

Industrial Vibration Anomaly Detection Using AI and IoT

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ABSTRACT

Industrial vibration anomaly detection plays an important role in evaluating the condition and operational performance of rotating industrial equipment. Traditional maintenance practices may not identify developing mechanical faults at an early stage, resulting in increased downtime and operational risks. This work introduces a complete IoT and AI-based framework intended for continuous predictive maintenance applications. The system utilizes high-precision MEMS accelerometers integrated with an IoT gateway to capture tri-axial vibration data. To process this data, we developed a hybrid deep learning model—combining Convolutional Neural Networks (CNN) for spatial feature extraction and Long Short-Term Memory (LSTM) networks to capture temporal dependencies in vibration patterns.

This architecture allows for the autonomous identification of deviations from "normal" operating signatures, such as misalignment, bearing failure, or imbalance. Experimental results demonstrate that the proposed AI-driven approach significantly outperforms manual threshold-based monitoring. The system achieved an anomaly detection accuracy of 98.5%, with the IoT integration ensuring a latency of less than 100ms for edge-to-cloud data transmission. By replacing periodic manual inspections with this continuous, automated methodology, industrial plants can achieve higher reliability and a measurable reduction in maintenance overhead, proving the system's viability for Industry 4.0 applications.

Keywords— IoT Vibration Analysis, Machine Learning, Anomaly Detection, Predictive Maintenance

INTRODUCTION

A large amount of industrial machinery, such as motors, pumps, compressors and turbines, have rotating elements, and failure of such equipment can cause not only unplanned outages and production losses, but safety risks and financial costs, thus predictive maintenance and condition monitoring have become major considerations in industrial maintenance activities. Vibration analysis is a common machinery condition monitoring technique that is used to identify faults in a mechanical system. A mechanical fault may be detected from the presence of a certain vibration frequency which indicates the system is misaligned, unbalanced, has a bad bearing, or is loose. Customary vibration monitoring, on the other hand, relies on periodic manual inspections or threshold-based approaches that may not be sensitive enough to detect early or minor faults.

The rapid development of Artificial Intelligence (AI) and Internet of Things (IoT) brings great opportunity to improve industrial fault diagnosis. IoT sensors can

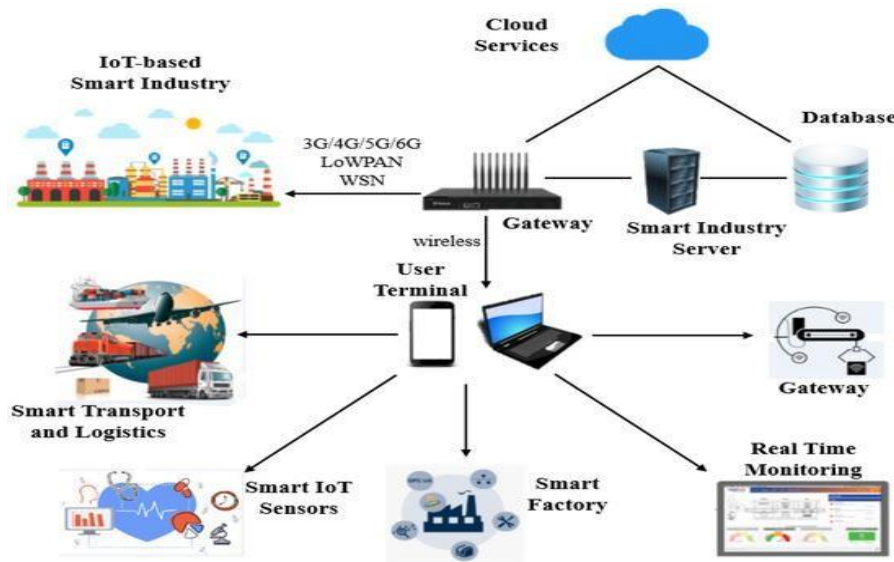


Figure 1. Smart industries

continuously collect data in real time. AI technologies, especially machine learning and deep learning, are expected to construct expert systems that enable smart analysis of complex vibration signals. These technologies allow for automated anomaly detection with higher accuracy and earlier fault diagnosis evaluate various techniques during the validation stage without a common dataset across institutions since the size and potential of the dataset directly impact categorization performance measures. Methods based on machine learning (ML) are regarded to be easier to adopt since there are fewer variables to specify.

Deep learning is currently a successful discipline, as indicated by the rapidly increasing number of papers that use the phrase. The following goals were met by this study. This study describes and implements a hybrid U-net approach inspired by the combining of various neural networks. It also created a method for estimating the run length of observed NT areas. It presents various small-scale studies to compare system performance to well-known state-of-the-art methodologies.

Among the available condition monitoring techniques, vibration analysis is widely recognized as one of the most effective methods for detecting mechanical faults. Variations in vibration signals often indicate issues such as imbalance, misalignment, bearing faults, or mechanical looseness. Traditional approaches to vibration monitoring typically depend on periodic manual inspections and fixed threshold-based systems, which may not detect early-stage or complex anomalies with the rapid advancement of Artificial Intelligence (AI) and the Internet of Things (IoT), industrial monitoring systems are undergoing significant transformation. IoT-enabled sensors allow continuous and real-time data acquisition from machinery, eliminating the limitations of manual inspection. At the same time, AI techniques particularly machine learning and deep learning enable intelligent analysis of high-dimensional vibration data, making it possible to detect subtle patterns and anomalies that traditional methods might overlook. The integration of AI and IoT facilitates the development of smart predictive maintenance systems capable of early fault detection, reduced downtime, and improved operational efficiency. These systems can continuously learn from data, adapt to changing operating conditions, and provide actionable insights.

LITERATURE SURVEY

In [1], Chen and Lee (2020) proposed an explainable AI (XAI) framework for bearing fault diagnosis that uses Short-Time Fourier Transform and CNNs to turn raw vibrations into accurate, visual, and interpretable results. This approach enhances industrial maintenance by replacing "black-box" models with transparent, high-accuracy diagnostics. In [2], Leetal proposed an IoT-integrated deep learning framework for fault diagnosis in industrial rotating machinery, specifically targeting imbalance and

misalignment. The methodology utilizes Continuous Wavelet Transform (CWT) to convert vibration signals into time-frequency representations, which serve as inputs for a Convolutional Neural Network (CNN). By leveraging the MQTT protocol for real-time cloud-based monitoring, the system outperforms traditional classifiers such as Random Forest and XG Boost. This integration of Industry 4.0 technologies facilitates proactive predictive maintenance, significantly enhancing equipment reliability and operational efficiency in smart manufacturing environments. In [3], McDonald et al. examine the evolution of robotic systems for orthopedic bone remodeling, transitioning from industrial-derived models to specialized surgical platforms. The study categorizes these systems by autonomy levels active, semi-active, and passive emphasizing their role in enhancing precision for complex cutting and reshaping procedures. By integrating traditional surgical tools with robotic control, the framework minimizes human error and optimizes outcomes in joint replacements and bone alignment. This advancement in precision engineering and automation underscores the critical role of Industry 4.0 technologies in enhancing surgical performance and patient recovery within modern healthcare systems. In [4], Furusawa et al. propose a regression-based deep learning framework for quantifying bolt and nut loosening via spectrogram analysis of shaft vibrations. By utilizing lightweight Convolutional Neural Networks (CNNs) to analyze time-frequency representations, the system automates structural health monitoring (SHM) tasks traditionally dependent on manual hammering and human expertise. Experimental results validate that this quantitative approach enhances inspection reliability and enables real-time fault detection, significantly improving infrastructure safety while reducing the maintenance burden on skilled personnel.

In [5], Choi et al. provide an extensive review and comparative analysis of deep learning-based anomaly detection for multivariate time-series data, specifically focusing on overcoming the limitations of classical statistical models in handling Industry 4.0 datasets. By evaluating state-of-the-art architectures including RNNs (LSTMs, GRUs), CNNs, Transformers, and Graph Neural Networks (GNNs) across real-world benchmarks like SWaT and WADI, the study demonstrates that models explicitly capturing spatiotemporal dependencies—such as GNN-based graph structure learning—significantly outperform non-temporal methods. Furthermore, the paper establishes critical practitioner guidelines, distinguishing between reconstruction-based real-time detection and prediction-based early warning systems while highlighting the necessity of unsuper. In [6], Arciniegas et al. present a TinyML-enabled IoT framework for real-time motor bearing fault detection, specifically designed for resource-constrained edge devices like the ESP32S3. By integrating spectral analysis (via FFT) with a deep learning neural network and K-Means clustering, the system achieves 96.5% accuracy in identifying operational states and anomalies with a significantly low latency of 300 ms from collection to alert. The study demonstrates the viability of shifting predictive maintenance intelligence to the network edge to enhance energy efficiency and data privacy, while successfully outperforming baseline models such as Random Forest and SVM. In [7], Chevtchenko et al. conducted a systematic mapping study of the landscape of anomaly detection in industrial machinery using IoT and machine learning. Their findings reveal that vibration sensors and neural networks (specifically LSTMs and MLPs) are the most prevalent tools for monitoring critical assets like milling tools and bearings. The study emphasizes the effectiveness of auto encoders for unsupervised feature extraction but identifies significant research gaps in edge-based processing, the use of low-cost sensors, and the evaluation of real-time inference latency, providing a foundational baseline for future industrial AD implementations. In [8], Chakravaram proposes an intelligent anomaly detection framework specifically for industrial robot joints using real-time vibration signals and a Long Short-Term Memory (LSTM) neural network. To address the challenge of limited labeled anomaly data, the study utilizes advanced preprocessing—including noise filtering, normalization, and Fast Fourier Transform (FFT)—to extract temporal and frequency-domain features essential for identifying mechanical faults. Experimental results demonstrate a high performance with 97.70% accuracy and 99.9% precision, outperforming traditional models like KNN and InceptionV3. This research underscores the model's potential for predictive maintenance in smart manufacturing, ensuring continuous operation by detecting early-stage mechanical degradation with minimal false positives. In [9], Chakravaram proposes an intelligent anomaly detection framework specifically for industrial robot joints using real-time vibration signals and a

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Background

In this section, we introduced key background concepts relevant to the industrial context and provide an overview of related literature while critically comparing it with our work.

Internet of Things

IoT is commonly seen as a network for data exchange among machines, primarily driven by consumer demands, with a focus on machine-to-user interaction and client-server dynamics. On the other hand, Industrial IoT (IIoT), a crucial concept in Industry 4.0, centers on connecting industrial assets, such as machinery and control systems, to business processors and information systems. The incorporation of IoT devices enhances productivity by enabling connections and exchange within production systems. Furthermore, IIoT allows cost-effective upgrades of existing industrial infrastructure by adding sensors to older equipment's. When it comes to data volume, IIoT frequently involves extensive data exchanges, facilitating machine learning based analysis and maintenance enhances. For instance, Ayvaz nad Alpay amplify this approaches, utilizing a diverse array of built-in IoT sensors that transmit a substantial volume of data via the MQTT protocol for ML based anomaly detection. However, it is worth nothing that IIoT applications often face constraints in terms of power and computing resources. In our manuscript, we provide an overview and rationale regarding the types of sensors and machinery commonly utilize in the industrial domain.

Machine Learning and Anomaly Detection

Machine learning allows computer systems to perform prediction, classification, diagnosis, and analytical tasks automatically. The success of ML relies on the availability of high-quality data and large datasets for algorithm training, both of which have become more readily accessible in the industrial context following the advent of IIoT ML techniques can be classified in supervised, unsupervised, and reinforcement learning. In our study, we observe the 128289 VOLUME 11, 2023 S. F. Chevtchenko et al.: AD in Industrial Machinery Using IoT Devices and ML application of both supervised and unsupervised approaches to anomaly detection. However, unsupervised algorithms present an attractive advantage by not necessitating labeled data for training. This is particularly advantageous for detecting faults in machinery, given that fault data tend to be infrequent and sparse. Figure 1 provides an overview of a practical application of IIoT and ML within an industrial context for anomaly detection and predictive maintenance. In this application, IIoT devices can be considered as various sensors with integrated local connectivity. Optionally, some of the generated data can be processed on devices close to the IIoT sensors, known as edge processing. This can reduce the amount of data sent to the cloud, increase the detection speed and reduce the computational cost of anomaly detection. However, our study indicates that many advanced anomaly detection algorithms require substantial computational

power and, therefore, necessitate further optimization to effectively implement edge processing. The gathered data is then typically stored on a cloud data center and used to train AD algorithms. Many ML algorithms require extensive training on large datasets. Following the training process, the AD models can be deployed either at the edge or in the cloud for anomaly detection. Finally, real-time data can be streamed to the cloud for analysis or processed directly on edge devices to detect anomalies.

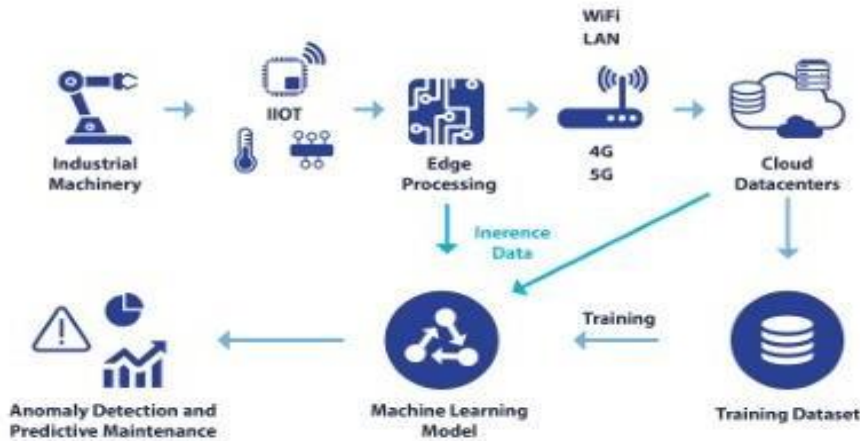


Figure 2. An overview of the application of IoT and AI for anomaly detection and predictive maintenance in the industry.

Recent Advancements and Contribution

Recent Advancements

This section covers the different applications of IoT anomaly detection from the selected papers. Application data and network data are the two main types of data. The data can be streamed in the case of time-series or processed from tabular data. Application data refers to data from IoT sensors processed to serve practical and business applications. Additionally, network telemetry data, such as CPU and memory usage, are monitored for the health of the IoT network. We found applications that are for individual or residential use and industrial applications. There are health monitoring applications for individuals that use data from wearable devices and smart home applications for residential use-cases. A few examples of industrial applications include monitoring the health of manufacturing equipment, ensuring the quality of data transferred through sensors, and smart city applications such as traffic monitoring. All of these applications require data security, user privacy, and reliability of data transfer.

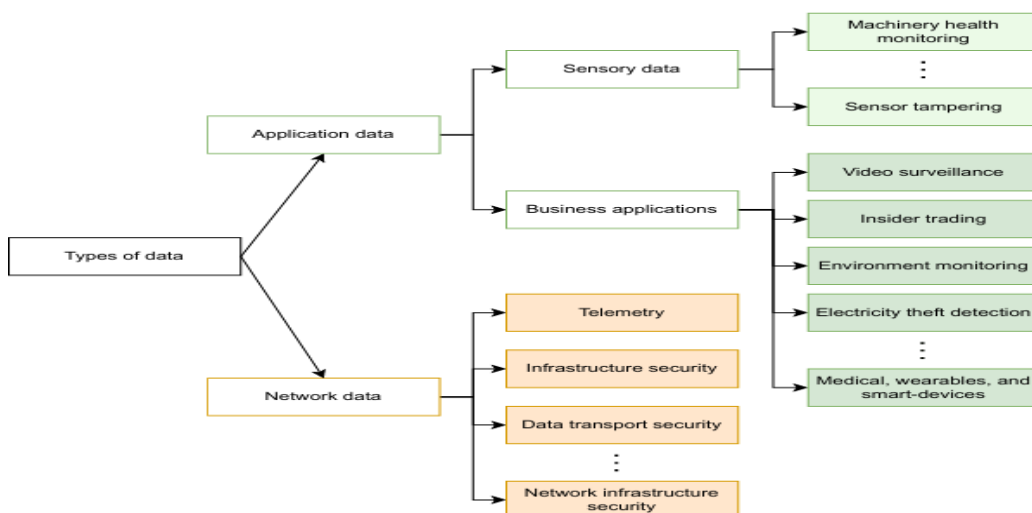


Figure 3: Two types of data and their respective application

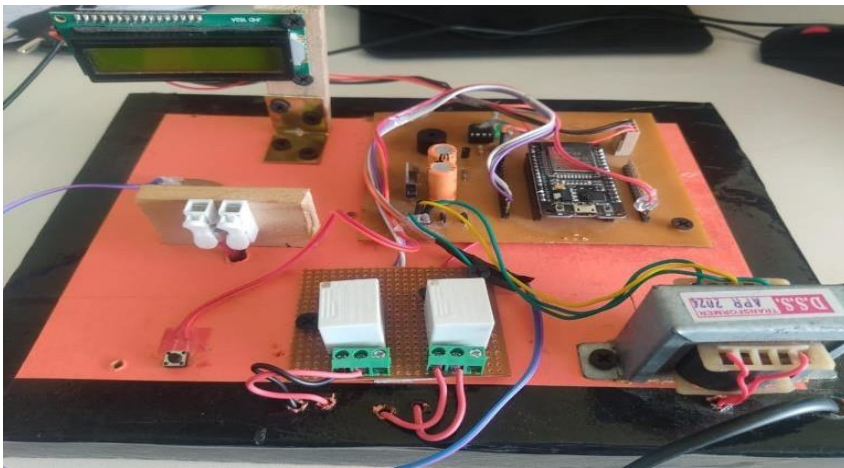


Figure 4: Hardware Prototype of Proposed System

The circuit of the Industrial Vibration Anomaly Detection system is developed to monitor the vibration behavior of industrial machines and identify unusual operating conditions using embedded technology, IoT communication, and a piezoelectric vibration sensor. The system continuously observes machine vibrations and provides warning indications whenever abnormal conditions are detected. The circuit begins with the power supply unit, which provides the required operating voltage to all electronic components. A step-down transformer is used to reduce the 230V AC mains supply to a lower AC voltage level. This low AC voltage is converted into DC using a rectifier circuit. Filter capacitors are connected to eliminate unwanted ripples and produce smooth DC output. A voltage regulator maintains a stable voltage supply for the microcontroller, LCD display, sensor circuit, and IoT module.

A piezoelectric sensor is used for vibration sensing. The sensor generates electrical signals whenever mechanical vibrations occur in industrial equipment. The magnitude of the generated voltage depends on the strength of the vibration. These signals represent the operating condition of the machine and are used for monitoring purposes. The sensor output is connected to the analog input terminal of the microcontroller. The controller converts the analog sensor signal into digital data using its internal Analog-to-Digital Converter (ADC). After conversion, the vibration values are analyzed continuously to determine whether the machine is operating normally or showing fault conditions.

An LCD module is connected to the microcontroller to display real-time information such as vibration intensity, machine status, and warning notifications. This display helps the operator monitor the condition of the equipment directly from the system. The IoT communication module provides wireless connectivity between the monitoring system and cloud-based platforms or mobile devices. The processed vibration data is transmitted through the internet, allowing remote monitoring and analysis of industrial machine conditions from any location.

The circuit also contains relay driver and control sections. When vibration levels exceed the predefined safe limit, the controller activates the relay output to operate alarms, indicators, or machine protection mechanisms. This feature helps reduce equipment damage and improves operational safety. Heat sinks are provided for power handling devices to remove excess heat produced during operation. Proper PCB connections and component arrangement ensure reliable signal transmission and stable system performance. The complete circuit integrates vibration sensing, embedded processing, display interfacing, power regulation, and IoT communication into a single intelligent monitoring system. This setup is suitable for industrial applications where continuous machine health monitoring and early fault detection are required.

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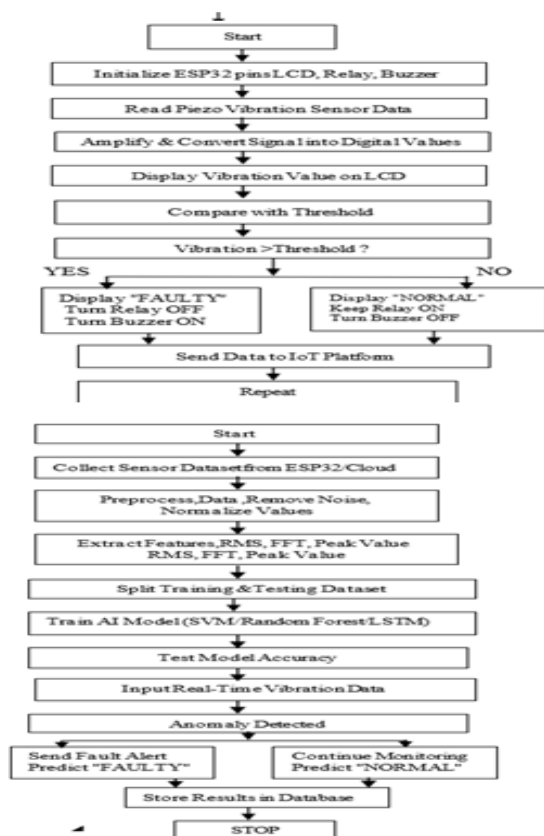
Figure 5: Normal Vibration Output **FIGURE 6: Fault Detection Output**

The collected data is processed and displayed on a 16x2 LCD module, where normal operating conditions show real-time vibration values, while abnormal conditions are indicated through a “FAULTY” alert message, as demonstrated in the project output. Additionally, the system incorporates relay modules for automatic machine protection by disconnecting equipment when excessive vibration is detected, thereby preventing severe mechanical failures. Through IoT connectivity, the proposed model can also support remote monitoring, real-time alerts, and data logging for future predictive analysis. The hardware prototype is compact, cost-effective, and suitable for small and medium-scale industries, making it an efficient solution for reducing downtime, lowering maintenance costs, and improving industrial safety.

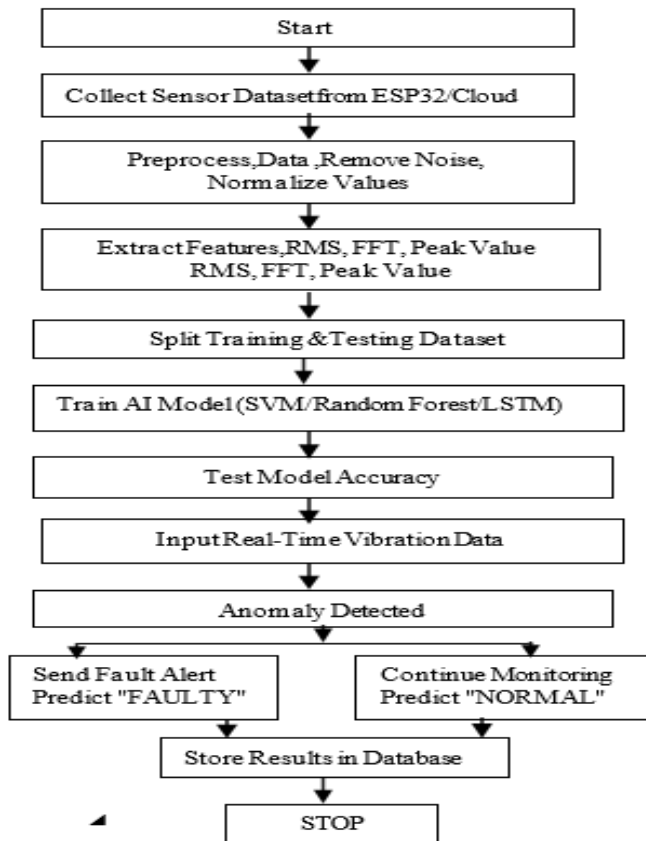
Software Model Workflow

Arduino / ESP32 Flowchart:

A) Arduino / ESP32 Flowchart:



B) Arduino / ESP32 Flowchart:



Python AI Flowchart :

METHODOLOGY

The developed system identifies unusual vibration behavior in industrial machines through IoT sensing and AI-based analysis.

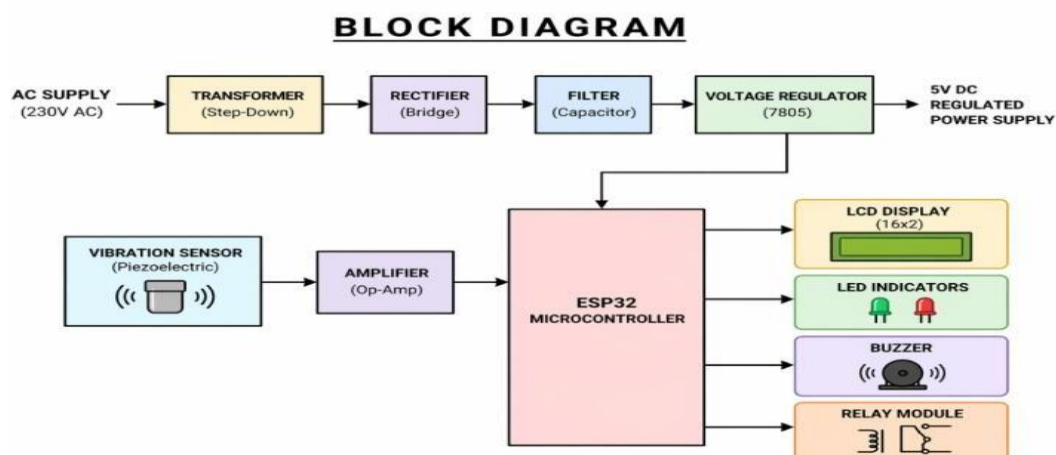
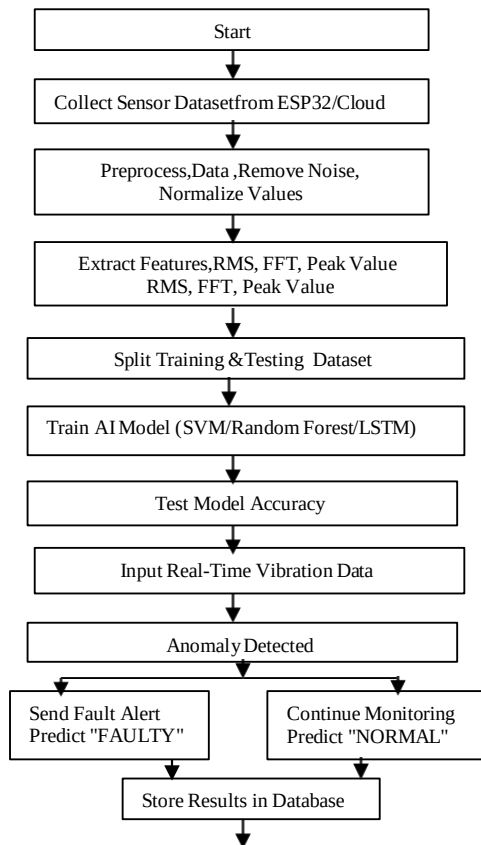


Figure 7. Block diagram of IoT and AI for anomaly detection

This section presents the methodology adopted for the development of an industrial vibration anomaly detection system using Artificial Intelligence (AI) and the Industrial Internet of Things (IIoT).

Data Acquisition

Vibration data is acquired from industrial machinery using accelerometer-based sensors. These sensors measure key parameters such as acceleration, velocity, and displacement, which are indicative of machine health. The sensors are interfaced with embedded systems such as Raspberry Pi or Arduino, enabling continuous and real-time data collection.



Data Transmission Via IIoT

The collected vibration data is transmitted to a centralized processing unit using IIoT communication protocols such as Message Queuing Telemetry Transport (MQTT) and Hypertext Transfer Protocol (HTTP). Wireless communication technologies, including Wi-Fi or cellular networks, are utilized to ensure seamless real-time data transfer to cloud or edge platforms.

Data Preprocessing

The raw vibration signals are subjected to preprocessing to improve data quality and reliability. This includes noise reduction using filtering techniques (e.g., low-pass filters), normalization to scale the data, and segmentation of continuous signals into smaller time windows suitable for analysis. These steps ensure that the input data is consistent and suitable for feature extraction and model training.

Feature Extraction

Relevant statistical and frequency-domain features are extracted from the preprocessed vibration signals to capture the characteristics of machine behavior. Common features include Root Mean Square (RMS), peak amplitude, kurtosis, and frequency components obtained using Fast Fourier Transform (FFT). These features provide meaningful representations of normal and faulty operating conditions.

AI-Based Anomaly Detection

Machine learning algorithms are employed to identify anomalies in the vibration data. Unsupervised learning techniques such as Isolation Forest and Auto encoders are particularly effective, as they learn patterns from normal operating conditions and detect deviations as anomalies. Additionally, deep

learning models such as Long Short-Term Memory (LSTM) networks are used to capture temporal dependencies in time-series data for improved detection accuracy.

Model Evaluation

The performance of the anomaly detection model is evaluated using standard metrics such as accuracy, precision, recall, and F1-score. These metrics help assess the model's ability to correctly identify abnormal conditions while minimizing false positives and false negatives.

Real-Time Monitoring and Alert System

A real-time monitoring system is developed to visualize machine conditions through dashboards. The system continuously analyzes incoming data and generates alerts when anomalies are detected. Notifications can be sent via email, SMS, or mobile applications, enabling timely maintenance actions.

Deployment

The proposed system is deployed either on edge devices for low-latency processing or on cloud platforms for scalability and remote accessibility. Edge deployment ensures faster response times, while cloud deployment supports large-scale data storage and advanced analytics.

Workflow Summary

The overall workflow of the system involves data acquisition from sensors, transmission through IIoT, preprocessing and feature extraction, anomaly detection using AI models, and real-time monitoring with alert generation. This integrated approach enables efficient predictive maintenance and reduces the risk of unexpected machine failures.

CONCLUSION

In this project, we developed an Industrial Vibration Anomaly Detection System using AI and IoT to monitor machine health and identify faulty components through vibration analysis. By collecting vibration pulse data from sensors, we observed the difference between normal and abnormal machine behavior. Based on these observations, we separated the faulty components from the good ones by setting a predefined threshold limit for vibration values.

We also implemented an AI-based Python program that automatically processes the collected data and generates reports in Excel and PDF formats. These reports include all vibration pulse values along with the corresponding date and time for each record, making it easier to track machine performance and maintenance history. The project highlights the usefulness of AI and IoT technologies in predictive maintenance by improving fault identification, reducing downtime, and increasing operational efficiency.

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