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Prediction of Health Status of Battery Using Super Learner Algorithm

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***Abstract*—A everyday battery survival pattern with very long testing periods, no contact estimate programs, or other devices will be useful in modern businesses. This abstract focuses on employing a super learner technique to estimate the remaining useful lifespan (RUL) for NMC-LCO 18650 batteries. The super learning algorithm has become a type of ensemble machine learn- ing that combines several different basic models to increase the accuracy of predictions. In this research, a set of features from the batteries were extracted, which includes current, temperature, voltage, and battery cycle, and the RUL was calculated utilizing a super learner algorithm. The linear regression model, the random forest, and two deep learning models used as basis models for the super learner algorithm. Mean absolute error (MAE), which as well as root mean squared error were two metrics used to assess the efficacy of this super learner algorithm. (RMSE). The outcomes demonstrate that with regard to of prediction accuracy, the super learner strategy exceeds the separate base models. In order to improve battery performance and lower maintenance costs, it is essential to be able to predict the of the RUL for NMC-LCO 18650 batteries. The suggested method is capable of being utilized as an accurate and dependable way for doing this.**

***Index Terms*—Artificial Intelligence, Battery life Time Prediction, Remaining Useful Lifespan, NMC-LCO 18650 Batteries, Ensemble Technique, Super Learner Algorthm, Data Science, Python Programming Language.**

I. INTRODUCTION

Batteries made of lithium-ion material, or Li-ion, are frequently used in commercial settings. To accomplish ideal operation and health management, it is important to forecast the health state of batteries. The greatest barrier to accurate battery health prediction is accuracy. In comparison to conventional NiMH or lead-acid batteries, lithium-ion (Li-ion) batteries offer a number of alluring advantages, including a higher energy density as well as nominal voltage, a lower self- discharge rate, and a longer lifespan. Li-ion batteries have thus been extensively used in numerous industrial devices. How- ever, a sudden battery failure can result in poor performance, operational problems, or even disastrous outcomes. Therefore, it is crucial to forecast the Li-ion batteries health in good time and with accuracy. In reality, Li-ion batteries' performance would progressively deteriorate over time as a result of ageingand effects from operating conditions. Two key markers for battery health conditions are the state-of-health (SOH) and remaining-useful-life (RUL). The overall useful capacity loss and resistance increase together make up the SOH, which stands for the battery ageing level. RUL stands for the duration from the current to the battery's end of useful life. Many different methods have been described in recent years for the Li-ion batteries SOH estimation as well as RUL prediction. The basis and requirement for the RUL forecast is a precise SOH estimation. Some of the most important variables for precise SOH along with RUL prediction is the health index [1].

Due to their appealing performance, LIBs (Lithium-ion batteries) are now the primary power source for EVs (Electric Vehicles) and are frequently used in the automotive, aircraft, and other industrial sectors. However, as batteries continue to be used and age, their health and performance will de- cline, which in some extreme instances could lead to safety accidents. Therefore, a precise RUL prediction is crucial for battery safety as well as for improved battery maintenance, ensuring that the battery functions at its best and extending its service life. Algorithms based on machine learning are used in data-driven methods to model the process of health degradation and forecast the RUL for a pack of batteries from understanding the historical database. For battery upkeep and secure operation of electric vehicles, it is crucial to accurately estimate the unused useful life (RUL) of lithium-ion batteries [2].

Storage of energy systems, electric vehicles, and transportable electronic devices are just a few of the many uses for lithium- ion batteries. In order to increase the battery's service life and guarantee the system's safe and dependable functioning, it is essential to accurately determine the batteries' state of health (RUL). The competitiveness of machine learning (ML) as well as deep learning (DL) methodologies for under- standing the behavior of complicated nonlinear systems has garnered growing attention. Battery RUL estimation has a lot of promise thanks to the growth of big information and cloud computing. The global energy system is altering to decreasecarbon emissions, address associated climate change, and deal with energy shortages. The use of fossil fuels is steadily declining as renewable energy sources such as wind, solar, and hydroelectric power develop quickly. The lithium-ion (li-ion) cells are used in many different applications, such as systems for storing energy, electric vehicles, and portable electronic devices, because of their high power and energy density, high energy efficiency, and comparatively extended cycle life. The secure and dependable operation of batteries, as well as their commercial viability, are crucial during long-term operation

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because they serve as a means of energy storage as well as the main supplier of energy for these devices [3]. The hybrid data-driven as well as model-based approach typically yields better RUL forecast outcomes. However, such integration is more difficult for online practical applications to implement because it takes more computational skill. To increase the precision as well as the dependability of the RUL prediction results, various data-driven approaches can also be integrated in addition to data-driven and model-based methods. It creates a battery's state of health, which aids in directing businesses. It's important to increase the Li-Ion battery-powered equipment's availability. It reducing the number of output hours lost to maintenance, minimizing maintenance costs, breakdowns, and downtime, and improving battery efficiency. Some of the most crucial factors right now for predicting component failure before it actually happens is the RUL [4].

Currently, lithium-ion batteries are used extensively. For systems for managing batteries (BMS) and logically scheduling the battery utilization, it is crucial to accurately predict the remaining useful life (RUL). There are issues like randomness and battery capacity regeneration brought on by parameter values and single-time prediction. The benefits of lithium-ion batteries, which include a high output voltage, a long cycle life, a high density of energy, and environmental friendliness, make them very popular today. Applications span a wide range of industries, including the military, aircraft, and electronics. The discharge capability of Li-ion batteries will progressively deteriorate over time. The three major causes are ageing of the separator, electrolyte changes, and material corrosion in the poles. These phenomena will cause a reduction in discharge capability, which will result in a deterioration of battery performance. For the system's batteries to operate safely and effectively, the battery control system is essential. To extend the service's life and ensure safety, BMS can effectively manage each unit and control the working state in a reasonable manner. Important components of the BMS include life prediction that is still helpful. The total amount of charge/discharge cycles a Li-ion battery can withstand before its performance or SOH deteriorates to a point in which it can no longer power the device is known as RUL [5].

The remaining chapters of the paper are as follows: chapter II is a description of the literature review; chapter III is a description of the proposed methodology; chapter IV is a description of the findings and discussion; and chapter V is a summary of our article on the system.

II. Literature Survey

Jiao, R et al., "Lithium-ion battery remaining usable life prediction using the conditional equations auto encoders-particle filter". In hopes of predicting the RUL of batteries, a novel PF architecture built around the conditional variation auto - encoder (CVAE) as well as a reweighting technique is put forth in this study. The standard prior distribution is first replaced with the CVAE algorithm, which is then integrated into in the PF architecture to lessen particle damage. In order to avoid losing particle variety, a reweighting approach is also used during particle resampling. Ultimately, the suggested CVAE-PF is used to forecast how the battery capacity would degrade, and the RUL can be calculated when the capacity reaches a predetermined failure threshold. Compared to some previous methods, the new technique is able to achieve greater prediction performance, according to the experimental data [6]. Xue, K et al., "A more effective generic hybrid prognostic approach based on PF-LSTM learning for RUL prediction". On the degradation modeling and RUL forecasting for lithium- ion batteries, the proposed in this work blended PF-LSTM prognostic strategy is shown and contrasted with some other adaptive learning as well as machine learning methods like the unscented classifier (UPF) as well as the radial basis function system (RBFN). The comparison results demonstrate that a hybrid PF-LSTM prognostic strategy with accurate equipment deterioration state characterization based on integrated hierarchical clustering analysis can achieve robust prediction performance. The more precise prognostic estimates in the density function of probability (PDF) of the prior or post distribution of storage capacity and RUL obtained by particles filtering can provide significant insights into the action guide for predictive maintenance [7].

Tang, T et al., "A hybrid strategy using a decomposition method and a neural network to anticipate the lithium-ion battery's remaining usable life". A unique remaining usable life prediction approach was proposed in order to address the issues of non-linearity, non-stationary, and low forecast precision of the initial capacity degradation information for lithium-ion batteries. To prevent the useful knowledge about the capability regeneration section from being lost, comprehensive ensemble empirical mode of decomposition adaptable noise is used to produce full adaptive deconstruction of the original data. Next, zero-crossing rate and novel fusion rules are utilized to create fused high- and low-frequency sections, which can reduce the total amount of incoming network components and operational expenses. The best outcomes, chosen using the least absolute error standard, contain the benefits of 2 high frequencies fusion rules [8]. Zhang, C et al., "A method for predicting future RUL and capacity for lithium- ion battery packs". In this study, an innovative hybrid approach that combines enhanced vibrational modal decomposed (VMD), particle filter (PF), and Gaussian mixture regression is proposed for predicting battery up with the intention and RUL (GPR). The collected battery capacity data is divided by the VMD algorithm into a number of residual sequencesand an ageing trend sequence, with the amount of modal layers being determined by the suggested probabilistic feedback confidence (PFC) approach. The ageing trend series and residual sequences are then, respectively, predicted using the predictive model of the PF and GPR algorithms. To confirm the viability of the suggested hybrid technique, future capacity as well as RUL prediction research for battery packs and rechargeable batteries is carried out. The contrasted experiment results show that the suggested approach works [9]. Sulzer, V et al., "The difficulty and potential of predicting battery longevity from field data." The commercial case for evs, permanent energy storage, and emerging applications like electric aero planes all depend on accurate battery life prediction. End-

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use applications' uncontrolled working environments, less accurate sensors, issues with data collecting and storage, and frequent accessibility to validation tests provide additional obstacles as a result. We investigate various techniques to estimate lifetime from field and laboratory data and propose that fusing machine learning methods with mathematical model is a promising approach, allowing implication of battery capacity from noisy data, evaluation of second scenario, and generalization to future usage scenarios. This study emphasizes the potential for field data insights to lower battery prices and enhance designs [10].

III. Proposed Methodology

The proposed technique gives details on how our system will be implemented. To locate and retrieve the necessary battery data, including target and predictor values, for working with. The gathered data must be pre-processed in accordance with the specifications. In this stage, the necessary dataset is gathered from the accessible resources and saved in CSV format. The processing dataset is split into sets for training and testing of data, and different algorithms for machine learning as well as deep learning models are developed. These models are only taken into consideration if they have a high accuracy rate. To create the four basis models that the Super-learner Algorithm needs, which include 2 different machine learning models as well as two deep learning models. To determine the best model depending on the degree of accuracy of the various models we created and examined. The super learner technique strategies are used to recommend the model having better performance based accuracy basis after the best accuracy of the many models built is manually examined.

*Explanation:*Data collection, data pre-processing, building ML models, building DL models, classification, and prediction are the five modules that we employ here for our system.

*Datasets Collection:*The practice of obtaining and analyzing information from a wide variety of sources is known as data collection. Data must be gathered and kept in a manner that makes sense for the specific business problem at hand if we are to use it to create useful artificial intelligence (AI) but also deep learning solutions. 14 NMC-LCO 18650 batteries with a nominal power of 2.8 Ah were investigated by the Hawaiian Natural Energy Institute after being cycled morethan 1000 times at 25°C. Eight features that were captured during battery cycling experiments are included in the dataset.

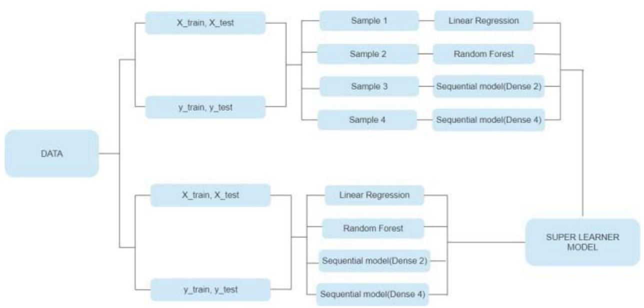

Fig. 1. Shown the Block Diagram of Project

SNO	NAME	DESCRIPTION
1.	Cycle Index	The battery's total number of charging and discharging processes.
2.	Discharge Time	Length of time it takes to discharge from completely charged through fully discharged.
3.	Time at 4.15V	The period of the charging cycle during which the battery is at 4.15 volts.
4.	Time Constant Current	When a steady current is used to charge the battery.
5.	Decrement 3.6-3.4V	Duration of battery drain from 3.6V towards 3.4V.
6.	Max. Voltage Discharge	The highest voltage that was recorded throughout the discharge cycle.
7.	Min. Voltage Charge	The lowest voltage that was recorded throughout the charge cycle.
8.	Charging Time	Represents the length of time that the charging process lasted.

Fig. 2. Input data features

*Data Pre-Processing:*All of the data should be converted into observable data before being preprocessed. We remove some erroneous and noisy data from the initial batch of data by performing this preprocessing. This will decrease memory usage and produce effective outcomes. Here, the many methods we employ include removing the superfluous features, retrieving the best features by working backward, \and standardizing the values.

*Model Implementation:*Here, we use Random Forest and Linear Regression to build two machine learning models. Sequential models with 2 dense layers and Sequential models with 4 dense layers are additionally available to the Building DL models.

Classification and Prediction Model: In this lesson, we will look at how to classify datasets in order to forecast battery lifetimes with high accuracy. Lastly, the prediction optimization is done on the system's accuracy rating. Lastly, assessing the accuracy of the prediction model and identifying the framework with higher accuracy.

IV. Results And Discussion

We talked about our system's output images in the outcomes and discussion section.

Figure 3 shows the list of all packages required.

```
import os
import warnings
warnings.filterwarnings('ignore')
import numpy as np
import pandas as pd
import scipy
from scipy.io import loadmat
import matplotlib.pyplot as plt
import seaborn as sns
import shutil
%matplotlib inline

import statsmodels.api as sm
from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor

from keras.models import Sequential
from keras.layers import Dense
from sklearn.metrics import mean_absolute_error, r2_score, mean_squared_error
```

Fig. 3. List of packages imported

Figure 4 shows the list of all features from the dataset.

```
data = 'Battery_RUL.csv'
df = pd.read_csv(data)
df.head()
```

	Cycle_Index	Discharge Time (s)	Decrement 3.6-3.4V (s)	Max. Voltage Dischar. (V)	Min. Voltage Charg. (V)	Time at 4.15V (s)	Time constant current (s)	Charging time (s)	RUL
0	1.0	2595.30	1151.488500	3.670	3.211	5460.001	6755.01	10777.82	1112
1	2.0	7408.64	1172.512500	4.246	3.220	5508.992	6762.02	10500.35	1111
2	3.0	7393.76	1112.992000	4.249	3.224	5508.993	6762.02	10420.38	1110
3	4.0	7385.50	1080.320667	4.250	3.225	5502.016	6762.02	10322.81	1109
4	6.0	65022.75	29813.487000	4.290	3.398	5480.992	53213.54	56699.65	1107

Fig. 4. List of all features in the dataset

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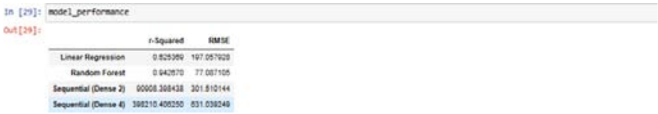
Figure 5 shows the Final Prediction Implementation of our system.


In [29]: model_performance

Out[29]:

	r-Squared	RMSE
Linear Regression	0.825369	197.057920
Random Forest	0.942670	77.087105
Sequential (Dense 2)	90908.398438	301.510144
Sequential (Dense 4)	398210.406250	631.038249

Fig. 5. Accuracy of the models built

V. Conclusion

The estimation of the state of a lithium-ion battery and the management of its health depend greatly on the RUL (Remaining Useful Life) prognosis. The advancements in the fields of AI as well as deep learning offer brand-new, promising techniques for predicting lithium-ion battery RUL. Through this model, we intend to contribute to the informational content that is available on lithium battery lifetime estimation techniques. By analyzing the accuracy metrics of all the algorithms employed in this project, the project offers the improved model performance that would estimate battery life with high accuracy.

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