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Implementation of a Battery Management System for Electric Vehicles Based on Hybrid Discriminative RBM Approach

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Abstract. All sorts of high-power devices rely on batteries; electric vehicles and hybrid electric vehicles are only two examples. The secure and dependable functioning of the batteries depends on a good BMS. Charging, state estimation, and battery modeling are some of the technical parts of BMSs that are briefly touched upon in this proposed. Choosing a method, doing preprocessing, extracting features, and training the model are all steps that must be executed in precisely the correct order. It comprises relative SOC and based SOC, and it may be easily calculated in preprocessing using the relationship between the energy level and the battery's properties. Principal component analysis (PCA) is a mathematical technique used in feature selection that determines a number of linked variables that account for as much variability in the data as feasible by reducing the number of uncorrelated variables. Using Hybrid Discriminative RBM, we trained the model. An impressive 96.88% accuracy was achieved, according to the results.

Keywords: Battery Management System (BMS)·Electric Vehicles (EV)·Hybrid Discriminative Restricted Boltzmann Machines (HDRBM).

1 Introduction

Predictions for the next presidential election have piqued the curiosity of both scholars and the broader public. The academic literature is dominated by two primary schools of thinking about election outcome prediction. There was an initial trend in political science. Political scientists have been working on models to predict elections since the 1980s. These models examine the interrelationships among economic development, a number of predictive variables, and the expected vote outcomes of a single presidential candidate, typically from the incumbent party. The second thread originates from the field of computer science. As big data on social media has grown in popularity in the 2010s, some academics have started to analyze Twitter sentiment as a predictor of future elections. Obtaining very accurate sentiment ratings from pertinent social media posts is usually the main goal. When voters see a candidate in a positive light, they are more likely to vote for that person. Although there are many scientific and practical advantages to both techniques, there are also some drawbacks. When using traditional models to forecast election outcomes, polling rates are essential. Poll surveys, however, can be expensive and time-consuming to conduct. The term "fake news" has grown in popularity as a blanket term for any deceptive material shared on the internet. Have examined the typology and distinguishing features of different types of incorrect information. Conversely, contend that further academic study is needed to examine where the prevalent disinformation comes from, how extensive it is, and what effects it has. The findings of this study add to the mounting evidence that the spread of politically motivated disinformation and false news can have serious consequences for society and government. The current conversation over the effects of the post-truth or fake news problem on society lacks evidence. Examples of such arguments include the claims made, who argue that the continued spread of disinformation poses a threat to democracy because it undermines public trust in government. The dissemination of misleading information is the most pressing social problem facing American adults today, according to a nationwide survey. The impact of such deceptive information on democratic processes has only been somewhat investigated, with only two studies addressing this significant issue are among the works that have focused on this topic previously. These works primarily involve experiments that examine how incorrect information influences people's opinions on the stories. An increasing amount of research has focused on electoral forecasting since its inception. Having trustworthy results projected is important for many people, including politicians, practitioners, and policymakers. This is true for both the present and the future. Such a feat would have an effect on party financing, political strategy, and strategic decisions. Big data, political markets, and polls have all played a role in creating complex models that try to make better predictions. More precise predictions were possible than with polls alone thanks to online data sources and the Internet in this case. People who utilize the Internet are more informed and more inclined to vote as a result. A number of studies have used search-volume indices such as Google Trends or tweet analysis to make predictions about online news, despite the fact that there are large datasets that contain this information found that there are a number of situations when looking at online news can help with financial, political, and economic predictions. An officially acknowledged group of people with shared political views and aims whose declared purpose is to influence government policy by electing party members to public office is called a political party. A political party takes over the government when it’s officially supported or approved candidates win the election. Also, they are in charge of political campaigns and making sure that people vote. To win elections and use those victories to shape public policy is the raison d'être of political parties. They need to rally a wide range of voters with shared values if they want to win. Whether their work is directly apparent to the public through the presentation of candidates or the electoral campaign, political parties perform multiple crucial functions that may influence the people who are eligible to vote. It's widely known that campaign appearances by candidates can also affect election outcomes. With the proliferation of social networking, microblogging, and blogging websites, individuals now have more methods than ever before to express themselves and generate vast quantities of data. Notable studies have consistently found little evidence to support the use of social media data for election prediction, and the criticism around this practice has been strong. You could begin to question these claims until you realize that most of these successful "predictions" happened after the election, when all the facts are known. Many famous studies that looked to have succeeded fell apart when evaluated objectively. Nevertheless, disregarding any technological worries, a comprehensive analysis of this topic uncovers some fascinating fundamental issues that occur in any attempt to understand and maybe predict human behavior using data from social media.

2. Literature Survey

Numerous technological advancements in recent years have contributed to a marked improvement in vehicle safety, with the goal of better protecting pedestrians and passengers [1]. On the other hand, more traffic means more pollution in cities. The European Union reports that cars are responsible for about 71% of the 28% of CO_2 emissions that originate from the transportation sector. Electric vehicles (EVs) have attracted a lot of interest and support around the world as a possible answer to pollution, fossil fuel conservation, climate change, and carbon emissions [2]. Electric vehicles offer numerous benefits over diesel-powered ones, such as reduced emissions, user-friendliness, reliability, comfort, and efficiency. For electric vehicles to be widely used, it is crucial that the battery storage system (BSS) works well and can be diagnosed [3]. This system needs to keep an eye on the charge-discharge cycles, regulate the power management, keep the cells in balance, and handle heat. The benefits of lithium-ion batteries over other EV battery types are high power density, low self-discharge rates, long lifespan, and high voltage [4]. Lithium batteries are temperature and age sensitive, therefore it's important to keep an eye on their operating conditions to avoid physical damage, ageing, and thermal runaways. Among the many critical functions performed by the BMS during EV operation are the following: verifying the battery's charge, energy, and health; controlling the temperature; and making sure the voltage is spread uniformly throughout the cells [5].However, batteries are quite sensitive when used in electric vehicles. Ensuring the safety of batteries is of utmost importance. Engaging in incorrect operations, such as overcharging or discharging, or applying excessive current or voltage, could cause the battery to age faster or even explode or catch fire [6]. The BMS is essential for ensuring the safety and effectiveness of batteries. [7]Internal state estimation, charging, and battery modelling are technologies that make up the battery management system (BMS) of electric vehicles. Having a reliable [8]battery model is essential for many tasks, including defect diagnosis, heat management, building real-time controllers, monitoring battery status, and activity analysis. Since certain battery internal states—like internal temperature, state of health (SOH), and state of charge (SOC)—are not easily observable yet play critical roles in managing the operation of batteries, reliable [9]estimating methods are necessary to monitor these states. Battery charging is also an essential part of BMS since it directly affects the service availability and operational safety of the battery. A well-thought-out charging strategy should safeguard batteries, keep temperature fluctuations to a minimum, and maximize energy conversion efficiency. When charging electric vehicles too rapidly, they lose a lot of heat and have a shorter lifespan, but when charged too slowly, they have the opposite effect [10]. Large temperature variance speeds up the ageing process and causes overheating and supercooling, both of which reduce the battery's service life. An increasing number of people are turning to electric vehicles (EVs) as a way to reduce pollution from vehicles that utilize conventional petrol or diesel engines [11]. In order to ensure the safe operation of electric vehicles, it is essential to have battery management systems (BMSs) that monitor the battery system [12]. Battery management systems (BMSs) play an important role in maintaining cell balance within the battery system. Powering each cell in series with a shunting resistor, energy dissipation is a simple method for balancing that makes use of the imbalanced energy [13]. One disadvantage of this technique is passive balancing, which leads to low efficiency due to the substantial energy lost during the balancing process. Several active balancing strategies have been proposed to improve balancing efficiency, including adjacent cell-to-cell (AC2C), direct cell-to-cell (DC2C), cell-to-pack (C2P), pack-to-cell (P2C), and cell-to-pack-to-cell (C2P2C) [14]. In order for active balancing to take place, either more energy is transferred to the lowest-energy cell or the higher-energy cell sends its excess energy to the lower-energy cell or the whole battery pack. Traditional BMSs frequently employ modularized architecture. A sensor is built into a battery module after numerous cells are connected in series or parallel. In the end, all of the sensors on the module are overseen by a centralized controller [15]. One important advantage of modular architecture is its low cost; this is mainly due to the fact that the BMS only utilizes one system controller. Unfortunately, fault tolerance isn't without its issues. A single faulty cell could trigger system-wide abnormalities in operation due to the physical coupling between all of the cells in the battery system.Therefore, the most significant challenge facing the car industry is developing a state-of-the-art battery system that is compatible with the technology. [16] Every year, ICEVs, BEVs, HEVs and PHEVs pay different amounts for petrol. Making cars more fuel efficient is the next challenge. The two primary areas are: Gearboxes, direct drive motors, and power electronics that are [17] "cable connected" to a remote controller are all components of an electric mechanical drive that can benefit from parasitic loss reduction efforts. This encompasses electric drive units with both fixed and variable speeds, in addition to various motor drives, belts, and gears. [18] The energy storage charging needs of electric vehicles, especially plug-in hybrids and battery electric vehicles, are posing a new challenge to the interconnection of utility systems.[19]Current approaches of estimating a battery's RUL (remaining usable life) function essentially in this way: The offline training data is used to initialize a nonlinear ageing model, which is then used to predict the battery RUL. After that, sophisticated online filters like PF are used in combination with the model. In order to forecast battery RUL, he and colleagues [20] proposed integrating the Dempster-Shafer theory with the Bayesian Monte Carlo (BMC) method. To set the parameters of the model, we first mixed training sets offline in accordance with Dempster-Shafer theory. As a next step, we used the BMC method to update the model parameters and forecast the RUL based on data collected from online battery capacity monitoring. When compared to the traditional PF-based prognostic method, our method produced more accurate predictions. Offline training data is required to initiate an ageing model, as stated in references [21]. Therefore, it is challenging to design acceleration ageing experiments that collect practical offline training data for lithium-ion batteries in scenarios that reflect their actual use. When it comes to pollution and ecological damage, the transport industry is at the top. But advancements in battery technology might have a positive impact on e-mobility applications like electric cars and hybrid locomotives. In order to transfer and distribute energy efficiently, electric vehicles and smart grid technologies depend on energy storage devices. There are a myriad of alternatives for energy storage because there is a vast variety of batteries accessible. It is essential for electric car applications to control the battery temperature. Public and private charging stations now offer additional outlets for electric vehicles, as their use continues to rise [22]. Greater voltage, greater efficiency, and longer lifespans for battery systems are urgently required to meet the increasing demand for electric vehicles, which in turn necessitates better means of monitoring batteries. Because they prevent damage and extreme temperatures from reaching Li-ion batteries, battery management systems are crucial for EVs. Because of differences in temperature, self-discharge, and cell impedance, cell balancing is an essential component of BMS operation. The two most prevalent kinds of cell balancing mechanisms are active and passive [23]. Most research have only examined the BMS's accuracy in estimating SOC and SOH, despite its promising future. Fault diagnostic methods have received little attention until the sensor stops functioning correctly; this can affect other data-gathering BMS operations, putting the safety of the battery system in much greater danger. As a result, identifying sensor failures is essential in guaranteeing that a BMS is functioning correctly [24].Readings from current, voltage, and temperature sensors are essential components of any reliable battery management system. Countless sensors measuring voltage, current, and temperature are integrated into every electric vehicle battery. [25] This greatly increases the likelihood that a single current or voltage sensor may be compromised. Low battery performance or even serious safety issues could be the result of faulty sensors.

3. Proposed System

There has been a dramatic shift in the spotlight on batteries recently, thanks to the rapid development of both the smart grid and electric vehicles (EVs). In order to make the battery a reliable, safe, and cost-effective solution, it is vital to enhance the performance of the battery management system (BMS), according to recent discussions about the lithium-ion (Li-ion) battery performance of the Boeing 787. Developing cells with higher power and energy densities is also important.

3.1 Preprocessing

3.1.1 Relative SOC

The following formula, deriving from the design capacity, states that the stored energy of a battery is directly proportional to its typical state of charge (SOC):

$$SOC_{typical}(n) = \frac{H(n)}{H_{rated}} \quad (1)$$

with Crated representing the intended capacity and $H(n)$ denoting the actual capacity as of time n. To get a good approximation of the usual SOC, though, complicated computations or measurements were needed. With the data preprocessing that can be easily calculated based on the relationship between battery properties and its energy level, working aimed to develop machine learning models of SOH estimate [22]. It needed indications relating to the battery's energy level, and using a conventional SOC was not necessary [26]. As a result, we linked the battery's energy level to a relative state of charge, or SOC for short. Here is how the relative SOC was determined using the available capacity during charging:

$$SOC^m(n) = SOC^m(n_0) + \frac{1}{H_{usable}^m}\int_{n_0}^{n} R_n dt \quad (2)$$

H_{usable}^m is the computed usable capacity, R_n is the charging current during the m -th cycle, and n_0 is the start time. One way to calculate the useable capacity is by integrating the current in the following way:

$$H_{usable}^m = \int_{n_0}^{n_{cutoff}} R_g dt \quad (3)$$

where n_0 is the commencement of the discharging process, n_{cutoff} is the time at which the battery voltage drops below the cutoff voltage, R_g is the current draining the battery at the m -th cycle, and H_{usable}^0 is set to Crated. This relative state of charge could be easily calculated while the battery was charging and could take on a number between zero and one hundred percent, regardless of the state of degradation of the battery. For that reason, we covered relative SOC data processing in this proposed.

3.1.2 SOC Based

Both the relative state of charge and the energy level of the battery are influenced by one another. So, we implemented SOC-based data sampling for this purpose. Data is gathered using a constant relative SOC interval while taking the battery's energy into account in SOC-based data sampling. Voltage, SOC, temperature difference, current, and cycles were the variables included in the dataset that was sampled using a constant relative SOC interval.

$$G_{socbase\#t}^m = \begin{pmatrix} SOC_1^m & SOC_2^m & \dots & SOC_f^m \\ W_1^m & W_2^m & \dots & W_f^m \\ R_1^m & R_2^m & \dots & R_f^m \\ \Delta N_1^m & \Delta N_2^m & \dots & \Delta N_f^m \\ m & m+1/f-1 & \dots & m+1 \end{pmatrix} \quad (4)$$

SOC_k^m, W_k^m, R_k^m, and ΔN_k^m are the k -th sampling points of the relative state of charge, voltage, current, and temperature differential during the m -th cycle in the t -th battery dataset, where f is the total number of sampling points during one charge cycle.

3.1.3 Time Based

Gathering information at regular intervals, time-based data sampling has been utilized in a lot of studies. It seemed like their procedure was fine because most equipment take readings at regular intervals. For the sake of comparison, we generated data using the identical components as the proposed SOC system. The dataset featured variables such as voltage, time, temperature difference, current, and cycles, all of which were collected using a fixed time period.

$$\Delta N_{timebase\#t}^m = \begin{pmatrix} n_1^m & n_2^m & \dots & n_f^m \\ W_1^m & W_2^m & \dots & W_f^m \\ R_1^m & R_2^m & \dots & R_f^m \\ \Delta N_1^m & \Delta N_2^m & \dots & \Delta N_f^m \\ m & m+1/f-1 & \dots & m+1 \end{pmatrix} \quad (5)$$

In the dataset for the t -th battery, the symbols n_k^m, W_k^m, R_k^m, and ΔN_k^m stand for the k -th time, voltage, current, and temperature differential sampling points at the m -th cycle, respectively. The total number of points sampled in a single charge cycle is denoted by f. It may find the temperature difference using this formula:

$$\Delta N_k^m = N_k^m - min(N^m) \quad (6)$$

that is, N^m is a collection of temperatures recorded at the m -th cycle, m stands for the number of cycles, and k for the k -th sample point.

3.2 Feature Selection

A good approach to building a top-notch BPNN model is to carefully choose the input data. Irrelevant data selection has a negative effect on training duration and estimate accuracy. A lithium-ion batteries complex nonlinear characteristics and electrochemical reactions become apparent as the input variables are changed.

Approximating SOC is thus possible with a wide range of approaches and a myriad of input features. Finding the key factors requires picking the most basic input variables, such as temperature, voltage, and current. These qualities, however, fail miserably when it comes to determining SOC and capturing the battery's nonlinear properties. Improved precision can only be achieved by adding new features [23]. The features are obtained from simple variables through integration $(\int rdt \int wdt)$ and derivatives (gw, g^2w, gr, g^2r). As a trade-off, convergence slows down when more input features are used, but accuracy increases otherwise [27]. If you want an accurate estimate of SOC, you must first ensure that the input variables are contributing and correlated appropriately. All models have their flaws, though, such as inaccurate results and tedious calculations. It is possible to estimate SOC by using principal component analysis to find the optimal number of input variables. A dimensionality reduction method, principal component analysis (PCA) can compress a massive dataset while keeping most of the information. Finding the correlated components that explain the majority of the data variability and reducing the number of uncorrelated variables is the goal of principal component analysis (PCA), a statistical technique. One way to represent a variable's variance is as the square root of the average deviation of its t values from the variable's mean, which is

$$W_r = \frac{1}{t-1}\sum_{k=1}^{t}(Q_{rk} - \bar{Q}_r)^2 \tag{7}$$

The covariance metric measures the linear correlation between the variables, which is

$$H_{rp} = \frac{1}{t-1}\sum_{k=1}^{t}(Q_{rk} - \bar{Q}_r)\left(Q_{pk} - \bar{Q}_p\right) \tag{8}$$

which is where H_{rp} stands for the covariance of variable r, Q_{rk} for the value of r in object k, Q_r for the mean of variable r, Q_{pk} for the value of p in object k, and Q_p for the mean of variable p

3.3 Model Training

3.3.1 Hybrid Discriminative RBM

The RBM is a kind of Boltzmann machine that includes both visible (q -vector) and hidden (c -vector) units in its bipartite connection network. Although all units in a given layer are linked to all units in every other layer, there is no inter-layer connectivity. Any direction of data flow is possible because the V-vector weights are constant. Restricted Boltzmann machines (RBMs) are a type of probabilistic model that uses a hidden variable layer to mimic a distribution over observable variables. Feature extractors known as Rational Behavioural Models (RBMs) were developed to address a range of learning problems. When applied as non-linear classifiers, RBMs outperform conventional neural networks and support vector machines [24]. To find the joint distribution of an input $q = \left(q_1, \ldots, q_g\right)$and a target class$u \in 1, \ldots, H$, the hidden layer of binary stochastic units $c = (c_1, \ldots, c_T)$ is utilized. Adding the class label u to the observable data is suggested. for RBM learning using a discriminative method. To calculate the energy function, use this formula: (9):

$$A(u,q,c) = -c^T Vq - l^T q - h^T e - g^T a_u - c^N Y a_u \tag{9}$$

The variables $\theta = (V, l.h, g, Y)$represent the model parameters. The distribution probabilities to values of $u, q\ and\ c$ are given by (10), which follows from (9).

$$i(u,q,c) = \frac{e^{-A(u,q,c)}}{O} \tag{10}$$

O is both a partition function and a normalizing constant in equation (10). It is easy to adapt the paper's simple description to support real-valued inputs; it currently only works with binary q inputs. Despite the fact that this function is typically unsolvable, it can be approximated using Gibbs sampling, which involves selecting a value for the hidden layer based on the current value of the visible layer [28]. Although initially developed to process binary input variables, the model can be readily modified to process integer, continuous, and non-binary values. Here is the process for calculating the conditional distributions:

$$i(q_r = 1|c) = sigm\left(\sum_p V_{pr} c_p + l_r\right) \quad (11)$$

$$i(c_p = 1|u, q) = sigm\left(\sum_r V_{pr} u_r + h_p + Y_{pu}\right) \quad (12)$$

$$i(u|c) = \frac{exp(\sum_p Y_{pu}\, c_p + g_u)}{\sum_{u^*} exp(\sum_p Y_{pu^*}\, c_p + g_{u^*})} \quad (13)$$

This can be accomplished by following the steps outlined in equation (14). This allows us to conclude the classification task. One way to look at (14) is that it could mean that the probability $i(u|c)$indicates how well the input fits with various filters, represented V_p of V, when using a set of inputs q to assign probabilities to a specific class u (where u^* means all classes). Biases Y_{pu} let us distinguish between classes that employ different filters, even while filters (weights) are shared across all classes.

$$i(u|c) = \frac{exp(g_u) \prod_p \left(exp\left(\sum_r V_{pr} q_r + Y_{ph} + Y_p\right) + 1\right)}{\sum_{u^*} exp(g_u^*) \prod_p \left(exp\left(\sum_r V_{pr} q_r + Y_{ph^*} + Y_p\right) + 1\right)} \quad (14)$$

Assume that out of N training samples, the k-th one is represented by (u_m, q_m). For RBM learning, one common generative objective function that ignores output modeling is shown in Equation (15). On the other hand, LP character recognition is best tackled with supervised discriminative training, as seen in (16).

$$Z_{gen} = -\sum_{m=1}^{T} logj\ (u_m, q_m) \quad (15)$$

$$Z_{disc} = -\sum_{m=1}^{T} logj\ (u_m, q_m) \quad (16)$$

Presented below are examples of hybrid restricted Boltzmann machines (HDRBMs) that are grounded in objective functions. Integrating generative training objectives with discriminative ones is one way to standardize the former.

$$Z_{hybrid} = Z_{disc} + \rho Z_{gen} \quad (17)$$

where the training data can be used to optimize the weight ρ.

4. Result and Discussion

The battery management system is a crucial component of all hybrid and electric vehicles. It is the job of the BMS to guarantee the safe and dependable operation of the batteries. In order to maintain the battery's safety and reliability, a battery management system (BMS) includes features such as cell balance, charge regulation, and state monitoring and assessment. Being an electrochemical product, the behavior of a battery might vary depending on operational and environmental circumstances. Uncertainty regarding a battery's performance impedes the execution of these operations.

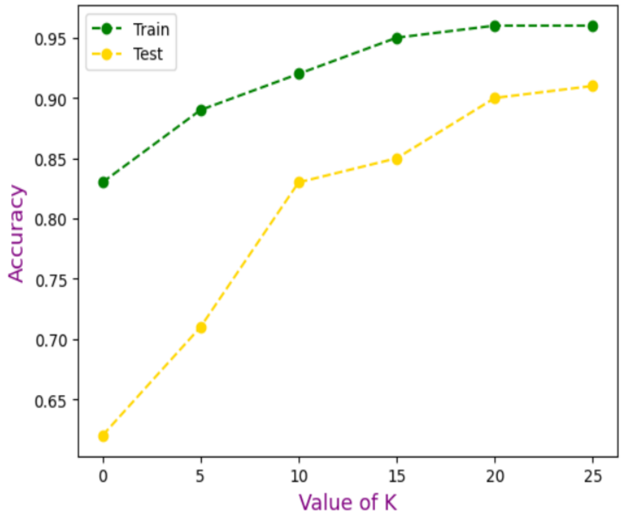

Fig. 1. Accuracy Value Under Different k

A key parameter that controls the HDRBM approach's classification outcomes is k. Figure 1 shows the accuracy of the classification with various values of k.

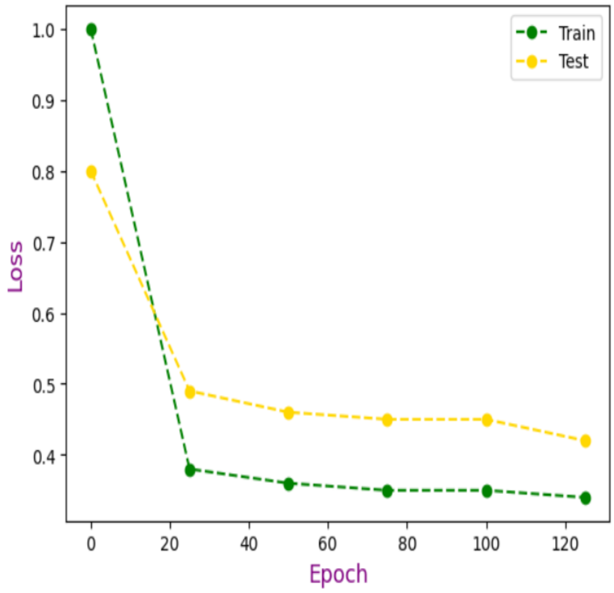

Fig. 2. Training and Validation Loss of HDRBM

Figure 2 shows that the full dataset is randomly divided into a training loss dataset comprising 34% and a validation loss dataset comprising 42%. This is done in order to train the HDRBM.

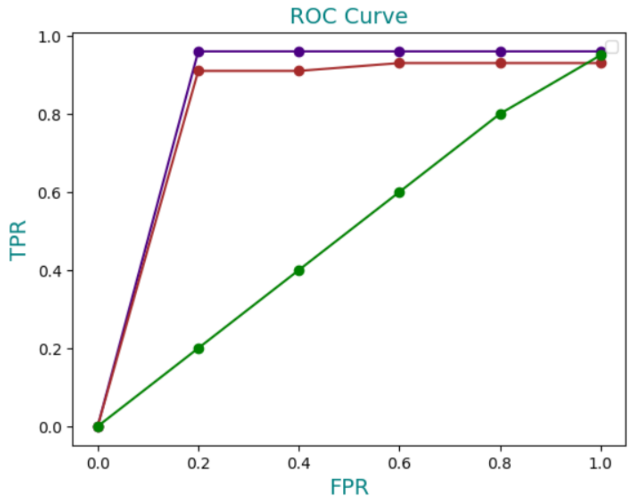

Fig. 3. Performance Validation Using Receiver Operating Characteristic (ROC) curve

The AUC-ROC curve is considered in this study since it is a popular performance measure for problems with binary classification. It can see the true positive rate on the x-axis and the false positive rate on the y-axis. Figure 3 shows the results of the receiver operating characteristic (ROC) validation.

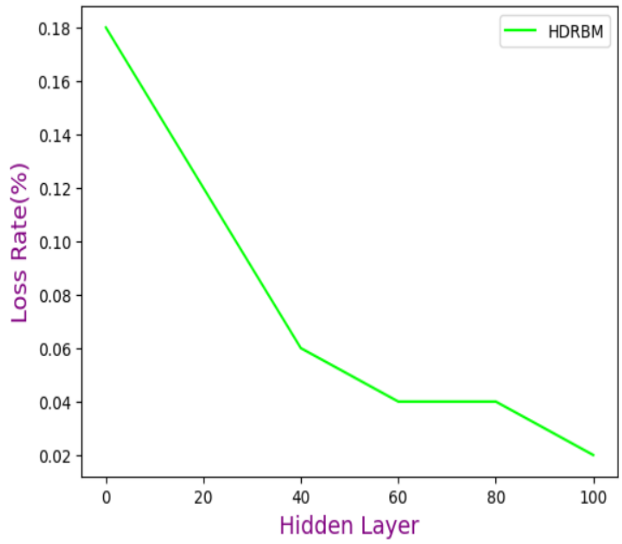

Fig. 4. The Impact of Adding More Hidden Layers on Training Loss

Unfortunately, as the number of hidden layers increases, so does the model's complexity, which in turn increases the computer's workload, wastes computational resources, and ultimately degrades the model's performance.

5. Conclusion

The battery is an essential part of electric vehicles, which are a new kind of sustainable transportation. At the moment, the most reliable method for storing energy in electric cars is to use lithium chemistry. However, there are still many unanswered questions about the findings. Choosing the best cell materials and developing electrical circuits and algorithms are two ways to improve battery use. The relative and based state of charge (SOC) can be simply computed in preprocessing by utilizing the energy level and battery property relationship. Feature selection makes use of principal component analysis (PCA), a mathematical technique that reduces the number of uncorrelated variables to a manageable level while still determining a number of connected variables that account for as much data variability as possible. On a regular basis, the suggested method outperforms, with an average accuracy rate of 96.68%.

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