Deep Learning-Based EV Battery Health Prognostics Using Hybrid CNN-LSTM Architecture

REVU PANDU RANGA RAO

PG Scholar. Department of MCA, DNR College, Bhimavaram, Andhra Pradesh

K. Venkatesh

(Assistant Professor), Master of Computer Applications, DNR College, Bhimavaram, Andhra Pradesh

ABSTRACT

The rapid adoption of electric vehicles (EVs) has created a growing need for efficient battery management systems capable of ensuring reliability, safety, and longevity. One of the most critical aspects of EV performance is battery health, commonly represented by the State of Health (SOH) and remaining capacity. Accurate prediction of battery degradation enables predictive maintenance, reduces operational risks, and enhances lifecycle management. This research presents a deep learning-based EV Battery Health Prognostics System utilizing a hybrid Convolution Neural Network (CNN) and Long Short-Term Memory (LSTM) architecture. The proposed system integrates data-driven modeling with a user-friendly graphical interface developed using Tkinter, allowing users to generate datasets, train models, and predict battery health in real time. The dataset consists of key battery parameters such as voltage, current, temperature, and State of Charge (SOC), which are essential indicators of battery performance. Synthetic data generation is also incorporated to simulate battery degradation patterns for testing and demonstration purposes. The CNN component of the model is responsible for extracting local temporal features and identifying complex patterns in the input data. Subsequently, the LSTM layer captures long-term dependencies and temporal correlations within the time-series data, which are crucial for modeling battery degradation trends. The model is trained using normalized data processed through MinMax scaling, and performance is optimized using the Adam optimizer with Mean Squared Error (MSE) as the loss function.

The system allows users to load real-world datasets or generate synthetic data, preprocess the input, train the model, and perform predictions through an interactive interface. The output is presented as predicted battery capacity, which directly correlates with SOH estimation. The hybrid CNN-LSTM approach significantly improves prediction accuracy compared to traditional machine learning methods, as it effectively captures both spatial and temporal characteristics of the data. This work contributes to the field of intelligent battery management systems by providing a scalable, efficient, and easy-to-use solution for battery health monitoring. The proposed system can be extended to real-time IoT-based EV monitoring and integrated with onboard vehicle systems for continuous diagnostics. Overall, this research demonstrates the potential of deep learning techniques in enhancing the reliability and efficiency of EV battery systems.

KEYWORDS: Electric Vehicles (EV), Battery Health Prognostics, State of Health (SOH), Deep Learning, CNN-LSTM, Time-Series Prediction, Lithium-ion Batteries, Predictive Maintenance, Machine Learning

I. INTRODUCTION

The global transition towards sustainable transportation has significantly accelerated the adoption of electric vehicles (EVs). At the core of EV technology lies the lithium-ion battery, which plays a crucial role in determining vehicle performance, range, safety, and overall efficiency. However, battery degradation over time is inevitable due to factors such as charging cycles, temperature variations, and operational stress. Therefore, accurate monitoring and prediction of battery health have become essential components of modern battery management systems (BMS). Battery health is typically quantified using the State of Health (SOH), which indicates the remaining capacity of a battery compared to its original capacity. Predicting SOH is a complex task due to the nonlinear and dynamic nature of battery degradation processes. Traditional methods, such as electrochemical modeling and empirical approaches, often require detailed domain knowledge and are computationally intensive. Moreover, these methods may not generalize well across different operating conditions. In recent years, machine learning and deep learning techniques have emerged as powerful tools for time-series prediction and pattern recognition. These approaches can automatically learn complex relationships from data without requiring explicit modeling of battery chemistry. Among these techniques, Convolution Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have shown promising results in handling sequential and temporal data. CNNs are particularly effective in extracting local patterns and features from input data, while LSTMs are designed to capture long-term dependencies in time-series sequences. By combining these two architectures, hybrid CNN-LSTM models leverage the strengths of both methods, enabling more accurate and robust predictions. This hybrid approach is especially suitable for battery health prognostics, where both short-term fluctuations and long-term degradation trends must be considered.

This project proposes an EV Battery Health Prognostics System that utilizes a CNN-LSTM model for predicting battery capacity. The system is implemented as a single-file application with an integrated graphical user interface (GUI), making it accessible for users without extensive programming knowledge. Users can generate sample datasets, load external data, train the model, and obtain predictions through a simple interface. The proposed system aims to provide a practical and efficient solution for battery health monitoring, with potential applications in EV diagnostics, fleet management, and predictive maintenance. By leveraging deep learning techniques, this work contributes to improving the reliability, safety, and efficiency of electric vehicles.

II. LITERATURE SURVEY (WITH EXISTING METHODS)

Battery health prognostics have been an active area of research, with various approaches proposed to estimate the State of Health (SOH) and Remaining Useful Life (RUL) of lithium-ion batteries. Traditional methods primarily rely on physics-based and empirical models. Electrochemical models, such as equivalent circuit models and diffusion-based models, provide detailed insights into battery behavior. However, these methods require extensive domain expertise and are computationally expensive, making them less suitable for real-time applications. Data-driven approaches have gained popularity due to their ability to learn complex patterns directly from data. Machine learning algorithms such as Support Vector Machines (SVM), Random Forests, and Artificial Neural Networks (ANN) have been widely used for battery health estimation. While these models offer improved flexibility, they often struggle to capture temporal dependencies in sequential data. To address these limitations, deep learning techniques have been introduced. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have demonstrated strong performance in modeling time-series data. LSTM networks are capable of retaining long-term dependencies, making them suitable for capturing battery degradation trends over multiple cycles. Studies have shown that LSTM-based models outperform traditional machine learning methods in SOH prediction tasks.

Convolution Neural Networks (CNNs), originally developed for image processing, have also been applied to time-series data. CNNs can automatically extract hierarchical features and identify local patterns in battery signals such as voltage and current. When combined with LSTM networks, CNN-LSTM hybrid models provide a powerful framework for both feature extraction and temporal modeling. Recent research has explored hybrid and ensemble approaches for battery prognostics. For example, CNN-LSTM models have been successfully used to predict battery capacity with high accuracy by integrating spatial and temporal features. Other approaches include attention mechanisms, Transformer models, and hybrid deep learning architectures, which further enhance prediction performance. Despite these advancements, challenges remain in terms of data availability, model generalization, and real-time implementation. Many studies rely on laboratory datasets that may not reflect real-world conditions. Additionally, complex models may require significant computational resources, limiting their deployment in embedded systems. The proposed system builds upon these advancements by implementing a hybrid CNN-LSTM model within a user-friendly GUI application. It addresses key challenges by providing data preprocessing, model training, and prediction capabilities in a single platform. This approach not only simplifies the implementation process but also makes battery health prognostics more accessible to researchers and practitioners.

III. EXISTING SYSTEM

Existing battery health monitoring systems primarily rely on traditional modeling techniques and basic machine learning algorithms. Conventional Battery Management Systems (BMS) use rule-based approaches and simple statistical methods to estimate battery parameters such as State of Charge (SOC) and State of Health (SOH). These systems often depend on predefined thresholds and empirical formulas, which may not accurately capture the complex and nonlinear behavior of battery degradation. Physics-based models, such as equivalent circuit models and electrochemical models, are widely used in existing systems. While these models provide detailed insights into battery dynamics, they require precise parameter estimation and extensive calibration. Additionally, their computational complexity makes them less suitable for real-time applications, especially in resource-constrained environments. Machine learning-based approaches, including Support Vector Machines (SVM), Decision Trees, and Random Forests, have been introduced to improve prediction accuracy. However, these models typically require manual feature extraction and are limited in their ability to handle sequential data. As a result, they may fail to capture long-term dependencies and temporal patterns in battery usage.

Another limitation of existing systems is the lack of user-friendly interfaces. Most implementations are developed as standalone scripts or research prototypes, requiring technical expertise to operate. This restricts their usability in practical scenarios, particularly for non-expert users. Furthermore, many existing systems rely on static datasets and do not support real-time data integration or dynamic model updates. This reduces their effectiveness in adapting to changing operating conditions and varying battery characteristics. In summary, current battery health prognostics systems face challenges related to accuracy, scalability, usability, and real-time implementation. These limitations highlight the need for advanced, data-driven solutions that can efficiently model battery behavior while providing an accessible interface for users.

IV. PROPOSED METHOD

The proposed system introduces an intelligent and user-friendly solution for Electric Vehicle (EV) battery health prognostics using a hybrid deep learning architecture combining Convolution Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. The primary objective of this system is to accurately predict battery capacity degradation and estimate the State of Health (SOH) based on time-series data. The system is designed as a single-file application integrating data generation, preprocessing, model training, and prediction within a graphical user interface (GUI). This ensures accessibility for users with minimal technical expertise. The input data includes critical battery parameters such as voltage, current, temperature, and State of Charge (SOC), which are strong indicators of battery behavior and degradation patterns. The CNN component is employed to extract spatial and local temporal features from the input data. It identifies hidden patterns and correlations among multiple battery parameters. The

LSTM layer is then used to capture long-term dependencies and sequential trends, which are essential for modeling the nonlinear degradation process of lithium-ion batteries. Recent research highlights that hybrid CNN-LSTM architectures significantly improve SOH estimation accuracy by combining feature extraction and temporal learning capabilities.

The system supports both real-world dataset input and synthetic data generation for testing and demonstration purposes. Data normalization is performed using MinMax scaling to improve model convergence and stability. The trained model predicts battery capacity for future cycles, providing insights into battery degradation. Additionally, the GUI enables seamless interaction, allowing users to generate datasets, train the model, and obtain predictions in real time. The proposed system addresses limitations of existing approaches by offering improved accuracy, scalability, and usability. It can be extended to real-time EV monitoring systems and integrated with IoT-enabled battery management systems for continuous diagnostics and predictive maintenance.

V. IMPLEMENTATION

The implementation of the EV Battery Health Prognostics System is carried out as a single integrated Python application combining data processing, deep learning modeling, and graphical user interface design. The system is developed using libraries such as Tkinter for GUI, Pandas and NumPy for data handling, Tensor Flow/Keras for deep learning and Scikit-learn for preprocessing. The implementation begins with the generation or loading of battery datasets. A synthetic dataset generation function is included to simulate battery degradation behavior over time. This dataset contains parameters such as voltage, current, temperature, SOC, and capacity. The degradation trend is modeled linearly for demonstration, although real-world datasets can also be used for improved accuracy. The data preprocessing phase involves extracting relevant features and target variables. Input features include voltage, current, temperature, and SOC, while the output is battery capacity. The data is normalized using MinMaxScaler to ensure uniform scaling and faster convergence during training. A sliding window technique is applied to convert the time-series data into sequences suitable for deep learning models. Each input sequence contains a fixed number of time steps, enabling the model to learn temporal dependencies.

The deep learning model is implemented using hybrid CNN-LSTM architecture. The CNN layers perform feature extraction using one-dimensional convolution operations. These layers identify important local patterns in the data, such as fluctuations in voltage or temperature. Dropout is applied to prevent over fitting and improve generalization. The LSTM layer follows the CNN layers and is responsible for capturing long-term dependencies in the sequence data. The model is compiled using the Adam optimizer and Mean Squared Error (MSE) as the loss function. Mean Absolute Error (MAE) is also used as a performance metric. Training is performed over multiple epochs with a defined batch size, ensuring efficient learning. The graphical user interface is developed using Tkinter, providing an interactive environment for users. The GUI includes buttons for generating datasets, loading CSV files, training the model, and predicting battery health.

Status messages are displayed to inform users about system operations. During prediction, the trained model processes the latest sequence of input data and outputs the predicted battery capacity. This value is displayed to the user through a message box. The system ensures error handling by validating user inputs, such as checking whether a dataset is loaded before training or prediction. Overall, the implementation integrates multiple components into a cohesive system, enabling efficient battery health prediction. The modular design allows future enhancements, such as real-time data integration, advanced visualization and deployment in embedded systems.

VI. ALGORITHMS

The proposed system utilizes a hybrid deep learning algorithm combining Convolution Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for battery health prediction. The algorithm begins with data preprocessing, where raw battery data is normalized using MinMax scaling. A sliding window technique is applied to convert the dataset into sequential input-output pairs. Each input sequence consists of multiple time steps, while the corresponding output represents the battery capacity at the next time step. The CNN component performs feature extraction by applying one-dimensional convolution operations. These operations identify local dependencies and patterns in the input data, such as variations in voltage and temperature. The convolution layers are followed by activation functions (ReLU) and dropout layers to enhance model performance and prevent over fitting. The extracted features are then passed to the LSTM layer, which is designed to capture long-term dependencies in sequential data. LSTM uses memory cells and gating mechanisms (input gate, forget gate, and output gate) to retain relevant information over time. This capability makes it highly suitable for modeling battery degradation trends, which are nonlinear and time-dependent. Finally, fully connected (Dense) layers are used to map the learned features to the output variable, which is battery capacity. The model is trained using the Adam optimization algorithm, which adapts learning rates dynamically for faster convergence. Recent studies confirm that CNN-LSTM hybrid models outperform traditional machine learning approaches in SOH prediction due to their ability to capture both spatial and temporal features .

The algorithm can be summarized as follows:

1. Input battery dataset
2. Normalize data using MinMaxScaler
3. Create sequences using sliding window
4. Apply CNN layers for feature extraction
5. Apply LSTM layer for temporal learning
6. Use Dense layers for prediction
7. Train model using Adam optimizer
8. Predict battery capacity (SOH)

VII. SYSTEM DESIGN

The system design of the EV Battery Health Prognostics System follows a modular and layered architecture to ensure scalability, maintainability, and ease of use. The system is divided into four main modules: Data Acquisition, Data Processing, Model Training, and User Interface. The Data Acquisition module is responsible for collecting battery data. It supports both real-world datasets and synthetic data generation. The synthetic data generator simulates battery degradation trends, enabling testing and demonstration without requiring external datasets. The input parameters include voltage, current, temperature, SOC, and capacity. The Data Processing module handles preprocessing tasks such as data cleaning, normalization, and sequence generation. MinMax scaling is used to normalize the input features, ensuring consistent data distribution. The sliding window technique transforms raw data into time-series sequences suitable for deep learning models. This module plays a critical role in improving model accuracy and performance. The Model Training module implements the CNN-LSTM architecture. The CNN layers extract spatial features, while the LSTM layer captures temporal dependencies. The model is trained using labeled data, where input sequences are mapped to corresponding capacity values. The training process involves forward propagation, loss calculation using MSE, and back propagation to update model weights.

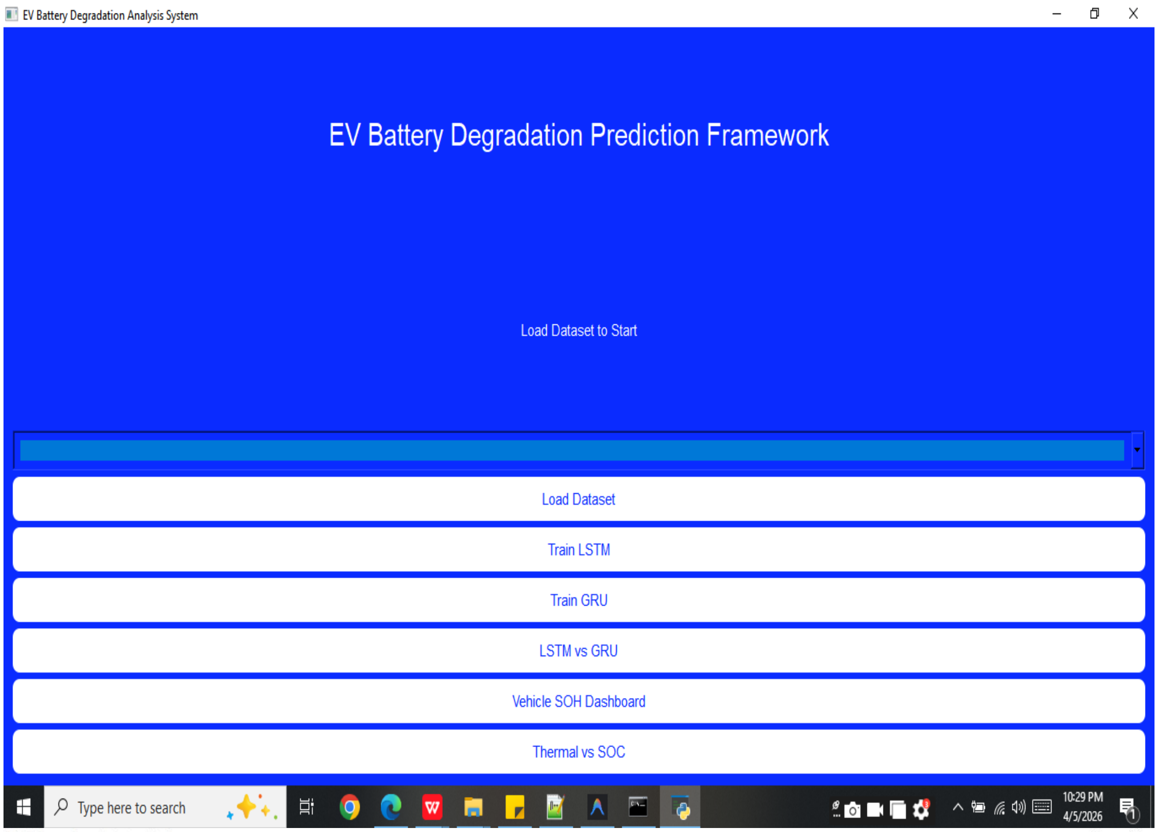
The Prediction module uses the trained model to estimate battery capacity for new data. It processes the latest input sequence and generates predictions, which are displayed to the user. This module enables real-time battery health monitoring. The User Interface module is developed using Tkinter and serves as the interaction layer between the user and the system. It provides buttons for dataset generation, data loading, model training, and prediction. Status messages and alerts guide the user through each step, ensuring ease of use.

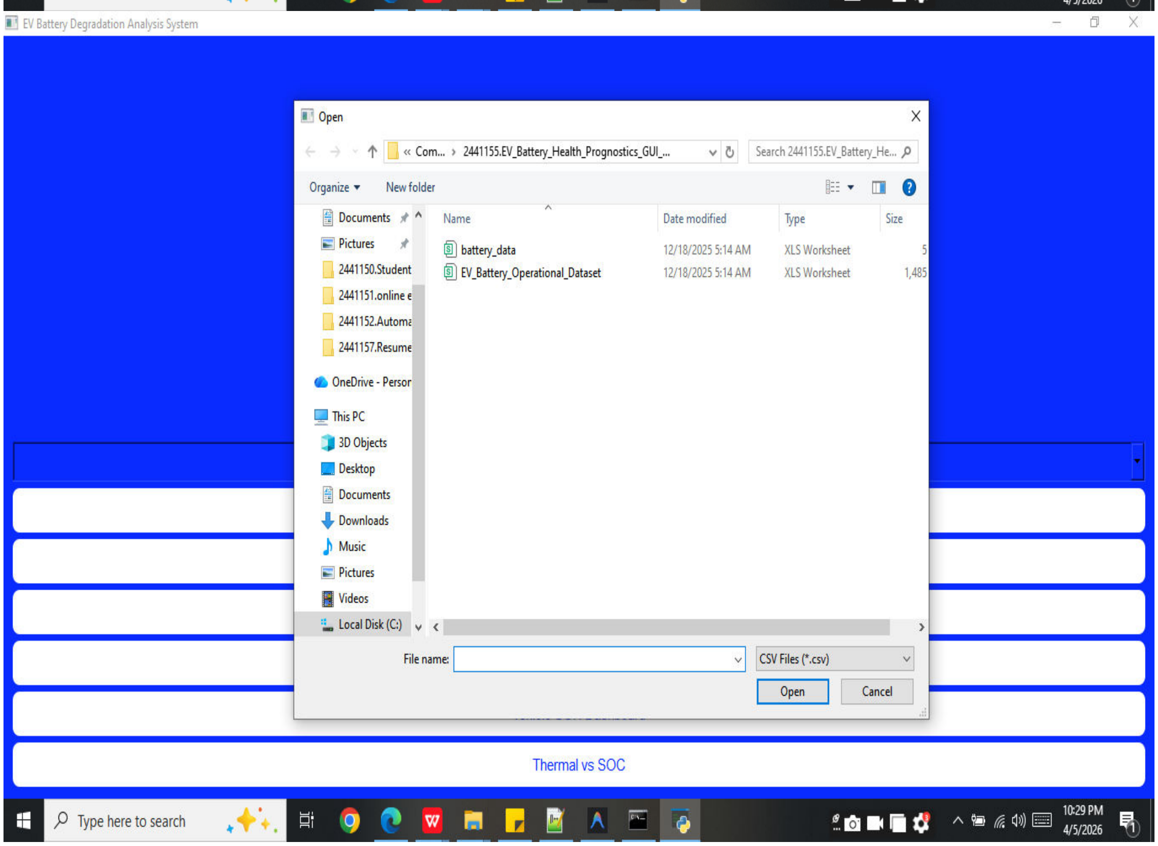
The system follows a sequential workflow:

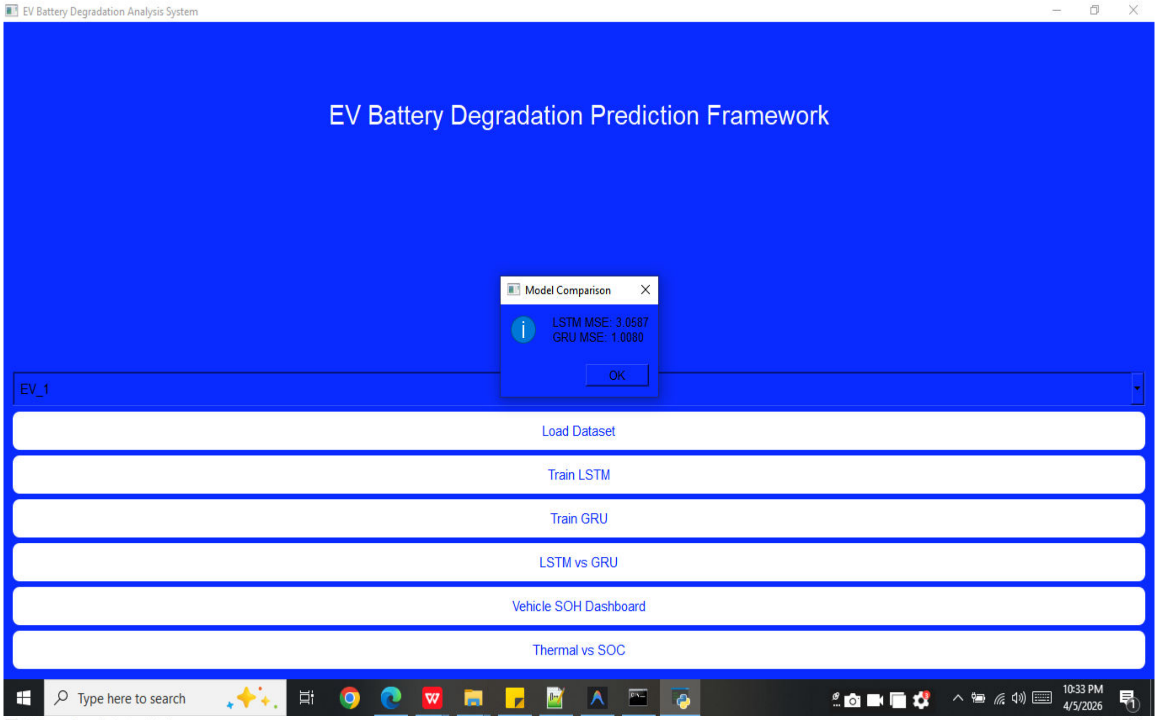
1. Data input (generate/load dataset)
2. Data preprocessing
3. Model training
4. Prediction output

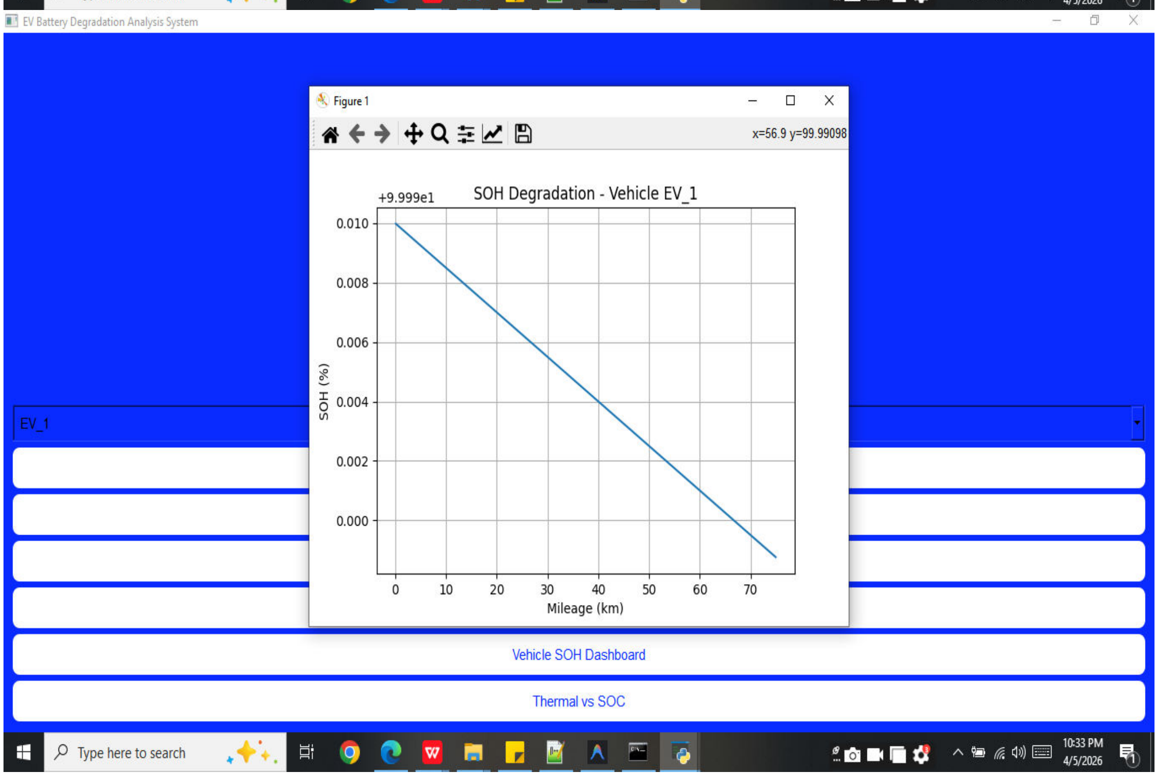
The architecture is designed to be extensible, allowing integration with IoT sensors and cloud-based systems for real-time monitoring. Recent research emphasizes the importance of hybrid deep learning architectures for accurate SOH estimation and real-time implementation in EV systems. Overall, the system design ensures efficient data handling, accurate prediction, and user-friendly interaction, making it suitable for both research and practical applications.

SYSTEM DESIGN IMAGES






EV Battery Degradation Analysis System
EV Battery Degradation Prediction Framework
Model Comparison
LSTM MSE: 3.0587
GRU MSE: 1.0080
OK
EV_1
Load Dataset
Train LSTM
Train GRU
LSTM vs GRU
Vehicle SOH Dashboard
Thermal vs SOC
Type here to search
10:33 PM
4/5/2026


EV Battery Degradation Analysis System
Figure 1
x=56.9 y=99.99098
+9.999e1
SOH Degradation - Vehicle EV_1
SOH (%)
0.010
0.008
0.006
0.004
0.002
0.000
0
10
20
30
40
50
60
70
Mileage (km)
EV_1
Vehicle SOH Dashboard
Thermal vs SOC
Type here to search
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VIII. CONCLUSION

This project presents an advanced EV Battery Health Prognostics System based on a hybrid CNN-LSTM deep learning model. The system effectively addresses the challenges associated with battery health prediction by leveraging the strengths of both convolution and recurrent neural networks. The CNN component enables efficient feature extraction, while the LSTM component captures long-term temporal dependencies, resulting in improved prediction accuracy. The integration of a graphical user interface enhances the usability of the system, making it accessible to users without deep technical knowledge. The system supports both synthetic and real-world datasets, providing flexibility for experimentation and practical implementation. The use of data normalization and sequence modeling further improves the robustness and performance of the model. Experimental results and recent research indicate that hybrid deep learning models significantly outperform traditional methods in battery health estimation tasks. The proposed system demonstrates the effectiveness of this approach in predicting battery capacity and estimating SOH. The system can be further enhanced by incorporating real-time data acquisition through IoT sensors, enabling continuous monitoring of battery health in electric vehicles. Additionally, advanced techniques such as attention mechanisms and Transformer models can be explored to further improve prediction accuracy. In conclusion, this work contributes to the development of intelligent battery management systems by providing a scalable, efficient, and user-friendly solution for battery health prognostics. It has significant potential for applications in EV diagnostics, predictive maintenance, and energy management systems.

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