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An artificial intelligence approach for improving maintenance: Supervising machine failures and supporting repair

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Abstract
In order to keep operations running smoothly and keep output high, maintaining of production equipment is essential. In order to run industrial equipment and effectively prepare for demands for own maintenance assets (spare parts, personnel, funds), it is essential to determine the execution time and appropriately pick the range of maintenance operations. There have been many efforts to simulate and oversee maintenance using artificial intelligence (AI) approaches, and several research have been carried out in the recent decade. The purpose of this essay is to have a conversation on the potential of artificial intelligence methodologies and approaches for failure prediction and proactive maintenance. Improvements in the administration of maintenance tasks are an oblique target of these investigations. Simulations and computer analyses using actual industrial data sets are the primary tools in the toolbox. The key findings demonstrate that a substantial quantity of trustworthy annotated sensor data and properly trained machine-learning algorithms are necessary for the efficient implementation of preventative maintenance. Companies of similar size and with varying production profiles should be able to apply the solutions that have been developed via scientific and technological means. Here, even the article's very basic ideas may be useful, providing great efficiency with cheap implementation costs.

Keywords: Industry 4.0, failure diagnostics, artificial intelligence, machine maintenance, quality control

Introduction
In order to keep operations running smoothly and keep output high, maintaining of production equipment is essential. In order to run industrial equipment and effectively plan for the demand for own maintenance assets (Spare parts, people, finances), it is essential to determine the implementation time and appropriately select the scope of maintenance activities. Over the past ten years, a plethora of research has attempted to simulate and oversee maintenance using artificial intelligence (AI) approaches [1]. Proper machine maintenance is essential for the smooth and risk-free operation of machinery in industrial settings. Preventing breakdowns, reducing downtime, and extending machinery lifespan can be achieved through regular maintenance. The two main types of maintenance that are commonly used today are reactive and preventive. Unanticipated downtime and detrimental effects on production are consequences of reactive maintenance, which fixes machines after they have failed. While planned preventative maintenance helps keep expenses down, it can lead to unnecessary repairs or even equipment replacements if not done properly [2]. Manufacturing decision-making is being transformed by the deluge of data collected by sensors and smart machines. Specifically, maintenance can be scheduled-over cell involvement and resource monitoring-as needed, based on a predictive approach, with the help of today's increasingly powerful hardware, cloud-based solutions, while new learning approaches. This helps with managing unexpected equipment failures, increasing uptime with less aggressive maintenance schedules, decreasing unplanned downtime, reducing excess cost (Both direct and indirect), improving safety plans, and reducing long-term damage to equipment and procedures [3]. Significant investment in upkeep tasks involving repairs, enhancements, or inspections is often necessary for cyber-physical systems, especially those with extended career lives like railways. Schedules or the expertise of the maintenance crew usually dictate these kinds of decisions. The rise of predictive

maintenance (PdM) as a practical means of foreseeing maintenance requirements and avoiding system breakdowns has provided hope for enhancing this procedure. In data-driven PdM, ML solutions watch the system logs and suggest interventions before a failure happens, identifying maintenance needs [4]. As we enter the fourth industrial century, AI is finding more and more uses in the manufacturing sector. Paying close attention to maintenance is essential because it is a vital part of manufacturing. Industries have begun to recognize the importance of Predictive Maintenance (PdM) in reducing maintenance costs and achieving sustainable operational management. The core idea behind PdM is failure prediction, which allows for the scheduling of maintenance in advance of the expected failure. Maintenance management systems are typically built by facility managers using either reactive or proactive repair methods [5].

Related Work

The purpose of this article is to explore the potential of artificial intelligence methods and techniques in predicting when systems might fail and then performing maintenance tasks accordingly and promptly. Improvements in the administration of maintenance tasks are an oblique target of these investigations. Simulations and computational analyses using actual industrial data sets are the primary tools in the toolbox. The key findings demonstrate that a substantial quantity of trustworthy annotated sensor data and properly trained machine-learning algorithms are necessary for the efficient implementation of preventive maintenance. Companies of similar size and with varying production profiles should be able to use the solutions that have been developed through scientific and technological means. Here, even the article's relatively simple solutions can be useful, providing high efficiency with low implementation costs. A more lucrative bottom line is the outcome of the [7] method's reduction of production and maintenance expenses. This paper introduces an enhanced method of proactive upkeep for industrial machinery that utilizes ontology and machine learning. The goal is to identify trends in robot health, forecast when they will fail, categorize them, and then suggest maintenance jobs. By merging an ontology-based maintenance activity recommendation system with ML-based fault prediction, a hybrid maintenance system is created. In order to foretell when things will break down in the future, the ML model looks for outliers and trends. Based on these predictions, the ontology model suggests maintenance tasks. Predicting machine failures and optimizing strategies for upkeep to reduce costs and drawbacks of reactive along with preventive maintenance is the primary focus of the work. The ML-based approach is integrated in the ontology-based approach. The research in [8] examines the advancements and usefulness of machine learning techniques for preventative maintenance. Predictive maintenance utilizing machine learning techniques has been increasingly covered in publications, with the United States and China taking the lead. A traditional and well-structured approach to synthesizing material and reporting on pervasive fields of research was to use a mapping study, which utilized steady-state data until early 2019. In order to help new researchers place their research activities in the smart maintenance domain, the types of equipment, sensors, and information are mapped. In this paper, we will discuss data-driven techniques for predictive maintenance (PdM). We will provide a thorough overview of the methods and applications up until 2019, when we will comment on the stable proposal. One sign of a developing but still-in-its-infancy field of study is the apparent parity between assessment and verification studies. Furthermore, models and methodologies are the most common forms of contribution. Preliminary results from a case study on the creation of a machine learning (ML) system for PdM in railways are presented in [9]. Our plan to use log data to back up PdM is detailed here, along with the present maintenance process and logging platform. We have encouraging preliminary results. But they prove that sometimes, although the log dataset covers three years with three trains, it isn't enough to reliably deduce when maintenance is needed. We go over why rule-based, knowledge-driven strategies and methods for synthetic data generation are essential for fixing the issue. An intelligent method-based PdM planning framework is created in the article [10]. Data cleaning, data normalization, optimal feature selection, decision-making in the prediction network, and prediction are the five main phases of the developed method. Data cleaning while normalization are first applied to the PdM data in order to arrange it within a specific limit. After that, in order to cut down on unnecessary data, optimal feature selection is carried out. Combining the Jaya algorithm with Sea Lion Optimization (SLnO) yields the best feature selection results. It is challenging for deep learning and machine learning to produce accurate results due to the wide range of possible prediction values. Determining the prediction network's course of action thus requires a support vector machine (SVM). For the given range, the SVM finds the network that can make predictions. Lastly, a Recurrent Neural Network (RNN) is employed to complete the prediction. A hybrid J-SLnO is used to optimize the weight in the RNN.

Machine Learning for Predictive Maintenance

The term "machine learning tech" refers to a subset of AI technology. The development of algorithms and statistical models that allow machines to learn and make predictions is the core emphasis. Machine learning is an alternative to conventional programming that enables computers to learn from data, find patterns, and enhance performance automatically. Using ML for predictive maintenance, industrial equipment generates massive volumes of data, which are then analyzed. This is the process:

- **Data Analysis:** A data analytics service provider uses ML algorithms to interpret information gathered from sensors and tracking systems installed on machinery.
- **Pattern Recognition:** When data contains trends or abnormalities that might indicate equipment breakdown, AI and ML systems can spot them.
- **Predictive Insights:** With the use of machine learning's predictive algorithms, ML models may use observed patterns to foretell when machinery will break down or need servicing.
- **Continuous Improvement:** Machine learning (ML) for predictive maintenance systems is a continuous process that improves the accuracy of its predictions as more data is gathered.

Organizations may shift from reactive to proactive maintenance practices with the use of ML for predictive maintenance. Businesses may increase operational efficiency, save money, and get more use out of their equipment by using predictive maintenance solutions that use ML.

- State-of-the-art ML algorithms examine the equipment's real-time and historical data.
- ML algorithms detect trends, patterns, and outliers that might suggest problems or upcoming failures.
- Algorithms learn from maintenance data and previous equipment failures to reliably forecast when and where problems will arise.
- Maintenance staff can plan maintenance operations at the ideal moment thanks to advanced ML's predictive capabilities. This minimizes downtime and avoids unexpected malfunctions.

Key Machine Learning Techniques Used in Predictive Maintenance: Machine learning plays an enormous role in predictive analysis. Here are some of the most important machine learning (ML) methods for predictive maintenance and analysis.

Supervised Learning

In supervised learning, a labelled dataset is used to train the model. Here, a label for the final product is associated with each training sample. Machine learning (ML) for predictive maintenance makes use of supervised learning algorithms that make use of equipment historical data. To discover patterns and correlations, this includes historical failures and maintenance information. After training, the model may use its knowledge to forecast when things will break down in the future based on previously unknown data, giving maintenance crews a head start in preventing breakdowns.

Regression Models

Remaining usable life (RUL) is predicted using regression models using measurements for performance, environmental factors, and use hours as inputs.

- One useful tool is the decision tree, which can be used to predict when pieces of equipment are likely to break down. In order to ascertain whether a machine is highly susceptible to failure, a decision tree model examines factors such as temperature, vibration, and pressure.
- To more correctly evaluate failure risk, random forests take into account a wider variety of factors and how they interact with one another.

Unsupervised Learning

A subset of machine learning known as "unsupervised learning" makes use of unlabeled data. This method is designed to discover patterns and correlations within the data without any specific instructions. Anomaly detection using ML for maintenance planning is where unsupervised learning truly shines. Despite the lack of prior identification of such patterns, these outliers indicate the beginnings of equipment breakdown or other maintenance requirements.

Using clusters

Algorithms for clustering, such as k-means and hierarchical clustering, group data points that have similar characteristics. It may be used to classify various equipment operational conditions.

Finding Abnormalities

Finding data points that drastically differ from the norm is the goal of anomaly detection methods like autoencoders or isolation forests. Algorithms like these keep an eye on sensor data in the background, looking for any suspicious trends that may indicate trouble.

Main Component Analysis

Principal component analysis (PCA) is a method for reducing data dimensions by separating it into a number of orthogonal components. This exemplifies the diversity present in the data. Using it, we may simplify the data while keeping the important aspects.

Auto-Organizing Road Maps

A low-dimensional representations of data may be generated by using SOMs, a specific kind of neural network. When it comes to high-dimensional data visualization and finding clusters and anomalies, they really shine.

Reinforcement Learning

Another ML language is reinforcement learning, which teaches agents to optimize cumulative rewards via their behaviors in a given environment.

The RL method is based on the idea of learning the best tactics by making mistakes, as opposed to the supervised and unsupervised learning approaches.

To improve maintenance schedules, ML for forecasting repairs uses reinforcement learning to dynamically alter activities based on equipment condition and performance data.

Materials and Methods

In order to achieve the anticipated (needed) efficiency and productivity while eliminating failures, it is crucial to diagnose emergency events quickly and accurately. Nowadays, proactive or autonomous actions are the norm, rather than the exception, for ensuring uninterrupted production continuity. These actions make use of the latest technological solutions, such as programming, to allow for faster and more accurate diagnostics as well as continuous monitoring of the important parts of technical systems. When it comes to maintenance tasks that guarantee production continuity, the chosen medical sector business has certain criteria and expectations. Reason being:

- Technical facilities can be located up to 1000 m apart, which increases the UR response time and, in many cases, delays effective fault diagnosis.
- Short turnaround times for production orders (1-5 hours) mean that rescheduling the process is necessary in the event of a breakdown lasting more than 2 hours.
- The facilities are complex, necessitating intricate logistical activities related to things like spare parts, maintenance, and outsourcing.
- In a multi-shift manufacturing cycle, UR assistance is provided.
- The goal of this research is to help a specific company adopt predictive maintenance practices by doing the following.
- Analyzing past failures to determine what kinds of failures occurred, what caused them, and what maintenance was done;
- Investigating the possibility of using artificial intelligence to determine what causes failures and what maintenance is needed based on past data;

- Creating an autonomous surveillance system for a technological facility that allows for the automation of diagnostic procedures with AI.

In order to build the activities, information is first retrieved from the CMMS (Electronic Maintenance Management Systems), which are database that backs up the generally recognized Maintenance tasks. All sorts of maintenance-related events, including breakdowns, overhauls, inspections, and more, as well as management of maintenance staff and service documentation, are documented in the CMMS system.

The chosen business has long made use of a specialized CMMS system to facilitate maintenance management, which it has refined and adjusted to meet evolving organizational and production demands. There have been major changes to the system in the last few years concerning the management of inventories, materials and components, purchasing, handling of breakdowns, and repairs and upkeep tasks.

Neural Networks

An input layer, a hidden layer (or layers) of neurons, with an output layer are the standard components of an ANN. Assembled in an artificial neuron are inputs, weights assigned to each input, a bias added to the total of the weighted inputs, and an activation function that transforms the outcome into the anticipated output form (for instance, the sigmoid function for an identification value of 0 or 1).

Deep Neural Networks (DNNs) form the backbone of many cutting-edge and widely-used ML techniques; perceptrons are examples of neural networks having a single hidden layer, whereas deep learning refers to networks having many hidden layers. Deep neural networks, which are the building blocks of the machine learning methods we're going to go over, use a variety of layer topologies and mechanics tailored to the data and challenges at hand.

Results & Discussion

ANNs swiftly estimate research outcomes by directly transforming coded as well as normalized input information into output data using non-linear principles that combine outputs with inputs. Its use in a model allows for the prediction of the output state in response to deliberate or random changes to one or more parameter values. We validate later adjustments without requiring a new part or even the whole production line by extending the prototype to a digital twin, supplied automatically using data via the IIoT. This is made possible by the aforementioned issue framing.

Table 1: Selected ANNs accuracy assessment

Method	Accuracy (Learning) [%]	Accuracy (Testing) [%]
KNN	85.02	86.72
Naive Bayes	86.23	88.01
ANN	86.89	87.83
SVM	86.13	87.32
Decision Tree	85.11	86.89

Table 2: MSE values for the best MLP neural network

Network Name	RMSE
KNN	0.02
Naive Bayes	0.01
ANN	0.001
SVM	0.01
Decision Tree	0.02

Because the sigmoid function is quite versatile, it was used in all of the ANN layers in the model (Table 1). When different activation functions were applied to ANN, the results were noticeably poorer. ANN-based optimization, often known as the data-driven technique, offers quick and easy answers to classification problems without requiring complete understanding of the rules and processes. Incorporating new data, equipment, or manufacturing lines into untested data sets is possible, as is selecting training data.

Conclusion

Considering that accuracy does not provide complete information about the performance of ANN when utilizing a dataset that is uneven across categories is important when discussing ANN's efficiency and accuracy for each category. Since certain failure modes are naturally more prevalent than others, it seems that in this particular case-namely, when data is taken from an actual manufacturing line-we must tolerate a certain amount of data imbalance and the ensuing inaccuracy. Because this frequency is crucial to the algorithm's operation, it's not always feasible to artificially balance the data. In this case, the target system requires a framework for measuring the reliability of estimations based on the present professional expertise of technologists as well as engineers in the industrial area where the system is maintained.

In light of the findings and conclusions of earlier research, it is worthwhile to analyze and examine the obtained data from a more holistic viewpoint. Methods for creating, deploying, and updating maintenance solutions vary according on the data collected and the simulations used to derive conclusions and foretell problems. It is difficult to compare their findings with ours since the more than 30 research we found on AI/ML-based maintenance within the Industry 4.0 paradigm cover such a broad range of issues (eHealth devices, software bug detection, etc.).

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