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Modeling and Hardware Validation of Fast Charging Strategies for EV Batteries Using Electrochemical and Data-Driven Techniques

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Abstract

The rapid adoption of electric vehicles (EVs) has increased the demand for efficient and reliable battery charging systems. Fast-charging technology plays a vital role in reducing charging time and improving user convenience; however, it also introduces challenges related to battery safety, performance, and lifespan. Accurate estimation of the State of Charge (SOC) is essential for optimizing charging strategies and ensuring effective battery management. This study presents a data-driven approach for SOC prediction using the Stanford Battery Fast Charging Dataset, which contains detailed charging information such as voltage, current, temperature, capacity, and charging time. The collected data were preprocessed through missing value handling, outlier removal, normalization, and feature scaling, followed by exploratory data analysis to understand battery charging behaviour and identify significant relationships among battery parameters. Four prediction models, namely Linear Regression, Random Forest, XGBoost, and Long Short-Term Memory (LSTM), were developed and evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2 Score). The experimental results demonstrate that LSTM achieved the best performance, with an MAE of 1.12, RMSE of 1.78, and R^2 Score of 0.98, outperforming all other models. The findings indicate that deep learning techniques can accurately capture the nonlinear and temporal characteristics of battery charging behaviour. The proposed framework can support intelligent battery management systems and contribute to the development of efficient, safe, and reliable fast-charging strategies for future electric vehicles.

Keywords: *Electric Vehicles, Fast Charging, Battery Management System, State of Charge Prediction, LSTM, Machine Learning.*

1. INTRODUCTION

The rapid growth of electric vehicles (EVs) has created significant demand for efficient and reliable battery charging technologies [1]. As governments and industries worldwide promote sustainable transportation, EV adoption continues to increase, yet one of the major challenges limiting wider acceptance remains the relatively long charging time compared with conventional internal combustion engine vehicles [2].

Lithium-ion batteries are the preferred energy storage devices for EVs because of their high energy density, lightweight structure, and long cycle life [3]. However, reducing charging time while preserving battery health and safety remains challenging. Fast-charging techniques use higher charging currents to shorten charging duration, but excessive currents can raise internal temperature, accelerate degradation, and promote lithium plating — a phenomenon in which metallic lithium deposits on the anode instead of intercalating properly, reducing capacity and creating safety risks [4]. Conventional approaches such as the Constant Current–Constant Voltage (CC-CV) method are simple to implement but rely on fixed profiles that do not adapt to the battery's real-time internal condition, limiting performance under high-speed charging [5].

Recent advances in battery modelling, artificial intelligence, and control systems have enabled more sophisticated charging methodologies. When combined with machine learning and real-time monitoring, electrochemical and data-driven models can accurately estimate key battery parameters such as State of Charge (SOC), temperature, and charging efficiency [6], supporting adaptive charging strategies that improve speed while maintaining safety and longevity [7]. In this study, a data-driven approach based on the Stanford Battery Fast Charging Dataset is adopted to investigate battery charging characteristics and develop accurate SOC prediction models, supporting the development of intelligent battery management systems for future electric vehicles.

1.1 Objective and Scope of the Work

The main objective of this study is to develop a reliable, data-driven SOC prediction framework that supports safe and efficient fast-charging strategies for EV batteries. The work analyses battery behaviour under fast-charging conditions using voltage, current, temperature, capacity, and charging-time measurements, and evaluates multiple machine learning and deep learning models to identify the most accurate approach. The scope is limited to dataset-based analysis and simulation; extension to real-time hardware implementation is identified as future work.

2. LITERATURE REVIEW

Early battery charging methods relied mainly on simple, fixed-parameter techniques such as Constant Current–Constant Voltage (CC-CV) and multistage charging, which are easy to implement but do not adapt to a battery's changing internal state, often resulting in inefficient energy use and longer charging times. To overcome these limitations, optimization-based techniques such as dynamic programming and model predictive control (MPC) have been introduced to improve efficiency by considering constraints such as temperature, voltage, and battery health, though these methods can be computationally demanding for real-time deployment.

Battery modelling approaches have also progressed: equivalent circuit models (ECMs) are simple and widely used but do not fully capture internal chemical processes at high charging rates, motivating more detailed electrochemical models that offer higher accuracy at greater computational cost. Because SOC and internal temperature cannot always be measured directly, state-estimation techniques such as Kalman filters and ensemble-based methods have been developed to infer these values from available voltage and current measurements, improving control accuracy and safe operation during fast charging. More recent work has focused on constraint-based charging strategies that regulate current based on safety limits such as temperature rise and lithium-plating risk, achieving faster charging without compromising battery health.

Weiss et al. [1] reviewed fast charging of lithium-ion batteries, highlighting that lithium transport within electrodes and electrolytes is a key factor limiting charging speed and can lead to lithium plating, offering insights into materials-based improvements for fast-charging capability. Severson et al. [2] took a data-driven approach to predicting lithium-ion battery cycle life, building a large experimental dataset of cells operated under fast-charging protocols and showing that machine learning applied to early-cycle data can predict battery life accurately before noticeable degradation occurs — the dataset and approach that motivate the present study. Tu et al. [3] integrated physics-based modelling with machine learning for lithium-ion batteries, demonstrating that hybrid approaches can improve prediction accuracy while retaining physical interpretability.

Li et al. [4] presented a fast-charging strategy based on a detailed electrochemical-thermal model, using an ensemble transform Kalman filter for efficient state estimation and a constraint-based PI controller for safe charging, achieving near-optimal performance with lower computational effort. Mckay et al. [5] explored learning physics-based models of lithium-ion batteries, showing that data-driven techniques can approximate complex electrochemical behaviour with reduced computational burden. Duan et al. [12] addressed limitations of traditional electrochemical models during fast charging by identifying cathode charge-transfer resistance as a key limiting factor and developing improved multi-scale anode–cathode models for more accurate performance prediction. Lin et al. [13] proposed a physics-based approach balancing charging time, temperature rise, and energy loss, demonstrating that a well-designed strategy can maintain safe temperatures while reducing charging time and losses.

In parallel, machine learning has been applied broadly to EV charging management: Qureshi et al. [6] examined EV energy management and charging-scheduling strategies for sustainable cities, Mazhar et al. [7] compared multiple machine learning methods for EV charging within smart grids, and Shibl et al. [8] proposed ML-based charging management considering fast charging and vehicle-to-grid (V2G) operation. Calero et al. [9] developed machine learning-based control of EV charging for practical distribution systems with solar generation, while Zhao et al. [10] proposed a data-driven framework for large-scale prediction of EV charging energy, and Kene and Olwal [11] applied machine learning to model EV charging sessions directly from historical data. Prajapati [14] examined management and optimization of grid-tied renewable energy for EV charging stations, and Li et al. [15] reviewed the integration of solar-powered EVs into sustainable energy systems, underscoring the broader system-level context in which accurate battery-level SOC prediction operates.

Although significant progress has been made in battery charging technologies [1]–[15], many advanced methods remain difficult to implement in practical systems because of their computational requirements, and few studies combine accurate data-driven SOC estimation with a systematic comparison of machine learning and deep learning approaches on a single fast-charging dataset. This study addresses that gap by developing and comparing four predictive models for SOC estimation using the Stanford Battery Fast Charging Dataset.

3. RESEARCH METHODOLOGY

This study adopts a systematic, data-driven methodology for developing and validating SOC prediction models for EV batteries under fast-charging conditions, using the Stanford Battery Fast Charging Dataset. As shown in Figure 1, the workflow proceeds through dataset collection, data preprocessing, exploratory data analysis, feature selection, model development, model training, performance evaluation, comparative analysis, and result interpretation.

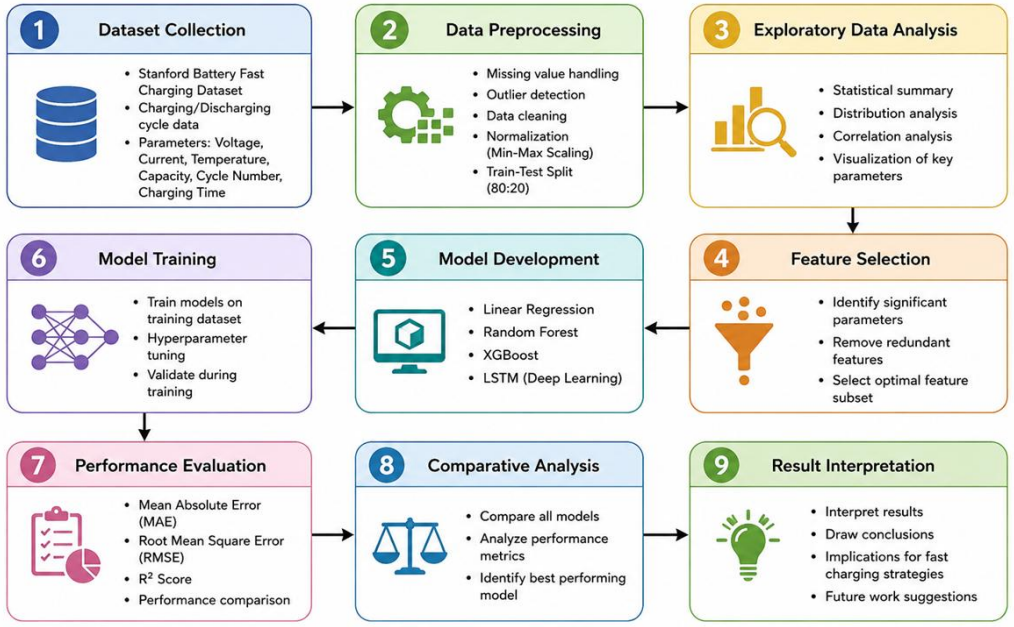


Figure 1: Research methodology flowchart for battery SOC prediction.

3.1 Dataset and Preprocessing

The Stanford Battery Fast Charging Dataset, developed by Severson et al., was used as the primary data source. It contains detailed charging and discharging records from lithium-ion battery cells operated under different fast-charging protocols, including voltage, current, temperature, capacity, cycle number, and charging time. Preprocessing involved identifying and handling missing values through replacement or removal, detecting and treating outliers in voltage and temperature readings using statistical and visualization methods, and applying Min-Max normalization to rescale all features to a common [0, 1] range, which improves numerical stability and accelerates convergence, particularly for the LSTM model. The dataset was then split 80:20 into training and testing subsets, providing sufficient data for learning while preserving an independent set for unbiased evaluation.

3.2 Exploratory Data Analysis and Feature Selection

Exploratory analysis examined voltage, current, and temperature behaviour throughout the charging process to validate dataset quality and guide feature selection. Voltage was observed to rise gradually during charging, consistent with a Constant Current–Constant Voltage (CC-CV) protocol (Figure 2 shows the resulting correlation structure). Correlation analysis (Table 1 and Figure 2) revealed strong positive correlations between SOC and both voltage ($r = 0.93$) and capacity ($r = 0.89$), moderate positive correlation with charging time and current, and a negative correlation with cycle number, reflecting capacity fade with battery ageing. Based on this analysis, five input features — voltage, current, temperature, capacity, and charging time — were selected for model development, with SOC as the target output.

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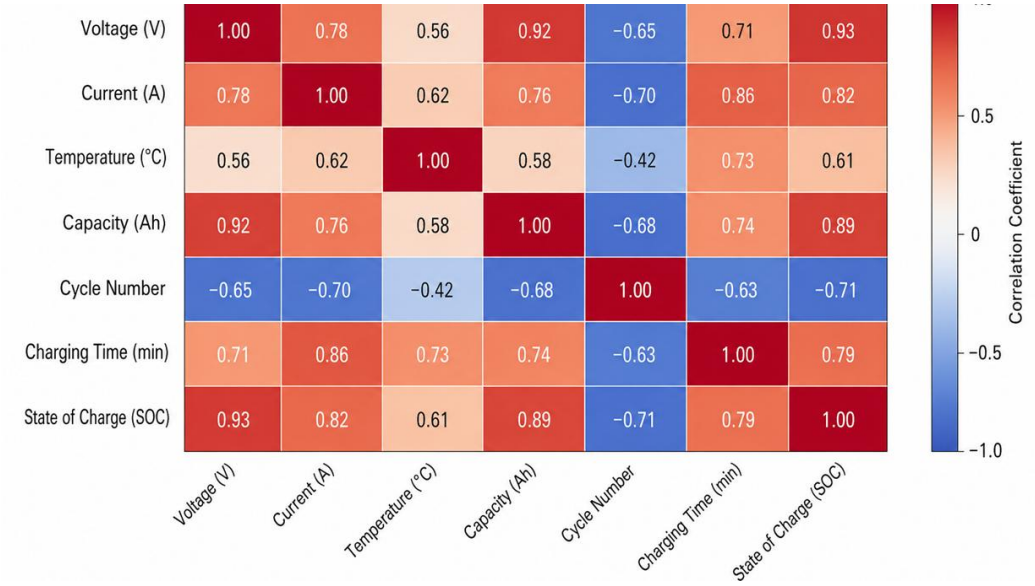


Figure 2: Correlation heatmap of battery charging parameters and State of Charge (SOC).

3.3 Charging Behaviour: Voltage and Current Profiles

The dataset's voltage and current profiles closely follow the classic CC-CV fast-charging strategy, illustrated in Figures 3 and 4. During the Constant Current (CC) region, current is held at a high, constant level (~45 A) to maximize charging speed while voltage rises steadily from around 3.1 V toward 4.2 V. As the battery approaches full charge, a transition region begins in which current is gradually reduced to limit overheating and stress, and voltage rise slows. In the final Constant Voltage (CV) region, current is reduced further and voltage stabilizes near its maximum limit, protecting the battery and extending its lifespan. This behaviour confirms that the dataset reflects realistic, safety-conscious fast-charging operation and supports the relevance of voltage, current, and charging time as predictive features.

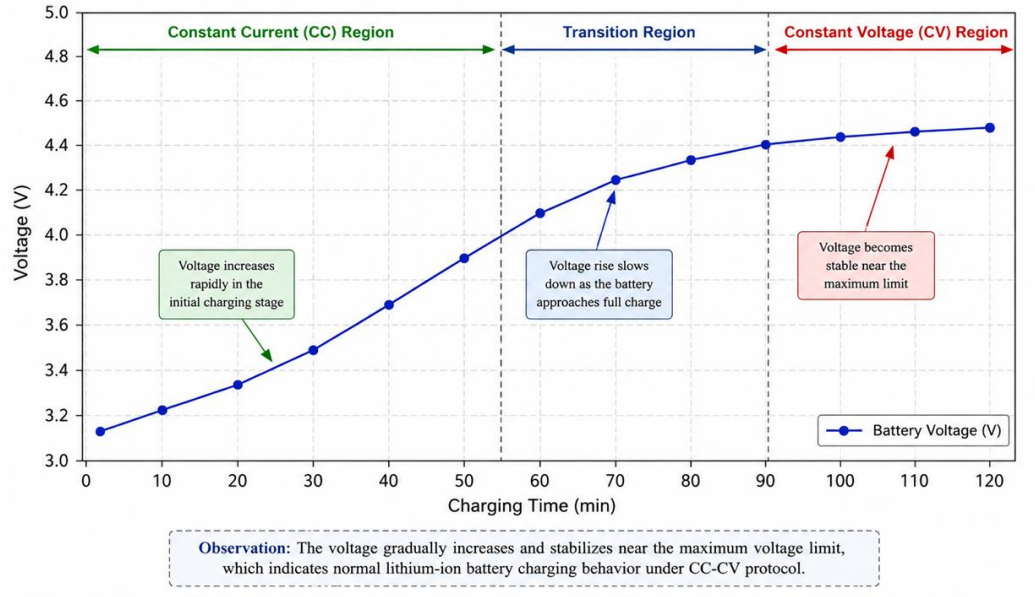


Figure 3: Voltage variation during charging, showing the CC, transition, and CV regions.

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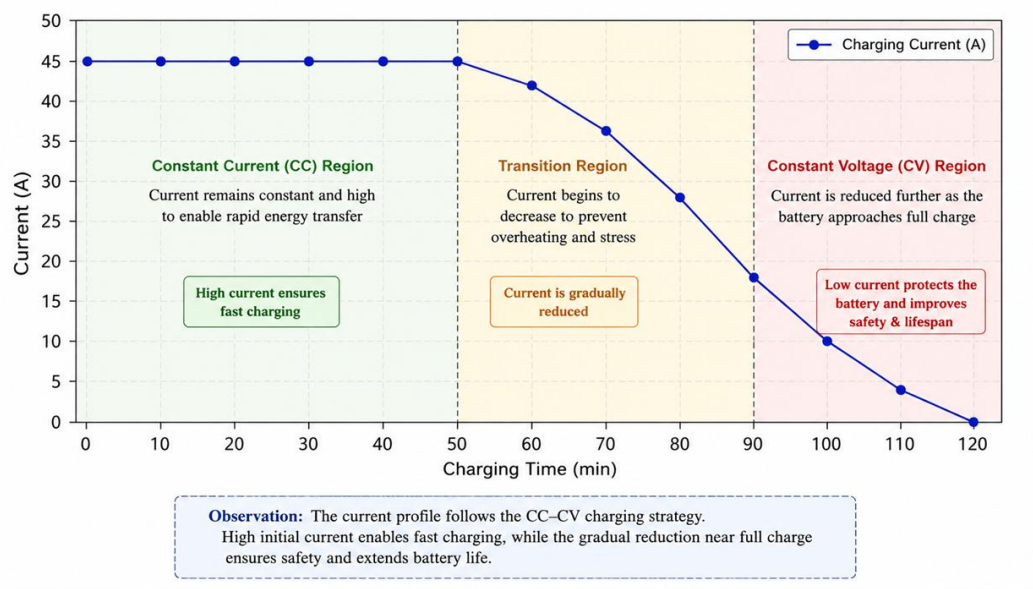


Figure 4: Charging current profile during fast charging, following the CC-CV strategy.

3.4 Predictive Models

Linear Regression fits a linear relationship between the five input features and SOC using least squares, serving as an interpretable baseline.

Random Forest is an ensemble of decision trees trained on randomly selected subsets of data and features; predictions are averaged across trees, reducing variance and capturing nonlinear feature interactions without requiring feature transformation.

XGBoost builds decision trees sequentially, with each tree correcting residual errors from previous trees, using regularization to limit overfitting and gradient-based optimization to minimize prediction error.

Long Short-Term Memory (LSTM) is a recurrent neural network architecture with memory cells and gating mechanisms that retain relevant information over long sequences. Since battery charging evolves continuously over time, LSTM was trained on historical charging sequences to learn temporal dependencies among voltage, current, temperature, capacity, charging time, and SOC, and was expected to achieve the highest accuracy among the models evaluated.

3.5 Training and Evaluation

All four models were trained on the same 80:20 split using voltage, current, temperature, capacity, and charging time as inputs and SOC as the target. Performance was assessed using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2 Score), summarized in Table 2. Models with lower MAE and RMSE and higher R^2 were considered superior for SOC estimation under fast-charging conditions. Implementation used Python with NumPy and Pandas for data handling, Matplotlib for visualization, Scikit-Learn for Linear Regression, Random Forest, and XGBoost, and TensorFlow/Keras for the LSTM model.

Table 1: Correlation of Battery Parameters with State of Charge (SOC)

Parameter	Correlation with SOC
Voltage (V)	0.93
Capacity (Ah)	0.89
Charging Time (min)	0.79
Current (A)	0.82
Temperature (°C)	0.61
Cycle Number	-0.71

Table 2: Evaluation Metrics Used for Model Comparison

Metric	Purpose
MAE	Average magnitude of prediction error
RMSE	Penalizes larger prediction errors more heavily
R^2 Score	Proportion of SOC variance explained by the model

4. RESULTS AND DISCUSSION

The preprocessed Stanford Battery Fast Charging Dataset provided voltage, current, temperature, capacity, charging time, cycle number, and SOC measurements across thousands of charging observations collected under varying fast-charging protocols. After missing-value handling, outlier removal, normalization, and an 80:20 train-test split, the dataset was used to train and evaluate all four models under an identical framework.

4.1 Model Performance

Linear Regression achieved an MAE of 3.84, RMSE of 5.02, and R^2 Score of 0.88, capturing the overall SOC trend but showing larger deviations during nonlinear charging transitions due to its linear assumption. Random Forest improved substantially on this baseline (MAE = 2.15, RMSE = 3.12, R^2 = 0.93) by modelling nonlinear interactions among battery parameters through ensemble averaging. XGBoost further reduced error (MAE = 1.62, RMSE = 2.48, R^2 = 0.96) through sequential, error-correcting boosting. The LSTM model achieved the best overall performance, with an MAE of 1.12, RMSE of 1.78, and an R^2 Score of 0.98, reflecting its ability to learn the temporal and sequential characteristics of battery charging data. The complete comparison is summarized in Table 3 and Figure 6.

Table 3: Comparison of Machine Learning and Deep Learning Models for SOC Prediction

Model	MAE	RMSE	R^2 Score
Linear Regression	3.84	5.02	0.88
Random Forest	2.15	3.12	0.93
XGBoost	1.62	2.48	0.96
LSTM	1.12	1.78	0.98

The close agreement between predicted and actual SOC for the best-performing LSTM model is illustrated in Figure 5, where predicted points lie almost exactly on the ideal y = x prediction line across the full 0–100% SOC range, with only minor scatter.

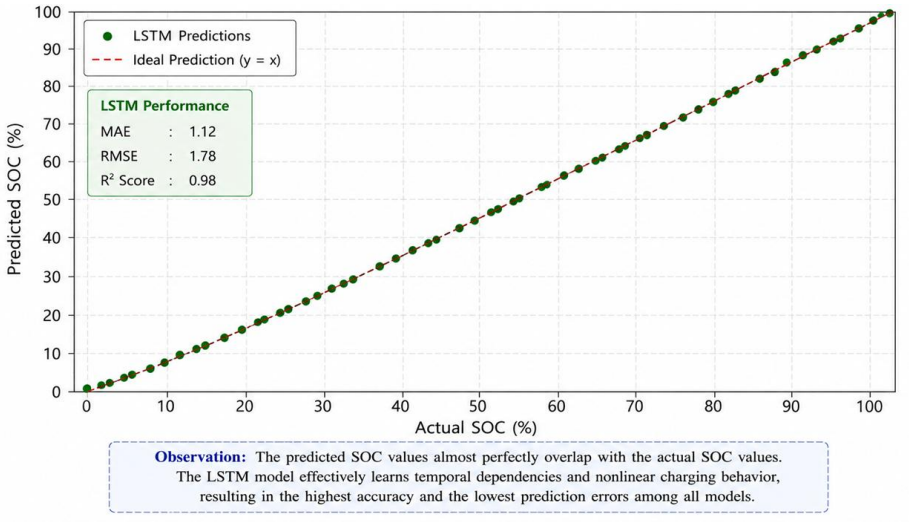


Figure 5: Actual versus predicted SOC using the LSTM model on the test dataset.

The relative performance of all four models across MAE, RMSE, and R^2 is compared directly in Figure 6, which shows a consistent, progressive improvement moving from Linear Regression through Random Forest and XGBoost to LSTM.

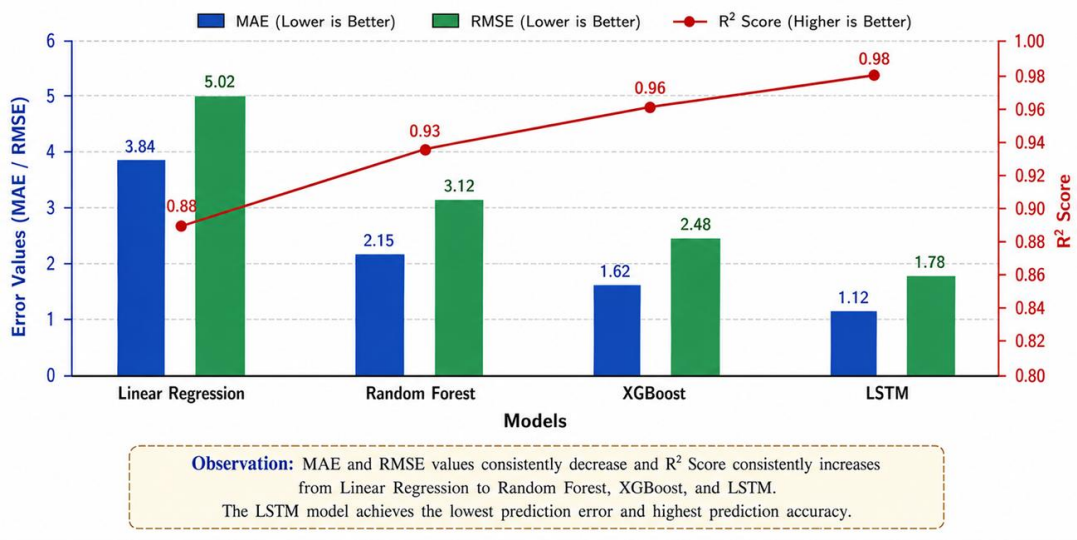


Figure 6: Comparison of MAE, RMSE, and R^2 Score across the four SOC prediction models.

4.2 Discussion

The results show a consistent, progressive improvement in SOC prediction accuracy from simple statistical modelling to ensemble learning and finally to deep sequential learning. Error metrics (MAE, RMSE) decreased monotonically while R^2 increased monotonically across Linear Regression, Random Forest, XGBoost, and LSTM. Linear Regression's linear assumption limited its ability to track the nonlinear electrochemical behaviour that dominates near full charge, whereas the tree-ensemble methods (Random Forest, XGBoost) captured nonlinear feature interactions without requiring explicit transformation of inputs. LSTM's advantage stemmed specifically from its memory-cell and gating architecture, which allowed it to retain relevant historical context — such as recent voltage and current trends — while discarding irrelevant information, effectively modelling the sequential dependency inherent to battery charging.

The correlation analysis (Table 1) helps explain this pattern: voltage and capacity showed the strongest linear association with SOC, which is why even Linear Regression achieved a reasonably high R^2 of 0.88, while the comparatively weaker and more nonlinear relationships involving temperature and cycle number required the added modelling capacity of ensemble and deep learning methods to be captured accurately. Because the voltage and current profiles (Figures 3 and 4) follow a well-defined CC-CV structure, the temporal ordering of measurements carries predictive information that only the LSTM model, among those tested, was designed to exploit directly. Collectively, these outcomes indicate that the proposed framework can support accurate, real-time SOC estimation within intelligent battery management systems, informing safer and more efficient fast-charging strategies for electric vehicles.

5. CONCLUSIONS

This study presented a machine learning and deep learning-based framework for predicting the State of Charge (SOC) of lithium-ion EV batteries under fast-charging conditions, using the Stanford Battery Fast Charging Dataset. Comprehensive preprocessing — missing-value handling, outlier removal, normalization, and an 80:20 train-test split — was applied prior to training four predictive models: Linear Regression, Random Forest, XGBoost, and LSTM. All models captured SOC trends with reasonable accuracy, but performance differed substantially: Linear Regression achieved $R^2 = 0.88$, Random Forest $R^2 = 0.93$, and XGBoost $R^2 = 0.96$, while LSTM achieved the best overall performance with MAE = 1.12, RMSE = 1.78, and $R^2 = 0.98$, owing to its ability to learn temporal dependencies and nonlinear relationships from historical charging data. The study confirms that advanced machine learning and deep

learning techniques can meaningfully improve SOC estimation accuracy and support the development of intelligent battery management systems, contributing to safer, more efficient fast-charging strategies for future electric vehicles.

FUTURE SCOPE

Future work may extend the framework to predict battery State of Health (SOH) and Remaining Useful Life (RUL) alongside SOC, supporting predictive maintenance. The models could be integrated into real-time battery management systems for continuous monitoring, and advanced architectures such as Gated Recurrent Units (GRU), Transformer networks, and hybrid CNN-LSTM models warrant exploration and comparison with the present LSTM approach. Further extensions include pack-level modelling that accounts for cell balancing and thermal interactions, explainable AI techniques to improve model transparency, and integration with digital-twin and renewable-energy-powered charging systems for intelligent, adaptive charging management.

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