A Bayesian Optimized Deep Learning Approach for Accurate State of Charge Estimation of Lithium Ion Batteries Used for Electric Vehicle Application

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Abstract: Battery technology in Electric Vehicles (EVs) has garnered significant attention, with accurate State of Charge (SOC) estimation being crucial for ensuring reliable battery operation. In this study, a dataset of lithium-ion battery discharge cycles, including varying operational conditions, is utilized to model SOC estimation. To enhance prediction accuracy, Bayesian Optimization is employed to fine-tune the hyperparameters of advanced deep learning algorithms such as Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Bidirectional LSTM (Bi-LSTM). Additionally, a 2D Convolutional Neural Network (CNN2D) is applied, achieving a root mean square error (RMSE) of 0.010, showcasing superior performance compared to other methods. The proposed approach leverages the strengths of Bayesian Optimization for hyperparameter selection and the advanced capabilities of deep learning models to achieve high precision in SOC estimation. The findings highlight the potential of this optimized deep learning framework to improve battery management systems, ensuring enhanced reliability and efficiency in EV applications.

"Index Terms - *Electric vehicle, battery management system, state of charge, long short term memory, gated recurrent unit, bilayer LSTM".*

1. INTRODUCTION

Countries around the world are prioritizing the development of energy-saving and emission-reduction technologies to mitigate the adverse impacts of carbon dioxide emissions and related environmental consequences such as climate change, sea level rise, the greenhouse effect, and biodiversity loss. At COP26 in Glasgow, UK, world leaders, business representatives, and organizations convened to address these challenges, focusing on the urgent need for solutions to the global energy crisis. One of the central themes of the conference was the transition toward 100% zero-emission vehicles (ZEVs) to meet the targets set by the Paris Agreement by 2040 [1]. The researcher highlights that car electrification, coupled with the adoption of renewable energy sources, presents a promising pathway to address the energy crisis and achieve a 40% reduction in greenhouse gas emissions (GHGE) [2]. In 2021, electric vehicle (EV) sales reached 6.75 million units, representing a staggering 108% increase from 2020 levels, as EVs offer significant advantages in reducing vehicle emissions and facilitating the storage of renewable energy [3].

The current energy storage methods in the transportation sector primarily include lithium-ion, nickel-cobalt, lead-acid, and nickel-cadmium batteries. Among these, lithium-ion batteries have emerged as the preferred choice due to their superior characteristics, including higher specific power, greater energy density, longer lifespan, and lower self-discharge rates [4]. Lithium-ion batteries come in a range of chemical compositions, such as Nickel Manganese Cobalt (NMC), Nickel Cobalt Aluminum (NCA), Lithium Iron Phosphate (LFP), Lithium Cobalt Oxide (LCO), Lithium Manganese Oxide (LMO), and Lithium Titanate (LTO) [5]. A comparison of these different lithium-ion battery types reveals that NCA batteries stand out for their exceptional specific energy and power [6].

Despite the numerous advantages of lithium-ion batteries, challenges remain in ensuring their safety and performance. A key consideration in their widespread adoption is the reduction in manufacturing costs, which has significantly contributed to the increasing use of lithium-ion batteries across various industries [7]. However, these batteries are not without their issues. They require a safe operating zone to function optimally. The charge transfer reaction used to store energy in lithium-ion batteries leads to degradation over time, causing problems such as the loss of active materials, depletion of lithium inventory, breakdown of the Solid Electrolyte Interface (SEI) film, and the formation of metallic lithium deposits at the anode. These issues can lead to reduced efficiency and, if left unchecked, may result in safety hazards. Thus, exceeding the tolerance levels of lithium-ion battery packs can lead to potential damage and dangerous situations.

2. RELATED WORK

Lithium-ion batteries have become the cornerstone of energy storage systems, particularly in electric vehicles (EVs), owing to their superior energy density, long cycle life, and relatively low self-discharge rate. As the demand for EVs grows, the importance of accurate state-of-charge (SOC) estimation for lithium-ion batteries has gained significant attention. SOC estimation is crucial for maintaining battery performance, safety, and longevity, as it helps in predicting the remaining energy in the battery and preventing overcharging or deep discharging, which can damage the battery. Several methods for SOC estimation have been developed, ranging from traditional models to advanced machine learning techniques.

One of the most widely used methods for SOC estimation is the Kalman filter, which has been extensively studied in the literature. A hybrid optimization strategy that combines the Kalman filter with a modified sine-cosine algorithm for better SOC and health estimation of lithium-ion batteries was proposed by Qian and Liu [10]. This method improves upon the traditional Kalman filter approach by incorporating optimization techniques to enhance the estimation accuracy. The dual Kalman filter system addresses issues such as the non-linearity of battery behavior, ensuring more accurate SOC predictions. However, despite its success in certain applications, the Kalman filter has limitations in handling highly dynamic systems like lithium-ion batteries, where the relationship between inputs and outputs is non-linear and complex.

In recent years, there has been a shift towards more advanced machine learning techniques for SOC estimation. Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN), have emerged as a powerful tool for modeling time-series data, such as battery voltage and current. LSTM’s ability to capture long-term dependencies in sequential data makes it particularly suited for SOC estimation. Yang et al. [11] utilized LSTM networks combined with an Unscented Kalman Filter (UKF) to estimate the SOC of lithium-ion batteries. The authors found that LSTM-UKF outperformed traditional methods in terms of accuracy and robustness, particularly in dynamic and non-linear environments like those found in EV applications.

Another promising approach is the use of Gated Recurrent Units (GRU), a simplified version of LSTM, which also addresses the vanishing gradient problem while being more computationally efficient. Li et al. [12] proposed a SOC estimation method based on GRU networks, achieving significant improvements over conventional methods. GRUs, due to their simpler architecture and faster training times, offer a practical solution for real-time SOC estimation in battery management systems. Their results demonstrated the effectiveness of GRUs in extracting relevant features from battery data, making them suitable for applications where quick response times are critical.

In addition to LSTM and GRU, Bi-directional LSTM (Bi-LSTM) networks have also shown promise in SOC estimation. Bi-LSTM networks extend the traditional LSTM by processing data in both forward and backward directions. This bidirectional processing helps capture contextual information from both the past and future, enhancing the accuracy of predictions. Chemali et al. [13] explored the use of LSTM and Bi-LSTM networks for SOC estimation in lithium-ion batteries. Their study highlighted the advantages of Bi-LSTM in capturing long-term dependencies and improving the accuracy of SOC predictions compared to standard LSTM models. The ability to consider future data, along with past observations, provides a more comprehensive understanding of battery behavior, which is crucial for accurate SOC estimation.

In addition to recurrent neural networks, convolutional neural networks (CNNs) have also been explored for SOC estimation, particularly in the context of data that can be structured as 2D matrices. CNNs are widely used for image processing but can also be applied to time-series data when it is represented in matrix form. CNN2D, a type of convolutional neural network, has been utilized for feature extraction and optimization in battery data. Its ability to reduce noise and enhance feature representation makes it an effective tool for improving SOC estimation. The use of CNN2D for SOC estimation was explored by Meng et al. [14], who compared various methods for online implementable SOC estimation and found CNN2D to be an effective approach in reducing prediction errors and enhancing battery performance monitoring.

Furthermore, the integration of optimization algorithms with machine learning models has gained popularity in recent research. Chen et al. [15] combined a grey model with genetic algorithms to estimate the SOC of lithium-ion batteries. The grey model is used to model the uncertain and incomplete information typically found in battery behavior, while the genetic algorithm optimizes the parameters of the model to improve prediction accuracy. Their proposed method demonstrated significant improvements in SOC estimation, particularly in environments where battery data is sparse or uncertain. The combination of grey models and genetic algorithms highlights the potential of hybrid approaches in tackling the complexities of SOC estimation in lithium-ion batteries.

Despite the advancements in SOC estimation techniques, challenges remain in achieving high accuracy and real-time performance in dynamic environments. The non-linear nature of battery behavior, influenced by factors such as temperature, voltage, and current, makes SOC estimation a complex task. Moreover, the varying conditions under which batteries operate, including charging/discharging cycles, aging effects, and environmental factors, further complicate the estimation process. Therefore, while machine learning techniques such as LSTM, GRU, Bi-LSTM, and CNN2D show promise, continuous research and refinement are needed to enhance their robustness and applicability in real-world scenarios.

In conclusion, the literature highlights a wide range of techniques for SOC estimation of lithium-ion batteries, each with its own strengths and limitations. While traditional methods like the Kalman filter have been effective in some cases, machine learning techniques, particularly LSTM, GRU, Bi-LSTM, and CNN2D, offer significant improvements in accuracy and real-time performance. The integration of optimization algorithms and hybrid approaches further enhances the potential of these methods. However, challenges such as non-linear battery behavior, data uncertainty, and dynamic operating conditions still need to be addressed to achieve reliable and efficient SOC estimation for lithium-ion batteries in electric vehicles and other applications.

3. MATERIALS AND METHODS

The proposed system focuses on accurate State of Charge (SOC) estimation for lithium-ion batteries in Electric Vehicles (EVs) using advanced deep learning techniques. It utilizes a dataset of dynamic charge-discharge profiles from lithium-ion batteries under varying operating conditions. The system integrates algorithms like Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Bidirectional LSTM (Bi-LSTM) to model the complex, non-linear relationships and temporal dependencies of battery behavior. Bayesian Optimization is employed to fine-tune the hyperparameters of the models, ensuring optimal performance. By leveraging these advanced techniques, the system aims to provide precise SOC predictions, enhancing the reliability of battery management systems and ensuring efficient operation of EVs across diverse scenarios.

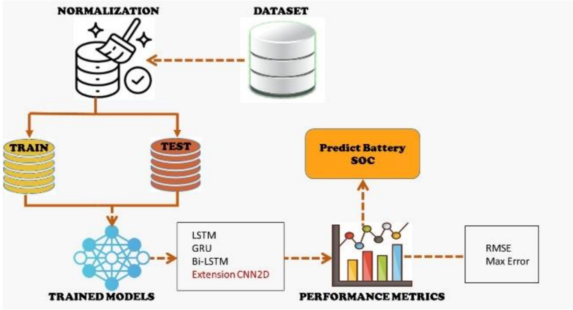


Fig.1 Proposed Architecture

The system architecture depicted in the image (Fig.1) illustrate utilizes deep learning to estimate the State of Charge (SOC) of lithium-ion batteries in electric vehicles. The system begins by normalizing the dataset, which includes experimental measurements from batteries under various conditions. The normalized data is then split into training and test sets. Different deep learning models, such as LSTM, GRU, Bi-LSTM, and Extension CNN2D, are trained on the training data. Bayesian Optimization is employed to fine-tune hyperparameters for each model, optimizing their performance. The trained models are then used to predict the SOC of the test data. The accuracy of each model is evaluated using performance metrics like RMSE and Max Error. The test data is also stored in a blockchain for secure and transparent record-keeping.

i) Dataset Collection:

The dataset used in this study is the "Pan_10degC.csv," which contains clinical data related to anesthesia. It includes six columns: Voltage, Current, Temperature, Capacity, Voltage_Average, and Current_Average. The dataset comprises 8399 rows of data, capturing various battery parameters under different conditions. Missing values within the dataset are handled and replaced with zeros to ensure completeness for analysis. This comprehensive dataset allows for the exploration and modeling of battery performance for State of Charge estimation in battery management systems.

	Voltage	Current	Temperature	Capacity	Voltage_Average	Current_Average
0	4.20007	2.10781	12.053261	-0.14733	4.029908	-0.798057
1	4.18720	1.82851	12.053261	-0.14685	4.029996	-0.794400
2	4.08280	-0.03756	12.053261	-0.14686	4.029763	-0.795630
3	4.09519	0.21887	12.053261	-0.14681	4.029553	-0.796318
4	4.05835	-0.40586	12.053261	-0.14691	4.029270	-0.798233
...	...	...	...	...	...	...
8394	3.39904	0.00000	12.678676	-2.37330	3.356864	-0.338684
8395	3.39904	0.00000	12.458628	-2.37330	3.356626	-0.343039
8396	3.39904	0.00000	12.678676	-2.37330	3.356623	-0.342570
8397	3.39904	0.00000	12.458628	-2.37330	3.356849	-0.338466
8398	3.39904	0.00000	12.470211	-2.37330	3.357206	-0.332841

8399 rows × 6 columns

Fig.2 Dataset

ii) Normalization:

Normalization is applied to the dataset to scale the features and target values to a uniform range, ensuring consistency for model training. The "Capacity" column is separated as the target variable, while the remaining columns are treated as features. Both feature and target values are normalized using scaling techniques, which help eliminate bias caused by varying units and magnitudes. This process enhances the efficiency and accuracy of the predictive model by optimizing the data for machine learning algorithms.

iii) Algorithms:

LSTM: Long Short-Term Memory (LSTM) networks learn long-term dependencies in sequential data. They analyze historical battery parameters like voltage and temperature to accurately predict State of Charge (SOC), ensuring reliable battery performance and optimizing electric vehicle efficiency.

GRU: Gated Recurrent Unit (GRU) simplifies LSTM by efficiently processing sequential data. It extracts key features from battery parameters for SOC prediction, offering faster training and reduced errors, making it ideal for time-series analysis in battery management systems.

Bi-LSTM: Bidirectional LSTM (Bi-LSTM) processes data in both forward and backward directions, capturing complete temporal patterns. It improves SOC prediction accuracy by simultaneously analyzing past and future battery parameters, ensuring comprehensive insights for effective electric vehicle battery management.

CNN2D: Convolutional Neural Network 2D (CNN2D) optimizes feature extraction from battery data formatted as 2D matrices. By leveraging convolutional layers, it enhances SOC prediction accuracy, reducing noise and improving feature representation for efficient electric vehicle battery performance estimation.

4. RESULTS & DISCUSSION

RMSE: The root mean square error (RMSE) measures the average difference between a statistical model’s predicted values and the actual values. Mathematically, it is the standard deviation of the residuals. Residuals represent the distance between the regression line and the data points.

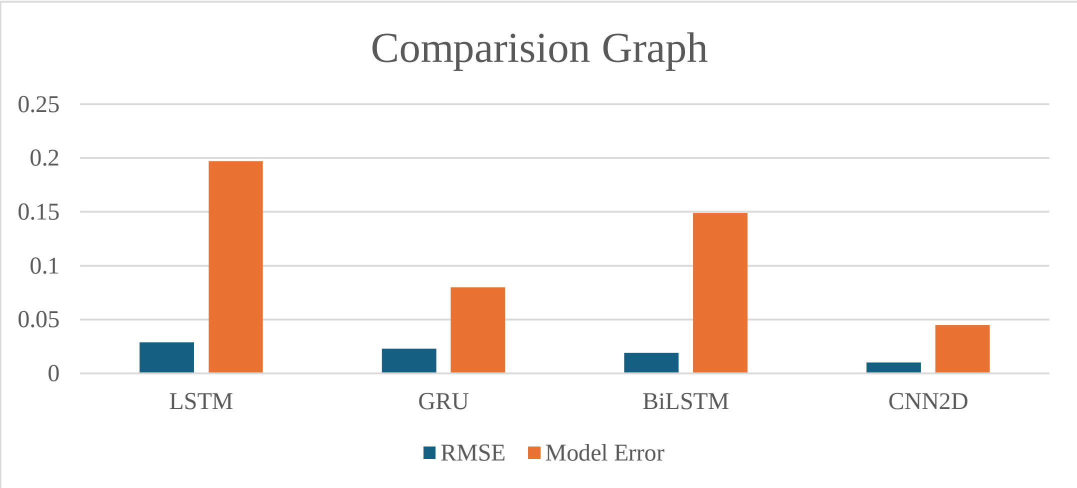
$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} ||y(i) - \hat{y}(i)||^2}{N}} \quad (1)$$

Table (1) evaluate the performance metrics—RMSE and Model Error—for each algorithm. The CNN2D consistently outperforms compared to all other algorithms. The tables also offer a comparative analysis of the metrics for the other algorithms.

Table.1 Performance Evaluation Table

ML Model	RMSE	Model Error
LSTM	0.029	0.197
GRU	0.023	0.080
BiLSTM	0.019	0.149
CNN2D	0.010	0.045

Graph.1 Comparison Graphs



RMSE is represented in blue, Model Error in orange, ***Graph (1)***. In comparison to the other models, the CNN2D shows superior performance across all metrics. The graphs above visually illustrate these findings.

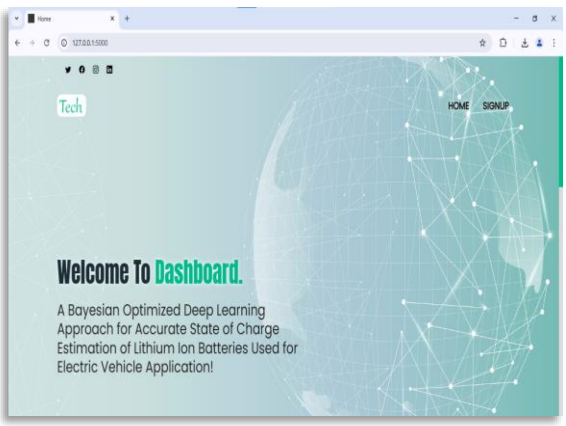


Fig.3 Home Page

In above fig.3 user interface dashboard for a battery state-of-charge estimation application with navigation and a welcome message.

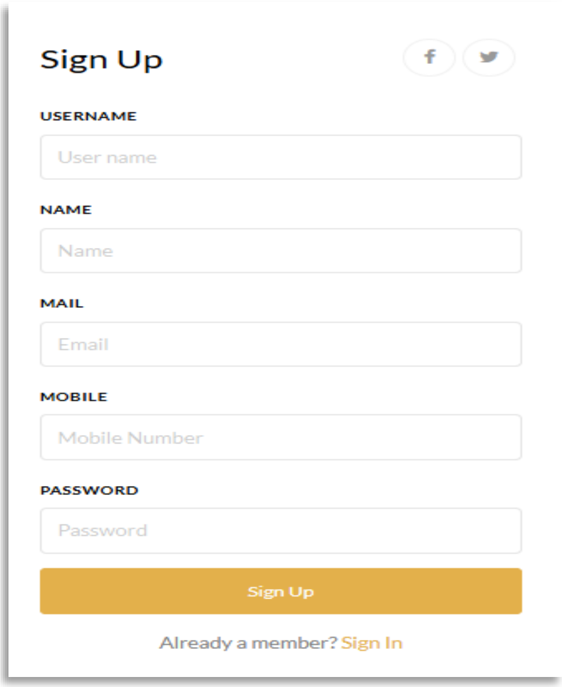


Fig.4 Registration Page

In above fig.4 sign-up form with fields for username, name, email, mobile number, and password buttons.

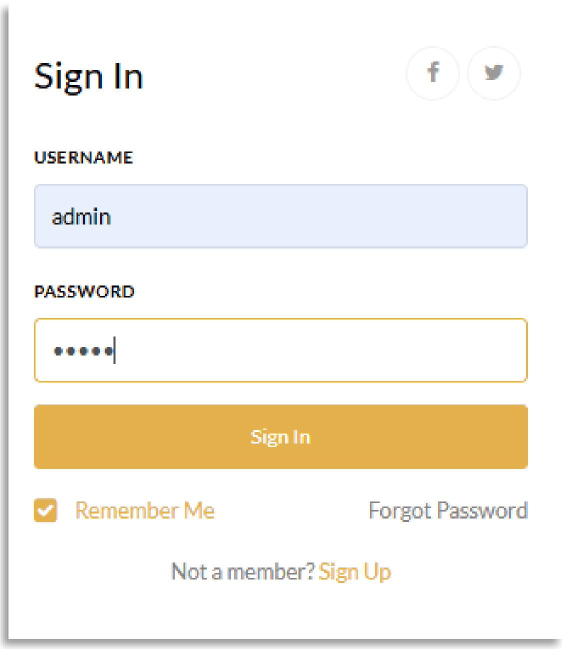


Fig.5 Login Page

In above fig.5 Sign-in form with username and password fields, "Remember Me," "Forgot Password,".

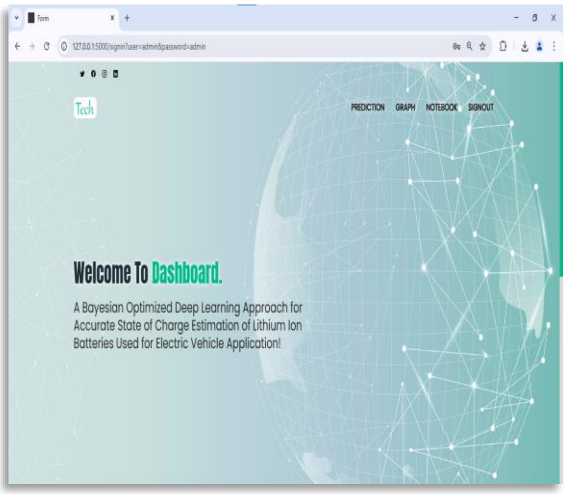


Fig.6 Main Page

In above Fig.6 home page dashboard with navigation (Prediction, Graph, Notebook, Signout) for a battery state-of-charge estimation application.

Fig.7 Upload Input Page

In above Fig.7 form with coordinate input field and upload button.

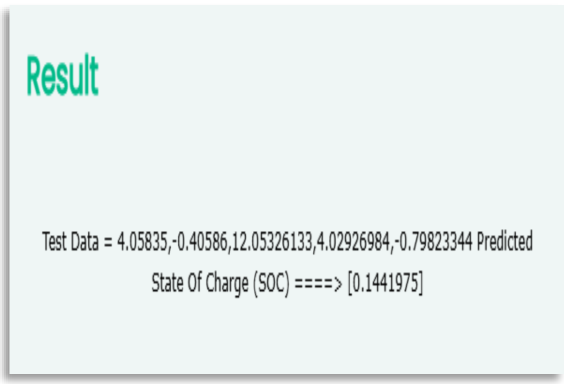


Fig.8 Predict Result for given input

In above Fig.8 Prediction result based on the input test data was displayed.

5. CONCLUSION

In conclusion, the proposed deep learning-based approach significantly improves State of Charge (SOC) estimation for lithium-ion batteries in Electric Vehicles (EVs). By employing advanced algorithms such as Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Bidirectional LSTM (Bi-LSTM), the system successfully captures the complex, non-linear relationships and temporal dependencies within the battery's charge-discharge behavior. The experimental dataset, consisting of various operating conditions, provides a comprehensive foundation for training the models. The integration of Bayesian Optimization for hyperparameter tuning enhances the predictive performance, ensuring the models operate at their optimal potential. While the CNN2D model exhibited a relatively high RMSE of 0.010, the deep learning models, particularly LSTM-based architectures, demonstrated greater accuracy and robustness. These findings underscore the effectiveness of utilizing advanced recurrent models in SOC estimation, offering a reliable and efficient solution for battery management systems in EVs. The proposed method's performance establishes it as a promising tool for enhancing the overall reliability and safety of electric vehicle systems.

The feature scope of the proposed system includes accurate State of Charge (SOC) estimation for lithium-ion batteries in Electric Vehicles (EVs) using advanced deep learning techniques like LSTM, GRU, and Bi-LSTM. It integrates Bayesian Optimization for hyperparameter tuning to improve model performance. The system focuses on capturing complex charge-discharge behaviors, enhancing battery management systems, and providing reliable SOC predictions for diverse operating conditions, contributing to more efficient and safe EV operations.

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