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Development of a Battery Life Cycle Predictor using Edge Impulse

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Abstract: Lithium-ion batteries are the ideal choice for energy storage systems due to aspects such as high energy density, long cycle life, and environmental friendliness. However, the battery is subject to aging which can lose capacity and frequently fail after a number of years. The accurate prediction of battery life has an important effect on the safe and reliable operation of the equipment. This paper proposed a prediction system of a life cycle of a lithium-ion battery (li-ion) using an Edge Impulse machine learning. A set of discharge voltage data was obtained when the li-ion battery was connected to a load to predict the life cycle of the battery. The dataset was analyzed using a regression block in the Edge Impulse to predict the battery life cycle. The training and testing result from the Edge Impulse showed the prediction after 1000 cycles of discharge and charging process. The accuracy of the datasets after training and testing is 95.83%. The deployment to the Arduino Nano 33 BLE sense also produces prediction results, a comparison with the result using Edge Impulse shows that the result is similar.

Keywords: Lithium-Ion Batteries, Life Cycle, Aging, Prediction, Discharge Voltage, Edge Impulse, Regression.

1. Introduction

The demand for the applications of rechargeable battery technology can be seen in electronic appliances such as electrical vehicles, electronic gadgets and medical devices as their source of power supply. A lithium-ion battery is a high-performance battery that utilises lithium ions as a key component of its electrochemistry and offers several advantages compared to other rechargeable batteries. Lithium-

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ion battery reliability and safety is a significant issue in the development of real-world applications. The performance of batteries degrades over time as their service life increases, potentially affecting not just the normal operation of electrical devices, but also posing major risks.

The number of charges and discharge cycles that a battery can complete before losing performance is known as its cycle life. The depth of discharge has a massive effect on the Li-ion battery's cycle life. The depth of discharge refers to how much of a battery's capacity is used. For example, a battery that has been depleted to 20% of its full energy capacity, has a much longer cycle life than one that has been discharged to 80% of its capacity with only 20% of its full energy charge remaining [1].

When lithium-ion battery ages, it’s the State of Health (SOH) falls. As a result, evaluating the battery's ageing state for safety and optimal functioning is crucial and necessary. There is a variety of methods for predicting the life cycle of a lithium-ion battery. In the conventional method to estimate the life cycle using the discharge capacity approach, it takes approximately two hours and 30 minutes for a single lithium-ion cell with a capacity of 2500mAh [2]-[4]. It takes too much time to predict a single battery. The development for this project is to decrease the amount of time to predict the life cycle of a lithium-ion battery using embedded machine learning in Edge Impulse.

2. Materials and Methods

The development of the battery life cycle predictor using Edge Impulse requires a circuit to connect with the rheostat, the lithium-ion battery, voltage sensor and Arduino Nano 33 BLE Sense as shown in Figure 1. The component is placed in the breadboard with correct polarity according to the discharge voltage circuit. A resistor is used to act as the load that can keep the current constant because this project uses a constant current (CC) process. The voltage sensor is used to calculate and measure the amount of discharge voltage in the battery and the data is collected using the Serial Terminal in the Arduino. In this project, the number of datasets that have been collected is approximately 200 datasets that contain discharge voltage every minute for 30 minutes.

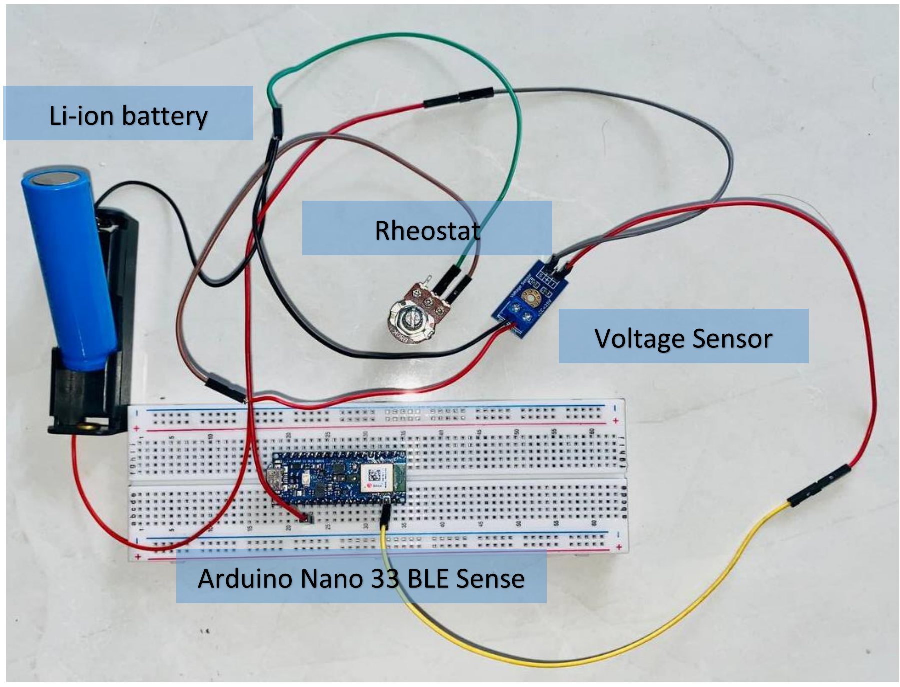

Figure 1: Discharge voltage circuit setup

Then, the datasets were exported to Edge Impulse for training and testing datasets using the three suitable blocks for this project, time series block, raw data block and regression block as shown in Figure 2. The time series block is used to input axes field lists in the datasets which are timestamp and voltage. The raw data block is used to make the datasets without pre-processing. The data was trained using the regression block model and the function of this model is to predict continuous value. In the regression block, the number of cycles is set to 1000 cycles as 1000 cycles of the charging-discharging process.

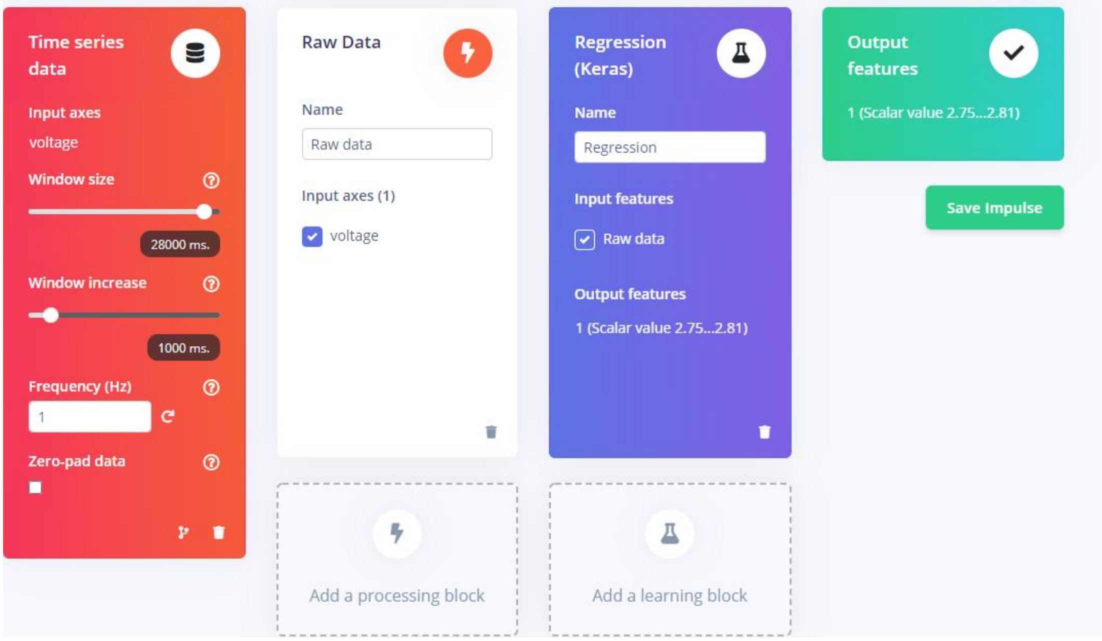

Figure 2: Blocks to create impulse

2.1 Methods

Figure 3 shows the flowchart of the project. Firstly, this project needs to design the discharge voltage circuit using MATLAB and the hardware to find the discharge voltage reading of the 2.5Ah and 1.2Ah lithium-ion batteries. From the circuit, the data of discharge voltage has been collected and if some of the data cannot be detected, the problem and error need to be identified and redesign the circuit to solve the problem. The data will be recorded in Microsoft Excel and will be imported to signal builder in MATLAB to view the data in the graph. Then, the dataset will then upload to Edge Impulse and created the impulse using three blocks that are suitable for this project which are the time series block model, the raw data block model and the regression block model. The data will be trained and tested using the regression block and if the train detects an error, identify the problem and retrain the data. Lastly, when the data successfully train, Edge Impulse can use the data to deploy into Arduino Nano 33 BLE Sense and predict the life cycle.

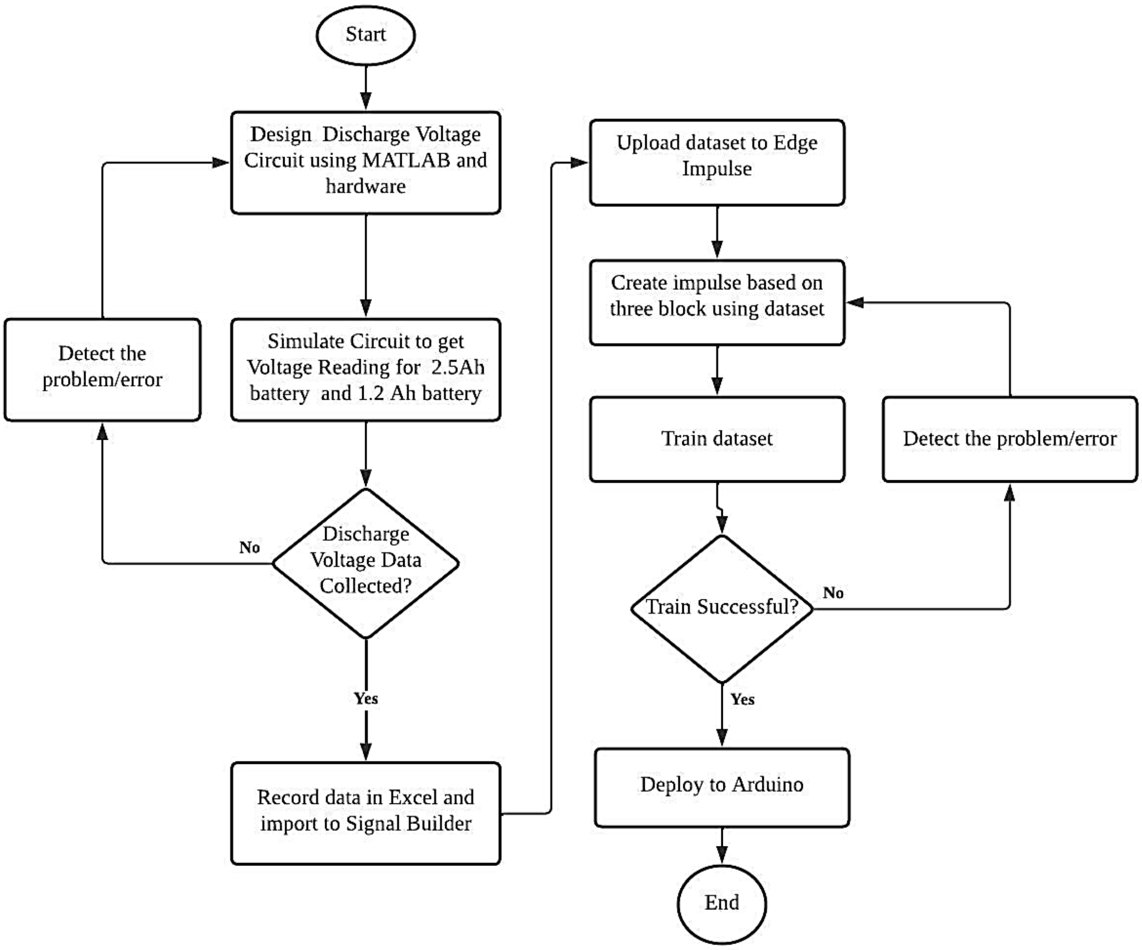

Figure 3: Flowchart of the project

3. Results and Discussion

After modeling the battery, the graph is studied and discussed, with the discharge voltage according to the battery model. The training performance of datasets in the Edge Impulse is shown using a neural network in the impulse design. The result shows the prediction of the battery life cycle based on the input data which is discharge voltage. The test was conducted two times with different storage capacities of the battery for comparison.

3.1 Battery voltage readings

The voltage reading was displayed in the serial terminal in the Arduino IDE with a one-minute sample time after the rheostat was connected to a 2.5A load current. Each battery will be collected from 100 different datasets to get a more accurate result in the prediction of the life cycle. After the data is collected in the serial monitor, the data will be copied and saved into an excel file in a table, the first column (x) is a timestamp and the second column (y) is a voltage value. The timestamp is incremented as 1000ms (1 min) because in the Edge Impulse uses ms for the time data. Then, the datasets will be uploaded to the signal builder in MATLAB to observe more easily the data that have been collected. Figure 4 shows the datasets of the li-ion battery after upload in the signal builder.

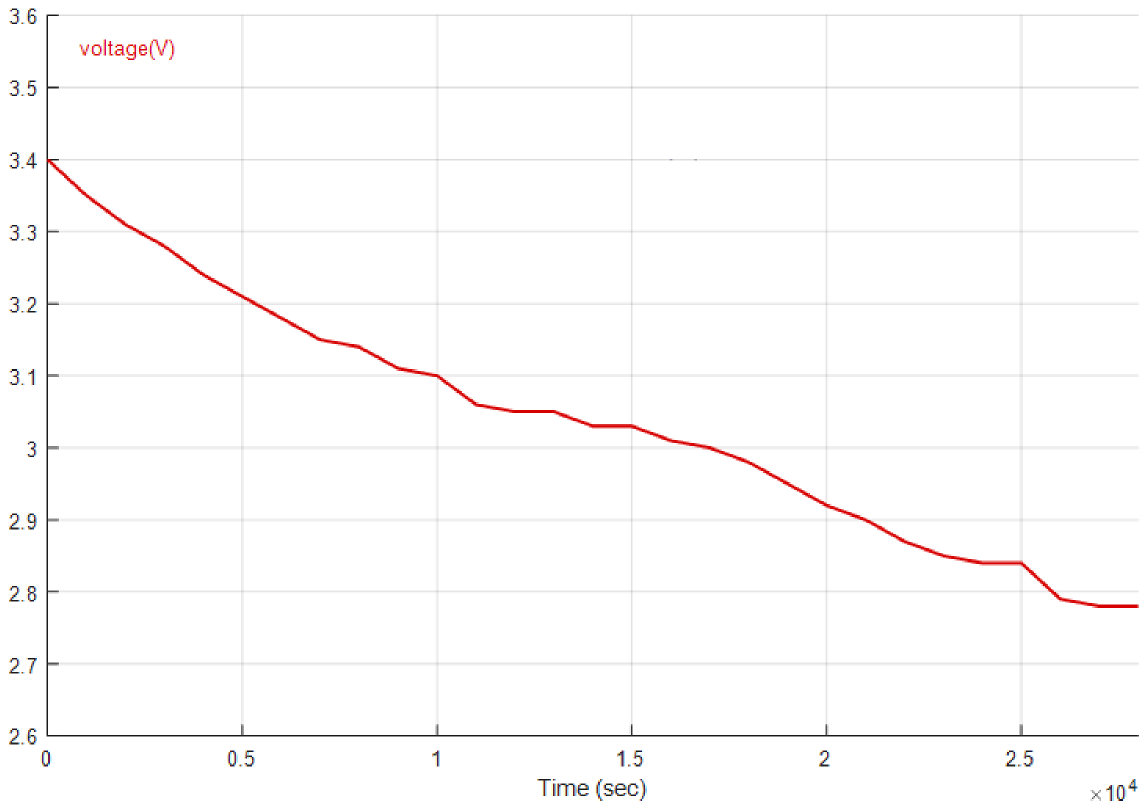

Figure 4: Discharge voltage pattern of Li-ion battery

3.2 Edge Impulse

All collected data for each battery was viewed on the Data Acquisition tab. In this tab, the data have been distributed for the model training purpose and model testing in the ratio of 88:12. The train/test split is a technique for training and evaluating the performance of machine learning algorithms. This technique prevents imbalanced datasets which might introduce bias during model training.

After collecting datasets for discharge voltage, this project can create impulse based on the building block. As mentioned in the methodology, three main building block which is time series data, raw data and regression has been used to train the data. In the generating features, the expected voltage can have been seen in the training list. The linear interpolation can calculate the estimated capacity by predicting the voltage. Once the training in the raw data block finished, the data was trained in the regression block. In the regression block, neural network settings are used to train the datasets. Figure 5 shows the result after the regression process.

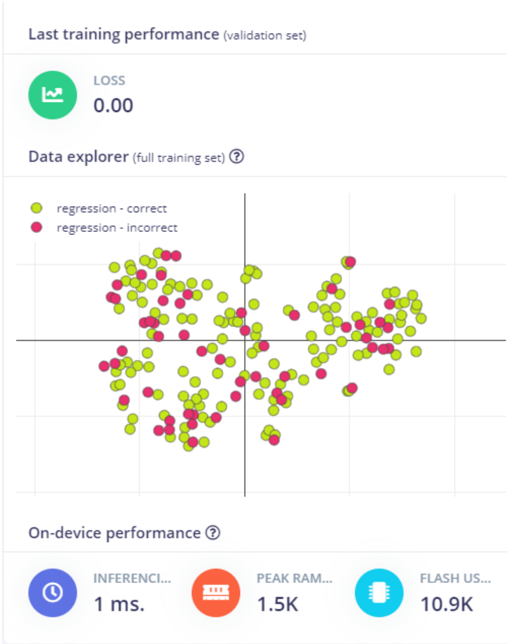

Figure 5: Result in regression block

After that, the dataset is tested in the Edge Impulse. The testing set is used to verify how well the model will perform on data after the model has been trained using only the training set. This will prevent the model from training, which is a common problem in the Edge Impulse. The model classified all of the samples in the test set and provide an overall accuracy rating for this model and the accuracy for the datasets is 95.83%. The live classification tab displayed the expected outcome and the predicted output of the discharge voltage with its accuracy. Figure 6 shows the live classification tab of the dataset sample.

Figure 6: The expected outcome and the predicted output of the discharge voltage

From Figure 6, the predicted value of discharged voltage after 1000 cycles can be seen. Its show that after the battery undergoes the charging and discharging process of 1000 cycle, the voltage drops quicker in the battery that will gradually lose its capacity to hold a charge. Then, the Edge Impulse will deploy the model in the Arduino IDE library and it can be used to upload to the Arduino 33 BLE sense. Arduino BLE is run using the coding and the result of the predicting using this is almost the same as in the live classification as shown in Figure 7.

```
Edge Impulse standalone inferencing (Arduino)
run_classifier returned: 0
Predictions (DSP: 0 ms., Classification: 0 ms., Anomaly: 0 ms.):
[2.87697]
    value: 2.87697
-0.33
Edge Impulse standalone inferencing (Arduino)
run_classifier returned: 0
Predictions (DSP: 0 ms., Classification: 0 ms., Anomaly: 0 ms.):
[2.87697]
    value: 2.87697
-0.33
Edge Impulse standalone inferencing (Arduino)
run_classifier returned: 0
Predictions (DSP: 0 ms., Classification: 0 ms., Anomaly: 0 ms.):
```

Figure 7: Prediction based on Arduino Nano

4. Conclusion

In conclusion, this project successfully demonstrates the modeling and prediction of discharge voltage of li-ion batteries using Edge Impulse. The voltage reading of the discharge current circuit is obtained with many different patterns from zero minutes until 30 minutes. By training and testing the datasets of discharged voltage, the Edge Impulse showed a successful prediction with high accuracy. In addition, the prediction system using Arduino Nano 33 BLE sense-based embedded machine learning was able to produce the result of the prediction of the discharge voltage.

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