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IoT-based Predictive Maintenance System for Industrial Machines with Machine Learning Algorithms

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ABSTRACT- Predictive maintenance is very important in today's industrial automation due to its significance in minimizing downtime. In this paper, an IOT-based predictive maintenance model for analyzing the state of industrial machines with the use of machine learning algorithms has been proposed. Sensors such as temperature and vibration modules are used to record the live data from the machinery. The collected data is then sent to the cloud through the microcontroller .The machine learning algorithms are used to analyze the data collected and identify any abnormality as well as predict the faults in advance. The performance of the system was tested on an industrial motor together with temperature and vibration sensors. The dataset included normal and faulty conditions for the test. The experiment has shown that the proposed system has above 90% fault detection accuracy. This technique improves the reliability of the equipment as well as cuts down the cost of maintenance. The system also offers the benefit of having real-time monitoring of the machine.

KEYWORDS- Maintenance Forecasting, Internet of Things, Connected Sensor networks, Automated Learning Algorithms, Smart Manufacturing, Thermal Tracking

I. INTRODUCTION

Failure of industrial machinery can lead to considerable financial loss and unplanned downtime during production processes [2]. Reactive and preventive maintenance approaches have proven to be ineffective either because of unexpected breakdowns and overspending for preventive services [1].
Predictive Maintenance (PdM) addresses the limitations of Standard Maintenance approaches by utilizing real-time data analysis to assess equipment condition and predict potential failures before they occur. Disparate reactive maintenance, which responds only after a breakdown, and preventive maintenance, which relies on fixed service schedules, predictive maintenance enables condition-based decision-making. This Strategic helps reduce unexpected downtime, enhancing maintenance activities, and improve overall operational and Productive efficiency.
The Internet of Things is really changing how we do maintenance on machines. Internet of Things devices can put sensors on machines that collect information all the time. These sensors look at things like how hot a machine's if it is vibrating, the pressure, how fast it is going and how much energy it uses. This helps us keep an eye on the machines and see how well they are working. The sensors send all the information they collect to a system that stores and looks at it. This way we can always check on the machines. Get a warning if something is going wrong with an Internet of Things machine. The Internet of Things is very important, for keeping machines running.
Machine learning is really important for making sure we can find faults and predict when things will fail. We use machine learning to look at a lot of data from sensors both from the past and in time. This helps machine learning find patterns that're not easy to see find things that are not normal and figure out how much longer things will work.
So, we can plan when to do maintenance at the time. This means we save money on maintenance things longer and production is more reliable. Machine learning and Internet of Things are a great way to make maintenance systems smarter and based on data in modern industries. Machine learning and Internet of Things are very useful, for this.

II. LITERATURE REVIEW

Mobley [1] mentioned that predictive maintenance is vital to lower the maintenance cost and enhance the reliability of the equipment. Further, Jardine et al [2] examined the methodologies employed in equipment diagnostics and prognostics for condition-based maintenance.
Ahmad and Kamaruddin [3] have examined time based and condition-based maintenance solutions for industrial contexts. These studies have shown that continuous monitoring and early defect detection can reduce production interruptions and improve operational efficiency. The advent of Industry 4.0 has transformed the conventional maintenance systems into intelligent maintenance systems.
Lee et al. [4] suggested an architecture of cyber-physical systems integrating IoT technology, real-time monitoring and intelligent decision-making ability. Such systems employ historical and real-time data to identify issues, optimize maintenance schedules and improve the usage of resources. Consequently, the reliability of equipment and maintenance systems has improved, enabling uninterrupted operations.

Zhang et al. [5] described the use of data-driven strategies to forecast equipment failure by examining data collected by sensors. Deep learning algorithms have received great attention because they can automatically learn important features from complicated sensor data.

Saeed and Nawaz [6] also identified challenges in real-time data processing, scalability, and the application of AI-based predictive maintenance systems in the industrial environment. Such limitations can restrict the use of predictive maintenance technology, especially for small and medium-sized enterprises.

Si et al.[7] studied data-driven ways to estimate the remaining usable life (RUL) of industrial equipment.

The concept of Internet of Things was established by Ashton [10] and the architecture and applications of IoT systems were discussed by and Serpanos and Wolf [8] and Gubbi et al. [9] respectively. IoT-enabled sensors and devices collect operational data in real time, enabling enterprises to monitor the health of equipment.

Moreover, Zhang et al. [5] and Gubbi et al. [9] and revealed that IoT-enabled maintenance solutions promote sustainable industrial operations by optimizing the utilization of resources and minimizing the need for superfluous maintenance.

Chen and Zhang [11] further stressed the importance of IoT based industrial monitoring systems to reduce equipment downtime and improve maintenance efficiency. This data-driven approach to maintenance allows industry to discover possible faults before they become problematic. With the combination of IoT with machine learning (ML), the predictive maintenance capabilities are significantly strengthened.

Carvalho et al. [12] provide a detailed analysis of machine learning algorithms for predictive maintenance applications, such as Decision Trees, Support Vector Machines (SVMs), and Artificial Neural Networks (ANNs). These methodologies help maintenance teams to identify the equipment degradation patterns and make preventive repair decisions. These approaches have proven good prediction performance with promising results for equipment breakdowns. Several research pointed to the importance of predictive maintenance systems in the actual manufacturing environments.

activities.

Despite the positives there are some challenges too. According to Carvalho et al. [12] and Nacchia et al. [13], many predictive maintenance systems require vast historical data, significant processing power and large storage resources.

III. PROBLEM STATEMENT

Machines are used by industries every day for production. When machines break down it causes delays in production, loss of money and extra repair costs. Most industries fix machines only when they stop working or at set times.

This approach is not very reliable because problems with the machine are often found late. Sensors gather data about machines using Internet of Things technology. This data includes temperature, vibration, pressure and motor details of the machine.

A person cannot continuously check these details small faults in machines may not be found right away and can turn into big problems over time.

The big issue that industries have is making a system that can keep an eye on machines all the time and tell when they might break down.

The idea is to use Internet of Things sensors to get information and Machine Learning algorithms to look at the information and find any problems with the machine. If the machine is likely to have a problem a message is sent to the person in charge about this issue with the machine.

The Predictive Maintenance System using Internet of Things will help industries save money reduce the time machines are not working make machines last longer and make work go smoothly.

Industries will really benefit from this Predictive Maintenance System and Internet of Things because it will help them in ways such as saving costs and minimizing machine downtime and also increasing machine lifespan and enhancing productivity with the help of Predictive Maintenance System and Internet of Things technology.

The Internet of Things and Predictive Maintenance System will make a difference, for industries.

They will be able to use their machines efficiently with the help of Internet of Things.

IV. PROPOSED SYSTEM ARCHITECTURE

The Internet of Things technology and machine learning are used to figure out when industrial machines need maintenance. Monitoring devices with sensors play a role in this. They can detect when something is going wrong by sensing things like vibrations and temperature. These sensors are attached to the machine and they collect data about how the machine is working. This data is then processed using computers like Arduino or ESP8266. These small computers can also send the data wirelessly using the Internet of Things technology. All the collected data is stored in databases on the cloud, where it is looked, at closely. Then machine learning is used to find any problems in the way the machine is working(show the Figure 1).

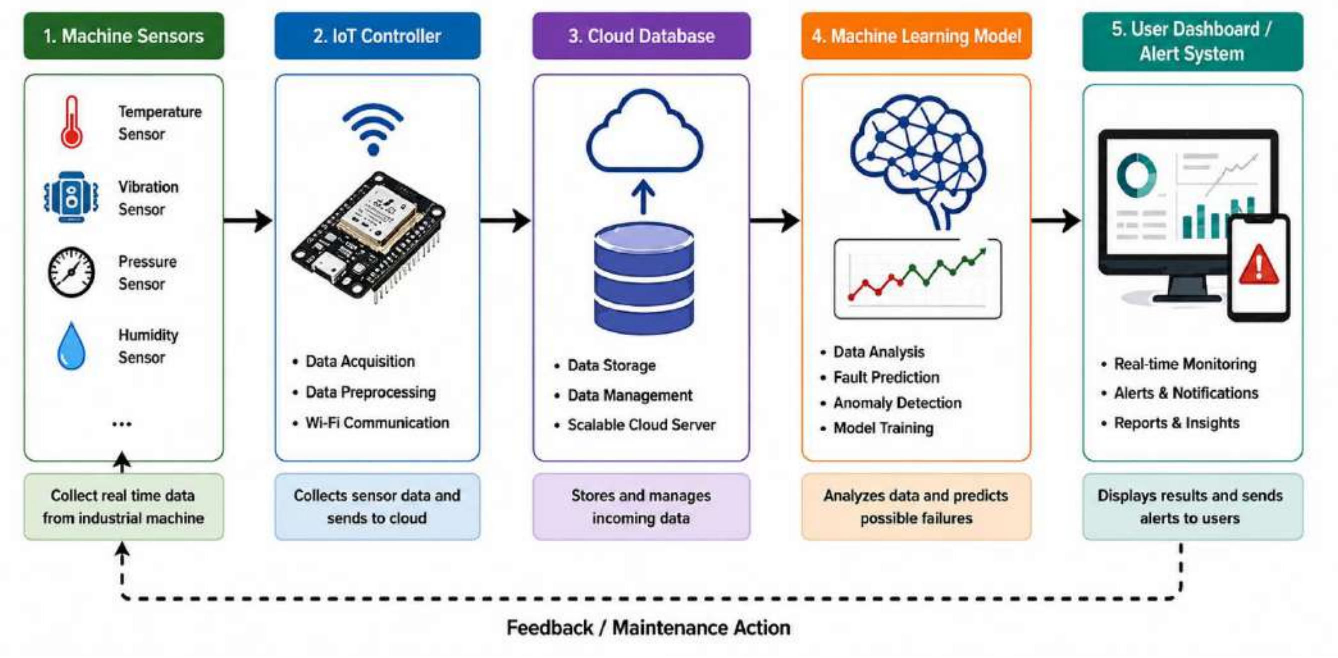

Figure 1: IoT-Based Predictive Maintenance System Architecture

V. METHODOLOGY

The system is going to be made so it can use the internet and special sensors to predict when an industrial motor needs maintenance. It will use temperature and vibration sensors to do this. The system will also use machine learning technology to make predictions about the motor. This means the system will be able to look at the data, from the temperature and vibration sensors and use that information to figure out when the industrial motor might need to be fixed. The industrial motor is an important part of a lot of machines and it needs to be
working properly. That is why the system is being developed to use machine learning technology to predict when the industrial motor needs maintenance.
The methodology includes the following steps (See the Figure 2):

A. Data Collection

We will put temperature and vibration sensors on the motor. This way we can get information about how the motor's working all the time. We will use temperature sensors, which are called LM35 to see how hot the motor gets. We will also use vibration sensors, which are called SW-420 to find out if the motor is vibrating much. If the motor is vibrating much that means something is wrong with it. We will get the information, from the sensors at times. The industrial motor and its temperature and vibration sensors will help us know what is going on with the motor.

B. Data Processing and Data Transfer

The sensor data will be processed by a microcontroller, which can be either an Arduino or an ESP32. We will get data from the analog sensor data. Then the digital data from the sensor will be transferred to the cloud using Wi-Fi. The sensor data will be sent to the cloud where it can be stored and used later. The microcontroller whether it is an Arduino or an ESP32 will play a role, in getting the sensor data to the cloud.

C. Data Storage and Data Pre-processing

Data transmission results in storing data in a platform like ThingSpeak.
The data is then cleaned up. This includes steps like reducing noise, filtering and making the data consistent. After that we categorize the dataset into two groups: faulty. We look at the data again to make sure it is normal or faulty. The IoT platform ThingSpeak stores the data we send. The data we send to ThingSpeak is processed. This processed data helps us identify if it is normal or faulty. We use ThingSpeak to store and analyze data. The data in ThingSpeak is checked for issues. We classify data thing Speak as normal or faulty. ThingSpeak is a platform we use. Data is sent to ThingSpeak. Then analyzed. The analyzed data in ThingSpeak shows results. The results, in ThingSpeak are either normal or faulty.

D. Machine Learning Model Creation

The machine learning algorithm looks at the data we got from the -processing step. We use an anomaly detection algorithm, like the Isolation Forest algorithm to figure out what is normal and what is not when it comes to how the machine's running. When we are training the machine learning algorithm, we use data that we have collected over time. The machine learning algorithm is really good at finding patterns in the data. The anomaly detection algorithm, such, as the Isolation Forest algorithm helps us to know when the machine is not working like it should be. We use the machine learning algorithm to make sure the machine is working properly.

E. Fault Prediction

The machine learning model is used to monitor the data in real time. It checks the machine learning model data all the time. If the machine learning model sees something like the temperature going up too much or the machine learning model vibration levels being too high then the machine learning model will know that something is going to go wrong before it actually does. This helps the machine learning model to tell us that there is a problem, with the machine learning model before it is too late.

F. Alert Generation and System Monitoring

When the system finds something is wrong it sends an alert to the user. The user gets this alert on a dashboard or, on an application. The system is always checking the machine so the user can see what is going on with the machine from else. This is really helpful because the user can keep an eye on the machine condition from away and the system always shows what is happening with the machine right now.

G. System Evaluation

The system is checked in a lot of ways including how accurate it's. The results show that the proposed solution is good at predicting problems and the solution is very reliable. The system performs well. The solution is really good, at predicting faults, which means the system is reliable.

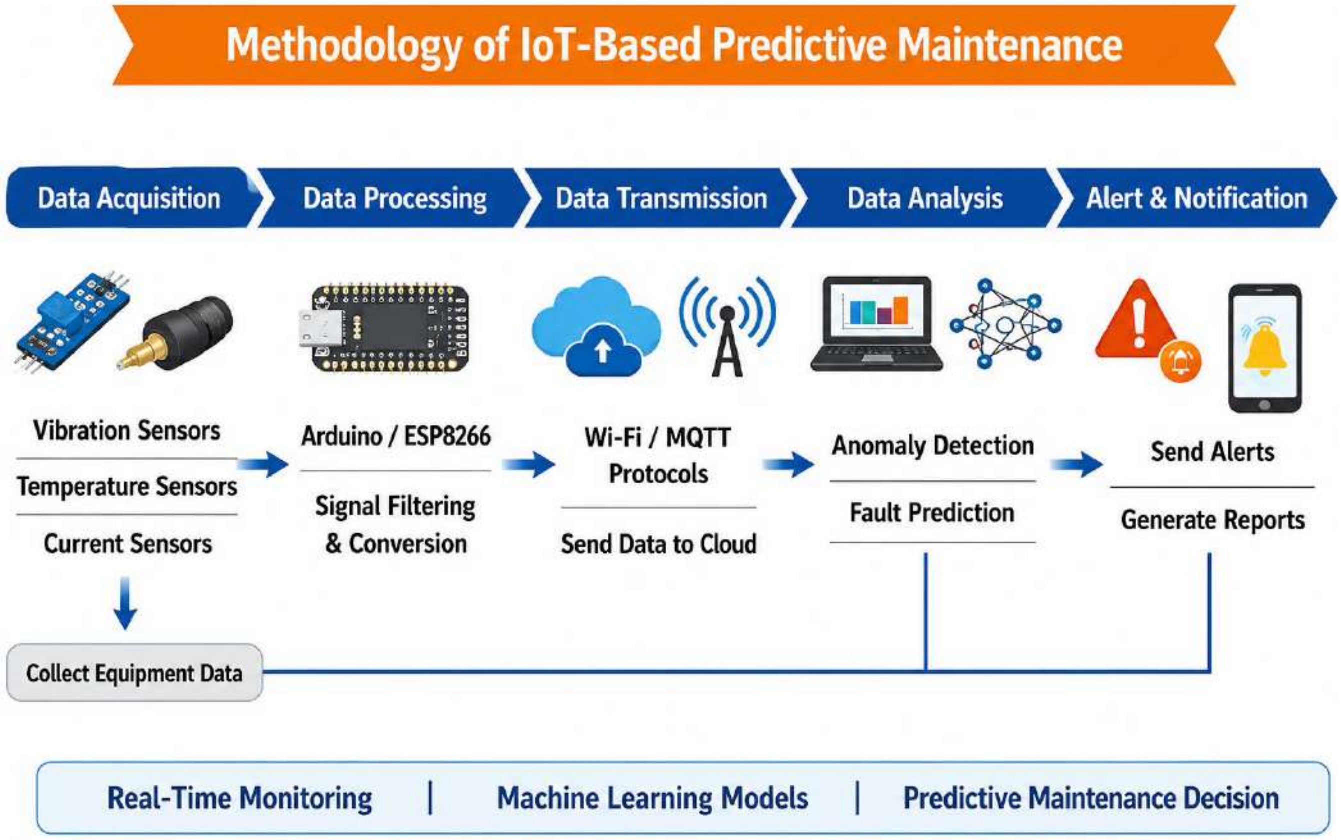

Figure 2: Methodology of IoT-Based Predictive Maintenance

VI. DATASET DESCRIPTION

The information we are working with comes from sensors on machines in factories. These sensors give us readings when the machines are being used in ways. We can get this information from sensors called IoT sensors that are attached to the machines or from datasets that people can use for free. Each piece of information in the dataset shows how a machine is working at a moment in time. The dataset is about the machines and what the sensors on the machines tell us. The machines are the thing we are looking at and the dataset is all, about the machines. The dataset includes the following attributes (See the table 1):

Table 1: Dataset attributes

Feature	Description	Unit
Temperature	Machine operating temperature	°C
Vibration	Vibration level measured by the sensor	mm/s
Humidity	Ambient humidity around the equipment	%
Pressure	Operating pressure of the machine	K Pa
Runtime Hours	Total machine operating hours	Hours
Failure Status	Machine condition (0 = Normal, 1 = Failure)	Binary

Before we start training the machine learning model, we need to get the collected data ready. This means we have to fix the data by removing or replacing values and making sure the sensor readings are all on the same scale. We do this so that all the different features are consistent with each other.

The data is then split into two groups: one for training the model and one for testing it. We use 80 percent of the data to train the machine learning model and save 20 percent to see how well the model works. The main thing we are trying to predict is whether the machine is working properly or if it is going to fail. To do this we use things, like temperature, vibration, humidity, pressure and how hours the machine has been running as input features. The machine learning model, which is called Logistic Regression can look at the data. Find patterns that show when a machine is starting to break down. This helps the model predict when a machine is likely to fail. We have a lot of data to work with about

10,000 records, which includes times when the machines were working normally and times when they failed. This helps make the predictive maintenance model more reliable and accurate.

VII. PROGRAM CODE (ARDUINO)

```
#include <ESP8266WiFi.h>
#include <Wire.h>
// Wi-Fi credentials
Const char* ssid = "your_SSID";
Const char* password = "your_PASSWORD";
// Temperature sensor pin
Int tempPin = A0;
Void setup () {
Serial. begin (115200);
WiFi. begin (ssid, password);
// Wait for WiFi connection
While (WiFi.status ()! = WL_CONNECTED) {
Delay (1000);
Serial. println ("Connecting to WiFi...");
}
Serial. println ("WiFi Connected");
}
Void loop () {
Int tempValue = analogRead (tempPin);
// Convert analog value to voltage
  Float voltage = tempValue * (3.3 / 1023.0);
// Convert voltage to temperature (LM35 type sensor assumption)
Float temperature = voltage * 100.0;
Serial.print ("Temperature: ");
Serial.println (temperature);
// Fault detection condition
If (temperature > 50) {
Serial.println ("Warning: Possible overheating detected!");
  }
Delay (2000);
}
```

A. Explanation of Program

This Arduino program is going to be used to make a system that can predict when maintenance is needed. The system will use the Internet of Things and the ESP8266 Wi-Fi module. It will also use a temperature sensor.
First the Arduino program will connect to the internet using Wi-Fi. Then it will start taking temperature readings all the time using the temperature sensor.

The temperature sensor is connected to A0. The temperature sensor gives us a reading that we have to change into a voltage reading. Then we use the LM35 sensor equation to change the voltage reading into the temperature. The Arduino program will show us the temperature, on the Serial Monitor at any time.
If the temperature goes above 50°C the Arduino program will send us a warning message. This message will tell us that the industrial machine is getting too hot and might get damaged. The Arduino program is using the Wi-Fi module and the temperature sensor to make sure the industrial machine does not get too hot. The temperature sensor and the ESP8266 Wi-Fi module are parts of the Arduino program. The Internet of Things is also important for the Arduino program to work properly. The Arduino program will help us take care of the machine by telling us when it is getting too hot.

VIII. MACHINE LEARNING MODEL

To figure out when equipment might break down this study uses a kind of computer program called supervised machine learning. The program uses something called Logistic Regression to make predictions because it's really good at sorting things into two groups. In this case the program decides if the machine is working normally or if it is going to fail. The program looks at information from sensors on the equipment to make its predictions. It uses temperature and vibration because these are signs of whether the machine is healthy or not. The program then says what it thinks the machines status is, with 0 meaning everything is okay and 1 meaning the machine might fail. The program calculates the chance of the machine failing using a math formula:
P(y=1) =\frac {1}{1+e^{-(w_1x_1+w_2x_2+b)}}
Where w_1 and w_2 are like special numbers that the program uses for temperature and vibration and b is a kind of adjustment value. The program figures these numbers out on its own when it is learning from the data. The program learns from sensor data that was collected when the machine was working in different ways. Before it starts learning the sensor readings are adjusted so the program can work better and so all the information is treated equally. When the program is ready it looks at sensor data and estimates the chance of the equipment failing in real time. If the program thinks the equipment might fail it sends a warning. The Logistic Regression model is used to make these predictions about equipment failure. The equipment failure is what the program is trying to predict. The Logistic Regression model uses equipment failure data to make predictions, about equipment fails. The system warns us when the chance of failure gets too high. This helps the maintenance team fix things before they break. That way we have downtime work better and our equipment lasts longer. The system does this by checking the equipment. It looks for problems that might cause a failure. When it finds one it sends out a warning. This way we can fix the equipment before it breaks. The goal is to keep the equipment running. We want to avoid breakdowns. That is why we use this system It helps us take care of our equipment We can plan for repairs. The system tells us when to act. It helps us work well. The equipment lasts longer. We save time and money.

IX. RESULTS AND DISCUSSION

The performance of the system was analyzed based on the experimental data gathered from the industrial motor in terms of normal and faulty situations. The model showed great efficiency in identifying faults, with an accuracy of 93%. The following confusion matrix shows the results:

Table 2: Performance Evaluation Using Confusion Matrix

	Predicted Normal	Predicted Fault
Actual Normal	45	3
Actual Fault	4	48

In table 2, results show a high number of correct positives and correct negatives. This proves that our model works well. It can detect increases in motor temperature and vibrations. These are two signs that something is wrong. Our model improves how well a machine runs by reducing the time it takes to fix problems. The models accuracy may change when we use data and in different factory settings. The model is good at detecting temperature and vibrations issues. It helps to get machines working again quickly. This is better than maintenance methods. The results are good, for our model. Figure 3 shows the graph of temperature and vibration as shown below.
Temperature → 35 38 42 48 52 55 60
Vibration → 0.2 0.3 0.5 0.7 1.0 1.2 1.5

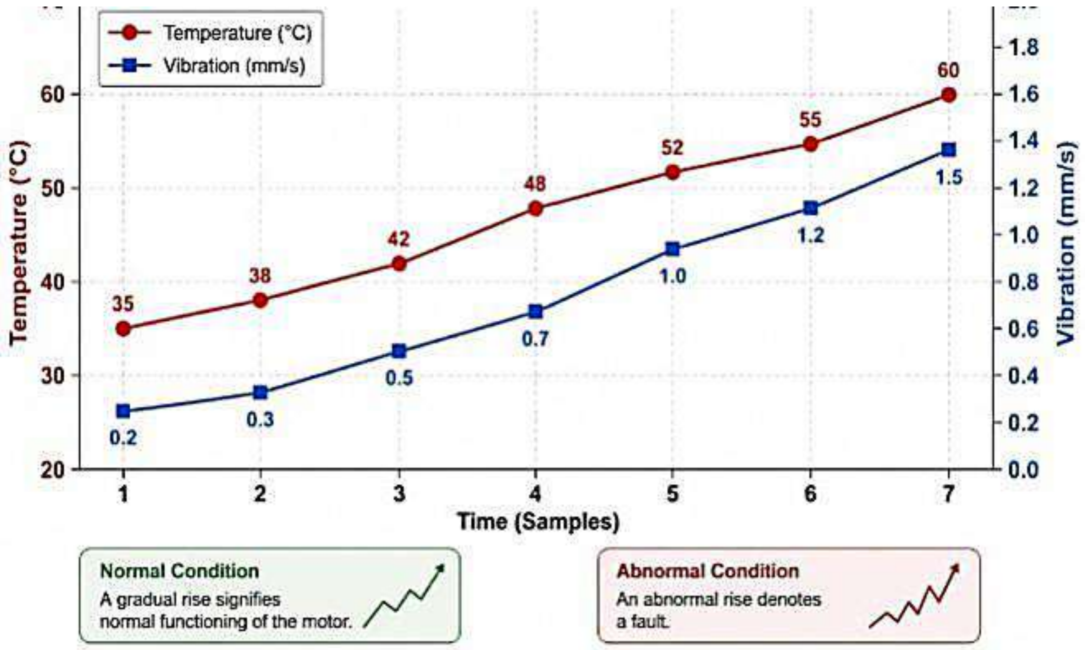

Figure 3: Temperature and Vibration Sensor Data Trend of the Industrial Motor

A gradual rise means the motor is working fine. An abnormal rise means there's a problem. Performance Metrics of the Predictive Maintenance Model The predictive maintenance model was tested using metrics.
These metrics came from a confusion matrix. In the below Figure 4, the results show that the model can tell the difference between faulty machine conditions. The model got an accuracy of 93.0%. This means most predictions were correct. The model predicted a fault with a precision of 94.12%. This means when the model said there was a fault it was usually right. This reduces alarms. The recall value was 92.31%. This shows the model can detect faults. This means most machine failures are found before they happen. The model also got a specificity of 93.75%. This means it can recognize operating conditions. This helps avoid maintenance. The F1-score was 93.20%. This shows the model does well in both precision and recall. The predictive maintenance model works well. It can predict faults and normal conditions. The model is good, at detecting machine failures. It helps prevent machine failures.

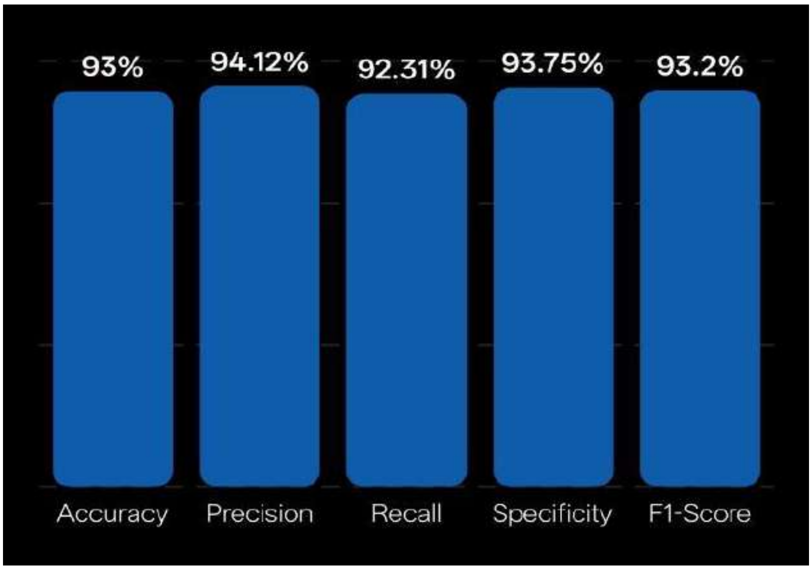

Figure 4: Performance Metrics of the Predictive Maintenance Model

Overall, the obtained metrics suggest that the proposed system provides dependable fault detection and can support timely maintenance decisions. Such performance can help reduce unexpected equipment
Downtime, improve operational efficiency, and enhance the reliability of industrial machinery.

X. LIMITATIONS

This system has some things about it. However, it also has some problems. One problem is that it needs an internet connection to send and receive data right away and to use the cloud to process it. This is not always possible in every factory or industrial place. The sensors also need to be accurate and working properly because mistakes can lead to results. The machine learning model used in this system is also important. It needs to be good and work well which depends on the data that is used to create it. The machine learning model and the data set are crucial to getting results, from this system.

XI. CONCLUSION

The combination of the Internet of Things with machine learning is considered to be a smart method to predict failures and implement predictive maintenance. The developed project proves that real-time IOT data regarding machine operations like temperature and vibrations can be gathered and analyzed on cloud computing platforms for forecasting. Programming techniques such as Arduino and Python have been used to gather data about the machine, pre-process it, and visualize the findings. Graphs show changes in machine operations and any abnormal increase in the readings indicates possible failures. The use of machine learning increases the accuracy of decision-making since the classification of the machine operation allows for decreasing the number of unexpected failures. Results obtained from experimental testing using collected data sets prove that this system can effectively detect the possible failure of machines. Thus, data modeling, programming, and graphing make this system feasible for practical use.

CONFLICTS OF INTEREST

The authors declare that they have no Conflicts of Interest.

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