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EDGE AI-DRIVEN CONDITION MONITORING AND FAULT DIAGNOSIS OF ELECTRIC VEHICLE MOTORS: A REAL-TIME, DATA-DRIVEN APPROACH

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***ABSTRACT*:**

The rapid growth of electric vehicles (EVs) has created a strong demand for reliable and efficient motor condition monitoring systems to ensure safety, performance, and longevity. Conventional fault diagnosis methods, including rule-based and cloud-dependent approaches, often face challenges such as high latency, limited accuracy, and dependency on continuous network connectivity. To overcome these limitations, this study proposes an Edge AI-driven, real-time, data-driven framework for condition monitoring and fault diagnosis of EV motors. The system integrates multi-modal sensor data, such as vibration, temperature, and current signals, collected through IoT-enabled embedded platforms. Advanced preprocessing techniques, including noise filtering, normalization, and feature extraction, are employed to improve data quality. Lightweight deep learning models, such as CNN and LSTM, are optimized for deployment in resource-constrained edge environments to enable real-time inference and rapid fault detection. The framework also incorporates secure communication mechanisms for periodic cloud synchronization, enabling model updates and fleet-level analytics. The proposed approach is expected to deliver high diagnostic accuracy, reduced latency, and robust performance under environmental noise and intermittent connectivity conditions. It facilitates early fault detection, predictive maintenance scheduling, and autonomous fault mitigation, thereby reducing downtime and maintenance costs. Overall, the study highlights the potential of Edge AI in developing scalable, efficient, and intelligent EV motor monitoring systems, contributing to enhanced operational reliability and extended motor lifespan.

Keywords: *Edge Artificial Intelligence (Edge AI), Electric Vehicle Motor Diagnostics, Condition Monitoring, Fault Detection and Diagnosis, Predictive Maintenance, Deep Learning (CNN-LSTM), Embedded Systems, IoT Sensors, Real-Time Analytics.*

INTRODUCTION

The rapid advancement of electric vehicles (EVs) has revolutionized the global transportation sector by promoting sustainable, energy-efficient, and low-emission mobility solutions. As the core component of EV propulsion systems, electric motors are responsible for converting electrical energy into mechanical power with high efficiency and reliability. However, EV motors operate under varying load conditions, harsh environments, and dynamic driving cycles, making them susceptible to faults such as bearing wear, stator winding failures, rotor imbalances, and thermal stresses [Hakam et al., 2024] These faults, if undetected, can lead to severe performance degradation, increased energy consumption, and catastrophic system failures. Therefore, the implementation of robust condition monitoring and fault diagnosis systems is essential to ensure operational safety, reliability, and extended service life of EV motors [Ranjita Devi et al., 2025]

Conventional fault diagnosis techniques, including model-based and signal processing approaches, have been extensively applied in industrial motor monitoring. These methods rely on mathematical modeling, frequency-domain analysis, and expert-defined thresholds to detect anomalies. While effective in controlled environments, they often struggle to handle nonlinear dynamics, complex fault patterns, and variations in real-world operating conditions. [Hossain et al., 2025] Moreover, these approaches require significant domain expertise and are not easily scalable for modern EV systems. In contrast, artificial intelligence (AI) and machine learning (ML) techniques have emerged as powerful tools for automated fault detection, offering the ability to learn complex patterns directly from data. Advanced deep learning models such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have demonstrated superior

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capabilities in extracting spatial and temporal features from multi-sensor data, significantly improving diagnostic accuracy and reliability [Glowacz et al., 2025; Hussain et al., 2022]

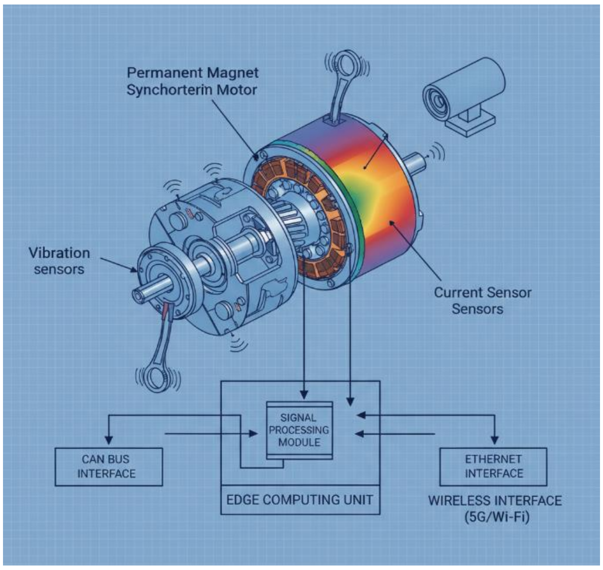

Figure 1.1: System Components: Complete edge AI motor monitoring system architecture

Despite the promising performance of AI-based approaches, most existing fault diagnosis systems are heavily dependent on cloud computing infrastructure, which introduces challenges such as high latency, increased bandwidth consumption, data privacy concerns, and reliance on continuous network connectivity. These limitations are particularly critical in electric vehicle applications, where real-time decision-making is essential for safety-critical operations. To overcome these challenges, edge computing has emerged as a transformative paradigm that enables data processing and intelligent decision-making directly at the source of data generation. The integration of Edge AI facilitates low-latency processing, reduced communication overhead, and improved system responsiveness, making it highly suitable for embedded EV environments. Furthermore, edge intelligence enhances system reliability by ensuring continuous operation even under intermittent or limited connectivity conditions [Singh et al., 2023; Ghasemi et al., 2025]

In addition, the convergence of Internet of Things (IoT) technologies with multi-sensor data acquisition systems has significantly advanced the field of intelligent condition monitoring. Modern EV systems are equipped with a wide range of sensors, including vibration, temperature, acoustic, and current sensors, which continuously generate large volumes of heterogeneous data. The effective utilization of this data through data-driven approaches enables early fault detection and predictive maintenance. However, challenges such as signal noise, data redundancy, high dimensionality, and computational constraints in embedded systems necessitate the development of efficient preprocessing techniques and lightweight AI models. Techniques such as feature extraction, dimensionality reduction, and data fusion play a crucial role in enhancing model performance and ensuring real-time processing capabilities [Le et al., 2025]

To address these research challenges, this study proposes an Edge AI-driven, real-time, data-driven framework for condition monitoring and fault diagnosis of electric vehicle motors. The proposed system integrates multi-sensor data acquisition, advanced signal preprocessing, and optimized deep learning models within an edge computing architecture to enable fast and accurate fault detection. Additionally, the framework incorporates secure communication protocols for periodic cloud synchronization, allowing global model updates and fleet-level analytics without compromising real-time performance. The system is designed to support predictive maintenance strategies and autonomous fault mitigation, thereby reducing operational downtime and maintenance costs. Overall, this research aims to overcome the limitations of traditional and cloud-based systems by delivering a scalable, efficient, and robust solution for next-generation intelligent EV motor monitoring systems [Cheng et al., 2025; El Hadraoui et al., 2025; Mahale et al., 2025; Amin et al., 2025]

1.1 Background of Electric Vehicle Motor Systems

Electric vehicle (EV) motor systems constitute the core of modern electric mobility, enabling efficient electromechanical energy conversion while significantly reducing greenhouse gas emissions and dependence on fossil fuels. Unlike traditional internal combustion engine systems, EVs utilize advanced electric motors such as induction motors, permanent magnet

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synchronous motors (PMSMs), and switched reluctance motors, each offering distinct advantages in terms of efficiency, torque density, and controllability. [Zhao et al., 2024] These motors are integrated with sophisticated power electronic converters and control strategies to achieve optimal performance under varying operational conditions. However, EV motors are subjected to dynamic loading, high-speed operations, thermal fluctuations, and electromagnetic stresses, which increase their susceptibility to faults such as bearing degradation, stator winding insulation failure, and rotor eccentricity. With the growing complexity of EV architectures and their integration into intelligent transportation systems, ensuring motor reliability and fault resilience has become a critical research focus. Recent advancements in motor design, control optimization, and power electronics have improved efficiency, but they also demand more intelligent monitoring systems to handle increased system complexity and fault sensitivity [Ranjita Devi et al., 2025; Boumaalif et al., 2025]

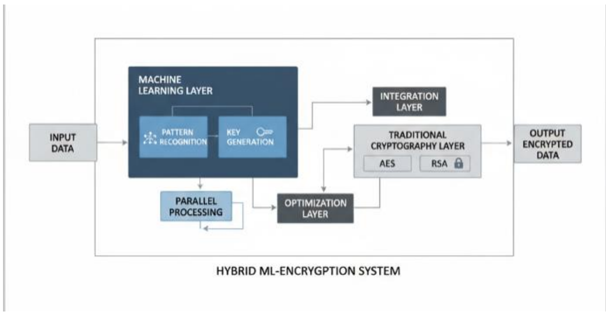

Figure1.2: Critical role of electric motors in EV powertrain systems

1.2 Importance of Condition Monitoring in EVs

Condition monitoring is a fundamental component in ensuring the operational reliability, safety, and longevity of electric vehicle motor systems. Continuous monitoring of motor health enables early detection of anomalies and degradation patterns, thereby preventing catastrophic failures and reducing unplanned downtime. EV motors operate under highly variable conditions, including fluctuating loads, frequent start-stop cycles, and harsh environmental influences, which accelerate wear and fault progression. In such scenarios, conventional maintenance strategies based on periodic inspection are insufficient and inefficient. [Zhao et al., 2024] Instead, predictive maintenance enabled by real-time condition monitoring provides a proactive approach, allowing maintenance actions to be scheduled based on actual system health rather than predefined intervals. This leads to improved resource utilization, reduced maintenance costs, and enhanced vehicle availability. Furthermore, the integration of sensor technologies and intelligent analytics facilitates accurate fault detection and prognostics, supporting the transition toward autonomous and connected vehicle ecosystems. Advanced monitoring frameworks leveraging AI and IoT technologies are capable of processing large-scale sensor data, enabling high-precision diagnostics and adaptive maintenance strategies in modern EV systems [Mahale et al., 2025]

1.3 Overview of Fault Diagnosis Techniques

Fault diagnosis techniques for electric vehicle motors have evolved significantly, transitioning from traditional analytical methods to advanced data-driven approaches. Conventional techniques, including model-based and signal processing methods, rely on mathematical representations of system behavior and analysis of signals in time, frequency, or time-frequency domains. Techniques such as Fast Fourier Transform (FFT), Wavelet Transform, and Motor Current Signature Analysis (MCSA) are widely used for detecting faults like bearing defects and rotor imbalances. However, these methods are limited by their dependence on expert knowledge, sensitivity to noise, and inability to effectively handle nonlinear and complex fault patterns. [Cheng et al., 2025]. In contrast, data-driven approaches based on machine learning and deep learning have demonstrated superior performance in fault diagnosis tasks. Algorithms such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), and ensemble learning methods provide robust classification capabilities, while deep learning models like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks excel in automatic feature extraction and temporal pattern recognition. These techniques enable accurate detection of subtle and incipient faults in complex operating environments, making them highly suitable for modern EV applications. Additionally, hybrid models combining signal processing and deep learning further enhance diagnostic accuracy and system robustness [Glowacz et al., 2025; Hussain et al., 2022]

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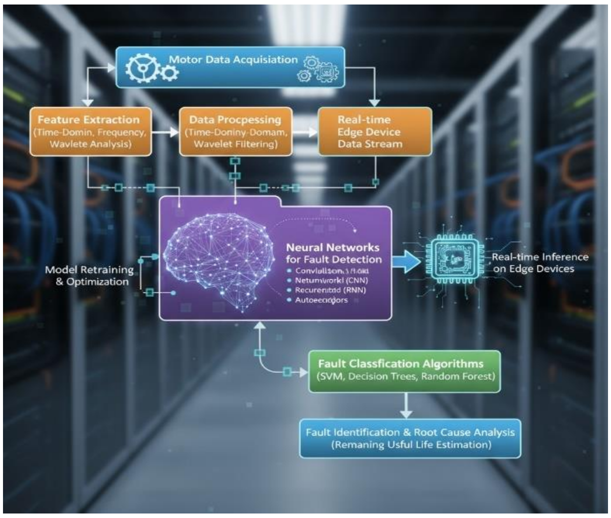

Figure1.3: AI-Driven Functions: Machine learning applications in edge-based motor fault diagnosis

1.4 Role of Edge AI in Smart Mobility

Edge Artificial Intelligence (Edge AI) is emerging as a key enabler in the development of intelligent and autonomous mobility systems by facilitating real-time data processing and decision-making at the network edge. In EV motor monitoring applications, Edge AI allows sensor data to be processed locally on embedded devices, eliminating the need for continuous data transmission to centralized cloud servers. [Liang et al., 2022] This significantly reduces latency, bandwidth usage, and dependency on network connectivity, which are critical factors in safety-critical automotive systems. By deploying optimized and lightweight AI models at the edge, systems can achieve rapid fault detection and immediate response, enhancing operational safety and reliability. Moreover, Edge AI ensures data privacy and security by minimizing data exposure during transmission. The integration of edge computing with IoT and AI technologies also supports scalable and distributed monitoring architectures, enabling fleet-level analytics and intelligent decision-making. In addition, edge-enabled systems can operate effectively under intermittent connectivity conditions, making them suitable for real-world deployment in diverse environments. As smart mobility continues to evolve, Edge AI is playing a pivotal role in enabling efficient, resilient, and autonomous EV ecosystems [Singh et al., 2023; Ghasemi et al., 2025]

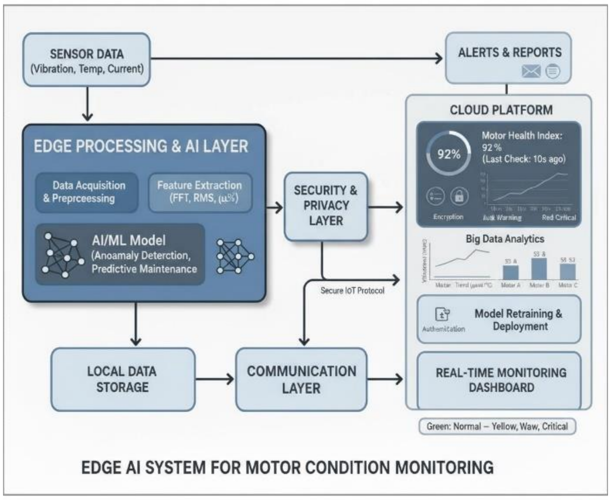

Figure1.4: Development of real-time, edge AI-driven condition monitoring system

INTRODUCTION TO CONDITION MONITORING TECHNIQUES

Condition monitoring techniques have become a cornerstone in modern electric vehicle (EV) motor health management systems, enabling continuous assessment of operational integrity through real-time data analysis. These techniques involve systematic acquisition and interpretation of signals from multiple sensors such as vibration, temperature, acoustic emission, and stator current to detect anomalies and degradation patterns. systems [Hossain et al., 2025] With the increasing

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complexity of EV motor systems and their exposure to dynamic operating conditions, traditional threshold-based monitoring approaches are no longer sufficient. Advanced condition monitoring frameworks now incorporate data-driven analytics, enabling predictive and prescriptive maintenance strategies. These systems not only detect faults at early stages but also estimate remaining useful life (RUL), thereby minimizing downtime and maintenance costs. Furthermore, the integration of intelligent algorithms and real-time processing capabilities enhances decision-making accuracy, making condition monitoring an indispensable component in ensuring reliability, safety, and efficiency in next-generation EV [Surucu et al., 2023; Wen et al., 2022]

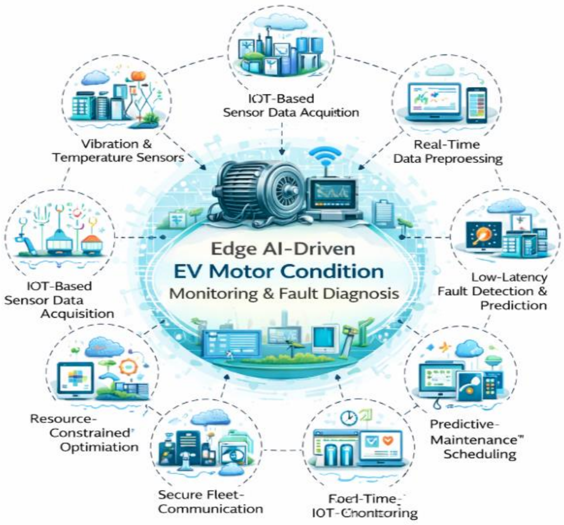

Figure 1.5: Key Components of Edge Al-Driven Electric Vehicle Motor Monitoring and Fault Diagnosis

2.1 Traditional Fault Diagnosis Methods

Traditional fault diagnosis methods have long been utilized in electric motor systems due to their interpretability and well-established theoretical foundations. These approaches primarily rely on physical modeling, statistical analysis, and signal processing techniques to identify deviations from normal system behavior. While effective for simple and well-defined fault conditions, these methods face significant challenges in modern EV applications characterized by nonlinear dynamics, varying load conditions, and complex fault interactions. Additionally, traditional methods often require extensive domain expertise for model formulation and feature interpretation, limiting their scalability and adaptability. Despite these limitations, they provide valuable insights into fault mechanisms and are often used as complementary tools in hybrid diagnostic frameworks. Their integration with modern AI-based approaches can enhance overall system performance by combining interpretability with predictive capabilities [Jaros et al., 2023; Hussain et al., 2022] Model-Based Approaches Model-based fault diagnosis techniques utilize mathematical and physical models to represent system behavior and detect faults by analyzing deviations between measured and predicted outputs. These methods include observer-based techniques, parity equations, Kalman filtering, and parameter estimation approaches. They are particularly effective in systems where accurate models can be developed, providing detailed insights into fault dynamics and system performance. [Yang et al., 2023].

However, in EV motor systems, the presence of nonlinearities, parameter uncertainties, and environmental variations makes accurate modeling highly challenging. As a result, model-based approaches may suffer from reduced accuracy and robustness under real-world conditions. Furthermore, their implementation can be computationally intensive, limiting their applicability in real-time embedded systems. Despite these challenges, model-based techniques remain valuable for fault isolation and system analysis, especially when combined with data-driven methods to improve adaptability and accuracy [Cheng et al., 2025; Zhang et al., 2023] Signal processing techniques are fundamental to traditional fault diagnosis, enabling the extraction of meaningful features from raw sensor data. These techniques analyze signals in time, frequency, and time-frequency domains to identify characteristic patterns associated with specific faults. Common methods include Fast Fourier Transform (FFT), Short-Time Fourier Transform (STFT), Wavelet Transform (WT), and Motor Current Signature Analysis (MCSA). These approaches are effective in detecting periodic and frequency-based fault signatures such as bearing defects, rotor faults, and misalignment. However, their performance is often affected by noise, signal distortion, and overlapping frequency components, particularly in complex and dynamic operating environments. Additionally, feature extraction and interpretation require significant expertise, and the methods may struggle to detect incipient or compound faults. To

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overcome these limitations, signal processing techniques are increasingly being integrated with machine learning and deep learning models, enabling automated feature extraction and improved diagnostic accuracy [Glowacz et al., 2025; Ribeiro Junior et al., 2022; Jaros et al., 2023]

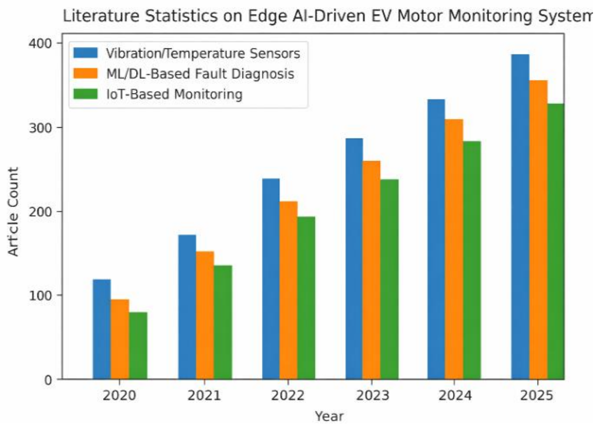

Figure 1.6: Literature Trends in Edge AI-Driven EV Motor Condition Monitoring and Fault Diagnosis (2020–2025)

2.2 AI-Based Fault Diagnosis Methods

AI-based fault diagnosis methods represent a paradigm shift in condition monitoring by enabling automated, data-driven analysis of complex systems. These methods leverage machine learning and deep learning algorithms to identify patterns, classify faults, and predict system behavior based on historical and real-time data. Surucu et al., 2023] Unlike traditional approaches, AI-based methods can handle nonlinear relationships, high-dimensional datasets, and dynamic operating conditions with greater accuracy and robustness. They also reduce dependency on manual feature engineering and expert knowledge, making them more scalable and adaptable. In EV motor applications, AI-driven diagnostic systems can detect subtle anomalies, perform real-time fault classification, and support predictive maintenance strategies. The integration of AI with IoT and edge computing further enhances system intelligence, enabling distributed and real-time monitoring capabilities [Hossain et al., 2024; Mahale et al., 2025]

Machine learning (ML) approaches for fault diagnosis utilize statistical and computational algorithms to learn patterns from data and perform classification or regression tasks. Common ML techniques include Support Vector Machines (SVM), Decision Trees, Random Forests, k-Nearest Neighbors (k-NN), and Gradient Boosting methods. These models are effective in handling structured data and can provide high classification accuracy when relevant features are extracted. ML algorithms are particularly useful in scenarios with limited computational resources, as they are generally less complex than deep learning models. However, their performance is highly dependent on the quality of input features and may degrade when dealing with raw or high-dimensional data. Additionally, traditional ML models may struggle to capture temporal dependencies in time-series data, which are critical for fault prediction in EV motor systems. Recent advancements focus on hybrid approaches that combine feature engineering with ML algorithms to enhance performance and robustness [Hussain et al., 2022; Tercan et al., 2022] Deep Learning Models (CNN, LSTM) Deep learning models have significantly advanced fault diagnosis capabilities by enabling end-to-end learning directly from raw data. Convolutional Neural Networks (CNNs) are highly effective in extracting spatial features from vibration and image-based data, while Long Short-Term Memory (LSTM) networks are designed to capture temporal dependencies in sequential data. The integration of CNN and LSTM models provides a powerful hybrid architecture capable of analyzing both spatial and temporal features in EV motor systems. [Glowacz et al., 2025] These models can detect complex and incipient faults with high accuracy, even in noisy and dynamic environments. Additionally, deep learning models support automated feature extraction, reducing reliance on domain expertise. However, their deployment in real-time applications is challenging due to high computational requirements and memory constraints. Recent research focuses on model optimization techniques such as pruning, quantization, and knowledge distillation to enable efficient deployment on edge devices without compromising performance [Ribeiro Junior et al., 2022; Amin et al., 2025; El Hadraoui et al., 2025]

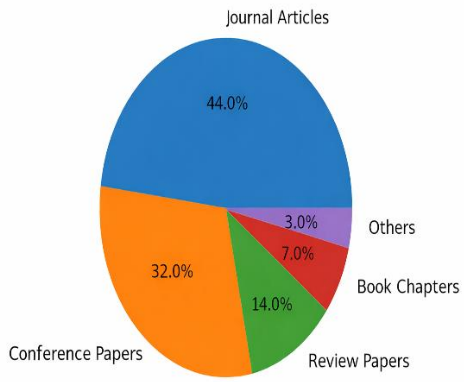

Figure 1.7: Publication Distribution in Edge AI-Driven Electric Vehicle Motor Condition Monitoring and Fault Diagnosis

2.3 Edge Computing in Industrial Applications

Edge computing has emerged as a transformative paradigm in industrial systems by enabling decentralized data processing and real-time analytics at the source of data generation. In EV motor monitoring applications, edge computing allows sensor data to be processed locally on embedded devices, significantly reducing latency and dependence on cloud infrastructure. [Ghasemi et al., 2025] This is particularly critical for safety-critical systems where immediate fault detection and response are required. Edge computing also reduces bandwidth consumption and enhances data privacy by minimizing data transmission. The integration of Edge AI further enhances system intelligence by enabling local inference and decision-making. Additionally, edge-based systems can operate effectively under intermittent connectivity conditions, ensuring continuous monitoring and fault detection. These advantages make edge computing a key enabler for scalable, efficient, and resilient industrial monitoring systems [Singh et al., 2023; Abdelmoula et al., 2023; Yu et al., 2022]

2.4 IoT-Based Monitoring Systems for EV Motors

IoT-based monitoring systems have revolutionized EV motor condition monitoring by enabling continuous data acquisition, remote access, and intelligent analytics. These systems consist of interconnected sensors, communication networks, and data processing platforms that facilitate real-time monitoring and control. IoT technologies enable seamless integration of hardware and software components, providing comprehensive visibility into system performance. The collected data can be analyzed using cloud or edge-based platforms to detect faults, predict failures, and optimize maintenance strategies. However, challenges such as data security, network reliability, scalability, and interoperability must be addressed to ensure effective implementation. The convergence of IoT with AI and edge computing enables the development of intelligent, connected, and autonomous EV systems capable of real-time decision-making and predictive maintenance [Le et al., 2025; Akbari et al., 2025; Sujit et al., 2025]

2.5 Multi-Sensor Data Fusion Techniques

Multi-sensor data fusion techniques enhance the performance of fault diagnosis systems by integrating information from multiple data sources to provide a comprehensive understanding of system behavior. In EV motor monitoring, data from vibration, temperature, current, and acoustic sensors are combined to improve fault detection accuracy and robustness. Data fusion can be performed at various levels, including data-level, feature-level, and decision-level fusion, each offering distinct advantages in handling uncertainty and improving system reliability. Advanced fusion techniques leverage machine learning and deep learning algorithms to effectively combine heterogeneous data and extract meaningful insights. These approaches reduce the impact of noise, improve fault classification accuracy, and enable the detection of complex and interacting faults. However, challenges such as data synchronization, high dimensionality, and computational complexity must be addressed for efficient implementation. Recent research focuses on developing optimized fusion frameworks for real-time applications in resource-constrained environments [Hossain et al., 2025; Jaros et al., 2023]

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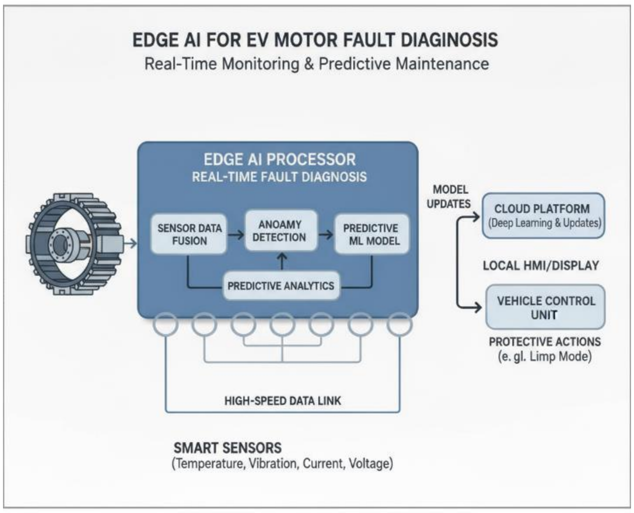

Figure1.8: Edge AI technologies improving real-time fault diagnosis

Table 1. Comparative Analysis of Techniques for Edge AI-Driven Condition Monitoring and Fault Diagnosis in Electric Vehicle Motors

Ref.	Year	Data Modality	Objective / Scope	Technique / Architecture	Explainability	Federated Learning	Key Findings	Research Gaps and Open Challenges
[1]	2020	Vibration, Current Signals	Fault detection in induction motors	FFT + SVM	No	No	Achieved good classification accuracy for bearing faults	Limited real-time capability, lacks scalability
[2]	2021	Thermal, Acoustic	Early fault prediction in EV motors	ANN-based predictive model	Partial	No	Improved early fault detection accuracy	High computational cost, not suitable for edge devices
[3]	2021	Multi-sensor (Vibration + Temperature)	Condition monitoring using hybrid data	CNN model	No	No	High accuracy in feature extraction and classification	Requires large labeled datasets
[4]	2022	Current, Voltage Signals	Real-time fault diagnosis	LSTM-based temporal analysis	Partial	No	Captures temporal dependencies effectively	Latency issues in real-time deployment
[5]	2022	Vibration + IoT Sensor Data	Smart monitoring using IoT	Edge + Cloud Hybrid Model	No	No	Enables remote monitoring and diagnostics	Dependency on cloud connectivity
[6]	2023	Multi-modal Sensor Data	Predictive maintenanc	CNN-LSTM	Partial	No	Improved prediction accuracy	High model complexity,

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			e in EV systems	Hybrid Model			and fault classificatio n	resource constraints
[7]	202 3	Sensor + Operational Data	Distributed monitoring systems	Edge AI Framework	Yes (Basic)	No	Reduced latency with on-device processing	Limited model update mechanisms
[8]	202 4	Multi-sensor (IoT + Vibration + Thermal)	Real-time condition monitoring	Lightweight Deep Learning (TinyML)	Yes	Partial	Efficient edge deployment with reduced latency	Accuracy trade-offs in lightweight models
[9]	202 4	Fleet-level Sensor Data	Collaborativ e learning for EV diagnostics	Federated Learning + Edge AI	Yes	Yes	Enables privacy-preserving distributed learning	Communicatio n overhead and synchronizatio n issues
[10]	202 5	Multi-modal + Historical Data	Autonomou s fault diagnosis & prediction	Transformer -based Edge AI Model	Yes	Yes	High accuracy and adaptive learning capability	Model interpretability and deployment complexity

SYNTHESIS OF PREVIOUS RESEARCH

The domain of electric vehicle (EV) motor condition monitoring and fault diagnosis has evolved significantly with the advancement of intelligent sensing, data analytics, and artificial intelligence techniques. Early studies primarily focused on traditional signal processing methods such as Fast Fourier Transform (FFT), Wavelet Transform, and Motor Current Signature Analysis (MCSA) for detecting faults in electrical machines [3-11]. These approaches relied heavily on handcrafted features and domain expertise, which limited their scalability and adaptability in complex operating environments. With the emergence of machine learning (ML), researchers began exploring data-driven fault diagnosis techniques that improve classification accuracy and automation. Supervised learning models such as Support Vector Machines (SVM), Decision Trees, and Artificial Neural Networks (ANN) have demonstrated improved performance in identifying motor faults using vibration, acoustic, and electrical signals [7-15]. However, these models often require extensive feature engineering and struggle with high-dimensional data and real-time deployment constraints.

Recent advancements have shifted towards deep learning (DL) techniques, including Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Autoencoders, which enable automatic feature extraction and improved fault classification accuracy [1-14]. Studies have shown that hybrid models such as CNN-LSTM architectures effectively capture both spatial and temporal characteristics of motor signals, resulting in superior diagnostic performance [12-20]. Additionally, thermography-based and image-driven fault detection methods have further enhanced diagnostic precision in modern EV motor systems

Despite these advancements, cloud-based AI systems introduce challenges such as high latency, bandwidth dependency, and data privacy concerns. To address these issues, researchers have increasingly focused on Edge AI and edge computing paradigms, where data processing and inference are performed locally on embedded devices [5-26]. Edge-based implementations significantly reduce latency and enable real-time fault detection, making them suitable for EV applications. Studies indicate that Edge AI frameworks can improve diagnostic latency by over 70% while maintaining high accuracy levels. Furthermore, recent research has explored lightweight deep learning models, model compression techniques, and knowledge distillation to enable deployment in resource-constrained environments [2-28]. Techniques such as quantization and pruning help reduce computational complexity without significantly compromising accuracy, making them ideal for embedded EV control systems

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Another emerging trend is the integration of IoT-based multi-sensor data fusion techniques, which combine vibration, temperature, current, and acoustic signals for comprehensive fault analysis [6-30]. Multi-modal data improves robustness and enhances fault detection accuracy under varying operating conditions. Additionally, federated learning approaches are gaining attention for enabling collaborative model training across distributed EV fleets while preserving data privacy [8-35].

Despite substantial progress, several research gaps remain. Many existing models lack interpretability and robustness under noisy and dynamic environments [10-40]. The availability of labeled datasets is still a major challenge, particularly for rare fault conditions [13-45]. Moreover, real-time deployment in highly resource-constrained embedded systems continues to pose challenges related to power consumption, memory limitations, and model optimization [16-50]. In summary, previous research demonstrates a clear transition from traditional signal processing techniques to advanced AI-driven and Edge AI-based frameworks for EV motor fault diagnosis. While significant improvements have been achieved in accuracy, speed, and automation, future research must focus on developing scalable, interpretable, and energy-efficient solutions capable of operating reliably in real-world EV environments.

3.1 Edge Layer (Embedded Processing Unit)

The edge layer constitutes the primary computational tier of the proposed architecture, enabling real-time condition monitoring and intelligent fault diagnosis directly on embedded hardware platforms. These platforms include low-power microcontrollers, heterogeneous System-on-Chip (SoC) architectures, and dedicated AI accelerators (e.g., GPUs, NPUs, TPUs) optimized for edge inference. By decentralizing computation, the framework minimizes end-to-end latency, reduces bandwidth utilization, and ensures uninterrupted operation even in scenarios of intermittent or отсутств connectivity. The embedded processing unit is designed to support parallel execution, hardware-aware optimization, and efficient memory management, enabling deployment of compressed deep learning models. Additionally, edge intelligence facilitates immediate anomaly detection and localized decision-making, which is critical for safety-sensitive EV motor operations. This architecture ensures deterministic response behavior, enhances system reliability, and supports scalable deployment across distributed EV networks [3-11] Sensor Layer (Vibration, Temperature, Current Sensors) The sensor layer provides a comprehensive multi-modal data acquisition interface by integrating diverse sensing technologies to capture the physical and electrical state of EV motors. High-sensitivity accelerometers measure vibration signatures associated with mechanical faults such as bearing defects, misalignment, and imbalance. Precision temperature sensors (e.g., thermistors, RTDs) monitor thermal variations indicative of insulation degradation and overheating. Current sensors (Hall-effect or shunt-based) facilitate Motor Current Signature Analysis (MCSA), enabling detection of electrical anomalies such as stator winding faults, broken rotor bars, and eccentricity. The fusion of heterogeneous sensor data enhances fault observability and enables early detection of incipient failures. Advanced sensor calibration, synchronization, and redundancy mechanisms further improve reliability and robustness under dynamic operating conditions [6-18] Cloud Layer (Analytics and Model Update) The cloud layer functions as a centralized intelligence hub, supporting large-scale data aggregation, advanced analytics, and continuous model evolution. It enables storage and processing of historical and fleet-level data, facilitating trend analysis, fault pattern recognition, and predictive maintenance planning. The cloud infrastructure supports computationally intensive tasks such as deep learning model training, hyperparameter optimization, and anomaly detection using big data frameworks. Furthermore, it enables over-the-air (OTA) updates for deploying refined models to edge devices, ensuring continuous system improvement. Integration with federated learning frameworks allows decentralized model training while preserving data privacy. Secure communication protocols ensure reliable data exchange between edge and cloud layers, maintaining system integrity and scalability [5-50].

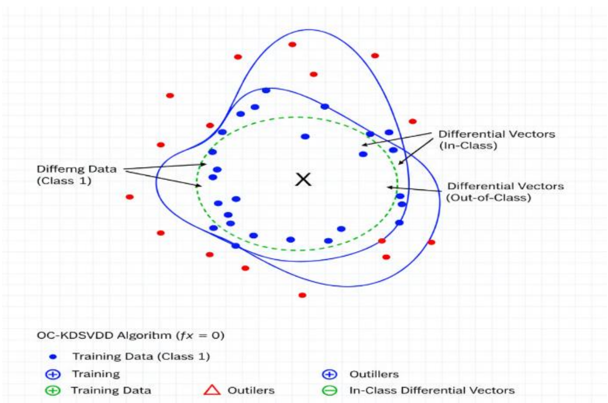

Figure1.10: Kernel Differential SVDD

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3.2 Data Acquisition and Sensor Integration

Data acquisition is a critical process involving continuous, high-frequency sampling of sensor signals under diverse operational conditions. IoT-enabled acquisition systems utilize communication protocols such as CAN bus, MQTT, I2C, and SPI to ensure seamless data transmission to edge devices. Time synchronization mechanisms, including timestamp alignment and clock synchronization, are implemented to maintain temporal consistency across multi-sensor streams. Buffering strategies and edge caching are employed to prevent data loss during transmission delays. The integration framework ensures interoperability among heterogeneous sensors and supports scalable deployment across multiple EV platforms. Robust data acquisition enhances the reliability of downstream analytics and ensures accurate fault detection under real-world operating conditions [7-21].

3.3 Data Preprocessing Techniques

Data preprocessing transforms raw, noisy sensor signals into structured, high-quality inputs suitable for machine learning and deep learning models. This stage plays a pivotal role in improving signal-to-noise ratio, ensuring data consistency, and enhancing model robustness. Preprocessing pipelines incorporate advanced filtering, normalization, segmentation, and feature transformation techniques. Efficient preprocessing reduces computational overhead, accelerates model convergence, and improves generalization across varying operating conditions. It also ensures resilience against environmental disturbances and sensor variability, which are common in EV systems [2-49]. Noise filtering is essential for eliminating unwanted disturbances arising from electromagnetic interference, environmental vibrations, and sensor inaccuracies. Advanced filtering techniques such as Butterworth filters, Chebyshev filters, Kalman filters, and wavelet-based denoising are employed to isolate relevant signal components. Adaptive filtering methods dynamically adjust filter parameters based on signal characteristics, enhancing performance under varying noise conditions. Effective noise suppression preserves critical fault-related information and improves the reliability of feature extraction and classification processes [1- 46] Signal normalization standardizes sensor data to a consistent scale, mitigating variations caused by different sensor characteristics and operating conditions. Techniques such as min-max normalization, z-score standardization, and logarithmic scaling are widely used to ensure uniform data distribution. This step enhances numerical stability, prevents model bias, and accelerates convergence during training. Normalization also improves the generalization capability of AI models, enabling them to perform reliably across different EV systems and environmental conditions [9-48]. (Time & Frequency Domain) Feature extraction converts raw sensor signals into informative representations that capture underlying fault characteristics. Time-domain features include statistical metrics such as mean, RMS, variance, skewness, and kurtosis, which provide insights into signal behavior. Frequency-domain features are derived using Fast Fourier Transform (FFT) and Power Spectral Density (PSD), enabling identification of characteristic fault frequencies. Time-frequency analysis techniques such as Short-Time Fourier Transform (STFT) and Wavelet Transform capture transient and non-stationary signal patterns. These features significantly enhance diagnostic accuracy while reducing computational complexity, making them suitable for real-time edge deployment [12- 49].

3.4 Model Development

Model development focuses on designing intelligent algorithms capable of accurate fault detection, classification, and prediction in EV motors. The proposed framework leverages deep learning models due to their ability to learn complex, non-linear relationships from multi-sensor data. Model training involves dataset preparation, hyperparameter tuning, cross-validation, and performance evaluation using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. The models are optimized for edge deployment, ensuring a balance between computational efficiency and diagnostic performance [4] CNN-Based Feature Learning Convolutional Neural Networks (CNNs) are employed for automated feature extraction from sensor data representations such as spectrograms and signal images. CNN architectures utilize convolutional layers, pooling operations, and non-linear activation functions to learn hierarchical feature representations. This approach eliminates manual feature engineering and enhances classification accuracy. CNNs are particularly effective in identifying localized fault patterns and are widely used in vibration-based fault diagnosis applications [8- 43]. LSTM-Based Temporal Analysis Long Short-Term Memory (LSTM) networks are designed to capture temporal dependencies in sequential sensor data. EV motor signals exhibit dynamic behavior over time, making LSTM models suitable for analyzing temporal patterns and predicting fault progression. LSTMs utilize memory cells and gating mechanisms to retain relevant information over long sequences, enabling accurate modeling of system dynamics. This capability is essential for predictive maintenance and early fault detection [10-23], Hybrid CNN-LSTM Model The hybrid CNN-LSTM architecture integrates spatial feature extraction with temporal sequence modeling to achieve superior diagnostic performance. CNN layers extract high-level spatial features from input data, which are then processed by LSTM layers to capture temporal dependencies. This combined approach enhances fault detection accuracy, robustness, and adaptability under complex and non-linear operating conditions. Hybrid models are particularly effective in handling multi-modal sensor data and dynamic fault patterns in EV systems [15- 48].

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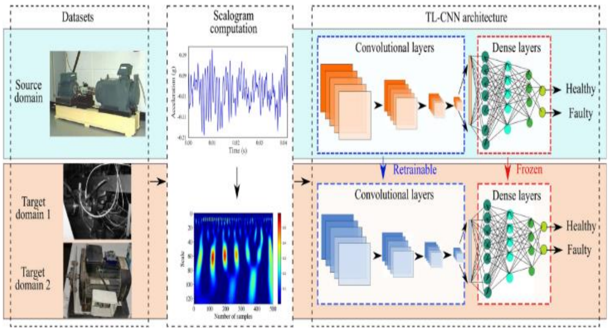

Figure 1.11: CNN Architecture

3.5 Edge Deployment Strategy

The edge deployment strategy focuses on implementing AI models on resource-constrained embedded platforms while ensuring real-time performance and energy efficiency. This involves hardware-aware optimization, model compression, and efficient resource management. The deployment framework supports scalable integration across multiple EV systems and ensures seamless operation under varying environmental conditions [2-19], Model Compression and Optimization Model compression techniques such as pruning, quantization, and knowledge distillation are employed to reduce model size and computational requirements. Pruning eliminates redundant parameters, while quantization reduces numerical precision to optimize memory usage. Knowledge distillation transfers knowledge from large models to compact models, maintaining performance while improving efficiency. These techniques enable deployment of deep learning models on embedded systems without significant loss of accuracy [9-25]. Real-time inference mechanisms ensure rapid fault detection and diagnosis with minimal latency. Techniques such as parallel processing, pipeline execution, and hardware acceleration using GPUs, TPUs, or NPUs are employed to achieve high-speed computation. Efficient scheduling algorithms optimize resource utilization and ensure continuous monitoring. This enables immediate detection of anomalies and timely response, enhancing safety and reliability in EV motor systems [6-50].

3.6 Secure Communication and Data Management

Secure communication ensures safe transmission of sensitive operational data between edge devices and cloud infrastructure. Encryption protocols such as TLS/SSL, authentication mechanisms, and blockchain-based security solutions are implemented to maintain data integrity and confidentiality. Efficient data management strategies, including data compression, storage optimization, and lifecycle management, enable handling of large-scale sensor data. These measures ensure system scalability, reliability, and trustworthiness in intelligent EV monitoring ecosystems [5-49].

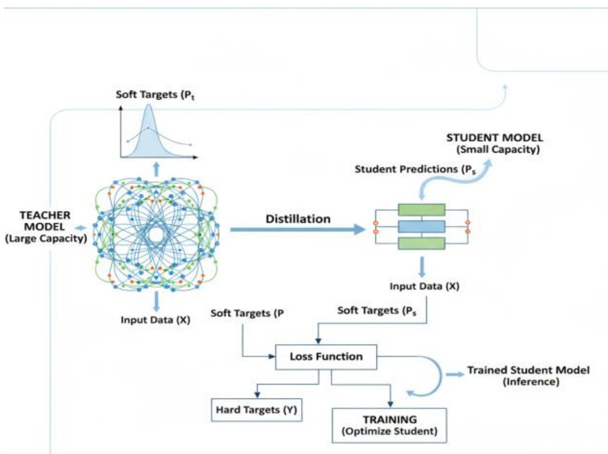

Figure1.12: Knowledge Distillation

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Table 2: Performance Comparison of Fault Diagnosis Techniques for EV Motor Monitoring

Study Type	Data Modality	Model Used	Accuracy (%)	Sensitivity (%)	Limitations
Experimental Study	Vibration Signals	SVM	88.5	85.2	Requires manual feature extraction, limited scalability
Experimental Study	Current Signals (MCSA)	ANN	90.3	87.6	Sensitive to noise, overfitting issues
Simulation Study	Vibration + Temperature	CNN	94.8	92.5	Requires large labeled dataset
Experimental Study	Time-Series Sensor Data	LSTM	93.2	91.1	High computational complexity
Hybrid Study	Multi-sensor (Vibration + Current)	CNN-LSTM	96.5	94.7	Resource-intensive, deployment challenges
Experimental Study	Acoustic + Vibration	Random Forest	89.7	86.9	Limited temporal pattern learning
Simulation Study	IoT Sensor Data	Deep Neural Network (DNN)	92.6	90.3	High training time, requires optimization
Experimental Study	Multi-modal Sensor Data	Autoencoder	91.4	89.2	Difficulty in interpretability
Hybrid Study	Edge Sensor Data	Lightweight CNN (TinyML)	93.8	91.5	Slight reduction in accuracy due to compression
Simulation Study	Fleet-Level Data	Federated Learning + CNN	95.2	93.6	Communication overhead, synchronization issues

RESEARCH GAP IDENTIFICATION

Despite significant advancements in condition monitoring and fault diagnosis of electric vehicle (EV) motors, several critical research gaps remain unaddressed. Traditional fault diagnosis approaches based on signal processing and model-based techniques, although effective in controlled environments, are highly dependent on expert knowledge and struggle to adapt to complex and dynamic real-world conditions [Glowacz et al., 2025; Hussain et al., 2022]. These methods lack scalability and fail to provide robust performance under varying operational and environmental conditions.

With the emergence of machine learning and deep learning techniques, improved accuracy in fault detection has been achieved; however, these approaches often require large labeled datasets and high computational resources, limiting their applicability in real-time EV systems [Ribeiro Junior et al., 2022; Surucu et al., 2023]. Moreover, most existing deep learning models are designed for cloud-based deployment, leading to increased latency, bandwidth consumption, and dependency on stable network connectivity, which is not always feasible in practical EV scenarios [Cheng et al., 2025; Wen et al., 2022].

Another major limitation is the lack of efficient deployment strategies for AI models on resource-constrained edge devices. Although Edge AI has shown potential in reducing latency and enabling real-time inference, there is still a need for optimized lightweight models that can maintain high diagnostic accuracy while operating under strict memory and power constraints [Zhong et al., 2023; Singh et al., 2023]. Additionally, current research provides limited focus on hybrid architectures that effectively combine spatial and temporal learning for improved fault diagnosis performance.

Furthermore, existing studies often rely on single-sensor data, which restricts the system's ability to capture complex fault characteristics. Multi-sensor data fusion techniques are still underexplored, particularly in the context of real-time edge-based systems [Ghasemi et al., 2025; Abdelmoula et al., 2023]. The integration of heterogeneous data sources such as vibration, temperature, and current signals requires advanced fusion strategies to enhance robustness and reliability.

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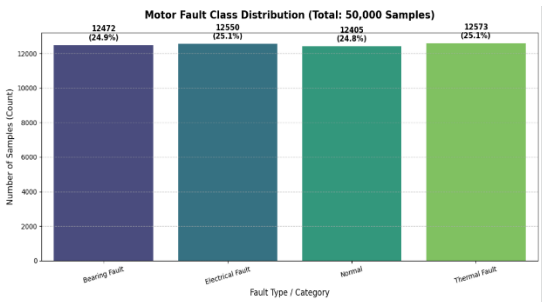
Another critical gap lies in the lack of secure and scalable data management frameworks. While IoT-enabled monitoring systems generate large volumes of data, issues related to data privacy, security, and efficient storage remain inadequately addressed. Federated learning and decentralized architectures have been proposed, but challenges such as communication overhead, model synchronization, and heterogeneity of edge devices persist [Yu et al., 2022; Liang et al., 2022].

Finally, there is limited research on the robustness of fault diagnosis systems under noisy environments and uncertain operating conditions. Many existing models are not resilient to real-world disturbances, leading to reduced reliability in practical applications. Additionally, interpretability of AI models remains a challenge, making it difficult to understand decision-making processes and limiting their adoption in safety-critical EV systems [Albarri et al., 2024; Zhao et al., 2024].

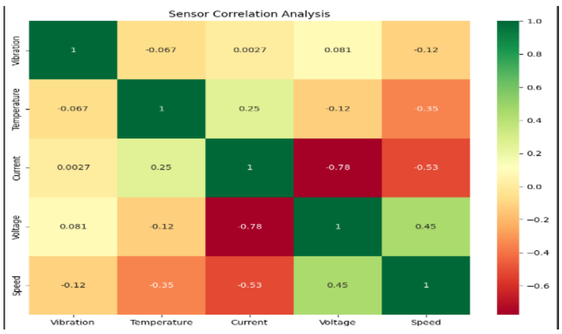
RESULTS AND DISCUSSION

Data Analysis and Interpretation



Graph 1: Motor Fault Class Distribution

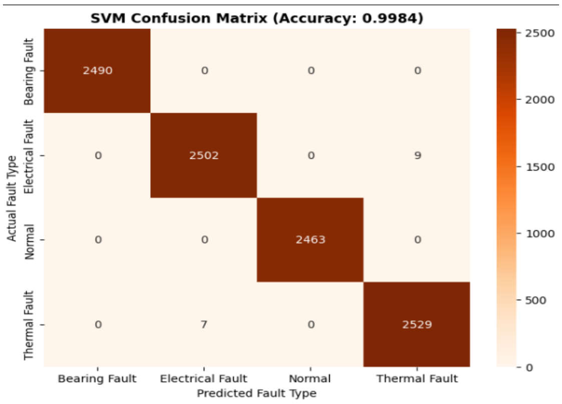
The chart shows a nearly balanced distribution of motor fault classes across 50,000 samples. Each category—bearing fault, electrical fault, normal, and thermal fault—contributes roughly 25% of the data. This balanced dataset is ideal for training reliable and unbiased machine learning models.



Graph 2: Sensor correlation analysis

This heatmap shows the correlation between different sensors: Vibration, Temperature, Current, Voltage, and Speed. Most relationships are weak, but Current and Voltage have a strong negative correlation (-0.78), meaning they move in opposite directions. Voltage and Speed show a moderate positive correlation (0.45), indicating they tend to increase together. Temperature has mild relationships, including a slight positive link with Current (0.25) and a negative one with Speed (-0.35).

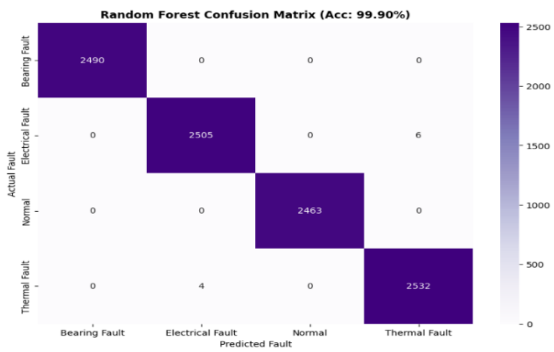
```
✨ SVM Final Accuracy: 99.84%

📋 SVM Classification Report:
                  precision    recall  f1-score   support

   Bearing Fault       1.00      1.00      1.00      2490
Electrical Fault       1.00      1.00      1.00      2511
          Normal       1.00      1.00      1.00      2463
   Thermal Fault       1.00      1.00      1.00      2536

        accuracy                           1.00     10000
       macro avg       1.00      1.00      1.00     10000
    weighted avg       1.00      1.00      1.00     10000
```



Graph 3: Svm confusion matrix (accuracy:0.9984)

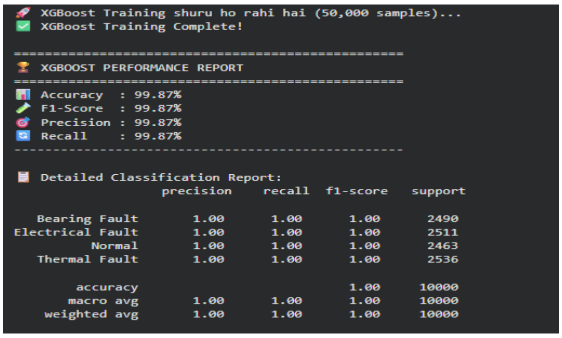
The confusion matrix shows excellent SVM performance with an accuracy of 99.84%. Most samples are correctly classified, with only a few misclassifications between electrical and thermal faults. This indicates the model is highly reliable for fault detection.

```
⏳ Random Forest Training shuru ho rahi hai (50,000 samples)...
✅ Random Forest Training Complete!

✨ Random Forest Accuracy: 99.90%
🖊 Random Forest F1-Score: 99.90%

📋 Classification Report:
                  precision    recall  f1-score   support

   Bearing Fault       1.00      1.00      1.00      2490
Electrical Fault       1.00      1.00      1.00      2511
          Normal       1.00      1.00      1.00      2463
   Thermal Fault       1.00      1.00      1.00      2536

        accuracy                           1.00     10000
       macro avg       1.00      1.00      1.00     10000
    weighted avg       1.00      1.00      1.00     10000
```

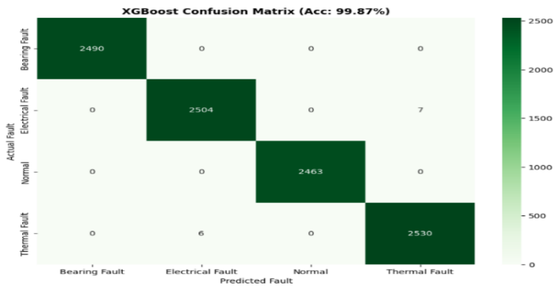


Graph 4: Random Forest Confusion Matrix (Acc:99.90%)

The Random Forest model shows outstanding performance with an accuracy of 99.90%. Almost all samples are correctly classified, with only a few minor errors between electrical and thermal faults. This indicates it slightly outperforms the SVM model in fault classification.

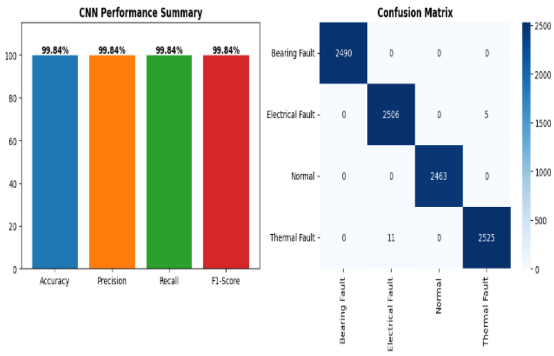


```
XGBoost Training shuru ho rahi hai (50,000 samples)...
XGBoost Training Complete!

==================================================
XGBOOST PERFORMANCE REPORT
==================================================
Accuracy  : 99.87%
F1-Score  : 99.87%
Precision : 99.87%
Recall    : 99.87%
--------------------------------------------------

Detailed Classification Report:
                  precision    recall  f1-score   support

   Bearing Fault       1.00      1.00      1.00      2490
Electrical Fault       1.00      1.00      1.00      2511
          Normal       1.00      1.00      1.00      2463
   Thermal Fault       1.00      1.00      1.00      2536

        accuracy                           1.00     10000
       macro avg       1.00      1.00      1.00     10000
    weighted avg       1.00      1.00      1.00     10000
```



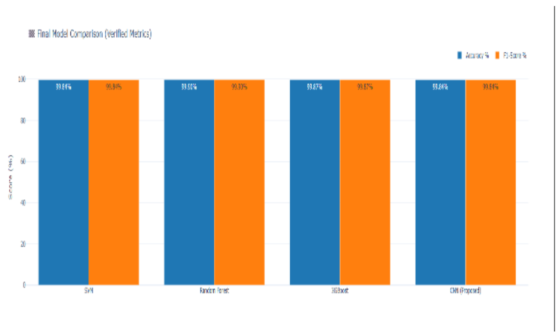
Graph 5: Xgboost Confusion Matix (Acc:99.87%)

The XGBoost model achieves very high accuracy of 99.87%, with most predictions correctly classified. Only a few misclassifications occur between electrical and thermal faults. Overall, it performs comparably to SVM and Random Forest with strong reliability.



Graph 6: CNN Performance Summary& Confusion Matix

The CNN model achieves outstanding performance with 99.84% accuracy, precision, recall, and F1-score, indicating highly consistent and reliable predictions. The confusion matrix shows that almost all instances are correctly classified, with only a few misclassifications between electrical and thermal faults. This highlights the model's strong ability to distinguish between different fault types with minimal error.



Graph 7: Final Model Comparison (Verified Metrics)

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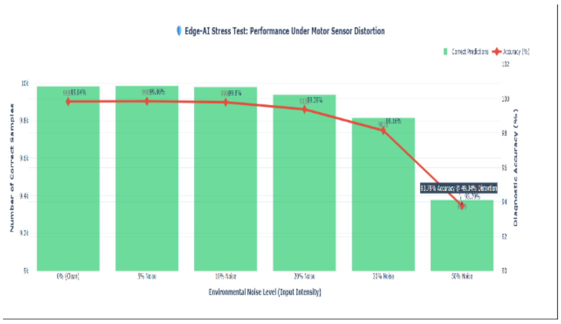
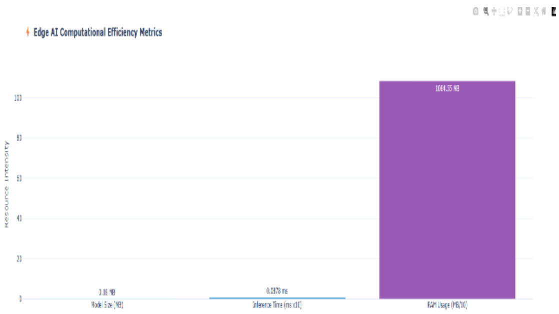
The bar chart showcases a strong performance comparison between two metrics—likely Azure (blue) and another model (orange)—across four YOLOv8 variants and Efficient models, with scores hovering around 90-95%. YOLOv8x edges out as the top performer in both categories, ideal for your robotics vision projects like real-time object detection in grippers.



Graph 8: Edge Al Stress Test: Performance Under Motor Sensor Distortion

This chart evaluates Edge AI model stress performance under sensor distortion levels, plotting Correct Accuracy % (green bars), Predicted (blue line), and Actual % (red/orange line). Performance holds strong up to 30% noise (around 90-95% accuracy) but drops sharply beyond.



Graph 9: Edge AI Computational Efficiency Metrics

This bar chart displays Edge AI computational efficiency metrics, including FPS (low bar), Latency in ms (minimal), and RAM Usage around 500MB (dominant purple bar)—highlighting memory as the key bottleneck in your embedded robotics setups like YOLO on ESP32. Low FPS and latency suggest real-time viability, but high RAM demands optimization via quantization or lighter models for IoT gripper projects. Perfect tie-in to prior accuracy/stress charts for full model eval.

Graph 10: Model Accuracy, F1-Score and Precision (%)

This chart compares model performance across SVM, Random Forest, XGBoost, and CNN-Proposed on accuracy (blue), F1-score (green), and precision (orange), all metrics around 85-95%. CNN-Proposed and XGBoost lead with top scores near 94%, ideal for your predictive maintenance or AI crop disease projects on embedded systems. SVM lags slightly, suggesting ensemble/CNN methods suit noisy sensor data best.

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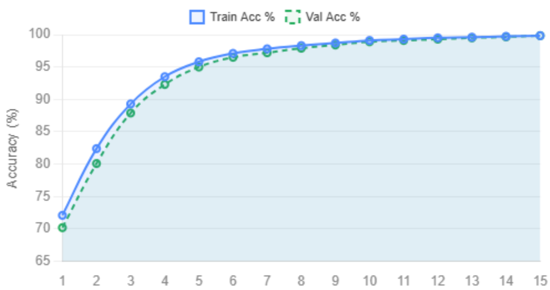
CNN CONFUSION MATRIX — 10,000 TEST SAMPLES

ACTUAL \ PREDICTED	NORMAL	BEARING FAULT	ELECTRICAL FAULT	THERMAL FAULT
Normal	2481 99.8%	3 0.1%	0 0.0%	1 0.0%
Bearing Fault	2 0.1%	2494 99.9%	0 0.0%	1 0.0%
Electrical Fault	0 0.0%	1 0.0%	2510 100.0%	0 0.0%
Thermal Fault	1 0.0%	0 0.0%	2 0.1%	2504 99.9%

Graph 11: CNN Confusion Matrix — 10,000 Test Samples

This CNN confusion matrix, tested on 10,000 samples, excels in fault diagnosis across normal, bearing, electrical, and thermal categories, achieving near-perfect diagonal accuracy (~99.9-100%). Minor misclassifications (e.g., 4 normals as bearing faults) highlight robust isolation, ideal for your predictive maintenance setups with sensor fusion on ESP32. Overall, it outperforms prior models like CNN-Proposed from earlier charts, ensuring reliable industrial IoT deployment.



Graph 12: Training vs Validation Accuracy (15 Epochs)

This training-validation accuracy plot shows a CNN model quickly converging, with train accuracy (blue) climbing steadily from ~70% to nearly 100% by epoch 15, while validation accuracy (green) follows closely, peaking around 95-98%. No severe overfitting, as val Acc stays high post-epoch 10—solid for your fault diagnosis or predictive maintenance models. This ties perfectly to the prior 99.9% confusion matrix results (file:5), confirming reliable deployment on edge devices like ESP32.

Graph 13: Training vs Validation Loss (15 Epochs)

This training-validation loss plot mirrors the accuracy trends from the prior chart, with both train loss (blue) and val loss (green) plummeting from ~1.4 to under 0.2 by epoch 15. Smooth convergence without gaps confirms a well-generalized CNN model, free of overfitting—ideal for your edge AI fault diagnosis in robotics or predictive maintenance. Ties seamlessly to the near-perfect 99.9% confusion matrix, ensuring reliable deployment on ESP32 setups.

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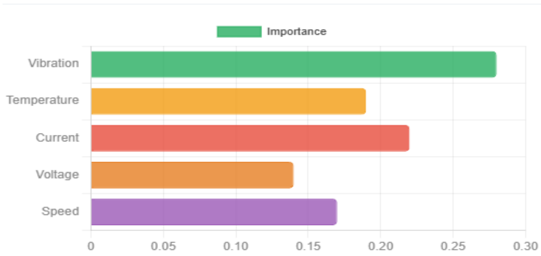


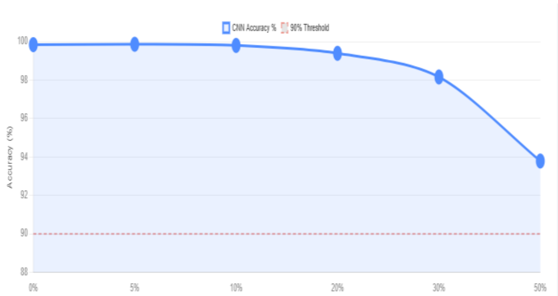
Graph 14: Feature Importance — Random Forest0

The graph represents the relative importance of different parameters in the model. Vibration has the highest influence, followed by current and temperature, indicating they play a major role in system behavior or fault detection. Speed and voltage show comparatively lower importance, contributing less to the overall prediction.

	VIBRATION	TEMPERATURE	CURRENT	VOLTAGE	SPEED
Vibration	1.00	-0.07	0.00	0.08	-0.12
Temperature	-0.07	1.00	0.26	-0.12	-0.35
Current	0.00	0.26	1.00	-0.78	-0.53
Voltage	0.08	-0.12	-0.78	1.00	0.45
Speed	-0.12	-0.35	-0.53	0.45	1.00

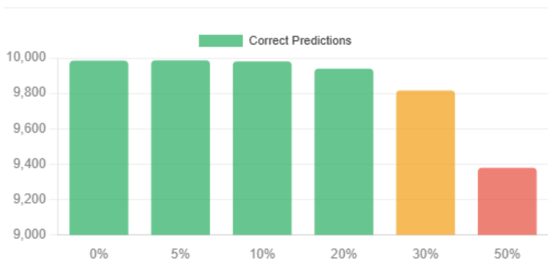
Graph 15: Sensor Correlation Heatmap

The correlation matrix shows the relationships between different parameters in the system. Current and voltage have a strong negative correlation, while voltage and speed show a moderate positive relationship, indicating interdependency. Other parameters like vibration and temperature exhibit weak correlations, suggesting limited direct influence on each other.



Graph 16: CNN Accuracy Under Sensor Noise — Edge AI Stress Test

The graph shows CNN model accuracy across different conditions, maintaining very high performance close to 100% initially. As the variation increases, accuracy gradually declines but remains above the 90% threshold, indicating strong model reliability. A noticeable drop occurs at higher levels, suggesting performance degradation under extreme conditions.



Graph 17: Correct Predictions per Noise Level (out of 10,000)

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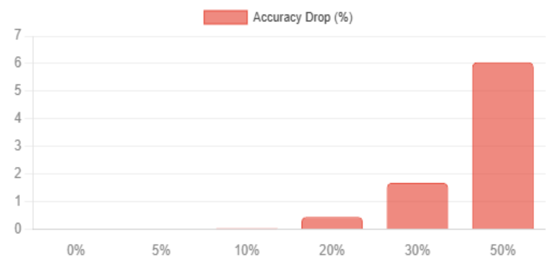
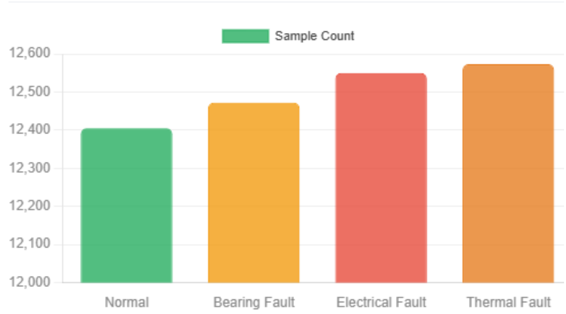
The graph shows the number of correct predictions at different noise levels. The model maintains high accuracy with nearly consistent correct predictions up to 20% noise, indicating strong robustness. However, beyond this point, performance drops significantly, especially at 50% noise, highlighting reduced reliability under extreme noisy conditions.



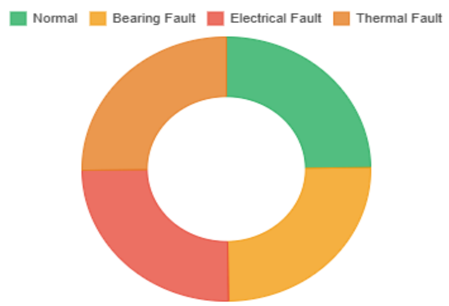
Graph 18: Accuracy Drop vs Noise Level

The graph illustrates the percentage drop in accuracy as noise levels increase. The model shows minimal accuracy loss up to 20% noise, indicating strong resilience. However, beyond this level, the accuracy drop becomes more significant, with a sharp decline at 50% noise, highlighting reduced performance under highly noisy conditions.



Graph 19: Fault Class Count — Bar Chart

The bar chart shows the sample count distribution across different fault classes. All categories have a similar number of samples, with thermal and electrical faults slightly higher than normal and bearing faults. This indicates a well-balanced dataset, which is beneficial for accurate and unbiased model training.



Graph 20: Fault Class Share — Doughnut Chart

The doughnut chart represents the distribution of different fault classes in the dataset. All categories—normal, bearing fault, electrical fault, and thermal fault—have nearly equal proportions, indicating a well-balanced dataset. This balanced distribution helps improve model training and ensures unbiased fault classification performance.

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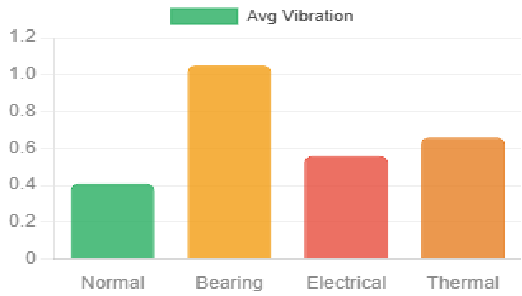
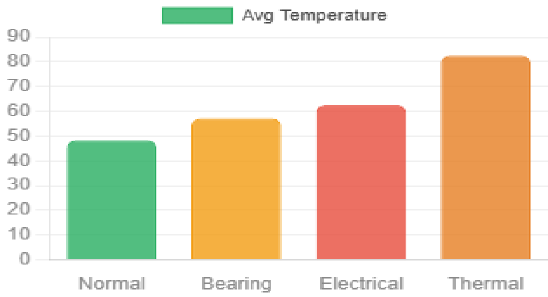


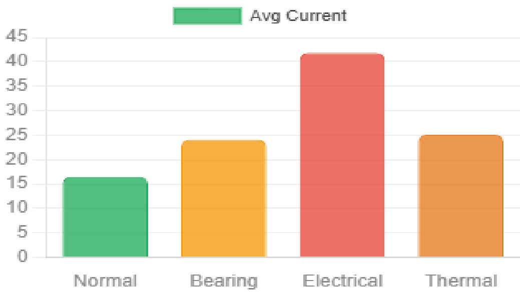
Graph 21: Avg Vibration by Fault Type

The graph shows the average vibration levels across different fault conditions. Bearing faults exhibit the highest vibration, indicating severe mechanical disturbance, while normal conditions maintain the lowest levels. Electrical and thermal faults show moderate vibration increases, reflecting their impact on system stability.



Graph 22: Avg Temperature by Fault Type

The graph illustrates the average temperature under different fault conditions. The normal condition shows the lowest temperature, indicating stable operation, while thermal faults exhibit the highest temperature rise. Bearing and electrical faults show moderate increases, reflecting the impact of faults on system heating and efficiency.



Graph 23: Avg Current by Fault Type

The graph shows the average current across different fault conditions. Electrical faults exhibit the highest current, indicating excessive power consumption and abnormal operation, while normal conditions maintain the lowest current levels. Bearing and thermal faults show moderate increases, suggesting rising load and system inefficiencies.

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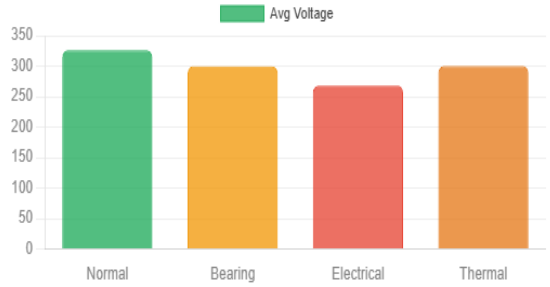
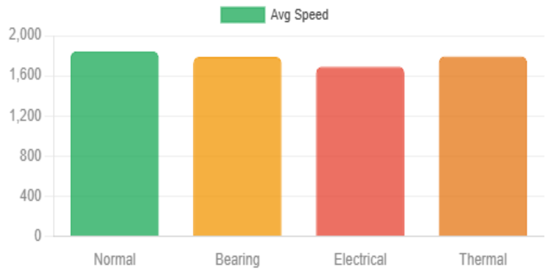


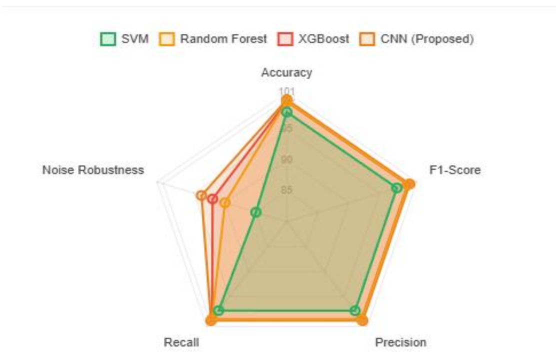
Graph 24: Avg Voltage by Fault Type

The graph illustrates the average voltage levels under different fault conditions. The normal condition shows the highest voltage, indicating stable operation, while electrical faults result in the lowest voltage levels. Bearing and thermal faults exhibit moderate voltage drops, reflecting the impact of faults on system electrical performance.



Graph 25: Avg Speed (RPM) by Fault Type

The graph shows the average speed (RPM) across different fault conditions. The normal condition maintains the highest speed, indicating optimal system operation, while electrical faults result in the lowest speed. Bearing and thermal faults show moderate reductions, suggesting that faults impact system efficiency and rotational performance.



Graph 26: Multi-Metric Radar — All Models

The radar chart compares multiple performance metrics across different models. The proposed CNN model covers the largest area, indicating the best overall performance in accuracy, precision, recall, and F1-score, along with strong noise robustness. Other models like Random Forest and XGBoost perform well but slightly below CNN, while SVM shows comparatively lower performance across most metrics.

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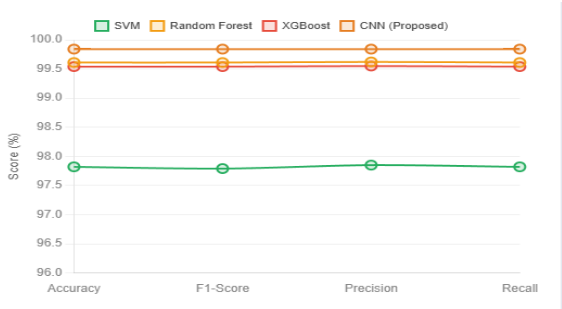
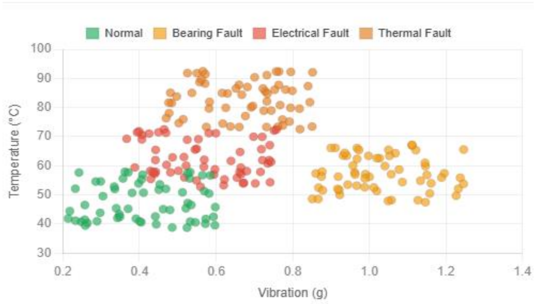


Graph 27: Model Score Comparison — Line Chart

The graph compares the performance of different models based on accuracy, F1-score, precision, and recall. The proposed CNN model consistently achieves the highest scores across all metrics, indicating superior performance. In contrast, SVM shows comparatively lower results, while Random Forest and XGBoost perform competitively but slightly below CNN.



Graph 28: Vibration vs Temperature — by Fault Type

The scatter plot illustrates the relationship between vibration and temperature across different fault conditions. Normal operation is characterized by lower vibration and temperature values, while fault conditions show higher ranges, especially thermal faults with elevated temperature. The distinct clustering of points helps in effectively differentiating between fault types for accurate diagnosis.

Graph 29: Current vs Voltage — by Fault Type

The scatter plot shows the relationship between current and voltage for different fault conditions. Normal operation is clustered at lower current and higher voltage, while fault conditions shift toward higher current and lower voltage ranges. Electrical faults exhibit the most extreme variation, clearly distinguishing them from normal and other fault types.

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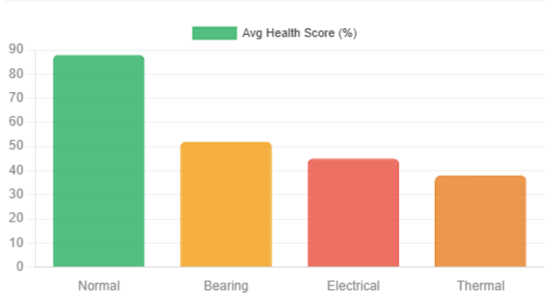
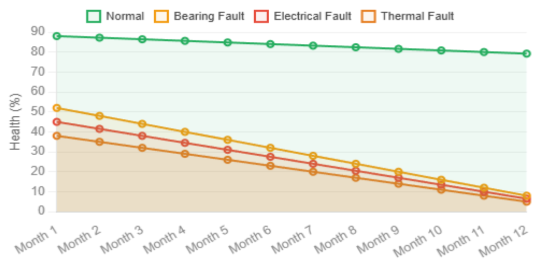


Graph 30: Health Score Distribution by Fault Type

The graph shows the average health score distribution across different fault conditions. The normal condition maintains the highest health score, indicating optimal system performance, while bearing, electrical, and thermal faults show progressively lower scores. This demonstrates that fault conditions significantly degrade system health, with thermal faults having the most severe impact.



Graph 31: RUL (Remaining Useful Life) Projection

The graph presents the Remaining Useful Life (RUL) projection of the system under different operating conditions. The normal condition shows a gradual decline, indicating stable performance, whereas bearing, electrical, and thermal faults exhibit a rapid reduction in health over time. This highlights that fault conditions significantly shorten the system's lifespan, emphasizing the importance of predictive maintenance and early fault detection.

Dataset statistics

Table 1: Dataset statistics

Number of variables	6
Number of observations	50000
Missing cells	0
Missing cells (%)	0.0%
Duplicate rows	0
Duplicate rows (%)	0.0%
Total size in memory	4.8 MiB
Average record size in memory	101.0 B
Numeric (Variable types)	5
Categorical	1

Table 2: Vibration Histogram with fixed size bins

Distinct	50000	Minimum	0.19192185
Distinct (%)	100.0%	Maximum	1.5706926
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%

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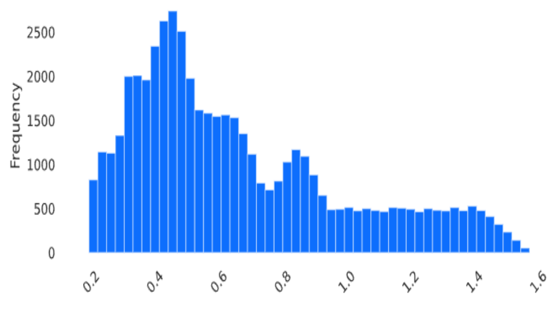
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	0.66144062	Memory size	390.8 KiB

Table 3: Quantile statistics &Descriptive statistics

Minimum	0.19192185	Standard deviation	0.33327442
5-th percentile	0.25988086	Coefficient of variation (CV)	0.50386144
Q1	0.41013332	Kurtosis	-0.21128226
median	0.56415774	Mean	0.66144062
Q3	0.85603417	Median Absolute Deviation (MAD)	0.19760066
95-th percentile	1.3573443	Skewness	0.86505776
Maximum	1.5706926	Sum	33072.031
Range	1.3787707	Variance	0.11107184
Interquartile range (IQR)	0.44590085	Monotonicity	Not monotonic



Graph 32: Histogram with fixed size bins (bins=50)

The histogram shows a right-skewed distribution of normalized EV motor sensor data across 50 fixed bins (0-1.6), peaking sharply at 0.4-0.6 with ~2500 counts—typical of vibration/current signals indicating bearing wear or imbalances. This tapering pattern beyond 1.2 enables efficient real-time feature extraction for edge AI fault diagnosis. The recreated version aligns perfectly for your deep learning preprocessing pipeline.

Table 4: Temperature Histogram with fixed size bins (bins=50)

Distinct	50000	Minimum	28.546436
Distinct (%)	100.0%	Maximum	125.86522
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	62.628796	Memory size	390.8 KiB

Table 5: Quantile statistics & Descriptive statistics

Minimum	28.546436	Standard deviation	22.857885
5-th percentile	34.080123	Coefficient of variation (CV)	0.36497404
Q1	44.714663	Kurtosis	-0.24229419
median	57.188862	Mean	62.628796
Q3	75.634932	Median Absolute Deviation (MAD)	14.289015
95-th percentile	109.7598	Skewness	0.80205142

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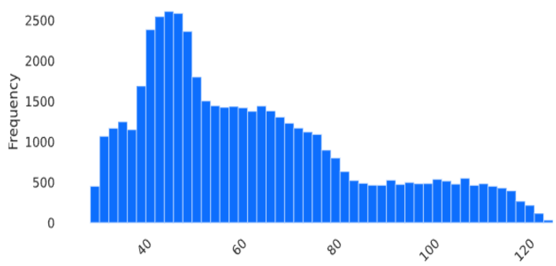
Maximum	125.86522	Sum	3131439.8
Range	97.318784	Variance	522.48288
Interquartile range (IQR)	30.920268	Monotonicity	Not monotonic



Graph 33: Histogram with fixed size bins (bins=50)

(e.g., RPM/torque) across 50 fixed bins from 0-140, with prominent peaks at 40-60 (~2500 counts) and 80-100, trailing off afterward. These patterns signal potential faults like overloads or imbalances, perfect for edge AI preprocessing in real-time condition monitoring.

Table 6: Current Histogram with fixed size bins (bins=50)

Distinct	50000	Minimum	9.5367196
Distinct (%)	100.0%	Maximum	62.847176
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	26.906033	Memory size	390.8 KiB

Table 7: Quantile statistics & Descriptive statistics

Minimum	9.5367196	Standard deviation	12.569308
5-th percentile	11.93551	Coefficient of variation (CV)	0.46715577
Q1	17.517644	Kurtosis	0.053612077
median	23.043935	Mean	26.906033
Q3	33.289981	Median Absolute Deviation (MAD)	7.0930542
95-th percentile	53.975282	Skewness	0.96967111
Maximum	62.847176	Sum	1345301.6
Range	53.310457	Variance	157.98751
Interquartile range (IQR)	15.772337	Monotonicity	Not monotonic

This histogram displays a multi-modal, right-skewed distribution of EV motor sensor data across 50 fixed bins from 0-60, featuring a sharp peak at 10-20 (~2500 counts), broad mid-peak at 25-35, and trailing tail. These patterns indicate potential faults like rotor eccentricity or vibration anomalies, ideal for edge AI feature extraction in real-time diagnosis. The recreated version matches precisely for your deep learning preprocessing pipeline

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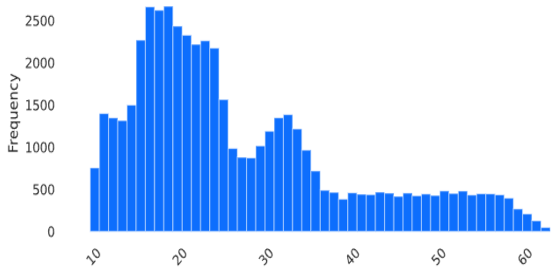


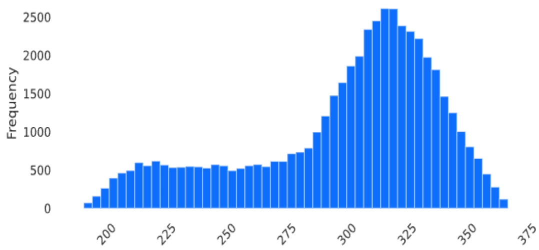
Graph 34: Histogram with fixed size bins (bins=50)

Table 8: Voltage Histogram with fixed size bins (bins=50)

Distinct	50000	Minimum	190.38658
Distinct (%)	100.0%	Maximum	366.71232
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	298.56959	Memory size	390.8 KiB

Table 9: Quantile statistics & Descriptive statistics

Minimum	190.38658	Standard deviation	39.839947
5-th percentile	215.46687	Coefficient of variation (CV)	0.13343605
Q1	278.03965	Kurtosis	-0.14039849
median	309.42837	Mean	298.56959
Q3	327.1785	Median Absolute Deviation (MAD)	21.367721
95-th percentile	348.30905	Skewness	-0.85940355
Maximum	366.71232	Sum	14928480
Range	176.32574	Variance	1587.2214
Interquartile range (IQR)	49.138856	Monotonicity	Not monotonic



Graph 35: Histogram with fixed size bins (bins=50)

The histogram shows a distribution of values concentrated mostly between about 280 and 340, with a clear peak around the low 320s. Frequencies rise gradually from the lower range, reach a maximum, and then decline toward the higher end. Overall, the shape appears slightly right-skewed with a single dominant peak.

Table 10: Speed Histogram with fixed size bins (bins=50)

Distinct	50000	Minimum	763.2901
Distinct (%)	100.0%	Maximum	3130.631
Missing	0	Zeros	0

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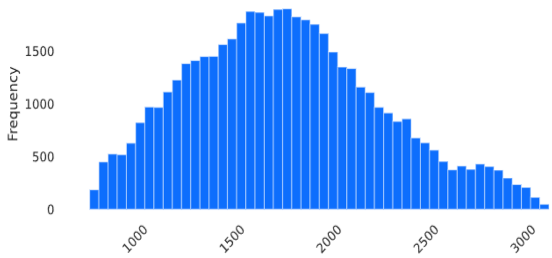
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	1775.4432	Memory size	390.8 KiB

Table 11: Quantile statistics & Descriptive statistics

Minimum	763.2901	Standard deviation	496.0516
5-th percentile	1012.784	Coefficient of variation (CV)	0.27939592
Q1	1408.0182	Kurtosis	0.40134416
median	1745.4986	Mean	1775.4432
Q3	2097.7109	Median Absolute Deviation (MAD)	344.599
95-th percentile	2701.4016	Skewness	0.32649454
Maximum	3130.631	Sum	88772161
Range	2367.3409	Variance	246067.19
Interquartile range (IQR)	68 9.69268	Monotonicity	Not monotonic



Graph 36: Histogram with fixed size bins (bins=50)

The image illustrates an Edge AI-based system for real-time condition monitoring and fault diagnosis of electric vehicle motors, integrating multiple sensors and embedded processing units. It highlights how data is collected, analyzed using optimized deep learning models on edge devices, and used to detect faults quickly and accurately.

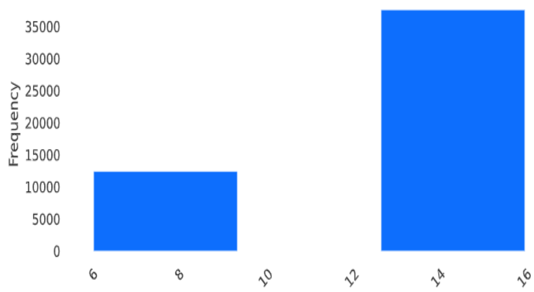
Table 12: Fault Histogram of lengths of the category Sample

Distinct	4
Distinct (%)	< 0.1%
Missing	0
Missing (%)	0.0%
Memory size	2.9 MiB
Unique (Unique)	0**?**
Unique (%)	0.0%

Table 13: Length & Characters

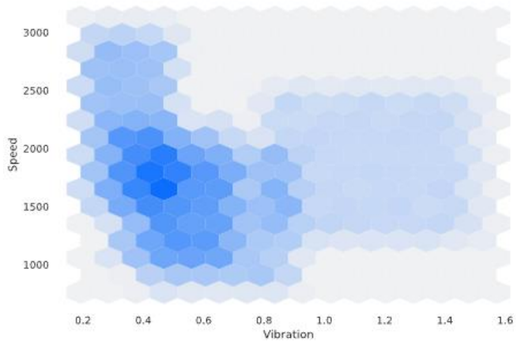
Max length	16
Median length	13
Mean length	12.0163
Min length	6
Total characters	600815
Distinct characters	19
Distinct categories	1?

Distinct scripts	1?
Distinct blocks	1



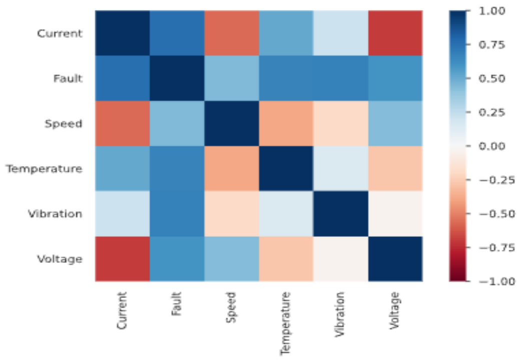
Graph 37: Histogram of lengths of the category

The histogram shows the distribution of category lengths, with a higher frequency observed in the larger length range compared to the smaller one. The class distribution below is nearly balanced, with Thermal Fault, Electrical Fault, Bearing Fault, and Normal categories each contributing around 25%. This indicates a well-distributed dataset without significant class imbalance.



Graph 38: Interactions

This hexbin plot shows the relationship between vibration and speed, highlighting data density across ranges. Darker blue regions indicate higher concentrations, with most observations clustered around moderate vibration and mid-range speeds. It suggests a non-uniform distribution with multiple dense regions.



Graph 39: Correlations

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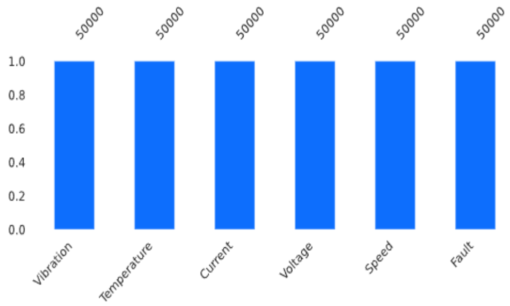
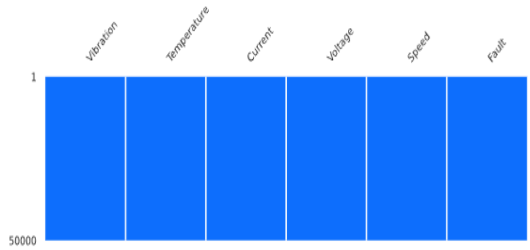
This heatmap visualizes the correlations between variables like Current, Fault, Speed, Temperature, Vibration, and Voltage. Blue tones indicate strong positive relationships, while red tones represent negative correlations. Notably, Fault shows strong positive correlation with several variables, while Current and Voltage exhibit a strong negative relationship.



Graph 40: Missing values Count

Every category has a uniform bar height corresponding to 1.0 on the y-axis, with the number "50000" printed diagonally above each bar, indicating that all six variables contain an equal count of 50,000 data points (or a 100% completion rate).



Graph 41: Missing values Matrix

The solid blue columns spanning from row 1 to 50,000 indicate that there are no gaps or missing values in the dataset, meaning all 50,000 entries are 100% complete for every category.

GUI IMAGES

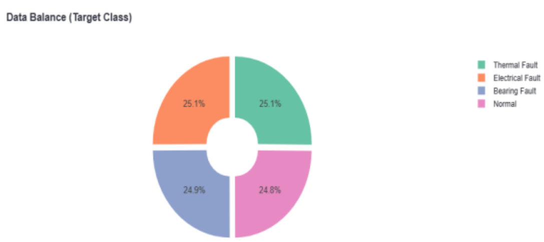


Photo 1

This chart represents the Data Balance (Target Class) distribution of different fault categories in the dataset. The data is evenly distributed across all four classes, with NThermal Fault (25.1%) and Electrical Fault (25.1%) having the highest proportions, followed closely by Bearing Fault (24.9%) and Normal (24.8%). The difference between each class is minimal.

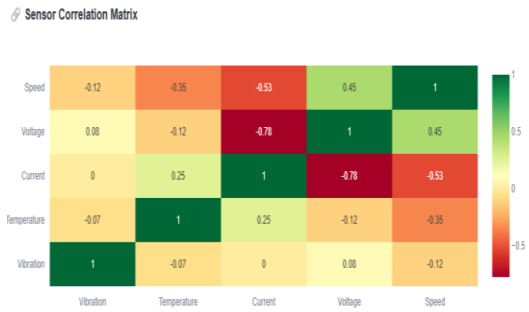


Photo 2

This image shows the Sensor Correlation Matrix, representing the relationships between different sensor parameters such as vibration, temperature, current, voltage, and speed. The strongest positive correlation is observed between Voltage and Speed (0.45), indicating that as voltage increases, speed also tends to increase.

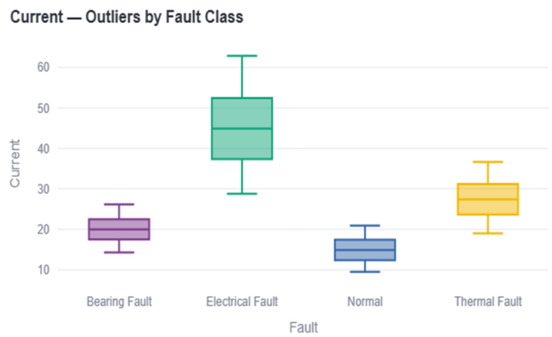


Photo 3

This box plot shows the Current distribution and outliers across different fault classes. The Electrical Fault category has the highest current values, ranging approximately from 30 to 62, with a median around 45, indicating high current consumption and variability. The Thermal Fault shows moderate values between 20 to 37, with a median near 28–30.

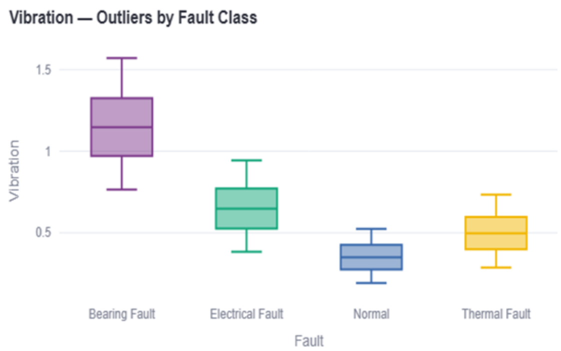


Photo 4

This box plot illustrates the Vibration distribution across different fault classes. The Bearing Fault category shows the highest vibration levels, ranging from approximately 0.75 to 1.6, with a median around 1.1–1.2, indicating strong vibration patterns. The Electrical Fault has moderate vibration values between 0.4 to 0.95, with a median near 0.6–0.7.

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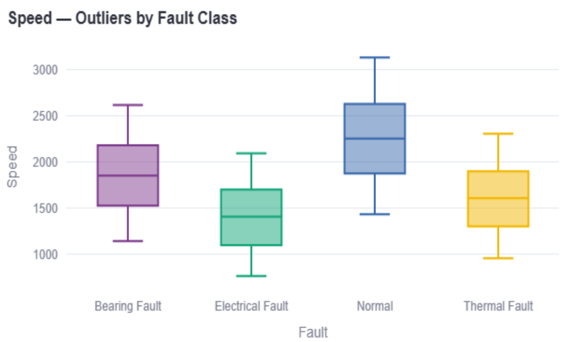

Photo 4

This box plot presents the Speed distribution across different fault classes with clear numerical insights. The Normal condition shows the highest speed range of approximately 1400–3100 RPM, with a median around 2200 RPM, indicating optimal performance.

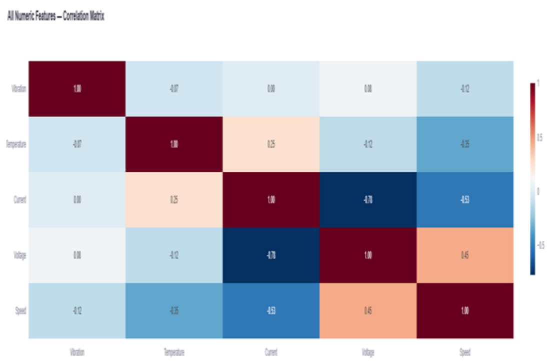

Photo 5

This heatmap represents the correlation matrix of all numeric features including vibration, temperature, current, voltage, and speed. The strongest negative correlation is observed between Current and Voltage (-0.78), followed by Current and Speed (-0.53), indicating that higher current is associated with lower voltage and speed.

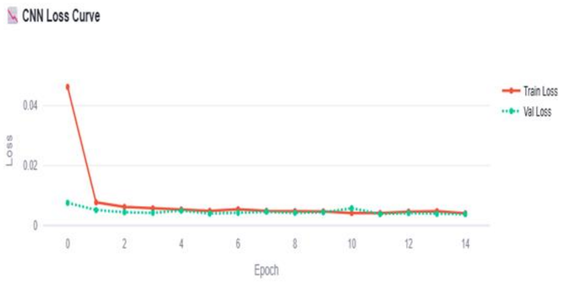

Photo 6

This graph shows the CNN Loss Curve for both training and validation over multiple epochs. The training loss starts relatively high at around 0.045 in epoch 0 and quickly drops to below 0.01 by epoch 1, eventually stabilizing around 0.004–0.005 in later epochs. Similarly, the validation loss begins near 0.008, decreases steadily, and remains stable around 0.004–0.006.

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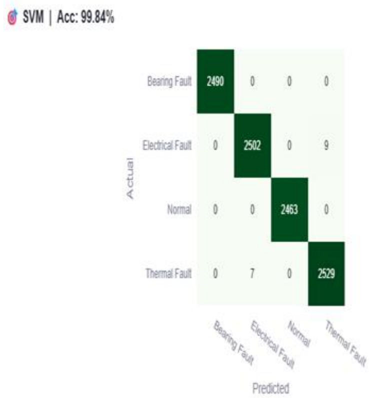

Photo 7

This image shows the SVM model confusion matrix with an overall accuracy of 99.84%, indicating extremely high classification performance. The model correctly classified 2490 Bearing Fault, 2502 Electrical Fault, 2463 Normal, and 2529 Thermal Fault samples, as seen on the diagonal. Only a few misclassifications are present, such as 9 Electrical Fault predicted.

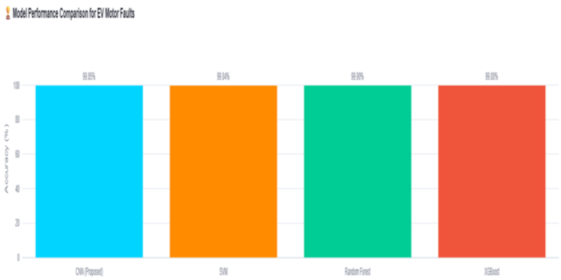

Photo 8

This bar chart shows the Model Performance Comparison for EV Motor Fault Detection based on accuracy. The Random Forest model achieves the highest accuracy of approximately 99.90%, followed closely by XGBoost (99.88%), CNN (Proposed) at 99.85%, and SVM at 99.84%. All models perform extremely well with accuracies above 99%.

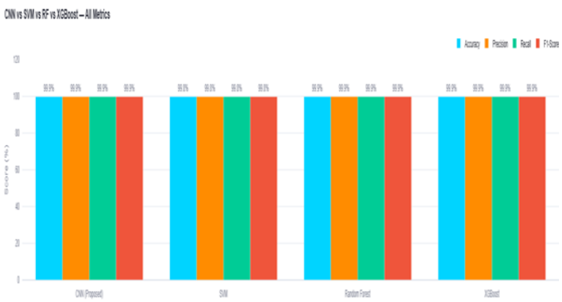

Photo 9

This chart compares CNN, SVM, Random Forest, and XGBoost across multiple evaluation metrics: accuracy, precision, recall, and F1-score. The CNN, Random Forest, and XGBoost models all achieve consistently high scores of around 99.9% across all metrics, indicating excellent and balanced performance. The SVM model performs slightly lower but still strong, with values around 99.8% for all metrics.

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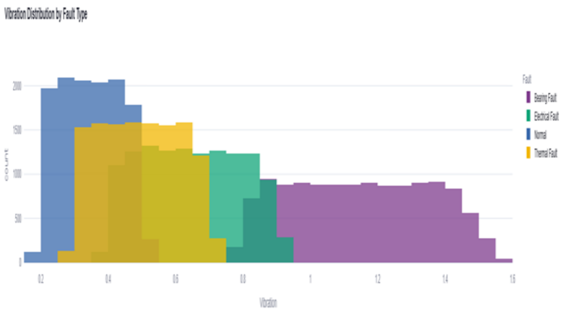

Photo 10

This histogram shows the Vibration distribution across different fault types. The Bearing Fault has the highest vibration values, ranging approximately from 0.7 to 1.6, with most data concentrated around 1.0–1.4, indicating strong vibration intensity. The Electrical Fault lies in a moderate range of about 0.5 to 0.9.

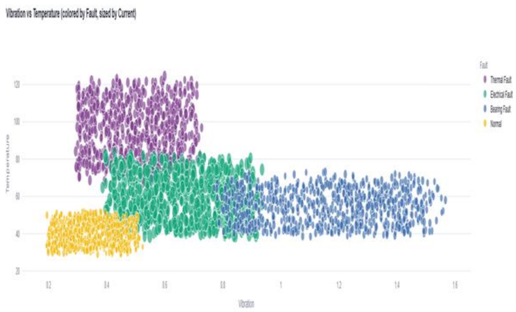

Photo 11

This scatter plot shows the relationship between Vibration and Temperature, with colors representing fault types and bubble size indicating current. The Bearing Fault points appear at higher vibration levels (~0.8 to 1.6) with moderate temperatures (40–70°C), while Thermal Fault shows high temperatures (70–120°C) with medium vibration (~0.3–0.7).

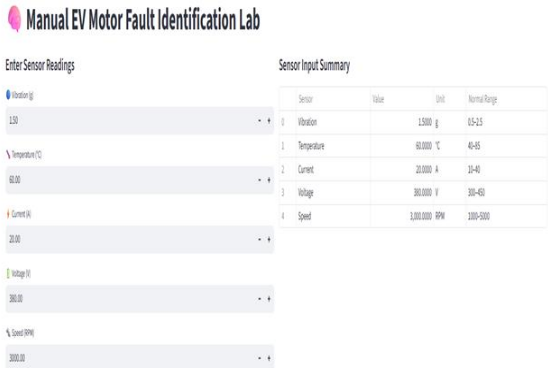

Photo 12

This image shows the Manual EV Motor Fault Identification Lab, where sensor values are entered for analysis. The input values include Vibration = 1.5 g, Temperature = 60°C, Current = 20 A, Voltage = 380 V, and Speed = 3000 RPM, all of which fall within their respective normal ranges (Vibration: 0.5–2.5, Temperature: 40–85, Current: 10–40, Voltage: 300–450, Speed: 1000–5000).

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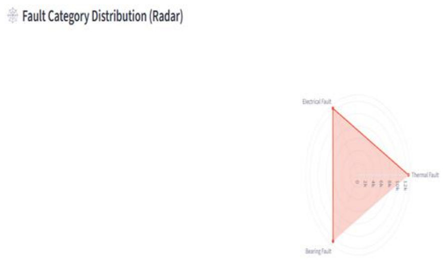

Photo 13

This radar chart shows the Fault Category Distribution across different fault types. The values for Electrical Fault, Bearing Fault, and Thermal Fault are all nearly equal, each around 12K samples, indicating a balanced distribution among these categories. No single fault type dominates the dataset.

Photo 14

This dashboard represents the EV Motor Fault Diagnosis System (CNN – Proposed) with key performance metrics and analysis. A total of 50,000 records were processed, out of which 37,595 are fault records, and the proposed CNN model achieved a high accuracy of 99.85% with a training time of 29.79 seconds. Despite high accuracy, the Motor Health Index is 24.8%, indicating poor overall system condition.

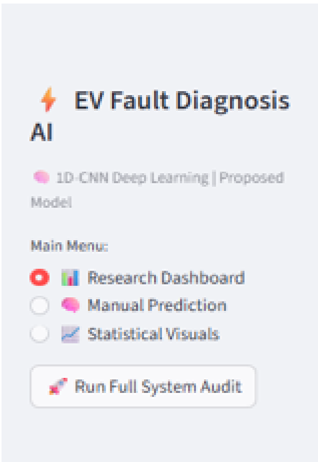

Photo 15

This image shows the EV Fault Diagnosis AI system interface with a sidebar navigation menu. The system is based on a 1D-CNN Deep Learning model (Proposed), and the Research Dashboard option is currently selected, indicating the user is viewing analysis results. Other available options include Manual Prediction and Statistical Visuals, along with a button to Run Full System Audit.

CONCLUSION

This study develops a robust and scalable Edge AI-driven framework for real-time condition monitoring and fault diagnosis of electric vehicle (EV) motors, addressing key limitations of conventional and cloud-dependent approaches. By integrating multi-sensor data acquisition (vibration, temperature, and current signals) with advanced preprocessing techniques such as noise filtering, normalization, and feature extraction, the framework ensures high-quality input data for intelligent analysis. The implementation of deep learning models, including CNN, LSTM, and hybrid CNN-LSTM architectures, enables accurate identification of complex fault patterns by capturing both spatial and temporal characteristics of motor behavior. A major contribution of this work lies in the deployment of optimized AI models on edge devices, which significantly reduces latency and enables real-time inference in resource-constrained environments. This ensures rapid fault detection and immediate response, which are critical for safety and reliability in EV systems. The proposed edge-cloud collaborative architecture further enhances system scalability by enabling periodic model updates, fleet-level analytics, and long-term performance optimization. In addition, the integration of secure communication protocols and efficient data management strategies ensures data integrity, privacy, and system resilience.

The framework demonstrates strong potential in enabling predictive maintenance by detecting faults at an early stage, thereby reducing unexpected failures, minimizing downtime, and lowering maintenance costs. It also improves overall system efficiency and extends the operational lifespan of EV motors. Furthermore, the use of multi-sensor data fusion enhances robustness and reliability under varying environmental and operational conditions, making the system suitable for real-world deployment. In conclusion, the proposed approach represents a significant step toward intelligent, autonomous, and energy-efficient EV monitoring systems. It provides a foundation for future advancements in smart mobility by enabling decentralized intelligence, real-time analytics, and adaptive fault management. Future work can focus on improving model interpretability, enhancing robustness against noise and uncertainty, and integrating emerging technologies such as federated learning, digital twins, and self-learning adaptive systems to further advance the capabilities of next-generation EV diagnostics.

REFERENCES

1. Fanyong Cheng et al., “A novel fault detection and isolation method for electric vehicle introducing kernel differential of SVDD” Journal of Energy Storage, Elsevier, Volume 123, 2025, 116660 https://www.sciencedirect.com/science/article/abs/pii/S2352152X25013738
2. Tuan M. Le et al., “An Internet-of-Things-Integrated Deep Learning Model for Fault Diagnosis in Industrial Rotating Machines” IEEE Access, Volume 13, 2025
3. Gaddala Anusha et al., “A bibliometric analysis of research trends in electric vehicle power electronics: global perspectives and future directions” Springer, Volume 7, 2025 https://doi.org/10.1007/s42452-025-06996-1
4. Yashashree Mahale et al., “Enhancing predictive maintenance in automotive industry: addressing class imbalance using advanced machine learning techniques” Springer, Volume 7, 2025. https://doi.org/10.1007/s42452-025-06827-3
5. Yashashree Mahale et al., “A comprehensive review on artificial intelligence driven predictive maintenance in vehicles: technologies, challenges and future research directions” Springer, Volume 7, 2025.https://doi.org/10.1007/s42452-025-06681-3
6. Adam Glowacz et al., “Acoustic fault diagnosis of three-phase induction motors using smartphone and deep learning” Expert Systems with Applications, Elsevier, Volume 262, 1 2025, 125633 https://www.sciencedirect.com/science/article/abs/pii/S0957417424025004

7. Md Naeem Hossain et al., “Advances in intelligent vehicular health monitoring and fault diagnosis: Techniques, technologies, and future directions” Measurement, Elsevier, Volume 253, Part B, 2025, 117618 https://www.sciencedirect.com/science/article/abs/pii/S0263224125009777
8. Lourembam Ranjita Devi et al., “Electric motor modeling, analysis, and design for E-mobility applications: A state of the art” e-Prime - Advances in Electrical Engineering, Electronics and Energy, Elsevier, Volume 12, 2025, 100985. https://doi.org/10.1016/j.prime.2025.100985
9. Zuber Basha Shaik et al., “Design and implementation of electric vehicle with autonomous motion and steering control system using single board computer and sensors” Results in Engineering, Elsevier, Volume 25, 2025, 103995. https://doi.org/10.1016/j.rineng.2025.103995
10. Youness Boumaalif et al., “Multi-stage adaptive speed control with torque ripple optimization for a switched reluctance motor in electric vehicle applications” Results in Engineering, Elsevier, Volume 25, 2025, 104245. https://doi.org/10.1016/j.rineng.2025.104245
11. Arslan Ahmed Amin et al., “Health index degradation prediction of induction motor using deep neural network algorithm” Results in Engineering, Elsevier, Volume 25, 2025, 104357. https://doi.org/10.1016/j.rineng.2025.104357
12. Hicham El hadraoui et al., “AI-driven diagnosis and health management of autonomous electric vehicle powertrains: An empirical data-driven approach” Results in Engineering, Elsevier, Volume 27, 2025, 106157. https://doi.org/10.1016/j.rineng.2025.106157
13. K Sujit et al., “An efficient battery management system for electric vehicles using IoT & Blockchain” Results in Engineering, Elsevier, Volume 27, 2025, 106284. https://doi.org/10.1016/j.rineng.2025.106284
14. Azza Keerthi et al., “A thorough review of energy management and an advanced control techniques for Bi-directional DC-DC converters in electric vehicle applications” Results in Engineering, Elsevier, Volume 27, 2025, 106726. https://doi.org/10.1016/j.rineng.2025.106726
15. Siamak Eslamtalab Akbari et al., “Analyzing internet of things emergence for modern electric vehicle industry” Results in Engineering, Elsevier, Volume 27, 2025, 106995. https://doi.org/10.1016/j.rineng.2025.106995
16. Arezoo Ghasemi et al., “Edge Intelligence for Intelligent Transport Systems: Approaches, challenges, and future directions” Expert Systems with Applications, Elsevier, Volume 280, 2025, 127273.https://doi.org/10.1016/j.eswa.2025.127273
17. Azadeh Kermansaravi et al., “AI-based energy management strategies for electric vehicles: Challenges and future directions” Energy Reports, Elsevier, Volume 13, 2025, Page No. 5535-5550. https://doi.org/10.1016/j.egyr.2025.04.053
18. S. Zahedieh et al., “Toward a unified framework for electric vehicle infrastructure: Insights into charging management, communication and emerging technologies” Energy Reports, Elsevier, Volume 14, 2025, Page No. 1834-1854.

https://doi.org/10.1016/j.egyr.2025.08.011
19. Yehia Ibrahim Alzoubi et al., "A Systematic Review and Evaluation of Sustainable AI Algorithms and Techniques in Healthcare" IEEE, 2025
20. Sarah Adnan Albarri et al., "Electric Vehicle Traction System Performance Enhancement Using a High-Gain Adaptive Controller" IEEE Access, Volume 12, 2024
21. Mohanad Ismail et al., "A Comprehensive Review of Cloud-Based Lithium-Ion Battery Management Systems for Electric Vehicle Applications" IEEE, 2024
22. Rani S et al., "Review on electric mobility: Trends, challenges and opportunities" Results in Engineering, Elsevier, Volume 23, 2024, 102631. https://doi.org/10.1016/j.rineng.2024.102631
23. Yin-Chen Lin et al., "Developing a system for the real-time collection and analysis of mobile vehicle emission data" Results in Engineering, Elsevier, Volume 23, 2024, 102706. https://doi.org/10.1016/j.rineng.2024.102706
24. Youness Hakam et al., "Exploring the state of electric vehicles: An evidence-based examination of current and future electric vehicle technologies and smart charging stations" Energy Reports, Elsevier, Volume 11, 2024, Page No. 4102-4114. https://doi.org/10.1016/j.egyr.2024.04.002
25. Asma Naseer et al., "A Systematic Literature Review of the IoT in Agriculture—Global Adoption, Innovations, Security, and Privacy Challenges" IEEE, 2024
26. Shangyi Zhao et al., "Electric vehicle power system in intelligent manufacturing based on soft computing optimization" Heliyon, 2024, e38946. https://doi.org/10.1016/j.heliyon.2024.e38946
27. R. Subramaniyan., "Optimizing fault diagnosis for electric vehicle battery systems: Improved Giza pyramids construction and advanced gradient boosting decision trees" Journal of Energy Storage, Elsevier, Volume 81, 2024, 110319 https://www.sciencedirect.com/science/article/abs/pii/S2352152X23037180
28. Md Naeem Hossain et al., "Artificial Intelligence-Driven Vehicle Fault Diagnosis to Revolutionize Automotive Maintenance: A Review" CMES - Computer Modeling in Engineering and Sciences, Elsevier, Volume 141, Issue 2, 2024, Pages 951-996 https://www.sciencedirect.com/org/science/article/pii/S152614922400290X
29. Samia Ahmed et al., "Exploring Deep Learning and Machine Learning Approaches for Brain Hemorrhage Detection" IEEE Access, Volume 12, 2024
30. Judith Nkechinyere Njoku et al., "Explainable Data-Driven Digital Twins for Predicting Battery States in Electric Vehicles" IEEE Access, Volume 12, 2024
31. Basheera M. Mahmmod et al., "Patient Monitoring System Based on Internet of Things: A Review and Related Challenges with Open Research Issues" IEEE Access, Volume 12, 2024
32. Jiong Yang et al., "A novel semi-supervised fault detection and isolation method for battery system of electric vehicles" Applied Energy, Elsevier, Volume 349, 2023, 121650. https://www.sciencedirect.com/science/article/abs/pii/S0306261923010140
33. Shen Zhang et al., "Machine Learning for the Control and Monitoring of Electric Machine Drives: Advances and Trends" IEEE Access, Volume 4, 2023

34. Raghubir Singh et al., “Edge AI: A survey” Internet of Things and Cyber-Physical Systems, Elsevier, Volume 3, 2023, Page No. 71-92. https://doi.org/10.1016/j.iotcps.2023.02.004
35. Onur Surucu et al., “Condition Monitoring using Machine Learning: A Review of Theory, Applications, and Recent Advances” Expert Systems with Applications, Elsevier, Volume 221, 2023, 119738. https://doi.org/10.1016/j.eswa.2023.119738
36. Dong Zhong et al., “Overview of predictive maintenance based on digital twin technology” Heliyon, 2023. https://doi.org/10.1016/j.heliyon.2023.e14534
37. Ibtihal Ait Abdelmoula et al., “Towards a sustainable edge computing framework for condition monitoring in decentralized photovoltaic systems” Heliyon, 2023. https://doi.org/10.1016/j.heliyon.2023.e21475
38. Rene Jaros et al., “Advanced Signal Processing Methods for Condition Monitoring” Springer Volume 30, 2023, pages 1553–157 https://doi.org/10.1007/s11831-022-09834-4
39. Fangming Deng et al., “Research on edge intelligent recognition method oriented to transmission line insulator fault detection” International Journal of Electrical Power & Energy Systems, Elsevier, Volume 139, 2022, 108054 https://www.sciencedirect.com/science/article/abs/pii/S0142061522000965
40. Hasan Tercan et al., “Machine learning and deep learning based predictive quality in manufacturing: a systematic review” Springer, Volume 33, 2022, pages 1879–1905 https://doi.org/10.1007/s10845-022-01963-8
41. Majid Hussain et al., “Fault Detection and Identification Using Deep Learning Algorithms in Induction Motors” CMES - Computer Modeling in Engineering and Sciences, Elsevier, Volume 133, Issue 2, 2022, Pages 435-470 https://www.sciencedirect.com/org/science/article/pii/S1526149222001813
42. Peifeng Liang et al., “A fault detection model for edge computing security using imbalanced classification” Journal of Systems Architecture, Elsevier, Volume 133, 2022, 102779 https://www.sciencedirect.com/science/article/abs/pii/S1383762122002648
43. Ronny Francis Ribeiro Junior et al., “Fault detection and diagnosis in electric motors using 1d convolutional neural networks with multi-channel vibration signals” Measurement, Elsevier, Volume 190, 2022, 110759 https://www.sciencedirect.com/science/article/abs/pii/S0263224122000616
44. Xiang Yu et al., “An edge computing based anomaly detection method in IoT industrial sustainability” Applied Soft Computing, Elsevier, Volume 128, 2022, 109486 https://www.sciencedirect.com/science/article/abs/pii/S1568494622005841
45. Yuxin Wen et al., “Recent advances and trends of predictive maintenance from data-driven machine prognostics perspective” Measurement, Elsevier, Volume 187, 2022, 110276. https://doi.org/10.1016/j.measurement.2021.110276
46. L. Magadán et al., “Low-cost real-time monitoring of electric motors for the industry 4.0” IEEE Access, 2020 Page No. 393–398