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Development Of Machine Learning Model to Predict the Battery Lifespan Using IoT



ABSTRACT. In recent times, the usage of batteries has increased greatly due to technological advancements. Batteries have become key components of our everyday life. Since some types of batteries can be recharged and reused multiple times, they find applications in a variety of sectors including health instruments, logistics and construction, firefighting and emergency, daily household applications, and military to name a few. This has led to high demand and higher capacity requirements of the batteries but also extended battery life, lower risks, and smaller size. Using our project - Development of Machine Learning Model to Predict the Battery Lifespan using IoT, we aim to predict the battery life by using data collected from various sensors by means of a machine learning model. Since we are dealing with large data, we upload the collected data to the cloud from which the data can be accessed for our machine learning model.

KEYWORDS: Li-ion Battery, lifetime prediction, Arduino Uno, NodeMCU, Thingspeak, machine learning, cycle life

1 INTRODUCTION

A battery is a storage device that converts chemical energy into electrical energy. They accept, store and release electricity on demand. Batteries play a crucial role in powering nearly all the devices we depend on throughout our lives. As the world begins a shift towards a more sustainable future driven by electricity, technology plays an ever-increasing role in society. Thus, batteries have become more important than ever.

1.1 NEED FOR STUDY

A lot of studies have been carried out to predict how many charging cycles a battery will last before it dies. Better predictions would enable more accurate quality assessment and improve long-term planning. But this has turned out to be difficult, because every battery ages differently, as determined by various factors including its usage and conditions it has been exposed to. Since batteries inherently involve chemical reactions that are reactive, the materials used in batteries are susceptible to alternate reactions that degrade battery performance. Contamination of the active chemicals gives rise to unwanted chemical effects which could result in various forms of cell failure such as overheating, pressure build-up, reduced capacity, increased impedance and self-discharge, and short circuits.

2 PROPOSED PLAN

The project was split into the following steps:

- To identify the factors affecting the battery lifespan
- To identify the sensors and peripherals required to acquire the data
- To design and implement a circuit to interface the sensors and peripherals and collect necessary data
- To alert the user if any parameters being monitored are abnormal
- To develop a machine learning model to predict remaining cycles

2.1 METHODOLOGY

2.1.1 DATA COLLECTION

This stage involves the collection of voltage readings, temperature, and humidity values of the battery pack being monitored. Temperature and humidity readings are collected using the DHT22 sensor. Voltage readings are obtained by using a buffer circuit which consists of a voltage follower setup followed by a comparator circuit which is used to collect individual voltage readings.

2.1.2 DATA TRANSMISSION

The voltage readings of the individual cells and the sensor readings are sent to the Arduino. The Arduino acts as the connecting bridge of the entire circuitry and is responsible for seamless transmission to further components. Node MCU is a Wi-Fi module and can be used to transfer collected data to the cloud. It takes the digital readings from the Arduino via serial communication and sends them to a web application called ThingSpeak, where the data can be visualised.

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2.1.3 CLOUD

The real-time data collected in the cloud (Thingspeak) is later used to predict the remaining cycles at a specific point in time.

2.1.4 MACHINE LEARNING

In this project, an online dataset comprising various parameters that can affect the lifespan of a battery was selected. The primary objective of this project is to build a machine-learning model that can accurately predict the lifespan of the battery based on these parameters.

After data cleaning and preprocessing, in order to train and evaluate the model, the dataset was split into train and test data. Additionally, an original test dataset was collected using the hardware device built, to evaluate the performance of the model accurately.

2.1.5 DATA PRESENTATION

Real time data can be viewed using ThingSpeak. Blynk App is used to generate user alerts in case of abnormal values of various parameter being monitored.

2.2 FLOWCHART

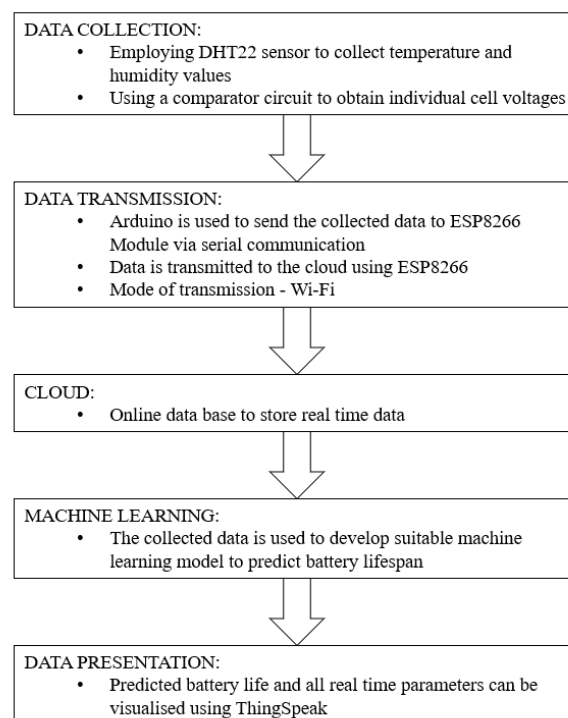


Fig. 1. Flowchart

3 HARDWARE

The main components used are Li-ion batteries, Arduino Uno, NodeMCU, LM324 op-amp, DHT22 sensor.

In the project, 18650 Li-ion cells shown in Fig 2.1 are used. It is called so because it is named after its 18mm × 65mm cylindrical size (diameter × height)



Fig. 2. Li-ion battery

DHT22 sensor was used to collect values of temperature and humidity. The sensor comes with a dedicated NTC to measure temperature and an 8-bit microcontroller to output the values of temperature and humidity as serial data. The sensor can measure temperature from -40°C to 80°C and humidity from 0% to 100% with an accuracy of $\pm 1^{\circ}\text{C}$ and $\pm 1\%$.



Fig. 3. DHT22 sensor.

There is a requirement for a Wi-Fi module in the project. The type required is ESP8266. NodeMCU is an LUA-based interactive firmware for Expressif ESP8622 Wi-Fi SoC, as well as an open-source hardware board that, unlike the other ESP8266 Wi-Fi modules, includes a CP2102 TTL to USB chip for programming and debugging, is breadboard-friendly, and can simply be powered via its micro-USB port.



Fig. 4. ESP – 12E NODEMCU

Arduino Uno as shown in Fig 5 is a microcontroller board based on the ATmega328P. It has 14 digital input/output pins, 6 analog inputs, a 16 MHz ceramic resonator (CSTCE16M0V53-R0), a USB connection, a power jack, an ICSP header, and a reset button.

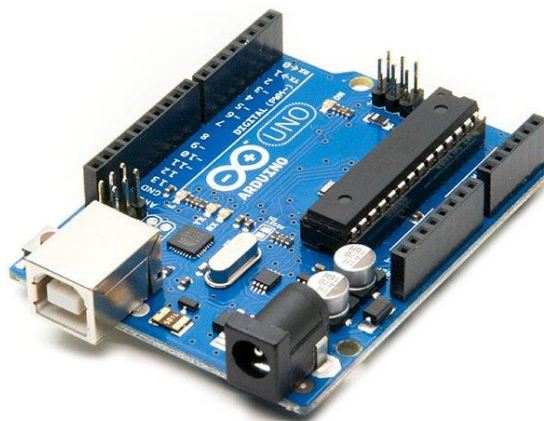


Fig. 5. Arduino UNO

The buffer circuit consists of three individual circuits namely,

- Potential divider circuit – A potential divider, also known as a voltage divider, is a circuit that takes a higher voltage and divides it by a fixed ratio according to the electronic components to produce a lower output voltage.
- Voltage follower circuit – The voltage follower circuit has a high input impedance which causes the output voltage to remain the same as the input, at the same time limiting the current.
- Comparator circuit – The comparator circuit is used to determine the individual cell voltages. This circuit employs the Operational Amplifier LM324 which is a high-voltage Op-Amp that can withstand up to 32V.

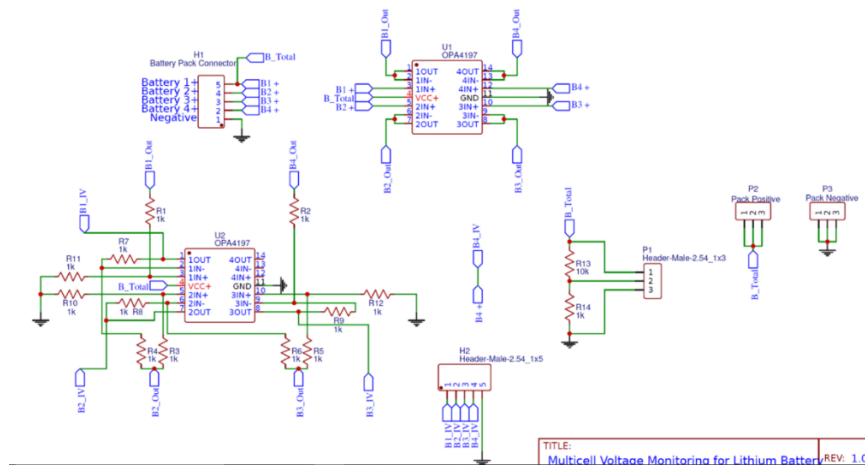


Fig. 6. Schematic diagram of the buffer circuit

The data received by the NodeMCU is shown in Fig. 8.

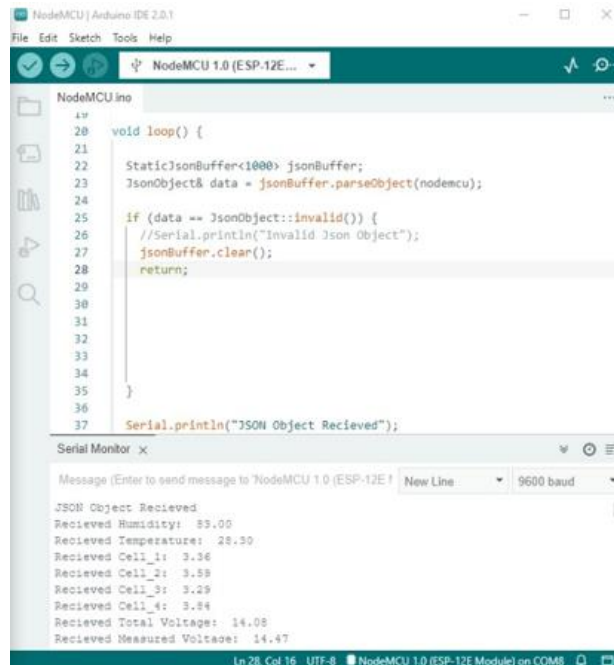


Fig. 8. Data received by the NodeMCU

Figure 8 shows the data received by the NodeMCU from the Arduino.

5 DATA VISUALISATION AND ALERT GENERATION

5.1 THINGSPEAK

ThingSpeak is an Internet of Things (IoT) analytics platform developed by MathWorks. It provides an easy-to-use cloud-based platform for collecting, analysing, and visualizing data from IoT devices in real-time. ThingSpeak allows users to create and manage IoT applications, known as "channels," which are virtual data streams that collect, store, and analyse sensor data from various sources. It is particularly useful for creating custom data analytics workflows, and visualising data in real-time.

The obtained values are sent through NodeMCU to the cloud platform.

5.2 BLYNK APP

The Blynk app can be used to create interactive and customizable IoT projects by connecting virtual buttons, sliders, graphs, and other widgets to physical devices or sensors. The data collected by the hardware circuit is sent to the Blynk App with the help of the Node MCU by means of Wi-Fi, in order to be visualised. A dashboard was set up for this purpose. This app was used to generate user alerts in case of any parameter displaying an abnormal value.

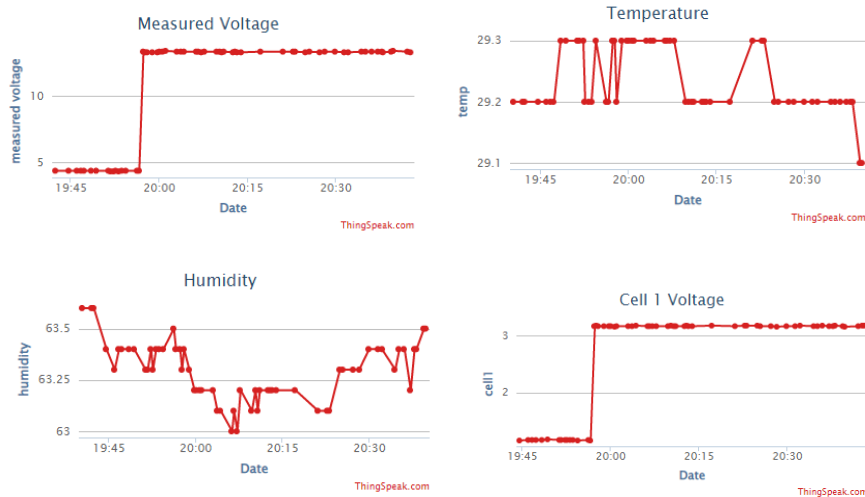


Fig. 9. Thingspeak graphical representation

Figure 9 shows the graphical values of each of the parameters.

6 PROTOTYPE

The final hardware model used to collect and transfer the data was implemented as seen in Fig 3.6. After assembling the chosen components as per the circuit diagram given in Fig 3.1, the code given in the sections 3.3 and 3.4 are pushed into the Arduino and the NodeMCU respectively. Once this is done, the data can be visualised with the help of the serial monitor.

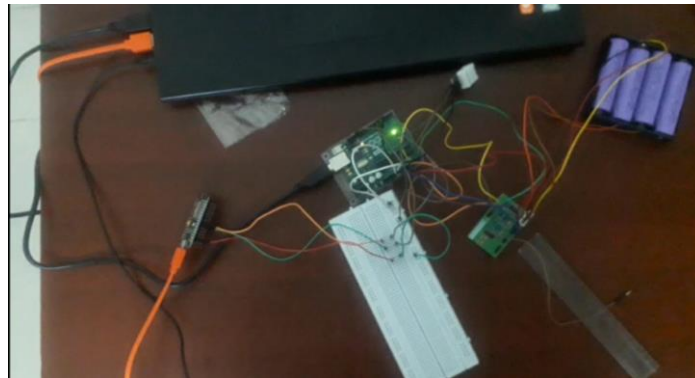


Fig. 10. Final Prototype

7 MACHINE LEARNING

Machine learning is an AI field where computer systems automatically improve performance on a task by learning from data, without explicit programming. It involves creating mathematical models that learn patterns and relationships in data for making predictions or decisions. There are three types: supervised learning (using labeled data), unsupervised learning (using unlabeled data), and reinforcement learning (maximizing rewards based on feedback).

7.1 EXPLORATORY DATA ANALYSIS (EDA)

EDA is a crucial part of data science, involving techniques like summary statistics, data visualization, and dimensionality reduction to explore and analyze data, revealing patterns and outliers. It provides valuable insights and a deeper understanding of the dataset's properties, structure, and relationships.

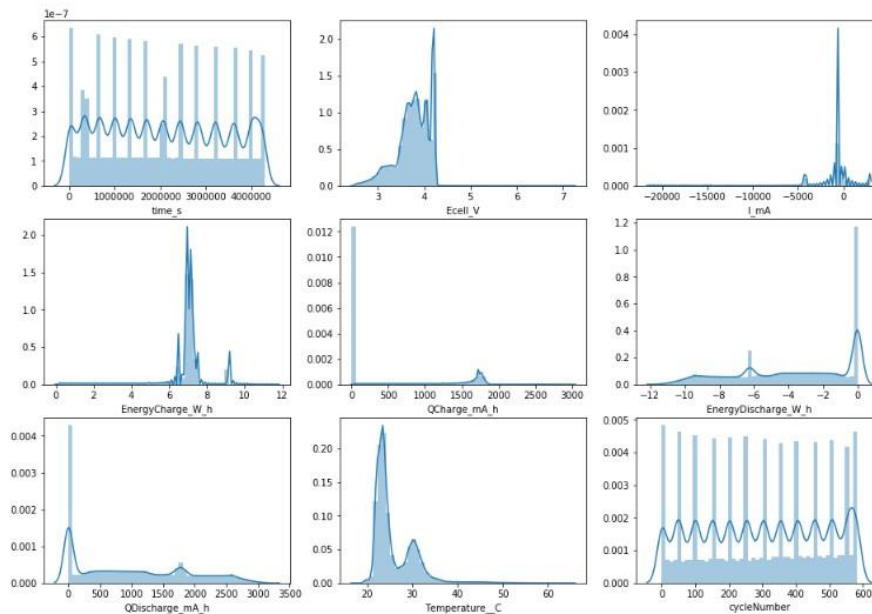


Fig. 11. Exploratory Data Analysis

Figure 6.4 explains about the data analysis done for each columns. From the graph shown we could see that not much outliers or anomalies were detected.

7.2 DATA CLEANING

The dataset required minimal cleaning efforts with no missing or duplicated values. Additionally, no anomalies or outliers were found, streamlining the data analysis process and enabling focus on feature engineering and modeling..

7.3 OBSERVATION

After comparison and analysis based on the evaluation metrics, it can be observed that the XGBClassifier outperformed the other models considered such as Logistic Regression, AdaBoost Classifier, Decision Tree Classifier etc. Thus, the XGBClassifier is deemed to be the most appropriate model for the dataset at hand and was selected to be used for predicting the remaining lifetime.

7.4 PREDICTING REMAINING LIFETIME

The XGBClassifier is a powerful model used to predict cycles and estimate remaining battery life. It learns patterns and relationships between features and the target variable, ensuring accurate predictions. Fine-tuning hyperparameters like learning rate and maximum depth improves the model's performance, but careful tuning is essential to avoid overfitting or underfitting. The respective code executes the classifier, generating the final dataframe (Fig. 6.14) with remaining cycles and time remaining.

	CyclesUsed	CyclesRemaining	Time Remaining (hrs)
0	0	600	1192.06
1	0	600	1192.05
2	0	600	1192.04
3	0	600	1192.03
4	0	600	1192.02
...
24336	20	580	1149.56
24337	20	580	1149.55
24338	20	580	1149.54
24339	20	580	1149.54
24340	20	580	1149.53

24341 rows × 3 columns

Fig. 12. Output Number of Cycles Remaining

8 CONCLUSION

During the project, parameters affecting battery lifespan were identified and real-time data for cell voltages, depth of discharge, state of charge, temperature, humidity, and number of cells were obtained. Components like temperature/humidity sensor, Wi-Fi module, and microcontroller were carefully chosen based on cost, efficiency, and availability. Codes for individual components were written, tested, and integrated. The final hardware model was successfully implemented, with measured values matching experimental ones. Later, an XGB Classifier was selected to develop the machine learning model for predicting battery lifespan. The model predicted remaining useful cycles, and the results were presented in a CSV output file.

9 FUTURE SCOPE

The current project aims to achieve the previously mentioned objective at a smaller scale. But the same model can be extended to higher battery systems, in terms of higher voltage as well as more number of cells. Such complicated systems will require a more detailed hardware design circuit or can employ different methods to obtain the required data. In the case of a battery management system such setups will already be existing. This model can be integrated with a battery management system to predict the remaining useful cycles of the cells in the battery

10 REFERENCES

1. C. Hommalai and S. Khomfoi (2011) "Battery Monitoring System by Detecting Dead Battery Cells", International Journal of Science and Research, Vol.1, pp. 5-15.
2. A. S. Dhotre, S. S. Gavasane, A. R. Patil, and T. Nadu (2014), "Automatic Battery Charging Using Battery Health Detection" International Journal of Engineering & Technology. Vol. 1, no. 5, pp. 486–490.
3. S. A. Mathew, R. Prakash, and P. C. John (2012), "A smart wireless battery monitoring system for electric vehicles," Int. Conf. Intel. Syst. Des. Appl. ISDA, pp. 189–193.
4. Multicell Voltage Monitoring for Lithium Battery Pack in Electric Vehicles articles, <https://circuitdigest.com/microcontroller-projects/multi-cell-voltage-monitoring-for-lithium-battery-pack-in-electric-vehicles>.
5. W. Menghua and X. Bing (2017), "A Real-time Android-based Monitoring System for the Power Lithium-ion Battery Used on EVs," 2017 10th Int. Conf. on Intelligent Computation Technology and Automation, pp. 245-249.
6. A. Rahman, M. Rahman and M. Rashid (2017), "Wireless battery management system of electric transport," IOP Conf. Ser. Mater. Sci. Eng. 260, 012029.
7. Diyu Gao, Yong Zhou, Tianzhen Wang, Yanping Wang (2020), A Method for Predicting the Remaining Useful Life of Lithium-Ion Batteries Based on Particle Filter Using Kendall Rank Correlation Coefficient. Energies, MDPI, 13 (16), pp.4183-4187.