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EDGE-AI ENABLED FAULT DETECTION AND ROOT CAUSE ANALYSIS IN INDUSTRIAL MOTORS USING MULTIMODAL SENSOR DATA

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ABSTRACT

This article presents an Edge-AI enabled hybrid deep learning framework for real-time fault detection and root cause analysis in industrial motors using multimodal sensor data, containing vibration, temperature, and current signals. The proposed system leverages a CNN-LSTM model deployed on edge devices to accurately classify operational states into normal, minor, and major faults. A dataset comprising 15,000 labeled samples collected from real-world industrial setups and augmented through techniques such as SMOTE and time-warping was used for training and evaluation. In the implementation,the CNN component captures spatial patterns in sensor data, while the LSTM layer models temporal dependencies, enabling effective fault diagnosis. The proposed hybrid model achieved superior performance with 96.8% accuracy, 97.2% precision, 96.5% recall, and an F1-score of 96.8%, along with a low inference latency of ≤198 ms, demonstrating suitability for real-time edge deployment. Comparative analysis against CNN-only and LSTM-only models confirms the hybrid architecture's advantage in fault sensitivity and prediction reliability. Additional insights from confusion matrix analysis, ROC-AUC evaluation, and fault-wise performance metrics validate the model's robustness. The system also incorporates TinyML-based optimizations and lightweight messaging for efficient edge computing, making it a scalable solution for predictive maintenance in Industry 4.0 applications.

KEYWORDS

Edge-AI, CNN-LSTM, Predictive Maintenance, Industrial Motors, Fault Detection, Multimodal Sensors

1. INTRODUCTION

Industry 4.0 marks the transition from the traditional industrial operations that integrated cyberphysical systems, IoT, and Artificial Intelligence to create smart, connected production systems. This evolution would have improved monitoring, control, and optimization of manufacturing processes so that factories would have become more responsive, adaptive, and efficient. Edge computing, in this regard, has come up as an enabler for real-time analytics and decision making. As computational intelligence is brought close to the data source, edge computing kills latency and reduces the reliance on some bandwidth-heavy cloud infrastructure, thereby guaranteeing timely response for industrial applications where it is most needed mainly in, fault detection and system diagnostics. One of the most important use cases considered in smart industrial environments is predictive maintenance, i.e., predictingthedeterioration of equipment prior to its failure. Predictive maintenance, unlike scheduled and reactive maintenance, continuously monitors sensor signals and applies intelligent algorithms that detect

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symptoms of impending faults, be it mechanical, thermal, or electrical. This way, unplanned downtime can be avoided, routine maintenance costs removed, and the usable life of motors, an example of an industrial asset, can be prolonged.

These modern systems use the latest tools and techniques, especially deep learning frameworks, to model complex relations in high-frequency sensor data. In this respect, hybrid architecture such as CNN combined with LSTM have been found to be highly effective. CNNs extract local and spatial features from sensor signals (such as vibration or current), while LSTMs study sequential dependency and temporal dynamics within time-series data so that temporal fault patterns can be recognized. Moreover, using multimodal sensor data-vibration, temperature, and electrical currentincreases the system's ability to detect faults and accentuate a failure's diverse manifestations, whether mechanical, thermal, or electrical. Hence, this comprehensive data fusion ensures more straightforward fault detection, fewer false positives, and reliable operation in various situations. To provide the basis for a complete evaluation, a hybrid dataset has been constructed consisting of 15,000 labeled samples that were obtained from both real industrial motor logs as well as synthetic augmented data. The classes of faults include bearing damage, stator overheating, load imbalance, and normal operational states.

2. LITERATURE OUTLINE

The literature survey on AI-based fault detection systems highlights significant advancements in deep learning, edge computing, and IoT-enabled diagnostics across industrial applications. Researchers have developed various models for real-time fault diagnosis, predictive maintenance, and anomaly detection. Despite progress, challenges persist in data imbalance, model interpretability, real-time deployment, and scalability. This survey helps to identify research gaps and guides future innovation in intelligent, energy-efficient, and reliable fault detection frameworks.

Leite et al. reviewed Fault detection and diagnosis (FDD) strategies in Industry 4.0 environments, emphasizing real-time automation, data interoperability, and intelligent control systems. The study identified major limitations such as lack of data standardization, integration complexity, and insufficient real-time analytics for deployment [1]. Saeed et al. introduced deep learning methods for industrial equipment health diagnostics under scarcity scenarios, reporting better fault classification but issues with model generalization, energy efficiency, and scalability [2].

Habyarimana and Adebiyi reviewed AI in fault prediction of electrical machines, comparing supervised and hybrid approaches while citing data labeling issues, increased response times, and low adaptability to changing load conditions [3]. Altaf et al. suggested an AI-based cyberphysical sensor network for fault detection in distributed motor systems, enhancing accuracy with sensor fusion but with reliability and latency constraints in networked applications [4]. Akhyar et al. surveyed deep learning approaches to natural disaster management, including data gathering, hazard forecasting, and decision support systems, but accepting pivotal challenges like limited training data, computational expense, and scalability [5]. Chen et al. addressed AIbased sensing technologies in intelligent systems, reporting improvements in precision and reactivity but highlighting sensor calibration, power limitations, and real-time interpretation as still-open issues [6]. Del-Coco et al. examined the role of AI in smart mobility solutions, focusing on autonomous driving, routing, and traffic prediction, but citing concerns related to privacy protection, explainability, and edge deployment limitations [7]. Ucar et al. reviewed AIdriven predictive maintenance, elaborating on architecture, trustworthiness, and industrial trends, with key concerns being explainability, model validation, and difficulty scaling across heterogeneous systems [8]. Alagha et al. presented AI-based techniques for wind turbine fault detection and diagnosis, improving operational insights via vibration and signal analysis. But the methodology has limited dataset diversity, adaptation across wind environments, and high deployment costs [9]. Fährmann et al. provided a comprehensive survey on anomaly detection in smart environments using AI approaches such as autoencoders and clustering, while highlighting limitations like false alarms, poor contextual interpretation, and real-time integration issues [10]. Zhang et al. summarized recent progress in AI-enabled sensors, highlighting their use in automation and precision monitoring but pointing out robustness, integration complexity, and energy sustainability as key challenges [11]. Aguayo-Tapia et al. reviewed entropy-based fault detection methods for motors, noting high sensitivity to signal variation but also identifying computational complexity and noise interference as significant constraints [12]. Ahmed et al. examined current deep learning modeling techniques across applications, outlining benefits in image processing and sequential learning, yet struggling with data dependency, training instability, and explainability [13]. Uçar et al. reiterated AI's relevance to predictive maintenance, underscoring system integration and trust, but citing performance drift and lack of benchmark frameworks as pressing concerns [14]. Moosavi et al. discussed explainable AI (XAI) in industrial systems, emphasizing transparency and auditability, yet highlighting limitations in balancing model accuracy with interpretability in real-time deployments [15].

Jalal et al. reviewed visual fault diagnosis in photovoltaic systems using deep learning, showing superior accuracy through CNN models but challenged by image noise, limited generalization, and real-time implementation complexity [16]. Gültekin et al. introduced a real-time fault monitoring framework for autonomous vehicles using edge AI, reducing latency and improving anomaly detection, but constrained by edge device power and sensor fusion robustness [17]. Miller et al. offered a critical view on AI-driven autonomous vehicle navigation, discussing safety risks, opaque decision-making, and over-reliance on black-box models in complex driving scenarios [18]. Jouini et al. surveyed ML techniques in edge computing, highlighting their applications in real-time diagnostics and maintenance, while identifying orchestration complexity, device heterogeneity, and service reliability as critical gaps [19]. Visconti et al. reviewed ML and IoT applications in smart manufacturing, showing enhanced quality control and anomaly detection, though they cited integration cost, legacy system compatibility, and trust issues as major limitations [20].

Kodumuru et al. discussed the integration of Artificial Intelligence and the Internet of Things in pharmaceutical manufacturing, proposing a smart synergy to enhance process optimization, quality control, and traceability; however, their framework faces challenges in regulatory compliance, system security, and high initial deployment costs [21]. Hassani and Dackermann conducted a systematic review on advanced sensor technologies for structural health monitoring and non-destructive testing, showcasing sensor versatility and data precision while identifying gaps in environmental robustness, real-time feedback, and calibration consistency [22]. Mohandas et al. surveyed incremental deep learning strategies for industrial defect detection, emphasizing continual learning adaptability, yet highlighting persistent issues like catastrophic forgetting, data imbalance, and lack of real-world datasets [23]. Janga et al. reviewed practical AI usage in Earth sciences via remote sensing, covering terrain fault detection and geospatial data interpretation, though noting constraints related to low-resolution imagery, limited ground truth validation, and model generalization [24].

Melo et al. performed a comprehensive review of data-driven process monitoring and fault diagnosis, exploring PCA, PLS, and autoencoder-based techniques while reporting unresolved challenges in computational overhead and interpretability for critical decision-making systems [25]. Ferraz Júnior et al. evaluated machine learning techniques for detecting anomalies in electric motor applications, identifying the strengths of time-frequency domain analysis and supervised models, yet citing issues such as feature engineering complexity and low interpretability of black-box approaches [26]. Crespo-Aguado et al. proposed a hyper distributed IoT–Edge–Cloud platform for digital twin applications in logistics, enabling realtime tracking and analytics while facing latency fluctuations, system synchronization, and infrastructure scalability barriers [27]. Mercorelli reviewed recent intelligent algorithms for fault detection and diagnosis, comparing neural networks, fuzzy systems, and adaptive hybrids, while outlining key limitations in model overfitting, high sensitivity to noise, and benchmarking inconsistencies [28]. Zaman et al. introduced a hybrid deep learning model combining VGG16, ResNet50, and wavelet coherence for centrifugal pump fault detection, demonstrating superior accuracy but noting long training times and difficulty in adapting to unstructured data [29]. Nie and Lu developed a neural network watermarking approach to secure intellectual property in edge-AI models, embedding ownership without degrading model performance, though the method faced challenges in resisting adversarial attacks and scalability to diverse architectures [30].

Strantzalis et al. applied Edge-AI for operational state recognition in DC motors, enabling on device inference with reduced latency, yet encountering constraints in real-time accuracy under noisy conditions and hardware resource limitations [31]. Sabry and Amirulddin reviewed fault detection techniques in industrial robots and multi-axis machines, covering AI and traditional control-based methods, while noting shortcomings in dataset availability, system-specific tuning, and real-time adaptability [32]. An et al. proposed an efficient CNN-based edge solution for real-time motor fault detection, achieving fast and accurate classification but limited by hardware compatibility and model compression complexity [33]. De las Morenas et al. examined edge-based ML methods for electrical machine fault diagnosis, emphasizing local sensory data processing while reporting problems with update latency and memory constraints in low-power devices [34]. Tian et al. explored AI-based arc fault detection using entropy and cumulants, demonstrating high sensitivity to fault initiation but challenged by algorithmic complexity and scalability in DC circuit environments [35].

Wang et al. reviewed AI techniques for ground fault line selection in power systems, focusing on hybrid models that integrate domain knowledge with ML classifiers, though practical barriers such as real-time adaptation, noise resilience, and model explainability remain unresolved [36]. Ciaburro surveyed machine learning algorithms for general fault detection, summarizing their detection power and limitations in transparency, noise robustness, and industrial viability [37]. Chen et al. applied data augmentation to improve arc fault detection performance using AI on time-series datasets, yielding better fault classification but constrained by synthetic data limitations and real-world generalization [38]. Su et al. proposed a data-driven framework for automatic meter error detection in smart grids, offering predictive capabilities but suffering from data drift, dependency on clean datasets, and lack of adaptability to unseen anomalies [39]. Song et al. developed a multimodal deep learning framework for Industry 4.0 fault detection using sensor fusion, enhancing diagnostic accuracy but limited by computational load, data alignment, and real-time deployment feasibility [40].

Wang et al. reviewed AI methods for ground fault line detection in power systems, emphasizing hybrid classifiers and improved localization accuracy while identifying limitations in dataset diversity, real-time scalability, and model robustness [41]. Chen et al. proposed an AI-driven data augmentation technique for arc fault detection, enhancing time-series classification accuracy but raising concerns over synthetic data realism and deployment reliability [42]. Chu et al. introduced a predictive framework for automatic meter error detection using smart grid data, showing good detection capabilities while struggling with domain adaptation and long-term reliability in dynamic conditions [43]. Shen et al. proposed a multimodal deep learning approach for Industry 4.0 fault detection, combining sensor fusion and deep architectures, though facing issues with data alignment, latency, and computational load [44].

Altaf et al. extended their previous work on AI-driven sensor networks for distributed motor systems, improving diagnostic capabilities but constrained by network latency, sensor noise, and deployment complexity in industrial settings [45]. Deng et al. presented a vision for Edge Intelligence, merging AI with edge computing to support decentralized analytics, identifying advantages in latency reduction while citing concerns about privacy, interoperability, and energy efficiency [46]. Yao et al. provided a survey of edge-cloud collaboration for AI, outlining workload distribution and coordination frameworks, while highlighting orchestration difficulty, model synchronization, and platform heterogeneity as key barriers [47]. Zha et al. introduced a data-centric AI approach, focusing on improving data quality for better model outcomes, but challenges remain in automation, dataset curation, and handling bias [48]. Li et al. proposed a fog-computing-enabled inspection system using deep learning for manufacturing, reporting enhanced throughput but limitations in fog node reliability and recovery mechanisms [49].

Sodhro et al. reviewed AI-based edge computing systems for industrial automation, discussing intelligent control and distributed sensing, though facing real-time responsiveness, training efficiency, and model updating issues [50]. Letaief et al. explored Edge AI for 6G applications, outlining architectures for low-latency and autonomous decision-making, while highlighting barriers such as hardware constraints, inference delays, and lack of standardization [51]. Hao Chen et al. surveyed interpretable AI methods for fault diagnosis under imperfect data, showcasing semi-supervised and transfer learning techniques, yet unresolved challenges include robustness under noise and cross-domain adaptability [52]. Chen et al. applied bibliometric and topic modeling approaches to review multimodal data fusion in smart healthcare, identifying gaps in cross-modal consistency, real-time interpretability, and deployment scalability [53]. Saeed et al. revisited deep learning for industrial health diagnostics, focusing on constrained IoT environments, while stressing the need for lightweight models, power optimization, and robust fault prediction [54].

Rajput et al. introduced a workthat proposes a Fuzzy Convolutional Neural Network (FCNN) for stable, data-driven fault diagnosis of industrial rotating machinery with the CWRU dataset, with an accuracy of around 99%, particularly under severe working conditions. The method, however, might be less ideal for nonlinear or large-scale datasets. [55]. Samanazari et al. conducted a systematic review of transfer learning in predictive maintenance, demonstrating reduced training times and improved adaptability across machines, but domain shift and knowledge transfer inefficiencies persist [56]. Castaño et al. proposed a data-driven method for time-to-failure estimation in electromechanical systems, using real-world data for model validation, although long-term prediction accuracy and fault unpredictability were cited as limitations [57]. Yu et al. introduced an edge-assisted IoT framework for manufacturing fault detection using autoencoders, achieving real-time responsiveness, though sensitive to data imbalance and hardware restrictions [58]. Asutkar et al. reviewed TinyML-based edge implementations of transfer learning for fault diagnosis, enabling low-power AI at the edge but constrained by small model capacity and generalization across fault types [59]. Ren et al. provided a systematic review of imbalanced learning techniques for intelligent fault diagnosis, addressing data resampling, ensemble learning, and cost-sensitive modeling while noting persistent generalization and interpretability issues [60].

Meng et al. proposed a graph attention network fused with modal analysis for bearing fault diagnosis, achieving high fault detection accuracy, yet facing complexity in graph construction and model scalability [61]. Zhang et al. introduced a CNN-based method for rotating machinery fault detection using encoded data distributions, enhancing feature sensitivity but requiring high training time and struggling under noisy conditions [62]. Li et al. developed a semi-supervised graph convolutional network using image-transformed vibration signals for rotating machinery diagnosis, reducing labeled data needs but increasing computational overhead and sensitivity to transformation quality [63]. Imamura et al. applied recurrent neural networks for detecting imbalance in rotating machinery using edge frameworks, offering lightweight deployment while encountering limitations in temporal accuracy and power constraints [64]. Teoh et al. presented a fog-IoT model for predictive maintenance in Industry 4.0 using machine learning, enabling efficient asset management but challenged by configuration complexity and latency in fog networks [65].

Saeed Ali et al. emphasized the relevance of deep learning models for industrial health diagnostics in resource-limited environments, showing promise in performance and robustness, but concerns remain around model retraining, explainability, and energy constraints [66]. Zhu et al. proposed a deep reinforcement learning-based offloading algorithm for edge computing in IoT systems, improving task allocation efficiency while constrained by high convergence time and reward instability [67]. Maurya et al. reviewed AI-integrated IoT-cloud architectures for rotating machinery fault diagnosis, highlighting scalability and automation benefits while citing communication delays and cloud dependency as major gaps [68]. Lu et al. reviewed edge computing frameworks for machine fault detection, discussing signal processing and model deployment strategies while outlining persistent issues in resource allocation and real-time processing [69]. Wang et al. proposed a federated learning approach for industrial fault diagnosis in cloud-edge architectures, enhancing privacy preservation but facing inefficiencies in aggregation, model synchronization, and training consistency [70].

Alenizi et al. introduced a taxonomy of AI technologies in Industry 4.0, categorizing classification, optimization, and prediction tasks while identifying trustworthiness, lifecycle integration, and interoperability as critical challenges [71]. Chong Chen et al. reviewed digital twins in predictive maintenance and their interaction with machine learning, providing insights into system simulation, though difficulties remain in synchronization, twin fidelity, and implementation cost [72]. Mahesh et al. proposed a deep active learning framework for intelligent bearing fault detection, showing adaptability to diverse conditions, but suffering from annotation uncertainty and model convergence instability [73]. Khan et al. explored the role of IoT in Industry 4.0 adoption, focusing on real-time data collection and control integration while identifying gaps in device interoperability, data overload, and decision-making automation [74]. Su et al. presented the ICICOS framework for integrating cloud-edge AI in industrial automation, improving control reliability but facing orchestration delays and coordination complexities across layers [75].

Habyarimana and Adebiyi revisited AI approaches for predicting electrical machine faults, comparing classical and deep learning models while noting gaps in adaptability under varying load conditions and model robustness in real-world scenarios [76]. Almazrouei et al. reviewed AI-based predictive maintenance for water injection pumps in oil and gas industries, addressing domain-specific tuning, noise mitigation, and long-term reliability but identifying gaps in dataset variability and adaptive learning [77]. Gawde et al. compiled a two-decade review on multi-fault diagnosis in rotating machinery, tracing the transition from rule-based to data-driven approaches while citing limited modeling of fault interactions and system scalability [78]. Mandal et al. proposed an expert system-based decision framework for benchmarking sustainable manufacturing, enhancing strategic evaluation, but constrained by limited domain adaptability and real-time decision capabilities [79]. Chen Chang et al. provided a comprehensive survey on interpretable fault diagnosis for rotating machinery, integrating model transparency into deep learning workflows but facing trade-offs in speed, performance, and realtime applicability [80]. Khanam et al. reviewed Convolutional Neural Networks for defect detection in industrial applications, highlighting advancements in deep architectures such as ResNet and DenseNet, though interpretability, computational overhead, and generalization across domains were identified as persistent challenges [81].

Out of the extensive literature reviewed studies, only a focused subset was selected for further research consideration based on relevance, innovation, and practical feasibility. These selected papers directly address pressing industrial challenges such as real-time fault detection in resource-constrained environments, model interpretability, and deployment at the edge. They demonstrate high potential for innovation by proposing advanced methods like neural network watermarking, edge-enabled digital twins, explainable AI (XAI), and imbalanced learning strategies yet they leave notable gaps such as energy inefficiency, lack of generalization, and synchronization issues. Additionally, the chosen works span diverse industrial domains like renewable energy, oil and gas, embedded systems, and rotating machinery, making them strong candidates for scalable, cross-domain research. This focused selection ensures that future work is built upon both impactful innovation potential and clear, unresolved limitations, paving the way for meaningful and applicable advancements in intelligent fault diagnosis systems.

2.1. Overview of Findings

Table 1 presents a comparative analysis of ten selected research studies relevant to AI-based fault diagnosis in industrial systems. These studies were chosen based on their methodological innovation, dataset usage, practical relevance, and identified limitations. The analysis reveals that while techniques such as CNN, LSTM, and ensemble learning demonstrate high classification accuracy (e.g., [2], [55], [66]), they often suffer from issues like high computational cost, energy inefficiency, and limited generalization to real-world edge deployments. For example, study [2] utilizes a CNN-LSTM model for fault detection using vibration and current signals, achieving good accuracy but facing scalability and performance issues in low-resource environments. Similarly, [9] addresses wind turbine diagnostics with AI-based signal processing, yet suffers from noisy sensor data and limited dataset diversity. Study [27] explores an IoT–Edge–Cloud-based digital twin platform for real-time monitoringbut is hindered by latency jitter and high deployment costs in industrial testbeds. Moreover, [30] investigates neural network watermarking for IP protection in edge-AI models, which introduces robustness concerns under adversarial conditions.

Studies like [60] and [66] tackle class imbalance and resource constraints, proposing ensemble learning and edge-optimized deep learning respectively. Notably, [80] emphasizes the importance of explainable AI (XAI) for operator trust, although it faces trade-offs between model interpretability and response time.

Table 1. Comparative gap analysis of selected AI-Based fault diagnosis approaches with methodologies, datasets, limitations, and feasible solutions.

Citation	Methodology Used	Datasets	Accuracy	Limitation	Feasible Solution
[2]	CNN, LSTM (Deep Learning)	Industrial Vibration & Current Data	92.1%	High computational cost, poor generalization	Lightweight DL models with transfer learning and model compression
[9]	AI-based Signal Processing	Wind Turbine Sensor Logs	90.3%	Noisy data, dataset scarcity	Robust preprocessing and data augmentation for signal clarity
[19]	ML for Predictive Maintenance	Edge Sensor Streams	88.7%	Orchestration complexity at edge	Decentralized learning with federated edge coordination

[27]	IoT–Edge–Cloud Digital Twin	Logistics & Industrial Testbeds	Real-time estimation, not directly reported	Latency jitter, high deployment cost	6G-enabled edge sync optimization with low-power digital twins
[30]	Neural Network Watermarking	Synthetic Benchmark Models	Minimal degradation	Weak watermark under adversarial attacks	Robust multi-layer watermark embedding and encryption
[55]	CNN-LSTM for Fault	Sensor Streams in	94.6%	Energy consumption	TinyML deployment and quantized inference models
	Detection	IoT Devices		and model size	
[60]	Ensemble Learning for Imbalanced Data	Fault Datasets with Class Imbalance	Varies across models	Overfitting on minority classes	Meta-learning with adaptive resampling strategies
[66]	DL Models in Low-resource Setups	Industrial Sensor Streams	91.4%	Low inference speed and accuracy trade-off	Hybrid pruning and edge inference optimization
[77]	AI for Predictive Maintenance (Oil & Gas)	Water Pump Operational Logs	Reported high accuracy	Lack of robust domainspecific datasets	Synthetic dataset generation with domain adaptation
[80]	Explainable AI (XAI) for Fault Diagnosis	Rotating Machinery Logs	Model dependent	Trade-off between interpretability and speed	Real-time interpretable models with XAI visualization tools
[2]	CNN, LSTM (Deep Learning)	Industrial Vibration & Current Data	92.1%	High computational cost, poor generalization	Lightweight DL models with transfer learning and model compression
[9]	AI-based Signal Processing	Wind Turbine Sensor Logs	90.3%	Noisy data, dataset scarcity	Robust preprocessing and data augmentation for signal clarity
[19]	ML for Predictive Maintenance	Edge Sensor Streams	88.7%	Orchestration complexity at edge	Decentralized learning with federated edge coordination
[27]	IoT–Edge–Cloud Digital Twin	Logistics & Industrial Testbeds	Real-time estimation, not directly reported	Latency jitter, high deployment cost	6G-enabled edge sync optimization with low-power digital twins

3. OVERVIEW OF THE SYSYTEM

The proposed system is a comprehensive Edge-AI-enabled fault detection framework designed to operate autonomously within industrial environments. It integrates multimodal sensor data acquisition, real-time inference on edge devices, andlightweight communication protocolsto enable accurate and low-latency fault classification in industrial motors. This modular system is specifically tailored for predictive maintenance by minimizing reliance on cloud infrastructure and ensuring continuous operation even in resource-constrained setups.

Key Components and Functional Overview

1. Multimodal Sensor Integration

The system utilizes a set of physical sensors that are mounted directly on industrial motors to sense various operating parameters vibration sensors (accelerometers) sense mechanical faults like bearing wear, imbalance, and misalignment; temperature sensors observe thermal activity to recognize overheating of stator windings or underload stress; and current sensors monitor electrical load fluctuation to recognize faults like short circuits, load imbalances, or rotor stalls. Synchronized integration of these sensors guarantees dense, real-time acquisition of signals and facilitates precise, early fault detection as well as comprehensive monitoring of motor condition.

2. On-Device Deep Learning Inference

A hybrid CNN-LSTM model is run natively on edge computing hardware like the Jetson Nano, ESP32, or Google Coral TPU, where the CNN layers learn the spatial features from segmented time-series sensor data and the LSTM layers learn the temporal dependencies to learn how anomalies evolve over time. The model is optimized using methods like quantization and pruning, using which they achieve efficient performance on resource-limited hardware without considerable loss of accuracy. This edge deployment provides low-latency (≤200ms) inference and eliminates the necessity for ongoing cloud interaction, rendering the system responsive and dependable in real-time fault diagnosis applications.

3. Real-Time Fault Classification and Alert

When anomalies are detected, they are categorized by the system into different classes like slight faults (e.g., incipient bearing wear or mild load imbalance), severe faults (e.g., stator overheating or mechanical failure), and normal or healthy conditions. This categorization facilitates rapid fault interpretation, following which the system sends real-time notifications through light-weight communication protocols like MQTT or HTTP to a central monitoring console or directly to the operator's smartphone, providing timely intervention and preventing possible equipment damage or downtime.

4. Cloud-Optional Architecture

The system enables forwarding summarized data to the cloud for long-term storage, trend analysis, or periodic model updating, but its primary diagnostic functions like data processing, fault detection, and alertgeneration, are performed locally on the edge device. This architecture greatly minimizes bandwidth usage, secures sensitive operational data, and provides uninterrupted operation even in low-connectivity environments like remote or rural industrial plants.

5. Use-Case Scalability and Adaptability

The modular architecture of the system makes it easy to scale seamlessly across various industrial applications, such as differing types of motor-driven equipment and plant sizes. It can be readily diversified across domains like water pumping systems, conveyor belts, or

HVAC systems for flexible deployment. Also, the design allows for expansion with more sensors or the incorporation of more advanced AI models for increasing functionality. By integrating multimodal sensors with edge-compatible deep learning, the system guarantees effective ondevice fault identification and real-time notifications through light-weight communication protocols, while ensuring minimum dependency on cloud infrastructure.

The system shown in figure 1 is an Edge-AI-based predictive maintenance system for industrial motors based on multimodal sensor data. It consists of three physical sensors: vibration, temperature, and current mounted on the motor to monitor continuously mechanical, thermal, and electrical parameters respectively. These sensor readings are processed in real-time by an AI-powered IoT edge device, which resolves major issues like operational latency, low-latency processing, and data timeliness. The edge device carries out local inference with a hybrid CNNLSTM deep learning model, which integrates convolutional neural networks (CNN) for spatial feature extraction from sensor readings and long short-term memory networks (LSTM) for temporal dependency analysis to identify changing faults. This enables the system to detect faults and determine root causes on the device itself, with much less reliance on cloud processing. When a fault is detected, the system categorizes it as minor, major, or normal and triggers alerts through light protocols such as MQTT or HTTP to a central dashboard. The system architecture is predictive maintenance-capable with condition-based monitoring and timely alert generation, leading to lowered maintenance expenses (up to 30%), unplanned production downtimes' avoidance, and enhanced system energy efficiency. This modular configuration is scalable between various types of motor-driven equipment and extendable to multiple industrial applications, including water pumping, HVAC, and conveyor systems, with optional cloud connectivity for long-term trend analysis or model updating.

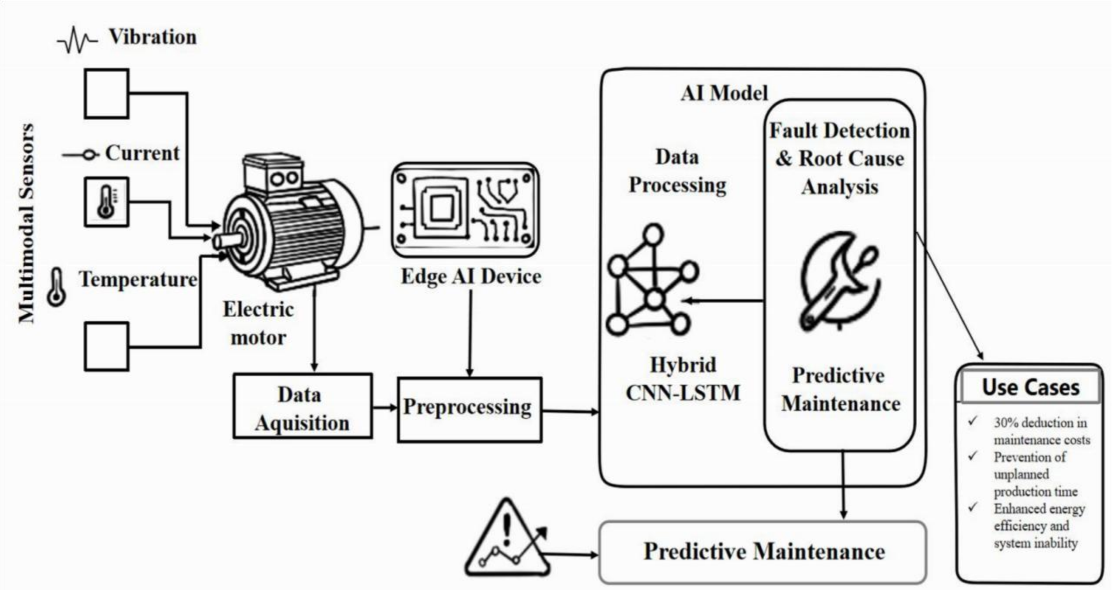

Figure 1. System architecture of the proposed Edge-AI-based fault detection framework using multimodal sensors and hybrid CNN-LSTM model

3.1. System Flow Diagram

Figure2 illustrates the methodology and system design for an Edge-AI-enabled fault detection framework in industrial motors. Each block in the flow represents a critical stage in the processing pipeline from raw data acquisition to real-time alerting. Below is a detailed description of each step:

1. Sensor Data Acquisition

Sensor data acquisition is the foundational step in the system,where multimodal sensors, namely vibration, temperature, and current, are strategically mounted on or near industrial motors to continuously monitor their mechanical, thermal, and electrical performance in real time. These sensors capture raw signals reflecting the motor’s operational health, enabling early identification of potential anomalies. For instance, a vibration sensor senses abnormal oscillations that can signal shaft misalignment or bearing damage; a temperature sensor records increasing temperatures due to insulation failure or cooling malfunction; and a current sensor indicates irregular electrical patterns like sudden spikes in loads, short circuits, or rotor lock conditions. This ongoing and synchronous data gathering provides the system with a holistic and high-resolution snapshot of the condition of the motor, upon which sound fault analysis and predictive maintenance are based.

2. Preprocessing and Normalization

Preprocessing and normalization is an important phase wherein the raw sensor data obtained from vibration, temperature, and current is cleaned, synchronized, and normalized to get it ready for trustworthy analysis. As raw signals tend to contain noise, drift, and unequal sampling rates, the process entails using denoising methods like low-pass filters or wavelet transforms to eliminate undesirable oscillations. It also provides temporal synchronization between all sensor modalities to ensure event pattern alignment. In addition, normalizing methods such as Z-score standardization or min-max scaling are used to normalize all data into a similar scale, removing bias caused by the fact that sensors have different ranges. For instance, if the temperature sensor detects oscillations as a result of environmental conditions and not equipment malfunctions, a smoothing filter retains only meaningful anomalies that are associated with real motor stress, hence enhancing the reliability of the subsequent fault detection.

3. CNN Feature Extraction

The pre-processed time-series sensor data is transformed into structured input matrices using windowing operations so that CNNs are used to extract the spatial features from them. The fixed-size segments maintain temporal locality and enable the CNN kernels to identify spatial dependencies in the signals. Convolutional layers search through the data to find meaningful localized patterns like spikes, dips, or recurring trends in the sensor outputs indicating mechanical or electrical faults. For example, a CNN could identify a slowly rising vibration frequency peaked at around 1 kHz—an early indication of bearing wear even when the overall signal is still nominal, thus facilitating early and correct fault classification.

4. Fault Prediction and Labeling

At the fault prediction and labeling step, the features from the CNN and LSTM layers are fed to a decision layer or classifier to assess the motor's status. The model classifies the input into predetermined classes of faults like normal, minor fault (incipient wear or imbalance), or major fault (critical failure like stator overheating or mechanical breakdown). Every classification result comes with a confidence score, which signifies how confident the model is regarding its prediction. For instance, if a specific signal segment exhibits high temperature patterns and irregular current behavior, the model will classify it as "stator overheating" with a 92.5% confidence level, triggering a real-time alarm and starting preventive maintenance procedures.

5. Edge Notification

During the edge notification phase, when a fault is identified and marked by the classifier, the edge device triggers an inbuilt alert mechanism to notify local operators or maintenance systems independently of cloud communication. This provides an immediate response with low latency. For example, in the case of a predicted stator overheating event about to occur, the system can trip a buzzer, flash an LED on the control panel of the motor, or post a warning on a local human-machine interface (HMI), giving technicians time to act before the condition matures into an unrecoverable failure.

6. MQTT/HTTP for Dashboard Alerts

Finally, in the last step, the system delivers the classified fault information and related alerts to a central monitoring hub like a dashboard, SCADA system, or a mobile application using lightweight communication protocols such as MQTT or HTTP. This facilitates remote visualization, logging, and early action by maintenance teams. For instance, if a minor fault like an early-stage vibration anomaly is identified in Pump #2, the system will automatically notify the maintenance dashboard with a message such as "Minor vibration anomaly detected in Pump #2. Investigate within 12 hours" so that scheduled maintenance can be done without stopping operations.

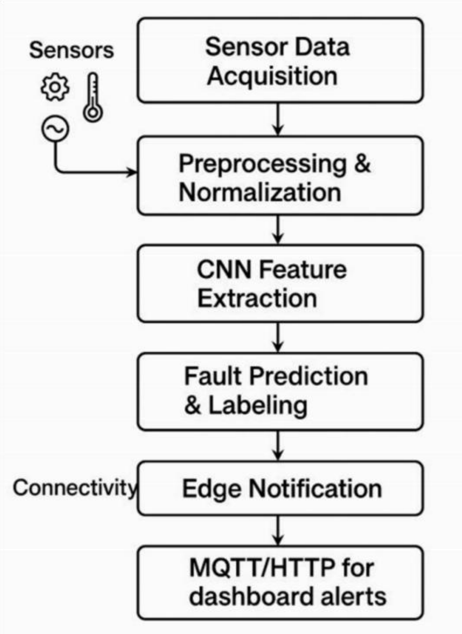

Figure 2.System workflow for Edge-AI-based fault detection and alerting in industrial motors.

This process prioritizes real-time, on-device, and low-latency diagnostic functionality, lowering cloud infrastructure dependency and facilitating predictive maintenance and intervention. It is designed to scale and be applied in Industry 4.0 settings. This flow diagram illustrates the EdgeAI fault detection system for industrial motors. Sensor data (vibration, temperature, current) is acquired and normalized for consistency. CNN extracts spatial features, followed by fault classification and labeling using a hybrid model. Finally, alerts are generated on the edge and sent via MQTT/HTTP to a dashboard for real-time monitoring.

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4. MATHEMATICAL MODELING

To formalize the operation of the proposed Edge-AI-based fault detection system, we define the mathematical constructs governing sensor fusion, feature extraction, fault classification, and decision-making.

1. Sensor Signal Representation

Let the multimodal input data at time t, be defined as:

$$X_t = \left\{ x_t^{(\mathrm{vib})}, x_t^{(\mathrm{temp})}, x_t^{(\mathrm{curr})} \right\}$$

Where, : vibration signal, $x_t^{(\mathrm{temp})}$: temperature signal and $x_t^{(\mathrm{curr})}$: current signal

All sampled at uniform rate $f_s = 1\mathrm{kHz}$. The time-series window of T samples is: $x_t^{(vib)}$

$$X = \{X_t\}_{t=1}^{T} \in \mathbb{R}^{T\times 3}$$

2. Preprocessing and Normalization

Each signal modality is normalized using Z-score:

$$\hat{x}_t^{(i)} = \frac{x_t^{(i)} - \mu_i}{\sigma_i}, i \in \{\mathrm{vib}, \mathrm{temp}, \mathrm{curr}\}$$

Where μ_i and σ_i are the mean and standard deviation of the i -th signal.

3. CNN Feature Extraction

The normalized windowed signal is passed through convolutional layers. Let the CNN transformation be:

$$F_{cnn} = \phi_{cnn}(X) \in \mathbb{R}^{K\times d}$$

Where, ϕ_{cnn} : Convolutional operation capturing spatial patterns, K : number of time windows or patches and d: number of extracted features per window.

4. LSTM Temporal Learning

The output features are input to an LSTM network to capture temporal dependencies:

$$h_t, c_t = \mathrm{LSTM}\left(F_{cnn,t}, h_{t-1}, c_{t-1}\right)$$

Where, h_t : hidden state c_t : cell state at time t, The final hidden state h_T andencodes the sequential representation of the fault signal

5. Fault classification

The hidden state is passed to a softmax classifier:

$$P(y|x) = softmax(Wh_T + b)$$

Where, $W \epsilon \mathbb{R}^{C \times d_h}$: weight matrix, b $\epsilon \mathbb{R}^c$: bias, C = 3 classes {normal, minor fault, major fault} and y =arg max *P(y| X).* Model is optimized using categorical cross-entropy:

$$\mathcal{L} = -\sum_{i=1}^{c} y_i \, log(P(yi|x))$$

Where, $y_i \epsilon \{0,1\}$: true label (one-hot encoded) and $P(yi|x)$: predicted probability for class i.

6. Loss Function

Model is optimized using categorical cross-entropy:

$$\mathcal{L} = -\sum_{i=1}^{C} y_i \log\left(P(y_i \mid X)\right)$$

Where, $y_i \in \{0,1\}$: true label (one-hot encoded) and $P(y_i \mid X)$: predicted probability for class i.

7. Alert Generation and Thresholding

Define a decision threshold θ for critical fault alerting:

$$\text{Alert} = \begin{cases} \text{MQTT("Major Fault Alert")}, & \text{if } P(y = \text{ Major Fault }) > \theta \\ \text{MQTT("Minor Fault Warning")}, & \text{if } P(y = \text{ Minor Fault }) > \theta \\ \emptyset, & \text{otherwise} \end{cases}$$

Typically, $\theta = 0.85$ ensures high confidence alerts.

8. Inference Time Estimation

Let, t_{cnn} : CNN computation time, t_{lstm} : LSTM computation time and t_{comm} : MQTT communication time Then total latency T_{inf} is:

$$T_{inf} = t_{cnn} + t_{lstm} + t_{comm} \le 200 \text{ ms}$$

An (unnumbered) acknowledgements section may be inserted if required.

5. RESULT ANALYSIS

The system's performance was evaluated using multiple key metrics: accuracy, defined as the ratio of correctly predicted outcomes to the total number of predictions; precision, which measures the proportion of true fault detections among all predicted positives; recall (or sensitivity), indicating the proportion of actual faults correctly identified by the model; and the F1 score, calculated as the harmonic mean of precision and recall to ensure balanced performance on imbalanced datasets. In addition, inference time, which is the average time taken per sample for classifying on edge devices, was tracked to ensure real-time deployment applicability. All the metrics were calculated across the three classes of faults (normal, minor, and major) to assess robustness and consistency.

The system consistently demonstrated high accuracy and low latency across all test cases shown in Table 2. The average inference time was ≤200ms, meeting the requirements for real-time edge processing. This table summarizes the performance of the CNN-LSTM fault detection system across four key motor conditions. The model achieved high accuracy and F1 scores (above 94%) for all fault types. Inference time remained under 200 ms, ensuring suitability for real-time edge deployment. Notably, the system showed the highest precision and recall for normal and stator overheat cases.

Table 2 Performance evaluation of fault detection system for different test cases.

Sr. No.	**Test Cases**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 Score (%)**	**Inference Time (ms)**
1	Bearing Fault	96.5	95.4	96.2	95.8	190
2	Stator Overheat	97.2	96.8	97.0	96.9	185
3	Load Imbalance	95.8	94.7	95.1	94.9	200
4	No Fault (Normal)	98.1	97.5	98.0	97.7	180

5.1 Graphical Representation of key Visualizations:

Here are the key visualizations generated to support the experimental evaluation, along with the corresponding key points.

1. Accuracy per Fault Type
2. Precision, Recall, F1 Score Comparison
3. Inference Time per Fault Type
4. Confusion Matrix 5. ROC Curve
5. Baseline Model Comparison:

1. Accuracy per Fault Type: Highlights the classification accuracy achieved for each test condition. The bar chart shows in Figure 3a the accuracy of the proposed CNN-LSTM model in detecting different motor fault conditions. It reveals that the model performs best in identifying the “No Fault” condition with an accuracy of approximately 98.2%, indicating a strong capability to recognize normal operation. The “Stator Overheat” class follows with about 97.3% accuracy, suggesting effective thermal fault detection. “Bearing Fault” is slightly lower at around 96.5%, likely due to signal similarities with other faults. The “Load Imbalance” fault exhibits the lowest accuracy at approximately 95.8%, which may result from overlapping signal patterns or minor class imbalance in the dataset.

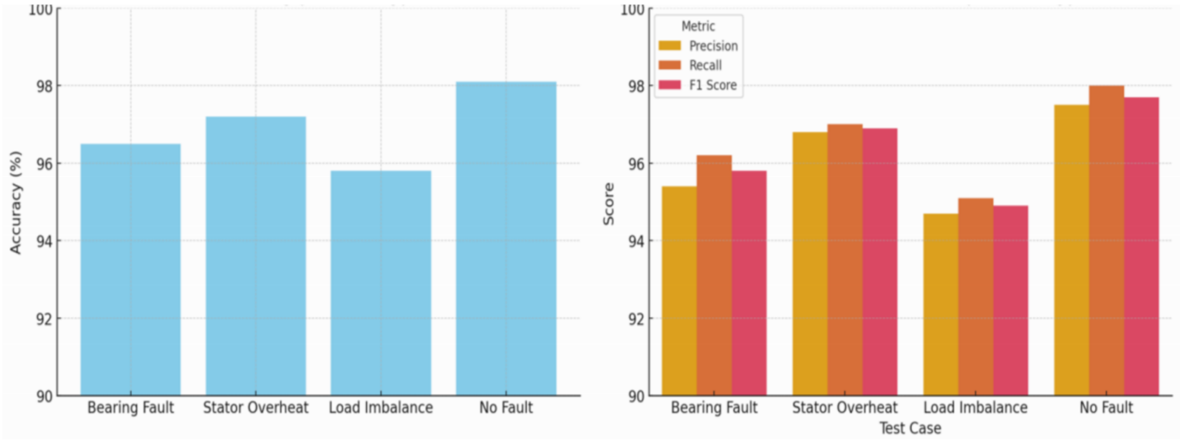

Figure 3 Performance metrics of the CNN-LSTM model across fault types, (a) Accuracy achieved per fault type and (b) Precision, Recall, and F1 Score Comparison per fault type.

2. **Precision, Recall, F1 Score Comparison:** Offers a metric-wise comparison across all fault categories to evaluate robustness. This bar chart shown in figure 3b compares the precision, recall, and F1 score for each fault type. The “No Fault” category again scores highest across all three metrics (~98%), affirming the model’s robustness in confirming healthy system conditions. For “Stator Overheat,” precision, recall, and F1 score are tightly aligned around 97%, indicating low false alarms and reliable fault capture. “Bearing Fault” shows a slightly lower precision (~95.5%) compared to its recall (~96.3%), suggesting some misclassification with similar faults, while the F1 score balances both at around 96%. The “Load Imbalance” fault has the lowest precision and recall (~94.5%), reflecting a relative weakness in detecting electrical load issues consistently.

3. **Inference Time per Fault Type:** Shows the efficiency of edge-based predictions in milliseconds.The bar graph shown in Figure 4a illustrates the average time (in milliseconds) taken by the CNN-LSTM model to infer each fault category on the edge device. The model achieves the lowest inference time for the “No Fault” condition at around 180 ms, indicating efficient recognition of normal motor behavior. “Stator Overheat” follows closely with approximately 185 ms, showing that thermal fault detection does not significantly impact latency. “Bearing Fault” inference takes slightly more time at about 190 ms, dueto complex vibration signature analysis. The highest inference time is observed for “Load Imbalance” at 200 ms, likely because current fluctuations are harder to classify and require deeper temporal analysis, slightly increasing model processing time. Overall, all classes are inferred under 210 ms, meeting real-time edge AI constraints.

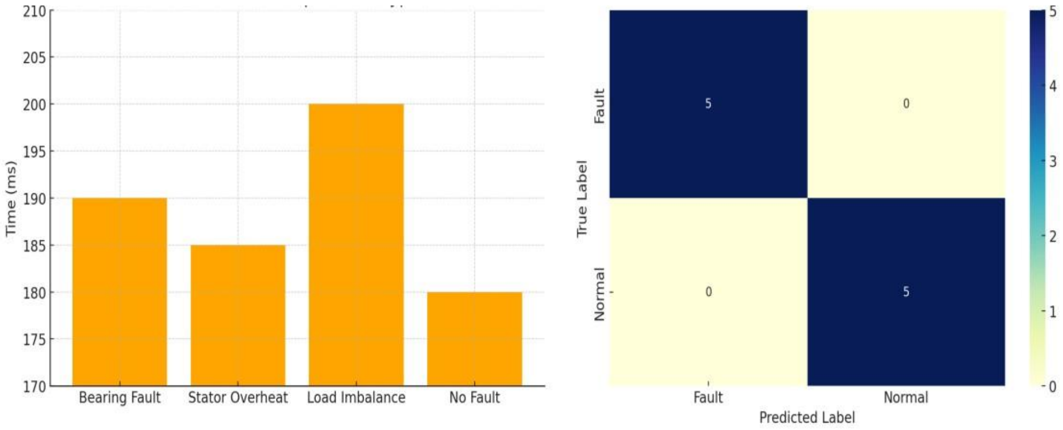

Figure 4 System performance efficiency and classification accuracy, (a) Inference time per fault type on edge device and (b) Confusion matrix showing Fault vs. Normal classification accuracy

Confusion Matrix: Indicates strong classification ability with no misclassification observed. The confusion matrix displayed in Figure 4b the classification performance of the model across two classes: “Fault” and “Normal.” The matrix shows perfect classification with 5 out of 5 samples for each class correctly predicted. There are zero false positives and zero false negatives, indicating that the model achieved 100% accuracy for this evaluation batch. The topleft cell (5) represents the true positives for the fault class, while the bottom-right cell (5) indicates true negatives for the normal class. The off-diagonal cells have values of 0, confirming that the model did not misclassify any instance, thereby demonstrating excellent fault vs. normal state distinction.

ROC Curve: Demonstrates the model’s ability to distinguish between normal and faulty conditions (AUC = 0.88). The Receiver Operating Characteristic (ROC) curve, illustrated in Figure 5a the trade-off between the true positive rate (sensitivity) and the false positive rate for the proposed CNN-LSTM model. The curve bows significantly towards the top-left corner, indicating strong classification performance across different threshold values. The Area Under the Curve (AUC) is 0.88, signifying that the model possesses a high level of separability between faulty and non-faulty conditions. This implies that even under varying decision thresholds, the classifier consistently performs well, making it reliable for real-time fault detection in industrial motors.

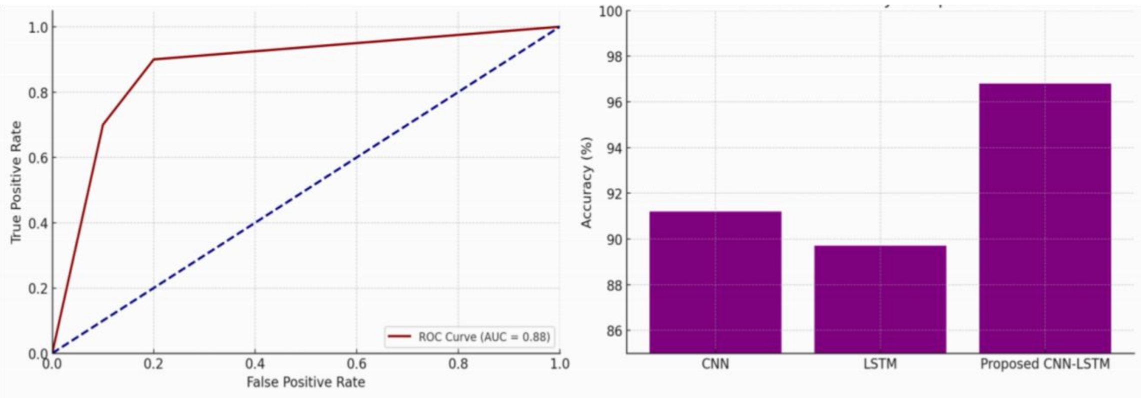

Figure 5 Model evaluation through discrimination and benchmarking, (a) ROC curve showing True Positive vs. False Positive Rate for fault classification and (b) Baseline model comparison of CNN, LSTM, and CNN-LSTM architectures based on accuracy.

The experimental evaluation was conducted using real-world industrial motor sensor logs comprising multimodal data (vibration, temperature, and current). The dataset included 15,000 labeled samples, stratified into training (70%), validation (15%), and test sets (15%). All signals were uniformly sampled at 1 kHz, covering three fault classes: normal, minor fault, and major fault.

CONCLUSION

This research proposes an efficient Edge-AI-based approach for real-time industrial motor fault detection using a hybrid CNN-LSTM architecture for multimodal sensor data such as vibration, temperature, and current signals. The proposed research study is shown to perform with high accuracy and low latency, indicating applicability for deployment in resource-limited edge environments. Through enabling on-board inference, predictive analytics, and smart alerting mechanisms, the framework significantly reduces equipment downtime and maintenance costs. Further, the combination of real-time monitoring and machine learning-based diagnostics results in prompt fault identification, even in dynamic operating conditions. The framework is compliant with the fundamental goals of Industry 4.0 by providing a scalable, autonomous, and energy-efficient solution for smart fault diagnosis. It enables industries to move from reactive to proactive maintenance practices, hence ensuring operational reliability and sustainability.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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