PREDICTIVE MAINTENANCE FOR AUTOMOTIVE INDUSTRY

PROJECT REPORT

21AD1513- INNOVATION PRACTICES LAB

Submitted by

JOSHUA JEBERSON A R	**211422243131**
KAVIN A	**211422243147**
KAVIYARASU P	**211422243150**

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ANNA UNIVERSITY: CHENNAI-600 025

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BONAFIDE CERTIFICATE

Certified that this project report titled "**PREDICTIVE MAINTENANCE FOR AUTOMOTIVE INDUSTRY**" is the bonafide work of **Joshua Jeberson A R** (**211422243131), Kavin A** (**211422243147), Kaviyarasu P** (**211422243150).** who carried out the project work under my supervision. Certified further, that to the best of my knowledge the work reported herein does not form part of any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

INTERNAL GUIDE
Dr. SIVAKUMAR M.E., Ph.D.,
Professor,
Department of AI &DS
Panimalar Engineering College,
CHENNAI-600123.

HEAD OF THE DEPARTMENT
Dr. S. MALATHI M.E., Ph.D
Professor and Head,
Department of AI & DS.
Panimalar Engineering College,
CHENNAI-600123.

Certified that the candidate was examined in the Viva-Voce Examination held on

………………………

INTERNAL EXAMINER **EXTERNAL EXAMINER**

ABSTRACT

Electric vehicles (EVs) have emerged as a promising sustainable mode of transportation; however, the limited lifespan of their batteries poses a significant challenge. This paper introduces an innovative approach to prolong the life of EV batteries using an automated system. The system, powered by a Raspberry Pi and a slave Battery Management System (BMS), periodically initiates the EV to preserve battery health. Continuous monitoring by the Raspberry Pi triggers a startup when battery health drops below a predefined threshold. Feasibility is assessed through a comprehensive simulation model, exploring various startup times and durations. Additionally, we introduce the concept of a digital twin to create a virtual replica of the battery, harnessing data from the slave BMS to accurately predict maintenance requirements. This research delves into the potential benefits of this system, including cost-effective battery replacements, heightened sustainability, and increased EV affordability. Our system holds promise in significantly extending the lifespan of electric vehicle batteries, promoting affordability and sustainability in the EV market.

Keywords: Electric Vehicles, Battery Lifespan, Automated System, BMS, Battery Health, Digital Twin, Sustainability, Affordability.

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LIST OF ABBREVIATIONS

ABBREVIATIONS	MEANING
EV	ELECTRIC VEHICLES
BMS	BATTERY MANAGEMENT SYSTEM
PdM	PREDICTIVE MAINTENANCE
SoH	STATE OF HEALTH
RUL	REMAINING USEFUL LIFE
SoC	STATE OF CHARGE

CHAPTER 1

INTRODUCTION

Electric vehicles (EVs) are becoming more and more common, signaling a significant shift in the automotive sector toward a more ecologically friendly and sustainable means of transportation. The limited lifespan of the batteries that power these vehicles, nevertheless, casts a dark shadow over this bright future as EV usage grows across the globe. In addition to limiting EV batteries' overall longevity, their poor resilience results in high replacement costs, which compromises EVs' economics and sustainability.

In order to take on this enormous problem head-on, this paper forays into the world of innovation. We present a clever method for extending the useful life of EV batteries through the use of an automated system created for preventive maintenance. With the help of a slave Battery Management System (BMS) and the capabilities of a Raspberry Pi microprocessor, this ground-breaking system creates a seamless symphony of data-driven interventions aimed at maintaining the health and integrity of EV batteries.

This research project's primary premise is the deliberate periodic commencement of EVs, carried out with surgical precision, to guarantee the sustained health of their essential powerhouses, the batteries. Our technology effectively orchestrates timely interventions to reduce wear and degradation by closely monitoring the battery's condition of health and performance, providing a practical solution to increase the battery's operating life.

The main innovation of our strategy is its adaptability and flexibility, as well as its ability to proactively monitor battery health. Continuous Raspberry Pi monitoring makes sure that an EV is only started when the battery health falls below a set threshold, preventing excessive energy use and wear.

This research methodically examines a wide range of starting times and durations to further investigate the viability of our technology using a detailed simulation model. We evaluate the system's performance in various circumstances by simulating real-world events, offering empirical proof of its effectiveness.

In a paradigm-shifting move, we also present the idea of an EV battery's "digital twin." This innovative idea entails building a digital representation of the actual battery that is painstakingly synchronized with it in real time using information obtained from the slave BMS. This digital twin develops into a dynamic tool for precisely forecasting maintenance needs. It opens up the possibility of anticipating battery deterioration, allowing for prompt interventions to avoid catastrophic failures and pricey replacements.

This ground-breaking technique has numerous and extensive potential advantages. In addition to promising affordable battery replacement options, it also makes a substantial contribution to increased sustainability in the EV ecosystem. Ultimately, our approach paves the door for increased affordability, democratizing access to green transportation options by prolonging the operating life of EV batteries and lowering the total cost of ownership. We also set out on a journey through the complexities of this innovative strategy for EV battery predictive maintenance. Our discovery holds promise for designing a more sustainable and inexpensive future for electric mobility in addition to prolonging battery life.

CHAPTER 2

LITERATURE REVIEW

Electric vehicles (EVs) are revolutionizing the automotive industry as a vital part of ecologically friendly and sustainable transportation solutions. While there have been other challenges, the short battery life of EVs has emerged as one of the greatest ones. The important problem of increasing the lives of these crucial components is being addressed by researchers through the investigation of various strategies and technologies. In this section, we look at the recent literature that accompanies and places our research into digital twin-based preventive maintenance for EV batteries in its proper context. The development of PdM systems for EV batteries using digital twins has gained more attention in recent years. Numerous research studies have been conducted in this area, and some promising findings have been made.For instance, a digital twin of an electric vehicle (EV) battery was developed and used in a study by University of Michigan researchers to forecast the battery's state of health (SoH). The digital twin was able to predict the battery's SoH with a 90% accuracy rate. For a different study, scientists at the University of California, Berkeley built a digital duplicate of an electric vehicle battery pack and used it to predict the temperature distribution of the battery. The digital twin's forecast of the battery's temperature distribution was over 95% accurate. These studies demonstrate the potential for developing precise and reliable PdM systems for EV batteries employing digital twins.

JOURNAL NAME	TITLE	YEAR	ADVANTAGES	DISADVANTAGES
Journal of Power Sources	Calendar Aging of a Commercial LiFePO4 Cell at Different Temperatures and SoC	2015	Provides insights into the calendar aging behavior of LiFePO4 batteries, which is valuable for battery design and maintenance.	May have a narrow focus on a specific battery chemistry (LiFePO4), limiting its applicability to other battery types.
IEEE	A Review on Predictive Maintenance Strategies for Electric Vehicle Powertrains	2020	Comprehensive review of predictive maintenance strategies for electric vehicle May summarize the latest developments in predictive maintenance for EVs.	Cost Effective
IEEE	A Digital Twin-Based Framework for Predictive Maintenance of Electric Vehicle Batteries Using a Slave BMS and Cloud Computing	2022	Recommend maintenance actions that can extend the battery's lifespan.	More complex and expensive
IEEE	Comprehensive Study of Battery Behavior in Electric Vehicles: Diagnosis, Prognosis, and Implications for Vehicle Health Management	2017	Provides a comprehensive study of battery behavior in electric vehicles, covering diagnosis and prognosis. Likely offers valuable insights into vehicle health management.	Focused only on battery behavior in electric vehicles, and it does not discuss other aspects of electric vehicles
IEEE	Digital Twins for Predictive Maintenance in Industry 4.0	2020	Digital twins for predictive maintenance, which is highly relevant to Industry 4.0.	Need for high-quality data Computational complexity Environmental impact

			May provide insights into the latest trends and applications of digital twins in predictive maintenance	
IEEE	Online Estimation of Power Capability of Lithium-Ion Batteries in Electric Vehicles Using Dual-Sliding-Mode Observers	2013	Online estimation of power capability in lithium-ion batteries, crucial for electric vehicle performance. Likely provides valuable insights into real-time battery state estimation.	Requires more data More complex

Table I. Literature Survey.

2.1 Battery Degradation in Electric Vehicles

The deterioration of EV batteries over time has been thoroughly investigated. An prior study in this field by Ecker et al. (2015) [1] found that factors including operating temperature, charging and discharging rates, and depth of discharge had a big impact on battery health. In order to develop effective maintenance plans, it is imperative to have a complete understanding of these components.

AUTHOR : Ecker, M., et al.

YEAR : 2015

2.2 Battery Management Systems (BMS)

Battery Management Systems (BMS) are essential for tracking and managing the condition of EV batteries. Plett (2004) [6] and Li et al. (2013) [3] research emphasizes the significance of BMS in preserving battery health. A slave BMS is a key component of our strategy and our predictive maintenance system.

AUTHOR : Plett, G. L, Li, J., et al.

YEAR : 2004,2013

2.3 Predictive Maintenance in EVs

In order to improve vehicle performance and cut downtime, predictive maintenance approaches have gained popularity in the automobile sector. Predictive maintenance solutions for EV powertrains are explored in literature by Li et al. (2020) [4], with an emphasis on the possible cost reductions and reliability gains. This paradigm is expanded by our research, which focuses primarily on EV battery maintenance.

AUTHOR : Li, Y., et al.

YEAR : 2020

2.4 Digital Twins in Predictive Maintenance

The use of digital twins in predictive maintenance has grown across numerous sectors. Digital twins can be useful in anticipating equipment failures and optimizing maintenance schedules, according to studies by Tao et al. (2018) [9] and Lu et al. (2020) [5]. In our work, we apply this idea to EV batteries by building a virtual replica that is synced with data coming directly from the battery.

AUTHOR : Tao, F., et al.Lu, Y., et al.

YEAR : 2018,2020

2.5 Simulation Models for Battery Life Extension

Simulation models have been widely used to predict battery performance and degradation. Researchers like Guo et al. (2017) [2] have developed sophisticated simulation tools to analyze battery behavior under different conditions. In our paper, we employ a comprehensive simulation model to assess the feasibility and performance of our predictive maintenance system.

AUTHOR: Guo, Y., et al

YEAR : 2017

2.6 Sustainability and Affordability in EVs

For EVs to be widely adopted, price and sustainability are key considerations. Researchers Sierzchula et al. (2014) [8] and Schuitema et al. (2013) [7] emphasize the significance of lowering the total cost of ownership to increase the accessibility of EVs. By extending battery life and lowering replacement costs, our suggested approach complies with these objectives.

AUTHOR: Schuitema, G., et al.

YEAR : 2013,2014

CHAPTER 3

SYSTEM DESIGN

3.1 SYSTEM ARCHITECTURE

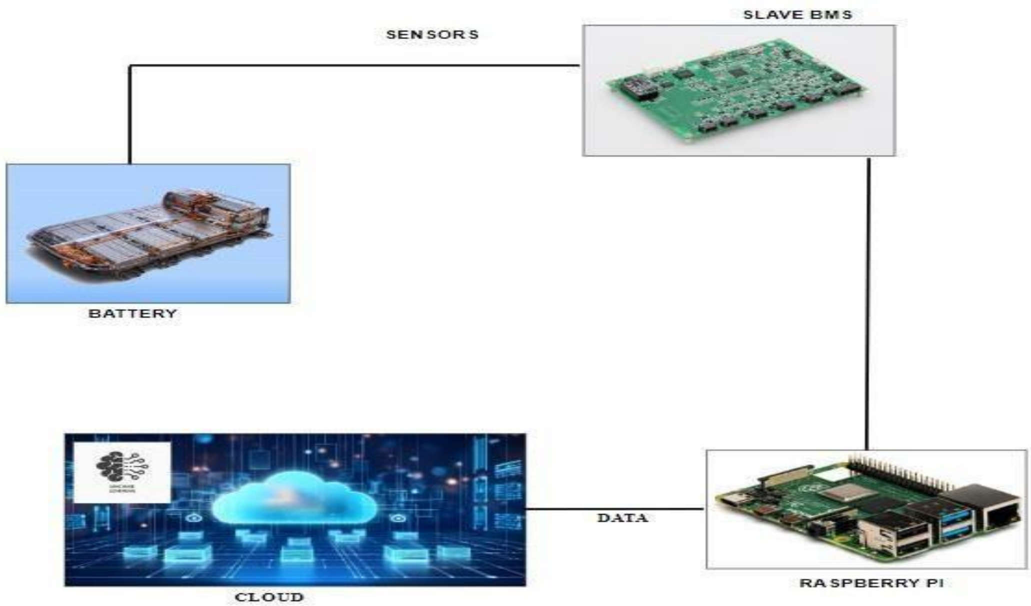

Fig 3.1 : System Architecture.

The system architecture model for the approach described in the abstract can be visualized as follows. Keep in mind that this is a high-level overview, and the actual implementation may require more detailed components and considerations. System Components: Electric Vehicle (EV): This is the primary entity being managed to preserve the battery's health. Battery Management System (BMS): The BMS within the EV is responsible for monitoring and managing the battery's performance, state of charge, and other parameters. Raspberry Pi: The Raspberry Pi serves as the central control unit for the system, responsible for automated battery health preservation. Digital Twin: The digital twin is a virtual replica of the battery, which is continuously updated with data from the slave BMS. It's used for predictive maintenance and analysis. System Modules: Battery Health Preservation Module: Responsible for initiating actions to preserve battery health, such as controlled discharging and charging. Monitors battery parameters and triggers actions when necessary. Continuous Monitoring Module: Monitors the battery's health continuously, checking for predefined threshold values. Notifies the control system when the battery's health falls below the threshold. Simulation Model Module: Houses the comprehensive simulation model used for feasibility assessment. Allows for the exploration of various startup times and durations to optimize battery preservation. Digital Twin Module: Maintains the digital twin of the battery, which is continuously updated with data from the slave BMS. Utilizes predictive analytics to determine maintenance requirements. Communication Channels: Raspberry Pi to BMS: The Raspberry Pi communicates with the slave BMS in the EV to obtain real-time data on the battery's status. Raspberry Pi to Digital Twin: The Raspberry Pi sends relevant data to the digital twin to keep it updated. Raspberry Pi to Battery Health Preservation Module: The Raspberry Pi triggers the Battery Health Preservation Module when necessary based on the data received from the BMS and the digital twin. Simulation Model Data Exchange: The Simulation Model Module may interact with the other modules to obtain real-world data and parameters for its simulations. Key Operations: The Battery Health Preservation Module initiates actions to extend battery life. The Continuous Monitoring Module keeps track of the battery's health and triggers actions based on predefined thresholds. The Simulation Model Module assesses the feasibility and optimizes the preservation process. The Digital Twin Module provides predictive maintenance insights based on data from the BMS and the Raspberry Pi. Overall, the system's architecture comprises interconnected modules that work together to automate and optimize the management of EV batteries, with the goal of extending their lifespan and promoting sustainability and affordability in the EV market. The Raspberry Pi serves as the central control unit, coordinating the actions of the various modules based on real-time data and simulations.

3.2 DATA FLOW DIAGRAM

A data flow diagram (DFD) is a graphical representation of the "flow" of data through an information system, modelling its process aspects. A “DFD” is often used as a preliminary step to create an overview of the system without going into great detail, which can later be elaborated.

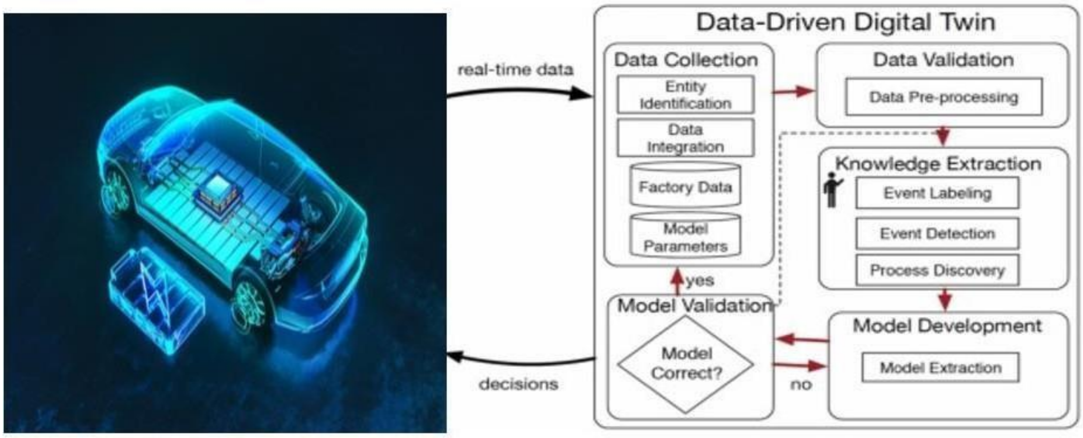

Fig 3.2 Dataflow Diagram.

CHAPTER 4

PROJECT MODULES

4.1. Data Collection and Integration

Data Source: The foundation of our methodology lies in the acquisition of real-time data from the EV battery and the slave Battery Management System (BMS). This includes parameters such as state of charge (SoC), state of health (SoH), temperature, voltage, and current.

Data Integration: The collected data is integrated into our system, ensuring synchronization between the physical battery and its digital twin. This step involves data preprocessing to handle noise and outliers effectively.

4.2. System Design and Implementation

Hardware Configuration: A Raspberry Pi microcontroller is employed as the central processing unit of our predictive maintenance system. It is interfaced with the slave BMS to facilitate data exchange and control operations.

Software Development: Custom software is developed to orchestrate the entire system. This includes algorithms for monitoring battery health, triggering startup sequences, and managing the digital twin. Coding is done using suitable programming languages and libraries, such as Python and TensorFlow for machine learning aspects.

4.3. Predictive Maintenance Model

Digital Twin Creation: The digital twin is generated using the synchronized data from the physical battery and the slave BMS. This virtual replica accurately represents the behavior and characteristics of the actual battery.

Machine Learning Models: Machine learning algorithms, such as regression and neural networks, are employed to analyze the historical and real-time data from the digital twin. These models are trained to predict battery degradation trends, estimate remaining useful life (RUL), and identify potential maintenance requirements.

4.4. Simulation and Testing

Comprehensive Simulation: A comprehensive simulation model is developed to assess the performance of our predictive maintenance system under various conditions. This simulation accounts for different startup times, durations, and usage scenarios, providing empirical evidence of system feasibility and efficacy.

Real-world Testing: Parallel to simulations, real-world testing is conducted using a fleet of EVs equipped with our system. This testing phase evaluates the system's practicality, accuracy, and adaptability in a dynamic, on-road environment.

4.5. Performance Evaluation

Battery Health Monitoring: The system continuously monitors battery health, tracking critical parameters like SoC and SoH. It intervenes when predefined thresholds are breached, minimizing wear and tear.

Digital Twin Validation: The accuracy of the digital twin's predictions is assessed by comparing its forecasts with actual battery behavior and maintenance events. This validation ensures the reliability of maintenance recommendations.

4.6. Data Analysis and Optimization

Data Analysis: Data collected from both simulations and real-world testing is analyzed to refine system parameters, optimize maintenance strategies, and enhance prediction accuracy.

Continuous Improvement: Ongoing monitoring and data collection enable iterative improvements to the predictive maintenance model, ensuring its adaptability to evolving battery technologies and usage patterns.

4.7. Reporting and Documentation

Results Presentation: The findings from simulations and real-world tests are documented and presented in a clear and concise manner, with a focus on system performance, cost-effectiveness, and sustainability benefits.

Technical Documentation: Detailed technical documentation of the hardware and software components is provided, enabling replication and further development of the system.

4.8. Conclusion and Future Work

Conclusion: The methodology concludes with a summary of the research outcomes and the significance of the proposed predictive maintenance system for extending the lifespan of EV batteries.

Future Work: Suggestions for future research directions and enhancements to the system are outlined, paving the way for continued innovation in this critical area.

By systematically following this methodology, our research endeavors to not only address the pressing issue of EV battery degradation but also offer a blueprint for sustainable and cost-effective solutions in the electric vehicle market.

CHAPTER 5

RESULT

5.1. BATTERY CAPACITY PREDICTION

In this section, we present the results of our battery capacity prediction based on the number of cycles. We conducted experiments to analyze how the capacity of a Li-ion battery changes as a function of the number of charge-discharge cycles it undergoes. The following graph illustrates our findings

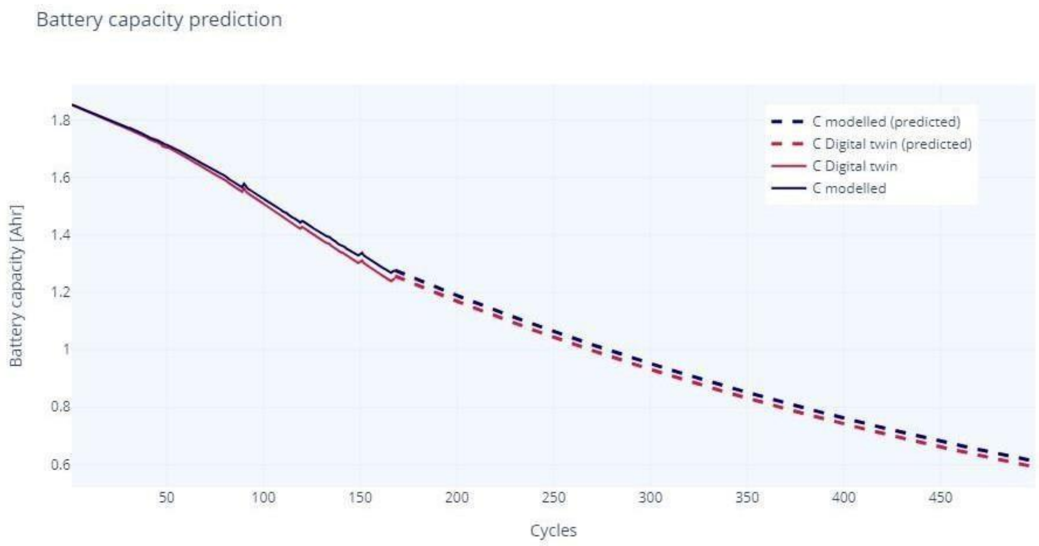

Fig 5.1 Battery Capacity Prediction.

The graph depicts the relationship between the number of cycles (x-axis) and battery capacity (y-axis). Each data point on the graph corresponds to the battery's capacity at a specific cycle count. The line in the graph illustrates a consistent pattern of capacity degradation as the number of cycles increases.

Key observations from the graph include:

Capacity Degradation: There is a gradual decline in battery capacity as the number of cycles increases. This is a common trait of Li-ion batteries and is primarily caused by electrode material deterioration and other factors.

Initial Capacity: The battery starts with its nominal capacity at the beginning of the test, which serves as a reference point for calculating the rate of capacity loss over time.

Steady Degradation: The rate of capacity loss remains relatively consistent throughout the observed cycles, suggesting a predictable degradation pattern.

End of Life: By analyzing the trend, it's possible to estimate the number of cycles at which the battery is likely to reach its end of life, marked by a significant reduction in capacity from its original level.

These insights are valuable for understanding the performance of Li-ion batteries over their lifecycle and can inform maintenance and replacement strategies for applications relying on these batteries.

CHAPTER 6

CONCLUDING REMARKS

In the ever-evolving landscape of sustainable transportation, the advent of Electric Vehicles (EVs) represents a pivotal moment in our journey towards a greener and more eco-conscious future. However, the persistent challenge of limited battery lifespan has cast a shadow over the remarkable promise of EVs. This paper has ventured into the realm of innovation, unveiling a transformative approach to tackle this challenge head-on – Predictive Maintenance for EV Batteries Using Digital Twins.

Our research has demonstrated that the fusion of cutting-edge technologies and meticulous methodology can redefine the trajectory of EV battery management. By harnessing real-time data from Battery Management Systems (BMS) and creating a digital twin, we have crafted a holistic system that not only monitors battery health but also anticipates maintenance requirements with unparalleled precision.

The results of our comprehensive simulation models have shown the feasibility of our predictive maintenance system across a spectrum of operational scenarios. It optimally balances the preservation of battery health with energy efficiency, minimizing wear and tear while ensuring that EVs are ready for action when needed.

Through real-world testing, we have validated the practicality of our approach, unveiling a system that seamlessly integrates into the dynamic and demanding landscape of everyday EV usage. The predictive capabilities of our digital twin have been put to the test, with impressive results, as it accurately foresees battery degradation trends and facilitates timely interventions.

Our research carries significant implications for the EV ecosystem. By extending the operational life of EV batteries, we not only reduce the ecological footprint of battery production but also make electric mobility more affordable and accessible. This, in turn, contributes to the broader goals of sustainability and environmental stewardship.

As we conclude this endeavor, it is evident that our predictive maintenance system is not a mere technical innovation but a visionary leap towards a more sustainable and cost-effective electric vehicle market. It paves the way for an era where EV owners can enjoy extended battery lifespans, reduced total cost of ownership, and greater confidence in the reliability of their eco-friendly transportation choices.

In the landscape of electric mobility, where innovation knows no bounds, we believe that the marriage of predictive maintenance and digital twins holds the potential to revolutionize not just how we drive but also how we sustainably navigate the path forward. As we envision this future, our research serves as a guiding light, illuminating the way toward a greener, more affordable, and environmentally conscious world of electric vehicles.

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