

# Vibration Analysis for condition Monitoring & Predictive Maintenance using Embedded TinyML

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**Abstract** - The motivation behind our task comes from the innately unquenching prerequisite of expanding functional productivity of a modern establishment. Notwithstanding consistently expanding difficulties of building tough stock chains that are getting more intricate constantly, ensuring that the margin time of basic modern gear is grinding away's base is perhaps the most noteworthy need of any administrator. Remembering these difficulties, we aim to develop a generalized, end-to-end plug and play system to predict an outage before it happens and alert the operator of any potential equipment malfunction using machine learning algorithms deployed at edge.

**Key Words:** Vibration analysis, Embedded TinyML, Condition monitoring, Maintenance, Arduino nano 33 BLE sense, Android app.

## 1. INTRODUCTION

Vibration analysis is a procedure that involves detecting the vibration levels and frequencies of machinery and then analysing how healthy the machines and their components are. While the inner workings and formulae used to calculate various types of vibration might become intricate, it all begins with the usage of an accelerometer to measure vibration by adopting the method of Predictive Maintenance (PdM), a process which involves continuously monitoring the state of machinery to predict which parts will fail and when. Maintenance can be planned in this way, and only the parts that are showing signs of degradation or damage can be replaced.

Predictive maintenance is based on taking measurements that allow for the prediction of which parts will fail and when they will fail. Machine vibration and plant operational data such as flow, temperature, and pressure are examples of these metrics.

The main benefits of PdM are: [4]

- Improved machine reliability through the effective prediction of equipment failures [4]
- Reduced maintenance costs by minimising downtime through the scheduling of repairs [4]
- Increased production through greater machine availability [4]

- Lower energy consumption [4]
- Improved product quality [4]

Whenever a piece of equipment is in activity, it produces vibrations. An accelerometer connected to the machine delivers a voltage signal that relates to the amount of vibration and the recurrence of vibration the machine produces, which is generally the times each second or moment the vibration occurs. [4] The accelerometer's data is taken care of promptly into an information authority (programming), which catches the sign as amplitude versus time (time waveform), frequency versus recurrence (Fast Fourier change), or both. All of this data is handled by PC modified calculations, which are then checked on by engineers or talented vibration experts to decide the machine's wellbeing and recognize potential faults, for example, detachment, lopsidedness, misalignment, grease concerns, and more. Vibration analysers may now accumulate, investigate, and convey information substantially more effectively on account of advancements in innovation, outstandingly remote innovation. Vibration analysers are presently amazingly convenient, can associate progressively with cell phones and tablets, and can make incredibly high-goal FFT[4]. Numerous vibrations instrument producers make their own applications to associate with each other. Most of vibration examination information is quickly shipped off the cloud and is accessible on your cell phone, PC, or straightforwardly from your program, just like with most trend setting innovations. Assuming that you're performing vibration investigation as an outsider expert, this is very convenient in light of the fact that you may uninhibitedly share spectra with your clients. [4]

### 1.1 Motivation

Both IoT and Machine Learning are bringing about a paradigm shift in the landscape. Getting hands on experience with these technologies and deploying them will enhance academic and career prospects.

Increasing amounts are being spent on improving operational efficiency of industrial set-ups. Providing cutting edge predictive maintenance solutions may help us position this as a product.

## 1.2 Objective and Outcome

### Objective:

- Build an Anomaly Detection Model using sklearn on Google Colab
- Export sklearn model and run inference for prototyping and debugging onboard the microcontroller-Arduino nano 33 ble sense
- Mobile Desktop Interface for condition monitoring environment setting for users
- Implementing CI/CD pipeline for periodic data collection and training for improving model accuracy

**Outcome:** an end-to-end condition monitoring and predictive maintenance system using machine learning for industrial equipment with a mobile & desktop application for user interface giving access of condition monitoring for numerous equipment at once where system performance increases with time as more and more data is collected.

## 2. METHODOLOGY

The test bench is used to guide the project's operations. Two scenarios are used to obtain data from the test bench. The servo motor is turned off at first, and this is the typical working state of the DC motor. When the servo motor is turned on, it begins to shake the board, causing unnatural vibrations.

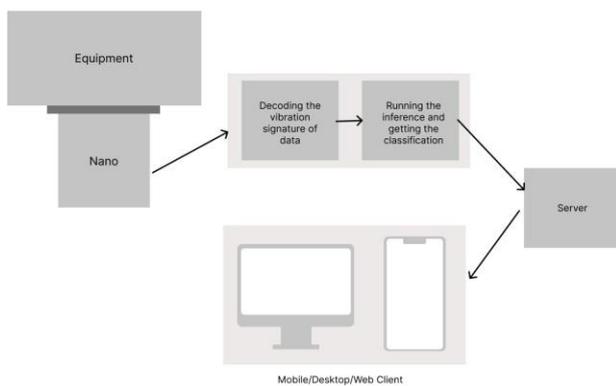


Fig -1: Block diagram

The accelerometer captures this vibration data using the Arduino nano 33 BLE sense. The data is then saved and converted to a csv file in order to train the ML model. The CSV file is read after it has been loaded into the Python function. The data is then utilized to train a machine learning model using Python's sklearn module and the random forest classifier. Once the model has been trained the Micromlgen's Python library is used to transform the ML model into an Arduino header file after it has been developed. The Arduino

code then uses this header file to compare the data from the live sensor (accelerometer). Based on the output, it forecasts either an anomaly 1 or no anomaly 0.

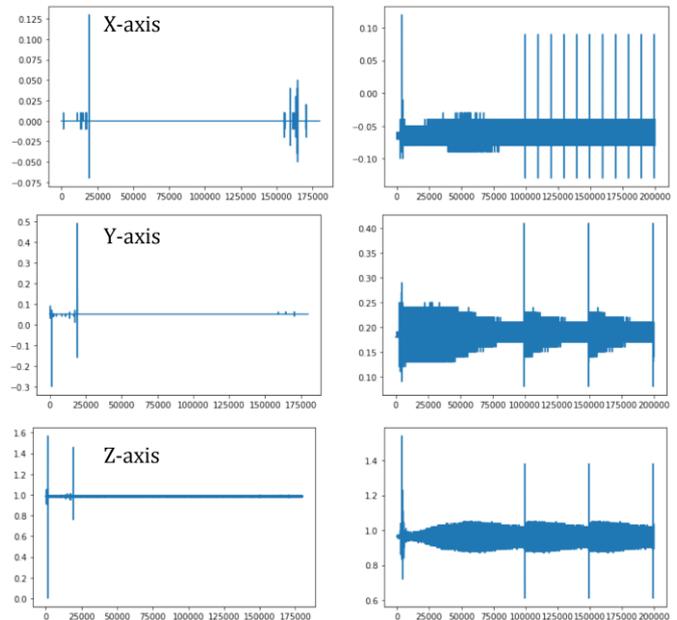


Chart -1: X, Y, Z -axis accelerometer reading with normal state and servo on.

The live sensor information and the predictions are then changed into JSON string and sent to the serial monitor. Whenever Node Red is working on the local host port 1880, information from the sensor is gathered on the sequential port. Since the information is in a string format, a node is utilized to change it over completely to a JSON string and transform it into a JSON record. This data is used to refresh the site with ongoing information that clients might see alongside expectations and accelerometer information on three axes. This data is likewise given to the Firebase ongoing information administration.

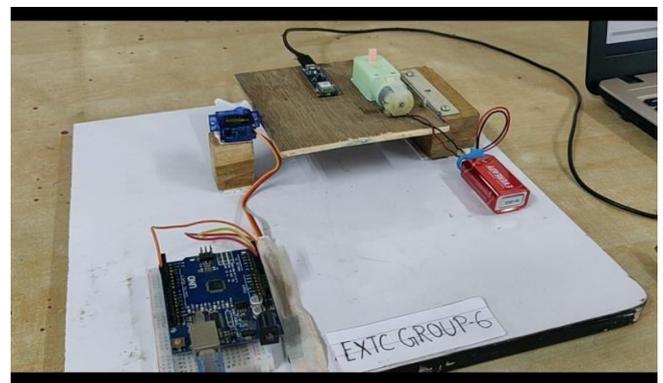


Fig -3: Test bench setup

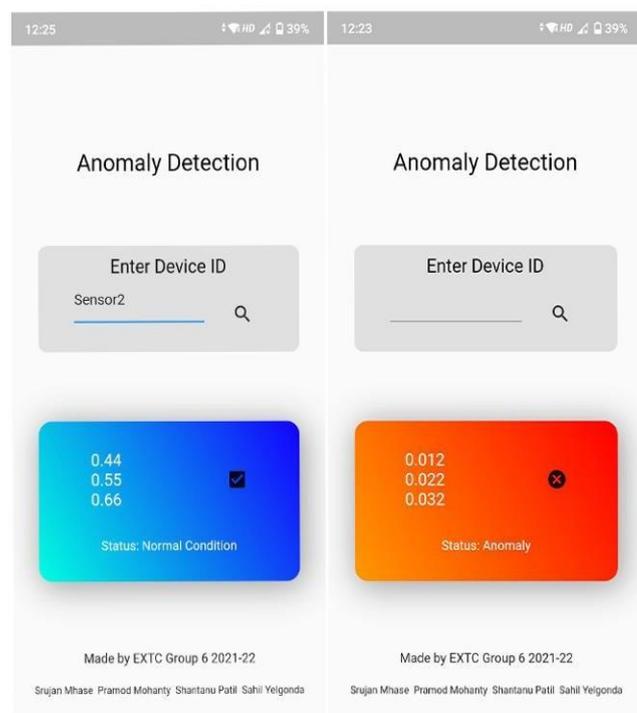
The firebase stores this data in two variants. First for future reference, a JSON report with randomly generated

labels is first put away in the information base, making a new single record with live sensor information and expectations for each reading. Second This sensor is additionally refreshed on a solitary JSON record which is expected to show the live sensor readings and comparing forecasts on the android application. The android application is created with the assistance of the flutter app development tool and the dart programming language.



**Fig -3:** Node-Red website dashboard

The Android app displays real-time sensor data as well as anomaly forecasts. Because the sensors are assigned to separate stages, the user can now check for discrepancies in sensor data in the Node Red interface. To view the sensor’s live data, simply enter the proper tag. This can be accomplished with any number of sensors.



**Fig -4:** Android application

### 3. CONCLUSIONS

Predictive maintenance and condition monitoring of heavy machinery are clearly needed in enterprises. Manufacturers are continually striving to increase output by maximizing resource utilization. Companies can save time and costs by keeping equipment downtime to a minimum, allowing them to service more consumers. TinyML-based technologies let us to carry out sophisticated tasks on low-powered portable devices, saving us money on expensive systems and equipment.

Keeping this in mind, we’ve briefly discussed the necessity for predictive maintenance and our project, followed by a thorough examination of existing solutions. We then considered various solutions and offered a structure for implementing our idea from the standpoint of product development.

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### REFERENCES

[1] Nariman L. Dehghani and Yousef Mohammadi Darestani and Abdollah Shafieezadeh Optimal Life-Cycle Resilience Enhancement of Aging Power Distribution Systems: A MINLP-Based Preventive Maintenance Planning Institute of Electrical and Electronics Engineers (IEEE), 8th Volume, 2020 10.1109/access.2020.2969997.

[2] Pablo Aqueveque and Luciano Radrigan and Francisco Pastene and Anibal S. Morales and Ernesto Guerra Data Driven Condition Monitoring of Mining Mobile Machinery in Non-Stationary Operations Using Wireless Accelerometer Sensor Modules Institute of Electrical and Electronics Engineers (IEEE), 9th Volume, 2021 10.1109/access.2021.3051583

[3] Ivar Koene and Ville Klar and Raine Viitala, IoT connected device for vibration analysis and measurement Elsevier BV, Volume 7, 2020, 10.1016/j.ohx 2020.e00109.

[4] Martin Pech and Jaroslav Vrchota and Jiří Bednář Predictive Maintenance and Intelligent Sensors in Smart Factory: Review MDPI AG, Sensors, Volume 21, Number 4, 2021, 10.3390/s21041470.