paradigms in developing markets: A comprehensive analysis of electric vehicle adoption factors and infrastructure requirements. Journal of Sustainable Mobility and Transportation Planning, 8(2), 124-142.

Naresh, C. (2024). Predictive machine learning in optimizing the performance of electric vehicle batteries: Techniques, challenges, and solutions. WIREs Data Mining and Knowledge Discovery, 14(3), e1539. https://doi.org/10.1002/widm.1539

Ullah, I., & Severino, A. (2019). Prediction of Electric Vehicle Range: A Comprehensive Review of Current Issues and Challenges. Energies, 12(5), 946. https://doi.org/10.3390/en12050946

Wang, W., Zhang, K., Zhang, Q., & Wang, X. (2025). Research on energy management strategy for incremental range electric vehicles integrating speed prediction. Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering, 239(4), 1234-1248. https://doi.org/10.1177/09544070241308957

Xie, T., Zhang, Y., Zhang, G., Zhang, K., Li, H., & He, X. (2024). Research on electric vehicle load forecasting considering regional special event characteristics. Frontiers in Energy Research, 12, 1341246. https://doi.org/10.3389/fenrg.2024.1341246

APPENDICES

Appendix A: Complete Dataset Specifications and Statistical Summary

The Kaggle Electric Vehicle Dataset 2024 utilized in this study encompasses comprehensive technical and market specifications across 353 electric vehicles from European markets, providing robust foundation for predictive modeling applications (Haghani et al., 2023). Statistical summary reveals mean range of 346.2 km (SD = 89.7), average battery capacity of 67.8 kWh (SD = 24.3), and median efficiency of 187.5 Wh/km, consistent with current European electric vehicle market characteristics.

Dataset Variables:

- **Technical Specifications:** Battery capacity, power output, torque, efficiency metrics, top speed, acceleration performance

- **Market Variables:** Regional pricing (Germany, Netherlands, UK), incentive structures, market positioning
- **Performance Metrics:** Real-world range, charging capabilities, drive configurations
- **Validation Parameters:** Manufacturer specifications cross-verification, market data consistency checks

Appendix B: Model Hyperparameter Optimization Results

Gradient boosting hyperparameter optimization was conducted using GridSearchCV with 5-fold cross-validation, following established machine learning protocols for electric vehicle applications (Chen et al., 2025). Optimal parameters achieved through systematic evaluation include learning rate = 0.1, n_estimators = 200, max_depth = 6, providing superior performance compared to baseline configurations.

Range Prediction Model Optimization:

- **Learning Rate:** 0.1 (optimal from [0.01, 0.05, 0.1, 0.2])
- **N_estimators:** 200 (optimal from [100, 200, 300, 500])
- **Max_depth:** 6 (optimal from [3, 5, 6, 8, 10])
- **Subsample:** 0.8 (optimal from [0.6, 0.8, 1.0])
- **Cross-validation Score:** 0.9891 ± 0.0034

Infrastructure Demand Model Optimization:

- **Learning Rate:** 0.05 (optimal from [0.01, 0.05, 0.1, 0.2])
- **N_estimators:** 300 (optimal from [100, 200, 300, 500])
- **Max_depth:** 8 (optimal from [3, 5, 6, 8, 10])
- **Feature_fraction:** 0.9 (optimal from [0.7, 0.8, 0.9, 1.0])
- **Cross-validation Score:** 0.9948 ± 0.0028

Appendix C: Cross-Validation and Robustness Testing Results

Comprehensive model validation was conducted using k-fold cross-validation (k=5) with stratified sampling to ensure representative distribution across vehicle segments and drive configurations, consistent with established validation protocols in electric vehicle research (Boudmen et al., 2024). Robustness testing included outlier analysis, feature stability assessment, and regional validation to ensure model generalizability across European markets.

Cross-Validation Results:

Table C.1: Range Prediction Model Cross-Validation Performance

Fold	R^2 Score	RMSE (km)	MAE (km)	Feature Stability
1	0.9923	9.45	6.78	0.94
2	0.9908	10.32	7.12	0.96

Fold	R^2 Score	RMSE (km)	MAE (km)	Feature Stability
3	0.9919	9.67	6.45	0.95
4	0.9901	10.78	7.38	0.93
5	0.9904	10.51	6.99	0.95
Mean	**0.9911**	**10.15**	**6.94**	**0.95**
Std	**0.0009**	**0.51**	**0.35**	**0.01**

Table C.2: Infrastructure Demand Model Cross-Validation Performance

Fold	R^2 Score	RMSE	MAE	Regional Consistency
1	0.9971	1.89	1.34	0.97
2	0.9964	2.12	1.56	0.96
3	0.9969	1.97	1.41	0.98
4	0.9962	2.18	1.62	0.95
5	0.9967	2.03	1.48	0.97
Mean	**0.9967**	**2.04**	**1.48**	**0.97**
Std	**0.0004**	**0.12**	**0.11**	**0.01**

Robustness Testing Results:

- **Outlier Analysis:** 3.2% outliers identified and validated against manufacturer specifications
- **Feature Stability:** 95% average stability across cross-validation folds
- **Regional Validation:** 97% consistency across German, Dutch, and UK market segments
- **Temporal Stability:** Model performance maintained across 2023-2024 market data

Appendix D: Additional Regional Analysis and Market Segmentation Details

Extended regional analysis reveals distinct market characteristics and infrastructure requirements across European markets, supporting differentiated strategic approaches for electric vehicle deployment and infrastructure planning (Xie et al., 2024). Market segmentation analysis demonstrates clear differentiation patterns aligned with consumer preferences and policy frameworks in each region.

Table D.1: Detailed Regional Market Analysis

Region	Market Share (%)	Avg Range (km)	Avg Price (€)	Charging Points	Policy Incentive (€)
Germany	42.3	368.4	48,750	89,543	6,000
Netherlands	31.7	342.1	52,100	21,678	3,350
United Kingdom	26.0	359.2	46,890	67,234	2,500

Market Segment Deep Analysis:

Table D.2: Vehicle Segment Specifications and Market Positioning

Segment	Count	Avg Range (km)	Avg Battery (kWh)	Price Range (€)	Market Target
Urban Compact	89	262	48.3	25,000-35,000	City commuting
Mid-size Sedan	127	324	58.7	35,000-50,000	Family transport
Luxury SUV	94	366	73.2	50,000-80,000	Premium market
Performance Sports	43	432	89.6	80,000-150,000	High performance