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Machine learning-enabled software-defined wireless sensor network architecture for battery monitoring in electric vehicles

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Abstract

For safe, optimal operation of electric vehicles, timely battery fault diagnosis and accurate determination of the battery's state of health (SoH) are essential. To address this challenge, this paper presents a long short-term memory (LSTM)-feature-based diagnostic-prognostic framework that incorporates software-defined wireless sensor networks, deep learning, and ensemble regression methods to intelligently monitor lithium-ion batteries. A controlled synthetic dataset was generated based on IEEE Standards 1188 and 1679 to represent charge-discharge behavior, operating variations, and battery degradation-related conditions. In the diagnostic module, an LSTM neural network uses voltage, current, and temperature data to diagnose multiple battery faults with 92% classification accuracy, an average area under the receiver operating characteristic curve of 0.997, and an average equal error rate of 0.007. In the prognostic module, a bagged and boosted decision tree model based on battery SoH predicts its value, with a root mean square error of 0.146, mean absolute error of 0.034, and R^2 of 0.999. The proposed framework enables comprehensive real-time diagnostics and prognostics for predictive maintenance, thereby improving vehicle operating safety and extending battery service life in next-generation electric vehicles.

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1. Introduction

Electric vehicles (EVs) and hybrid vehicles have gained popularity in recent years because they depend less on non-renewable fossil fuels (Palanisamy & Lala, 2024). Although the first electric automobile was invented in 1890, interest in EVs later declined as gasoline- and steam-powered vehicles became more prevalent (Sheng *et al.*, 2025). Unlike conventional vehicles, EVs use electric motors rather than internal combustion engines that rely on gasoline or other fossil fuels. EVs commonly use lithium-ion batteries, which can be charged using electricity generated from renewable or non-renewable energy sources. Unlike batteries in consumer electronic devices, EV batteries must store large

amounts of energy and operate at high power levels while meeting the vehicle's weight and size constraints (Nguyen-Tien *et al.*, 2025). For EVs, a battery management system (BMS) is essential for monitoring and managing key parameters, including energy, power, temperature, speed, power consumption, state of charge, and battery health, and for preventing overcharging and overdischarging. These functions help maintain EV performance and functionality while protecting the battery and extending its service life (Belkhier *et al.*, 2024; Sepasiahoooyi & Abdollahi, 2024).

An EV's reliability is strongly influenced by the operating conditions and the battery pack's degradation state. Lithium-ion batteries can experience electrical, thermal, sensing, and degradation-related abnormalities, including overvoltage, undervoltage, overcurrent, overtemperature, capacity degradation, and cell imbalance. Therefore, reliable battery management requires continuous monitoring, effective fault diagnosis, and accurate state-of-health (SoH) assessment (Machlev, 2024). The nonlinear, time-dependent nature of battery degradation makes it challenging to accurately identify abnormal operating conditions.

Recent developments in artificial intelligence (AI) and deep learning (DL) have provided effective approaches for learning nonlinear relationships and temporal patterns from battery operating data. Machine-learning (ML) and DL methods have therefore been increasingly investigated for SoH estimation and battery prognostics (Massaoudi *et al.*, 2024; Ren & Du, 2023). However, fault diagnosis and SoH estimation are often addressed as separate tasks, while the sensing and communication architectures required for continuous battery monitoring are not always integrated with the learning framework. This highlights the need for an integrated monitoring approach that combines battery data acquisition, temporal fault diagnosis, and health estimation within a common framework.

Governments and industry stakeholders worldwide have invested substantially in promoting EV adoption through incentives such as tax subsidies and charging infrastructure development. Nevertheless, challenges related to battery reliability, degradation, and service life remain. AI and advanced data analytics offer potential solutions by improving energy management strategies, enabling predictive maintenance, and enhancing battery operating efficiency (Cavus *et al.*, 2025). AI-based battery management systems are also increasingly used for SoH and state-of-charge estimation. Furthermore, developments in wireless power transfer, vehicle-to-grid systems, and smart charging are reshaping transportation and energy ecosystems (Madani *et al.*, 2024). Because lithium-ion batteries are susceptible to overvoltage, undervoltage,

overheating, and progressive performance degradation, EV safety and performance depend strongly on accurate battery health assessment and timely detection of abnormal operating conditions (Kulkarni *et al.*, 2025). The nonlinear nature of battery degradation can also limit the conventional BMS-based approaches, potentially resulting in inaccurate SoH estimation and reduced reliability.

Recent advances in AI, DL, and ensemble-based regression have enabled powerful approaches to identify temporal patterns and predict battery faults and degradation with improved accuracy (Akbar *et al.*, 2022; Mamidi *et al.*, 2025). The present study aimed to design and implement an integrated, real-time long short-term memory with feature-based diagnostic-prognostic framework (LSTM-FB-DPF) for lithium-ion batteries in EVs. The framework integrates software-defined wireless sensor networks (SDWSNs), DL, and ensemble regression to support reliable battery SoH estimation by combining fault diagnosis and predictive maintenance (Khawaja *et al.*, 2023; Kosuru & Kavasseri Venkitaraman, 2023; Pathak *et al.*, 2025; Ramakrishnan & Radhakrishnan, 2022). The proposed architecture aimed to improve battery reliability and safety, extend battery service life, and enable proactive maintenance through an intelligent, energy-saving, and scalable monitoring system.

1.1. Research gap and system-level contribution

Existing AI-based battery-monitoring approaches have demonstrated the utility of individual techniques for fault diagnosis, feature learning, and SoH estimation. However, these functions are often treated as separate analytical tasks, and the sensing and communication layers are also frequently developed independently of the learning models. The proposed LSTM-FB-DPF framework addresses this separation by establishing a coordinated information flow from distributed battery sensing to diagnostic and prognostic assessment.

The proposed framework's systemic contribution is therefore not the introduction of a new individual learning algorithm, but the functional integration and interaction of its constituent components. The SDWSN layer enables distributed acquisition and controlled transmission of voltage, current, temperature, and battery-health-related data. The autoencoder then learns a compact nonlinear representation of the collected multivariate data, reducing redundant information before diagnostic analysis. These learned representations are provided to the LSTM-based diagnostic module, which captures temporal dependencies for multiclass battery-fault identification. In parallel, the ensemble regression module processes degradation-related information to estimate battery SoH. Therefore,

each component performs a distinct analytical function required by subsequent stages of the framework.

This coordinated structure provides three system-level contributions. First, it integrates distributed battery sensing and intelligent data analysis within a common SDWSN-based architecture. Second, it combines nonlinear feature representation with temporal sequence learning to support multiclass fault diagnosis rather than relying solely on isolated signal thresholds. Third, it links fault diagnosis and SoH estimation within a unified diagnostic–prognostic workflow, enabling assessment of both abnormal operating conditions and longer-term battery health within a common monitoring framework. Consequently, the LSTM-FB-DPF architecture represents an integrated system-level contribution that extends beyond the independent application of SDWSN, autoencoder, LSTM, or ensemble regression techniques.

2. Methodology

The proposed methodology was based on an LSTM-FB-DPF for intelligent monitoring of lithium-ion batteries in EVs. The proposed architecture incorporates an SDWSN, DL-based fault diagnosis, and ensemble learning-based

SoH estimation. The objective was to provide integrated battery-monitoring functions, including early fault diagnosis and SoH estimation under defined operating conditions.

Figure 1 illustrates the SDWSN architecture. Intelligent battery monitoring in EV systems integrates SDWSNs with advanced ML analytics to enable real-time, adaptive battery-health monitoring.

As shown in Figure 1, sensor nodes are installed throughout the EV battery pack to continuously monitor key variables, such as temperature, voltage, current, and SoH. The sensor network then wirelessly transmits the collected data to sink nodes. These sink nodes aggregate the multisensor data and transmit them to the software-defined networking (SDN) controller using the OpenFlow protocol, enabling centralized network management and dynamic configuration to optimize energy use and improve fault tolerance. The SDN controller communicates with a database server, where it stores and analyzes the collected data for historical assessment. ML models can then process the incoming data to provide predictive information, identify anomalies, and predict potential battery faults or failures. The architecture enables intelligent data-driven

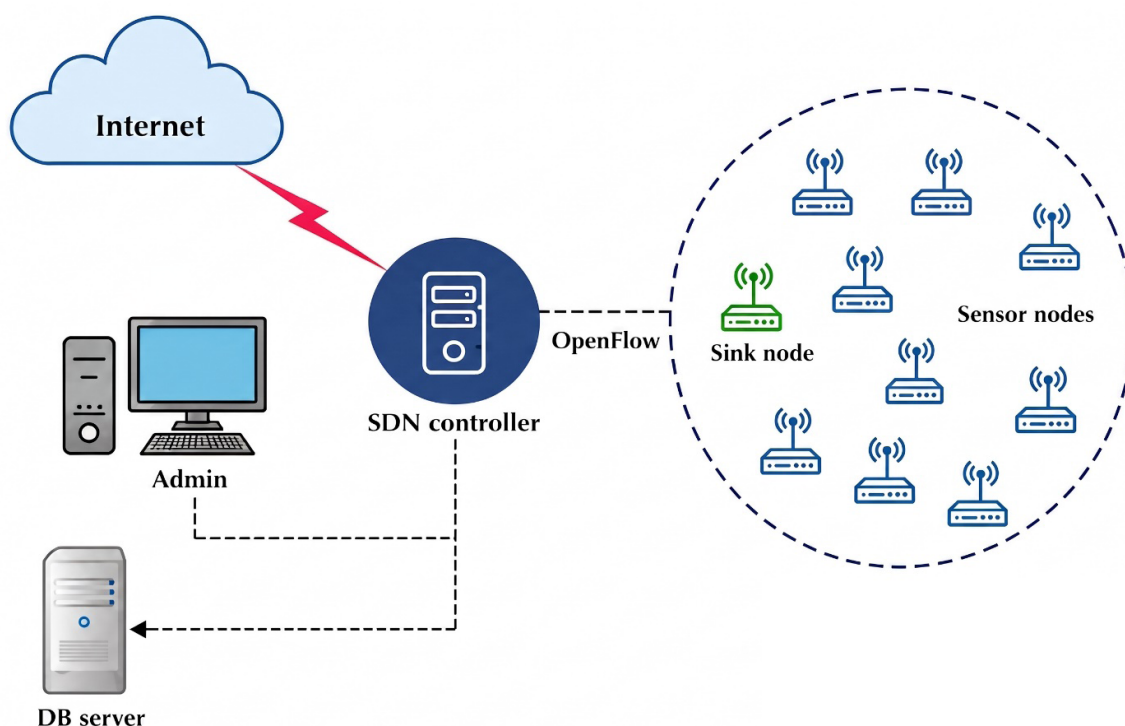


Figure 1. ML-enabled SDWSN architecture for intelligent battery monitoring in an EV system

Abbreviations: DB: Database server; EV: Electric vehicle; ML: Machine learning; SDN: Software-defined networking; SDWSN: Software-defined wireless sensor network.

decision-making through scalable communication and centralized, programmable network control. This integrated structure is intended to improve reliability, minimize energy consumption, and facilitate integration with cloud infrastructure and remote monitoring systems. Figure 2 illustrates the overall workflow of the proposed LSTM-FB-DPF module, including data acquisition, preprocessing, feature extraction, fault diagnosis, prognostic analysis, and performance evaluation.

Figure 3 illustrates the unrolled LSTM network and the internal gating structure of an LSTM cell. The fault-detection problem for lithium-ion batteries is formulated as a time-series classification problem, as the task involves identifying abnormalities in voltage, current, and temperature patterns under different operating and environmental conditions. The LSTM network learns

complex time-dependent interactions and non-uniform dynamics associated with battery operation by capturing long-range dependencies and mitigating the vanishing-gradient problem.

2.1. Software-defined wireless sensor network-based battery monitoring

Sensor nodes distributed throughout the EV battery pack continuously measure key battery characteristics. The sensors measure voltage, current, temperature, cell imbalance, and SoH-related parameters. The measured data are wirelessly transmitted to sink nodes, which subsequently forward the data to a centralized SDN controller using the OpenFlow protocol.

The SDN controller dynamically regulates data routing and network resource allocation to enable energy-efficient

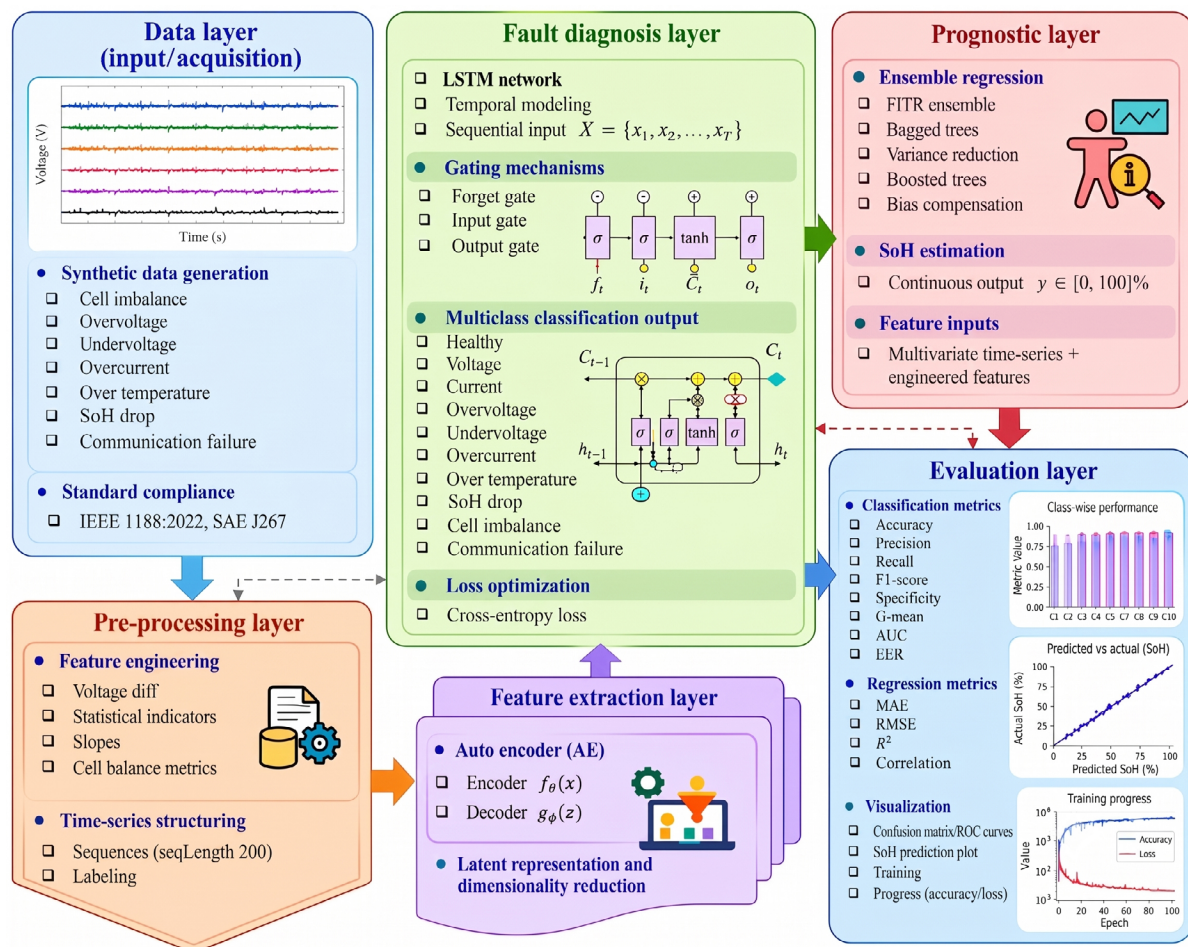


Figure 2. Workflow of the LSTM-FB-DPF module

Abbreviations: AUC: Area under the receiver operating characteristic curve; EER: Equal error rate; LSTM-FB-DPF: Long short-term memory with feature-based diagnostic-prognostic framework; MAE: Mean absolute error; RMSE: Root mean square error; ROC: Receiver operating characteristic; SoH: State of health.

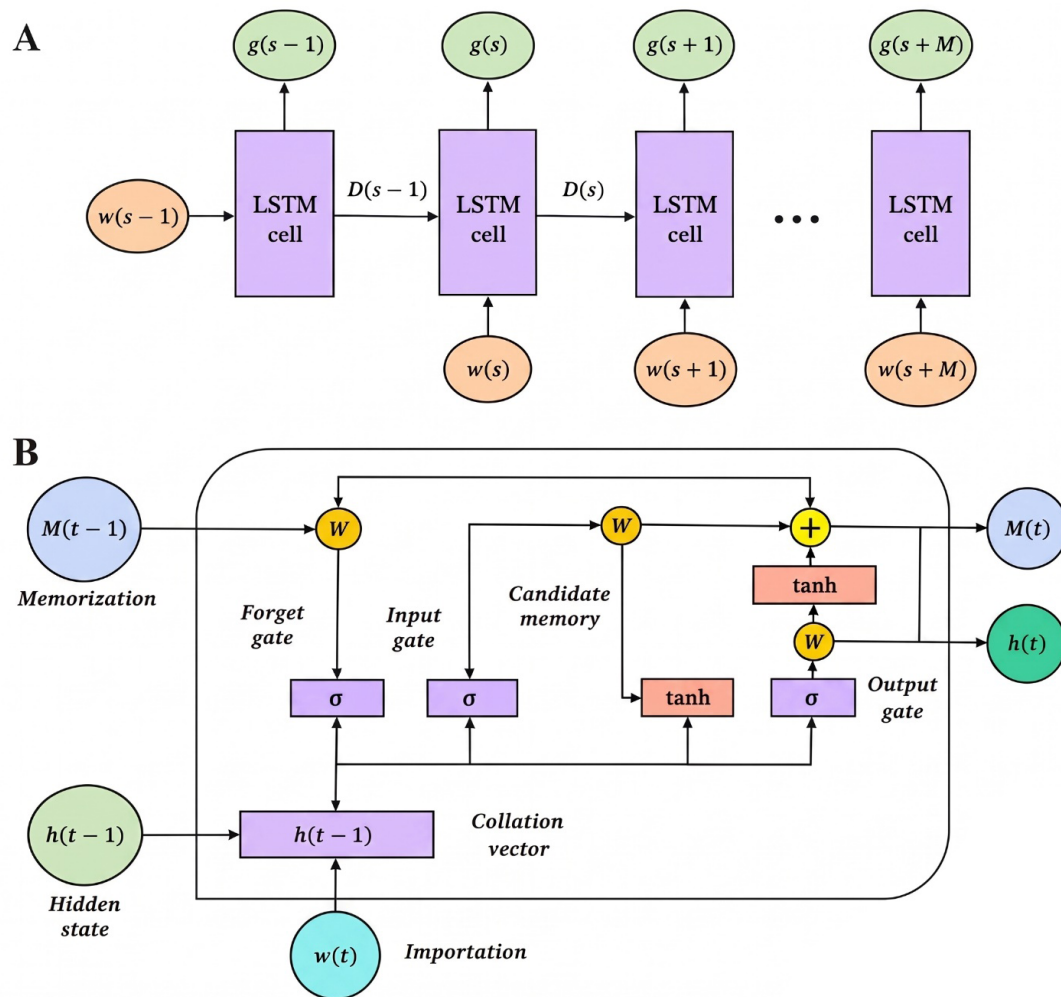


Figure 3. LSTM network architecture. (A) Unrolled architecture of the LSTM network across sequential time steps and (B) internal structure of an LSTM cell with gating mechanisms.
Abbreviation: LSTM: Long short-term memory.

and fault-tolerant data transmission. The collected measurements are stored for offline analysis and are simultaneously processed using ML algorithms to diagnose faults and assess health in real time.

2.2. Synthetic data generation

A synthetic multivariate time-series dataset was developed to represent the operating and degradation characteristics of lithium-ion batteries under controlled EV monitoring conditions. The dataset used voltage, current, temperature, and SoH as the primary battery variables. The synthetic dataset was created to provide a controlled environment for evaluating the proposed LSTM-FB-DPF framework for fault diagnosis and SoH estimation.

The data-generation process consisted of four main

stages: baseline operating-profile generation, degradation variation, fault-condition generation, and data labeling. First, charge–discharge sequences were generated to represent normal battery operating behavior. Variations in voltage, current, temperature, and SoH were introduced across the sequences to represent different operating conditions.

Fault conditions were then introduced into the corresponding time-series signals. Overvoltage and undervoltage were represented by abnormal voltage deviations, whereas overcurrent was represented by abnormal current variations. Overtemperature was introduced through abnormal temperature excursions. Voltage and current sensor faults were represented by abnormal measurement patterns, whereas SoH drop

and cell imbalance were represented by degradation-related changes. Communication failure was represented by interruptions of the expected monitoring-data transmission pattern.

Each generated sequence was assigned a corresponding operating-condition label. We considered 10 conditions: healthy, voltage sensor fault, current sensor fault, overvoltage, undervoltage, overcurrent, overtemperature, SoH drop, cell imbalance, and communication failure. These conditions represent sensor-level, electrical, thermal, degradation-related, and communication-related abnormalities.

The generated dataset consisted of sequences containing 200 samples each. Approximately 800–4,000 sequences were generated for the considered operating conditions. The dataset was divided at the sequence level into 80% training data and 20% test data. This separation was used to evaluate the model using previously unseen sequences. Because the present dataset is synthetically generated and did not contain independently identified battery-level or experimentally measured cycle-level records, strict battery-wise or cycle-wise separation was not available. Therefore, the reported results should be interpreted as sequence-level validation under a controlled synthetic-data setting. Stricter cycle-wise or battery-wise validation using independent battery trajectories is an important direction for future work.

IEEE Standards 1188 and 1679 were used as reference guidance for battery characterization, operating behavior, degradation, and failure considerations. The standards were not treated as the dataset itself; rather, the synthetic records were generated using the controlled procedure described above. Therefore, the generated dataset was used for controlled methodological evaluation of the proposed framework, while validation using real-world battery measurements remains an important direction for future work.

2.2.1. Representation of realistic battery behavior

The synthetic signals were designed to represent the main variables and operating abnormalities relevant to EV battery monitoring, including voltage, current, temperature, SoH-related degradation, cell imbalance, sensor faults, electrical faults, thermal faults, and communication interruption. Normal charge–discharge sequences were first established, after which controlled variations were introduced to represent degradation and fault conditions. Therefore, the generated data represent the temporal changes a battery diagnostic system may need to monitor while maintaining controlled conditions for model evaluation. However,

these synthetic representations should not be considered equivalent to experimentally measured EV battery data because the dataset does not fully reproduce factors such as measurement noise, cell-to-cell variation, detailed aging history, environmental effects, and interacting degradation mechanisms. Therefore, the synthetic dataset provides a controlled basis for evaluating the proposed framework, whereas its performance under real battery operating conditions requires validation using independent experimental or publicly available real-world datasets.

2.2.2. State-of-health reference generation

Because SoH is not a directly measured sensor variable, we treated it as a reference degradation variable in the synthetic dataset. We generated the reference SoH values to represent the progressive reduction in available battery capacity under the considered degradation conditions. We used these reference values as the ground-truth targets for the ensemble-based SoH estimation model. We did not apply a separate measurement-error model to the reference SoH values in the present synthetic dataset. Therefore, the reported mean absolute error (MAE), root mean square error (RMSE), R^2 , and correlation values represent prediction errors relative to the controlled reference SoH trajectory.

The reference SoH trajectory was constructed as a controlled degradation variable representing the progressive reduction in available battery capacity across the generated operating sequences. The trajectory was varied across degradation-related conditions so that the model received different health states rather than a single fixed SoH value. Gradual and abrupt changes were incorporated to represent controlled degradation patterns associated with SoH drop and other operating conditions considered in the synthetic dataset. The resulting reference values were assigned as the target outputs for the ensemble regression model. This formulation provides a controlled prediction task in which the model maps available battery measurements, including voltage, current, temperature, and engineered statistical indicators, to the corresponding continuous SoH target without directly receiving the target value as an input. However, because the reference trajectory was synthetically generated and did not include independent measurement uncertainty or experimentally observed aging variability, the prediction task remains controlled and may be less challenging than real-world SoH estimation. Therefore, the R^2 of 0.999 indicates extremely close agreement between the predicted and controlled reference SoH values under the present synthetic conditions, but it should not be interpreted as evidence of near-perfect SoH estimation for real-world EV batteries.

2.3. Feature extraction

A lower-dimensional representation of the battery data was derived using an autoencoder-based feature-extraction mechanism to capture the most informative characteristics associated with different fault conditions. The autoencoder was trained to learn a compact data representation by minimizing the reconstruction loss while preserving nonlinear relationships among the battery parameters. The extracted features were subsequently used as inputs to the LSTM-based fault-diagnosis module.

2.4. Long short-term memory-based fault diagnosis

The battery fault-diagnosis problem was formulated as a multivariate time-series classification problem. An LSTM network was employed to capture the temporal dependencies and dynamic patterns present in voltage, current, and temperature measurements. The extracted features were fed into the LSTM network to identify temporal patterns associated with different battery operating conditions. The LSTM network's final outputs were subsequently fed into a softmax classifier to identify the corresponding fault conditions. The model was trained using cross-entropy loss and the Adam optimizer to classify healthy and faulty operating conditions under smooth-load, noisy, and dynamic operating conditions. SoH estimation using an ensemble was performed similarly to the first two approaches.

2.5. Ensemble-based state-of-health estimation

Ensemble-based SoH estimation is also performed in the same way as the first two methods. Battery SoH estimation was performed using an ensemble regression model implemented as a FITR ensemble. The model combines bagged decision trees to reduce prediction variance and boosted decision trees to reduce prediction bias.

The ensemble model was designed to capture the nonlinear dynamics associated with battery degradation and provide SoH estimates under different operating conditions. The resulting SoH estimates were used to assess the applicability of the ensemble regression approach for battery health monitoring.

2.6. Diagnostic–prognostic workflow integrations

The proposed LSTM-FB-DPF integrates SDWSN-based data acquisition, autoencoder-based feature extraction, LSTM-based fault diagnosis, and ensemble-based SoH estimation into a unified diagnostic–prognostic workflow. This integrated structure establishes a coordinated data-processing pathway from battery sensing and data transmission to fault identification and battery health estimation. The framework therefore provides a basis for

applying the proposed LSTM-FB-DPF approach in EV battery management systems.

The autoencoder is a nonlinear feature-extraction block that can learn compact, fault-discriminative representations from high-dimensional battery health data. Theoretically, an autoencoder has two main parts: the encoder operation f_θ and the decoder operation g_ϕ . Functional equivalences of the autoencoder are represented by **Equations 1** and **2**.

$$f_\theta(x) = \sigma(WM_e x + bv_e) \quad (1)$$

$$g_\phi(z) = \sigma(WM_d z + bv_d) \quad (2)$$

where σ is an activation function (e.g., rectified linear unit (ReLU)/sigmoid), x represents the input feature vector, z signifies the latent feature representation, $WM_e x$, $WM_d z$ are the encoder and decoder function weight matrices, bv_e , bv_d are the encoder and decoder module bias vectors. The training objective minimizes the reconstruction loss $L(x, \hat{x})$, expressed as **Equation 3**.

$$L(x, \hat{x}) = \|x - \hat{x}\|_2^2 \quad (3)$$

where $\hat{x}$ represents the reconstructed output; the mean-squared reconstruction error is denoted as $\|x - \hat{x}\|_2^2$, ensuring that the latent representation z preserves essential fault-related features while eliminating redundant or noisy variations. This learned embedding captures nonlinear correlations among voltage, current, temperature, SoH, and cell imbalance parameters, providing a compressed information-rich feature space that enhances the downstream LSTM-FB-DPF classifier's accuracy and stability in multiclass fault diagnosis.

An LSTM cell comprises three gating mechanisms, such as the forget (oblivion) gate (f_t), the input gate (i_t), and the output gate (o_t), along with a memory compartment phase, which collectively control data flow across time steps. The forget gate selectively recollects relevant historical data from the prior cell phase C_{t-1} and discards irrelevant portions expressed in **Equation 4**.

$$f_t = \sigma(W_f \cdot [h_{t-1} x_t] + b_f) \quad (4)$$

where W_f is the weight matrix and b_f is denoted as the bias vector of the forget gate, σ denotes the sigmoid activation function, $h(t+1)$ is the hidden state from the prior time step, and x_t is the input at the present time period. The output $f_t \in [0,1]$ represents the retaining factor for each component of the prior cell state.

The input gate i_t regulates the incorporation of original data from the current input, while the candidate cell phase

$\bar{C}_t$ encodes potential updates to the memory expressed in **Equations 5 and 6**.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (5)$$

$$\bar{C}_t = \tan h(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (6)$$

Here, W_i, W_c are the weight matrices, b_i, b_c are the bias vectors, and $\tanh$ ensures candidate positions lie in $[-1, 1]$, facilitating the representation of strong and weak features. The cell state is then updated according to **Equation 7**.

$$C_t = f_t \odot C_{t-1} + i_t \odot \bar{C}_t \quad (7)$$

where $\odot$ denotes the Hadamard product and $\bar{C}_t$ is a candidate cell position (computed via a $\tanh$ activation). This formulation ensures a controlled combination of previous memory and new information. The output gate o_t filters the memory content to generate the hidden phase h_t , which serves as both the input for the next time step and the final output for the current one, as represented in **Equations 8 and 9**.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (8)$$

$$h_t = o_t \odot \tan h(C_t) \quad (9)$$

The LSTM network in this structure is trained on multivariate time-series data that includes voltage, current, and temperature data from different charge-discharge cycles, including normal operation and various faults, such as overvoltage, undervoltage, overcurrent, overtemperature, and capacity fade. The network is trained to map sequence input patterns $X = \{x_1, x_2, \dots, x_T\}$ to fault labels $Y = \{y_1, y_2, \dots, y_T\}$ that are equivalent to temporary oscillations and sustained squalor or tendencies.

The combination of LSTM's temporal feature-extraction property with its associated gating mechanisms makes it robust to classification in the presence of measurement noise and variable operating conditions. During training, the network also maximizes the cross-entropy loss function in **Equation 10**.

$$\mathcal{L} = -\frac{1}{N} \sum_{n=1}^N \sum_{k=1}^K y_{n,k} \log \hat{y}_{n,k} \quad (10)$$

where N is the number of sequences, K is the number of fault classes, $y_{n,k}$ is the ground truth label, n is the

index of each training sample, ranging from 1 to N , and $\hat{y}_{n,k}$ is the predicted probability for class k . We compared 10 operating conditions against the proposed LSTM-FB-DPF model, including healthy, voltage sensor fault, current sensor fault, overvoltage, undervoltage, overcurrent, overtemperature, SoH drop, cell imbalance, and communication failure. Such conditions are sensor-level anomalies (voltage/current faults, communication failure), electrical/thermal anomalies (overvoltage, undervoltage, overcurrent, overtemperature), and performance degradation conditions (SoH drop, cell imbalance). Using temporal variability in voltage, current, temperature, and cell-balancing signals, the model mimicked both short-term transient signatures and long-term degradation signatures.

The SoH regression problem is defined as mapping time-series features X_t comprising raw voltage V_t , current I_t , temperature T_t , and engineered statistical indicators, to a continuous SoH value $y_t \in [0, 100]\%$ representative of the residual volume of the battery. The ensemble model predicts the SoH as a weighted combination of M base learners $f_m(\cdot)$. Its prediction module is expressed in **Equation 11**.

$$\hat{y} = \sum_{m=1}^M \alpha_m f_m(X) \quad (11)$$

where $\hat{y}$ is the predicted SoH, $f_m(\cdot)$ is the m^{th} decision tree learner, α_m is the weight assigned to the m^{th} learner (learned during boosting or uniform for bagging), and M is the total quantity of base learners in the ensemble.

In the bagged regression stage, multiple decision trees $f_b(X)$ are trained independently on bootstrap samples drawn from the dataset. The final SoH prediction is computed as the average of all base learners expressed in **Equation 12**.

$$\hat{y}_{bag} = \frac{1}{B} \sum_{b=1}^B f_b(X_b) \quad (12)$$

where B denotes the number of bootstrap samples/base learners, X_b is the input features for the b^{th} bootstrap sample, $f_b(X_b)$ signifies the prediction of the B^{th} tree, and $\hat{y}_{bag}$ is an ensemble SoH estimate.

Bagging reduces prediction variance and can help mitigate overfitting, as exemplified by random forest (RF) models. Random selection of features at every split may also be applied to further decorrelate the base learners.

During the boosted regression phase, trees are learned sequentially, and their outputs reduce the residual errors of the preceding ensemble output. The model enables

predictions to be refined cyclically based on **Equations 13** and **14**.

$$r^{(m)} = y - \hat{y}^{(m-1)} \quad (13)$$

$$\hat{y}^{(m)} = \hat{y}^{(m-1)} + \eta f_m(X) \quad (14)$$

where $r^{(m)}$ is a residual after the $(m-1)^{\text{th}}$ tree, $\hat{y}^{(m)}$ denotes the updated ensemble prediction, $f_m(X)$ represents the prediction of the m^{th} boosted tree, η denotes the learning rate controlling the contribution of each tree, and m signifies the total number of boosted trees.

Accuracy is the sum of the classifier's correctness across all test sequences. It is the ratio of correctly predicted samples to the total number, as shown in **Equation 15**.

$$Accuracy = \frac{\sum_{i=1}^N 1(y_i = \hat{y}_i)}{N} \quad (15)$$

where y_i signifies the true label of the i^{th} sample, $\hat{y}_i$ is a predicted label of the i^{th} sample, N is the total number of test samples, and $1(\cdot)$ is an indicator function (1 if true, 0 otherwise). High accuracy implies that the model is discriminative between two or more fault classes. Precision (P), calculated using **Equation 16**, is the ratio of true cases correctly predicted out of the total number of cases that are labeled as a particular fault.

$$P = \frac{TP}{TP + FP + \epsilon} \quad (16)$$

Here, TP denotes a true positive, FP denotes a false positive, and ϵ is a small constant used to prevent division by zero. This metric assesses the reliability of positive predictions and plays a significant role in determining misclassification risk, particularly for sensitive fault conditions. Recall/sensitivity (R) measures the proportion of actual fault occurrences that are correctly identified by the model and is expressed in **Equation 17**.

$$R = \frac{TP}{TP + FN + \epsilon} \quad (17)$$

On the other hand, FN denotes a false negative; high recall ensures that most faults are detected, which is important for battery safety. Specificity (S) measures the proportion of correctly identified negative cases and indicates the model's ability to avoid false alarms. Specificity is expressed in **Equation 18**.

$$S = \frac{TN}{TN + FP + \epsilon} \quad (18)$$

Let TN denote true negatives. High specificity provides assurance that healthy or non-faulty sequences are not incorrectly classified as faulty. F1-score (F1) is defined as the harmonic mean of precision and recall and is calculated using **Equation 19**.

$$F1 = \frac{2 \cdot P \cdot R}{P + R + \epsilon} \quad (19)$$

It provides a single measure of classifier performance and is particularly useful for imbalanced datasets. The area under the receiver operating characteristic curve (AUC) measures the classifier's ability to distinguish between classes across different classification thresholds, as expressed in **Equation 20**.

$$AUC = \int_0^1 TPR(FPR) d(FPR) \quad (20)$$

where TPR is the true positive rate, and FPR is the false positive rate; a larger AUC indicates better overall separability of fault types. Equal error rate (EER) represents the point where the false positive rate equals FPR, measured using **Equation 21**. A lower EER suggests a more balanced and reliable classifier.

$$EER = FPR|_{FPR=FNR} \quad (21)$$

The geometric mean (G-Mean) combines the sensitivity and specificity of all classes, providing a single measure of multiclass classification performance, and is shown in **Equation 22**.

$$G - Mean = \sqrt{\text{mean}(RS)} \quad (22)$$

In this case, S is specificity, and R is recall; it penalizes poor performance on any one class.

2.7. Regression metrics for state-of-health estimation

The MAE, calculated using **Equation 23**, represents the mean absolute difference between the estimated and actual SoH values.

$$MAE = \frac{1}{N} \sum_{i=1}^N (\hat{y}_i - y_i)^2 \quad (23)$$

where $\hat{y}_i$ denotes a predicted SoH, N signifies the number of data samples, and y_i is the true SoH. A smaller MAE indicates more accurate, predictive results. RMSE

emphasizes larger errors, as it is the square root of the mean squared prediction error and gives greater weight to larger errors. It is sensitive to outliers and indicates major prediction errors, calculated using Equation 24.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (\hat{y}_i - y_i)^2} \quad (24)$$

The R^2 represents the proportion of variance in the actual SoH values that is explained by the model. An R^2 value closer to one indicates better agreement between the estimated and actual SoH values and, generally, a better model fit, as expressed in Equation 25.

$$R^2 = 1 - \frac{\sum_{i=1}^N (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (25)$$

where $\bar{y}$ denotes the mean of the observed SoH values. The correlation coefficient (Corr) measures the linear relationship between predicted and actual SoH values. A value close to one indicates strong agreement and reliable trend prediction, as shown in Equation 26.

$$Corr = \frac{Cov(\hat{y}, y)}{\sigma_{\hat{y}} \sigma_y} \quad (26)$$

where $Cov(\hat{y}, y)$ denotes the covariance between predicted and true values, and $\sigma_{\hat{y}}$ and σ_y signify the standard deviations of predicted and true values.

3. Results and discussion

The LSTM-FB-DPF framework was evaluated using a controlled synthetic lithium-ion battery dataset comprising 10 operating conditions, including normal, sensor fault, electrical fault, thermal fault, degradation-related faults, and communication failure.

3.1. Fault diagnosis performance

The LSTM-based fault classification model achieved 92% test accuracy, indicating its ability to learn temporal patterns from multivariate battery data. The model identified most fault types, including overvoltage, undervoltage, overcurrent, overtemperature, sensor faults, SoH drop, and cell imbalance, with high accuracy and precision.

A minor overlap was observed between the normal and communication-failure classes, which exhibited similar low-variance signal patterns. The mean AUC of 0.997

indicates high overall class separability, while the mean EER of 0.007 indicates a low overall error rate under the controlled synthetic-data conditions.

3.2. State-of-health estimation performance

The ensemble-based SoH estimation model (FITR ensemble) demonstrated high predictive accuracy, with an MAE of 0.034, an RMSE of 0.146, and an R^2 of 0.999. The estimated SoH values reproduced the controlled degradation-related variations represented in the synthetic reference trajectories, including both gradual and abrupt changes. In comparison, the baseline regression model showed substantially higher prediction errors, indicating lower agreement with the controlled reference SoH trajectories.

3.3. Discussion

Based on these findings, incorporating LSTM-based temporal fault diagnosis and ensemble-based SoH estimation provides an integrated diagnostic-prognostic framework for EV batteries. The proposed system can identify various battery fault conditions and estimate battery health under the controlled synthetic operating conditions considered in this study. Integration with SDWSN provides a basis for distributed battery monitoring and may support predictive maintenance and smart battery management applications. However, the reported performance should be interpreted in the context of the synthetic nature of the dataset. The generated fault signatures, degradation patterns, and operating variations were based on controlled representations and may not fully capture the complexity of real-world EV battery environments, where measurement noise, cell-to-cell variability, environmental effects, aging history, sensor uncertainty, and interacting degradation mechanisms can affect diagnostic and SoH estimation performance. Therefore, the high mean AUC of 0.997 and R^2 of 0.999 demonstrate the framework's effectiveness under the defined synthetic conditions but should not be interpreted as direct evidence of equivalent performance in real-world EV batteries.

The high classification and regression metrics should be interpreted in relation to the controlled nature of the synthetic dataset. The fault conditions were generated using predefined variations in the corresponding battery signals, and the training and testing data were obtained from the same synthetic generation framework. Therefore, similarities in the underlying signal-generation patterns may contribute to the high predictive performance. The present sequence-level split evaluates the models' ability to classify and estimate previously unseen generated sequences, but it does not completely eliminate the possibility that closely related patterns occur across the

training and testing sets. Accordingly, the reported mean AUC of 0.997, R^2 of 0.999, and correlation of 1.000 should be considered as results under the defined synthetic conditions rather than evidence of equivalent performance on independent battery populations. Independent battery-wise or cycle-wise validation using experimentally measured or publicly available datasets is required to further assess the proposed framework's generalization. Future work will therefore consider real-world battery-data validation and hardware-in-the-loop testing.

Figure 4 presents representative voltage time-series responses for selected battery fault conditions. Although voltage responses may overlap across fault types, the proposed LSTM-FB-DPF does not rely on voltage alone for fault classification. Instead, the diagnostic model uses multivariate battery information, including voltage, current, and temperature, together with SoH-related and cell-related information where applicable. The proposed LSTM-FB-DPF approach was evaluated for multiclass battery fault diagnosis and SoH prediction using 800–4,000 sequences representing 10 operating conditions in the synthetic lithium-ion battery dataset. The hardware and software used to generate and analyze the synthetic battery dataset included an Intel i7-12700K central processing unit, NVIDIA RTX 3090 graphics processing unit, 64 GB random-access memory, and a two TB NVMe solid-state drive. LSTM networks, feature extraction, model training, and visualization were implemented in MATLAB R2023a

(The MathWorks, Inc., USA) using the Deep Learning Toolbox, Statistics and Machine Learning Toolbox, and Signal Processing Toolbox. The synthetic battery data were divided into training and test sets, with 80% of the sequences used for training and 20% reserved for testing. This sequence-level split enables the LSTM network to learn temporal patterns across operating conditions while evaluating it on previously unseen sequences. In particular, overvoltage and undervoltage primarily affect voltage behavior; overcurrent is additionally associated with current variations, and overtemperature produces corresponding temperature changes. SoH drop and cell imbalance conditions are represented through degradation- and cell-related variations. Therefore, the final fault classification is based on the combined temporal behavior of multiple battery signals rather than on an isolated voltage pattern.

Figure 5 shows the LSTM model's training progress over 50 epochs and 10,000 iterations. The accuracy curve in Figure 5A shows rapid convergence, with training accuracy exceeding 90% by approximately 2,000 iterations and reaching about 95%, while test accuracy reaches approximately 91%. The loss curve in Figure 5B shows a consistent reduction in both training and test losses, with occasional spikes when undervoltage and SoH drop occur simultaneously, suggesting greater complexity or ambiguity in these synthetic fault patterns. Overall, these trends indicate that the LSTM model learned temporal

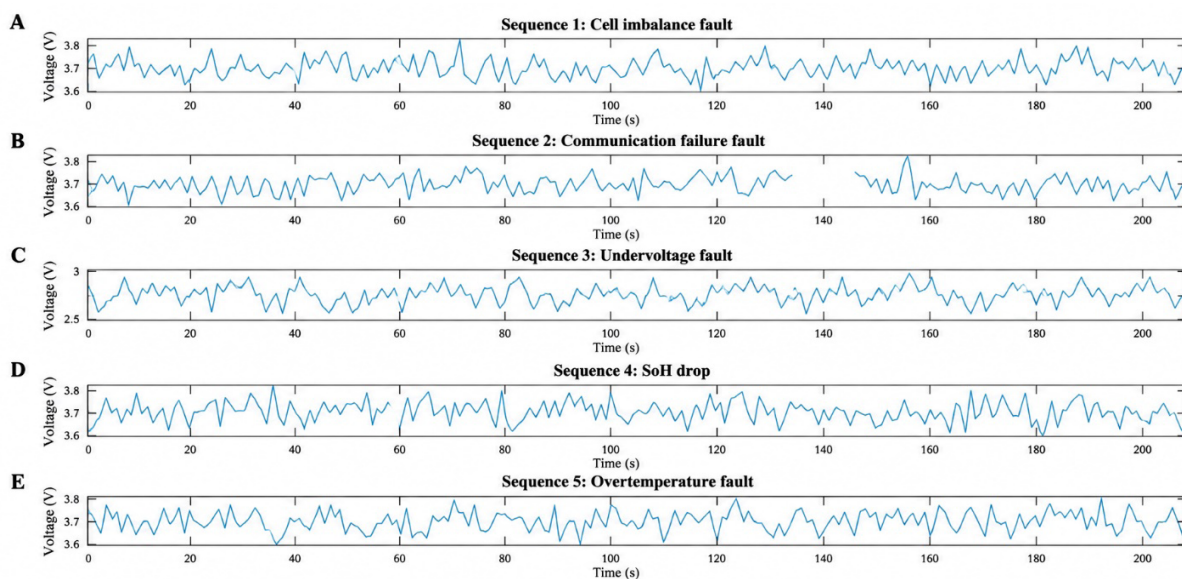


Figure 4. Time-series representation of lithium-battery voltage responses under selected fault conditions: (A) Cell imbalance fault, (B) communication failure fault, (C) undervoltage fault, (D) State-of-health (SoH) drop/capacity fade fault, and (E) overtemperature fault.

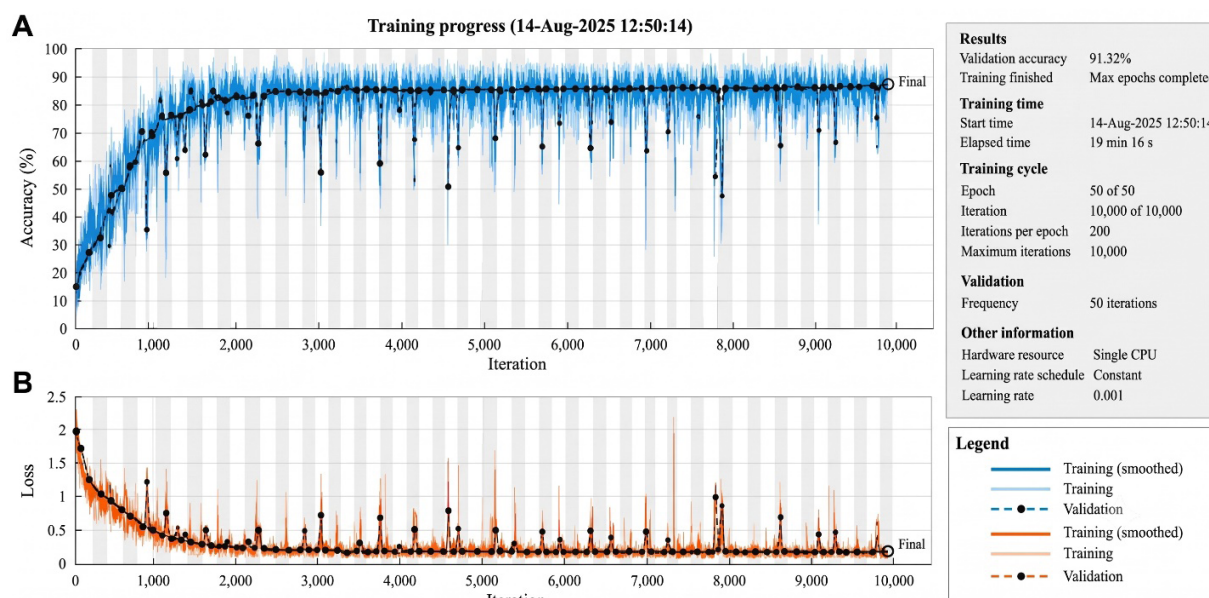


Figure 5. Training progress. (A) Accuracy and (B) loss curves.

fault representations from the training sequences while maintaining comparable performance on the previously unseen test sequences.

Table 1 shows the performance analysis of the suggested LSTM-based multiclass fault model for lithium-ion battery systems. The proposed LSTM-FB-DPF model was tested for multiclass fault detection and SoH prediction of lithium-ion batteries using a complex synthetic dataset comprising 10 operating conditions.

Figure 6 presents the confusion matrix of the trained LSTM-based diagnostic model across the 10 operating conditions, including healthy, voltage sensor fault, current sensor fault, overvoltage, undervoltage, overcurrent, overtemperature, SoH drop, cell imbalance, and communication failure. The classifier achieved high diagnostic performance for most fault categories, while the healthy class showed precision, recall, and F1-score values of 0.000. This result indicates that the model did not correctly identify healthy samples as the healthy class in the evaluated test set, although the specificity for this class was 1.000. The lower performance of the healthy class is associated with the class distribution and overlap between normal and some low-variance signal patterns in the controlled synthetic dataset. The communication failure class also showed lower precision (0.556) and F1-score (0.714), indicating some overlap with other signal patterns. Therefore, the classification performance should not be

interpreted as uniformly robust across all classes. The mean AUC of 0.997 and mean EER of 0.007 indicate strong overall class separability under the controlled synthetic-data conditions, but the healthy-class results demonstrate the need for further validation with more balanced and independent battery datasets.

Table 2 compares the complete LSTM-FB-DPF framework with the reduced autoencoder + classifier configuration. The complete framework achieved a test accuracy of 92.00%, whereas the autoencoder + classifier configuration achieved 88.50%. The 3.50 percentage-point difference indicates the benefit of incorporating temporal learning into the diagnostic workflow under the controlled synthetic-data setting. The comparison also supports the complementary roles of nonlinear feature representation and temporal sequence learning. The autoencoder provides compact feature representations, while the LSTM captures temporal dependencies across multivariate battery measurements. However, this comparison does not quantify each architectural component's contribution separately. In particular, this study did not conduct isolated evaluations of the autoencoder, LSTM, feature-processing components, and ensemble model. Therefore, the 92.00% versus 88.50% comparison should be interpreted as comparative evidence for the integrated diagnostic structure rather than as a complete component-wise ablation study. Future work will include a more comprehensive ablation analysis with independently evaluated architectural components.

Table 1. Performance metrics of the long short-term memory-based multiclass battery fault detection model

Class	Precision	Recall (sensitivity)	Specificity	F1-score	Area under the receiver operating characteristic curve	Equal error rate
Healthy	0.000	0.000	1.000	0.000	0.978	0.043
Voltage sensor fault	1.000	1.000	1.000	1.000	1.000	0.000
Current sensor fault	1.000	1.000	1.000	1.000	1.000	0.000
Overvoltage	1.000	1.000	1.000	1.000	1.000	0.000
Undervoltage	1.000	1.000	1.000	1.000	1.000	0.000
Overcurrent	1.000	1.000	1.000	1.000	1.000	0.000
Overtemperature	1.000	1.000	1.000	1.000	1.000	0.000
SoH drop	1.000	1.000	1.000	1.000	1.000	0.000
Cell imbalance	1.000	1.000	1.000	1.000	1.000	0.000
Communication failure	0.556	1.000	0.911	0.714	0.991	0.022

G-Mean: 0.944

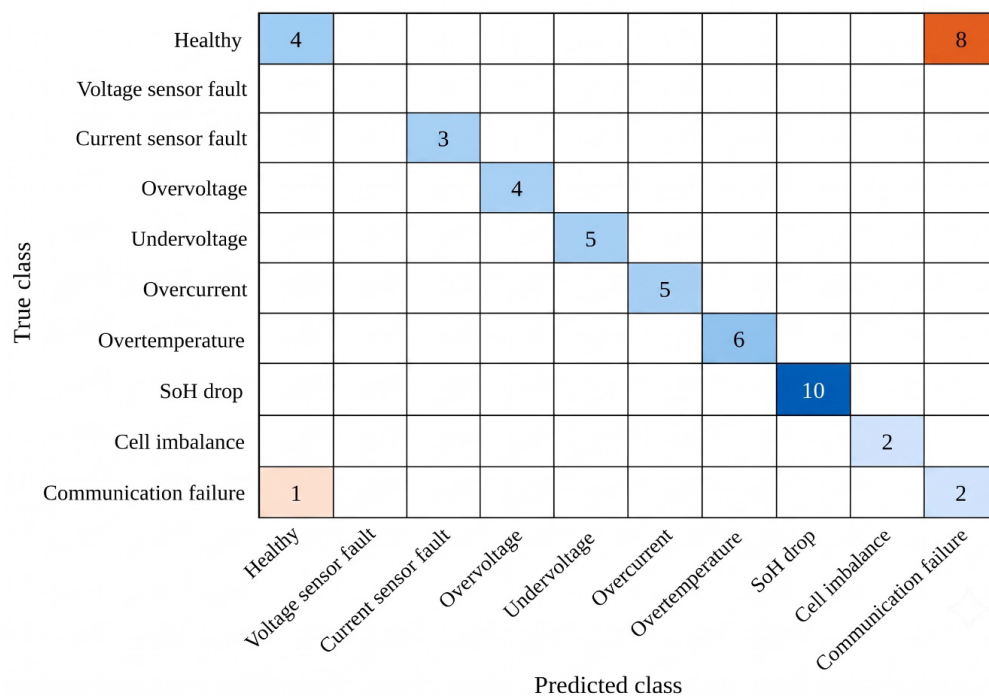


Figure 6. Confusion matrix for battery fault classification

Table 3 compares the fault-classification performance of the proposed LSTM-FB-DPF with representative conventional and DL baseline models under the same evaluation setting. Support vector machine (SVM), RF, artificial neural network (ANN), convolutional neural network (CNN), LSTM, and the reduced autoencoder + classifier configuration were considered as baseline approaches. The proposed LSTM-FB-DPF achieved a test accuracy of 92.00%, compared with 84.80% for SVM, 86.70% for RF, 87.60% for ANN, 89.40% for CNN, 90.30% for LSTM, and 88.50% for the reduced autoencoder + classifier configuration. The higher accuracy obtained by LSTM-FB-DPF indicates the benefit of combining nonlinear feature representation with temporal sequence

Table 2. Overall performance summary of the proposed LSTM-FB-DPF model

Metric	Value
Test set accuracy	92.00%
FC accuracy on averaged sequences	92.00%
Mean AUC	0.997
Mean EER	0.007
Reduced autoencoder + classifier accuracy	88.50%

Abbreviations: AUC: Area under the receiver operating characteristic curve; EER: Equal error rate; FC: Fully connected; LSTM-FB-DPF: Long short-term memory with feature-based diagnostic-prognostic framework.

Table 3. Comparative fault-classification performance of baseline models and the proposed framework

Model	Test Accuracy (%)
SVM	84.80
Random forest	86.70
ANN	87.60
CNN	89.40
LSTM	90.30
Autoencoder + Classifier	88.50
LSTM-FB-DPF (proposed)	92.00

Abbreviations: ANN: Artificial neural network; CNN: Convolutional neural network; LSTM: Long short-term memory; LSTM-FB-DPF: Long short-term memory with feature-based diagnostic-prognostic framework; SVM: Support vector machine.

learning within the integrated diagnostic architecture under the controlled synthetic-data setting.

Figure 7 presents the ROC curves for the individual fault classes. The mean AUC of 0.997 indicates high overall class separability, while the mean EER of 0.007 indicates a low overall error rate under the controlled synthetic-data conditions. The slightly lower AUC values for the healthy and communication failure classes are consistent with the misclassification observed in the confusion matrix. These results indicate strong class separability for most fault categories within the defined synthetic operating conditions.

Table 4 shows the regression performance of the proposed ensemble learning-based SoH estimation model, with an MAE of 0.034, an RMSE of 0.146, an R^2 of 0.999, and a correlation of 1.000 under the controlled synthetic-data setting. The highest AUC of 1.00 indicates near-perfect separability across most classes, except for healthy (AUC = 0.98) and communication failure (AUC = 0.99), which show slightly lower results, consistent with the misclassification recorded in the confusion matrix. These curves confirm that the LSTM model shared strong fault-specific behaviors, including temporary voltage dips, strong current spikes, and thermal anomalies, resulting in highly accurate fault distinction. These small deviations suggest that further temporal perturbation or data augmentation could improve real-world generalization.

Table 4. Performance metrics of the ensemble-based SoH estimation model

Metric	Value
MAE	0.034
RMSE	0.146
R^2	0.999
Correlation	1.000

Abbreviations: MAE: Mean absolute error; R^2 : Coefficient of determination; RMSE: Root mean square error; SoH: State of health.

Figure 8 presents the reference and predicted SoH values across the synthetic test samples. The horizontal axis represents the sample index and does not correspond to chronological battery usage or aging cycle number. Variations in the reference SoH values represent the controlled degradation conditions introduced during synthetic data generation. The predicted SoH values follow the corresponding reference values with relatively

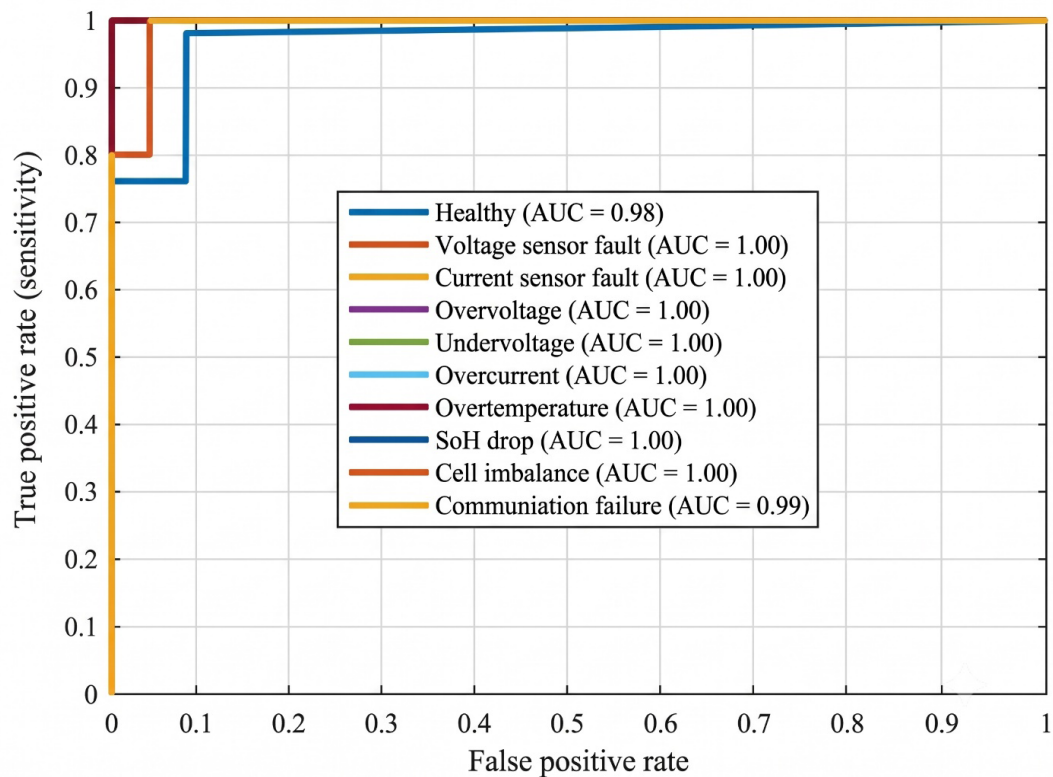


Figure 7. Receiver operating characteristic curves for battery fault classification
Abbreviation: AUC: Area under the receiver operating characteristic curve.

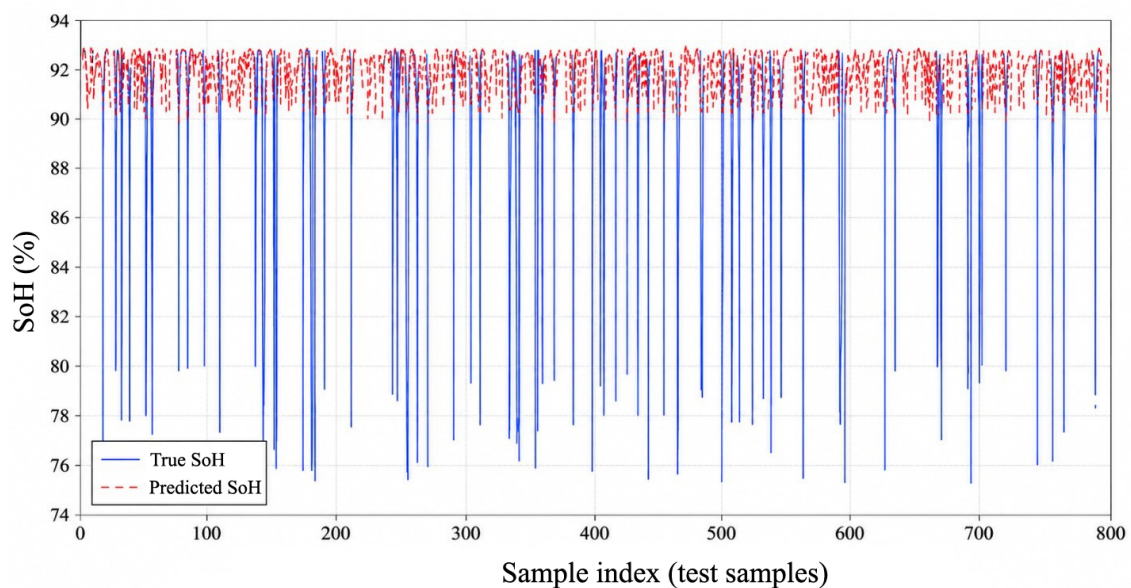


Figure 8. Reference and predicted SoH across synthetic test samples using the FITR ensemble
Abbreviation: SoH: State of health.

small deviations. The model achieves an MAE of 0.034 and an RMSE of 0.146, while an R^2 value of 0.999 and a correlation coefficient of 1.000 indicate strong agreement between the predicted and reference SoH values. Because the dataset is synthetic and the samples are not arranged in chronological battery-life order, Figure 8 should be interpreted as a regression-validation plot rather than an experimental battery aging curve.

Table 5 indicates the pre-ensemble optimization baseline of the comparative SoH estimation model. The ensemble regression closely approximates the controlled reference SoH trajectory with slow degradation trends and sharp spikes caused by synthetic stress tests (e.g., sudden bursts of current or more aggressive aging conditions). The small deviations reflect the nonlinearity of battery degradation; however, the model shows high predictive performance, suggesting that the engineered features, including voltage differentials, statistical indicators, and charge–discharge slopes, strongly correlate with SOH evolution. This validation highlights the practical usefulness of ensemble learning with feature extraction in long-term reliable battery health prognosis.

Table 5. Performance metrics of the comparative SoH estimation model (baseline evaluation)

Metric	Value
MAE	3.5530
RMSE	4.7721
R^2	0.0420
Correlation	0.2875

Abbreviations: MAE: Mean absolute error; R^2 : Coefficient of determination; RMSE: Root mean square error; SoH: State of health.

4. Conclusion

The LSTM-FB-DPF framework provides an integrated system-level approach for intelligent monitoring of lithium-ion batteries in EVs. Under the controlled synthetic-data conditions considered in this study, the LSTM diagnostic module achieved 92% operational-scenario accuracy with a mean AUC of 0.997, while the ensemble-based prognostic module achieved an R^2 of 0.999 and an RMSE of 0.146 for SoH estimation. These results demonstrate the proposed framework's ability to perform integrated fault diagnosis and SoH estimation within the defined synthetic operating conditions. The integration of SDWSNs, DL, and ensemble regression provides a potential basis for distributed battery monitoring and may support future predictive-

maintenance and battery-management applications. However, the present results do not directly establish real-world, real-time functionality, improved operational safety, or extended battery service life, as the evaluation used controlled synthetic data. Therefore, these practical benefits should be considered potential applications rather than directly demonstrated outcomes of the present study.

Future work will focus on validation using real-world driving and battery data under different load and measurement-noise conditions, together with hardware-in-the-loop testing to assess computational delay and real-time functionality. Future studies will also explore integrating the framework with edge computing and expanding fault coverage to other battery chemistry types, including lithium iron phosphate and nickel–manganese–cobalt. The integration of the framework with smart-grid systems and remote monitoring can also be investigated to support the development of advanced smart BMSs.

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Conflict of interest

The authors declare that they have no competing interests.

Author contributions

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Investigation: Prabu R, Kumar N

Methodology: Prabu R, Kumar N

Writing–original draft: Prabu R, Kumar N

Writing–review & editing: Prabu R, Kumar N

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data

Data will be made available upon request to the corresponding author.

Further disclosure

The authors are fully responsible for the originality, validity, and integrity of the content of their manuscript, including any material that has been generated by GenAI tools.

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