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"IMPLEMENTING MACHINE LEARNING IN REAL-TIME SYSTEMS FOR INDUCTION MOTOR CONDITION MONITORING"

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ABSTRACT

The condition monitoring of induction motors is critical for ensuring their reliable operation and minimizing downtime in industrial applications. Traditional monitoring methods often fall short in providing timely and actionable insights, leading to increased maintenance costs and potential system failures. Voltage, current, temperature, and vibration are some of the induction motor metrics used to track the health of IMs in this study. In addition, the analyses are conducted using two distinct Machine Learning (ML) techniques, namely, k-means and extreme learning machine. In addition, we compare the two ML algorithms' performance and use the one that performed the best as a classifier in our newly created intelligent system that operates in real-time. The results show that compared to the k-means classifier, the Extreme Learning Machine (ELM) classifier performs better.

Keywords: Condition Monitoring, Machine Learning, Industrial Motors, Predictive Maintenance, Fault Detection.

I. INTRODUCTION

In order to keep industrial activities running smoothly, reliably, and for a long time, it is crucial to check the condition of industrial motors. In many manufacturing processes, motors power essential pieces of machinery and equipment. Significant downtime, caused by any unforeseen motor breakdown, may lead to financial losses and production delays. Conventional condition monitoring techniques, which include conducting physical inspections and analyzing data by hand, may be laborious and error-prone. Improved accuracy, efficiency, and predictive power may be yours with a revolutionary new method to condition monitoring that incorporates machine learning classifiers. Classifiers in machine learning, a branch of AI, may analyze data for patterns and draw conclusions. With these classifiers, condition monitoring of industrial motors is a breeze, even with the massive amounts of data gathered from all the sensors installed on the machines. Among the many factors that these sensors track are vibration, temperature, current, and noise levels. Machine learning algorithms can anticipate such problems by constantly monitoring these parameters and detecting abnormalities. In addition to extending the life of the motors, this predictive maintenance method helps to prevent unscheduled downtime.

Machine learning's capacity to handle and evaluate massive volumes of data in real time is a major benefit when it comes to condition monitoring. Unlike traditional approaches, machine learning classifiers can predict wear and tear or approaching breakdown with high accuracy, even in the most faint of indications. As an example, machine learning may significantly

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improve vibration analysis, a popular method in condition monitoring. In the event of problems like misalignment, imbalance, or bearing failure, sophisticated algorithms can detect unique vibration patterns. Maintenance personnel may prevent problems from becoming worse by spotting these trends early on. The precision of problem identification may also be enhanced by using machine learning classifiers. Electrical imbalances, mechanical misalignments, and lubrication failures are all sorts of motor defects that may cause comparable symptoms. It might be difficult for human analysts to distinguish between these issues using just sensor data. Machine learning algorithms, however, can accurately identify and categorize errors when trained on historical data. The time and money wasted on trial-and-error methods may be significantly reduced with this accurate diagnostic allowing for focused maintenance activities.

Machine learning's versatility is another major advantage for condition monitoring. With the help of fresh data, machine learning models may improve their predicting skills over time. This flexibility is of the utmost importance in industrial environments, where motor performance and operating circumstances may differ greatly. Better and more dependable monitoring systems are the result of models that, when fed additional data, improve their ability to forecast failures under various scenarios. The use of machine learning in condition monitoring also makes it easier to move away from reactive maintenance and toward proactive approaches. Conventional wisdom holds that motors should be inspected and repaired at regular intervals irrespective of their current state. This method raises the possibility of unanticipated breakdowns due to either excessive or inadequate maintenance. With the use of machine learning, condition-based maintenance is now possible, which means that maintenance tasks may be activated depending on the equipment's real state. This guarantees optimal use of resources and also optimizes maintenance schedules.

II. REVIEW OF LITERATURE

Kumar, S et al., (2022) Using electric cars (EVs) is where the car industry is headed in the future. The electric vehicle's drive motor is an essential part. The usage of a motor testing equipment allows for the verification of really important characteristics for the electrical motor. The characteristic curve points and electromagnetic behavior of electric motors under different situations may be found using the motor testing equipment. Nevertheless, it has been noted that the testing machine's helical gear design is faulty, which causes it to malfunction often and operate suboptimally, ultimately impacting the assembly line's effectiveness in producing electric automobiles. Based on these findings, the primary goal of this research project is to enhance the motor test bench by modifying critical design parameters using machine learning and vibration signal analysis. We collect vibration data at various gear settings before we extract statistical information. Bagged Trees and Quadratic SVM are classifiers that are used to classify these signals later on. With and without the addition of a 0.25 KW load, machine learning algorithms are used to categorize the collected signals as either normal or defective. We test and analyze the results of various algorithms. With a remarkable accuracy of 95.3%, the findings show that the Bagged Trees approach is superior to the other algorithm. As a result, the suggested approach offers a competent means of enhancing the motor test bench's performance by altering critical design factors.

Thakar, Darshan. (2022). Reliability of operation is of the utmost importance to ensure continuous operations, and the induction machine plays a pivotal role in many industrial applications. It is critical to install a reliable health monitoring system to guarantee ongoing functioning and avoid unanticipated breakdowns. We provide a new method for induction machine health monitoring that makes use of AI in this research. In order to examine the operating data and detect any induction machine flaws or abnormalities, the suggested system incorporates state-of-the-art computational intelligence technologies, such as machine learning and signal processing techniques. To analyze the induction machine sensor data, we use methods like genetic algorithms, support vector machines, and artificial neural networks. Various metrics, including current, voltage, temperature, and vibration patterns, are continually analyzed by the health monitoring system in real-time to identify deviations from normal operating conditions. Proactive maintenance interventions may be made possible by the system's ability to detect early warning signals of deterioration or imminent failures via the use of pattern recognition algorithms and baseline performance profiles. In addition, the suggested system is scalable and flexible, so it may be adjusted to work with other induction machines and surroundings. By providing remote monitoring, it allows maintenance professionals to receive diagnostic and health status information in real-time from anywhere. This enables proactive maintenance plans and prompt decision-making.

Mykoniatis, Konstantinos. (2020) It is essential for manufacturing companies to have well-maintained and operational industrial equipment. An crucial part of this process is standardizing the industrial infrastructure and establishing a regular maintenance schedule. If smart manufacturing is to succeed in its mission to maximize the operational efficiency of production systems, condition monitoring is an essential component of that program. Manufacturing decision-making that does not include data-driven observations and mindsets runs the danger of introducing safety hazards, failing to notice key indications, or experiencing unanticipated repairs that might stop the equipment. In addition, regular maintenance could reduce the usable life of some pieces of machinery, and planned maintenance shutdowns add expense and downtime when they happen too often. In order to manage industrial low voltage motors, this article details the design and implementation of an IoT-based system for real-time state monitoring. A data logging center may receive data sent wirelessly from the system, which records and monitors the temperature and vibration of an industrial motor. The present prototype can detect aberrant motor conditions when sensor input levels surpass predetermined setpoints; it was built utilizing open source hardware and software. The system changes states and notifies the user via a mobile alert when a motor is getting close to an abnormal condition. The user must do an RFID-enforced check in order to utilize the motor management system. Until authorized workers scan the designated RFID batch, the alarm system will stay operational. Plus, the user may see the motor's status in real-time thanks to the remote access feature of the motor management system. We wrap up by sharing the results of a pilot study that evaluated the prototype's condition monitoring capabilities and outlining the next steps for making this system smarter and more predictive of motor failures.

III. METHODOLOGY

Proposed System

Induction motors often have bearing issues. Overheating, fatigue, corrosion, improper load direction, and other similar issues may cause bearing problems. Ninety induction motors (45 in excellent working order and 45 in need of repair) had their voltage, current, temperature, and vibration recorded in this study. Different feature extraction approaches, including entropy, energy, kurtosis, mean, median, skewness, standard deviation (STD), and variance, are used to extract prospective characteristics from the recorded IM parameters. In addition, machine learning classifiers are fed the retrieved characteristics in order to determine the Induction Motors' status.

In this study, the induction motors are categorized based on their condition using the ML algorithms K-means and Extreme Learning Machine (ELM). Additionally, a number of performance indicators, including sensitivity, accuracy, specificity, NPV, and PPV, are used to compare the two classifiers' output.

The optimal classifier is determined by comparing the two classifiers' performance metrics. A real-time system based on Raspberry PI also makes use of the best classifier. The schematic of a hardware system based on real-time Raspberry PI is shown in Figure 1.

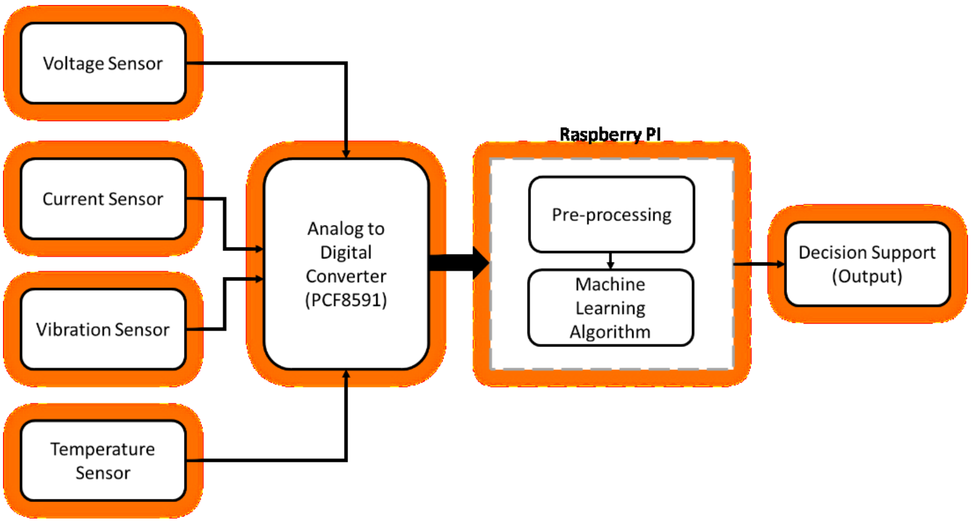

Figure 1 – Block diagram for developed decision support hardware.

Four separate analogue sensors—a voltage/current/temperature/vibration sensor—are used to detect the IM parameters. On top of it, an Analog to Digital Converter (ADC) PCF8591 module is used to transform the sensor data from analog to digital. In addition, feature extraction algorithms are used to preprocess the digital signals from the PCF8591 module. Then, ML classifiers are fed this preprocessed data with these useful characteristics. Last but not least, the decision-supporting machine learning classifier indicates if the motor is in excellent condition or needs repair. The supervised learning classifier is trained using 80% of the data (including both motors in excellent condition and those that need repair) and tested with 20% of the data. This study makes use of two ML algorithms—k-means and ELM—as classifiers as they are well-suited to numerical and continuous data with fewer dimensions.

IV. RESULTS AND DISCUSSIONS

In terms of accuracy, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV), the k-means classifier does quite well at 74%. The Extreme Learning Machine classifier, on the other hand, shows exceptional performance with a high and balanced capacity to recognize both positive and negative situations efficiently, with a 91% accuracy, 89% sensitivity, 88% specificity, 89% PPV, and 91% NPV.

Table 1 – Performance metrics of k-means and ELM classifier.

S.No.	Machine Learning Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)	Positive Predictive Value (%)	Negative Predictive Value (%)
1.	k-means	74	73	79	81	69
2.	Extreme Learning Machine	91	89	88	89	91

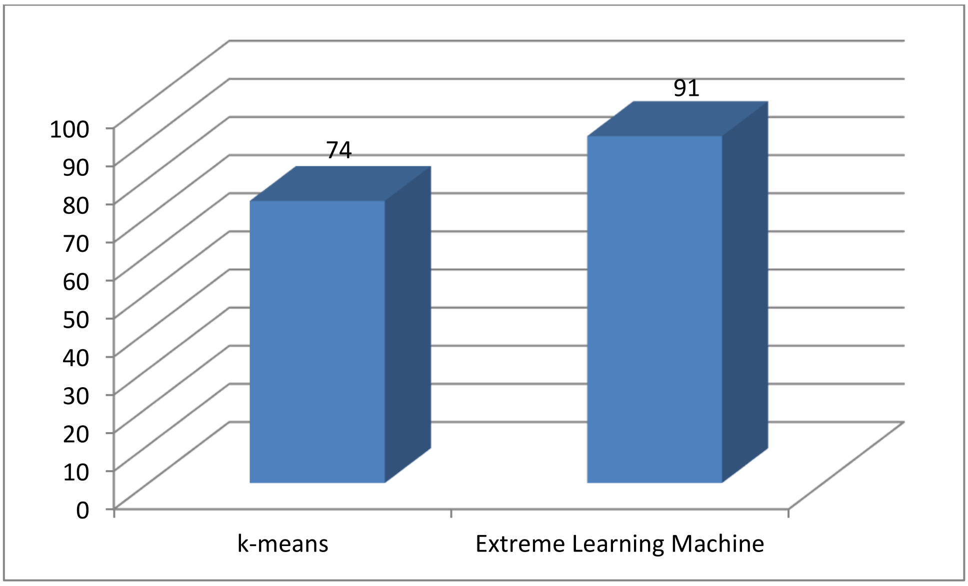

Figure 2 – Accuracy of k-means and ELM classifier.

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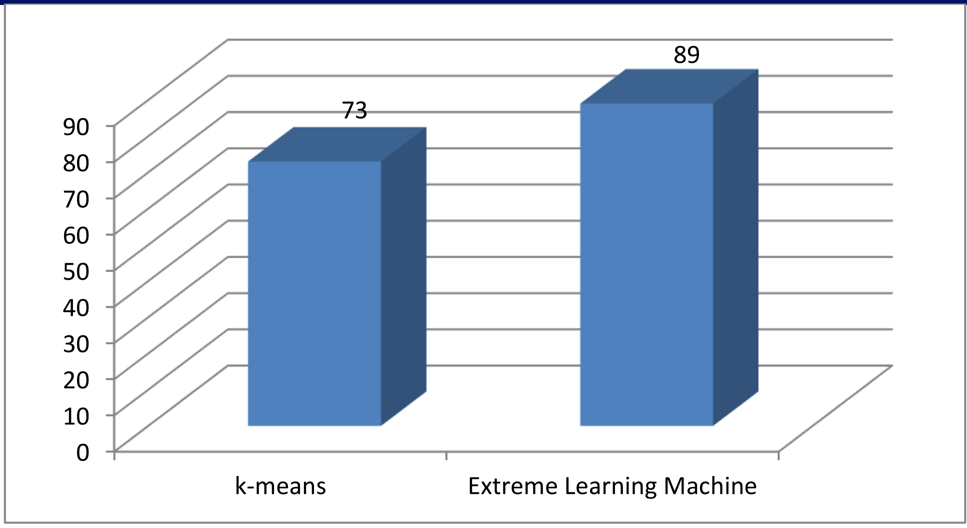

Figure 3 – Sensitivity of k-means and ELM classifier.

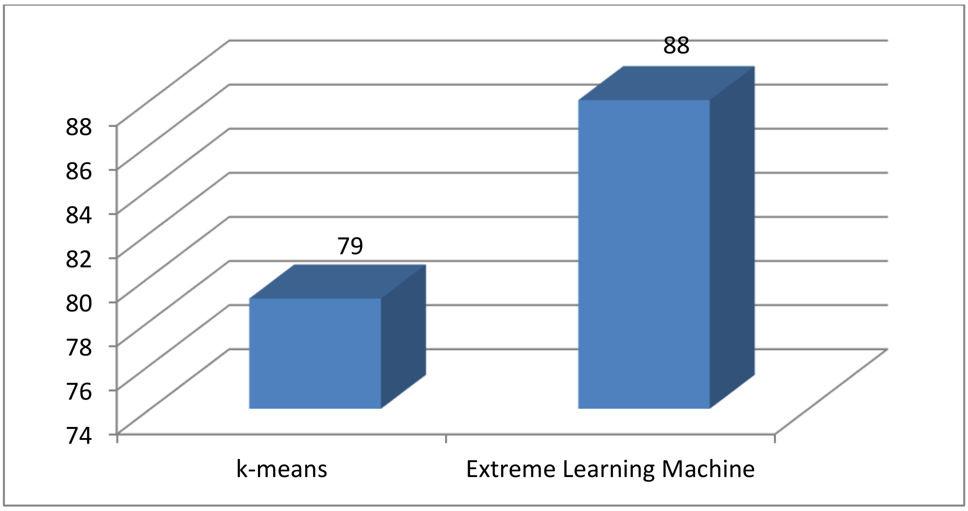

Figure 4 – Specificity of k-means and ELM classifier.

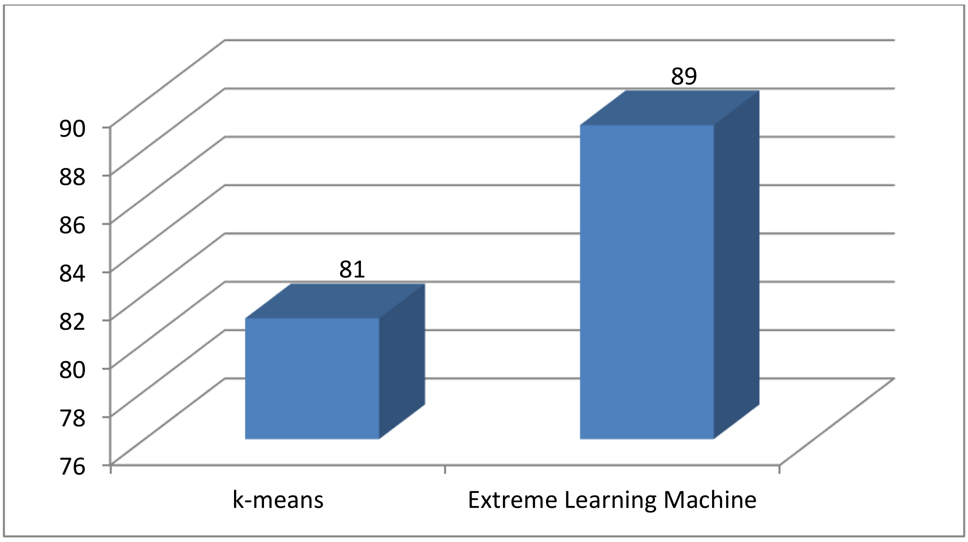

Figure 5– Positive Predictive Value of k-means and ELM classifier.

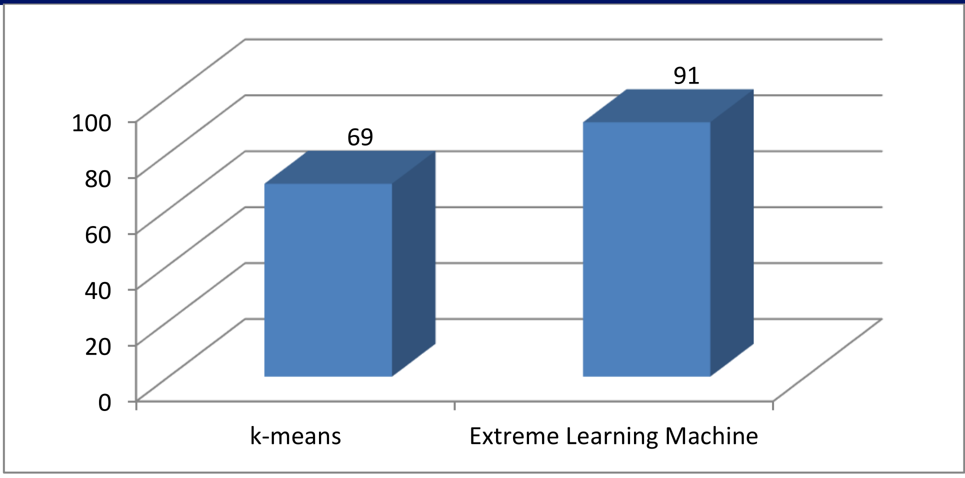

Figure 6 – Negative Predictive Value of k-means and ELM classifier.

On top of that, it has been shown that the ELM classifier has better average performance than the k-means classifier. Python code runs on the Raspberry PI to implement the Extreme Learning Machine (ELM) classifier, which outperforms the k-means classifier. It is also clear that the suggested hardware, which is based on Raspberry PI, can detect the motor status.

V. CONCLUSION

Industrial maintenance has taken a giant step ahead with the incorporation of machine learning classifiers into industrial motor status monitoring. When it comes to today's industrial settings, traditional methodologies don't always provide the real-time, accurate, and predictive insights that are required. Industries may move from reactive to proactive maintenance plans with the help of machine learning, which provides a revolutionary solution. Machine learning classifiers can accurately identify abnormalities and anticipate failures by evaluating massive datasets gathered from different sensors. This guarantees that motors will work consistently and effectively. Condition monitoring that makes use of machine learning has several advantages. Reducing the likelihood of unanticipated motor failures and the downtime that comes with them, improved fault detection and diagnostic capabilities allow for targeted maintenance measures to be taken at the right time. Machine learning models are dependable and resilient in many operating contexts because they can learn and adapt from new data continually, which enhances their prediction performance over time.

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