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AIM-MC: Artificial Intelligence and Machine Learning for Motor Condition Monitoring on STM32 IoT Platforms

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ABSTRACT: Industrial motors operate continuously under harsh mechanical and electrical condi- tions, making them vulnerable to faults such as bearing wear, shaft misalignment, and overload. Undetected faults result in downtime, increased maintenance costs, and safety risks. This paper presents a low-cost AI and TinyML-based Condition-Based Monitoring (CBM) system for industrial motors using vibration and current analysis. The proposed system employs an ADXL345 accelerometer for vibration sensing and an ACS712 current sensor for overload detection. Time-domain vibration features, specifically RMS values, are extracted and processed using a rule-based algorithm and a TinyML model trained us- ing Edge Impulse. An STM32 microcontroller performs real-time fault classification, while fault status is transmitted to the Blynk IoT platform via a NodeMCU (ESP8266) module. Experimental results show that the proposed system achieves high fault detection accuracy with low computational overhead, making it suitable for Industry 4.0 applications.

KEYWORDS: Condition-Based Monitoring ,Fault Diagnosis ,Industrial Electric Motors ,Vibration Signal Analysis ,Current Monitoring ,TinyML ,Edge Computing

I. INTRODUCTION

Industrial motors (IM) are the most critical driving elements in modern industrial systems [1]. They convert electrical energy into mechanical energy and are responsible for driving a wide variety of mechanical loads. Almost every industrial process depends on motors for material handling, production, cooling, pumping, and automation. Industries such as manufacturing, power generation, oil and gas, mining, textiles, chemical processing, food processing, and water treatment heavily rely on electric motors for their day-to-day opera- tions. They are nothing new as well. Research on industrial motors has been going on for a little over a century [6].

With the introduction of Artificial Intelligence (AI), the face of industrial motors is changing. Research in Industrial Internet of Things (IIoT) has been extensively going over the past decade and AI-Driven Internet of Things (IoT) has evolved IIoT into the new era [4, 1]. There are many applications of IM in the IIoT environments, including:

- Conveyor belt systems in manufacturing plants
- Pumps in water supply, irrigation, and chemical processing
- Compressors in refrigeration and air-conditioning systems
- Fans and blowers for ventilation and cooling
- Machine tools such as lathes, milling machines, and CNC equipment
- Robotic arms and automated assembly lines

They play a pivotal role in the industrial automation and IIoT. The Internet of Things (IoT) plays a critical role in modern industrial environments. Through the deployment of IoT devices, the performance and operational condition of industrial machinery can be continuously monitored. Moreover, industrial processes become increasingly autonomous, thereby

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reducing the need for human intervention. IoT devices also enable the optimization of industrial operations, ultimately leading to lower manufacturing costs. The widespread adoption of IoT technologies in the industrial domain has given rise to a new computing paradigm known as the Industrial Internet of Things (IIoT). IIoT can be formally defined as "the network of intelligent and highly interconnected industrial components deployed to achieve high production rates and reduced operational costs through real-time monitor- ing, efficient management, and control of industrial processes, assets, and operational time". The fourth industrial revolution, referred to as Industry 4.0, places a strong emphasis on the automation of manufacturing systems. IIoT represents one of the core enabling technologies driving Industry 4.0.

Artificial Intelligence of Things (AIoT) is an increasingly popular computing paradigm that brings together two cutting-edge technologies, AI and the IoT [1]. As discussed earlier, a typical IoT system is made up of a large number of sensor-enabled devices that contin- uously collect data from their surrounding environment. This results in massive volumes of data being generated at a rapid pace. To make sense of this data and turn it into useful insights, efficient data processing and decision-making mechanisms are needed.

AI provides powerful tools for analyzing large and complex datasets, identifying pat- terns, and making intelligent decisions with minimal human involvement. When these AI techniques are applied to handle data processing and decision-making tasks within IoT sys- tems, the combined approach is referred to as AIoT. In recent years, AIoT has attracted significant attention, particularly in industrial applications, where it has been used to im- prove system efficiency, enhance automation, and support smarter, data-driven operations.

Owing to their widespread use in industrial environments, even brief interruptions in motor operation can result in substantial production losses, potential equipment damage, and serious safety risks. In large-scale industrial facilities, unplanned motor downtime can cost thousands of dollars per hour, underscoring the critical importance of reliable motor operation. As a result, maintaining the health and availability of industrial motors has be- come a key concern in modern automated and data-driven manufacturing systems enabled by IIoT and AIoT technologies.

Industrial motors are typically designed for continuous and heavy-duty operation. In many applications, they run for extended periods or even operate continuously, 24 hours a day, while being exposed to varying mechanical loads and harsh operating conditions. Over time, these demanding conditions subject motors to multiple forms of stress that can accelerate wear and increase the likelihood of failure.

During operation, industrial motors experience several types of stresses, including:

- Mechanical stresses arising from rotating components, imbalance, misalignment, and load variations.
- Thermal stresses caused by heat generated in windings, bearings, and other compo- nents
- Electrical stresses resulting from voltage fluctuations, harmonics, insulation degrada- tion, and overload conditions
- Environmental stresses such as dust, moisture, vibration, and changes in ambient temperature

II. RELATED RESEARCH

The cumulative effect of these mechanical, thermal, electrical, and environmental stresses often leads to gradual performance degradation and, if left unaddressed, unexpected motor failures [3]. Traditional maintenance strategies, such as reactive maintenance or periodic scheduled inspections, are often insufficient in modern industrial settings, as they may fail to detect early-stage faults or result in unnecessary downtime and maintenance costs. This has created a strong demand for more intelligent and proactive maintenance approaches [2].

In this context, AIoT-enabled condition monitoring has emerged as a promising solution for improving the reliability and availability of industrial motors. By integrating IoT sensors with industrial motors, key operational parameters such as vibration, temperature, current, voltage, and acoustic signals can be continuously monitored in real time. These sensors generate large volumes of data that reflect the motor's operating condition and health status. AI techniques can then be applied to this data to perform automated fault diagnosis and predictive maintenance. Machine learning and deep learning models are capable of identifying subtle patterns, anomalies, and trends that are often difficult to detect using traditional rule-based methods. This enables early detection of faults such as bearing defects, rotor imbalance, insulation degradation, and

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misalignment, well before they evolve into critical failures. As a result, AIoT-based predictive maintenance allows maintenance actions to be sched- uled based on the actual condition of the motor rather than fixed time intervals. This not only reduces unplanned downtime and maintenance costs but also extends equipment life- time and enhances operational safety. Consequently, AIoT-driven condition monitoring and fault diagnosis play a vital role in supporting the objectives of Industry 4.0 by enabling smarter, more reliable, and cost-effective industrial operations. [4] discusses an AI-driven Anomaly-Agent designed for IoT and IIoT environments. It can detect any anomalies in the resource constrained environments. Using an AI agent the authors overcame the limitations of the traditional ML and AI. AI does not only work with industrial motors and automation, research in AI - Driven IIoT has been adopted in various applications such as water management. The authors in [5] identify that industrial wastewater inflows pose major challenges for sewage treatment plants, often exceeding what plants are designed to handle and damaging structures and op- erations. To address this, they propose a cloud-based IoT model that continuously monitors key wastewater quality parameters — specifically pH (power of hydrogen) and tempera- ture — at the inlet of the treatment system using IoT sensors. These sensor readings are transmitted in real time to a cloud server via an IIoT Wi-Fi module. If the system detects impermissible or unexpected wastewater, it triggers SMS alarms and notifications and auto- matically controls valves to redirect water flow to appropriate treatment paths. The system also supports real-time data visualization and remote monitoring, improving responsiveness and decision-making.

III. PROPOSED AIM-MC ARCHITECTURE

AIM-MC is an AI driven IIoT application to monitor the condition of a motor using STM32. One of the most frequent causes of motor failure is bearing damage. Bearings support the rotor and ensure smooth rotation. When bearings wear out, vibration increases, friction rises, and eventually the motor may seize or overheat. Similarly, shaft misalignment causes uneven mechanical loading, which results in excessive vibration and accelerated wear of bearings and couplings. Electrical overload leads to overheating of windings, insulation breakdown, and eventual motor burnout [2, 3].

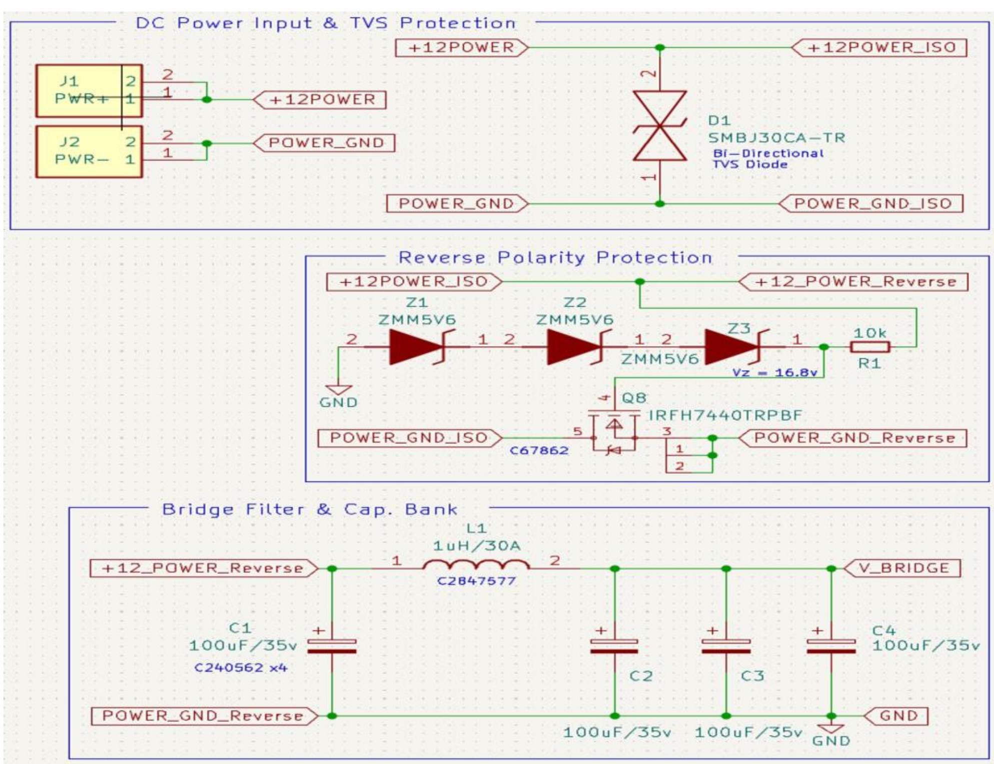

Figure 1: Block Diagram of the Circuit

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In traditional industrial setups, motors are often monitored only through basic electrical parameters such as current, voltage, and temperature. While these parameters can detect se- vere faults, they do not provide early warning of mechanical degradation. Many mechanical faults such as bearing defects and misalignment first appear as changes in vibration patterns long before electrical symptoms become visible. Therefore, vibration analysis has become one of the most powerful tools for assessing the health of industrial motors. Every rotat- ing machine produces a unique vibration signature when operating normally. When a fault begins to develop, this vibration signature changes. By continuously monitoring vibration levels, it is possible to detect abnormal conditions at an early stage and prevent catastrophic failures.

With the advancement of embedded systems, sensors, and artificial intelligence, modern motor monitoring systems are now moving towards Condition-Based Monitoring (CBM). In CBM, the actual condition of the motor is measured in real time using sensors such as accelerometers and current sensors, and intelligent algorithms are used to analyze the data. This allows maintenance to be performed only when necessary, reducing downtime, main- tenance cost, and equipment damage. In this project, industrial motors are monitored using a vibration sensor (ADXL345) and a current sensor (ACS712), combined with an STM32 microcontroller and TinyML algorithms. This enables real-time, low-cost, and intelligent motor health monitoring suitable for both small-scale and large-scale industrial applications. The neural network architecture for the proposed TinyML-based AIM-MC model was

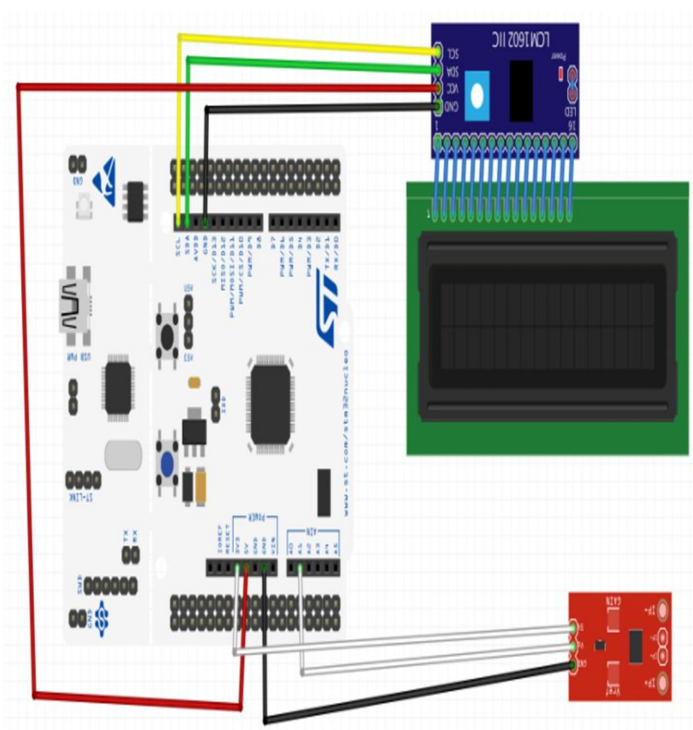

Figure 2: Overall Architecture of the AIM-MC

carefully designed to ensure efficient execution on resource-constrained edge devices while maintaining reliable performance. The model takes tri-axial accelerometer data as input, with an input layer consisting of three neurons corresponding to the X, Y, and Z axes. These inputs are processed through two fully connected hidden layers to enable effective feature extraction and non-linear representation learning. The first hidden layer contains 20 neurons and uses the Rectified Linear Unit (ReLU) activation function to introduce non-linearity while keeping computational complexity low. This is followed by a second hidden layer with 10 neurons, also employing the ReLU activation function to further refine the learned features. Finally, the output layer is composed of three neurons that classify the system's operational state—Stopped, Average Speed, High Speed, and Anomaly—using the Softmax activation function to produce normalized probability

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scores for each class. This lightweight yet expressive architecture strikes a balance between accuracy and efficiency, making it well suited for real-time inference in TinyML and edge-computing environments.

The root mean square (RMS) vibration values are computed independently for the X, Y, and Z axes of the accelerometer data using the expression:

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} X_i^2}$$

In the above expression, N represents the number of samples and X_i denotes the indi- vidual acceleration measurements along a given axis. RMS values effectively quantify the vibration energy of the system and serve as a robust and widely used indicator for detect- ing mechanical abnormalities and incipient faults. Based on these extracted RMS features, a rule-based fault classification approach is employed to identify specific operating condi- tions. A system is classified as healthy when the average RMS values remain low across all axes, indicating stable operation. A bearing fault is identified when vibration is predom- inantly concentrated along a single axis, suggesting localized mechanical degradation. Mis-alignment faults are characterized by distinct directional vibration patterns across multiple axes, while overload conditions are detected when the motor current exceeds a predefined threshold, signaling excessive mechanical or electrical stress on the system.

IV. EXPERIMENTAL EVALUATION

This section discusses the experimental evaluation of the proposed AIM-MC prototype.

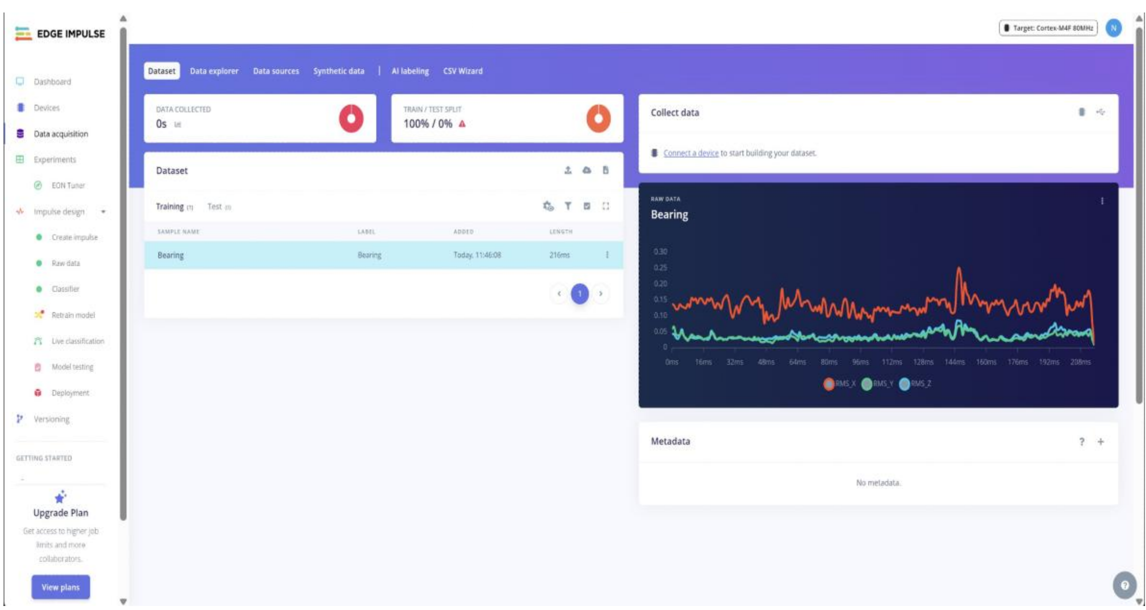

Figure 3: Bearing Collect Data

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Fig. 3 Edge Impulse dataset interface being used to collect and visualize vibration data for a bearing fault condition as part of a TinyML-based motor vibration monitoring system. "Bearing" has been recorded, with a duration of approximately 216 ms, and the current train/test split is 100% training and 0% testing as the data is still being collected.

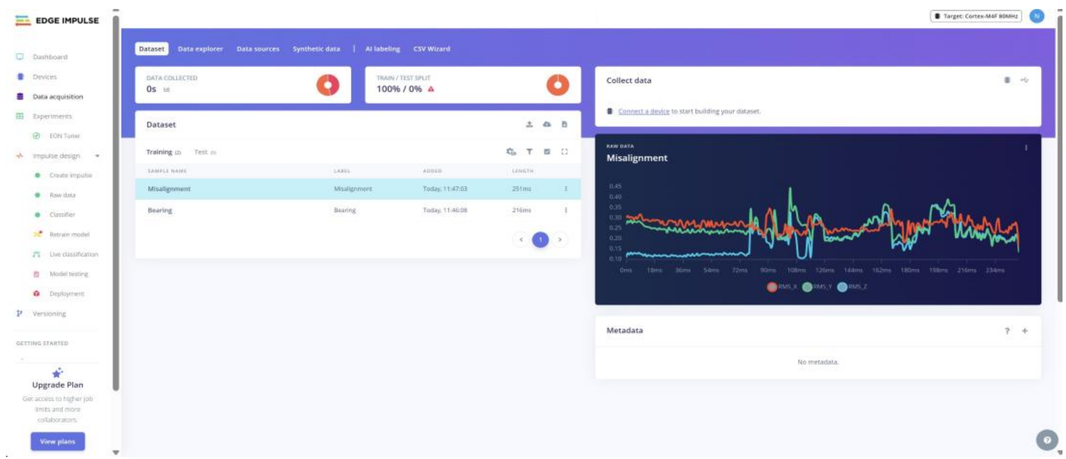

Figure 4: Misalignment Collect Data

Fig. 4 shows the dataset after collecting vibration data corresponding to a motor mis- alignment fault. The misalignment sample has a duration of approximately 251 ms, and the dataset is still fully allocated to training (100% training, 0% testing). The raw data plot on the right visualizes the RMS vibration signals along the X, Y, and Z axes over time. Un- like the bearing fault case, the misalignment condition exhibits significant vibration activity across multiple axes, with noticeable fluctuations and intermittent peaks occurring simul- taneously in more than one direction. This multi-axis and directional vibration pattern is characteristic of shaft or coupling misalignment, where uneven mechanical forces cause os- cillations that propagate across the system rather than remaining localized to a single axis.

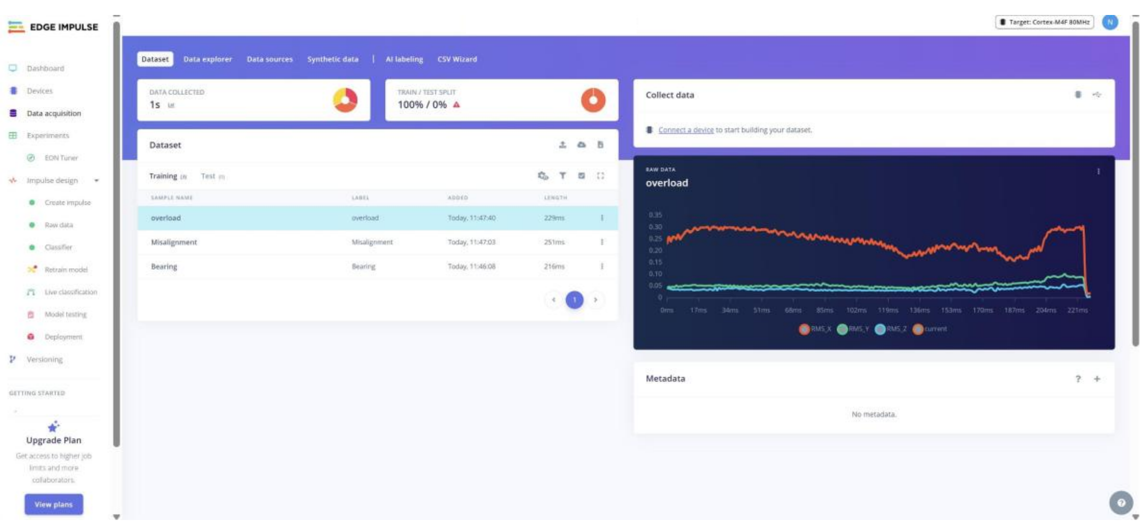

Figure 5: Overload Collect Data

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Fig. 5 shows the dataset interface during the collection and visualization of data for an overload operating condition in the motor vibration monitoring system. The overload sample has a duration of approximately 229 ms.

Table 1: RMS Vibration Values for Different Operating Conditions

Condition	X_{RMS}	Y_{RMS}	Z_{RMS}
Healthy	0.02	0.01	0.01
Bearing Fault	0.06	0.03	0.02
Misalignment	0.18	0.12	0.05

Table 2: Classification Accuracy Comparison

Table 2: Classification Accuracy Comparison

Method	Accuracy (%)
Rule-Based	87
TinyML	95

The RMS vibration values clearly differentiate the motor's operating conditions by high- lighting variations in vibration energy across the three axes. Under healthy conditions, RMS values remain low and balanced, indicating stable operation. Bearing faults show a mod- erate increase in vibration, particularly along the X-axis, reflecting localized mechanical degradation. In contrast, misalignment produces significantly higher RMS values across multiple axes, demonstrating strong directional vibration patterns typical of shaft or cou- pling misalignment. The classification accuracy results further emphasize the effectiveness of the proposed approach: while the rule-based method achieves reasonable performance with an accuracy of 87%, the TinyML model significantly improves fault classification accu- racy to 95% by learning complex patterns from multi-axis vibration data. This comparison confirms the advantage of TinyML for robust and accurate motor fault diagnosis on edge devices.

V. CONCLUSION

The experimental results demonstrate that the proposed TinyML-based motor condition monitoring system can effectively distinguish between different operating states and fault conditions using lightweight vibration and current features. The RMS vibration patterns captured along the X, Y, and Z axes exhibit clearly distinguishable signatures for bearing faults, misalignment, and overload conditions, while the inclusion of motor current mea- surements further enhances fault discrimination, particularly for overload detection. The Edge Impulse platform proved to be an efficient tool for data acquisition, visualization, la- beling, and model preparation, enabling rapid development of a resource-efficient machine learning model suitable for edge deployment. AIM-MC results confirm that combining RMS-based vibration analysis with rule-based and ML-driven classification provides a reli- able, low-power, and scalable solution for real-time motor health monitoring in embedded and industrial IoT applications.

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