

AI Assisted SoC Prediction using Real-World Driving Patterns
in Electric Vehicles to Improve Battery Efficiency

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering Degree in Automobile Engineering

By

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INSTITUTE OF SCIENCE AND TECHNOLOGY

(DEEMED TO BE UNIVERSITY)

Accredited with Grade "A" by NAAC

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the Bonafide work of **RAMESH KUMAR.P (Reg.No39860017)**, **SURYA CHANDRA RAO (Reg.No39860010)** who carried out the project entitled “**AI Assisted SoC Prediction using Real-World Driving Patterns in Electric Vehicles to Improve Battery Efficiency**” under my supervision from November 2022 to April 2023.

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DATE: 26-04-2023

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ABSTRACT

As environmental degradation and oil prices continue to rise, one crucial element of electric vehicles (EVs) that are expected to enter the transportation market is the energy storage system. The majority of electric vehicles (EVs) rely on lithium-ion batteries for electricity. Rechargeable lithium-ion batteries are frequently used to power portable electronics, electric vehicles (EVs), and hybrid electric vehicles (powered both by fuel and electricity). With time, the battery's performance gradually deteriorates, which might be disastrous. Even though current methods for data-driven fault prediction perform well for the precise processes they were trained on, they frequently struggle to adapt to changes. in operational or environmental conditions, for instance. This study uses continuous learning, which offers flexibility and enables the automated adaptation of previously learned information to new tasks, to address this issue. Continuous learning is a lifelong process of learning and evolution based on an ever-increasing input of data while maintaining prior knowledge. To make SoC, a battery dataset is used. Accurate SoC calculation may minimize unanticipated system outages and keeps the battery from being overcharged and over discharged, which might harm the internal structure of batteries permanently. In order to assess if the battery is good or defective, this project gives information like the State of Charge (SoC) of the battery. Finally, the result of SoC prediction using real-world driving patterns in Electric vehicles to improve battery Efficiency is 78.02525.

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CHAPTER 1

INTRODUCTION

1.1 GENERAL INTRODUCTION

Fully electric batteries, also known as traction batteries, are used to drive the electric motors of lead acid electric vehicles (BEVs) and hybrid electric vehicles (HEV). Li-ion cells make up the majority of these batteries, which are recyclable (secondary). High ampere-hour (or kilowatt-hour) capacity are what these packs were designed with in consideration. Significant packs set themselves out from beginning, lights, and ignition (SLI) batteries since they are designed to deliver electricity for a longer period. Smaller, lighter batteries are recommended since those who boost the driver's efficiency while lowering unsprung mass. Cells for autonomous vehicles can be identified by their reasonably high strength ratio, calorific value, and capacity factor. Most today's lithium batteries have vastly lower specific energies than petroleum products, which frequently affects the cars' potential all-electric endurance. Due to their high battery capacity in relation to their weight, lithium batteries and lithium polymer batteries are the most popular battery types in contemporary electric cars. Lead-acid ("flooded", "deep-cycle," and "valve-regulated lead acid"), nickel-cadmium, buffalo nickel nickel-metal hydride, and, less frequently, zinc-air and sodium nickel chloride ("zebra") batteries are other types of battery packs used in electric cars. Batteries' electrical capacity, or "electric charge," is measured in ampere hours or coulombs, with the overall energy being expressed in kilowatt-hours. Demands have fuelled advancements in lithium-ion renewable technology since the late 1990s. from mobile platforms, laptop computers, power tools, and portable electronics. The demand for BEVs and HEVs has profited from these increases in efficiency and power density. In contrast to traditional power storage methods like metals, lithium-ion batteries enable daily drain and replenishment at any level of charge. The energy storage for a BEV or HEV makes up a sizable amount of the price. As of December 2019, the cost of batteries for electric cars has dropped 87% per kilowatt-hour since 2010. As of 2018, a variety of automotive categories provide automobiles with an all-electric range of more than 250 miles (400 km), such as the Tesla Model S. In terms of expenses,

the cost of running a BEV on electricity is a fuel costs are a tiny percentage of those for comparable engines with combustion, indicating greater energy efficiency.

1.2 TECHNOLOGIES USED

1.2.1 Machine Learning

The scientific discipline of algorithms enables machines to acquire knowledge without explicit programming. Some of the most intriguing breakthroughs that has ever been developed is machine learning. The capacity for instruction is what, as the name suggests, gives the computer a more human-like quality. Nowadays, reinforcement learning is being actively employed, maybe in a lot more areas than one might think.

Algorithmic analytics, which concentrates on developing judgments using machines, is closely connected to a subgroup of computer vision, although not all reinforcement learning is statistics teaching. The discipline of machine learning benefits from the tools, theory, and application fields that come from the research of mathematical programming. Data mining is a related area of research that focuses on unlabelled data for exploratory data analysis. Deep learning is also known as predictive when it comes to solving business problems. Machine learning is the technique by which computers figure out how to perform duties something without being specifically taught to do so. Algorithms use available data to learn in order to do certain jobs. For straightforward jobs given to computers, Techniques that teach the machine how to do each process required to solve the problem at hand may be created; the machine does not need to be trained. Such a person could find it challenging to practically create the necessary strategies for ever-more demanding occupations. In practise, it could be more advantageous to have the computer develop its own process than to have human programmers specify each essential step.

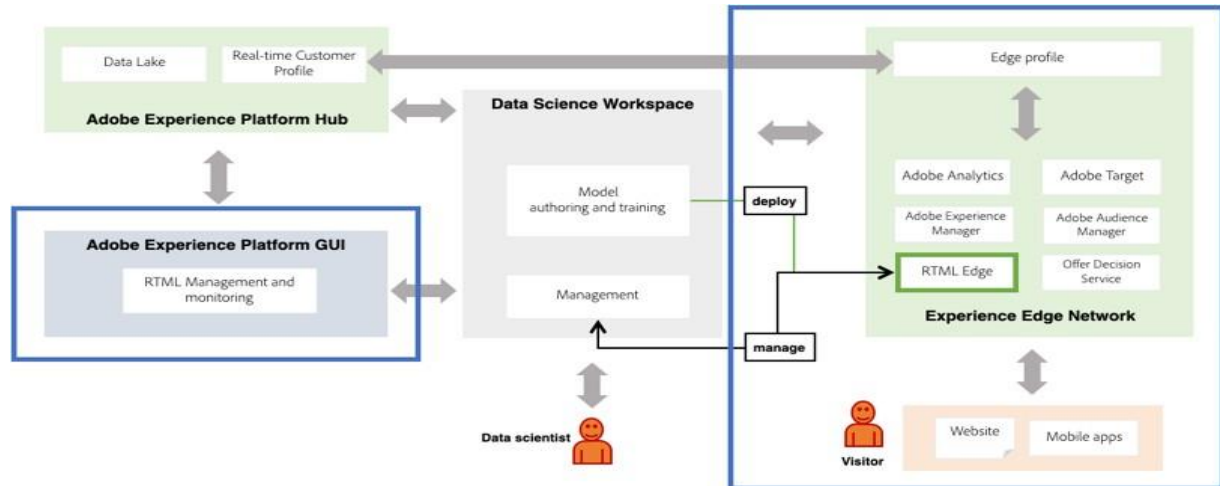


Fig1.1: Architecture for learning algorithms

1.2.2 Machine learning approaches

According to the type of "message" or "responses" that the educational model has access to, In principle, systems based on machine learning categorised into three major categories.

1.2.3 Supervised learning

Supervised learning is a type of machine learning that involves a teacher or supervisor providing labelled data to train the machine. This involves using data that is already labelled with the correct answer to train the machine. Once the machine has been trained, it can then analyse new sets of data and provide accurate outcomes based on the previously labelled data. Essentially, the machine learns from the labelled data to accurately classify or predict outcomes for new data. It is an effective method for solving a wide range of problems and is widely used in various applications. However, it is important to ensure that the training data used for supervised learning is accurate and unbiased to avoid producing incorrect outcomes.

Supervised learning is a type of machine learning in which an algorithm is trained to learn a mapping function that connects input variables (x) to output variables (Y). The goal is to develop an accurate mapping function that can predict output variables based on input variables. During the training process, the algorithm is provided with a set of

labelled input/output examples to learn from, and it adjusts its parameters until it can accurately predict output variables for new input variables. This type of learning is widely used in various applications, such as image recognition, speech recognition, and natural language processing. It is an essential technique for developing predictive models that can solve a wide range of problems.

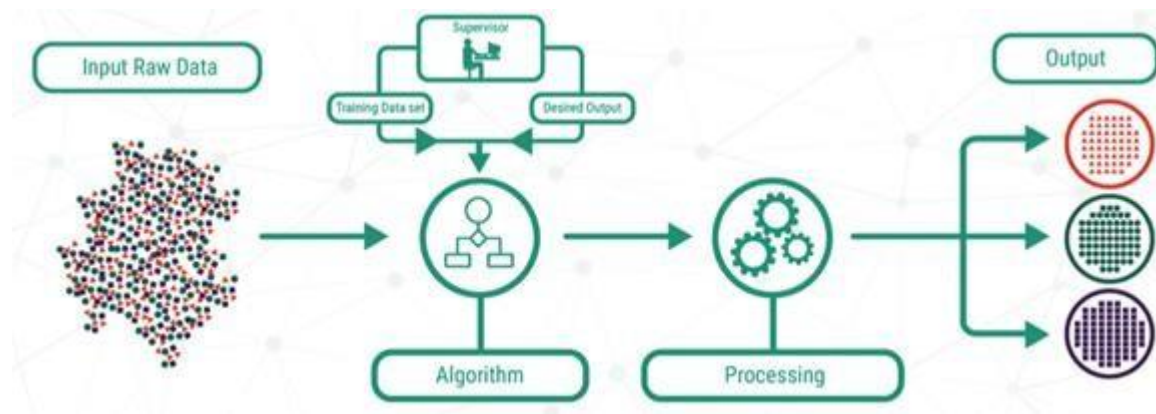


Fig1.2: Supervised learning flowchart

1.2.4 Unsupervised learning

Unsupervised learning is a type of machine learning in which an algorithm is trained using data that is not labelled or classified. In this approach, the algorithm is given unstructured data and is expected to identify patterns, similarities, and differences in the data without being directed by a teacher or pre-defined categories.

Unlike supervised learning, where the machine is given labelled data and taught to classify it, unsupervised learning requires the machine to find structure in the unlabelled data by itself. Essentially, it involves the algorithm exploring the data and identifying any inherent relationships or groupings that may exist within it[1].

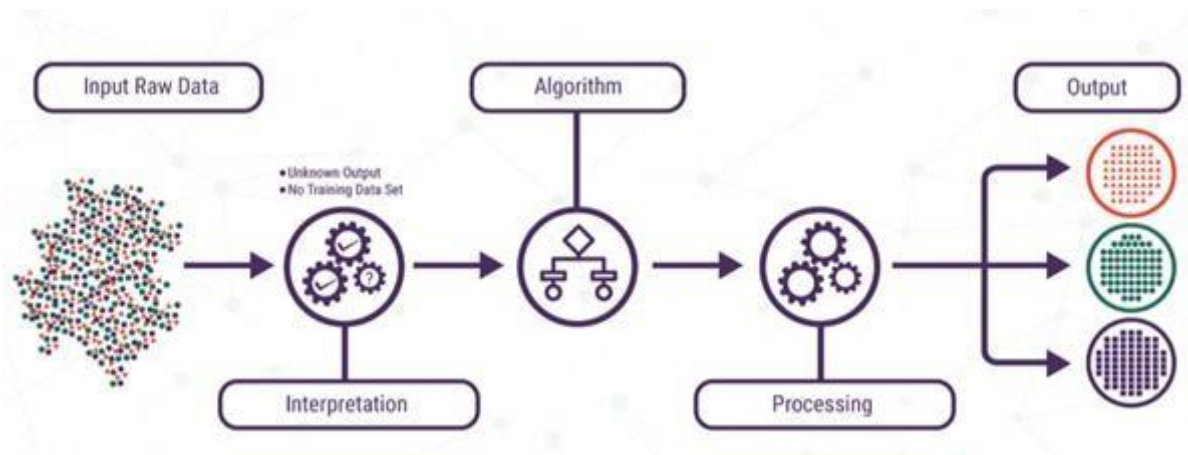


Fig1.3: Unsupervised learning flowchart

1.2.5 Reinforcement learning

A computer program is designed to achieve a specific goal while interacting with a constantly changing environment. During its navigation of the problem space, the program is given feedback in the form of rewards, which it seeks to maximize. In other words, the program receives reinforcement based on its actions and adjusts its behaviour accordingly in order to achieve the desired outcome. This process involves ongoing interaction between the program and the environment, with the goal of optimizing performance and achieving success in the given task[2].



Fig4: Reinforcement learning flowchart.

1.3 OBJECTIVES OF THE PROJECT

- To develop a model to estimate the status of the battery using continual learning.
- To develop a user-friendly model to improve battery life and performance.

1.4 SCOPE OF THE PROJECT

- It can be used in battery industries.
- It can be used in electric vehicles.

CHAPTER - 2

LITERATURE SURVEY

2.1 INTRODUCTION

The results of a poll on battery capacity optimization are detailed below, along with a summary of the most often used methods at the moment.

2.2 LITERATURE SURVEY

2.2.1 An intelligent prediction method for estimating state of charge (SOC) consumption in electric vehicles, which employs continual reinforcement learning based on real-world data.

The growing adoption of electric vehicles (EVs) has led to several challenges, particularly in the control and forecasting of charge status (SOC) during long-range trips that involve varying altitudes. This issue requires a more efficient approach to energy consumption and vehicle recharge planning. To address this challenge, a new SOC estimate method relies on meta-experience replay (MER) with reservoir and persistent learning sampling is proposed in this paper. The algorithm combines the Reptile meta-learning approach with experience replay to improve the stability of reinforcement learning. The algorithm considers various critical factors for accurate SOC prediction factors include speed, distance travelled, and route altimetry consumed and regenerated battery capacity. To make the trip satellite data information less dimensional, a modified principal components analysis technique is applied. The experimental results indicate that the proposed algorithm provides a productive SOC estimate, and it continually learns and improves its performance during the trip[3].

Pros:

calculation of the SOC levels which is effective.

Cons:

Low accuracy rate in real time data.

2.2.2 An approach that combines data-driven techniques to estimate the state-of-health and predict the remaining useful-life of lithium-ion batteries.

Lithium-ion (Li-ion) batteries must have a forecast of their state-of-health (SOH) and remaining-useful-life (RUL) in order to operate at peak efficiency and remain healthy. Although, achieving high accuracy in battery health prediction remains a significant challenge. In this study, the authors propose a novel hybrid composite computation approach for precise Li-ion battery SOH and RUL prediction.

To determine the natural connection among the selected health indicator and practical SOH, two random learning algorithms are integrated. The nonlinear autoregressive (NAR) structure is designed based on the estimated SOH to reduce the prediction error in RUL. Additionally, the authors propose a Bootstrap-based uncertainty management method the RUL's forecast range to be evaluated objectively.

The suggested approach demonstrates maximum precision in predicting the SOH and RUL of batteries, as evidenced by test results on two publicly available datasets. It is also due to the lack of extra hardware requirements or service interruptions it is suited for online real situations like energy storage systems and electric automobiles[4].

Pros:

Maintenance of this system is easy.

Cons:

Implementing this method in real time is tedious.

2.2.3 A method for predicting the health of lithium-ion batteries used in electric vehicles, which relies on data from an actual battery management system.

In this paper, a slowly moving technique is proposed to estimate the condition of battery packs and to anticipate their remaining usable life. The cell's partial charge voltage curve yields the health indication. A quadratic ageing model based on capacity data inside a moving window is used to anticipate the capacitors estimated usable life, and a Monte

Carlo approach is utilised to create prediction uncertainty. A real battery management system used in electric cars use the capacity estimate and remaining usable life forecast methodologies. We gather and use experimental data from cells that were tested at ambient temperature (25 °C and 40 °C) and current rates (1C and 2C). According to the implementation findings, the capacity estimation errors were no more than 1.5%. The residual usable life estimations' root mean square errors have been within 20 cycles. during the last 20% of battery lifetime, and the major coverage of the 95% error bars is 20 periods[5].

Pros:

The methodologies for capacity estimate and RUL forecasting were used in an actual BMS. The purpose was to verify their performance.

Cons:

Locating the optimal parameter sets for PF-based and machine learning methods is generally challenging. It is a difficult task.

2.2.4 The creation of a model to assess the degradation of lithium-ion batteries for the purpose of evaluating their lifespan.

Our study suggests a semi-empirical approach for calculating the real value of ageing. lithium-ion batteries in irregular cycling operations, which is crucial in the design and management of storing energy. The prototype pel combines basic findings and battery deterioration hypotheses from aging test results and can be adjusted for different types of cells. The model coefficients can be tuned a primary season approach is used based on data from the vendor. included to identify stress cycles from irregular operations. The model's effectiveness is demonstrated through an assessment of the degradation incurred by a battery energy storage system giving PJM regulating market synchronous generators[6].

Pros:

A simulation of approximate pack deterioration was proposed for estimating volume deterioration in erratic power delivery. The model was demonstrated to be useful

for BES applications.

Cons:

Accurate modelling requires careful design of experiments to isolate the effects of inter-related factors.

2.2.5 A method that combines modelling and data to estimate the state of health and predict the remaining useful life of a Li-Ion battery.

Due to their nonlinear and time-varying deterioration, Li-ion batteries in electric cars are not predictable in terms of their condition and remaining usable life. This article suggests a way for fusing model data. Due to their nonlinear and time-varying deterioration, Li-ion batteries in electric cars are difficult to predict in terms of their condition and future usable life. This article suggests a way for fusing application model. that combines a data-driven, dynamic performance of power deterioration with a particle filter to estimate state-of-health and predict remaining useful life. The degradation model uses Norton equivalent model of the current battery internal impedance and polarization resistance are used as response variable, with capability deterioration acting as the parameter value. Investigations on power ageing are carried out to validate the proposed method, showing its accuracy and robustness in estimating state-of-health and predicting enduring usefulness at ambient temperature[7].

Pros:

The degradation model can be retrained to suit various copper elements in those other reactors.

This allows for the adaptation of the format to various battery types.

Thus, the model can be applied to batteries other than Li-ion batteries.

Cons:

The present degradation approach does not offer improved and quicker estimation of state-of-health.

2.2.6 How to choose between optimizing an electric vehicle's battery life or its efficiency when using a battery or supercapacitor.

This article presents a new energy management technique for a vehicle using batteries and supercapacitors that can be tuned to achieve different objectives. The study investigates two potential goals for adding a supercapacitor pack to an experimental vehicle that uses lead-acid cells, enhancing performance and endurance or lowering peak waves to prolong battery pack. The study compares the benefits of hybridization to those obtained by increasing the battery pack's size by a similar mass as the supercapacitors. Factors such as regenerative braking and supercapacitor characteristics are considered, and the study concludes that while supercapacitors can effectively reduce peak battery currents, their impact on range extension is limited. To make supercapacitors cost-effective for the test vehicle at current prices, A minimum 50% increase in storage lasts is necessary[8].

Pros:

The drive efficiency is enhanced, leading to an increased driving range.

Cons:

The financial viability of adding a supercapacitor pack to a battery-powered vehicle requires a battery life extension of at least 50%.

2.2.7 How long can LFP cells last in reuse applications after their first use.

The financial viability of adding a supercapacitor pack to a battery-powered vehicle requires a battery life extension of at least 50%.The growing use of battery storage applications in electric vehicles and grid storage has led to a large used battery market, which can be recycled or reused in second-life applications. The challenge is to accurately estimate the remaining useful life (RUL) of a battery for reuse and to predict the number of second-life cycles it can support. This study proposes health indicators (HIs) and effective algorithms for RUL estimation and classification, including regularized logistic regression (RLR), MLR for many variables and MLP for layered perceptron's (MLP). Additionally, a multiple expert system combining these techniques is proposed for advanced solutions. The algorithms are assessed using a current lithium iron phosphate

(LFP) data set from the Toyota Research Institute, and the findings for the estimate of RUL rounds with minimal errors are good. and the prediction of capacity evolution.[9]

Pros:

The article suggested straightforward yet efficient algorithms to categorize used cells into "Short RUL" and "High RUL" groups with reasonable accuracy.

Cons:

While this approach is applicable for determining RUL of any cell chemistry and type, training the algorithms would require a specific dataset for that particular type of cell. This would enable the algorithms to learn and make accurate predictions. By using different health indicators and classification and regression techniques, this method can be used to estimate the RUL of various batteries, including those used in electric vehicles and grid storage.

2.2.8 Electric Vehicle Battery Aging Management with Active Adaptation

Electric vehicle cost is greatly influenced by the battery pack, so ensuring that the battery pack lasts as long as the vehicle is crucial. To address this, a battery aging management framework has been proposed to control Maximum battery loss while preserving passable driving characteristics, such as range, recharge time, and drivability. The methodology creates a multi-objective, multi-input optimisation problem by maximising the maximal state of charge and the charge depth. That is solved online using an iterative algorithm. A self-learned, Markov-chain-based driving style model is incorporated into the optimisation technique to make the approach adaptable. Many simulations demonstrate that the suggested method performs better than an offline benchmark policy and a simplistic methodology over a 200,000 km lifespan[10].

Pros:

The proposed online approach can adapt to changes in the driver's behaviour, making it a significant advantage.

Cons:

The proposed framework did not address situations where there are uncertainties in the model and non-linear fading.

2.2.9 Estimating How Much Charge is Left in Lithium-Ion Batteries Using a Proportional-Integral Observer

The accurate estimation of state-of-charge (SOC) for lithium-ion (Li-ion) batteries is crucial for the development of electric drive vehicles (EDVs). In this study, For the purpose of calculating the SOC of Li-ion cells in EDVs, a proportional-integral (PI) observer is suggested. By analysing popular model-based SOC estimation methods. The convergence of the PI observer with model errors is verified, and the proposed method is validated using a simple RC battery model and an experimental battery test bench. Results show that the PI-based SOC estimation method is accurate, with errors during the urban dynamometer driving schedule (UDDS) drive cycle including both recognized and hypothetical beginning SOC situations, inside that 2% inaccuracy zone[11].

Pros:

The proposed SOC evaluation strategy is based on a PI observer, which has a straightforward design and implementation. It has been validated through experiments and found to be accurate within a 2% error band.

Cons:

The SOC estimation error is small when using the proposed PI observer, even with a simple battery model, due to its compensation for modelling errors and uncertainties. This makes it a valuable tool for estimating the SOC in lithium-ion batteries in EDVs. Experimental validation using the UDDS drive cycle showed that the PI-based SOC estimation results were generally within a 2% error band for both known and unknown initial SOC cases.

2.2.10 How to monitor the safety of lithium-ion batteries with impedance-based management.

The implementation of multifrequency impedance measurements for individual cell monitoring in lithium-ion batteries has been sluggish as a result of growing size and power needs. A low-power multifrequency impedance-based battery management solution, nevertheless, has been developed for multi-cell batteries with varying capacities. This system ensures battery safety and efficiency by identifying and acting on emerging mismatches and abnormalities in individual cells, including those caused by over-discharge, over-charge, internal and external shorts, and calendar aging. Compared to conventional BMS, the impedance based BMS continuously tracks and identifies changes in each cell's internal state in real-time during device rest, discharge, and recharging[12].

Pros:

A low-power BMS was presented using a multi-frequency impedance meter for checking on solitary rechargeable battery cells. It tracks and acts on emerging mutations and other problems in every cell ensuring battery safety and efficiency. This BMS is more effective than conventional BMS that merely keep an eye on the heat transfer and cell energies.

Cons:

This procedure' implementation is laborious and time-consuming.

2.2.11 The Effect of Ageing on the Technical Feasibility of Reusing Batteries

The reuse of retired electric vehicle batteries is suggested as a way to reduce electric vehicle costs. While the economic feasibility of this solution has been analysed in literature and demonstrated by car manufacturers, little is known about the way that second-hand batteries degrade. This study aims to assess the effects of State of Health and ageing history on second life battery performance in two separate topics. Results indicate that the first life battery's ageing history strongly influences the depreciation and functionality of the rechargeable battery pack, emphasizing the importance of proper ensuring the project integration of battery new chance through surveillance and pack management[13].

Pros:

The article outlines a methodology for evaluating the performance and degradation of Li-ion batteries in their second life. It emphasizes the importance of monitoring and battery selection in ensuring the viability of this solution.

Cons:

This method only proved for the particular Li-ion cell.

2.2.12 The Art of Battery Management and Diagnosis for Smart Grids

This article introduces an innovative battery management system (BMS) that individually monitors and manages each battery in a series array. The BMS continuously measures Each car's battery temperature, existing, and energy are used to determine its own state of charge (SoC) and C-rates, allowing for unique charging profiles and advanced diagnostics. Pulsed charging is used with an independent battery circuit for SoC rebalancing, a steady supply to the load is maintained. A monodirectional DC-DC amplifier keeps the level of the output voltage stable. until the problem is corrected. The BMS is done previously with various loads, especially strong burst tons and tons[14].

Pros:

The system's cost is reduced by eliminating the need for a bi-directional converter. Charging the batteries from a low voltage DC source also contributes to the system's affordability. The system is versatile and can be applied in various situations.

Cons:

The BMS that was created can monitor voltage and SoC for each battery. The monitoring system is limited to these specific functions. The battery array can be effectively managed through this BMS.

2.2.13 How to Use Different Kinds of Batteries to Reduce Diesel Generators in Renewable Microgrid Energy Management

The use of solar photovoltaic (PV) to assist microgrid operators in reducing costs can be challenging because load needs are uncertain and PV power supply is sporadic.

To deal with this, a battery energy management system (BEMS) has been proposed for microgrids that use solar energy and diesel power (DGs) as their primary sources of electricity. The BEMS manages multiple types of batteries to reduce DGs' operating hours and takes into account battery characteristics when making charging and discharging decisions to extend battery life. Real-world data is used to verify the effectiveness of the BEMS, and numerical simulations show that it can reduce DGs operating hours, decrease By regulating the charging and discharging pace, you can minimise PV power variations and lengthen standby time[15].

Pros:

The focus is on advocating the use of batteries instead of relying on diesel generators.

Cons:

The execution of this project demands a significant amount of both physical space and financial resources.

2.2.14 Managing Battery Heat in Real Time for Hybrid Electric Vehicles that are Connected and Automated with an Iterative Approach

Connected and automated hybrid electric vehicles (CAHEVs) have emerged as a promising solution for the impact on current mobility of ability to reduce emissions, improve fuel economy, reduce traffic, and improve safety. Nevertheless, the environmental regulation of the power supply (BTM) in CAHEVs poses a significant challenge since lithium-ion batteries are highly sensitive to temperature changes. Therefore, an energy efficient and practical BTM strategy is essential to enhance battery operating temperature and conserve energy. To address this, this study implements dynamic programming (DP) for a BTM system in CAHEVs, which aims to achieve optimal cooling/heating energy savings for batteries. To improve the real-time capacity, an iterative technique is suggested to incrementally strategy the optimal monitoring system in a multidimensional search space. The suggested iterative DP technique utilises combined CAHEV and future road knowledge. utilising a model predictive control

approach to enhance system effectiveness and power efficiency. The proposed BTM strategy is validated using hardware-in-the-loop (HIL) using a Toyota Prius PHEV model as a foundation, using the UDDS and WLTC driving cycles. The outcomes show that the suggested BTM technique is both practical and successful, leading to a tremendous reduction in BTM energy consumption[16].

Pros:

The proposed approach for enhancing power productivity and system reliability involves a BTM strategy based on dynamic programming (DP) to determine the global optimum.

Cons:

Efficiency of this system is low.

2.2.15 A Reliable Model for Battery Energy Storage Charging

Future electric utilities depend significantly on stored energy from batteries., and it is necessary to integrate its operation model into the latest financial concepts, required compliance, and market settling. Yet, existing models that depict how large-scale battery energy storage operates systems are often inaccurate because they do not consider the dependency of the charging power on the battery's state of energy. This can lead to significant financial losses for market players who are unable to provide the anticipated supplies and/or adhere to their ahead-of-time schedule. This work attempts to resolve the problem and close the gap across extra energy operating models and low-level recharging restrictions. proposes a method for measuring the dependence of battery discharge in a lab ability on its state of energy, which can be applied to any lithium polymer batteries and type. The research also develops a precise linear battery charging model that closely resembles the limitations of actual lithium ion. To assess the practicality of the suggested model in real-world circumstances, it is contrasted to models that are often used in academia, and the battery operating schedules provided all models are empirically contrasted with one another. acquired findings[17].

Pros:

A laboratory procedure is proposed in this paper to accurately determine the Recharging rate is dependent on the battery's energy level.

Cons:

This method requires lot of calculation and time consuming.

2.3 INFERENCE FROM LITERATURE SURVEY

Based on the referenced papers, it can be inferred that the major drawbacks are:

1. The accuracy of RUL prognostics is significantly influenced by a variety of uncertain factors.
2. Implementing this method in real time is tedious.
3. The existing method only proved for the particular Li-ion cell.
4. The existing method requires lot of calculation and time consuming.
5. Efficiency of the system is low.

CHAPTER - 3

Aim and scope of the present investigation.

3.1 EXISTING SYSTEM

The rapid adoption of electric vehicles (EVs) brings up several challenges such as managing and predicting the state of charge (SOC) during long-range trips with varying altitude profiles, which increases energy consumption and the need for vehicle recharging. In this study, a novel SOC estimation algorithm is proposed that employs continuous learning and meta experience replay (MER) with a basic example. The algorithm ophidian meta-learning is combined, and experience replay techniques to stabilize the reinforcement learning process. The proposed approach takes into account important factors such as speed, travel time, route altimetry, consumed battery capacity, and regenerated battery capacity to predict the SOC in EVs. The path derived from satellite data's complexity is decreased using a revised network-based analysis. While the vehicle traverses the routes, the experimental findings show an effective SOC estimate and rising expertise agreement.

3.2 DISADVANTAGES OF EXISTING SYSTEM

1. MAE and RSME obtained after the training is less for accurate prediction
2. Virtual data are integrated in between which will affect the actual prediction.
3. Only one kind of vehicle has been focused to perform the estimation whereas the battery condition varies with different vehicle suspension systems and its load.

3.3 PROPOSED SYSTEM

The goal of this project is to utilize Continual Learning, which is a lifelong learning technique that continuously builds on previously acquired knowledge while adapting to new tasks. To achieve this, appropriate datasets will be collected from research websites and pre-processed using the pr inciple component analysis technique. The battery dataset will then be used to generate State of Charge (SoC) estimates. Machine learning algorithms such as XGB regression will be employed for training, validating and evaluating the datasets. The accurate estimation of SoC is crucial in preventing

unpredictable system interruptions and avoiding overcharging or discharging of batteries, which may result in permanent damage. Hence, this project aims to provide valuable information regarding the status of batteries by providing reliable SoC estimates.

3.4 ADVANTANGES OF PROPOSED SYSTEM

1. Cheap and Effective Solution for monitoring the battery status.
2. Generic system development suitable for all kind of vehicles
3. Easy to implement in real life.
4. Maintenance of this system is easy.

3.5 SYSTEM ARCHITECTURE

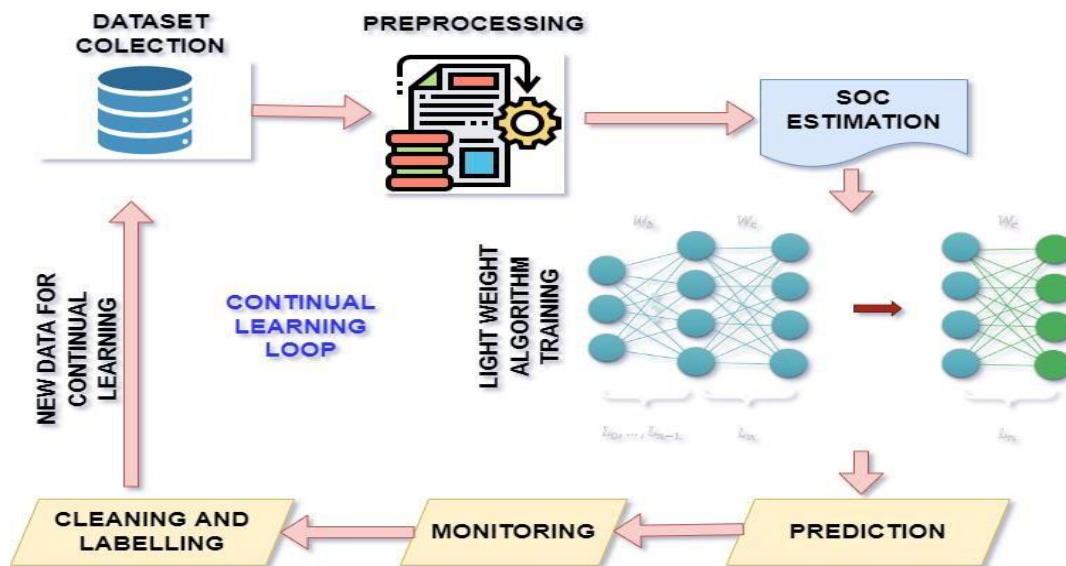


Fig.3.1: Proposed System Architecture

3.6 WORKING

The aim of this project is to predict the SoC estimation of batteries through the application of machine learning algorithms. The initial step is collecting datasets from relevant research websites that include all required parameters. Next, the dataset is pre-processed using the principal component analysis technique which reduces the

dimensionality of the data and increases its interpretability. The data is then trained using machine learning algorithms such as XGB regression which is a free software module that offers a reliable implementation of the gradient boosting method. After applying the machine learning algorithm, training is done using the training dataset, and validation of the model is done using the test dataset. Validation of the model is necessary for assessing the accuracy of the predictions made by the trained model. The evaluation of the machine learning model is also done to test its performance in various circumstances. The SoC is estimated using a battery dataset to prevent overcharging and discharging which may damage the internal structure of the batteries. Finally, the continual learning method is applied to decrease the error rate and enhance the prediction accuracy of each cycle of training. This project provides an accurate estimation of the State of Charge (SoC) of batteries.

CHAPTER – 4

METHODS AND ALGORITHMS USED

4.1 MODULE DESCRIPTION

1. Dataset Collection
2. Dataset Pre-processing
3. Training using Machine Learning Algorithm
4. Validation and Evaluation
5. Prediction of SoC and applying Continuous learning method

4.1.1 Dataset Collection

In this project, we are going to collect the dataset for battery life management, and It'll be submitted to the machine learning algorithm for activation. Efficiency rises with more datasets available.

A dataset is a collection of information that is utilized in solving complex real-world issues, with machine learning being the primary technique used. It is currently the best-performing approach for predictive tasks, and it requires a lot of data as fuel. The more labelled data accessible, the better the model will perform. This concept has even been tested on a massive scale by Google, who used a 300 million picture database. Using a machine learning algorithm in a practical setting, data must be continuously fed to maintain and enhance its functionality. During the era of computer vision, data is unquestionably the most asset. The process of collecting data can be broken down into three steps.

Classification. An algorithm can be designed to provide answers to binary yes-or-no questions or to classify inputs into multiple classes, such as identifying whether an image contains grass, trees, or bushes, or identifying whether an image contains cats, dogs, or birds.

Regression. To determine a numerical value using an algorithm, regression algorithms can be used to estimate values based on multiple factors. This is particularly useful in

situations where determining the correct price for a product may be time-consuming and involve numerous variables.

Ranking. Certain machine learning algorithms are designed to rank objects based on their features. This ranking is often employed in video streaming services to suggest movies or to show customers products that they are likely to buy based on their previous search and purchase history.

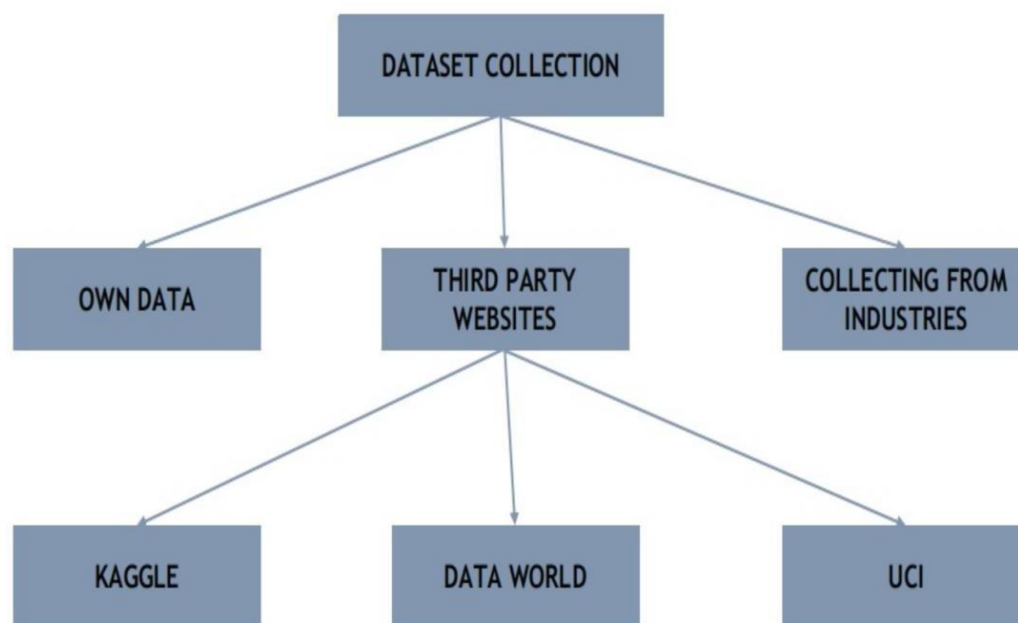


Fig4.1: Dataset collection

4.1.2 Dataset Pre-processing

In this project, principal component analysis technique is used for dataset pre-processing.

Principal Component Analysis (PCA) is a well-known method used in unsupervised learning to decrease the dimensionality of data. Its main goal is to make the data more understandable while minimizing the loss of information. By finding the most important features in a dataset, it simplifies the process of plotting data in 2D and 3D. The PCA technique enables the identification of a sequence of linear combinations of variables.

These combinations are known as Principal Components (PCs) and are straight lines that capture most of the variance of the data. The PCs have both direction and magnitude and are the orthogonal projections of data onto a lower-dimensional space.

A sort of unsupervised machine learning method called principal component analysis (PCA) aids in decreasing the complexity of a dataset. It includes a statistical technique called that uses an adaptive algorithm to turn the dataset's associated characteristics into a set of linearly uncorrelated ones. Principle Components are the name given to these novel traits. The use of PCA in exploratory data analysis and predictive modelling is very common since it helps to identify clear patterns in the dataset by reducing variances. Finding a lower-dimensional surface onto which to project the high-dimensional data allows for simpler analysis and visualisation.

The Principal Component Analysis (PCA) algorithm evaluates the variance of each attribute to identify high attribute values that provide a good split between classes, which ultimately reduces dimensionality. PCA is widely used in various implementations in the real world such as image processing, movie systems for giving suggestions and maximizing power distribution in messaging services. As a method of feature extraction, PCA retains the important variables while discarding the least important ones.

The principal components extracted from a dataset using PCA are fewer in number than the original features of the dataset. These components possess certain characteristics are given below:

1. The principal component is formed by the linear combination of the original features of the dataset.
2. The principal components are orthogonal to each other, meaning that there is no correlation between any pair of variables.
3. The significance of each principal component decreases as we move from the first component to the n th component, where n is the number of components. This means that the first principal component has the highest importance, while the n th principal component has the least importance.

4.1.3 Training using Machine Learning Algorithm

because once information has indeed been collected and preprocessed, the next step is to use a machine learning algorithm, like XGBoost regression, to train the model.

XGBoost is an open-source software library that implements the gradient boosting algorithm in an efficient and effective manner. Since its release, it has gained popularity and has often been a key component of winning solutions in various machine learning competitions. XGBoost is particularly useful in solving regression predictive modelling problems that require predicting numerical values, such as predicting a dollar amount or a person's height.

Gradient boosting is a type of ensemble machine learning algorithm that can be used for regression or classification problems. It involves constructing ensembles of decision tree models by fitting trees one at a time and correcting prediction errors made by previous models. Gradient boosting is named after the loss gradient that is minimized during model fitting, much like in neural networks. XGBoost, or Extreme Gradient Boosting, is a fast and efficient open-source implementation of the gradient boosting algorithm. It was developed by Tianqi Chen and Carlos Guestrin in 2016 and is designed to be both computationally efficient and highly effective. XGBoost has become popular for its fast execution speed and superior model performance, particularly on structured or tabular datasets. It is often used by winners of machine learning competitions on Kaggle.[18]

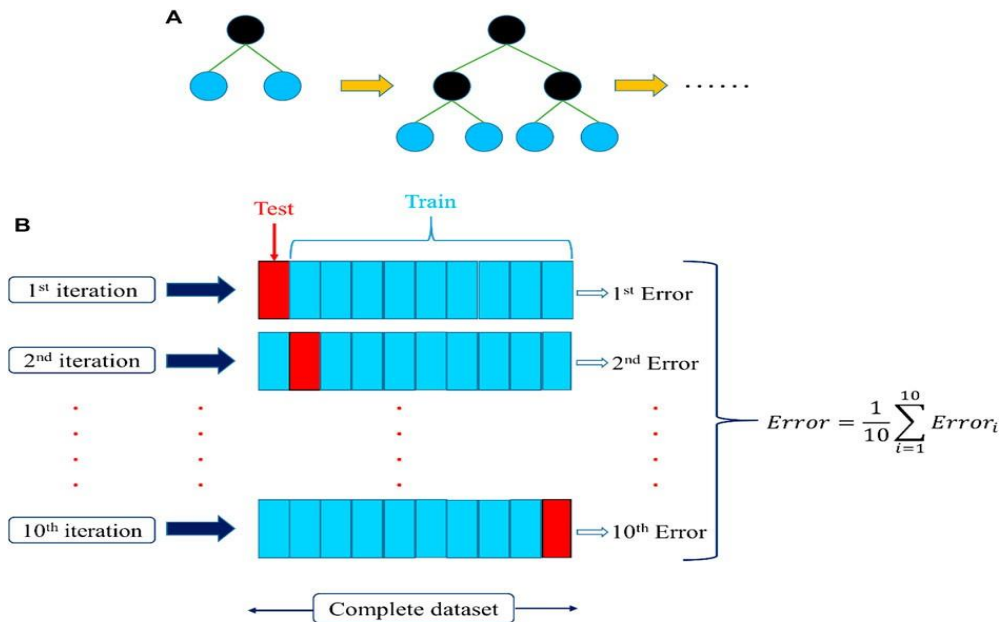


Fig.4.2: XGB Regression

4.1.4 Validation and Evaluation

Once the machine learning model is trained using the XGB regression algorithm, the dataset is subjected to validation and evaluation. Validation involves verifying the accuracy of the predictions made by the model, while evaluation is a comprehensive assessment of the machine learning model's performance under various conditions. This includes evaluating the performance of deep learning algorithms during the training process, as well as determining the accuracy of the predictions made in different scenarios.

4.1.5 Prediction of SoC and applying Continuous learning method

The SoC is produced from a battery dataset after performing validation and evaluation. Estimating the SoC is crucial as it helps prevent unpredictable disruptions to the system and protects the battery from being excessively stored or drained, which might result in long-term damage. The continual learning method is then applied to reduce the error rate and improve the accuracy of SoC estimation. This enhances the prediction in each training cycle.

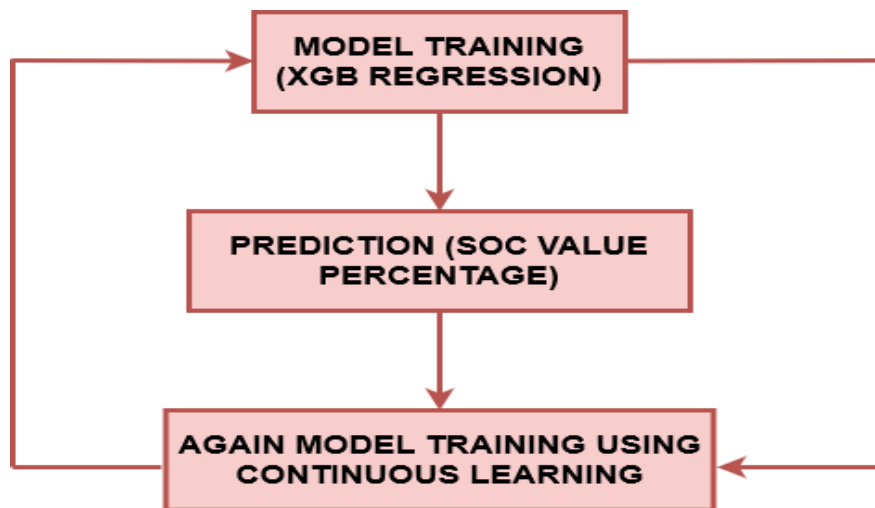


Fig.4.2: Prediction of SoC and applying Continuous learning method.

4.2 Software Requirement

The Software Requirement Specification serves the purpose of providing a detailed specification of the analysis task and ensuring comprehensive information about

the software's requirements, behavior, and functional performance constraints. Its primary objective is to clearly define the application manufacturer's technical characteristics in a clear and plain approach.

4.3 GOOGLE COLAB

The chosen IDE for this project is Google Colaboratory, which is a cloud based Jupyter notebook environment available for free. This platform enables us using our machine learning to teach and deep learning models using CPUs, GPUs, and TPUs

The chosen IDE for this project is Google Colaboratory, which is a cloud-based Jupyter notebook environment available for free. This platform enables us to train our machine learning and deep learning models using CPUs, GPUs, and TPUs.

Google Collab gives us three types of runtimes for our notebooks:

1. CPUs,
2. GPUs, and
3. TPUs

Collab provides us with the opportunity to execute our tasks for a continuous period of 12 hours. However, once this time limit is reached, the entire virtual machine is reset, and we are required to begin again. It is possible to run multiple tasks in succession within the allotted 12-hour timeframe.

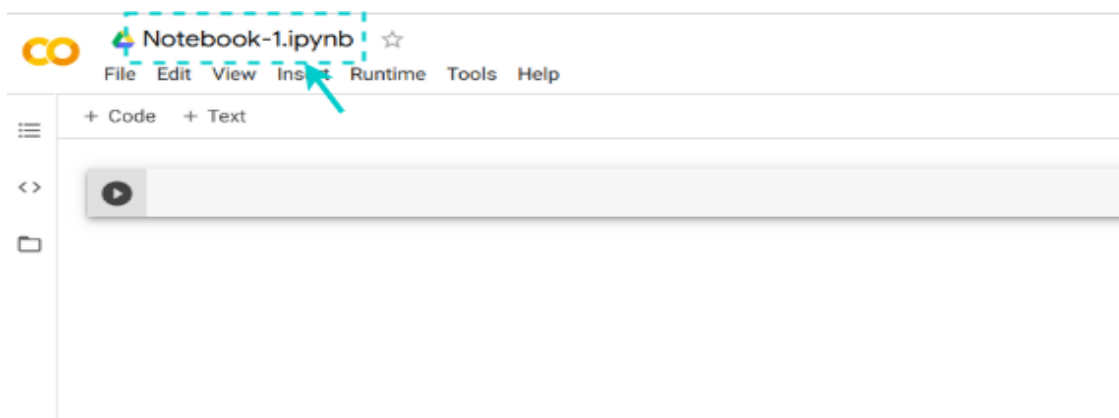


Fig.4.3: Google Collab Notebook

Through Collab notebooks, we can use CPU, GPU, and TPU instances simultaneously, albeit with shared resources. These notebooks offer a platform to combine executable code, rich text, images, HTML, LaTeX, and other features in a single document. Our personalized Collab notebooks are saved in our Google Drive account, and can be easily shared with colleagues or friends, who can even comment or edit the content. These notebooks are essentially Jupiter notebooks hosted by Collab. For more information, see the Overview of Collab, or use the provided link to create a new Collab notebook.

Google Collab provides various capabilities for developers to execute, such as the following.

1. As a developer, we can utilize Google Collab to perform several tasks, such as writing and executing Python code,
2. making, publishing, and exporting notes,
3. importing and saving notebooks from and to Google Drive,
4. transferring GitHub, posting journals there, integrating outside data,
5. integrating PyTorch, TensorFlow, Keras, and OpenCV,
6. And accessing a free cloud service that includes a free GPU.

4.4 ARDUINO

The Arduino software provides a user-friendly interface for beginners, while also offering advanced users the flexibility they need. This software is compatible with Mac, Windows, and Linux operating systems. Teachers and students alike utilize Arduino to construct affordable scientific equipment, test to learn about robots and computing, or to study the sciences and develop ideas. Interactive prototypes are created by designers and architects, and performances by artists and musicians utilising Nintendo. and to develop new musical instruments. Makers often use Arduino to create projects featured at the Maker Faire. Arduino serves as an important tool for learning new skills, and individuals of all backgrounds - from children and hobbyists to artists and programmers - can start experimenting through kit instructions or by exchanging ideas with fellow members of the Arduino community.

Aside from Arduino, several There are several different chips and architectures for tactile computing, some of which offer comparable functionalities. They include Parallax Basic Stamp, Net media's BX-24, Phi gets, and MIT's Handy board. The complexity of programming is packaged by all these devices. into user-friendly interfaces. While Arduino also simplifies microcontroller work, it presents several advantages for teachers, students, and hobbyists that other systems may not provide.

1. One advantage of Arduino is its affordability, as Arduino boards are comparatively less expensive than other microcontroller platforms. It is even possible to construct the least expensive version of the Arduino module by hand, and the pre-assembled modules cost less than \$50.
2. Another advantage of Arduino is its cross-platform compatibility, as the Arduino Software (IDE) operates on Windows, Macintosh OSX, and Linux operating systems. In contrast, most microcontroller systems are limited to Windows.
3. The Arduino Software (IDE) provides a programming environment that is both straightforward and easy-to-use for beginners, while also offering advanced users the flexibility they need. Additionally, for teachers, the software is based on the Processing programming environment, making it convenient for students who are familiar with that programming environment.
4. Arduino's Software is open source, which allows skilled developers to add to it. Those who are intrigued in the scientific intricacies can switch from Arduino to the AVR C programming language, which may be expanded using C++ modules. That underpins it. Additionally, AVR-C code can be incorporated directly into Arduino programs, if desired.
5. Another advantage of Arduino is its equipment that is extendable and platform agnostic. A Creative Commons licence allows for the publication of Arduino board blueprints, allowing qualified design engineers to produce their own versions of the module., improving and extending it as they see fit. Even inexperienced users can build the breadboard version of the module to gain a better understanding of how it works and save money in the

	Source(Lat)	source(Long)	Destination(Lat)	Destination(Long)	Speed(km)	Distance(km)	Altmetry1	Altmetry2	Altmetry3	Altmetry4	Altmetry5	Altmetry6	Altmetry7	Altmetry8	Altmetry9	Altme
0	0.696847	0.590618	3.533119	3.482597	0.715390	-0.827989	-0.326223	-0.375700	-0.591562	-0.832727	-0.799519	-0.879765	-0.879084	-0.794356	-0.665220	-0.8
1	0.810676	0.602167	3.530955	3.478028	0.564037	0.197265	-0.329554	-0.367878	-0.619050	-0.830940	-0.870980	-0.934071	-1.000598	-0.845139	-0.671549	-0.9
2	0.810676	0.602167	3.530955	3.478028	1.093773	1.814982	-0.329554	-0.356526	-0.443237	-0.677427	-0.377396	-0.362867	0.070819	1.179942	0.244492	2.1
3	0.810676	0.602167	3.530955	3.478028	-0.041377	1.562870	-0.329554	-0.356485	-0.351110	-0.390683	-0.746989	-0.648722	-0.868196	-0.781562	-0.520431	-0.6
4	-0.496134	-0.199738	-0.246020	-0.263160	-0.192730	-0.865806	-0.243861	-0.201034	0.030737	0.989420	0.227837	0.216353	0.000901	-0.281683	0.127028	0.2
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
995	0.810676	0.602167	-0.304018	-0.342156	1.774864	1.138482	-0.330475	-0.225143	0.279245	0.985858	2.006532	1.800021	0.534351	0.209669	0.717042	-0.6
996	0.696847	0.590618	3.533119	3.648241	-0.268407	-0.827989	-0.326223	-0.375700	-0.591562	-0.832727	-0.799519	-0.879765	-0.879084	-0.794356	-0.665220	-0.8
997	0.810676	0.602167	3.530955	3.422813	-1.176527	0.197265	-0.329554	-0.367878	-0.619050	-0.830940	-0.870980	-0.934071	-1.000598	-0.845139	-0.671549	-0.9
998	0.696847	0.590618	-0.273388	-0.244503	0.488360	-0.827989	-0.326223	-0.375700	-0.591562	-0.832727	-0.799519	-0.879765	-0.879084	-0.794356	-0.665220	-0.8
999	0.810676	0.602167	-0.304018	-0.342156	0.715390	1.138482	-0.330475	-0.225143	0.279245	0.985858	2.006532	1.800021	0.534351	0.209669	0.717042	-0.6

1000 rows x 17 columns

Activate Windows

Fig.5.2: Pre-Processing (Standard Scaler)

The below shows the data has been normalized using principles component analysis.

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
0	-2.757275	0.783840	4.416263	-1.328489	1.255356	-0.224829	-0.272087	0.135679	-0.020924	-0.106019	-0.202463	-0.080177	-0.043944	0.031298	0.009748	-0.008471	-0.000041
1	-2.893983	1.871272	4.144839	-0.540471	0.687671	0.070451	-0.346068	-0.312349	-0.130007	0.064654	0.032451	0.044454	-0.085100	-0.015438	-0.009825	0.009395	-0.000074
2	-0.878345	5.191488	2.758315	-1.692794	-0.636299	0.475949	0.211098	0.592449	0.002667	0.014100	-0.156774	0.051688	0.030399	-0.069754	0.006723	0.002427	-0.000200
3	-2.466042	3.027370	3.800628	0.441526	-0.022675	0.784374	0.143298	-0.709957	0.008438	0.451047	0.040795	-0.001597	-0.108949	-0.011302	0.025470	-0.013537	-0.000442
4	0.515033	-1.230995	-0.158163	-0.564394	0.515019	0.287391	0.204562	0.226234	0.918123	0.347938	0.011102	0.111937	-0.000545	0.020243	-0.006209	-0.000541	0.000312
5	1.673339	-1.686638	-0.207998	-1.186960	0.244329	1.590627	-0.071003	0.285492	-0.772489	0.273482	0.038046	-0.003512	0.001481	0.000597	0.000755	-0.000466	-0.000049
6	0.104946	0.590367	-1.215891	-2.229704	-0.493388	0.323295	-0.831989	-0.835153	0.293275	0.043311	-0.097276	-0.101161	0.007464	-0.064162	0.005923	0.001484	-0.000152
7	8.593087	-0.012892	1.142686	0.467490	-0.484017	-0.982217	-0.464520	-0.215610	-0.072168	0.047046	0.041978	0.023034	-0.003349	-0.021746	0.000738	-0.002635	0.000303
8	-1.616987	-2.301987	0.506121	0.897975	-0.323002	-0.182287	0.590085	0.476440	0.205410	-0.101491	0.095502	-0.110588	-0.033245	-0.068511	0.005743	0.001263	0.000013
9	-2.164484	-2.002172	0.128897	0.360843	-0.836888	0.278781	0.048857	-0.289776	-0.134383	-0.474847	-0.097216	0.174436	0.008541	-0.055964	-0.039626	-0.013640	-0.000381

Fig.5.3: Dataset Pre-Processing (PCA)

The below figure shows the correlation between each feature in dataset and values denoted between 1 to -1.

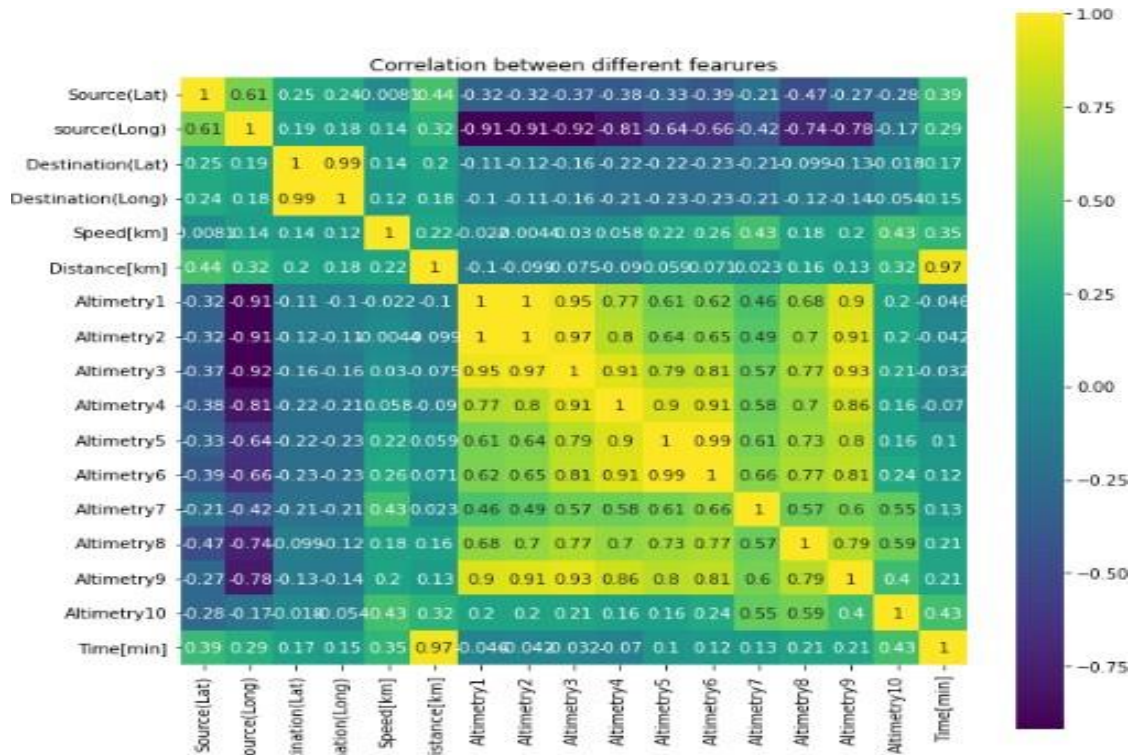


Fig.5.4: Heat Map

The discern underneath suggests how, after applying the PCA pre-processing, the values decrease within a sure variety, that is expressed with the aid of the developed dispersion coefficient.

The below figure shows after applying the principles component analysis percentage of variance that is attributed by each of the selected components and it is projecting all the features into small number of features.

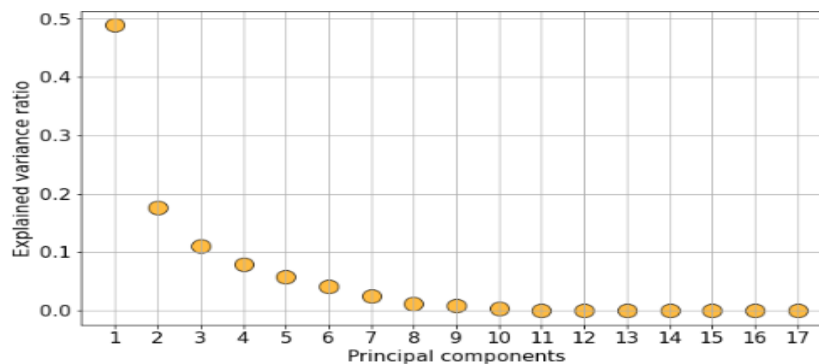


Fig.5.5: Explained Variance Ratio

The below figure shows, after applying PCA pre-processing technique first two principal components how feature data is scattered.

The figure below indicates how, using the previous PCA method, the 2 first predominant components scatter the given feature.

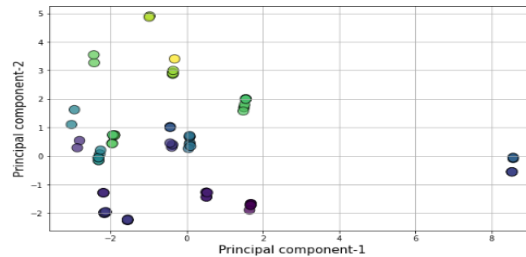


Fig.5.6: Explained Variance Ratio for first two principal component analysis.

The above figures show the first two principal components has selected first component for direction in the space along which projects have the largest variance and second component for direction which maximizes variance among all direction.

The below figure shows the metrics for trained model.

	Training_score	Testing_score	K_Fold_Cross_training	K_Fold_Cross_testng	Mse_Train	Mse_Test	Rmse_Train	Rmse_Test	Mape_train	Mape_train	R2_Score_Train	R2_Score_Test
total data	0.949643	0.897244	0.944417	0.813126	21.354593	42.79993	4.621103	6.542166	0.051868	0.081646	0.949643	0.897244

Fig.5.7: metrics for trained model

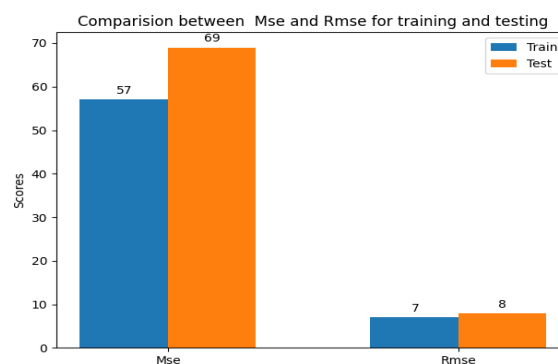


Fig.5.8: MSE and Rmse comparison for training and testing

The above figure shows comparison between Mse and Rmse metrics for training and testing by analyzing Mse metrics small error difference for training and testing and Rmse error rate which is only difference one percentage.

The below figure shows the prediction of soc value for single input.

```
while True:
    try:
        X = list(map(float, input("Enter input values: ").split(" ")))
    except:
        break
    X = np.array(X).reshape(1,-1)
    input_data = scaler.transform(X)
    pca_trans = pca.transform(input_data)
    pred = model_old.predict(X)
    print("Predicted soc value is:",pred[0])
    x1 = np.append(X,pred)
    df.loc[len(df.index)] = x1
    df_data = df.iloc[:, :-1]
    pca_trans = pca.transform(df_data)
    dfx_trans = pd.DataFrame(data=pca_trans)
    model_old.fit(dfx_trans.values,df.iloc[:, :1],xgb_model = model_old)
```

Enter input values: 12.9830 80.2594 147.5358 214.8122 70 137.0 5.9826 4.0188 8.96590 3.4065 14.25980 11.6881 22.7474 19.46530 7.0822 11.01580 159
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have valid feature names, but StandardScaler was fitted with feature names
warnings.warn(
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have valid feature names, but PCA was fitted with feature names
warnings.warn(
Predicted soc value is: 78.02325

Fig.5.9: Prediction Value

CHAPTER – 6

SUMMARY AND CONCLUSION

6.1 CONCLUSION

The project has been successfully implemented to predict the accurate estimate of SoC of the battery using the machine learning algorithm and display the generated result to the user. The machine learning algorithm such as XGB regression is used to predict the outcome of the SoC battery. This also helps in improving the battery life and performance eventually and prevents the battery to become worse. This project can be implemented in electric vehicle and battery industries. The scope for this project is wide enough in coming time.

6.2 SUMMARY

Soon, we will explore the implementation of this project in the electric vehicle industry, which can lead to more accurate detection of battery health status. This project has the potential for development and adaptation in various ways in the electric vehicle field. As a result, it offers promising prospects in the future where manual predictions can be replaced with cost-effective computerized production.

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