Elite *Journal of Scientific Research and Review*. Volume 2 Issue 5(2024), Pp. 34-50
https://epjournals.com/journals/EJSRR

Predictive Maintenance (Ai) In Power Generation for Rotating Machines Based on Vibration Analysis

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Abstract
Predictive maintenance, aided by Artificial Intelligence (AI), has emerged as a game-changing approach that will revolutionize how to manage and maintain machinery especially rotating machinery particularly in power generation equipment. Traditional preventive maintenance approaches have proven to be expensive and time-consuming, and frequently fail to detect possible issues before they occur. Case in point is the Callide Power Station's Unit C4 incident. In 2021, an offshore platform experienced a catastrophic failure of gas turbine generator due to a sudden bearing failure. The incident took place on May 25, 2021, at the Callide Power Station's Unit C4. This breakdown resulted in substantial damage to the transmission network. The primary cause was discovered as high system vibrations and inadequate maintenance of the lubrication systems, which are critical for the smooth operation of the bearings. This paper presents predictive maintenance (Pd.M.) as a leveraging solution to abrupt failure in rotating machines. The paper focuses on vibration analysis as a major determinant of the equipment health.

***Keywords**: Predictive Maintenance (Ai), Power Generation, Rotating Machines, Vibration Analysis*

Introduction

Though considered as a more proactive approach to maintenance, Predictive maintenance (Pd.M.) has been adamantly adopted by critical system forerunners due to the data intensive procedural demand once adopted. Which still remains as a major challenge to the industry especially the vibration parameter large datasets required in power generation systems. The vibration parameter is an important predictor of the health and performance of rotating machinery. Vibration is the oscillation or back-and-forth movement of machines or components, which is frequently produced by imbalances, misalignments, or worn-out parts. We can identify possible faults before they cause equipment failure or downtime by analysing vibration data. Several vibration metrics are used to evaluate equipment health, including: Amplitude is intensity of vibration, often measured in units of displacement, velocity (e.g., inches per second or mm/s). Frequency is the number of oscillations the rotating shaft completes per second, typically measured in revolutions per minute (RPM). Phase is the time connection between a vibration signal and a reference point, such as the rotation of a shaft. Orbit is a polar representation of the vibration signal that depicts the movement of a shaft or bearing over time. Spectrum: A graphical representation of a vibration signal in the frequency domain, displaying the amplitude and phase of different frequency components.

Displacement, which quantifies the entire movement of a vibrating component, is critical for low-frequency vibrations. It aids in detecting faults such as imbalance, misalignment, and mechanical looseness. The basic equation is: $x(t)=X\sin(\omega t+\phi)$ where $x(t)$ is the displacement at time t, X is the maximum displacement (amplitude), ω is the angular frequency, and ϕ is the phase angle. For imbalance, the rotor's centre of mass is not parallel to the rotational axis, resulting in a periodic displacement that peaks at the rotational frequency. Where X in the displacement equation ($x(t)=X\sin(\omega t+\phi)$) is the magnitude of the imbalance. The velocity and acceleration measurements will validate the presence of imbalance by identifying comparable peaks at the rotational frequency and its harmonics.

Velocity is the rate at which displacement changes and is used to describe mid-range frequencies. It offers a more accurate estimate of the energy transmitted during vibration, frequently exposing bearing and gear mesh difficulties. The equation for velocity is the derivative of displacement $v(t)=dx(t)/dt=X\omega\cos(\omega t+\phi)$. Velocity is directly proportional to the kinetic energy of the vibrating system, providing information on the energy transfer inside the machine. This aids in determining the severity and potential consequences of mechanical problems.

Velocity measurements are effective throughout a large frequency range, making them appropriate for identifying medium frequency issues like as bearing failures and gear mesh difficulties, which may not be apparent using displacement or acceleration alone. In the case of misalignment, the vibration velocity signal may exhibit periodic oscillations at frequencies corresponding to the rotational speed and its harmonics. The nature and severity of the misalignment (angular, parallel, or combination) may be determined by analysing these velocity peaks. Machinery vibrations can be caused by several sources, including imbalances, misalignments, bearing wear, manufacturing faults, lubrication difficulties, impacts, and resonances. Ignoring vibrations can lead to poor performance, early failures, equipment damage, and decreased dependability. Identifying and addressing the underlying causes of vibrations is critical for maintaining mechanical performance and preventing interruptions.

The power generating industry, which serves as the backbone of our modern infrastructure, has a slew of challenges in meeting the demands of a growing industry and a quickly expanding technological landscape. Power generation systems, which are critical for guaranteeing a dependable energy supply, are plagued by maintenance inefficiencies and unplanned downtime. Thus, its critical to adopt game changer innovations like predictive maintenance to leverage the challenges the critical system challenges. As earlier mentioned, the paper proposes vibration analysis of rotating machines based on the fact that different machines have different vibration pattern based on their health and performance at the moment

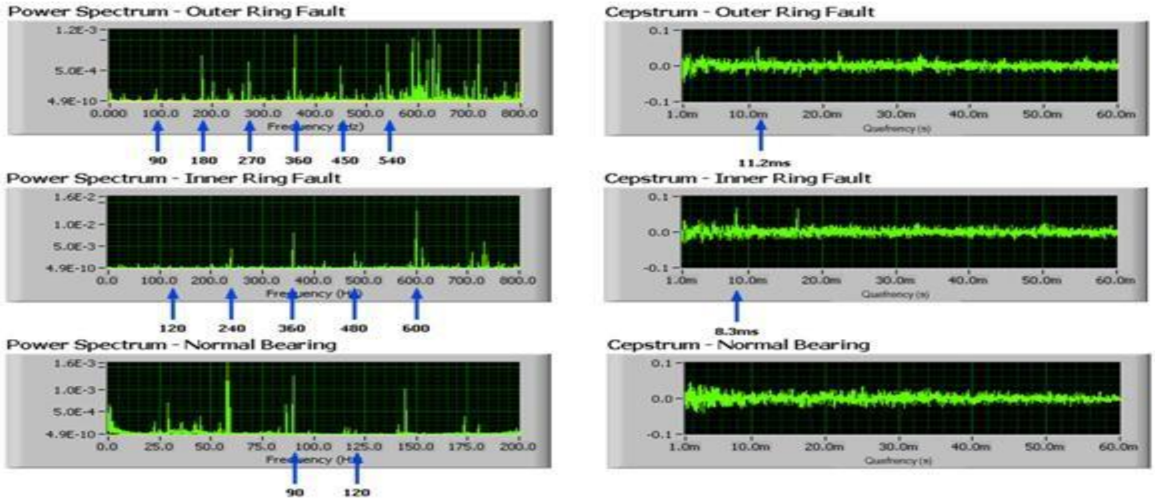


Figure 1: Vibration pattern of normal and faulty bearing [source: National instruments]

In a review of the Callide C4 incident, the CS Energy report on the Callide C4 indicates the catastrophic event root cause as excessive system vibration. The root cause identified as excessive system vibrations and insufficient maintenance of the lubrication systems, which are crucial for the smooth operation of the bearings. The abnormal system vibration caused misalignment of bearing causing a plurality of cascading events that eventually led to the revolution of the shaft at over 730^0 C thus breaking, and forcing the red-hot shaft to pop out of its axis. The review asserts if innovative solutions such as predictive maintenance based on vibration analysis are adopted then such vibration abnormality can be detected at an infant stage.

The pros and implications of implementation of this work are exorbitant and multi-faceted varying from one industry to another. Industries with critical systems would be a great beneficiary one they consider adoption of the innovation, industries like power generation where rotating machinery are inevitably used, oil and gas industry employing both drilling and rotational equipment, aviation industry with rotating critical systems like ailerons in aircrafts and other mechanical systems. These industries and governments will realize drastic uptime and ensure increase in returns, low levels of risks and work continuity.

Related literature

Predictive maintenance has attracted increased attention in the power production industry because of its potential to revolutionize plant maintenance. Traditional approaches, such as reactive and preventative maintenance, frequently fail to adequately manage equipment health, resulting in unplanned downtime and costly repairs. This literature study investigates the current approaches to maintenance in power plants, the fundamental causes of breakdowns, and the current technology utilized for predictive maintenance.

Review of the existing traditional maintenance techniques.

Maintenance in power plants has traditionally relied mostly on the following approaches: Breakdown, Corrective, and Preventive maintenance as explained below.

a) Breakdown Maintenance.

Breakdown maintenance prioritizes immediate fixes over the long-term health of equipment. This reactive strategy results in poorly planned repairs that focus on getting machines back up and running, rather than preventing future breakdowns. The two main disadvantages are high expenses owing to hasty repairs and partial remedies that just address symptoms rather than fundamental problems. This eventually leads to more frequent repairs and higher total maintenance costs [1].

b) Corrective Maintenance.

Corrective Maintenance, unlike reactive breakdown maintenance, focuses on scheduled repairs to keep equipment in good working order. It tries to reduce malfunctions and improve plant systems. Fixing problems as they develop, having trained specialists perform thorough repairs, and validating functionality before restarting are all important. This proactive strategy addresses not only mechanical concerns but also any divergence from optimal performance, resulting in lower overall maintenance expenditures [1].

c) Preventive maintenance:

This is a schedule-based technique in which equipment is serviced or examined at regular intervals. While it decreases the chance of unanticipated failures, it can be inefficient and costly because it frequently requires the replacement or service of components that may still have a long operational life. Preventive maintenance extends beyond simply fixing items. Ideally, it eliminates problems by conducting regular checks and fixing possible concerns before they produce breakdowns. While some factories do basic maintenance such as lubrication, a true program employs inspections and numerous approaches to proactively resolve issues and keep equipment working smoothly. This comprehensive strategy includes preventive, predictive, and remedial maintenance for all plant systems [1].

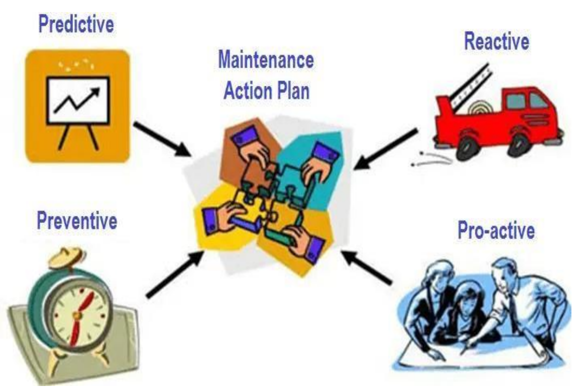


Figure 2 Showing the different maintenance techniques.

Source [1].

Both of these old maintenance procedures are suboptimal in terms of maximizing equipment uptime, cost-efficiency, and dependability, resulting in an increased demand for more modern and data-driven alternatives.

The reasons for malfunctions in power plants are varied and can be ascribed to a variety of factors, including:

a) Wear and Tear: Due to continuous operation, equipment wears and tear with time, resulting in the degradation of vital components.

b) Vibration and Mechanical Stress: Rotating machinery, such as motors and generators, are especially prone to failure due to excessive vibration and mechanical stress.

c) Temperature and Environmental Conditions: Extreme temperature swings and harsh environmental conditions can hasten the depreciation of equipment and contribute to breakdowns.

d) Component Failure: Individual component failures, such as bearings or seals, can cause cascading failures throughout the system [2].

2.3 Predictive maintenance of existing technologies

In recent years, predictive maintenance systems have evolved dramatically. Among the existing technologies and approaches currently employed in power plants are:

a) Vibration Analysis: Vibration analysis is a popular approach for determining the condition of spinning machinery. It entails using accelerometers and sensors to monitor vibrations in machinery. Deviations from established vibration patterns can alert you to impending failures, allowing you to schedule maintenance accordingly.

b) Infrared thermography: This technique is used to detect anomalous temperature trends in equipment. Potential difficulties, such as electrical problems or worn components, can be indicated by hot areas or abnormal thermal signatures.

c) Oil Analysis: Oil samples from machinery are analyzed to detect impurities, wear particles, and other irregularities, providing information on the state of important components.

Currently, over € 1,500 billion is spent annually on maintenance, repair, and renovation (MRO) in the EU alone, and over € 7,000 billion globally. The MRO directly supports approximately 50 million jobs and indirectly supports 150 million. However, MRO requirements are increasing and becoming increasingly difficult to achieve, particularly in times of financial crises and decreased budgets [9].

In a paper published by A.Kane [3] , the goal of the research is to discover certain connections and patterns that can help predict and, eventually, prevent failures. In the manufacturing industry, equipment is frequently used without a scheduled maintenance method. This technique frequently results in unanticipated downtime due to unforeseen breakdowns. This paper seeks to implement an ML to predict deviations in patterns. The ML-based predictive technique evaluates live data and attempts to determine the association between particular parameters to predict system failure or schedule equipment repair. Data from the tubing machine's many sensors is continuously retrieved and saved on the company server. This is because of the huge number of data collected, the company uses the Mongo database. The data collected from the sensors is cleaned and preprocessed to identify relevant features for data analysis and the discovery of patterns and correlations between the parameters. The cleaned data is then used to train a machine-learning model that predicts parameter values over time. The algorithm can detect any anomalies in the operation of the machinery [4].

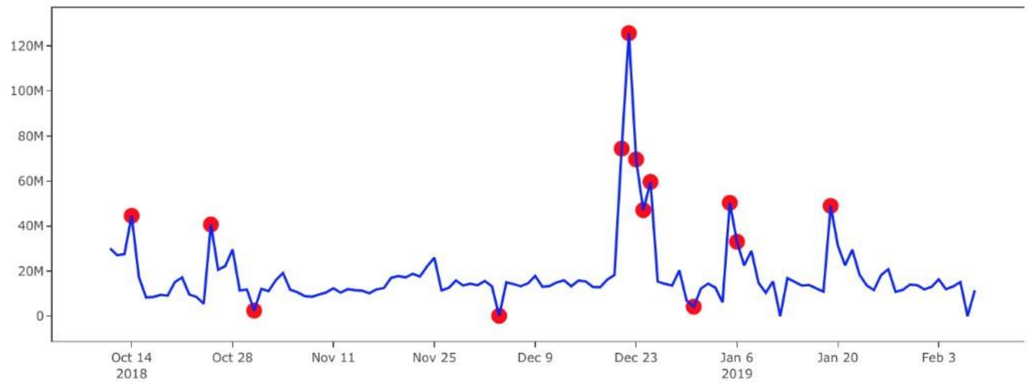


Figure 3 Showing an algorithm that displays anomalies during the operation of machinery.
Source: [4]

In a study made at Zhengzhou University [5], failures such as bearing wear, blade damage, impeller imbalance, shaft misalignment, cavitation, water hammer, and so on are common while using centrifugal pumps. It is critical to employ smart sensors and digital Internet of Things (IoT) systems to monitor the real-time operational status of pumps and detect probable breakdowns. This helps to achieve predictive pump maintenance and improve machine health management intelligence. Wireless sensors, cable sensors, data collectors, and cloud servers make up the majority of the system. Then, using the microelectromechanical system (MEMS) chip, a wireless vibration temperature integrated sensor, a wired vibration temperature integrated sensor, and a data collector are designed to monitor the pump's working status. The wireless sensor sends data to the server using the NB-IoT communication protocol. However, due to the battery power supply, the collecting and gearbox require electrical power, reducing battery life.

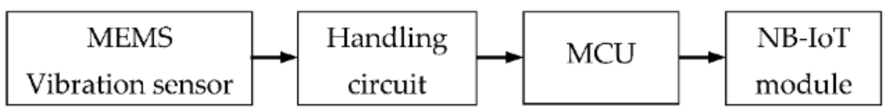


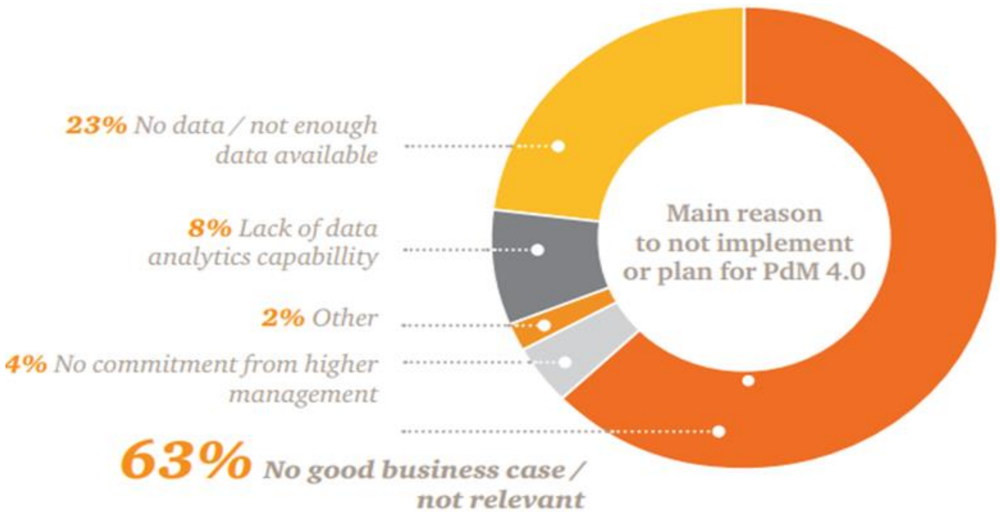
Figure 4 Showing a block diagram of a wireless sensor circuit.

Source: [5]

Predictive Maintenance, PdM 4.0.

According to a survey made by Kantar TNS in three countries: Belgium, Germany and the Netherlands, an architecture was suggested. This architecture contains the following building blocks; Assets, sensors and connectivity, the integration layer, data management, IT operation management, Analytics, business intelligence and reporting, End to end security and many others. Also, 60% of surveyed organizations are either using Pd.M. 4.0, piloting it, or planning to do so soon. Despite recent advancements, many firms' predictive maintenance capabilities still fall short of meeting Pd.M. 4.0 standards. To fully benefit from Pd.M. 4.0, companies will require significant effort and resources [6].

According to a Study made by Mark Haarman, considering 268 European companies from various sectors, Pd.M. decreased costs by 12%, improved availability by 9%, extended the lifetime of an aging asset by 20%, and reduced safety, health, environmental and quality risks by 14% [6].



According to Arxiv's study, they recommend that a model capable of operating with little data be adopted, which we were able to accomplish in our project, hence closing the gap in their study. Our Model can also be integrated into existing maintenance management systems by use of an audible microphone [7].

Considering the above research, with the advantages of predictive maintenance addressed, there is a need to embrace predictive maintenance as a way of ensuring the effective and constant operation of machines without fail.

VIBRATION ANALYSIS

The vibration analysis of rotating equipment requires systematic evaluation of vibration pattern. The following have to be achieved to develop a smooth systematic flow of the system

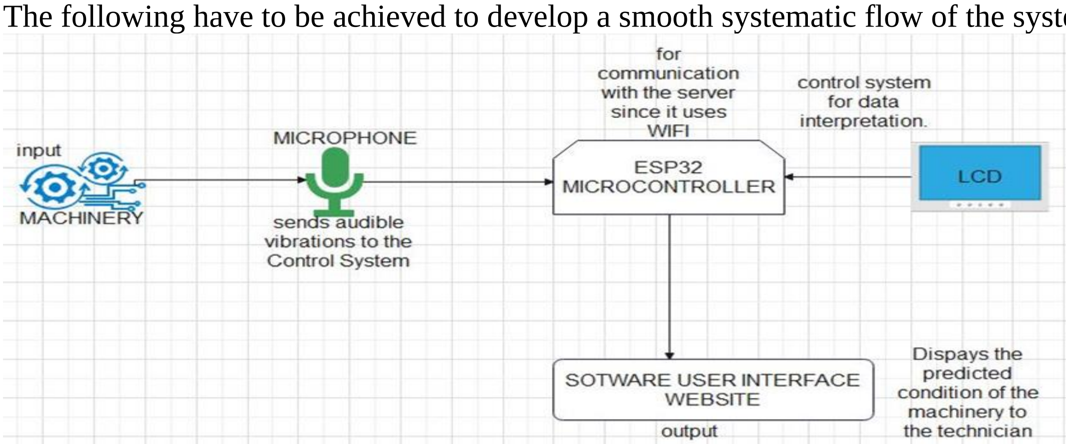


Figure 5: System context Diagram.

To develop a strong data infrastructure to collect and integrate data from multiple sensors, and monitoring devices using a database.

We recorded clips of audible vibrations using our prototype machinery i.e., induction motors. These records were used in training the machine learning model considering the normal, abnormal, and artifact cases. Therefore, we combined hardware components i.e., microcontroller, an audible microphone, Convolutional Neural Network (CNN) machine learning model for real-time analysis of audible vibrations.

This enabled the model to make data-driven decisions thus improving operational efficiency, and increasing overall system reliability

Audible Microphone was connected to the microcontroller to record audible vibrations caused by the machinery while in operation. In addition to the audible microphone, existing monitoring systems such as rotational speed sensors are integrated with the microcontroller to offer complete data collecting.

Data Synchronization is achieved with the audible microphone and monitoring systems(microcontroller) data are synchronized to ensure temporal alignment and proper data transmission. Data Transfer (Wireless Communication) is achieved using the microcontroller which supports wireless communication (e.g., Wi-Fi or Bluetooth), allowing for smooth data delivery to an external server. Data collected from the audible microphone and monitoring devices is packed in standardized formats for efficient transmission and processing. A dedicated server on a computer was configured to accept and store data delivered by the microcontroller

To develop an AI-powered predictive maintenance algorithm that uses historical data and real-time sensor data to forecast equipment health and potential breakdowns using python

A machine learning model called Convolutional Neural Network (CNN) was used to analyze audible vibrations in real-time. This was done to create an AI-powered predictive maintenance system that uses datasets and real-time sensor data to anticipate equipment health and future failures, which was implemented using Python. It analyzes audible vibrations in real-time, a Convolutional Neural Network (CNN) model is constructed using Python libraries like TensorFlow.

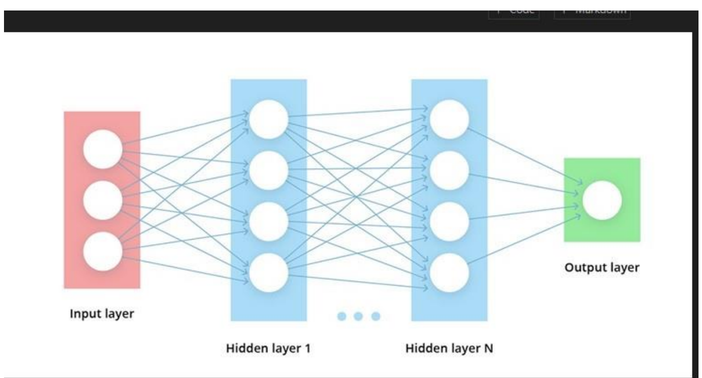


Figure 6: The CNN ML model illustration.

The status of the machinery was determined using past maintenance datasets recorded. These datasets provided the foundation for training and verifying the predictive maintenance algorithm. Real-Time Sensor Data is collected via the microcontroller which captures real-time sensor data from the audible microphone while the equipment operates, in addition to past datasets.

Data preprocessing

Signal Conditioning is achieved when raw audio signals recorded by the audible microphone are pre-processed to eliminate noise, normalize amplitudes, and boost key aspects indicating equipment health. Feature Extraction techniques are employed for extracting informative features from pre-processed audio recordings include spectral characteristics, temporal patterns, and frequency-domain representations.

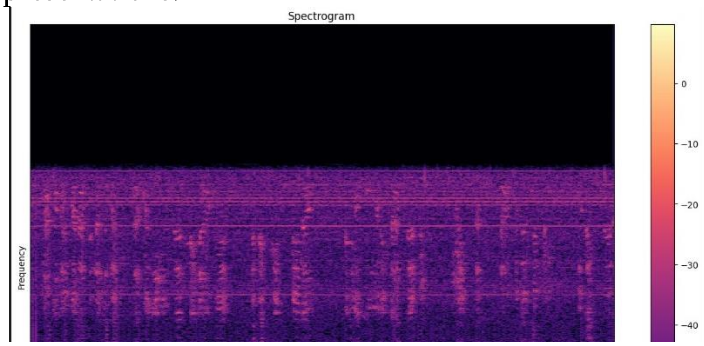
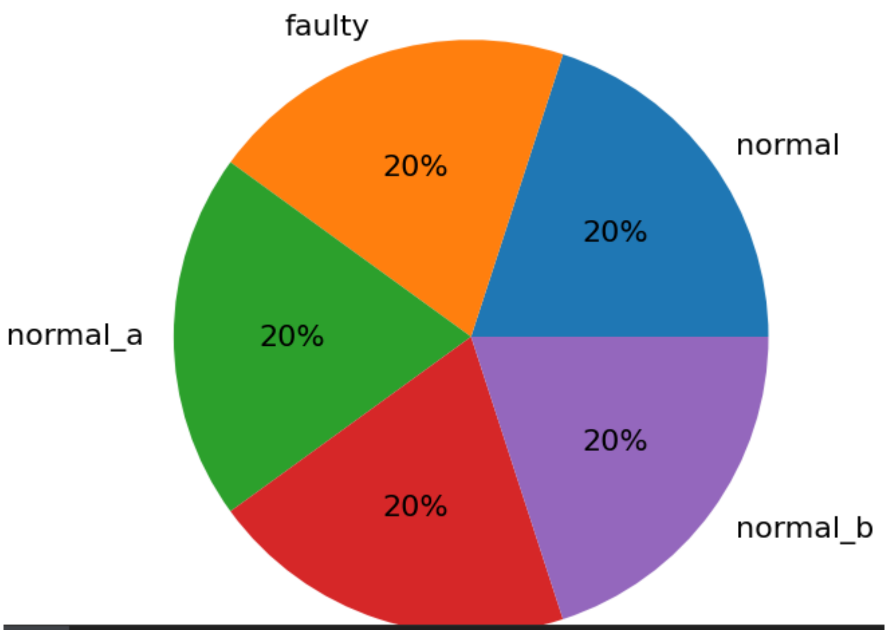


Figure 7 A graph showing feature extraction by the model.

A CNN model architecture is created and implemented with Python packages like TensorFlow. The model consists of many convolutional layers, followed by pooling layers and fully linked layers for classification.

EDA Visualization



Artifact-noise that means nothing to us, but might be presented to the model

Faulty- unexpected sound from the machine that is not expected during normal operation

Normal-a -a type of sound that the machine can make during normal operation

Normal-b -a type of sound that the machine can make during normal operation

Normal -ideal sound that the machine makes during normal operation

Unlabeled -random sound of any category

The end result model grades them as:

Normal -(Include normal-b and normal-a) - okay sound for operation

Faulty - The dangerous sound

Artifact - noise that means nothing to us

Waveform

Sound is the pressure of air as it propagates to our ears. Digital audio file is gotten from a sound sensor that detects sound waves and converts them to electrical signals. Specifically, its telling us about the displacement and how it changes over time

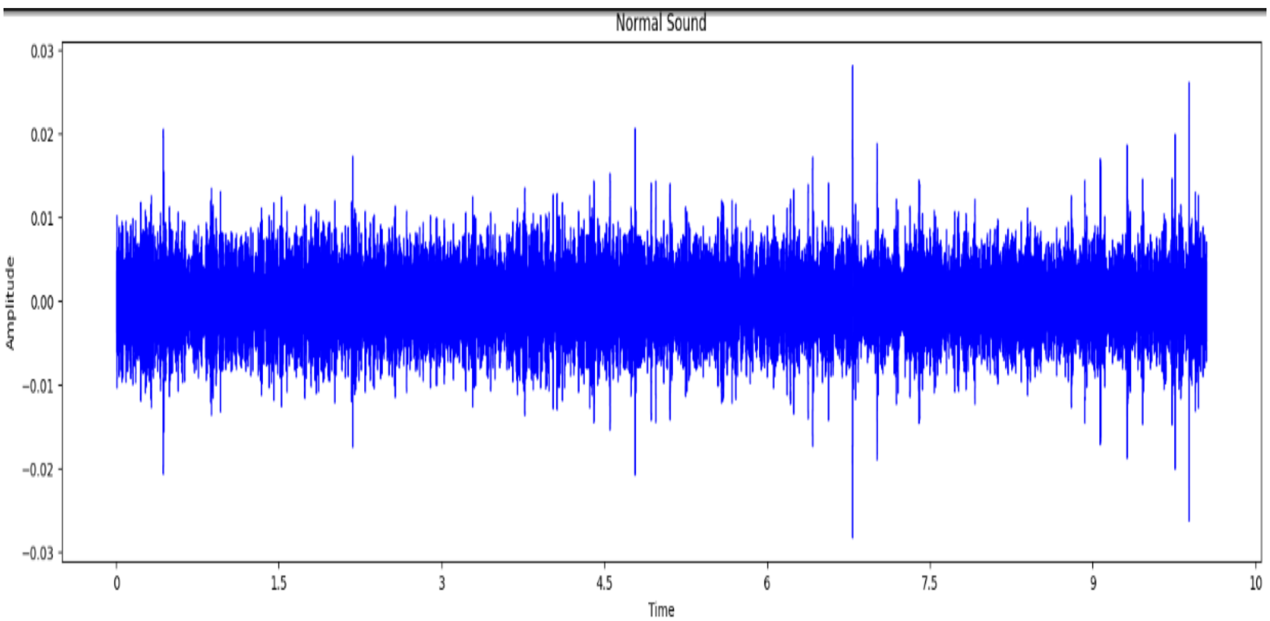


Figure 8 sowing waveform of captured sound

The X axis represents time. Y axis measures the displacement of the air molecules, this is where amplitude comes in.it measures how much the air particles are displaced from there resting position

Spectrum

A sound spectrum is a representation of a sound, usually a short sample of a sound in terms of the amount of vibration at each individual frequency .it is usually presented as a graph of either power or pressure as a function of frequency. The power or pressure is usually measured in decibels and the frequency is measured in vibrations per second (or hertz). The spectrum expresses the frequency composition of the sound and is obtained by analyzing the sound. A sound spectrum is usually represented in a coordinate plane where the frequency is plotted along the axis of abscissas and the amplitude A, or intensity, of a harmonic component with a given frequency is plotted along the axis of ordinates.

The Fast Fourier Transform (FFT) is a technique for computing a sequence's Discrete Fourier Transform (DFT) or inverse (IDFT). The DFT turns a time-domain signal into frequency-domain components. FFT is commonly used in signal processing to analyse the frequency content of signals. It aids comprehension of the signal's frequency domain properties by converting signals to the frequency domain makes it easier to detect and delete redundant information, hence aiding data compression. In the frequency domain, it is easy to remove undesired frequencies from a signal.

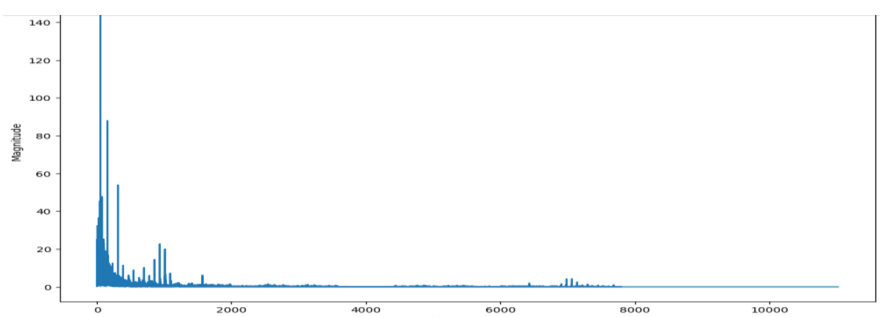
```
fft_normal = np.fft.fft(normal_sound_sample)
magnitude_normal = np.abs(fft_normal)
freq_normal = np.linspace(0,sample_rate, len(magnitude_normal))
half_freq = freq_normal[:int(len(freq_normal)/2)]
half_magnitude = magnitude_normal[:int(len(freq_normal)/2)]
```

FFT formula

$X[k]=\sum_{n=0}^{N-1} x[n]\cdot e^{-jN2\pi kn}$

for k=0,1, 2…, $N-1$

Here, $X[k]$ represents the frequency domain components, x[n] represents the time domain samples, and $e^{-j2\pi Nkn}$ are the complex exponential basis functions.



Spectrogram

As humans we sense sound not only on a particular time by its intensity but also by its pitch. The pitch is the frequency of the sound, higher pitch corresponds to higher frequency and vice versa. A spectrogram is a visual representation of the spectrum of a frequency of a signal as it varies with time. When applied to an audio signal spectrogram are sometimes called sonographs, voicegrams

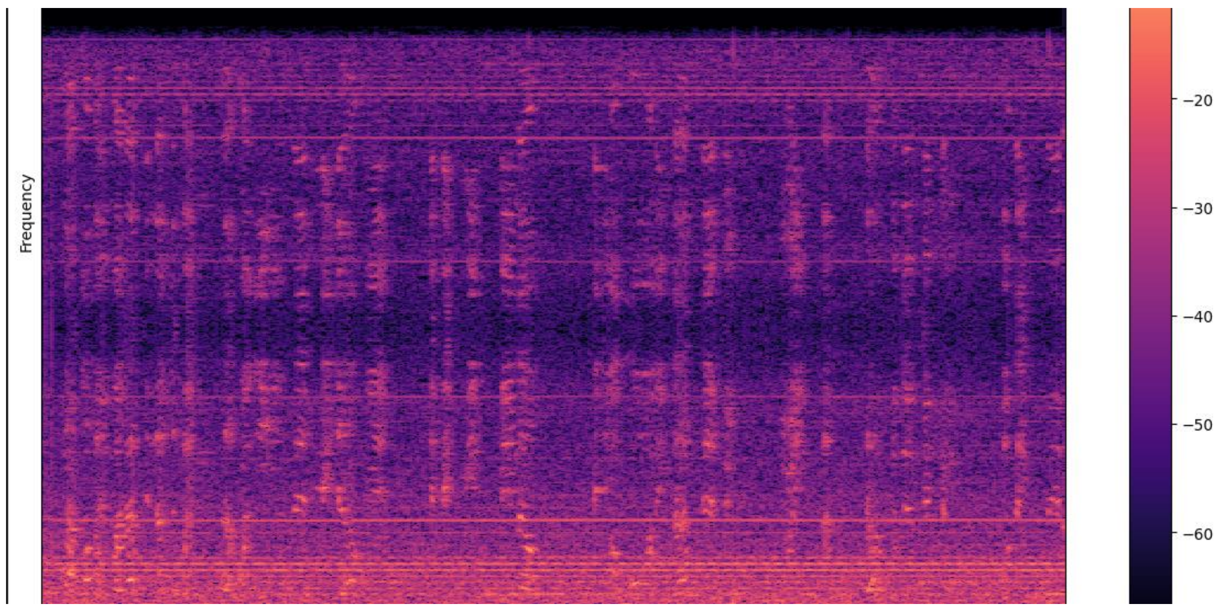


Figure 9 showing sound spectrogram

The image above represents a sound .X-axis for time, y-axis is for frequency and the color is for the intensity

MFCCs

As earlier stated ,we cant take the raw audio signal as input to our model because there will be a lot of noise in the audio signal .it is observed that extracting features from the audio signal and using it as input to the base model will produce much better performance than directly considering raw audio signal as input .MFCC is the widely used technique for extracting the features from the audio signal .In sound processing the ,Mel frequency cepstrum (MFC)is a representation of the short term power spectrum of a sound ,based on a linear cosine transform of a log power spectrum on a nonlinear Mel scale of frequency.

Mel _frequency cepstral coefficients (MFCCs) are coefficients that collectively make up an MFC .They are derived from a type of a cepstral representation of the audio clip (a nonlinear spectrum of a spectrum).The difference between the cepstrum and the Mel frequency cepstrum is that in MFC ,the frequency bands are equally spaced on the Mel scale which approx9imates the human auditory systems response more closely than the linearly spaced frequency bands used in the normal spectrum .This frequency wrapping can allow for better representation of sound e.g. in audio compression

MFCCs are derived as follows

Step 1: Take the Fast Fourier Transform of a signal

Convert the time-domain signal $x\ (t)$ to the frequency domain via FFT.

$X(f)$=FFT($x(t)$)

The FFT generates a complex-valued spectrum from which we may obtain the magnitude spectrum: $|X(f)|=[R(X(f))^2+j(X(f))^2]^{0.5}$ Where R and j denote real and imaginary part respectively

Step 2: Map the spectrum obtained above onto the Mel scale using triangular overlapping windows alternatively, cosine overlapping windows The Mel scale approximates how the human ear responds to various frequencies. The Mel scale, $M\ (f)$, is defined as $M(f)=2595\log_{10}(1+f/700)$

Apply a set of triangular (cosine) overlapping windows to the magnitude spectrum to map it onto the Mel scale. $S[m]=\sum k=1K|X(fk)|\cdot Hm(fk)$

where $Hm(f)$ is the triangular (or cosine) filter, and K is the number of filters. Each filter $Hm(f)$ is defined to cover a range of frequencies and overlap with adjacent filters.

Step 3: Take the logs of the powers at each of the Mel frequencies. Convert the Mel filter bank energies to a logarithmic scale to simulate human sense of loudness.

$\log(S[m])$

Step 4; Take the discrete cosine transform of the list of the Mel log powers as if it were a signal

$C[n]=\sum_{m=1}^{M}\log(S[m])\cdot\cos(\pi n/M(m+1/2))$ where $C[n]C[n]$ are the MFCCs, nn is the index of the coefficient, and MM is the number of Mel filters.

Apply the discrete cosine transform to the log Mel spectrum. This stage decorrelates the coefficients and condenses the most important information into the first few coefficients.

Step5: The MFCCs are the amplitudes of the resulting spectrum. The MFCCs are the coefficients C[n] obtained by DCT. Typically, just the top 13 coefficients are utilised since they reflect the most important aspects in speech processing.

The CNN model is trained on recorded datasets, with each sample classified as normal or faulty or artifact. Training entails optimizing model parameters to reduce loss and increase forecast accuracy. We evaluate the trained model against distinct validation datasets to determine its generalization performance and identify any overfitting or underfitting concerns. Real-time predictions are achieved after training, the CNN model is connected with the microcontroller via the WIFI network which connects to the server in Realtime. The trained CNN model analyses incoming sensor data from the audible microphone in real-time. Predictions on equipment health and probable failures are generated in real-time on the interface. Advanced Anomaly Detection Algorithms are used, edge-cutting anomaly detection approaches, such as Isolation Forests, One-Class SVM, or deep learning-based autoencoders, discover deviations from normal operating circumstances thus displaying results on the interface

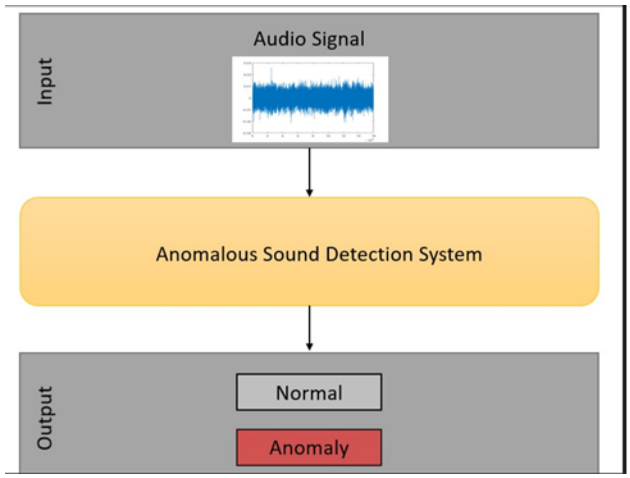


Figure 10: Block diagram of system.

RESULTS AND ANALYSIS

The predictive maintenance AI system shows encouraging results in accurately forecasting equipment operating conditions based on auditory vibrations. The CNN ML model, trained on historical datasets and installed on the server and is connected to the microcontroller, and it accurately categorizes equipment situations as faulty, artifact or normal in real-time. The combination of audible vibration analysis with CNN ML models and real-time processing on the microcontroller allowed for the attainment of predictive maintenance goals. By continually monitoring equipment health and recognizing abnormalities, the system enabled proactive maintenance practices.

Artifact Condition Analysis.

Artifact result is due to environmental noise, such as background talk or ambient vibrations, occasionally causing artifact conditions, resulting in false alerts. These artifact circumstances were successfully reduced using signal processing techniques and noise filtering algorithms, assuring the accuracy of predictive maintenance estimates.

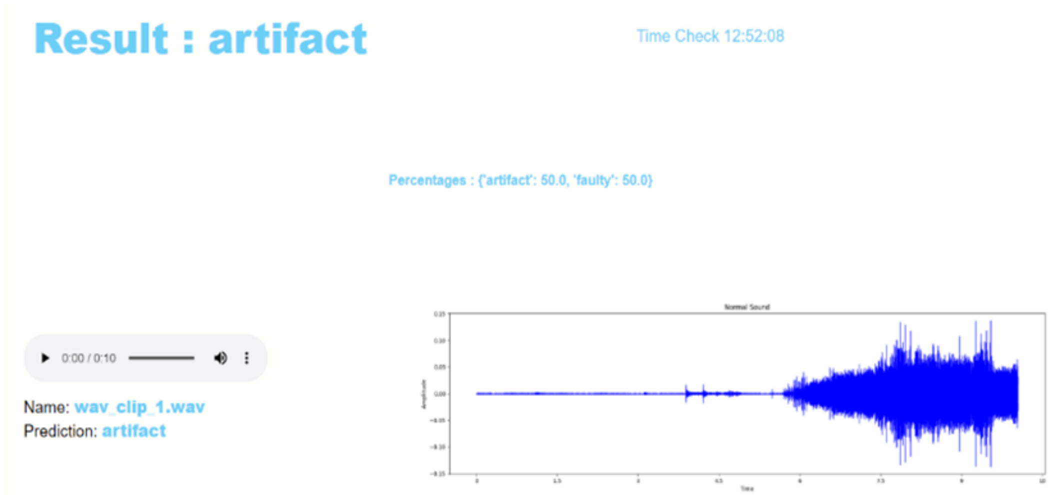


Figure 11: Artifact result on the interface in real-time.

Faulty Condition Detection.

During testing, the system effectively identified a variety of equipment vibration deviations from normal vibration. The CNN model detected specific vibration patterns associated with fault type, allowing for prompt maintenance notification to avoid catastrophic failures.

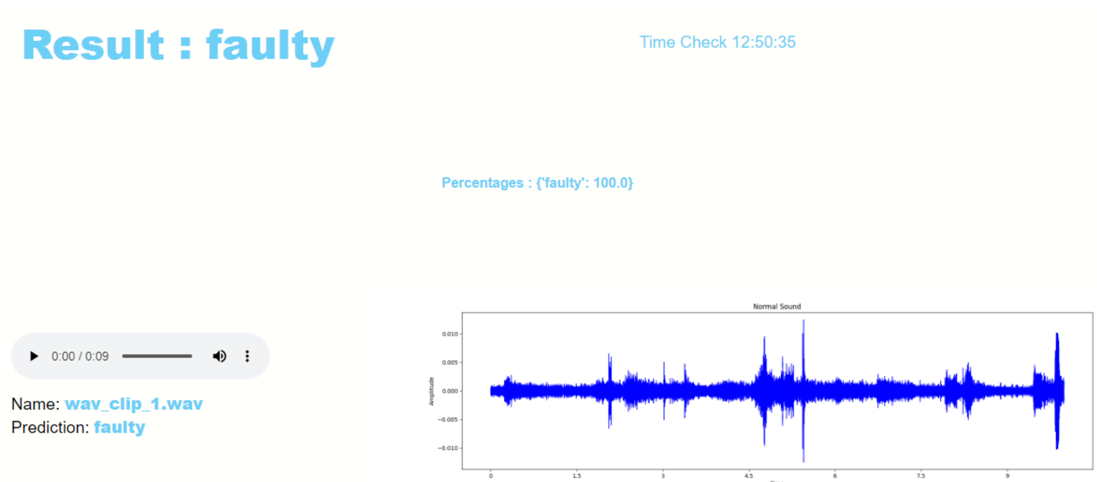


Figure 12: Interface display when the machinery condition is faulty.

Normal state Recognition.

When the machinery functioned within normal parameters, the system correctly identified the state as normal. This gave assurance of equipment health and reduced needless maintenance operations, hence increasing operating efficiency.

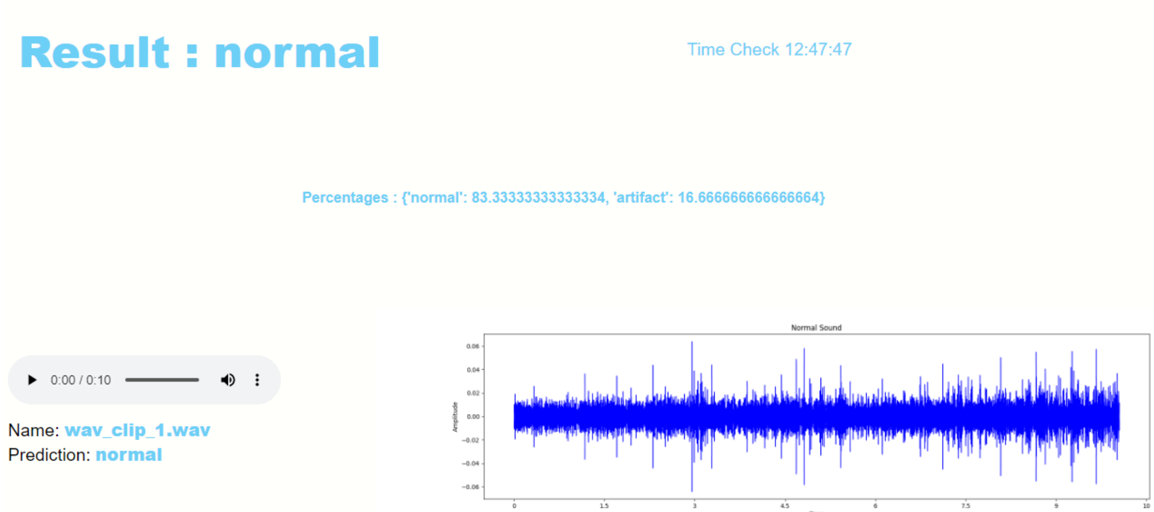


Figure 13: *Interface display when the machinery condition is Normal.*

Conclusion

In conclusion, the project revealed the potential of predictive maintenance AI, which uses audible vibrations to improve equipment health monitoring and maintenance processes in industrial settings. The system accurately predicted the operating status of equipment by integrating hardware components such as the ESP32 microcontroller and audible microphone, as well as a CNN ML model for real-time analysis. By using audible vibrations as a diagnostic tool, the system enabled proactive maintenance interventions, decreasing downtime, lowering repair costs, and increasing operating efficiency. The successful detection of problematic circumstances and the recognition of normal operating states highlight the efficiency of the predictive maintenance AI system in improving equipment dependability and safety.

Future Research Agenda

Continuous Model Improvement, which involves refining the model to give more accurate precise root cause of the fault in real-time

Combination of other parameter models i.e. temperature, voltage, current levels with the vibration CNN model already developed to give a robust more accurate results based on other parameters

Cost analysis of implementation in the industry of Pd.M. based on vibration analysis

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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