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Predictive Maintenance of Industrial Machines using Machine Learning

Swarangi Gaurkar[1], Aniket Kotalwar[2], Shivani Gabale[3]

Abstract *- Modern manufacturing processes face huge downtime caused due to mechanical failures in Industrial Machines. Conventionally preventive maintenance is being used by various companies to manage and handle these failures. Preventive maintenance is the process of checking, testing, and analyzing the equipment at regular intervals to determine its proper functioning. These frequent checking processes require huge costs leading to greater investment in maintenance. Whereas predictive maintenance is the concept through which an equipment's shutdown period can be determined through its behavior. This approach decreases the number of frequent checking to maintain machines. The research paper has been proposed with an aim to build a system that can reduce the downtime cost in the manufacturing processes in the industries with the use of predictive maintenance. The predictive maintenance will be condition-based depending on various factors such as volume flow, temperatures, vibrations, power consumption, and other such factors in the hydraulic system. The hydraulic system will be continuously analyzed using an MTN2285/2P sensor and the data will be processed by the algorithms. Through the machine learning algorithms, we will determine the working and condition of certain mechanical parts. During the research, we have determined the changes in data patterns according to the changes in working of the hydraulic system. Thus, the research paper concludes that building a condition-based health monitoring system for Industrial Machines can help plan downtimes in advance and hence reduce maintenance costs.*

Key Words: Predictive Maintenance, Preventive Maintenance, Neural Networks, downtime costs, maintenance cost, Machine learning, Internet of things, Long Short-Term Memory, Random Forest Algorithm, Recurrent Neural network, vibration.

1.INTRODUCTION

In industries, machinery requires frequent maintenance for proper working. The research paper has been prepared with an aim to decrease the downtime maintenance costs of the industrial machines [13]. Predictive maintenance can be defined as the integration of algorithms and techniques used to determine the condition of in-service equipment so that its maintenance can be scheduled [1]. In predictive maintenance data analysis tools and methods are used to detect operational anomalies or defects in the processes. The research paper will discuss the hydraulic system and its maintenance schedule through predictive analysis. The hydraulic system will be continuously assessed through sensors at various equipment points that will gather the data of pressures, vibrations, temperatures, power consumption, cooling efficiency, volume flow, and others. Long Short Term Memory and Random Forest Algorithm will be implemented on the gathered data to predict their behavior. Through these algorithms, data will be processed to obtain the changes in the values of parameters like vibration. Temperature etc. so that the breakdown period of any equipment can be predicted. The research paper will discuss machine learning algorithms such as neural networks, long short-term memory, research methodologies, results and future scope.

2. LITERATURE REVIEW

Industrial business practices consist of various machinery and equipment that work for longer hours. These machineries are maintained through the process called preventive maintenance which refers to all scheduled or planned maintenance procedures [5]. And this process of regularly checking the equipment is performed so that the machine does not break down. However preventive maintenance costs many irrelevant costs and repetitive checking. It leads to greater costs that cannot be afforded frequently. Therefore, a new concept called predictive maintenance can be implemented in such machines to reduce the downtime cost and decrease the number of checking. Through predictive maintenance, the total time required in all the checking and the total cost spent in all the checking is reduced tremendously. Machine learning is the process of predicting output values by implementing programs on a huge gathered data of core values [7].

[9] proposed productive maintenance to be a useful way to reduce machine downtime and its associated costs. The researchers have raised the challenge with the early fall detection in the long-term running. The time-varying harmonics disturb the vault features during the machining process. Existing methods used to analyze the complex data are time-consuming and inefficient. The paper proposes a new technique for early fault detection by selecting the impulse responses from vibrations automatically under time-varying conditions.

Condition monitoring has been prevailing in industrial machinery failures for years. The idea of protecting failures has been in the industries to reduce the cost of machine maintenance. [6] paper describes a system that collects data from 30 industrial pumps at a thermochemical plant. This data is gathered and processed through the Random Forest

Algorithm to establish relevant information. The paper has articulated the challenges that arise during implementing the machine learning algorithms on the data and Systems performance.

Industrial Internet of Things can be defined as the internet of things technologies used in the manufacturing processes to harness the data gathered from the sensors implemented on the machinery [11]. The Industrial Internet of Things is used to gain valuable insights from machine information along with the data kind components for predictive modelling [2]. The researchers have explored the use of autoregressive integrated moving average forecasting trauma plating machines to predict quality defects downtime and maintenance. Machine learning has been proved to be an important component in the industrial Internet of Things for quality management and quality control. It enhances the performance and improves the manufacturing process.

[14] Fault detection has been an important subject prevailing in industries in recent years. Detecting fault at an early period is important to reduce the break time cost and also to ensure proper running of the manufacturing processes. The research paper has proposed unsupervised learning for predictive maintenance by the system on the exhaust fan. Algorithms such as PCAT2 statistic, Fuzzy C-Means clustering, Hierarchical clustering, K-Means, and model-based clustering are used by the researchers for predictive maintenance. These algorithms are used and the best one suitable for predictive maintenance has been proposed for ensuring robustness.

Predictive maintenance has been gaining huge importance due to the high cost invested in maintenance. Internet of things can be implemented in the process of maintenance propose machine learning methodologies to be applied on the predictive maintenance and the related challenges [15]. A bathtub curve has been used to indicate the failure of equipment that illustrate the health of the machinery and their components. Due to the rising complexity of the industrial systems nowadays sensors have been installed to monitor the machines continuously. The parameters obtained from the sensors are then processed and supervised to obtain maintenance information.

[16] has analyzed a systematic approach monitoring a hydraulic system and the breakdown of its components. Different scenarios have been analyzed by using the sensor data fetched in the raw form that is then experimented with using Linear Discriminant Analysis. Linear Discriminant Analysis lets the researchers classify all the conditions and their abilities. The working cycle and maintenance have been successfully implemented by the researchers and the classification rate of random load cycles.

3. RESEARCH METHODOLOGIES

Manufacturing industries are highly dependent on the continuity of their business processes. The equipment and machinery are big and they are assembled into a large system to perform continuous work. These machines need maintenance and repairing frequently so that they work in a constant cycle and do not raise issues. Traditionally, a preventive maintenance approach has been used by the industries to maintain the machines. Through preventive maintenance, a machine is checked frequently or after a pre-determined number of running cycles. This allows the industries to prevent the undesired breakdown of the machines. It also lets the industries repair and maintains the machines according to their timings. However, frequent analysis is time-consuming as well as expensive. This approach has been used traditionally and has become a contemporary approach.

In recent years, machine learning is gaining huge attraction from all fields. It has become a sensation that can be implemented on any type of machine to make it smart. Industries are turning to machine learning to make strategic decisions easily and for achieving efficient results. Machine learning is training the machines from historical data so that they can predict future results based on their analysis. In the process of machine learning, data is gathered in a raw form and is then processed into meaningful information that can be processed by the system. The research paper proposes predictive maintenance for a hydraulic system. The hydraulic system has been designed in such a way that it functions to pressurize the fluids from the pump. It consists of major components such as actuators, valves, pumps, reservoirs, and motors. The predictive maintenance system will gather information through the sensors implanted on these components. UCI Machine Learning Repository has been used in the Predictive analysis system.

3.1 Assumptions and Dependencies

We have developed a predictive maintenance system on a hydraulic system for reducing the maintenance and breakdown costs of the repairing. Given below are some of the assumptions and dependencies for the system:

a) The system will require a high-speed internet connection to transfer the data on a remote system.

b) Minimum technical requirements of the application have been met by the hydraulic system.

c) Data gathered from the sensors is in a continuous time series.

d) Edge device will require a power supply for continuous working.

e) The high secure communication channel has been used for the data transfer on the IoT cloud.

f) Data training and analysis for predicting the maintenance is performed on a high graphical processing unit for effective, efficient, and quick prediction.

3.2 Functional requirements

3.2.1 Recording of Data

The predictive maintenance system for the hydraulic system has been designed. MTN2285/2P vibration sensor will be attached to the various parts of the hydraulic machine. A local storage drive is used for storing the data collected by the sensor. Vibration sensor collect the vibration intensity values of the machine components.

3.2.2 Data Storage

In this stage, data is stored and collected from the MTN2285/2P sensors in a time-series format. The gathered data is stored in two types of formats as follows:

Main Storage (Operational storage): A data lake is used to store the operational data through an online IoT cloud. The data stored in this data lake is for pre-processing and analyzing the data.

Backup storage: On-board memory extension through the microcontrollers is used to take backup of the data in case of failures or power loss.

3.2.3 Data transfer

It involves data movement from the edge device to a remote interface or a repository. This remote repository is an IoT cloud that acts as a data lake for the storage of data. The data transfer takes place through a secure communication channel which is provided by the IoT cloud.

3.2.4 Data pre-processing and processing

Data pre-processing is the process of transforming raw data into meaningful data that comprises information. The data-pre-processing stage consists of the following stages:

1. Data cleaning: Data cleaning is required as the raw data consists of irrelevant or undesired elements. It manages the feeding of missing data, noisy or polluting data through the procedures such as outlier detection, regression, binning, clustering, and others.

2. Data Transformation: Data needs to be transformed into variable forms so that it can be used for the desired function. Firstly, in the data normalization stage, data is normalized for scaling the data values into the desired range. In the next phase, attributes are selected as per suitability. The data mining system generates new attributes from the existing or known attributes for easing the mining process. The final stage of data transformation is discretization. In this stage, numeric attribute raw values are replaced by the conceptual level or interval level values.

3. Data Processing: In this stage, the neural network algorithms are applied by the server for processing the data. Random Forest models are used for predicting the data using sensor-created values such as pressure, volume, temperature, vibrations, power consumption, and others.

3.3 System Architecture

The system architecture for the predictive maintenance system consists of several components such as Arduino driven sensors, hydraulic system (industrial machine), server, ThingSpeak cloud for IoT (data lake), storage, and others. The Edge device- Arduino Uno has been used in the system to record the vibrations of the hydraulic system. The edge device uses an Arduino desktop IDE for the user interface. MTN/2285-2P type of sensor has been used that is effective in sensing the vibrations. The system components are communicated through a local Wi-Fi network using an ESP8266 Wi-Fi module. A micro-SD card has been used for the local storage of the raw data in case of internet connectivity issues. Apache KAFKA communication channel or ThingSpeak is used for transferring the raw data to the storage and processing units. An XL6009 DC Booster transformer has been used along with the NVidia GeForce GTX (940 MHz) GPU. The edge device has been programmed by using libraries such as Tensor flow 2.0, Keras, and Python 3.6 programming language. UCI Machine Learning Repository has been used while implementing the system and gathering the data from the hydraulic pump.

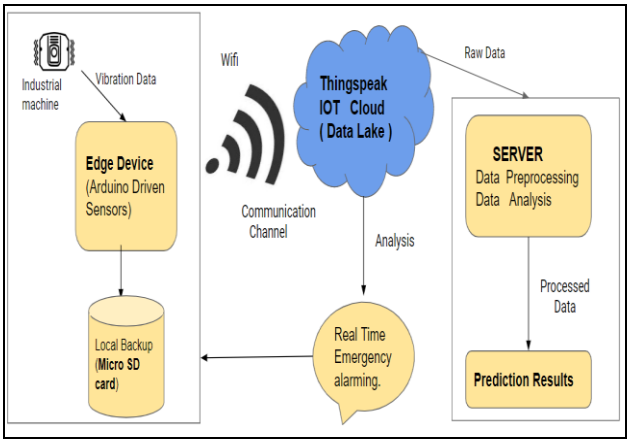

Figure 1: System Architecture

For implementing the predictive maintenance, vibration values from the vibration sensors will be gathered. The vibration sensor will store the values in the SD card and will also transfer the values to the IoT cloud. The values are stored onto the SD card for backup in case of power or internet failures. The raw values from the loud will then be sent to the predictive analysis system database. The user will register through the user interface to the system. An authentication message will be sent to the user that needs to be confirmed for further access. After confirming successfully, the user can log in to the device. The device can be a mobile or a desktop as per the user's suitability and easier accessibility. The predictive analysis system will suggest the user with the prediction results from the vibration values gained from the IoT cloud. The user can then react as per the prediction results. Additionally, the system is capable of sending regular and emergency notifications to the user on the device.

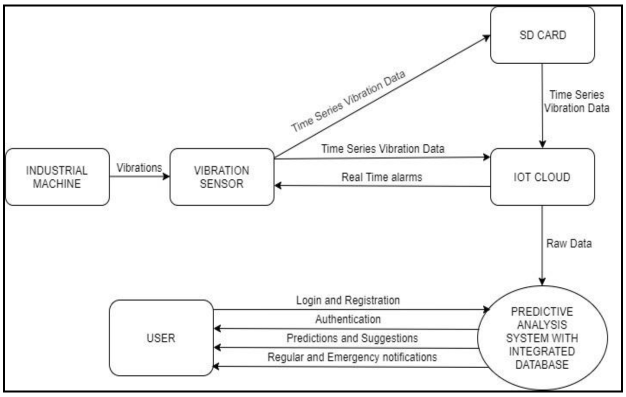

Figure 2: Data Flow diagram

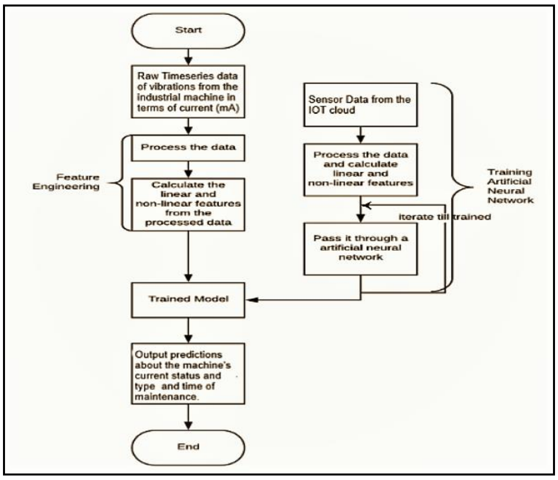

Figure 3: Flow chart

3.4 Software Implementation

The predictive analysis system for the hydraulic system has been implemented using a V-shaped SDLC software model. The model can be defined as the sequential building of software in a series such that every development phase has an associated testing phase. It is also called a verification and validation model that is based on testing of every phase and start of another phase only on successful testing of the previous phase. In the verification stage, the research methodologies for the Predictive analysis system were built. On the planning of every stage, a test case was conducted to ensure the working of the model. Functional as well as non-functional testing was performed at every testing level after the completion of the previous level.

Design Phase:

Requirement Analysis: In this stage, the requirements of the predictive maintenance for industrial machines were gathered.

System Design: A hardware and software communication setup was created in this phase for the successful development of the system design.

Architectural Design: The complete system architecture was broken down in this phase into individual units to analyze their challenges. The communication in the internal components was assessed in this phase.

Module Design: In this phase, the detailed and deeper design insights of every component were defined to form a Low-level design.

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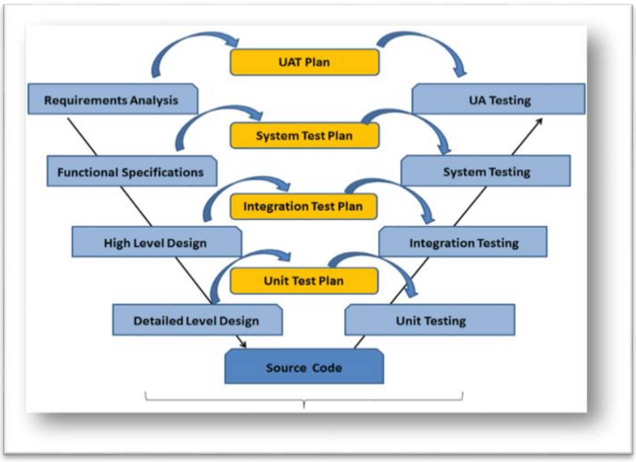

Figure 4: SDLC Model

Testing Phase:

Unit Testing: During the individual module design phase, unit test plans are formulated for individual testing.

Integration testing: After the successful testing of the units, integrated testing is performed. Integration testing confirms the efficient flow of information between the modules.

System Testing: System testing consists of the functional working, interdependencies, and communication between the system components. The non-functional and functional requirements of the system are tested in this phase.

User Acceptance Testing (UAT): This is the last stage of testing where the overall system requirements were tested to match the benchmark standards.

3.5 Algorithms

Artificial neural networks are a part of machine learning that is used for or data learning and predicting. Neural networks concept of node layers categorized as input layer hidden layers and output layers. Each node connects to multiple hidden nodes that form the output layer nodes [4]. A node is associated with a threshold value and a wait and get activated when the threshold value is crossed by any of the neurons. On activation, the neuron transfers the information to the next neuron. Neural network algorithms are used to train the data from the raw data to improve the accuracy of Machines. Artificial Neural networks let high data clustering at a higher velocity to gain strategic decisions in industrial business practices.

3.5.1 Recurrent Neural Networks

Recurrent neural networks on the other hand are the neurons having an internal memory. Recurrent neural networks have internal memory which allows them to perceive the information inside about the previous or historical data. It makes the algorithm more accurate and precise in predicting. In order to gain high accuracy and precision in predicting the breakdown of industrial machines, we have used recurring neural networks. They are best suited in applications including time series, text, financial data, audio, speech, video, and others. A recurrent neural network is better than the feed-forward neural networks as they can analyze the current as well as the existing or historical information at the same time [8]. This makes them more precise in predicting the results. however, feed-forward neural networks do not have the memory option that they make predictions based on the current input. RNNs are used in handwriting recognition or caption recognition as they are based on the previous input and results. However, RNNs have major drawbacks related to exploding gradients and vanishing gradients. These gradients create a change in the results of the next prediction.

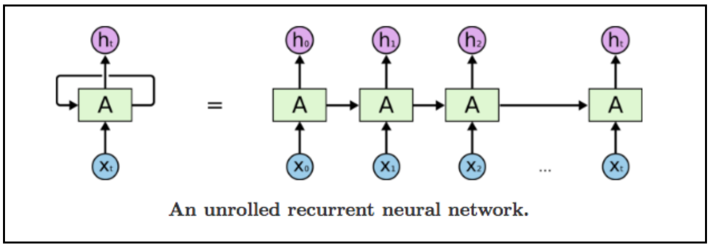

Figure 5: Recurrent Neural network

Steps:

The first node in the recurrent neural network takes the input X (0) from the sequence to produce h (0). The second node takes the input from the input sequence X (1) and h (0) to form h (1). In this way, the output produced from the previous nodes is considered before making predictions.

Current state:

ht = f(ht-1, xt)

Applying Activation Function: ht= tanh (Whhht-1 + Wxhxt)

W: weight;

h: single hidden vector

Whh: weight at the previous hidden state

Wxh: weight at current input state

tanh: Activation function, that implements a non-linearity that squashes the activations to the range [-1.1]

Output:

yt = Whyht

Yt: output state;

Why: weight at the output state.

3.5.2 Long Short-Term Memory (LSTM)

Long Short-tern Memory algorithm has been designed to eradicate the problem caused by the gradients in the recurrent neural networks [3]. LSTM is beneficial as it solves the problem of remembering past data. Time series having unknown duration time lags can be best treated with the Long Short Term Memory networks. Therefore, as LSTM solves the vanishing gradient issue it has been used in the predictive analysis of the hydraulic system. LSTM has proved beneficial in the process as the data is in the time series form consisting of a vanishing gradient. The model is trained and processed by the back-propagation method.

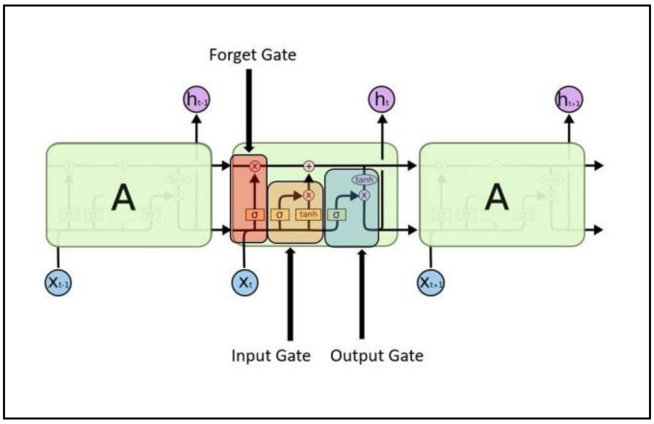

Figure 6: LSTM Network

LSTM includes the following gates:

1. Input gate: The values from the input series are discovered at the input gate. The sigmoid function passes the values from 0,1…n. Initially, asset values get a weightage from tanh function based on their significance from -1 to 1.

$$i_t = \sigma\left(W_i.\left[h_{t-1}, x_t\right] + b_i\right)$$

$$\sim C_t = tanh\left(W_c.\left[h_{t-1}, x_t\right] + b_C\right)$$

Forget gate: The sigmoid function discards the undesired information from the blocks. It creates the output from 0 and 1 from each number in the cells based on the previous and the current inputs.

$$f_t = \sigma\left(W_f.\left[h_{t-1}, x_t\right] + b_f\right)$$

Output gate: The output is decided based on the memory block and the input block. Specific values are passed through 0 and 1 by the sigmoid function. tanh gives weightage to the initial values where the weight ranges from -1 to 1 multiplied by the weight of the sigmoid.

$$o_t = \sigma\left(W_o.\left[h_{t-1}, x_t\right] + b_o\right)$$

$$h_t = o_t * \tanh(C_t)$$

3.5.3 Random Forest Algorithm

Random Forest Algorithm is a machine learning algorithm used for classification and regression. Random forest algorithm is based on assemble learning that can be defined as the process of combining various classifiers to resolve a complicated problem and enhance the performance of the system [12]. It can also be defined as a classifier comprising of numerous decision trees of various subsets from the given data set that is the average to read it accurately. The highest number of forest trees or decision trees increases the Accuracy and Precision of the solution random forest algorithm has been used in the protective analysis of the hydraulic system as it takes less training time. The algorithm predicts outputs with higher accuracy for large databases and improves efficiency. The most important asset of the random forest algorithm is that it maintains the level of accuracy even if the data set has missing elements. It can be applied to a varied range of regression problems and prediction problems. It takes a fewer number of parameters to produce the output and deals with complex data sets with high dimensions. The algorithm is mostly used for classification and for predicting the time series of univariate and multivariate.

Steps:

Random samples from the data set are selected.

A decision tree for every sample set is formed.

The prediction result of every decision tree is formed.

A vote for every prediction is performed.

The final result is selected from the most voted prediction result.

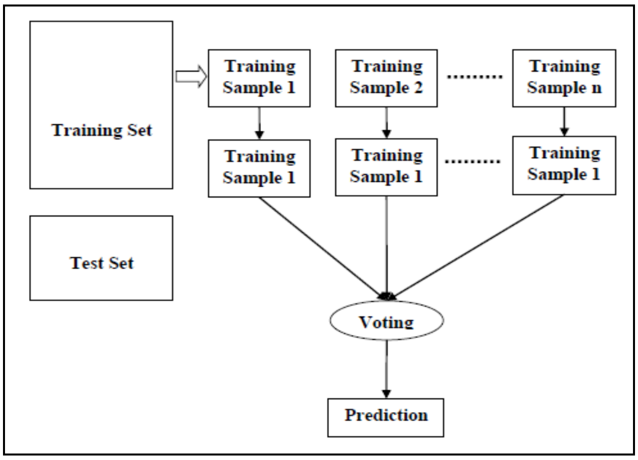

Figure 7: Random Forest Algorithm

Time series forecasting

The Random Forest Algorithm is similar to regression. Given below is the formula for RFA:

xt = g(xt−1, . . . , xt−k), t = k + 1, . . . , n + 1 .

g = function gained by training of random forest that can be used for forecasting xn+1, given x1, x2,...xn.

K= lagged variables.

The function g is obtained by training the RF algorithm using a training set of size n − k. In each sample of the fitting set the dependent variable is xt , for t = k + 1, . . . , n + 1, while the predictor variables are xt−1, . . . , xt−k.

3.6 Risk Analysis and Mitigation

Data misinterpretation: At times, data can be misinterpreted due to time lag or other misleading elements. It can cause false maintenance requests leading to unnecessary maintenance procedures thus diluting the aim of predictive maintenance. Therefore, to sustain the aim defined through the predictive maintenance system, the risk can be mitigated through the data cleaning process.

Delay: Due to low internet connectivity a delay can be caused in the communication process. This will lead to delayed maintenance alarms leading to a larger time in the realization of the maintenance. The risk can be mitigated by setting a high-speed internet connection or broadband for continuous signals.

Training workers: Predictive maintenance is new to the industrial market. In such cases, it is hard for the managers to make the workers realize the system's worth. Therefore, the industries need to conduct awareness programs to make the employees and workers aware of machine learning and predictive maintenance.

Data security: Cybercrime has been increased tremendously in recent years. The data stored on the cloud can be disturbed by the invaders. Therefore, this risk can be mitigated by adding an extra layer of security to the system.

3.7 Limitations

Financial obstacles: Industrial companies may not implement the sensors and other related components effectively due to its high cost. The predictive maintenance method is new to the industry and it has not gained much acceptance. Hence, industries may find investing in such systems to be worthless. Thinking and perspectives of the industrialists can limit the implementation of the project. Human interactions with the machines can pose challenges to the system and it can hamper the predictive maintenance results. Companies may also not pay attention to gathering the data appropriately which can hamper the data collection process.

4. RESULTS

We have successfully built an IoT enabled system prototype which is capable of sending data from remote industrial machines using vibrational sensors to ThingSpeak cloud for IoT using Arduino UNO as the edge device.

Using the Hydraulic Pump dataset from UCI Machine Learning Repository, the condition of 4 hydraulic components (cooler, valve, pump and accumulator) was monitored.

The LSTM algorithm was used to train on the given dataset. This analytical model was used to classify sequential data from various sensors like Pressure, Temp, Power

Given below are the 4 types of faults that may occur in a Hydraulic Pump with the accuracy of classification using the LSTM model.

Table 1: LSTM model results

Faults / failures	Accuracy(in %)
Cooling	100
Valve condition	95
Pump Leaks	99
Hydraulic Accumulator	97

Table 2: Random Forest model results

Faults / failures	Accuracy (in %)
Cooling	98.9
Valve condition	64
Pump Leaks	98.6
Hydraulic Accumulator	65

We have successfully predicted the Remaining Useful Life of the hydraulic system in case of all four faults, thus reducing maintenance costs and maximizing equipment's life.

5. CONCLUSION

From the overall discussion, it can be summarized that the breakdown costs in the industries can be reduced through the implementation of the predictive maintenance system. The research has been successfully performed on a hydraulic system using the current data. The predictive analysis system discussed in the paper is capable of detecting four types of faults or failures in the system and notifying the user to prevent them. The life of the hydraulic system after predicting the four faults has also been discussed in the research paper. Thus, it can be concluded that the system is capable of reducing the cost of maintenance and maximizing an equipment's life.

6 Future scope

Health care systems: Predictive analysis system can be implemented in the health care system in the emergency departments. The system can be implemented in real-time clocks to generate alarms for medicinal purposes. The system will create an alert to the health professionals comprising of the patient health fluctuations. It will guarantee speedy treatment and attention to the patients.

Integrated systems: Predictive systems can be further utilized by a variety of machines in an integrated system. The proposed system can be implemented on various machines having variable properties and characteristics.

Higher efficiency: A more detailed and deep learning models and algorithms can be implemented in the system to achieve higher performance and enhance the results.

Enhanced edge device: Along with alarms and alerts, the edge device can be encoded to have basic analytical abilities for detecting common faults.

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APPENDICES

1 Hardware Interface

a) Vibration Sensor (MTN2285/2P) accelerometer for recording vibration values.

b) DC Booster to step up the arduino power supply.

c) ESP 8266 Wi-Fi module to send the data to the cloud via the internet.

d) Micro SD Card module to create a data backup on SD Card.

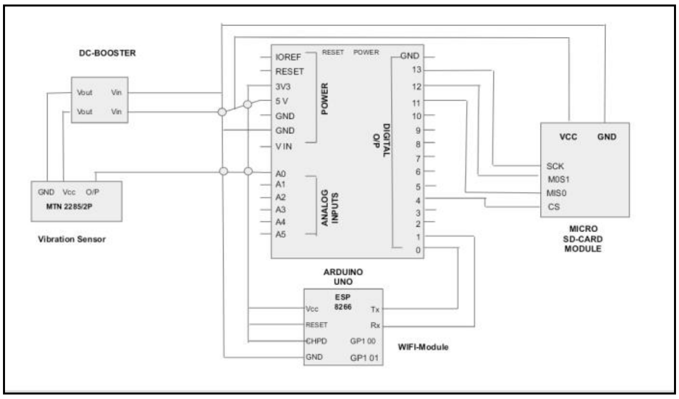

Figure 8: Hardware Interfacing Diagram

2 Database Requirements

Data will be continuously stored on an online IOT enabled cloud in a time series format. The dataset is in the form of a csv file containing the timestamp and corresponding vibration values from the sensor. The sensor gives output in Amperes (4 - 20 mA).

Timestamp	Vibration Values (calibrated- (0-1023))
17:25:28.377	888
17:25:29.365	889
17:25:30.380	890
17:25:31.360	892
17:25:32.376	893

Table 2: Sample Dataset

The research used MTN2285/2P sensor to detect changes in vibration. However, to correctly predict faults in machines more number of parameters like temperature, pressure, power consumed etc are required.

For this reason, we used UCI dataset (https://archive.ics.uci.edu/ml/datasets/Condition+monitoring+of+hydraulic+systems) for hydraulic system and below is the description of the parameters in the dataset.

Additional features to be taken into account to train the analytical model:

a) Pressure bar 100 Hz

b) PS2 Pressure bar 100 Hz

c) PS3 Pressure bar 100 Hz

d) PS4 Pressure bar 100 Hz

e) PS5 Pressure bar 100 Hz

f) PS6 Pressure bar 100 Hz

g) EPS1 Motor power W 100 Hz

h) FS1 Volume flow l/min 10 Hz

i) FS2 Volume flow l/min 10 Hz

j) TS1 Temperature Â°C 1 Hz

k) TS2 Temperature Â°C 1 Hz

l) TS3 Temperature Â°C 1 Hz

m) TS4 Temperature Â°C 1 Hz

n) CE Cooling efficiency % 1 Hz

o) CP Cooling power (virtual) kW 1 Hz

p) SE Efficiency factor % 1 Hz

3. Tools and technologies used

Operating System: Windows 10, Ubuntu 18.01 (64 bit) with NVidia GeForce 940 MHz graphic processing unit.

IDE:

Arduino 1.8.10 desktop IDE for encoding the microprocessor which acts as the edge device.

Google colab for implementation of the analytical model

Jupyter notebook for local analysis

4 Programming languages:

Arduino programming language to program the Arduino UNO microcontroller.

Python 3.5 along with its libraries like keras, pandas, numpy, tensor flow, matplotlib, seaborn for implementation of the analytical model.

Safety Requirements

The predictive analysis system should be given a continuous power supply and it should be optimal in nature. Less or excessive current can damage the system and the results. The edge device is sensitive due to which the power sensitivity has to be maintained. The system should be setup at a considerable distance from the sensors to prevent damage from the rigorous vibrations. It ensures the continuous working of the system.