Data-driven estimation of Battery State of Health and Remaining Useful life

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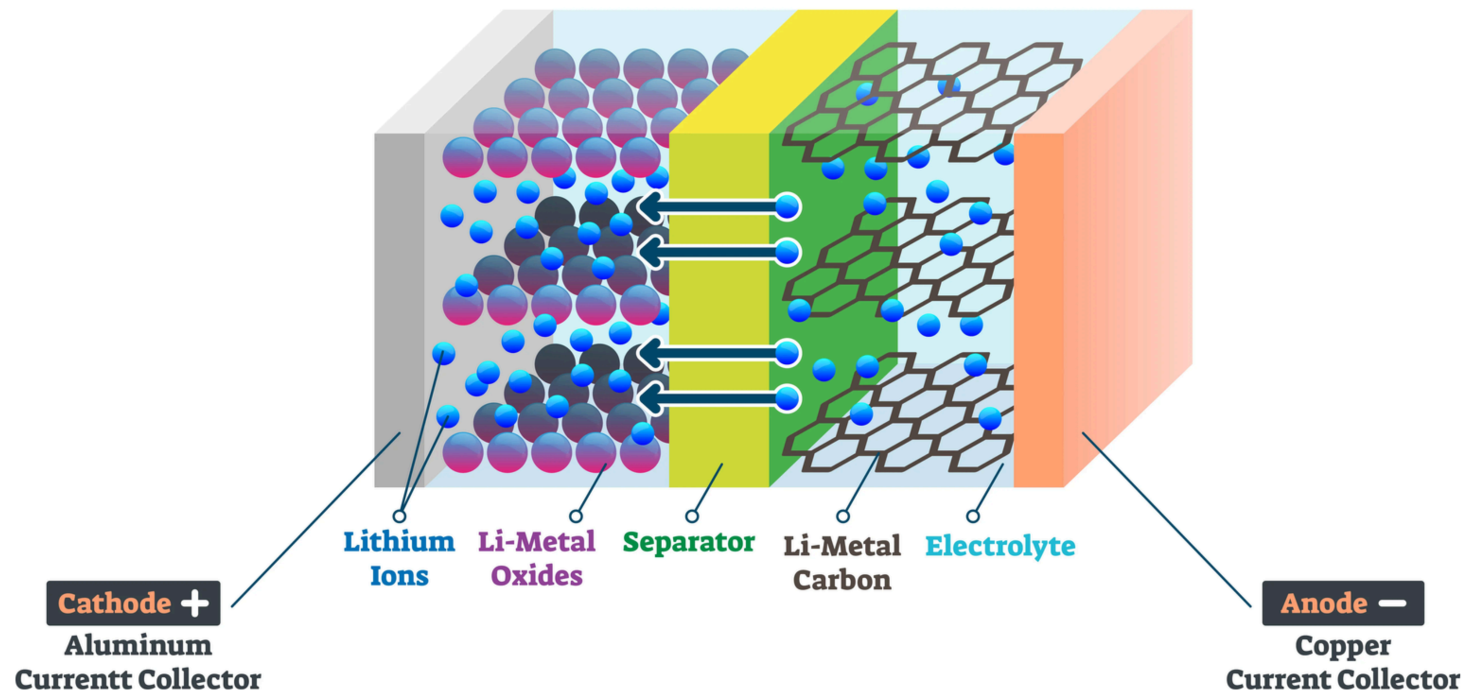
01. Introduction

The rising demand for electric vehicles (EVs) necessitates lithium-ion (Li-ion) batteries, despite degradation concerns. Predicting battery state of health (SOH) is vital for determining end of life (EOL), where SOH and remaining useful life (RUL) metrics are pivotal.

Li-ion battery degradation involves physical and chemical changes, including the formation of a solid electrolyte interface (SEI) layer and lithium plating. SEI impacts electrode performance, while lithium plating reduces capacity and safety.

Given the complexity of degradation mechanisms, data-driven approaches are preferred for SOH and RUL prediction. Feature engineering and extracting battery health indicators are critical for accurate predictions.

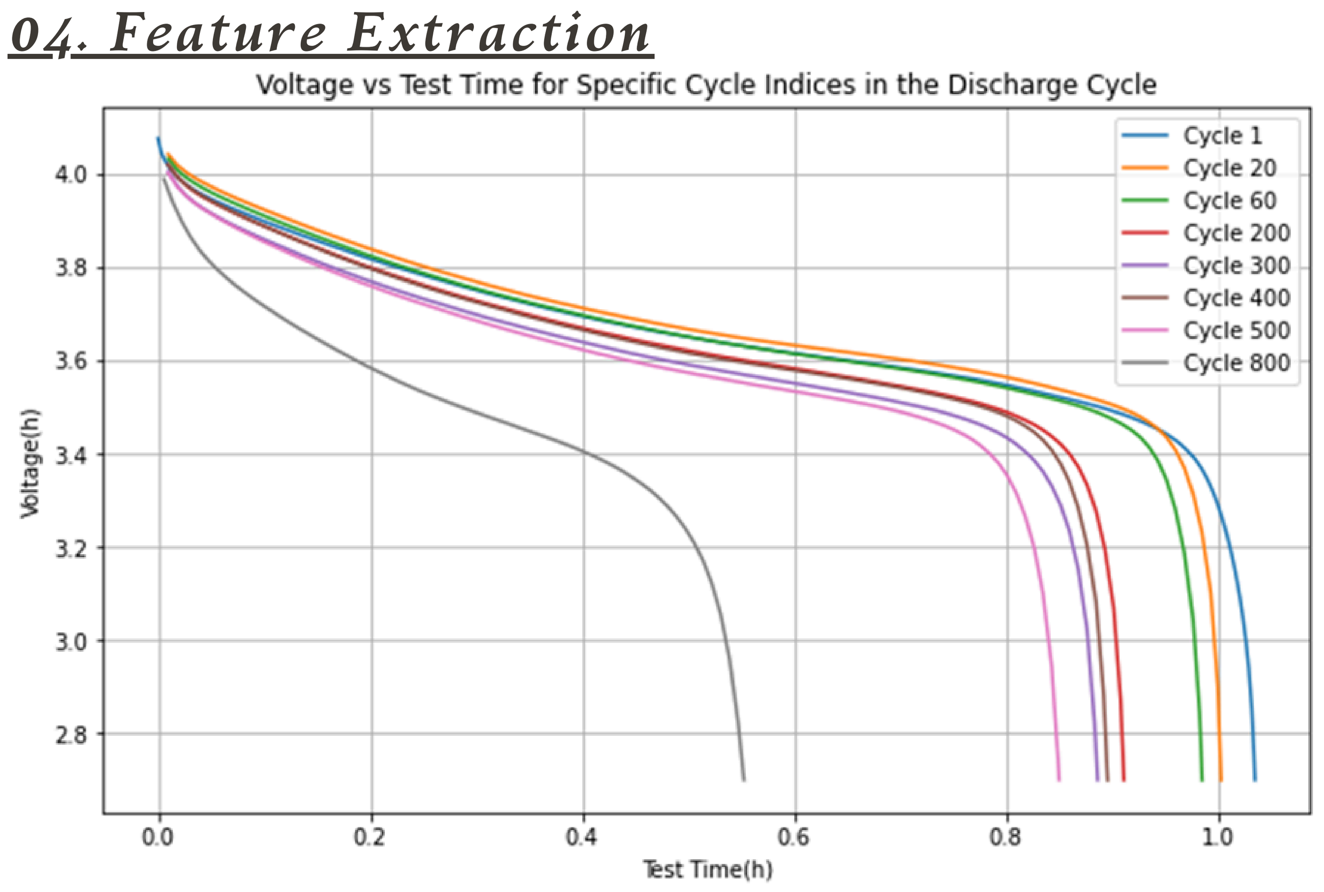


02. Aims

Aims

- Use data-driven models to predict battery SOH and RUL
- Improve on existing models from literature using feature engineering, more advanced models and hyperparameter tuning

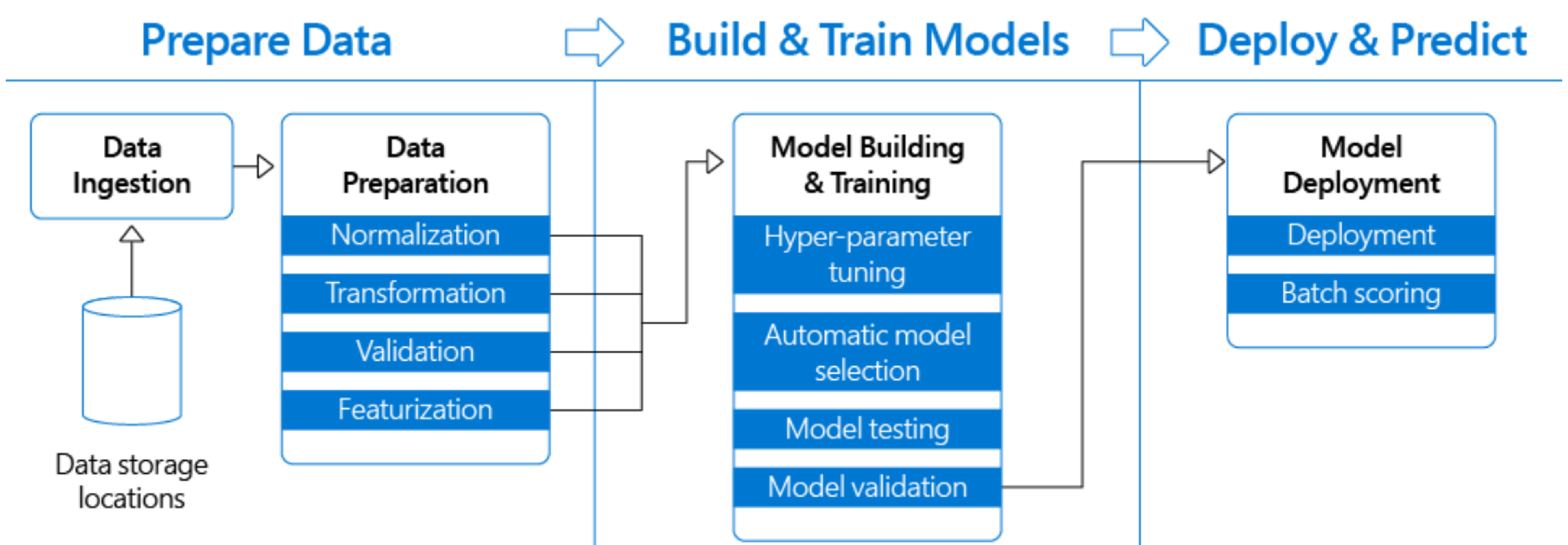
04. Feature Extraction



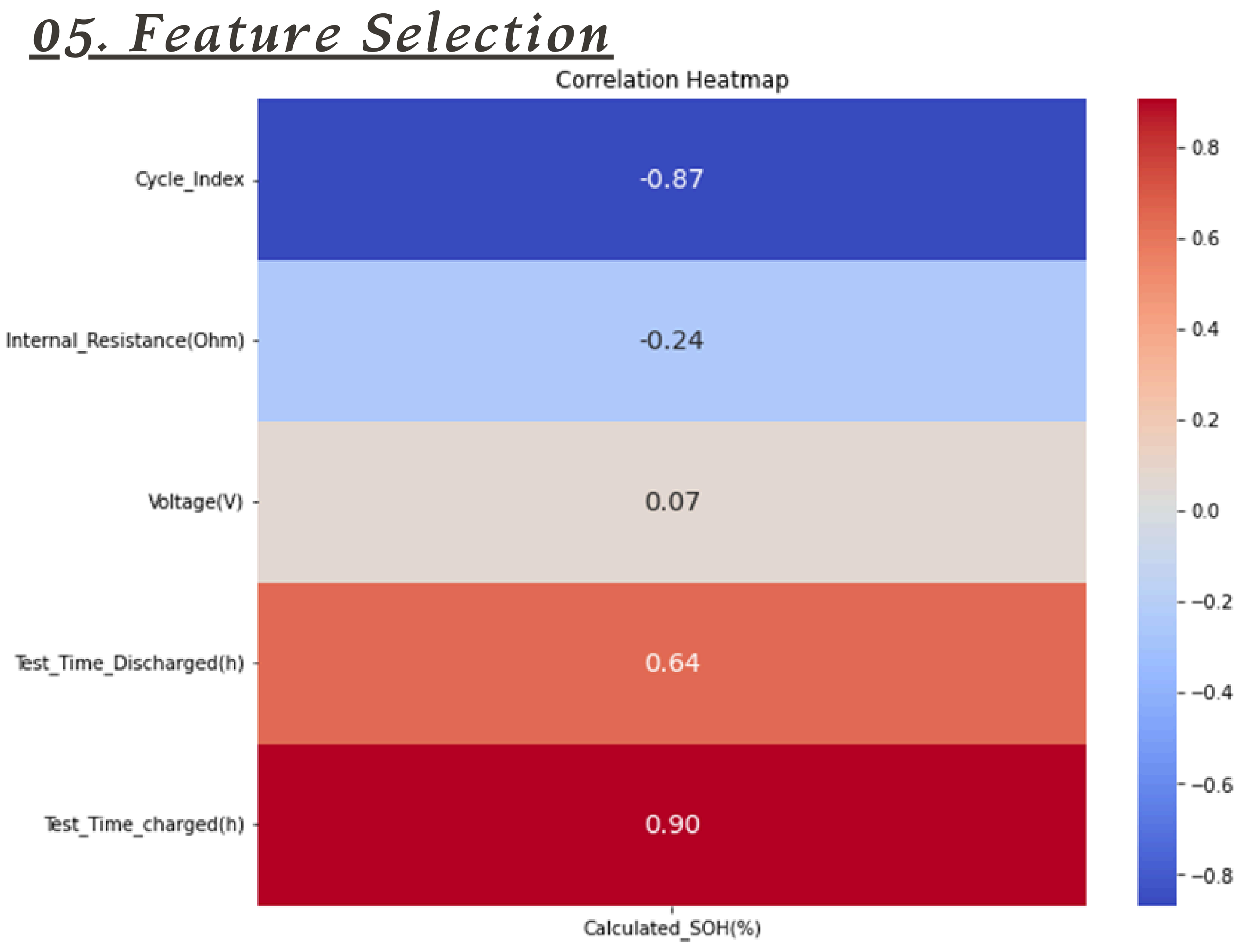
As the battery ages with continuous use, its internal resistance typically rises, resulting in a shorter time needed for full discharge. Monitoring the time to achieve full discharge (HI2), particularly corresponding to the discharge voltage of the constant current (CC) operating mode, is crucial for assessing battery health. Additionally, HI1 represents the time needed for full battery charging.

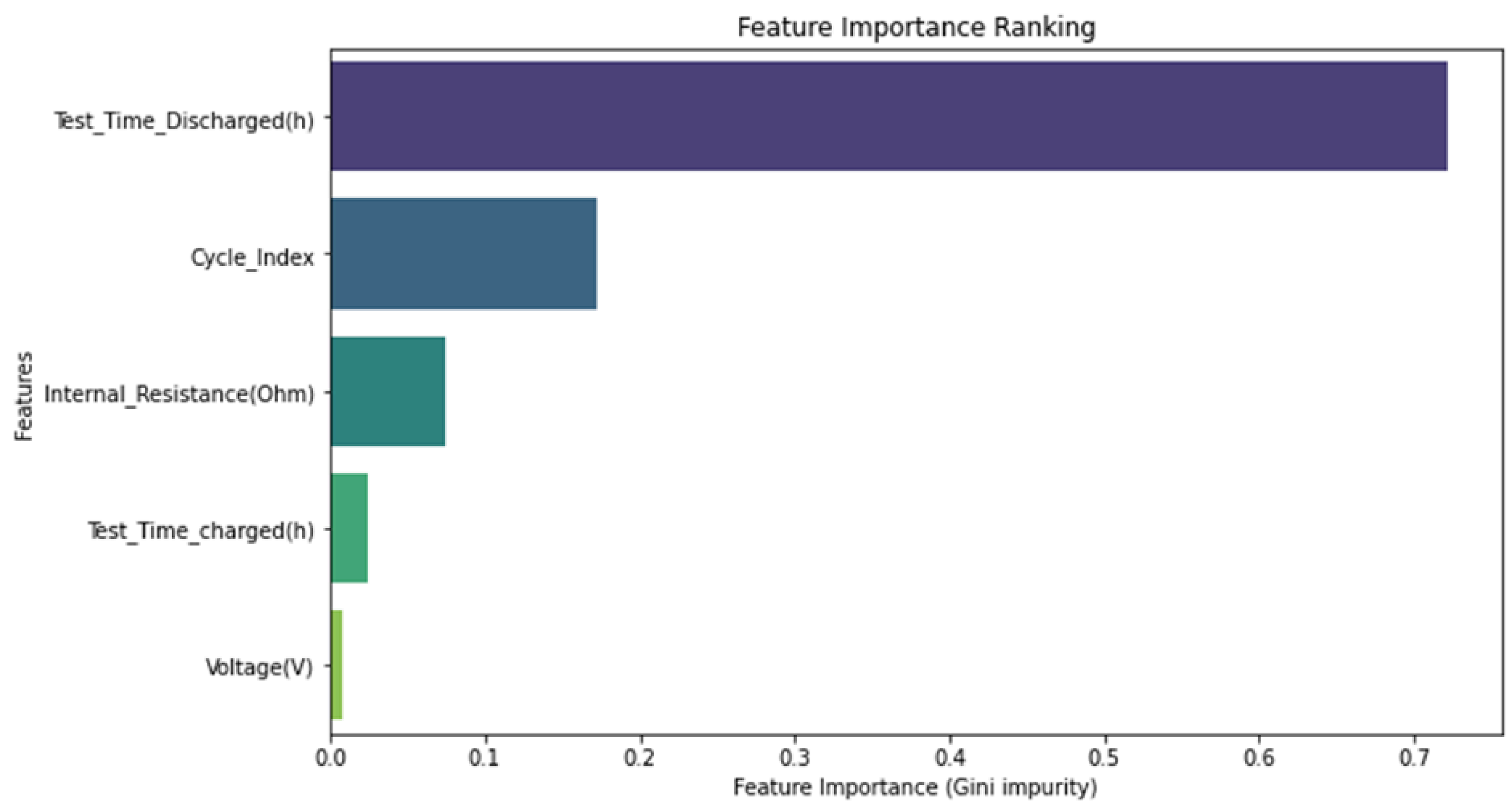
03. Methodology

The project methodology, depicted in the accompanying figure, involved utilizing a dataset sourced from the Center for Advanced Life Cycle Engineering (CALCE), comprising CS2 prismatic cells subjected to identical charge profiles. Data preprocessing included the removal of NaN values and rows exhibiting abnormal peaks in the state of health (SOH). Subsequently, the dataset underwent training and testing phases using various models, including CNN, LSTM, GRU-RNN, FNN, and GPR.



05. Feature Selection





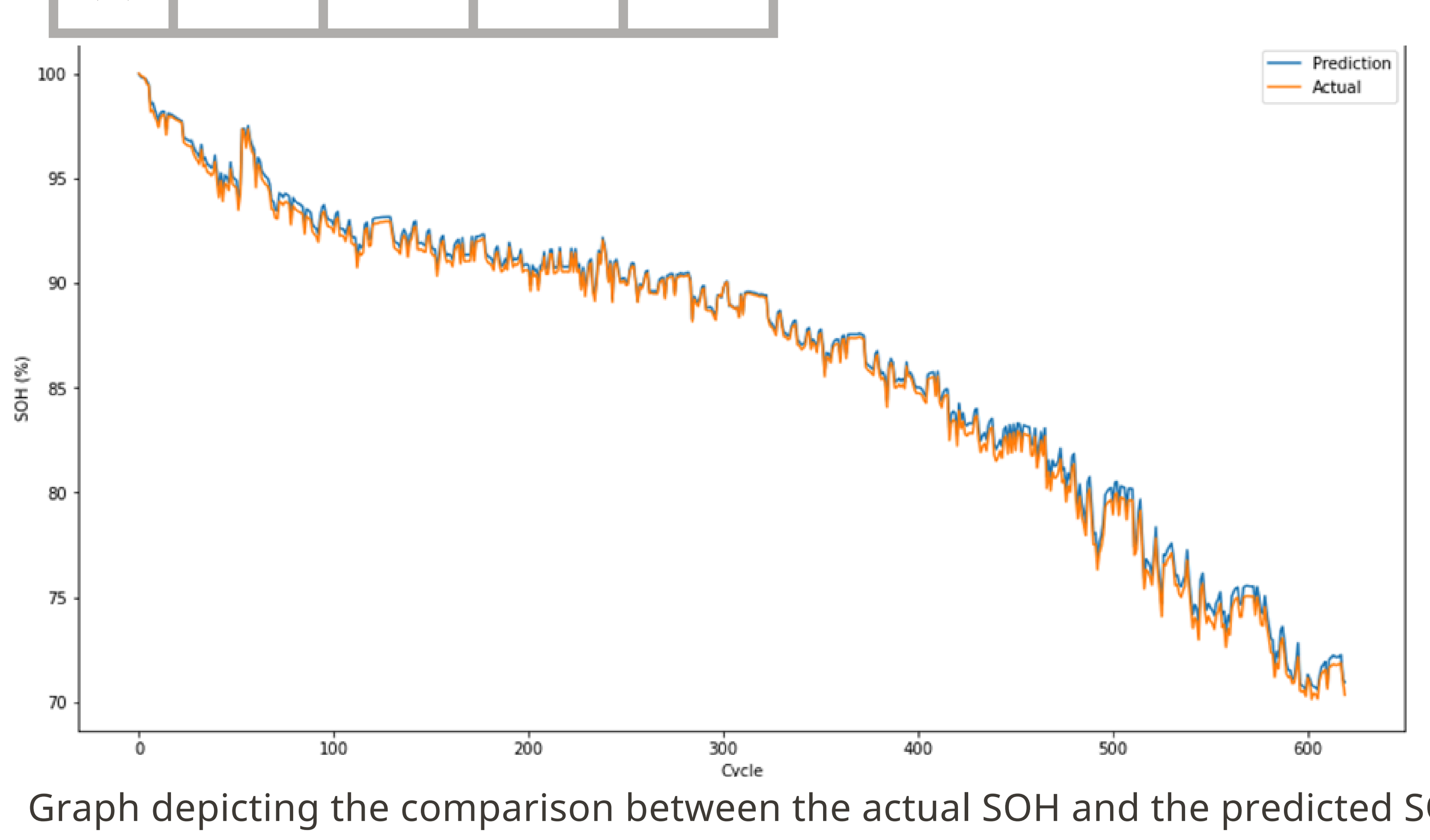
The feature selection involved using correlation heatmap and Gini importance. Gini importance, along with the correlation matrix, was chosen for its independence from variable correlation, favoring numerical variables. In the initial feature evaluation, a DNN was built, revealing that voltage negatively affected performance. Training with cycle_index, HI1, and HI2 alongside voltage resulted in an MSE of 24.53%, whereas training with internal resistance yielded an MSE of 9.87%. The optimal features were found to be HI1, HI2, and the cycle index.

06. Results/Findings

The project successfully replicated feature extraction techniques from literature and compared various models' performance. Notably, the LSTM and GRU-RNN emerged as superior models, with the GRU-RNN selected due to its efficiency with smaller datasets. However, performance deteriorated with fewer training batteries. GPR models showed promise but require further hyperparameter tuning. The models demonstrated adaptability to unseen data but may suffer from overfitting. Features like cycle count and capacity decrease were crucial for RUL prediction, with GRU-RNN and LSTM models achieving MSEs of 2.6921% and 1.6979%, respectively. Further research into RUL estimation models and testing at various points before EOL is recommended.

	DNN	FNN	GRU	LSTM
MSE (%)	1.0528	0.3337	0.1284	0.3772

The table shows the model perfomance when tested on unseen data using optimal features.



Graph depicting the comparison between the actual SOH and the predicted SOH obtained from the GRU model when trained and tested on unseen data.

07. Conclusion and Further Work

The project aimed to develop data-driven models for battery SOH prediction, starting with reproducing literature models and enhancing their performance through parameter tuning and feature engineering. Feature selection methods, including correlation analysis and Gini importance, were crucial. The FNN model replicated literature results with a MSE of 0.3337%, outperforming Dai et al.'s model. The LSTM and GRU-RNN performed best, consistent with literature, with MSEs of 0.3772% and 0.1248%, respectively. Future work involves incorporating diverse battery data, including temperature data, automating hyperparameter tuning, analyzing datasets with alternating discharge currents, and exploring advanced algorithms like extreme gradient boosting.

08. References

BEng Mechanical Engineering

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