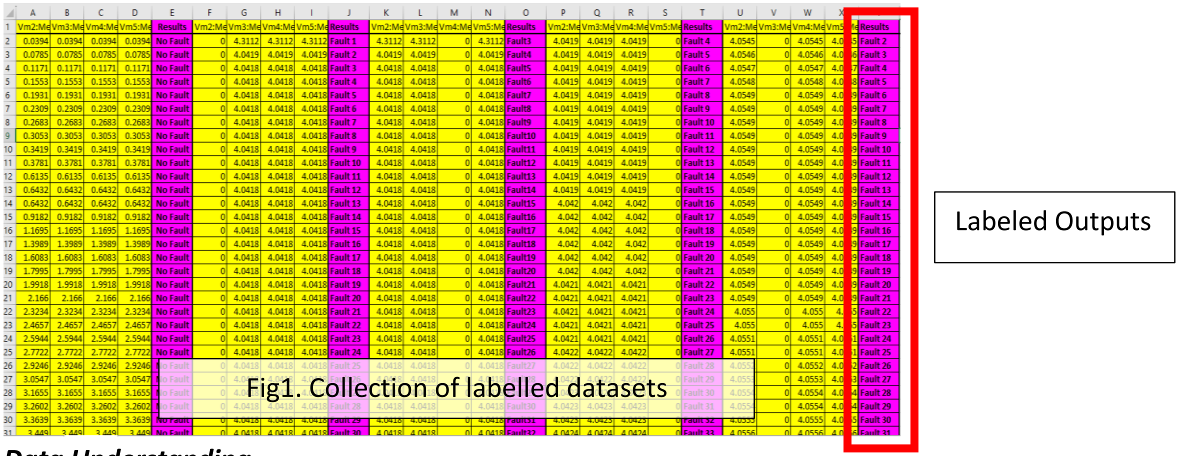
Creating Neural Networks for Battery Fault Detection and Predictive Modeling

Introduction

The creation of a digital twin for battery systems involves multiple technical components, including data collection, fault detection algorithms, and predictive modeling. Below paragraphs delves into the intricate details of these components, with a particular emphasis on data collection, neural network development for fault detection, and the utilization of LSTM networks for predictive modeling.

Data Collection

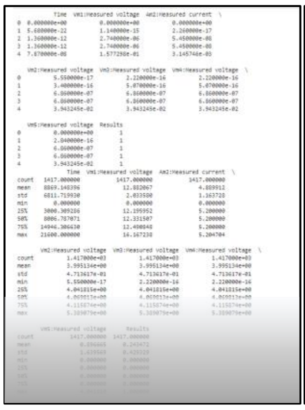
- ***Dataset Selection***
  A comprehensive and well-curated dataset forms the foundation of a robust digital twin. Hence, an extensive and diverse dataset was meticulously collected, encompassing various scenarios such as "typical battery operation," "varied fault types," and data obtained from different spatial locations within the battery system. This meticulously compiled dataset further includes data from multiple sources, including battery management systems, integrated sensors, and historical records. These sources provide a multifaceted array of parameters, including voltage, current, temperature, state of charge, and capacitance, resulting in a rich and varied dataset for analysis.



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	
1	Vm2:Me	Vm3:Me	Vm4:Me	Vm5:Me	Results	Vm2:Me	Vm3:Me	Vm4:Me	Vm5:Me	Results	Vm2:Me	Vm3:Me	Vm4:Me	Vm5:Me	Results	Vm2:Me	Vm3:Me	Vm4:Me	Vm5:Me	Results	Vm2:Me	Vm3:Me	Vm4:Me	Vm5:Me	Results
2	0.0394	0.0394	0.0394	0.0394	No Fault	0	4.3112	4.3112	4.3112	Fault 1	4.3112	4.3112	0	4.3112	Fault3	4.0419	4.0419	4.0419	0	Fault 4	4.0545	0	4.0545	4.0545	Fault 2
3	0.0785	0.0785	0.0785	0.0785	No Fault	0	4.0419	4.0419	4.0419	Fault 2	4.0419	4.0419	0	4.0419	Fault4	4.0419	4.0419	4.0419	0	Fault 5	4.0546	0	4.0546	4.0546	Fault 3
4	0.1171	0.1171	0.1171	0.1171	No Fault	0	4.0418	4.0418	4.0418	Fault 3	4.0418	4.0418	0	4.0418	Fault5	4.0419	4.0419	4.0419	0	Fault 6	4.0547	0	4.0547	4.0547	Fault 4
5	0.1553	0.1553	0.1553	0.1553	No Fault	0	4.0418	4.0418	4.0418	Fault 4	4.0418	4.0418	0	4.0418	Fault6	4.0419	4.0419	4.0419	0	Fault 7	4.0548	0	4.0548	4.0548	Fault 5
6	0.1931	0.1931	0.1931	0.1931	No Fault	0	4.0418	4.0418	4.0418	Fault 5	4.0418	4.0418	0	4.0418	Fault7	4.0419	4.0419	4.0419	0	Fault 8	4.0549	0	4.0549	4.0549	Fault 6
7	0.2309	0.2309	0.2309	0.2309	No Fault	0	4.0418	4.0418	4.0418	Fault 6	4.0418	4.0418	0	4.0418	Fault8	4.0419	4.0419	4.0419	0	Fault 9	4.0549	0	4.0549	4.0549	Fault 7
8	0.2683	0.2683	0.2683	0.2683	No Fault	0	4.0418	4.0418	4.0418	Fault 7	4.0418	4.0418	0	4.0418	Fault9	4.0419	4.0419	4.0419	0	Fault 10	4.0549	0	4.0549	4.0549	Fault 8
9	0.3053	0.3053	0.3053	0.3053	No Fault	0	4.0418	4.0418	4.0418	Fault 8	4.0418	4.0418	0	4.0418	Fault10	4.0419	4.0419	4.0419	0	Fault 11	4.0549	0	4.0549	4.0549	Fault 9
10	0.3419	0.3419	0.3419	0.3419	No Fault	0	4.0418	4.0418	4.0418	Fault 9	4.0418	4.0418	0	4.0418	Fault11	4.0419	4.0419	4.0419	0	Fault 12	4.0549	0	4.0549	4.0549	Fault 10
11	0.3781	0.3781	0.3781	0.3781	No Fault	0	4.0418	4.0418	4.0418	Fault 10	4.0418	4.0418	0	4.0418	Fault12	4.0419	4.0419	4.0419	0	Fault 13	4.0549	0	4.0549	4.0549	Fault 11
12	0.6135	0.6135	0.6135	0.6135	No Fault	0	4.0418	4.0418	4.0418	Fault 11	4.0418	4.0418	0	4.0418	Fault13	4.0419	4.0419	4.0419	0	Fault 14	4.0549	0	4.0549	4.0549	Fault 12
13	0.6432	0.6432	0.6432	0.6432	No Fault	0	4.0418	4.0418	4.0418	Fault 12	4.0418	4.0418	0	4.0418	Fault14	4.0419	4.0419	4.0419	0	Fault 15	4.0549	0	4.0549	4.0549	Fault 13
14	0.6432	0.6432	0.6432	0.6432	No Fault	0	4.0418	4.0418	4.0418	Fault 13	4.0418	4.0418	0	4.0418	Fault15	4.042	4.042	4.042	0	Fault 16	4.0549	0	4.0549	4.0549	Fault 14
15	0.9182	0.9182	0.9182	0.9182	No Fault	0	4.0418	4.0418	4.0418	Fault 14	4.0418	4.0418	0	4.0418	Fault16	4.042	4.042	4.042	0	Fault 17	4.0549	0	4.0549	4.0549	Fault 15
16	1.1695	1.1695	1.1695	1.1695	No Fault	0	4.0418	4.0418	4.0418	Fault 15	4.0418	4.0418	0	4.0418	Fault17	4.042	4.042	4.042	0	Fault 18	4.0549	0	4.0549	4.0549	Fault 16
17	1.3989	1.3989	1.3989	1.3989	No Fault	0	4.0418	4.0418	4.0418	Fault 16	4.0418	4.0418	0	4.0418	Fault18	4.042	4.042	4.042	0	Fault 19	4.0549	0	4.0549	4.0549	Fault 17
18	1.6083	1.6083	1.6083	1.6083	No Fault	0	4.0418	4.0418	4.0418	Fault 17	4.0418	4.0418	0	4.0418	Fault19	4.042	4.042	4.042	0	Fault 20	4.0549	0	4.0549	4.0549	Fault 18
19	1.7995	1.7995	1.7995	1.7995	No Fault	0	4.0418	4.0418	4.0418	Fault 18	4.0418	4.0418	0	4.0418	Fault20	4.042	4.042	4.042	0	Fault 21	4.0549	0	4.0549	4.0549	Fault 19
20	1.9918	1.9918	1.9918	1.9918	No Fault	0	4.0418	4.0418	4.0418	Fault 19	4.0418	4.0418	0	4.0418	Fault21	4.0421	4.0421	4.0421	0	Fault 22	4.0549	0	4.0549	4.0549	Fault 20
21	2.166	2.166	2.166	2.166	No Fault	0	4.0418	4.0418	4.0418	Fault 20	4.0418	4.0418	0	4.0418	Fault22	4.0421	4.0421	4.0421	0	Fault 23	4.0549	0	4.0549	4.0549	Fault 21
22	2.3234	2.3234	2.3234	2.3234	No Fault	0	4.0418	4.0418	4.0418	Fault 21	4.0418	4.0418	0	4.0418	Fault23	4.0421	4.0421	4.0421	0	Fault 24	4.055	0	4.055	4.055	Fault 22
23	2.4657	2.4657	2.4657	2.4657	No Fault	0	4.0418	4.0418	4.0418	Fault 22	4.0418	4.0418	0	4.0418	Fault24	4.0421	4.0421	4.0421	0	Fault 25	4.055	0	4.055	4.055	Fault 23
24	2.5944	2.5944	2.5944	2.5944	No Fault	0	4.0418	4.0418	4.0418	Fault 23	4.0418	4.0418	0	4.0418	Fault25	4.0421	4.0421	4.0421	0	Fault 26	4.0551	0	4.0551	4.0551	Fault 24
25	2.7722	2.7722	2.7722	2.7722	No Fault	0	4.0418	4.0418	4.0418	Fault 24	4.0418	4.0418	0	4.0418	Fault26	4.0422	4.0422	4.0422	0	Fault 27	4.0551	0	4.0551	4.0551	Fault 25
26	2.9246	2.9246	2.9246	2.9246	No Fault	0	4.0418	4.0418	4.0418	Fault 25	4.0418	4.0418	0	4.0418	Fault27	4.0422	4.0422	4.0422	0	Fault 28	4.0552	0	4.0552	4.0552	Fault 26
27	3.0547	3.0547	3.0547	3.0547	No Fault	0	4.0418	4.0418	4.0418	Fault 26	4.0418	4.0418	0	4.0418	Fault28	4.0422	4.0422	4.0422	0	Fault 29	4.0553	0	4.0553	4.0553	Fault 27
28	3.1655	3.1655	3.1655	3.1655	No Fault	0	4.0418	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0	Fault 30	4.0554	0	4.0554	4.0554	Fault 28
29	3.2602	3.2602	3.2602	3.2602	No Fault	0	4.0418	4.0418	4.0418	Fault 28	4.0418	4.0418	0	4.0418	Fault30	4.0423	4.0423	4.0423	0	Fault 31	4.0554	0	4.0554	4.0554	Fault 29
30	3.3639	3.3639	3.3639	3.3639	No Fault	0	4.0418	4.0418	4.0418	Fault 29	4.0418	4.0418	0	4.0418	Fault31	4.0423	4.0423	4.0423	0	Fault 32	4.0555	0	4.0555	4.0555	Fault 30
31	3.449	3.449	3.449	3.449	No Fault	0	4.0418	4.0418	4.0418	Fault 30	4.0418	4.0418	0	4.0418	Fault32	4.0424	4.0424	4.0424	0	Fault 33	4.0556	0	4.0556	4.0556	Fault 31

Fig1. Collection of labelled datasets

- ***Data Understanding***
  Once all data are collected, a profound understanding of the data and the identification of critical patterns is employed. Using differential analysis and correlation analysis, we examined the relationship between various parameters and the output labels. The correlation analysis, utilize statistical techniques to quantify the degree to which two variables are associated. The differential analysis observes how variations in one parameter relate to changes in another.



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           Time  Vm1:Measured voltage  Am2:Measured current  \
0  0.000000e+00          0.000000e+00          0.000000e+00
1  5.680000e-22          1.140000e-15          2.260000e-17
2  1.360000e-12          2.740000e-06          5.450000e-08
3  1.360000e-12          2.740000e-06          5.450000e-08
4  7.870000e-08          1.577298e-01          3.145746e-03

   Vm2:Measured voltage  Vm3:Measured voltage  Vm4:Measured voltage  \
0          5.550000e-17          2.220000e-16          2.220000e-16
1          3.400000e-16          5.070000e-16          5.070000e-16
2          6.860000e-07          6.860000e-07          6.860000e-07
3          6.860000e-07          6.860000e-07          6.860000e-07
4          3.943245e-02          3.943245e-02          3.943245e-02

   Vm5:Measured voltage  Results
0          0.000000e+00        1
1          2.040000e-16        1
2          6.060000e-07        1
3          6.060000e-07        1
4          3.943245e-02        1
               Time  Vm1:Measured voltage  Am2:Measured current  \
count   1417.000000           1417.000000           1417.000000
mean    8869.148396             12.882067              4.889912
std     6811.719930              2.033580              1.163728
min        0.000000              0.000000              0.000000
25%     3000.309286             12.195952              5.200000
50%     8806.787071             12.331507              5.200000
75%    14946.306630             12.490848              5.200000
max    21600.000000             16.167238              5.204704

       Vm2:Measured voltage  Vm3:Measured voltage  Vm4:Measured voltage  \
count          1.417000e+03          1.417000e+03          1.417000e+03
mean           3.995134e+00          3.995134e+00          3.995134e+00
std            4.713617e-01          4.713617e-01          4.713617e-01
min            5.550000e-17          2.220000e-16          2.220000e-16
25%            4.041815e+00          4.041815e+00          4.041815e+00
50%            4.069813e+00          4.069813e+00          4.069813e+00
75%            4.115874e+00          4.115874e+00          4.115874e+00
max            5.389079e+00          5.389079e+00          5.389079e+00

       Vm5:Measured voltage      Results
count           1417.000000  1417.000000
mean               0.896665     0.243472
std                1.639569     0.429329
min                0.000000     0.000000
25%                0.000000     0.000000
50%                0.000000     0.000000
75%                0.000000     0.000000
max                4.041318     1.000000
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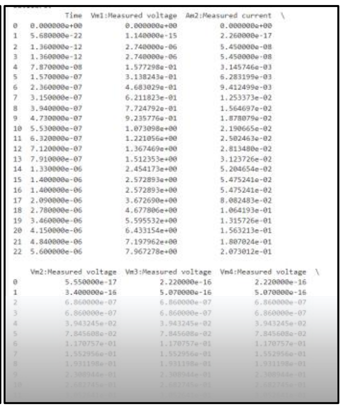

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            Time  Vm1:Measured voltage  Am2:Measured current  \
0   0.000000e+00          0.000000e+00          0.000000e+00
1   5.680000e-22          1.140000e-15          2.260000e-17
2   1.360000e-12          2.740000e-06          5.450000e-08
3   1.360000e-12          2.740000e-06          5.450000e-08
4   7.870000e-08          1.577298e-01          3.145746e-03
5   1.570000e-07          3.138243e-01          6.283195e-03
6   2.360000e-07          4.683029e-01          9.412499e-03
7   3.150000e-07          6.211823e-01          1.253373e-02
8   3.940000e-07          7.724792e-01          1.564697e-02
9   4.730000e-07          9.235776e-01          1.878079e-02
10  5.530000e-07          1.073098e+00          2.190665e-02
11  6.320000e-07          1.221056e+00          2.502463e-02
12  7.120000e-07          1.367469e+00          2.813480e-02
13  7.910000e-07          1.512353e+00          3.123726e-02
14  1.330000e-06          2.454173e+00          5.204654e-02
15  1.400000e-06          2.572893e+00          5.475241e-02
16  1.400000e-06          2.572893e+00          5.475241e-02
17  2.090000e-06          3.672690e+00          8.082483e-02
18  2.780000e-06          4.677806e+00          1.064193e-01
19  3.460000e-06          5.595532e+00          1.315726e-01
20  4.150000e-06          6.433154e+00          1.563213e-01
21  4.840000e-06          7.197962e+00          1.807024e-01
22  5.600000e-06          7.967278e+00          2.073012e-01

    Vm2:Measured voltage  Vm3:Measured voltage  Vm4:Measured voltage  \
0           5.550000e-17          2.220000e-16          2.220000e-16
1           3.400000e-16          5.070000e-16          5.070000e-16
2           6.860000e-07          6.860000e-07          6.860000e-07
3           6.860000e-07          6.860000e-07          6.860000e-07
4           3.943245e-02          3.943245e-02          3.943245e-02
5           7.845608e-02          7.845608e-02          7.845608e-02
6           1.170757e-01          1.170757e-01          1.170757e-01
7           1.552956e-01          1.552956e-01          1.552956e-01
8           1.931198e-01          1.931198e-01          1.931198e-01
9           2.308944e-01          2.308944e-01          2.308944e-01
10          2.682745e-01          2.682745e-01          2.682745e-01
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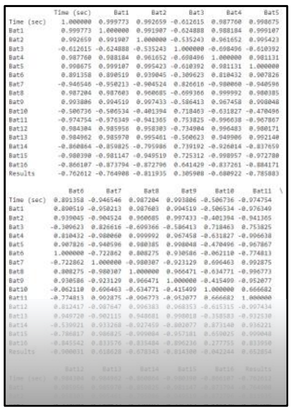

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            Time (sec)      Bat1      Bat2      Bat3      Bat4      Bat5
Time (sec)    1.000000  0.999773  0.992659 -0.612615  0.987760  0.998675
Bat1          0.999773  1.000000  0.991907 -0.624888  0.988184  0.999107
Bat2          0.992659  0.991907  1.000000 -0.535243  0.961652  0.995423
Bat3         -0.612615 -0.624888 -0.535243  1.000000 -0.698496 -0.610392
Bat4          0.987760  0.988184  0.961652 -0.698496  1.000000  0.981131
Bat5          0.998675  0.999107  0.995423 -0.610392  0.981131  1.000000
Bat6          0.891358  0.890519  0.939045 -0.309623  0.810432  0.907826
Bat7         -0.946546 -0.950213 -0.904524  0.826616 -0.980060 -0.940596
Bat8          0.987204  0.987603  0.960685 -0.699366  0.999992  0.980385
Bat9          0.993886  0.994519  0.997433 -0.586413  0.967458  0.998048
Bat10        -0.506736 -0.506534 -0.401394  0.718463 -0.631827 -0.470496
Bat11        -0.974754 -0.976349 -0.941365  0.753825 -0.996638 -0.967867
Bat12         0.984304  0.985956  0.958303 -0.734904  0.996483  0.980171
Bat13         0.984962  0.985970  0.995461 -0.560623  0.949906  0.992140
Bat14        -0.860864 -0.859825 -0.795986  0.739192 -0.926014 -0.837659
Bat15        -0.980390 -0.981147 -0.949519  0.725312 -0.998957 -0.972780
Bat16        -0.866107 -0.873794 -0.872796  0.641429 -0.837261 -0.884171
Results      -0.762612 -0.764908 -0.811935  0.305908 -0.680922 -0.785883

                Bat6      Bat7      Bat8      Bat9     Bat10     Bat11  \
Time (sec)  0.891358 -0.946546  0.987204  0.993886 -0.506736 -0.974754
Bat1        0.890519 -0.950213  0.987603  0.994519 -0.506534 -0.976349
Bat2        0.939045 -0.904524  0.960685  0.997433 -0.401394 -0.941365
Bat3       -0.309623  0.826616 -0.699366 -0.586413  0.718463  0.753825
Bat4        0.810432 -0.980060  0.999992  0.967458 -0.631827 -0.996638
Bat5        0.907826 -0.940596  0.980385  0.998048 -0.470496 -0.967867
Bat6        1.000000 -0.722862  0.808275  0.930586 -0.062110 -0.774813
Bat7       -0.722862  1.000000 -0.980307 -0.923129  0.696463  0.992875
Bat8        0.808275 -0.980307  1.000000  0.966471 -0.634771 -0.996773
Bat9        0.930586 -0.923129  0.966471  1.000000 -0.415409 -0.952077
Bat10      -0.062110  0.696463 -0.634771 -0.415409  1.000000  0.666682
Bat11      -0.774813  0.992875 -0.996773 -0.952077  0.666682  1.000000
Bat12       0.812417 -0.987647  0.996383  0.968353 -0.615315 -0.997434
Bat13       0.949720 -0.902115  0.948681  0.998018 -0.358583 -0.932538
Bat14      -0.539921  0.933268 -0.927459 -0.802077  0.873140  0.936221
Bat15      -0.786817  0.986825 -0.999084 -0.957181  0.659025  0.999048
Bat16      -0.845542  0.833576 -0.835484 -0.896236  0.277755  0.833950
Results    -0.900031  0.618628 -0.678343 -0.814300 -0.042244  0.652854

               Bat12     Bat13     Bat14     Bat15     Bat16   Results
Time (sec)  0.984304  0.984962 -0.860864 -0.980390 -0.866107 -0.762612
Bat1        0.985956  0.985970 -0.859825 -0.981147 -0.873794 -0.764908
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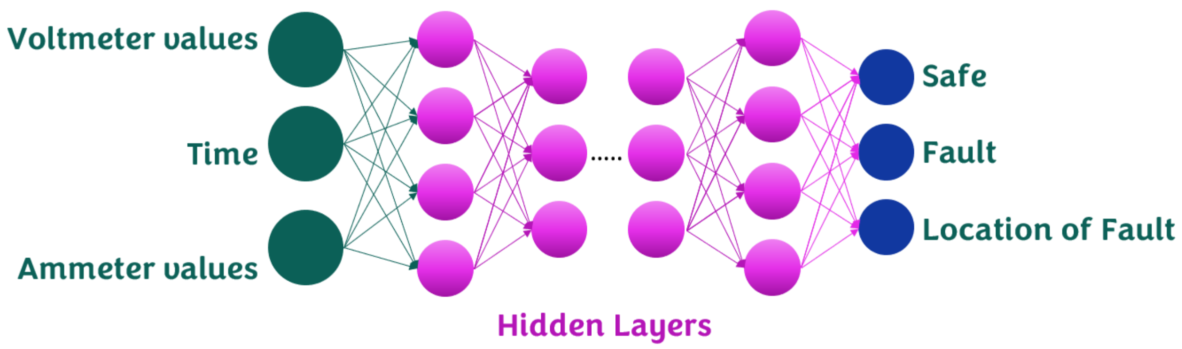
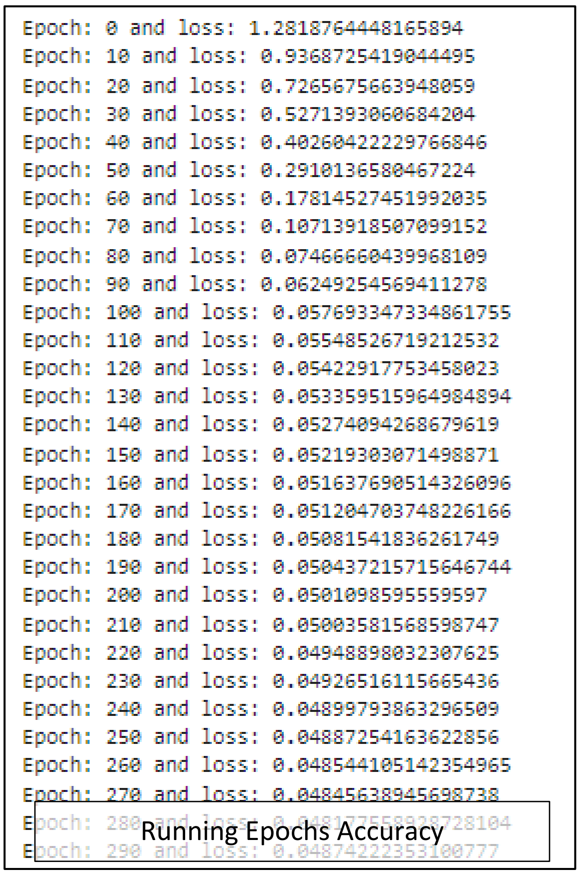
Neural Network Model

The development of the neural network model is a pivotal stage in the creation of a digital twin for battery system. The neural network architecture begins with careful consideration of the input features, output features and hidden layers as hyperparameters to improve accuracy. For this battery, we selected the 4 voltmeters and the general voltage and current of the battery as the input layers. Through the hidden layers, features are extracted to predict the output. The model is constantly trained by configuring the hidden layers to improve the accuracy of prediction to be high as possible.





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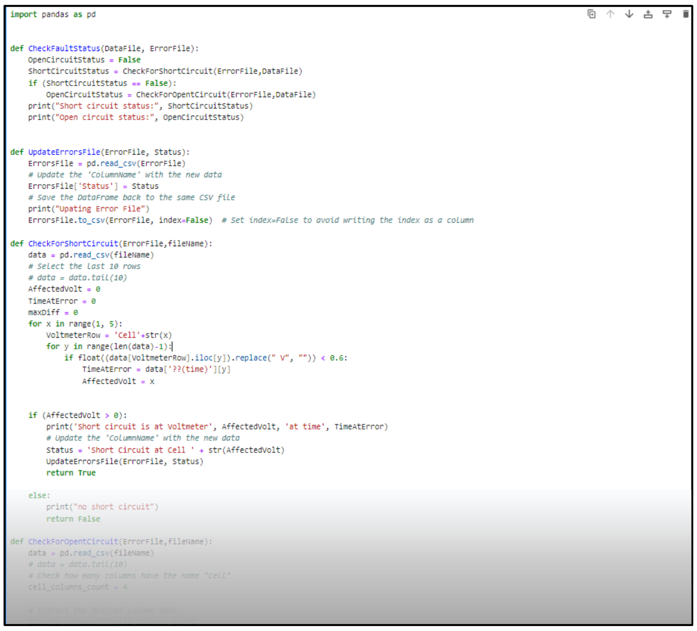
Epoch: 0 and loss: 1.2818764448165894
Epoch: 10 and loss: 0.9368725419044495
Epoch: 20 and loss: 0.7265675663948059
Epoch: 30 and loss: 0.5271393060684204
Epoch: 40 and loss: 0.40260422229766846
Epoch: 50 and loss: 0.2910136580467224
Epoch: 60 and loss: 0.17814527451992035
Epoch: 70 and loss: 0.10713918507099152
Epoch: 80 and loss: 0.07466660439968109
Epoch: 90 and loss: 0.06249254569411278
Epoch: 100 and loss: 0.057693347334861755
Epoch: 110 and loss: 0.05548526719212532
Epoch: 120 and loss: 0.05422917753458023
Epoch: 130 and loss: 0.053359515964984894
Epoch: 140 and loss: 0.05274094268679619
Epoch: 150 and loss: 0.05219303071498871
Epoch: 160 and loss: 0.051637690514326096
Epoch: 170 and loss: 0.051204703748226166
Epoch: 180 and loss: 0.05081541836261749
Epoch: 190 and loss: 0.050437215715646744
Epoch: 200 and loss: 0.0501098595559597
Epoch: 210 and loss: 0.05003581568598747
Epoch: 220 and loss: 0.04948898032307625
Epoch: 230 and loss: 0.04926516115665436
Epoch: 240 and loss: 0.04899793863296509
Epoch: 250 and loss: 0.04887254163622856
Epoch: 260 and loss: 0.048544105142354965
Epoch: 270 and loss: 0.04845638945698738
Epoch: 280 and loss: 0.048177558928728104
Epoch: 290 and loss: 0.04874222353100777
```

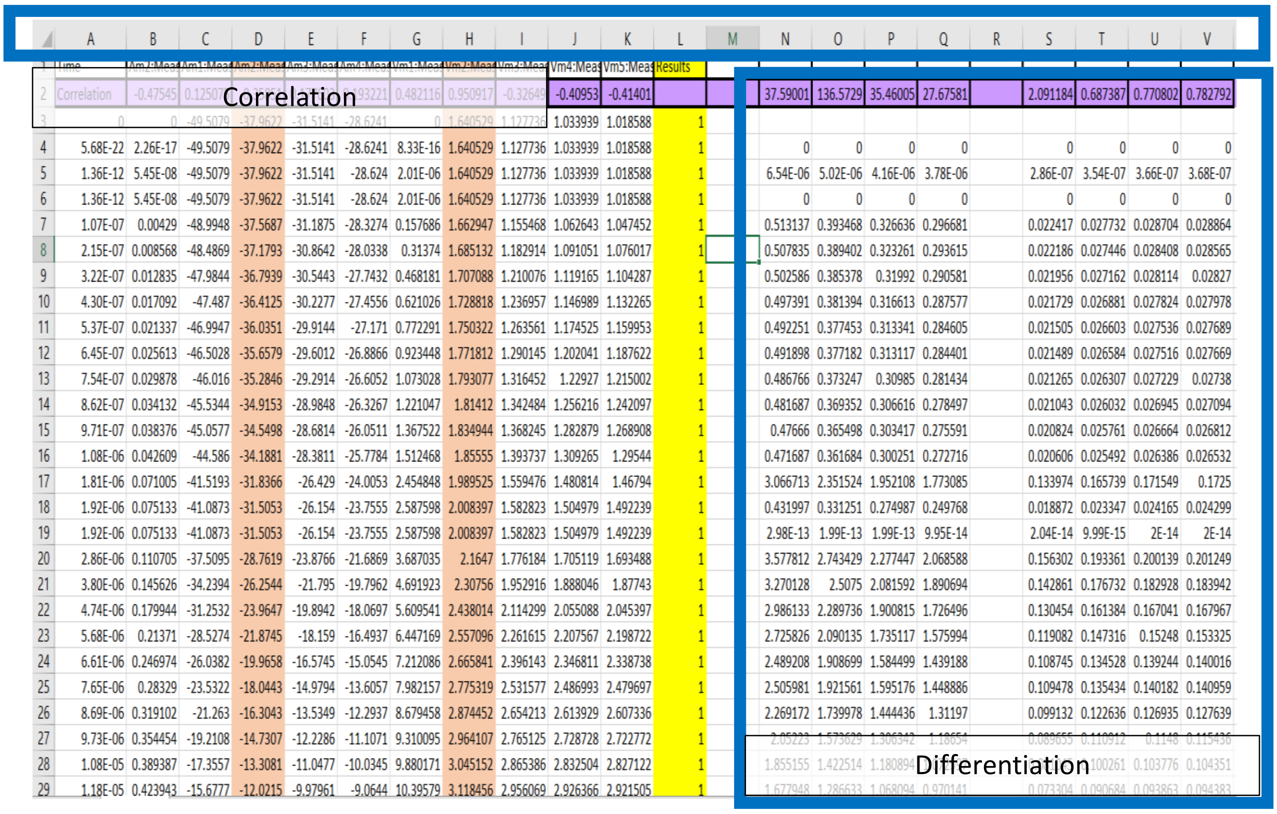
Running Epochs Accuracy

Algorithm Development

An algorithm is meticulously formulated based on the discerned pattern within the dataset compilation. The algorithm adapts and processes any incoming unlabeled data, enabling the prediction of the battery's status, alongside the identification of fault type and its precise location within the battery. This approach is called a "Rule-Based Algorithm". After getting a clear understanding of the cause-and-effect relationships within the battery system, an algorithm is created so that the probability of false prediction is highly unlikely.



```python
import pandas as pd


def CheckFaultStatus(DataFile, ErrorFile):
    OpenCircuitStatus = False
    ShortCircuitStatus = CheckForShortCircuit(ErrorFile,DataFile)
    if (ShortCircuitStatus == False):
        OpenCircuitStatus = CheckForOpentCircuit(ErrorFile,DataFile)
    print("Short circuit status:", ShortCircuitStatus)
    print("Open circuit status:", OpenCircuitStatus)


def UpdateErrorsFile(ErrorFile, Status):
    ErrorsFile = pd.read_csv(ErrorFile)
    # Update the 'ColumnName' with the new data
    ErrorsFile['Status'] = Status
    # Save the DataFrame back to the same CSV file
    print("Upating Error File")
    ErrorsFile.to_csv(ErrorFile, index=False)  # Set index=False to avoid writing the index as a column

def CheckForShortCircuit(ErrorFile,fileName):
    data = pd.read_csv(fileName)
    # Select the last 10 rows
    # data = data.tail(10)
    AffectedVolt = 0
    TimeAtError = 0
    maxDiff = 0
    for x in range(1, 5):
        VoltmeterRow = 'Cell'+str(x)
        for y in range(len(data)-1):
            if float((data[VoltmeterRow].iloc[y]).replace(" V", "")) < 0.6:
                TimeAtError = data['??(time)'][y]
                AffectedVolt = x


    if (AffectedVolt > 0):
        print('Short circuit is at Voltmeter', AffectedVolt, 'at time', TimeAtError)
        # Update the 'ColumnName' with the new data
        Status = 'Short Circuit at Cell ' + str(AffectedVolt)
        UpdateErrorsFile(ErrorFile, Status)
        return True

    else:
        print("no short circuit")
        return False

def CheckForOpentCircuit(ErrorFile,fileName):
    data = pd.read_csv(fileName)
    # data = data.tail(10)
    # Check how many columns have the name "Cell"
    cell_columns_count = 4
```

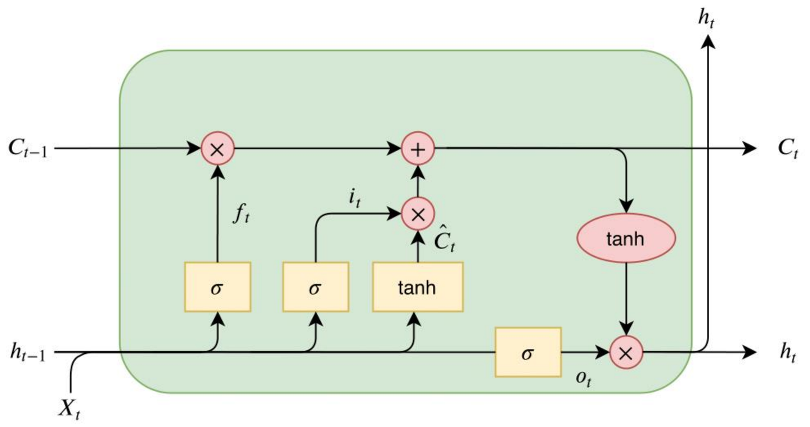

Correlation
Differentiation

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
1	Time	Am2:Meas	Am1:Meas	Am2:Meas	Am3:Meas	Am4:Meas	Vm1:Meas	Vm2:Meas	Vm3:Meas	Vm4:Meas	Vm5:Meas	Results										
2	Correlation	-0.47545	0.12507	[illegible]	[illegible]	0.193221	0.482116	0.950917	-0.32649	-0.40953	-0.41401			37.59001	136.5729	35.46005	27.67581		2.091184	0.687387	0.770802	0.782792
3	0	0	-49.5079	-37.9622	-31.5141	-28.6241	0	1.640529	1.127736	1.033939	1.018588	1										
4	5.68E-22	2.26E-17	-49.5079	-37.9622	-31.5141	-28.6241	8.33E-16	1.640529	1.127736	1.033939	1.018588	1		0	0	0	0		0	0	0	0
5	1.36E-12	5.45E-08	-49.5079	-37.9622	-31.5141	-28.624	2.01E-06	1.640529	1.127736	1.033939	1.018588	1		6.54E-06	5.02E-06	4.16E-06	3.78E-06		2.86E-07	3.54E-07	3.66E-07	3.68E-07
6	1.36E-12	5.45E-08	-49.5079	-37.9622	-31.5141	-28.624	2.01E-06	1.640529	1.127736	1.033939	1.018588	1		0	0	0	0		0	0	0	0
7	1.07E-07	0.00429	-48.9948	-37.5687	-31.1875	-28.3274	0.157686	1.662947	1.155468	1.062643	1.047452	1		0.513137	0.393468	0.326636	0.296681		0.022417	0.027732	0.028704	0.028864
8	2.15E-07	0.008568	-48.4869	-37.1793	-30.8642	-28.0338	0.31374	1.685132	1.182914	1.091051	1.076017	1		0.507835	0.389402	0.323261	0.293615		0.022186	0.027446	0.028408	0.028565
9	3.22E-07	0.012835	-47.9844	-36.7939	-30.5443	-27.7432	0.468181	1.707088	1.210076	1.119165	1.104287	1		0.502586	0.385378	0.31992	0.290581		0.021956	0.027162	0.028114	0.02827
10	4.30E-07	0.017092	-47.487	-36.4125	-30.2277	-27.4556	0.621026	1.728818	1.236957	1.146989	1.132265	1		0.497391	0.381394	0.316613	0.287577		0.021729	0.026881	0.027824	0.027978
11	5.37E-07	0.021337	-46.9947	-36.0351	-29.9144	-27.171	0.772291	1.750322	1.263561	1.174525	1.159953	1		0.492251	0.377453	0.313341	0.284605		0.021505	0.026603	0.027536	0.027689
12	6.45E-07	0.025613	-46.5028	-35.6579	-29.6012	-26.8866	0.923448	1.771812	1.290145	1.202041	1.187622	1		0.491898	0.377182	0.313117	0.284401		0.021489	0.026584	0.027516	0.027669
13	7.54E-07	0.029878	-46.016	-35.2846	-29.2914	-26.6052	1.073028	1.793077	1.316452	1.22927	1.215002	1		0.486766	0.373247	0.30985	0.281434		0.021265	0.026307	0.027229	0.02738
14	8.62E-07	0.034132	-45.5344	-34.9153	-28.9848	-26.3267	1.221047	1.81412	1.342484	1.256216	1.242097	1		0.481687	0.369352	0.306616	0.278497		0.021043	0.026032	0.026945	0.027094
15	9.71E-07	0.038376	-45.0577	-34.5498	-28.6814	-26.0511	1.367522	1.834944	1.368245	1.282879	1.268908	1		0.47666	0.365498	0.303417	0.275591		0.020824	0.025761	0.026664	0.026812
16	1.08E-06	0.042609	-44.586	-34.1881	-28.3811	-25.7784	1.512468	1.85555	1.393737	1.309265	1.29544	1		0.471687	0.361684	0.300251	0.272716		0.020606	0.025492	0.026386	0.026532
17	1.81E-06	0.071005	-41.5193	-31.8366	-26.429	-24.0053	2.454848	1.989525	1.559476	1.480814	1.46794	1		3.066713	2.351524	1.952108	1.773085		0.133974	0.165739	0.171549	0.1725
18	1.92E-06	0.075133	-41.0873	-31.5053	-26.154	-23.7555	2.587598	2.008397	1.582823	1.504979	1.492239	1		0.431997	0.331251	0.274987	0.249768		0.018872	0.023347	0.024165	0.024299
19	1.92E-06	0.075133	-41.0873	-31.5053	-26.154	-23.7555	2.587598	2.008397	1.582823	1.504979	1.492239	1		2.98E-13	1.99E-13	1.99E-13	9.95E-14		2.04E-14	9.99E-15	2E-14	2E-14
20	2.86E-06	0.110705	-37.5095	-28.7619	-23.8766	-21.6869	3.687035	2.1647	1.776184	1.705119	1.693488	1		3.577812	2.743429	2.277447	2.068588		0.156302	0.193361	0.200139	0.201249
21	3.80E-06	0.145626	-34.2394	-26.2544	-21.795	-19.7962	4.691923	2.30756	1.952916	1.888046	1.87743	1		3.270128	2.5075	2.081592	1.890694		0.142861	0.176732	0.182928	0.183942
22	4.74E-06	0.179944	-31.2532	-23.9647	-19.8942	-18.0697	5.609541	2.438014	2.114299	2.055088	2.045397	1		2.986133	2.289736	1.900815	1.726496		0.130454	0.161384	0.167041	0.167967
23	5.68E-06	0.21371	-28.5274	-21.8745	-18.159	-16.4937	6.447169	2.557096	2.261615	2.207567	2.198722	1		2.725826	2.090135	1.735117	1.575994		0.119082	0.147316	0.15248	0.153325
24	6.61E-06	0.246974	-26.0382	-19.9658	-16.5745	-15.0545	7.212086	2.665841	2.396143	2.346811	2.338738	1		2.489208	1.908699	1.584499	1.439188		0.108745	0.134528	0.139244	0.140016
25	7.65E-06	0.28329	-23.5322	-18.0443	-14.9794	-13.6057	7.982157	2.775319	2.531577	2.486993	2.479697	1		2.505981	1.921561	1.595176	1.448886		0.109478	0.135434	0.140182	0.140959
26	8.69E-06	0.319102	-21.263	-16.3043	-13.5349	-12.2937	8.679458	2.874452	2.654213	2.613929	2.607336	1		2.269172	1.739978	1.444436	1.31197		0.099132	0.122636	0.126935	0.127639
27	9.73E-06	0.354454	-19.2108	-14.7307	-12.2286	-11.1071	9.310095	2.964107	2.765125	2.728728	2.722772	1		2.05223	1.573629	1.306342	1.18654		0.089655	0.110912	0.1148	0.115436
28	1.08E-05	0.389387	-17.3557	-13.3081	-11.0477	-10.0345	9.880171	3.045152	2.865386	2.832504	2.827122	1		1.855155	1.422514	1.180894	[illegible]		[illegible]	0.100261	0.103776	0.104351
29	1.18E-05	0.423943	-15.6777	-12.0215	-9.97961	-9.0644	10.39579	3.118456	2.956069	2.926366	2.921505	1		1.677948	1.286633	1.068094	0.970141		0.073304	0.090684	0.093863	0.094383

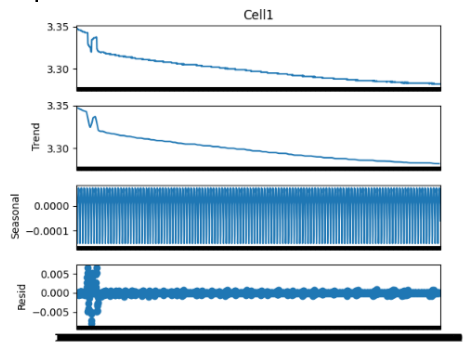
`

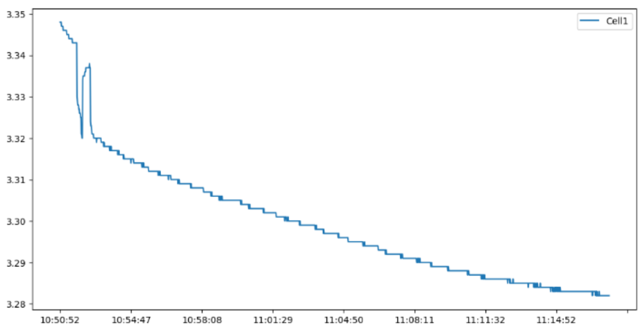
Predictive Modeling with LSTM

- ***About LSTM***
  LSTM stands for Long Short-Term Memory, which is a type of Recurrent Neural Network. This model is well suited for handling time-series data as it captures long-term dependencies.

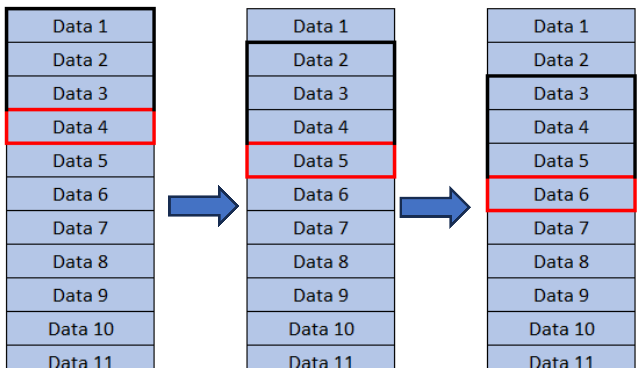


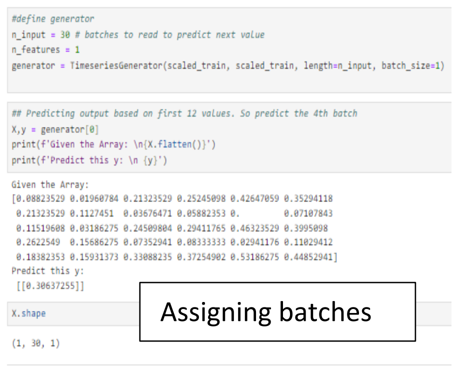
- ***Data Preparation***
  In the realm of predictive modelling, the focus is primarily on data representing normal battery operation of a working battery. This data is meticulously preprocessed to suit the requirements of LSTM networks.





The training data is input as ***n*** batches, and it is trained to predict the next value (***n + 1***). The number ***n*** is decided after several runs to get better accuracy.
for eg ***n*** = 3:





```
#define generator
n_input = 30 # batches to read to predict next value
n_features = 1
generator = TimeseriesGenerator(scaled_train, scaled_train, length=n_input, batch_size=1)
```

```
## Predicting output based on first 12 values. So predict the 4th batch
X,y = generator[0]
print(f'Given the Array: \n{X.flatten()}')
print(f'Predict this y: \n {y}')
```

```
Given the Array:
[0.08823529 0.01960784 0.21323529 0.25245098 0.42647059 0.35294118
 0.21323529 0.1127451  0.03676471 0.05882353 0.         0.07107843
 0.11519608 0.03186275 0.24509804 0.29411765 0.46323529 0.3995098
 0.2622549  0.15686275 0.07352941 0.08333333 0.02941176 0.11029412
 0.18382353 0.15931373 0.33088235 0.37254902 0.53186275 0.44852941]
Predict this y:
 [[0.30637255]]
```

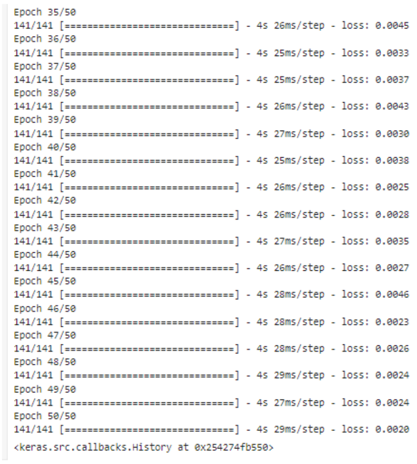
```
X.shape
```

```
(1, 30, 1)
```

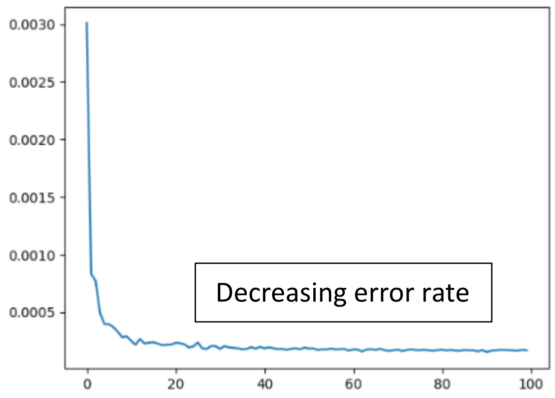
Assigning batches

- ***Training and Optimization***

  The LSTM model is trained using the preprocessed dataset, with a specific emphasis on its capacity to predict future values of a healthy battery. The predictive accuracy of this model is enhanced by tuning in the hyperparameters, mainly the batch size and the learning rate.

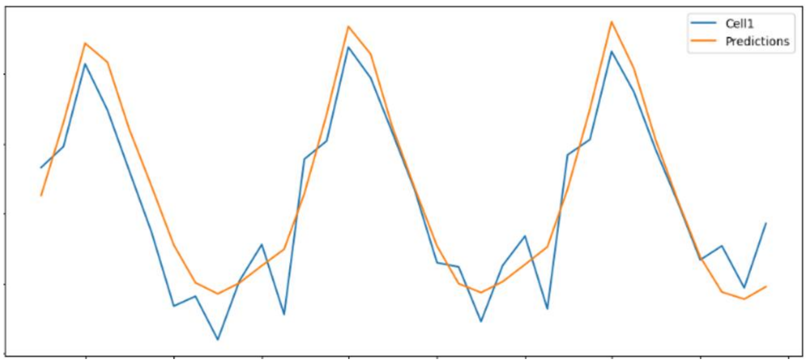


```
Epoch 35/50
141/141 [==============================] - 4s 26ms/step - loss: 0.0045
Epoch 36/50
141/141 [==============================] - 4s 25ms/step - loss: 0.0033
Epoch 37/50
141/141 [==============================] - 4s 25ms/step - loss: 0.0037
Epoch 38/50
141/141 [==============================] - 4s 26ms/step - loss: 0.0043
Epoch 39/50
141/141 [==============================] - 4s 27ms/step - loss: 0.0030
Epoch 40/50
141/141 [==============================] - 4s 25ms/step - loss: 0.0038
Epoch 41/50
141/141 [==============================] - 4s 26ms/step - loss: 0.0025
Epoch 42/50
141/141 [==============================] - 4s 26ms/step - loss: 0.0028
Epoch 43/50
141/141 [==============================] - 4s 27ms/step - loss: 0.0035
Epoch 44/50
141/141 [==============================] - 4s 26ms/step - loss: 0.0027
Epoch 45/50
141/141 [==============================] - 4s 28ms/step - loss: 0.0046
Epoch 46/50
141/141 [==============================] - 4s 28ms/step - loss: 0.0023
Epoch 47/50
141/141 [==============================] - 4s 28ms/step - loss: 0.0026
Epoch 48/50
141/141 [==============================] - 4s 29ms/step - loss: 0.0024
Epoch 49/50
141/141 [==============================] - 4s 27ms/step - loss: 0.0024
Epoch 50/50
141/141 [==============================] - 4s 29ms/step - loss: 0.0020
<keras.src.callbacks.History at 0x254274fb550>
```



- ***Evaluation and Validation***

  The performance of the LSTM model is evaluated and compared with the original dataset for comparison.


Cell1
Predictions