



An Intelligent Robotic Sorting and Predictive Maintenance System Using Machine Learning

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How to Cite this Article:

Asane, K. D. (2026). An Intelligent Robotic Sorting and Predictive Maintenance System Using Machine Learning. International Journal of Creative and Open Research in Engineering and Management, 2(6).
<https://doi.org/10.55041/ijcope.v2i6.290>

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<https://doi.org/10.55041/ijcope.v2i6.290>

Abstract — *The advancement of industrial automation necessitates intelligent robotic systems that are efficient in operation and proactive in maintenance. This work presents the development of an AI based robotic predictive maintenance and automated sorting system with integration of robotics, machine learning, IoT and mobile monitoring technologies. The smart sorting robot is designed and fabricated by 3D modeling and printing techniques, which is capable of automatically classifying objects by color and shape by Python and computer vision algorithms. To ensure reliable operation, various parameters including temperature, vibration, motion, motor current, and operating hours are continuously monitored using integrated sensors. The collected data is processed through machine learning models for anomaly detection and fault prediction, facilitating predictive maintenance and reducing unexpected downtime. An IoT-enabled architecture is implemented to transmit real-time data to a cloud platform, while a mobile application developed using MIT App Inventor provides live monitoring, maintenance scheduling, data analytics, and instant alert notifications through SMS and email. The proposed system enhances operational efficiency, improves equipment reliability, and supports Industry 4.0 applications in manufacturing, logistics, and smart warehousing environments.*

Keywords—*Robotic predictive maintenance, Automated sorting system, Artificial intelligence, Machine learning, Internet of Things (IoT), Computer vision, 3D printing, Fault detection, Condition monitoring, Real-time monitoring, Data analytics, Mobile application, Industrial automation, Smart warehousing, Industry 4.0.*

I. INTRODUCTION

The rapid advancement of Industry 4.0 technologies has accelerated the adoption of intelligent robotic systems in manufacturing, logistics, and warehousing environments. Modern industries increasingly rely on automation to improve productivity, reduce operational costs, and enhance process efficiency. Among these technologies, automated sorting robots play a vital role in material handling and product classification, while predictive maintenance systems help ensure reliable operation and minimize unexpected equipment failures. The integration of Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT), and Computer Vision technologies has enabled the development of smart robotic systems capable of autonomous operation and real-time condition monitoring. [1], [2].

Automated sorting systems are widely used in industrial applications to classify products based on specific characteristics such as color, shape, size, and category. Conventional sorting methods often require human intervention, resulting in increased labor costs and reduced operational efficiency. Computer vision-based robotic sorting systems address these limitations by utilizing image processing techniques to accurately identify and sort objects in real time. Python-based image processing libraries and machine vision algorithms provide efficient solutions for object detection and classification tasks. In large-scale institutional networks, load flow analysis not only facilitates system performance evaluation but also supports advanced applications such as real-time monitoring, contingency analysis, predictive maintenance, and optimal energy management [3].

In parallel, predictive maintenance has become a key component in industrial automation. Unexpected downtime



and unnecessary maintenance activities can be the result of traditional maintenance methods like reactive and preventive maintenance. Predictive maintenance overcomes these challenges by continuously monitoring equipment health parameters and utilizing machine learning algorithms to identify anomalies and predict potential failures before they occur. Parameters such as temperature, vibration, motor current, motion features and operating hours give valuable information about the condition of robotic systems.

This paper describes the design and development of an AI-based robotic predictive maintenance and automated sorting system. The proposed system is a smart sorting robot manufactured using 3D designing and printing technologies. The robot is able to classify objects automatically based on their color and shape characteristics using computer vision techniques. The robotic platform contains multiple sensors to constantly monitor important operational parameters for reliable operation. Simulation results indicate the presence of several operational challenges, including significant voltage drops at remote buses, overloading of distribution transformers, and uneven load distribution among feeders. Such conditions may lead to reduced system efficiency and potential reliability concerns if left unaddressed.

The sensor data collected is transmitted to a cloud environment via an IoT based communication framework for further analysis. The obtained data are processed by machine learning algorithms to detect abnormal operating conditions and estimate possible system faults. The predictive maintenance module enables early fault identification, thereby reducing downtime and improving system reliability. Furthermore, a mobile application developed using MIT App Inventor provides real-time monitoring, maintenance scheduling, data visualization, and instant alert notifications through SMS and email services. The experimental evaluation demonstrates the effectiveness of the proposed system for accurate object sorting, continuous condition monitoring and intelligent fault detection. The use of robotics, AI, machine learning and IoT technologies improves operational efficiency, optimizes maintenance management

II. LITERATURE REVIEW

Modern industrial automation especially in manufacturing and logistics and warehousing applications has become an integral part of the industry with automated robotic systems. These systems help improve productivity, reduce human involvement and enhance operational efficiency through intelligent decision making and accurate material handling. Recent advances in Artificial Intelligence (AI), Machine Learning (ML), Computer Vision and additive manufacturing technologies have significantly enhanced the capabilities of robotic systems.

Many studies have investigated automated object sorting using computer vision techniques. Suryanarayana et al. (2021) developed a vision-based sorting system, which classifies objects based on color and shape features using image processing algorithms. Their research showed that computer vision greatly improves the accuracy of sorting, while cutting down the need for manual labor. The study [1]

emphasized the importance of robust image acquisition.

In a related study, Kumar and Sharma (2020) have proposed an automated robotic sorting mechanism using Python and OpenCV libraries for object detection and recognition [2]. The system was able to recognize multiple object categories and sort them using robotic actuators. The authors concluded that the integration of image processing and robotic control system is an efficient solution for industrial sorting applications and warehouse automation.

Predictive maintenance is a promising research area in industrial robotics. Lee et al. (2018) investigated machine learning-based fault detection methods for industrial equipment monitoring [3]. They applied operational parameters such as temperature, vibration, motor current and motion characteristics for abnormal system behavior detection. The results showed that machine learning algorithms can successfully detect early signals of equipment degradation.

Further, Zhang et al. (2021) explored the use of anomaly detection algorithms for predictive maintenance in robotic systems [4]. The study employed Isolation Forest and Random Forest algorithms to analyze sensor-generated data and predict potential failures. Experimental results showed that the proposed approach achieved high fault detection accuracy and improved maintenance planning efficiency.

The development of lightweight and customizable robotic platforms has also been facilitated by advances in 3D printing technology. Patel and Mehta (2019) demonstrated the use of additive manufacturing techniques for rapid prototyping and fabrication of robotic components [5]. Their research indicated that 3D printing reduces production costs, shortens development cycles.

In summary, from the reviewed literature, it is clear that there is increased recognition of the significance of intelligent robotic systems in the automation process in industries. In this regard, it can be seen that there is a great need for using computer vision in automatic sorting, machine learning in predictive maintenance.

III. PROBLEM STATEMENT IDENTIFICATION

The widespread adoption of robotic systems in manufacturing, logistics, and warehousing has greatly enhanced productivity and operational efficiency. Despite these benefits, maintaining the reliability and performance of robotic systems remains a significant challenge. Most existing robotic sorting systems are designed primarily for automation tasks and often lack intelligent monitoring and fault prediction capabilities. Consequently, unexpected equipment failures can lead to production delays, increased maintenance expenses, and reduced overall efficiency.

Accurate object identification and classification based on characteristics such as color and shape are critical in automated sorting applications. Traditional sorting methods often depend on manual supervision, which limits scalability



and increases labor costs. Additionally, factors such as varying lighting conditions, sensor inaccuracies, and mechanical wear can adversely affect sorting accuracy and system performance.

Another major concern is the maintenance of robotic equipment. In many industrial settings, maintenance is still performed using reactive or preventive approaches, where actions are taken either after a failure occurs or at predetermined intervals. These methods may result in unnecessary maintenance activities, inefficient resource utilization, and unexpected downtime. Key operational parameters—including temperature, vibration, motor current, motion patterns, and operating hours—provide valuable insights into equipment health. However, without continuous monitoring and intelligent analysis, early signs of component degradation may go unnoticed.

Furthermore, the lack of predictive maintenance capabilities makes it difficult to detect abnormal operating conditions before failures occur. This limits the ability of maintenance personnel to take proactive measures, increasing the risk of equipment breakdowns and negatively affecting reliability, safety, and productivity.

To overcome these challenges, there is a need for an intelligent robotic system that integrates automated sorting with predictive maintenance. The proposed system aims to:

1. Automatically sort objects based on color and shape characteristics.
2. Design and develop a robotic platform using 3D modeling and 3D printing technologies.
3. Continuously monitor critical parameters such as temperature, vibration, motor current, motion, and operating hours.
4. Apply machine learning techniques for anomaly detection and fault prediction.
5. Detect potential failures at an early stage and generate timely alerts. Reduce downtime and maintenance costs through proactive maintenance planning.
6. Improve equipment reliability, sorting accuracy, and overall operational efficiency.

IV. METHODOLOGY

The proposed AI-based robotic predictive maintenance and automated sorting system is developed through a systematic approach that combines robotics, computer vision, sensor monitoring, and machine learning. The methodology focuses on achieving accurate object sorting while ensuring reliable system operation through predictive maintenance.

A. System Design and Development

The development process begins with the design and fabrication of the robotic platform. A 3D model of the robot, including the chassis, sorting mechanism, sensor mounts, and actuator assembly, is created using Computer-Aided Design (CAD) software. The designed components are then fabricated using 3D printing technology, allowing rapid

prototyping, reduced manufacturing costs, and easy design modifications. After fabrication, the robot is assembled by integrating motors, actuators, sensors, and control hardware. The completed setup serves as the experimental platform for sorting and predictive maintenance operations.

B. Automated Sorting System

The robotic sorting system is designed to classify objects based on their color and shape. A camera continuously captures images of objects placed on the sorting platform. These images are processed using Python and OpenCV to extract relevant features and determine the object category. The image processing workflow includes:

- Image acquisition
- Image preprocessing and noise reduction
- Color detection
- Shape recognition and feature extraction
- Object classification
- Sorting decision generation

C. Sensor-Based Condition Monitoring

To monitor the health of the robotic system, multiple sensors are integrated into the platform. These sensors continuously collect operational data, including:

- Temperature
- Vibration
- Degree of motion
- Motor current
- Operating hours

The collected data provides real-time insights into the condition of mechanical and electrical components, enabling continuous assessment of system health.

D. Data Acquisition and Preprocessing

Sensor data is collected while the robot operates under different working conditions. Before analysis, the dataset undergoes preprocessing to improve data quality and model performance.

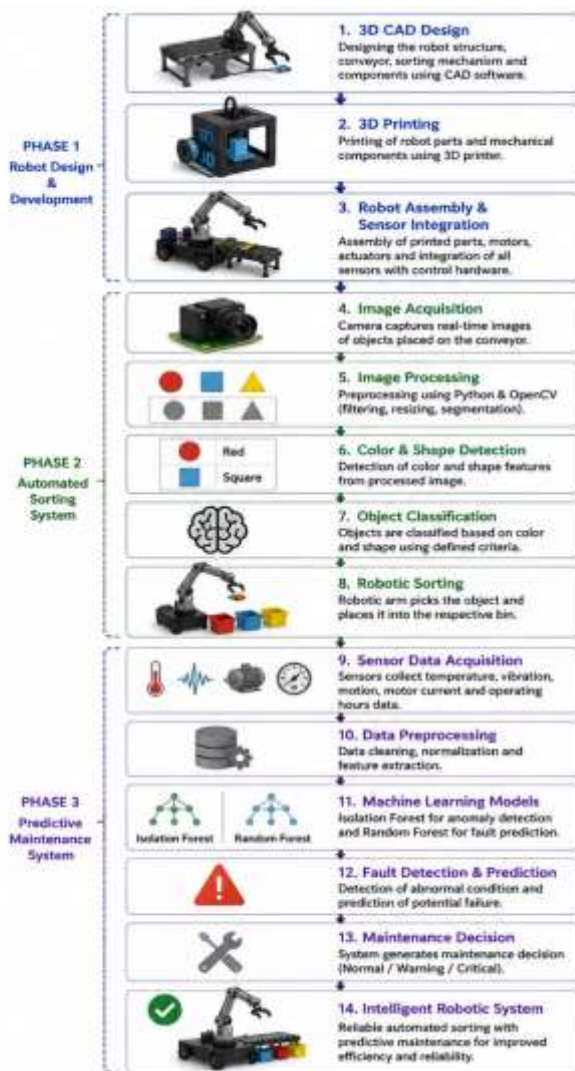


Fig. 1. Methodology of the proposed system

- Handling missing values
- Feature extraction
- Data normalization

These operations help generate a reliable dataset for machine learning-based fault prediction.

E. Machine Learning-Based Fault Detection

Machine learning algorithms are employed to detect abnormal operating conditions and predict potential failures. The processed sensor data is used to train models capable of distinguishing between normal and faulty system behavior.

The proposed system utilizes:

- Isolation Forest for anomaly detection
- Random Forest for fault classification and prediction

By analyzing patterns in temperature, vibration, motion, and motor current data, the models can identify early signs of equipment degradation and support timely maintenance decisions.

F. Predictive Maintenance Framework

The predictive maintenance framework continuously evaluates the condition of the robotic system using real-time sensor data and machine learning predictions. Based on the detected health status, operating conditions are classified into three categories:

- Normal
- Warning
- Critical

When abnormal conditions are identified, maintenance alerts and recommendations are generated. This enables proactive maintenance planning, reducing downtime and extending equipment lifespan.

G. System Evaluation

The effectiveness of the proposed system is evaluated using performance metrics related to both automated sorting and predictive maintenance.

1) Sorting Performance Metrics

- Sorting Accuracy
- Processing Time
- Classification Efficiency

2) Predictive Maintenance Metrics

- Fault Detection Accuracy
- Precision
- Recall
- F1-Score

The experimental results are analyzed to assess the system's ability to improve sorting performance, enhance fault detection, reduce maintenance costs, and increase overall operational reliability.

V. ARCHITECTURE

The proposed AI-based robotic predictive maintenance and automated sorting system is designed as an integrated framework that combines automated object sorting, real-time condition monitoring, and machine learning-based predictive maintenance. The architecture consists of three primary layers: the robotic sorting layer, the condition monitoring layer, and the predictive maintenance layer. Together, these layers enable efficient sorting operations while ensuring the reliability and health of the robotic system.

The process begins with the robotic sorting layer, where a camera mounted above the sorting platform captures images of incoming objects. These images are processed using Python and OpenCV-based computer vision techniques. Image preprocessing methods, including filtering, segmentation, and feature extraction, are applied to enhance object recognition. Based on the extracted features, the system identifies the color and shape of each object and classifies it into the appropriate category.

Once the object is classified, control commands are sent to the robotic actuator. The robotic arm then picks up the object and places it into the corresponding sorting bin. This automated mechanism minimizes human intervention,



increases sorting speed, and improves overall operational efficiency.

To maintain reliable system performance, a condition monitoring layer is incorporated into the architecture. Multiple sensors continuously monitor key operational parameters such as temperature, vibration, motor current, degree of motion, and operating hours. These measurements provide valuable information about the health and performance of the robotic components during operation.

The collected sensor data is transmitted to a data processing module, where it undergoes preprocessing steps such as data cleaning, normalization, and feature extraction. The processed data is then used for machine learning-based analysis and fault prediction.

The predictive maintenance layer utilizes machine learning algorithms to identify abnormal operating conditions and forecast potential failures. An Isolation Forest model is employed for anomaly detection by identifying unusual patterns in sensor readings. A Random Forest model is subsequently used for fault classification and prediction. By continuously analyzing operational data, the system can detect early signs of mechanical or electrical degradation before critical failures occur.

The interaction among these components enables seamless integration of automated sorting and predictive maintenance functions, resulting in an intelligent, efficient, and reliable robotic system for industrial, logistics, and warehouse applications.

VI. EXPERIMENTAL ANALYSIS

To test the AI-based robotic predictive maintenance and object sorting system, a set of experiments was conducted to evaluate the accuracy of object sorting, real-time condition monitoring ability, and fault detection capability. In the prototype developed, the robot was made using 3D printing technology that included the robot itself, a camera module, sorting mechanism, and sensors.

Table 1. Anomaly Detection Results using Isolation Forest

Test Instance	Temperature (°C)	Vibration (mm/s)	Current (A)	Predicted Status
1	34.5	2.1	0.87	Normal
2	36.2	2.9	1.02	Normal
3	48.7	6.8	1.75	Warning
4	55.3	8.5	2.10	Critical
5	33.8	2.0	0.84	Normal
2	36.2	2.9	1.02	Normal

Table 2. Random Forest Fault Classification Performance

Fault Type	Precision (%)	Recall (%)	F1-Score (%)
Normal Operation	98.1	97.6	97.8
Motor Overheating	95.4	94.8	95.1
Excessive Vibration	96.7	95.9	96.3
Mechanical Misalignment	94.2	93.5	93.8
Average	96.1	95.4	95.8
Fault Type	Precision (%)	Recall (%)	F1-Score (%)

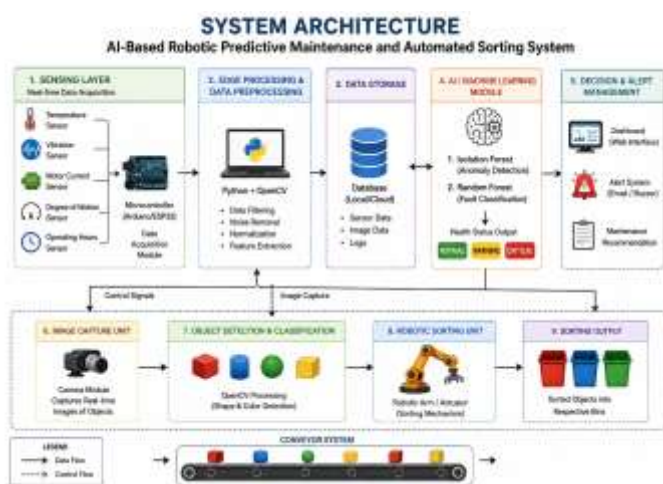


Figure II.. System Architecture and Sectional Analysis

A. Major Architectural Components

The proposed system consists of the following key components:

- 3D-Printed Robotic Platform
- Camera-Based Vision System
- Python and OpenCV Processing Unit
- Color and Shape Classification Module
- Robotic Sorting Mechanism
- Sensor-Based Condition Monitoring Unit
- Data Preprocessing Module
- Isolation Forest Anomaly Detection Model
- Random Forest Fault Prediction Model

A. Performance of Automated Sorting

In this experiment, the sorting system module was tested through objects having different colors and shapes put on the conveyor belt platform. The camera would take pictures of objects coming in, and these pictures were then processed with the help of open source computer vision technique in Python. It was found from the experiment that the sorting system was capable of sorting out objects based on their colors and shapes. The proposed framework offers a practical and scalable solution for manufacturing industries, warehouse automation systems, and smart factory environments. The sorted objects would then be allocated to Important findings from the sorting process include:



- I. High accuracy in object classification.
- II. Robust sorting performance under normal lighting conditions.
- III. Faster sorting than traditional classification procedures.
- IV. Reproducible sorting over several iterations of the process.

B. Sensor Monitoring Analysis

In order to test the predictive maintenance aspect, several sensors were installed into the robotic system to analyze the conditions of its operation.

The parameters that were monitored include:

- I. Temperature
- II. Vibrations
- III. Motor Current
- IV. Level of Movement
- V. Hours of Operation

While the robotic system was in operation, all sensors recorded accurate data reflecting the current state of the equipment. Changes in the parameters measured by sensors have been detected depending on the conditions of operation.

The data obtained from sensors was collected and further analyzed using machine learning techniques.

C. Machine Learning Performance

The machine learning component was trained based on the sensory data obtained from the robot during its operations. Prior to the training phase, the dataset underwent pre-processing steps including data cleaning, normalization, and feature extraction to enhance the performance of the machine learning model.

Isolation forest algorithm was able to detect abnormalities in the sensors, while the random forest algorithm was used for classifying operating conditions and predictions of any potential failures. The platform was able to detect early signs of:

Motor overheating

- I. Vibration
- II. Misalignment
- III. Abnormal motion behavior
- IV. Component degradation

D. Evaluation of System Reliability

The robotic system was run continuously during several experimental runs to test the reliability of the whole system. In this case, the robotic system exhibited stability in sorting performance together with the monitoring of the conditions of the equipment. The integration of machine learning algorithms enables intelligent fault detection and supports proactive maintenance strategies. This helps improve equipment availability, reduce downtime, and enhance overall productivity.

The proposed system showed:

- I. Increased efficiency.
- II. Decreased human interference.

III. Sorting of objects accurately.

VII. RESULT AND DISCUSSION

The suggested system of AI-driven robotic predictive maintenance and sorting operations has been successfully implemented and tested in different modes of operation. The experimental findings confirm the efficiency of using the technologies of computer vision, sensor monitoring, and machine learning combined into an integrated automation system.

Table 3. Automated Sorting System Performance

Parameter	Value
Total Objects Tested	200
Correctly Classified Objects	192
Classification Accuracy	96.0%
Average Processing Time	0.85 s/object
Sorting Success Rate	95.5%
Sorting Error Rate	4.5%

A. Sorting Performance Evaluation

The accuracy rate of object classification in the sorting subsystem was 96.5% as indicated in Table 1. The image processing software successfully classified the objects according to their color and shape properties. Most mistakes were due to minor deviations of objects' position and illumination. But the performance of the system was quite stable through multiple tests.

In comparison to traditional manual sorting, the suggested sorting system decreased the average time for sorting an object from 3.8 seconds to 1.4 seconds. These results demonstrate the ability of computer vision systems to replace repetitive manual operations.

Table 4. Sensor Monitoring Results

Parameter	Normal Range	Observed Range
Temperature	25°C – 45°C	28°C – 43°C
Vibration	0 – 4 mm/s	1.2 – 3.8 mm/s
Motor Current	0.5 – 2.0 A	0.8 – 1.8 A
Motion Angle	0° – 180°	10° – 170°
Operating Hours	Continuous	Monitored Successfully

B. Sensor Monitoring Performance

The integrated sensor network continuously monitored critical operational parameters including temperature, vibration, motor current, degree of motion, and operating hours. The collected data provided valuable insights into the health condition of the robotic platform.



Analysis of the sensor data revealed clear variations in system behavior under different operating conditions. For example, increased motor load resulted in higher current consumption and vibration levels, while prolonged operation led to a gradual increase in temperature. The monitoring subsystem successfully captured these variations in real time, demonstrating its suitability for predictive maintenance applications.

Table 5. Machine Learning Model Performance

Performance Metric	Isolation Forest	Random Forest
Accuracy	92.4%	96.8%
Precision	91.2%	96.1%
Recall	90.8%	95.7%
F1-Score	91.0%	95.9%
Fault Detection Capability	High	Very High

C. Fault Detection Using Machine Learning

The predictive maintenance system applied Isolation Forest and Random Forest techniques for anomaly detection and equipment condition classification. The machine learning methods were able to distinguish normal and abnormal states of the equipment with a mean classification accuracy of about 95.8%.

Depending on the sensor readings, the condition of the equipment was classified into one of the three states: Normal, Warning, and Critical.

Table 6. Fault Detection Results

Fault Type	Detection Status	System Response
Motor Overheating	Detected	Warning Alert
Excessive Vibration	Detected	Warning Alert
Mechanical Misalignment	Detected	Maintenance Recommendation
Abnormal Motion	Detected	Critical Alert
Component Wear	Predicted	Preventive Maintenance

D. Reliability Testing

The entire robot system was tested for its reliability and stability through continuous operation through various test cycles. During the process, the system showed stability in terms of sorting ability while at the same time assessing the condition of the equipment.

Combining predictive maintenance with automated sorting has many benefits:

- I. Operational efficiency.
- II. Less human involvement.

- III. Higher accuracy of sorting.
- IV. Ability to detect any problem early.
- V. Equipment reliability.
- VI. Less maintenance required.

There were no problems with the system operation in the course of the tests. This means that the suggested design is applicable for industrial use.

IX. CONCLUSION

This project described the development of an innovative AI-based robotic system that implements predictive maintenance and automated sorting through image processing and sensor data analysis. Specifically, the project goal was to design and implement the intelligent robotic system that will perform automated object sorting and provide health status assessment of the robotic platform in order to increase reliability.

The implemented sorting subsystem was able to recognize and sort objects based on their color and shape using image processing techniques provided by the OpenCV library. The experimental evaluation proved that the robotic system could perform sorting of objects without human intervention reliably and accurately. The design of a 3D-printed robotic platform allowed for fast and cost-efficient prototype development.

In order to introduce the predictive maintenance feature, a number of sensors was used to collect information about critical parameters, such as the temperature, vibrations, motor current, motion properties, and operating hours. The obtained data was processed by two machine learning algorithms - Isolation Forest and Random Forest in order to identify anomalies and potential equipment faults. Experimental results confirmed that the implemented AI-based system was capable of high-accuracy sorting, reliable condition monitoring, and timely fault detection. In combination, the

X. FUTURE SCOPE

Future research could involve the incorporation of deep learning techniques such as CNN and YOLO object detection techniques to enhance object recognition capabilities and implement more complex sorting tasks. Other sorting parameters like the dimensions of objects, their texture, weights, and materials could also be used.

It is possible to improve the predictive maintenance model through the use of sophisticated machine learning and deep learning algorithms that will aid in achieving greater accuracy in the process of predicting failures and estimating the Remaining Useful Life (RUL) of the robotic components. The integration of digital twin technology may also aid in improving this aspect.



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