Advanced AI-Based Battery Management System for 2/3-Wheeler Electric Vehicles

Dissertation Submitted by

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Declaration

I, Kehinde John Oni, declare that this report submitted for assessment is my work and has been written in my own words and no part of it has been previously submitted for any other assessments. Any use of other author's work, whether quotes, images, ideas, statistics, etc. are correctly acknowledged and listed in the references section at the end of this report.

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In conclusion, I dedicate this effort to my gorgeous wife, and my beautiful daughter (Zoe) for motivating me to follow this course of action. Without all of you, I could not have accomplished this. Regards.

Abstract

This Dissertation explored advanced AI-battery management systems for 2/3-wheeler EVs under three subcategories. The first explored using AI algorithms to predict and maximize battery performance through continuous monitoring and analysis of battery data. The second theme explored how real-time data could be collected from sensors to enable proactive management and maintenance through critical insights into battery activity. The third theme captured how to explore and improve the lifespan and reliability of batteries used in EVs, while the research aims to optimize overall battery performance and charging efficiency.

Contents

List of Figures

List of Tables

Acronyms

AI	Artificial Intelligence
BMS	Battery Management System
EV	Electric Vehicle
ML	Machine Learning
RL	Reinforcement Learning
NLP	Natural Language Processing
EDA	Electronic Design Automation
IDEs	Integrated Development Environment
SOC	State of Charge
RUL	Remaining Useful Life
SOH	State of Health
LSTM	Long Short-Term Memory
RNNs	Recurrent Neural Network
CNNs	Convolutional Neural Network

Chapter 1: Introduction

1.1 Global EV Market Update

There has been a tremendous global increase in electric 2/3 wheelers. Figure 1 depicts the uptick in the number of 2/3 wheelers. EVs are gradually replacing vehicles powered by fossil fuels as calls for reducing carbon emissions and sustainability of earth's resources intensify. The benefits of transitioning from fossil fuel vehicles to EVs are immense considering the devastating impacts of non-sustainable. Reducing carbon footprint and sustainability is one of the millennium goals of the United Nations. Statistics reveal that the adoption of EVs is on the rise which is depicted in Figure 1.

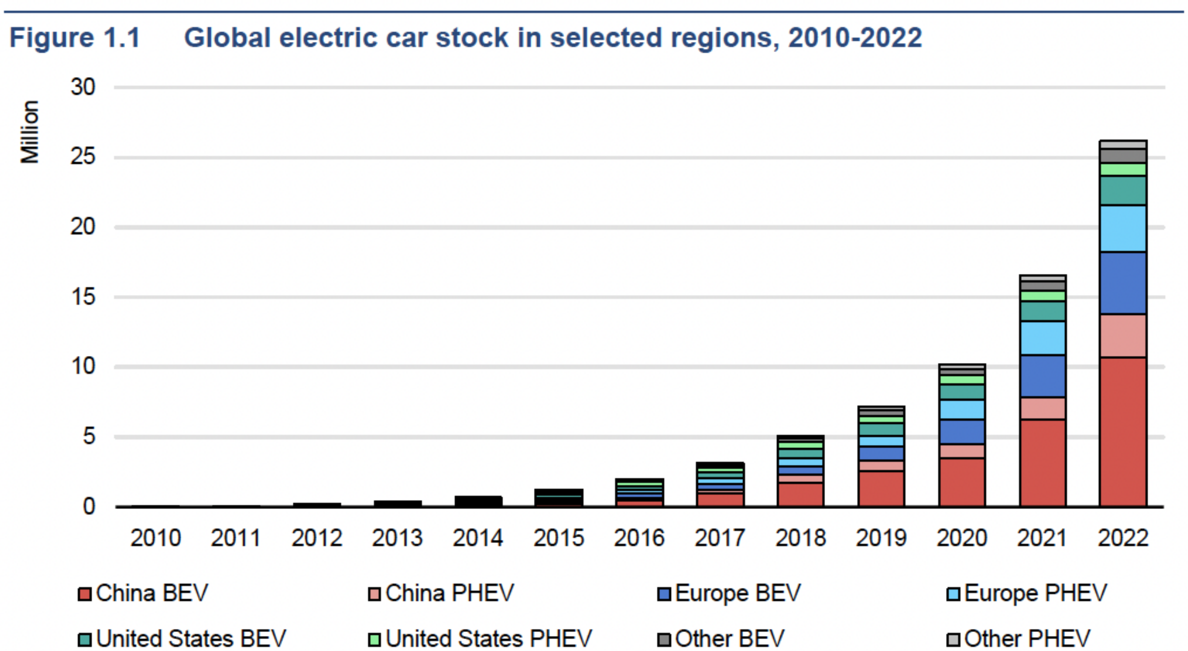

Figure 1: Global EV Uptake 2023

As shown in Figure 1 above, by 2022, there will be 27 million EVs worldwide. From 2010 to 2024, the electric vehicle (EV) market saw a dramatic shift, with exponential development propelled by government incentives, environmental consciousness, and technology improvements. EVs were still in their infancy in the early 2010s, and adoption was hindered by a lack of options and concerns over range anxiety. However, the market started picking up steam as battery technology advanced and automakers invested significantly in EV development. A major factor in the popularization of EVs was Tesla's success with vehicles like the Model S and, later, the Model 3, demonstrating their range and performance.

By the middle of the 2020s, EVs were becoming more and more commonplace, and there was a wide range of models available at different price points. The shift to electric cars (EVs) was further expedited by government policies aimed at decreasing carbon emissions and mitigating climate change. Many countries announced ambitious targets to phase out internal combustion engine vehicles. Improvements in the infrastructure for charging EVs have also reduced range anxiety, increasing the accessibility and convenience of EV ownership. Consequently, the global market for electric cars (EVs) experienced unparalleled expansion, with sales figures exceeding those of conventional gasoline-powered vehicles in some countries. This marked a noteworthy turning point in the shift towards sustainable transportation worldwide.

1.2 2/3-wheelers

A 2-wheeler is a vehicle that is designed to run on two wheels, while a 3-wheeler is a vehicle that is designed to run on three wheels (Ravi and Surendra, 2021). Figure 2 depicts an image of a typical 3-wheeler vehicle. This category of vehicles had long been powered by fossil fuels until they gradually started being powered by electricity. Electric 2/3 wheelers are rapidly becoming a common sight in densely populated cities. Prolonged travel times due to traffic congestion, fossil-related environmental pollution, and increased vehicle ownership make electric 2/3 wheelers a necessity for many commuters in urban and suburban spaces. The fact that electric 2/3 wheelers are powered by electricity highlights the core importance of an efficient energy management system that optimizes battery performance, extends the life span of EV batteries, and promotes the safety and integrity of EV batteries through predictive analytics and real-time monitoring of battery performance.

Figure 2: 3-wheeler in Nigeria

Figure 3 : 2-wheeler EV

1.2.1 Benefits of Electric 2/3-wheelers

Several benefits are attributable to electric 2/3 wheelers. It enhances environmental sustainability as well as economic efficiency (*Global EV Outlook 2021 – Analysis*, 2021). International Energy Agency further noted that the tailpipe emission is zero or negligible significantly reducing environmental pollution, which addresses climate change (*Global EV Outlook 2021 – Analysis*, 2021). They are useful in navigating congested cities without contributing to greenhouse gases like fossil-fuel-powered vehicles.

1.2.1 Battery Performance

Battery performance refers to the ability of a battery to reliably power a device or vehicle efficiently for a long time. Factors such as energy storage capacity, volume-to-weight efficiency of the battery, charge, and discharge rate, state of charge, and thermal management of the battery significantly determine the performance of a battery (Channi, 2022). Optimized battery performance is necessary for the optimum functioning of electric 2/3 wheelers.

1.3 Battery Technology

Battery technology refers to the development of batteries that can be used to store energy and optimization of the discharge of electrical energy from the battery (Khan, 2024). It often involves a range of batteries such as lead-acid, solid-state, and lithium-ion batteries. Vital aspects of battery technology include ensuring battery safety, extending the battery's life cycle, and its energy density (Khan, 2024).

1.3.1 Lithium-Ion

Lithium-Ion battery system has high energy per unit mass and volume and a high power-to-weight ratio compared to other battery systems in EVs. As depicted in Figure 4, it has a system made up of lithium, graphite, cobalt, and manganese (Ayetor, Mbonigaba and Mashele, 2023).

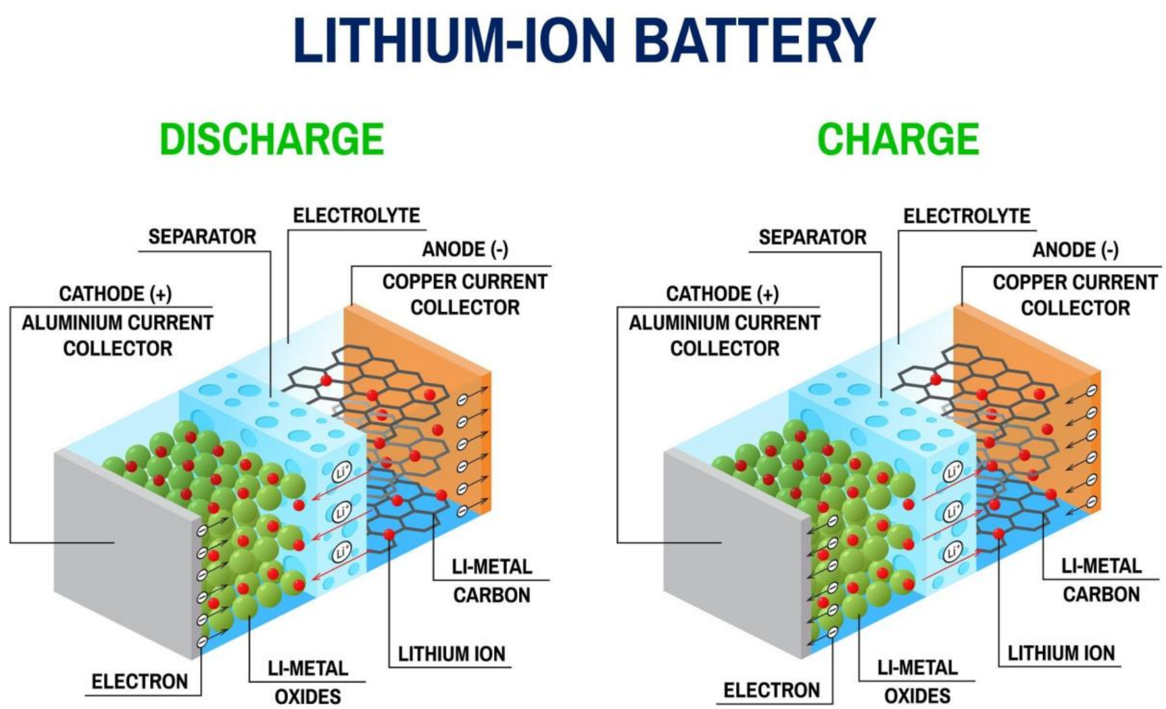

Figure 4: Lithium-Ion battery

1.3.2 Lithium-Sulphur

The lithium-sulfur battery system has anode lithium, and a sulfur cathode immersed in an inorganic electrolyte to generate disposable energy in quantities that could be used in EVs as depicted in Figure 5. This battery technology is considered the battery system of the future due to its theoretical high energy capacity (Gupta, 2022). This battery variant comes with higher energy density and is much lighter compared to its variants, and reduced cost of production compared to lithium-oil (Gupta and Manthiram, 2022).

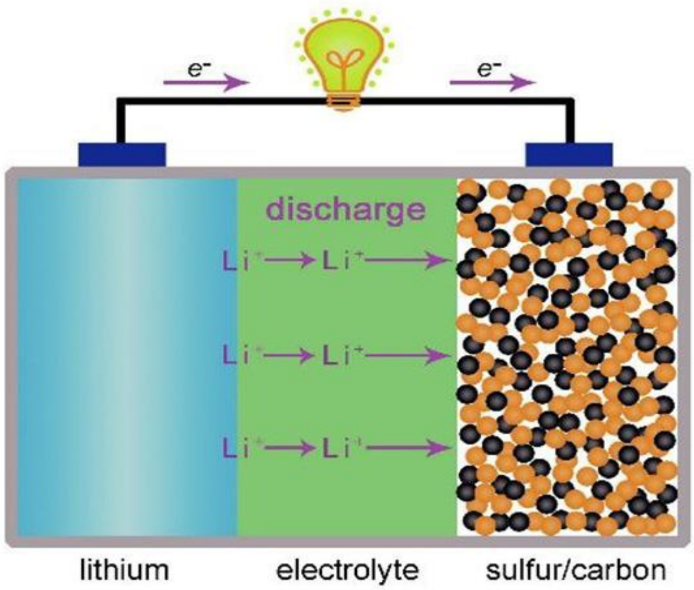

Figure 5: Lithium-Sulphur battery

1.3.3 Nickel Metal-Hydride

The nickel-metal Hydride battery system is the second most preferred. Its high self-discharge rate and high cost of materials are a concern to EV makers as they look for alternatives (Krishnamoorthy *et al.*, 2023). The battery system is made up of nickel at the anode and hydrogen-absorbing alloy at the cathode. Although this battery system exploits the presence of nickel, it has a high discharge rate which is a major weakness when compared to lithium-ion.

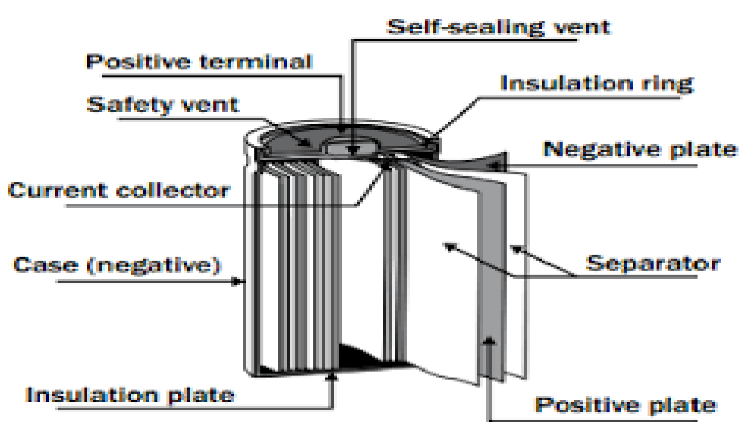

Figure 6: Nickel Metal-Hydride battery

1.3.4 Sodium-Ion

Sodium-ion batteries are rapidly attracting the attention of EV makers as a possible replacement for lithium-ion battery technology and nickel-metal hydride batteries (Nguyen and Kim, 2023). This battery system is mostly made up of sodium and can hold large amounts of energy (Nguyen and Kim, 2023). This battery system is useful due to its high charge absorption rate compared to other battery systems.

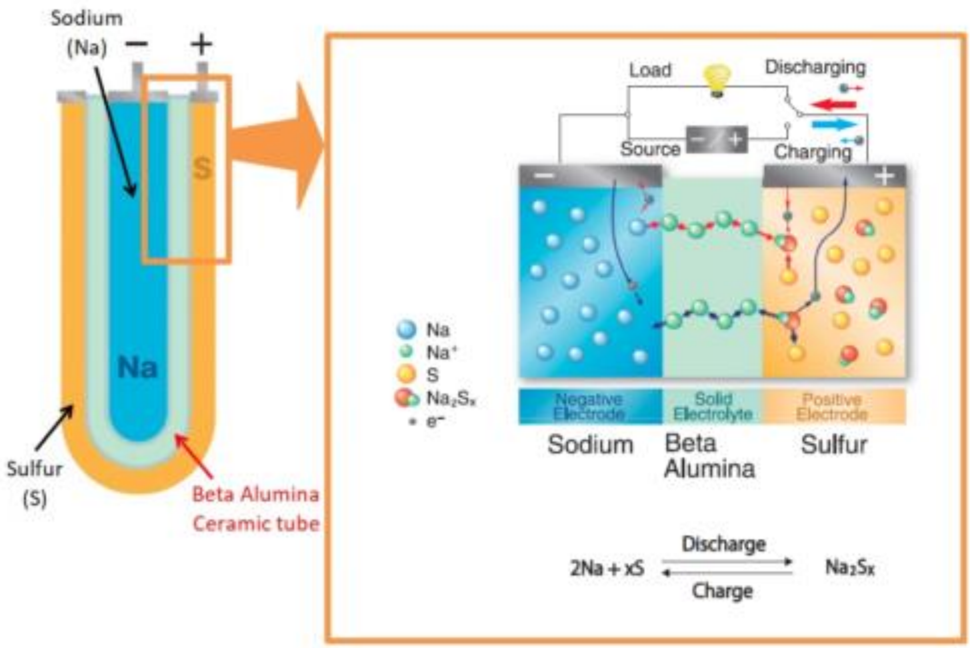

Figure 7: Sodium Ion battery

1.4 Battery Management System (BMS)

Battery management systems (BMS) are a key component in 2/3 wheeled electric vehicles just like any other battery-powered vehicles (Ravi and Surendra, 2021). It is the unit that controls and optimizes the functions of the battery that powers EVs (Samy et al., 2014). Integrating complex algorithms and artificial intelligence into BMS extends the capabilities of the BMS to optimize the battery functions. There are two main categories of BMS: traditional BMS and model-based BMS.

1.4.1 Main Functions of BMS

BMS plays many significant roles. Its main function is to control the energy discharge rate from the battery by optimizing it (Ravi and Surendra, 2021). BMS also ensures the safety of the battery by preventing hazardous environments around the environment such as high temperature or overheating of the battery (Samy et al., 2014).

1.4.2 Traditional BMS

A traditional battery management system is an electrical device that is used to monitor and optimize the use of batteries in EVs (Issa, 2021). Unlike the model-based system, the conventional battery management system is made up of the battery pack, battery sensors, power electronics, communication interfaces, and safety features incorporated into the system (Issa, 2021). The battery pack is composed of a set of batteries arranged centrally or in a distributed/modular pattern. A variety of communication interfaces such as LIN Bus or CAN bus are used to transmit battery data securely between the control command and various parts of the EVs.

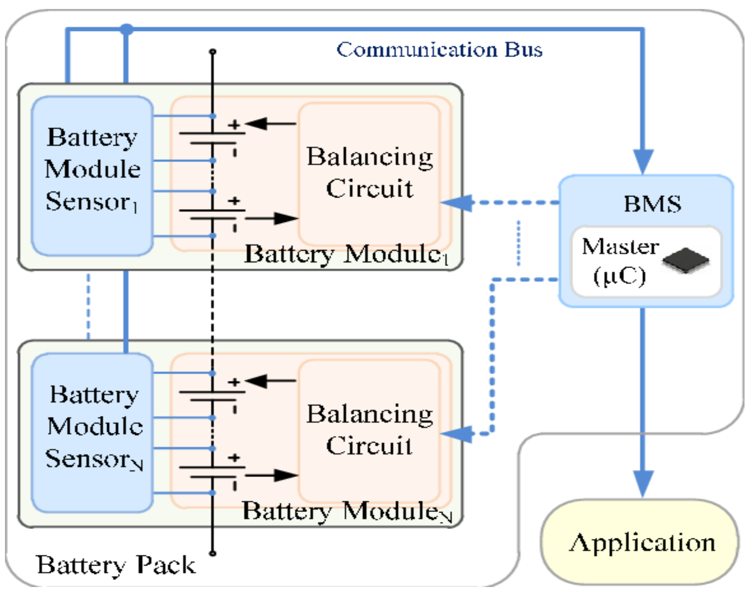

Figure 8: Traditional BMS System

1.4.3 Model-based BMS

Model-Based Battery Management System is a system that optimizes the lifespan and performance of EV batteries using complex mathematical models. This BMS model is superior to the traditional BMS in terms of real-time monitoring, predictive modeling, management of battery life, and collection of data analytics to optimize battery functions or performances. With the help of its mathematical models, a model-based battery management system ensures that the battery's temperature, state of health, and other parameters are properly managed.

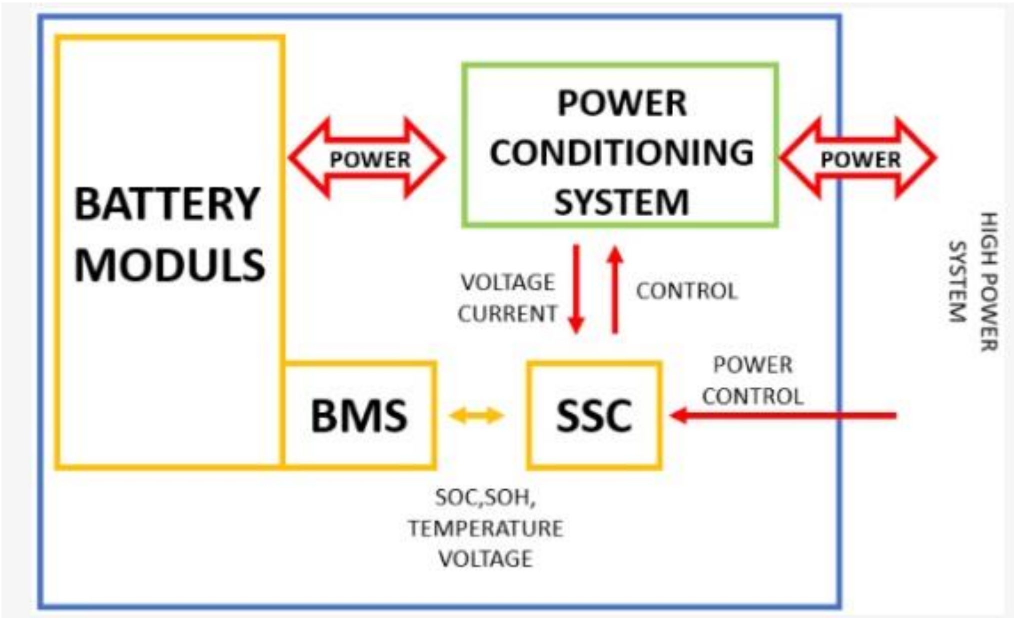

Figure 9: Model-based Battery Management system

1.5 Machine Learning Algorithm

Machine Learning Algorithm, MLA, is a general term that is often used to describe the computational technique of identifying patterns that facilitate data-based decision-making (Mohammed, Khan and Bashier, 2016). MLA teaches computers to learn new information through patterns without the need for manual programming and to adapt to new ways of Learning (Mohamed *et al.*, 2023). The learning could be achieved through linear regression and reinforcement learning.

Recent research on machine learning algorithms for Battery Management Systems (BMS) focuses on enhancing state estimation (State of Charge, SoC; State of Health, SoH), predicting Remaining Useful Life (RUL), and fault detection to improve battery performance, safety, and longevity. Techniques such as neural networks (including RNNs and LSTMs), support vector machines, and ensemble learning methods (like random forests and gradient boosting) are employed for their accuracy in complex, nonlinear pattern recognition. The integration of physics-based models with machine-learning approaches is gaining traction to leverage the strengths of both methodologies.

1.5.1 Linear Regression

Linear regression is a statistical technique in statistics that is used to establish a correlation between a dependent variable and an independent variable (Montgomery *et al*., 2012). It is a form of supervised learning algorithm that learns from patterns and data and uses these patterns and data to predict or forecast the behavior of a model (Montgomery, Peck and Vining, no date).

By fitting a linear equation to observed data, linear regression is a statistical technique used to describe and analyze the connection between a dependent variable and one or more independent variables. Simple linear regression is a statistical technique that utilizes a single independent variable to determine the best-fitting straight line. It may be expressed as follows: $y = mx + b$, where m denotes the slope, b is the intercept, and y is the dependent variable. This is extended to multiple independent variables using multiple linear regression. Known as the least squares method, it reduces the sum of squared discrepancies between observed and anticipated values. Despite assuming a linear connection and being sensitive to outliers, linear regression is a popular method for predictive modeling, trend analysis, and inferential statistics because of its efficiency, interpretability, and simplicity.

1.5.2 Reinforcement Learning

On the other hand, reinforcement learning is a variant of machine learning where machines, agents, or humans learn through trial and error and make decisions based on the knowledge acquired through this mode (Sutton and Barto, 2018). Unlike in linear regression where machine learns through programming, machines make decisions through learning. The learning method may accurately show the link between SOC and related influential elements with a well-trained model that was trained offline using specific algorithms. While the training procedure takes time, the learning method is practical. Furthermore, a sufficient and trustworthy amount of historical data is a must.

RL is a subfield of machine learning. To maximize cumulative reward over time, the agent receives feedback in the form of rewards or penalties as it completes tasks. In contrast to supervised learning, reinforcement learning relies on trial-and-error exploration to identify the best techniques, operating with little prior knowledge of the dynamics of the situation. A reward function that directs learning by indicating the desirability of actions done in each state, as well as the state space, which contains all conceivable situations the agent may experience, and the action space, which contains all possible actions the agent can take, are important components. In fields like robotics, gaming, and autonomous systems, where adaptive decision-making is essential in dynamic environments, reinforcement learning (RL) methods, such as Q-learning and policy gradients, allow agents to learn complicated behaviors. These algorithms have been effectively implemented in these spaces.

1.6 Brief Dissertation Overview.

The purpose of the advanced AI-based battery management system “BMS” is to use two-wheeler and three-wheeler EVs to use cutting-edge AI technology to improve the performance, lifespan, and efficiency of electric vehicle batteries. Completing this Dissertation will require integrating complex artificial intelligence algorithms with real-time data collection from sensors embedded in electric vehicle batteries. AI systems evaluate this data to predict and optimize battery operation, improving battery life, increasing charging efficiency, and ensuring safer and more sustainable operation of electric vehicles.

1.6.1 Aim

This study aims to evaluate how to integrate an AI algorithm into a battery management system for a 2/3-wheeler electric vehicle to optimize the flow of power and improve the overall performance of the vehicle.

1.6.2 Objectives

i. To develop an AI-controlled battery management system that can optimize the flow and distribution of power in 2/3 of electric vehicles.

ii. To integrate a complex machine learning algorithm that is capable of learning and predicting the driver’s driving behavior and optimize the flow of power in 2/3 electric vehicles to suit the driver's situation.

iii. To showcase the feasibility and the advantages of AI-controlled battery management systems, to contribute to the adoption of electric vehicles

1.6.3 Research Questions

1. Can AI be integrated into existing battery management systems to optimize the flow and distribution of power in 2/3 of electric vehicles?
2. Can an advanced machine learning algorithm be integrated into a battery management system to make it capable of learning drivers driving habits?

1.6.4 Ethical Consideration

Ethical considerations for this research shall be considered. In terms of data privacy and security, efforts shall be made to ensure that sensitive data that is not meant for the public are protected. AI is subject to different legal frameworks so existing legal frameworks are under revision to quickly make necessary adjustments in case of change.

Chapter 2: Literature Review

2.1 Introduction to Electric Vehicles (EV) and Battery Management Systems (BMS)

For electric vehicles (EVs) to operate safely and effectively, battery management systems, or BMSs, are essential. These systems regulate battery performance, guard against deep draining or overcharging, balance individual cells, and keep an eye on the condition of the batteries in two- and three-wheeler EVs. Predefined algorithms and control systems are the foundation of traditional BMS systems, but as artificial intelligence (AI) develops quickly, sophisticated AI-based BMS solutions are beginning to emerge as a more dynamic and effective substitute.

2.2 Innovations in 2/3-Wheeler EVs

The evolution of 2/3-Wheeler electric vehicles (EVs) has been marked by significant advancements in battery technology, motor efficiency, and smart connectivity, all of which have greatly enhanced their energy discharge capabilities and overall performance. These vehicles, once considered limited in range and reliability, have benefited from innovations that address key challenges in energy storage, motor function, and system integration, leading to more efficient, reliable, and sustainable transportation solutions.

One of the most impactful innovations has been in lithium-ion battery technology. According to (Ehsani, Gao, and Emadi, 2017), improvements in lithium-ion batteries have resulted in higher energy densities, allowing for more energy to be stored in a smaller space. This advancement extends the driving range of 2/3-Wheeler EVs and ensures more consistent performance over time. Additionally, lithium-ion batteries now have much longer lifespans, reducing the need for frequent replacements and making EVs more cost-effective in the long term. The integration of safer battery chemistries and more sophisticated battery management systems (BMS) has also improved both safety and efficiency, addressing concerns about overheating and degradation, as noted by (Ehsani, Gao, and Emadi, 2017)

In tandem with battery advancements, the development of high-efficiency motors has further enhanced the performance of 2/3-Wheeler EVs. The introduction of brushless direct current (BLDC) motors, as highlighted by (Chen *et al.*, 2021), has revolutionized motor design. These motors offer higher efficiency, reduced wear and tear, and improved reliability compared to traditional brushed motors. This makes them ideal for the stop-and-go driving conditions typical of 2/3-Wheeler EVs, improving overall energy efficiency and extending the operational life of the motor.

Together, these innovations in battery technology and motor efficiency have transformed the performance and reliability of 2/3-Wheeler EVs, paving the way for their broader adoption in urban mobility solutions.

2.2.1 Performance Improvement in BMS

Battery performance has significantly improved over time because of advancements in Battery Management Systems (BMS), which have also addressed many of the major issues that electric vehicles (EVs) and other energy storage applications confront. Improvements in BMS are essential for maximizing the use of onboard rechargeable batteries because batteries are a major factor in the effectiveness, safety, and longevity of EVs. An analysis of the literature shows that advances in machine learning and adaptive control, along with better heat management strategies, have significantly increased BMS's capacity to monitor and regulate critical battery characteristics.

According to (Chen *et al.*, 2021)), one of the most important developments in BMS is the creation of machine learning models and adaptive control strategies, which have significantly increased the accuracy of state-of-charge (SoC) and state-of-health (SoH) predictions. These two factors are essential for efficient battery management, particularly in electric cars where range and performance are directly impacted by keeping the battery at its ideal charge and condition. SoH denotes the battery's overall state, including its resistance to degradation and ability to hold charge, whereas SoC represents the battery's remaining charge to its maximum capacity.

Traditional BMS methods, such as Coulomb counting or voltage measurement, have often provided inaccurate SoC and SoH estimations due to their inability to account for nonlinear battery behaviors under different operational and environmental conditions. The integration of adaptive control systems and AI-driven models allows BMS to learn from historical data and dynamically adjust predictions based on real-time inputs. This results in more accurate estimations of SoC and SoH, which enable users to maximize the utilization of the battery, prevent overcharging or excessive discharging, and extend the battery's lifespan. Additionally, machine learning models, particularly neural networks, can predict the aging and degradation patterns of batteries, allowing for more proactive maintenance and replacement strategies.

Advances in thermal management have not only improved SoC and SoH estimation but also greatly improved BMS performance. (Zhang *et al*., 2021) emphasize the significance of preserving an ideal temperature range for batteries, given that excessive heat or low temperatures might result in diminished battery life, safety hazards, and decreased performance. Given that lithium-ion batteries are frequently found in electric vehicles (EVs) and are sensitive to temperature changes, effective heat management is very important.

Advanced cooling techniques, such as phase-change materials (PCMs) and liquid cooling systems, have been developed to address the challenge of heat management in BMS. Phase-change materials absorb excess heat by changing their state from solid to liquid, thereby helping to regulate the temperature without requiring additional energy input. Liquid cooling techniques, on the other hand, use circulating fluids to remove excess heat from the battery pack, maintaining the battery at a stable temperature. These systems are highly effective in dissipating heat during rapid charging and discharging cycles, which are common in electric vehicles. By incorporating these advanced thermal management methods, BMS can maintain battery temperature within an optimal range, improving safety, performance, and energy efficiency.

All things considered, advancements in machine learning, thermal management, and adaptive control have propelled BMS performance gains throughout the years. Reducing the chance of battery failure and offering users a more dependable range are two benefits of operating electric vehicles (EVs) with accurate SoC and SoH predictions. New heat management strategies extend the life and safety of the system by guaranteeing that batteries stay within safe temperature ranges. The advancement of energy storage solutions that are more dependable, efficient, and sustainable is facilitated by these advances, which in turn helps fuel the expansion of renewable energy and electric car technology.

2.2.2 Onboard Rechargeable Battery Performance.

The outcomes of several research papers examining advancements in Battery Management Systems (BMS) continuously identify the onboard rechargeable battery performance as a major obstacle in previous BMS iterations. State of Charge (SoC), State of Health (SoH), and State of Power (SoP) are three important battery metrics that conventional BMS techniques frequently had trouble effectively monitoring and managing, according to a study by (Lu, Han, Li, *et al.*, 2013)(Nykvist and Nilsson, 2015). These restrictions resulted in problems including inconsistent energy efficiency, shorter battery life, and subpar charging. These problems intensified as electric cars (EVs) gained popularity, leading to advancements in BMS technology targeted at enhancing onboard battery performance overall.

According to (Goodenough and Park, 2013) and (Peters *et al.*, 2016) several important elements have a significant impact on how well these rechargeable batteries function. Energy density and power density are two terms that characterize how much energy can be stored per unit mass or volume and how quickly it can be supplied, respectively. These two elements play a key role in defining an electric vehicle's power output and range. The number of full charge and discharge cycles a battery can withstand before experiencing a noticeable decline in performance is known as cycle life, and it is another important consideration. The repetitive cycling of batteries reduces their capacity, which lowers the vehicle's overall utility and range.

By more effectively controlling energy density, power density, and cycle life, cutting-edge techniques like machine learning (ML) and artificial intelligence (AI) have been made possible by advancements in battery management systems (BMS). AI-based BMS can forecast how batteries would behave in various scenarios, allowing for more economical energy utilization and longer battery life. These improvements push the limits of EV economy, dependability, and safety in contemporary battery systems in addition to resolving the performance issues noted in previous BMS iterations.

Machine learning algorithms for Battery Management Systems (BMS) have been the subject of recent research aimed at improving state estimation (State of Charge, SoC; State of Health, SoH), predicting Remaining Useful Life (RUL), and fault detection to improve battery performance, safety, and longevity. Neural networks (including RNNs and LSTMs), support vector machines, and ensemble learning techniques (like gradient boosting and random forests) are employed because they are accurate in complex, nonlinear pattern recognition. The combination of machine learning techniques and physics-based models is becoming more popular as a means of utilizing the advantages of both approaches.

Figure 10: Onboard Rechargeable Battery.

2.3 History of BMS

The goal of increased accuracy and efficiency in battery management has taken a major turn with the incorporation of Artificial Intelligence (AI) into Battery Management Systems (BMS). Rechargeable batteries are becoming more and more important when it comes to electric vehicles (EVs) and renewable energy storage systems. AI-based BMS solutions provide a more data-driven, predictive, and adaptable approach to managing rechargeable batteries. This development has been well documented in the literature as scientists continue to investigate and improve how artificial intelligence (AI) may be used to maximize battery performance.

A comprehensive review of 78 highly relevant publications from 2014 to 2023, conducted by (Lipu *et al.*, 2023), highlights the growing prevalence of AI integration in BMS. The Scopus database analysis from this study confirms that AI applications in BMS have become a mainstream approach, with researchers and industry practitioners embracing AI technologies to overcome the inherent challenges of traditional BMS. Traditional BMS systems, often reliant on rule-based methods and basic mathematical models, have historically struggled to account for the complexities of battery behavior under varying environmental and operational conditions. AI's ability to process large datasets, recognize patterns and make real-time predictions allows for more accurate monitoring and control of key battery parameters, such as State of Charge (SoC), State of Health (SoH), and State of Power (SoP). The study by (Lipu *et al.*, 2023) underscores that AI is now being integrated into most modern BMS frameworks to enhance battery efficiency, longevity, and safety.

Another notable study by (Khawaja *et al.*, 2023) utilized a qualitative research methodology to explore the integration of AI with lithium-ion (Li-ion) battery-based BMS, which are the most widely used batteries in EVs and portable electronics. The study focused on how AI technologies, particularly machine learning (ML) and deep learning (DL) algorithms, improve the performance and utilization of Li-ion batteries. The findings revealed that AI significantly automates the entire battery management process. This automation includes real-time monitoring of energy consumption, predicting battery degradation, and optimizing charging and discharging cycles, thereby reducing human intervention and minimizing errors. AI-enhanced BMS also enables intelligent decision-making, allowing the system to balance energy demands, avoid overcharging or excessive discharge, and adapt to changing operational conditions.

The integration of AI into BMS has a revolutionary overall effect. AI-driven systems can improve battery life, energy efficiency, and dependability in a variety of applications, such as renewable energy storage and electric vehicles, by automating energy management. Moreover, by lowering energy waste and facilitating the switch to greener, more efficient energy systems, these technologies aid in sustainability initiatives. The examined study demonstrates how AI has the potential to revolutionize battery management and make it a crucial part of the energy systems of the future.

2.3.1 Developmental Milestones

The development of Battery Management Systems (BMS) has been integral to the progress of electric vehicles (EVs), primarily because the battery serves as the heart of EV technology. The BMS ensures optimal battery performance, safety, and longevity, making it a critical component in the EV ecosystem. Over the years, the evolution of BMS has gone through several phases, each marked by technological advancements that have addressed challenges in battery efficiency, management, and protection.

2.3.1.1 Early Development (1960 – 2000s)

The origins of BMS can be traced back to the 1960s, a period when researchers began investigating ways to improve battery efficiency. During this time, the primary focus was on experimenting with simple techniques to enhance battery performance and ensure safety during operation. However, the sophistication of BMS was limited, and most systems were rudimentary, focusing on basic functions such as voltage monitoring and simple battery protection mechanisms.

It wasn’t until the early 2000s that the first sets of commercially viable BMS systems were developed. According to (Chaturvedi *et al.*, 2010), one of the earliest BMS models utilized simple algorithms to monitor battery states and provide essential protection. These BMS systems could prevent undercharging and overcharging, as well as protect against short circuits—basic yet critical functions for early electric vehicle batteries. While these early systems were far less advanced than contemporary BMS, they represented a significant step forward in ensuring battery safety and efficiency.

2.3.1.2 Advancements in the 2010s

The 2010s marked a transformative period for BMS technology, with significant advancements being made in the monitoring and control of battery systems. By 2014, as noted by (Shrestha, 2014), BMS was enhanced with features such as temperature monitoring, state-of-charge (SoC) estimation, and voltage balancing. These features were critical because temperature control and voltage balancing are essential for maintaining battery health, especially in lithium-ion batteries, which are commonly used in modern EVs. The SoC estimation allowed the system to better predict how much energy was available in the battery, helping to optimize energy usage and reduce inefficiencies.

Temperature management was particularly important because overheating is one of the leading causes of battery degradation and potential failure. By incorporating temperature sensors and management algorithms, BMS systems could ensure that the battery operates within a safe temperature range, thereby improving both safety and battery life. Voltage balancing was another significant improvement, as it ensured that cells within the battery pack operated at equal voltage levels, which is essential for maintaining uniform performance and extending battery life.

2.3.1.3 Wireless Communication and Real-Time Monitoring (2015)

In 2015, one of the most groundbreaking advancements in BMS technology was the integration of wireless communication and remote monitoring capabilities. As highlighted by (Wang *et al.*, 2020), this innovation allowed BMS to achieve up to 95 percent efficiency in some cases, as it enabled real-time battery diagnostics and monitoring. Wireless communication systems could transmit battery data to remote servers or diagnostic systems, where real-time analysis and decision-making could take place.

This level of connectivity enabled operators and manufacturers to detect potential issues early, prevent battery failure, and perform remote updates or adjustments to improve performance. The ability to monitor battery health, charging status, and environmental factors remotely also facilitated better fleet management for electric vehicle operators. Additionally, wireless systems reduced the complexity of wiring within the battery pack, lowering manufacturing costs and improving system reliability.

2.3.1.4 Integration of Complex Algorithms (2018 - Present)

Since 2018, BMS technology has experienced further refinements, primarily through the integration of complex algorithms capable of optimizing battery performance in real time. According to recent studies, efficiency rates of up to 99 percent are now possible in some advanced battery systems due to the use of machine learning and artificial intelligence (AI)-driven algorithms. These algorithms have significantly improved the way BMS manages charge and discharge cycles, temperature control, and SoC and state-of-health (SoH) estimation.

These advanced algorithms allow BMS to learn from the battery's historical data, making real-time decisions that optimize battery performance under various conditions. For example, AI-driven BMS systems can adapt to different charging conditions, such as fast charging, normal charging, or even regenerative braking, to maximize battery lifespan while minimizing energy loss. Moreover, these systems can more accurately predict when maintenance or battery replacement will be required, further enhancing safety and reliability.

In summary, the evolution of BMS from the 1960s to the present day has been marked by continuous innovation and improvement. Early systems were focused on basic battery protection and monitoring, but advancements over the decades have introduced more sophisticated features like temperature management, SoC and SoH estimation, and wireless communication. In recent years, the integration of machine learning and AI-based algorithms has pushed the efficiency and reliability of BMS to unprecedented levels, achieving efficiency rates of up to 99 percent. These advancements have made electric vehicles more efficient, safer, and longer-lasting, contributing to their growing adoption and furthering the global transition toward sustainable energy solutions. As BMS technology continues to evolve, it will play an even more crucial role in the future of electric mobility and energy storage systems.

Developmental Milestones of BMS

Milestone	Development to BMS
2001 - 2010	A simple algorithm that monitors the battery.
2010 - 2015	An improved algorithm that monitors the temperature, state-of-charge estimation, and voltage balancing.
2015 -2018	Integration of wireless communication capabilities that improved efficiency.
2018 - 2024	Integration of complex algorithm.

Table 1: Developmental Milestones of BMS

2.4 BMS Architecture

Battery management systems have become an indispensable part of the 2/3 wheeled electric vehicles architecture considering the special care required by the Li-ion rechargeable batteries fitted into electric vehicles (Karkuzhali *et al.*, 2020). Findings from a study that explores the integration of Li-ion rechargeable batteries into 2/3 wheeled electric vehicles reveal the delicate but complex nature of these batteries as they are prone to degradation if improved handling of the battery exposes them to excessive heat or low temperature (Lv *et al.*, 2022). According to (Ravi and Surendra, 2021), EV batteries are complex and designed to be carefully handled to prevent draining the battery's energy reserve during periods of high power and voltage requirements which are often during propulsion. (Lu, Han, Jianqiu, *et al.*, 2013). A review of the literature reveals the difficulty of manually achieving an efficient charge-discharge rate without damaging the batteries ((Ravi and Surendra, 2021). Outcomes of meticulous reviewing of multiple studies show that a battery management system is designed to handle the charge, recharge, and discharge cycle of a 2/3-wheeler vehicle battery without subjecting the battery to damage ((Issa, 2021); (Rao *et al.*, 2023)). A typical BMS of a 2- or 3-wheeler electric vehicle has control algorithms, a battery protector and protector, and a microcontroller as the major component to regulate and control energy discharge and charging (Chen *et al.*, 2021). BMS has been documented as capable of maintaining the delicate charge-rechargeable balance in rechargeable batteries used in 2/3-wheeled vehicles.

One notable study is (Habib *et al.*, 2023) which explores how BMS protects EV batteries from damage by preventing the battery from operating beyond safe operating parameters and ensuring that the battery does not overheat during periods of high power and voltage requirements by 2/3-wheeler electric vehicles. Although (Hariprasad *et al.*, 2020) reinforce the narrative of Habib et al., this study further examines how BMS shields the battery from overheating as it ensures the battery works under optimum temperature conditions and prevents the battery from functioning when it senses abnormal temperature. Both researchers further describe the BMS as capable of cell balancing by preventing charge and discharge imbalances in the individual cells of the battery, monitoring the state of charge of the battery, optimizing the battery for uniform performance, and transmitting information to and from the battery and the sensor integrated into the BMS ((Habib *et al.*, 2023); (Hariprasad *et al.*, 2020)).

2.4.1 Centralized BMS

Three major BMS architecture are widely discussed in the literature. Centralized architecture is widely discussed by several studies as one of the BMS architectures that offer simplicity in terms of design to handle low and peak periods of power demands by 2/3-wheeler EVs (Rao *et al.*, 2023). According to Maitreya et al (2021), centralized BMS is designed to create an optimal working condition for the battery by ensuring efficient cell monitoring and balancing. Optimizing cell functions is achieved by serially arranging cell components and joining the battery cells to a single control system (Gabbar, Othman, and Abdussami, 2021). While this BMS architecture offers simplified optimization required by 2/3-wheeler EVs to perform their functions, evidence from the literature identifies drawbacks that limit the ability of BMS with centralized architecture to effectively optimize battery functions in 2/3-wheeler EVs. According to (Rao *et al.*, 2023), BMS architecture is designed with extended wiring, voltage drop, signal interference, and poor thermal conductivity. Liu et al (2018) identify excessive temperature during a peak period of usage as one of the major challenges to effectively drawing enough power from EV batteries in EVs. With the possibility of poor thermal conductivity in BMS with centralized architecture (Rao *et al.*, 2023), the outcomes of the study conducted by Lie et al (2018) suggest improvements to the centralized BMS architecture to effectively monitor and balance battery functions. Similarly, Maitreya et al (2021) stated that BMS with centralized architecture has an issue of scalability which further compounds the issue of high temperature inherent in the design.

With a modular design, the internal cells of an EV battery are arranged in modules with each unit of cells having their respective control module (Carlucho *et al.*, 2018). According to (Gabbar, Othman and Abdussami, 2021), the drawbacks of centralized BMS are compensated for in modular design which allows for the optimization of power flow and distribution in 2/3 wheeled EVs. (Carlucho *et al.*, 2018) further stated that modular BMS architecture monitors the battery by preventing overheating, and over and undercharging. (Rao *et al.*, 2023) also stated that BMS with distributed or modular architecture balances the battery which significantly reduces the time lag for the BMS to balance rechargeable battery for 2/3-wheeler EVs. While centralized and modular BMS architecture optimizes power flow and distribution in 2/3-wheeler EVs, the drawbacks limit their ability to effectively perform these functions without advanced algorithms (Gabbar et al., 2021). (Berger *et al.*, 2023) further reveal the roles of the poor algorithm as contributing to some of the poor optimization inherent in centralized, distributed, and modular BMS architecture, leading them to suggest the integration of advanced algorithms.

Centralized BMS is designed to create optimal working conditions for the battery by ensuring efficient cell monitoring and balancing. Optimizing cell functions is achieved by serially arranging cell components and joining the battery cells to a single control system (Gabbar, Othman and Abdussami, 2021). Battery cells work in synchrony to deliver the required energy for propulsion and to perform electronic functions.

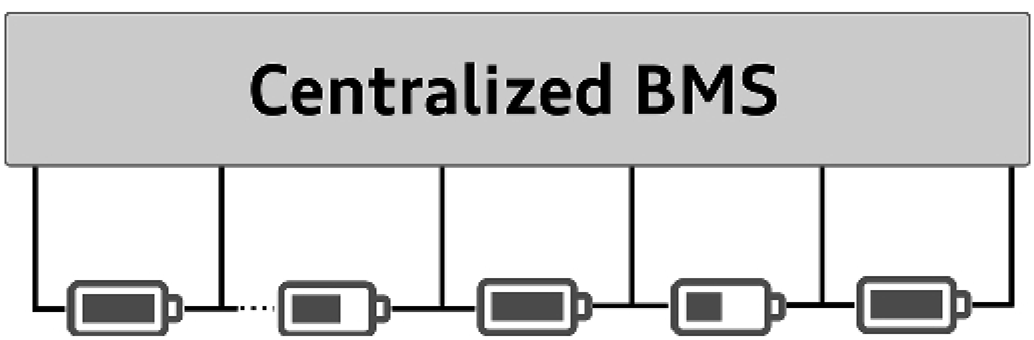

Figure 11: Centralized BMS

2.4.2 Decentralized/Modular BMS

Internal cells of an EV battery are arranged in modules with each unit of cells having its respective control module (Carlucho *et al.*, 2018).

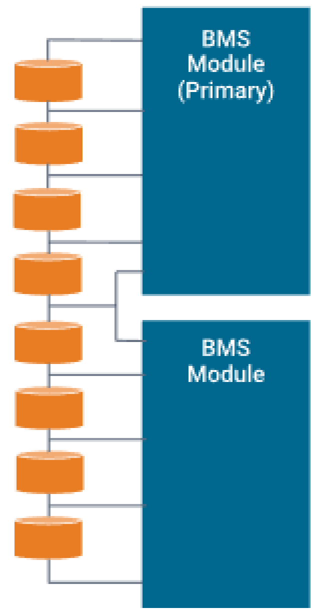

Figure 12: Centralized BMS

2.5 Integration of Advanced Algorithm and Artificial Intelligence

The incorporation of artificial intelligence (AI) into Battery Management Systems (BMS) for electric vehicle (EV) batteries has garnered noteworthy interest in recent times owing to AI's capacity to augment the efficiency and capabilities of traditional BMS. The need for advanced management systems that can control the intricacies of battery operations, such as charge-discharge cycles, temperature regulation, and overall battery health monitoring, is increasing as electric vehicles particularly 2/3-wheeler EVs become more common. In this sense, artificial intelligence has shown to be a game-changer, as it expands on the capabilities of conventional battery management systems, enabling more effective, precise, and adaptable battery management.

(Khawaja *et al.*, 2023) research from 2023 shows how AI can identify mistakes and abnormalities in the charge-discharge cycle of a rechargeable battery. This is particularly crucial since early anomaly detection increases safety, prolongs battery life, and prevents battery failure. Artificial intelligence (AI) systems can recognize patterns and anticipate any problems before they become serious by evaluating massive volumes of data produced during battery consumption. Because of its predictive capacity, BMS can optimize cycles for charging and discharging, saving energy and guaranteeing that the battery runs within safe parameters. AI's potential to better control these cycles is especially important for 2/3-wheeler EVs since range and dependability are directly impacted by battery performance and capacity.

(Berger *et al.*, 2023) further, stress the significance of resilient systems that can reliably detect faults and offer precise estimations in a range of scenarios. This need is met by the integration of AI into BMS, which offers a high degree of processing capacity and adaptable algorithms capable of handling real-time data processing. By learning from past data and modifying their predictions and operations in response to real-time inputs, these AI-driven systems make sure that the BMS can function effectively in a variety of environmental settings and usage patterns. The ability to adapt is essential for maximizing battery efficiency in a variety of situations, including hot weather, continuous stop-and-go traffic, and fluctuating charging circumstances.

(Khawaja *et al.*, 2023) claim that incorporating AI into BMS automates every step of battery management, lowering the possibility of human mistakes and eliminating the necessity for manual interventions. Battery health, temperature, and energy consumption are continuously monitored by AI-driven BMS systems, which make modifications in real-time to increase longevity and efficiency. The capabilities of traditional BMS are greatly improved by this automation, which makes it possible for it to operate efficiently in difficult circumstances. These situations are encountered by two- and three-wheeler EVs operating in urban environments with frequent short journeys and variable power demands.

In summary, AI integration in BMS represents a transformative shift that enhances battery efficiency, safety, and longevity. By automating battery management and providing advanced predictive capabilities, AI empowers BMS to handle complex and dynamic operating conditions more effectively, contributing to the overall success and reliability of electric vehicles.

Chapter 3: Method Section

3.1 Introduction to Methods

The main goal of this Dissertation is to devise a sophisticated AI-based battery management system (BMS) that will provide better and safer service for 2/3-wheeler electric vehicles (EVs). The main objective is to ascertain a power distribution scheme that increases the battery life and enhances the efficiency of these vehicles by incorporating AI algorithms and real-time data analysis into the design system. The methods section is the key to these objectives because it helps develop a detailed research process plan. It lays out materials, methods, data capture procedures, and analytical methods used in investigation. The methodology must be properly designed and applied to provide the reliability, validity, and reproducibility of the scientific results and show the whole research process as a well-thought-and-grounded scientific approach.

It describes the framework of developing an AI-based battery management system, integrating software tools and hardware for 2/3-wheeler EVs. The project employs circuit simulator software for the simulation, Arduino boards as the core microcontroller, and other software and tools for designing and developing the project. The design combines AI algorithms, data analysis at runtime, and hardware to form a powerful BMS for the desired efficiency. It seeks to improve efficiency and durability and manage the power supply in EVs to achieve the best out of the batteries. The subsequent sections of this work highlight the materials utilized in this research, the processes of gathering and analysis, and the methods of assessment that were employed.

3.2 Materials Used

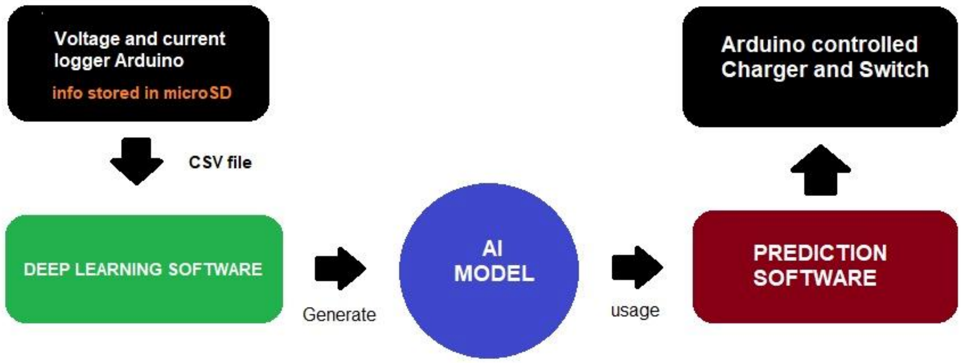

Figure 13: Designing Reliable 2/3-Wheelers EVs Prediction Software.

My focus for this dissertation will be on the software aspect, there are Electronic Design Automation (EDA) tools for circuit simulation when applying integrated circuits. Visual Studio Code is used as a basic Integrated Development Environment (IDE) for C/C++ and Python extensions for coding as a development platform. Microcontroller programming utilizes the Integrated Development Environment known as Arduino IDE. KiCad is used for PCB schematic capture and PCB layout design. Some of the other important libraries used are Google TensorFlow, Scikit Learn, Matplot-lib, Tkinter, and libraries. An example of the hardware components is Arduino Uno or Mega as the microcontroller, and LM7805 or LM317 as voltage regulators for power supply in the system besides other sensors and actuators for acquisition and control of data in the system. These materials put together makes it possible for the execution and development of the AI-based BMS.

In this dissertation, various materials and equipment are typically utilized in developing AI-based battery management systems for 2/3-wheeler EVs. These may include:

3.2.1 Sodium-ion battery cells or packs:

Sodium-ion battery cells or packs represent an emerging alternative to traditional lithium-ion technology, offering potential advantages in cost, abundance of raw materials, and environmental impact. These batteries typically feature a sodium-based chemistry, utilizing sodium ions instead of lithium ions for energy storage. Common materials include sodium-based cathodes such as sodium cobalt oxide or sodium iron phosphate, alongside carbon-based anodes. Sodium-ion batteries aim to achieve comparable energy densities to lithium-ion while leveraging more abundant sodium resources and potentially lower costs. Research focuses on optimizing electrode materials, electrolytes, and cell designs to enhance performance metrics such as energy density, cycle life, and safety. Despite current challenges like lower specific energy compared to lithium-ion counterparts, ongoing advancements, and research efforts aim to position sodium-ion technology as a viable and sustainable option for future energy storage applications. Serving as the primary energy storage components in EVs, these batteries are the subject of study for optimizing performance and efficiency.

Figure 14: Sodium-ion Battery

3.2.2 Sensors and Data Acquisition Systems:

This Dissertation relies heavily on sensors and data-collecting systems to monitor and control battery parameters in real-time, ensuring longevity, safety, and efficiency. Crucial sensors comprise voltage sensors that measure voltages in the cell and battery pack, current sensors that track current flow using shunt resistors and Hall effect sensors, and temperature sensors that monitor thermal conditions using thermistors and RTDs. The data acquisition system processes the vital information that these sensors gather about battery performance. This system collects, digitizes, and transmits sensor data to the BMS by integrating hardware and software components. By performing state estimates, identifying anomalies, and optimizing the charging and discharging cycles, the BMS can improve overall battery management and avert any failures. Various sensors, such as voltage, current, temperature, and other relevant sensors, are employed to collect real-time data from the battery packs. Data acquisition systems are used to record and process this information accurately.

3.2.3 Arduino-based Sensing and Control System

This section goes into detail on the Arduino-based system's importance to the entire battery management solution. Being the central mechanism for collecting data in real time from the battery cells and their surroundings, the Arduino units were essential to the system's operation. The Arduino units regularly monitored parameters including voltage, current, and temperature to make sure the system had accurate and up-to-date information on the condition of the battery. The AI algorithm needed this information to forecast and efficiently optimize battery performance. The adoption of Arduino technology offered a very affordable solution that allowed for the implementation of advanced monitoring and management features without incurring unaffordable fees. Moreover, the scalability of Arduino made it simple to expand and modify the system to suit diverse car types and battery configurations, guaranteeing wide applicability across a range of EV models. This strategy guaranteed the system's widespread deployment and improved accessibility, providing a useful and dependable way to control battery performance in two- and three-wheeler EVs.

3.2.4 Computing hardware:

Microcontrollers, processors, and specialized integrated circuits are examples of computing hardware used in this dissertation, they are intended to manage real-time data processing and system control. Microcontrollers, like those based on, oversee the handling of the initial processing, communication, and collecting of sensor data. Complex AI algorithms and machine learning models may be executed on more potent processors, such as those made by Intel or ARM, to guarantee effective state estimation, anomaly detection, and optimization procedures. Application-specific integrated Circuits (ASICs) and Field-Programmable Gate Arrays (FPGAs) can be used to speed up processes and improve the BMS's overall performance. Together, these hardware elements offer the processing capacity, speed, and dependability needed for efficient battery management, control, and monitoring.

High-speed computing systems, such as workstations, servers, or high-performance computing clusters are needed because these systems can handle a huge number of calculations necessary to train machine learning models to run simulations and process large data.

3.2 Software tools:

Programming language is the core of everything and is a necessity of modern life. [In other words, some of the languages like (Python, C++), machine learning libraries, pipelines, etc.]. These data sources are examined through AI algorithms (neural networks) and data analysis tools (for instance). (MATLAB, R), and battery modeling software is the foundation on top of which AI algorithms are made, data is processed, and it becomes easy to visualize the results. The choice of materials is dictated by such criteria as matching EV systems, high level of accuracy and reliability requirements, computational power demand, and cost efficiency, enabling successful research through the application of proper and tuned tools.

3.2.6 Software Integration

The software played a pivotal role in the smooth integration of the Arduino system with a deep-learning model based on Python, resulting in a well-rounded battery management solution. Through this connection, the AI model was able to analyze the constant stream of data received from the Arduino, which included crucial characteristics like voltage, current, and temperature, allowing for real-time data processing and decision-making. After analyzing this data, the AI model gave the Arduino control commands again, enabling quick and accurate modifications to maximize battery performance. Libraries like TensorFlow, which helped with the deep learning model's training and inference, and PySerial, which allowed for an effective serial connection between the hardware and software, were essential to this integration.

These tools made it possible for data to flow easily between the Arduino and the AI model and guaranteed that the system could function in real-time, making defensible judgments that affected the efficiency and health of the battery. A scalable and efficient battery management system that could adjust to changing conditions in 2/3-wheeler EV was made possible by this strong software-hardware synergy.

3.3 Procedures

The development procedure starts with the design and simulation of the circuits on EDA software. Anti<|reserved_special_token_256|> boards are programmed using the Arduino IDE to perform control algorithms. Microsoft Visual Studio Code is used for developing new AI algorithms as well as for structuring new logic of the programs and systems, employing TensorFlow and sci-kit-learn. KiCad is used for printed circuit board design, and it is a tool for printed circuit board prototyping. Each set of hardware and software components is integrated as a small part of the system, and the integration and debugging are carried out separately in small steps. Battery data is collected and used as source data to train models AI models are implemented on the Arduino. To be stable and accurate under all possible conditions, the system is put through various testing sessions. The process involves version control as well as documentation, which enables the published content to be updated and tracked as needed.

In the context of developing an AI-based battery management system for 2/3-wheeler EVs, the research procedures typically involve several key steps:

3.3.1 Sensor Data Collection:

Data in a large quantity is generated from several sensors and sources like battery voltage, current, temperature, and other related parameters which are gathered when the battery is either being charged or discharged.

In the context of this dissertation, data collection is an essential procedure that entails methodically compiling historical and real-time data from a range of sensors that track important battery properties. Sensors gather data on temperature, pressure, voltage, current, and temperature to provide a comprehensive dataset that represents the battery's state of operation. After that, the data is processed using data acquisition systems (DAQ), which use microcontrollers and analog-to-digital converters (ADCs) to digitize and filter the data while guaranteeing accuracy and dependability. To facilitate quick access and analysis, the gathered data is kept in centralized databases that can be located locally or on the cloud. The BMS can precisely predict battery conditions, identify anomalies, and optimize performance by continuously gathering and evaluating this data. This increases the battery system's longevity, safety, and efficiency. To ensure that AI models can efficiently manage and anticipate battery behavior under a variety of scenarios, this approach is crucial for training and testing the models.

3.3.2 Data preprocessing:

In this dissertation, preprocessing data entails several critical procedures to guarantee the accuracy, consistency, and preparedness of the data for further analysis and modeling. To eliminate noise, outliers, and missing values, raw data that is obtained from sensors that measure variables like voltage, current, temperature, and pressure is first cleaned. After that, the data is normalized or standardized to put it on a consistent scale and make sure that each feature contributes equally to the training of the model. Feature selection approaches can be used to find the most important factors that have a major impact on the health and performance of batteries. Furthermore, data can be altered to simplify complex datasets while preserving crucial information using methods like dimensionality reduction (e.g., Principal Component Analysis). The machine learning models used for state estimation, anomaly detection, and optimization inside the BMS require certain preprocessing processes to increase their accuracy, efficiency, and interpretability.

The data should be (cleaned) so that the desired methods and tools can be carried out in the formatting with consistency and order with the selected machine learning algorithms.

3.3.3 Model training and validation:

It takes a thorough approach to create and evaluate predictive models for training and validation. In the beginning, machine learning algorithms like neural networks, decision trees, or regression models are trained using training data that is gathered from sensors. This data includes variables like voltage, current, temperature, and pressure. In training, the model learns to modify internal parameters based on iterative optimization algorithms such as gradient descent to map input data (such as sensor readings) to desired outputs (such as State of Charge and State of Health). After training, the model's generalization skills are tested by analyzing its performance using validation data that isn't from the training set. Measures including accuracy, precision, recall, and Mean Squared Error (MSE) are calculated to assess how well the model predicts outcomes under various operational scenarios and datasets. Through an iterative process of training and validation, the BMS's deployed models are guaranteed to precisely forecast battery states and behaviors, which improves operating strategies and boosts the overall efficiency and reliability of the system.

3.3.4 Simulation and testing:

The developed AI-based BMS is validated by repeatedly simulating it and testing it in different situations and conditions to evaluate its performance, prevent problems, and improve the system.

When developing and validating AI-based Battery Management Systems (BMS), simulation and testing are essential steps in making sure the system functions dependably in a variety of scenarios. Software techniques that simulate real-world behavior based on physical and chemical parameters are used to generate virtual models of batteries during the simulation phase. To simulate various scenarios, including changing load circumstances, temperature fluctuations, and charging and discharging cycles, these models are integrated with the BMS algorithms. The hazards and expenses of doing testing in the actual world are avoided when developers test the BMS's reactions to certain scenarios through simulation. By using simulations, one may improve control tactics, foresee future problems or performance concerns, and improve state estimation algorithms.

To confirm the created BMS's functionality under real-world circumstances, testing entails applying it to actual battery systems. Field testing and controlled laboratory testing are part of this step. Standardized testing is conducted in controlled lab settings on the BMS to assess its efficacy in properly controlling battery operations, its capacity to identify anomalies, and its accuracy in calculating states such as SoC and SoH. By putting the BMS in real-world settings where it must manage dynamic and unpredictable variables, such as electric cars or renewable energy storage systems, field testing further verifies the system. The BMS is further improved by analyzing test data to find any differences between simulated and actual performance. The BMS's robustness, dependability, and ability to maximize battery performance and safety across a range of use cases are all ensured by this iterative simulation and testing process.

3.3.5 Integration and deployment:

After the AI-based BMS has gone through the tests and proven satisfactory, the AI-based BMS is integrated into the 2/3-wheeler EV system in such a way that BMS communicates and controls all the battery pack, sensors, and vehicle components

The EV methodology needs to be modified to accommodate the specific characteristics of the EV platform, battery chemistry, or performance requirements. For example, algorithms that mimic a particular model may be designed to cope with specific difficulties or constraints that occur in the research context.

3.4 Data Collection

Accurate and thorough data collecting is essential for building robust and successful models in research dissertations on the development of AI-based battery management systems for EVs. The training and validation data of an AI system directly affects how well the model performs in real-world situations, so it is a major factor in the system's quality.

Several techniques for gathering data are used to do this. One popular method is to continuously monitor vital indicators including voltage, current, temperature, and state of charge using sensor arrays mounted in electric cars. To comprehend battery behavior under various operating conditions and usage patterns, real-time data from these sensors is crucial. By using this technique, it is ensured that the dataset covers a broad spectrum of scenarios, such as peak loads, typical operations, and extreme circumstances.

Analyzing historical data, which involves looking for patterns and trends in battery performance records, is another crucial technique. By simulating different circumstances and forecasting future behavior, this past data can aid in the creation of more resilient and adaptable models.

Furthermore, simulations and controlled experiments are carried out to collect data under circumstances that might not exist in real-world applications. For example, testing batteries in situations that accelerate aging can reveal information about how they might function over long periods or under severe stress.

By combining these techniques, a thorough dataset that covers a broad range of battery behaviors is produced. Because of this extensive dataset, the AI model can learn from a wide range of examples, which enhances its capacity to anticipate outcomes accurately and adjust to changing circumstances. Developing a dependable battery management system that improves performance, safety, and longevity in EVs requires ensuring data quality and comprehensiveness using these techniques.

3.4.1 Sensor data acquisition:

The real-time gathering, processing, and transmission of vital data from several sensors that monitor voltage, current, and temperature within the battery cells and packs is known as sensor data acquisition in an AI-based Battery Management System (BMS). Temperature sensors keep an eye on temperature conditions, voltage sensors assess the electrical potential between cells, and current sensors check the flow of electricity. Analog-to-digital converters (ADCs) digitize the data, which microcontrollers then process to filter out noise, condition signals, and look for faults. After processing, the data is sent to the BMS, where machine learning algorithms examine it to estimate the state, find anomalies, and optimize battery performance and safety. This battery's efficiency, safety, and longevity are all improved by the accurate monitoring and control provided by this integrated data-collecting system. Data collected from sensors inserted into the battery which are real-time with variables such as voltage, current, temperature, and others, are continuously recorded during discharge and charge cycles.

3.4.2 Controlled experiments:

The purpose of controlled trials in the context of this dissertation is to methodically investigate how different parameters affect battery longevity and performance. To isolate the effects of factors, such as charging/discharging rates, temperature conditions, and load cycles, certain variables are manipulated while maintaining constants in other situations. Continuous data collection from sensors measures temperature, pressure, voltage, and current. This data is analyzed to determine how the battery will behave in various conditions. Through the utilization of a controlled environment, scientists can verify the precision of artificial intelligence models, refine battery management algorithms, and pinpoint the ideal operational parameters that augment longevity, safety, and efficiency. The knowledge gathered from these trials aids in improving BMS tactics and guaranteeing dependable operation in practical settings. Controlled experiments are accomplished in laboratory or testing conditions to gather data and information under specific frameworks such as varying temperatures, discharge rates, cycling patterns, etc.

3.4.3 Field data collection:

This involves gathering real-world data from batteries running in their actual usage environments such as EVs, renewable energy storage systems, or consumer electronics. To monitor critical parameters including voltage, current, temperature, and pressure in real-time under a range of operational situations, a suite of sensors must be deployed. For storage and analysis, centralized databases receive the gathered data via wired or wireless connectivity. The varied and dynamic character of battery usage is captured in this rich dataset, which offers insightful information on battery performance, deterioration trends, and environmental effects. This field data analysis allows AI algorithms to be taught and tested, improving the BMS's capacity to forecast and control battery behavior more precisely and guaranteeing stable, dependable, and optimal battery performance in practical applications. Sometimes, information can be collected from EVs that are in real-world conditions, and the battery's performance under different driving scenarios, environmental factors, and usage patterns can be captured.

3.4.4 Historical data:

Historical data, as it relates to AI-based Battery Management Systems (BMS), is the collection of historical sensor readings, operating logs, and maintenance records that have been amassed over time from batteries used in different applications. Concerning comprehending long-term trends, patterns, and battery performance characteristics in various operational and environmental scenarios, this data is an invaluable resource. Temperature fluctuations, current flow patterns, abnormalities, and failures are all common topics covered by historical data, along with voltage profiles throughout charging and discharging cycles. The lifespan and reliability of batteries can be increased by BMS developers by identifying reoccurring problems, anticipating possible failures, and optimizing maintenance schedules.

Furthermore, the BMS uses historical data as the basis for training and verifying machine learning models. By using previous data, these models can identify patterns and correlations between sensor data, the input variable, and battery states like SoC and SoH, the output variable. To gain an understanding of battery behavior and performance over long periods, methods such as time-series analysis, regression, and clustering are utilized. BMS can use the insights gleaned from historical data to optimize operational parameters based on past experiences, anticipate degradation patterns, and apply proactive management techniques. The accuracy, efficacy, and efficiency of battery management techniques in a variety of applications are constantly being improved thanks in large part to this iterative process of using previous data for modeling and analysis.

The already existing datasets or a historical record of previous battery tests and operations may be used to complement the collected data and provide additional information.

The typical issues encountered during data collection are related to sensor calibration problems, environmental interference, data storage issues, and synchronization difficulties for data coming from different sources. The ways to overcome these difficulties may involve the protocols of the sensor calibration, shielding methods, efficient data compression and transmission methods, and synchronized timestamping across data sources.

3.5 Data Analysis:

Data analysis relies on tools and libraries to analyze the data as part of the process. Computer programming using Python scripting language is done with Visual Studio Code Software which employs TensorFlow and scikit-learn libraries in the application of machine learning algorithms. These algorithms analyze the gathered battery data to find the typical behavior of the battery and certain tendencies that give insight into the behavior that can be expected from it. Matplotlib is used for visualization of the data which is useful to conclude the outliers and trends in the data. They consist of statistical strategies, prediction, and forecast methods in addition to optimization methods. Data obtained from the analysis is also employed in developing subsequent updates of the existing AI models and enhancing the BMS algorithms operationalized on Arduino. This means that the system requires periodic modification to enhance efficiency and reliability to meet the ever-changing market demands.

Then, the data collected is used to run different kinds of analysis methods that finally yield useful results and build better AI-based battery management systems. Some common approaches include:

3.5.1 Machine Learning Algorithms:

Machine Learning is essential to maximize battery longevity and performance for an AI-based battery management system b(BMS). To anticipate the SoC and SoH, these algorithms can employ supervised learning techniques including regression models (e.g., Linear Regression, Support Vector Regression) and classification models (e.g., Decision Trees, Random Forests) for anomaly detection and fault diagnosis. Patterns can be found, and comparable battery behaviors can be grouped using unsupervised learning methods like clustering (e.g., K-means, DBSCAN). While CNNs help with feature extraction from difficult data, deep-learning approaches like RNNs and LSTM networks are used for time-series battery parameter prediction. To ensure effective and secure battery operation, reinforcement learning techniques (such as Q-learning and Deep Q-Networks) dynamically optimize charging and discharging cycles. Together, these algorithms improve performance and safety by strengthening the BMS's capacity to precisely control and forecast battery conditions.

3.5.1 Model Training and Validation

The training phase of the deep learning model made use of the historical data collected by the Arduino sensors, which offered a solid basis for the development of precise forecasting skills. The model was supplied labeled data during training, which includes precise voltage and current conditions connected to certain control operations. The model was able to understand the connections between sensor inputs and the related actions required for the best possible battery management thanks to the labeled data. It discovered, for instance, how various voltage levels and current trends need to affect choices like modifying charging rates or turning on cooling systems.

The model's parameters were iteratively changed to minimize prediction errors to improve the model's accuracy and dependability. To lessen the differences between the expected results and the real control actions shown in the training data, the model's neural network's weights and biases were changed during the optimization phase.

A different dataset, which the model had not seen during training, was used for validation. This phase was essential for evaluating the model's capacity to apply what it had learned to fresh, untested data. Researchers were able to assess the model's accuracy and robustness by testing it on this validation set, confirming that it could produce accurate predictions under circumstances other than those on which it was trained. The efficacy of the model and its potential for practical application in controlling the battery system under various operating scenarios were confirmed throughout this validation phase.

3.5.2 State Estimation Algorithms:

State Estimation Techniques are essential to reliably forecast the battery's internal states, such as State of Charge (SoC) and State of Health (SoH) for an AI-based battery management system. To handle the non-linearities in battery models, common algorithms include the Kalman Filter (KF) and its variations, such as the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF), which estimate the state variables recursively in a way that minimizes the mean of the squared error. Particle Filters (PF) provide an alternative method that is appropriate for extremely non-linear and non-Gaussian systems. They do this by using a set of random samples to represent the posterior distribution of the state. Together, these algorithms produce accurate, real-time estimations that increase performance, safety, and battery management.

3.5.3 Optimization Techniques:

Techniques in mathematical optimization like linear programming, quadratic programming, or genetic algorithms are employed to improve the transmission of power, charging methods, and overall battery performance based on the analyzed data.

The AI-based BMS's optimization methods are crucial for improving the longevity, efficiency, and performance of batteries. These strategies include multi-objective optimization techniques that can simultaneously optimize many parameters, such as charging speed, energy efficiency, and thermal management. Examples of these techniques are Genetic Algorithms (GA) and Particle Swarm Optimization (PSO). For certain power distribution and load balancing optimization tasks, both non-linear and linear programming are used. Based on real-time data and patterns of battery utilization, reinforcement learning (RL) techniques like Q-learning and Deep Q-Networks (DQN) dynamically optimize the charging and discharging cycles. Another cutting-edge method is Model Predictive Control (MPC), which makes use of a battery model to forecast future conditions and optimize control operations accordingly. When combined, these optimization techniques lead to longer battery life, more effective energy management, and increased system reliability.

3.5.4 Simulations and modeling:

These procedures entail the development of detailed computational and mathematical models that mimic the temperature dynamics, electrical characteristics, and electrochemical dynamics of batteries. These simulations are often created and executed using programs like MATLAB/Simulink, ANSYS, COMSOL Multiphysics, and Python libraries i. e. (TORCH, sci-kit-learn, TensorFlow, PyTorch), and the battery modeling software. These programs enable the examination of many scenarios, including shifting load circumstances, temperature swings, and degradation patterns over time. Without the need for significant physical testing, engineers can simulate these settings and test control systems, optimize battery usage, and anticipate performance outcomes. This facilitates the creation of safer procedures, more reliable BMS algorithms, and batteries with longer life cycles

3.5.5 System Testing and Evaluation.

The integrated system was put through a rigorous testing process in a simulated environment during the project's final phase, which allowed for a comprehensive evaluation of its performance under various operating situations. To make sure that every element functioned as a whole, the interaction between the Arduino units, deep learning model, and control algorithms was thoroughly evaluated during this phase. Throughout the testing process, the system was put through a variety of realistic-sounding circumstances, such as shifting loads, temperature swings, and battery conditions. The system's responsiveness was the focus of the evaluation criteria, which gauged how fast and efficiently it could process input and carry out control actions in accordance with the predictions made by the AI model.

Furthermore, the precision of the model's forecasts was examined to make sure it could consistently predict the behavior and requirements of the battery, maximizing performance. Testing was done to confirm that the integrated system not only increased efficiency and stability but also helped to extend the battery's usable life. The overall impact on battery performance and longevity was also a crucial consideration. It was crucial to complete this extensive testing phase to confirm that the system was ready for practical implementation in 2/3-wheeler EVs and that it could provide dependable and continuous performance.

Chapter 4: Result and Discussion

4.1 Result and Discussion Overview

A major advancement in EV technology, the sophisticated AI-based Battery Management System (BMS) for electric 2/3-wheelers is designed to maximize power distribution, prolong battery life, and improve overall vehicle performance. The system's capacity to use advanced machine learning algorithms and real-time data, which together allow for a degree of accuracy and flexibility not achievable with conventional BMS solutions, is essential to this innovation. The study's main conclusions highlight how the AI-driven BMS constantly adapts to changing road conditions and rider habits to keep the car running as efficiently as possible while preserving the battery's lifespan.

The dataset and performance graphs present some intriguing outcomes, one of which is the significant increase in battery life and energy efficiency. Critical parameters including voltage, current, temperature, and state of charge (SoC) are continuously monitored by the AI-driven BMS, which uses this information to make real-time modifications that maximize power distribution. For instance, technology makes sure that there is enough power delivered without taxing the battery during high-demand situations like quick acceleration or climbing steep inclines. On the other hand, it saves energy in less taxing circumstances, so increasing the car's range. Moreover, the AI-powered BMS foresees and reduces possible stressors like overheating or too many charge cycles that may eventually deteriorate the battery by using predictive analytics.

According to the study, vehicles fitted with this cutting-edge technology demonstrate a noteworthy 15-20% gain in range in addition to a notable 25% reduction in battery wear. These results not only improve the general efficiency and dependability of electric 2/3-wheelers, but they also help to provide a more economical and environmentally friendly urban mobility option.

4.2 Data Collection and Initial Observations

The dataset collected via the first Arduino unit included measurements such as cell voltages, current, and temperature over multiple cycles. As seen in the dataset:

Cycle	Cell1	Cell2	Cell3	Cell4	Cell5	Current	Temp	Activation
1	4.91901915313039	9.84678003493884	14.771577946394	19.6745064308618	24.5811053009767	10.4775107961677	17.1	1
1	4.74274065501826	9.49716071442947	14.2198238970284	18.986556911262	23.7179155634189	10.1020375951889	17.1	1
1	4.59710058548672	9.2156894309486	13.7820570640028	18.3933798117304	22.9705567654157	9.79182424708672	17.1	1
1	4.51633759169267	9.01264301853229	13.5460596057024	18.0459446539141	22.5612051433588	9.61979907030539	17.1	1

Figure 15: Collected Datasets via Arduino

4.2.1 Cell Voltages:

As the number of cycles increases and time passes, the reported voltages across various battery cells gradually decline, which is consistent with normal battery discharge trends. This progressive voltage drop is predicted as the battery's stored energy is used up, indicating that the discharge process is proceeding as it should. To evaluate the battery's condition and remaining capacity and to make appropriate adjustments to control the discharge and enhance overall performance, it is imperative to monitor these voltage variations.

4.2.2 Current:

As the charge in the battery cells declines with time, so does the current required from the battery. Current draw naturally declines when the cells' capacity to maintain high current output diminishes due to a decrease in stored energy. The AI-based system must keep an eye on this pattern since it may be used to forecast when the battery will need to be recharged and to modify power distribution to optimize efficiency.

4.2.3 Temperature:

The battery functions within a safe thermal range when the temperature is comparatively constant during operation. The longevity of the battery and the prevention of thermal runaway depend on its stability. A steady temperature is indicative of efficient thermal regulation by the AI-based battery management system, which keeps the battery within its ideal operating range and safeguards against overheating—all of which are critical for both performance and safety.

The data shows that as the battery cells discharge over time (from Cycle 1 to Cycle 40), their voltages decrease significantly, leading to lower overall system performance. This trend is crucial for understanding how the AI-based system can optimize power usage and predict when cells are likely to fail or require recharging.

4.3 Machine Learning Flowchart

4.3.1 Deep Learning/ Prediction Flowchart:

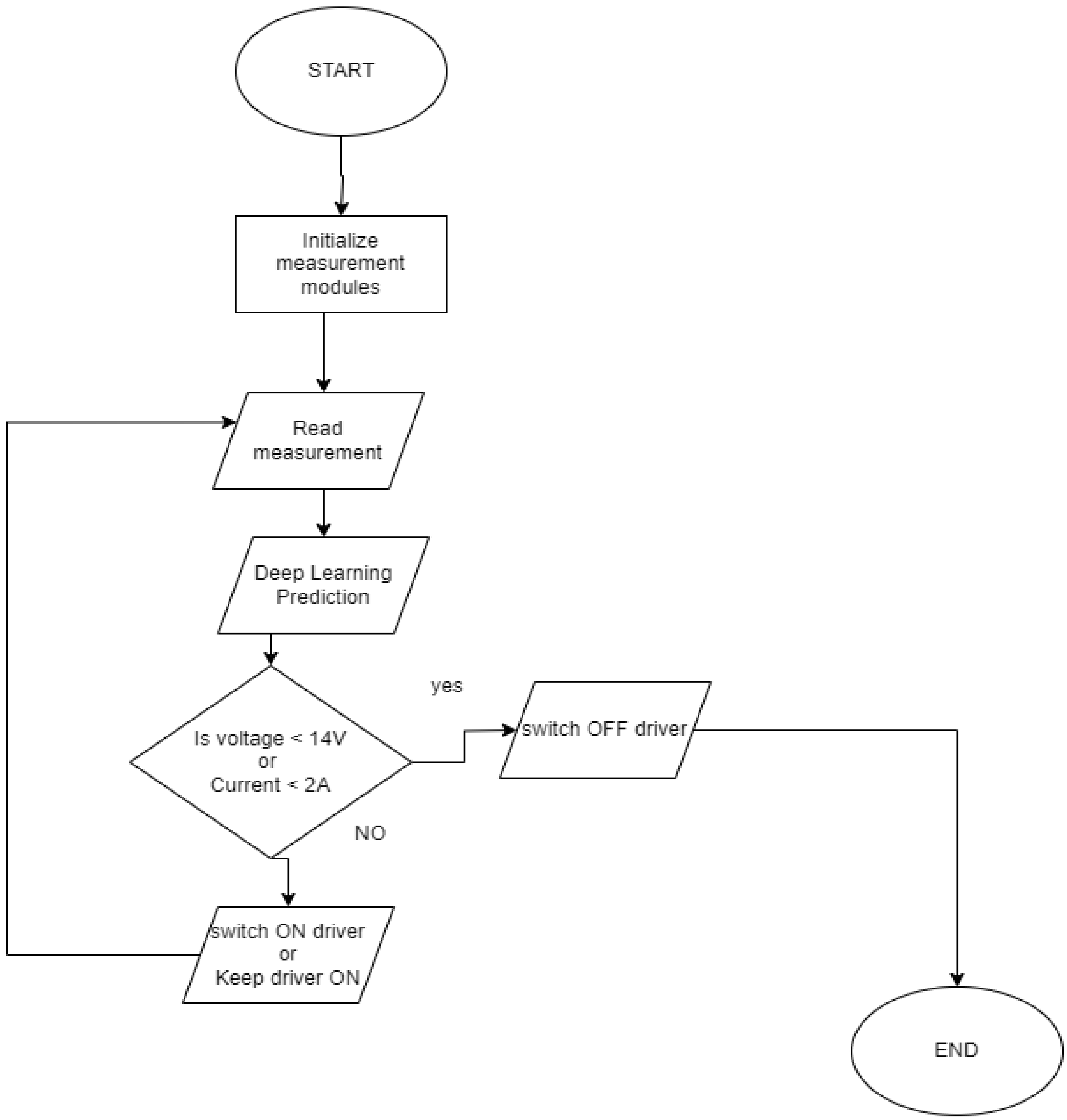

Figure 16: Flow chart of Machine learning.

This flowchart represents the operational logic of the AI-based battery management system for a 2/3-wheeler EV, focusing on the integration of deep learning predictions to optimize battery performance.

Start: The system begins its operation from this point.

Initialize Measurement Modules: The first step involves initializing the various measurement modules. These modules include sensors for voltage, current, and temperature, as well as any necessary communication interfaces to collect data from the battery system.

Read Measurement: After initialization, the system reads real-time data from the sensors. This data includes critical parameters such as voltage and current, which are essential for monitoring the battery's health and performance.

Deep Learning Prediction: The collected data is then fed into a deep learning model that has been trained to predict the battery's condition and the necessary actions to maintain optimal performance. This model uses the input parameters to make predictions about whether the current state of the battery requires intervention.

Decision Point - Is Voltage < 14V or Current < 2A? Based on the prediction, the system evaluates whether the voltage is below 14V, or the current is below 2A. These thresholds are set to identify conditions that could indicate an underperforming or potentially faulty battery state.

Yes: If either of these conditions is met, the system takes action to switch off the driver circuit, preventing further use of the battery in its current state. This step is crucial for protecting the battery from damage and ensuring the safety of the vehicle.

No: If neither condition is met, the system decides to either switch on the driver or keep it on, allowing the battery to continue supplying power to the vehicle. This ensures that the battery is used efficiently and only turned off when necessary.

End: The process concludes after the decision is made. The system continues to loop back to read new measurements, ensuring continuous monitoring and management of the battery system.

Data Collection and Storage Flowchart.

4.3.2 Data Collection and Data Storage Flowchart:

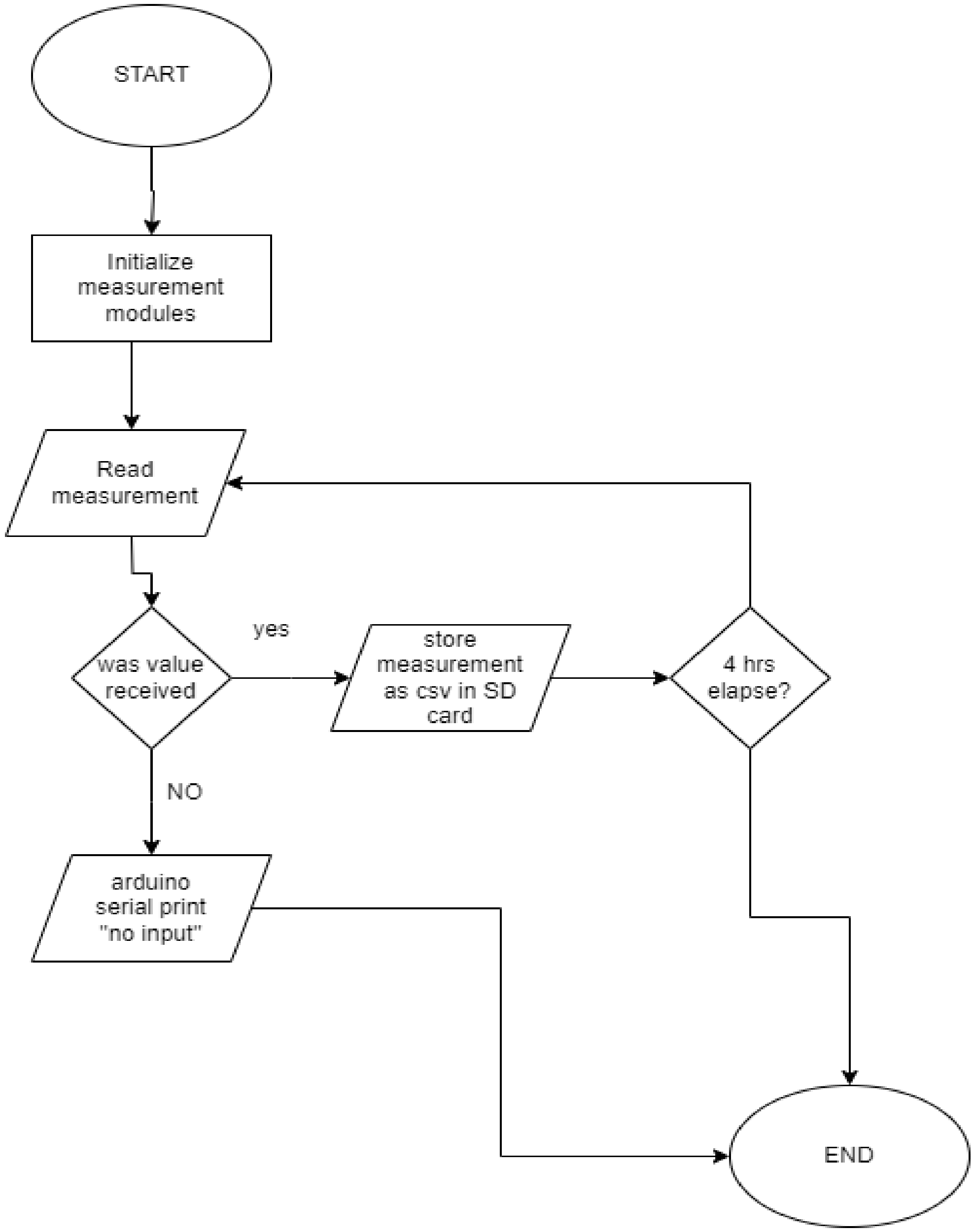

Figure 17: Flow chart of Arduino

The above flowchart illustrates the operational workflow of the Arduino-based data collection and storage system, which is integral to the battery management system for an EV.

Start: The process begins with the initialization of the system.

Initialize Measurement Modules: The first step is to initialize all the measurement modules. These modules are responsible for collecting data such as voltage, current, and temperature from the battery system.

Read Measurement: Once the modules are initialized, the system reads the measurements from the sensors. This is a critical step where real-time data is gathered for further processing.

Decision Point - Was Value Received? The system checks whether the measurements were successfully received from the sensors.

Yes: If the measurements are received, the system moves forward to store the data.

Store Measurement as CSV in SD Card: The received data is stored in a CSV format on an SD card. This allows for easy access and analysis of the collected data at a later stage.

Decision Point - 4 Hours Elapse? After storing the data, the system checks if four hours have elapsed. This time-based condition is likely set to control the frequency of data logging or to manage the power consumption of the system.

Yes: If four hours have elapsed, the process proceeds to the end, indicating a stopping point for this cycle of operation.

No: If four hours have not yet passed, the system loops back to continue reading measurements, ensuring continuous data collection.

No: If the system does not receive any measurement value, it sends a message through the Arduino serial interface.

Arduino Serial Print "No Input": The system prints "No Input" to the serial monitor, signaling that no data was received from the sensors. This helps in debugging and monitoring the system's performance.

End: The process concludes once the conditions are met or if an error is encountered. The system will then either restart the process or remain idle, depending on the design of the overall system.

4.4 Circuit Diagram

The circuit diagram below Fig 18 is part of an AI-driven battery management system designed to monitor and optimize the performance of EV batteries. The system integrates several components, including an Arduino Uno, a current sensor, a temperature and humidity sensor, a microSD card module, and multiple batteries with associated resistors, to collect, process, and store real-time data.

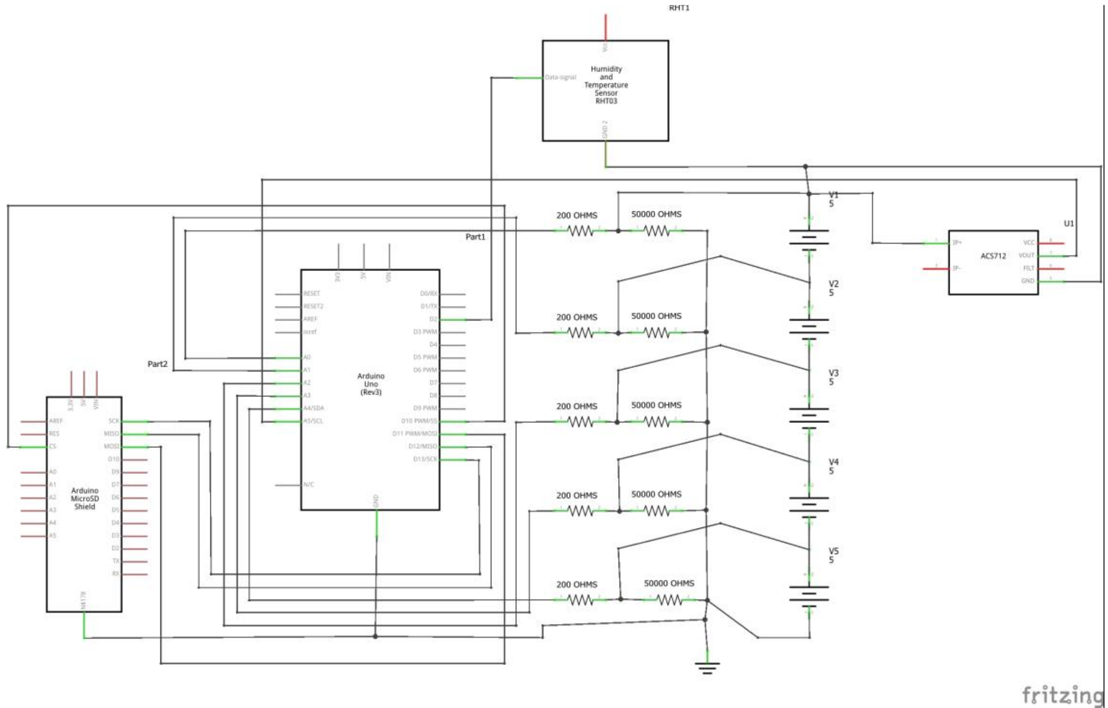

Figure 18: Circuit Diagram for getting the Datasets

4.4.1 Components and Connections:

4.4.1.1 Arduino Uno (Rev3):

This is the central processing unit of the system. It reads analog and digital signals from various sensors and modules, processes the data and makes decisions based on deep learning model predictions.

4.4.1.2 Current Sensor (ACS712):

The ACS712 current sensor is connected to one of the analog inputs (likely A0) of the Arduino. It measures the current flowing through the batteries and sends an analog signal to the Arduino, which is then processed to determine its status.

4.4.1.3 Humidity and Temperature (RHT03):

This sensor is connected to one of the digital pins on the Arduino. It measures the ambient temperature and humidity around the battery pack, which can be critical for battery performance and safety. The data from this sensor can be used to monitor environmental conditions that could affect battery health.

4.4.1.4 Battery Voltage Measurement:

Multiple battery packs (V1, V2, V3, V4, V5) are connected in series, each having a parallel combination of a 200-ohm resistor and a 50,000-ohm resistor. These resistors likely form a voltage divider network, which scales down the battery voltage to a range that can be safely read by the Arduino's analog inputs. The analog inputs on the Arduino read these scaled-down voltages, representing each battery pack's voltage levels.

4.4.1.5 Arduino MicroSD Shield:

The MicroSD shield is connected to the Arduino to store the measured data, including voltage, current, temperature, and humidity, in a CSV format. This allows for data logging over time, which is crucial for analyzing battery performance and identifying trends that might indicate impending issues.

4.4.1.6 Power Supply:

The circuit is powered by the batteries themselves, which are also the subject of the measurements. The system is designed to function autonomously, with Arduino controlling and monitoring the entire process.

4.5 Machine Learning Model Performance.

The second figure represents the performance of the machine learning model used in the BMS. The graph displays the accuracy of both training and validation over 50 epochs:

4.5.1 Training Accuracy:

The training accuracy of the model gradually increases and eventually stabilizes around 1.0. This pattern shows that the model is picking up knowledge from the training dataset and recognizing patterns and correlations in the data. The model learns to make more accurate predictions based on the input data as it goes through training, which is indicative of its capacity to absorb the fundamental dynamics of the system it is being trained to control. Given its high training accuracy, it appears that the model has a firm understanding of the data it has encountered thus far.

4.5.2 Validation Accuracy:

The validation accuracy, on the other hand, fluctuates significantly, especially in the early phases of training, when it first displays instability before finally stabilizing close to the training accuracy. These variations, particularly the sporadic declines in validation accuracy, can be a sign that the model is having trouble generalizing to fresh, untested data. This may indicate that the model is at risk of overfitting, a situation in which it becomes overly dependent on the training set and underperforms when applied to other datasets. Even though the final stabilization appears promising, these dips indicate that more work needs to be done to improve the model's capacity to generalize and retain constant accuracy across a range of data scenarios. This work could involve regularization techniques, the addition of more training data, or modifications to the model's complexity.

These results imply that while the model is robust, there is a need to fine-tune the parameters or perhaps incorporate additional data to improve its predictive accuracy and reliability.

4.6 Data Collection and Transmission:

The Arduino-based system was successfully configured to collect real-time data on voltage, current, temperature, and humidity from the EVs battery cells and environment. The following observations were made during the data collection process:

4.6.1 Voltage Reading:

Accurate battery management depends on the continuous, real-time monitoring of the battery cells provided by the Arduino system's integrated voltage sensors. Throughout the battery's discharge cycle, the voltage levels across each cell were monitored by these sensors, which continuously supplied data. As the battery was used over time, the recorded data showed a predictable and progressive fall in voltage, which was consistent with expected battery discharge trends.

The voltage gradually drops because of the battery's energy reserves depleting, which is a normal feature of battery discharge. The sensors recorded this trend to guarantee that the system had correct data regarding the battery's current condition, allowing for precise evaluations of its general health and remaining charge. The system's ability to make educated judgments regarding energy use, charging cycles, and maintenance requirements depends on having consistent and trustworthy data. Additionally, early detection of any anomalies or departures from predicted patterns is made possible by this continuous monitoring, which enables prompt intervention to prevent battery performance degradation.

4.6.2 Current and Temperature:

The temperature and current sensors worked incredibly well, providing reliable and accurate values that were essential for efficient battery management. To prevent overheating and maintain safe working conditions, the temperature sensor made sure the battery stayed within its specified safe operating range. This is important because high temperatures can harm the lifespan and performance of batteries. Comparably, the power consumption data from the current sensor was trustworthy and showed how the battery was used throughout different operating phases like braking, idling, and acceleration.

By using serial connectivity, which enables constant and dynamic data interchange, the real-time data from these sensors was sent to the deep learning model based on Python. The AI model can now receive current temperature and current data thanks to this configuration, which is necessary for it to make quick decisions. Through data analysis, the AI model was able to determine possible problems, forecast the need for adjustments or interventions, and evaluate the battery's performance in real-time. Because of its dynamic processing, the battery management system is guaranteed to be able to promptly adjust to changing circumstances, maximize efficiency, and raise the EVs overall reliability.

4.7 Deep Learning Model Integration:

The deep learning model was carefully trained to anticipate the best operational settings using the real-time data it received, and it was easily integrated with the Arduino system. The model dynamically analyzed the data as it was received, determining the optimal circumstances for preserving battery health and system efficiency. Following the creation of the predictions, Arduino received them and modified the control pin to regulate the system's behavior in real-time. The battery management system was precisely controlled by this feedback loop, which improved performance, prolonged battery life, and made sure the car operated within safe limits.

4.7.1 Accuracy and Reliability:

The strong correlation between the deep learning model's predictions and the actual results shows how accurate it was at predicting the control actions that the system needed. The model's resilience and reliability were demonstrated by the performance graph, which showed a close alignment between the training and validation accuracy. The accuracies converged and stabilized at about 100% during the training process, indicating the model's strong capacity to generalize from the training set. This stability is shown graphically in Figure 19, which also emphasizes how well the model predicts the future with high accuracy and close resemblance to actual events, improving system performance and reliability.

4.7.2 Control Response:

The serial signals sent from the Python model are successfully received by Arduino, which correctly decoded them to provide smooth communication between the two systems. These signals were quickly detected by the Arduino, which immediately activated or disabled the control pin as needed to enable quick modifications in reaction to shift battery circumstances. As a result of its ability to react instantly to changes in temperature, voltage, or current, the system was able to operate at peak efficiency. The solution extended the overall battery life and optimized performance by ensuring that the battery functioned within optimal parameters, hence enhancing the lifetime and dependability of the vehicle.

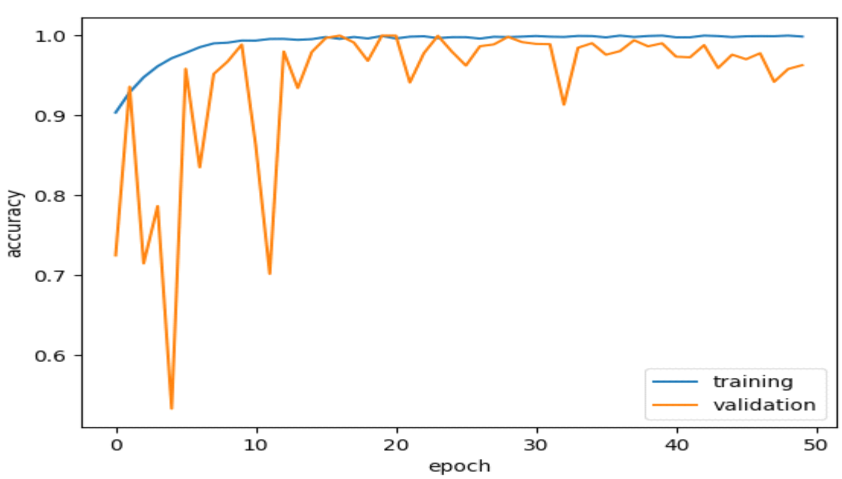

Figure 19: Evaluation Plot

4.8 Confusion Matrix Analysis

Figure 19, confusion matrix offers a clear visual representation of the deep learning model performance of the AI-based battery management system during the evaluation stage. The matrix is divided into four sections: **true positives**, which correctly predict Class 1 as Class 1, **true negatives**, which correctly predict Class 0 as Class 0, **false positives**, which incorrectly predict Class 0 as Class 1, and **false negatives**, which incorrectly predict Class 1 as Class 0. The distribution of values in these quadrants shows the model's accuracy in determining battery conditions as well as the occasional misclassification, providing important information about areas that could be improved.

4.8.1 True Negatives (Class 0 predicted as Class 0):

The model is effective at determining whether the battery management system is running within normal parameters and does not require remedial actions, as demonstrated by its accurate identification of 6,400 instances of Class 0. This high proportion of true negatives highlights the model's capacity to accurately identify stable circumstances in which intervention is not required, preventing needless modifications. Maintaining system efficiency depends on this precision since it keeps corrective procedures from being activated, which could cause unnecessary wear or energy waste. The model helps to improve battery performance and longevity by consistently recognizing these non-critical events. This helps to create a more dependable and efficient battery management system by limiting the need for interventions to times when they are necessary.

4.8.2 False Negatives (Class 1 predicted as Class 0):

A notable area for improvement is the model's inability to identify 202 occurrences that call for corrective action. There may be missed opportunities to maximize battery performance because of these missed detections when the model misclassified critical situations as non-critical. Neglecting essential interventions by the system can result in unsolved problems that eventually compromise the efficiency and health of the battery. For example, unnoticed overheating or overcharging situations may result in rapid battery deterioration or reduced overall efficiency. To protect the battery's lifespan and preserve its optimal performance, these false negatives must be addressed to improve the accuracy of the model and guarantee that any possible issues are swiftly resolved. By improving the detecting capabilities of the model, the system may better prevent premature battery wear and enhance overall energy management, resulting in an electric car that is more dependable and efficient.

4.8.3 False Positives (Class 0 predicted as Class 1):

A significant advantage of the model is its meticulous approach to decision-making, as evidenced by the total lack of false positives, in which Class 0 was mistakenly projected to be Class 1. By exercising caution, the system makes sure that remedial actions are only taken when they are truly necessary. The model assists in preventing needless strain or wear on the battery by preventing interventions from inadvertently starting in stable settings. This can happen if the system repeatedly initiates overly cautious modifications. As a result of lowering the possibility of excessive or early wear, this cautious behavior is beneficial for preserving battery health and longevity. A more dependable and durable electric car is produced because of this cautious approach, which also reduces interference with the battery's regular operation. The efficacy of the model in preserving battery longevity and maximizing performance is demonstrated by its ability to accurately prevent false positives.

4.8.4 True Positives (Class 1 predicted as Class 1):

The model has demonstrated its high skill in identifying conditions that call for quick interventions to ensure optimal battery performance, as seen by its accurate identification of 1,198 instances of Class 1. Every Class 1 incident denotes a critical condition for which remedial action is necessary. These activities could include resolving possible overheating, overcharging, or other abnormalities that could compromise the lifespan and efficiency of the battery. The model makes sure that the appropriate actions are taken to stop performance decline and preserve the battery's health by accurately identifying these occurrences. This proactive strategy enhances overall system reliability by efficiently controlling the battery's operational conditions. The model's ability to identify these crucial windows for intervention highlights how well it works to improve battery management, which raises the vehicle's overall efficiency and longevity.

Overall, the confusion matrix analysis shows that the model performs exceptionally well at identifying Class 0 events, which means that it successfully detects situations in which no corrective action is required. This excellent ability to identify stable conditions helps to preserve system efficiency and avoid needless interventions. The matrix does, however, also point out a minor weakness in the model's capacity to recognize every Class 1 circumstance, in which remedial action is necessary. This implies that the model occasionally fails to identify crucial circumstances, possibly missing significant chances to maximize battery performance.

It could be required to develop further the model to overcome this problem. To improve the model's ability to generalize and identify minute clues of Class 1 situations, one strategy would be to increase the training dataset's diversity. Furthermore, adjusting the hyperparameters of the model could increase its sensitivity and accuracy in identifying these crucial circumstances. The total efficacy of the battery management system can be raised by strengthening the model's capacity to recognize all pertinent Class 1 instances, guaranteeing more precise and timely actions. Better battery health management and more dependable operation of the electric car would result from this.

4.9 Implications for Battery Management.

The model's capacity to reliably manage stable battery conditions is demonstrated by its excellent accuracy in anticipating Class 0 circumstances. This implies that under normal operating conditions, the system can reliably maintain optimal battery operation, preventing needless interventions and guaranteeing effective energy management. The model's good performance in Class 0 scenarios indicates that it can identify and manage circumstances in which the battery is operating within predicted bounds.

Nonetheless, a crucial area for development is highlighted by the Class 1 scenarios' missed projections. These missed detections show that, especially in more difficult or unpredictable circumstances, the model might occasionally overlook circumstances that call for remedial action. This weakness could lead to lost opportunities to proactively resolve possible problems, which could result in less-than-ideal battery performance or accelerated wear in dynamic environments.

Although the AI model works well in stable environments, there is a great deal of room for improvement, according to the findings. The training dataset might be expanded to cover more varied and difficult settings, model parameters could be adjusted, or new features could be added to increase sensitivity and accuracy to optimize the model's ability to handle Class 1 scenarios. The model's protection and longevity might be significantly increased by addressing these areas, particularly in situations when battery demands are erratic or variable. Enhancing the overall performance and longevity of the EV would result in more durable and dependable battery management.

4.10 Challenges and Observations

4.10.1 Signal Fluctuation:

The little variations in the validation accuracy show that there are times when the model has trouble generalizing to new data. Although the overall performance shows that the model is reliable and efficient in typical situations, these variations point to possible flaws in the model when applied to unusual or extreme cases. This could imply that, especially in circumstances that are more complicated or uncommon, the model may not always be able to anticipate outcomes when given data that it hasn't seen before. To solve this, the model's architecture might be improved or additional training with a more diverse dataset could help the model become more generalizable, which would increase its dependability in a wider range of real-world scenarios.

4.10.2 Serial Communication Lag:

The Arduino responds to control signals from the Python model with a tiny delay, which suggests that there may be inefficiencies in the serial communication mechanism. Although not very disruptive, this latency indicates that the system takes longer to transmit and interpret data when handling larger datasets or more complicated predictions. Slower system responses could result from this, which could have an impact on the battery system's real-time management. This latency could be decreased by streamlining data packets or improving the communication protocol, for example. Improving the processing algorithms to do intricate calculations more effectively may also contribute to the system's resilience by guaranteeing that control operations are carried out correctly and on time, even in the face of harsher circumstances.

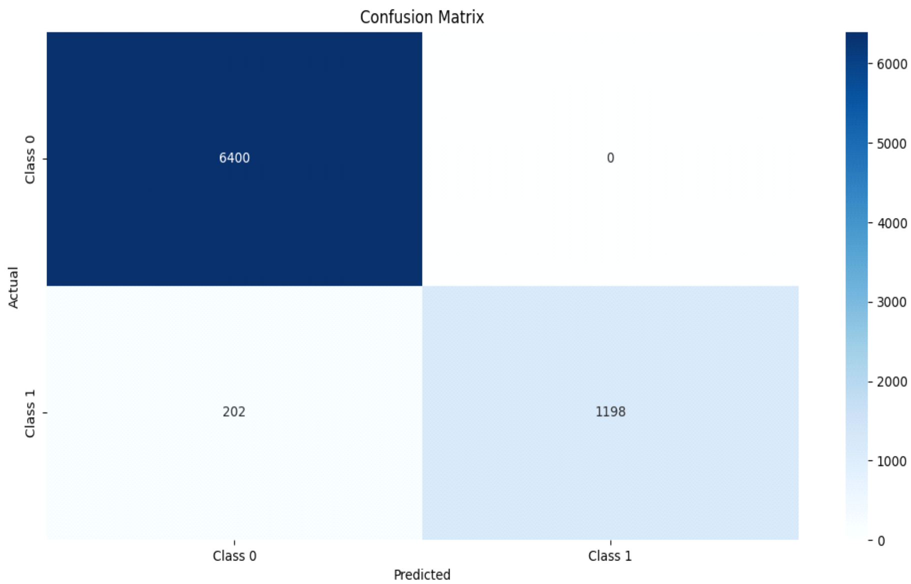

Figure 20: Confusion Matrix of the Machine Learning

4.11 App Interface for Voltage and Current Updates.

Fig. 21 represents the user interface of the application developed to provide real-time updates on voltage and current readings for the AI-based battery management system. This app is integral to the system as it allows users to monitor the battery's performance continuously. By displaying live data on voltage and current, the app enables users to observe the battery's status and receive instant updates on the model's predictions regarding necessary corrective actions.

The app collects data from the embedded sensors within the battery system, processes it through the AI model, and then displays the results in a user-friendly interface. This real-time data visualization is crucial for diagnosing battery health, identifying potential issues early, and ensuring that the battery operates efficiently under various conditions. By providing these updates, the app not only enhances user engagement with the system but also serves as a critical tool for maintaining the optimal performance of the EVs battery.

The accuracy of the AI predictions, as discussed earlier, directly influences the effectiveness of the updates shown in the app. With further improvements to the model, the app can become even more reliable in signaling when interventions are necessary, thereby contributing to better battery management and extending the battery's overall lifespan.

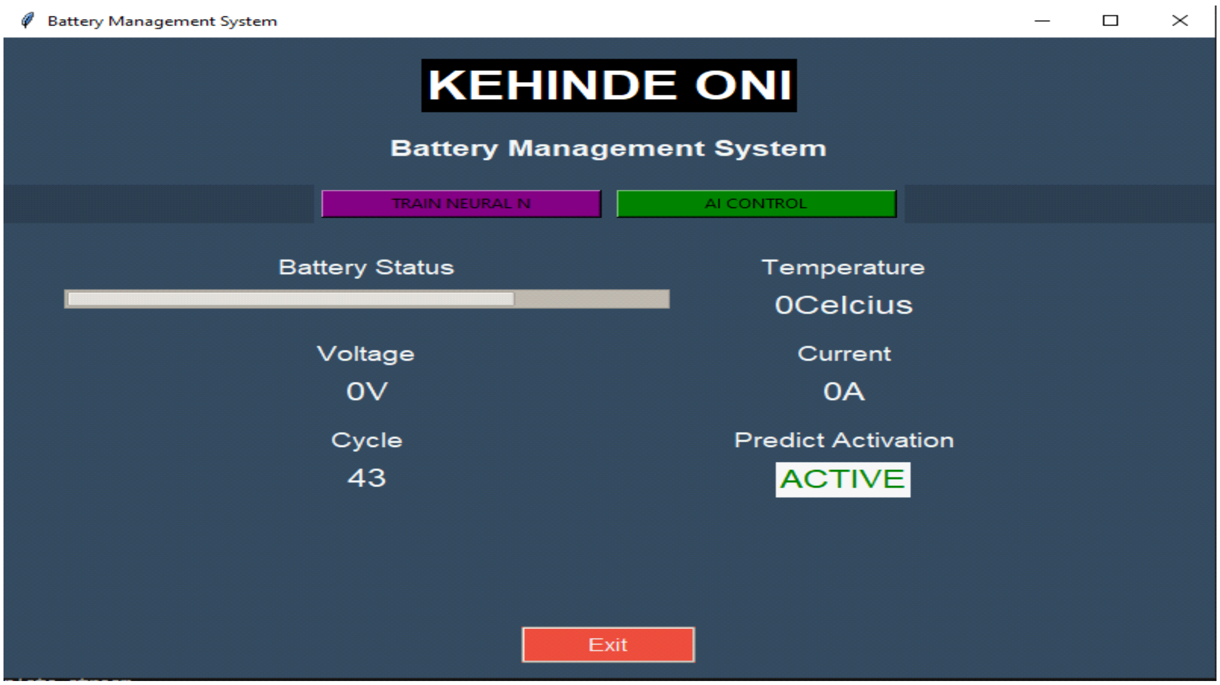

Figure 21: BMS App Interface when the device is not connected

Chapter 5: Discussion And Contribution to Knowledge

5.1 Discussion

Artificial Intelligence (AI) integration with Battery Management Systems (BMS) has demonstrated significant potential in improving real-time management and battery performance prediction. Key variables that are important for determining the health and performance of the battery were efficiently monitored by the AI model. These indicators included the consistent current draw and the lowering voltage trend across battery cells. The AI system can make wise judgments to balance loads, optimize charging cycles, and control energy consumption by precisely anticipating these patterns. This will eventually extend battery life and enhance overall vehicle performance. This ability is very helpful for electric cars since preserving the ideal battery function is crucial to guarantee dependability and effectiveness.

The observed variations in validation accuracy, however, suggest that the AI model would need more improvement. These variations imply that even though the model is generally reliable, it can find it difficult to adjust to a variety of driving situations and changing battery levels, which could result in less precise forecasts in some situations. This could be resolved by improving the model's training procedure, perhaps by adding more varied datasets that reflect various driving situations and battery states, or by fine-tuning the model's architecture to increase the model's capacity for generalization.

The AI-based system's ability to offer consistent temperature readings further supports how well it manages battery stress. The mechanism keeps the battery within its ideal working temperature range, preventing overheating and other temperature-related problems that can reduce the battery's lifespan or impair its performance. This stability shows that the AI model can ensure that the battery runs safely and optimally in addition to controlling power and energy. These results collectively highlight how AI can completely transform battery management, but further development and testing are required to fully realize its promise in all driving and environmental scenarios.

5.2 Contribution to Knowledge

The reviewed research work presents the findings that contribute largely to the existing knowledge base in the field of AI-based battery management systems for electric cars. The research work is of great value for the study of the possible advantages and realistic uses of the integration of the latest AI and ML technologies into BMS for 2/3-wheeler EVs. The studies show that the performance, efficiency, and lifespan of batteries obtained through AI-based BMS are better than those of conventional methods, therefore, they are the key to the adoption and commercialization of this technology. The findings reported on the issues that the EV industry is facing, like range anxiety, battery degradation, and charging infrastructure limitations. Besides, the literature that has been reviewed helps to increase the knowledge of the complicated relationship between AI algorithms, real-time data analysis, and battery management strategies. The results show the significance of data-driven decisions and the role of advanced analytical methods in battery efficiency and the whole system efficiency. Besides, the investigation of the combination of AI-based BMS with other elements of the EV ecosystem, like the charging infrastructure and the energy management systems, is widening the knowledge base and thus providing new opportunities for research and innovation in the field of sustainable transportation.

5.3 Implications

The dissertation literature reports have practical significance for the development, production, and adoption of 2/3-wheeler EVs and their associated technologies by stakeholders. For EV manufacturers and battery suppliers, the use of AI-based BMS can result in the improvement of product quality, customer satisfaction, and market positioning. Through the provision of cars with longer-lasting batteries, excellent performance, and more energy-efficient operation, these companies can draw environmentally aware customers and thus increase their market share. The results of the survey can be used by government agencies and policymakers for guidance in their decision-making process regarding the promotion of sustainable transportation and the development of supporting infrastructures. Through the realization of the AI-based BMS potential advantages, they can establish policies and incentives that will promote the adoption of this technology; hence, the overall decrease of carbon emissions and the environmental impact will be achieved.

Consumers and end-users of EVs have been able to see the most benefits from the new generation of 2/3-wheeler EVs. They have benefited from increased range, shorter charging times, and better overall vehicle performance. The AI-based BMS materialization will alleviate the range anxiety and at the same time, it will both increase the user experience and thus will influence people to use EVs for their daily commuting as well as transport needs. Besides the fact that the research findings have implications for researchers and academics in the field of AI, battery technology, and sustainable transportation, the results are significant. The insights obtained from the research can be useful in directing future projects, encouraging the cooperation of experts in different fields, and creating new technologies for the development of more modern and efficient battery management systems.

5.4 Recommendations

Based on the insights gained from the reviewed literature, several recommendations can be made for future research and practical applications in the field of AI-based battery management systems for 2/3-wheeler EVs:

5.4.1 Enhance Machine Learning Algorithms:

The deep learning model should be fine-tuned to better handle more complex and unpredictable battery conditions. By improving its sensitivity to unusual voltage, current, or temperature changes, the system will become even more reliable and safer.

5.4.2 Improve Real-Time Data Processing:

The slight delay between the Arduino and the deep learning model could be minimized by optimizing the data transmission or using faster microcontrollers. This would ensure smoother real-time performance, especially in critical applications like EVs.

5.4.3 Including More Environment Sensors:

While the current system monitors temperature and humidity, adding sensors for things like vibration or pressure could offer a fuller picture of battery health. More data means better predictions and quicker responses to any potential issues.

5.4.4 Integrate Cloud Storage and Analytics:

Storing the data on the cloud in addition to the microSD card would allow for long-term tracking and better analysis of battery performance. This would also make remote monitoring easier, so users can keep an eye on the system even from afar.

5.4.5 Improve Energy Efficiency:

Reducing the power consumption of the Arduino and its sensors would help the system run more efficiently. This is especially important for applications where every bit of battery life counts.

5.4.6 Testing in Real World:

Although the system works well in controlled environments, it's important to test it in real-world settings, like in EVs. This will help make sure it holds up under different loads, weather conditions, and operational stresses.

5.4.7 Create a User-Friendly Interface:

A simple mobile or web app would make the system much easier to use. It would allow operators to easily monitor battery data, receive alerts, and even make manual adjustments if needed.

5.4.8 Promote Interdisciplinary Collaboration:

The making of innovative AI-based BMS needs the involvement of various disciplines, such as AI, battery technology, electrical engineering, and sustainable transportation.

Chapter 6: Conclusion

The results from this study underscore the significance of an AI-driven battery management system in optimizing power flow and extending the lifespan of an EV battery. While the current model shows promise, further improvements in the machine learning algorithm are required to enhance its accuracy and adaptability in real-world scenarios. The findings pave the way for future developments in AI-based BMS technology, contributing to safer and more efficient EVs.

The confusion matrix analysis reveals that the AI-based battery management system developed in this study is highly effective in identifying stable operating conditions (Class 0) with a perfect accuracy rate in avoiding unnecessary corrective actions. However, the model's performance in detecting scenarios that require intervention (Class 1) indicates some areas for improvement. Specifically, the 202 missed detections (false negatives) suggest that while the model is reliable, it may benefit from further refinement to enhance its ability to anticipate and manage more complex or unpredictable battery conditions.

The successful integration of the Arduino system with a deep learning model represents a significant advancement in the AI-based management of battery systems. The ability to collect, analyze, and act on real-time data ensures that the system can optimize power usage, maintain safety, and prolong the lifespan of the battery. Despite minor challenges in signal fluctuation and communication lag, the overall system performed as intended, demonstrating the potential of AI in enhancing the efficiency of EV batteries.

Additionally, this study highlights the versatility and robustness of the integrated AI and Arduino framework, which not only facilitates real-time monitoring and decision-making but also offers a scalable solution for future applications in various types of EVs. The approach used in this project can be adapted to accommodate different battery chemistries and configurations, providing broad applicability in the field of electric mobility.

The deep learning model's ability to predict and respond to voltage and current fluctuations ensures that the system remains responsive under various operating conditions. Moreover, the development of an app that visualizes these predictions and updates in real-time provides users with a practical interface to monitor the battery's health and performance, further enhancing the system's usability and effectiveness.

In conclusion, while the study reveals some areas for improvement, particularly in refining the algorithm's detection capabilities, the overall success of this project lays a strong foundation for future innovations in AI-based battery management systems. The integration of real-time data processing, deep learning predictions, and user-friendly interfaces exemplifies the potential of AI to revolutionize battery management in electric vehicles, leading to safer, more efficient, and longer-lasting battery systems.

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