Battery early cycle life prediction through deep learning

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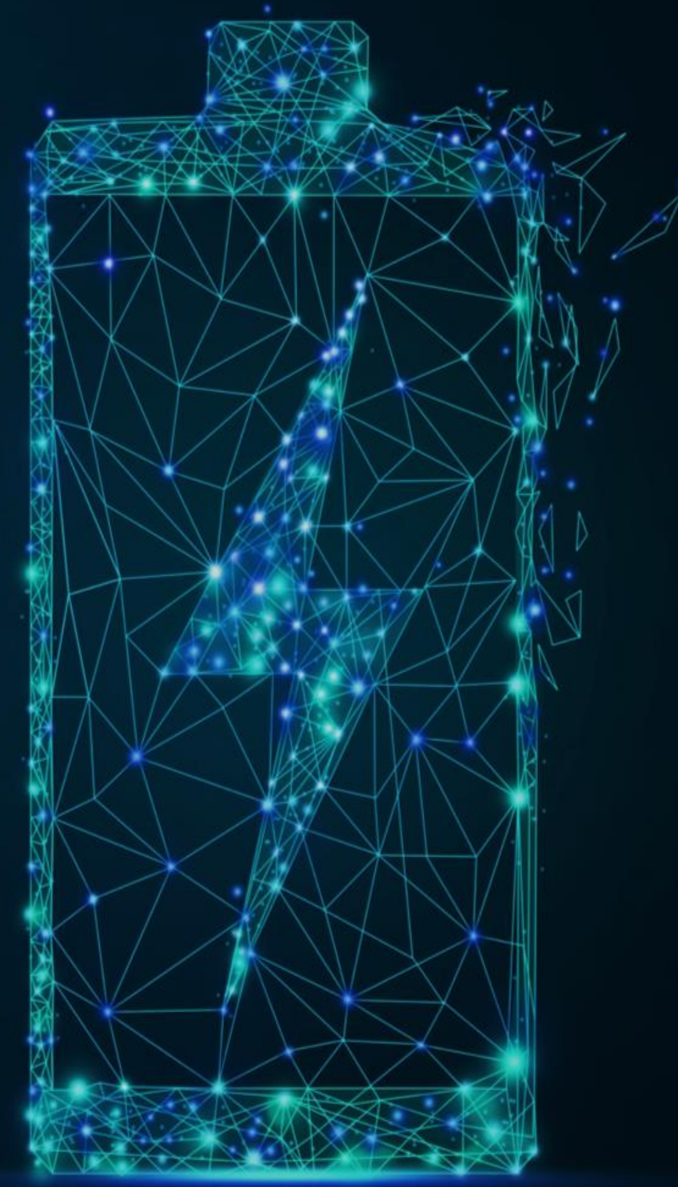
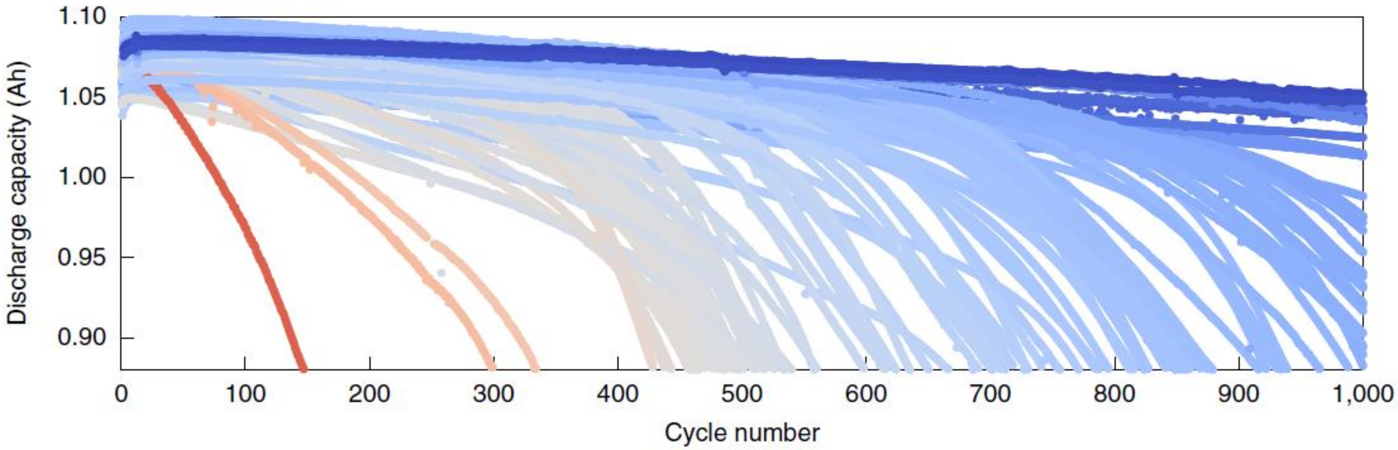


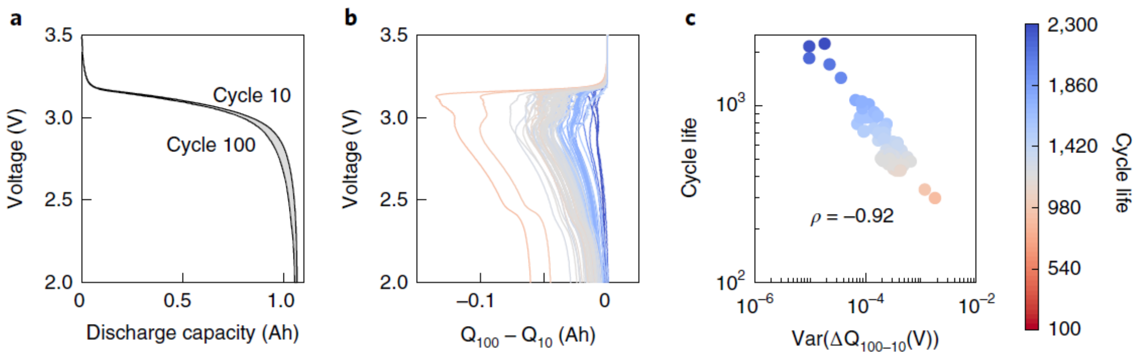
Background

Long battery lifetime entails delayed feedback of performance



Nature Energy, **2019**, *4*, 383-391

Inspiration and Motivation



Found Variance of ΔQ100-10(V) (log scale) has high correlation to the cycle life

(energy dissipation on voltage)

Table 1 | Model metrics for the results shown in Fig. 3

	RMSE (cycles)			Mean percent error (%)		
	Train	Primary test	Secondary test	Train	Primary test	Secondary test
'Variance' model	103	138 (138)	196	14.1	14.7 (13.2)	11.4
'Discharge' model	76	91 (86)	173	9.8	13.0 (10.1)	8.6
'Full' model	51	118 (100)	214	5.6	14.1 (7.5)	10.7

Train and primary/secondary test refer to the data used to learn the model and evaluate model performance, respectively. One battery in the test set reaches 80% state-of-health rapidly and does not match other observed patterns. Therefore, the parenthetical primary test results correspond to the exclusion of this battery.

Discharge model : six features based on only on discharge cycle information

Full model : nine features (adding temperature, resistance)

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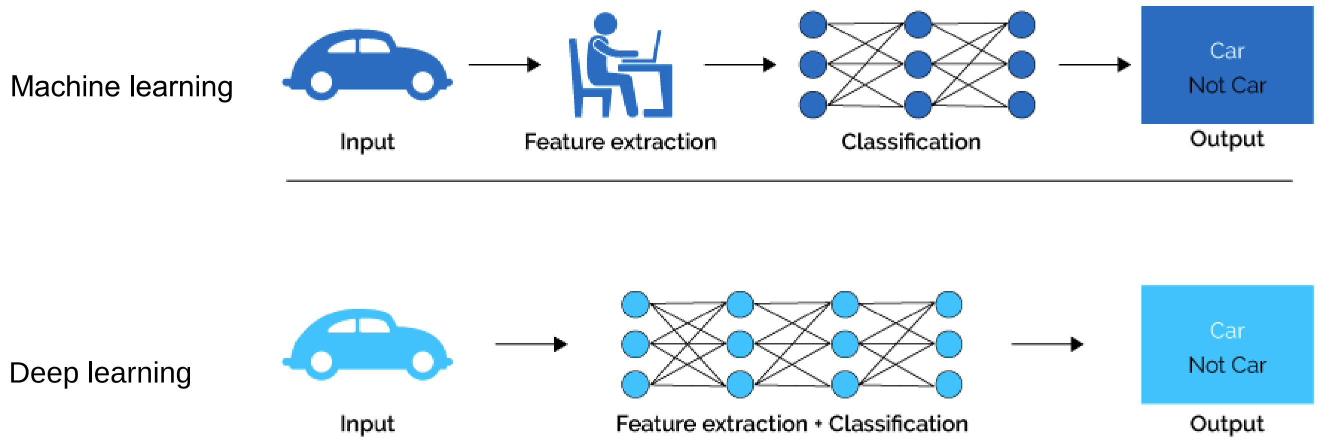
Deep learning v.s Machine learning



Advantage of deep learning model:

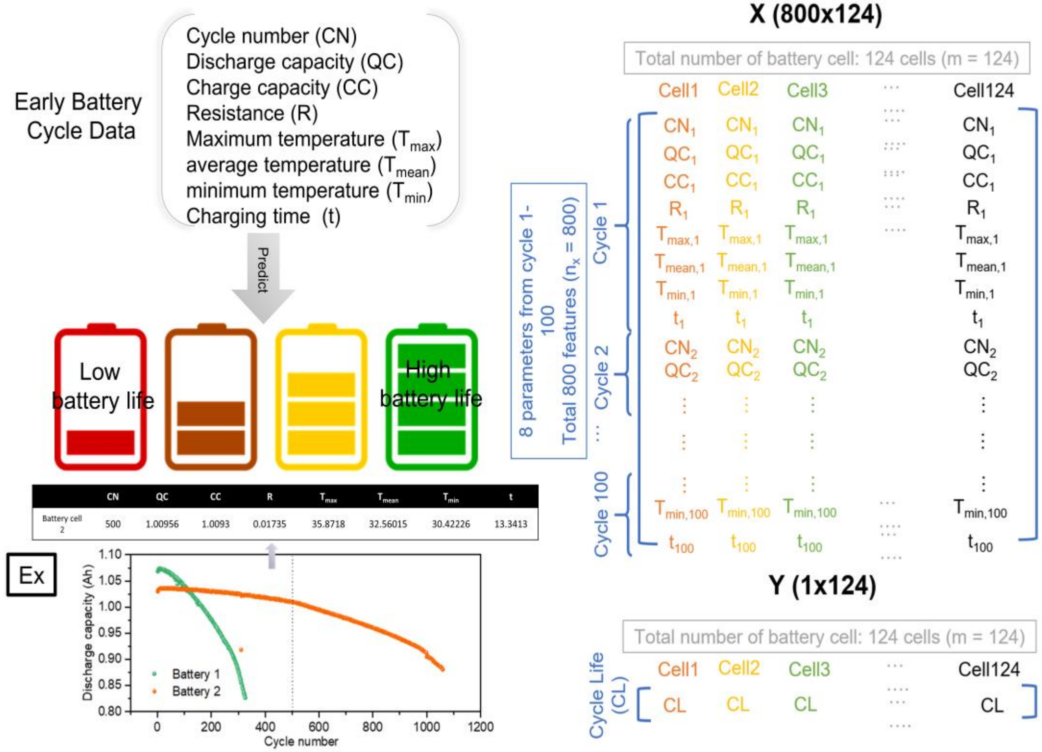
1. No need to have domain knowledge / Worry less about the feature engineering
2. Deep learning outperform other technique if the data size is large
3. Can deal with complex problems. ex. image classification, natural language processing.

Disadvantage of deep learning model:

1. Computation power
2. Less interpretability

https://blog.thinkwik.com/insights-of-the-machine-learning-and-the-deep-learning/

Data set (from Toyota research institute)



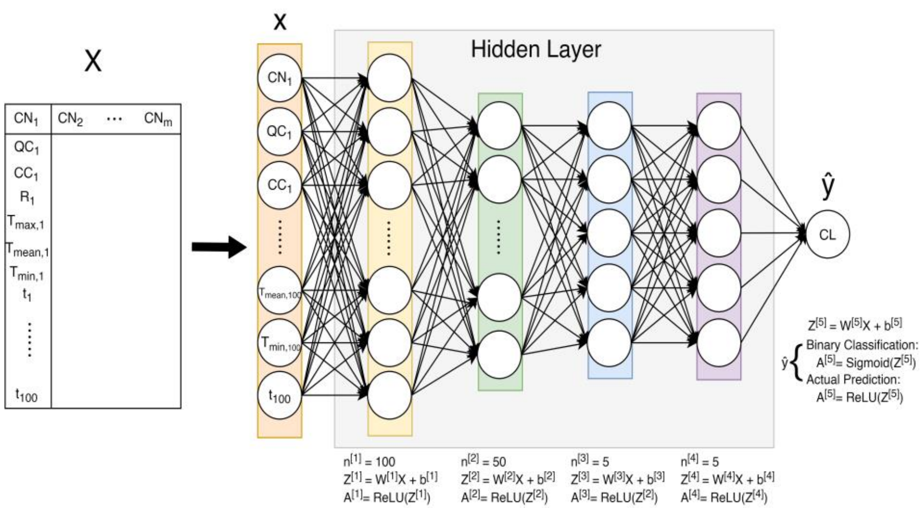
1. allocate 60% of our total to the train set, 20% to the validation set, and 20% to the test set.
2. preprocessed our dataset by normalizing and shuffling and removing battery cells that does not reach 80% capacity and noisy channels resulted from instrument noises.
3. Cycle life is defined as the number of cycles until 80% nominal capacity.
4. to use binary classification, we classified cell into “low-lifetime” (y = 0 when cycle life < 550) and “high-lifetime” (y = 1 when cycle life ≥ 550).

Method/Model

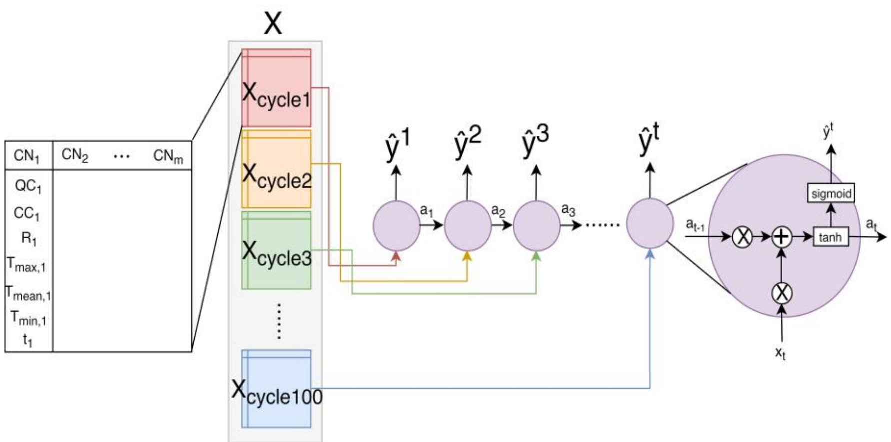
1. Loss function for binary classification:

   Binary cross-entropy loss $J_{BCE} = \frac{1}{m}\sum L(\hat{y}, y) = \frac{1}{m}\sum(-y\log\hat{y} - (1-y)\log(1-\hat{y}))$

2. Adam was used as the optimizer



Fully-connected neural network (FCNN) model



Recurrent neural network (RNN) model

Optimization/Result

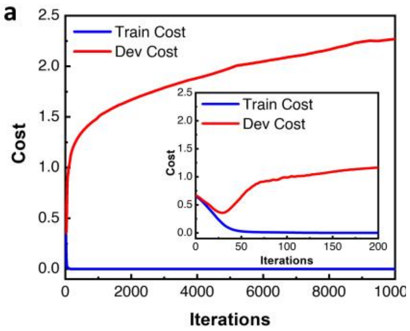
Result for binary classification / FCNN model

First n cycles with best learning rate (LR)	5 cycles	10 cycles	50 cycles	100 cycles
	LR=0.001	LR=0.001	LR=0.001	LR=0.001
Training accuracy (%)	100	100	100	100
Validation accuracy (%)	92	100	100	93
Test accuracy (%)	83	88	87	94

1. Learning rate was optimized based on the test accuracy.
2. Compared between validation accuracy and test accuracy, there was over-fit issues.

   → Early-stopping was implemented, and test accuracy could be slightly improved using 5 cycles or 10 cycles

First n cycles with best learning rate (LR)	5 cycles	10 cycles	50 cycles	100 cycles
	LR=0.001	LR=0.001	LR=0.001	LR=0.01
Training accuracy (%)	99	97	99	99
Validation accuracy (%)	100	90	100	100
Test accuracy (%)	85	90	85	87



FCNN v.s RNN

Result for binary classification / FCNN model

First n cycles with best learning rate (LR)	5 cycles	10 cycles	50 cycles	100 cycles
	LR=0.001	LR=0.001	LR=0.001	LR=0.01
Training accuracy (%)	99	97	99	99
Validation accuracy (%)	100	90	100	100
Test accuracy (%)	85	90	85	87

Result for binary classification / RNN model

First n cycles with best learning rate (LR)	5 cycles	10 cycles	50 cycles	100 cycles
	LR=0.0005	LR=0.0005	LR=0.0005	LR=0.0005
Training accuracy (%)	96	97	98	98
Validation accuracy (%)	100	91	95	91
Test accuracy (%)	95	87	87	95

The test accuracy using only first 5, 10, 100 charge-discharge cycles with RNN shows better performance than fully-connected network.

Compared with machine learning model which has 95.1 test accuracy using the first 5 cycles, the deep learning model can also achieve similar performance.

Conclusion & Outlook

1. Deep learning model (RNN and FCNN) was applied to predict battery cycle life using early cycle data (binary classification).
2. RNN model performs better than FCNN
3. Compared with machine learning model which has 95.1 test accuracy using the first 5 cycles, the deep learning model can also achieve comparable performance. Without knowing the important feature (ΔQ), deep learning model did show the ability to achieve similar performance.
4. Using X-ray tomography images taken before cycling may potentially be used to detect manufacturing defect with using deep learning model.