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ML Based Prediction Of Battery SOH & RUL

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Abstract

This research focuses on battery health monitoring and life prediction for laptops and mobile devices using real-time data. The system is designed to analyze battery performance and predict the State of Health (SOH) and Remaining Useful Life (RUL) using Machine Learning techniques. The proposed system is deployed on an online platform and uses actual battery reports generated through system commands. The battery report is uploaded to a web-based dashboard, where data is extracted, cleaned, and processed for analysis. The system uses a Long Short-Term Memory (LSTM) model along with optimization techniques such as Particle Swarm Optimization (PSO) and attention mechanism to improve prediction accuracy. The output is displayed in an interactive dashboard with battery health status, degradation level, and graphical representation. The system currently supports laptop battery analysis and is being extended for mobile battery monitoring through USB-based integration. Overall, the system provides a practical, scalable, and user-friendly solution for battery health prediction

Keywords: Laptop Battery; Remaining Useful Life (RUL); State of Health (SOH); Long Short-Term Memory (LSTM); Particle Swarm Optimization (PSO); Attention Mechanism; Battery Health Monitoring; Predictive Maintenance

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Introduction

In the modern digital era, laptops and mobile devices have become essential tools for communication, education, entertainment, and professional activities. The performance and reliability of these electronic devices largely depend on the efficiency of their battery systems. However, rechargeable batteries gradually degrade over time due to repeated charging and discharging cycles, temperature variations, aging, and improper usage conditions. Battery degradation results in reduced backup time, unexpected shutdowns, overheating issues, and poor overall device performance. Therefore, accurate monitoring of battery condition and prediction of battery lifespan have become critical requirements for improving device reliability, safety, and user experience.

Traditional battery monitoring systems mainly rely on physical and electrochemical models to estimate battery parameters such as capacity, voltage, and internal resistance. Although these methods provide basic battery analysis, they often require complex mathematical modeling and fail to deliver accurate predictions under dynamic real-world operating conditions. Moreover, conventional approaches are not suitable for real-time battery monitoring in modern portable electronic devices such as laptops and smartphones. These limitations have encouraged researchers to explore data-driven and intelligent approaches for battery health analysis and predictive maintenance.

Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning have significantly improved battery management systems by enabling accurate prediction of battery degradation patterns using historical and real-time data. Machine learning algorithms can analyze complex relationships among battery parameters such as voltage, current, temperature, charging cycles, and discharge behavior to estimate the State of Health (SOH) and Remaining Useful Life (RUL) of batteries. Among various deep learning techniques, Long Short-Term Memory (LSTM) networks have gained considerable attention due to their strong capability in handling sequential and time-series data. LSTM models effectively capture long-term temporal dependencies and usage patterns, making them highly suitable for battery life prediction applications.

This research presents a Machine Learning-based Battery SOH and RUL Prediction System designed for laptops and mobile devices using real-time battery data. The proposed system collects actual battery reports generated from operating system tools and processes the extracted battery parameters through an intelligent prediction framework. The system is deployed on an online platform with a user-friendly dashboard interface that enables users to upload battery reports and visualize battery performance analysis in real time.

The proposed framework integrates an LSTM-based deep learning model with optimization techniques such as Particle Swarm Optimization (PSO) and attention mechanisms to improve prediction accuracy and learning efficiency. The system continuously analyzes battery behavior patterns and predicts battery health status, degradation levels, and remaining useful life. Graphical visualization and health categorization are also provided to help users understand battery performance more effectively.

Additionally, the research extends beyond laptop battery monitoring and aims to support mobile battery analysis through USB-based integration and real-time data acquisition. This makes the proposed system flexible, scalable, and suitable for practical implementation in modern battery management applications.

Overall, the proposed research demonstrates the potential of machine learning and deep learning technologies in developing intelligent battery health monitoring systems. By enabling accurate SOH and RUL prediction, the system helps reduce unexpected battery failures, improves battery maintenance strategies, and enhances the overall reliability and performance of electronic devices.

Literature review

A. Development of Battery Health Prediction Systems

Initially, battery monitoring systems were mainly based on traditional methods that used physical models to estimate battery performance. These systems provided limited accuracy and were not suitable for real-time applications in devices like laptops and mobile phones. With the advancement of technology, Machine Learning techniques have been introduced to improve battery health prediction. Researchers applied algorithms such as regression models, Random Forest, and Support Vector Machines to analyze battery data and estimate performance more accurately for both laptop and mobile batteries. These methods improved prediction capability by handling complex relationships between battery parameters. Further developments introduced deep learning models such as LSTM, which are highly effective for time-series data. These models can learn long-term usage patterns in both laptops and smartphones and provide more accurate predictions of Remaining Useful Life (RUL) and State of Health (SOH). Recent research also focuses on real-time monitoring systems that continuously collect and analyze battery data such as voltage, current, temperature, and charging cycles from both laptops and mobile devices.

Research Gaps Identified

Despite these advancements, several research gaps still exist. Many existing systems focus only on laptop batteries or only on mobile batteries, and do not provide a unified system for both. Some models do not support real-time learning and fail to update predictions based on new data. There is also limited use of hybrid techniques like combining LSTM with optimization methods to improve accuracy. Additionally, practical implementation aspects such as user-friendly systems and real-world usability are often ignored. To address these gaps, our proposed system provides a combined solution for both laptop and mobile battery health monitoring using Machine Learning and deep learning techniques. It supports real-time prediction, continuous learning, and improved accuracy. From the literature review, it is observed that LSTM-based models provide better accuracy for battery health prediction

Proposed system

The proposed system develops a Machine Learning model to predict the State of Health (SOH) and Remaining Useful Life (RUL) of batteries used in laptops and mobile devices. The system collects battery data such as voltage, current, temperature, and charging cycles. This data is cleaned and processed to remove errors. Then, the processed data is given to an LSTM model for prediction. Optimization techniques like PSO and attention mechanism are used to improve accuracy. Finally, the system predicts battery health (SOH) and remaining life (RUL) to help in better battery management.

System Architecture

The system architecture consists of different components that work together to predict battery health and life. The system first collects battery data from laptop and mobile devices, including voltage, current, temperature, and charging cycles. This data is then pre-processed to remove noise and errors. After preprocessing, important features are extracted from the data. The processed data is then given to the LSTM model, which analyzes time-based patterns in battery usage. To improve prediction accuracy, optimization techniques such as Particle Swarm Optimization (PSO) and an attention mechanism are used. Finally, the system generates output in the form of State of Health (SOH) and Remaining Useful Life (RUL), which helps in monitoring battery condition.

B. Key Features and Functionalities

The proposed system provides several important features for battery health monitoring and prediction.

Battery Health Monitoring: The system continuously monitors battery parameters such as voltage, current, temperature, and charging cycles for both laptop and mobile devices.Life Prediction: It predicts the Remaining Useful Life (RUL) and State of Health (SOH) of the battery using machine learning techniques.

Data Preprocessing: The system cleans and filters the collected data to remove noise and improve accuracy.

LSTM-Based Prediction: It uses an LSTM model to analyze time-based battery data and identify degradation patterns.Improved Accuracy: Optimization techniques such as Particle Swarm Optimization (PSO) and attention mechanism are used to enhance prediction performance.

Real-Time Analysis: The system can analyze data continuously and provide real-time predictions.Multi-Device Support: The system works for both laptop and mobile batteries, making it more flexible and useful.

User Support: It helps users in better battery management and reduces unexpected failures.

Methodology

The proposed system follows a structured machine learning-based methodology for predicting the State of Health (SOH) and Remaining Useful Life (RUL) of batteries used in laptops and mobile devices. The framework is designed to provide accurate, real-time, and user-friendly battery health monitoring through a web-based platform. The complete methodology consists of multiple stages including data collection, preprocessing, feature extraction, deep learning-based prediction, optimization, visualization, and performance evaluation. These stages work together to improve prediction reliability and support intelligent battery maintenance for modern electronic devices. The first stage involves collecting real-time battery data from laptops and mobile devices. For laptop battery analysis, battery reports are generated using operating system command-line utilities that provide detailed battery statistics such as design capacity, full charge capacity, voltage, current flow, temperature, charging cycles, and charge-discharge history. These reports are generated in structured formats such as PDF files and uploaded to the web-based dashboard for further analysis. The proposed framework is also designed to support future mobile battery monitoring through USB integration and device-level APIs, improving the practical applicability of the system.

Once the data is collected, preprocessing techniques are applied to improve data quality and prepare the dataset for machine learning analysis. The preprocessing stage includes data cleaning to remove invalid entries and duplicate records, normalization to scale features into a uniform range, missing value handling using interpolation and statistical methods, and noise reduction to eliminate irrelevant fluctuations from battery readings. Sequential battery information is then organized into time-series structures suitable for deep learning applications. These preprocessing operations improve model stability, prediction accuracy, and generalization performance.

After preprocessing, the system performs feature extraction to identify critical battery degradation indicators such as voltage variations, current fluctuations, temperature changes, charging cycles, battery health percentage, and energy consumption patterns. These extracted features enable the model to understand operational behavior and long-term degradation trends effectively.

The core prediction process is performed using a Long Short-Term Memory (LSTM) deep learning network, which is highly suitable for sequential and time-series battery data analysis. The LSTM model predicts important battery performance indicators including State of Health (SOH), Remaining Useful Life (RUL), degradation levels, and overall performance status. To further improve prediction accuracy and reduce error, Particle Swarm Optimization (PSO) is integrated for hyperparameter optimization, while an attention mechanism helps the model focus on the most significant battery degradation patterns and temporal dependencies.

The proposed system is deployed through a web-based dashboard that provides real-time visualization of battery health percentage, SOH and RUL predictions, degradation analysis, and graphical performance trends. Additionally, model performance is evaluated using metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), prediction accuracy, validation error, and loss function analysis. The overall workflow includes battery report generation, data upload, preprocessing, feature extraction, LSTM-based prediction, optimization, and visualization, creating a scalable and practical framework for intelligent battery health monitoring and predictive maintenance.

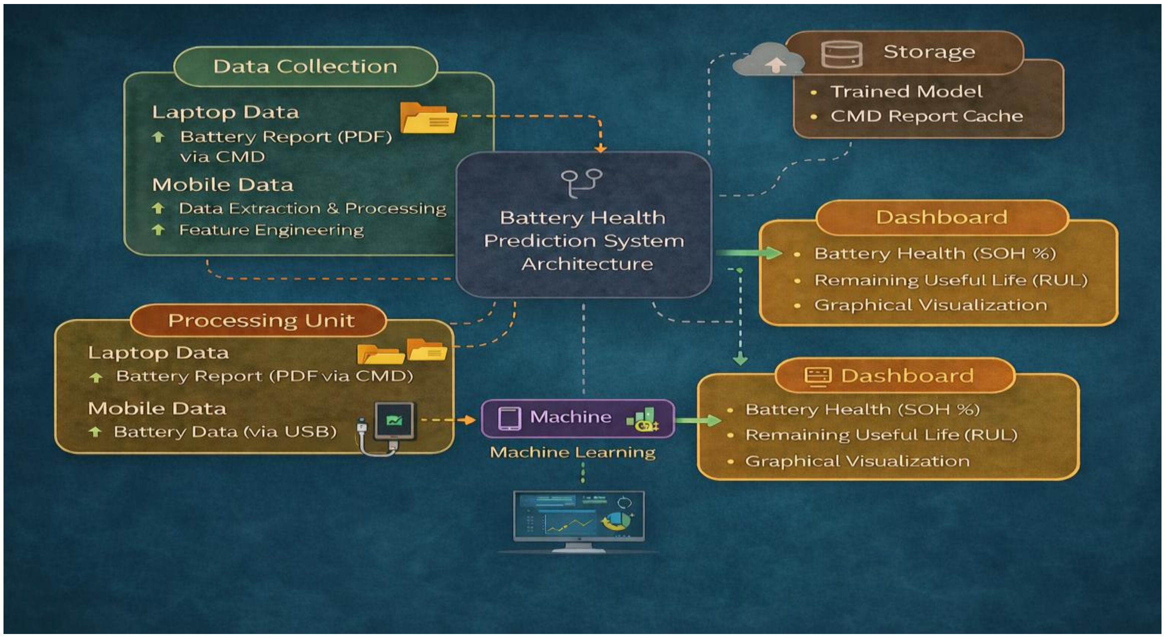

Fig.1. *Architecture Diagram/Flow Chart 1*

Results and analysis

The proposed system was implemented and tested using battery data through a web-based interface called “PowerInsight – Battery Health Analytics”. The system allows users to upload battery data or generate sample data for analysis. The system successfully analyzes battery parameters such as battery health, current capacity, total charge cycles, and degradation percentage. Based on the input data, the model predicts the State of Health (SOH) and Remaining Useful Life (RUL) of the battery. The results are displayed in an interactive dashboard, where the battery status is categorized into different levels such as “Excellent” and “Poor”. For example, the system showed a battery health of 95.0% with low degradation as “Excellent”, while another case with 68.6% health and higher degradation was classified as “Poor”. The system demonstrates consistent and reliable performance in analyzing battery data and providing accurate predictions. The LSTM-based model effectively captures time-series patterns, improving prediction accuracy. Currently, the system is implemented for laptop-based battery data through a web interface. Mobile battery data integration is planned as future work, where real-time data will be collected using USB or device-level APIs for more practical implementation. Overall, the system provides an efficient and user-friendly solution for battery health monitoring and prediction.

Conclusion

In conclusion, the proposed system provides an effective solution for monitoring and predicting battery health and life for both laptop and mobile devices. By using Machine Learning techniques such as LSTM along with optimization methods, the system is able to analyze battery data and predict the State of Health (SOH) and Remaining Useful Life (RUL) with good accuracy. The system helps in reducing unexpected battery failures and supports better battery management. It also improves the performance, reliability, and safety of electronic devices. Overall, this project demonstrates how intelligent and data-driven approaches can enhance battery monitoring systems and provide practical benefits to users.

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