iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: IV Month of publication: April 2026

DOI: https://doi.org/10.22214/ijraset.2026.79405

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

Machine Learning for Predictive Maintenance in Industries

Dr.D.A.Shahakar[1], Aniket Khadse[2], Anjali Paikrao[3], Payal Mahure[4], Vaibhavi Kadam[5], Shrushti Khawale[6], Dimpal Panekar[7], Deep Bhuyar[8]

Abstract: In industrial environments, unexpected machine failures can lead to increased downtime, high maintenance costs, and reduced productivity. Traditional maintenance strategies such as reactive and preventive maintenance are often inefficient as they either respond after failure or rely on fixed schedules without considering the actual condition of equipment.Toovercome these limitations, predictivemaintenancehasemergedas aneffectiveapproachthatenables early fault detection based on real-time data analysis.

This paper presents a machine learning-based predictive maintenance system designed for industrial applications. The proposed system utilizes sensors to continuously monitor key parameters such as temperature, vibration, and current. The collected data is processed and analyzed using machine learning algorithms to identify patterns and detect anomalies that indicate potential equipment failures. The model is trained using historical data to improve prediction accuracy and reliability.

Theresultsdemonstratethattheproposedsystemcaneffectively predictfaultsin advance,thereby reducingunplanned downtime and optimizing maintenance schedules. Additionally, the system enhances operational efficiency and extends the lifespanof industrial machinery.Thisstudy highlightsthe potential of machinelearningtechniquesintransforming traditional maintenance practices into intelligent and data-driven solutions.

Keywords: Predictive Maintenance, Machine Learning, Industrial Automation, Fault Detection, Real-Time Monitoring, Sensor Data Analysis, Condition Monitoring, Anomaly Detection, Industrial IoT (IoT), Equipment Failure Prediction.

I. INTRODUCTION

In modern industrial environments, the reliability and continuous operation of machinery are critical for maintaining productivity and reducing operational costs. Unexpected equipment failures can lead to significant downtime, financial losses, and safetyrisks. Traditionally, industries have relied on reactive maintenance (repair after failure) and preventive maintenance (scheduled servicing). However, these approaches often result in either unnecessary maintenance or delayed fault detection.Withtheadvancementofdigitaltechnologiesanddata-drivensystems,predictivemaintenancehasemergedasamore efficient and intelligent solution. Predictive maintenance utilizes real-time monitoring and historical data to predict potential failures before theyoccur. This approach not onlyminimizes downtime but also optimizes maintenance schedules and extends equipment lifespan.

Machine Learning (ML), a subset of artificial intelligence, plays a vital role in enhancing predictive maintenance systems. ML algorithms can analyze large volumes of sensor data such as temperature, vibration, pressure, and current to identify patterns and anomalies associated with machine faults. Unlike traditional rule-based systems, ML models can learn fromdataand improvetheirpredictionaccuracyovertime. Despite significantprogress,manyexistingsystemsfacechallenges such as limited accuracy, lack of real-time implementation, and inability to handle multi-parameter data effectively. These limitations highlight the need for a more robust and scalable predictive maintenance framework.

Thisresearchaimstodevelopamachinelearning-basedpredictive maintenancesystemforindustrialapplications.The proposed system focuses on real-time data acquisition using sensors and applies ML algorithms to predict potential machine failures. The objective is to improve fault detection accuracy, reduce unexpected downtime, and enhance overall system efficiency.

II. WORKING PRINCIPLE

A. System Overview

The proposed system is designed to implement a real-time predictive maintenance framework for an induction motor by integratingsensing,processing,communication,andprotectionmechanisms.

Thesystemcontinuouslymonitorskeyoperational parameters such as temperature, vibration, and current, which are critical indicators of motor health.The overall operation is based on a data-driven monitoring approach, where sensor data is acquired, processed, analyzed, and used to detect abnormal conditions. Upon detection of faults, appropriate control actions such as alert generation and system shutdown are executed to ensure safety and reliability.

B. PowerSupplyandProtectionMechanism

The system is powered through an AC mains supply, which is first passed through an energy meter to monitor overall power consumption. A Miniature Circuit Breaker (MCB) is installed to provide protection against over current and short-circuit conditions. The AC supply is converted into regulated DC using a Switched Mode Power Supply (SMPS). Further voltage regulation is achieved using DC-DC buck converters to provide stable voltage levels required by the microcontroller, sensors, andcommunication modules. Incase of excessive currentflow,the MCBautomaticallytrips,therebydisconnectingthe system and preventing equipment damage.

C. DataAcquisitionLayer

Thedataacquisitionlayerconsistsofmultiplesensorsthatcontinuouslymonitortheoperatingconditionoftheinductionmotor:
Temperature Sensor: Measures the thermal condition of the motor and helps in identifying overheating issues.
VibrationSensor:Detectsmechanicalirregularitiessuchasmisalignment,imbalance,orbearingfaults.
CurrentSensor:Measurestheelectricalcurrentdrawnbythemotorandisusedtodetectoverloadandshort-circuitconditions.
Thesesensorsgeneratereal-timesignalscorrespondingtothephysicalparameters,whicharethenfedintotheprocessingunit.

D. Data Processing Unit

The Arduino UNO microcontroller serves as the central processing unit of the system. It performs the following functions: Acquisitionofsensordata,Conversionofanalogsignalsintodigitalform,Filteringandconditioningofsensorinputs ,Comparison of real-time values with predefined threshold limits. Based on this analysis, the system classifies the operating condition into different states such as normal, warning, critical, and fault.

E. CommunicationModule

The ESP32 module is used for wireless communication and IoT integration. It transmits the processed data to external platforms such as cloud servers or monitoring dashboards.
Thisenables: Remote monitoring of system parameters.Data storage forhistorical analysis.Integration with Machine Learning models for predictive analysis

F. FaultDetectionandDecisionLogic

The fault detection mechanism is based on threshold-based and pattern-based analysis of sensor data.A gradual increase in temperatureandvibrationindicatesnormaloperationalvariation.Asuddenriseincurrentindicateselectricalabnormalitiessuch as overload or short circuit. Simultaneous abnormal variations in multiple parameters indicate severe fault conditions.The system continuously evaluates these parameters and determines the operational state of the motor.

G. ControlandProtectionSystem

Arelaymoduleisincorporatedtocontrolthepowersupplytothe motor.Undernormalconditions, therelayremainsenergized, allowingthemotortooperate.Whenabnormalconditionsaredetected:Thesystemgeneratesanalertusingabuzzer,Therelayis deactivated to disconnect the motor. In severe fault conditions, the MCB trips automatically, ensuring complete system shutdown and protection.

H. DisplayandAlertMechanism

An LCD display is used to provide real-time visualization of system parameters such as temperature, vibration, current, and system status. Additionally, a buzzer is activated during abnormal conditions to provide immediate auditory alerts to the operator.

I. MachineLearningIntegration

The systemsupports Machine Learning-basedpredictivemaintenance byutilizingthecollectedsensor data.The datais usedto trainmodelsthatcanidentifypatternsassociatedwithnormalandfaultyconditions.Thisenables:Earlyfaultprediction,Improveddecision-makingaccuracy,Reductioninunexpectedfailures.

J. SystemOperationWorkflow

Theoveralloperationofthesystemcanbesummarizedasfollows:

The system is powered ON through the AC supply. Sensors continuously collect real-time data from the motor. Arduino processes and analyzes the sensor data. ESP32 transmits the data for remote monitoring and analysis.The system evaluates the conditionofthemotor.Ifabnormalconditionsaredetected:Alertsaregenerated,Relaydisconnectsthemotor.Incaseofsevere fault: MCB trips, System shuts down completely

III. RESULT

The developed predictive maintenance system was tested under both normal and fault conditions of the induction motor. Real- time data of temperature, vibration, and current were continuously monitored and recorded.The system successfully captured the variation in parameters over time and identified the transition from normal operation to fault conditions.

AnalysisofTemperatureandVibration:

Sr.no	Time	Temperature(C)	Vibration(mm\s)	Systemstatus
1	50	42	2.0	Warning
2	60	48	2.5	Warning
3	70	55	3.2	Critical
4	80	62	4.2	FaultDetected
5	90	70	5.5	Shutdown

Table1:TemperatureandVibrationAnalysis

From the above data, it is observed that both temperature and vibration increase gradually with time. Initially, the system operates within a warning range, indicating minor deviations from normal conditions.

At around 70 seconds, the system enters a critical state where temperature and vibration exceed safe thresholds. Further increase leads to fault detectionat 80 seconds, and eventually, at 90 seconds, the system reaches a shutdown condition .This behavior indicates that increasing vibration and temperature are strong indicators of mechanical degradation and impending failure.

AnalysisofCurrentVariation:

Sr.No	Time(ms)	Normalcurrent(A)	FaultCurrent(A)	SystemCondition
1	0	5	5	Normal
2	10	5.2	5.3	Normal
3	20	5.1	5.5	Normal
4	30	5.3	20	FaultStarts
5	40	5.2	50	SevereFault
6	50	5.4	100	ShortCircuit
7	60	5.3	0	MCBTrips

Table2:Real-TimeCurrentAnalysis

Thecurrentremainsnearlyconstant(~5A) duringnormaloperation,indicatingstable motor performance.However,at 30ms,a sudden increase in fault current is observed, marking the initiation of a fault condition .The current rapidly rises to 50A and then to 100A, representing severe fault conditions such as overcurrent or short circuit. At 60 ms, the current drops to zero, indicating the successful tripping of the MCB and shutdown of the system .This demonstrates the system’s ability to detect electrical faults and activate protection mechanisms in real time.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

Thisanalysisclearlyshowstherelationshipbetweenelectricalandmechanicalparametersduringfaultprogression.

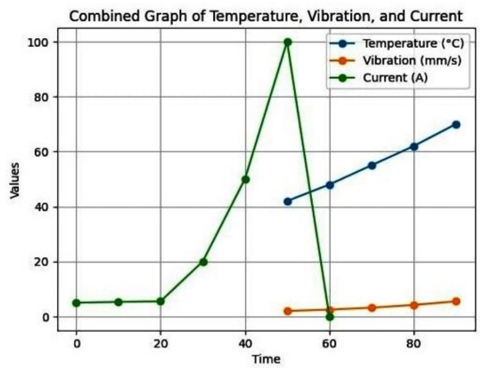


Fig.Thegraphshowsreal–timeTemperature,Vibrationandcurrentthenasuddenincreaseindicatesa faultcondition

IV. CHALLENGES AND FUTURE SCOPE

A. Challenges:

Despite the advantages of machine learning-based predictive maintenance, several challenges remain in its practical implementation:

1) DataQualityandAvailability

Accurate predictions require large volumes of high-quality data. However, in industrial environments, data is often noisy, incomplete, or inconsistent.

2) Real-TimeDataProcessing

Processing continuous streams of sensor data in real time is computationally intensive and can lead to delays in decision-making.

3) ModelAccuracyandReliability

Machine learning models may sometimes produce incorrect predictions, such as false positives or false negatives, which can affect maintenance decisions.

4) IntegrationwithExistingSystems

IntegratingmodernML-basedsolutionswithlegacyindustrialsystemsiscomplexandmayrequiresignificantmodifications.

5) HighImplementationCost

Theinitialcostofdeployingsensors,dataacquisitionsystems,andmachinelearninginfrastructurecanbehigh.

B. FutureScope:

1) AdoptionofDeepLearningTechniques

Advancedtechniquessuchasneuralnetworksanddeeplearningcanfurtherimprovepredictionaccuracyandperformance.

2) Integration with IoT and Cloud Computing

Combining predictive maintenance withIoT andcloud platforms willenablereal-time monitoring, remote access,andscalable solutions.

3) ImplementationofEdgeComputing

Processingdataattheedge(nearthesource)willreducelatencyandimproveresponsetimeforcriticalapplications.

4) DigitalTwinTechnology

Creatingadigitalreplicaofmachinescanenablereal-timesimulationandmoreaccuratefaultprediction.

5) Automated Maintenance Systems

Futuresystemsmaybecomefullyautomated,capableofschedulingandperformingmaintenancewithminimalhuman intervention.

V. APPLICATION

1) ManufacturingIndustry

Predictive maintenance is used to monitor the health of machines such as CNC machines, motors, and conveyors. It helps indetecting potential failures in advance, thereby preventing production interruptions.

2) PowerGenerationSystems

Inthermalandhydroelectricpowerplants,predictivemaintenanceisappliedtoturbines,generators,andtransformers.It ensures continuous power generation by identifying faults such as overheating and excessive vibration.

3) OilandGasIndustry

Machine learning models are used to monitor pipelines, compressors, and drilling equipment. These systems help in detecting leakages, pressure variations, and equipment faults, reducing the risk of accidents.

4) AutomotiveIndustry

Predictive maintenance is applied in assemblylines and robotic systems to ensure smooth operation. It also helps in predicting failures in vehicle components during testing and production.

5) SmartFactories(Industry4.0)

Insmartmanufacturingenvironments,predictivemaintenanceisintegratedwithIoTsystemstoenablereal-timemonitoringand automated decision-making for maintenance scheduling.

VI. CONCLUSION

The proposed system successfully demonstrates a cost-effective and efficient approach for predictive maintenance of an induction motor using real-time monitoring and Machine Learning concepts. The experimental setup, as illustrated in the implemented hardware model, integrates Arduino UNO, ESP32, and multiple sensors including temperature, vibration, and current sensors to continuously analyze motor health conditions.

From the observed results, it is evident that the system is capable of identifying gradual as well as sudden variations in key parameters. Under normal operating conditions, temperature and vibration show a steady increase within permissible limits, while current remains stable. However, during fault conditions, a significant rise in current is observed, accompanied by increased vibration and temperature, indicating the onset of electrical and mechanical faults.

The system effectively classifies operational states into different stages such as warning, critical, and fault conditions. At the critical stage, early warning signals are generated, allowing preventive action before complete system failure. In severe fault conditions, suchasshortcircuits, thesystemactivates protective mechanismsincludingrelaydisconnectionand MCBtripping, ensuring complete shutdown and preventing equipment damage.

The graphicalanalysisand tabulated datafurther validate therelationshipbetweenelectricaland mechanical parametersduring fault progression. The sudden spike in current followed by a drop to zero confirms the successful operation of the protection system.

Additionally, the integrationof ESP32enablesreal-time datatransmission, making the system suitable for IoT-basedindustrial applications. The collected data can be further utilized for training Machine Learning models to enhance predictive accuracy and enable intelligent decision-making.

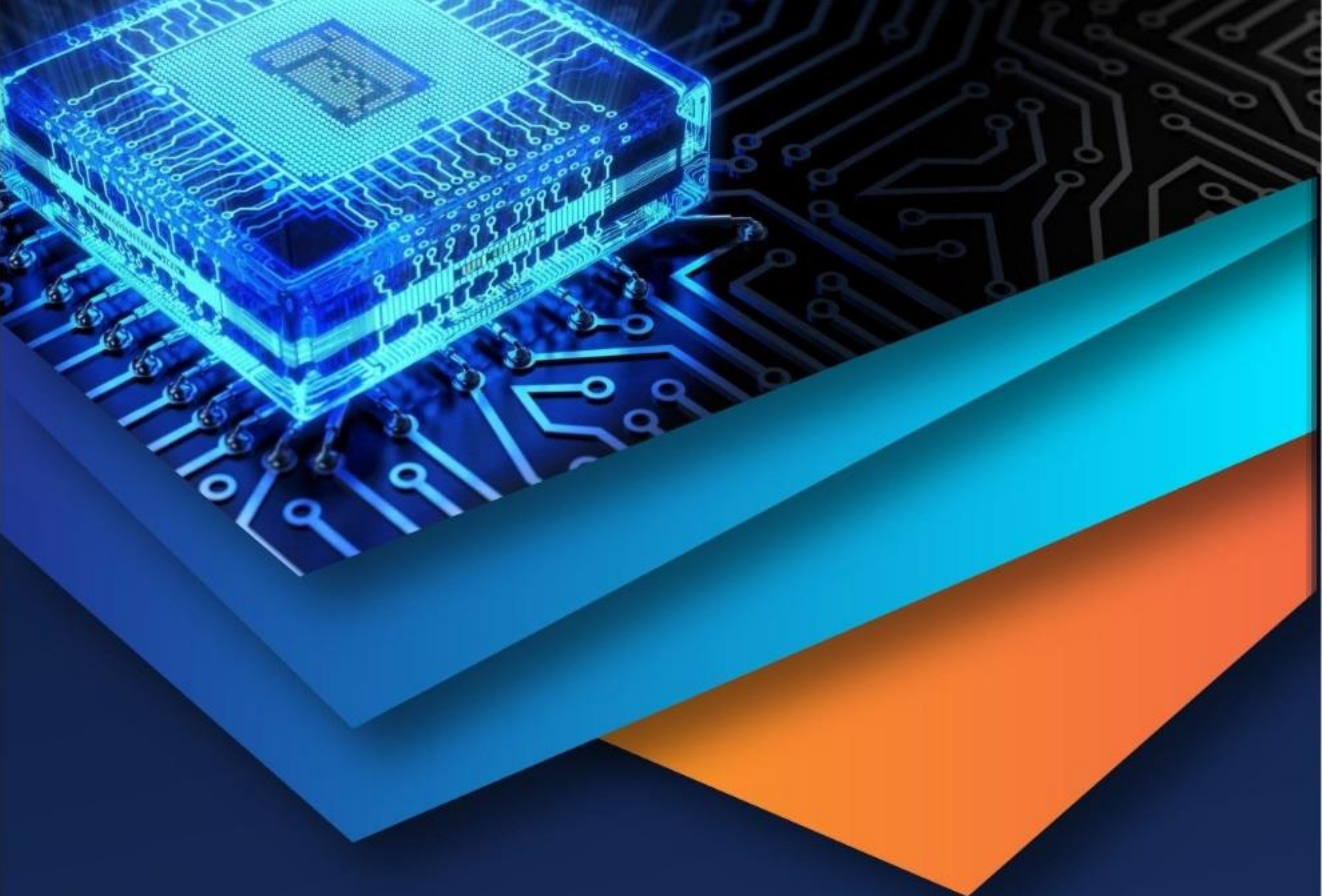
Overall, the developed system provides a reliable and scalable solution for industrial condition monitoring. It significantly reducesunexpecteddowntime,improvesoperationalsafety, andminimizesmaintenancecosts.The practicalimplementationof thissystemdemonstratesitspotentialfor real-worldindustrialapplicationsandsupportstheadvancementofsmartmaintenance systems in the context of Industry 4.0.

REFERENCES

[1] Masani, K. I., Oza, P., &Agrawal, S.(2019). PredictiveMaintenance and MonitoringofIndustrialMachine usingMachine Learning. ScalableComputing: Practice and Experience.

[2] Dwivedi,P.,Khan,Z.,Ansari,H.,Chand,J.,Singh,M.K.,Sagheer,T.,&Pandey,D.(2022).PredictiveMaintenanceandMonitoringofIndustrial Compressors Using Machine Learning: A Proactive Approach. Metallurgical and Materials Engineering

[3] Sisode,M.,&Devare,M.(2023).AReviewonMachineLearningTechniquesforPredictiveMaintenanceinIndustry4.0.AtlantisPress
[4] Tyagi,R.(2024).DeepLearningforPredictiveMaintenanceinSmartManufacturing—AReview.JournalofArtificialIntelligenceandComputing.
[5] Singh,R.K.,Sharma,P.,&Verma,A.(2025).MachineLearningApproachesforPredictiveMaintenanceinIndustrialIoTSystems.IJARERS.
[6] :Kane,A.P.,Kore,A.S.,Khandale,A.N.,Nigade,S.S.,&Joshi,P.P.(2022).PredictiveMaintenanceusingMachineLearning.arXivResearchPaper.
[7] Maheshwari, S., Tiwari, S., Rai, S., & Singh, S. (2024). Comprehensive Study of Predictive Maintenance in Industries Using ClassificationModels and LSTM Model
[8] Saxena,M.(2025).UtilizingMachineLearningforPredictiveMaintenanceintheIndianManufacturingSector.AIROJournal.



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY