

## Introduction

In today's world, the demand for energy across multiple sectors is on the rise, sparking a surge of interest in clean electricity solutions. Batteries have emerged as a dominant energy storage technology in a variety of applications such as electric vehicles (EVs), portable devices, and smart grids, but they come with challenges, including degradation over time.

The growing global need for energy is pushing the demand for better energy storage technologies. In fact, the market for size is valued at \$9.21 billion in 2021 and is estimated to grow from \$10.88 billion in 2022 to \$31.20 billion by 2029, with a CAGR of 16.9%.<sup>[1]</sup>

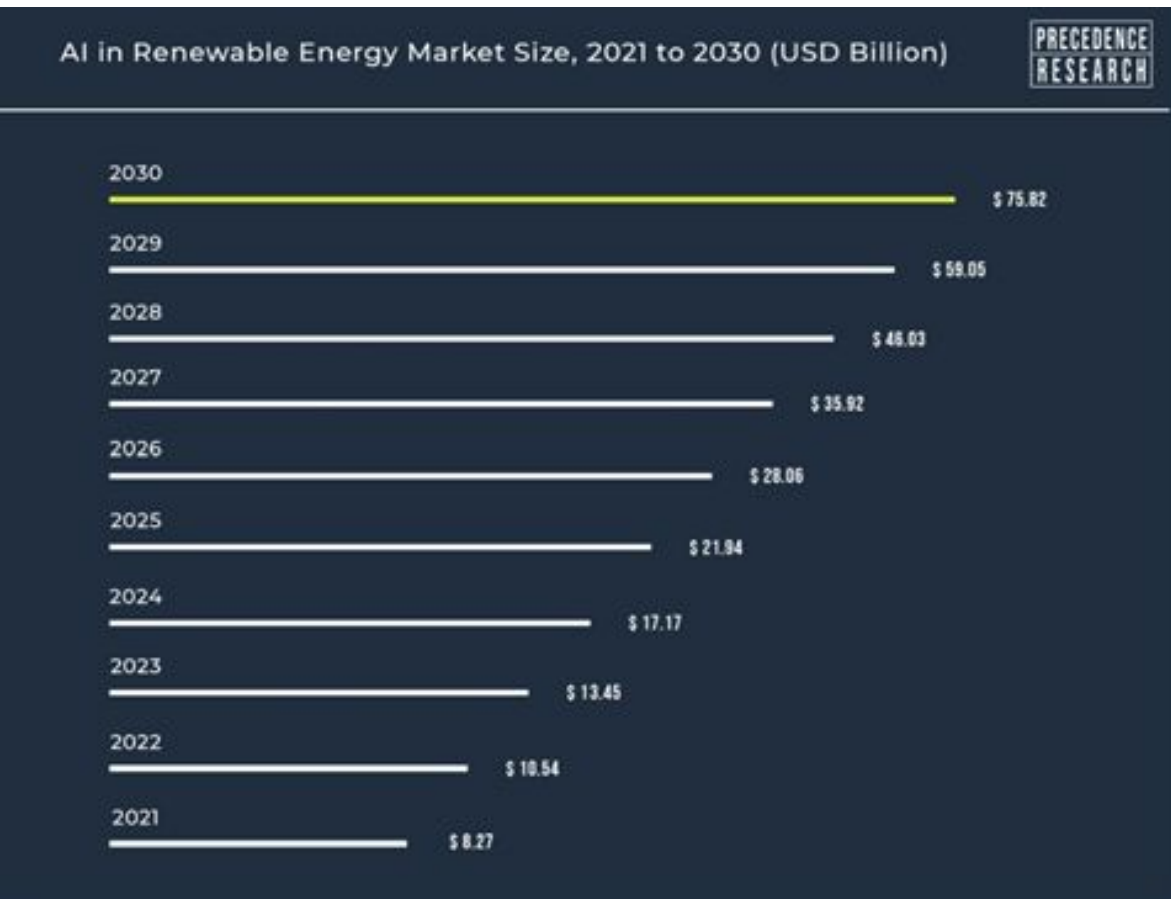


Figure 1. Market Size Growth of AI in Renewable Energy <sup>[2]</sup>

This project proposes a web application that provides a user-friendly dashboard with battery data analytics and employs data-driven machine learning to predict battery life cycle. Accurately predicting state of health, state of charge, and remaining useful life of batteries is crucial for reliable battery management systems.

## Methodology

### Regression

Battery life cycle prediction has been important to measure the quality of a battery, as well as to monitor the state of health. Knowing the total life cycle of a battery would provide insight to battery replacement and safety assurance. Regression is used to study the patterns of battery behaviors, predict the remaining life cycles, and monitor the state of charge. Linear regression and random forest regression is used to solve this problem.

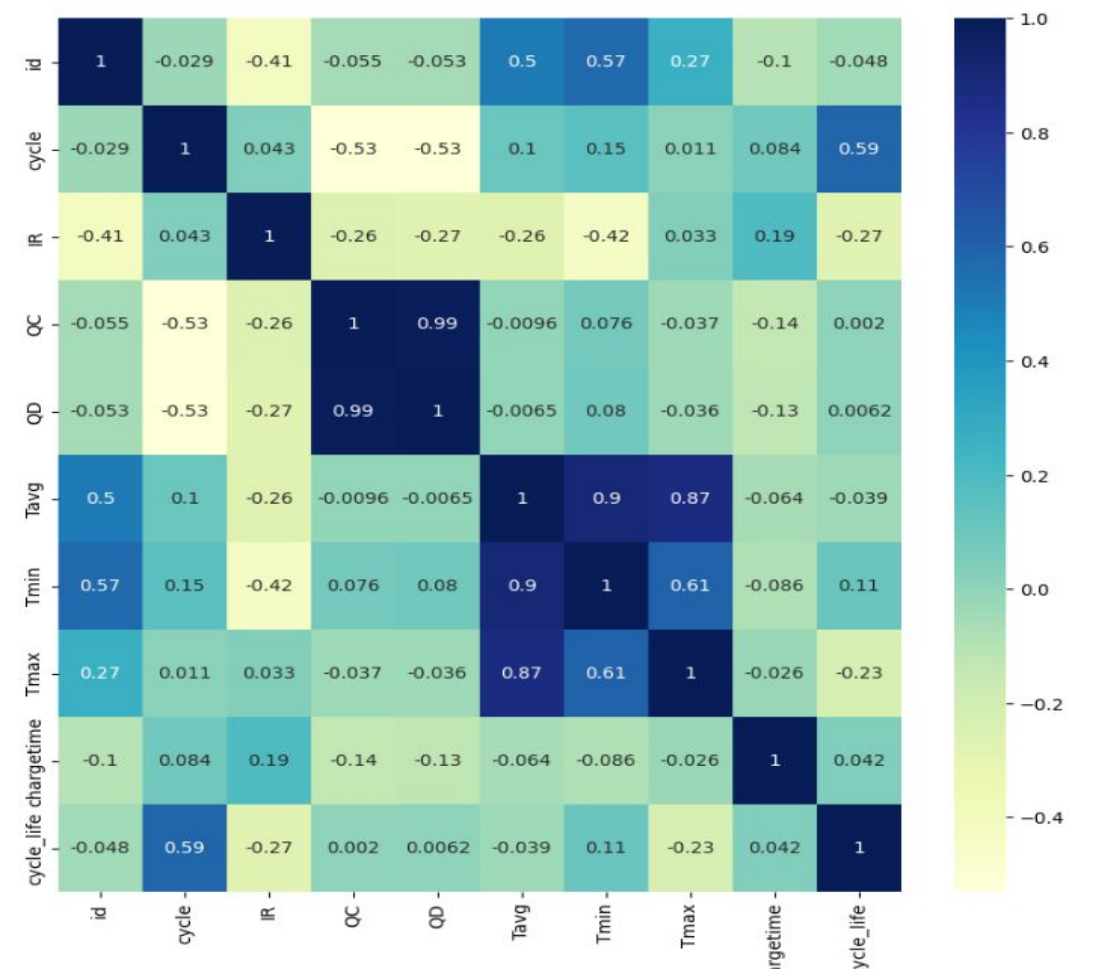


Figure 2. Feature Correlation Heatmap

## Methodology

Features are selected from the raw data by correlations. High correlated features are used to compute a dataset that represents the summary of each charge cycle.

Further feature transformation is used to reduce the error of the prediction and improve the model. Through research, additional features are computed from the raw data, such as variance of voltage between cycles, and the increase of internal resistance.

### Neural Network

While regression can predict an approximate prediction of battery life cycle, neural network is better at finding hidden patterns and make better predictions.

According to research findings, LSTM has demonstrated consistent performance as a model for battery quality predictions. For our project, we implemented LSTM with an input layer containing all the features in the dataset, LSTM layer of 50 nodes with an activation function ReLU, and output layer (dense layer) with single output neuron that predicts the cycle life.

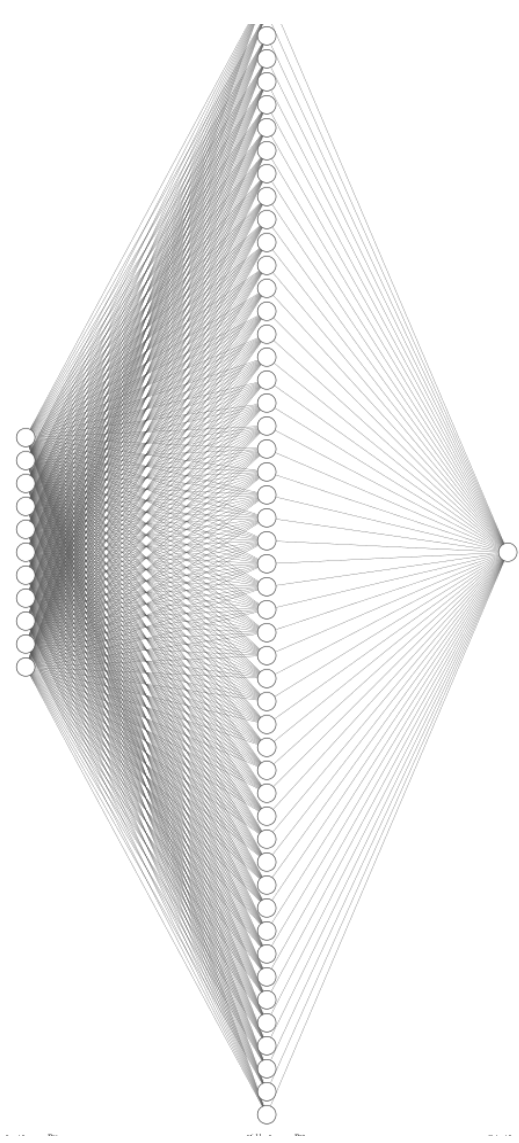


Figure 3. LSTM model

### Classification

Classification serves as a method to classify the condition of the batteries. Classification labels are assigned to each battery based on the percentage of the cycle completed.

Batteries with a percent < 0.3 are assigned a '2', batteries >= 0.3 and less than 0.7 are assigned a '1', and percents >= 0.7 are assigned a '0'. We implemented a neural network MLP Classifier model to provide accurate predictions, allowing us to effectively categorize batteries into different conditions for further analysis.

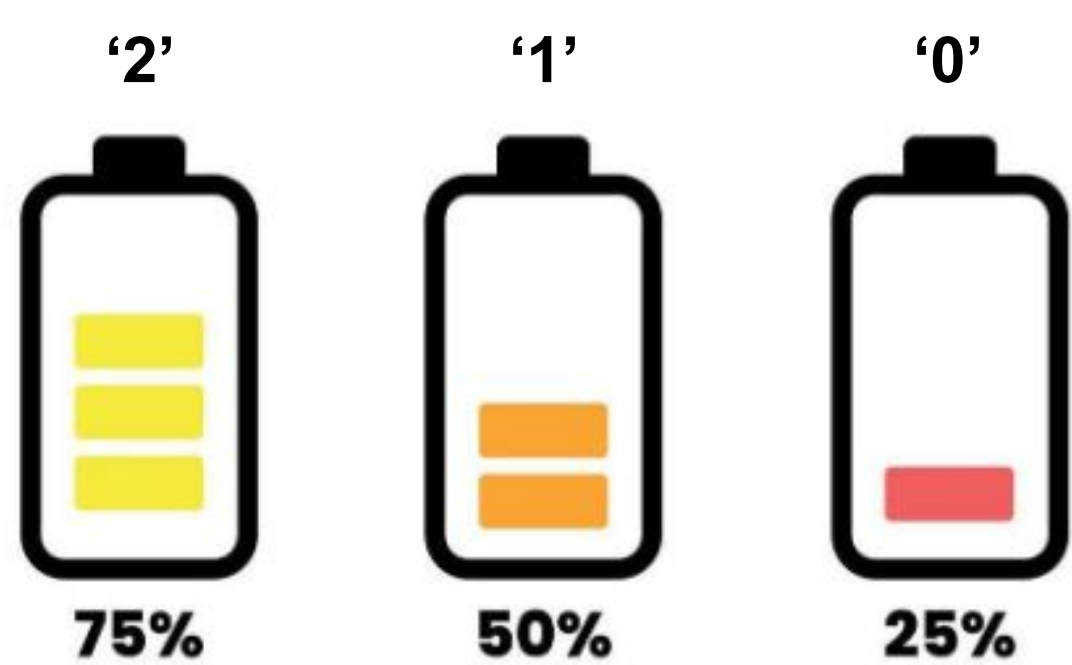


Figure 4. Classification Labels

## Technologies

### Tech Stack



- Front-End: Users connect to the service through a client built with React.
- Back-End: Receives and sends RESTful API requests to frontend, and database.
- Database: Users data are stored and managed using MongoDB.

### Machine Learning Model Deployment

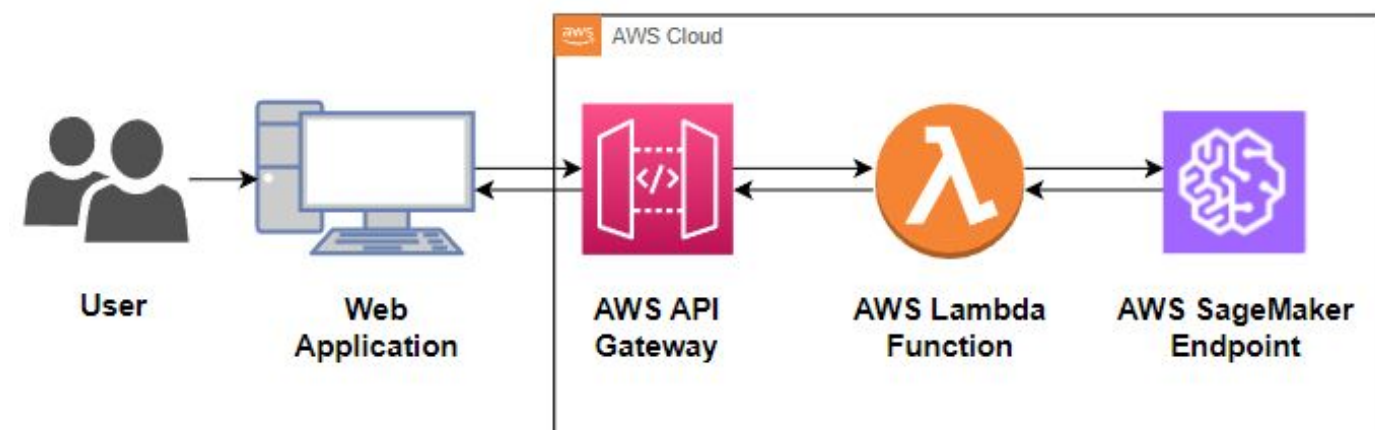


Figure 6. Deployment Architecture Diagram

When a user accesses the models, the client's app sends a REST-style request from the client app to the API gateway. The API gateway establishes a connection with an AWS lambda function, which transmits the request to the Sagemaker endpoint. The Sagemaker endpoint processes the data, makes a prediction, and returns it to the lambda function. The prediction is then relayed to the API gateway

## Analysis and Results

Our dashboard displayed a summary of the data analysis, and prediction results based on our sample data set. Users are able to monitor the overall performance of the battery storage on cloud in real time.

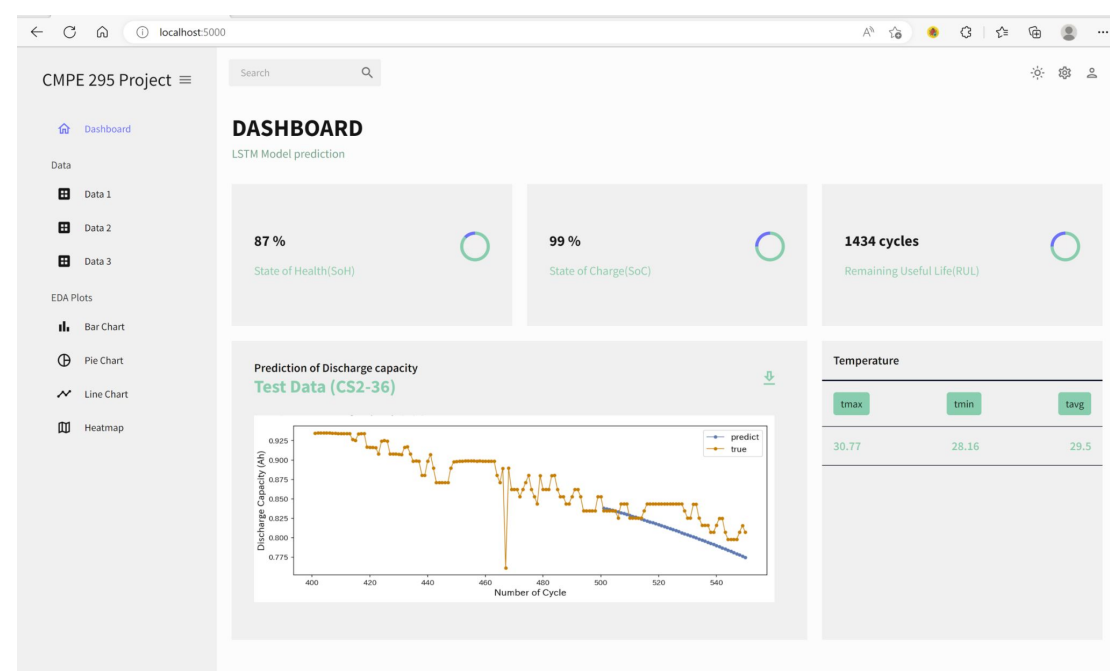


Figure 7. Dashboard Page

One of our best model was LSTM using 'rmsprop' optimizer and 'MSE' loss function as parameters. Prediction results of discharge capacity of a battery test data for 300 to 800 cycles are displayed below.

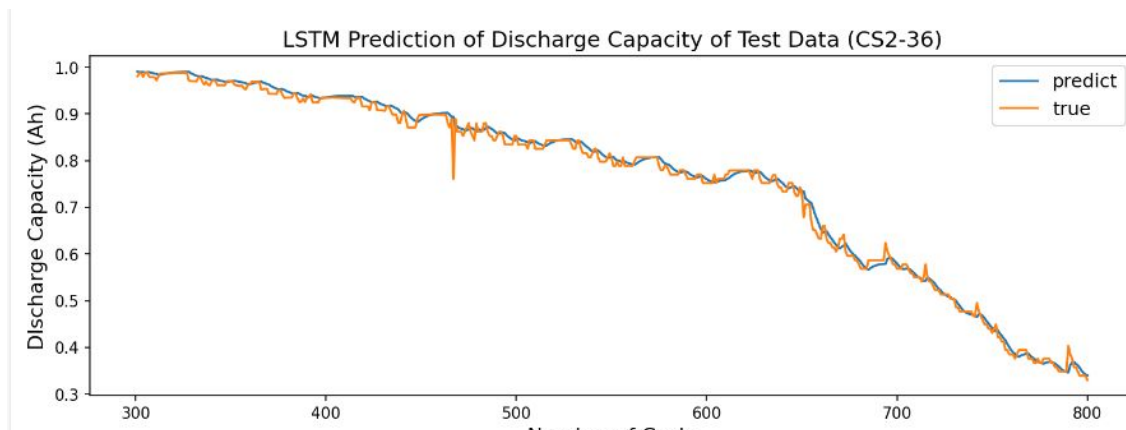


Figure 8. LSTM Prediction of Discharge Capacity of Test Data

Our models have achieved a good performance compared to other studies in our literature survey. Our random forest regressor and neural network regression models has achieved a low error with the exploration of feature transformation and model architecture.

Model	RMSE (cycles)	RMSE (cycles) - [Other studies]
Regression	268 (Linear)	119 (GPR) [3]
Random Forest	85	151 [3]
Neural Network	0.00017775749299095287	0.42 [4]

Figure 8. Model Performance

## Summary/Conclusions

The primary objective of this project is to enhance the efficiency of green energy storage systems, concentrating on battery quality by predicting battery state-of-health, state-of-charge, and remaining useful life using various machine learning and deep learning methods.

The application's intuitive user interface provides a feasible way of accessing battery diagnostics and battery quality forecasting.

## Key References

[1] Fortune Business Insights. (2022, December 6). *Battery energy storage market size to hit USD 31.20 billion by 2029: Exhibit a CAGR of 16.3%*. GlobeNewswire News Room. <https://www.globenewswire.com/en/news-release/2022/12/06/2568160/0/en/Battery-Energy-Storage-Market-Size-to-Hit-US-D-31-20-Billion-by-2029-Exhibit-a-CAGR-of-16-3.html>

[2] Precedence Research. (2022, May 1). *AI in renewable energy market size to surpass US\$ 75.82 bn by 2030*. GlobeNewswire News Room. <https://www.globenewswire.com/en/news-release/2022/05/01/2433085/0/en/AI-in-Renewable-Energy-Market-Size-to-Surpas-s-US-75-82-Bn-by-2030.html>

[3] Z. Fei et al., "Early prediction of battery lifetime via a machine learning based framework," *Journal of Energy Storage*, vol. 40, pp. 120205, 2021, doi: <https://doi.org/10.1016/j.est.2021.120205>.

[4] X. Shu, J. Shen, G. Li, Y. Zhang, Z. Chen and Y. Liu, "A Flexible State-of-Health Prediction Scheme for Lithium-Ion Battery Packs With Long Short-Term Memory Network and Transfer Learning," in *IEEE Transactions on Transportation Electrification*, vol. 7, no. 4, pp. 2238-2248, Dec. 2021, doi: [10.1109/TTE.2021.3074638](https://doi.org/10.1109/TTE.2021.3074638).

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