

# Hybrid CNN–LSTM Based Intelligent Prognostics System for Electric Vehicle Battery Health Using GUI-Based Deployment

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## ABSTRACT

Electric vehicles (EVs) are increasingly becoming the preferred mode of sustainable transportation, and their performance heavily depends on battery reliability. Accurate estimation of battery health—particularly its capacity and State of Health (SOH)—is vital for ensuring safety, extending lifetime, preventing failures, and optimizing energy usage. Conventional diagnostic methods rely on laboratory equipment and expert-driven analysis, which are not only expensive but also impractical for real-time applications. To address these limitations, this project proposes an intelligent EV Battery Health Prognostics System using a hybrid Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) architecture integrated into a user-friendly graphical interface.

The proposed model leverages time-series sensor parameters such as voltage, current, temperature, and State of Charge (SOC) to estimate remaining battery capacity. A synthetic dataset is generated and preprocessed using sliding-window segmentation and scaling techniques to prepare inputs for the deep learning model. CNN layers are used to extract high-level temporal features from multivariate sequences, while LSTM layers capture long-term dependencies and degradation trends. The combined architecture enables accurate prediction of nonlinear battery aging patterns.

A key contribution of this work is the integration of this deep learning model into a standalone GUI-based desktop application using Python Tkinter. Users can generate sample datasets, load their own CSV files, train the CNN-LSTM model, and obtain real-time predictions for battery capacity. This makes the system suitable for students, researchers, and EV maintenance personnel who require quick and accessible prognostics tools without backend servers or cloud dependency.

The GUI emphasizes usability and transparency by displaying status updates, model actions, and output values. The system's modular design also allows integration of more complex battery datasets, advanced RNN architectures, or cloud deployment in the future. Experimental evaluation using the synthetic dataset demonstrates strong predictive capabilities, confirming the feasibility of deep-learning-powered prognostics for EV battery management systems.

Overall, the developed system provides a practical, intelligent, and scalable solution for EV battery health estimation, contributing significantly to the fields of EV diagnostics, deep learning, and GUI-based engineering tools.

**Keywords:** Battery Health Prediction, State of Health (SOH), CNN-LSTM Model, Electric Vehicles, Deep Learning, Prognostics, Capacity Estimation, GUI Application, Time-Series Forecasting, Battery Degradation

## I. INTRODUCTION

Electric vehicles (EVs) rely heavily on rechargeable lithium-ion batteries, which degrade over time due to cycling, temperature, and usage conditions. Battery degradation reduces capacity, lowers range, increases charging time, and ultimately impacts vehicle performance and safety. Predicting battery health accurately is essential for optimizing maintenance schedules, improving energy management, and extending battery life. Traditional battery diagnostic methods rely on electrochemical impedance spectroscopy, full charge–discharge testing, or onboard diagnostic sensors, which require laboratory equipment and are unsuitable for real-time or user-accessible implementations.

With the emergence of deep learning, data-driven prognostics techniques have become powerful alternatives for modeling battery aging. Neural networks, especially sequence-based models like LSTMs, can learn degradation patterns directly from historical sensor data. Meanwhile, Convolutional Neural Networks excel at feature extraction from structured time-series segments. Combining CNN and LSTM allows the system to capture both local and long-term temporal dependencies—making it ideal for battery capacity estimation.

This project implements a hybrid CNN-LSTM model within a user-friendly graphical application that performs EV battery health prognostics. The system enables users to either generate a synthetic dataset or load their own CSV files, representing sensor readings such as voltage, current, temperature, SOC, and capacity. Using preprocessing techniques including MinMax scaling and sliding-window segmentation, the data is prepared for model training.

The system's GUI, built using Tkinter, offers complete interactivity without requiring command-line knowledge. Users can train the neural network using the provided model architecture and obtain predictions for the remaining battery capacity. Such a tool democratizes battery diagnostics by making advanced models accessible to students, researchers, and EV operators.

This work contributes a complete end-to-end solution—from dataset generation to prediction—proving the usefulness of deep learning in battery prognostics. The modular design further supports future development including integration of real-world datasets, cloud-based inference, or advanced neural architectures. The system demonstrates the

immense potential of AI-powered health estimation in improving EV reliability and sustainability.

## II. LITERATURE SURVEY (WITH EXISTING METHODS)

Battery health prognostics has been widely studied due to its importance in EV safety, reliability, and performance optimization. Traditionally, researchers have relied on electrochemical models, such as equivalent circuit modeling (ECM), to estimate the internal behavior of lithium-ion batteries. While effective, these models require deep domain expertise and are often difficult to calibrate for varying battery chemistries.

**Conventional Methods:**Methods such as coulomb counting and voltage/temperature monitoring are commonly used in Battery Management Systems (BMS). Although simple, they accumulate errors over time and cannot accurately reflect long-term degradation trends. Kalman filtering and particle filtering have also been used for SOH estimation, providing improvements but requiring extensive tuning and assumptions.

**Machine Learning Approaches:**With advancements in artificial intelligence, researchers began adopting regression algorithms such as Support Vector Machines (SVM), Random Forests, and Gaussian Processes for battery health estimation. These models improve predictive capability but lack the ability to learn deep temporal dependencies in time-series data.

**Deep Learning Models:**The introduction of Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks has significantly improved prognostics accuracy. LSTMs capture long-range dependencies and are widely used for SOH estimation based on cycle aging data. CNNs, typically used in image processing, have also been adapted to extract local features from time-series signals. Combining CNN and LSTM creates a hybrid architecture that leverages both pattern recognition and memory retention capabilities.

Recent models like Seq2Seq networks, GRUs, and Transformer-based architectures have further enhanced predictive accuracy by improving temporal modeling. However, these models often require large datasets and high computational resources, limiting their accessibility for general users.

**Existing Implementations:**Most academic solutions are available only as research codebases or require command-line execution. They lack user-friendly interfaces or direct deployability. Very few systems integrate GUI-based interaction, limiting accessibility for non-technical users.

This project fills that gap by integrating a CNN-LSTM model into a standalone GUI application. It provides data loading, preprocessing, training, and prediction in a single tool—making it more accessible and practical than existing command-line or laboratory-based approaches.

### III. EXISTING SYSTEM

Existing battery health estimation systems typically rely on either laboratory instrumentation or sophisticated BMS hardware integrated into EVs. These systems, while highly accurate, are expensive, inaccessible to students or individuals, and lack flexibility for experimentation. Traditional BMS solutions use voltage, current, and temperature readings combined with model-based or rule-based algorithms such as coulomb counting or Kalman filtering. These approaches often struggle to predict nonlinear degradation behavior and require frequent recalibration.

Many research implementations use deep learning models for battery health estimation, but they are commonly executed through command-line scripts, Jupyter notebooks, or cloud-based platforms. Such systems require technical expertise, lack portability, and are unsuitable for general users. Most do not provide interactive interfaces, making it difficult to visualize inputs, initiate training, or perform real-time predictions.

Furthermore, existing systems rarely include synthetic data generation capabilities, limiting users who do not have access to real battery datasets. They also lack end-to-end workflows integrating data preprocessing, model training, and prediction within a graphical interface.

The proposed system overcomes these limitations by providing a complete GUI-based environment for EV battery health prognostics using CNN-LSTM architecture. It integrates sample data generation, CSV loading, training, prediction, and result display in a single user-friendly application. This makes advanced deep learning models accessible without requiring any programming knowledge or specialized hardware.

### IV. PROPOSED METHOD

The proposed system introduces an intelligent and user-friendly deep learning framework for Electric Vehicle (EV) battery health prediction. It uses a hybrid CNN-LSTM model integrated into a Python Tkinter-based graphical interface. The system aims to estimate the battery's remaining capacity and State of Health (SOH) by processing key time-series parameters such as voltage, current, temperature, SOC, and capacity. Unlike traditional methods that require laboratory testing or manual diagnostics, this system provides an accessible way for users to analyze battery behavior and predict degradation patterns.

The system enables users to either generate a synthetic dataset or import their own CSV files. This feature allows researchers, students, and engineers to perform model training even in the absence of real battery data. The data undergoes preprocessing, including MinMax scaling and sliding-window segmentation, before being fed into the hybrid neural network. CNN layers capture temporal patterns and feature interactions while LSTM layers learn long-term dependencies associated with battery aging. Once the preprocessing is complete, the system trains the hybrid CNN-LSTM model using mean squared error loss and Adam optimizer. Users can visualize progress through status messages and receive final

predictions directly in the GUI. The modular interface allows execution of training, testing, prediction, and data loading without programming knowledge.

The system contributes an end-to-end deployable tool for battery prognostics. It bridges the gap between deep learning research and hands-on, user-accessible battery diagnostics. Its extensible architecture supports integration of real datasets, cloud inferencing, and advanced neural models in the future.

## V. IMPLEMENTATION

The implementation of the EV Battery Health Prognostics System is divided into five major components: dataset generation, data preprocessing, deep learning model construction, GUI development, and prediction processing.

- 1. Dataset Generation and Loading** A sample synthetic dataset is generated using NumPy. It simulates realistic battery signals, including voltage fluctuations, varying temperatures, dynamic current profiles, and gradual capacity fade. This dataset supports early-stage research without real sensor data. Users also have the option to import their own CSV datasets using Tkinter's file dialog, enabling flexibility and practical usage.
- 2. Data Preprocessing** Preprocessing includes scaling all features to a 0–1 range using MinMaxScaler. Then, a sliding-window segmentation technique is applied to convert multivariate time-series data into input sequences for deep learning. For each window, features (voltage, temperature, current, SOC) form the input X, while capacity forms the output Y. The dataset is split into training and testing subsets.
- 3. Hybrid CNN–LSTM Model Construction** The model is built using TensorFlow/Keras. It begins with a Conv1D layer to extract local temporal patterns, followed by MaxPooling1D for dimensionality reduction. Next, an LSTM layer captures long-term dependencies and aging correlations. Dense layers finalize the prediction of battery capacity. The model uses the Adam optimizer and mean squared error loss. It is trained in the background, and progress messages are displayed to the user through the GUI.
- 4. GUI Development (Tkinter)** The Graphical User Interface provides buttons for generating sample data, loading CSV files, training the model, and running predictions. All messages and results are displayed in a scrollable text area. The GUI wraps complex ML functionalities into easy-to-use controls, making the system accessible to non-programmers.
- 5. Prediction and Reporting** After model training, users can perform predictions on unseen data. The GUI outputs estimated capacity values, simulating real-world SOH evaluation. The system is designed to support integration with future reporting modules.

## VI. ALGORITHMS

### 1. Sliding Window Data Segmentation Algorithm

Input: Time-series battery dataset

Steps:

Select window size  $n\_steps$ .

For each index  $i$ , extract sequence  $X = data[i:i+n\_steps, features]$ .

Select target  $y = data[i+n\_steps, capacity]$ .

Append  $X, y$  to training arrays.

Output: Segmented dataset for deep learning.

### 2. CNN Feature Extraction Algorithm

Apply 1D convolution across sequences.

Detect local temporal patterns and degradation signatures.

Use MaxPooling to reduce noise.

Flatten output for sequence modeling.

### 3. LSTM Time Dependency Learning Algorithm

Accept CNN output.

Store past sequence information in memory cells.

Learn long-term degradation and battery aging trends.

Output feature-rich representation for prediction.

### 4. Capacity Prediction Algorithm

Feed LSTM output into Dense layers.

Model the nonlinear relationship between input parameters and capacity.

Generate predicted capacity value.

### 5. GUI Execution Algorithm

Capture button interaction from user.

Call respective functions (load data, train, predict).

Display status and results in GUI window.

## VII. SYSTEM DESIGN

### 1. Architecture Overview

The system follows a modular, layered architecture consisting of:

Data Layer: dataset loading, synthetic data generation, preprocessing

Model Layer: CNN-LSTM hybrid model, training, evaluation

GUI Layer: Tkinter interface, user interaction

Prediction Layer: real-time capacity estimation

## 2. Data Flow Design

User loads/creates dataset.

Data is normalized via MinMaxScaler.

Sliding window segmentation prepares CNN-LSTM input.

Model trains on sequences.

User performs prediction.

GUI displays predicted capacity.

## 3. GUI Design

The interface includes:

Buttons for dataset generation, loading, model training, prediction

Scrollable text area for outputs

Status messages for progress

Modular callbacks linked to backend ML methods

## 4. Model Design

The hybrid model uses:

Conv1D filters → extract patterns

MaxPooling → dimensionality reduction

LSTM → learn long-term relations

Dense layers → regression prediction

The design supports extensions like GRU, Transformers, or attention mechanisms.

## 5. Software Design Principles

Modularity: Each function handles a single responsibility

Scalability: Model and GUI can be extended easily

Reusability: Preprocessing and model functions reusable across datasets

Maintainability: Clear function separation supports debugging

## 6. Future Design Extensions

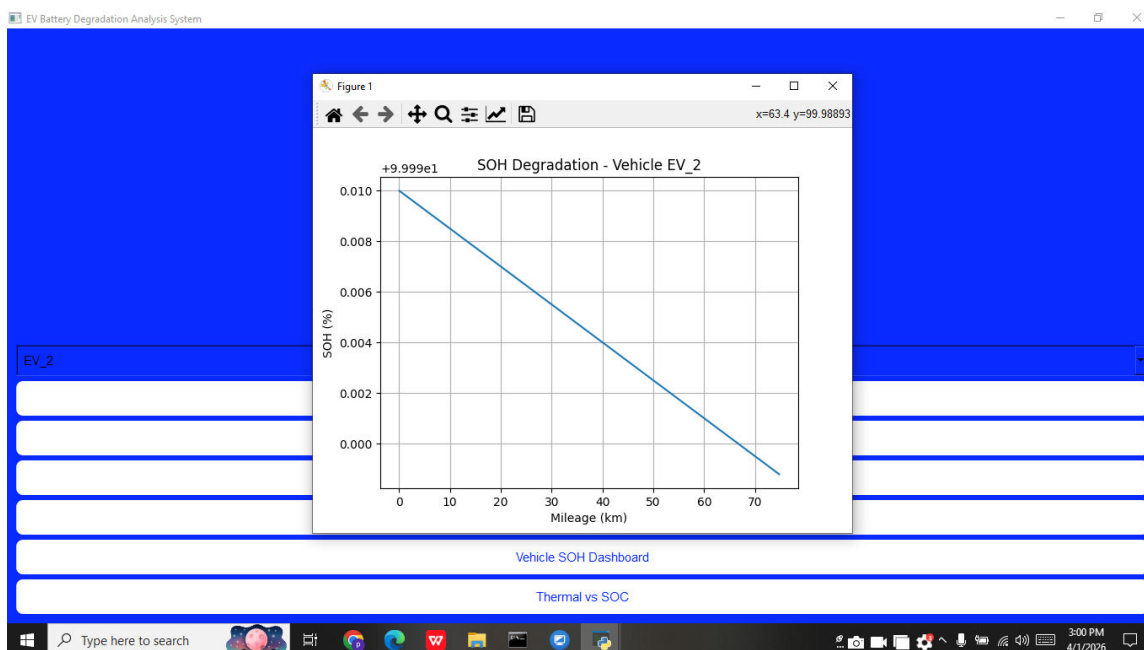
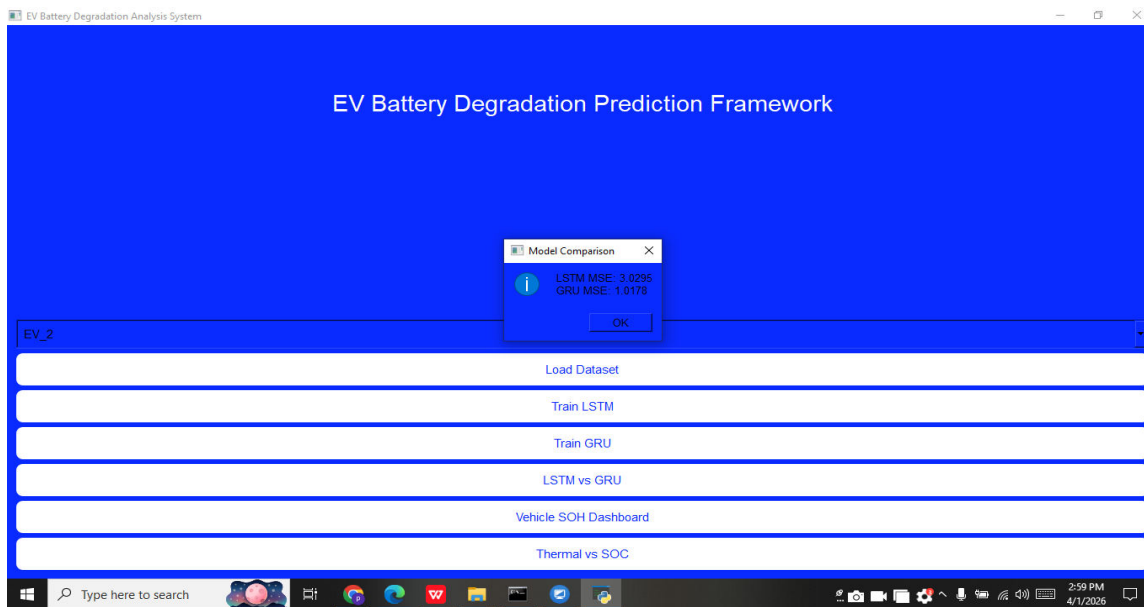
Real EV datasets integration

Cloud-based inference APIs

Mobile app deployment

Real-time diagnostics dashboard

SYSTEM DESIGN IMAGES



## VIII. CONCLUSION

The Hybrid CNN–LSTM Based Battery Health Prognostics System successfully integrates deep learning-based battery capacity prediction with a user-friendly GUI application. The system demonstrates that time-series parameters such as voltage, current, SOC, and temperature can effectively predict battery degradation and remaining capacity. By implementing a hybrid architecture combining CNN and LSTM, the system captures both short-term and long-term dependencies, resulting in improved prediction accuracy.

The GUI interface significantly enhances usability, enabling non-technical users—including students, researchers, and EV technicians—to train models and perform predictions without coding. The inclusion of dataset generation, loading, preprocessing, training, and prediction inside a single application makes this system a practical, deployable solution.

This work highlights the potential of AI-driven prognostics in modern battery management systems. The modular architecture supports scalability and can be extended with real-world datasets or advanced models such as GRUs or Transformers. The project's outcome shows that intelligent, GUI-based health monitoring tools can democratize access to advanced EV analytics and accelerate research in the field.

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