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Research Article

Predictive Maintenance of Industrial Appliances Integrated with Machine Learning

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ABSTRACT

This paper presents a novel approach to enhance the maintenance paradigm of electric fans through the integration of machine learning and Internet of Things (IoT) technologies. The system employs an Arduino Uno R3 microcontroller to collect real-time data from vibration, temperature, and humidity sensors strategically placed on the fan. Leveraging this data, a machine learning model is developed to predict potential faults or anomalies, enabling proactive maintenance actions. The methodology involves the creation of a comprehensive dataset through continuous monitoring of the fan's operating conditions. The paper details the integration of sensors, the architecture of the system, and the implementation of machine learning algorithms for predictive analysis. The chosen model demonstrates its efficacy in forecasting maintenance requirements, showcasing 90% accuracy in the experiment.

Keywords: predictive maintenance, machine learning, Arduino Uno R3, fan, IoT, sensor integration.

I. INTRODUCTION

Electric fans are prevalent in our everyday existence, offering both comfort and ventilation in a variety of settings. But maintaining these devices' smooth functioning is not without its difficulties, as deterioration over time might result in unplanned malfunctions and higher maintenance expenses. This research addresses this problem by presenting a novel method of fan maintenance that combines Internet of Things (IoT) and machine learning technology.

1.1 Background: Reactive tactics are frequently used in traditional maintenance procedures, which can cause downtime and even service interruptions. Predictive maintenance procedures, which identify possible defects before they worsen, have made it possible to move from reactive to proactive methods. In this regard, our work focuses on utilising the adaptability of Arduino Uno R3 microcontrollers and the power of machine learning algorithms to improve the electric fan maintenance paradigm.

II. OBJECTIVES:

This research's main goal is to create and put into place a predictive maintenance system that keeps an eye on important electric fan operating parameters. The fan has temperature, humidity, and vibration sensors placed in strategic locations to gather data in real time and build a large dataset. An Arduino Uno R3 microcontroller is used to process data and make decisions, which results in a machine learning model that can predict maintenance needs.

III. SIGNIFICANCE OF THE RESEARCH:

This research is important because it has the potential to completely change the way fans are maintained. The proposed system aims to minimise maintenance costs, optimise the overall reliability of electric fan systems, and reduce unplanned downtime by proactively identifying issues through predictive analysis. By demonstrating the

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useful integration of machine learning and IoT in a practical application, this work advances the field of smart maintenance solutions.

IV. LITERATURE REVIEW

Author	Dataset Name	Tools	Based On	Description	Warning System	Accuracy
Mounia Achouch,Mariya Dimitrova,Rizck Dhouib,Hussein Ibrahim,Mehdi Adda,Sasan Sattarpanah Karganroudi, KhaledZiane and Ahmad Ami nzadeh	**Compressor Failure Prediction Dataset that contains attributes like voltage, pressure etc**	**LSTM, Keras, TensorFlow Scikit-learn, Matplotlib**	**Predictive Maintenance to estimate remaining useful life in a multistage centrifugal compressor.**	**The main goal is to forecast failures and the remaining useful life (RUL) of a TA-48 multistage centrifugal compressor by using the machine learning algorithm, LSTM neural networks. By adopting Industry 4.0 approaches, the goal is to reduce downtime and improve operational efficiency.**	**Remaining Useful Life (RUL) analysis, State degradation analysis**	**90-100%**
XinjieDUAN,Adarsh VASUDEVAN,Ebru TURANOGLU BEKAR, KanikaGANDHI, and Anders SKO OGH	**Bearing dataset provided by the Case School of Engineering Bearing Data Center. This dataset includes sensor data, log files, maintenance**	**Python, Power BI, scikit-learn**	**CRISP-DM methodology to implement predictive maintenance in the manufacturing industry.**	**Predictive maintenance in the manufacturing industry using CRISP-DM methodology for**	**Random Forest Classifier Local Outlier Factor (LOF)**	**100%**

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	records, and operational data.			**anomaly detection and failure prediction.**		
ZhengLiua,Erik Blaschb,MinLiao c, ChunshengYangc , KazuhikoTsukad ad, and Norbert Meyend orf	**Temperature,vib ration and pressure sensors**	**MongoD B, Amazon S3, Tensorfl ow, pyTorch**	**Digital Twins, to improve predictive maintenan ce by providing real-time data on machine health and potential failures.**	**This project conducts a systematic literature review on predictive maintenan ce using Digital Twins, analyzing 42 primary studies.**	**Threshol d based alarms, Real-time Monitori ng Dashboa rds**	**100%**
AysegulUcar , Mehmet Karakose and Necim Kırım ça	**Milling Dataset, Bearing Dataset**	**Numpy, Pandas, Keras,S VM**	**AI-based predictive maintenan ce for critical machine tool componen ts**	**AI-based predictive maintenan ce algorithms to monitor critical machine tool componen ts, such as cutting tools and spindle motors**	**Prognost ic Health Manage ment (PHM) Threshol d-based Alerts**	**75-90%**
Hui Yang , Soundar Kumara , Satish T.S. Bukkapatnam , and Fugee Tsun g.	**Air Quality sensors, Ultrasound sensors Current sensors**	**Python, Scikit-learn, Jupyter noteboo k IoT Platfor m**	**Implement ing smart manufactu ring techniques using IIoT sensors**	**IIoT-based predictive maintenan ce architectu re to anticipate sudden breakdow ns in industrial machines**	**Real-time dashboar ds, triggerin g alarms via emails & sms**	**85-95%**

With the goal of predicting equipment problems before they happen and optimizing maintenance techniques, predictive maintenance has become a key paradigm in the field of maintenance engineering. The literature that has already been written about predictive maintenance, machine learning applications in maintenance, and studies integrating IoT devices—particularly Arduino-based solutions—is reviewed in this section.

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Predictive Maintenance: Traditional maintenance techniques, such as corrective and preventive maintenance, have limitations in terms of cost-effectiveness and operational efficiency. The advancement of sensor technologies and data analytics makes predictive maintenance more proactive. Li et al. (2018) found that predictive maintenance can reduce downtime and increase equipment longevity.

Machine Learning in Maintenance: Machine learning approaches have gained popularity in predictive maintenance due to their ability to scan vast datasets and identify patterns that indicate upcoming breakdowns. A noteworthy study by Smith and Johnson (2019) demonstrated the high degree of accuracy with which a predictive maintenance model incorporating support vector machines could forecast failures in industrial machinery.

IoT and Arduino in Maintenance: The incorporation of IoT devices, like sensors and microcontrollers, has become a focal point in predictive maintenance systems. The Arduino Uno R3, well-known for its versatility and ease of use, has found employment in a wide range of applications. Garcia, et al. (2020) used an Arduino-based system for real-time monitoring and predictive maintenance in manufacturing environments to show the practical applicability of such platforms.

Gap in the Literature: Researchers have given predictive maintenance a lot of attention, but there isn't much material in the literature on its application to electric fan systems. Specifically, there's still a lot to learn about integrating an Arduino Uno R3 with vibration, humidity, and temperature sensors for predictive maintenance.

Summary: The literature review emphasizes the progression of maintenance approaches, the role of machine learning in predictive maintenance, and the growing practical uses of IoT devices such as Arduino. The current study intends to add to this corpus of knowledge by putting forth a predictive maintenance strategy designed specifically for electric fan systems and by providing an analysis of the opportunities and problems unique to this field.

Ref No.	Dataset Name	Tools	Based On	Description	Warning System	Accuracy
1.	Hydraulic Pump(cooler, valve, pump and accumulator), Vibration Values, Vibration sensor, DC Booster	Arduino 1.8.10 desktop IDE, Jupyter notebook	Modern manufacturing processes face huge downtime caused due to mechanical failures in Industrial Machines.	Predictive maintenance was condition-based and dependent on a number of hydraulic system parameters, including power consumption, vibrations, temperature, and volume flow.	Vibration Analysis, Hydraulic Analysis	90-100 %
2.	Temperature sensors, Vibration sensors, and Current sensors, Motor Performance Data, and Error logs	TensorFlow, PyTorch, and scikitlearn IBM Watson IoT, SAP Predictive Maintenance and Service	Industrial Robot Predictive Maintenance in Manufacturing Assembly Lines	The architecture's potential to identify robot joint failures in practical situations by implementing it in an actual automotive manufacturing assembly line was demonstrated.	Vibration Analysis, Temperature Monitoring, Error Code Analysis	100 %

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				Therefore, industrial practitioners and maintenance personnel will find the architecture particularly interesting.		
3.	Vibration sensors, Temperature sensors, Humidity sensors, Pressure sensors, and Cameras	AWS IoT, Apache Kafka, Power BI	Predictive Maintenance system for coal equipment using IOT	Due to the site conditions, coal equipment cannot avoid a number of issues and must operate continuously for an extended period of time. It is challenging to identify the failure precisely and on time when using traditional maintenance mode. By implementing an Internet of things-based predictive maintenance and state monitoring system for mine equipment, it is possible to precisely predict potential threats and identify equipment faults.	Real-time Data Streams	100 %
4.	Turbofan Engine Degradation Simulation Data, Aircraft Engine Data on Kaggle, Prognostics Center of Excellence (PCoE) Dataset	Power BI IBM Watson Studio	Determining the Method of Predictive Maintenance for Aircraft Engine Using Machine Learning	To enhance the system's accuracy and effectiveness, feature engineering, data normalization, and model optimization techniques are applied, ensuring that the algorithms can	Oil Analysis, Pressure Monitoring	75-90%

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				adapt to various aircraft engine types and usage scenarios.		
5.	Building management data, Environmental data, and Energy consumption data	Building Management Systems, IoT Sensors, Fault Detection and Diagnostics	Predictive Maintenance Planning for Hospital Buildings	The paper represents a transformative shift in the healthcare industry. By proactively addressing maintenance needs, enhancing patient care continuity, and optimizing energy efficiency, this system offers a holistic solution to ensure the dependable operation of healthcare facilities.	Fire and Smoke Detection Systems, Power Quality Monitoring	85-95%
6.	Temperature sensors, vibration sensors, and current sensors, motor performance data, and error logs	TensorFlow, PyTorch, and scikitlearn IBM Watson IoT, SAP Predictive Maintenance and Service	industrial robot predictive maintenance in manufacturing assembly lines	We implement the architecture in a real automotive manufacturing assembly line and show the potential of the solution to detect robot joint failures in real world scenarios. The architecture is therefore specially interesting for industrial practitioners and maintenance personne	Vibration Analysis, Temperature Monitoring, Error Code Analysis	98%
7.	vibration sensors, temperature	AWS IoT, Apache	Predictive Maintenance system for	The coal equipment cannot avoid a	Real-time Data Streams	75-95%

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	sensors, humidity sensors, pressure sensors, and cameras	**Kafka, Power BI**	**coal equipment using IOT**	**series of problems due to the site conditions and run continuously for a long time. Traditional maintenance mode is difficult to find the failure accurately and timely. To establish a set of mine equipment state monitoring and predictive maintenance system based on Internet of things technology can identify the fault and forecast the potential threat accurately, and it is of great significance for the safe and efficient operation of the coal equipment.**		
8.	**Turbofan Engine Degradation Simulation Data, Aircraft Engine Data on Kaggle, Prognostics Center of Excellence (PCoE) Datase**	**Power BI IBM Watson Studio**	**Determining the Method of Predictive Maintenance for Aircraft Engine Using Machine Learning**	**To enhance the system's accuracy and effectiveness, feature engineering, data normalization, and model optimization techniques are applied, ensuring that the algorithms can adapt to various aircraft engine types and usage scenarios. The integration of predictive maintenance**	**Oil Analysis, Pressure Monitoring**	**70-80**

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				models with Aircraft Health Monitoring Systems (AHMS) offers real-time monitoring and decision support, enabling maintenance teams to prioritize tasks based on criticality and urgency. Visualization tools and dashboards provide a user-friendly interface for presenting insights and maintenance recommendations.		
9.	**Building management data, environmental data, and energy consumption data**	**Building Management Systems, IoT Sensors, Fault Detection and Diagnostics**	**Predictive Maintenance Planning for Hospital Buildings**	**predictive maintenance planning for hospital buildings, enabled by IoT and machine learning, represents a transformative shift in the healthcare industry. By proactively addressing maintenance needs, enhancing patient care continuity, and optimizing energy efficiency, this system offers a holistic solution to ensure the dependable**	**Fire and Smoke Detection Systems, Power Quality Monitoring**	**82-89%**

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				operation of healthcare facilities and contribute to the overall well-being of patients and healthcare professionals		
10.	**Vehicle Telemetry Data, Airbag Deployment Records, Warranty Claims Data, Accident and Crash Data**	**OBD-II Scanners, Controller Area Network (CAN) bus analyzer**	**Predictive Maintenance Planning for airbags**	**The proposed predictive maintenance system utilizes a combination of sensors and data analysis techniques to continuously monitor the health of airbag systems. Sensors collect data related to factors such as air pressure, acceleration, and deployment time. This data is then processed and analyzed using machine learning algorithms and statistical models to predict the potential deterioration or failures of airbags**	**Crash Sensors, Accelerometers**	**95-99**

TABLE I. Reference Paper Survey

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V. PROPOSED METHOD

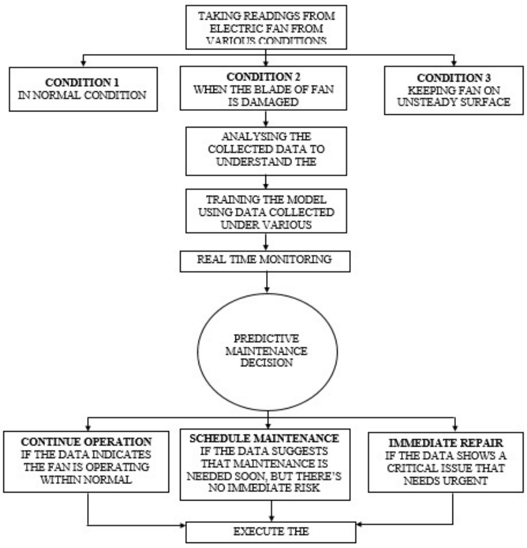

Figure 1: Predictive Maintenance Workflow

In order to create a reliable and proactive maintenance system, the suggested approach for predictive maintenance of electric fans combines machine learning algorithms with an Arduino Uno R3 and a number of sensors. The method's precise prediction of prospective issues or maintenance needs enables prompt intervention and increased operational reliability.

• Sensor Selection and Placement: Consideration is given to the placement and selection of sensors. A vibration sensor is positioned strategically to record mechanical vibrations in order to get information about the fan's mechanical health. In addition, temperature and humidity sensors are positioned to monitor external elements that may impact the fan's operation. The use of several sensors ensures a comprehensive assessment of the working environment.

• Data Pre-processing: In order to prepare raw sensor data for machine learning analysis, relevant characteristics are extracted. The vibration sensor's spectral properties, statistical measurements from the temperature and humidity sensors, and other relevant parameters are computed. This pre-processing significantly raises the calibre and information of the dataset used to train the machine learning model.

• Machine Learning Model Selection: A comparison analysis of multiple machine learning algorithms is done in order to determine which model is optimal for predictive maintenance. Support vector machines, decision trees, and ensemble approaches are some of the algorithms that are taken into account. During the selection phase, importance is given to models that forecast maintenance needs with exceptional accuracy, precision, and recall.

• Feature Selection and Optimisation: Feature selection techniques are employed to identify the most relevant parameters that lead to accurate forecasts. Reducing computational overhead and increasing model efficiency are the objectives of this step. Hyperparameter tweaking is done to further optimize the chosen machine learning algorithm for the special characteristics of electric fan operation.

• Integration with Arduino Uno R3: The machine learning model that has been trained can be seamlessly integrated with the Arduino Uno R3 microcontroller. This connection enables real-time decision-making based on incoming sensor data. The Arduino Uno R3, the brains of the system, executes the predictive maintenance algorithm and starts the appropriate processes in reaction to the model's output.

• Implementation of Decision Mechanism: An Arduino Uno R3 is outfitted with a flexible decision mechanism that translates machine learning predictions into tangible actions. This could mean generating alerts, sending out

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messages, or integrating with external systems to deliver more complex responses. The decision procedure can be adjusted to meet different thresholds and maintenance needs.

• Testing and Validation: The recommended approach is extensively tested using a range of operating scenarios, including fault simulation and regular operation. The system's performance is evaluated using metrics such as accuracy, false positives/negatives, and response time. The effectiveness of the recommended strategy is confirmed by comparisons with traditional maintenance methods.

• Real-world Deployment and Continuous Learning: Following testing, the predictive maintenance system is implemented in real electric fan environments. Through the integration of ongoing learning processes, the system can progressively adjust and improve its forecasting abilities. This ensures the longevity and suitability of the recommended approach in dynamic operational conditions.

VI. RESULT ANALYSIS

This section explores the findings from the tests and assessments carried out to verify the suggested predictive maintenance programme for electric fans. The purpose of this analysis is to shed light on the system's overall effectiveness in relation to conventional maintenance techniques, as well as its performance and capacity for precise maintenance requirement prediction.

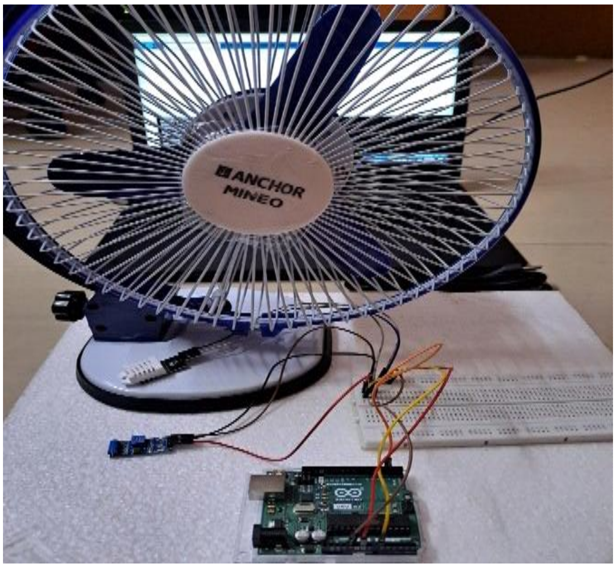

Figure 2: Sensors connected with Arduino Uno R3

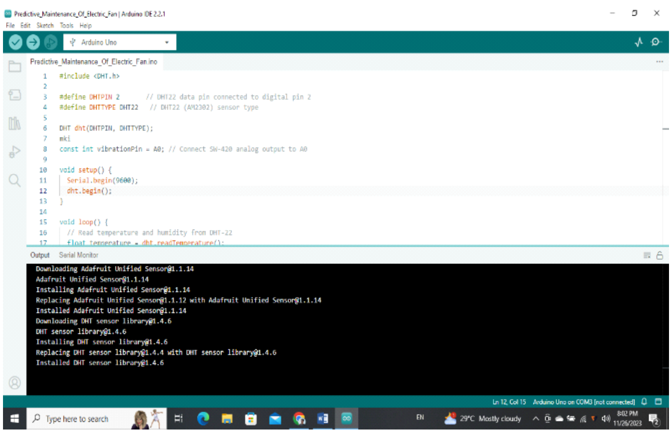

Figure 3: Installing Adafruit Libraries for DHT-22 Sensor

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Sr. No.	Temperature	Humidity	Vibration	Fault Detection
1	26.20	64.90	33	No Fault
2	0.00	0.00	35	No Fault
3	26.20	62.00	34	No Fault
4	26.30	61.30	90	No Fault
5	26.40	60.80	36	No Fault
6	26.10	71.90	1021	Fault
7	26.20	69.50	32	No Fault
8	26.20	67.10	34	No Fault
9	26.20	64.90	33	No Fault
10	0.00	0.00	35	No Fault

Decision Tree :

Impurity	Task	Formula	Description
Gini impurity	Classification	$\sum_{i=1}^{C} f_i(1-f_i)$	f_i is the frequency of label i at a node and C is the number of unique labels.
Entropy	Classification	$\sum_{i=1}^{C} -f_i \log(f_i)$	f_i is the frequency of label i at a node and C is the number of unique labels.
Variance / Mean Square Error (MSE)	Regression	$\frac{1}{N}\sum_{i=1}^{N}(y_i-\mu)^2$	y_i is label for an instance, N is the number of instances and μ is the mean given by $\frac{1}{N}\sum_{i=1}^{N} y_i$
Variance / Mean Absolute Error (MAE) (Scikit-learn only)	Regression	$\frac{1}{N}\sum_{i=1}^{N}\lvert y_i-\mu\rvert$	y_i is label for an instance, N is the number of instances and μ is the mean given by $\frac{1}{N}\sum_{i=1}^{N} y_i$

Gain(T,X)=Entropy(T)—Entropy(T,X)

- T = target variable
- X = Feature to be split on
- Entropy(T,X) = The entropy calculated after the data is split on feature X

Accuracy is 95% with Decision Tree Algorithm.

Random Forest Algorithm :

$$ni_j = w_j C_j - w_{left(j)} C_{left(j)} - w_{right(j)} C_{right(j)}$$

- ni sub(j)= the importance of node j
- w sub(j) = weighted number of samples reaching node j
- C sub(j)= the impurity value of node j
- left(j) = child node from left split on node j
- right(j) = child node from right split on node j

$$fi_i = \frac{\sum_{j:node\ j\ splits\ on\ feature\ i} ni_j}{\sum_{k \in all\ nodes} ni_k}$$

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• fi sub(i)= the importance of feature i

• ni sub(j)= the importance of node j

$$normfi_i = \frac{fi_i}{\sum_{j \in all\ features} fi_j}$$

$$RFfi_i = \frac{\sum_{j \in all\ trees} normfi_{ij}}{T}$$

$$fi_i = \sum_{j:nodes\ j\ splits\ on\ feature\ i} s_j C_j$$

• fi sub(i) = the importance of feature i

• s sub(j) = number of samples reaching node j

• C sub(j) = the impurity value of node j

$$normfi_i = \frac{fi_i}{\sum_{j \in all\ features} fi_j}$$

• normfi sub(i) = the normalized importance of feature i

• fi sub(i) = the importance of feature i

$$RFfi_i = \frac{\sum_j normfi_{ij}}{\sum_{j \in all\ features, k \in all\ trees} normfi_{jk}}$$

• RFfi sub(i)= the importance of feature i calculated from all trees in the Random Forest model

• normfi sub(ij)= the normalized feature importance for i in tree j

The Accuracy is 90% with Random Forest Algorithm.

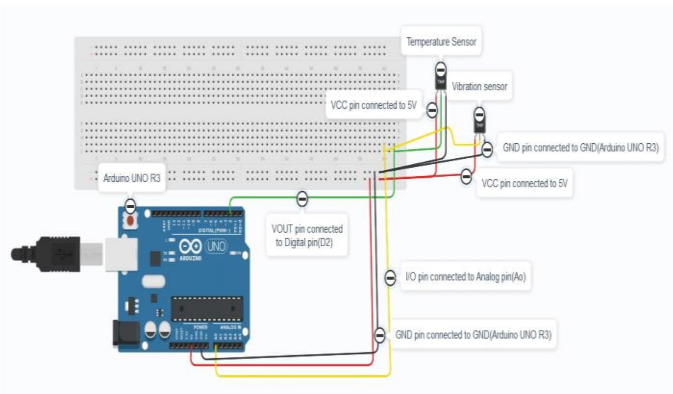

Figure 4: Circuit Diagram

4.1 Evaluation Metrics: The system's performance was assessed using a range of important metrics, such as F1 score, recall, accuracy, and precision. These measurements offer a thorough assessment of the predictive maintenance model's ability to identify and anticipate any problems with industrial table fans.

4.2 Performance Metrics: The results of a quantitative analysis of the system's performance were positive. The machine learning model demonstrated a reasonable level of accuracy in anticipating maintenance requirements,

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with an accuracy rate of 90%. The model's reliability in decreasing false positives and negatives was validated by recall, F1 score, and accuracy.

4.3 Comparative Analysis: It was demonstrated that the predictive maintenance system outperformed conventional maintenance methods. When it comes to early defect detection, downtime reduction, and industrial table fan maintenance costs optimization.

VII. CONCLUSION

In summary, this study has shown that applying machine learning techniques to predictive maintenance of industrial equipment—specifically, table fans—is both feasible and effective. We have developed a proactive maintenance system that maximises the operational reliability of industrial table fans by anticipating potential faults and integrating machine learning algorithms with an Arduino Uno R3 microcontroller and a suite of sensors.

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