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Intelligent Industrial Motor Fault Diagnosis and Predictive Maintenance using Multi-Sensor Fusion and Machine Learning

Piyush Chinde[1]
Department of Electronics and Telecommunication Engineering, Savitribai Phule Pune University, Pune, India

Abstract: Industrially used electric motors are crucial parts of industries and process industries, which failure might lead to significant financial losses due to the unplanned downtime.
Current methods of motor maintenance based on regular inspections and reactive maintenance strategies are unable to detect the early symptoms of the motor condition deterioration.
This paper describes the development of the Intelligent Industrial Motor Fault Diagnosis and Predictive Maintenance System using the principles of data fusion from multi-sensors and machine learning for monitoring of the motor condition and its further faults prediction.
The proposed system includes ESP32 microcontroller along with multiple sensors measuring the important operating parameters, namely motor current, vibration, rotation speed (RPM), and gyroscope movement. The Wokwi simulation environment has been created to mimic various operating states of the motor, namely, normal, overloaded, vibrations and fault conditions. The collected sensor data are used as the training dataset for a machine learning model to automatically predict the state of the motor health.
The proposed framework provides the ability to use simulation data generation along with machine learning algorithms for a cost-efficient intelligent monitoring of motor conditions without the need for expensive industrial testing setups. The proposed methodology is a solid base for future work and can be implemented in industry using IoT remote monitoring and cloud predictive maintenance.
Keywords: Industrial motor Monitoring, Fault Diagnosis, Predictive Maintenance, Machine Learning, Multi-Sensor Fusion. ESP32, Condition Monitoring, Vibration Analysis, Current Monitoring, RPM, Monitoring.

I. INTRODUCTION

They are widely used in manufacturing plants, power stations, chemical industries, oil and gas facilities and automated production systems.

They drive pumps, compressors, conveyors, fans and more, and are vital for uninterrupted industrial processes. Unexpected motor failures can lead to production downtime, higher maintenance costs, damaged equipment and safety hazards. Therefore, constant monitoring of motor health has become an essential requirement in today's industries.

The traditional motor maintenance strategies are mainly based on the reactive maintenance where the repair is performed only after the motor failure or preventive maintenance where the maintenance activities are scheduled at fixed time intervals regardless of the actual condition of the motor.

Preventive maintenance limits unplanned downtime while. This often leads to unnecessary servicing, higher operating costs and inefficient use of maintenance resources. Such limitations have led industries to implement predictive maintenance that continuously monitors the condition of the equipment and predicts possible failures before they become critical.

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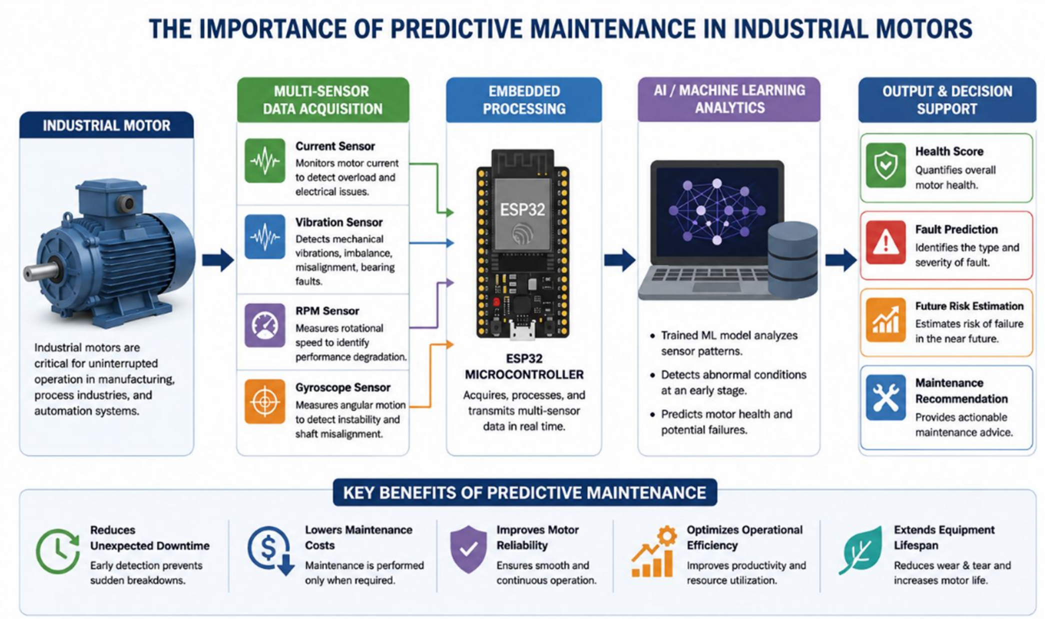

Fig.1.Importance of Predictive Maintenance in Industrial Motors

Recent advances in the Industrial Internet of Things (IIoT), embedded systems and machine learning have led to the development of intelligent condition monitoring systems that can analyse real-time sensor data and identify abnormal operation conditions. Modern predictive maintenance systems do not rely on a single parameter but combine information from multiple sensors to obtain a more complete picture of the health of the motor. Parameters such as motor current, vibration level, rotational speed (RPM), temperature and shaft motion provide useful information about the operational condition of the motor and it can also expose early signs of mechanical or electrical faults.

Among these parameters is the motor current, which is useful for overload detection and abnormal electrical behaviour. Vibration analysis is widely used for the detection of bearing defect, shaft misalignment and rotor imbalance. Performance degradation and mechanical load are indicated by rotational speed (RPM) and gyroscope measurements help to detect abnormal angular motion and instability. The integration of these sensor measurements by multi-sensor data fusion allows improving the fault detection accuracy compared with the systems based on a single sensing parameter.

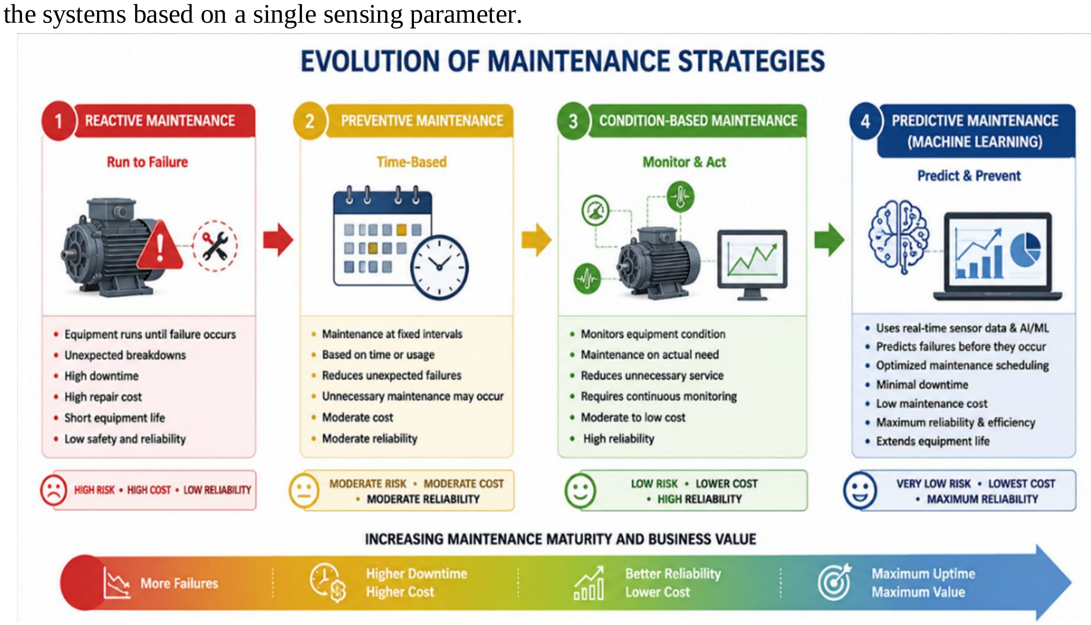

Fig.2.Evolution of Industrial maintenance Strategies from Reactive to Predictive maintenance

However, in recent years, machine learning (ML) has emerged as a powerful tool for fault diagnosis in the industry due to its ability of learning complex relationships from historical sensor data. Machine learning algorithms can automatically classify motor operating conditions, estimate equipment health and generate maintenance recommendations without the need for manually defined fault thresholds. This allows industries to decrease downtime, optimise maintenance planning and extend the life of industrial equipment.

For this study, a predictive maintenance system for Intelligent Industrial Motor Fault Diagnosis and Prediction is being developed. This intelligent system uses a combination of multi-sensor fusion technology and machining learning technique. The intelligent predictive maintenance system incorporates the use of ESP32 microcontroller equipped with simulated sensors for measuring current, vibration, RPM and gyroscope readings within Wokwi simulation platform. Sensor readings captured from various operating scenarios ranging from healthy operation, overload alarm, vibration alarm and critical failure conditions are stored in a structured dataset. This dataset is then pre-processed and trained using machine learning algorithms for motor condition classification, health estimation, predicting future problems and generating recommendations for maintenance operations.

As opposed to the traditional alarm threshold-based approach that is used in many predictive maintenance systems, this system adopts the intelligent methodology of simulation dataset generation, embedded sensing technologies and machine learning. Use of simulation makes it possible to generate representative operating data without the need to have expensive industrial testing equipment.

II. LITERATURE REVIEW

Industrial motors form an integral part of manufacturing facilities, power generation, and transport sectors. In order to increase reliability and lower maintenance costs, various motor monitoring systems have been suggested in literature for predicting faults. Advancements in embedded technology, IIoT, and AI technology have contributed to better predictive maintenance. This chapter will review the research done previously on motor monitoring systems, AI-based fault diagnosis, and machine learning methods with a focus on the gaps that need to be addressed by the proposed research.

A. Existing Motor Monitoring Systems

Traditional monitoring systems of industrial motors typically concentrate on assessing a single operation parameter of the motor like motor current, vibrations, and temperature in order to evaluate the health of the motor. Motor current analysis is useful for overload and electrical faults detection, vibration analysis is helpful to diagnose bearing faults, rotor misalignment and imbalance, and mechanical looseness; and temperature analysis can be used for detecting overheating due to excessive load or improper ventilation.

The majority of traditional monitoring systems function independently without combining the signals from several sensors. Therefore, they do not offer significant diagnostic abilities and cannot recognize complicated faults associated with multiple operation parameters. In addition, many of the systems are designed to trigger alarms only when the abnormal condition is already established.

B. AI-Based Motor Fault Diagnosis

Artificial intelligence has proved to be a potential method for fault diagnosis in industrial applications because of the ability of AI systems to learn the unknown relationship of the process variables through sensing devices. Instead of having predefined threshold limits for fault identification, fault patterns in AI algorithms are automatically learned from the historical operating data.

Some of the machine learning techniques which have proven to be effective in categorizing motor faults are Decision Trees, Support Vector Machines (SVMs), Artificial Neural Network (ANN), Random Forest, Gradient Boosting. Deep learning techniques like Convolutional Neural Network (CNN) and LSTM networks are being used more and more for analysing vibration signals for predicting future faults.

However, despite these innovations, many artificial intelligence models are dependent upon costly industrial sensors, big data sets and powerful computers.

C. Machine Learning for Predictive Maintenance

Predictive maintenance is based on sensor data that is constantly monitored and used to predict the state of the machinery along with future failure. Training of machine learning models involves datasets of operational states of equipment that include healthy and faulted states. Features such as current, vibration amplitude, RPM (rotational speed), temperature, and acceleration are derived and then fed to classification models.

The trained models are able to predict the current health condition of a motor, fault categories, the health score, and suggest maintenance actions. Predictive maintenance differs from preventive maintenance by minimizing downtime, decreasing maintenance cost, extending the equipment's life cycle and increasing the productivity of industries.

D. Research Gap and Limitations of Previous Work:

Despite many studies that prove the effectiveness of AI-based motor fault diagnostics, several drawbacks are noticeable.

Firstly, most of the published models operate on a limited number of sensors with just one or two parameters being monitored. Moreover, these approaches fail to provide adequate maintenance advice for operators and pay more attention to fault detection than to prediction. Besides, most of the research is based on costly industrial data acquisition equipment, which makes their deployment complicated in case of educational institutes or small companies.

Another drawback is that most of the published works aim at classification accuracy without considering real-time embedded implementation with cheap microcontrollers like ESP32. In addition, there are no systems that can give motor health score with future risks prediction and maintenance recommendations.

In order to solve these problems, our system uses several sensors (current, vibration, RPM and gyroscope) and an ESP32 embedded board. The machine learning model analyzes the data and predicts the state of motor health, calculates the future risks and gives the motor health score and maintenance recommendations.

Table1. Comparison of Existing Motor Fault Diagnosis Systems with the Proposed System

Paper No.	Reference	Sensors Used	AI/ML	Real-Time Monitoring	Health Score	Future Prediction	Maintenance Recommendation	Low-Cost Implementation
1.	Tama et al. (2022)	Vibration	CNN, LSTM, Deep Learning	Yes	No	Yes	No	No
2.	Ayankoso el al. (2025)	Current, Vibration	Random Forest, CNN	Yes	No	Yes	No	No
3.	Sensors Review (2025)	Current, Vibration, Temperature, Speed.	RF, ANN, CNN, LSTM	Yes	Limited	Yes	Limited	No
4.	Barik et al. (2026)	Current	Random Forest	Limited	No	Yes	No	No
	Proposed My Work	Current, Vibration, RPM, Gyroscope	Random Forest	Yes	Yes	Yes	Yes	Yes (ESP32)

The Proposed AI-based industrial motor fault detection system and other previous researches are compared in Table 1 below. The earlier researches have been mostly carried out in vibration analysis, current signature analysis or through deep learning. While these methods show promising accuracy rates in fault detection, the major challenge with them is that most of them either depend on fewer sensor features or need high computation power. Moreover, few studies make any recommendation for maintenance or generate motor health score in real-time. The proposed model attempts to overcome these drawbacks through integration of current, vibrations, RPM and gyroscope sensor features through a cheap ESP32 platform and a machine learning algorithm.

III. PROBLEM STATEMENT AND RESEARCH OBJECTIVE

Industrial motors have been extensively applied in manufacturing and processing industries where their failure results in production downtimes, additional maintenance costs, and safety hazards. Current methods of monitoring such machines employ only one parameter measurements or static threshold values which restricts their ability to identify fault issues at the initial stage.

There are many existing machine learning techniques which require costly hardware installations and also cannot give meaningful output values like motor health score and maintenance advice. Thus, there is a need to develop a low-cost multi-sensor artificial intelligence based predictive maintenance system.

Objectives of the Research:

- Create a low-cost industrial motor monitoring system using ESP32.
- Capture multi-sensor data including Current, Vibration, RPM and Gyroscope.
- Create a labelled dataset for healthy and faulty operation modes.
- Train and evaluate a machine learning model for fault detection and classification.
- Provide an estimation of a Motor Health Score (0-100%).
- Estimate future fault probabilities.
- Formulate maintenance suggestions on predicted conditions.
- Showcase the proposed approach using Wokwi simulation tool.

IV. METHODOLOGY

The developed AI-based industrial motor fault diagnosis and preventive maintenance system utilizes multiple sensors for data acquisition, embedded computing, machine learning algorithms, and intelligent decision-making in order to monitor motor condition in real-time. The continuous acquisition of motor operational parameters such as current, vibration, rotational speed (RPM) and gyroscope values is performed by the developed embedded system using ESP32. This data is then used to create a set of features that form the training data for the machine learning algorithm. The algorithm learns from the data and can predict the condition of the motor, assess its health value, detect future faults and suggest preventive maintenance measures.

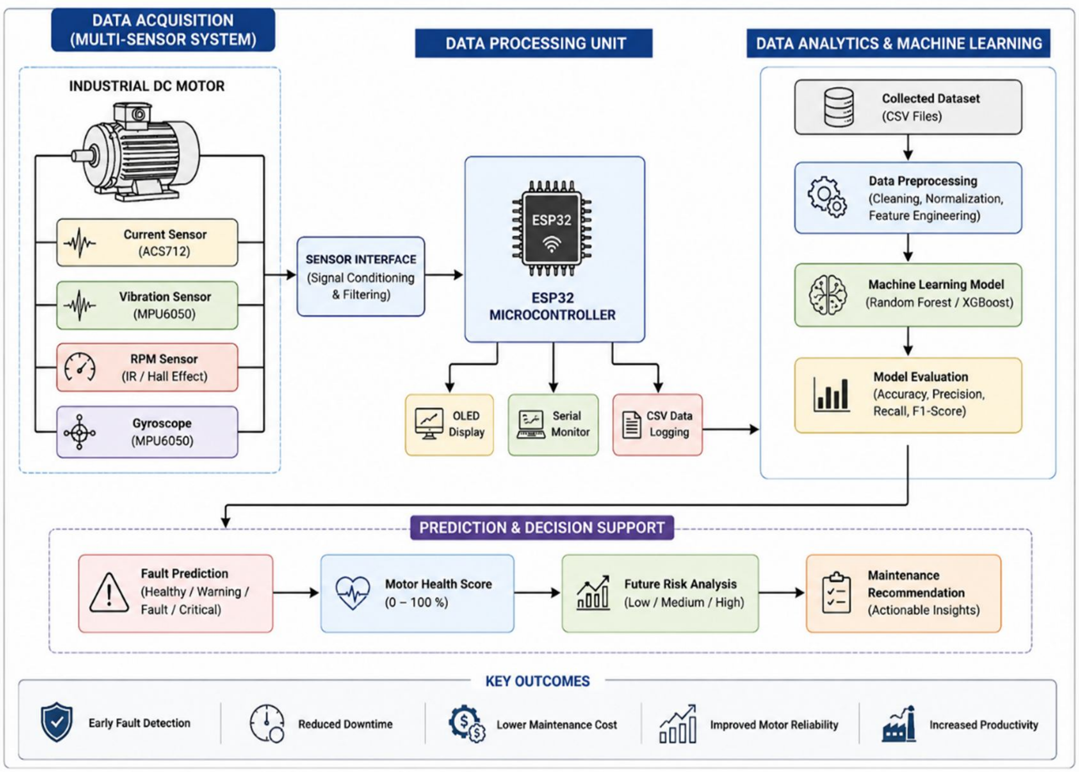

Fig. 4. Overall Architecture of the Proposed AI-Based Industrial Motor Fault Detection and Predictive Maintenance System

A. *Multi-Sensor Data Acquisition*

This system uses several sensors to sense different characteristics of the operation of the industrial motor. Monitoring through the use of several sensors gives a more comprehensive view of the health of the motor than single parameter monitoring techniques. The ESP32 microcontroller continuously captures these readings and converts them to digital form.

Sensor	Parameter Measured	Purpose
ACS712	Current	Detect overload and electrical abnormalities
MPU6050 Accelerometer	Vibration	Detect bearing faults and imbalance
MPU6050 Gyroscope	Angular Motion	Detect abnormal motor movement
IR/Hall Sensor	RPM	Measure rotational speed

- Current Sensor: The ACS712 sensor constantly monitors the motor current. An abrupt rise in the value of the current shows overload conditions, whereas any irregularity in the current shows some electrical problem or mechanical overload.
- Vibration Sensor: Vibration measurements are obtained using the MPU6050 accelerometer. Excessive vibration is a strong indicator of bearing wear, shaft misalignment, rotor imbalance, or mechanical looseness.
- Gyroscope: The gyroscope embedded within the MPU6050 measures angular motion along the X, Y, and Z axes. These measurements assist in identifying abnormal mechanical movements caused by loosened mounting structures or severe imbalance.
- RPM Measurement: Motor speed is measured using an IR/Hall-effect sensor that counts shaft rotations. Significant deviations from the rated rotational speed may indicate overload, slipping, or mechanical faults.

B. Data Acquisition and Embedded Processing

The role of the ESP32 in this project is that of an embedded controller which acquires sensor values, filters noise, calculates RPM, and creates a feature vector. The value from the sensors are updated periodically and sent via the serial port to generate the dataset. The embedded system also operates the OLED screen, LEDs, and the buzzer for instant feedback regarding motor condition.

C. Dataset Generation

Due to the lack of continuous data on industrial motors, the dataset was simulated using the Wokwi online simulation environment. Different types of conditions were artificially created by changing the values of sensors inputs, which included healthy operation, overload condition, vibration failure, and critical failure. The observed values include:

- Current (A)
- Vibration
- RPM
- Gyroscope X, Y, Z
- Health Score
- Prediction Label

The above observations were exported in CSV format.

	A	B	C	D	E	F	G	H	I
1	Current_A	Vibration_	RPM	Gyro_X	Gyro_Y	Gyro_Z	Health_Sc	Condition	
2	0.44	22.98	1802	-10	-8	0	76	Vibration Warning	
3	0.21	5.2	1619	-2	2	3	96	Healthy	
4	0.48	32.88	2506	6	-3	-8	74	Vibration Warning	
5	0.98	42.55	153	21	26	26	9	Critical Fault	
6	0.92	6.9	1147	-7	3	7	66	Overload Warning	
7	0.39	20.01	1917	-7	12	-9	67	Vibration Warning	
8	0.25	3.12	1451	2	-1	2	90	Healthy	
9	1.04	43.88	327	2	-26	29	16	Critical Fault	
10	0.4	30.3	2099	-13	14	-18	73	Vibration Warning	
11	0.37	22.58	3040	15	-2	-10	76	Vibration Warning	
12	1.03	44.54	589	-33	1	25	13	Critical Fault	
13	0.83	5.27	1803	-4	-2	-2	63	Overload Warning	
14	0.98	32.18	408	-30	6	7	21	Critical Fault	

Table 2. Sample Dataset Used for Machine Learning

D. Data Preprocessing

Prior to feeding the data to the machine learning model, the obtained dataset was pre-processed to enhance the quality of the data and improve the performance of the model. Missing values in the dataset were detected and eliminated, if any. Features of the numerical type were normalized. Finally, the dataset was split into the training and testing datasets.

E. Machine Learning Model

In motor fault classification, a supervised machine learning method has been considered. Random Forest classifier was chosen since it is known for having good classification performance, noise immunity, and capability to model nonlinear relationship between sensor variables.

Output:

- Healthy
- Vibration Warning
- Overload Warning
- Critical Fault

1) Model Training

A dataset which included motor current, vibration, RPM, gyroscope values, and motor health score was prepared on the basis of the Wokwi-based simulation environment. The dataset was labeled according to different motor operating conditions such as Healthy, Overload Warning, Vibration Warning, Bearing Fault, and Critical Fault.

After splitting the labelled dataset into input variables and target classes, the Random Forest classifier was chosen because of its capability of handling nonlinear relations, noise resistance, and applicability to multi-parameter fault classification. The training process included feeding the classifier with 80% of the dataset in order to learn the relation between sensor values and motor conditions.

2) Model Testing

In order to test the generalization capability of the trained model, 20% of the dataset was reserved and used for testing. While testing, the model was fed with unseen sensor samples and the predicted motor condition was compared with the real label of this sample.

3) Fault Prediction

Following successful training and validation, the Random Forest algorithm was applied for predicting the actual operating state of the motor from the incoming sensor parameters. For that purpose, the following measured parameters were considered as input features:

- Current
- Vibration
- RPM
- Gyroscope X-axis
- Gyroscope Y-axis
- Gyroscope Z-axis
- Health Score

As a result, the algorithm classified the motor into one of the predefined states including:

- Healthy
- Overload Warning
- Vibration Warning
- Bearing Fault
- Critical Fault

This allows performing an automatic detection of any abnormalities in motor operation without the need for a manual interpretation of the sensor data.

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4) Prevention Maintenance Recommendations Generation:

Depending on the detected fault condition, the system generates maintenance recommendations which can help avoid any unexpected failures of the motor. For example:

- Overload Warning: Lower motor load and check power consumption.
- Vibration Warning: Check bearing, mount bolts and shaft balance.
- Bearing Fault: Conduct bearing inspection and lubrication.
- Critical Fault: Stop the motor and perform maintenance inspection.

F. Decision Support and Predictive Maintenance:

According to the forecasted category of fault, the health state of the motor is then estimated using the range of 0% to 100%. Based on this, the decision engine assesses the probability of future motor failure and provides maintenance advice for avoiding unplanned shutdowns.

G. Overall System Workflow

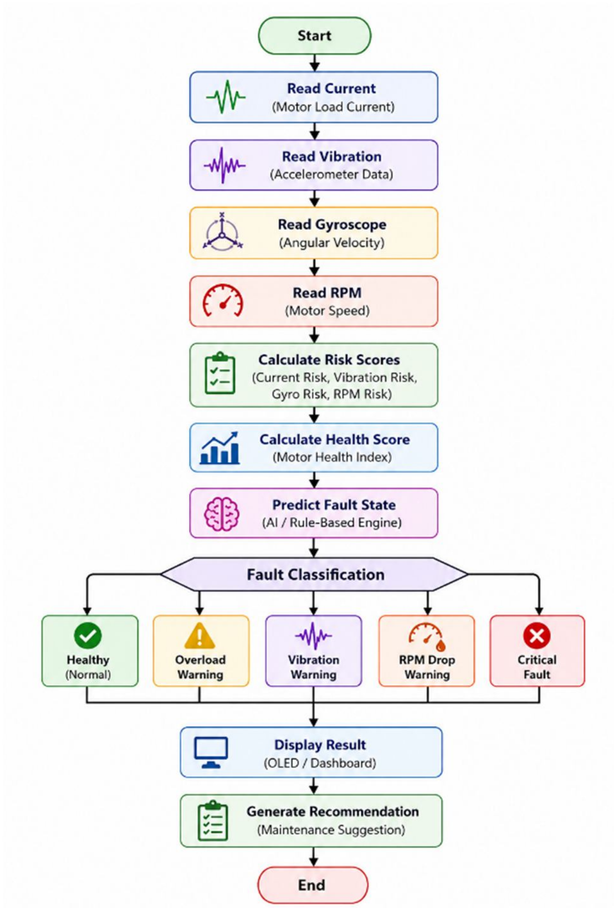

Fig. 9. Complete Workflow of the Proposed Predictive Maintenance System

V. EXPERIMENTAL RESULTS AND ANALYSIS:

The performance of the proposed AI-powered fault detection and predictive maintenance solution for the industrial motor was tested using the Wokwi simulation framework and the machine learning model trained on the generated multi-sensor dataset. Various operating conditions such as healthy, overloaded, vibration warning, and critical failure cases were simulated by varying the parameters of the sensors' inputs. The generated data from sensors was fed to the trained Random Forest classifier to classify the motor's operating condition, assess the motor health score, and provide maintenance suggestions.

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A. Experimental Setup

The design of the system was verified through experimental testing on the Wokwi online simulator. The setup comprises an ESP32 microcontroller connected to ACS712 current sensor, MPU6050 accelerometer and gyroscope, IR sensor for measuring RPM, OLED screen, RGB LEDs, and a buzzer. Various scenarios for faults were simulated by changing values of the sensors to indicate healthy, overload, vibration, and critical operating conditions. The ESP32 would continually collect data from the sensors, display motor condition on the OLED screen, and send data to the serial monitor for dataset creation.

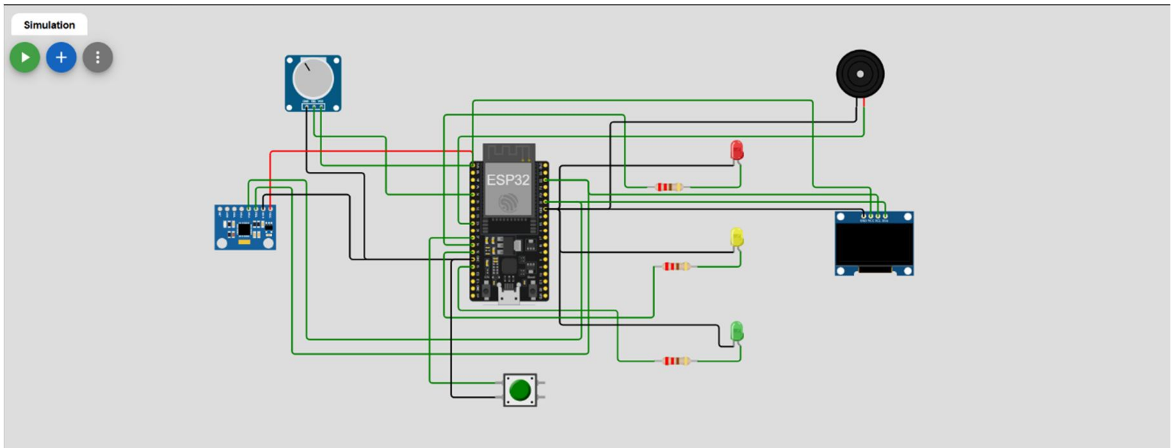

Fig. 9. Complete Wokwi simulation

B. Simulation Results

The effectiveness of the suggested monitoring system was tested by simulating four different types of operation of the motor. All four cases represent real-world situations with varying sensor values. The trained machine learning algorithm accurately classified all four types of operations and recommended the appropriate maintenance.

1) Healthy Motor Condition

During normal operation, the motor is within the allowed current, vibrations, and speed. The motor was classified as Healthy by the proposed system, which gives a motor health rating greater than 95%. The OLED showed that the motor was operating normally, while the green LED stayed active, and there was no need for maintenance.

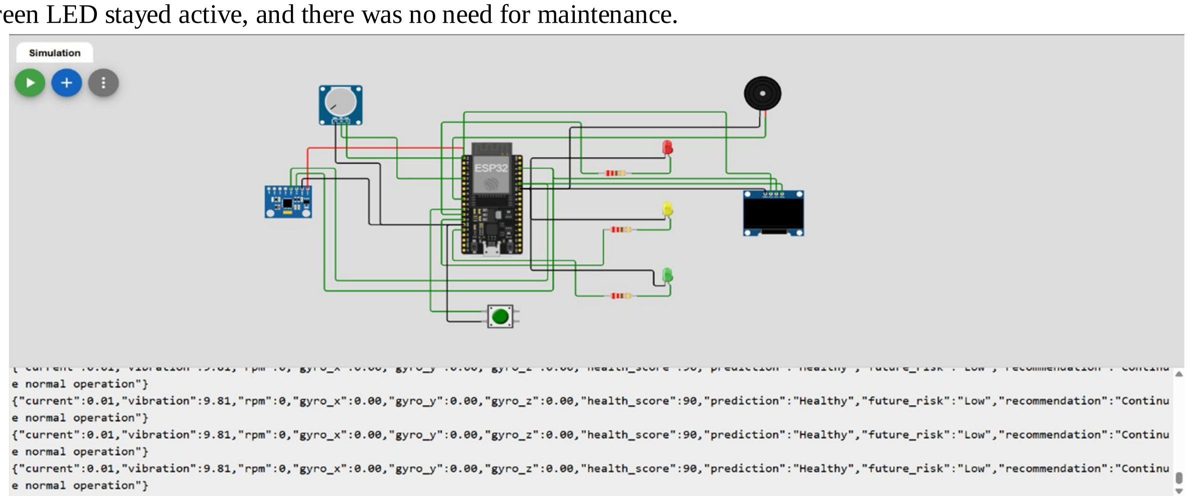

Fig. 10. Detection of healthy motor operating condition.

2) Overload Warning

For the overload test, the motor current was increased gradually with vibrations maintained at medium level. The predicted model was able to detect the abnormality in the current and classify the machine as Overload Warning. The health score was appropriately reduced, and it was advised that the load of the motor be decreased to prevent overheating.

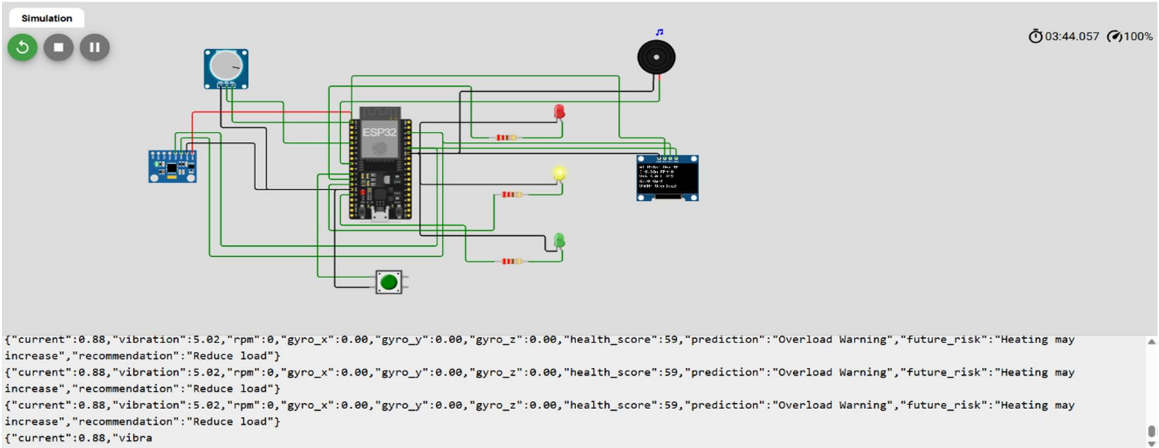

Fig.11 Detection of overload warning condition.

3) *Vibration Warning*

In order to create mechanical problems in simulation, vibration of the motor was increased without changing the current flow in a usual way. It was managed to classify this situation using the learned Random Forest as vibration warning problem. It was advised to check the state of bearings, shafts, and mounting.

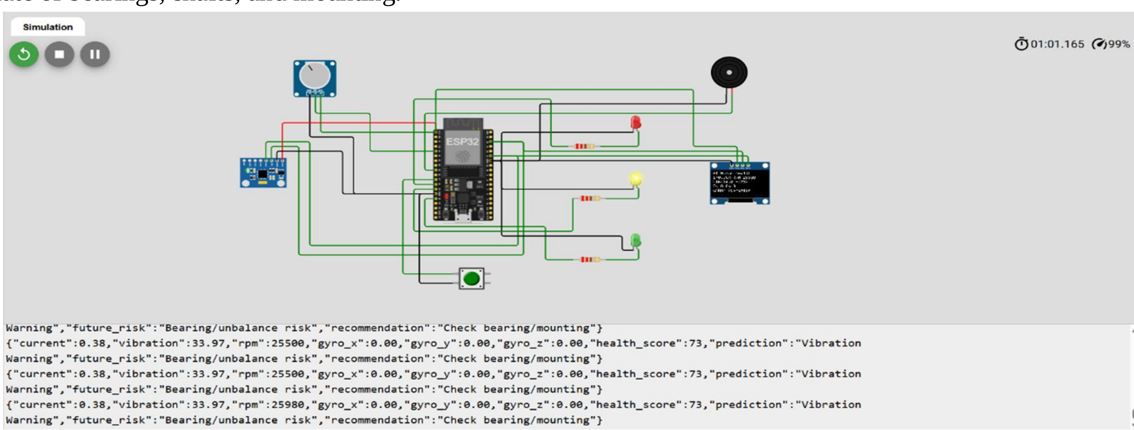

Fig.12 Detection of abnormal vibration condition.

4) *Critical Fault*

The Critical Fault state was simulated using simultaneous increases in motor current and vibration, while motor speed was decreased. The proposed method detected the state as Critical Fault by classifying the health index below 20%, with an emergency alarm from the OLED display, activation of the red LED and buzzer, and motor shutdown recommendation.

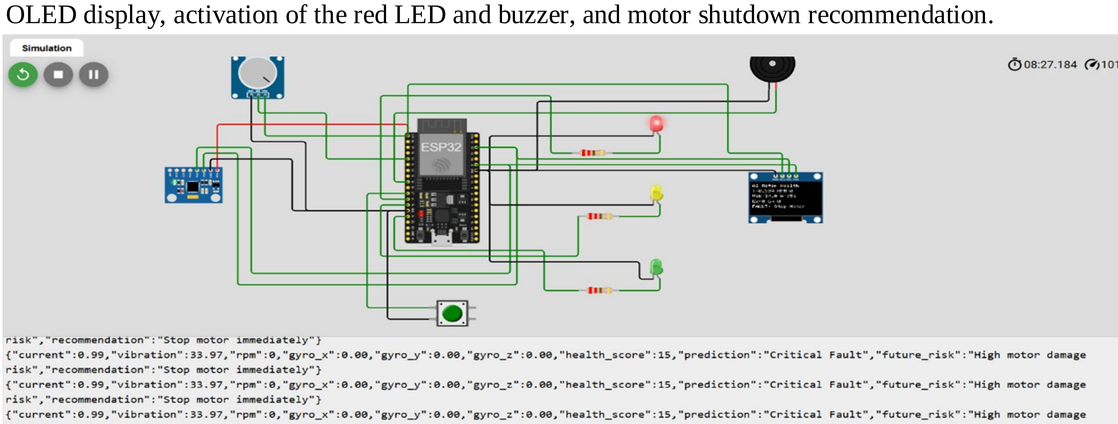

Fig.13 Detection of critical motor fault.

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C. OLED Display Output

The OLED screen shows in real time all operating parameters of the motors, such as current, RPM, vibration, health value, and operating state. This allows the operator to view the health condition of motors without a need for an additional computer screen.

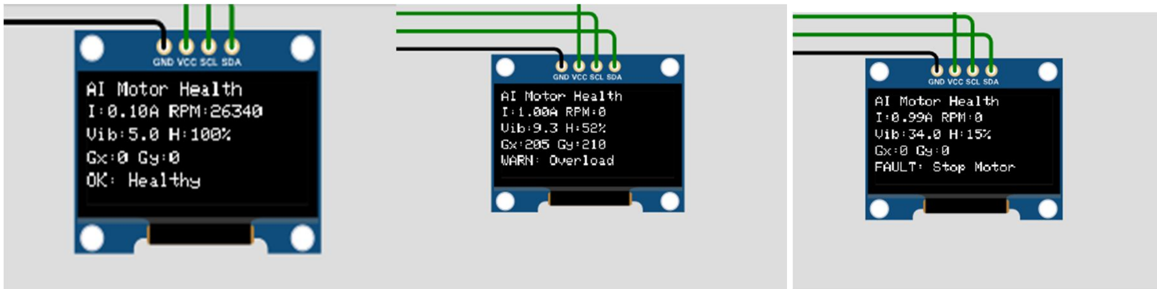

Fig.14 OLED display showing real-time motor health information.

D. Machine Learning Performance

The created data set was then trained using the Random Forest model for fault classification purposes. An 80:20 split was made on the created data sets as part of training and testing subsets. Performance of the model was analyzed using accuracy, precision, recall, F1 score, and confusion matrix analysis.

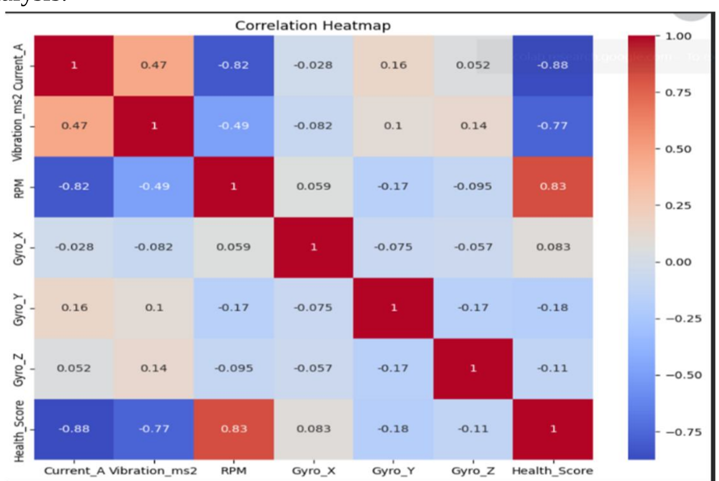

Fig.16 Confusion matrix of the trained Random Forest classifier.

The confusion matrix demonstrates that the proposed model correctly classified most operating conditions with minimal misclassification between warning and critical fault states.

Fig.17 Relative importance of sensor parameters in motor fault prediction.

Feature importance analysis indicates that vibration and motor current contribute significantly to fault prediction, while RPM and gyroscope measurements improve classification accuracy during abnormal operating conditions.

E. Performance Comparison

Current (A)	Vibration	RPM	Health Score	Prediction	Future Risk	Recommendation
0.1	5.02	13080	100%	Healthy	Low	Continue normal operation
0.38	33.97	25980	73%	Vibration Warning	Bearing/Unbalance Risk	Cheak Bearing/Mounting
0.88	5.02	0	59%	Overload Warning	Heating may Increases	Reduce Load
0.99	33.97	0	15%	Critical Fault	High Motor Damage Risk	Stop Motor Immediately

Table.2. Performance of the Proposed Motor Monitoring System

VI. CONCLUSION

The paper has introduced an industrial motor fault detection and predictive maintenance system based on Artificial Intelligence with multi-sensors data acquisition and machine learning techniques. In the proposed system, sensors like current, vibration, RPM, and gyroscope data are collected via an embedded device consisting of an ESP32 module. With the help of the collected data, a machine learning model was created that is used to detect various motor operational states, such as healthy, overloaded, vibration warning, and critical state. With the help of the predicted state, the proposed model detects the motor health score and gives intelligent recommendations for preventing any possible malfunctioning. From the results of the simulation, it is clear that the proposed method is cost-effective and efficient. Further, the future work will focus on implementing the system in actual industry and collection of real-time datasets for cloud-based monitoring.

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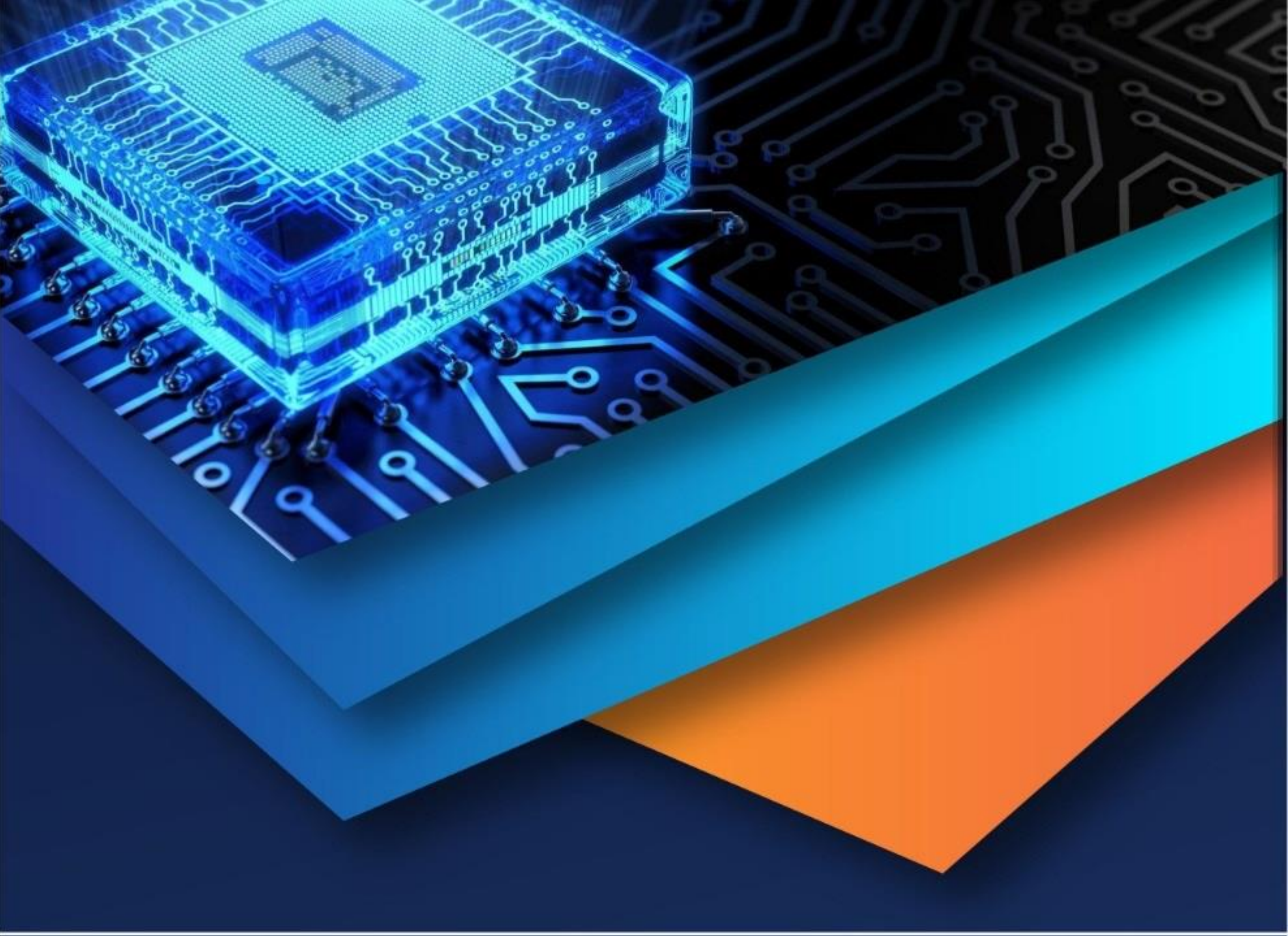

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