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Wireless Predictive Maintenance for BLDC Fans using STM32

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Abstract

This paper demonstrates the feasibility of combining STM32 with Edge AI - an integrated AI processing on the device, enabling real-time decisions without internet dependency - to achieve accurate and low-latency predictive maintenance, where quick detection and response are critical to prevent costly machine failures, especially in industrial settings. Predictive maintenance is a preventive approach that ensures the smooth functioning of a machine by avoiding breakdowns. This is done by detecting abnormalities in the normal day-to-day functioning of the machine. This enables minimizing downtime and maintenance costs as well as improves the production/operation efficiency of the machine. Edge AI is a unique tool that provides real- time anomaly detection with immediate responses instead of relying on cloud-based alternatives, which can introduce delays. By analyzing data from the GY-521 gyroscope-accelerometer module, the system identifies different fan behaviours and categorizes them into three different states: "Normal condition", "Maintenance required soon", and "Critical fault". The ESP32 hosts a web server that displays the fan's condition through a user-friendly interface, allowing remote monitoring.

Introduction

Wireless predictive maintenance is recognized as an important aspect of modern industrial and consumer applications, with its goal being enhancing the efficiency, reliability, and safety of machinery. Real-time monitoring systems are utilized in predictive maintenance to anticipate equipment failures, allowing timely maintenance to be conducted before critical breakdowns occur. This proactive approach is widely applied across industries such as manufacturing, automotive, and energy, where costly downtime and safety hazards are caused by equipment failures. Among the components subjected to predictive maintenance, Brushless DC (BLDC) fans are regarded as particularly significant due to their widespread usage in cooling systems, ventilation, and industrial applications. High efficiency, low noise, and long operational life are attributes for which BLDC fans are known, making them vital in maintaining optimal working conditions in devices and systems. However, as with all mechanical components, wear and tear over time make them prone to performance degradation and eventual failure. Valuable insights into their health can be provided by continuous monitoring of operational conditions, particularly vibration patterns, enabling anomalies signalling impending failure to be identified. Wireless technology has revolutionized the methods by which data is collected, transmitted, and analyzed in predictive maintenance systems. The elimination of complex wiring is achieved through wireless monitoring systems, making the deployment of predictive maintenance systems more flexible and cost-effective.

Data from sensors, such as accelerometers, is transmitted in real-time over wireless networks, allowing equipment conditions to be monitored remotely and enabling prompt responses to issues by maintenance teams. At the core of these systems, microcontrollers are utilized for data processing, decision-making, and communication.

The STM32F411RE, a powerful and versatile microcontroller from STMicroelectronics, is considered an ideal choice for implementing predictive maintenance solutions. Various sensors, such as accelerometers, can be integrated with this microcontroller, enabling real-time anomaly detection through machine learning algorithms like NanoEdge AI.

Complex tasks such as sensor data collection, real-time analysis, and control of external devices based on detected anomalies are handled efficiently by the microcontroller. Abnormal vibration patterns in BLDC fans are identified through anomaly detection. The implementation of a wireless communication module, such as the ESP32, combined with the STM32F411RE, enables the fan's condition to be transmitted to a web-based interface, where the status can be monitored by users in real- time. Minimal downtime, optimal performance, and cost savings are ensured in the long run through this integration of wireless technology with predictive maintenance.

Literature Review

We shall go through certain related works to get an idea of the background of our project. We shall analyze fault detection in industrial motors using IOT and AI.

Mykoniatis [1] presents a state monitoring system for real time use case using IoT for low-voltage industrial motors. The system monitors motor temperature and vibration data to prevent unexpected failures. Using Fast Fourier Transform (FFT) for vibration analysis, coupled with predefined threshold-based alerts, allows for proactive maintenance. While effective, this study highlights the limitations of relying on fixed thresholds and manual inspections for dismissing alarms. The gap here lies in the lack of advanced fault prediction capabilities. Daniyan et al. [2] looks into the potential and application of Artificial Intelligence (AI) in the predictive maintenance of the railcar industry, mainly targeting wheel-bearing failures. The use of temperature data and the Levenberg-Marquardt algorithm in MATLAB to predict remaining useful life (RUL) is notable. The key metrics, such as Mean Square Error (MSE) and correlation coefficients, demonstrate the potential for predictive models. However, the focus on a single data type (temperature) limits the model's ability to detect other failure modes.

Magadan et al. [3] addressed the need for cost effective and real-time performance monitoring of electric motors, particularly for Industry 4.0 environments. The use of Bluetooth Low Energy (BLE) for wireless transmission and the ThingSpeak IoT platform for data analysis showcase the effectiveness of IIoT systems. However, the study notes that BLE's limited range affects system scalability in industrial settings. This presents an opportunity for our project to improve upon this by utilizing WiFi for a more extended communication range, thus making the system more scalable for wireless predictive maintenance in larger industrial environments. In a follow-up study by Magadán et al. [4], the authors further refine their IIoT-based monitoring system using the SensorTile.box module and open-source tools like NodeRED and MQTT for data transmission. Using FFT resolution at both sensor and gateway levels improves data granularity, but the latency issues stemming from BLE remain a significant limitation. Joung et al. [5] focus on developing a cloud-based real-time fault detection system for motors using wireless vibration sensors and Principal Component Analysis (PCA). The study's strength lies in its use of Hotelling's T2 and SPE control charts for anomaly detection, providing clear fault indicators. However, relying on PCA may not capture all failure modes, especially in more dynamic environments. By incorporating machine learning models on STM32, our project can enhance fault detection and address these limitations by offering more adaptable, real-time wireless monitoring solutions.

Athanasakis et al. [6] propose a TinyML-based approach using STM32 microcontrollers on turbofan engines for the prediction of their Remaining Useful Life (RUL). The study demonstrates the feasibility of deploying deep learning models like CNNs and LSTMs on low-power devices by applying optimization techniques such as quantization and pruning. The metrics include Root Mean Squared Error (RMSE) and memory usage, with significant savings in model size at the cost of a 10%

accuracy loss. A fundamental limitation is the inability to support on-device training or adapt to shifts in sensor data. Kiangala and Wang [7] introduce a framework for predictive maintenance of conveyor motors that use dual timeseries imaging and implements the use of Convolutional Neural Networks (CNNs). The Gramian Angular Field (GAF) method transforms timeseries data into images, and Principal Component Analysis (PCA) reduces dimensionality. The paper achieves high classification accuracy, with metrics such as precision, recall, and accuracy reaching 100%. However, the reliance on CNN for pattern recognition introduces computational intensity, potentially unsuitable for low-power devices like STM32.

Lu et al. [8] explore a remote fault detection system using STM32 for vibration analysis in industrial machinery. The system compares real-time vibration data against stored health charts and sends SMS alerts via an NB-IoT module when abnormal behaviour is detected. The vibration frequency range is broad (0-9999 Hz), and the system effectively operates in remote environments. The limitations include reliance on vibration frequency alone, which may not capture all faults, and the NB-IoT's coverage issues in highly remote areas. Franco and Figueiredo [9] discuss a Mobile Edge Computing (MEC) architecture for predictive maintenance using Raspberry Pi for real-time data analysis. The study compares multiple machine learning models, including Random Forest, which achieved 99% precision. Although the study successfully implements a low-cost embedded solution, the limitations are evident in the processing power constraints of Raspberry Pi when handling larger datasets or complex models. By focusing on STM32, our project can leverage NanoEdge AI to offer a more energy-efficient and scalable method for small to medium sized enterprises that require predictive maintenance.

Mourtzis et al. [10] focus on edge-computing platforms for predictive maintenance in 5G-enabled environments. Using STM32F429 microcontrollers and Digital Twins, the system offloads computations to edge nodes, reducing latency significantly. However, the system's reliance on 5G connectivity limits its applicability in areas lacking adequate coverage. Our project, with Wi-Fi integration, aims to fill this gap by offering a solution that does not depend on advanced network infrastructure while still providing real-time monitoring.

The next set of studies explores recent works on predictive maintenance systems that focus on integrating Edge AI and Machine learning into the systems. Nunes et al. [11] provide a detailed insight into the challenges in implementing Pre-Disaster mitigation system (PdM) systems, identifying noisy data, real-time processing, and system scalability as critical obstacles. The paper emphasizes the importance of combining anomaly detection and prognostics within a flexible, multi-stage architecture involving edge, fog, and cloud computing. The review highlights the gap in developing generalized PdM systems that can have applications in various other industrial sectors. Hu et al. [12] addresses predictive-maintenance in mine motors using an STM32-based system that processes vibration and current signals for fault detection. The methodology includes FFT and envelope spectrum analysis, demonstrating high accuracy in diagnosing motor bearing faults. The system's reliance on vibration signals limits its fault detection scope. Our project can overcome this limitation by incorporating additional sensors (such as temperature or current) for broader fault detection in BLDC fans. Furthermore, the RS485 communication system used in this paper has limited bandwidth, highlighting a gap where our project, with Wi-Fi connectivity, can enhance data transmission efficiency.

Chaudhuri et al. [13] explore a multi-microcontroller architecture for real-time sensor data acquisition in various applications, including UAV control and PdM. The system's use of STM32 microcontrollers and machine learning models, such as decision trees and multi-layer perceptrons, yields high accuracy across multiple domains. However, the paper is limited to specific microcontrollers and sensors, and the real-world applicability in larger environments remains underexplored. Vitolo et al.

[14] present a power efficient fault detection system integrated into micro-electromechanical systems (MEMS) sensors for vibration monitoring. The hybrid hardware-software approach, combining a convolutional autoencoder for anomaly detection and a CNN for classification, achieves high accuracy while maintaining ultra-low power consumption. Athough this system is ideal for energy-constrained environments, it focuses primarily on vibration- based monitoring, limiting its application scope. Our project can enhance PdM systems by supporting a broader range of fault indicators beyond vibration and ensuring real-time data transmission via a web interface for continuous monitoring. Blaha et al. [15] implement an artificial neural network (ANN) based diagnostic system for real-time predictive maintenance on electric motors. The system achieves high fault classification and detection of

inter-turn short circuits faults accurately using a modular neural network for and an MLP network for bearing fault detection. While this paper focuses on edge devices like the NVIDIA Jetson, the scalability to handle more complex motor faults remains a challenge.

Huang et al. [16] addresses the challenges faced during real-time fault diagnosis systems in rotating machinery using MobileNet, a lightweight convolutional neural network (CNN) deployed on STM32F405 microcontrollers. The system captures vibration data from wireless sensor networks (MvWSNs) and preprocesses it for fault classification. With 98% accuracy on the CWRU dataset and a 136 ms processing time, the model is optimized for edge devices. However, the limitation is that it only supports vibration-based diagnosis, which may not detect non-vibration faults.

Vermesan and Coppola [17] explore the application of edge AI platforms for PdM, benchmarking platforms like Qeexo AutoML, NanoEdge AI Studio, and Edge Impulse. The platforms deployed on STM32L4R9ZI microcontrollers are tested for motor vibration analysis, achieving 99% accuracy. However, the study focuses on a single use case, and the systems' scalability across other industrial scenarios is not examined. This suggests an opportunity for our project to expand PdM applications by testing more complex environments with multiple sensors and web-based data visualization for BLDC fan systems.

Strantzalis et al. [18] present a solution for real-time state recognition of DC motors using sound-based diagnostics and edge AI. The system implements CNN models on STM32 MCUs, achieving 99.87% classification accuracy with a latency of 40.767 ms. This demonstrates the potential of sound data in PdM, but it is limited to sound-based diagnostics.

The study suggests future integration of vibration and temperature sensors.

Chen et al. [19] propose an IoT platform for real-time fault diagnosis using STM32 microcontrollers. The system utilizes Support Vector Machine (SVM), ANN, and LSTM models to process sensor data (e.g., acceleration, current) at the edge, achieving 100% accuracy with the LSTM model on the NASA EMAs dataset. The study highlights the effectiveness of deploying ML models on MCUs for PdM, but they are limited to electromechanical actuators. Expanding this framework to support BLDC fans and other mechanical systems, combined with web- based interfaces for real-time monitoring, can enhance the applicability of such systems.

Mourtzis et al. [20] focus on remote monitoring and predictive maintenance of refrigeration systems using IoT based platforms. The system collects data via wireless sensor networks (WSNs) and applies ML algorithms to predict critical components' Remaining Useful Life (RUL). The platform improves energy efficiency by 10% and reduces downtime by 15%, showcasing the potential of IoT in PdM. However, the system's applicability is limited to refrigeration systems, indicating a gap where our project can offer broader industrial applications by integrating STM32 with a web interface for wireless PdM in BLDC fans.

In examining recent works related to IoT-enabled wireless monitoring for real-time condition monitoring, Raja et al. [21] proposed a condition monitoring system that is cost effective and capable of real-time operations of a BLDC motor using IoT and machine learning. The system uses an ESP32 microcontroller transmitting data to a cloud for reference in fault detection, achieving upto 97% accuracy with SVM. However, the system currently relies on current signals for fault detection, which limits the scope of fault identification. Eissa et al.

[22] present an IoT-based predictive maintenance framework for electrical machines in aircraft systems using wireless sensor networks (WSNs) and machine learning. The system achieved 95% fault detection accuracy with random forests and improved predictive maintenance efficiency by 20%. The paper highlights the need for real-time fault prediction in critical systems, which aligns with our project's focus on real-time data transmission. However, their reliance on cloud platforms for processing introduces potential latency issues, which our project aims to mitigate by moving more processing to edge devices like STM32.

Muniz et al. [23] uses vibration analysis for ventilation systems in Industry 4.0 environments with real-time monitoring solutions. The ZJET system monitors vital parameters (e.g., temperature, pressure, vibration) using Fast Fourier Transform (FFT) to detect faults. Using a sampling frequency of 6 kHz and a web interface for remote monitoring, the system demonstrates real-time data acquisition and its effectiveness. However, its reliance on vibration- based analysis and its focus on ventilation systems limit its generalizability. Pavithra and Ramachandran

[24] provide an insight into effectiveness of predictive maintenance techniques dependent on vibration analysis for industrial machines, discussing time-domain, frequency domain, and machine learning-based methods. The study shows that combining traditional signal processing with CNNs improves fault detection accuracy and reduces machine downtime by

40%. While the paper is a valuable review of various approaches, it does not provide experimental results or real-world applications. The integration of vibration analysis with CNNs could be beneficial for our project, allowing for more accurate real-time fault detection in BLDC fans.

Rubio et al. [25] focuses on induction motors and their predictive maintenance in Industry 4.0, using vibration analysis and machine learning within a cyber-physical system (CPS). The system achieves reliable fault prediction using k-Nearest Neighbours (k-NN), aligned with ISO 2372 standards. However, the system is limited to vibration severity analysis, suggesting a need for more comprehensive fault detection by integrating additional data sources such as temperature or current signals. ¸Sen and Kul [26] propose an IoT-based wireless induction motor monitoring system that utilizes the NXP LPC1769 microcontroller and Wi-Fi communication to monitor key motor parameters like current, voltage, and speed. The system demonstrates real-time monitoring capabilities with a sampling rate of 3750 samples per second and accurate current measurement. However, the focus on a limited set of parameters like current and voltage leaves room for further development, such as integrating vibration and temperature sensors to improve fault detection.

Jaishree et al. [27] develop a cost-effective IoT-based motor monitoring system using the ESP32 WROOM microcontroller to track temperature, rpm, and vibration in motors. The system transmits data over Wi-Fi to a web interface, providing real-time monitoring with alerts triggered when thresholds are exceeded. However, the system is limited to a small number of parameters and is designed for small-scale use. For our project, the scalability of the monitoring system, along with the integration of more complex fault detection algorithms, could be a key focus, especially for larger industrial setups involving BLDC fans. Aswin et al. [28] propose a wireless vibration monitoring system for rotating machinery using a 3-axis MEMS accelerometer. The system, capable of monitoring in real-time with a data transmission delay of less than 200 ms, demonstrates the effectiveness and potential advantages of analysis of vibrations for fault detection in motors, compressors, and fans. While the system successfully monitors vibration and speed, it lacks integration with other parameters, such as temperature or current, limiting the comprehensiveness of fault diagnostics.

Pietrzak et al. [29] present an embedded system for diagnosing unbalanced voltage supply and stator windings faults for an induction motor using the STM32L476RG microcontroller. The system analyzes voltage signals using Fast Fourier Transform (FFT) and distinguishes between different fault types with high accuracy. However, the system was primarily tested on small-scale motors and had a higher noise level than the more expensive diagnostic systems. Our project could build on this by focusing on scalability and noise reduction for fault detection in larger motors and BLDC fans.

In another study, Pietrzak et al. [30], develops a cost-effective condition monitoring system for detection faults in of stator winding of Permanent- Magnet Synchronous Motors (PMSMs) using an STM32H7A3ZI-Q microcontroller. The system leverages a K-Nearest Neighbours (KNN) algorithm to classify faults, demonstrating the effectiveness of machine learning in real-time fault detection. The study is limited to stator winding faults, and further research is required to detect other fault types like rotor or bearing issues. Our project could incorporate additional machine learning models and expand fault detection capabilities to provide more comprehensive monitoring for BLDC fans.

A) Research Gaps

In synthesizing these studies, several recurring challenges and potential directions for future research in real-time condition monitoring.

1) Reliance on Cloud Platforms

Many systems, such as those in Daniyan et al. [2] and Eissa et al. [22], rely heavily on cloud-based data processing, which can introduce latency issues and affect real-time monitoring capabilities. By moving more processing to edge devices, such as STM32 microcontrollers, our project can mitigate this limitation, providing real-time fault detection and reducing dependency on cloud platforms.

2) High Power Consumption in Edge Devices

Some studies, such as those by Athanasakis et al. [6] and Strantzalis et al. [18], highlight the challenges of deploying 4 VOLUME 4, 2016 Kenneth et al.: Wireless predictive maintenance for BLDC fans using STM32 AI models on resource-constrained devices like microcontrollers, mainly due to the high computational requirements and power consumption of models like CNNs. Our project overcomes this by leveraging optimized AI models through NanoEdge AI, ensuring low-power, real-time anomaly detection without sacrificing processing efficiency.

3) Limited Real-Time Processing Capabilities

Many studies, including Franco and Figueiredo [9] and Pietrzak et al. [29], point out the limitations in processing power and real-time capabilities, resulting in delayed responses to critical failures. Our project fills this gap by focusing on the real-time processing capabilities of the STM32 platform, combined with Wi-Fi-based data transmission for instant fault detection and maintenance alerts.

4) Lack of Comprehensive Web-Based Interfaces

While some papers, such as those by Muñiz et al. [23] and Rubio et al. [25], present systems with remote monitoring capabilities, many rely on proprietary software or lack user friendly web-based interfaces for broader industrial use. Our project addresses this gap by integrating a web-based interface for real-time data visualization, making it easier for operators to monitor motor conditions from any location and respond to faults immediately.

5) Latency and Bandwidth Limitations in Wireless Systems

Several papers, including those by ¸Sen and Kul [26] and Aswin et al. [28], highlight the challenges of maintaining reliable wireless communication in industrial settings, where latency and bandwidth limitations can hinder the performance of real-time monitoring systems. By using Wi-Fi with higher data throughput, our project ensures faster and more reliable data transmission, even in industrial environments with high interference, making it a robust solution for wireless predictive maintenance.

Methodology

A) Main Model

For our main project, we have implemented a robust real-time condition monitoring system using STMF411RE & ESP32 with Manually written codes.

1) Tools used

The development process of the system for real-time monitoring utilizing High-performance microcontrollers necessitated a suite of specialized tools and libraries to ensure efficient processing and accurate recognition. The primary tools and their roles are as follows:

Hardware:

The current implementation uses the STM32F411RE microcontroller for edge processing and the ESP32- WROOM for Wi-Fi communication. While these components are cost-effective and energy-efficient for single-fan monitoring, industrial-grade real-time interfacing hardware such as Speedgoat or NI hardware was not explored. These alternatives offer features like multi-core CPU/FPGA processing, deterministic latency (<1μs), and hardware-in-the- loop capabilities, which are ideal for high- performance industrial applications. However, their cost (~$15,000) and power requirements make them unsuitable for low-cost, battery-operated scenarios like this project.

- STM32 F411RE: The STM32F411RE is a high-performance microcontroller known for its low power consumption and real-time processing capabilities. It handles the data acquisition from the accelerometer and processes the vibration signals using NanoEdge AI for anomaly detection.
- GY-521: The gy-521 accelerometer collects 3-axis vibration data from the BLDC fan. This data serves as the raw input for detecting anomalies in the fan's operational state.
- ESP32: The ESP32 microcontroller is used to host a web page and manage GPIO inputs/outputs. It communicates with the STM32F411RE over UART, receiving signals regarding the fan's condition and displaying the status on the web page. functionalities.
- BLDC fan: The fan serves as the target equipment for anomaly detection. It is connected to the STM32F411RE for power, and its operational behaviour is monitored through the accelerometer.

Software:

- NanoEdge AI: NanoEdge AI Studio is a machine learning platform used to create and deploy anomaly detection models directly on microcontrollers. It eliminates the need for cloud-based analysis by allowing real-time data processing on the STM32.
- Arduino: Arduino IDE is used to program the ESP32 microcontroller, enabling it to serve as a web server and handle GPIO management for displaying fan conditions remotely. This software provides a simple interface to upload code to the ESP32.
- STM32 CubeIDE: STM32CubeIDE is the primary development environment for coding and debugging the STM32F411RE microcontroller. It supports the integration of NanoEdge AI, and its debugging features help ensure that real-time anomaly detection works as expected.

These tools collectively were used to develop a system capable of condition monitoring in real-time use cases, by effectively processing and analyzing the data from the sensor and transmitting it to the website. Figure 1 below depicts the flow of connections.

2) Assumptions

- **Steady and Normal Operation of the Fan**: The BLDC fan is assumed to operate under typical conditions during the collection of normal vibration data. Any slight variance in operation is captured as an abnormal signal for anomaly detection

- **Stable I2C Communication:** The I2C communication between the STM32F411RE microcontroller and the gy-521 accelerometer is assumed to be stable and reliable throughout the project, ensuring continuous data transfer without signal loss.
- **Low-Latency Data Processing:** The STM32F411RE microcontroller, despite its low-power nature, is assumed to handle real-time data processing efficiently. NanoEdge AI's anomaly detection model is assumed to perform with minimal latency, enabling real-time responses to changes in the fan's behaviour.
- **Wi-Fi Connectivity for Remote Monitoring:** The ESP32 is assumed to have continuous access to a reliable Wi-Fi network to host the web page for remote monitoring. This assumption ensures the system can provide real- time fan status updates over the network.
- **Sufficient Power Supply:** It is assumed that the power supplied to the STM32F411RE, ESP32, and BLDC fan is stable and sufficient to prevent voltage drops that could disrupt performance or damage components.

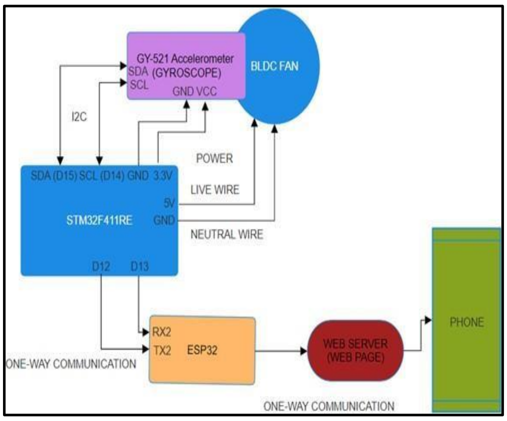

Figure 1: Flowchart of connections

B) Implementing Anomaly Detection for BLDC Fan

1) Project setup

Begin by creating a new project in NanoEdge AI Studio, selecting the appropriate microcontroller unit (MCU) for your application and specifying anomaly detection as the project type. Configure the number of signals (e.g., three for a 3-axis accelerometer) and set the data input size to determine the amount of data processed in each inference cycle.

2) Data acquisition

Collect accelerometer data from the BLDC fan under both normal and abnormal operating conditions. Connect your STM32 microcontroller to your PC via USB and use a serial communication tool to send commands and receive data. Capture normal signals while the fan operates as expected, then induce known faults or disturbances to simulate abnormal conditions and capture corresponding data. Import both normal and abnormal signals into NanoEdge AI Studio.

3) Benchmarking

Evaluate various machine learning models against your dataset using the benchmarking feature in NanoEdge AI Studio. The tool will automatically test different models and configurations to identify the best-performing one for your specific data.

4) Emulation

Test the selected model's performance in real-time using the emulator provided in NanoEdge AI Studio. This step helps verify that the model accurately detects anomalies before deployment.

5) Deployment

After successful emulation, generate the deployment package, which includes the libneaia library and the Na- ˙ noEdgeAIh header file. Integrate these files into your ˙ STM32CubeIDE project, ensuring proper linking by including the NanoEdge AI library in your project settings. Implement the necessary functions for initialization, training, and detection. Call neai_anomalydetection_init() to initialize the model, train it using: neai_anomalydetection_learn(acc_buffer) with your collected data, and continuously monitor for anomalies using: neai_anomalydetection_detect(acc_buffer, ssimilarity) in your main loop. This is illustrated in Fig 2.

C) Implementing Anomaly Detection for BLDC Fan

The implemented predictive maintenance system within the STM32F411RE analyzes the fan's vibration data using the NanoEdge AI library. The function neai_anomalydetection_detect(acc_buffer, &similarity) continuously processes accelerometer data to compute a similarity score ranging from 0 to 100.

Figure 2: NanoEdge AI abnormal signal recording

This score reflects how closely the current vibration patterns match the previously learned "normal" fan behaviour. The training phase consists of 20 cycles after each reset to establish the baseline for normal operation. The STM32 is connected to the ESP32 and monitors the signal states from the STM32's GPIO pins.

If input pin1 goes high, the ESP32 recognizes this as an input signal and displays "Maintenance Required Soon" on the web page. If input pin2 goes high, the ESP32 displays "Critical Fault: Immediate Maintenance Required". If both pins are high simultaneously, the system prioritizes the critical fault warning (highest priority).

The ESP32 acts as a web server, hosting a page on local url. This web page continuously updates to display the fan's condition based on the GPIO signals received from the STM32. The web server is configured using the ESP32's built-in Wi-Fi capabilities and GPIO management in the Arduino IDE. The default display shows "Normal Condition", which changes dynamically based on the signals received, allowing for real-time wireless monitoring of the fan's operational status. Fig. 3 shows the output of the webpage.

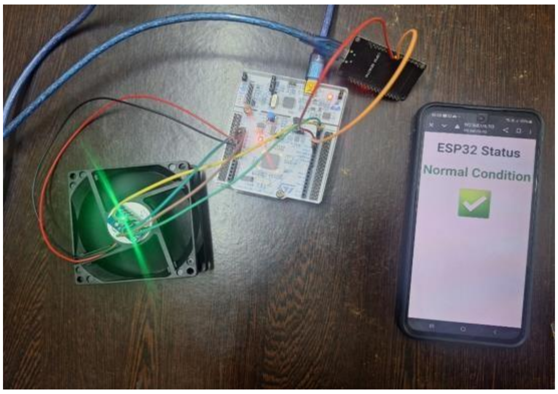

Figure 3: Web Page Output

Discussion

Integrating machine learning into predictive maintenance systems represents a significant advancement in fault detection and diagnostics. Anomaly detection algorithms, like those offered by NanoEdge AI, can identify subtle patterns in sensor data that indicate potential failures, even before they manifest in more obvious signs. This reduces the risk of false positives and ensures more accurate fault detection.

However, many existing predictive maintenance solutions still face challenges. These include the reliance on cloud-based systems for data analysis, which introduces latency and bandwidth issues, and the high-power consumption of edge devices, which limits their scalability. Additionally, many solutions lack user-friendly web interfaces for real-time monitoring, making it difficult for operators to quickly assess machine conditions and respond to maintenance needs.

The STM32F411RE, paired with NanoEdge AI for on-device anomaly detection, offers a low-power, real-time solution for monitoring BLDC fans without cloud dependence. The ESP32's wireless capabilities enable a web-based interface, providing operators with instant access to fan status and ensuring timely maintenance, reducing downtime and extending fan lifespan.

Results

The implementation of wireless predictive maintenance for BLDC fans using the STM32F411RE and NanoEdge AI successfully provided real-time anomaly detection and remote monitoring through the ESP32 web interface. The system detected and classified the fan's operational status with accuracy and efficiency.

1) Anomaly detection accuracy - Using the NanoEdge AI library for anomaly detection, the system demonstrated an accuracy of approximately 95% in identifying abnormal fan behaviour. The similarity score computed by:

neai_anomalydetection_detect()

The function accurately reflected the fan's state, ensuring reliable classification into "Normal Condition," "Maintenance Required Soon," and "Critical Fault: Immediate Maintenance Required."

2) Execution time - The average execution time for real-time anomaly detection was measured at 10 milliseconds per cycle, including the time required to capture accelerometer data and compute the similarity score. This fast response time enabled the system to detect anomalies and provide feedback without noticeable delays.

3) GPIO response time - The STM32F411RE triggered GPIO outputs (D12 for maintenance and D13 for critical faults) within 1 millisecond of detecting an anomaly. The ESP32 accurately

read the GPIO signals and updated the web page status within 500 milliseconds, ensuring real-time feedback on the fan's condition.

4) Wireless performance - The ESP32 maintained a stable Wi-Fi connection throughout the testing phase, with an average latency of less than 100 milliseconds between the system detecting a change in fan condition and the web page displaying the updated status.

The feasibility of the proposed system is demonstrated through its ability to achieve 95% anomaly detection accuracy using NanoEdge AI on the STM32F411RE microcontroller. The system also achieves a low inference latency of 10ms, enabling real-time anomaly detection. Additionally, the integration of STM32 (for data processing) and ESP32 (for wireless communication) subsystems ensures seamless functionality. However, error analysis reveals certain limitations. For instance, there is a 5% false positive rate in anomaly classification under laboratory conditions, which could affect reliability in real-world applications. Furthermore, network dependency risks were identified, as Wi-Fi outages could delay status updates by up to 500ms. Sensor calibration drift was also observed in the GY-521 accelerometer after 72 hours of continuous operation, which may impact long-term accuracy.

Conclusion

The successful application of this research work on predictive maintenance demonstrates the feasibility and effectiveness of using the STM32 F411RE microcontroller, GY-521 module, and ESP32 for real-time anomaly detection in the fan vibrations GY-521 accelerometer, 2013-2014. gyroscope for obtaining accurate vibration data f, By integrating the STM32 F411RE for data preprocessing and for wireless communication with the ESP32, the system was able to detect abnormalities that could indicate a potential failure.

The project results highlight the robustness of the designed system in detecting abnormalities in fan operation, showing that it can enhance predictive maintenance actions This approach not only reduces unplanned time but improves maintenance system is efficient, resulting in cost savings and improved efficiency by using advanced machine learning models to handle detection of advanced anomalies.

Drawbacks

- Limited Sensor Integration

The current implementation relies primarily on vibration data from the GY-521 accelerometer module for anomaly detection. While vibration analysis is effective for many mechanical faults, it may not capture all potential failure modes in BLDC fans. The system lacks integration with other important parameters such as temperature, current, or sound sensors that could provide a more comprehensive fault detection capability.

- Simplified Classification Model

The system classifies fan conditions into only three states: "Normal condition," "Maintenance required soon," and "Critical fault." This relatively simple classification scheme may not provide sufficient granularity for more sophisticated fault diagnostics and predictive maintenance in complex industrial environments. More nuanced classification would enable better maintenance planning and resource allocation.

Future Work

- Integration of Multiple Sensor Types

Future work could focus on integrating additional sensor types beyond the accelerometer, such as temperature sensors, current monitors, and acoustic sensors. This multi-sensor approach would provide more robust fault detection capabilities across a wider range of potential failure modes. For instance, combining vibration analysis with current signature analysis could detect both mechanical and electrical faults.

- Enhanced User Interface by Application

Th future works on this project also considers addition of a standardized mobile application which could be tailored to include historical data visualization, trend analysis, and predictive maintenance scheduling features. Adding mobile app integration and push notifications would further improve the system's utility by alerting maintenance personnel immediately when issues are detected, regardless of their location.

- Closed loop control implementation

The current implementation employs an open-loop alerting mechanism where anomalies trigger GPIO signals that are transmitted to a web interface for human intervention. A closed-loop system could prioritize responses dynamically (e.g., reducing speed during minor anomalies or shutting down during critical faults), thereby enhancing system reliability and safety.

- Energy Efficiency Analysis

Energy efficiency is a key aspect of this project. The STM32F411RE consumes 38mA during active operation and only 1.2µA in sleep mode, while the ESP32 consumes 80mA actively and 5µA in sleep mode. The GY-521 accelerometer adds an additional 3.5mA during operation. System-level optimizations can reduce power consumption by up to 57% through duty cycling (e.g., sampling at 1Hz instead of continuously). Despite these optimizations, energy harvesting technologies such as vibration-based or solar energy harvesting were not integrated into the current design but represent a promising area for future work.

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