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AI-Powered Fault Detection in DC Motor Using STM32

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Abstract

This work presents the design and implementation of an embedded artificial intelligence system for real-time fault detection in a direct current (DC) motor using the STM32 Nucleo-F411RE microcontroller. The objective of the study is to develop a low-cost and efficient predictive maintenance solution capable of identifying abnormal motor behavior at an early stage. Vibration and temperature signals are acquired using an MPU6050 sensor and processed directly on the microcontroller without relying on cloud-based computation. Statistical and time-domain features are extracted from the sensor signals and used to train a lightweight anomaly detection model using NanoEdge AI Studio. The trained model is deployed on the STM32 platform to enable on-device inference with minimal memory consumption. Experimental validation is carried out under both normal and induced faulty operating conditions to evaluate classification performance. The system demonstrates high detection reliability with optimized RAM and Flash utilization, making it suitable for resource-constrained embedded environments. The proposed solution reduces latency, enhances data security, and eliminates dependency on external servers. The architecture can be extended to multi-motor industrial systems for scalable predictive maintenance. This approach contributes toward intelligent edge-based monitoring systems that improve equipment reliability, reduce downtime, and support Industry 4.0 applications, and demonstrates the potential of compact embedded AI systems to enable intelligent, autonomous, and efficient motor health monitoring in modern industrial environments.

Keywords: STM32 microcontroller, STM32CubeIDE, NanoEdge, machine learning model, artificial intelligence

INTRODUCTION

In industrial environments, unexpected motor failures can significantly affect productivity and operational efficiencies. Even small mechanical irregularities, such as shaft imbalance, bearing wear, or overheating, may gradually develop into serious faults if not detected at an early stage. Therefore, intelligent condition monitoring systems are increasingly adopted to ensure reliability and minimize downtime. Among the various monitoring techniques, vibration analysis is considered one of the most reliable indicators of the mechanical health of rotating systems. Variations in the vibration patterns often provide early warning signs of internal structural degradation. Temperature monitoring further complements vibration analysis by identifying the thermal stress conditions caused by friction or electrical overload.

Conventional monitoring approaches typically rely on manual inspection or cloud-based data analysis. Although cloud platforms offer high computational power, they introduce latency, require continuous connectivity, and raise data security concerns. In contrast, embedded edge-

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based intelligence enables real-time processing directly on the microcontrollers. This approach reduces the dependency on external infrastructure and ensures faster response times. With advancements in lightweight machine learning frameworks, deploying anomaly detection algorithms on resource-constrained embedded systems has become feasible.

The STM32 Nucleo-F411RE microcontroller provides sufficient processing capability, low power consumption, and peripheral support for implementing such intelligent monitoring systems. By integrating sensor data acquisition, feature extraction, and AI inference within a single embedded platform, the proposed system achieves efficient real-time fault detection. Anomaly detection is particularly suitable for motor monitoring applications because it learns normal operational behavior and identifies deviations without requiring extensive labelled fault data sets. Thus, the integration of embedded systems and artificial intelligence offers a practical and scalable solution for predictive maintenance in modern industries.

LITERATURE SURVEY

A Self-Supervised Learning Approach for Anomaly Detection in Rotating Machinery

This study is based on an anomaly detection method for rotating machinery that does not require labeled fault data; instead, it learns representations from unlabeled vibration time series. Uses a self-supervised representation learning strategy based on cycle consistency. The idea is to generate augmented versions of the vibration signal sequences and train a neural embedding model so that the corresponding augmentations map close in the latent space. The method is trained on normal (healthy) machine data only, making it suitable for early fault detection, where fault labels are scarce. By enforcing consistency between augmented pairs, the model learns a feature space in which anomalies (deviations from learned normal patterns) can be detected as outliers [1].

Micro-Electro-Mechanical Systems (MEMS) Accelerometer-Based Condition Monitoring and Fault Diagnosis of Induction Motors

This paper presents a condition monitoring and fault diagnosis framework for induction motors using low-cost MEMS accelerometers to monitor vibration signals. MEMS accelerometers are deployed on the motor housing to capture vibration signals that reflect the mechanical conditions (imbalance, misalignment, bearing wear, etc.). Data from these low-cost sensors is used for signal processing and fault identification algorithms, which may include statistical analysis and machine learning models. The use of MEMS sensors enables compact, cost-effective, and scalable monitoring solutions in industrial environments [2].

Real-Time Bearing Fault Diagnosis Based on Convolutional Neural Network and STM32 Microcontroller

The author proposed a real-time bearing fault diagnosis by implementing a lightweight CNN model on an STM32 microcontroller, emphasizing edge-level processing. A 1-D Convolutional Neural Network was trained on vibration data (e.g., the Case Western Reserve University (CWRU) bearing dataset) to classify bearing health conditions.

The trained CNN was optimized and deployed directly on a resource-constrained STM32H743VI microcontroller using tools such as CubeAI, enabling real-time inference (≈19 ms per diagnosis). It achieves high classification accuracy (~98.9%) for different types of bearing conditions despite limited computing resources [3].

Unsupervised Anomaly Detection Using Vibration Signals for Rotating Machinery

This study is based on the automatic detection of anomalies in rotating machinery using unsupervised learning on vibration signals, particularly focusing on cases where only healthy data are available for training. Models like autoencoders, temporal convolutional autoencoders, or one-class classifiers are trained using healthy vibration data to learn a compact representation of "normal"

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behavior. During deployment, a reconstruction error or distance metric is used to flag deviations as anomalies. A recent example of such methods proposes a memory-augmented temporal convolutional autoencoder that enhances representation learning across time scales to better distinguish normal vs. anomalous states and improve robustness to noise. The model learns the statistical structure of normal vibration patterns, and anomalies produce high reconstruction errors or unusual distances in the feature space [4].

COMPARATIVE ANALYSIS

The comparison indicates that while several existing approaches achieve high accuracy, many rely on computationally intensive models or cloud-based processing methods. The proposed system focuses on lightweight embedded deployment with minimal memory usage while maintaining reliable anomaly detection performance. This makes it suitable for low-cost industrial applications, where resource efficiency is critical, as shown in Table 1.

PROBLEM STATEMENT

DC motors are prone to faults, such as abnormal vibration and overheating, which can lead to performance degradation and unexpected failures. Conventional fault detection methods are inefficient and cannot identify early-stage abnormalities. The proposed system aims to develop an AI-powered fault detection system for a DC motor using an STM32 microcontroller, which enables monitoring of motor parameters in real time and accurate fault detection, thereby enabling reliable and predictive maintenance [5, 6].

PROPOSED MODEL

An AI-powered predictive maintenance system for DC motors using the STM32 Nucleo-F411RE microcontroller, NanoEdge AI Studio, and sensors such as the MPU6050 (vibration) and SSD1306 organic light-emitting diode (OLED) (display) was developed to perform the analysis of vibration and leverage temperature data in conjunction with embedded machine learning, which enables the system to detect early motor fault indications directly on the device without relying on cloud computing. This approach offers a real-time, secure, low-cost, and efficient solution for reducing downtime, extending the motor lifespan, and improving industrial safety [7].

The proposed system implements an AI-driven predictive maintenance system for DC motors using an STM32 Nucleo-F411RE microcontroller, NanoEdge AI Studio, and sensors, including the MPU6050 for vibration monitoring and an SSD1306 OLED display. The system uses embedded machine learning to process vibration and temperature data, enabling it to detect early signs of motor faults on the device without depending on cloud computing. This approach offers a real-time, secure, low-cost, and efficient solution for reducing downtime, extending motor lifespan, and improving industrial safety [8].

The overall architecture of the proposed system is illustrated in Figure 1.

Table 1. Comparative analysis.

Ref. no.	Technique used	Platform	Accuracy	Edge deployment	Limitation
[1]	Self-supervised learning	PC-based	High	No	High computational cost
[2]	MEMS + Signal processing	Industrial setup	Moderate	Partial	Limited intelligence
[3]	CNN-based diagnosis	STM32H743	98%	Yes	Higher memory requirement
[4]	Autoencoder-based anomaly detection	Workstation	High	No	Require a large dataset
[5]	NanoEdge AI anomaly detection	STM32F411	90%	Yes	Limited training samples

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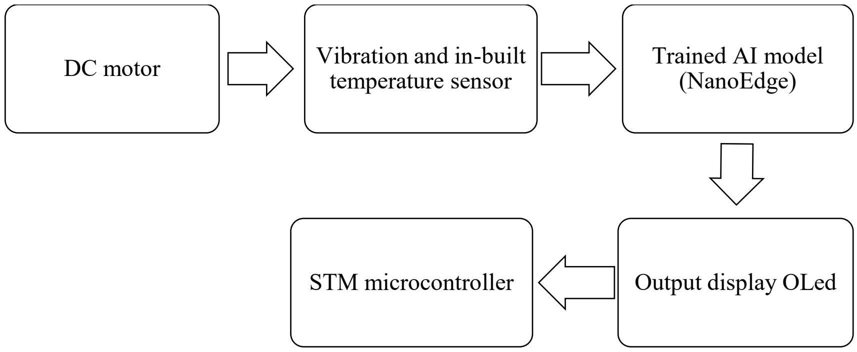

Figure 1. The block diagram depicts the architecture of the proposed system

The system follows a structured workflow for AI-powered fault detection in DC motors. Vibration and temperature data were collected from the MPU6050 sensor using the STM32 Nucleo-F411RE under both healthy and faulty motor conditions. The data was pre-processed by cleaning, labeling, and extracting statistical and frequency features. Machine learning models, such as decision trees, SVM, or lightweight neural networks, were trained, evaluated, and optimized for embedded deployment. The trained model was then integrated into the STM32 firmware to enable real-time monitoring and fault detection, with the output displayed on an OLED screen. Finally, the system was tested under different conditions, and optimizations were performed to improve the accuracy, response time, memory usage, and energy efficiency for reliable industrial applications [9–10]. The system was implemented using the following steps:

- *Data acquisition:* A DC motor was operated under normal and faulty conditions (e.g., mechanical imbalance, misalignment, and overheating). The MPU6050 sensor was used to collect real-time vibration (accelerometer) and temperature data during motor operation. Data was collected through the STM32 Nucleo-F411RE board via I2C and transmitted to a computer for preprocessing and model training.
- *Data preprocessing:* The collected sensor data were cleaned and formatted. Features such as the mean, standard deviation, and frequency-domain characteristics of the vibration signals were extracted. The dataset is labeled based on the motor condition, that is, Healthy or Faulty.
- *Model training:* A Machine Learning classification model (e.g., Decision Tree, SVM, or a lightweight neural network) is trained using the pre-processed data. The model was evaluated for accuracy, precision, recall, and F1-score.
- *Model deployment:* The trained model was converted to TensorFlow Lite Micro or a similar format. The model is integrated into the STM32 firmware using embedded C/C++ or STM32CubeIDE. The STM32 is programmed to collect data from the MPU6050 sensor, to check the AI model data in real-time, and display the motor status on an OLED screen.
- *Real-time testing and evaluation:* The complete system was tested under various operating conditions. The model predictions were validated against the actual motor conditions. The performance metrics, such as detection accuracy, response time, and system reliability, were recorded.
- *Optimization:* The code and model were optimized to fit within the STM32 memory constraints, and the power consumption and sensor stability were evaluated to ensure reliable real-world performance.

Hardware

- *DC motor:* The primary machine is monitored for health and faults during operation. The DC motor used in the experiments is shown in Figure 2.
- The MPU6050 (vibration sensor) measures the vibration (acceleration) and angular movement of the motor. It includes a built-in temperature sensor for monitoring heat levels. The MPU6050 Vibration Sensor used for the experiment is shown in Figure 3.

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- The STM32 Nucleo-F411RE is a powerful advanced RISC machines (ARM) Cortex-M4 microcontroller development board for running the AI model and interfacing with all sensors in real time. The STMicroelectronics board used for the experiments is shown in Figure 4.
- The L298N motor driver module controlled the speed and direction of the DC motor, acting as an interface between the STM32 board and motor. The motor driver used for the experiments is shown in Figure 5.
- *OLED display (e.g., 0.96" I2C OLED):* Displays the motor status (Healthy or Faulty), sensor readings, or AI output directly on the hardware. The OLED Display used for the experiments is shown in Figure 6.

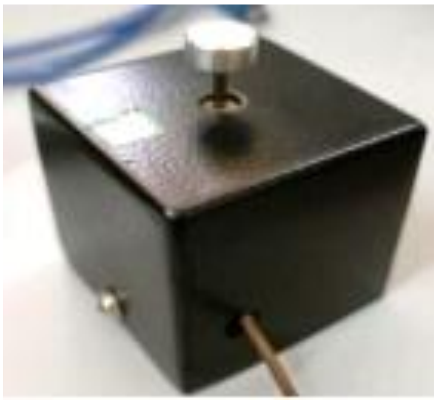

Figure 2. DC motor.

Figure 3. MPU6050.

Figure 4. STM32 Nucleo-F411RE.

Figure 5. Motor driver.

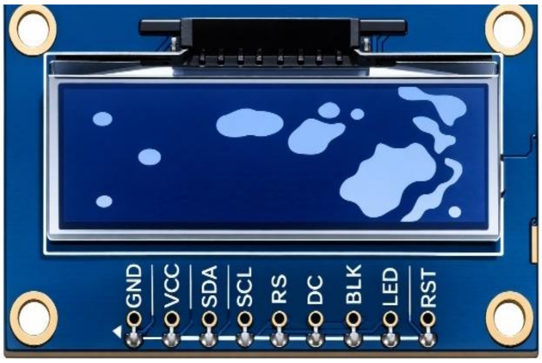

Figure 6. OLED.

Software

1. *Development environment:* STM32CubeIDE was used for firmware development, debugging, and peripheral configuration.
2. *Machine learning toolkit:* NanoEdge AI Studio enabled model training with vibration/temperature data and generated C-based libraries for embedded deployment.
3. *Firmware libraries:* The STM32 HAL libraries managed the peripherals (GPIO, I2C, UART, Timers), whereas cortex microcontroller software interface standard (CMSIS) provided low-level Cortex-M4 access.
4. *Communication protocols:* I2C was used to interface the MPU6050 sensor and the SSD1306 OLED display, supported by a lightweight driver library.
5. *Data processing and AI inference:* Real-time sensor data are acquired, features are extracted, and processed by the NanoEdge AI library to classify motor states (normal/anomalous).
6. *Programming language:* All firmware, including AI logic and display functions, was implemented in the C language for efficiency.
7. *Debugging tools:* The onboard ST-LINK/V2 debugger enables firmware flashing, real-time debugging, and execution monitoring.

RESULTS

After training and deploying the AI model using the NanoEdge AI Studio and integrating it with the STM32 Nucleo-F411RE board, the system was evaluated under diverse operating conditions to assess its performance. To assess its effectiveness in distinguishing between normal and anomalous motor behavior, the vibration data collected for normal and abnormal motor operations are shown in Figures 7 and 8, respectively.

The performance of the proposed anomaly detection model was evaluated using metrics such as accuracy, balanced accuracy, and confusion matrix. Accuracy is defined as the ratio of correctly classified samples to the total number of samples. Balanced accuracy considers both sensitivity and specificity, making it suitable for datasets with near-equal class distributions. The confusion matrix results demonstrated zero false positives and zero false negatives during testing, indicating a stable classification performance under the conditions of the collected dataset. Memory utilization remained below 1 kB of RAM and less than 1 kB of Flash, confirming the feasibility of deployment on resource-constrained, embedded systems.

CONCLUSION

The proposed system successfully demonstrated an embedded AI-based approach for real-time fault detection in DC motors using the STM32 Nucleo-F411RE platform. By integrating vibration and temperature sensing with an optimized anomaly detection model, the system enables the accurate identification of abnormal motor behavior under different operating conditions. The deployment of the trained model directly on the microcontroller ensures low latency, reduced power consumption, and complete independence from the cloud infrastructure. Experimental evaluation confirms reliable classification performance with minimal memory usage, making the solution suitable for industrial environments with constrained computational resources. The implementation highlights the feasibility of edge intelligence in predictive maintenance applications. Overall, the proposed framework offers a scalable, cost-effective, and secure monitoring system that can be extended to broader industrial machinery health monitoring scenarios. The overall system performance and real-time anomaly detection results are shown in Figure 9.

The anomaly detection model was optimized using NanoEdge AI Studio, where 16,379 libraries were benchmarked. The best library achieved a Quality Index of 99.9 and a Balanced Accuracy of 90%, showing excellent classification capability. The memory usage remained extremely low, requiring only 0.9 kB RAM and 0.3 kB Flash, making it ideal for deployment on STM32 microcontrollers.

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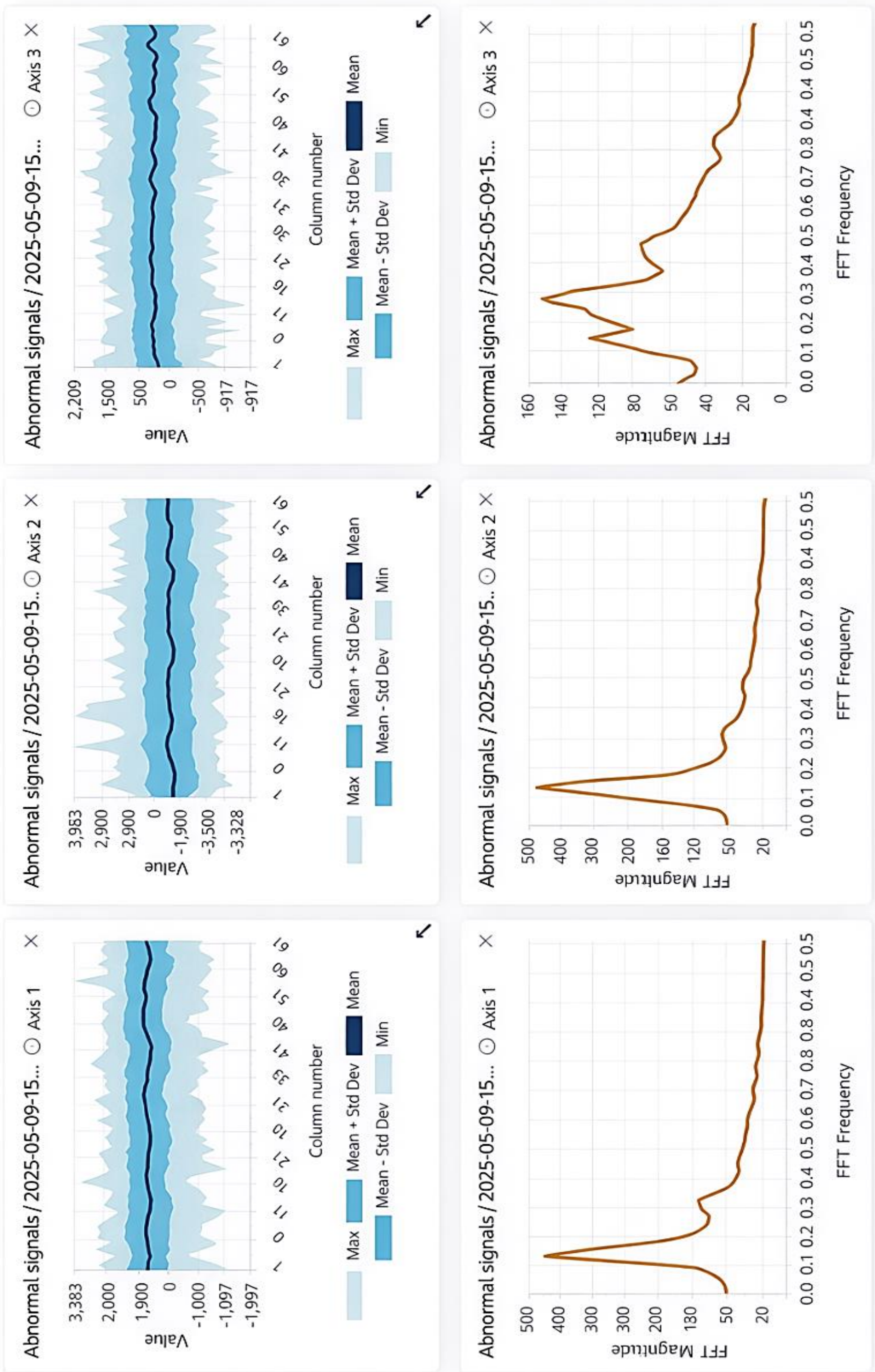

Figure 7. Vibration data during normal motor operation.

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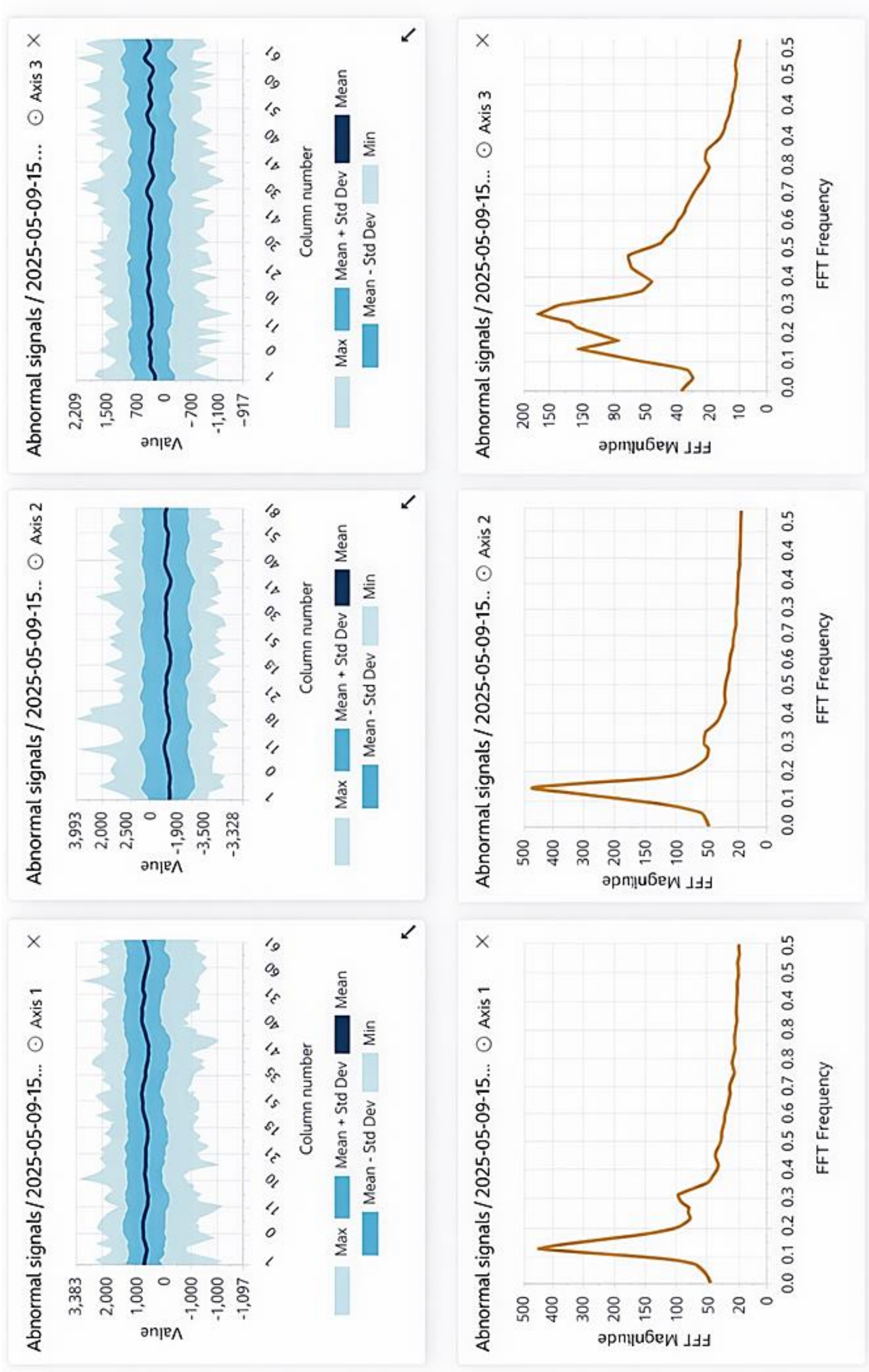

Figure 8. Vibration data during abnormal motor operation.

Figure 9. Results: overall system performance and real-time anomaly detection.

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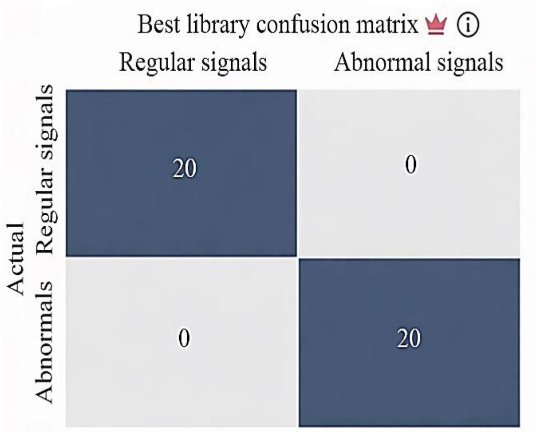

Figure 10. Confusion matrix from NanoEdge AI model.

The dataset consisted of 102 abnormal and 100 normal vibration signals collected using an MPU6050 sensor. The selected model classified both categories with 100% confidence level. The confusion matrix demonstrated perfect performance, with all regular and abnormal signals correctly identified and no misclassifications.

Overall, the model provides highly reliable, lightweight, and accurate anomaly detection that is suitable for real-time embedded motor health monitoring. The confusion matrix obtained from the trained anomaly detection model is shown in Figure 10.

Future Scope

In future work, collecting a larger and more diverse dataset, testing multiple motors, and introducing varied fault conditions (e.g., bearing wear, misalignment, and overheating) will significantly improve the robustness of the model and broaden its industrial applicability. Edge-to-cloud connectivity can be added using wireless modules (Wi-Fi/Bluetooth) for remote monitoring and analysis. The framework can be extended to support multiple motors or machines, making it a flexible platform for large-scale industrial health monitoring. Future iterations can include mobile/web dashboards and automated maintenance triggers to further reduce downtime and enhance safety.

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