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Original Article

A Deep Learning-Based Sensor Fault Detection Intelligent Battery Management System for Electric Vehicles

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***Abstract** - As the green movement gains momentum, all types of Electric Vehicles (EVs), such as electric automobiles, buses, trains, motorcycles, and bicycles, are becoming more and more prevalent. The way EVs manage their energy will be significantly influenced by future design, and developments in low-cost sensing and computation will be assessed to create more efficient systems that can be tailored to suit a range of battery types and vehicles with wildly disparate performance needs. Battery Management Systems (BMS) rely on the collection and transmission of data from battery sensors. Because inaccurate battery data from sensor failures, communication issues, or even cyberattacks can cause significant harm to BMS and lower the total reliability of applications based on BMS, such as electric cars, the battery sensors' lifespan and the BMS's transmission data must be evaluated. For a BMS to function properly, sensor data is required. For electric car battery systems to be secure and sustainable, effective detection of sensor failures is essential. This study proposes a deep learning-based method for battery data, specifically lithium-ion batteries, to detect and categorize abnormal battery sensor and gearbox data. The issue of optimizing real-time battery management systems is examined since this performance suggests increased battery thermal stability, efficiency, and durability.*

***Keywords** - Electric Vehicles, Battery Management System (BMS), Deep Learning, BMS sensor fault detection.*

1. Introduction

A significant portion of greenhouse gas emissions and environmental degradation is attributed to the transportation industry [1]. Nonetheless, this industry may benefit from the advancement of battery-powered energy storage technologies, such as hybrid locomotives, electric cars, and other e-mobility applications [2]. The preservation of green spaces in metropolitan areas has been made possible by the slow shift to an Intelligent Transport System (ITS) from a conventional transport system [3]. In this sense, EVs' dependability and safety become essential for capturing a sizable portion of the market. EVs are composed of several components, each of which is susceptible to various types of issues. Nonetheless, the battery system and electric motor drive are its essential parts, and these are typically where an EV's primary issues arise. Therefore, the proper functioning of these components is crucial and requires careful observation [4]. In Machine Learning (ML), LIB BMS, health, state of charge, and remaining usable life have long been utilized to effectively, consistently, and precisely predict several essential LIB conditions. The potential benefits of Machine Learning (ML)-based approaches over traditional LIB defect detection and diagnosis methods, including model-, knowledge-, and signal-processing-based methods, have spurred a significant amount of research on ML-based data-driven methods in recent years [5]. Accurate evaluation of critical parameters and proper battery storage system diagnostics and operation are essential for the efficacy of electric vehicles [25]. However, significant problems such as battery overcharging, overdischarge, excessive heat, cellular unbalancing, thermal runaway, and fire dangers can result from improper surveillance and security protocols for the battery storage system [6]. As larger and higher-performance battery packs become increasingly necessary, various cell balancing strategies are being focused on [7]. A reliable estimate of SOC, SOH, and RUL in BMS significantly influences EV performance and efficiency, thereby enhancing battery longevity, safety, and dependability [24]. However, estimating the Degradation of battery capacity and changing ambient conditions make SOC, SOH, and RUL difficult [8]. To mitigate potential serious risks and enhance system safety and dependability, it is crucial to monitor the entire EV platform while driving in various operating conditions using online-based data collection, analysis, fault identification, and categorization [9]. In essence, Battery Management Systems (BMSs) are crucial for improving battery condition monitoring effectiveness and safeguarding against internal and external short circuits, excessive current, and voltage [22]. Over the past decade, numerous BMSs and their applications have been the subject of numerous studies and patents; however, many remain unexplored [10]. To address the EV charging issue, the emphasis is now on using data-driven approaches rather than relying just on intuition. Video, music, image, and natural language recognition are just a few of the numerous domains that have profited from massive data sets and ML, or machine learning [11]. Regarding electric cars, propulsion is powered by rechargeable batteries. For electric car batteries to operate safely and dependably, online monitoring and charge status estimations are essential [23]. The battery's lifespan may be increased, and the electric vehicles can reduce their dependence on external power sources by implementing battery and ultra-capacitor considerations in an Energy Management System (EMS) [12]. Strong, real-time techniques for identifying anomalous or defective battery sensor data are still lacking in existing approaches, despite the rising popularity of electric vehicles and the growing need for dependable BMS. Inaccurate battery status estimation, decreased system reliability, and potential safety issues may result from the current BMS architectures' frequent inability to handle sensor failures, communication faults, and cyber-related interruptions. Additionally, the majority of studies do not fully utilize cutting-edge deep learning techniques and newly developed low-cost sensing to improve the accuracy and lifespan of sensor data transmission in lithium-ion battery systems. To improve the thermal stability, efficiency, and long-term durability of EV battery systems, a research gap exists in the development of an intelligent, deep learning-based solution that can precisely recognize and classify anomalous battery sensor and gearbox data in real-time.

The main contributions of the Paper are as follows:

- By guaranteeing the accuracy and dependability of sensor data used in battery management tasks, the proposed approach addresses the optimization of real-time BMS.
- The deep learning model contributes to longer battery life and safer EV operation by improving battery thermal stability, efficiency, and overall durability.
- The solution enhances the security and sustainability of battery systems by providing a reliable method for identifying sensor failures.
- It reduces the possibility of inaccurate sensor readings, which may result in decreased performance, safety problems, or even the failure of vital battery operations.

The paper is organized as follows: the first section introduces the topic and explains the need for this endeavor. The 2nd section contains the related works. The paper's suggested methodology is presented in Section 3rd. The results and discussion are presented in Section 4. Lastly, the conclusion is included in section 5th.

2. Related Works

P. Vasanthkumaret al (2022) [13]. In HEVs, an efficient Battery Management System (BMS) is often used to display the battery's State-of-Charge (SOC), although this remains a challenging problem. For HEVs, an accurate SOC estimation model is required because overcharge and over-discharge are known consequences of battery deterioration. Hicham, Chaoui, et.al (2018) [14]. This includes human-like expertise representations and hand-engineered policies. To avoid working at the level of complex vehicle dynamics, this study develops a resource allocation technique for deep reinforcement learning-based electric vehicles. Lang et al. (2021) [15]. This article reviews the use of AI approaches in recent years. Fault classification and feature extraction are the two main stages of AI-based FDD. It is examined how various signal processing methods can be applied to feature extraction. Specifically, In 2024, Sundaramoorthi, R. et al. [16]. The project focuses on improving traditional EVs through better energy storage systems and their various uses. To increase the energy storage and gearbox efficiency of EVs, power extraction is optimised using a Maximum Power Point Tracking (MPPT) method enhanced by Particle Swarm Optimisation (PSO) and Ant Colony Optimisation. Additionally, voltage levels are raised using a SEPIC converter. Hicham et al. (2024) [17]. To address the aforementioned issues, this study proposes a revolutionary smart digital system that enables customization and sterilization of the system. The proposed architecture employs a multi-layered strategy. It uses transfer learning techniques and incorporates numerous intelligent digital twin models at various levels of abstraction. S. Bhuvaneswari et al (2024) [18]. A smart electric vehicle design with an Intelligent Battery Management System (IBMS) enabled by a Smart Battery Management System (SBMS) is presented in this study. Advanced components, including an alarm system, ACS758 current sensor, CYHVS025T voltage sensor, DS18B20 temperature sensor, and Microcontroller (MCU), are all integrated within the SBMS. In 2022, Vellingiri et al. [19]. Developing is the primary goal of this effort. To accurately estimate SOC, the method under consideration employs a Long Short-Term Memory (LSTM) and a Hybrid Convolutional Neural Network (HCNN-LSTM) model.

Hong et al. (2024) [20]. Battery defects that fall into the following categories are examined in this paper: mechanical, electrical, thermal, inconsistent, and ageing. With an emphasis on data-driven approaches, it offers popular defect detection techniques from both mechanistic and symptomatic viewpoints.

These methods are applied to actual automobiles and provide theoretical guidance for the pre-warning of battery hazards. Balan et al. (2022) [21]. To efficiently automate and assist with crucial duties, such as the brake system, this study constructs a driver identification system using a thorough approach (Principal Component Analysis, PCA, and Random Forest, abbreviated as RF). Using work models, it simulates A low-cost real-time driver-assisted technique to test job schedule ability and investigate various scenarios prior to EV deployment.

The majority of current research on BMS focuses on conventional signal-processing or model-based techniques for monitoring lithium-ion batteries, which often rely heavily on predetermined thresholds, manually created features, and simplified battery models. These methods typically lack resilience against cyberattacks or unexpected sensor behaviors, and their capacity to identify intricate, nonlinear sensor failures or communication anomalies is constrained. Furthermore, the majority of current solutions are less successful in contemporary EV contexts where thermal stability and efficiency are crucial, since they do not offer real-time, intelligent classification of anomalous sensor or gearbox data. On the other hand, the proposed study presents a deep learning-based system that can accurately detect and classify anomalous sensor and transmission signals in real time by directly learning complex patterns from battery data. By utilizing cutting-edge data-driven methodologies instead of relying on conventional rule-based monitoring, this strategy enhances overall EV battery safety, performance, and durability, supports a range of battery types, and improves diagnostic reliability.

3. Proposed System

Model-tuning methods are employed to develop algorithms for continuous learning, and vehicle controllers that utilize deep learning often incorporate input sensor data. The sensor data collection and processing used in electric vehicle controllers for feature extraction and optimisation is shown in the block diagram below. Furthermore, this paper focuses on methods for obtaining performance analysis from gathered sensor data.

Process Overview: The research principle described in the paper is centred on the diagnosis of sensor faults in BMS systems using deep learning. As shown in Figure 1, the research is divided into six crucial parts. "Research Process Overview."

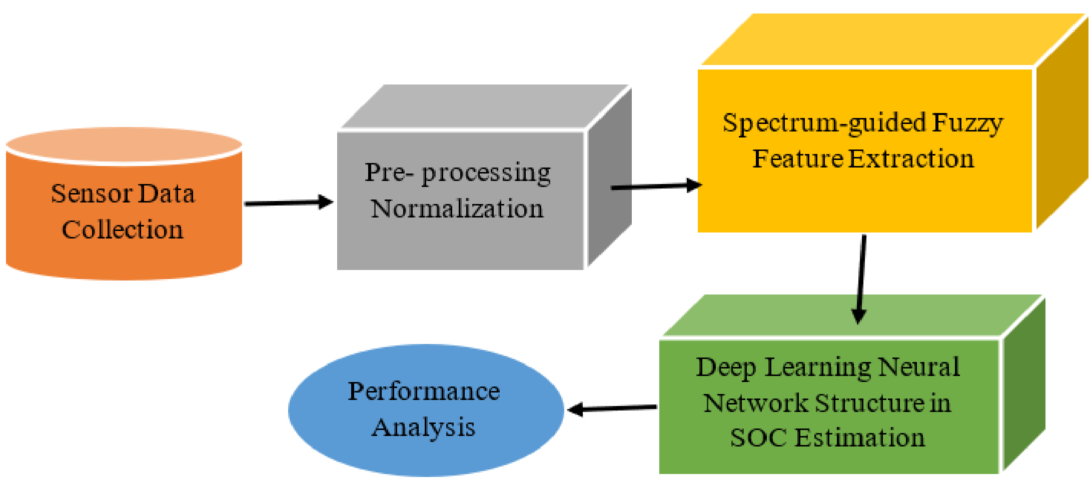

Fig. 1 Overview of research process

Step 1: Gathering sensor data that represents the external characteristics of the battery is the first stage. To accurately achieve specified fault isolations, Information about the internal state of batteries can be gathered using novel sensors, such as integrated sound and pressure sensors.
Step 2: Sensor sample datasets undergo initial processing to ensure their plausibility and standardize the data, preparing them for further processing and analysis.
Steps 3 and 4: The Spectrum-guided Fuzzy Feature Extraction theorem serves as the basis for data processing and rearranging the features in the feature extraction model that receives the sample datasets. The retrieved data is used to determine features for the Structure of SOC estimation using deep learning neural networks.
Step 5: The final stage of the study involves assessing the "Performance Analysis" framework. The evaluation of metrics, including f1-score, accuracy, precision, and recall, is based on mean square error and root mean square error.

3.1. Sensor Data Collection

Only the external characteristics of the battery are displayed in the data collected by the sensors; the inside conditions are not. Furthermore, the features of each defect are not always evident, and there is a connection between multiple problems. As a result, it remains quite challenging to accurately detect faults and separate them from unknown fault data. Features can be accessed through new sensors (integrated pressure sensors, sound sensors, etc.). The data gathered from the sensor samples is shown in Table 1 for the feature extraction model. To facilitate the effective processing of big battery datasets, the model is trained utilizing a GPU-enabled hardware configuration for experimental implementation. While an early stopping condition based on validation loss is used to avoid overfitting and guarantee ideal model convergence, a batch size is chosen to strike a compromise between memory consumption and training stability. Additionally, variables for fault categorization are extracted from the fault data.

Table 1. Sample sensor data

Battery Voltage (V)	Battery Current (A)	Battery Temperature (◦C)	State of Charge (%)	State of Health (%)	Charge/ Discharge Status	Charging Power (KW)	Charging Time (h)
384	81	35.2	75.2	95	Charging	10	2
385	85	35.4	75.3	94.7	Discharging	10	2.01
386	87	35.6	75.6	94.5	Charging	10	2.03
387	89	35.7	75.8	94.4	Discharging	10	2.05
388	90.2	35.9	75.9	94.3	Charging	10	2.07

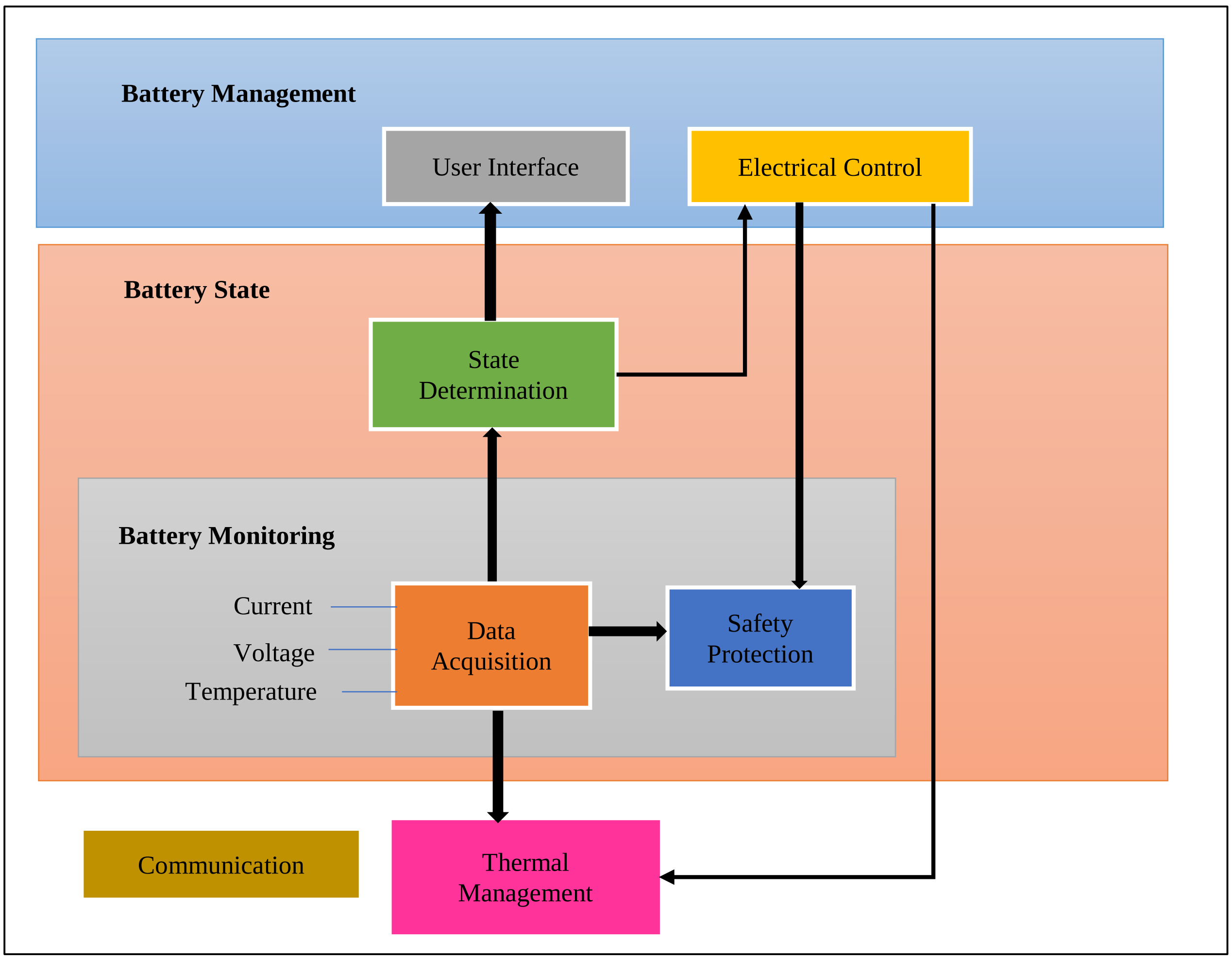

Fig. 2 Block diagram of battery management system

3.1.1. Battery Management System

Comprehensive and advanced BMSs are currently found in portable devices, such as laptop computers and mobile phones, although they are not yet fully integrated in EVs. This is because, compared to a portable electronic item, the battery in an automobile has hundreds of times more cells. A car's battery is also designed to be a long-lasting and high-power energy source. Stated differently, EV and HEV batteries must deliver high voltage and high current. As a result, EV BMSs are significantly more complex than those for portable devices.

Figure 2 illustrates how these ideas can be integrated into a generic BMS structure, highlighting its fundamental features. Three different topologies, centralized, distributed, and modular, have been used in BMSs from the standpoint of hardware structure. Nonetheless, the roles of the BMSs are comparable in each scenario. A layer structure for battery management, condition, and monitoring was implemented to categorize the various BMS functions.

The battery pack features several sensors to gather information at the detection layer. System security is ensured, and battery health is assessed through real-time data collection and analysis. In contrast, the battery state determines the charge time, discharge schedule, cell equalisation, and temperature management between cells. Several sensors are built into the battery pack to gather information at the monitoring layer. System security is ensured, and battery health is assessed through real-time data collection. Cell equalisation and discharge methods are based on battery condition, which is also communicated to the user interface, as well as charge time and temperature management among cells.

3.1.2. Performance Comparison with Other Batteries

Table 2 compares the characteristics of Li-ion batteries using different energy storage techniques, based on various operating conditions. The comparison indicates that its energy density is good, ranging from 110 to 160 Wh/Kg. Another benefit of Li-ion batteries for use in electric vehicles is their broad working temperature range. Battery weight is one crucial factor for EVs. As a result, compared to traditional batteries, Li-ion batteries are lighter and smaller in size.

Table 2. Performance analogy of Li-ion batteries with other batteries

Battery Type	Lead-Acid	Ni-MH	Zn-Br	Ni-Cd	Li-Ion
Energy Density (Wh/Kg)	40-60	80-105	50-90	40-60	115-170
Power Density	185	500-1000	-	145	1800
Temperature (°C)	-30-60	-30-60	-30-60	-50-60	-30-60
Running Voltage(v)	3	1.30	1.68	1.30	3.9
Self-Discharge	less	more	less	Moderate	less
Energy Efficiency	75	80	85	85	85

Li-ion battery characteristics are compared to those of other batteries in Table 2. Compared to other battery types, Li-ion batteries have a more linear discharge capability, as has been noted in earlier articles.

3.2. Normalize the Input Data

Step 1: Normalize the input data in accordance with the definition of the decision-making matrix. This implies that intervals between 0 and 1 should be used to arrange the input data. Normalisation comes in two varieties.

Step 1.1 Normalization 1 (Linear):

$$t_{ij} = \frac{x_{ij} - x_{ij}}{x_{ij} - x_{ij}}, i = 1,2, \ldots\ldots, m; j = 1,2, \ldots\ldots, n; \quad (1)$$

Step 1.2 Normalization 2 (Vector):

$$t_{ij}^{*} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^{2}}}; i = 1,2, \ldots., m, j = 1,2, \ldots\ldots, n; \quad (2)$$

For both criterion kinds (min and max), the normalisation methods from step 1 are applied.

Step 2: The weights of the criteria are multiplied by the Collectively Averaged Normalised decision-making matrix to produce a weighted DM matrix.

$$t\hat{}_{ij} = W_{ij}.t_{ij}^{norm}; \quad i = 1,2, \ldots., m; j = 1,2, \ldots, n; \quad (3)$$

Step 2.1 Aggregated averaged normalization

Equation 4 is used to do the aggregated averaged normalisation.

$$t_{ij}^{norm} = \frac{\beta t_{ij} + (1-\beta) t_{ij}^{*}}{2}; i = 1,2, \ldots\ldots., m; j = 1,2, \ldots., n \quad (4)$$

Where t_{ij}^{norm} Denotes the normalisation of the aggregated average. β, which ranges from 0 to 1, is a weighting factor. We took β to be 0.5 in this instance.

Step 3: The Aggregated Averaged Normalised decision-making matrix is multiplied by the weights allocated to the criteria to produce a weighted DM matrix.

$$t\hat{}_{ij} = W_{ij}.t_{ij}^{norm}; i = 1,2, \ldots\ldots., m; j = 1,2, \ldots., n; \quad (5)$$

Step 4: It is necessary to summarize the normalized weighted values of the criterion types min (Li) and max (Ai) independently.

This can be calculated by applying Equation 6 and Equation 7:

$$L_i = \sum_{j=1}^{n} t_{ij}\hat{}(\min); i = 1,2, \dots \dots, m; j = 1,2, \dots, n; \quad (6)$$

$$A_i = \sum_{j=1}^{n} t_{ij}\hat{}(\max); i = 1,2, \dots \dots, m; j = 1,2, \dots, n \quad (7)$$

Step 5: Ascertain the final ranking of the alternatives. The final Ranking (Ri) of the alternatives must be determined using Equation 8:

$$R_i = L_i^{\lambda} + A_i^{(1-\lambda)}; \quad i = 1,2, \dots \dots \dots, m; \quad (8)$$

Where λ represents the criterion type's coefficient degree, and Ri is the label of the ranked alternatives. We assumed that the value λ was 0.5 because both kinds of criteria were present. Nevertheless, when considering the type of criterion, variations of the parameter λ can be produced. For instance, if the decision-making problem has one criterion of type max and two criteria of type min, the coefficient λ should be 2/3.

3.3. Spectrum-Guided Fuzzy Feature Extraction

Remarkable is the fact that when driving in real-time, the typical expression of the timeseries data may be impacted by sudden changes in driver behavior. After activating the sample window, the SFFE adaptively modifies the window size based on frequency-domain properties. It is designed to guarantee classification accuracy while adaptively determining the minimum size of a sliding window that is more suitable. By adaptively modifying the size of the short-term sliding window, it should be possible to eliminate the expression of the time-series data. The essential characteristics of the dynamic driving signals are readily captured by considering their spectral properties, which can then be used as a key variable to adjust the window size. Time-domain extraction is guided by the integration of all spectral properties, which is inspired by fuzzy encoding technology. This equalises each element's contribution to the window size. The suggested approach extracts three-by-three combinations from the time and frequency domains using fuzzy encoding technology. That is, nine sets of additional features. Figure 3 illustrates how their mapping relation is expressed. The goal of this improved time-domain extraction is to remove the impact of abrupt changes in driver behavior on the characteristic expression of the time-series data. To date, the driver recognizer has been trained using 15 sets of features extracted from the original operating signals.

3.4. Deep Learning Neural Network Structure in SOC Estimation

By estimating the relationship between input data (voltage, current, temperature, power, capacity, etc.) and output data (SOC) using the currently available data, a model is constructed to predict the State of Charge (SOC) of a Li-ion battery based on the deep learning theory of computer science. Neural networks can be categorised as single, hybrid, or trans structures based on their numerous configurations.

3.4.1. MLP Type DNN

Deep Neural Networks (DNNs) are the source of multi-layer perceptrons, commonly known as artificial neural networks, by increasing the training parameters and improving the arithmetic power. Their benefits include not restricting the input's dimensionality, being extremely flexible with the data, and theoretically being able to fit any function nonlinearly. However, when the network has a large number of parameters, it is susceptible to over-fitting. A deep neural network with eight neurons in each of its four hidden layers is shown in Figure 4.

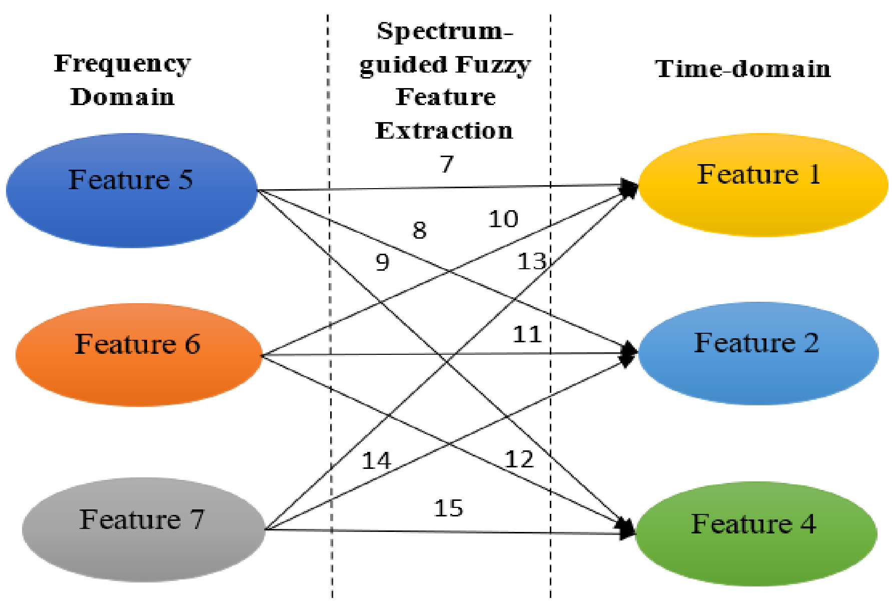

Fig. 3 Spectrum-guided fuzzy feature extraction using a mapping relation

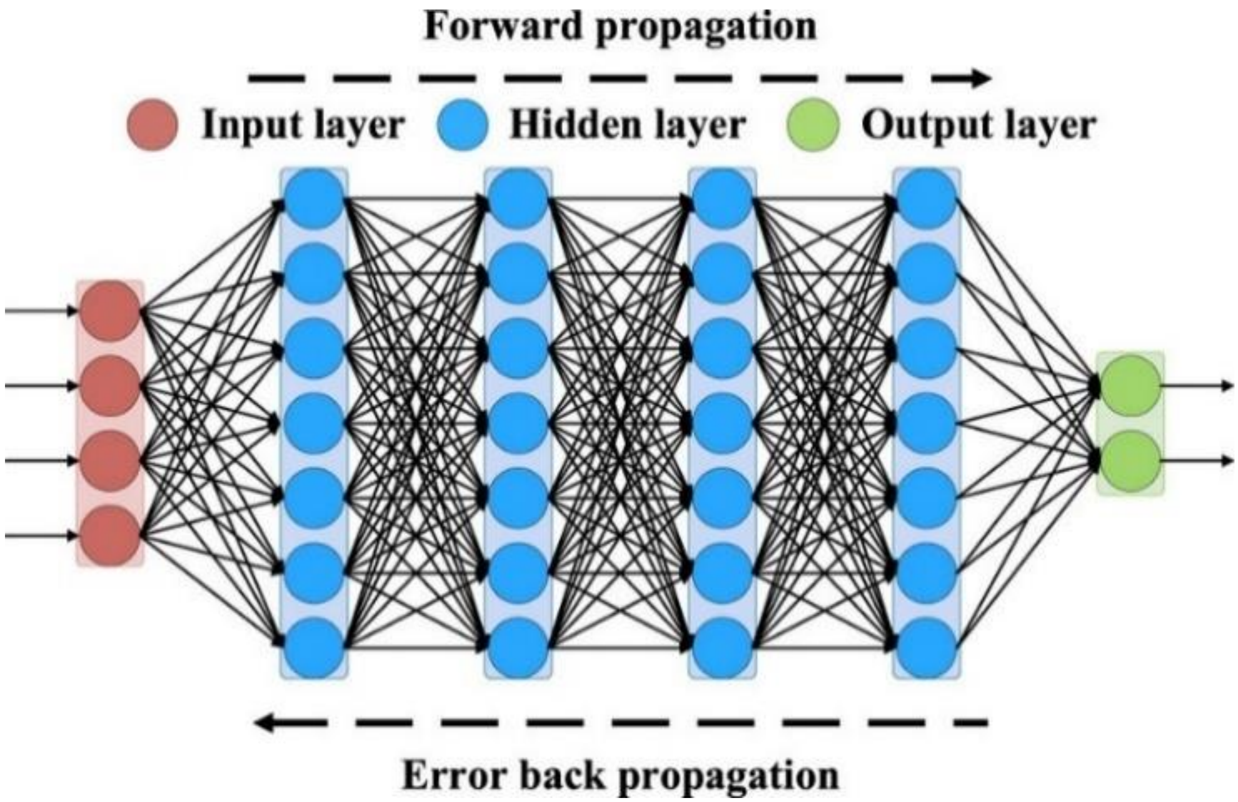

Fig. 4 Deep Neural Network with four hidden layers

To create a model for SOC estimation, a DNN was used to evaluate the Panasonic 18650 lithium battery in a range of temperatures and operating conditions. Current, voltage, average voltage, and average current were among the inputs that were included in the data collection and were gathered under temperature fluctuations ranging from 10 to 25 ◦C. Another person confirmed each temperature.

3.5. Performance Analysis

Deep Learning (DL) performance analysis in Electric Vehicles (EVs) is a new field of study that integrates automotive technology with artificial intelligence to optimise and enhance EVs in a number of ways. When it comes to managing massive data sets, identifying significant patterns, and offering real-time insights for EV performance enhancement, deep learning approaches are especially helpful. This article explains the application of deep learning to electric vehicle performance analysis. By examining past charge/discharge cycles, temperature fluctuations, and other pertinent factors, the Remaining Usable Life (RUL) of EV batteries can be predicted using deep learning algorithms.

3.5.1. Performance Measures

One of the most important measures for classifying deep learning networks is the confusion matrix. According to the Confusion matrix, the remaining values.

$$Accuracy = \frac{TP}{TP+TN+FP+FN} \tag{9}$$

$$Sensitivity = \frac{TP}{TP+TN} \tag{10}$$

$$Precision = \frac{TP}{TP+FP} \tag{11}$$

$$Recall = \frac{TP}{TP+FN} \tag{12}$$

4. Result and Discussion

Li-ion battery data processing requires a significant amount of storage space, and the numerous issues, although in addition to solving the issues of gradient disappearance and explosion, LSTM is capable of handling Li-ion battery statistics for SOC throughout the long-term prediction. The calculation parameters for the SOC estimate lead to a protracted training period. Selecting a suitable deep learning framework for estimating SOC is a multi-factor challenge that is influenced by the data, precision outcomes, time consumption costs, and other factors. The first consideration is the number and quality of available data; in other words, an SOC estimate with a data-driven deep learning algorithm will work well in a data system with lots of high-quality data.

When choosing a deep learning structure, both the training duration and the SOC estimation accuracy must be considered. This is because, as most cases show, training time and SOC estimation accuracy are positively correlated, but once training time reaches a certain threshold, the precision of SOC estimation will not increase significantly.

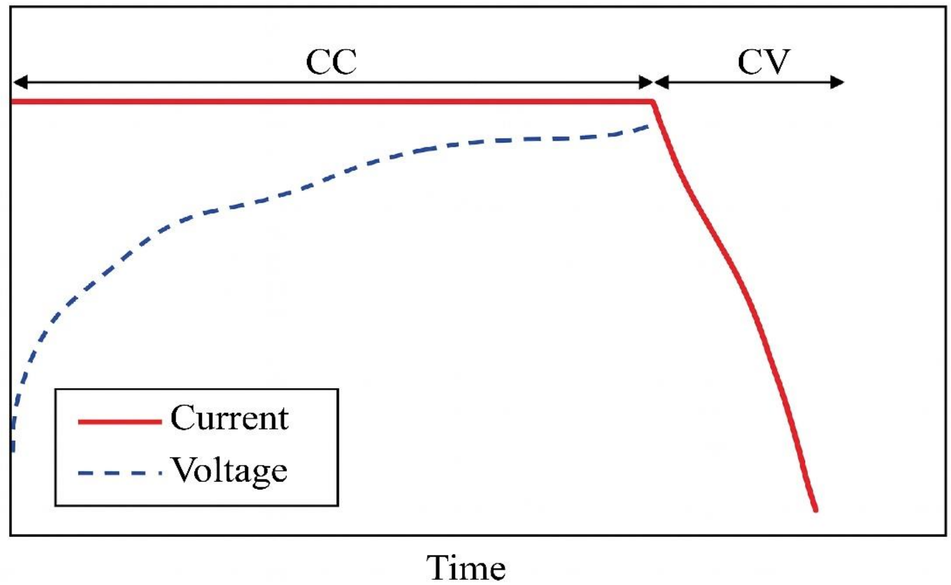

Fig. 5 Battery current and voltage of CC-CV charging approach

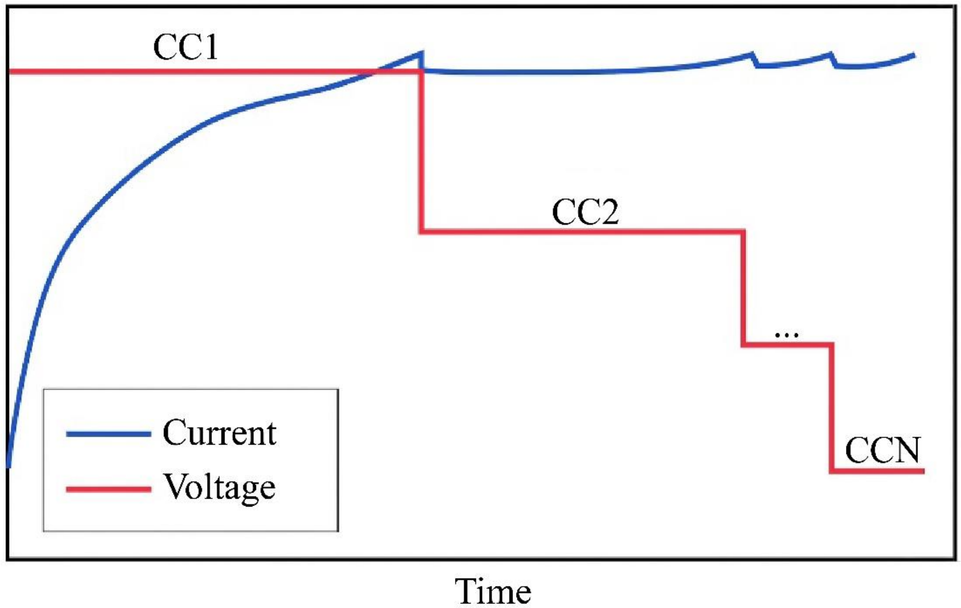

Fig. 6 Battery voltage and current using the MCC charging method

A Hybrid Charging method called CC-CV has been proposed by combining CC and CV charging, as illustrated in Figure 5. This method involves initially charging a battery with a predetermined constant current in the CC phase, which raises the battery voltage to the highest safe threshold. The battery then steps down the charging current continuously as it enters the CV phase with a predetermined constant voltage. Until a goal capacity or a terminal value of the declining current is attained, this CV phase will come to a conclusion. With some adjustments, the conventional CC-CV method is also used to charge Li-ion batteries. Initially, it is used to charge lead acid batteries using fixed values of constant voltage and constant current that are advised by battery manufacturers. Constant current in Li-ion battery CC-CV charging applications should be significantly higher than that of lead acid batteries, which are typically selected between 0.5 and 3.0 C, due to the higher terminal voltage and charge acceptance of Li-ion batteries. As seen in Figure 6, MCC charging is another well-liked conventional charging method.

This method has been effectively created to charge a variety of battery types, including lead-acid batteries. Figure 7 displays the battery's charging and discharging curves at normal temperatures throughout a range of cycle counts. Figure 8 displays the battery's charging and discharging curves throughout a range of cycles at room temperature.

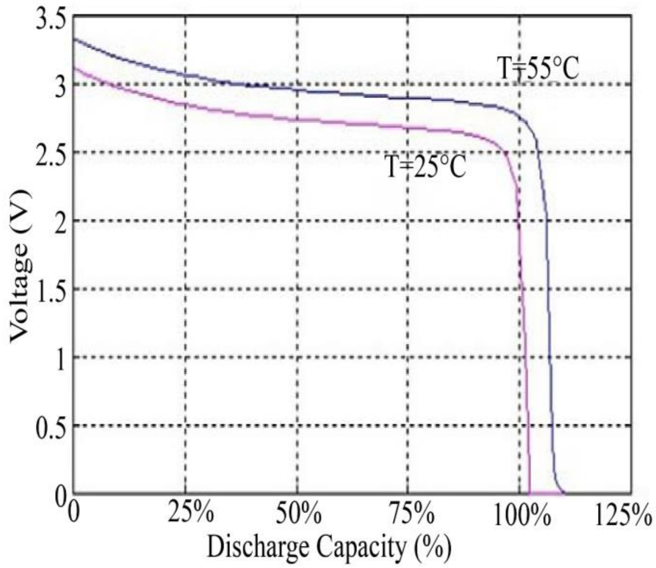

Fig. 7 Battery discharge curves that were simulated at various temperatures

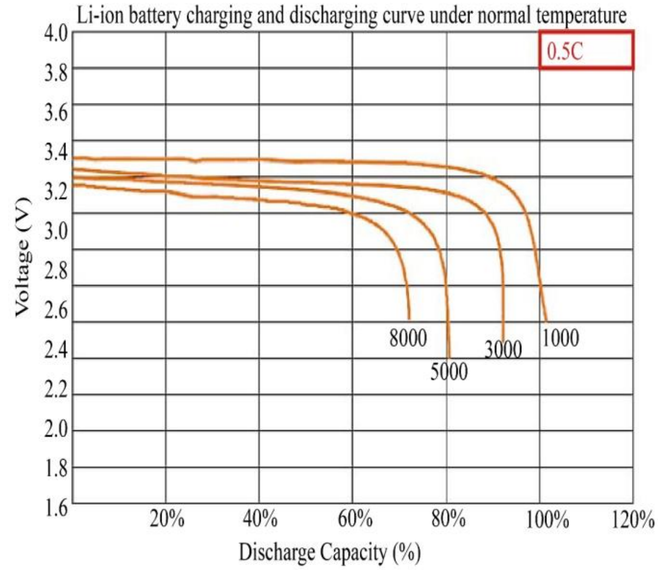

Fig. 8 The battery's real draining curves over different numbers of cycles

4.1. Comparing the Various Models

We contrast the proposed model with the CNN and LSTM deep learning algorithms to confirm its benefits. Figure 9 and Table 3 present the results of the comparison. To get the best results, we additionally test these models in a variety of ways. The recommended model outperforms the compared models, according to extensive testing. For instance, the LSTM takes longer to train when the sample sequence is longer. The suggested model trains in 6 hours compared to 30 hours for the LSTM for the same length of sequence, whereas the proposed model's training impact is more accurate. Given the same sequence length, the two differ, but the proposed models.

Table 3. A comparison of many models

Fragment Length	Our Model	LSTM	Normal CNN
33	52.68	53.00	50.00
65	63.59	60.50	52.37
129	68.29	67.99	63.47
257	86.22	80.76	71.46
513	90.48	82.48	74.51
1025	93.35	84.50	81.50
2049	95.39	90.51	91.98
4097	97.49	99.01	91.50
10,00	96.00	77.10	86.51
30,000	97.28	77.50	86.38

Figure 10 shows the machine learning methods in Table 3 with the highest performance accuracy. Additionally, there are noticeable differences between different machine learning techniques. Although DF and decision trees perform the best and worst, respectively, on our dataset, our model still has a reasonable accuracy.

Table 4. Four measurement indicators

Accuracy	Recall	Precision	F-Measure
93.44	96.23	91.20	93.60
94.73	97.49	92.77	95.03
91.94	82.91	99.76	90.65
97.48	96.22	98.71	97.45

We replicated the methods used in similar research using our dataset, and then we compared them. This is more than just a comparison between deep learning and traditional machine learning methods. Our performance is better than theirs, as shown by Table 4, which clearly displays the four measurement indications.

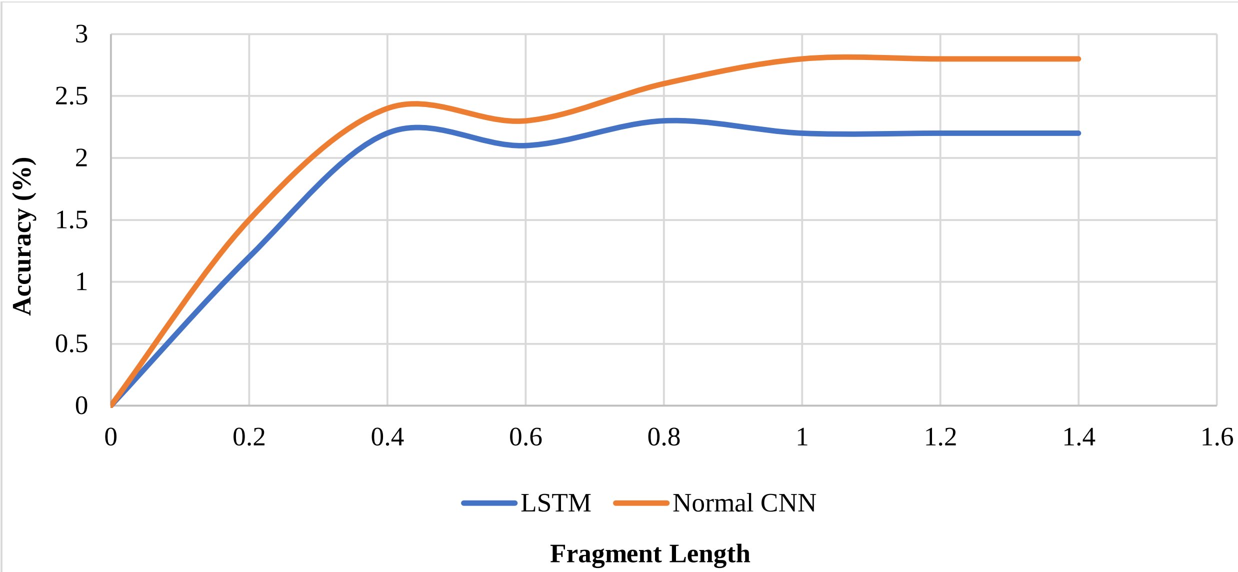

Fig. 9 Comparison of different models

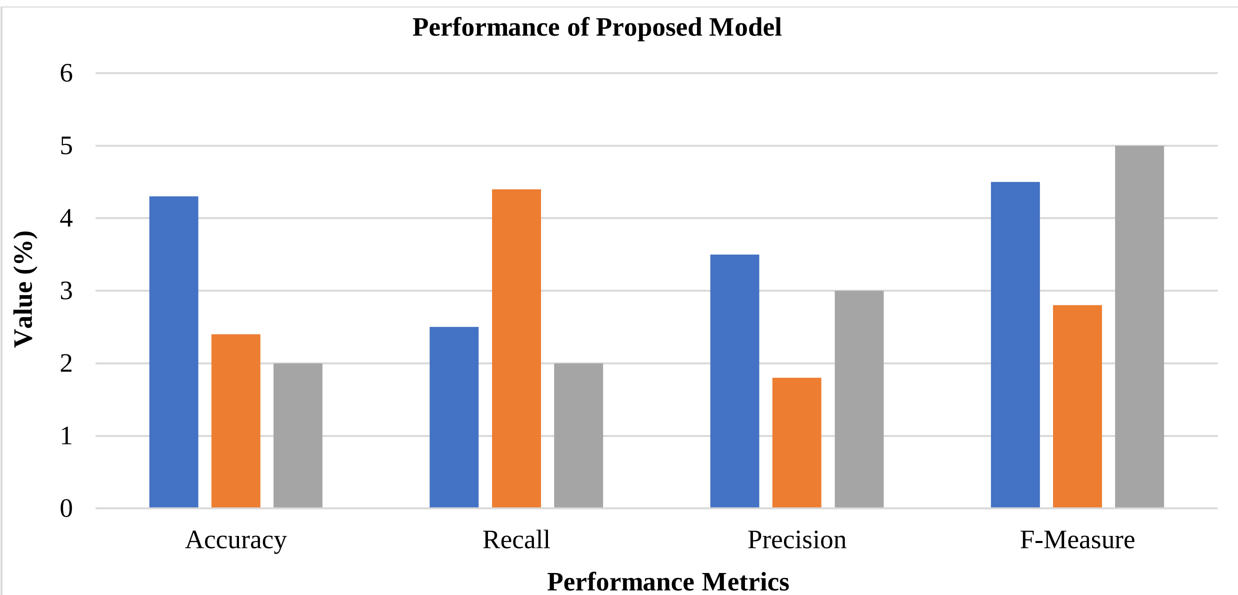

Fig. 10 Performance of proposed model

5. Conclusion

Estimating the state of charge of EV lithium batteries using deep learning sits at the nexus of battery chemistry, data science, and computer science. Currently, there are still a lot of intricate issues in the deep learning and battery domains that are challenging to comprehend or resolve. Deep learning techniques outperform mathematical models in terms of efficiency, but they lack a more thorough comprehension of how battery state parameters. The design and management principles of batteries for electric cars are covered in this article, with an emphasis on sensor defect detection. High accuracy (97.48%), precision (98.71%), recall (96.22%), and F-Measure (97.41%) are attained; however, performance is subpar when compared to existing methods. Electric vehicle safety is largely dependent on BMSs, which manage the packs of rechargeable battery electronics. To increase the control system's efficiency and recognition accuracy, a better SFFE technique has been created. Future research might include incorporating the suggested model into real-time embedded BMS hardware, verifying performance in a range of driving and environmental scenarios, and extending the strategy to multi-sensor fusion for more accurate defect identification.

Acknowledgments

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