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Machine Learning-Based Iot Sensor Data Analysis

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Abstract
Through early machine defect detection, costly breakdown prevention, downtime reduction, and maintenance optimization, predictive maintenance using IoT sensors eventually saves maintenance costs and production losses. Using pre-processed machine steps and speeds data, this study creates a predictive maintenance system that uses AdaBoost machine learning to identify real-time machine stops in knitting machines. It predicts six different sorts of stops: gate, feeder, needle, completed roll, idle, and lycra. Primarily, sensor devices used in energy management systems are low on computing power, memory, and battery capacity, and it is difficult to recharge the battery of sensors. The primary aim of this research work is to explore the problem of energy usage in the scenario of IoT devices with different energy demands. IoT devices execute data, send packets, read sensor values, and control devices. Due to doing these operations, the device will lose some power, which might restrict network operation. There exist various numbers of packets transmitted and received by various communication devices and various packet lengths.
Keywords: *productivity, hyperparameter, idle stop, maintenance*

INTRODUCTION

The capacity of devices to sense and understand their surroundings through the utilization of multiple sensors and actuators is the foundation of the Internet of Things [1]. The devices can use sensors such as accelerometers, motion detectors, cameras, GPS receivers, temperature, humidity, pressure and so on. IoT devices can learn from their environment and tune by taking information from the real world. IoT systems are dependent upon sensing and perception to collect information from the real world and offer devices context-aware information. IoT devices are able to perceive a range of physical phenomena and influence their surroundings because they are equipped with a wide variety of sensors and actuators. Along with temperature, humidity, pressure, motion sensors, cameras, GPS receivers, accelerometers, gyroscopes, magnetometers, light, proximity, and others may exist in these sensors. Specific attributes or features of the environment, such as temperature, humidity, pressure, motion, location, orientation, light intensity, sound intensity, and closeness, are measured by each sensor. Some examples of sensors that measure different aspects of an environment include temperature, humidity, pressure and motion. GPS receivers calculate the location of the sensor, accelerometers and gyroscopes measure acceleration and angular velocity, magnetometers measure magnetic fields, light sensors measure light intensity, and proximity sensors detect the presence of objects close by [9]. Today, wireless sensor networks are becoming increasingly vital and famous among researchers across various disciplines. The package of WSN is created to enable real-time, scalable monitoring of common environments. Power optimization, routing, identification of obstacles, security, and others are main configurations for WSN. All these constraints demand more priority enhancements to suit the requirements of the implementation environment. Numerous research approaches offer solutions to each contributing factor of WSN [3]. Through the combination of link disruption, load balancing, and distance measurements, it can analyze high, precise measurement enhancements[4]. It is a method that is rooted in a fully green power target tracking formula that defines network security for sensor nodes and proposes a set of policies for enhancing strength, efficacy, target observation, and efficiency [2]. To obtain the suggested condition monitoring system and confirm its feasibility, a test rig is constructed in an actual circular knitting machine [13].

REVIEW OF LITERATURE

Convolutional Neural Networks (CNNs) are a deep learning technique that has been developed for diagnosing circular knitting machine faults. The technique diagnosis's fault kinds by extracting characteristics from vibration signals and using a SoftMax classifier; experimental findings show that the method's accuracy is satisfactory. Other methods, like as XGBoost and LSTM, have shown successful in predictive maintenance, such as in wind turbines using SCADA data, despite CNNs' need for big training datasets. Although these techniques can identify irregularities and allow for prompt correction, knitting machines have not yet been the subject of their application [5].Using a Deep Belief Network (DBN) as the feature extractor and a Gaussian process (GP) for DBN hyper-parameter tuning, the study compared Bayesian optimization models with deep learning models. Empirical results showed that machine failure time prediction was accurate, outperforming traditional machine learning techniques [6]. Therefore, due to variations in complexity and particular contextual factors, cross-case comparisons of performance are inadequate. A smart Predictive Maintenance (PdM) system for industrial equipment using machine learning (ML) techniques, Message Queuing Telemetry Transport (MQTT), and the Industrial Internet of Things (IIoT) was compared in another study. Five machine learning models—k-nearest neighbor (KNN), support vector machine (SVM), random forest (RF), linear regression (LR), and naïve bayes (NB)—process real-time data from vibration, current, and temperature sensors in electrical motors in order to identify anomalies and forecast failure. Effective communication between gateways, sensors, and the cloud server is made possible by the MQTT protocol [10]. When it comes to motor operation, Random Forest (RF) provides the best accuracy and optimal maintenance schedules to reduce downtime and expenses [11].

MATERIALS AND METHODS

These studies make use of a variety of variables and algorithms to identify certain machine problems and anticipate the machine's remaining in life (RUL). However, further study is needed to create predictive maintenance systems for circular knitting machines that are more precise, comprehensive, and effective. The literature does not fully address the diagnosis of different machine failures to support comprehensive predictive maintenance systems. Additionally, it was difficult to assess the approaches' practicality in the real world by presenting demonstrations of them on genuine, functioning machinery.

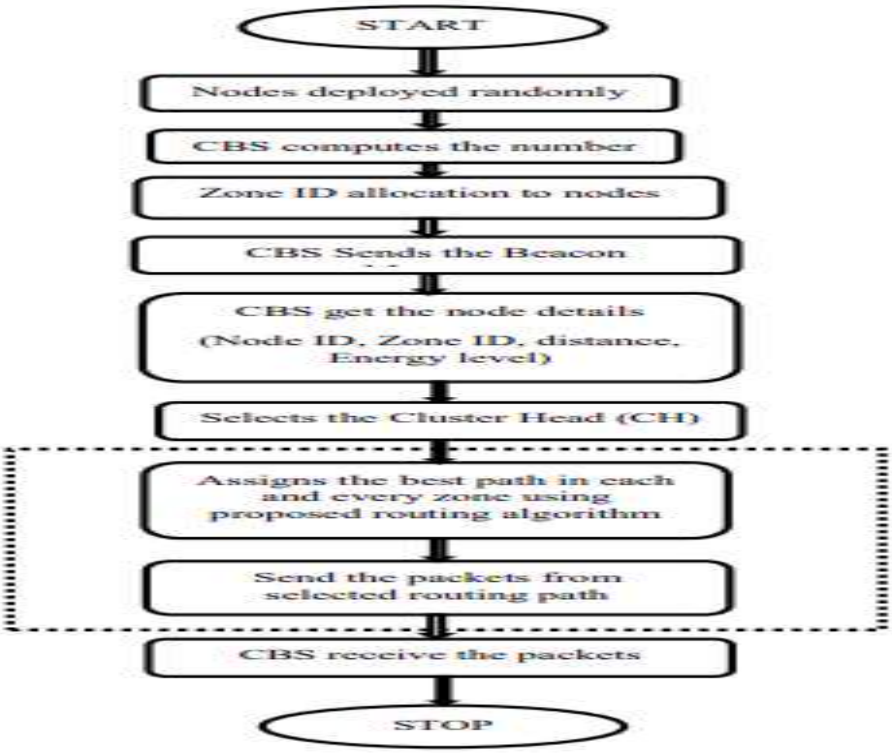

Figure 1: Proposed framework

In order to prevent long-term machine failures, the current research suggests a predictive maintenance technique that forecasts machine halt and the cause of stoppage (failure). To have a complete maintenance approach, several sensing devices are used to consider multiple reasons of failure. Through the use of IoT systems, ML-based classifiers are able to recover the readings of such devices. Its distinctive features, such real-time monitoring, a proven machine learning model, and an integrated database, show that it is moving away from traditional approaches and toward new, useful ones. To verify the new predictive maintenance system's practicality, an actual circular knitting machine is employed. The system performs well with high accuracy. Furthermore, it also holds a huge prospect to minimize downtime, enhance the availability of machinery, and increase productivity in the textile sector [7][8].

RESULT AND DISCUSSION

It discussed new developments in manufacturing sector maintenance techniques, focusing on the transition from reliability enhancement to adaptive and adaptive maintenance planning in the age of smart manufacturing[14]. examined how AI and ML are being used in the knitting industry, particularly in light of their revolutionary potential [12].

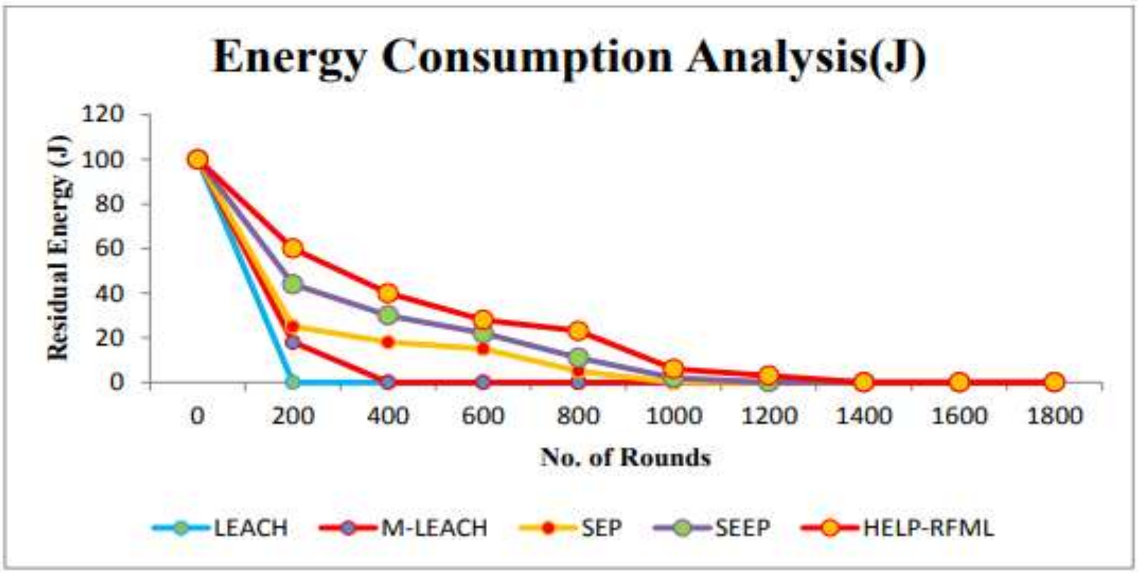

Figure 2: Energy consumption analysis

The study placed a strong emphasis on using technology completely at every level, including product sourcing, design, manufacture, distribution, and sale.

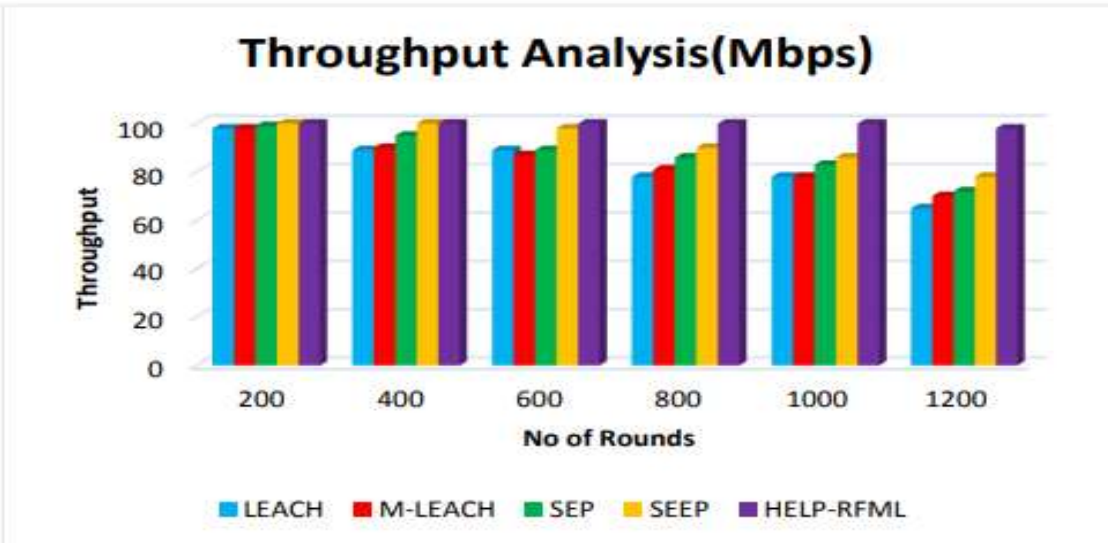

Figure 3: Throughput analysis

Predictive maintenance in knitting manufacturing is made possible by the use of AI and ML, which improve fiber classification, thread prediction, problem detection, and dye recipe prediction. A mechanism for making ambiguous decisions is created. According to a case study on sewing machine needles, it works well for predictive maintenance planning [15].

CONCLUSION

The stop duration manager effectively handles manual stoppages brought on by staff interventions and precisely tracks and analyses stoppage durations, even in complex situations like concurrent stoppages. The system intelligently distributes stoppage reasons, efficiently tracks interference durations, and maximizes machine work time. The goal of future study is to apply the system on different machines and broaden the data inputs to include more stop types, encompassing all incipient failures. The dispersed machine is a valuable tool since it assists in integrating the human mode of thinking into system design. This analysis employed skeptical reasoning to evaluate the best extraordinary handle for a package sent from a delivery sensor node to an eviction node. The most impressive node price is calculated using diffusion system input parameters, sensor network power, and internet traffic, final outcome are the optimum node price. The network controller is the fish tank node. Mileage is the shortest connecting route for every single sensor node. It serves as a portal (excursion point) for this WSN and consolidates all community information. Only the sink node makes the decision of what cost to charge each sensor unit node to the gate, packs the main course for every sensor unit node and indicates the direction time table of the sensor node.

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