Smart Fault Detection in Electric Vehicles Using Battery and Motor Operation Data Driven Deep Learning

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***Abstract*—As electric vehicles (EVs) become more widespread, early detection of component faults is essential for safety and reliability. This study proposes a smart fault detection system that analyzes daily EV operation data using deep learning models and notifies users of potential defects via a mobile application. We developed two models: an LSTM-based battery fault detection model and a CNN-LSTM-based motor fault classification model. Both models showed strong performance on real-world datasets. For demonstration, the motor model was deployed in a physical setup, achieving near-perfect classification under simulated fault conditions. The results validate the feasibility and potential of deep learning-based fault diagnostics for EVs, emphasizing the need for further real-world validation.**

***Index Terms*—Electric Vehicle(EV), Fault Detection, Deep Learning, Predictive Maintenance, Time-Series Classification.**

I. Introduction

As electric vehicles (EVs) become more prevalent, ensuring the reliability of key components such as batteries and motors is critical. In particular, early detection of faults can prevent safety issues and reduce maintenance costs. However, real-time fault diagnosis remains a challenge due to the complexity and variability of EV systems. This study proposes a simple fault detection system that combines deep learning models with a mobile app for fault diagnosis. Two models are developed: a Long Short Term Memory (LSTM) based classifier for battery anomaly detection and a Convolutional Neural Network-Long Short Term Memory (CNN-LSTM) based multi-class classifier for motor fault diagnosis. As shown in Fig. 1, once the vehicle becomes idle, the recorded data is transmitted to an AI server for fault diagnosis, and the results are then delivered to the user's smartphone to support proactive fault management. In this study, the system is implemented and tested in a simulated environment.

II. Fault Detection

A. Datasets

1) Battery Dataset: We utilized a publicly available EV battery anomaly detection dataset [1]. The dataset includes 200,000 labeled time-series samples from 198 electric vehicles, with each sample containing 128 time steps. The dataset is 57.3% labeled defective and 42.7% normal.

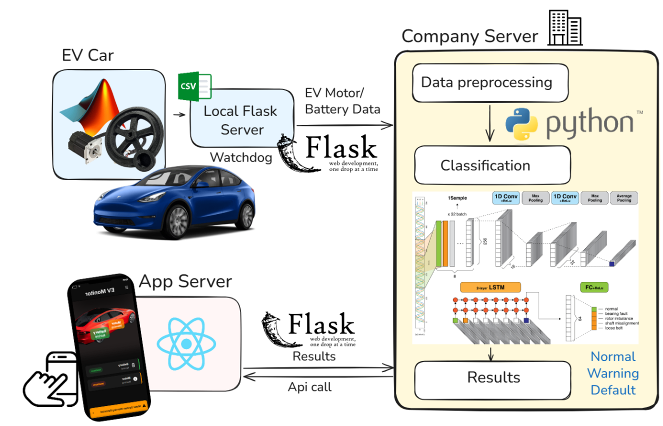

Fig. 1. The system architecture: The system represents the vehicle, company (AI server), and consumer app components working together for diagnosis and notification.

2) Motor Dataset: We employed the publicly available motor fault detection dataset from the AI Hub platform [2], containing three-phase current signals (I_a, I_b, I_c) from subway ventilation motors rated 5.5 kW and 11 kW. The dataset includes 5 fault categories: Normal, Rotor Unbalance, Bearing Fault, Loose Belt, and Sensor Fault.

B. Models

1) Battery Module: We implemented a binary classification model using a two-layer LSTM network. The input is a sequence of 128 time steps with 7 features, denoted as $\mathbf{X} \in \mathbb{R}^{B\times 128\times 7}$. Only the last hidden state $\mathbf{h}_{128}$ is used for classification. To handle class imbalance, we applied a weighted binary cross-entropy loss. The model was trained using the Adam optimizer with a learning rate of 10^{-2}.

2) Motor Module: To capture both local spectral patterns and temporal dependencies across windows, we employ a compact 1D CNN followed by a two-layer bidirectional LSTM (Fig. 2). The input tensor is $\mathbf{X} \in \mathbb{R}^{B\times S\times 3\times 256}$, where B is the batch size, S is the window sequence length, and each window contains three-phase current signals with 256 time samples per phase. The CNN encodes local features within each window,

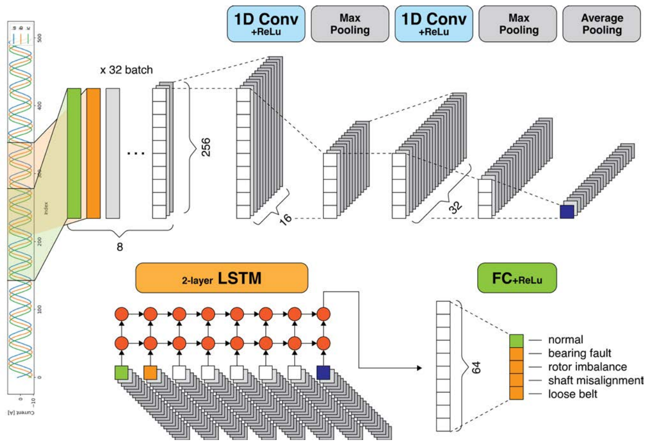

Fig. 2. CNN-LSTM architecture for motor fault classification: Local signal features are first extracted by 1D CNN layers, followed by BiLSTM layers to capture sequential dependencies across time windows.

which are then sequentially processed by the BiLSTM to capture inter-window dynamics. A final fully connected layer produces class logits $\hat{\mathbf{y}} \in \mathbb{R}^{B\times 5}$, which are passed through a softmax to produce class probabilities. Weights are initialized using He normal initialization. Training is performed using the Adam optimizer with a learning rate of $\mathrm{lr} = 10^{-3}$, along with cross-entropy loss and a Reduce-on-Plateau scheduler.

III. Demonstration

To validate the practical feasibility of the proposed fault detection system, we implemented a real-world-like integrated setup. For testing, we simulated a simplified EV motor system using a custom 3D-printed wheel. The system was implemented using a TI LAUNCHXL-F28379D controller and BOOSTXL-DRV8305 inverter, driving a TEKNIC M-2310P permanent magnet synchronous motor (PMSM). The motor was controlled via a voltage-by-frequency (V/f) method to maintain a constant speed of 300 RPM. As shown in Fig 3, rotor unbalance faults were simulated by attaching weights of 0g, 50g, and 100g, representing normal, warning, and fault conditions. A three-class CNN-LSTM model was trained specifically for this setup, and the predictions were transmitted to a mobile app in real time via the AI server.

IV. Results

A. Battery Fault Detection

The LSTM-based battery fault detection model achieved an accuracy of 92.09%, a precision of 98.94%, a recall of 87.13%, and an F1 score of 92.66%. As shown in Fig. 4, the confusion matrix confirms that the model successfully distinguishes between normal and defective battery states.

B. Motor Fault Detection

The CNN-LSTM model for motor fault classification achieved an F1 score of 88.49%, with a precision of 88.58% and recall of 89.62%. All five classes recorded AUC values above 0.75, confirming the model's effectiveness in multi-class

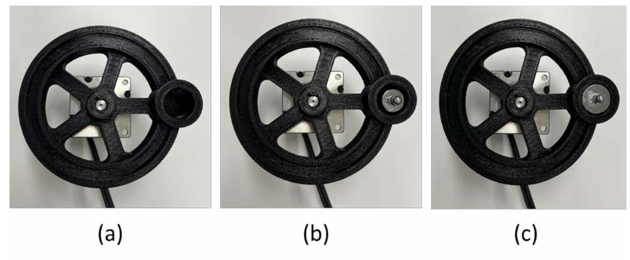

Fig. 3. Motors used in the demo: (a) normal (0g), (b) warning (50g), and (c) fault condition (100g).

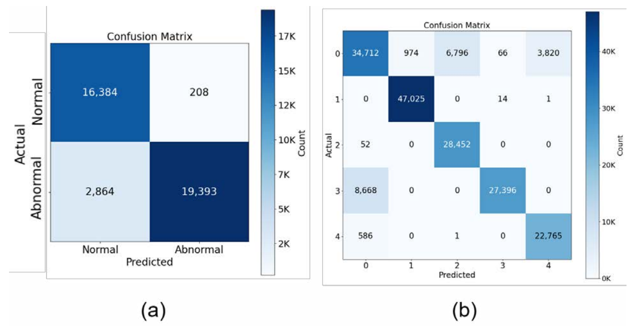

Fig. 4. Confusion matrix of models: (a) Battery fault detection model results. (b) Motor fault detection model results.

fault detection. For the demonstration model, a total of 1,401 samples were evaluated—457 normal, 469 warning, and 475 fault cases. The model correctly identified all 1,401 samples without any misclassification.

V. Conclusion

We presented deep learning-based fault detection models for EV batteries and motors using LSTM and CNN-LSTM architectures, respectively. Both models showed high performance on public datasets, confirming their effectiveness. In addition, A simplified physical test of motor fault classification was implemented with artificially simulated faults. This served as a proof-of-concept for the model's applicability. Future work will extend validation to a broader set of EV traction motors that exhibit real, naturally occurring faults across multiple vehicle models and operating conditions.

Acknowledgment

This work was supported by the research project "Convergence technologies for artificially intelligent society".

References

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