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# Battery Life Improvement Using Battery Management

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***Abstract: One of the greatest challenges faced by Electric Vehicle (EV) manufactures is insufficient charging stations. Estimating the aging of the battery in the electric vehicle helps the driver to predict the driving range of the vehicle. This paper proposes a battery management system that is developed to predict remaining battery charge of the Electric Vehicle. The aging of the lithium-ion (Li-Ion) battery present in the electric vehicle is predicted using different machine learning and deep learning algorithms. The parameters such as voltage, current and temperature are taken from the sensors connected to the LPC2148 ARM board and the values are given as dataset to the Long Short-Term Memory (LSTM), Decision Tree (DT), K-Nearest Neighbors (KNN), Naïve Bayes (NB) and Support Vector Machine (SVM) Algorithms. The experimental results indicate that for real-time data Naïve Bayes algorithm gave the best results in terms of metrics such as Accuracy, Precision, Recall and F1-score. Naïve Bayes produced results with the accuracy rate of 88% and used to calculate the Remaining Battery Capacity which helps predicting the aging of the lithium- ion battery.***

***Keywords: Electric Vehicle (EV), Lithium-Ion (Li-Ion), State Of Charge (SOC), Battery Management System (BMS), Long Short-Term Memory (LSTM), Decision Tree (DT), KNearest Neighbors (KNN), Naïve Bayes (NB) and Support Vector Machine (SVM).***

## I. INTRODUCTION

The aim of using LSTM technique for Battery Management System (BMS) is to leverage deep learning capabilities to accurately estimate battery aging. By utilizing LSTM networks, which are well-suited for modeling sequential data, the goal is to capture the temporal dependencies and patterns in battery parameters over time and make predictions about the battery's aging.

The specific objectives of using LSTM for battery aging estimation include:

- Accurate Prediction: Develop a model that can accurately predict battery aging based on historical battery parameters, such as voltage, current, temperature, SoC, and cycle count. The LSTM network's ability to capture long-term dependencies in sequential data makes it a suitable choice for accurately modeling battery behavior over time.
- Long-Term Dependency Modeling: Traditional machine learning algorithms may struggle to capture long-term dependencies in sequential battery data. LSTM networks excel at capturing these dependencies, allowing the model to learn complex patterns and trends in battery aging, which can be crucial for accurate estimation.
- Real-Time Estimation: Design an LSTM-based model that can estimate battery aging in real-time, making it suitable for integration into a BMS. This enables proactive management of battery health, early detection of degradation, and optimization of battery performance.
- Generalization: Train the LSTM model to generalize well to unseen battery data and different battery chemistries. This allows the model to be applicable to a wide range of battery types and improve its effectiveness in estimating aging across various battery systems.
- Comparison with Other Techniques: Compare the performance of the LSTM-based model with other machine learning algorithms commonly used in battery aging estimation, such as SVM or random forest. Assess the superiority of LSTM in capturing temporal patterns and achieving better accuracy in predicting battery aging.
- Adaptability and Scalability: Design the LSTM-based model with the flexibility to adapt and scale to different battery sizes, chemistries, and operating conditions. This ensures that the model can be applied to diverse battery systems with varying characteristics.

The ultimate aim is to develop an LSTM-based model that can accurately estimate battery aging, facilitate optimal battery management, improve battery lifespan, and enhance the overall performance and reliability of battery-powered systems

The impacts of air pollution and global warming that is caused due to greenhouse gas emissions from fuel based vehicles have increasingly attracted great attention towards the eco-friendly electric vehicles (EVs). The transport industry accounts for the large amount of greenhouse gas emission and pollution to the environment. The transport sector can be improved by the introduction of the environmentally friendly Hybrid Electric Vehicle (HEV), Battery Electric Vehicle (BEV), Fuel Cell Electric Vehicle (FCEV) and Plug-in Hybrid Electric Vehicle (PHEV).

Among these Battery Electric vehicles (BEV) are currently the best choice in terms of public and personal transportation for the environment. Because of high cell voltage, low self-discharge rate, high energy density, light weight, long lifetime and low maintenance Li-ion batteries have gained high popularity when compared to other batteries. Range, cost, and battery life cycle are the main challenges for the development of Li-Ion battery systems for electric vehicles [4].

A battery can support only a finite, limited number of charge and discharge cycles. A sufficiently long battery life is necessary to avoid battery replacements during the vehicle's lifetime. To achieve this, a study on lithium-ion battery aging behavior in electric vehicles are essential. Every battery at any instant has a capacity value known as state of charge (SoC) which reduces with energy usage. Range of an EV depends on the SoC of the battery.

Therefore, battery management system (BMS) is important to make sure that the battery is operated in its specified safety limits [3]. One of the most important tasks of the BMS is to predict the state of charge. SOC provides percentage of the remaining battery charge. SOC can be calculated based on three battery parameters such as voltage, current and temperature. Through SOC we can identify when the battery needs to be recharged and how long the vehicle can be driven without recharging the battery [7].

The transportation sector is responsible for a significant proportion of greenhouse gas emissions and environmental degradation. However, the development of battery-powered energy storage devices, including electric vehicles, hybrid locomotives, and other e-mobility applications, has the potential to positively impact this sector. Energy storage systems are essential components of smart grid and electric vehicle technologies, enabling the efficient transmission and distribution of energy. With a variety of batteries available on the market, there are numerous options for energy storage purposes.

For EV applications, battery heat control is crucial. Internationally, EV charging stations are extensively utilized, and ports at both private and public charging stations have been increased [1]. Due to the growing dependence on EVs, high voltages, high efficiency, and longer life-span battery systems are necessary, requiring improved battery monitoring techniques. Electric vehicles employ battery management systems (BMS) to monitor, regulate, and shield Li-ion batteries from harsh conditions and abuse. Cell balancing, which occurs as a result of differences in a cell impedance, temperature, and self-discharge characteristics, is one of the crucial functions of BMS.

Cell balancing systems are divided into passive and active types [2]. The battery management system may perform a wide range of tasks, but most academics concentrate on estimating the state of charge (SOC) and state of health (SOH), and fault diagnostic approaches received little attention until recent incidents involving battery systems in EVs. Additionally, if the acquisition sensor is faulty, other BMS activeities that depend on data-gathering may be hampered, further affecting the battery system's safety. Hence, sensor fault diagnostics is crucial for ensuring a BMS's smooth functioning [3]. A overview block diagram for battery management system is demonstrated

The battery management systems cannot function without the data that the current, voltage, and temperature sensors collect. Due to hundreds of such sensors used in electric vehicle battery packs to monitor the currents, voltages, and temperatures for each battery cell, the risk of a problem occurring in a single voltage or current sensor has considerably increased. A sensor malfunction may lead to poor battery performance or possibly significant safety risks [4].

The BMS in EVs consists of a large number of circuits, parts, power electronics, sensors, actuators, diodes, capacitors, inductors, transformers, switches, converters, and safety equipment, all of which are managed by a large number of algorithms, models, and control signals. The creation of suitable algorithms for BMSs has been the subject of much study. Model-based techniques and intelligent methods are the strategies used in BMSs the most often [5].

Since the invention of electricity, the scientists across the world have been investigating a method to store the energy and to use it when it is required. This resulted in the creation and evolution of the energy storage (ES) industry [1]. Increasing the accuracy and efficiency of battery model is a hot research which can enhance the development of several sectors. Such these sectors are the electric vehicles (EVs), which include ES and consider to be a green energy and draw the attentions for many researchers.

## II. LITERATURE SURVEY

**[1] Yichun Li, Mina Maleki, Shadi Banitaan, Mingzuoyang Chen, "Data-Driven State of Charge Estimation of Li-ion Batteries using Supervised Machine Learning Methods", IEEE International Conference on Machine Learning and Applications, January, 2022.**

Recently, electrical vehicles (EVs) have attracted considerable attention from researchers due to the transition of the transportation industry and the increasing demand in the clean energy domain. State of charge (SOC) of Li-ion batteries has a significant role in improving the efficiency, performance, and reliability of EVs. Estimating the SOC of the Li-ion battery cannot be done directly from inner measurements due to the complex and dynamic nature of these kinds of batteries.

**[2] Prakash Venugopal, S. Siva Shankar , C. Phillip Jebakumar, Rishab Agarwal, Hassan Haes Alhelou, S. Sofana Reka, And Mohamad Esmail Hamedani Golshan, "Analysis of Optimal Machine Learning Approach for Battery Life Estimation of Li-Ion Cell", IEEE Access, November, 2021.**

State of health (SOH) and remaining useful life (RUL) are two major key parameters which plays a major role in battery management system. In recent years, various machine learning approaches have been proposed to estimate SOH and RUL effectively for establishing the battery conditions. In the proposed work establishes an effective method to predict the battery aging process with accurate battery health estimation with real time simulations and hardware approach.

**[3] Thiruvonasundari Duraisamy, Deepa Kaliyaperumal, "Machine Learning-Based Optimal Cell Balancing Mechanism for Electric Vehicle Battery Management System", IEEE Access, September, 2021.**

Cell balancing is a vital function of battery management system (BMS), which is implemented to extend the battery run time and service life. Various cell balancing techniques are being focused due to the growing requirements of larger and superior performance battery packs. The passive balancing approach is the most popular because of its low cost and easy implementation. As the balancing energy is dissipated as heat by the balancing resistors, an appropriate thermal scheme of the balancing system is necessary, to keep the BMS board temperature under a tolerable limit.

**[4] Kailong Li, Yunlong Shang, Quan Ouyang, and Widanalage Dhammika Widanage, "A Data-Driven Approach With Uncertainty Quantification for Predicting Future Capacities and Remaining Useful Life of Lithium-ion Battery", IEEE Transactions On Industrial Electronics, Vol. 68, No. 4, April 2021.**

Predicting future capacities and remaining useful life (RUL) with uncertainty quantification is a key but challenging issue in the applications of battery health diagnosis and management. This article applies advanced machine-learning techniques to achieve effective future capacities and RUL prediction for lithium-ion (Li-ion) batteries with reliable uncertainty management. To be specific, after using the empirical mode decomposition (EMD) method, the original battery capacity data is decomposed into some intrinsic mode functions (IMFs) and a residual.

**[5] Tsung-Wen Sun and Tsung-Heng Tsai, "A Battery Management System with Charge Balancing and Aging Detection Based on ANN", IEEE International Symposium on Circuits and Systems, April, 2021.**

A battery management system with aging detection based on artificial neural network (ANN) for the state of charge (SOC) balancing is proposed in this paper. The charger adopts a single-inductor multiple-output architecture to achieve charge balancing among different battery cells. In constant current mode, the pulse charging is utilized to improve the charging speed and slow down the aging rate.

Moreover, an ANN is proposed to detect the state of health (SOH) of the battery cells and improve the accuracy of the SOC estimation. TSMC 0.35-pm process and TensorFlow are used for simulations. A 94% power efficiency of the charger is achieved. The active area of this design is 1.5 × 1.5 mm $^2$ . Experimental results show that 0.32% root-mean square errors for the SOC estimation is obtained.

**[6] Yizhao Gao;Kailong Liu;Chong Zhu;Xi Zhang;Dong Zhang,"Co-Estimation of State-of-Charge and State-of- Health for Lithium-Ion Batteries Using an Enhanced Electrochemical Model", IEEE Transactions on Industrial Electronics, March, 2021.**

Real-time electrochemical state information of lithium-ion batteries attributes to a high-fidelity estimation of state-of-charge (SOC) and state-of-health (SOH) in advanced battery management systems. However, the consumption of recyclable lithium ions, loss of the active materials, and the interior resistance increase resulted from the irreversible side reactions cause severe battery performance decay. To maintain accurate battery state estimation over time, a scheme using the reduced-order electrochemical model and the dual nonlinear filters is presented in this article for the reliable co-estimations of cell SOC and SOH.

Specifically, the full-order pseudo-two-dimensional model is first simplified with Padé approximation while ensuring precision and observability. Next, the feasibility and performance of SOC estimator are revealed by accessing unmeasurable physical variables, such as the surface and bulk solid-phase concentration. To well reflect battery degradation, three key aging factors including the loss of lithium ions, loss of active materials, and resistance increment, are simultaneously identified, leading to an appreciable precision improvement of SOC estimation online particular for aged cells. Finally, extensive verification experiments are carried out over the cell's lifespan. The results demonstrate the performance of the proposed SOC/SOH co-estimation scheme.

**[7] Yuanliang Fan; Jing Wu; Zitao Chen; Han Wu; Jianye Huang, "Data-driven state-of-charge estimation of lithium-ion batteries", International Conference on Power Electronics Systems and Application, February, 2021.**

Accurate estimation of state-of-charge (SOC) is essential for battery management system. This paper proposes a data-driven method for estimating the SOC of lithium-ion batteries. Long and short-term memory (LSTM) neural networks are designed for estimation of SOC, in which the currents and temperatures of the battery are defined as the inputs of the neural network, while the output of the neural network is considered as the SOC.

Basing on these input and output data, the neural network is trained, which is further used as a model for estimating the SOC. The simulation results verify that the proposed method can meet the accuracy requirements about estimation of the SOC for battery management system.

## III.. PROPOSED METHOD

To estimate battery aging in a Battery Management System (BMS) using deep learning and machine learning algorithms, one popular approach is to utilize Long Short-Term Memory (LSTM) networks. LSTM is a type of recurrent neural network (RNN) that can capture long-term dependencies in sequential data. Here's a proposed method using LSTM:

- Data Collection: Gather a dataset containing battery parameters (voltage, current, temperature, SoC, cycle count) and corresponding aging information. This data can be collected from battery testing or monitoring systems.
- Sequence Generation: Transform the collected data into sequential data by organizing it into fixed-length sequences. For example, you can create sequences of a fixed number of data points, where each sequence represents a time window of battery measurements.
- Feature Extraction: Extract relevant features from the sequential data. These features can include statistical measures, time-domain features, or frequency-domain features. Feature engineering techniques can be applied to enhance the representation of the battery behavior within each sequence.
- Data Preprocessing: Normalize or scale the features to ensure they have comparable ranges. Split the dataset into training and testing sets, typically using a ratio like 80:20 or 70:30, respectively.
- LSTM Model Design: Design an LSTM-based architecture for battery aging estimation. The LSTM network can take the sequential data as input and learn to model the dependencies and patterns within the battery measurements.
- Model Training: Train the LSTM model using the training set. During training, the model learns to predict the battery aging based on the input sequences. The parameters of the LSTM network, such as the number of LSTM layers, hidden units, and learning rate, need to be tuned.
- Model Evaluation: Evaluate the trained LSTM model using the testing set. Use performance metrics such as mean squared error (MSE) or mean absolute error (MAE) to assess the model's accuracy in predicting battery aging.
- Fine-tuning and Optimization: Fine-tune the LSTM model using techniques like regularization, dropout, or gradient clipping to prevent overfitting and improve generalization. Hyperparameter tuning can also be performed to optimize the model's performance.
- Comparison with Other Models: Compare the performance of the LSTM-based model with other machine learning algorithms such as SVM or random forest. This analysis helps determine the effectiveness of the LSTM approach in battery aging estimation.
- Deployment and Monitoring: Once satisfied with the model's performance, deploy it in a real-time BMS environment to estimate battery aging. Continuously monitor the system's performance and periodically retrain the model with updated data to adapt to changing battery behavior.

It's important to note that this is a high-level overview, and the specific implementation details may vary based on your dataset and requirements. Experimentation and domain expertise are necessary to fine-tune the approach for your specific battery system. Additionally, additional techniques such as attention mechanisms or ensembling models can be explored to further improve the accuracy of battery aging estimation.

Fig.1 depicts the flow diagram of the proposed system where the data is split into training and testing dataset.

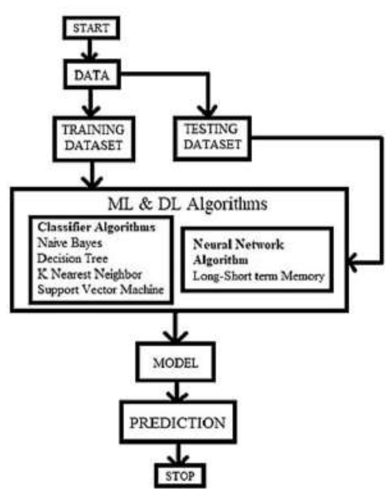


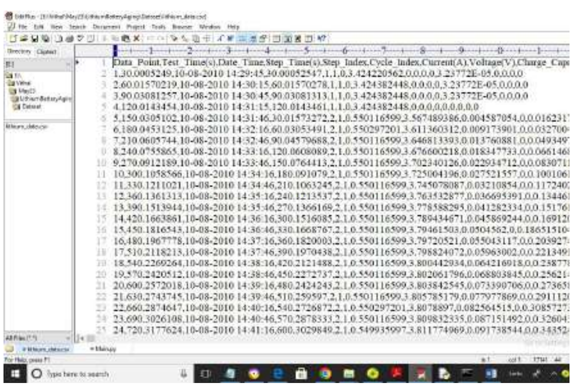

Fig.1. Flow Diagram of the proposed model

The training data is fed into ML and DL algorithms. The data is split as 80% and 20% of training and test data. The training is carried out with the machine learning and deep learning algorithm. The test data is then feedback into the algorithms to obtain the model. Once the model is obtained the prediction is performed based on the prediction formula by retraining the selected model.

## IV. RESULT

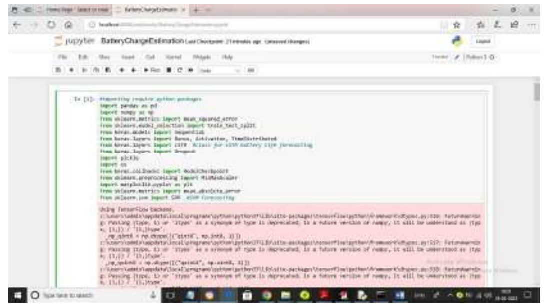
In this project we are estimating charge/aging/battery life of lithium batteries by employing deep learning algorithm called LSTM (long short term memory) and then compare its performance with machine learning algorithm called SVM. Both algorithm performance is evaluated in terms of Mean Square Error (MSE) and Mean Absolute Error (MAE). MSE or MAE refers to difference between original and predicted values so the lower the difference the better is the algorithm.

In both algorithm LSTM is giving less MSE and MAE values compare to SVM. To train both algorithm we have used lithium charge and discharge batter dataset from KAGGLE and below screen showing dataset details

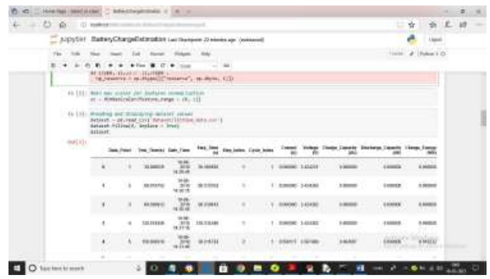


In above dataset screen first row contains dataset column names and remaining rows contains dataset values and by using above dataset values we will train and test SVM and LSTM algorithms performance.

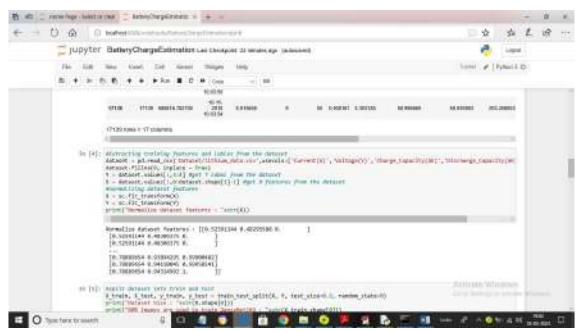
We have coded this project using JUPYTER notebook and below are the code and output screens with blue colour comments



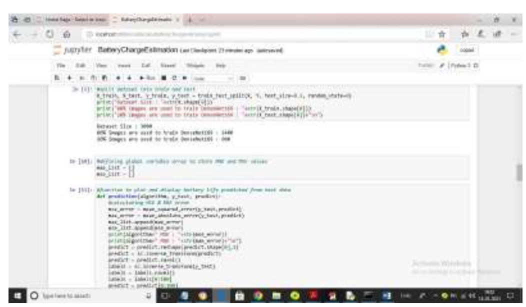
In above screen we are loading require packages and classes



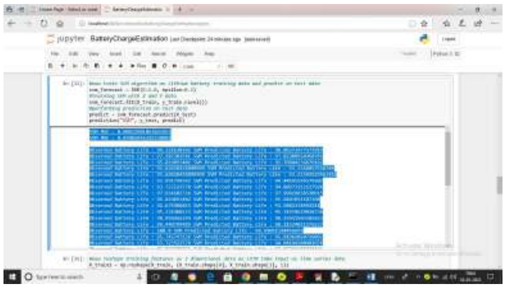
In above screen we are defining class to normalize dataset values and then reading and displaying dataset details



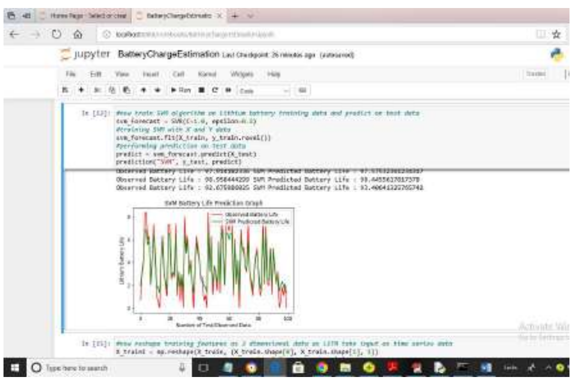
In above screen we are extracting X and Y features from the dataset and then normalizing those values using MINMAX scaler



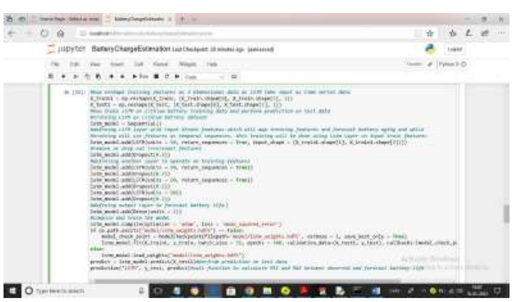
In above screen we are splitting dataset into train and test where application using 80% dataset values for training and 20% for testing and then defining function to calculate MSE, MAE values



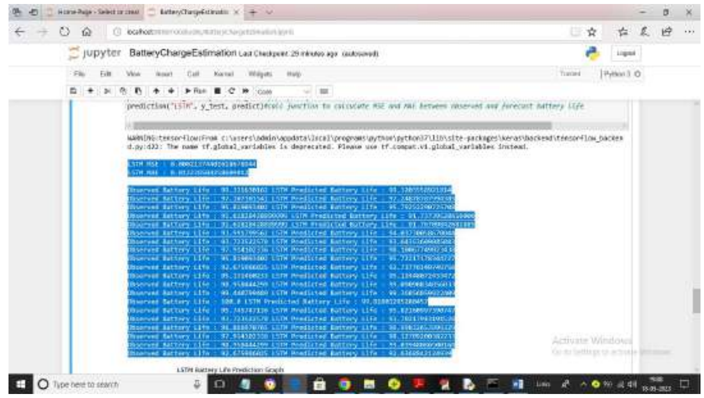
In above screen we are training SVM algorithm on training data and then performing prediction on test data and we can see SVM output in blue colour lines where first two lines displaying SVM MSE and MSE values and then displaying original test data battery life and SVM predicted battery life and in below screen we can see original and predicted life in graphical format



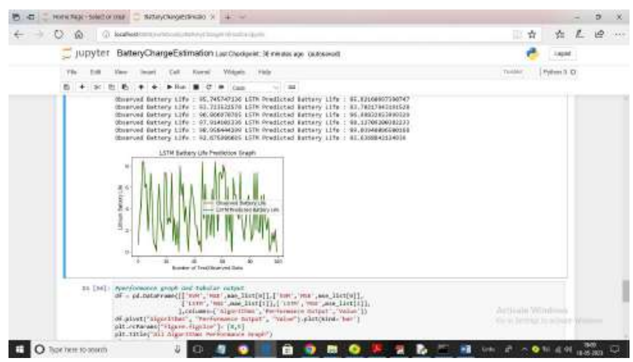
In above graph x-axis represents NUMBER of TEST data and y-axis represents battery life. Red line represents original battery life and green line represents SVM predicted battery life and we can see both lines are overlapping with little gap so we can say SVM prediction is good but not accurate as both lines must fully overlap to show close difference between original and predicted values



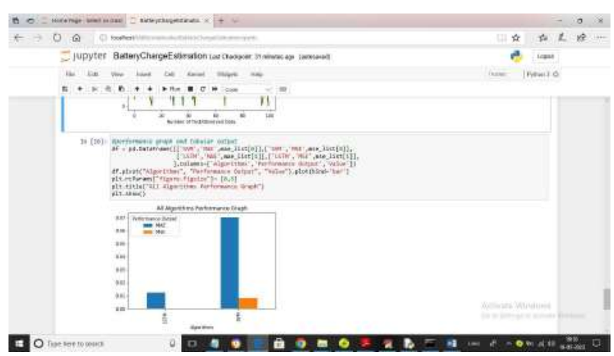
In above screen we are showing code for LSTM algorithm and after executing above block will get below output



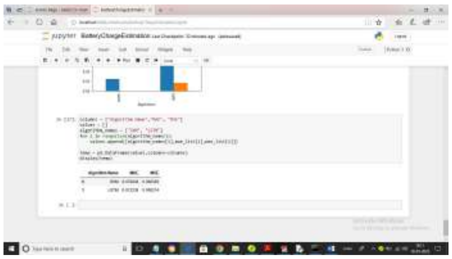
In above screen if first two blue lines we can see LSTM MSE and MAE error which is lower compare to SVM and in other lines we can see both original and LSTM predicted batter life is very close with minute difference and below is the graph of LSTM prediction



In above graph we can see both original battery life and LSTM predicted battery life is fully overlapping without any gap so we can say LSTM is accurate in predicting battery life



In above graph we are showing SVM and LSTM graph on MSE and MSE values and in both algorithms LSTM has got less error of MSE and MAE



In above screen we can see both algorithms performance in tabular format and above table clearly shows which algorithm is best in battery life prediction

## V. CONCLUSION

In this paper the battery management system to predict the battery capacity was developed and the method was implemented using different machine learning and deep learning algorithms. The fourclassification metrics such as accuracy, precision, recall and F1-score are calculated and the naïve bayes algorithm is found to be best to predict aging of the battery by producing high accuracy of 88% while analysing real-time data. This method will allow us to predict the battery life and helps the driver to estimate the driving range of the vehicle. The real-time implementation of this technique will be highly applicable for the estimation of lithium-ion battery capacity in electric vehicles.

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