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Predictive Maintenance of Electric Motors Using Machine Learning, IoT and Vibration Analysis

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Abstract

This research presents the design and development of an IoT-based predictive maintenance system for electric motors aimed at reducing unscheduled industrial downtime and maintenance costs. The system utilizes an ESP32 microcontroller integrated with a high-precision industrial-grade accelerometer to monitor three-axis vibration signatures in real-time. Raw vibration data is acquired via the Serial Peripheral Interface (SPI) protocol and transmitted to a host workstation where a Convolutional Neural Network (CNN), developed using the MATLAB Deep Learning Toolbox, performs real-time feature extraction on RGB-mapped spectrograms generated through Short-Time Fourier Transform (STFT). The model is trained using supervised learning to distinguish between 'Normal' and 'Faulty' operational states—simulated during testing via uneven motor mounting—to provide early warning signals. Remote monitoring and instant fault notifications are facilitated through the Blynk IoT framework, which provides a live dashboard for vibration visualization and mobile alerts to ensure prompt technical intervention. Experimental results validated the system's reliability in accurately identifying anomalies and predicting potential failures, demonstrating that an affordable yet high-performance diagnostic tool can be successfully implemented for smarter industrial maintenance.

1. Introduction

Electric motors are the fundamental drivers of modern industry, converting electrical energy into mechanical energy to power a vast array of processes. These machines are significant energy consumers, accounting for approximately 50% of global electricity usage and 70% of industrial electricity consumption. Given this critical role, any operational failure leads to severe financial and logistical consequences. Unscheduled shutdowns resulting from motor failure are extremely costly, estimated at approximately $50 billion per year for industrial manufacturers (Ali et al., 2024). Beyond direct repair expenses, such downtime compromises worker safety and creates detrimental ripple effects across supply chains.

To mitigate these risks, industrial maintenance strategies have evolved from Reactive Maintenance (RM) and Preventive Maintenance (PM) toward Predictive Maintenance (PdM). Karuppusamy (2020) states that the primary objective of predictive maintenance is to forecast failures immediately prior to their occurrence, thereby maximizing equipment lifespan and preventing unexpected downtime. Industry studies corroborate the economic value of this approach: a study by Deloitte (2022) indicates that implementing PdM can reduce equipment breakdowns by up to 70% and lower maintenance costs by approximately 25%. Similarly, a survey of

European companies found that PdM led to a 12% reduction in maintenance costs, a 9% increase in asset availability, and a 20% extension of asset lifetime (PwC, 2018).

2.0 Methodology

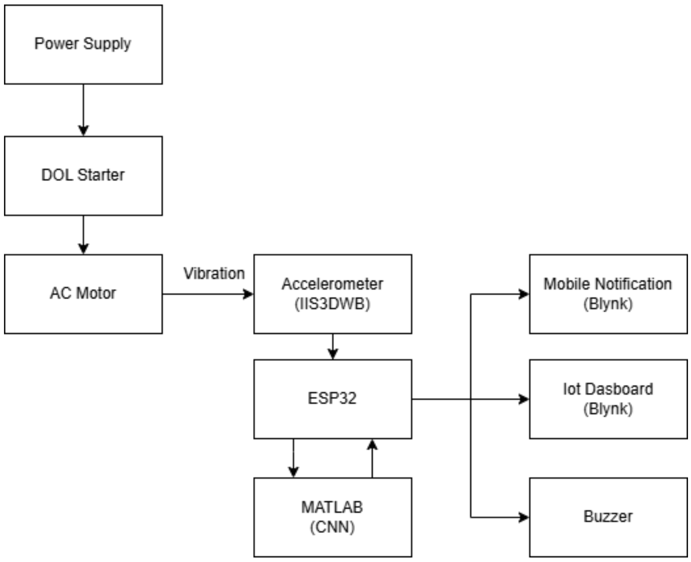


Fig. 2.0 System Block Diagram

The proposed system integrates hardware and software for real-time predictive maintenance of an AC motor through vibration analysis. The motor is controlled with a Direct-On-Line starter, with its mechanical vibrations monitored by a high-performance IIS3DWB accelerometer. This sensor data is acquired by an ESP32 microcontroller, which serves as the primary gateway for data transmission to MATLAB. In MATLAB environment, a Convolutional Neural Network (CNN) processes the vibration signals to perform fault classification and health assessment. Based on the model's output, the ESP32 communicates with the Blynk IoT platform to provide remote monitoring via a mobile dashboard and instantaneous notifications, while simultaneously triggering a local buzzer for immediate on-site alerting in the event of a detected fault.

2.1 Hardware Configuration and Material Preparation

The monitoring system was constructed using an ESP32 microcontroller as the central processing unit and a STEVAL-MKI208V1 (IIS3DWB) industrial-grade accelerometer for vibration sensing. The accelerometer was interfaced with the microcontroller via the Serial Peripheral Interface (SPI) protocol to facilitate high-speed data transmission. To ensure accurate vibration transmissibility, a custom sensor mount was designed using AutoCAD and fabricated using 3D printing technology. A piezoelectric buzzer was integrated into the circuit to serve as a local acoustic alarm for immediate fault indication.

2.2 Experimental Data Acquisition

The Experimental data collection was conducted by operating a 3-phase AC induction motor under two distinct conditions: 'Normal' and 'Faulty'. The 'Normal' state represented optimal operation, while the 'Faulty' state was simulated by introducing mechanical imbalance through uneven motor mounting. Continuous vibration data was acquired along the X, Y, and Z axes at 500ms intervals. The raw sensor data was logged and organized into structured datasets using Microsoft Excel to prepare for signal processing.

2.3 Signal Processing and Model Development

The acquired time-domain vibration signals were processed using MATLAB's Signal Processing Toolbox. To facilitate image-based classification, the raw signals were converted into 2-dimensional RGB-mapped spectrograms using Short-Time Fourier Transform (STFT). A Convolutional Neural Network (CNN) was constructed using the MATLAB Deep Learning Toolbox, consisting of convolutional layers, batch normalization, ReLU activation, max pooling, and a softmax classification layer. The model was trained using Supervised Learning to classify the input spectrograms into the predefined operational categories.

2.4 IoT Integration and Performance Evaluation

The real-time monitoring capability was established using the Blynk IoT framework. The ESP32 was configured to transmit processed status updates to the Blynk cloud via Wi-Fi. The performance of the system was evaluated by analyzing the CNN's classification accuracy on a validation dataset and verifying the latency of the push notifications and dashboard updates on the mobile application

3.0 Results And Discussion

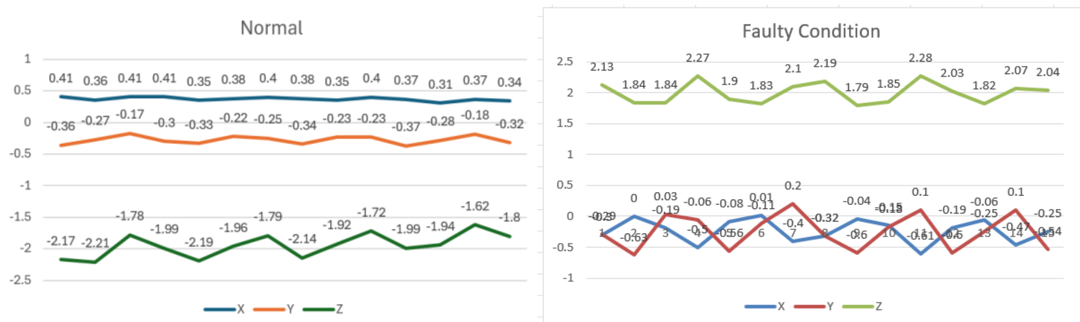
3.1 Overview of Experimental Results

This section presents an overview of the experimental results obtained from the deployment of the IoT-based predictive maintenance system. The performance of the system was evaluated by analyzing the vibration signatures of an AC induction motor under two distinct operational states: 'Normal' and 'Faulty'. The effectiveness of the Convolutional Neural Network (CNN) in distinguishing these states via RGB-mapped spectrograms was investigated, alongside the responsiveness of the Blynk IoT platform in facilitating remote monitoring. The results are discussed with reference to the signal characteristics observed in the time and frequency domains.

3.2 Vibration Signal Characteristics

The time-domain vibration data acquired from the STEVAL-MKI208V1 (IIS3DWB) accelerometer provided a baseline for evaluating motor health.

Figure 3.1 illustrates the comparative vibration amplitude for normal and faulty conditions. Under 'Normal' operating conditions, the motor exhibited stable vibration patterns with minimal amplitude fluctuation, maintaining low-variance acceleration values across the X, Y, and Z axes.



(a) (b)

Fig. 3.1 vibration amplitude for normal (a) and faulty conditions (b)

Conversely, the 'Faulty' condition, simulated by uneven motor mounting, resulted in erratic vibration signatures characterized by significant amplitude spikes and instability. As shown in the data analysis, the faulty state produced distinct deviations from the baseline, validating the sensitivity of the industrial-grade accelerometer in detecting mechanical anomalies. The clear separation in signal characteristics between the two states confirms that the raw acceleration data contains sufficient determinative features for machine learning classification.

3.3 Spectrogram Analysis and CNN Classification

To enable deep learning classification, the raw time-domain signals were transformed into the frequency domain using Short-Time Fourier Transform (STFT). File Naming and Delivery

Figure 3.2 presents the comparison of RGB-mapped spectrograms generated from the vibration data. The spectrogram representing the 'Normal' state displays a uniform distribution with low spectral energy, indicating smooth operation. In contrast, the 'Faulty' spectrogram exhibits distinct broadband noise and harmonic peaks, represented visually as scattered vertical streaks in the green and red color channels.

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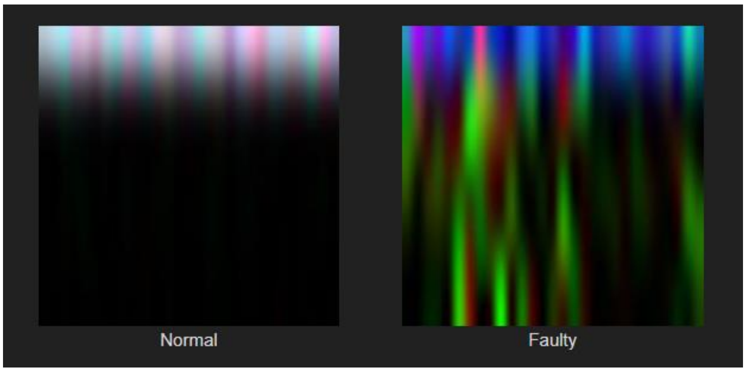

Fig. 3.2 Comparison of RGB-mapped spectrogram representations for Normal and Faulty motor operation

To ensure the robustness of the CNN model against overfitting, data augmentation techniques were applied to the dataset. Noise injection was utilized to simulate environmental jitter, while amplitude scaling (random factors between 0.98 and 1.02) mimicked minor fluctuations in power supply and load. The sliding window segmentation technique was further employed to generate 120 unique spectrograms from the original dataset, providing a diverse training set for the neural network. The distinct visual patterns observed in the spectrograms allowed the CNN to successfully extract features and classify the motor's operational condition with high reliability

3.4 IoT System Response and Monitoring

The integration of the ESP32 microcontroller with the Blynk IoT framework demonstrated effective real-time system response. Upon the detection of a 'Faulty' pattern by the CNN, the system successfully triggered the piezoelectric buzzer and transmitted a "Fault Detected" push notification to the mobile dashboard. The latency between fault detection and notification was minimal, ensuring that technical personnel could receive immediate warnings. The live dashboard provided a continuous visualization of the vibration metrics, allowing for remote verification of the system's status..

3.5 Summary of Results

The experimental results validate the efficacy of the proposed predictive maintenance framework. The system successfully differentiated between normal and faulty motor operations through the analysis of vibration data. The use of the IIS3DWB sensor provided high-fidelity data that, when converted into spectrograms, enabled the CNN to perform accurate fault diagnosis. Furthermore, the successful deployment of the Blynk platform confirmed the system's capability to support real-time remote monitoring, fulfilling the objectives of reducing potential industrial downtime through early fault detection.

4. Conclusion

This study was conducted to design and evaluate the effectiveness of an IoT-based predictive maintenance system for electric motors using deep learning techniques. The experimental results demonstrated that the integration of the ESP32 microcontroller with the industrial-grade STEVAL-MKI208V1 (IIS3DWB) accelerometer provided a robust platform for acquiring high-fidelity vibration data. The application of a Convolutional Neural Network (CNN) on RGB-mapped spectrograms successfully enabled the automated classification of 'Normal' and 'Faulty' motor states, validating the efficacy of image-based fault diagnosis.

Furthermore, the implementation of the Blynk IoT framework facilitated real-time remote monitoring and immediate alert generation, thereby addressing the critical need for timely intervention in industrial environments. The transition from low-cost consumer sensors to the IIS3DWB sensor significantly improved signal clarity, ensuring that mechanical noise did not compromise the diagnostic accuracy. These findings highlight the significant potential of combining affordable IoT hardware with advanced signal processing to create cost-effective predictive maintenance solutions that can minimize unscheduled downtime and operational costs.

Future research is recommended to enhance the system's autonomy by implementing Edge Computing, allowing the CNN model to be deployed directly onto the microcontroller for on-device inference. Additionally, integrating Sensor Fusion by combining vibration data with current and temperature readings would further improve classification reliability and reduce false alarms. Finally, transitioning to robust industrial communication protocols such as LoRaWAN is suggested to ensure reliable data transmission in large-scale manufacturing environments.

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References

Ali, U., Ali, W., & Ramzan, U. (2024). An Improved Fault Diagnosis Strategy for Induction Motors Using Weighted Probability Ensemble Deep Learning. ArXiv. https://arxiv.org/abs/2412.18249

Carvalho, T. P., Soares, F. A. A. M. N., Vita, R., Francisco, R. da P., Basto, J. P., & Alcalá, S. G. S. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. Computers & Industrial Engineering, 137(1), 106024. https://doi.org/10.1016/j.cie.2019.106024

Deloitte. (2022). Predictive Maintenance and The Smart Factory. Deloitte United States. https://www2.deloitte.com/us/en/pages/operations/articles/predictive-maintenance-and-the-smart-factory.html

Pavithra, R., & Ramachandran, P. (2025). Predictive Machine Health Monitoring Using Deep Convolution Neural Network for Noisy Vibration Signal of Rotating Machine Using Empirical Mode Decomposition. Springer Nature Applied Sciences, 7(4). https://doi.org/10.1007/s42452-025-06650-w

PwC. (2018). Beyond the hype: PdM 4.0 delivers results. https://www.pwc.be/en/documents/20180926-pdm40-beyond-the-hype-report.pdf