

# **TITLE: PREDICTIVE MAINTENANCE OF AC MOTOR USING MACHINE LEARNING**

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## **ABSTRACT**

Industrial machines are frequently used without a scheduled strategy for checking or repairing. This leads to unexpected downtime, due to unplanned failures. Replacing components on a regular basis to minimize unplanned machines outages comes under orderly and timely maintenance. In recent times, with the emergence of industry 4.0 and Internet of things(IOT), there is a greater emphasis on predictive maintenance techniques, which will reduce the value of downtime while boosting the supply required of industrial components. Predictive maintenance can promote industrial processes by eco- friendly means and extending usable lifetimes of equipment. A data-driven modelling technique will be discussed and used to evaluate a motor failure. To design and develop a system for Predictive Maintenance of Motor using various sensors like ACS712 for current, ZMPT101B for voltage, LM35 for temperature, DHT11 for Humidity, SW420 for vibration and using ESP32 as microcontroller, with IoT based monitoring and Machine Learning model for prediction of failure of AC motor. Our project will be able to predict the maintenance and failure probability of the single phase, 0.5HP, 1400 rpm, AC motor using data from various parts and further refining and analysing the data using the machine learning algorithms in an effective manner.

## **KEYWORDS**

ML-Machine learning

CNN-Convolutional Neural Network

AI-Artificial Intelligence

IOT-Internet of Things

RF-Random Forest

DT-Decision Tree

## **PROJECT DEFINITION**

There is a emergence of industry 4.0, in this ML, AI and Predictive Maintenance are widely used. Industries require these techniques to maintain their industrialassets in proper conditions like plants, machinery etc. Collection of very large amount of data from various components and further analyzing that data for the purpose of developing an automatic problem detection and diagnostic system with the objective of decreasing downtime, boosting component utilization rate and enhancing component reliability as well as increasing their remaining useful lives. Because of the digital revolution in Industry 4.0, various information methods, computerized control and communication networks, large volumes of data can now be collected fromvarious components and to further refining and analyzing the data with the goal to reduce downtime, increasing utilization and increasing remaining lives of the components. Our project will predict the timings for the maintenance of motor based on the historical data collected using sensors, for this ML algorithms will be applied on the datasets.

## **NEED FOR PREDICTIVE MAINTENANCE**

Timely monitoring of machines is done in predictive maintenance to analyses and find faults. If and only if an ambiguity is found, maintenance is proposed and carried out.

In the 21<sup>st</sup> century, the usage level of predictive maintenance has increased in industry. Spreadsheets were prevalent in the early 1970s, to get permit for maintenance work based on conditions.

In recent time there is no such need. Predictive maintenance is now considered as an important method to reduce cost of maintenance, downtime of repair and inventory

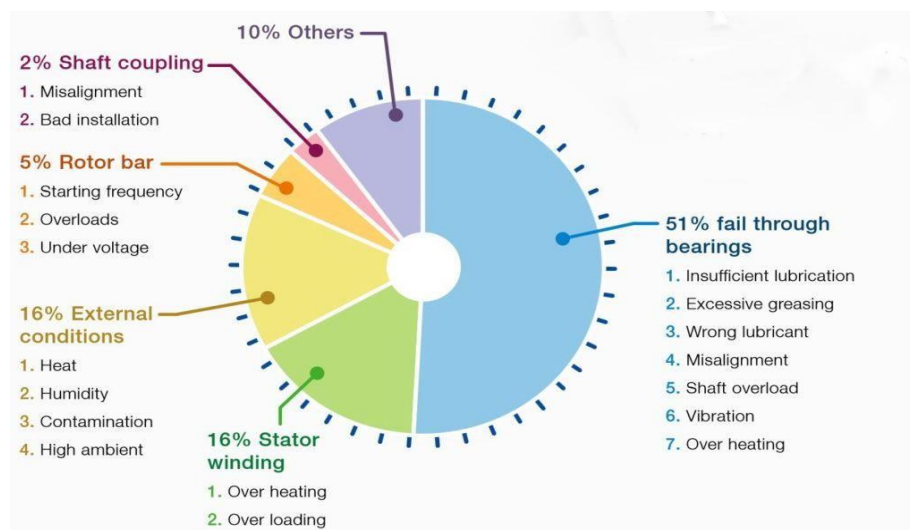
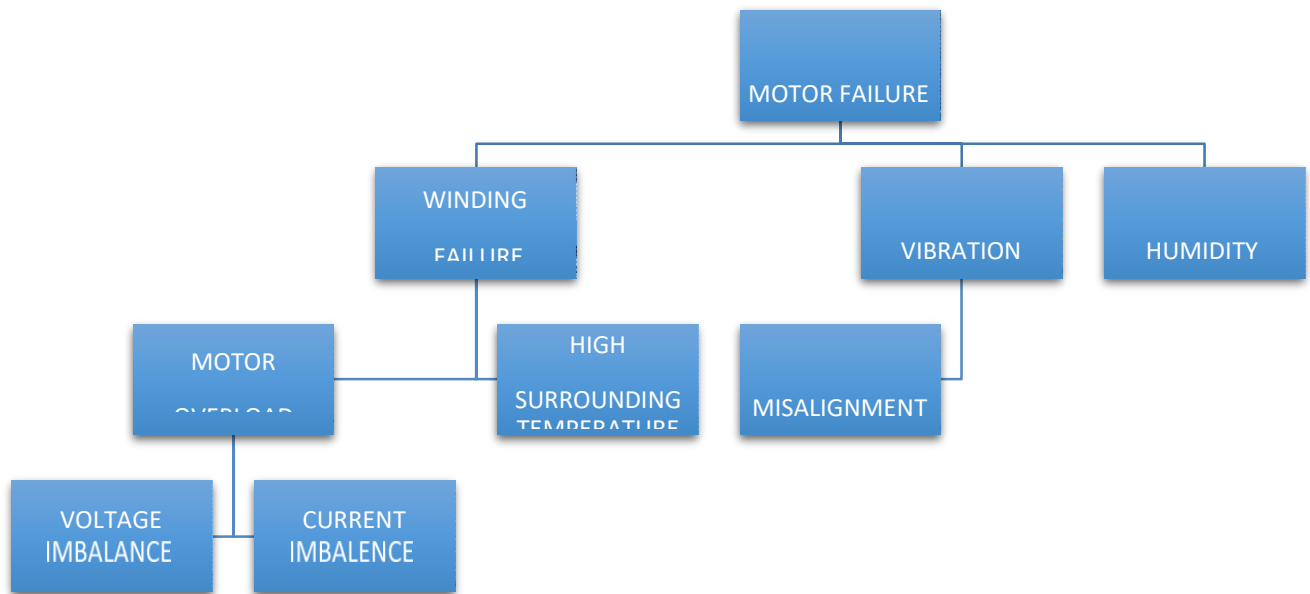
## **BENEFITS OF PREDICITVE MAINTENANCE**

- Increase in machine productivity.
- Improved repair time & product quality.
- Interval between overhauls get extended.
- Machine life gets increased.
- Proper planning of the resources of repair.
- To manufacture quality products.

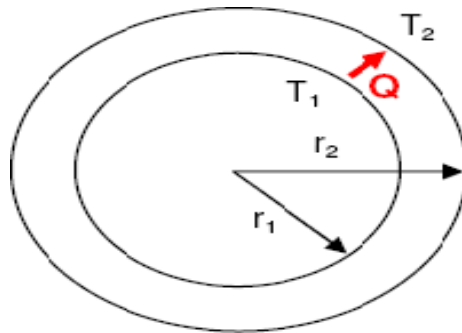
## **LITERATURE SUMMARY**

Timely monitoring of machines is done in predictive maintenance to analyses and find faults. If and only if an ambiguity is found, maintenance is proposed and carried out. In the 21<sup>st</sup> century, the usage level of predictive maintenance has increased in industry. Spreadsheets were prevalent in the early 1970s, to get permit for maintenance work based on conditions. In recent time there is no such need. Predictive maintenance is now considered as an important method to reduce cost of maintenance, downtime of repair and inventory.

## REASONS FOR FAILURE OF MOTOR



## CALCULATIONS



### Temperature

Rate of heat conduction  $Q = -KA \frac{dT}{dx} = \frac{T_1 - T_2}{R_{th}}$

Considering motor casing as a hollow cylinder, Thermal resistance  $(R) = \frac{\ln(R_2/R_1)}{2\pi \cdot K \cdot L}$  Where,

$Q$  = Rate of heat transfer =  $V \cdot I = 230 \cdot 4 = 920 \text{ J/s}$  or Watt  $K$  = Thermal conductivity of the material =  $80 \text{ W/mK}$   $L$  = characteristics length of the cylinder =  $145.64 \cdot 10^{-3} \text{ m}$   
 $\pi = 3.14$  = constant

$dT/dx$  = Temperature gradient in hollow cylindrical body  $A$  = Area perpendicular to direction of heat flow

$T_1$  = Inner Temperature of the casing =  $102^\circ \text{ Celsius}$  (class F insulation material melting temperature)

$T_2$  = Outer Temperature of the casing  $R_2$  = Outer radius of the casing =  $79.17 \cdot 10^{-3} \text{ m}$

$R_1$  = Inner radius of the casing =  $64.17 \cdot 10^{-3} \text{ m}$

$R_{th}$  = thermal resistance =  $\ln(79.17 \cdot 10^{-3} / 64.17 \cdot 10^{-3}) / (2 \cdot 3.14 \cdot 80 \cdot 145.64 \cdot 10^{-3})$

$R_{th} = 2.8694 \cdot 10^{-3} \text{ K/Watt}$  or  $\text{K-s/JQ} = T_1 - T_2 / R_{th}$

$920 = T_1 - T_2 / 2.8694 \cdot 10^{-3}$

$T_2 = 2.64$

$T_2 = 102 - 2.64$

$T_2 = 99.36^\circ \text{ Celsius}$

## **Vibrations**

Failure because of vibrations can be caused if the natural frequency of the casing material gets matched with the frequency of the working motor, so resonance can take place.

So taking the threshold frequency as the natural frequency of the casing material

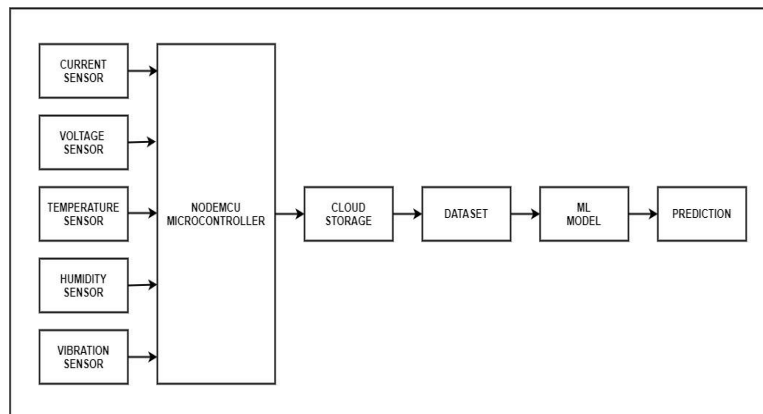
Natural frequency=50 Hz

## **Current and Voltage**

For the single phase 230V, 50 Hz, 1440 rpm, 0.5 HP AC motor the threshold values are found out using the power rating. So the threshold values are of Current=4A, voltage=230 volts

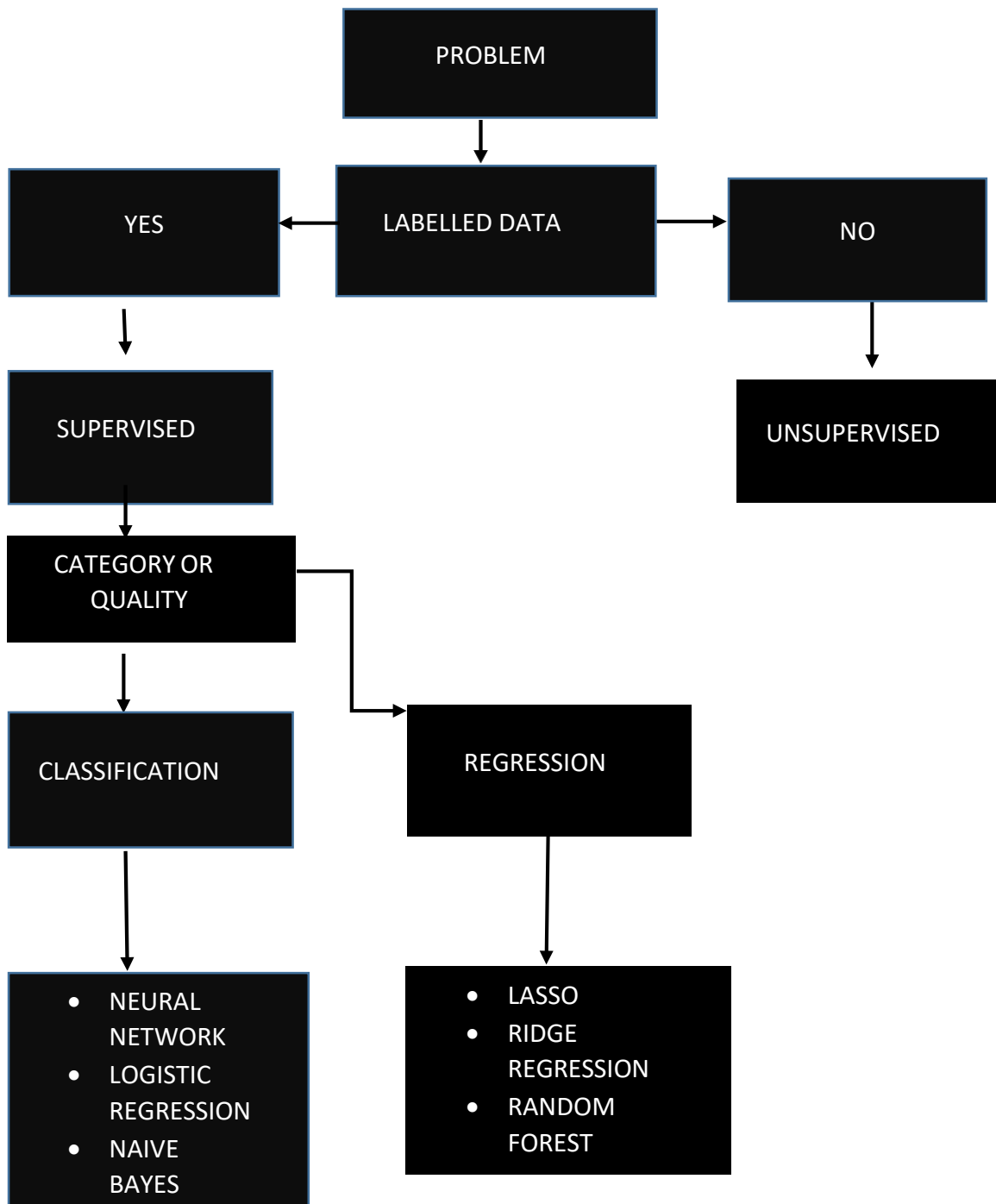
# PROJECT METHODOLOGY

## Process Diagram



1. Sensors have been used to monitor and collect data.
2. The data collected have passed to ESP32 Microcontroller.
3. ESP32 microcontroller is chosen because it supports inbuilt Wi-Fi. Hence data can be directly stored to cloud storage over the internet.
4. Cloud Storage that we have used for storing data is ThingSpeak Cloud. It supports data storage along with visualizations. Once sufficient amount of data was collected it was been exported intoExcel .csv format.
5. The data exported from ThingSpeak Cloud is the dataset whichwas used as a dataset for Machine Learning.
6. Pre-processing steps such as exploration, cleaning and transformation of dataset was done using Python.
7. ML prediction models like Logistic Regression, RF, DT, Naïve Bayes etc. can be used for predictive maintenance of motor andto predict failures in motor.
8. Visualisation of the data can be done using Python Modules such as matplotlib, seaborn,etc.

## MACHINE LEARNING ALGORITHMS



### Types of Machine Learning

Machine learning can be said as the branch of artificial intelligence and computer science whose prime focus is on algorithms and data used to improve the way humans learn, gradually it improves the accuracy.

Machine learning can be divided into three types

1. Unsupervised ML
2. Supervised ML
3. Reinforced ML

### Unsupervised Machine Learning

It uses the ML algorithms which use datasets and clusters to analyse, which are in the unlabelled form, in this type of machine learning human intervention is not required. The algorithm by itself tries to find some relation or some sort of pattern from the given data set to predict the future values.

### Supervised Machine Learning

It uses the machine learning algorithms which are used to analyze the data and clusters which are in the labelled form. It allows to collect data and produces data output from the previously known experiences.

### Reinforced Machine Learning

It uses the ability of making decisions, it focuses on achieving best behaviour in the surrounding to achieve best rewards. This can be understood by interacting with surrounding and learning how it reacts.

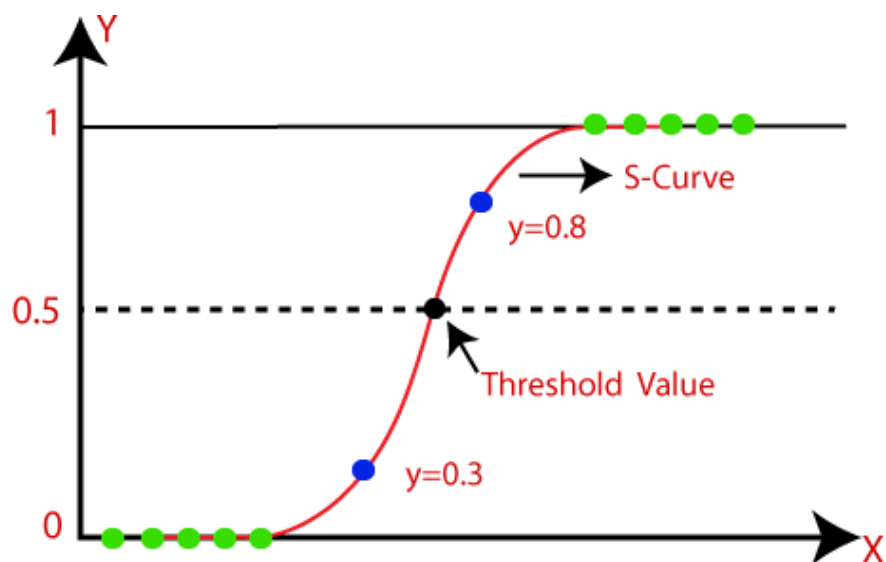
### ALGORITHM USED:

In supervised ML, Classification or Regression types are used.

Classification type which can be used to predict the values and data separated into classes

Regression is the type which gives the value of the output in the numerical form

For the predictive maintenance of motor, supervised form of ML is used, as we have collected the data from the motor using various sensors. We have collected the readings and have compiled up to 1500 set of readings. Most of the data in these dataset is of no use because of the garbage or unnecessary values, so pre-processing of the data is required before applying the machine learning algorithm. Most of the unusual data is removed, then the data is divided into 80% and 20%. The 80% data is the one on which ML algorithm is applied to train it, then the trained algorithm is used for the rest 20% data to check how accurately the algorithm works. This results can again be compiled with the earlier set of readings and ML algorithm can be applied to it, some new set of readings can be used to check the results. With iterations, we can improve the accuracy of our algorithm by using more and more data.



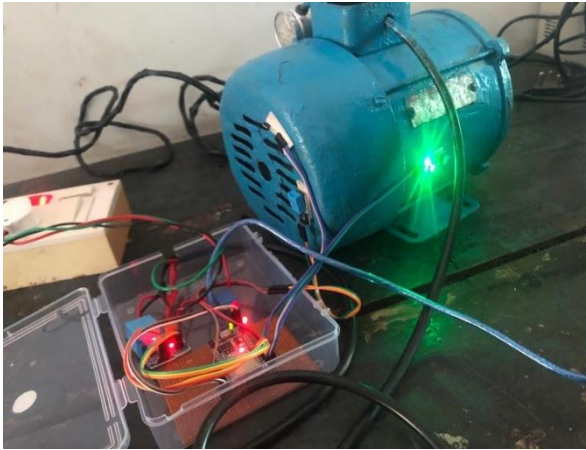


		Predicted Class		
		Positive	Negative	
Actual Class	Positive	True Positive (TP)	False Negative (FN) Type II Error	<b>Sensitivity</b> $\frac{TP}{(TP + FN)}$
	Negative	False Positive (FP) Type I Error	True Negative (TN)	<b>Specificity</b> $\frac{TN}{(TN + FP)}$
		<b>Precision</b> $\frac{TP}{(TP + FP)}$	<b>Negative Predictive Value</b> $\frac{TN}{(TN + FN)}$	<b>Accuracy</b> $\frac{TP + TN}{(TP + TN + FP + FN)}$

It is used for evaluating factors such as recall, accuracy, specificity and precision along with AUC-ROC curve

## DATA COLLECTION AND APPLICATION OF MACHINE LEARNING

### TEST SET-UP



The motor is connected with various sensors and the live data gets feed in the thing speak cloud.

### Formation of datasets

The graphs of the data that we have obtained in the thingspeak cloud. The data from the thingspeak cloud is exported as .csv file





Data in the .csv form

created_at	entry_id	current	voltage	vibration	temperature	latitude	longitude	relay_status	humidity	failure
2022-03-15T17:17:51+05:30	1	1.93809	238.647	0	37.1184			1	25	yes
2022-03-15T17:18:07+05:30	2	2.3526	215.625	0	37.3626			0	25	no
2022-03-15T17:18:24+05:30	3	3.65493	152.061	0	37.2405			0	46	no
2022-03-15T17:18:41+05:30	4	2.42001	195.747	0	37.1184			0	26	no
2022-03-15T17:19:00+05:30	5	2.63263	177.104	0	37.1184			0	26	no
2022-03-15T17:28:39+05:30	6	2.59452	212.772	0	37.1184			0	20	no

Fig:8.4

## **APPLICATION OF MACHINE LEARNING ALGORITHM**

As we have divided our datasets in two types train and test, but similar type of conditions is to be applied on the both, so we first combine them and apply the required conditions. After this we drop the column of “failure” for the test dataset because that is the value which we are going to predict.

In our set of readings, there are 10 columns of these “voltage”, “vibration”, “current”, “humidity”, “temperature”, “failure” are useful, remaining columns like “longitude”, “latitude”, “time”, “Relay Status” are not important. So, we need to drop these columns, for that we have used drop syntax.

As in our problem we are going to do the predictive maintenance of motor, the output value should be in the form of classes “yes” or “no”, do the motor required maintenance or is the motor going to fail. So we are going to apply the classification type of algorithm.

In classification type, we have used logistic regression model of classification for the prediction using python, from sklearn.linear model we have imported logistic regression and gridsearchCV is imported from sklearn.model selection.

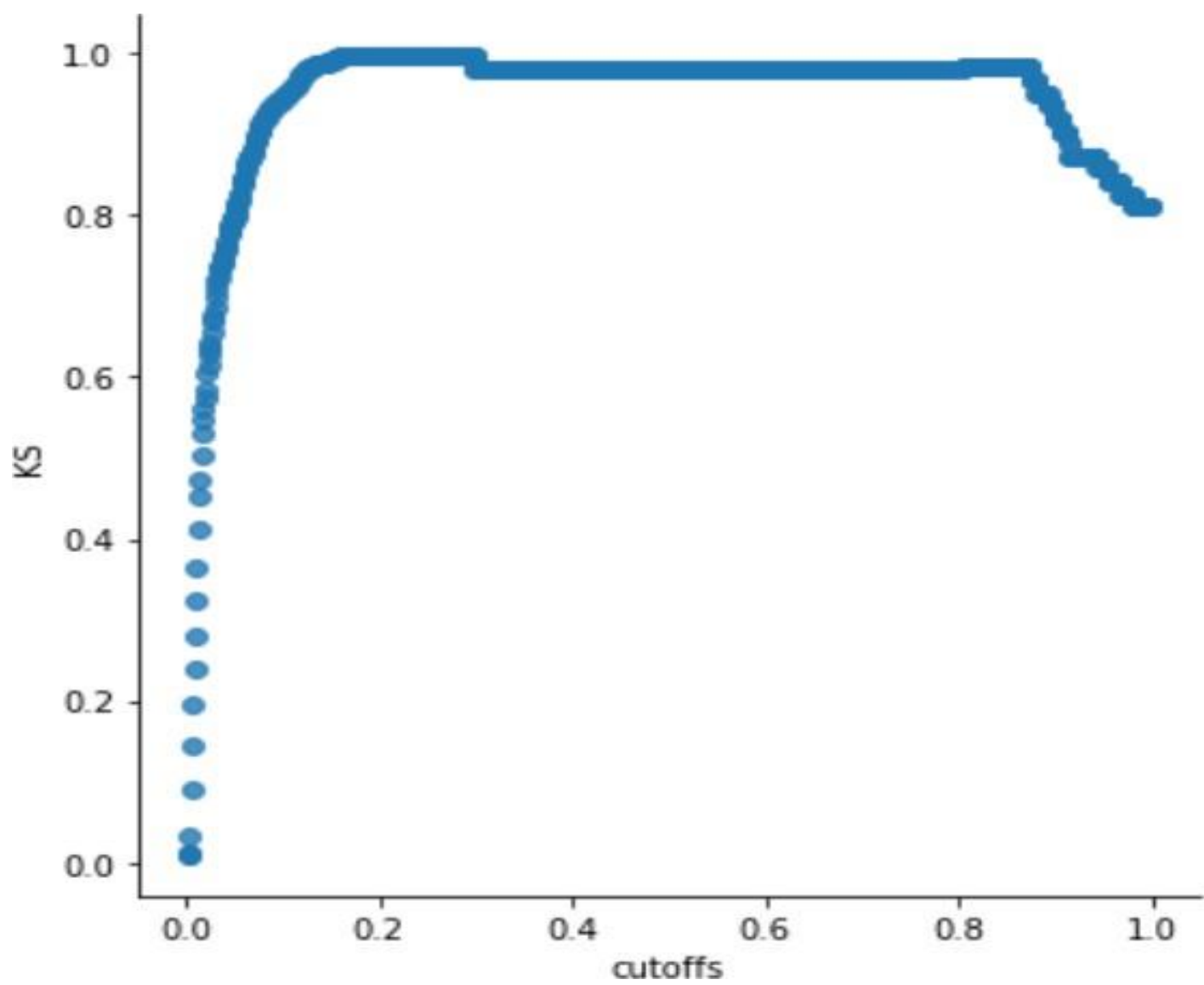
In logistic regression type, we get a S-curve having some threshold value, the values above the threshold values having some context like yes/failure and the values below the threshold have opposite context with respect to earlier. In this manner getting the accurate threshold value which can closely predict the output is important.

**RESULT TABLE**

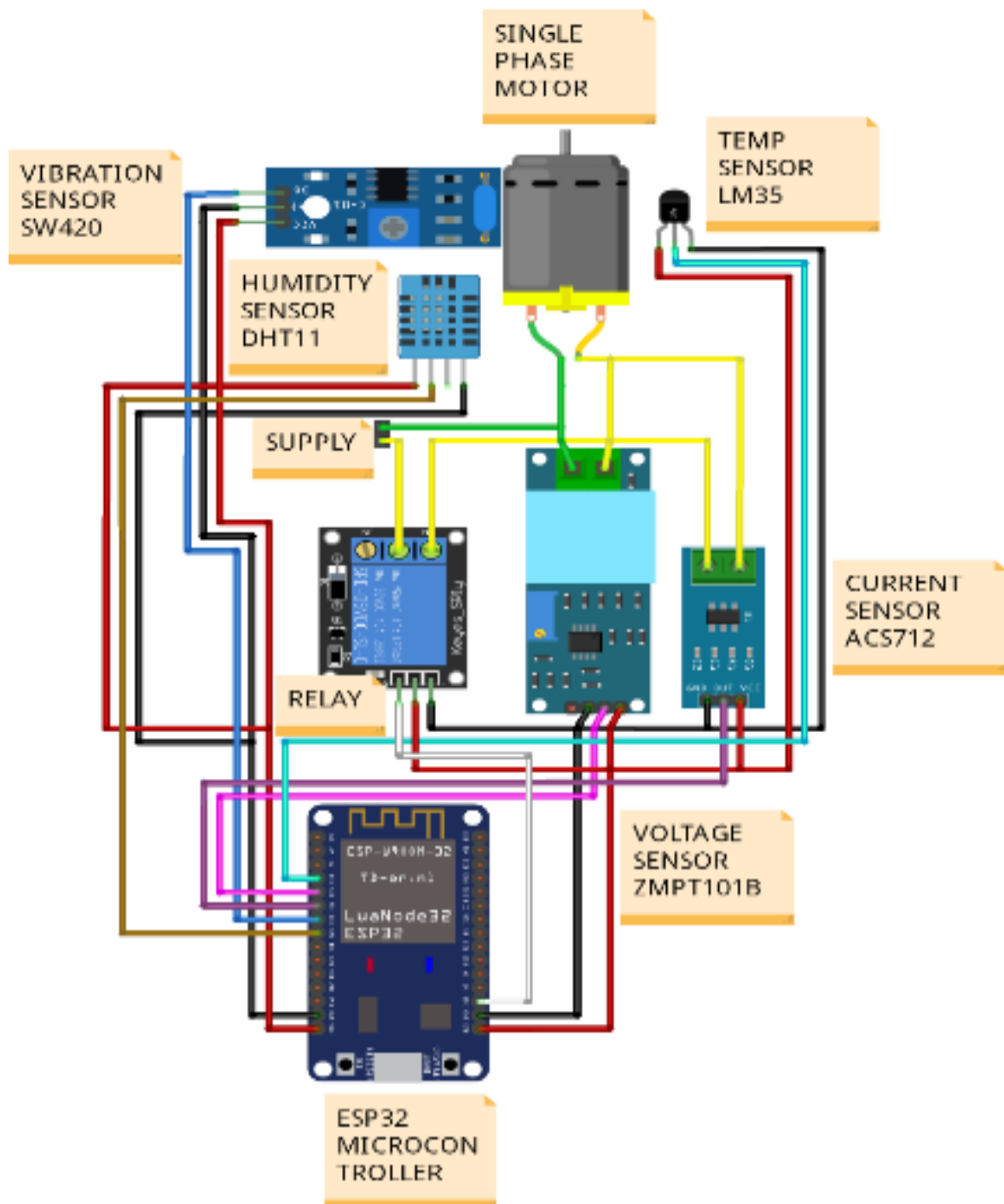
Model with rank: 1  
Mean validation score: 0.983126 (std: 0.049935)  
Parameters: {'C': 888.8889, 'class\_weight': 'balanced', 'penalty': 'l2'}

Model with rank: 2  
Mean validation score: 0.982919 (std: 0.049877)  
Parameters: {'C': 333.3334, 'class\_weight': 'balanced', 'penalty': 'l2'}

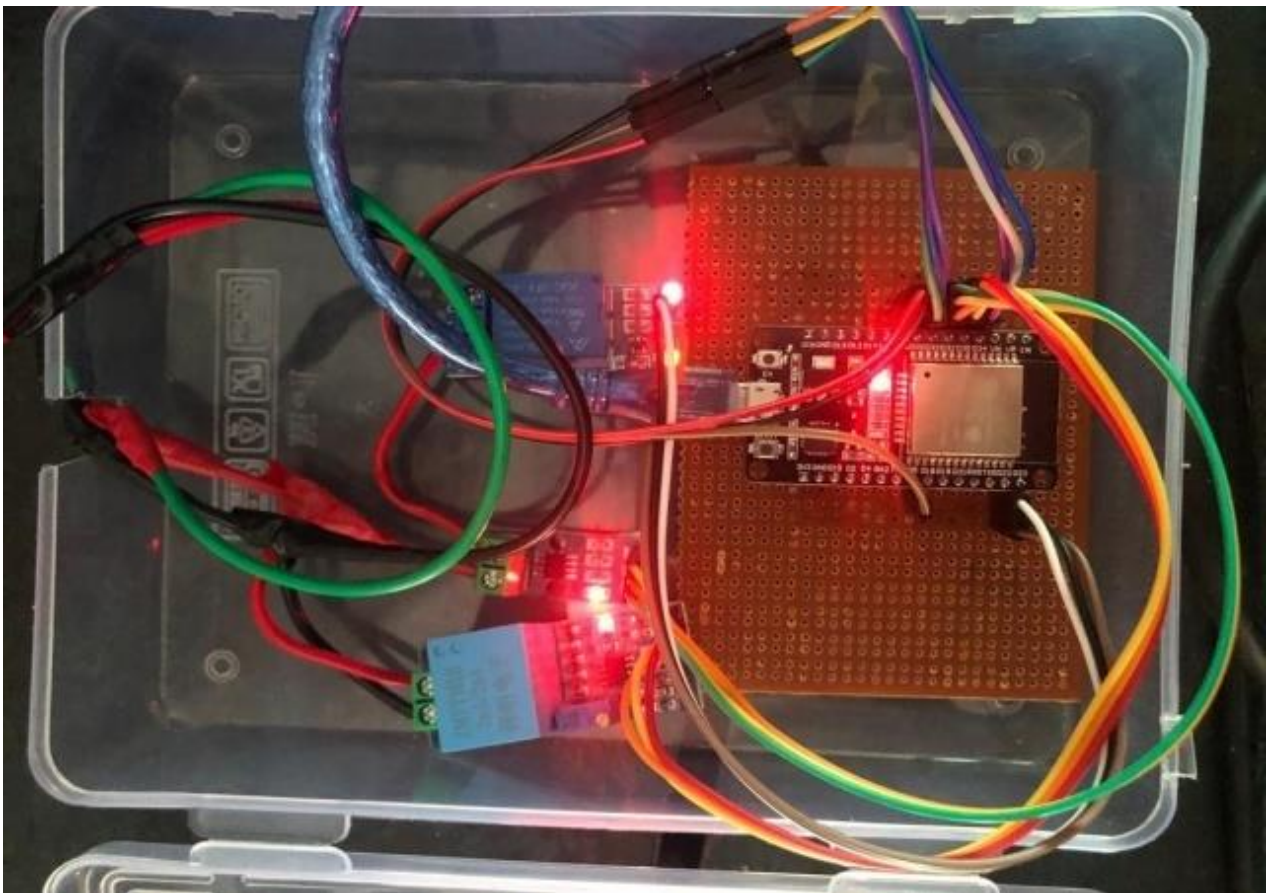
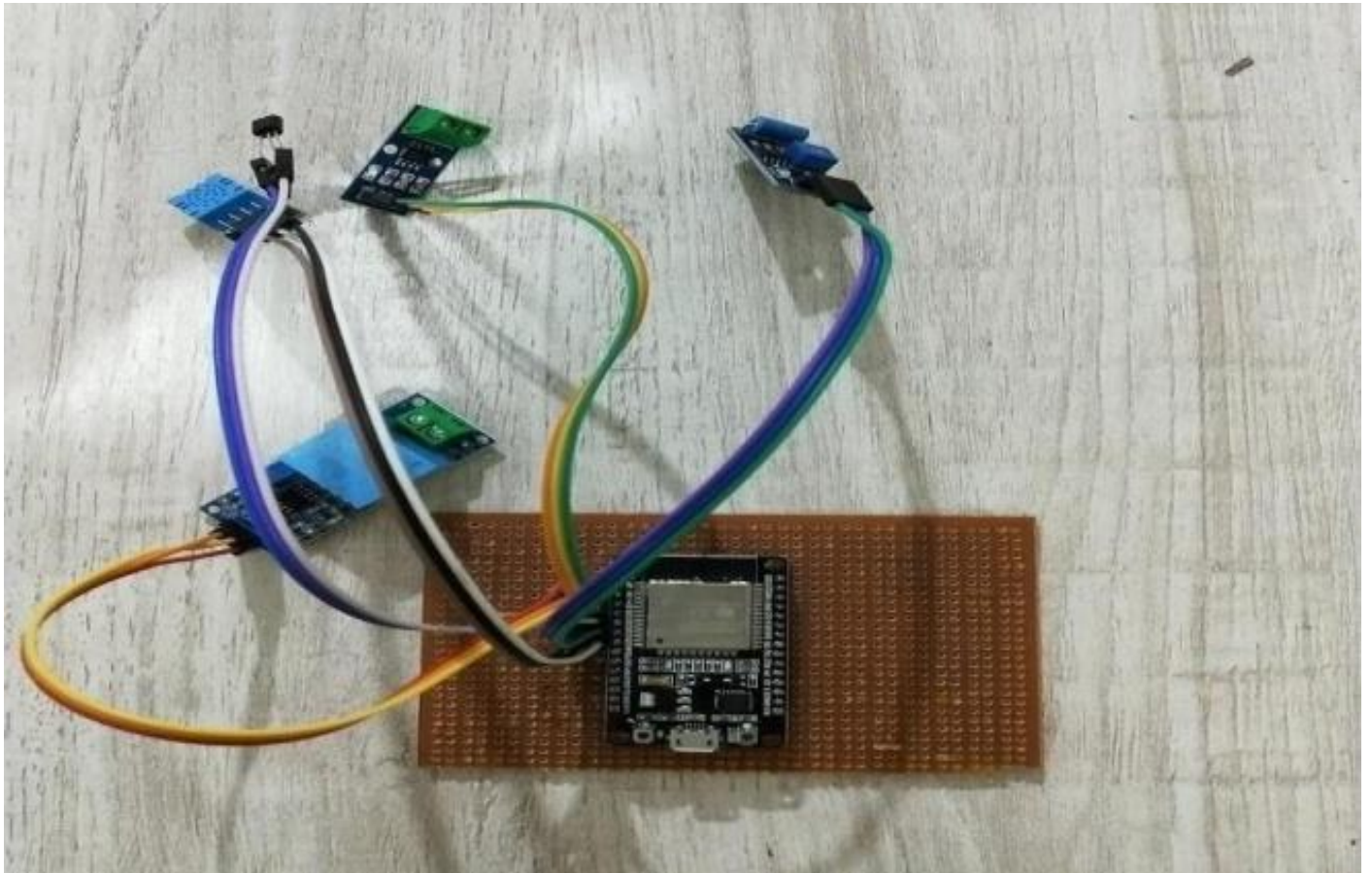
Model with rank: 2  
Mean validation score: 0.982919 (std: 0.049877)  
Parameters: {'C': 1000.0, 'class\_weight': 'balanced', 'penalty': 'l2'}



## CIRCUIT DIAGRAM







## CONCLUSIONS

After detecting and diagnosing faults, predictive maintenance necessitates continual monitoring of motor. Only when fault is discovered, maintenance work is scheduled and carried out. After applying logistic regression algorithm on the train datasets, we got the value of KS as 0.80, so this is the threshold value. This algorithm is then applied to test dataset and the output in terms of 0 and 1 are obtained. We get the final result in the form of csv file, if the final value is [1,0], the motor failure chances are low. But if we get the values as [1,1] then the motor failure chances are high.

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