AI BASED HEALTH MONITORING SYSTEM OF INDUSTRIAL MACHINES

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In the name of ALLAH, the Most benevolent, the Most Courteous

CERTIFICATE OF CORRECTNESS AND APPROVAL

This is to officially state that the thesis work contained in this report

"AI-BASED HEALTH MONITORING SYSTEM OF INDUSTRIAL MACHINES"

is carried out by

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under my supervision and that in my judgement, it is fully ample, in scope and excellence, for the degree of Bachelor of Electrical (Telecom.) Engineering in Military College of Signals, National University of Sciences and Technology (NUST), Islamabad.

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DECLARATION OF ORIGINALITY

We hereby declare that no portion of work presented in this thesis has been submitted in support of another award or qualification in either this institute or anywhere else.

ACKNOWLEDGEMENTS

Allah Subhan'Wa'Tala is the sole guidance in all domains.

Our parents, colleagues and most of all supervisor, **DR ATA UR REHMAN** without your guidance.

The group members, who through all adversities worked steadfastly.

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ABSTRACT

Industries are essential assets of an economy. Industrial machines such as rotors, motors, pumps etc. are building blocks of an industry. The maintenance of these bodies is important to keep them in working state.

Many maintenance techniques are available for machine monitoring, but most of them include corrective maintenance, routine maintenance, and emergency maintenance. These techniques are not efficient enough in terms of being cost effective, time saving, and prolonging machines life expectancy.

The world is moving towards new technology based on AI models. Such models are being used, in order to automate the industrial sector as well. One such innovative technology is AI based, predictive machine maintenance.

Machine learning can be used to always monitor industrial machines via anomaly detection. It works on data acquired from machines, which can be vibrational data, sound data and so on. This innovation is new and is helping the industrial sector in becoming more productive and efficient.

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Chapter 1: Introduction

The capital cost of industrial machinery is substantial, and its efficient usage is dependent on low operating and maintenance costs. Machinery condition monitoring and diagnostics have become industry standard tools for meeting these standards. By eliminating accidental outages of machinery, lowering downtime for repairs, and improving reliability and safety, condition monitoring systems have resulted in significant savings. status monitoring is a technique for sensing the health of equipment and analysing the data to determine operational information and equipment status. This is done to discover and diagnose possible problems early in their development and to fix them with suitable corrective measures before they cause plant failure and other catastrophic repercussions.

1.1 Overview

Machine status tracking is becoming more popular in industry because of the need to improve machine reliability, efficiency, and reduce production costs caused by machine breakdowns. Condition tracking is done when you need to know how a machine is doing. To figure out if it is wrong, using reasoning and observation. Condition monitoring is also the method or process of keeping an eye on how a machine works in order to guess when it will need repair or estimate the current before it breaks down or gets worse in a big way. The status of the machine. Condition tracking has become more important in many businesses as the need for normal machine repair has grown. Unexpected failures or shutdowns can cause serious accidents and cost the company a lot of money.

1.2 Types of machine maintenance techniques

The term maintenance points to the technical, administrative, and managerial work and actions which are done to retain the life of an item or restore it is a way in which it can perform the required functions.

It is very important to have good maintenance methods to keep our machines in working condition for longer and with efficiency. There are numerous ways available to maintain machines health.

The main types include corrective maintenance, emergency maintenance, preventive maintenance and CBM.

1.2.1 Corrective maintenance

It is a technique in which maintenance is done after faults are detected and then the item is put. into its working condition.

1.2.2 Preventive maintenance

It is a type of maintenance carried out at predetermined intervals or at prescribed. criteria to reduce the failure and damaging of an item.

1.2.3 Emergency maintenance

This type of maintenance is undertaken under emergency situations when the machines are failing and need monitoring and care.

Chapter 2: Introduction to CBM

2.1 What is CBM?

In contrast to more traditional methods that rely on condition-based maintenance (CBM), condition-based maintenance (CBM) is the primary strategy for scheduling maintenance interventions. to more traditional solutions that rely on time-based maintenance. Even in modern industrial systems, an effective CBM approach has the potential to deliver significant benefits for industrial organizations' competitiveness (e.g., better system availability and safety management, decreased maintenance costs, increased product quality).

The availability of earlier literature evaluations is not surprising given that CBM is a well-established study subject. One of them examines global CBM industry practices, explaining fundamental principles such as the requirement for planned maintenance.

2.2 Benefits of CBM

Condition-based maintenance (CBM) offers many benefits, including reduced number of unplanned failures, improved equipment availability, reliability and worker safety. CBM is performed while the asset is operating, reducing the chances of disruption to normal operations and reducing the cost of asset failure2. Other benefits of CBM include increased production output, longer asset life cycle, improved planning and better decision making through data analytics in Industry 4.0 era3. CBM development platforms can accelerate time to market and end-to-end system-level solutions for condition monitoring and predictive maintenance can be implemented using CBM4. CBM is a lean method that aims to streamline flow and eliminate waste, making it an efficient and effective maintenance strategy.

2.3 Types of CBM techniques

The most popular types of condition-based monitoring methods are vibration analysis and vibration monitoring, oil analysis, and temperature tracking.

Other condition-based tracking methods include:

• Infrared thermography

• Ultrasonic analysis

• Analyzing electrical systems and keeping an eye on the pressure

Traditional condition tracking was mostly based on sound analysis, but more modern, new methods use devices to measure different factors. There are two main types of condition monitoring: checking the state and keeping track of how the performance changes over time. Real-time, constant, condition-based tracking and predictive maintenance solutions are becoming more important as makers try to increase output and use of assets while lowering maintenance costs and downtime.

2.4 Problem Statement

It is important to always keep an eye on the health of machines, since sudden breakdowns or shutdowns can cause major accidents and cost the company money. Because of this, utilities must come up with ways to prevent equipment breakdowns, shorten downtime, lower upkeep costs, and make equipment last longer. When programmers are given a lot of data, two problems can happen. The amount of data is too much for engineers to handle, and it is not always clear how a plant item's health, condition tracking data, and other data are related. Because of this, it is hard to get useful information from tracking data. Also, in many cases, experts can come to the wrong opinions because of the growing number of measurement data and the push to find problems quickly. So, to get rid of the need for human control, we need tools that are very smart.

2.5 Proposed Solution

A reliable, fast, and automated diagnostic technique that allows relatively unskilled operators to examine data and make critical decisions without the need for a condition monitoring expert to diagnose problems is essential to this problem.

There are numerous characteristics of a machine that can be monitored,

Some of which are electrical, current, temperature and vibrational analysis.

In this project we will work on vibrational analysis to monitor the health of machines.

2.6 INDUSTRIAL MAINTENACE TECHNIQUES IN PAKISTAN:

Modern engineering systems and industrial processes are getting more and more difficult at a very fast rate. In today's changing working settings, it's getting harder to keep track of how reliable the systems are. In this situation, condition-based maintenance (CBM) is the best way to plan maintenance work. This is in comparison to time-based maintenance, which has been used in the past. Pakistan is having adequate number of industries, but these industries lack innovative and smart maintenance techniques. Our industrial sector relies on maintenance techniques such as routine maintenance, emergency maintenance and risk-based maintenance. These are not cost effective neither they provide for a timely anomaly detection.

2.7 RELEVANT SDG's

Our project is relevant with SDG number 8 and 9 which are the following:

- **Decent work and economic growth:**

This SDG is quite relevant with our project since it is all about making the industrial work a lot easier and expanding the anomaly detection systems for all types of machines available in the industrial sector for a better health monitoring system.

- **Industry, innovation, and infrastructure:**

The project paves way for industrial innovations and smart infrastructure. The AI-BASED Anomaly detection makes the industry far more efficient and useful by reducing machinery downtime, maintenance cost as well as prolonged machine life.

2.8 Literature review

-Machine Condition Monitoring Using Artificial Intelligence: The Incremental Learning and Multi-agent System Approach Christina Busisiwe Valakati

- Condition-based maintenance with both perfect and imperfect maintenance actions

Eric Levart

- Rastegari, A., and Salonen, A. (2015), "Strategic Maintenance Management:

Formulating

-Maintenance Strategy", International Journal of Condition Monitoring and

Diagnostic

Engineering Management.

Chapter 3: Research methodology

3.1 RESEARCH METHODOLOGY

We have worked on vibrational parameter of machines to get the required data. The vibrational data will be collected from the machine via sensors and any changes in its patterns will detect anomalies.

3.2 Vibration based condition monitoring.

Most of the time, the vibration-based tracking device is used for status monitoring. It is based on the idea that everything makes waves. When a machine is in Normal working state, its movements are smooth and constant. When there is a problem or a change in the way the system works, the sound range changes. It can't be beat.

A way to find problems in systems that move. Machines have very complicated mechanical structures that move back and forth, and parts that are related to each other pass on these movements. This makes a frequency range linked to the machine that describes how a healthy machine works. Every problem with a spinning machine causes it to vibrate in a certain way. These movements can be logged and compared to reference files to find the problem and fix it. Usually, several sound signs and steady factors like load are looked at in each machine.

3.3 Use of sensors in vibrational CBM

Vibration sensors, such as accelerometers, are used in conditional control (CBM) to measure machine motion and detect mechanical errors in motion, such as drive component failure, imbalance, looseness, and bearing defects1. Analog devices are used to provide high-quality CBM2 with MEMS vibration sensors, precision transducers, linear, isolation and power technologies. CBM is designed to monitor the condition of machine parts such as ball bearings, and bearing diagnosis is also done with vibration sensors. Wireless Vibration Monitoring and a wireless Vibration sensor are also available for the CBM4. From the vibration sensor, it accurately shows the status of various engines and is a good starting point for the CBM5 program.

3.4 How do vibration sensors work in CBM.

Vibration sensors, such as accelerometers, measure engine movement and detect emerging mechanical faults, such as faults in drivetrains or faulty motor bearings. Analog devices are used to provide high quality CBM and MEMS vibration sensors, precision transducers, linear, isolation and power technologies. Vibration sensors work by detecting the vibration of a device and converting it into an electrical signal that can be analyzed to determine the status of the device. The electrical signal is then processed using software techniques to detect performance degradation and take planned corrective action. As sensors become more affordable and with more embedded processing power, more and more cost-effective applications for CBM will become possible. PTC provides accelerometers, vibration sensors and accessories for industrial CBM applications.

3.5 Object of interest:

The object of interest is an anomaly, that will get detected by any unfamiliar. vibrational patterns occurring in the machine. The vibrations will continuously be acquired and read via the sensors and fed into the AI modal.

3.6 Type of Dataset:

The procedure of gathering, preprocessing, and mining a dataset from AC electric equipment, followed by training a CNN (Convolutional Neural Network), ANN (Artificial Neural Network), and LSTM (Long Short-Term Memory) machine learning model.

Dataset Gathering:

The initial phase entails gathering information from AC electric devices. To measure factors like voltage, current, temperature, power, speed, and other pertinent properties, numerous sensors and devices may be used. To ensure diversity in the collection, the data should be collected over an extended period and under various operational situations.

Preprocessing:

Preprocessing is required to clean up and prepare the raw data for the machine learning models' training after it has been acquired. The preprocessing procedures could involve:

Taking out any noise or outliers from the data.

handling missing values using imputation or deletion methods.

standardizing or normalizing the data to make sure that all the features have a comparable scale. If applicable, encoding categorical variables.

creating training, validation, and test sets from the dataset.

Convolutional neural networks:

CNNs, are particularly useful for processing organized data that resembles a grid, like photographs or time series data. CNNs can be used to extract spatial or temporal properties from the collected data in the setting of AC electric equipment. The following steps are needed to train a CNN model on this dataset:

Create the CNN model's architecture, deciding on the variety, number, and kind of convolutional, pooling, and fully connected layers.

The training set is used to train the model, and backpropagation and gradient descent optimization are used to modify the weights of the model.

Utilizing the validation set, assess the model's performance, and adjust the hyperparameters as necessary.

ANN (Artificial Neural Network):

Artificial neural networks, or ANNs, are frequently employed in a wide range of machine learning tasks. They are made up of interwoven layers of input, hidden, and output neurons. An ANN can be used to capture intricate correlations between input features and output variables in the case of data from AC electric machines.

The following are the steps for training an ANN model:

Create the architecture of the ANN, considering the structure of the output layer, the size and number of hidden layers, and activation methods.

Set the network's weights to zero.

Long Short-Term Memory (LSTM):

Recurrent neural networks (RNNs) of the LSTM variety are appropriate for sequential data, such as time series. Data from AC electric machines frequently contain time-dependent measurements; hence LSTM is an excellent choice for modelling such data. The following procedures are used to train an LSTM model:

Design the LSTM architecture, considering the dropout regularization, hidden units, and LSTM layer count.

Chapter 4: Equipment

4.1 Equipment

The equipment used for the modal consists of various parts in which the most important aspect is the sensor used for the vibration analysis.

4.2 STMelectronics (Sensor):

Since the project uses a vibrational component and the vibration monitoring system requires large amounts of data to be stored. Vibration is often measured with multiple sensors mounted on different parts of the machine and for this purpose the sensor we used for our work is STEVAL-BFA001V2B.

4.3 STEVAL-BFA001V2B

The STEVAL-BFA001V2B is an industrial design reference kit for Condition Monitoring (CM) and Predictive Maintenance (Pd.M.) in line with IEC61000-4-2/4 and EN60947 standards for industrial uses. The device is made up of a very small industrial sensor board (50 x 9 x 9 mm) that was made for real industrial uses and connections, wires, plugs, and adapters for industrial communication scenarios.

The STEVAL-BFA001V2B kit manages key factors from weather, vibration, and sound monitors to provide predictive maintenance, which is the early discovery of problems in tracked equipment. It can speed up the creation of easy-to-use technology solutions and proofs of concept (PoCs) for handling motors, pumps, and fans. The kit uses advanced time- and frequency-domain signal processing for shaking analysis. It runs on an embedded high-performance MCU with changeable limits for alerts and alarms and shows the process on the edge. The sensor point is meant to be small and tiny so that it can be placed very close to the gadget being watched. The power control stage uses a voltage range of 18 to 32 V to make the low voltage that the digital sensor and MCU need.

4.4 SENSOR CHARACTERISTICS

Kit Contents:

- Censor point

- Communication adapter board

- programming and debugging interface

-Cables and connectors

• Main supply voltage: 18 - 32 V.

• Main components of sensor points: -

-Absolute Digital Pressure Sensor (LPS22HB)

- Relative humidity and temperature sensor (HTS221)

-Digital microphone sensor (IMP34DT05)

- IO-Link PHY device (L6362A)

- EEPROM (M95M01-DF) for data storage

• Microphone algorithm:

- PDM to PCM

- Sound Pressure Level (SPL)

- Audio FFT

4.5 OTHER COMPONENTS AND WORKING:

-RS-485/422:

A generic RS-485/422 USB adapter is a device that allows communication between a computer with a USB port and a network or device that uses RS-485/422 communication protocol. The purpose of this adapter is to enable the computer to communicate with and control various devices that use the RS-485/422 protocol, such as industrial control systems, PLCs (Programmable Logic Controllers), and other types of machinery.

RS-485/422 is a serial communication protocol that uses differential signaling to transmit data over long distances, making it suitable for industrial and other applications where communication distances may be several hundred meters. However, most computers and laptops do not have a built-in RS-485/422 port, which is why a USB adapter is needed to connect them to devices that use this protocol.

A generic RS-485/422 USB adapter typically includes a USB interface, a UART (Universal Asynchronous Receiver-Transmitter) chip, and an RS-485/422 transceiver. The UART chip is responsible for converting the data between the USB and RS-485/422 interfaces, while the transceiver is responsible for transmitting and receiving the data over the RS-485/422 network. Some adapters may also include other features, such as surge protection, isolation, or a terminal block for easy wiring.

Overall, the purpose of a generic RS-485/422 USB adapter is to provide a convenient and easy-to-use solution for connecting a computer with a USB port to devices and networks that use the RS-485/422 protocol. It enables communication and control of industrial machinery and other devices, making it a useful tool for engineers and technicians in various industries.

-STEVAL-IDP004V1:

The STEVAL-IDP004V1 is a development kit for evaluating and prototyping applications based on the ST25DV dynamic NFC/RFID (Near Field Communication/Radio Frequency Identification) tag IC. The purpose of this board is to enable developers and engineers to easily integrate dynamic NFC/RFID tag functionality into their applications, such as electronic devices, wearables, and IoT (Internet of Things) systems.

The ST25DV dynamic NFC/RFID tag IC provides an interface for data transfer between an NFC-enabled device and a host system. It supports both NFC Type 5 and ISO/IEC 15693 protocols and has a wide range of features, including non-volatile memory, password protection, energy harvesting, and wireless charging capabilities. The STEVAL-IDP004V1 development kit can be used for a wide range of applications that require NFC/RFID tag functionality, such as contactless payment, access control, asset tracking, and smart packaging. The board provides a flexible and scalable solution for integrating dynamic NFC/RFID tag functionality into various types of electronic devices and IoT systems.

The purpose of the STEVAL-UKI001V1 is to enable developers and engineers to evaluate and prototype industrial IoT solutions using the STWIN platform.

The STWIN platform integrates various sensors and features, including motion sensors (accelerometers, gyroscopes, magnetometers), environmental sensors (temperature, humidity, pressure, gas), and a microphone, as well as a microcontroller, Bluetooth Low Energy (BLE), and Wi-Fi connectivity. The STEVAL-UKI001V1 development kit provides a complete solution for evaluating and testing the capabilities of the STWIN platform.

The STWIN platform and the STEVAL-UKI001V1 development kit can be used for various industrial IoT applications, such as predictive maintenance, asset tracking, smart agriculture, and smart city solutions, among others. The platform provides a flexible and scalable solution for collecting and analyzing data from various sensors and communicating the data to cloud-based or edge-based applications for further processing and analysis.

- Serial Wire Debug SWD:

Serial Wire Debug which is a debug and programming interface used in microcontrollers and other embedded systems. SWD provides a bi-directional communication interface between the debugger or programmer and the microcontroller, allowing for real-time debugging, flash programming, and other operations.

SWD uses two signals: SWDIO (Serial Wire Debug Input/Output) and SWCLK (Serial Wire Debug Clock). SWDIO is used for data transmission between the debugger/programmer and the microcontroller, while SWCLK is used to synchronize the data transfer. SWD is a two-wire interface, which makes it more compact and simpler than other debugging interfaces such as JTAG (Joint Test Action Group), which uses a larger number of pins. SWD is also faster than JTAG, making it a popular choice for debugging and programming microcontrollers in embedded systems. SWD is supported by various microcontroller manufacturers, including ARM, which has standardized the SWD interface as part of the ARM Debug Interface Architecture.

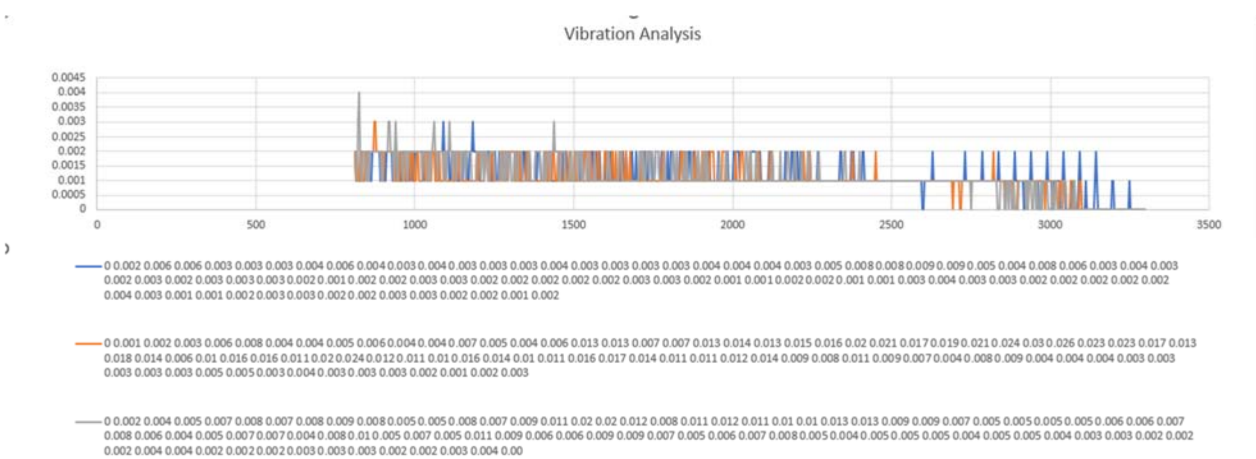
Chapter 5 Implementation of CNN, ANN, and LSTM

5.1 Introduction

Downtime is the most serious issue in an Industry which effects the productivity of the machine. Machines would remain closed in their downtime, which is a billion dollars loss to the industry.

It has an impact on 5%–10% of productivity. The industry becomes more productive overall when downtime is decreased. We can evaluate the issues and decrease the industry's downtime with the aid of machine learning approaches. These techniques use different algorithm on the historical data of the Machines. Machine learning model helps us to minimize the maintenance cost, enhance productivity and efficiency.

The most common cause of system failure in industrial machines is that it’s crucial to find the problem before it manifests itself. Therefore, we collect data from the machine, create patterns on the display, and learn about system faults from the patterns utilizing predictive maintenance using machine learning modules.



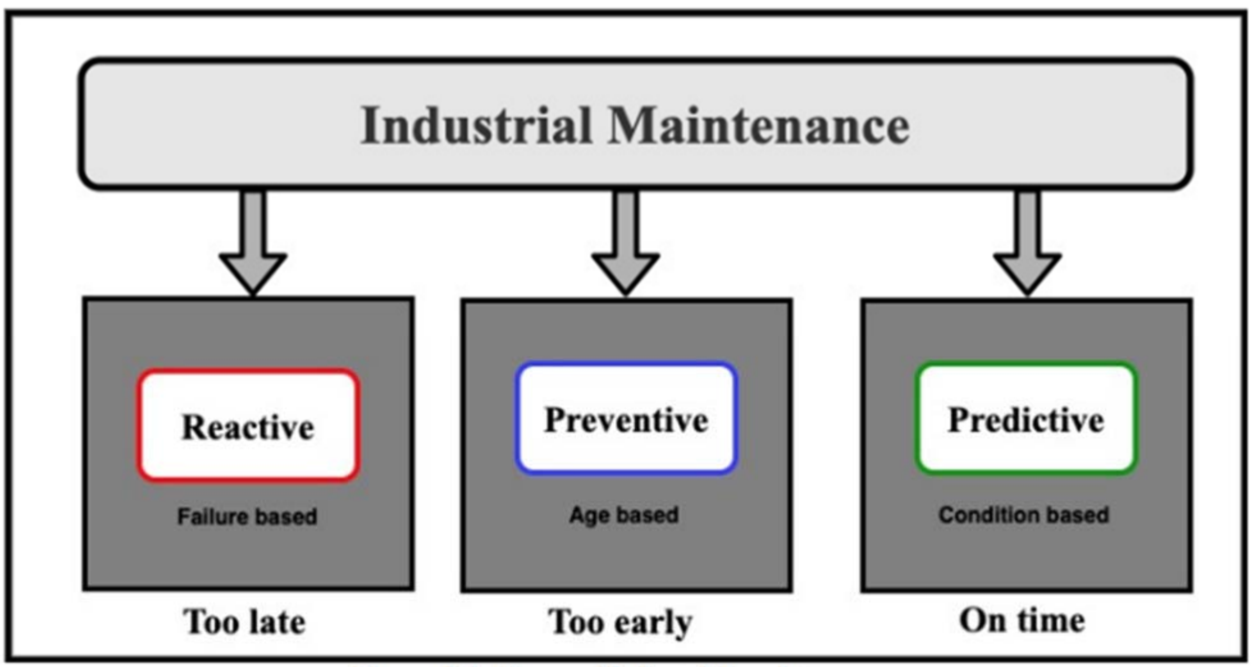
Machine Learning Modules find the correlation between the different parameters and predict system failures.

Vibration sensors are used to retrieve data from the machine and analyze it graphically. The data was retrieved, cleaned, and preprocessed to separate key features for data analysis, identify patterns, and discover correlations between various parameters. The machine learning model was trained using the cleansed data.

The objective is to use machine learning, ANN, CNN, and LSTM techniques to deploy sophisticated machine learning models to forecast the failure before the machine goes down.

The most typical industrial maintenance types are:

1. Reactive
2. Preventive
3. Predictive

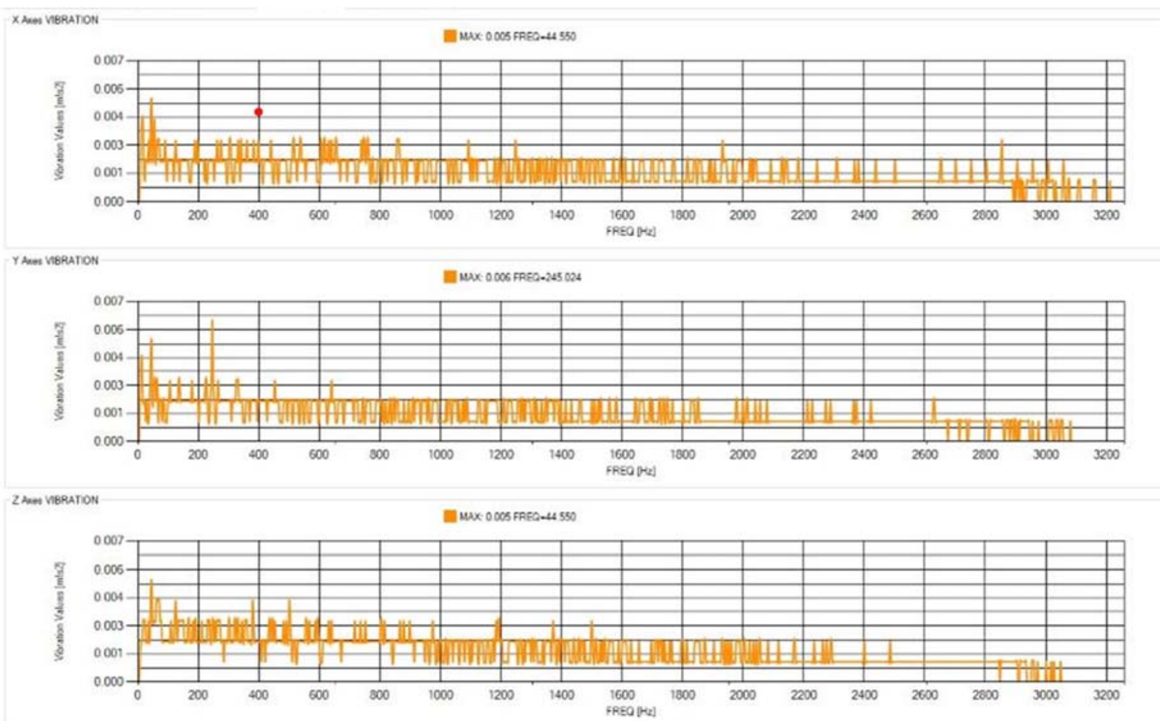


5.2 Methodology Steps:

Our Analysis is based on the Vibration dataset of the Machines.

- **Collect the Dataset:**

Gather the data and enter it into the computer system in this stage. Data is gathered by sensors, which transform vibrational vibrations into electrical signals. The machine has sensors for collecting vibration data. Then adjust and enhance the output signals after converting analogue to digital signals.



VIBRATION DATA VISUALS AQUIRED FROM STEVAL SENSOR

- **Preprocessed the Data:**

The raw data that is gathered from the machine must first be transformed into useful data. Then, purge the data using a variety of methods, including normalization, scaling, and filtering. to recognize trends and patterns.

- **Select the Machine Learning Module:**

In this we select the Machine Learning module which predicts the fault based on historical dataset.

- **Train the Module:**

The preprocessed data was run through a module to train the algorithm using the dataset's neurons. These neurons are arranged in layers and help transport information. The tuning, training, and testing procedures for the CNN model are discussed in this section. To determine the best hyperparameters for the ML problem, the tuning stage is crucial. The hyperparameters discovered in the preceding stage should be used for the training. In the test step, the model should finally be assessed.

- **Efficiency of Module:**

Then check the efficiency of the module. Our model selection also depends upon the efficiency of a Model.

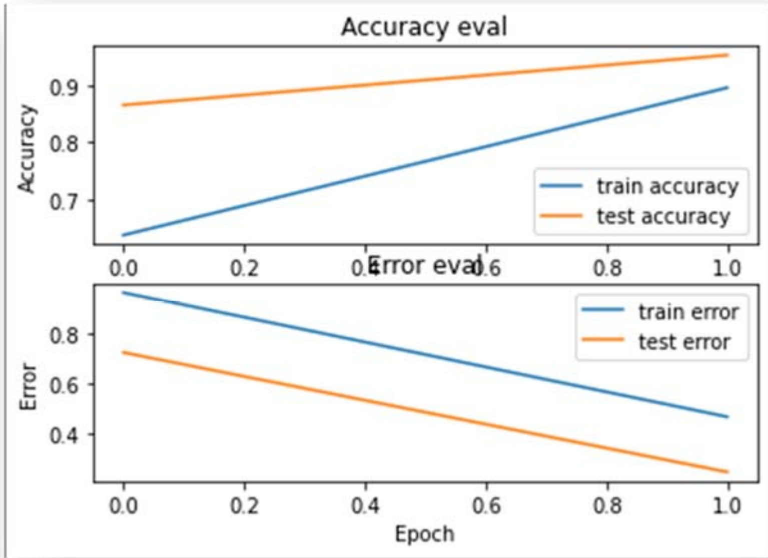
- **<u>Conclude the results:</u>**

In this step fault can be determined.

5.4 Implementation of LSTM:

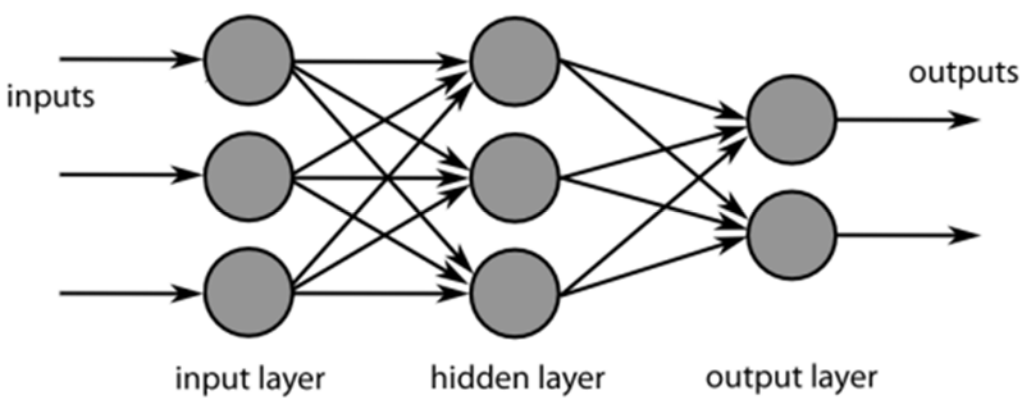
LSTM is a Long-Short term Memory is a type of recurrent neural network which is used for predictive maintenance of Machines, they can learn the pattern and relationship from the historic Data and make accurate predictions on it.

LSTM are the extension type of RNN that can be used for time series data analysis. They are used for Predictive maintenance of machines can learn pattern that is helpful in fault detection of machines, it usually used real time data to diagnose the fault.



Accuracy and Error Plot

Collect the data from the sensor, the data we collect is vibration data. It predicts the future value of the sensors. Then we do feature engineering to convert the data into features that act as input to the LSTM. This can be done by the several techniques such as Time-domain analysis and frequency domain analysis.



Architecture of LSTM

The key benefit of the LSTM is that it can handle complicated patterns and non-linear correlations in the data. It increases machine reliability and reduces downtime.

An unsupervised NN with the goal of discovering the best representation of the input data is known as an autoencoder. Its architecture typically comprises of a latent space representation layer of the input dataset sandwiched between an input layer, an output layer, and hidden layers made up of two symmetric neural networks representing the encoder and decoder.

The encoder compresses input data into the latent space when it is given to the auto-encoder, while the decoder decompresses the encoded representation into the output layer. The result of the encoded-decoded process is then compared to the original input data, and any errors are subsequently transmitted back through the architecture to change the network's weights.

The LSTM is a specific kind of RNN that consists of a series of repeating NN modules, enabling it to maintain long-term memories from many timesteps in the past at any given moment.

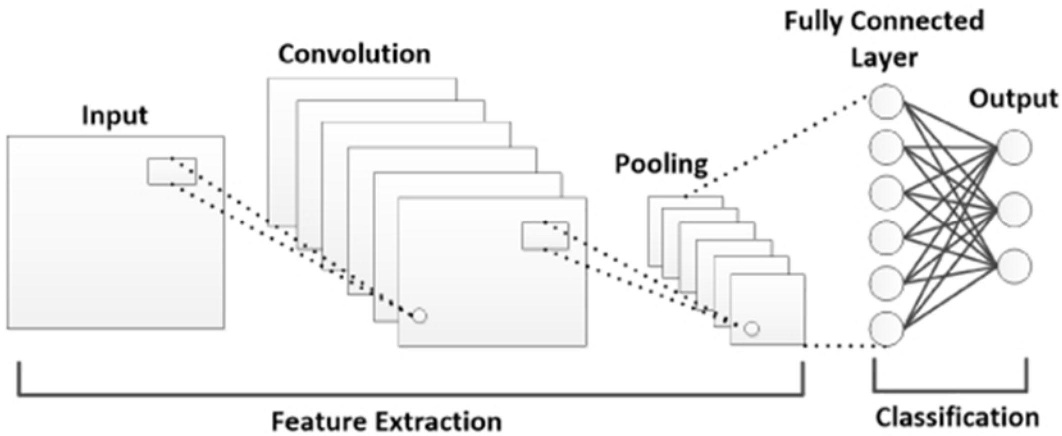
Normalization: The raw data come from many different sensors with a wide range of values. The LSTM classifier needs to be trained on these different types of data, so it must normalize each feature value by its mean and standard deviation. After normalization, all traits have the same range from 0 to 1.

Labelling the data: Before the data can be put into categories, it needs to be marked. The suggested way lets data labels be set up based on the time windows that operation planners use to prepare maintenance and production jobs based on failure prognostics data.

Formalization: For the LSTM input layer to train the models and make predictions, it needs a 3D tensor. In fact, the raw data for time series data must be set up as a 3D array with three dimensions: sample (ns), time step (nt), and feature (nf).

LSTM Classifier architecture: An LSTM network, which is a type of recurrent neural network, can fix the problem of disappearing gradients caused by the repeated use of the recurrent weight matrix. It includes the LSTM cell blocks, which are made up of different parts called the input gate, forget gate, and output gate.

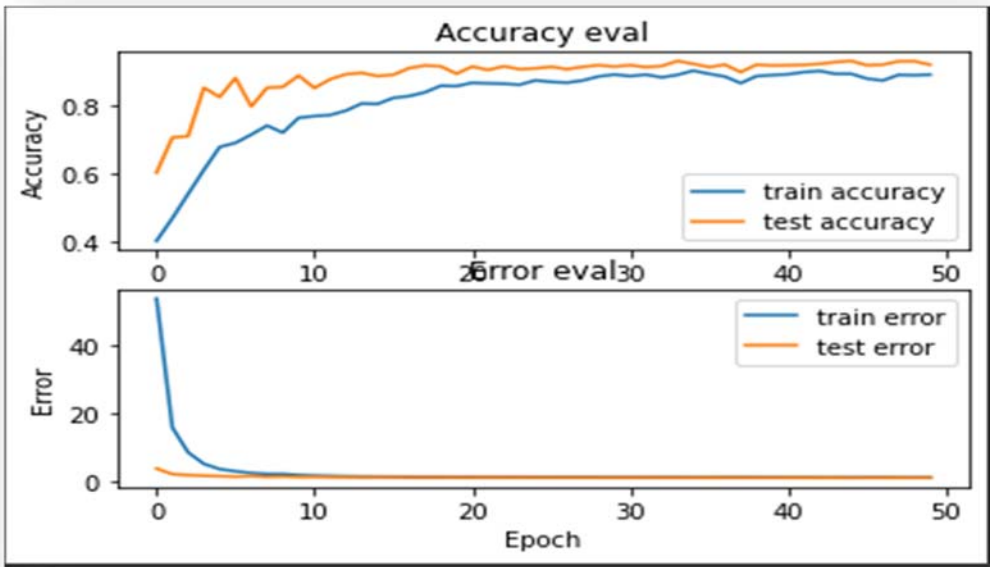
Machine Learning for Predictive Maintenance: A subset of machine learning is artificial intelligence. It's used to find secret trends in the data. When creating a support vector regression model, the parameters must be chosen with care.



5.3 Implementation of CNN:

CNN is Convolution Neural Network belongs to supervised algorithm; it speeds up the training process and is used for image and video data. We also used it in predictive maintenance. Data is collected from the sensors for preprocessing and then do feature extraction using several techniques such as feature detection and edge detection etc.

The three layers of a CNN model pooling layer, fully connected layer, and convolution layer. To tackle complex issues, we are adopting a non-Linear Relue activation function. Using CNN, the output can be obtained by calculating the weights and biases after the input has been passed through the model in the backward propagation method. The difference between the output projected and real is then used to determine the loss, and the weight is changed to reduce the loss. To achieve better results, repeat the procedure.



Accuracy and Error Plot

5.4 Feature Extraction:

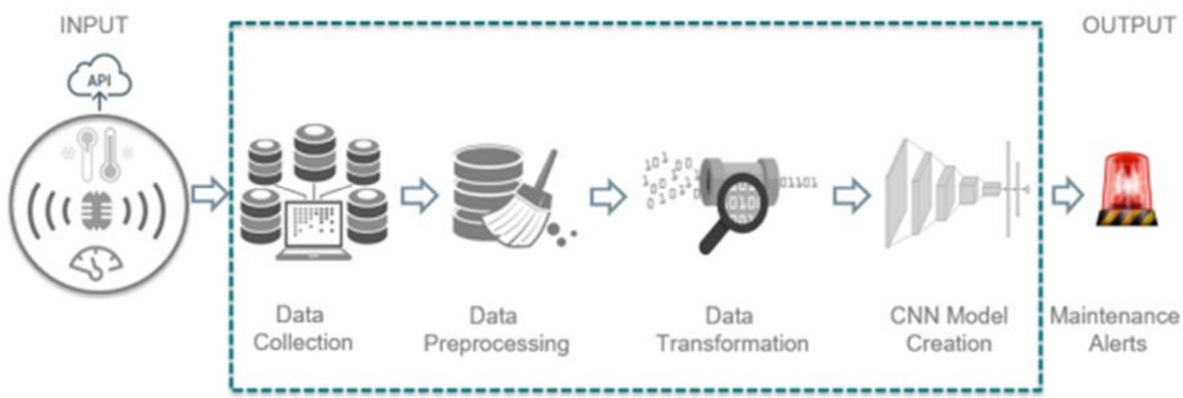
To create data vectors, feature extraction and selection techniques are used. approaches for feature extraction that are used to handle missing values, reduce dimensionality, and fix data abnormalities. By deleting the redundant properties from the input vectors, feature selection minimizes the retrieved features. The initial input data's dimensions are reduced by feature extraction into a feature set with a smaller number of dimensions that nevertheless contains most of the essential data. The reliability of the monitoring mechanism and the caliber of the collected characteristics determine how robust a machine learning algorithm is. After getting the electrical signal, methods for signal processing are used to pull out the traits and things that show a problem. In signal processing, there are five ways to pull out features: the time domain, the frequency domain, the time-frequency domain, and information based on a model.

Signals in the time domain that haven't been changed into another domain, like the frequency domain. The goal is to figure out what the original signal was by looking at the series of discrete data. Standard measures include the peak-to-valley ratio, root-mean-square (RMS), the mean, the area under the curve, the slope, the shape factor, the variance, and the entropy.

In frequency-domain, the signal's intensity is spread out over several different frequencies. We used frequency domain analysis to get a thorough look at the signals because most of the important information may be hidden in the frequency domain rather than the time domain. We used sine waves in the Fourier Transform to get the frequency domain output. A fast Fourier transform is done to find the DTF. FFT was used in business to improve how signal analysis was done.

5.5 Condition Diagnosis:

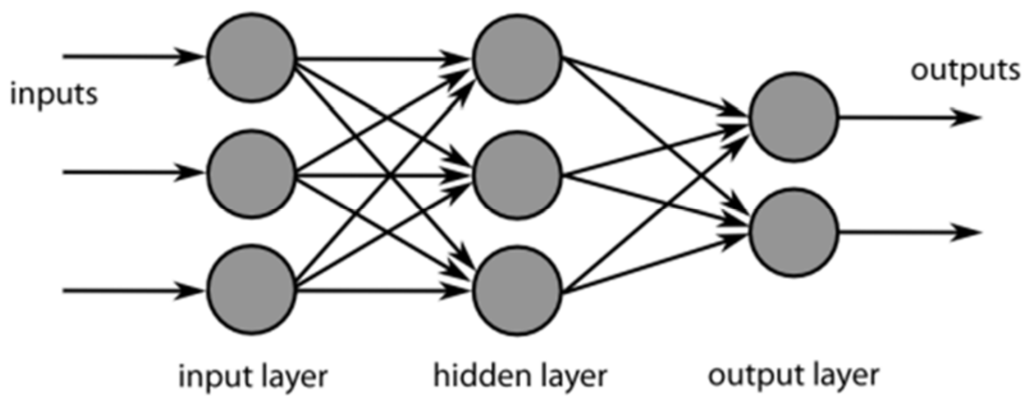
In this stage, we use machine learning models to locate the error. First, data processing is used to train the model's intelligent algorithm for fault detection. Finding the machine's defective location is the next step. The magnitude of the discovered fault is evaluated and quantified in the following phase. Predicting the remaining time or life of the monitored gear is the final step.



CNN Model Training and CNN Model Testing considering 60% of the data as training set and the remaining 20% as validation set and 20% as testing set. These sets are randomly sampled from the whole dataset.

5.6 Implementation of ANN:

A frequently used method for technical diagnosis and fault identification is vibration diagnosis of rotating equipment. Diagnostic tools can help identify not only common mechanical failures such imbalance, misalignment, gear, and bearing issues but also faults brought on by electricity. Currently, electrical quantity measurement is the primary method used to diagnosis electrical problems; nevertheless, mechanical vibration measurement can be highly beneficial in identifying flaws that are difficult to detect electrically. However, vibration-based diagnosis can identify defects that are missed by solely measuring electrical quantities.



There can be two reasons for this fact:

• While a fault's manifestation in the electrical signal domain is relatively weak (for example, in the early stages of the fault) and cannot be accurately quantified due to a low signal-to-noise ratio, the vibration signal successfully conveys information to allow for enough fault detection.

• Since a failure cannot be seen in the electrical domain, measuring mechanically generated signals can aid in accurate fault identification.

Two categories of retrieved features are typically utilized in vibration diagnosis:

• Time domain characteristics: These features are derived from the time signal and primarily consist of statistical metrics like RMS value, standard deviation, kurtosis, etc. Features derived from translated domains are known as translated domain features. The most common transformations employed in vibration diagnostics include the frequency transform, Hilbert transform, Gabor transform, Z-transform, etc. It is important to note that just part of the frequency lines representing potential faults are brought to the input of the NN and not the entire frequency spectrum, for example. As a result, the input data and computational complexity of the pre-processing techniques are significantly reduced.

Artificial neural networks are used to teach computer systems how to make decisions like humans do, including how to recognize patterns in data, classify it, and recognize faces and voices. Neurons make up an ANN. As a processing unit, each neuron processes one or more inputs (xi).

Layers are used to build neurons, and an ANN may comprise one or more layers. Each layer's output becomes the input for the following layer.

The input and output with predetermined values are supplied into the ANN model during training. Many activation processes employ sigmoid, SoftMax, and leaky Relu. The error is then.

minimized by the optimization algorithm.

$$MSE = \frac{\sum_{j=0}^{P}\sum_{i=0}^{N}(d_{ij}-y_{ij})^2}{NP}$$

ANN models are employed by industrial machines for preventative maintenance. Because preventive maintenance wastes resources, predictive maintenance is much better. Information gathered by the sensors from the device. Preprocess the data after analysis to use it for training.

Two ANNs were created to detect anomalous behavior of the e-motor and the bearing on the edge device in real-time.

Chapter 6 Conclusion

The project illustrates how we can make use of AI BASED techniques and models such as LSTM, ANN and CNN to process and detect vibrational data for faults along with sensors to always acquire the vibrations from the machines. It is a smart way of anomaly detection discarding all other less effective and traditional methods of machine maintenance. This work has economic impact as it is new to the industry and is efficient in its nature. Condition based maintenance is far more accurate and precise in error detection and health maintenance with multiple rewards and advantages.

6.1 Suggestions for future research

The proposed modal with embedded artificial intelligence techniques and automatic modeling and simulation will allow to reduce investment and operating costs. This is achieved by reducing the number of steps by making certain assumptions, improve the use of equipment through better planning and understanding of challenges and situations where problems can occur.

6.2 Future work:

Different measurement data should be added to the current model in future work. Since models work in a changing environment and need to be updated as their knowledge environment changes, future work should look into putting incremental learning systems into CBM systems. Ensure that agents are able to adapt, hence the learning effect in this system should also be studied. The system should also be investigated to be scalable.

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