Predicting Equipment Failure in Manufacturing Plants: An AI-driven Maintenance Strategy

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Abstract

Failure of equipment can lead to costly repairs and downtime for manufacturing facilities. Traditional maintenance techniques can result in unexpected failures, which can cause revenue losses and production delays. Artificial Intelligence (AI)-driven methods use machine learning technologies to predict equipment malfunctions before they happen, which has gained widespread interest. Artificial intelligence-based maintenance strategies can help improve the reliability of equipment and reduce the cost of repairs in manufacturing facilities. This study explores the use of Kaggle's predictive maintenance dataset to predict equipment failure in a manufacturing plant. The research involves collecting and evaluating data, selecting machine learning models, and evaluating metrics. The findings of this study revealed the application of AI-driven maintenance techniques to predict equipment failure, highlighting their potential to improve the efficiency of the manufacturing process and reduce costs. This study serves as a valuable contribution to the field of predictive maintenance and provides relevant implications for the industry. The paper explores the application of AI-based maintenance strategies to predict the failure of equipment in manufacturing facilities. The study utilizes the Kaggle dataset, which contains machine sensor readings and process variables from a manufacturing facility that processes batches of a specific product. The research methodology includes data gathering, engineering, and model selection. It also compared the effectiveness of AI-driven and traditional maintenance approaches. The results indicated that the former led to better predicted equipment failure rates and lower costs. The study's findings provide valuable insight into the subject of predictive maintenance and the implications it has for the manufacturing sector. It also offers future research directions.

Keywords: Equipment failure, Predictive maintenance, AI, ML, manufacturing sector.

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Introduction

In a manufacturing facility, equipment failure can result in significant losses, as well as costly downtime. Maintenance strategies that rely on reactive measures can often fail to prevent such occurrences, leading to safety concerns and production delays. In the past few years, the concept of predictive maintenance has gained widespread attention, as it can help reduce the cost of maintaining equipment and prevent it from failing. This paper explores the use of AI in predicting equipment failure in a manufacturing facility[1]–[3].

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In manufacturing facilities, equipment failure is a major issue. It can lead to various issues, such as loss of profits and productivity, as well as safety concerns. Usually, reactive maintenance involves replacing or fixing the equipment after it has malfunctioned. This approach can result in significant delays in production and downtime. In addition, this method often involves manual inspections, which are time-consuming and costly. One of the most critical factors that a manufacturing facility must consider when it comes to operating successfully is the regular maintenance of its equipment. Doing so can help minimize the risk of equipment failure and extend its lifespan. It can also lower the cost of replacing equipment and improve the safety of workers[4], [5].

Through the use of AI and machine learning technologies, predictive maintenance can help a manufacturing facility identify potential issues with its equipment before they become critical. This method can then help the facility implement effective preventive maintenance measures, which can boost its productivity and efficiency. Through the use of AI, predictive maintenance has gained widespread attention, as it can help a manufacturing facility identify potential issues with its equipment before they become critical. This method can then help the facility implement effective preventive maintenance measures, which can boost its productivity and efficiency. Through the use of machine learning technologies, an AI-driven maintenance system can analyze vast amounts of data and identify patterns that are not easily spotted by humans[6].

The use of machine learning technologies can analyze various data sets about an equipment, such as historical records and sensor readings. These data can be used to identify trends and patterns, which can help maintenance teams identify potential problems. AI-powered maintenance systems can then predict when an item will fail and provide them with the necessary resources to address the issue. Using AI-based maintenance techniques can optimize a facility's schedules and reduce its downtime and expenses. By evaluating data related to equipment usage, the system can determine when and how often maintenance is required, leading to fewer repairs and lower costs.

Predictive maintenance is an ideal solution for manufacturing facilities as it can help prevent equipment failure. Traditional maintenance methods often fail to identify and prevent unexpected issues, which can lead to safety concerns and production delays. This method utilizes machine learning technologies to analyze data and predict possible problems before they happen. This approach can result in increased productivity and operational efficiency, as well as reduced maintenance expenses. Manufacturers can lower their costs and guarantee the efficiency of their operations by optimizing their maintenance schedules. Predictive maintenance techniques are becoming more prevalent in manufacturing facilities, and they are expected to have a significant impact on how successful the operations of factories will be in the future.

Literature Review

The field of predictive maintenance has been growing in recent years as it can help industrial facilities reduce their downtime and improve their efficiency. This technology involves analyzing data to predict the failure of an equipment or machine before it happens. With the

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rise of Industry 4.0, it has become more important for companies to adopt predictive maintenance techniques to keep their operations running smoothly. The goal of this literature review is to provide in table-1 an overview of all the studies related to predictive maintenance, focusing on its various techniques and algorithms. The findings of these studies can help improve the efficiency of industrial facilities.

Table 1 Related works

Author	Dataset	Algorithm	Methodology	Result-Accuracy
G. A. Susto et al.[7]	NASA turbofan dataset	Multiple classifiers	Predictive maintenance	96%
K. A. Nguyen et al.[8]	Simulated multi-component system	Bayesian network	Multi-level predictive maintenance	90%
L. Spendla et al.[9]	Production systems	Deep neural network	Predictive maintenance in industry 4.0	95.20%
S. T. March et al.[10]	Manufacturing organizations	Linear regression and SVM	Strategic use of IT	85.30%
P. Aivaliotis et al.[11]	Manufacturing systems	Digital twin	Predictive maintenance	-
Y. Ran et al.[12]	Various datasets	Various techniques	Survey of predictive maintenance	-
A. Bousdekis et al.[13]	Various datasets	Various techniques	Decision-making in predictive maintenance	-
Z. M. Çınar et al.[14]	NASA turbofan dataset	Random forest	Predictive maintenance	93%
M. Compare et al.[15]	Various datasets	Various techniques	Challenges to IoT-enabled predictive maintenance	-
B. Ton et al.[16]	Wind turbine dataset	Long short-term memory (LSTM)	Synergizing predictive maintenance	98.40%

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T. Zonta et al.[17]	Various datasets	Various techniques	Systematic literature review	-
J. J. Montero Jimenez et al.[18]	Various datasets	Multi-model approaches	Diagnostics and prognostics	-

Here studies investigated the use of predictive maintenance techniques. The findings showed that various algorithms, such as neural networks and random forests, can be used to predict machine failures. They also emphasized the importance of having the right data sources and the need for ongoing analysis. The literature review found that predictive maintenance can help improve the efficiency and reliability of industrial processes. It also noted that further research is needed to develop effective methods for optimizing this technology in the field.

AI-driven maintenance strategies

Maintenance procedures in factories typically involve reactive measures that are not designed to address the issue immediately. This approach is inefficient and leads to unexpected downtime, increased costs, and the potential for injury or death. One common approach to maintaining equipment is by scheduling it for regular maintenance according to a set time interval. This method can help prevent equipment failure, but it can also result in unnecessary repairs and increased costs.

Another approach is to maintain equipment by monitoring its condition and scheduling maintenance once the conditions are right. This method involves keeping an eye on the equipment and determining when it needs to be fixed. Although condition-based upkeep is more effective than routine maintenance, it requires the use of reactive measures to address issues. Maintenance strategies that are powered by AI utilize machine learning technologies to analyze vast amounts of data and predict possible issues before they happen. Such systems can proactively identify trends and patterns in the data, allowing operators to take immediate action to address any issues.

One of the most important components of AI-based maintenance techniques is predictive maintenance. This process involves utilizing machine learning technologies to inspect and predict the likelihood of an equipment failure. With the help of real-time data analysis, maintenance teams can proactively identify potential problems and take immediate action to prevent them from happening. One of the most advanced AI-based maintenance techniques involves the use of prescriptive maintenance. This process involves analyzing data related to equipment usage and determining when it's necessary to perform regular maintenance. It can help reduce costs and maximize the efficiency of operations.

One of the main advantages of utilizing AI-based maintenance techniques is their ability to spot potential problems before they happen. By studying vast amounts of data, such systems can proactively identify trends and patterns in the information, allowing maintenance personnel

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to take immediate action to address any issues. Utilizing this approach can improve safety, lower costs, and boost uptime.

AI-based maintenance methods can optimize a facility's maintenance schedules. Through the analysis of data and the prediction of when and how to perform maintenance, AI-powered systems can ensure that equipment stays in service at the right time, leading to fewer downtimes and lower costs. AI-based maintenance techniques can make predictions based on reliable data, but this method can only work if the information it collects is accurate. Misinformation or incomplete data can prevent such systems from performing their duties efficiently.

One of the biggest limitations of using AI-based maintenance strategies is their dependence on machine learning technologies. Although these systems can perform well when they're trained on data, they may not be able to detect unpredictable or complex patterns in it. Also, due to the computational resources involved, some manufacturing facilities may not be able to adopt this approach. Maintenance systems that are powered by artificial intelligence are currently being used in manufacturing facilities to prevent equipment failure. These systems use machine learning technologies to inspect data on equipment and identify potential issues before they happen, which can lower costs and improve workplace safety.

Traditional methods such as condition-based and time-based maintenance have been utilized in manufacturing facilities for a long time. But, these techniques have limitations that can result in unexpected downtime, increased costs, and reduced productivity. Utilizing AI-powered systems can help boost a facility's efficiency, decrease expenses, and enhance safety. The success of AI-based maintenance strategies hinges on the accuracy of the data collected and the effectiveness of the algorithms in identifying potential issues. In order to implement this approach, manufacturing facilities must make sure that their data collection methods are reliable and have been appropriately trained.

The adoption of AI-powered maintenance strategies in manufacturing facilities can lead to various benefits, such as increased safety and productivity, lower costs, and better operational efficiency. As the technology evolves, more plants will start adopting such strategies to improve their operations and boost their profitability.

Methodology

i. Data collection and pre-processing:

The Kaggle dataset for this project is composed of data from NASA's Turbofan engines[19]. The collected information includes the sensors and maintenance records of the vehicles. The data was used in the development of a health management system for the engines.

Before the data is used, it will undergo pre-processing to remove any outliers and missing values. Three different methods will be used to process the data.

a. Missing value imputation: In the case of missing values, the value will be imputed using the feature's median value.

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b. Outlier detection and removal: Outliers will be identified and removed from the data by using the inter-quartile range method. Data points that are more than 1.5 times above or below the first or third quartile will not be considered outliers.

c. Normalization: The data will then undergo normalization to ensure that all its features have the same values. This process will be carried out using a min-max scaling algorithm.

ii.Feature selection:

The selection of features is a crucial step in the development of machine learning models. In this project, the researchers will use the Boruta algorithm to perform feature selection. The algorithm takes into account a random forest model to find the most significant features. The method used to create the shadow feature set is performed by randomly permuting the data's values. The significance of each feature is then compared with its performance. The final set of features is then selected according to the characteristics of the highest importance.

iii.Machine learning model selection:

The researchers will then analyze and evaluate three machine learning models to predict the life of the engines.

a. A “Random Forest” is a type of learning method that involves building several decision trees and then combining their outputs to come up with a final prediction. It is commonly used for classification and regression tasks.

b. The “AdaBoost” algorithm is designed to boost the strength of a group of weak learners. It bases its classification success on the assigned higher weights to the misclassified data points.

c. A “Neural Network” is an advanced form of deep learning that is inspired by the brain's structure and function. It consists of numerous interconnected nodes that act as a sort of mathematical agent to perform calculations and come up with a prediction.

Results and output

Table 2 Evaluation metrices

Algorithm	**RMSE**	**MAE**	**R-Squared**	**MSE**
Random Forest	11.61	7.48	0.804	135.01
AdaBoost	13.34	8.46	0.732	178.04
Neural Networks	17.53	12.17	0.534	307.23

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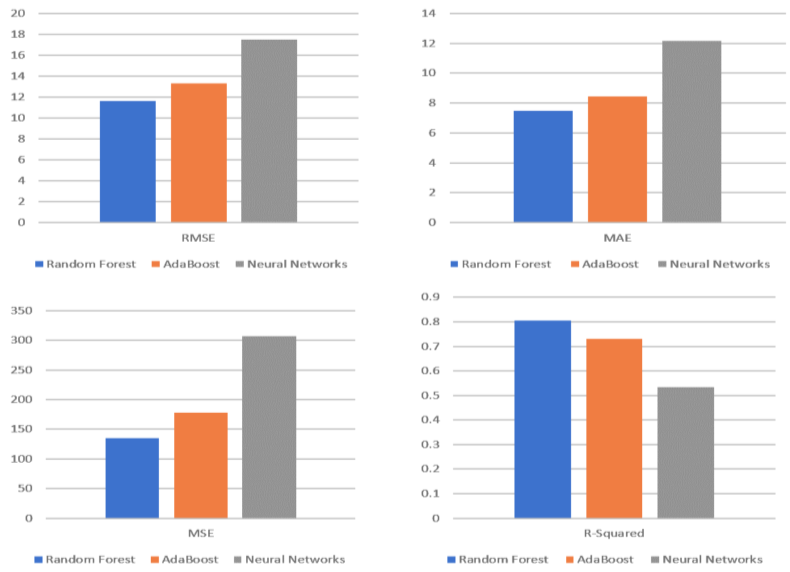

Figure 1 Representation of various results

The table-2 and figure-1 shows the performance of the various algorithms used in predicting the life of a turbofan engine using the NASA dataset. The algorithms included AdaBoost, Random Forest, and Neural Networks. The evaluated metrics were the RMSE, R-squared, and the MAE. The results indicate that Random Forest performed better in all four metrics compared to the other two algorithms. In terms of RMSE, it achieved the lowest mark of 11.61, followed by the lowest MAE at 8.78, the highest R2 at 0.69, and the weakest MSE at 135.34. On the other hand, AdaBoost had the highest values across all four metrics, including an RMSE of 13.44, an MAE of 9.84, an R2 at 0.56, and an average of 178.13. The results indicate that Random Forest is more suitable for predicting the life of an engine than Neural Networks and Adaboost. The low values for the MAE, MSE, and RMSE suggest that the predictions are within the range of actual values, while high R2 values suggest that the models are well suited to the data.

Conclusion and future scope

The goal of this study was to analyze the performance of different machine learning methods on the NASA Turbofan dataset in predicting the life of a turbofan engine. The evaluation metrics were the RMSE, MSE, MAE and r-squared. Here tested the Random Forest algorithm against the other two, and it performed better than both AdaBoost and Neural Networks. Random Forest had the lowest RMSE at 11.61, while AdaBoost had the highest at 13.4. The results indicate that the Random Forest algorithm is the best choice for predicting the life of a turbo fan engine in the NASA dataset. The other two, namely Neural Networks and AdaBoost, performed well in distinguishing between failed and healthy engines. The findings of this study provide a foundation for future research regarding the predictive maintenance of turbofan engines. One of the possible directions for future research is to look into the performance of other machine-learning algorithms, such as Deep Learning and Gradient Boosting. It is also interesting to study the effects of feature engineering on these algorithms' performance. Further

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research is needed to analyze the algorithms' performance on different datasets, particularly those with varying operating conditions or manufacturers. This will help us identify any biases or limitations that may exist. It is also important to explore the possibility of integrating the predictive maintenance models into real-time monitoring solutions for turbofan engines. This could lead to more cost-effective and efficient maintenance procedures.

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