Pattern Recognition Project

Project Report

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2K18/EE/179.   2K18/EE/194

Lithium Ion Battery Life Predictor using Convolutional Neural Networks

Abstract

- The modelling of Non-Linear Data has always been a challenging task for analysts and researchers for a long time. While some techniques have been developed to model complex systems by studying their physical characteristics and statistical data. With the rise of Machine Learning and Deep Learning techniques it is imperative to develop a technique which can learn from the past telemetry data of the system and use it to make accurate predictions about the system. One such use case is to predict the Remaining Useful life (RUL) of Li-Ion Batteries. In this study, we aim to develop a model that uses deep learning to predict the RUL of Li-Ion batteries by the analysis of its charging and discharging data over a certain number of cycles.

Keywords

- Remaining Useful Life (RUL)
- Lithium-ion battery
- Neural Network
- Capacity Estimation
- Battery Degradation
- Charging Cycle

Lithium ion batteries are the most widely used batteries in the world with applications in a large no. of electric devices like Mobile Phones, Laptops, Watches etc. Our study aims to predict the lifetime of a lithium ion battery by analysing it's charging and discharging cycle. For years researchers have tried 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. We AIM to apply different Machine Learning models on the largest dataset of its kind to check which model performs better in terms of accuracy as well as computational costs.

Quality assessment	**Long-term planning**
How good is my battery right now?	When do I have to react to a failing battery?

Review of Literature

Kristen A. Severson et al. (2019)

- **Title:** Data-driven prediction of battery cycle life before capacity degradation
- **Dataset Used:** Toyota Research Institute Dataset (Experimental)
- **Objective:** Apply machine-learning tools to both predict and classify cells by cycle life.
- **Research Methodology:** Develop a feature-based approach to build an early-prediction model. Features, which are linear or nonlinear transformations of the raw data, are generated and used in a regularized linear framework.The final model uses a linear combination of a subset of the proposed features to predict the logarithm of cycle life.
- Finding/Results: Coming Up Next
- Observation (Research Gap): The success of the model is rationalized by demonstrating consistency with degradation modes that do not manifest in capacity fade during early cycles but impact the voltage curves.(Physical or Empirical Methods)

Table 2 | Model metrics for the classification setting with a cycle life threshold of 550 cycles

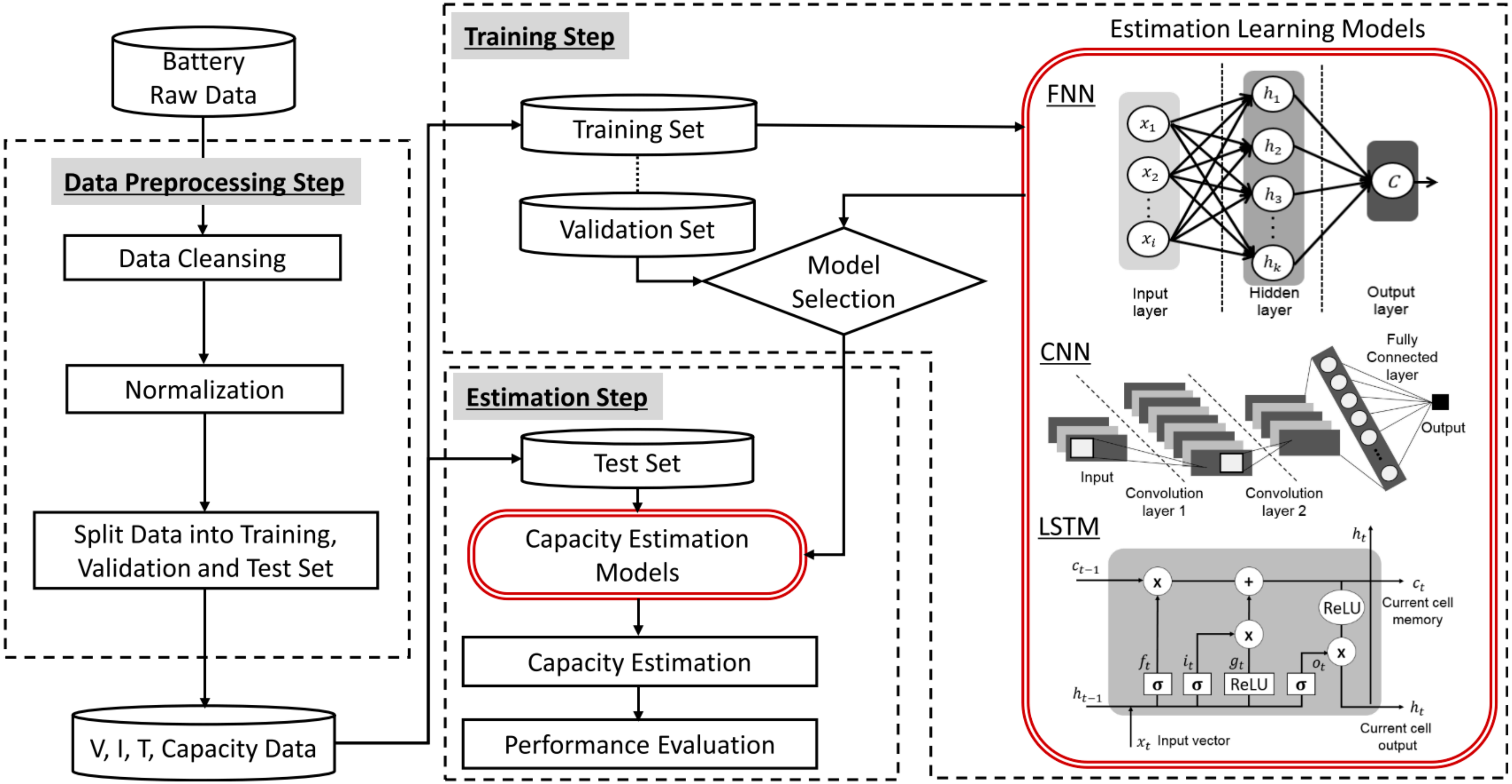
	Classification accuracy (%)		
	Train	Primary test	Secondary test
Variance classifier	82.1	78.6	97.5
Full classifier	97.4	92.7	97.5

Train and primary/secondary test refer to the data used to learn the model and evaluate model performance, respectively.

cting cycle life using the first 100
ıpacity) and **4.9%** test error using
This work highlights the promise
ıodelling to predict the behaviour

Y Choi, S. Ryu, K Park et al. (2019)

- **Title:** Machine Learning-Based Lithium-Ion Battery Capacity Estimation Exploiting Multi-Channel Charging Profiles
- **Dataset Used:** NASA Dataset
- **Objective:** estimating battery capacity exploiting multi-channel charging profiles based on FNN, CNN and LSTM.
- Research Methodology: Coming Up Soon
- Finding/Results:
- Observation (Research Gap) : Proposed method can be extended by considering an online method which adaptively updates the internal parameters of physics-based equations affecting actual degradation in real-time practical operation.


Battery
Raw Data
Data Preprocessing Step
Data Cleansing
Normalization
Split Data into Training, Validation and Test Set
V, I, T, Capacity Data
Training Step
Training Set
Validation Set
Model Selection
Estimation Step
Test Set
Capacity Estimation Models
Capacity Estimation
Performance Evaluation
Estimation Learning Models
FNN
Input layer
Hidden layer
Output layer
CNN
Input
Convolution layer 1
Convolution layer 2
Fully Connected layer
Output
LSTM
Current cell memory
Current cell output
Input vector
ReLU

Y.Li, K.Liu, A.Foley et al. (2019)

- **Title:** Data-driven health estimation and lifetime prediction of lithium-ion batteries: A review

- **Dataset Used: NA**

- **Objective:** To review and discuss all the methods used for Battery RUL estimation

- **Research Methodology: NA**

- Finding/Results: Among all, the machine learning techniques, supported by a platform of open-source tools and data sharing, has the potential to revolutionize the battery health management system.

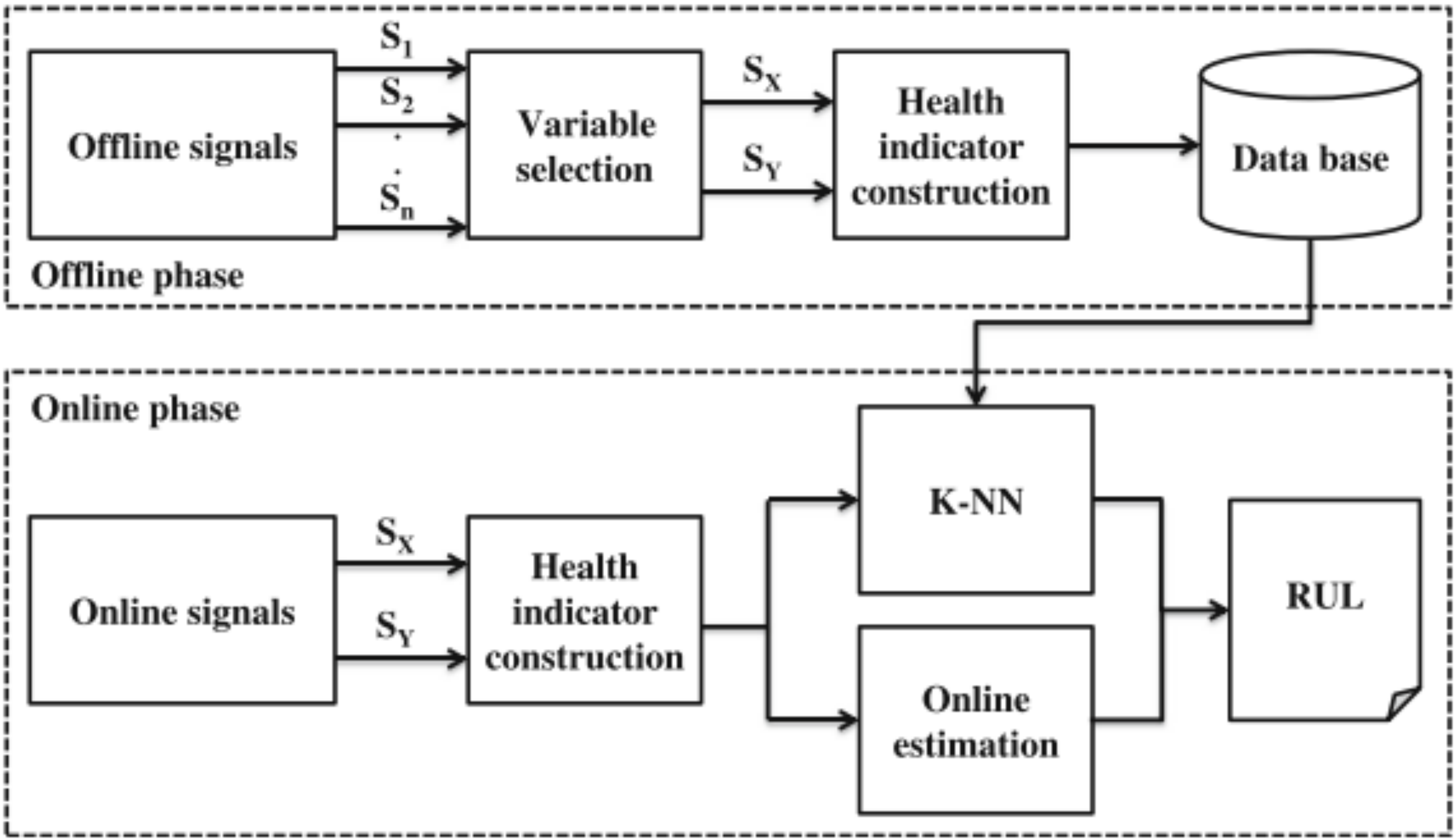
- Observation (Research Gap): None that we know of

Table 7
A comparison of battery health prediction methods.

			Advantages	Disadvantages
Analytical model with data fitting		Semi-empirical model	● Easy to be built up and quick to produce predictions; ● Easy of extracting model parameters; ● Low computational effort; ● Easy to be implemented on BMS for online application by monitoring the parameter of cycling conditions, time and/or numbers.	● Extensive laboratory tests over the entire operating range are required, which are time consuming and economically costly; ● Difficult to develop suitable laboratory ageing tests to analyse the interaction between different ageing processes and link them to lifetime expectancy on an experimental basis; ● Poor generalizability. Developed models are restricted to a specific battery type and operating conditions.
		Empirical ageing model with filtering	● Only a small amount of ageing data is required for setting up the model; ● Estimation errors are updated based on the real measurement.	● High computational effort and which increases the difficulties for online application.
ML	Non-probabilistic	**AR model**	● Simple structure; ● Easy to identify parameters; ● Easy to implement.	● Easy to cause under-fitting problems due to its linear regression type; ● Poor generalization ability; ● Bad long-term prediction ability.
		ANN	● Strong ability to consider nonlinearities; ● RNN owns strong long-term RUL prediction ability due to recurrent links; ● High prediction accuracy.	● Potential to cause over-fitting problem; ● Poor uncertainty management ability; ● Performance highly depends on the training process.
		SVM	● High prediction accuracy; ● Non-parametric; ● Robust to outliers; ● Low prediction time.	● High computational cost; ● Poor uncertainty management ability; ● Requires cross validation procedure to determine hyper-parameters.
	Probabilistic	**GPR**	● Provide covariance to generate uncertainty level; ● Non-parametric; ● Being flexible.	● Performance is highly affected by kernel functions; ● High computational cost.
		RVM	● Generate PDF directly; ● Non-parametric; ● Realize high sparsity; ● Avoid cross validation process.	● Plenty of data is required for modelling; ● Large time and memory consumed training process; ● Easy to fall into the local optimization problem; ● Potential to cause over-fitting problem.

A. Mosallam · K. Medjaher · N. Zerhouni (2014)

- **Title:** Data-driven prognostic method based on Bayesian approaches for direct remaining useful life prediction
- **Dataset Used:** Custom + NASA
- **Objective:** estimating battery capacity exploiting multi-channel charging profiles based on FNN, CNN and LSTM.
- Research Methodology: Coming Up Soon
- Finding/Results: An Unsupervised RUL Estimation Framework
- Observation (Research Gap) : It should be tested using data sets with variable operating conditions and after introducing maintenance interventions. Different classifica- tion/regression models should be tested in the proposed framework.

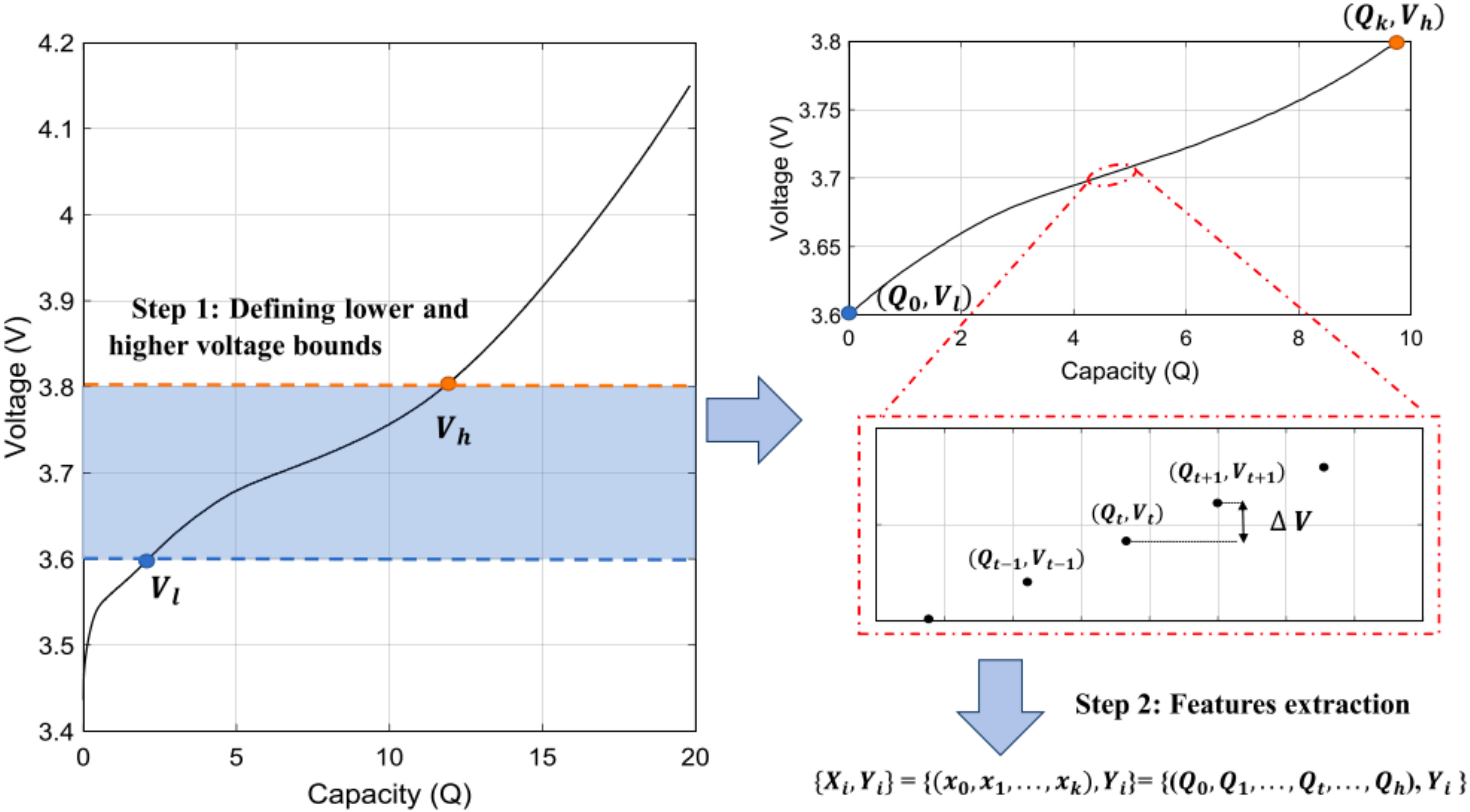

Offline signals
S1
S2
Sn
Variable selection
SX
SY
Health indicator construction
Data base
Offline phase
Online phase
K-NN
Online signals
SX
SY
Health indicator construction
Online estimation
RUL

B.Saha · K. Goebel · J. Christopher (2009)

- **Title:** Comparison of Prognostic Algorithms for Estimating Remaining Useful Life of Batteries
- Dataset Used: NASA Dataset
- **Objective:** Estimating battery capacity using ARMA, Relevance Vector Machine and Extended Kalman Filter **Research Methodology: Coming Up Soon**
- **Finding/Results**: Combined Bayesian regression-estimation approach implemented as a RVM-PF framework has significant advantages over conventional methods of RUL estimation like ARIMA and EKF. ARIMA, being a purely data-driven method
- Observation (Research Gap) : None that we feel can be covered in our study

Y.Li, C. Zou, M. Berecibar et al (2018)

- **Title:** Random forest regression for online capacity estimation of lithium-ion batteries
- Dataset Used: Custom Data Set
- **Objective:** Estimating battery capacity using feature extraction along with Random forest classifier
- **Research Methodology: Coming Up Soon**
- **Finding/Results**: Evaluated the health states of different batteries under varied cycling conditions with a root-mean-square error of less than 1.3% and a low computational requirement
- Observation (Research Gap) : None that we feel can be covered in our study



Step 1: Defining lower and higher voltage bounds
Voltage (V)
Capacity (Q)
V_h
V_l
(Q_k, V_h)
(Q_0, V_l)
(Q_{t+1}, V_{t+1})
(Q_t, V_t)
(Q_{t-1}, V_{t-1})
ΔV
Step 2: Features extraction
$\{X_i, Y_i\} = \{(x_0, x_1, \ldots, x_k), Y_i\} = \{(Q_0, Q_1, \ldots, Q_t, \ldots, Q_h), Y_i\}$

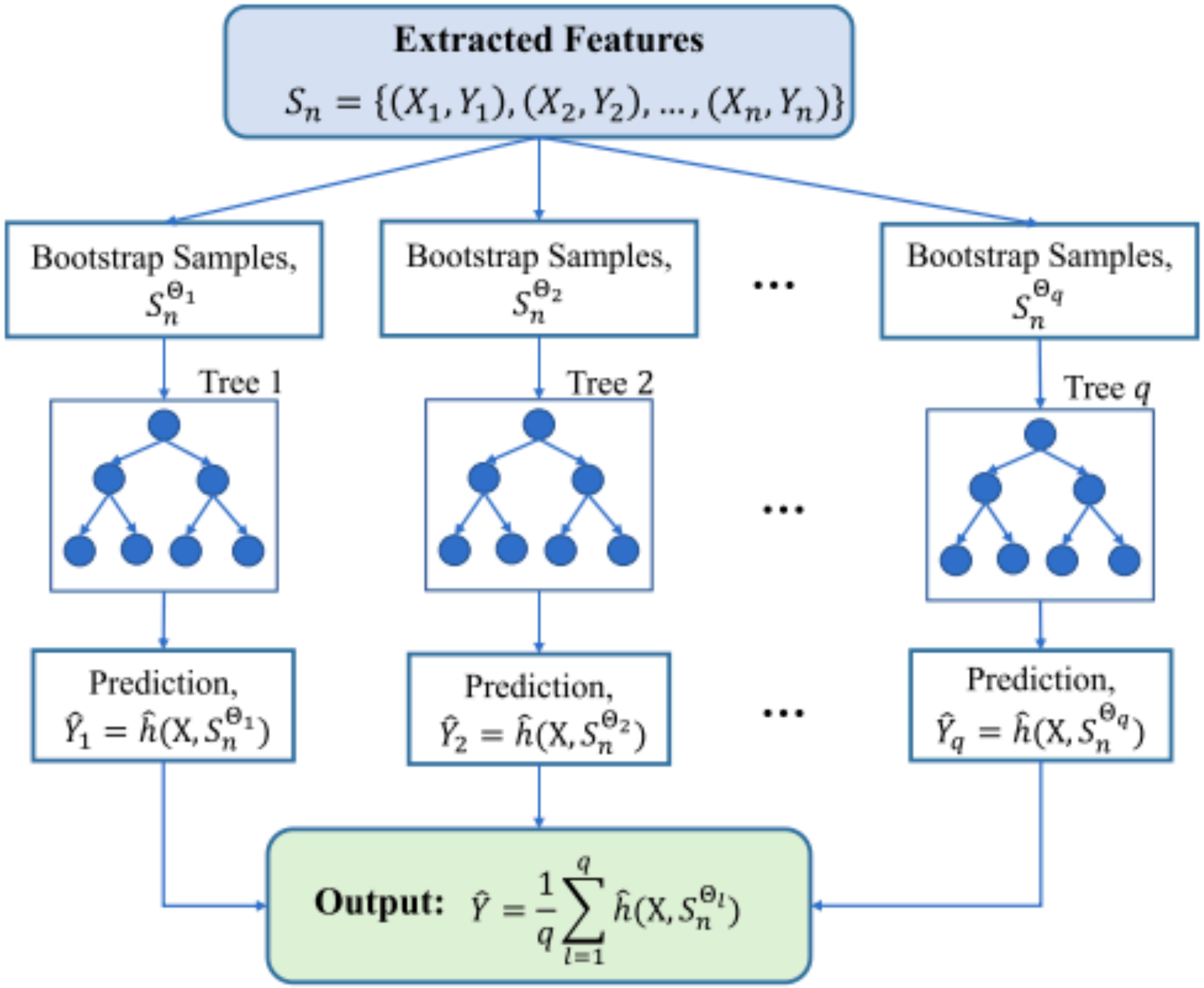
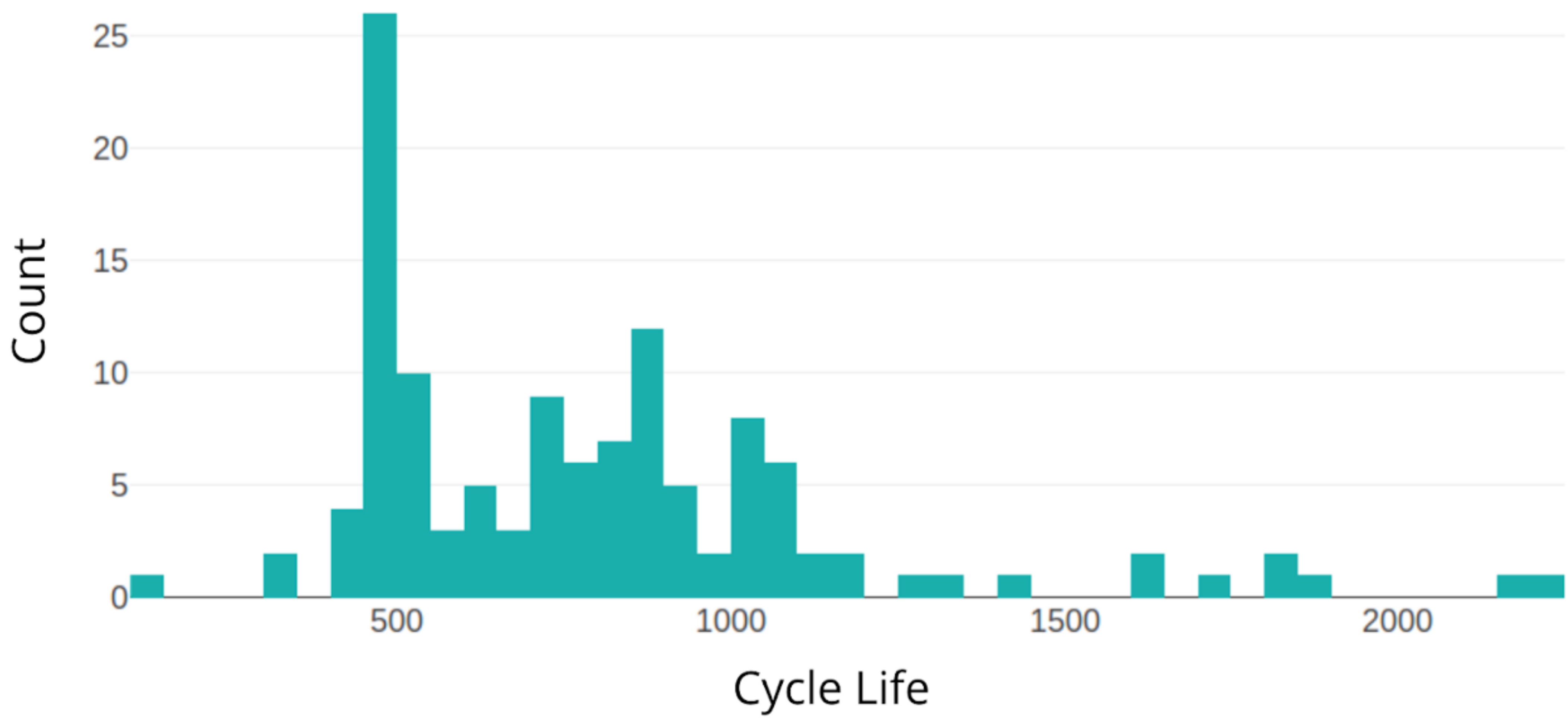


Fig. 3. Illustration of Random forest regression construction.

Research Methodology

About the Dataset

- We use a comprehensive dataset consisting of 124 commercial lithium iron phosphate/ graphite cells cycled under fast-charging conditions, with widely varying cycle lives ranging from 150 to 2,300 cycles.
- Each cell is charged and discharged according to one of many predetermined policies, until the battery reaches 80 percent of its original capacity (meaning the battery has become too unreliable for normal use and is considered “broken”).



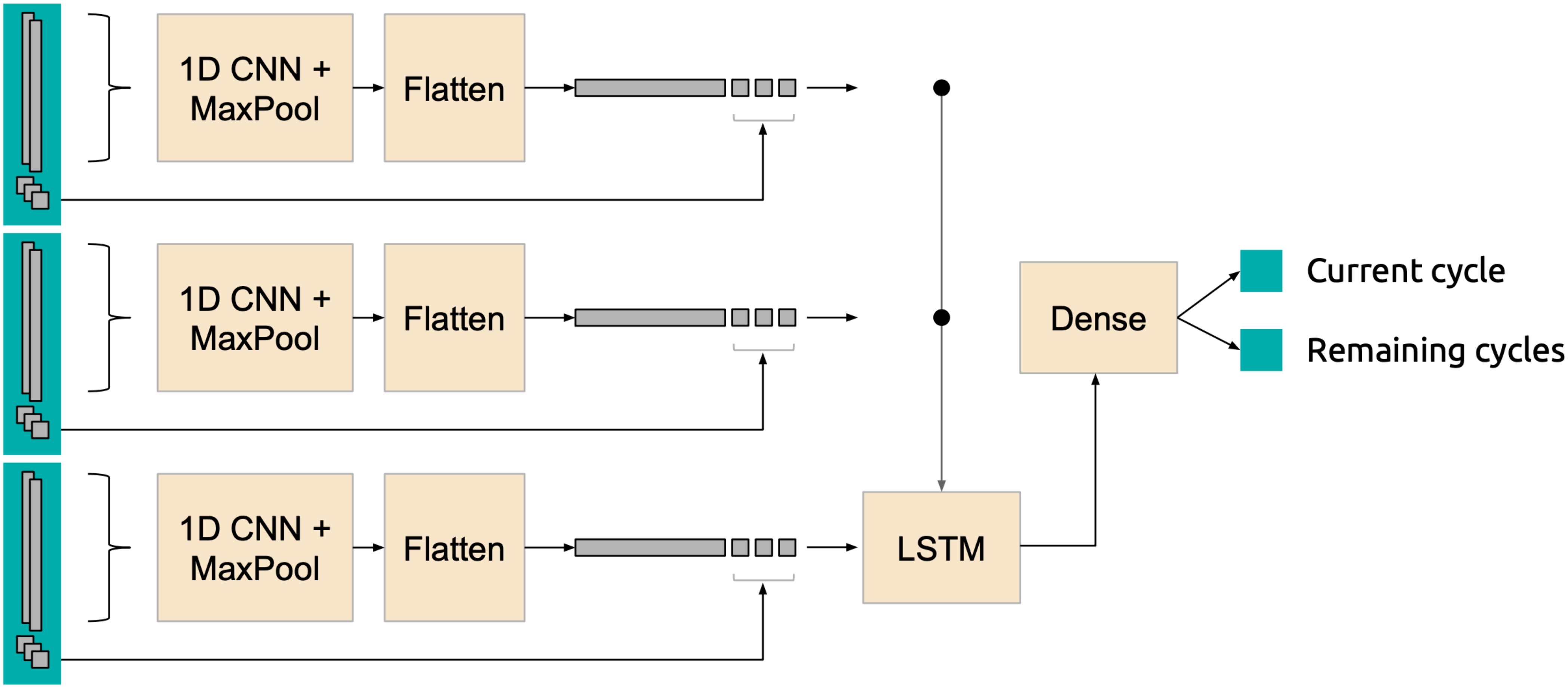
25
20
15
10
5
0
Count
500
1000
1500
2000
Cycle Life

The dataset is divided into three “batches”, representing approximately 48 cells each. Each batch is defined by a “batch date”, or the date the tests were started. Each batch has a few irregularities, as detailed on the page for each batch.

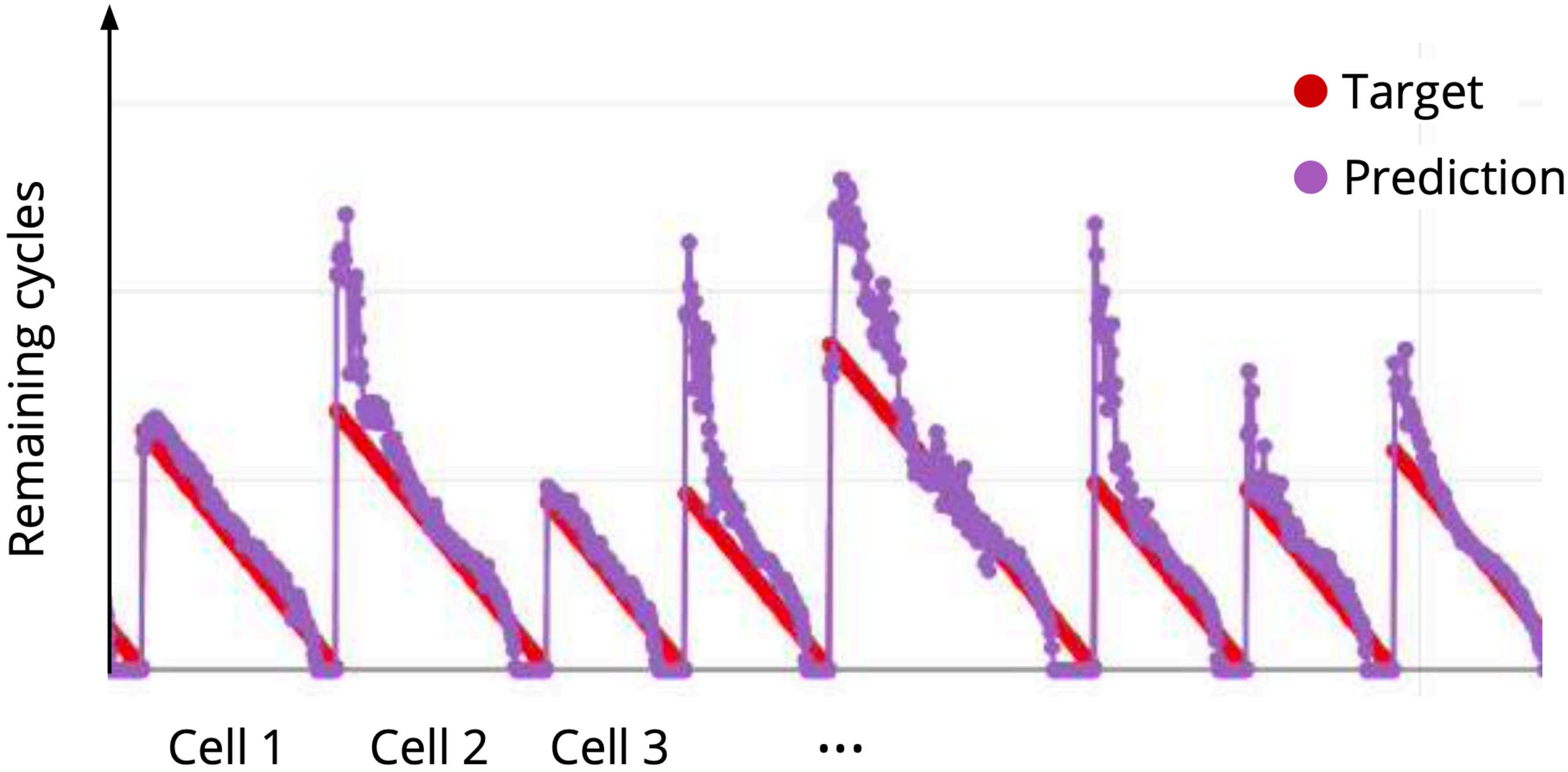
The data associated with each battery (cell) can be grouped into one of three categories: descriptors, summary, and cycle.

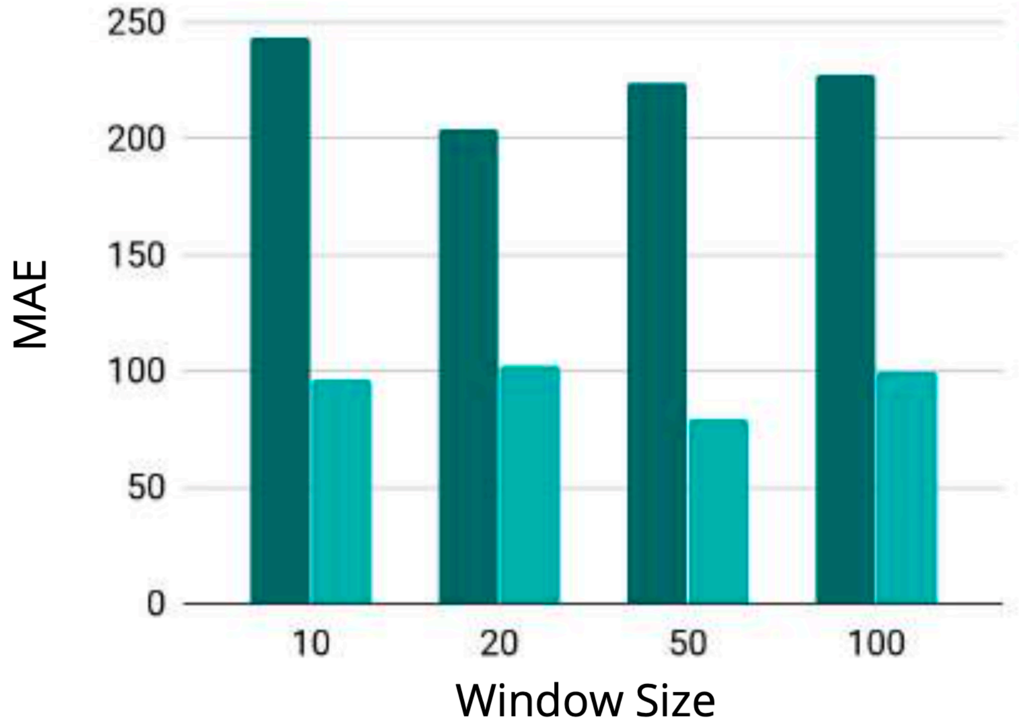
- **Descriptors** for each battery include charging policy, cycle life, barcode and channel.
- **Summary data** include information on a per cycle basis, including cycle number, discharge capacity, charge capacity, internal resistance, maximum temperature, average temperature, minimum temperature, and chargetime.
- **Cycle data** include information within a cycle, including time, charge capacity, current, voltage, temperature, discharge capacity. We also include derived vectors of discharge dQ/dV, linearly interpolated discharge capacity and linearly interpolated temperature.

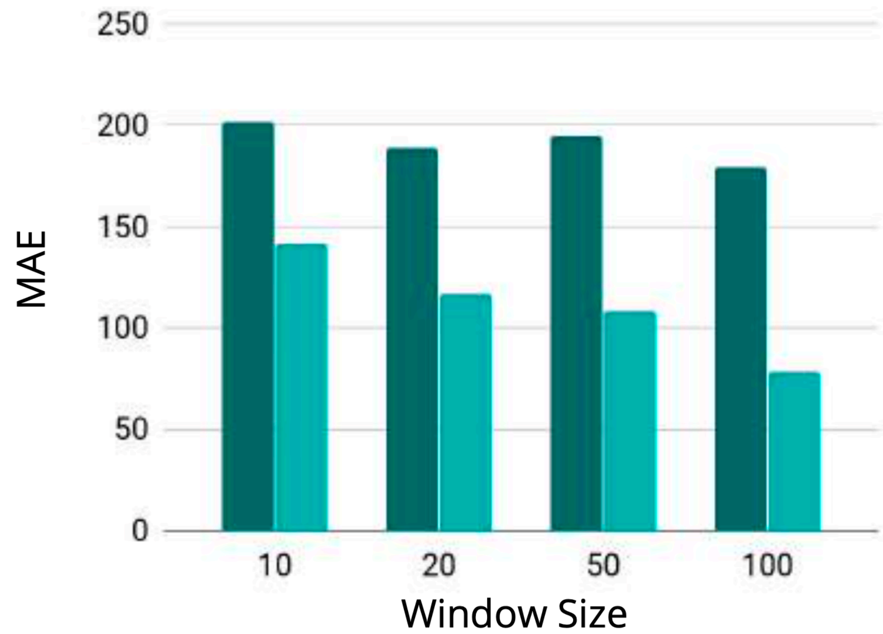
- The initial Data Pre-processing step involved taking the voltage range during discharging as the reference instead of time and then Interpolating the charge and temperature over voltage. The entire data was then resampled 1000 equidistant voltage steps to make the measurements uniform. After this, the data was used to train a neural network which gave predictions about the current cycle and remaining no. of cycles of the battery.
- Thus, the RUL can be characterized by the following equation:
  $RUL = CEOL - CM$
- C_{EOL}**:** the total number of charge-discharge cycles that the battery undergoes before End of Life
  C_M**:** the total number of cycles the battery has undergone during usage when the last measurement was taken.


1D CNN + MaxPool
Flatten
1D CNN + MaxPool
Flatten
1D CNN + MaxPool
Flatten
LSTM
Dense
Current cycle
Remaining cycles

Results


Remaining cycles
Target
Prediction
Cell 1
Cell 2
Cell 3
...

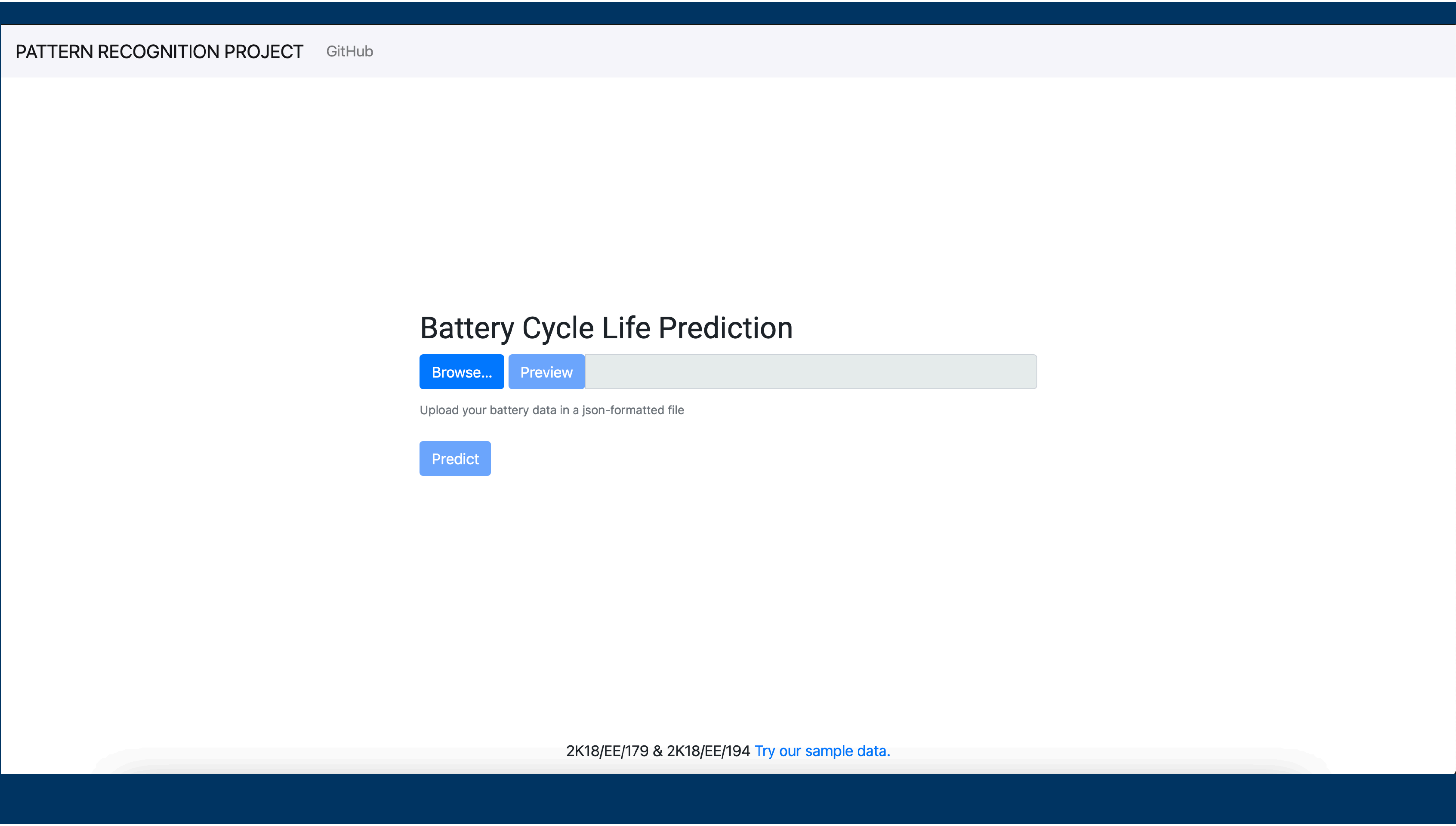

250
200
150
100
50
0
MAE
10
20
50
100
Window Size


250
200
150
100
50
0
MAE
10
20
50
100
Window Size

Model Deployment

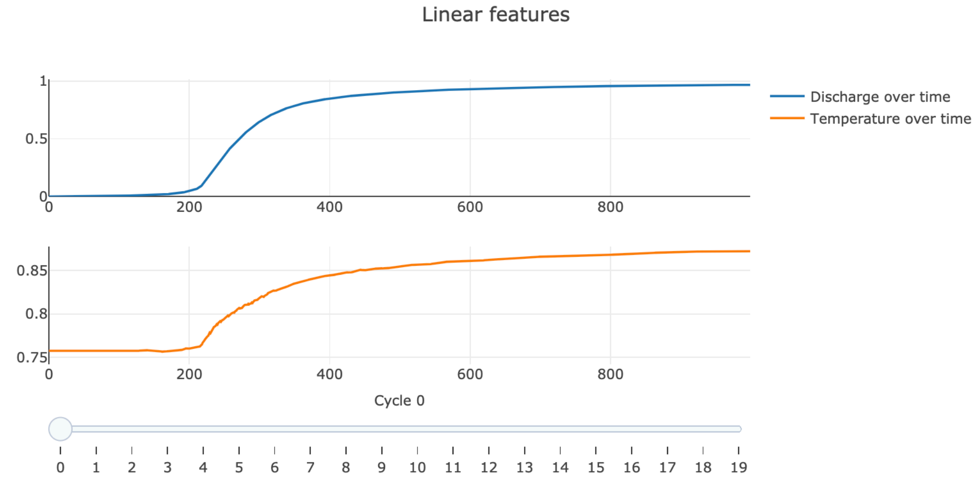
Flask

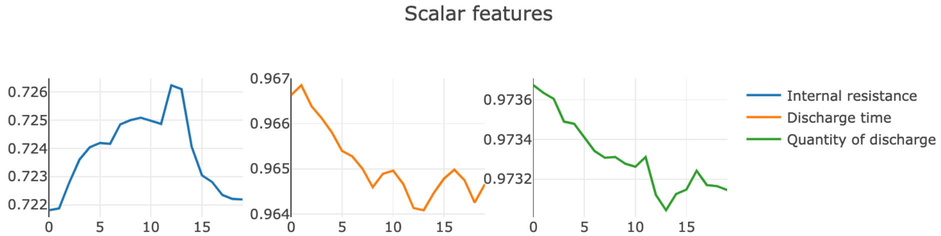
JS


PATTERN RECOGNITION PROJECT
GitHub
Battery Cycle Life Prediction
Browse...
Preview
Upload your battery data in a json-formatted file
Predict
2K18/EE/179 & 2K18/EE/194 Try our sample data.

PATTERN RECOGNITION PROJECT GitHub

Your Uploaded Data





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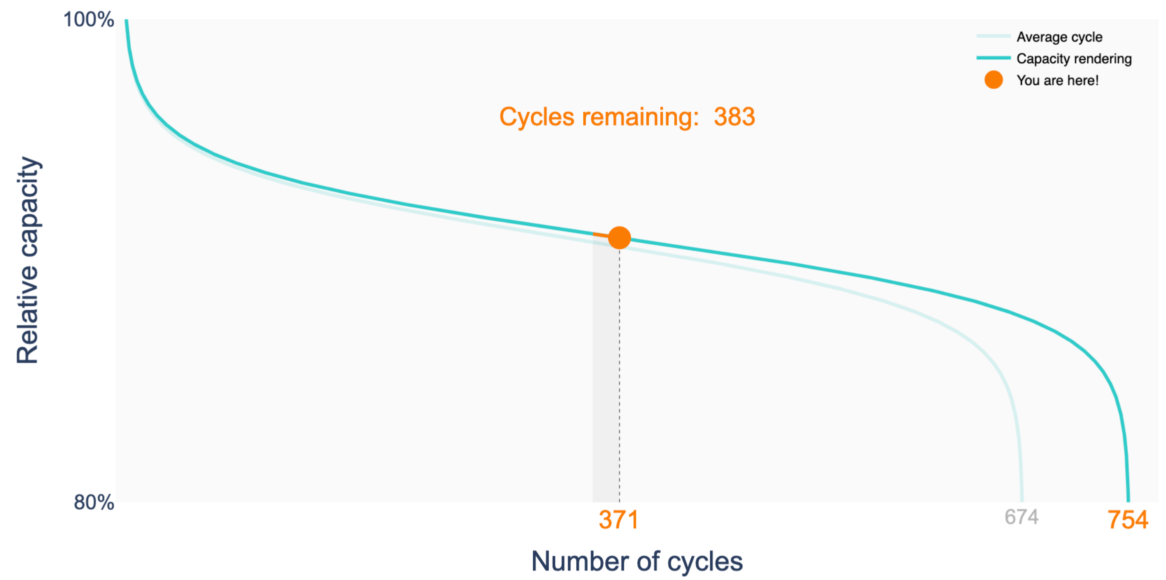
Your Battery Lifetime



Thank You