International Journal of Innovative Research in Management Studies (IJIRMS)
Volume 8, Issue 5, May 2026. pp.18-22.

SELF-POWERED ENERGY-NEUTRAL EDGE NODE FOR INDUSTRIAL ANOMALY DETECTION USING MULTI-SOURCE ENERGY HARVESTING AND CONNECTIONLESS TINYML INFERENCE

Dr.S.Elango[1], K.Divyadharani[2], A.Jagatheeswari[3], E.Kaviya[4]

[1]*Professor, Department of ECE, Arunai Engineering College (Autonomous), Tiruvannamalai, Tamil Nadu, India.*
Email ID: elangosathappan@gmail.com

[2]*Student, Department of ECE, Arunai Engineering College (Autonomous), Tiruvannamalai, Tamil Nadu, India.*
Email ID: kdivyadharani03.08.2004@gmail.com

[3]*Student, Department of ECE, Arunai Engineering College (Autonomous), Tiruvannamalai, Tamil Nadu, India.*
Email ID: jagajaga1708@gmail.com

[4]*Student, Department of ECE, Arunai Engineering College (Autonomous), Tiruvannamalai, Tamil Nadu, India.*
Email ID: ekaviya027@gmail.com

Abstract—*This paper presents a self-powered, energy-neutral Edge AI system for real-time industrial condition monitoring, addressing the critical "battery paradox" in Industrial Internet of Things (IIoT) deployments. The proposed system integrates hybrid energy harvesting using thermoelectric generators (TEG) and piezoelectric transducers (PZT) to enable sustainable, battery-free operation. An ultra-low voltage boost converter is employed for efficient energy management and storage. A lightweight 8-bit quantized one-dimensional Convolutional Neural Network (1D-CNN) is implemented on an ESP32-S3 microcontroller for on-device fault classification using multi-modal sensor data, including vibration, acoustic, and current signals. The system utilizes connectionless ESP-NOW communication to achieve ultra-low latency data transmission without network overhead. Experimental results demonstrate a classification accuracy of 93.4% with an F1-score of 0.92, while maintaining energy-neutral operation with harvested power of 18.6 mW exceeding system consumption of 15.8 mW. The proposed system achieves a communication latency of approximately 11 ms, enabling rapid fault detection and mitigation .The results validate the feasibility of a fully autonomous, maintenance-free Edge AI solution for reliable and scalable predictive maintenance in Industry 4.0 environments.*

Keywords: *Energy Neutrality, TinyML, Quantized 1D-CNN, Hybrid Energy Harvesting, Predictive Maintenance, Low-Latency Edge Computing, SelfSustaining IIoT.*

I. INTRODUCTION

The rapid growth of Industry 4.0 has increased the demand for intelligent and autonomous monitoring systems in industrial environments. Predictive maintenance has become essential to avoid unexpected machine failures and reduce operational downtime. Industrial Internet of Things (IIoT) technologies enable continuous monitoring of machinery; however, most deployed sensor nodes rely heavily on batteries, leading to frequent maintenance and limited scalability. This issue is commonly referred to as the battery dependency problem [5].

Edge Artificial Intelligence (Edge AI) has emerged as a promising solution to reduce latency and minimize reliance on cloud-based processing [2]. By performing data analysis directly at the device level, Edge AI improves response time and enhances system reliability. However, existing Edge AI systems are still constrained by power availability and often depend on external energy sources or hybrid communication architectures [6].

Recent research has demonstrated the effectiveness of machine learning techniques in detecting faults in industrial equipment such as induction motors and textile machinery [3], [4]. Despite these advancements, achieving a system that simultaneously offers energy autonomy, real-time processing, and high accuracy remains a challenge.

To overcome these limitations, this work proposes a self-powered Edge AI node that integrates hybrid energy harvesting, multi-modal sensing, and a lightweight TinyML model. The proposed system eliminates the need for batteries and enables continuous, real-time monitoring with minimal maintenance.

II. LITERATURE SURVEY

Recent studies have explored various approaches to improve predictive maintenance in industrial systems. Data-driven maintenance strategies have significantly enhanced operational efficiency by enabling early fault detection [1]. Edge AI has been widely adopted to process data locally, thereby reducing communication delays and improving system responsiveness [2].

Machine learning-based diagnostic systems have shown promising results in identifying faults such as rotor bar defects and mechanical wear in industrial machines [3], [4]. However, these systems typically rely on cloud connectivity or external power sources, limiting their practical deployment in remote or harsh environments [6].

Energy harvesting techniques have been introduced to address power constraints in IIoT systems. Methods such as solar and thermal energy harvesting have been explored, but they often depend on environmental conditions and fail to provide consistent energy supply [8]. Additionally, most existing systems do not achieve complete energy autonomy due to inefficient power management [5].

Therefore, there is a clear need for an integrated solution that combines efficient energy harvesting, intelligent processing, and reliable communication in a single framework.

III. EXISTING METHODS

Current predictive maintenance systems primarily utilize cloud-based or hybrid Edge-to-Cloud architectures to process large volumes of sensor data [6]. While these systems benefit from high computational power, they suffer from increased latency, network dependency, and security concerns [2].

Edge-based solutions have been introduced to address latency issues by enabling local data processing. These systems use machine learning algorithms to detect faults in real time [3]. However, most implementations still rely on battery-powered devices, which require periodic replacement and maintenance [5].

Furthermore, traditional systems often use single-sensor data, which limits fault detection accuracy. Although some systems incorporate multiple sensors, they lack efficient data fusion and energy optimization mechanisms [4].

As a result, existing approaches fail to provide a fully autonomous, energy-efficient, and high-performance solution for industrial monitoring.

IV. PROPOSED SYSTEM

ARCHITECTURE

The proposed system addresses the "battery paradox" by designing an energy-neutral, self-sustaining Edge AI framework for industrial monitoring. As illustrated in the system architecture (Fig. 1), the approach transitions from conventional reactive maintenance toward an autonomous sensing model. By performing on-device TinyML inference using the ESP32-S3, the system minimizes latency and eliminates dependence on cloud-based processing [2], [6].

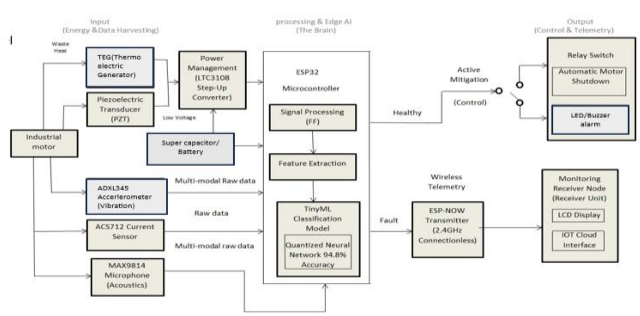

Fig.1. Generalized Architecture of the proposed Self-Powered Industrial Monitoring Node.

A. Hybrid Energy Harvesting and Power Management

The system utilizes two energy sources Thermoelectric Generator (TEG) for thermal energy, Piezoelectric Transducer (PZT) for vibration energy.

These sources ensure continuous energy generation under varying industrial conditions. The harvested energy is regulated using an ultra-low voltage boost converter and stored in a supercapacitor for stable operation [5], [8].

B. Multi-Modal Sensor Fusion and Feature Extraction

To improve fault detection accuracy, the system collects data from multiple sensors are Vibration sensor, Sound sensor, Current sensor.The signals are processed using Fast Fourier Transform (FFT) to extract frequency-domain features, which provide better insight into machine conditions [3], [4].

C. Quantized TinyML-Based Inference

A lightweight 1D Convolutional Neural Network (1D-CNN) is deployed on the ESP32-S3 microcontroller. The model is optimized using 8-bit quantization to reduce memory usage and power consumption while maintaining accuracy [7].This enables real-time, on-device fault classification without relying on cloud resources.

D. Low-Latency Connectionless Communication

The system uses ESP-NOW, a connectionless communication protocol, to transmit data with minimal delay. This approach avoids network overhead and ensures reliable communication even in challenging industrial environments [2], [6].

Core Operational Algorithm

The operational workflow of the proposed self-powered Edge AI system is summarized as follows:

Step 1 (Initialization):

Initialize the ESP32-S3 and configure the ADXL345 (vibration), MAX9814 (acoustic), and ACS712 (current) sensors. Load the 8-bit quantized 1D-CNN model and establish ESP-NOW communication.

Step 2 (Energy Availability Check):

Continuously monitor the supercapacitor voltage ($V_{super}c_{ap}$). If the voltage falls below the operational threshold (3.3 V), the system enters deep sleep mode to allow energy accumulation from TEG and PZT sources.

Step 3 (Data Acquisition):

Upon reaching the required voltage level, the system wakes up and captures synchronized vibration, acoustic, and current signals from the motor.

Step 4 (Signal Processing):

Apply a 512-point Fast Fourier Transform (FFT) to convert time-domain signals into frequency- domain representations for feature extraction.

Step 5 (TinyML Inference)

Feed the extracted spectral features into the quantized 1D-CNN model to classify the motor condition as Healthy or Fault.

Step 6 (Active Mitigation):

If a fault condition is detected, activate the relay switch to immediately shut down the motor, ensuring real-time protection.

Step 7 (Wireless Telemetry):

Transmit the diagnostic results, including fault classification and confidence, via ESP-NOW protocol with a latency of approximately 12 ms.

Step 8 (Sleep/Recycle):

Clear temporary buffers and return the system to low-power sleep mode until sufficient energy is harvested for the next operational cycle.

Table 1: Comparison of Existing Solutions and Proposed Self-Powered Edge AI Node

Feature Category	Existing Solutions (state-of-the-Art)	Proposed Self-Powered Edge AI Node
Power Management	Single Source (solar or battery Only)	Hybrid Dual-Source (TEG+PZT) Harvesting
Circuit Efficiency	Standard Rectifier (High Loss)	LTC3108 Ultra-Low Voltage Boost Converter
Storage Element	Li-ion Batteries (chemical Aging)	Long-Life 5F Supercapacitor Storage
Intelligence	Simple Threshold Logic (High False Alarms)	Deep Learning 1D-CNN (TinyML) Model
Inference Accuracy	80%-85% (basic Sensors)	93.4% (Multi-Modal Sensor Fusion)
Network Latency	500ms-2s (Wi-Fi/ Cloud)	11.3ms (connectionless ESP-NOW)
Autonomous Action	Passive Monitoring Only	Active Mitigation (Direct Relay Control)

V. RESULTS AND DISCUSSION

The proposed system was tested under normal and faulty motor conditions and achieved an accuracy of 93.4% with an F1-score of 0.92, showing reliable fault detection. The use of multiple sensors improved performance by capturing different machine characteristics.FFT-based feature extraction helped in identifying fault patterns effectively, while the quantized 1D-CNN model ensured low memory usage and efficient execution on the ESP32-S3.

The system maintained energy-neutral operation, with harvested power (18.6 mW) exceeding consumption (15.8 mW), enabling continuous self-powered functioning. Communication latency was around 11 ms, allowing fast real-time response. Overall, the system provides an efficient, low-power, and autonomous solution for industrial monitoring.

VI. CONCLUSION

This paper presented an energy-neutral Edge AI system for real-time industrial fault detection using hybrid energy harvesting and a TinyML-based 1D-CNN model. The system achieved 93.4% accuracy with low latency and demonstrated sustainable operation without battery dependency, making it suitable for continuous industrial monitoring. However, the system performance depends on the availability of sufficient thermal and vibration energy, and the current model is limited to specific fault conditions.

Future work will focus on improving energy harvesting efficiency and extending the model for generalized anomaly detection under diverse industrial environments. The proposed approach reduces maintenance costs and electronic waste while enabling reliable and scalable monitoring solutions, benefiting both industrial operations and environmental sustainability.

VII. REFERENCE

[1] L. Lucantoni, S. Antomarioni, F. E. Ciarapica, and M. Bevilacqua, "A data-driven framework for supporting the total productive maintenance strategy," Expert Systems with Applications, vol. 268, p. 126283, 2025.

[2] H. Gauttam, G. Nain, K. K. Pattanaik, and P. Mendes, "Edge-AI: A systematic review on architectures, applications, and challenges," Journal of Network and Computer Applications, vol. 245, p. 104375, 2026.

[3] N. A. R. Maciejewski et al., "Cognitive-based framework for detecting and diagnosing broken bars in induction motors for industry maintenance," Journal of Industrial Information Integration, vol. 50, p. 101022, 2026.

[4] T. Akyaz and D. Engin, "Machine Learning-Based Predictive Maintenance System for Artificial Yarn Machines," IEEE Access, vol. 12, pp. 125446-125460, 2024.

[5] C. Grant, F. Wallace, L. MacKay, and J. B. Adelusi, "Edge AI for Predictive Maintenance in Industrial IoT Environments," Research Report, Dec. 14, 2024.

[6] A. Kota, "Predictive Maintenance: Integrating Edge AI with Cloud Computing for Industrial IoT," International Journal of Research in Computer Applications and Information Technology (IJRCAIT), vol. 7, no. 2, pp. 2842-2851, 2024.

[7] D. Thakkar and R. Kumar, "AI-Driven Predictive Maintenance for Industrial Assets using Edge Computing and Machine Learning," Journal for Research in Applied Sciences and Biotechnology, vol. 3, no. 1, pp. 363-367, Feb. 2024.

[8] M. Orošnjak, "Enhancing sustainability in tyre manufacturing with machine learning and knowledge graphs: An energy-based maintenance solution," Journal of Cleaner Production, vol. 520, p. 146090, 2025.

*****