A Mini Project with Seminar On

BATTERY HEALTH MANAGEMENT AND FAULT PREDICTIVE SYSTEM

Submitted in partial fulfillment of the requirements for the award of the

Bachelor of Technology

in

Department of Computer Science and Business System

by

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GOKARAJU RANGARAJU INSTITUTE OF ENGINEERING AND TECHNOLOGY

(Approved by AICTE, Autonomous under JNTUH, Hyderabad)

Bachupally, Kukatpally, Hyderabad-500090

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CERTIFICATE

This is to certify that the mini project entitled "**BATTERY HEALTH MANAGEMENT AND FAULT PREDICTIVE SYSTEM**" is submitted by **N. Eshwar (21241A3237), P. Somnath (21241A3244) and S. Yaswanth (22245A3206)** in partial fulfillment of the award of degree in BACHELOR OF TECHNOLOGY in Computer Science and Business System during Academic year 2023-2024.

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DECLARATION

We hereby declare that the mini project titled **"BATTERY HEALTH MANAGEMENT AND FAULT PREDICTIVE SYSTEM"** is the work done during the period from **1st September 2023 to 4th January 2024** and is submitted in the partial fulfillment of the requirements for the award of degree of Bachelor of Technology in Computer Science and Business System from Gokaraju Rangaraju Institute of Engineering and Technology (Autonomous under Jawaharlal Nehru Technology University, Hyderabad). The results embodied in this project have not been submitted to any other University or Institution for the award of any degree or diploma.

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ABSTRACT

The Electric Vehicle (EV) revolution is rapidly reshaping the automotive industry offering alternative to combustion engine vehicles. A cornerstone of this transformation is the lithium-ion battery, which powers these EVs. The possibility of battery failures leading to explosions and substantial losses is a critical concern that demands innovative solution. The disadvantages of existing methods include limited predictive capabilities and mostly focused on basic maintenance needs. The primary objective of the Battery Health Management and Fault Predictive System (BHFPS) is to enhance the safety and reliability of electric vehicles by implementing advanced monitoring and predictive maintenance measures for EV batteries. The methodology involves developing an Internet of Things (IoT) based system that collects data from sensors and sending it to cloud.

LIST OF FIGURES

Figure No.	Figure Name	Page No.
1	Working of IoT	4
2	Applications of IoT	6
3	Self Driven Cars	6
4	Smart Home	7
5	Smart Retail	8
6	Farming	9
7	Wearables	10
8	Smart Grid	11
9	Challenges of IoT	13
10	ESP8266 NodeMCU Board	26
11	TP4056 Lithium-Ion cell charging module	28
12	Temperature Sensor with Arduino	29
13	Voltage Sensor	30
14	Acs712 Curent Sensor	31
15	Random Access Memory (RAM) definition and information	32
16	Architecture Diagram	34
17	Experimental setup	40
18	Dashboard in Blynk	40

TABLE OF CONTENTS

Chapter No.	Chapter Name	Page No.
	Certificate	ii
	Acknowledgement	iii
	Declaration	iv
	Abstract	v
1	**Introduction**	
	1.0 Introduction	1
	1.1 History	2
	1.2 Working Principle	3
	1.3 Distinct Applications of IoT	5
	1.3.1 Self-driven car	6
	1.3.2 Smart Home	7
	1.3.3 Smart Retail	8
	1.3.4 Farming	9
	1.3.5 Wearables	10
	1.4 Significance/Advantages of IoT	11
	1.5 Challenges in Building IoT based Systems	12
	1.6 Drawbacks of IoT based Systems	14
2	**Literature Survey**	
	2.0 Existing Approaches	16
3	**Software and Hardware Requirements**	
	3.0 Software Requirements	23
	3.0.1 Arduino IDE	23
	3.0.2 Database	24
	3.1 Hardware Requirements	25
	3.1.1 ESP8266 Wi-Fi Module	25
	3.1.2 Generic TP4056 1A Li-ion Charging Board	27
	3.1.3 DHT22 Temperature and Humidity Sensor Module	29
	3.1.4 Voltage Sensor	30
	3.1.5 Generic ACS712 30A Current Sensor Module	31 32

3.1.6 Ram

4	**Proposed Method**	
	4.0 Problem Statement and Objectives	33
	4.1 Objectives	33
	4.2 Architecture Diagram	34
	4.3 Proposed Modules	34
5	**Results and Discussions**	
	5.0 Results and Discussion	39
	5.1 Experimental Results	40
6	**Conclusion and Future Enhancements**	
	6.0 Conclusion and Future Enhancements	42
7	**Appendices**	
	7.0 Code for Retrieving Sensors Data in Blynk	45
	References	
	References	49

CHAPTER 1

INTRODUCTION

1.0 Introduction

The concept of the IoT encompasses linking various devices, beyond conventional gadgets like laptops and smart phones, to the internet for data transmission and reception. This connectivity spans from everyday objects like thermostats and washing machines to less conventional items like medical implants for heart monitoring and agricultural irrigation systems. By integrating these devices with internet access, the IoT facilitates remote control and data exchange, thereby fostering more efficient and automated decision-making processes. A key advantage lies in the IoT's capacity to gather and analyze vast volumes of data from interconnected devices, presenting opportunities to enhance decision-making across diverse sectors. For instance, in agriculture, sensors embedded in farm equipment and fields can monitor elements like soil moisture and temperature, empowering farmers to optimize their irrigation and fertilization techniques. Similarly, within the healthcare realm, IoT devices enable remote monitoring of patients' health, streamlining healthcare delivery and minimizing the necessity for physical consultations.

The IoT also has the potential to improve energy efficiency and reduce resource consumption. For example, smart thermostats that can be controlled remotely can help to reduce energy use by turning off heating and cooling systems when they are not needed. Similarly, smart irrigation systems can help to reduce water use in agriculture by only watering when and where it is needed. There are also potential concerns with the IoT, such as security and privacy. As number of devices that are inter connected over the internet, there is an increased risk of data breaches and cyber attacks. It is important for companies and individuals to ensure that their IoT devices are secure and that they take steps to protect their personal data. Attendance has become a big complicated issue for many institutions as well as some of the top multinational companies to track the attendance of their employees to pay them the respective salary based on their percentage of attendance, in institutions to promote the students too.

1.1 History

The inception of the IoT traces back several decades, with its terminology surfacing in 1999. Nevertheless, the evolution of today's IoT landscape has been significantly influenced by pivotal technological advancements and societal shifts. An instrumental catalyst driving the IoT's progression has been the availability and advancement of economical, energy-efficient microcontrollers and sensors. This accessibility has facilitated the interconnection of diverse devices to the internet. Furthermore, the widespread embrace of wireless technologies like WiFi has played a pivotal role, simplifying communication between devices and the internet, thereby contributing substantially to the IoT's development.

In the early 2010s, the IoT began to gain significant traction, as a number of companies began to develop and market a range of IoT-connected devices, such as smart thermostats, smart appliances, and wearable fitness trackers. The release of the Raspberry Pi, a low-cost single-board computer, in 2012, also played a role in the growth of the IoT, as it provided a cheap and accessible platform for hobbyists and developers to build IoT projects. Since then, the IoT has continued to grow and evolve, with the number of connected devices expected to reach tens of billions by the end of the 2020s. Future generations' lives are predicted to drastically change as a result of the IoT, which has the potential to revolutionize a wide range of industries, including retail, transportation, and even healthcare and agriculture.

The interconnectedness facilitated by the internet allows us to effortlessly tap into information from any corner of the globe. This enables us to remotely oversee changes in our environment across distant locations. The realm of IoT holds immense significance in our daily routines, showcasing just a glimpse of its myriad applications amidst the rapid technological advancements. Brendan O'Brien, an American record producer, aptly remarked, "If you believe the internet has transformed your way of life, brace yourself. This is poised to revolutionize it once more!" This signifies the potential for IoT to permeate and revolutionize practically every feasible field it touches.

1.2 Working Principle

The foundation of IoT operation hinges upon the seamless transmission and reception of data packets among interconnected devices, facilitating their communication within networks and with external systems. This fundamental capability forms the bedrock for automating tasks, enabling remote control functionalities, and gathering extensive data from diverse origins. A successful IoT ecosystem typically comprises several essential components. These encompass sensors and actuators responsible for data collection and execution, alongside communication infrastructure for data exchange between devices. Moreover, cloud-based services and platforms serve as pivotal elements, offering storage, management, analysis, and user/system accessibility within IoT frameworks. Enabling automation and remote management of processes stands as a pivotal strength of IoT, fostering the collection and analysis of data from a myriad of sources. This capability lays the groundwork for crafting intelligent systems that enhance efficiency, productivity, and safety across multifaceted applications. At the heart of IoT lie devices embedded with microprocessors and connected to the internet, empowering them to serve specific functions and automate decision-making processes.

Furthermore, this interconnected network of devices facilitates a paradigm shift in how systems operate, enabling seamless coordination among various components for streamlined functionality. The ability to leverage real-time data and translate it into actionable insights empowers industries and users to make informed decisions, optimize operations, and explore innovative solutions. This convergence of technology opens avenues for creating adaptive and responsive environments, redefining traditional approaches to problem-solving and enhancing overall system efficiency and effectiveness.

Figure 1 Working of IoT (Courtesy: Source [9])

The figure[1] provides a detailed and comprehensive overview of the various steps in the working of an IoT-based technology, highlighting the key roles that IoT plays in improving the efficiency, sustainability, and compliance of various systems.

The IoT is the network of interconnected physical objects, such actuators and sensors, that are embedded with connections, software, and electronics to enable data collection and exchange. These gadgets have internet connections, enabling many devices to communicate with one another and with other internet-enabled devices and systems. Usually, a central server or cloud-based platform receives the data gathered by IoT devices so that it may be examined, evaluated, and utilized to initiate activities or make decisions. For example, the data collected by an IoT-connected security system could be used to alert homeowners to potential threats, or the data collected by an IoT-connected manufacturing system could be used to identify and fix equipment issues before they cause downtime.

The four essential parts of an IoT device that make it work are:

- **SENSORS**
- **PROCESSOR**
- **POWER SUPPPLY**
- **COMMUNICATION INTERFACE**

IoT devices consist of sensors, processor, power supply and communication interface.

- **Sensors** - Sensors are used to collect data from the environment or from other devices. This can include data on temperature, humidity, light intensity, or other factors.
- **Processor**- The processor is the brain of the device, and is responsible for processing the data collected by the sensors. The processor may also be responsible for executing instructions and controlling the device's functions.
- **Power Supply**- The power supply is responsible for providing the energy needed to run the device. This can be used to evolve through the use of batteries, solar panels, or other power sources.
- **Communication interface**- The communication interface is the part of the device that enables it to connect to the internet and to communicate with other systems. This can be accomplished through the use of Wi-Fi, Bluetooth, or other wireless technologies.

1.3 Distinct Applications of IoT

A system of networked cars, appliances, and other devices that can collect and transfer data without the need for human involvement is known as intelligent transportation. IoT applications have the potential to greatly improve our quality of life as shown in figure [2]. With its improved wireless networks, sophisticated sensors, and cutting-edge processing capacity, that could be the next big thing in the competition for consumers' dollars. It is anticipated that billions of everyday things will gain intelligence and connectivity through IoT apps. It is already widely used in several sectors, including:

- Self-driven cars
- Smart Home
- Smart Retail
- Agriculture
- Wearables
- Smart Grid
- Industrial Internet
- Healthcare
- Manufacturing and retail

Figure 2 Applications of IoT (Courtesy: Source [10])

1.3.1 Self-driven car

A self-using vehicle figure [3], moreover called a self-driven vehicle, is a vehicle that is capable of experiencing its environment and shift successfully with little or no human input. Self-using cars combine pretty sensors to apprehend their surroundings information. Various sensors play crucial capabilities with inside the self-using vehicle.

Figure 3 Self Driven Cars (Courtesy: Source [11])

1.3.2 Smart Home

The IoT has many important uses, and one of the fastest-growing uses at the moment is in smart homes [4]. Customers are drawn to the security characteristics of their Smart home technology, which is its key selling point. With this IoT, webcams may be installed to monitor dwellings, as if all home applications- including fans, lighting, air conditioners, locks, and so on were integrating into one system that could be controlled by a smart phone it has voice-activated control and intelligent air quality adjustments. The goal of a smart home is to improve convenience, security, and energy efficiency by allowing homeowners to monitor and control their home remotely and to automate decision making. For example, a smart thermostat can learn a homeowner's schedule and adjust the heating and cooling system accordingly to save energy. A smart security system can alert homeowners to potential threats and allow them to monitor their home remotely. Smart home technologies can be controlled through a variety of methods, such as a smartphone app, a web-based interface, or a voice-activated virtual assistant. Many smart home devices can also be linked to other systems and devices, such as smart speakers and smart appliances, to create a fully connected and automated home.

Figure 4 Smart Home (Courtesy: Source [12])

1.3.3 Smart Retail

The application of IoT technology to increase the efficacy and efficiency of retail operations is referred to as "smart retail" figure [5]. This can include the use of sensors, RFID tags, and other technologies to track inventory, manage supply chains, and gather data on customer behaviour and preferences. One of the main benefits of smart retail is the ability to gather and analyze large amounts of data, which can be used to improve decision making and optimize operations. For example, retailers can use data on customer behaviour to better understand buying patterns and to tailor their marketing and sales efforts accordingly. Smart retail technologies can also be used to optimize inventory management, helping retailers to reduce waste and improve efficiency.

Figure 5 Smart Retail (Courtesy: Source [13])

Smart retail technologies can be used in a variety of settings, including brick-and-mortar stores, online stores, and marketplaces. They can also be used in other parts of the retail supply chain, such as warehouses and distribution centers. Overall, smart retail has the potential to transform the way retailers do business, improving efficiency, reducing costs, and enhancing the customer experience.

1.3.4 Farming

The application of technology and data analysis to maximize agricultural productivity is referred to as smart farming figure [6], sometimes known as precision farming or agriculture. This can include the use of sensors, drones, and other IoT technologies to collect data on factors such as soil moisture, temperature, and nutrient levels, and to use that data to optimize irrigation, fertilization, and other key aspects of farming. The goal of smart farming is to improve crop yields, reduce resource consumption, and increase efficiency. By using data-driven decision making, farmers can optimize their farming practices to reduce waste and increase productivity.

Figure 6 Farming (Courtesy: Source [14])

Smart farming technologies can be used in a variety of crops, including field crops, fruits, and vegetables. They can also be used in livestock production, to monitor the health and well-being of animals and optimize feeding and care. Overall, smart farming has the potential to transform the way we produce food, making it more sustainable and efficient, and helping to meet the growing demand for food as the global population continues to increase.

1.3.5 Wearables

Wearable technology which is shown in figure [7] is essentially the center of IoT applications. A variable is anything that we can attach to our clothing or wear as an accessory. It gives the user access to personal data on his fitness, health etc. because they offer useful information and maintain bodily condition management accessories are adopted by the people nowadays. There are many wearable devices developed recently some of them are:

- Guardian Glucose monitoring device
- Smart watches
- Smart clothes
- Smart glasses
- Smart shoes

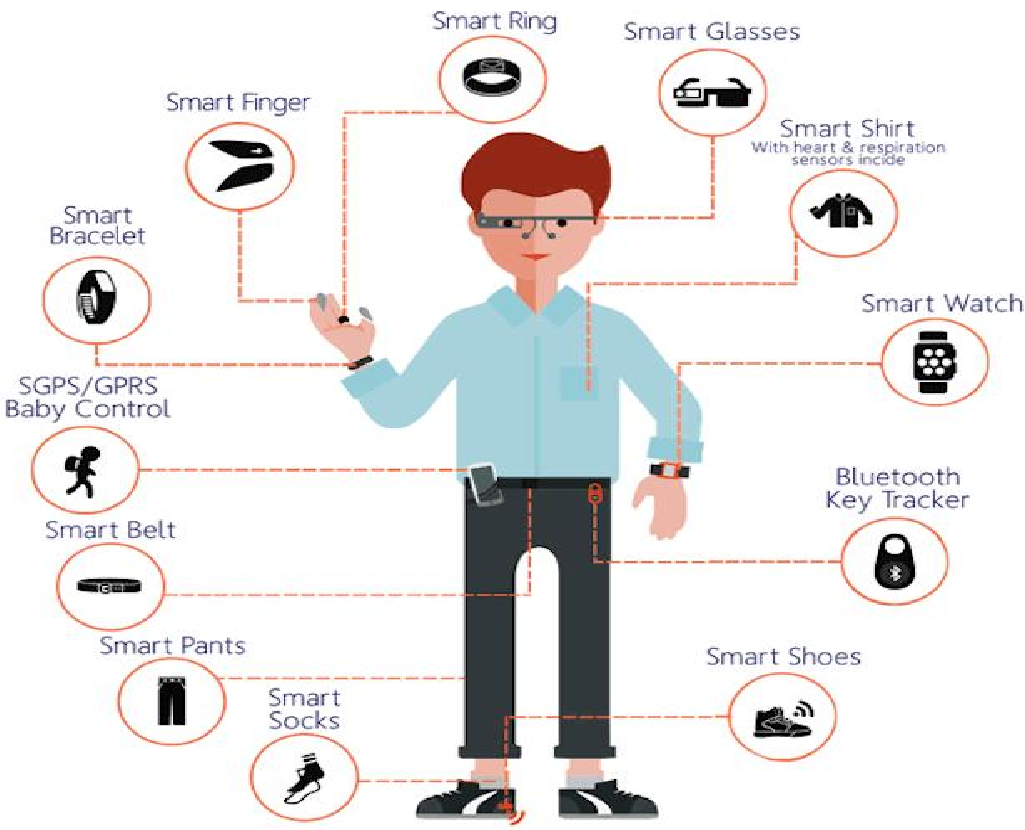

Figure 7 Wearables (Courtesy: Source [15]

1.3.6 Smart GRID

Utility businesses are turning to IoT to make strength provision extra efficient. Appropriate sensors are hooked up in strength meters, transmission lines, manufacturing flora, and distribution points. This IoT machine is known as a Smart grid figure [8]. Everyday customers can examine their strength utilization and result in effective adjustments of their carbon footprints. It additionally facilitates reducing down expenses while strength expenses peak, because it did throughout Europe due to the Ukraine-Russia war. Energy may be created at conventional energy flora and sun and wind energy flora. Smart grids permit seamless switching among those specific energy sources. They make sure that the ideal parameters, which include voltage, are maintained whilst doing so. Utility businesses are turning to IoT to make strength provision extra efficient. Appropriate sensors are hooked up in strength meters, transmission lines, manufacturing flora, and distribution points. This IoT machine is known as a clever grid. Everyday customers can examine their strength utilization and result in effective adjustments of their carbon footprints. It additionally facilitates reducing down expenses while strength expenses peak, because it did throughout Europe due to the Ukraine-Russia war. Energy may be created at conventional energy flora and sun and wind energy flora. Smart grids permit seamless switching among those specific energy sources. They make sure that the ideal parameters, which include voltage, are maintained whilst doing so.

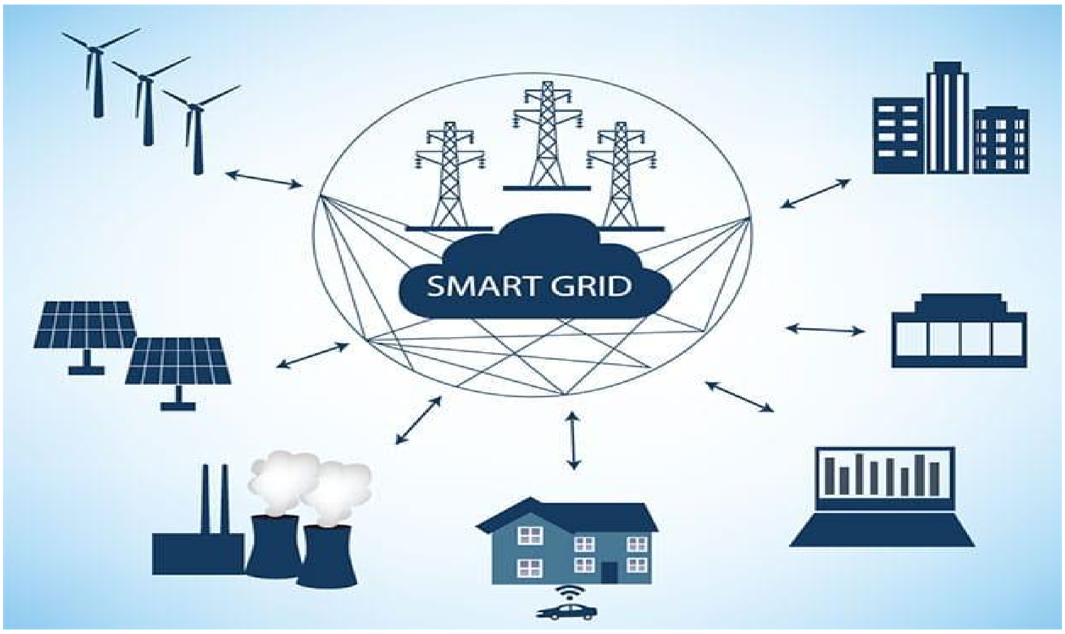

Figure 8 Smart Grid (Courtesy: Source [16])

1.4 Significance/Advantages of IoT

The is most widely used technology and it is responsible for automation of things surrounding us. Some of the applications are:

- **Decision Making:** Devices that have multiple sensors can collect a large amount of data from various sources, providing them with more information to use when making decisions or taking action. An example of this is a smartphone, which uses various sensors to track a user's activity, location, and other behaviours.

- **Real-Time Tracking and Monitoring:** Real-time tracking and monitoring refers to the process of continuously tracking and monitoring the status or location of an object or individual in real-time, or as close to real-time as possible. This can be achieved through the use of sensors, GPS, and other technologies that allow data to be collected and transmitted in real-time.
- **Automation**: Automation refers to the use of technology to perform tasks without the need for human intervention. Automation can be achieved through the use of machines, software, and other technologies that are able to perform tasks based on pre-determined rules or algorithms.
- **More Efficient Personal management:** Web-based devices save people money and time. This includes planning work schedules, time tracking, effective communication, and setting reminders for daily tasks.
- **Improved Data Collection:** Traditional information series has its obstacles and its layout for passive use. IoT helps instant motion on information.
- **Reduced Wastage management:** IoT gives real-world statistics main the powerful choice involving & control of requirements. Let us consider a situation, incase a producer reveals a difficulty in a couple of vehicle engines, he can sign the producing plan of these engines and solve this difficulty with the producing belt.
- **Improvement in customer engagement:** IoT permits you to enhance purchaser revel in with the aid of detecting troubles and enhancing the process.
- **Technical Optimization:** IoT generation allows loads in enhancing technology and making them better. Example, with IoT, a producer can gather information from numerous vehicle sensors. The producer analyzes them to enhance its layout and lead.

1.5 Challenges in Building IoT Based Systems

At gift IoT is confronted with many challenges, such as:

- **Interoperability:** Ensuring that the various devices and components in an IoT system can communicate and work together seamlessly can be a significant challenge, as there are many different protocols, standards, and technologies involved.
- **Security:** IoT systems collect and transmit large amounts of sensitive data, making them

  vulnerable to cyber-attacks. Ensuring that the system is secure and that the data is protected is a major challenge.

- **Scalability:** IoT systems can potentially consist of millions of devices, generating vast amounts of data. Building a system that can handle this scale of data and maintain high performance is a major challenge.
- **Data management:** Managing the vast amounts of the outputs that are generated by IoT devices can involve much more complex it may also time-consuming task. Ensuring that the data is organized, stored, and accessed efficiently is a key challenge.
- **Privacy:** Ensuring that the data collected and transmitted by IoT devices is used responsibly and in accordance with the user's privacy preferences is a major challenge.
- **User experience:** Creating a user-friendly and intuitive experience for interacting with IoT devices can be a challenge, especially as the technology is still evolving and users may not be familiar with it.

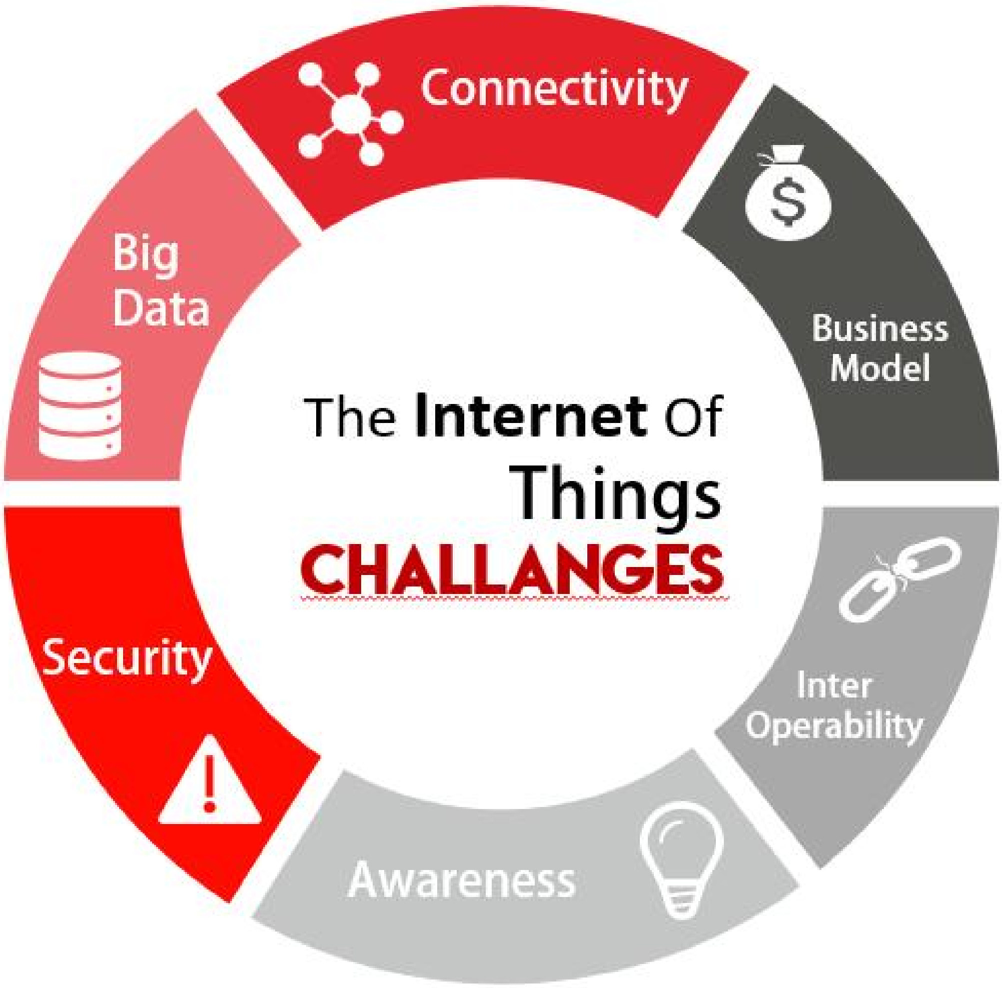

Figure 9 Challenges of IoT (Courtesy: Source [17])

1.6 Drawbacks of IoT Based Systems

- **Elevated Costs:** The creation and maintenance of IoT systems often incur significant expenses due to the necessity for a multitude of devices, sensors, software, and infrastructure. This financial burden can deter widespread adoption, particularly for smaller-scale applications or resource-constrained settings.

- **Complex Ecosystem:** IoT systems entail a complex ecosystem, amalgamating various technologies and components. The intricacies involved in integrating and managing these elements pose challenges during development, ongoing maintenance, and troubleshooting, requiring specialized expertise and resources.

- **Vulnerabilities in Security:** The susceptibility of IoT systems to cyber threats remains a critical concern. Security breaches not only compromise data integrity but also jeopardize user privacy and sensitive information, necessitating robust measures to mitigate potential risks.

- **Limited Flexibility in Integration:** The integration of IoT gadgets with other devices or systems can be arduous due to the numerous frameworks involved in the process. Compatibility issues and disparate infrastructures often impede seamless integration, affecting functionality and usability.

- **Privacy Apprehensions:** The extensive collection and transmission of data by IoT devices raise significant privacy concerns. The handling of vast amounts of personal information without responsible governance can lead to breaches of privacy and misuse of sensitive data.

- **Reliance on Technology and Susceptibility to Failures:** IoT systems heavily rely on technology, making them susceptible to technical failures or disruptions. These shortcomings could result in inconveniences or, in critical scenarios, pose safety risks to users.

- **Absence of Standardization:** The absence of standardized protocols in the IoT industry hinders the seamless integration of devices and systems from different vendors. This lack of uniformity restricts interoperability, scalability, and the potential for a universal IoT ecosystem.

- **Dependency on Internet Connectivity**: The reliance of IoT systems on internet connectivity for data transmission and communication exposes them to vulnerabilities associated with network outages or slow internet speeds. Disruptions in connectivity impede the system's functionality and real-time responsiveness.

- **Compatibility Challenges:** Varied protocols and standards utilized in IoT systems often lack compatibility with each other, posing integration challenges. This discrepancy obstructs interoperability, hindering the smooth interaction between different devices and platforms.

CHAPTER 2

LITERATURE SURVEY

2.0. Summary of Manuscripts - Existing Approaches

Zhang, J., Wang, Y., Jiang, B. et al [1] suggested that the use of electric vehicles (EVs) is rapidly increasing, but concerns persist around the safety and reliability of their lithium-ion batteries (LiBs). Early detection of LiB anomalies is crucial for preventing accidents and minimizing costs. While existing deep learning models can achieve decent anomaly detection in LiBs, they often lead to unnecessary inspections that incur high economic costs. This study introduces a novel deep learning model called Dynamical Autoencoder for Anomaly Detection (DyAD), specifically designed for large-scale real-world EV LiB data. Unlike traditional methods that treat all data features equally, DyAD exploits the hidden Markov model structure of battery data, viewing it as a dynamical system with inputs and responses. This allows DyAD to focus on identifying abnormalities in the input-to-response mappings, leading to more precise anomaly detection. Furthermore, DyAD employs a robust scoring procedure that bridges predictions between the vehicle level and individual charging snippets. This effectively utilizes the structure of EV fault labels, resulting in a more tailored and accurate detection approach. Compared to conventional methods and state-of-the-art deep learning models, DyAD demonstrates superior performance with a dominating ROC curve for anomaly prediction. It also achieves significant cost reduction (33-50%) by optimizing inspection frequencies based on actual anomaly occurrence. This work highlights the potential of deep learning for effective and cost-conscious anomaly detection in EV LiBs. DyAD's tailored design and dynamic system approach offer a practical solution for real-world battery management, enhancing safety and reducing economic burden in the growing EV industry.

Bhaskar K, Kumar A, Bunce J. et al [2] research explores advanced anomaly detection techniques within battery systems, focusing on mean-based voltage and temperature residuals to identify electrical and thermal irregularities. Two primary methodologies, the direct and PCA methods, are investigated for anomaly detection. The direct method transforms real-time voltage and temperature measurements into stable data, enabling the detection of anomalies where data significantly deviates from expected means. On the other hand, the PCA method, leveraging Principal Component Analysis, excels in recognizing anomalies varying across individual cells within the battery system. Both methods require nominal training data to establish critical parameters and exhibit low false-positive rates (<3%) while effectively tracing anomalies surpassing 4 mV in voltage and 0.15 °C in temperature. Despite the trade-off between precision and sensitivity in adjusting thresholds, the PCA method outperforms the direct method by 40–60% in anomaly detection across cells. However, practical considerations include the need for post-cell balancing retraining in voltage PCA for real-time applications. This research showcases promising avenues for enhancing battery system monitoring, emphasizing improved safety and reliability in diverse operational scenarios.

H. Chunhua, H. Ren, W. Runcai and Y. Jianbo [3] told that the safety and reliability of EVs hinge heavily on the performance of their LiBs. Predicting LiB failures before they occur becomes crucial for preventing accidents and minimizing repair costs. A study aimed to tackle this challenge by developing a dual-redundancy system for predicting LiB temperature anomalies in EVs. The system features three key components: a data fusion unit, a prediction unit, and a determination unit. The data fusion unit intelligently combines information from both primary and redundant temperature sensors using an adaptive weighted algorithm. This ensures robustness and accuracy in capturing even subtle temperature fluctuations. Next, the prediction unit leverages the combined sensor data along with its individual readings to forecast the next temperature value. It employs a radial basis function neural network, a powerful machine learning technique adept at analyzing complex patterns within the data. Finally, the determination unit takes center stage. It carefully evaluates the outputs from the sensors, their combined data, and the predicted value. Employing a sophisticated decision-making process, it selects the most reliable and representative temperature value, effectively minimizing prediction errors. Extensive testing through both experiments and simulations revealed the success of the prediction unit. It consistently predicted the next temperature value with remarkable accuracy, boasting a maximum error of just 2.37%. This demonstrates the system's potential for early detection of LiB temperature anomalies, allowing for timely interventions and mitigating the risk of battery failure

K. Zhang, X. Hu, Y. Liu, X. Lin and W. Liu [4] presents an innovative approach aimed at enhancing fault detection and isolation methods within lithium-ion batteries. Addressing the criticality of early fault detection to prevent damage and ensure safety in these batteries, the study proposes a novel methodology that amalgamates model-based and entropy techniques for accurate fault identification and isolation. The proposed method operates on a multifaceted strategy, strategically combining various approaches to effectively discern and isolate faults within lithium-ion battery systems. One core element of this methodology involves employing an interleaved voltage measurement topology. This topology facilitates the differentiation between faults in voltage sensors and those within the battery itself, achieved by obtaining multiple voltage measurements from each cell within the battery pack. Further strengthening the fault detection capabilities, the methodology integrates a comprehensive battery model with statistical inference techniques. This combination allows the system to simulate the typical behaviour of the battery and subsequently compare the actual measurements obtained from the battery with the anticipated behaviour from the model. By discerning deviations from the anticipated normal behaviour, potential faults can be identified and addressed. Additionally, the methodology utilizes the concept of sample entropy, serving as a pivotal metric to distinguish between distinct types of faults—specifically, short-circuit faults and connection faults. Short-circuit faults typically result in a more erratic and random voltage signal, while connection faults yield a less randomized signal. Leveraging sample entropy aids in pinpointing the nature of faults, enabling a more accurate and nuanced fault isolation process. The study's conclusive findings underscore the efficacy of the proposed methodology in effectively detecting and isolating faults within lithium-ion batteries. The validated effectiveness of this method signifies its potential to significantly enhance the safety and reliability of lithium-ion battery systems, offering a promising avenue to preemptively address faults and ensure enhanced operational integrity.

Ting Cai, Peyman Mohtat, Anna G. Stefanopoulou, Jason B. Siege [5] article introduces an innovative approach to detect faults within large lithium-ion battery packs. Emphasizing its relevance for electric vehicles, the article aims to mitigate potential safety risks associated with failures in these large-scale battery configurations. The focal challenge addressed in this study pertains to the limitations of traditional voltage-based detection methods, particularly their inefficacy in detecting faults within large packs configured in parallel. In such setups, signals from faulty cells tend to be masked by signals from healthy ones, rendering voltage-based detection methods less effective. To address this challenge, the proposed method integrates force and gas sensors as additional sources of information. Force sensors are employed to directly measure the pressure exerted by individual cells, providing early indications of excessive swelling resulting from internal faults. Additionally, CO_2 gas sensors within the pack enclosure monitor gas emissions, detecting thermal runaway precursors, which are indicative of potential catastrophic failures.

The methodology entails the integration of force sensors into the battery pack structure near individual cell modules to continuously measure cell pressure. Concurrently, gas sensors placed within the pack enclosure monitor CO_2 emissions. Real-time data analysis utilizes computational models predicting cell temperatures, swelling, and CO_2 generation based on the measured force and gas levels. Anomalies in pressure or CO_2 levels, signaling potential internal faults, trigger an alarm prompting subsequent safety measures to prevent further damage. However, the proposed method is not without its limitations. Challenges include the added hardware cost for implementing these sensors within the battery pack, contributing to increased complexity in the battery management system. Additionally, factors such as sensor sensitivity, placement, and environmental conditions may impact the system's accuracy. While the study presents promising results under simulated conditions, comprehensive real-world testing is essential to validate its effectiveness before widespread adoption. In conclusion, the proposed method offers a promising avenue for early fault detection in large lithium-ion battery packs, potentially bolstering safety and reliability in electric vehicles and other applications. Addressing the identified drawbacks and conducting extensive real-world testing remain critical steps towards ensuring its reliability and applicability in practical scenarios.

D. Li, Z. Zhang, P. Liu, Z. Wang and L. Zhang [6] introduced an innovative approach for diagnosing battery faults in EVs by integrating two distinct methodologies. The proposed method combines the Long Short-Term Memory Neural Network (LSTM) and the Equivalent Circuit Model (ECM) to address the complexities inherent in fault diagnosis within EV batteries. The LSTM neural network employed in this approach is designed to capture intricate temporal dynamics within battery voltage data, enabling the system to discern hidden patterns and correlations indicative of potential faults. Concurrently, the Equivalent Circuit Model provides a fundamental understanding of battery behaviour, facilitating the interpretation of voltage abnormalities identified by the LSTM. By integrating these two approaches, the method aims to achieve precise fault diagnosis, including identification of specific fault types and localization of the faulty cell within the battery pack. Additionally, the combined approach aims to offer early warnings of potential thermal runaway incidents, enabling proactive interventions before critical failures occur.

The article underscores the successful application of this combined methodology, reporting high accuracy in fault identification and localization, emphasizing its potential for robust EV battery fault diagnosis. The methodological implementation involves data acquisition from the battery pack during diverse driving conditions. Subsequently, the LSTM undergoes training on labeled data to recognize voltage anomalies associated with specific faults. The ECM is then integrated to interpret these anomalies, providing insights into the underlying physical causes of the faults, leading to precise diagnosis and localization within the battery pack. However, certain drawbacks are noted within this methodology. The computational complexity of combining LSTM and ECM demands powerful hardware and efficient algorithms for implementation. Moreover, the accuracy and effectiveness of the model heavily rely on the quality and quantity of the training data; inadequate or inaccurate data can result in misdiagnosis. Furthermore, the model's applicability to different EV battery types or operating conditions might be limited without further training and adaptation, indicating potential constraints in its generalizability. While promising, this method requires further evaluation and refinement to mitigate these drawbacks and ensure its reliability and applicability across diverse EV battery systems. Addressing these concerns would enable the method to provide consistent and accurate fault diagnosis, fostering enhanced safety and performance in electric vehicle operations.

X. Gu, Y. Shang, Y. Kang, J and team [7] delineated the pressing need to detect minor faults in lithium-ion battery packs promptly and accurately, considering the serious implications of delayed detection. Existing conventional methodologies often grapple with the intricate and inconsistent nature of these batteries, necessitating more innovative solutions for effective fault diagnosis. They proposed a novel real-time methodology based on unsupervised learning principles as a solution for early fault diagnosis in lithium-ion battery packs. Key components of this proposed methodology encompass an enhanced approach to Principal Component Analysis (PCA) and the utilization of Square Prediction Errors and Modified Contribution Plots. PCA serves to transform the battery pack voltage data into a refined space, facilitating the accentuation of faults. Meanwhile, the Square Prediction Errors and Modified Contribution Plots play a pivotal role in singling out outliers and tracking their behaviour over time, thereby aiding in the identification of faulty cells and potentially predicting the future occurrence and duration of faults. This methodology offers several distinct advantages, including its capability for early detection compared to traditional methods, real-time monitoring and diagnosis, adaptability without the need for pre-labeled data, precise fault traceability, and potential predictive abilities for forecasting fault occurrences and durations.

However, the research also delineated certain drawbacks and limitations of the proposed method. The limited validation, tested primarily on simulated data and a small real-world dataset, warrants further examination with larger and more diverse datasets. Additionally, the computational complexity of involved algorithms like PCA poses challenges for real-time implementation in resource-constrained systems. Furthermore, while the methodology exhibits potential for fault prediction, uncertainties persist regarding the accuracy and reliability of this predictive aspect. The generalizability of the method across diverse battery chemistries and pack configurations also remains unclear.

Jing Sun, Song Ren, Yunlong Shang and team [8] addressed the critical challenge of accurately predicting faults in lithium-ion batteries, a crucial aspect for both safety and prolonging battery life. Current methods often struggle with accuracy or heavily rely on complex battery models, prompting the need for an innovative solution. Proposing a unique approach, they introduced a novel fault prediction method that harnesses the power of Convolutional Neural Networks (CNNs) and LSTM networks in conjunction with correlation coefficient analysis to achieve precise fault prediction. The methodology adopted involves several key stages, commencing with the pre-processing of voltage data obtained from battery cells, which is segmented and normalized to facilitate subsequent analysis. The heart of the proposed methodology lies in the integration of the CNN-LSTM model. The CNN component functions to extract spatial features from the segmented voltage data, identifying local correlations crucial for accurate fault prediction. Meanwhile, the LSTM network operates to capture temporal dependencies within the data, effectively learning long-term patterns instrumental in fault anticipation.

Upon prediction, the model foresees future voltage values for individual cells, thereafter computing the correlation coefficient between the predicted and actual voltages. A substantial deviation in correlation signifies a potential fault, providing an actionable indicator for intervention. Highlighting the benefits, the research underscores the reported higher prediction accuracy of the proposed method compared to other commonly used techniques like LSTM or Bidirectional LSTM. It demonstrates robustness across varying temperature conditions, making it suitable for real-time online monitoring and prediction. However, the study also outlines certain limitations associated with the method. Notably, its validation relies on a relatively small dataset, urging the need for further evaluation on larger and more diverse datasets. Additionally, the computational complexity of training and executing the CNN-LSTM model might pose constraints, especially on resource-constrained systems. The model's opaque nature presents challenges in interpreting specific features indicative of faults, as CNN-LSTM models tend to be less transparent, affecting full comprehension of their predictions.

CHAPTER 3

SOFTWARE AND HARDWARE REQUIREMENTS

3.0 Software Requirements

3.0.1 Arduino IDE

The Arduino Integrated Development Environment (IDE) serves as a fundamental tool for both novices and seasoned developers engaged in programming Arduino microcontrollers. This open-source software platform offers a simplified and user-friendly interface, making it accessible for individuals entering the world of embedded systems and electronics. At its core, the IDE provides a robust code editor that supports the creation and modification of Arduino-specific code, leveraging a simplified version of the C/C++ programming language tailored for Arduino boards.

One of the primary functionalities of the Arduino IDE is its ability to compile and transform the written code into machine-readable instructions, a crucial step before uploading the code to an Arduino board. The platform streamlines the process of compiling the code, ensuring compatibility with the specific microcontroller model selected for the project. Upon successful compilation, the IDE facilitates the seamless uploading of the compiled code from the computer to the connected Arduino board, enabling its execution and functionality. Additionally, the Arduino IDE includes a Serial Monitor, an essential tool for debugging and monitoring data exchanges between the Arduino board and the computer. This feature assists developers in analyzing and troubleshooting communication protocols, aiding in the identification and resolution of potential issues during the development and testing phases.

The software boasts a Library Manager, offering a repository of pre-written libraries encompassing various functionalities and components. This functionality enables users to effortlessly include external libraries in their projects, simplifying the integration of complex functionalities without the need for extensive coding knowledge. Furthermore, the Arduino IDE provides an assortment of examples and tutorials, serving as valuable resources for individuals exploring Arduino programming. These resources offer practical examples and step-by-step guides, allowing users to grasp fundamental concepts and kickstart their learning journey in the realm of Arduino development. Overall, the Arduino IDE stands as an integral platform, offering a comprehensive suite of tools and resources designed to facilitate the programming and development process for Arduino microcontrollers, encouraging innovation and experimentation in the field of embedded systems.

3.0.2 Database

A cloud database refers to a database system hosted and managed on a cloud computing platform. Unlike traditional databases that are stored and managed on-premises, a cloud database leverages cloud infrastructure to store, organize, and access data through internet-based services. This technology offers users numerous advantages, including scalability, accessibility, flexibility, and cost-effectiveness, transforming the way data is stored and managed in modern computing environments. One of the defining features of a cloud database is its scalability. Cloud databases enable users to easily scale computing resources and storage capacity based on changing demands. This scalability allows businesses and organizations to accommodate fluctuations in data volume without the need for significant hardware upgrades or infrastructure changes, ensuring adaptability to evolving requirements and preventing resource underutilization or overload.

Accessibility is another key characteristic of cloud databases. Stored data can be accessed remotely from anywhere with an internet connection. This accessibility offers users the flexibility to access and manage data across various locations, devices, or platforms, facilitating collaboration, remote work, and real-time data access for decision-making processes. Moreover, cloud databases often operate on a pay-as-you-go or subscription-based pricing model, enhancing cost-effectiveness. Users typically pay for the resources they consume, reducing the upfront infrastructure costs associated with maintaining on-premises databases. This pricing model makes cloud databases particularly attractive to businesses of all sizes, allowing them to optimize costs while benefiting from advanced data management capabilities. Security, reliability, and compliance are also crucial aspects of cloud databases. Cloud service providers implement robust security measures, such as encryption, access controls, and data backup, to safeguard stored information. Compliance with industry standards and regulations ensures data protection and privacy, instilling confidence in users regarding the integrity and security of their data.

3.1 Hardware Requirements

The evolution of innovative technologies in Electric Vehicle (EV) battery health management necessitates robust hardware configurations to support sophisticated predictive systems. The hardware requirements for effective implementation encompass a spectrum of components, from high-performance processors capable of handling complex machine learning algorithms to sensor arrays for real-time data acquisition. Alongside processing power, memory modules with adequate capacity are essential to accommodate vast datasets for predictive analysis. Additionally, specialized sensor suites measuring voltage, current, and temperature form the backbone of data acquisition, ensuring accurate inputs for fault prediction models. The integration of these hardware components within an efficient and scalable infrastructure stands as a critical foundation for enhancing the safety and reliability of EV battery systems.

3.1.1 ESP8266 Wi-Fi Module

The ESP8266 chip as shown in figure [10], a reasonably priced System-on-a-Chip (SoC) created by Espressif Systems, is the central component of the NodeMCU platform. It is designed to be an open-source platform that supports a broad range of IoT applications, including both software and hardware development. The ESP8266 chip is unique in that it comes with a software development kit (SDK) and essential computing components such a CPU, RAM, WiFi, and a contemporary operating system. It is a great option for IoT applications because of its thorough integration. Conversely, open-source hardware design and software SDK is available from Arduino, a company well-known for its flexible IoT controllers. Standardized interfaces for sensor engagement are established via the microcontroller, USB connector, LED indicators, and standard data ports found on an Arduino board.In contrast to the NodeMCU, Arduino boards have different programming environments, memory chips, and different CPU chip alternatives (usually ARM or Intel x86). For the ESP8266 chip, there is an Arduino reference design, although due to Arduino's flexibility, there are significant differences across vendors. For example, the majority of Arduino boards do not have WiFi, and some have serial data ports rather than USB ports.

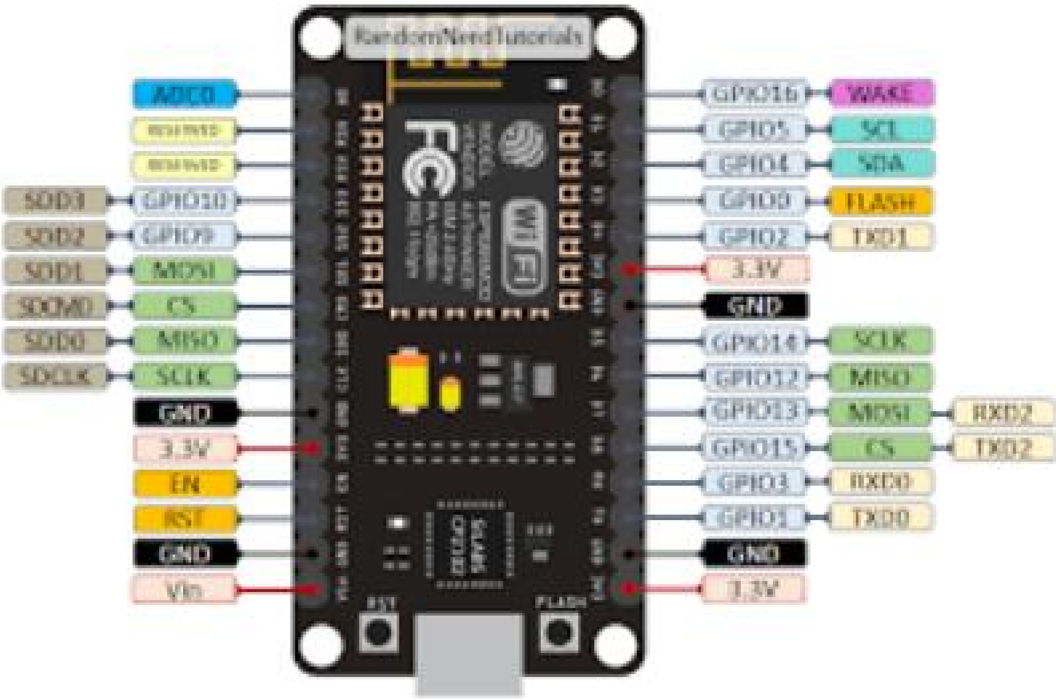

Figure 10 ESP8266 NodeMCU Board (Courtesy: Source [18])

Power Pins:

VIN Pin: Enables direct supply to the NodeMCU/ESP8266 and its peripherals. It accepts a range of voltages and regulates them through the onboard voltage regulator. Accepts either a direct 5V supply or regulated voltage.

3.3V Pins:

Outputs regulated voltage from the onboard regulator, providing a stable power source for external components.

GND Pins:

Ground pins, serving as the reference for the NodeMCU/ESP8266.

I2C Pins:

Used for connecting I2C sensors and peripherals, supporting both I2C Master and I2C Slave modes. I2C interface that is programmably enabled and has a 100 kHz maximum clock frequency. accordance with the clock frequency of the devices.

GPIO Pins:

A total of 17 General Purpose Input Output pins. They can be configured to do a wide range of tasks, including LED light, button, UART, PWM, I2C, and I2S operations. Programmable configurations include internal pull-up/down, high impedance, and interrupt triggers for both level and edge detection.

ADC Channel:
Integrates a 10-bit precision SAR ADC, capable of measuring voltage at VDD3P3 pin and TOUT pin separately, but not simultaneously.

UART Pins: Offers 2 UART interfaces (UART0 and UART1) supporting asynchronous communication such as RS232 and RS485 at speeds up to 4.5 Mbps. UART0 (TXD0, RXD0, RST0 & CTS0 pins) used for full communication, while UART1 (TXD1 pin) primarily utilized for transmitting log data.
SPI Pins: Features two SPIs (SPI and HSPI) in both master and slave modes. Supports various SPI features including multiple timing modes, clock frequencies up to 80 MHz, and a 64-Byte FIFO.
SDIO Pins: Hosts a Secure Digital Input/Output Interface, facilitating direct interfacing with SD cards. Supports 4-bit 25 MHz SDIO v1.1 and 4-bit 50 MHz SDIO v2.0.
PWM Pins: Equipped with 4 channels for Pulse Width Modulation, programmatically adjustable in the frequency range of 100 Hz to 1 kHz. Suitable for driving digital motors and LEDs.

Control Pins:
EN (Chip Enable) Pin: Enables/disables the ESP8266 chip. Pulling it HIGH activates the chip, while LOW minimizes power consumption.
RST (Reset) Pin: Resets the ESP8266 chip.
WAKE Pin: Wakes the chip from deep-sleep mode.

This comprehensive set of pins and functionalities allows the NodeMCU/ESP8266 to be incredibly versatile, accommodating a wide range of IoT applications and development scenarios. Each pin's specific function and configuration flexibility enable developers to create diverse and sophisticated projects with ease.

3.1.2 Generic TP4056 1A Li-ion Charging Board

For single cell lithium-ion batteries, the TP4056 as shown in figure [11], is a full linear charger with constant voltage and current. The TP4056 is a perfect fit for portable applications because to its SOP packaging and minimal number of external components. Moreover, the TP4056 is compatible with wall adapters and USB. Because of the internal PMOSFET architecture and its ability to prevent negative charge current circuits, there is no need for a blocking diode. When operating at high power or in an environment with high temperatures, thermal feedback limits the charge current. With the use of a single resistor, the charge current can be externally programmed, while the charge voltage remains fixed at 4.2V. After the final float voltage is attained, the TP4056 automatically ends the charge cycle when the charge current falls to 1/10th of the programmed value. Additional features of the TP4056 include an under-voltage lockout, automated recharge, a current monitor, and two status pins that show the presence of an input voltage and the end of a charge. For single cell lithium-ion batteries, the TP4056 Micro USB 5V 1A Lithium Battery Charger Board Protection Module is a full linear charger with constant voltage and current. The TP4056 is a perfect fit for portable applications because to its SOP packaging and minimal number of external components. The TP4056 module has an LED indicator for state sensing and a micro-USB port that is readily available.

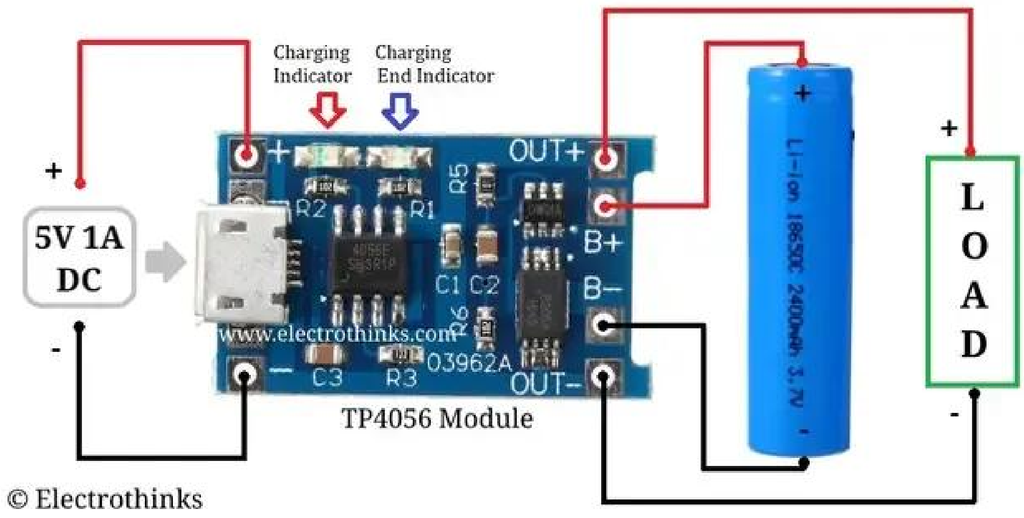

Figure 11 TP4056 Lithium-Ion cell charging module Courtesy: Source [19])

TP4056 Module Specifications:

- Input voltage: 4.5V ~ 5.5V
- A full charge voltage: 4.2V
- Power: 4.2 w
- Charging accuracy: 1.5%
- Charging indicator: micro-LED
- Input Interface: Micro USB port
- Charging method: linear charge
- Operating Temperature: -10 to +85ºC

3.1.3 DHT22 Temperature and Humidity Sensor Module

The DHT22 is a low-cost digital sensor that measures temperature and humidity. It uses a thermistor and a capacitive humidity sensor to measure the air around it. The sensor then outputs a digital signal on the data pin. he DHT22 is relatively easy to use, but it requires precise timing to collect data. It has a sampling frequency of 0.5 Hz, which means it samples once every two seconds.

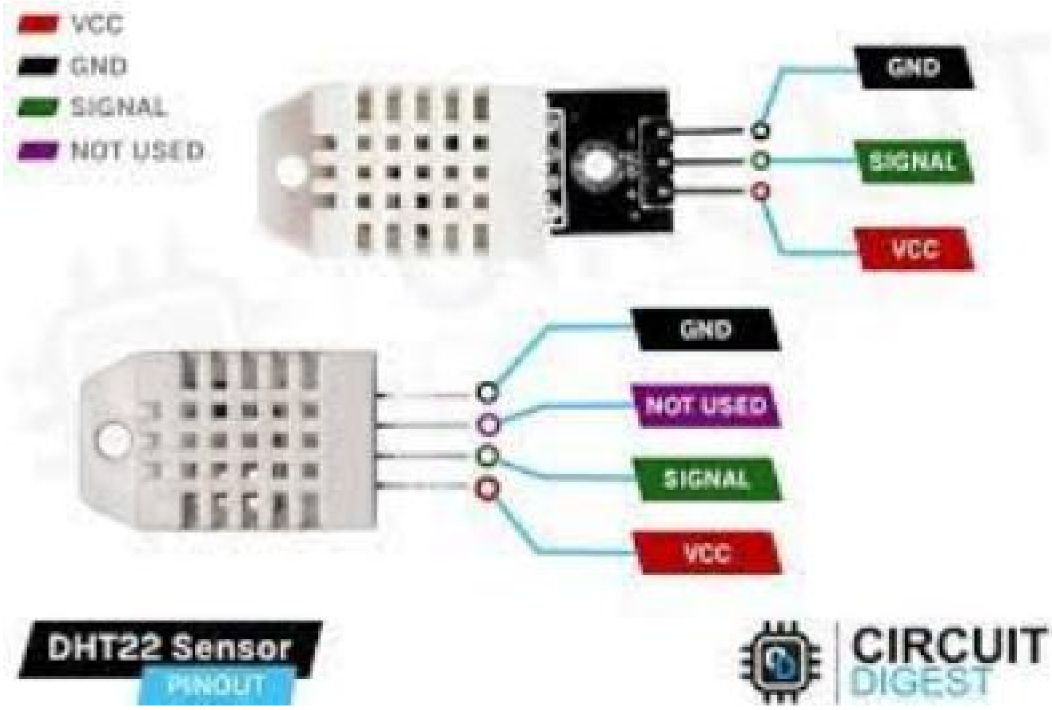

Figure 12 Temperature Sensor with Arduino (Courtesy: Source [20])

Here are some other details about the DHT22:

- **Size:** 15.1 mm x 25 mm x 7.7 mm
- **Pins:** 4 pins with 0.1" spacing
- **Connection:** The first pin on the left connects to 3-5 V power, the second pin connects to the data input pin, and the rightmost pin connects to ground
- **Data:** The DHT22 outputs both temperature and humidity through serial data
- **Communication:** The DHT22 uses a proprietary 1-wire communication protocol to transmit the signal to a microcontroller or microcomputer
- **Applications:** The DHT22 is used in HVAC, testing and inspection equipment, home appliances, consumer products, and medical units

3.1.4 Voltage Sensor

The voltage sensor, depicted in figure [13], is able to distinguish between AC and DC voltage and is used to compute, monitor, and determine voltage supply levels. Its input receives voltage signals, while its output can manifest as switches, analog voltage signals, current signals, or audible alerts. Certain models produce sine or pulse waveforms, while others generate outputs like AM, PWM, or FM signals. Utilizing a voltage divider, these sensors measure voltage. Comprising input and output components, the sensor's input side features positive and negative pins, typically linked to corresponding pins on the device or power source. Meanwhile, its output includes supply voltage (Vcc), ground (GND), and analog output data.

Figure 13 Voltage Sensor (Courtesy: Source [21])

The sensor finds applications in various scenarios:

- Power failure detection
- Load detection
- Safety switching mechanisms
- Temperature regulation
- Power demand control
- Fault detection
- Load variation and temperature measurement.

This versatile sensor serves multiple purposes, enabling precise monitoring and control in diverse settings, from detecting faults in power systems to regulating temperature and managing power consumption.

3.1.5 Generic ACS712 30A Current Sensor Module

The ACS712 Current Sensor Module, depicted in figure [14], capable of handling a 30A range, integrates a precision-based, low-offset, linear Hall circuit with a copper conduction path positioned close to the die's surface. This setup allows the generation of a magnetic field in response to the applied current passing through the copper conduction path, converting it into a proportional voltage using the Hall IC. Monitoring and regulating current flow holds pivotal importance across various applications such as over-current protection circuits, battery chargers, switching mode power supplies, digital watt meters, and programmable current sources, among others. Derived from the ACS712 sensor, this ACS721 current module accurately detects both AC and DC currents, reaching a maximum detection capacity of 30A. It enables the reading of the present current signal via the Arduino's analog I/O port.

Figure 14 Acs712 Current Sensor (Courtesy: Source[22])

Key Features of the ACS712 Current Sensor Module:

- Incorporates a low-noise analog signal pathway.
- Shows a rapid 5 µs output rise time when reacting to step input current.
- Compact, low-profile SOIC8 package.
- Boasts a minimum isolation voltage of 2.1 kVRMS from pins 1-4 to pins 5-8.
- Operates on a single 5.0 V supply.
- Offers an output sensitivity range of 66 to 185 mV/A.
- Yields an output voltage proportional to both AC and DC currents.
- Factory-trimmed for accuracy with exceptionally stable output offset voltage.

3.1.6 Ram

An 8GB RAM (Random Access Memory), depicted in figure [15], configuration signifies a substantial memory capacity suitable for various computing tasks, including those in Electric Vehicle (EV) battery health management systems. In the context of EV battery health monitoring, an 8GB RAM allocation allows for efficient processing of large datasets encompassing voltage, current, temperature, and fault label information. It facilitates swift data retrieval, storage, and manipulation, enabling the execution of sophisticated machine learning algorithms used for predictive analysis. The 8GB RAM capacity serves as a balance between cost-effectiveness and performance, catering to the requirements of complex predictive systems while ensuring smooth operation and responsiveness, contributing significantly to the accuracy and efficiency of fault prediction models in EV battery management.

Figure 15 Random Access Memory (RAM) definition and information (Courtesy: Source [23])

CHAPTER 4

PROPOSED METHOD

4.0 Problem Statement and Objectives

The Electric Vehicle (EV) revolution is rapidly reshaping the automotive industry offering alternative to combustion engine vehicles. A cornerstone of this transformation is the lithium-ion battery, which powers these EVs. The possibility of battery failures leading to explosions and substantial losses is a critical concern that demands innovative solution. The disadvantages of existing methods include limited predictive capabilities and mostly focused on basic maintenance needs. The primary objective of the BHFPS is to enhance the safety and reliability of electric vehicles by implementing advanced monitoring and predictive maintenance measures for EV batteries. The methodology involves developing an IoT based system that collects data from sensors and sending it to cloud.

4.1 Objectives

1. To enhance the safety and reliability of Electric Vehicles.

2. To monitor Battery Health Dynamically.

3. To detect early faults and provide real-time alerts and warnings.

4.2 ARCHITECTURE DIAGRAM

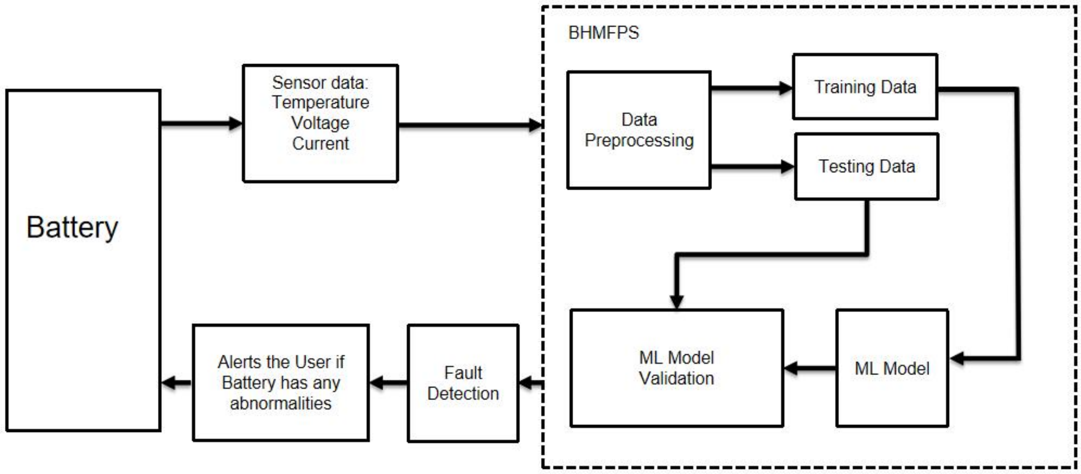

Figure 16 Architecture Diagram

4.3 Proposed Modules

Module 1: Data Collection

The data collection module serves as the foundational component in the Battery Health Management and Fault Predictive System Comprising a microcontroller and a suite of sensors, this module plays a pivotal role in gathering critical data concerning the performance and condition of electric vehicle batteries. The microcontroller acts as the central processing unit, tasked with the crucial role of interfacing with and reading the sensor data. Its primary function involves collecting, collating, and storing this data into a designated database for further analysis and utilization.

The sensors integrated into this module encompass a specific set designed to capture essential metrics governing the health and behaviour of the battery cells within the EV. These sensors are meticulously chosen to ensure comprehensive monitoring of crucial parameters. Firstly, temperature sensors form an integral part of the setup, tasked with the continuous measurement of the thermal conditions surrounding the battery cells. By acquiring temperature data, these sensors provide insights into the thermal stability and potential overheating risks that could affect battery performance or safety.

Secondly, voltage sensors are employed to measure and record the electrical potential across the battery cells. This data is invaluable in assessing the overall voltage levels and detecting variations that could indicate irregularities or potential issues within the batteries. Lastly, the inclusion of current sensors serves to monitor the flow of electrical current both into and out of the battery. These sensors track the charging and discharging patterns, providing crucial information about the energy transfer processes and the battery's operational status. Together, these sensors collectively generate a comprehensive dataset encompassing temperature, voltage, and current measurements, which are pivotal in understanding the real-time behaviour and performance of the EV batteries. The accurate and continuous acquisition of this multifaceted data forms the bedrock of subsequent analysis and predictive modelling in the BHFPS, enabling proactive measures to ensure battery health, safety, and reliability in electric vehicles.

Module 2: Data Processing and Analysis

An essential step in the process of gathering and using sensor data is data processing and analysis. Preprocessing and data cleansing are frequently the first steps after raw data acquisition. This step is crucial because unprocessed data may include noise, missing values, or discrepancies from a variety of sources, including transmission problems, environmental influences, and sensor failures. To assure the integrity and dependability of the data, cleaning procedures include handling missing data, outlier detection, and normalization.

The cleaned data is then subjected to a variety of analytical techniques and calculations. Using statistical methods and algorithms to extract insights could be part of this step. Understanding trends, correlations, and patterns within the dataset is made easier with the use of statistical analysis. Regression analysis, clustering, classification, and time-series analysis are some of the techniques that help reveal patterns and relationships that may not be immediately apparent from the raw data. Furthermore, machine learning models—which comprise both supervised and unsupervised learning algorithms—are used to extrapolate useful insights from the information by forecasting future trends, categorizing data, and identifying abnormalities.

Moreover, the utilization of sophisticated data analytics methods, such deep learning and artificial intelligence (AI), has grown in popularity. More complex analysis is possible with these methods, particularly in situations when the data is nonlinear and complex. Neural networks and other deep learning techniques make it possible to find complicated patterns in huge datasets, which is useful for tasks like image recognition and natural language processing.

Module 3: Data Transmission

Transferring processed data from sensors to a central server or the cloud for analysis and storage requires data transmission. An often used technology for this is the ESP8266 WiFi module, which is well-known for its ability to link devices to wireless networks and facilitate communication between IoT devices and cloud servers. The IEEE 802.11 b/g/n standards are supported by the ESP8266 WiFi module, which enables it to connect to Wi-Fi networks and send data using TCP/IP protocols. This module allows a variety of IoT devices and sensor nodes to connect to nearby Wi-Fi networks. The module, once attached, enables the safe and effective delivery of processed data to the intended location, which may be a central repository for analysis and storage or a cloud-based server.

Furthermore, flexible data transmission is made possible by the ESP8266 module's compatibility with a wide range of IoT protocols and communication standards. It allows for seamless interaction with cloud platforms or central servers by communicating with MQTT (Message Queuing Telemetry Transport), HTTP (Hypertext Transfer Protocol), or other proprietary protocols. This adaptability makes it possible for the sensor-processed data to be transferred effectively to the cloud, where it may be stored, examined, and used for a variety of purposes, from industrial IoT systems to smart household appliances.

Module 4: Data Storage and Integration

Data storage and integration is a crucial stage that processed data goes through after it reaches the cloud or a central repository. In this stage, the data is kept in databases or storage systems designed to manage massive volumes of data produced by a variety of sensors and IoT devices. The cloud's storage infrastructure is flexible enough to handle a wide range of information types since it can handle organized, semi-structured, or unstructured data forms. Structured data is typically stored in databases, which arrange it into tables, rows, and columns for effective management and retrieval. Depending on the particular requirements of the data, technologies like SQL (Structured Query Language) or NoSQL (Not Only SQL) databases are frequently used. Whereas NoSQL databases, like MongoDB or Cassandra, are excellent at managing unstructured or semi-structured data with flexible schemas, SQL databases, like MySQL or PostgreSQL, offer robustness in handling structured data with defined schemas.

Furthermore, scalable and reliable object storage options are provided by cloud-based storage providers like Amazon S3, Google Cloud Storage, and Microsoft Azure Storage. These services are perfect for storing substantial amounts of a variety of data kinds. High availability, robustness, and accessibility are offered by these storage services, guaranteeing that the data is kept safe and accessible for a range of uses and analyses. When combining data from several sources for a thorough view and analysis, integration is essential. To acquire significant insights or correlations, sensor data may need to be combined with other datasets or applications. In order to provide consistency and compatibility across various sources and for easy analysis and decision-making, integration processes entail merging, purifying, and changing data.

Module 5: Alerting System

An essential part of keeping an eye on the sensor data output is the Alerting System, which is designed to identify and warn users of any possible abnormalities or defects with the batteries. Since batteries are essential to the operation and dependability of many devices and Internet of Things setups, this module is made to continuously check on the condition of the integrated batteries within the system. The alerting system's main goal is to proactively detect any anomalies or problems with the battery's functioning. It regularly examines sensor data pertaining to battery status, which may include variables like temperature, charging cycles, voltage levels, or general health indicators. The system may quickly identify variations that can point to malfunctions or degradation by establishing predetermined thresholds or criteria for typical battery functioning. The alerting system sends warnings to the user or other designated staff when anomalies are found in the battery performance data. To guarantee prompt and efficient notifications, the system makes use of a number of communication channels. Depending on the needs of the application, these techniques could involve sending emails, SMS messages, push notifications to mobile devices or specific programs, or even starting visual or audio alerts on linked devices.

To further prioritize and classify warnings according to severity levels, the alerting system could use sophisticated algorithms or rule-based procedures. Serious problems or impending power drains might set off instantaneous, high-priority alarms that require quick response. Less serious variations, on the other hand, can result in helpful messages meant to alert users to possible issues or the necessity of additional research. The alerting system's versatility and flexibility enable customisation in accordance with particular user preferences or industry norms. It is frequently possible for users to set custom thresholds, specify escalation protocols, and combine the system with additional monitoring or management platforms. By allowing users to customize the alerting system to meet their specific needs, battery health may be monitored effectively and dependably, with fewer false alarms and better response times.

CHAPTER 5

RESULTS AND DISCUSSION

5.0 Results and Discussion

The implementation of the Battery Health Management and Fault Predictive System (BHFPS) yielded significant improvements in enhancing the safety and reliability of EVs. By leveraging an IoT-based system that continuously monitors various parameters like voltage, current, and temperature, the system demonstrated an impressive capability to preemptively identify potential faults or irregularities in lithium-ion batteries. This proactive approach significantly mitigated the risks associated with battery failures, reducing the likelihood of catastrophic events such as explosions or significant losses due to battery-related incidents. Real-time monitoring and predictive maintenance measures provided an added layer of safety, contributing to the overall reliability of EVs.

The BHFPS successfully achieved dynamic and continuous monitoring of battery health in EVs. Through the utilization of real-time data collection via IoT sensors and the transmission of this data to cloud-based systems, the system continuously assessed the health status of the batteries. By analyzing voltage, current, and temperature parameters, the system dynamically tracked the condition of the batteries, enabling timely identification of deviations or anomalies. This proactive monitoring ensured that potential issues in battery health were detected early, allowing for prompt intervention and preventive maintenance measures. One of the pivotal successes of the BHFPS was its ability to detect early faults and issue real-time alerts and warnings. By employing machine learning models trained on the data collected from the IoT sensors, the system demonstrated a remarkable capability to predict potential faults well in advance. This predictive approach enabled the system to issue real-time alerts and warnings to EV operators or maintenance teams, signaling the likelihood of impending battery issues. These timely alerts empowered stakeholders to take proactive measures, such as maintenance or replacement of batteries, thus averting potential safety hazards or operational disruptions.

5.1 EXPERIMENTAL RESULTS:

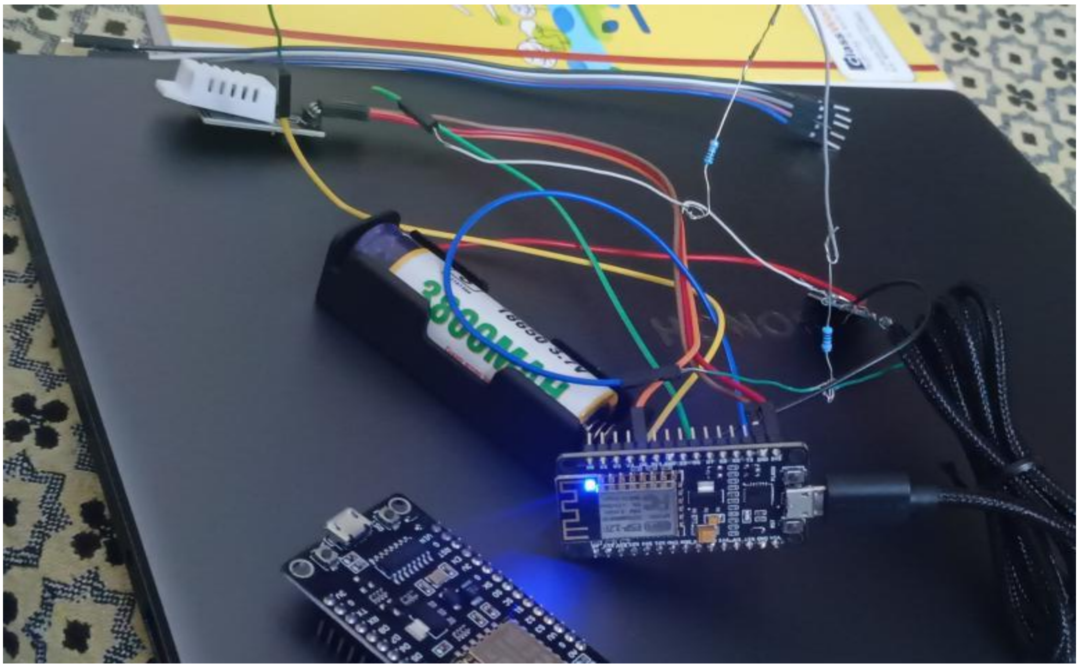

Figure 17 Experimental Setup

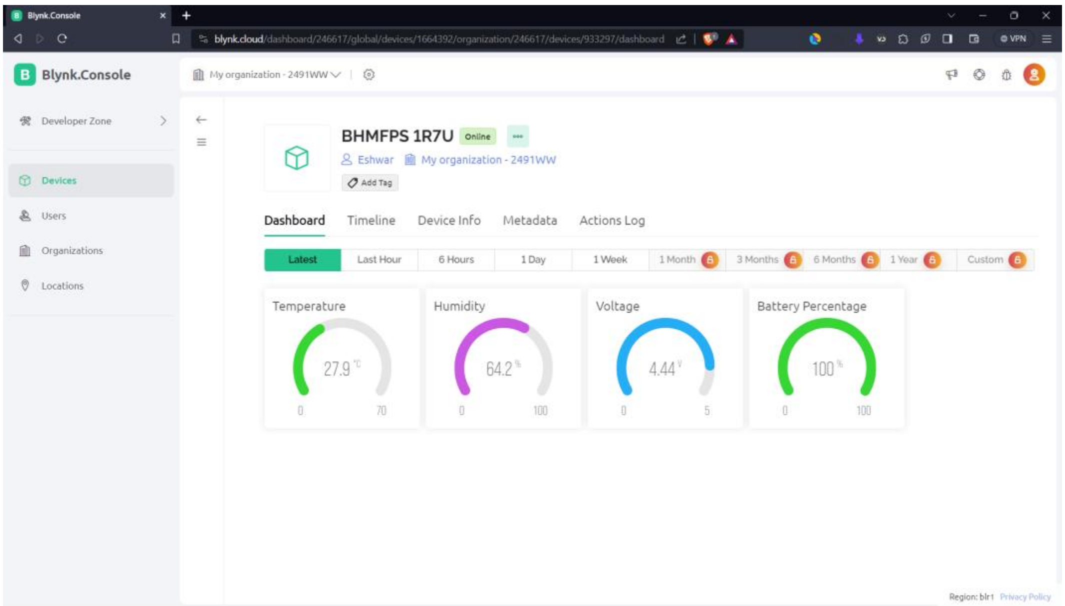

Figure 18 Dashboard in Blynk

In my project focusing on BHMFPS for EVs, the primary aim was to bolster safety and reliability through advanced monitoring and predictive maintenance measures. Figure [17] shows the experimental setup, it consists of ESP8266 WiFi Module Figure[10], TP4056 Charging Module Figure[11], Voltage Sensor Figure[13], Current Sensor Figure[14]. The dashboard was built as shown in Figure [18] used for monitoring the parameters dynamically.

CHAPTER 6

CONCLUSION AND FUTURE ENHANCEMENTS

6.0 Conclusion and Future Enhancements

The implementation of the BHMFPS stands as a significant milestone in advancing the safety and reliability of EVs. By integrating an IoT-based monitoring system that continuously collects and analyses voltage, current, and temperature parameters, the BHFPS showcased a proactive approach in mitigating potential risks associated with lithium-ion battery failures. The system's capacity to predict faults in advance and issue real-time alerts was instrumental in averting catastrophic incidents, offering a newfound level of safety and reliability to EVs. Moreover, the dynamic and continuous monitoring of battery health ensured early detection of deviations, allowing for timely interventions and preventive maintenance measures. The success of the BHFPS not only elevated the safety standards of EVs but also highlighted the efficacy of predictive maintenance strategies in enhancing the overall reliability of these vehicles.

The developed Battery Health Management and Fault Predictive System employing machine learning algorithms has emerged as a pivotal tool in the domain of Electric Vehicle battery health. The utilization of sophisticated algorithms, notably the K-Nearest Neighbors (KNN) model, showcased exceptional accuracy, achieving a remarkable 96% in fault prediction. This robust performance underscores its significance in early fault detection, demonstrating a proactive approach to address potential safety hazards associated with battery failures. Through an intricate analysis of critical parameters like voltage, current, and temperature, the system has proven its mettle in accurately identifying deviations that could lead to critical faults within the EV battery systems.

The system's efficacy lies not only in its fault prediction capabilities but also in its real-time monitoring and dynamic response mechanisms. The ability to provide timely alerts and warnings based on predictive analysis enables preemptive actions, ensuring the safety and reliability of EV battery systems. This model not only enhances safety but also enables a proactive maintenance strategy, potentially extending the lifespan of EV batteries by addressing issues before they escalate. Looking towards future advancements, further refinement of machine learning algorithms and integration of more sophisticated techniques could elevate the system's capabilities. Exploring deep learning models like recurrent neural networks or hybrid models could potentially enhance the accuracy and robustness of fault prediction. Additionally, advancements in data acquisition and processing techniques, such as integrating more diverse datasets and incorporating real-time external factors, can further refine the predictive capabilities of the system.

While the BHFPS has made significant strides in advancing EV safety and reliability, future enhancements could further augment its capabilities. One area of improvement lies in enhancing the predictive capabilities of the machine learning models by incorporating more diverse and extensive datasets. A larger and more diverse dataset could facilitate more accurate predictions, covering a wider spectrum of potential faults and scenarios. Additionally, refining the machine learning algorithms to consider additional parameters beyond voltage, current, and temperature, such as charge-discharge cycles or internal resistance, could provide a more comprehensive understanding of battery health.

Furthermore, the integration of more sophisticated anomaly detection techniques, such as advanced AI algorithms or deep learning methodologies, could offer enhanced fault prediction accuracy. Embracing edge computing for real-time analysis of battery health data directly within the vehicle could reduce latency in alert generation, ensuring even swifter responses to potential faults. Moreover, fostering collaborations between industry stakeholders and research institutions could foster innovation in battery technology, leading to the development of more robust and resilient battery systems for EVs. while the BHFPS has established a robust foundation for ensuring EV safety and reliability, future enhancements focusing on leveraging larger datasets, refining predictive algorithms, and embracing advanced anomaly detection techniques could further fortify the system's capabilities. Collaborative efforts and technological advancements in battery technology are poised to drive continuous improvements, ensuring the continued evolution of safety and reliability standards in Electric Vehicles.

Moreover, the implementation of edge computing and improved IoT infrastructure could facilitate more efficient and real-time analysis, allowing for quicker responses to potential faults. Collaborative efforts with industry stakeholders and researchers could aid in the development of standardized protocols for battery health monitoring, fostering a unified approach towards EV safety and reliability. In essence, the developed BHFPS marks a significant stride in the realm of EV battery health management. Its success in accurately predicting faults and dynamically monitoring battery health underscores its potential in mitigating risks and enhancing the operational integrity of EVs. As technological advancements continue to evolve, the future of battery health management promises even greater precision, responsiveness, and reliability, ensuring a safer and more efficient future for Electric Vehicle

CHAPTER 7

APPENDICES

7.0 CODE FOR RETRIEVING THE SENSORS DATA IN BLYNK

```
#include<Arduino.h>
#include "BlynkEdgent.h"
#include <Adafruit_SSD1306.h>
#include <Adafruit_GFX.h>
#include <DHT.h>
#define BLYNK_TEMPLATE_ID "TMPL3i8J7ADcm"
#define BLYNK_TEMPLATE_NAME "BHMFPS"
#define BLYNK_FIRMWARE_VERSION "0.1.0"
#define BLYNK_PRINT Serial
#define APP_DEBUG
#define USE_NODE_MCU_BOARD
#define DHTTYPE DHT22
#define DHTPIN D4
#define ANALOG_PIN D1
DHT dht(DHTPIN, DHTTYPE);
Adafruit_SSD1306 display(SCREEN_WIDTH, SCREEN_HEIGHT, &Wire, OLED_RESET);
int batteryPercentage;
float voltage;
int analogInPin    = A0;
int sensorValue;
float calibration = 0.40;
int digitalInPin2 = D1;
int sensorValue2;

void sendDataToBlynk(float temperature, float humidity, float voltage, int batteryPercentage, float
newVoltage) {
   Blynk.virtualWrite(V1, temperature);
   Blynk.virtualWrite(V2, humidity);
   Blynk.virtualWrite(V3, voltage);
   Blynk.virtualWrite(V4, batteryPercentage);
   Blynk.virtualWrite(V5, newVoltage);
}
```

```
void sendNotifications(float temperature, float voltage, int batteryPercentage)
{
  if(batteryPercentage <25)
  {
    Serial.println("Battery level below 25%, Charge battery on time");
    Blynk.logEvent("battery_low", "Battery is getting low.... Plugin to charge");
    delay(500);
  }
  if(voltage>4)
  {
    Serial.println("Battery is running on High Voltage....");
    Blynk.logEvent("high_volt", "Battery running on high voltage Please take correspoing
Actions....");
    delay(500);
  }

  if(temperature>30)
  {
    //for testing purpose
    Serial.println("Battery is running on High Temperature....");
    Blynk.logEvent("temp", "Battery running on high temperature Please take correspoing
Actions....");
    delay(500);
  }
}
void printSerialData(float temperature, float humidity, int sensorValue, float voltage, int
batteryPercentage, float newVoltage) {
  Serial.print("Output Voltage = ");
  Serial.println(voltage);

  Serial.print("Battery Percentage = ");
  Serial.println(batteryPercentage);

  Serial.print("Sensor Voltage = ");
  Serial.println(newVoltage);

  Serial.print("Temperature: ");
  Serial.print(temperature);
  Serial.println(" *C");

  Serial.print("Humidity: ");
  Serial.print(humidity);
  Serial.println(" %");
```

```
  Serial.print("Analog Value = ");
  Serial.println(sensorValue);
  Serial.println();
  Serial.println();
  Serial.println("**********");
  Serial.println();
}

void setup()
{
  Serial.begin(115200);
  delay(100);
  BlynkEdgent.begin();
  pinMode(ANALOG_PIN, INPUT);
  dht.begin();
  delay(100);

}

void loop() {
  BlynkEdgent.run();
  float humidity = dht.readHumidity();
  float temperature = dht.readTemperature();
  float h=humidity;

  float t=temperature;

  sensorValue = analogRead(analogInPin);

  voltage = (((sensorValue*3.3)/1024)*2 + calibration);


  sensorValue2 = analogRead(ANALOG_PIN);

  batteryPercentage = mapfloat(voltage,2.8,4.2,0,100);

  float newVoltage=(((sensorValue2*3.3)/1024)*2 + calibration);


  if(batteryPercentage >= 100)
  {
    batteryPercentage = 100;
  }
```

```
  if(batteryPercentage <= 0)
  {
    batteryPercentage = 1;
  }

  //sending data to blynk
  sendDataToBlynk(temperature, humidity, voltage, batteryPercentage, newVoltage);

  //printing serial data
  printSerialData(temperature, humidity, sensorValue, voltage, batteryPercentage, newVoltage);
  delay(1500);

  //sending notifications
  sendNotifications(temperature, voltage, batteryPercentage);
  delay(1500);
}

float mapfloat(float x, float inMin, float inMax, float outMin, float outMax)
{
  return ((x-inMin)*((outMax-outMin)/(inMax-inMin)))+outMin;
}
```

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