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Analyzing and Predicting the Battery Health of Battery Energy in EV

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Abstract

The most widely used energy storage components in products like electric cars, portable electronics, and energy storage systems are lithium batteries. On the other hand, if lithium batteries are not regularly checked, they may perform worse, have a shorter lifespan, or even explode or cause serious harm. Our proposal is to develop a state of health monitoring system for lithium batteries and an algorithm for estimating the state of charge based on the state of health results to avert such mishaps. Additionally, since speed control affects the rotational speed of motors and other machinery, it is required in electric cars. This directly affects how the machine operates and is essential to the caliber and result of the work. Li-ion batteries have a lot of energy in them, and thermal runaway accelerates quicker the more power is in the battery itself. If the battery is fully charged and something happens inside it, then thermal runaway would happen quickly. To overcome this, fire protection of electric vehicles is necessary. Energy maintenance is also required to extend battery life and maximise performance. By monitoring the battery's performance, the system may adjust the charging and discharging parameters to ensure that it is continuously operating within its safe operating parameters.

Keywords: Lithium batteries, rotational speed, health monitoring, accelerates, energy storage

INTRODUTION

Battery monitoring is a critical aspect of electric vehicles (EVs) as the battery is the primary source of power for the vehicle. The battery pack in an EV is typically made up of several individual battery cells that work together to provide the necessary power to the vehicle. Monitoring the performance and health of these individual cells is important for ensuring the safety and reliability of the vehicle. The temperature, state of health (SOH), and state of charge (SOC) of the battery are commonly monitored using sensors and electronic control units (oecus) in EV battery monitoring systems. These technologies predict the battery's deterioration over time and estimate the remaining driving range using a variety of models and algorithms. To maximize battery performance and prolong battery life, battery monitoring is also necessary. The system may regulate the charging and discharging characteristics to guarantee that the battery is consistently running within its safe operating limits by keeping an eye on its performance.

Manufacturers of EVs are raising production to meet the rapidly rising consumer demand. Both established and emerging automakers will need to quickly increase their production of EVs while concurrently lowering their pricing in order to compete with the ever-increasing demand for EVs. However, for automakers hoping to thrive in the next few years, producing EVs presents a unique set

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of difficulties. Businesses can virtually create and test whole facilities, including assembly processes, by creating digital twins of both their products and production processes. These facilitate the shift to high-volume production more quickly without sacrificing the quality of the final product.

LITERATURE REVIEW

Using electrochemical impedance spectroscopy, pulse characteristic curve analysis, battery capacity measurement, and observational checks, the external and internal properties of retired lithium-ion batteries from EVs are assessed. In order to evaluate the relationship between battery capacity and impedance, non-parametric statistical tests have been implemented. The findings indicate that capacity measurement and observational checks are merely initial methods for sorting and screening defunct batteries from electric cars [1].

A model-data-fusion approach was presented by Gao et al. for estimating the condition of health and remaining useful life of batteries. To simulate the complex degradation behaviors of batteries, a dynamic and data-driven model of battery degradation was established. That model takes the capacity degradation as the state variable and the internal resistance and polarization resistance from the battery Thevenin model as the input variables. It is then combined with the metabolic gray model and multiple-output Gaussian process regression [2].

In order to comprehend the relative benefits and drawbacks of each converter mode and aid in the selection of the best mode, Mukherjee and Strickland provided a detailed analysis and comparative research of all the converter modes along with their switching performances. To validate the analysis, a comprehensive examination of every converter mode as well as comprehensive experimental findings derived from a multimodular converter prototype utilizing hybrid batteries have been provided [3].

Severson et al. produce a comprehensive dataset by cycling 124 commercial lithium iron phosphate/graphite cells under fast-charging conditions. The cycle lifetimes of the cells vary greatly, ranging from 150 to 2,300 cycles. Utilizing discharge voltage curves from first cycles that have not yet shown capacity decline, they employ machine learning techniques to forecast and categorize cells according to their cycle life [4]. Vermeer et al. reviewed aging research and empirical and semiempirical modeling approaches, emphasizing the shortcomings and difficulties of the various models while concentrating on the patterns seen across studies [5]. Based on actual EV operating data, Wang et al. introduced a cell inconsistency evaluation model for series-connected battery systems. From a huge number of operation data of electric taxis, three consistency indicators are extracted: the charging voltage curve, internal resistance, and open-circuit voltage (OCV) [6].

A unique multistage system planning model, which incorporates a battery energy storage system (BESS), was proposed by Yang et al. In addition to using new batteries, the BESS described in this article uses SLBs in an echelon configuration and takes into account the battery's many lifespan cycles according to its SOH [7]. In order to effectively forecast and predict the SOH of lithium-ion batteries for EVs using noisy data, Maleki et al. suggested a hybrid framework [8]. The key findings for simulating Li-ion battery performance and deterioration in EV applications, as well as their applicability to BESS applications, were evaluated by Urquizo et al. [9].

Xiong et al. created a moving-window-based technique to forecast the remaining useful life of lithium-ion batteries as well as an efficient health indicator to show the SOH of the batteries. The cells' partial charge voltage curve served as the basis for extracting the health indicator [10].

Proposed System

Our suggested solution for electric cars makes use of machine learning methods like the XG Boosting algorithm and Random Forest. It involves real-time monitoring of battery parameters such as current, voltage, and temperature and integrates for state-of-charge estimation, health assessment, and degradation prediction.

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Block Diagram

Block Diagram Working

The primary objective of the battery management system (BMS) is to maintain the battery's voltage, current, and temperature within the safety operation range when it is being charged, discharged, and, in some situations, left open circuit.

As seen in Figure 1, the BMS precisely ascertains the battery's SOH and SOC, two crucial factors needed to guarantee the battery's lifespan.

The data is securely stored and accessible via a cloud-based platform, enhancing battery efficiency, reliability, and lifespan. The system reduces operational costs and promotes sustainability.

MODULES NAME

- Data collection
- Data preprocessing
- Data splitting
- Modeling

Data Collection

Now is the moment for a data analyst to take the reins and steer the machine learning implementation process. A data analyst's duties include locating reliable sources and methods for gathering extensive, pertinent data, analyzing it using statistical methods, and interpreting the findings.

Data Preprocessing

Pre-processing is the process of transforming unprocessed data into a format suitable for machine learning. A data scientist can use an applied machine learning model to obtain more accurate findings when the data is organized and tidy. The method entails sampling, cleaning, and data formatting.

Data Splitting

Training, test, and validation sets are the three subsets into which a dataset utilized for machine learning purposes should be divided.

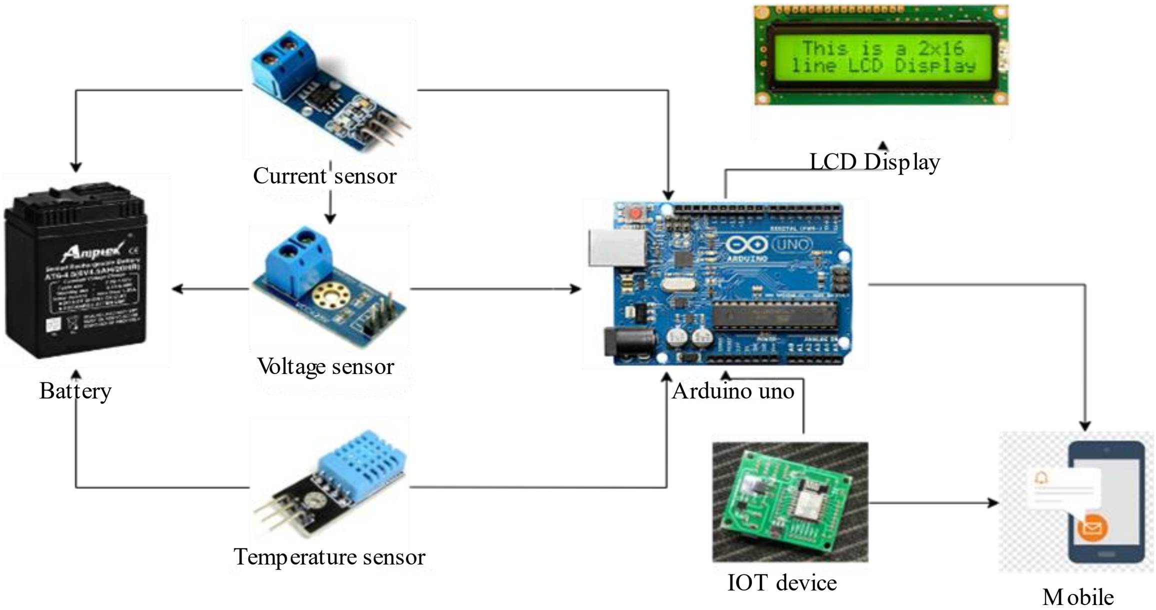

Figure 1. Block diagram of the components attachment.

Training set: To train a predictive algorithm and determine the ideal parameters it needs to learn from information, a data scientist utilizes a training set.

Test set: To assess the trained model's generalization potential, a test set is required. The latter refers to a model's capacity, after training over training data, to spot patterns in fresh, unknown data.

Modeling

Model training: It's time to train the model with this limited number of values. A popular machine learning approach called random forest aggregates the output of several decision trees to produce a single outcome. Its versatility and ease of use, combined with its ability to handle both regression and classification problems, have driven its popularity.

The algorithm's quick ability to make accurate predictions makes the model a go-to model for many competitions, such as the Kaggle competition. The common cases for the XG Boost applications are regression prediction, such as house pricing prediction.

ALGORITHM USED

- Random Forest Regression algorithm
- XG Boost Regression algorithm

Random Forest Algorithm

One type of supervised machine learning algorithm is random forest. Using various samples, it constructs decision trees and uses the majority vote for categorization and the average vote for regression.

The XG Boost Algorithm

Extreme Gradient Boosting, or XG Boost, is a distributed, scalable gradient-boosted tree of decisions machine learning package. By analyzing a tree of if-then-else true/false feature inquiries and determining the minimal number of questions required to assess the probability of making a good decision, decision trees provide a model that predicts the label.

FUTURE ENHANCEMENT

In the realm of EVs, future advancements in battery health analysis and prediction are poised to revolutionize the industry. Utilizing sophisticated machine learning algorithms and advanced sensor technologies, upcoming systems will not only monitor the current state of EV batteries but also forecast their health over time. These enhancements will enable proactive maintenance strategies, optimizing battery performance, extending lifespan, and ensuring safer and more reliable EV operation. By harnessing real-time data and predictive analytics, manufacturers and users alike will benefit from improved efficiency, reduced downtime, and greater overall sustainability in the burgeoning EV market.

OUTPUT AND RESULT

- Using the IoT device, the sensors are connected from the transmitter of the Arduino to the receiver of the IoT device.
- Collecting the data shown in Figure 2 in real-time and storing it in the IoT cloud.
- An enormous network that facilitates IoT applications and devices is known as an IoT cloud. This comprises the servers, storage, and underlying infrastructure required for processing and operations in real time. The services and standards required for linking, controlling, and safeguarding various IoT devices and apps are also included in an IoT cloud.
- Signing in the app on the mobile using the link (http://iot25.com/IOT_2k18_Full_Options/login.php) or simply with (http://www.iot25.com). Shown in Figures 3 and 4.
- Using an IoT device, the hotspot of mobile is linked. And the current location has been updated via hotspot on mobile. The temperature, current, and voltage level are indicated to the user of the mobile via messages.

- The uploaded data can be extracted as Excel format and applied to a machine learning algorithm on that data (Figure 5).
- Then the accuracy will be predicted, as shown in Figures 6–8.

When it comes to predicting battery health in practical situations, the machine learning (ML) approach produces a model that is very accurate and reliable. An online knowledge-based service for battery health was developed using the previously built machine learning model [11]. Numerous other actions can be carried out with this web service, including monitoring battery behavior and testing battery health. Using the same method, other identical solutions for various systems can be obtained. As additional performance metrics, R-squared, mean square error, and the default efficiency of the ML algorithmic module were used. The efficacy of a fit is evaluated using the R-squared as a benchmark.

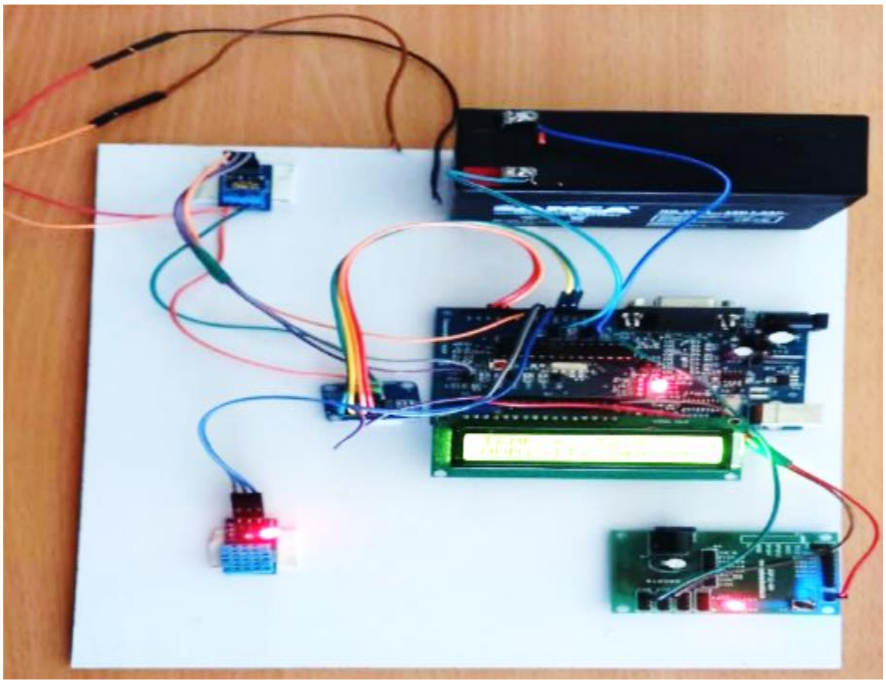

Figure 2. Collect real time data using IOT sensor.

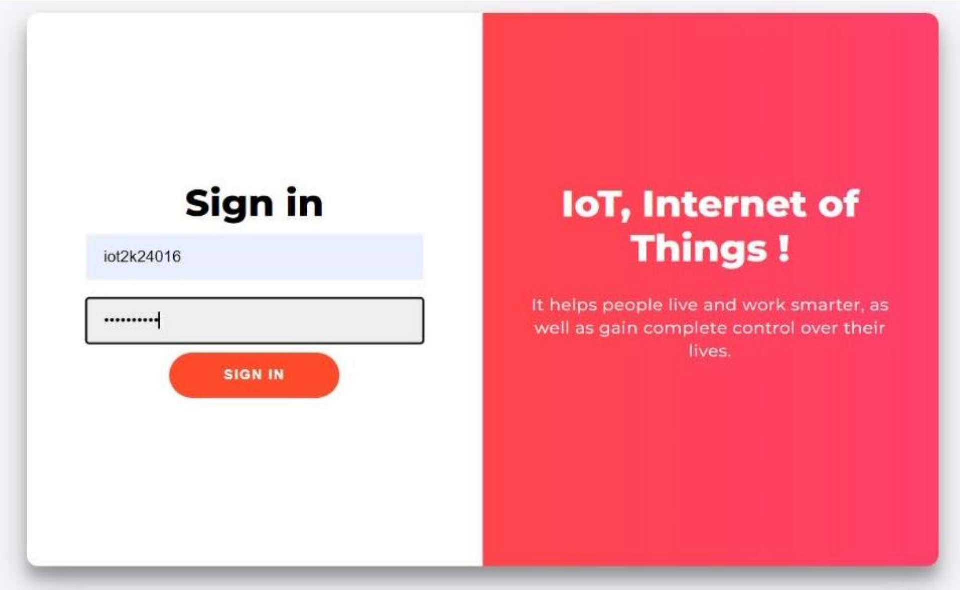

Figure 3. Visualization of IoT cloud.

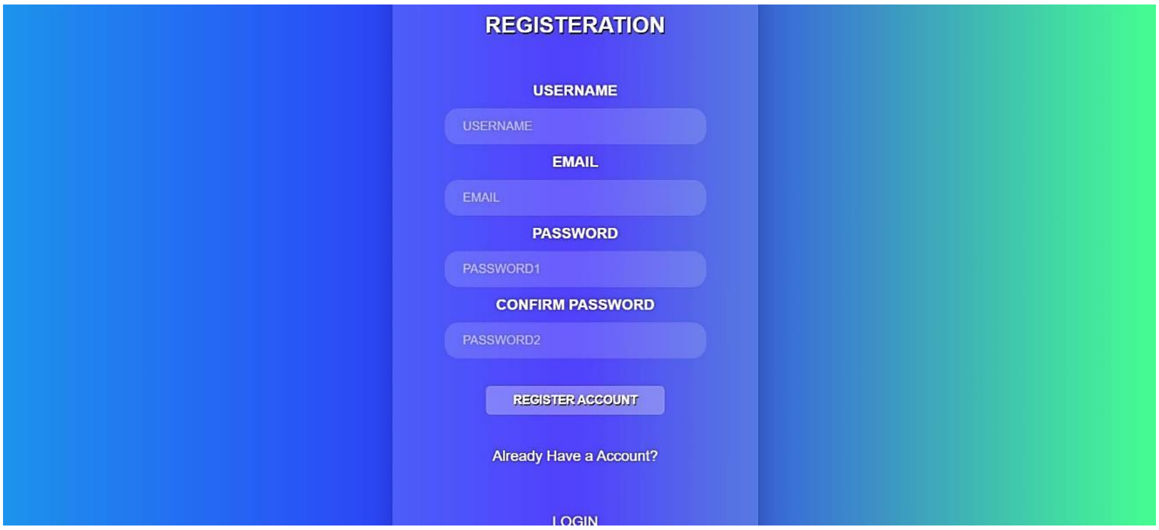

Figure 4. Applying machine learning algorithm.

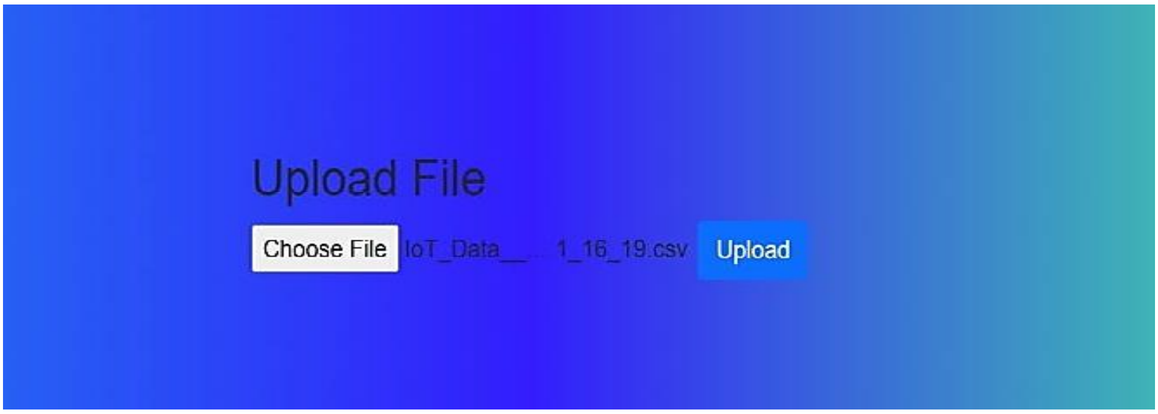

Figure 5. Upload the converted excel data.

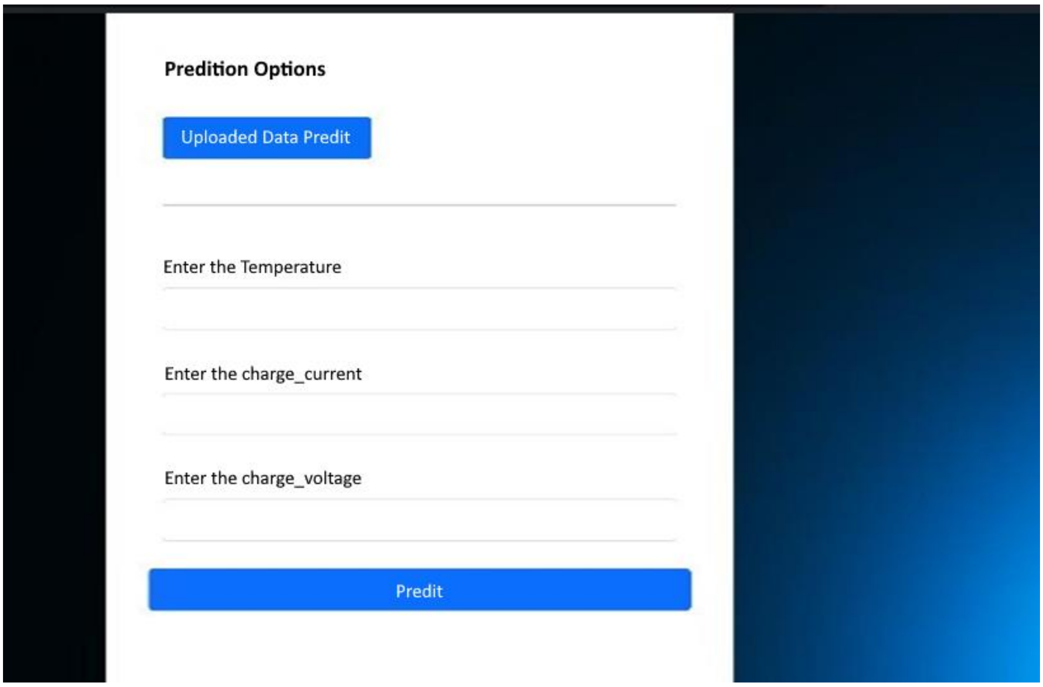

Figure 6. Predict individual or group of data.

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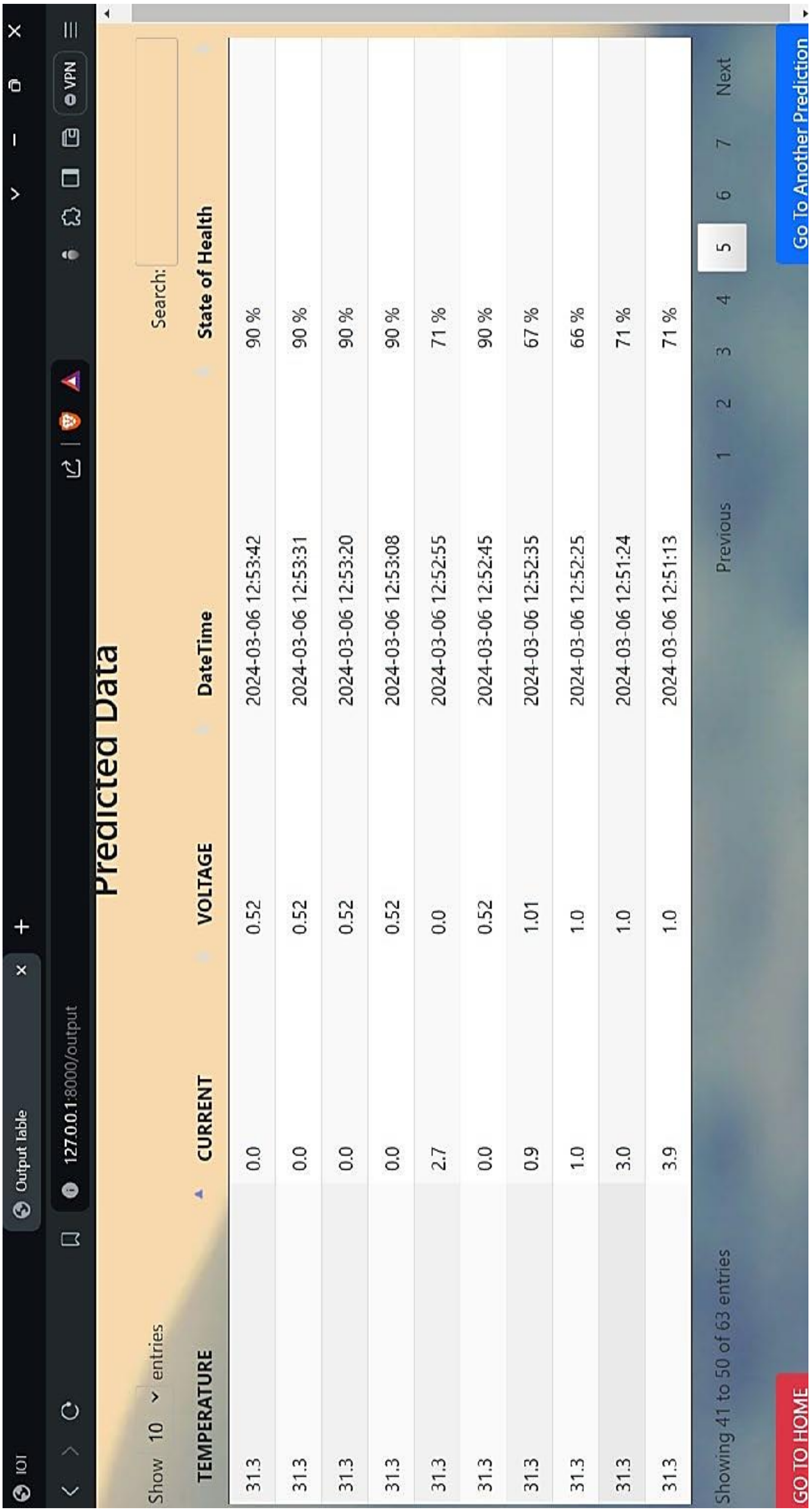

TEMPERATURE	CURRENT	VOLTAGE	DateTime	State of Health
31.3	0.0	0.52	2024-03-06 12:53:42	90 %
31.3	0.0	0.52	2024-03-06 12:53:31	90 %
31.3	0.0	0.52	2024-03-06 12:53:20	90 %
31.3	0.0	0.52	2024-03-06 12:53:08	90 %
31.3	2.7	0.0	2024-03-06 12:52:55	71 %
31.3	0.0	0.52	2024-03-06 12:52:45	90 %
31.3	0.9	1.01	2024-03-06 12:52:35	67 %
31.3	1.0	1.0	2024-03-06 12:52:25	66 %
31.3	3.0	1.0	2024-03-06 12:51:24	71 %
31.3	3.9	1.0	2024-03-06 12:51:13	71 %

Figure 7. Predict group of data.

Figure 8. Predict individual data.

The statistical examination of recorded data characteristics of electrical battery aging during use in EVs is described by Barré et al. [12] Li et al. address potential next-generation techniques and concentrate on the difficulties associated with real-time battery health management [13]. A thorough analysis of the various estimating methods is done by Lipu et al. [14] in order to forecast SOH and RUL in a comparable way. The findings point out the categories, traits, and assessment procedures that have benefits and drawbacks for EV applications. Dong et al. introduced a probabilistic approach for health forecasting and battery deterioration modeling based on dynamic Bayesian network (DBN) features gathered from the charging process [15].

Techniques to Assess Battery Health

1. *Impedance spectroscopy by electrochemistry (EIS):* Battery impedance can be measured across a frequency range using the EIS approach. Researchers can determine details about the internal resistance, capacity, and SoH of the battery by examining the impedance data.
2. *The Coulomb Counting Method:* Monitoring the quantity of charge passing through and leaving the battery is part of this method's assessment of the battery's capacity and SoC. The SoH can be found by comparing the measured capacity to the rated capacity.
3. *Temperature and voltage monitoring:* A battery’s performance and possible deterioration can be understood by keeping an eye on its temperature and voltage while it is in use. Unusual temperature or voltage trends may point to battery health problems.
4. *Data analytics and machine learning:* Large battery usage records can be analyzed by machine learning algorithms to find trends and forecast performance in the future. Artificial intelligence techniques such as decision trees, neural networks, and support vector machines are used to develop predictive models for battery health.

EVs are becoming more and more popular since they reduce greenhouse gas emissions and reliance on fossil fuels. An EV battery is a crucial component that powers the vehicle. The efficiency, affordability, and general uptake of EVs depend heavily on the condition and lifespan of these batteries. This article highlights the significance of preserving peak battery performance and prolonging battery life as it examines the techniques and technology used to assess and forecast the health of EV batteries.

Maintaining vehicle performance, maximizing battery lifespan, ensuring cost effectiveness and safety, and projecting the health of EV batteries are all dependent on analysis and prediction. Technological developments in machine learning, monitoring, and electrochemistry have greatly improved our capacity to evaluate and forecast battery health. Research and development in this area will be essential to advancing battery technologies and the overall sustainability of electric transportation as EV use rises.

Battery Health-related Factors

Various factors impact the condition and functionality of EV batteries:

- *Temperature:* Batteries can deteriorate more quickly in extremely hot or cold temperatures.
- *Charging cycles:* A battery's longevity is influenced by the quantity of charge-discharge cycles it experiences.
- *Depth of discharge:* The battery's lifespan is affected by how much of it is discharged throughout each cycle.
- *Charging rates:* Rapid charging can cause the battery to become more stressed and produce more heat, which accelerates degradation.
- *Battery chemistry:* The ability of various battery chemicals to withstand stressors varies.

The pulse discharge voltage is a crucial metric for assessing the uniformity of retired batteries. Warburg impedance is the primary component affecting battery capacity loss when viewed through the lens of impedance, followed by charge transfer resistance. Ohmic resistance and capacity loss are not correlated.

CONCLUSION

In conclusion, the integration of machine learning and IoT technologies for analyzing and predicting the battery health of energy systems in EVs represents a transformative leap forward in the automotive industry. By harnessing the power of real-time data collection, advanced analytics, and predictive modeling, these innovations offer unparalleled insights into battery performance and longevity. This proactive approach enables manufacturers to implement targeted maintenance strategies, optimize operational efficiency, and enhance overall reliability. Moreover, it empowers users with the confidence of knowing their EVs are equipped with cutting-edge systems capable of maximizing battery lifespan and minimizing downtime. As we continue to push the boundaries of innovation, the synergy between machine learning and IoT will undoubtedly drive the future of electric mobility towards greater sustainability and efficiency.

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