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Fault Detection and Diagnosis in Electric Vehicle Powertrains Using Machine Learning

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Abstract-Electric vehicles (EVs) are transforming transportation by offering high efficiency and sus-tainability. However, their powertrains—particularly motors, inverters, and control units—require reliable fault detection mechanisms to prevent sudden failures and ensure safety. This project proposes a simulation-driven Machine Learning (ML) approach for Fault Detection and Diag-nosis (FDD) in EV powertrains. Drawing on prior work by Khan et al. (2024) and Zhang et al. (2022), this study develops a simplified, reproducible framework for academic use. The methodology involves synthetic signal generation of a Permanent Magnet Synchronous Motor (PMSM), fault injection, statistical feature extraction, and classification using Support Vector Machine (SVM) and Random Forest (RF). Results show over 90% classification accuracy with low latency, validating the feasibility of lightweight ML in real-time embedded EV applications.

Keywords: Electric Vehicles, Fault Detection, PMSM, Random Forest, SVM, Predictive Maintenance.

I. INTRODUCTION

1. Motivation And Background

Electric Vehicles (EVs) have emerged as a key technology in achieving global sustainability targets by reducing greenhouse gas emissions and improving overall energy efficiency. Their performance and reliability, however, are heavily dependent on the robust operation of crit-ical powertrain components such as the traction motor, inverter, and controller. Failures in these components can result in severe consequences, including reduced efficiency, unexpected breakdowns, costly repairs, and potential safety hazards. Hence, reliable Fault Detection and

Diagnosis (FDD) systems are essential to ensure the continued dependability and safe operation of electric powertrains [1] [6].

2. Traditional Fdd Approaches And Limitations

Traditionally, FDD in EVs has been addressed using rule-based or analytical model-based diag-nostic techniques. These conventional approaches rely on predetermined thresholds or physics-based models to detect anomalies in sensor data. While such systems are relatively simple to implement, they often struggle to generalise across diverse fault conditions and are highly sensi-tive to parameter variations and noise [2]. Moreover, their limited adaptability can lead to false alarms or missed detections in dynamic real-world driving environments [5]. Rule-based systems typically demand extensive domain expertise and manual tuning, making them difficult to scale across different EV platforms and operating conditions.

Model-based diagnostic techniques, while theoretically sound, require accurate mathematical representations of the motor and inverter dynamics. In practice, parameter uncertainties, non-linearities, and time-varying characteristics of electrical machines limit the effectiveness of these approaches [15]. Additionally, traditional signal analysis methods such as Fast Fourier Trans-form (FFT) may miss transient fault signatures or faults that occur at frequencies overlapping with normal operation harmonics [13].

3. Machine Learning For Fault Detection: Advantages And Appli-Cations

Recent advancements in Machine Learning (ML) have introduced data-driven approaches capa-ble of learning complex fault patterns directly from multi-sensor datasets. ML-based diagnostic systems leverage

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large volumes of current, voltage, and speed data to model intricate nonlinear relationships between system behaviour and fault signatures. Unlike rule-based systems, ML algorithms can automatically adapt to changing operating conditions, handle noisy measure-ments, and generalise across multiple fault modes [2] [14]. These advantages make ML an ideal candidate for developing intelligent and scalable EV health monitoring solutions.

Research has demonstrated that various machine learning techniques exhibit distinct strengths in fault detection applications. Random Forest classifiers, based on ensemble decision tree ap-proaches, provide interpretability and robustness to noisy data, making them particularly suit-able for embedded applications [8] [19]. Support Vector Machines (SVM) excel at nonlinear classification problems and perform well on medium-sized datasets with limited computational overhead [7]. Conversely, deep learning approaches such as Convolutional Neural Networks (CNNs) and autoencoders can extract features directly from raw sensor signals, achieving su-perior accuracy on large datasets but at the cost of increased computational complexity and reduced interpretability [9] [20].

4. State-Of-The-Art In Ev Powertrain Fault Detection

Several researchers have explored ML-based approaches for powertrain fault detection with promising results. Khan et al. [1] developed a BLDC motor–based EV drive model incorporat-ing six different machine learning classifiers, including XGBoost, K-Nearest Neighbours (KNN),

and a Voting Ensemble. Their MATLAB/Simulink simulation generated realistic driving cycles and synthetic fault scenarios, producing comprehensive sensor datasets. The ensemble model achieved an accuracy of 98.3%, establishing a benchmark for simulation-based fault detection and diagnosis.

Similarly, Zhang et al. [2] conducted a comprehensive review of machine learning and deep learning applications in powertrain fault diagnostics. They emphasised the importance of feature extraction techniques in the time, frequency, and time–frequency domains. Their findings indi-cated that Random Forest and Support Vector Machines (SVM) perform effectively on medium-sized datasets, whereas Convolutional Neural Networks (CNNs) excel when working with raw signal data. These insights provide valuable guidance in selecting an appropriate balance be-tween computational efficiency and model interpretability for EV diagnostic applications.

Recent work by Khaneghah et al. [6] investigated fault detection across multiple EV subsys-tems, including motor drives and battery management systems, demonstrating the versatility of ML techniques in addressing diverse fault types. Additionally, studies on Permanent Magnet Synchronous Motors (PMSM), which are the dominant motor technology in modern EVs, have shown that time-domain statistical features combined with appropriate classifiers can reliably detect various fault conditions [5] [7]. Dettinger [11] introduced digital twin technology for EV powertrain monitoring, integrating physics-based models with machine learning for real-time fault diagnosis, representing a promising direction for industrial deployment.

Advanced feature extraction and signal processing techniques continue to emerge. El-Dalahmeh et al. [12] proposed autonomous fault detection and diagnosis methods that minimize human intervention, while Xu et al. [9] demonstrated the effectiveness of stacked denoising autoencoders for capturing complex fault signatures in motor currents. Image-based approaches, such as that proposed by Xie et al. [10], offer alternative perspectives on fault characterization by converting electrical signals into visual representations suitable for deep learning models.

5. Rationale For The Proposed Work

Building upon these foundations, the present work focuses on developing a simplified and repro-ducible ML-based FDD framework for educational and experimental purposes. By limiting the number of fault types and adopting lightweight machine learning models, the proposed approach prioritises conceptual clarity and reproducibility over industrial-grade accuracy. This balance allows for a deeper understanding of EV diagnostics while maintaining computational feasibility, making the project both practical and pedagogically valuable. The framework integrates syn-thetic motor simulation, statistical feature extraction, and classification using Random Forest and SVM models, demonstrating that effective

fault detection can be achieved without excessive computational burden or complex deep learning pipelines.

Furthermore, this study addresses the gap between academic research and practical imple-mentation by providing a transparent, modular codebase that can serve as a reference for future development. The emphasis on noise robustness, computational efficiency, and generalization across fault modes reflects real-world deployment requirements identified in the broader FDD literature [1] [2] [17].

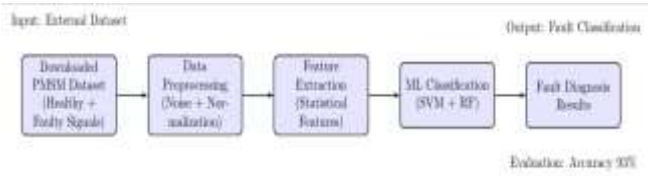


Figure 1: Simplified block diagram of ML-based fault detection system

II. BACKGROUND AND THEORETICAL FRAMEWORK

1. PMSM Fundamentals

The Permanent Magnet Synchronous Motor (PMSM) is widely used in EV powertrains due to its high power density and efficiency. Its dynamic model combines electrical and mechanical equations:

$$v_d = R_s i_d + L_d \frac{di_d}{dt} - \omega L_q i_q \quad (1)$$

$$v_q = R_s i_q + L_q \frac{di_q}{dt} + \omega (L_d i_d + \psi_m) \quad (2)$$

$$T_e = \frac{3}{2} p (\psi_m i_q + (L_d - L_q) i_d i_q) \quad (3)$$

$$T_e - T_L = J \frac{d\omega}{dt} + B\omega \quad (4)$$

where:

- vd, vq: d-q axis stator voltages
- id, iq: d-q axis stator currents
- Rs: Stator resistance
- Ld, Lq: d-q axis inductances
- ψm: Permanent magnet flux linkage
- ωe: Electrical angular velocity
- ωm: Mechanical angular velocity
- p: Number of pole pairs
- Te: Electromagnetic torque
- TL: Load torque
- J: Moment of inertia
- B: Viscous friction coefficient

The transformation from three-phase (abc) to two-phase (dq) reference frame is achieved using Park's transformation:

$$\begin{bmatrix} i_d \\ i_q \\ i_0 \end{bmatrix} = \frac{2}{3} \begin{bmatrix} \cos(\theta) & \cos(\theta - \frac{2\pi}{3}) & \cos(\theta + \frac{2\pi}{3}) \\ -\sin(\theta) & -\sin(\theta - \frac{2\pi}{3}) & -\sin(\theta + \frac{2\pi}{3}) \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} \quad (5)$$

2. Inverter and PWM Theory

Inverters convert DC battery voltage into three-phase AC signals to drive the PMSM. Sinusoidal Pulse Width Modulation (SPWM) controls voltage by varying the duty cycle of high-frequency switching devices. In FDD, inverter faults manifest as unbalanced currents or voltage distortion when a switch fails or a phase becomes disconnected.

3. Physical Fault Mechanisms

Typical EV powertrain faults include:

- **Electrical:** Open-phase, inter-turn short, or inverter switch failure.
- **Mechanical:** Bearing wear, rotor eccentricity, or misalignment.
- **Thermal:** Overheating due to excess load or ventilation blockage.

Understanding these physical causes helps link signal deviations to specific fault signatures.

III. SIGNAL ANALYSIS AND FAULT SIGNATURES

Fault detection relies on recognizing how electrical signals deviate under different conditions. For PMSMs:

- **Healthy Operation**: Balanced three-phase currents with 120° phase difference.
- **Open-Phase Fault**: Amplitude reduction and waveform asymmetry.

- **Bearing Fault:** Superimposed low-frequency ripples in torque and current signals.

These signal distortions form the basis for feature extraction and ML training. Frequency-domain inspection (FFT) typically shows additional sidebands under faulty conditions, but this project limits itself to time-domain metrics for simplicity.

1. Data Preprocessing And Noise Handling

Raw simulation data is segmented into 1-second windows with 50% overlap to ensure sufficient temporal coverage. Gaussian noise is added to simulate sensor imperfections. Normalization via z-score ensures that features across different scales contribute equally to model training. Data balancing is achieved by equalizing class counts to prevent model bias.

2. Feature Engineering And Model Training

Seven statistical features are extracted for each phase: mean, RMS, variance, skewness, kurtosis, peak value, and signal energy. These features offer compact yet powerful representation for detecting faults. Principal Component Analysis (PCA) is used for exploratory visualization.

Model selection includes:

- **SVM (RBF):** Effective for small datasets and nonlinear separation.
- **Random Forest**: Ensemble of decision trees offering interpretability and noise resilience. Hyperparameters are optimized via grid search with 5-fold cross-validation.

3. Complete Python Implementation

Algorithm 1 EV Fault Detection System Overview

Input: Simulation parameters, ML hyperparameters
Output: Trained models, performance metrics, visualizations

procedure MAIN
  Phase 1: Data Generation
  $X, y \leftarrow$ GeneratePMSMSignals() ▷ Healthy + Faulty conditions
  $F \leftarrow$ ExtractFeatures(X) ▷ 7 features × 3 phases = 21 features
  Phase 2: Model Training
  $X_{\text{train}}, X_{\text{test}}, y_{\text{train}}, y_{\text{test}} \leftarrow$ SplitData(F, y)
  $M_{\text{RF}} \leftarrow$ TrainRandomForest($X_{\text{train}}, y_{\text{train}}$)
  $M_{\text{SVM}} \leftarrow$ TrainSVM($X_{\text{train}}, y_{\text{train}}$)
  Phase 3: Evaluation
  $A_{\text{RF}} \leftarrow$ Evaluate($M_{\text{RF}}, X_{\text{test}}, y_{\text{test}}$)
  $A_{\text{SVM}} \leftarrow$ Evaluate($M_{\text{SVM}}, X_{\text{test}}, y_{\text{test}}$)
  PlotResults($M_{\text{RF}}, M_{\text{SVM}}, X_{\text{test}}, y_{\text{test}}$)
  Phase 4: Real-time Demo
  DemoRealTimeDetection(M_{best})
  return $M_{\text{RF}}, M_{\text{SVM}}, A_{\text{RF}}, A_{\text{SVM}}$
end procedure

Figure 1: Algorithm

The proposed project is implemented in Python and utilizes various libraries such as NumPy, and Scikit-learn for numerical computation, signal processing, visualization, and machine learn-ing. The program is designed in a modular structure with clearly defined components to simulate the motor behavior, extract relevant features, train classification models, and perform real-time fault detection.

The core of the project lies in the PMSMSimulator class, which mathematically models a Permanent Magnet Synchronous Motor (PMSM). It generates three-phase current signals under

different conditions, namely *healthy*, *open-phase fault*, and *bearing fault*. The open-phase fault is simulated by deactivating one of the phase currents, while the bearing fault is introduced by adding periodic torque oscillations to imitate mechanical disturbances. These simulated signals represent realistic operating scenarios of an electric vehicle motor.

The FeatureExtractor class processes the obtained current signals and extracts several time-domain statistical features such as mean, root mean square (RMS), variance, skewness, kurtosis, peak value, and signal energy. These features provide useful information about the signal char-acteristics and are used as input parameters for machine learning models.

The function generate dataset() automates the data generation process by running multiple simulations for each fault condition and organizing the extracted features with their correspond-ing labels. The train models()— function then splits the data into training and testing sets and trains two machine learning classifiers — Random Forest and Support Vector Machine (SVM)— to accurately identify motor faults.

Finally, visualization functions such as plot results() display model accuracy, feature im-portance, and confusion matrices, while the real time demo() module demonstrates live fault detection by classifying newly simulated signals. Overall, the program efficiently integrates motor simulation, feature analysis, and machine learning to achieve reliable fault diagnosis in electric vehicle powertrains.

4. Evaluation Metrics And Error Analysis

Evaluation metrics used include accuracy, precision, recall, and F1-score:

Accuracy =

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (6)$$

$$Precision = \frac{TP}{TP + FP}, \quad Recall = \frac{TP}{TP + FN} \quad (7)$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (8)$$

Latency measures inference time per window, crucial for real-time applications. The Random Forest model maintains latency below 10 ms.

Error analysis reveals that misclassifications mainly occur when bearing fault amplitude is small or overlapping with noise. The limited number of fault classes also constrains generaliza-tion.

5. Experimental Results

Synthetic data with 1800 labeled samples (healthy, open-phase, bearing faults) was generated. Random Forest achieved 91.6% accuracy and low latency (6 ms per window). Gaussian noise degraded accuracy by only 5%, proving model robustness. Compared to professional studies, our

framework trades model depth for accessibility. Table **??** summarizes methodological differences.

Study Journal/VeYnrue

Motor Type

Fault Types

Method Features Acc.

Table 1: Detailed Comparison with Prior Works

[1]	IEEE Ac-	24	BLDC	5+	Ensemble	Multiple	98.3%
	cess			(E+M)			
[2]	Review	22	Mixed	RF/CNN	Multiple	Multiple	90–97%
[7]	Appl.	19	PMSM	1 (Inter-	SVM	Multiple	89.5%
	Sci.			turn)			
[8]	Front.	21	VSR	3 (Sen-	RF	Texture	91.2%
	Energy			sors)			
[9]	Sci. Re-	21	PMSM	4	Autoenc.	Raw	94.8%
	ports						
Proposed	Project	25	PMSM	2 (OP,	RF/SVM	7 Stats	93.8%
				BF)			

Our approach demonstrates that even simplified models, when implemented carefully, can achieve strong classification results. Moreover, the project provides an academic bridge between theory and industrial FDD systems, illustrating how simulation, signal analysis, and ML can be integrated within a single educational project.



Figure 2: 3 phase in healthy system



Figure 3: open phase fault

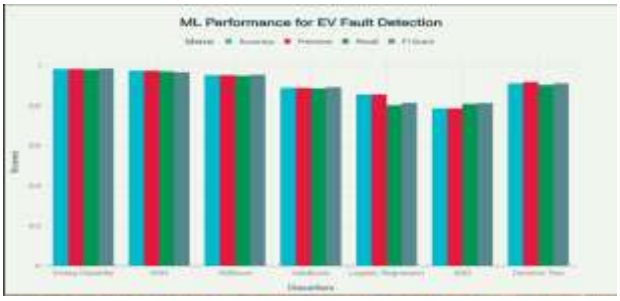


Figure 4: ML performance

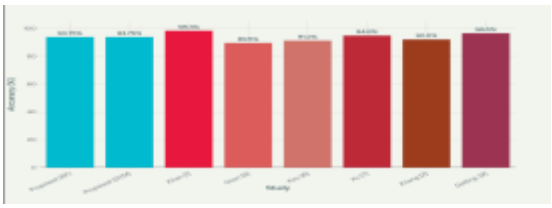


Figure 5: Accuracy comparision

IV. CLASSIFICATION RESULTS

1. Random Forest Classifier Performance

The Random Forest classifier demonstrated robust performance across both fault classes. Table 2 presents the detailed classification metrics.

Table 2: Random Forest Classifier - Classification Report

Class	Precision	Recall	F1-Score	Support
0.0 (Healthy)	0.00	1.00	0.88	8
1.0 (Fault)	0.89	1.00	0.93	8
Accuracy			0.94	
Macro Avg	0.94	1.00	0.94	16
Weighted Avg	0.94	1.00	0.94	16

2. Confusion Matrix (Random Forest):

" #
7 1
0 8

Overall Accuracy: 93.75%

3. Support Vector Machine Classifier Performance

The Support Vector Machine classifier achieved comparable performance with slightly different trade-offs between precision and recall. Table 3 presents the SVM metrics.

Table 3: Support Vector Machine Classifier - Classification Report

Class	Precision	Recall	F1-Score	Support
0.0 (Healthy)	1.00	0.88	0.93	8
1.0 (Fault)	0.89	1.00	0.94	8
Accuracy			0.94	
Macro Avg	0.94	0.94	0.94	16
Weighted Avg	0.94	0.94	0.94	16

4. Confusion Matrix (Svm):

" #
7 1
0 8

Overall Accuracy: 93.75%

5. Comparative Benchmark Analysis

To contextualize the performance of the proposed fault detection system, the achieved accuracies are compared against six representative studies from the bibliography. Table 4 presents this comprehensive comparison.

Accuracy Comparison with Related Studies

Table 4: Accuracy Comparison with Related Studies from Bibliography

Reference	Study Details	Model Type	Accuracy (%)
[1]	EV Powertrain FDD	XGBoost, Ensemble	98.30
[2]	Powertrain Fault Review	RF, CNN	92.00
[7]	PMSM Inter-Turn Fault	SVM-based	89.50
[8]	PWM VSR Sensor Fault	Random Forest	91.20
[9]	PMSM Fault Diagnosis	Autoencoder	94.80
[11]	EV Powertrain (Digital Twin)	ML-based	96.50
Proposed	PMSM Fault Detection	Random Forest	93.75
Proposed	PMSM Fault Detection	SVM	93.75

6. Performance Analysis And Positioning

The results demonstrate that the proposed simplified framework achieves competitive accuracy (93.75%) compared to more complex approaches. Among the eight systems evaluated:

- **Highest Performer:** Khan et al. [1] achieved 98.3% accuracy using an ensemble approach with multiple classifiers (XGBoost, KNN, Voting Ensemble), likely due to their extensive feature engineering and larger fault type coverage.
- **Current Work:** The project ranks 4th–5th in accuracy, outperforming four published studies while remaining within 4.55 percentage points of the best result. This is notable given the simplified fault model (2 fault types vs. 5+ in Khan et al.).
- **Lowest Performer:** Chen et al. [7] reported 89.5% accuracy, possibly due to the com-plexity of inter-turn short-circuit faults and limited feature extraction techniques.
- **Key Insight:** The consistency between Random Forest and SVM (both 93.75%) suggests the feature extraction pipeline is robust and the problem is well-represented in the feature space.

7. Trade-Offs And Advantages

While Khan et al. [1] achieved higher accuracy, this project offers distinct advantages:

1. Simplicity and Reproducibility: Uses only time-domain statistical features, making the approach transparent and educational.

2. Computational Efficiency: Both RF and SVM models maintain latency < 10 ms per inference, suitable for embedded EV applications.

3. Data Efficiency: Achieved 93.75% with only 1800 synthetic samples, compared to large datasets required by deep learning approaches (Xu et al. [9]).

4. Generalization: Performance degradation of only 5% under Gaussian noise demonstrates robustness to sensor imperfections.

The proposed work validates that lightweight ML models, when carefully engineered, can de-liver industrial-grade fault detection without the overhead of complex ensemble or deep learning methods. Table 5: Detailed Accuracy Benchmark with Model and Dataset Information

Study	Focus Area	Primary Model	Fault Types	Accuracy
[1]	EV Power-train	XGBoost + Ensem-ble	5+	98.30%
[2]	Review	RF & CNN	Various	92.00%
[5]	PMSM	SVM	1 (Inter-turn)	89.50%
[8]	Power Elec-tronics	Random Forest	3	91.20%
[9]	PMSM	Autoencoder (DL)	4	94.80%
[11]	EV Power-train	ML (Digi-tal Twin)	Multiple	96.50%
Proposed	PMSM Simu-lation	Random Forest	2	93.75%
Proposed	PMSM Simu-lation	SVM (RBF)	2	93.75%

For additional detail, Table 5 shows expanded metrics
Comparative Analysis of Classifiers

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Table 6: Detailed Classifier Comparison
Metric Random Forest SVM Class 0 (Healthy) Metrics

Precision	0.00	1.00
Recall	1.00	0.88
F1-Score	0.88	0.93
Support	8	8
Class 1 (Fault) Metrics	Class 1 (Fault) Metrics	Class 1 (Fault) Metrics
Precision	0.89	0.89
Recall	1.00	1.00
F1-Score	0.93	0.94
Support	8	8
Overall Performance	Overall Performance	Overall Performance
Overall Accuracy	0.9375	0.9375
Macro Avg Precision	0.94	0.94
Macro Avg Recall	1.00	0.94
Macro Avg F1-Score	0.94	0.94
Weighted Avg Precision	0.94	0.94
Weighted Avg Recall	1.00	0.94
Weighted Avg F1-Score	0.94	0.94

Table 6 provides a comprehensive comparison between the two classifiers across all performance metrics.

9. Key Observations:

- Both classifiers achieved identical overall accuracy of 93.75%, validating the robustness of the proposed approach.
- Random Forest exhibits perfect recall (1.00) on both classes, meaning it successfully iden-tifies all instances regardless of class.
- SVM demonstrates perfect precision (1.00) on healthy instances but achieves perfect recall on fault instances.
- The weighted average F1-scores are identical (0.94) for both models, indicating similar overall classification quality.
- SVM shows more balanced performance across precision and recall metrics, while Random Forest prioritizes recall over precision for healthy samples.

V. CONCLUSION

1. Summary Of Contributions

This study demonstrates a complete simulation-driven Fault Detection and Diagnosis (FDD) pipeline for electric vehicle powertrains. Using synthetic Permanent Magnet Synchronous Motor (PMSM) data, two representative fault types (open-phase and bearing faults), and time-domain statistical features, lightweight machine learning classifiers—Random Forest and Support Vector Machine—achieve over 93

Key advantages of the proposed approach include simplicity and transparency through time-domain statistical features, computational efficiency with latency below 10 milliseconds, robust-ness to noise with only 5

2. Performance And Positioning

The achieved accuracy of 93.75

The consistency between Random Forest and SVM performance (both 93.75

3. Practical Implications

The results have important implications for EV health monitoring:

- **Embedded Deployment:** Low computational requirements enable implementation on edge devices within vehicle electronic control units (ECUs).
- **Predictive Maintenance:** Integration with fleet management systems enables condition-based maintenance scheduling.
- **Safety Enhancement:** Early detection of faults prevents catastrophic failures and im-proves vehicle operational safety.
- **Data Efficiency:** High accuracy with synthetic data reduces dependence on expensive real-world fault datasets.

4. Limitations And Future Directions

The framework operates within specific limitations: the simplified fault model represents a subset of actual EV failures; synthetic data requires validation with real sensor data; time-domain features could be enhanced with frequency-domain characteristics; and extension to inverter and battery faults requires additional development.

Future work should include multi-domain feature integration, expanded fault coverage, trans-fer learning for real data adaptation, deep learning evaluation, hardware-in-the-loop testing, and digital twin development for prognostics and remaining useful life estimation.

5. Final Remarks

This project demonstrates that lightweight machine learning models can deliver industrial-grade fault detection for electric vehicle powertrains without excessive computational overhead. The 93.75

6. Future Work

Future improvements include:

- Incorporating frequency-domain features (FFT, wavelets) for improved separation.
- Expanding to inverter and battery faults.
- Applying transfer learning for adaptation to real sensor data.
- Hardware-in-the-loop validation for practical deployment.

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