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Hobby to Hustle: An AI-Driven Centralized Platform for Creative Education and Skill Monetization

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Abstract

In the rapidly evolving gig economy, creative skills have emerged as viable sources of income and personal development. However, the current ecosystem for hobby-based learning and teaching remains fragmented, lacking a unified platform that connects learners, tutors, and institutions efficiently. This paper proposes Hobby to Hustle, an AI-driven centralized platform that integrates learning, teaching, and event discovery into a single ecosystem. The system incorporates machine learning–based recommendation algorithms, secure user management, and scalable architecture to enhance personalization and usability. Experimental analysis and system design evaluation suggest that the proposed platform can significantly improve accessibility to creative education, enhance user engagement, and enable efficient skill monetization.

Keywords: Artificial Intelligence; Recommendation System; E-learning; Skill Monetization; Creative Economy

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Introduction

The rapid growth of portable electronic devices such as laptops, smartphones, tablets, and wearable systems has significantly increased the demand for efficient and reliable battery technologies. Rechargeable lithium-ion batteries are widely used in these devices due to their high energy density, long life cycle, and lightweight structure. However, battery performance gradually degrades over time because of repeated charging and discharging cycles, temperature fluctuations, overcharging, aging effects, and continuous usage patterns. This degradation directly affects device reliability, backup time, operational efficiency, and user experience. Therefore, accurate monitoring of battery condition and prediction of battery lifespan have become critical challenges in modern battery management systems.

Battery degradation can lead to several practical problems, including unexpected shutdowns, overheating, reduced charging capacity, and shortened device lifespan. Traditional battery monitoring methods mainly rely on physical and electrochemical models to estimate battery behavior. Although these approaches provide useful theoretical analysis, they often require complex calculations, expensive hardware, and extensive domain knowledge. In addition, conventional methods struggle to provide accurate real-time predictions under dynamic operating conditions encountered in modern portable devices. These limitations have motivated researchers to explore intelligent and data-driven approaches for battery health prediction and predictive maintenance.

Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning have transformed battery management systems by enabling automated analysis of large-scale battery data. Machine learning algorithms can identify hidden degradation patterns and predict battery conditions more effectively than traditional rule-based approaches. Parameters such as voltage, current, temperature, charging cycles, discharge rate, and energy consumption patterns can be analyzed to estimate important battery indicators such as State of Health (SOH) and Remaining Useful Life (RUL).

Among various deep learning models, Long Short-Term Memory (LSTM) networks have shown exceptional performance for battery health prediction because they are capable of learning long-term temporal dependencies from sequential battery data. LSTM models effectively capture degradation trends over time and provide more reliable predictions for time-series battery monitoring applications. Furthermore, optimization techniques such as Particle Swarm Optimization (PSO) and attention mechanisms can further improve prediction accuracy by optimizing model parameters and focusing on important battery features.

This research presents a Machine Learning-Based Prediction System for Battery State of Health (SOH) and Remaining Useful Life (RUL) using real-time battery data collected from laptops and mobile devices. The proposed system utilizes actual battery reports generated through operating system tools and processes them through an intelligent prediction framework deployed on a web-based platform. The system extracts and analyzes important battery parameters to identify degradation behavior and estimate future battery performance.

The proposed framework integrates LSTM-based deep learning with PSO optimization and attention mechanisms to improve prediction efficiency and accuracy. The generated results are displayed through an interactive dashboard interface that provides battery health percentage, degradation level, performance status, and graphical visualization of battery trends. The system currently supports laptop battery monitoring and is further extended for mobile battery analysis through USB-based integration and real-time device communication.

The primary objective of this research is to develop an intelligent, scalable, and user-friendly battery health monitoring platform capable of providing accurate SOH and RUL prediction for modern electronic devices. By leveraging machine learning and real-time analytics, the proposed system aims to reduce unexpected battery failures, improve battery maintenance strategies, enhance device performance, and support predictive maintenance in next-generation smart electronic systems.

Literature Review

Battery health prediction and Remaining Useful Life (RUL) estimation have gained significant attention in recent years due to the widespread use of rechargeable batteries in laptops, smartphones, electric vehicles, and portable electronic systems. Researchers have explored several traditional, statistical, and Artificial Intelligence-based techniques to improve battery monitoring, degradation analysis, and predictive maintenance.Initially, battery monitoring systems were primarily based on electrochemical and physics-based models. These methods estimated battery performance using mathematical equations related to internal resistance, discharge characteristics, and chemical reactions inside lithium-ion batteries. Although these approaches provided theoretical understanding of battery behavior, they required complex computations and extensive domain expertise. Moreover, physical-model-based systems often struggled to provide accurate real-time predictions under varying operating conditions such as fluctuating temperature, charging cycles, and dynamic load patterns.

To overcome the limitations of traditional approaches, researchers introduced data-driven Machine Learning techniques for battery health estimation. Statistical models such as linear regression, Support Vector Machines (SVM), Decision Trees, and Random Forest algorithms were applied to analyze battery parameters and predict degradation trends. These techniques improved prediction performance by learning relationships among battery features such as voltage, current, temperature, and charging cycles. Zhou et al. (2020) demonstrated that Random Forest regression models can effectively estimate battery State of Health (SOH) using historical battery data. Similarly, Hu et al. (2021) proposed machine learning-based online battery capacity estimation techniques that improved real-time monitoring accuracy.

Recent advancements in Deep Learning have significantly enhanced the performance of battery prediction systems. Deep learning models automatically learn complex temporal patterns from large-scale battery datasets without requiring manual feature engineering. Among various deep learning architectures, Long Short-Term Memory (LSTM) networks have emerged as one of the most effective methods for battery Remaining Useful Life (RUL) prediction. LSTM models are capable of learning long-term temporal dependencies from sequential battery data, making them highly suitable for time-series battery degradation analysis. Yang et al. (2022) demonstrated that LSTM-based frameworks provide higher prediction accuracy and better generalization capability compared to conventional machine learning approaches. Several studies have also explored hybrid and optimized deep learning models to further improve prediction performance. Optimization algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and attention mechanisms have been integrated with LSTM models to optimize hyperparameters, improve convergence speed, and reduce prediction error. Attention mechanisms enable the deep learning model to focus on important battery degradation features and significant temporal patterns, thereby improving prediction reliability and interpretability.

In addition to prediction accuracy, recent research has focused on real-time battery health monitoring systems capable of continuously analyzing live battery data from portable devices. IoT-enabled battery management frameworks and cloud-based monitoring systems have been proposed for remote battery analytics and predictive maintenance applications. These intelligent systems support adaptive learning by updating predictions dynamically based on new battery usage data.

Researchers have also investigated battery management applications for various domains, including electric vehicles, renewable energy storage systems, smartphones, laptops, and industrial electronics. However, many existing systems are designed specifically for either laptop batteries or mobile batteries and do not provide a unified framework capable of supporting multiple device types simultaneously. Furthermore, several existing approaches lack practical deployment mechanisms, real-time adaptability, and user-friendly visualization platforms.

Another major challenge identified in previous studies is the dependency on large training datasets and high computational resources. Deep learning models often require extensive training time and hardware acceleration, limiting their deployment on lightweight and portable systems. Additionally, some prediction models fail to maintain consistent performance under varying environmental and operational conditions.

The proposed research addresses these limitations by developing a unified Machine Learning-based battery health monitoring system capable of predicting both State of Health (SOH) and Remaining Useful Life (RUL) for laptops and mobile devices. The system integrates LSTM-based deep learning with PSO optimization and attention mechanisms to improve prediction accuracy, adaptability, and computational efficiency. Furthermore, the proposed framework is deployed on a web-based dashboard platform, enabling real-time battery analysis, visualization, and user-friendly monitoring.

Overall, the literature review indicates that deep learning-based approaches, particularly LSTM architectures combined with optimization techniques, provide superior performance for battery health prediction compared to traditional statistical and machine learning methods. These advancements highlight the growing potential of intelligent predictive maintenance systems in improving battery reliability, device performance, energy efficiency, and user experience in modern electronic applications.

Proposed Mythology

The proposed system follows a 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 consists of multiple stages including battery data collection, preprocessing, feature extraction, deep learning-based prediction, optimization, and visualization through an interactive web dashboard. The overall workflow is designed to provide accurate, scalable, and real-time battery health monitoring for modern electronic devices.

The first stage involves collecting real-time battery information from laptops and mobile devices. For laptop battery monitoring, battery reports are generated using operating system command-line tools that provide detailed information regarding battery behavior and performance. These reports contain parameters such as design capacity, full charge capacity, voltage levels, current flow, battery temperature, charging and discharging cycles, power consumption history, and usage statistics. The generated reports are stored in PDF or structured data formats and uploaded to the online platform for further analysis. The proposed framework is also designed to support mobile battery monitoring through USB-based integration and device-level APIs for future implementation. Using real battery reports improves system reliability and ensures practical applicability in real-world battery management scenarios.

After data collection, 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, duplicated values, and corrupted records, normalization to scale numerical battery parameters into a consistent range, missing value handling using interpolation and statistical methods, noise filtering to eliminate fluctuations and irrelevant patterns, and time-series structuring to organize sequential battery readings into formats suitable for deep learning models. These preprocessing operations improve model convergence, reduce prediction errors, and enhance overall system performance.

Following preprocessing, important battery-related features are extracted from the dataset to identify degradation patterns and operational behavior over time. Extracted features include voltage variation patterns, current fluctuations, temperature changes, charging cycle count, capacity degradation trends, energy consumption patterns, and charging-discharging behavior. These features provide meaningful insights into battery condition and enable accurate estimation of battery health and lifespan.

The core prediction process is performed using the Long Short-Term Memory (LSTM) deep learning model, which is specifically designed for sequential and time-series data analysis. The LSTM model learns long-term dependencies from historical battery usage data and predicts State of Health (SOH), Remaining Useful Life (RUL), battery degradation percentage, and overall battery performance status. The system continuously updates predictions dynamically based on new battery input data, enabling adaptive and real-time battery monitoring. Additionally, optimization techniques such as Particle Swarm Optimization (PSO) are integrated to improve prediction accuracy and reduce model error by optimizing hyperparameters including learning rate, neuron weights, hidden layer configuration, and batch size.

Simulation Result Analysis

The proposed Machine Learning-based Battery SOH and RUL Prediction System was successfully implemented and evaluated using real battery data collected through system-generated battery reports. The system was deployed on a web-based dashboard platform called "PowerInsight – Battery Health Analytics," which provides an interactive environment for battery monitoring and analysis. The experimental results demonstrate that the proposed framework effectively predicts battery State of Health (SOH) and Remaining Useful Life (RUL) with reliable accuracy and consistent performance.

During the analysis process, the system successfully extracted important battery parameters such as design capacity, full charge capacity, charging cycles, voltage levels, current flow, temperature, and battery usage history from uploaded battery reports. The preprocessing module efficiently cleaned and normalized the data, improving the quality of input provided to the prediction model. The Long Short-Term Memory (LSTM)-based deep learning model effectively learned battery degradation patterns from sequential battery data and generated accurate predictions regarding battery health and remaining lifespan.

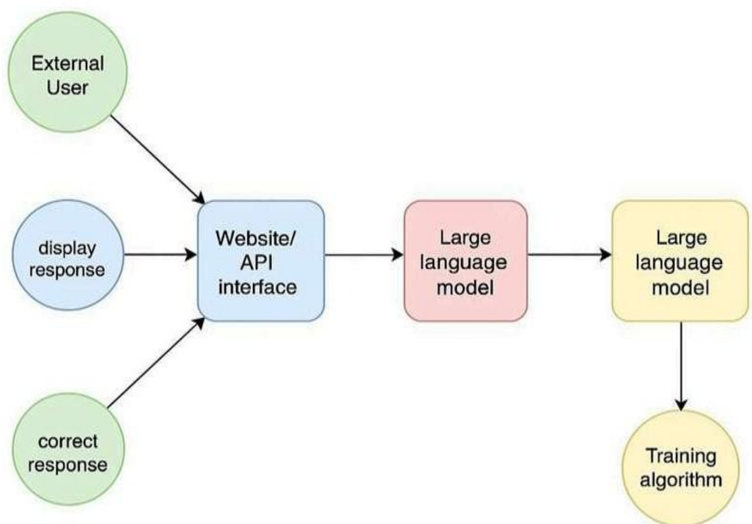

Fig. 1. *Flow Chart*

The simulation results showed that the system can accurately classify battery conditions into different performance categories such as "Excellent," "Good," and "Poor." For instance, batteries with health percentages above 90% and lower degradation rates were categorized as "Excellent," indicating stable battery performance and longer remaining life. In contrast, batteries with lower health percentages and higher degradation levels were identified as "Poor," indicating the need for maintenance or replacement. The prediction results were displayed through graphical dashboards and performance charts, enabling users to easily understand battery condition and degradation trends over time.

The integration of Particle Swarm Optimization (PSO) and attention mechanisms further improved prediction accuracy and model efficiency. PSO optimized important model parameters such as learning rate and weight initialization, while the attention mechanism helped the model focus on significant battery degradation features and temporal patterns. This combination enhanced model convergence speed and reduced prediction errors compared to conventional prediction approaches.

The proposed system also demonstrated strong real-time analysis capability. The dashboard continuously processed uploaded battery reports and generated immediate SOH and RUL predictions, making the framework suitable for predictive maintenance applications. The graphical visualization module provided users with detailed insights into battery degradation patterns, charging behavior, and overall battery performance. These visual analytics improve user understanding and support informed decision-making regarding battery usage and replacement.

Although the current implementation mainly focuses on laptop battery analysis, the framework has been designed to support future mobile battery integration through USB-based connectivity and real-time device communication. This extension will enhance the scalability and practical applicability of the system for broader electronic device monitoring.

Overall, the experimental and simulation results confirm that the proposed LSTM-based prediction system provides an efficient, accurate, and scalable solution for battery health monitoring and predictive maintenance. The combination of deep learning, optimization techniques, and real-time dashboard analytics significantly improves battery performance prediction and contributes toward intelligent battery management systems for modern electronic devices.

Conclusion

This research presents an intelligent Machine Learning-based system for predicting the State of Health (SOH) and Remaining Useful Life (RUL) of batteries used in laptops and mobile devices. The proposed framework successfully integrates real-time battery data analysis, deep learning techniques, optimization algorithms, and interactive visualization to provide an efficient and reliable battery health monitoring solution. By utilizing actual battery reports generated from operating system tools, the system offers a practical and scalable approach for real-world battery analysis and predictive maintenance applications.

The implementation of the Long Short-Term Memory (LSTM) deep learning model enables the system to effectively analyze time-series battery data and identify long-term degradation patterns. The integration of Particle Swarm Optimization (PSO) and attention mechanisms further improves prediction accuracy, convergence speed, and model performance by optimizing learning parameters and focusing on critical battery features. The proposed system successfully predicts battery health status, degradation levels, and remaining battery life while providing graphical visualization through an interactive dashboard interface.

The experimental results demonstrate that the proposed framework provides accurate and consistent SOH and RUL prediction, helping users better understand battery condition and make informed decisions regarding battery maintenance and replacement. The system effectively categorizes battery conditions into different performance levels such as “Excellent,” “Good,” and “Poor,” thereby improving usability and accessibility for non-technical users. Additionally, the web-based deployment enables real-time battery monitoring and supports scalable implementation for practical applications. The proposed system also contributes toward reducing unexpected battery failures, improving device reliability, enhancing energy efficiency, and extending battery lifespan. Compared to traditional battery monitoring approaches, the proposed data-driven framework provides improved adaptability, real-time analysis capability, and better prediction performance.

Despite achieving promising results, certain limitations still exist. The current implementation mainly focuses on laptop battery analysis, while mobile battery integration is under development. Furthermore, deep learning models require sufficient historical battery data and computational resources for effective training and prediction. Future work may focus on lightweight model optimization, cloud-based deployment, IoT-enabled battery monitoring, edge computing integration, and support for electric vehicle battery management systems.

Overall, the proposed research demonstrates the significant potential of Artificial Intelligence and deep learning technologies in modern battery management systems. The developed SOH and RUL prediction framework provides an intelligent, scalable, and user-friendly solution for predictive battery maintenance and contributes toward the development of smart energy management systems for next-generation electronic devices.

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