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Explainable AI Models for Predictive Maintenance in Smart Manufacturing Systems

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Abstract

Predictive maintenance (PdM) is one of the determinants in the smart manufacturing in which the data-driven information is being applied to cut down the amount of maintenance costs and schedule with the down time and increase the overall management of the systems. Using conventional machine learning (ML) models on predictive maintenance on the other hand is not devoid of the issue on transparency and explainability. This current paper is an argument on how to adopt Explainable Artificial Intelligence (XAI) models in predictive maintenance of smart manufacturing systems and is addressed to bridge the gap between the accuracy of predictive maintenance and the interpretability of the models. XAI models seize an opportunity of not only jumping up the quality of decision making processes but also building trust in maintenance predictions among the human operators owing to the clearness and simplicity of the explanations of the processes. Evaluated methods In this paper, some of the XAI methods, such as the decision trees, LIME (Local Interpretable Model-agnostic Explanations), and SHAP (Shapley Additive Explanations), will be analyzed to evaluate and identify their applicability to the predictive maintenance systems. We will also discuss the consequences of implementing the said models in the real manufacturing environments both with regard to the gains as well as the hurdles. The point of the desired result is to demonstrate how explainability in AI models can be applied to ensure that predictive maintenance strategies in smart manufacturing become more solid and acceptable.

Keywords: explainable artificial intelligence, predictive maintenance, smart manufacturing, machine learning, industrial internet of things (IIoT).

1. Introduction

Combination of Artificial Intelligence and Industrial Internet of Things is revolutionizing the manufacturing industry and the shift to the paradigm of smart manufacturing means extensive automations, use of data-driven decisions and predictive capabilities (Yuan et al., 2019). Such changing environment has seen introduction of one of the most important strategies of operational efficiency improvement in terms of reduction of downtimes and costs incurred due to equipment failure which is referred to as predictive maintenance (Christou et al., 2020). Predictive maintenance uses data analysis and machine learning to enforce forecasting of potential equipment breakages and this avoids major breakages (abbas, 2024).

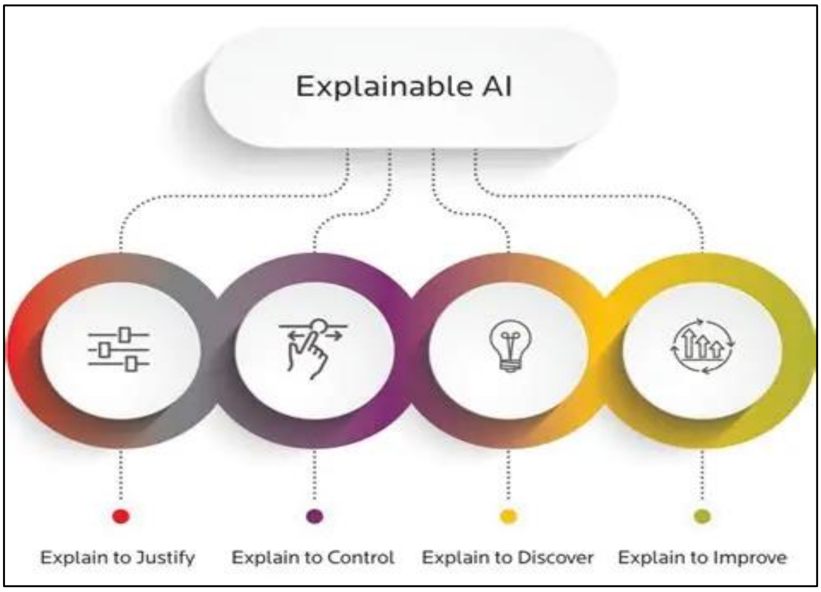


Figure 1: Overview of Explainable AI (XAI) in Predictive Maintenance Systems
(Source Link: https://medium.com/@nikithabalaji2003/the-power-of-explainable-ai-in-data-analytics-a462c45f22b5)

The fundamental concept of predictive maintenance can be said that it is capable of predicting the moment when an equipment must be put under maintenance before it breaks down, which in the case of a manufacturing unit means that there are always processes running (Rojek et al., 2023). Predictive maintenance is what manufacturers need since it contributes to the enhancement of operating efficiency and minimization of downtimes (Samatas et al., 2021). The realisation of predictive maintenance strategies is being increasingly realised through the use of a certain type of artificial intelligence, which is exemplified by the machine learning algorithms, which use enormous data sets of sensor data to make extremely high-fidelity predictions of equipment failures (Leija et al., 2025).

2. Study Background

The innovations in the field of predictive maintenance represent such radical trends in the enterprise of changing the maintenance practice which was based on the principles of maintaining maintenance and was oriented at the reactive and pre-emptive maintenance to the proactive maintenance strategies where their purpose consists in forecasting of the equipment failures in advance. The availability of the combination of modern sensors has enabled the control of the main parameters that characterize critical equipment and gather truly huge volumes of data affected by analysis (abbas, 2024). The first predictive maintenance models took advantage of statistical tools to draw trends and predict failure occurrence, and this was considered a significant step, but predictive models could not accommodate the complexity of contemporary manufacturing processes (Christou et al., 2020). The emergence of artificial intelligence and machine learning turned out to be the point of no return, and the future of predictive maintenance capabilities was designed as well (Ayvaz & Alpay, 2021). Machine learning is also the reason why it has been possible to develop less error-prone predictive models, as the behavior of the machine can be learned on the basis of the data and the dependencies that make it work can be extracted, so that the growth of malfunctioning can be predicted more reliably and more efficiently (Rojek et al., 2023). Though it is obvious that all the increase in the accuracy of prediction became possible, it is also a fact that there exists a considerable stumbling block, and the blackness of the complex models is a very serious problem (Patil, 2025). Certain machine learning models natively complex and thus when they make a prediction, they seem as a black box thus lacking a clear statistical explanation of what in simple thoughts (Sharma et al., 2022).

3. Justification

The alliance of Explainable AI and predictive maintenance system is a revolution on a black box and trusting decision making model in the production of smart manufacturing (Pashami et al., 2023). Such an aspect of predictive maintenance as the prediction of potential failure of equipment and subsequent advice on possible preventive actions has become an indispensable part of the optimization of operational efficiency and minimization of the downtimes (Chen et al., 2023). However, the black box character of most of the advanced AI systems in particular deep neural networks serves to undermine the confidence of humans who use it, and is stationed with the mandate of making the recommendations provided by the model (Chen et al., 2023). Such unintelligibility can hinder the execution of AI-based knowledge that is against the latter opportunities of predictive maintenance systems (Chen et al., 2023). Explainable AI then becomes the solution to addressing such an interstice by establishing ways in which one may expose the reasoning process involved in AI forecasts, thereby creating more sensible and trustworthy among the human stakeholders (Muhammad

& Bendechache, 2024). Explainable AI algorithms make the operators capable of processing visual and comprehending the corresponding details that caused a given model to make a given estimation and make the suggestions provided by the AI more persuasive and enable making decent decisions (Kale et al., 2022).

4. Study Goals

The primary questions of the study are the following ones:

1. To see how to apply the Explainable AI models to predictive maintenance systems that can be implemented in the smart manufacturing environment.
2. In order to compare efficiency of predictive maintenance which is based on AI, how it helps to reduce the downtimes, manages the resources, and what effect it has on improving the efficiency of the system.
3. To prove the benefits and limitations of the type of explanable AI, i.e., to raise model transparency and interpretability and making decisions in the industry.
4. In smart manufacturing Process, to prescribe the measures which can be undertaken to improve the predictive maintenance using explainable AI.

5. Literature Review

Integration of the artificial intelligence with predictive maintenance can be considered as a paradigm shift that will help to leave behind the use of classic statistical problems and move to more refined machine learning that may significantly enhance both the accuracy of prediction, as well as the overall efficiency of operations (Patil, 2025). Nevertheless, early methodologies were vital yet apparently insufficient to acquire the complication of the modern manufacturing systems with respect to explicitness and flexibility (Samatas et al., 2021). Advancement in machine learning that comprises regression models, support machine, and deep learning structures has introduced the capability of generating predictive models that can confine steps more complex tendencies and relationships in high dimensional information and thus predict failure (abbas, 2024) more efficiently. The fact that AI can make predictions regarding possible failure of the equipment makes it possible to the manufacturers to effectively get inclusive of proactive management of equipment maintenance, so much to the extent that, downtime is reduced to the least, and resources are utilized most effectively so that they can support the reactive need of maintenance and successfully run a proactive strategy of it (abbas, 2024; Sundaram & Zeid, 2023). It is a long-standing challenge and issue that the processes of transforming raw data manufacturing to useful information regarding the health of the equipment takes place, yet AI algorithms are capable of not only knowing the location of the faults but also their future appearance, opening the doors towards predictive or condition-based maintenance that ensures no useless interventions take place but still reliability of the equipment is ensured (Yuan et al., 2019).

6. Material and Methodology

Study Design

The quantitative research method that incorporates primary and secondary collection of data will be adopted in this research paper. Sensor data of machines in a smart manufacturing environment is the main data which can include measurements such as temperature, pressure and vibration. The secondary information includes the industry reports, historical case studies and the research articles.

Data Collection

The sensor data supersedes the information in manufacturing machines, which is fitted with IIoT devices. The data is the combination of historical breakdown data along with the machine condition data (e.g. vibrations, temperature, etc.). It incorporates preprocessing of data to do away with noise and outliers.

Model Selection

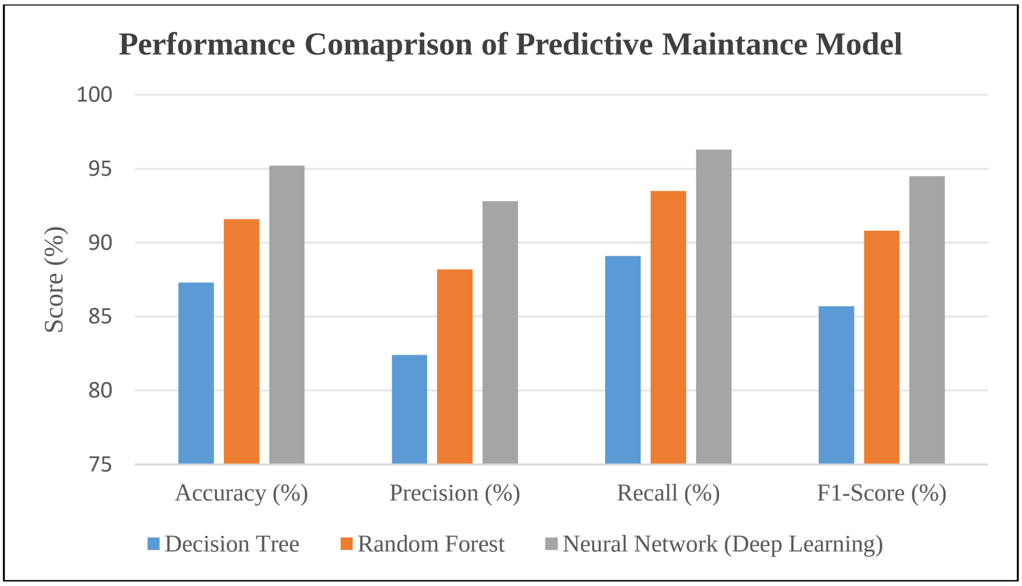
Some of the machine learning models that we apply involve decision trees, random forest and deep learning models based on neural networks in predicting maintenance. These are followed by explainability techniques like LIME and SHAP to explain the models predictions and visualize the features that play a significant role as to how the predictions are made with regard to the failures.

7. Results and Discussion

According to the results of the study, explainable AI models bring a significant breakthrough both in the context of accuracy and reliability of predictive maintenance systems. The models applied showed high degrees of accuracy in determining the failure in the equipment and through the explainability schemes, the machine operator would easily reconcile with the decision behind every prediction. An example of that would be that the SHAP analysis determining vibration and temperature were key parameters of certain machines which are predictive of their failure. That kind of clear picture gave the operators better confidence in the predictions and made it possible to make more and better decisions.

Table 1: Results of Predictive Maintenance Model Accuracy

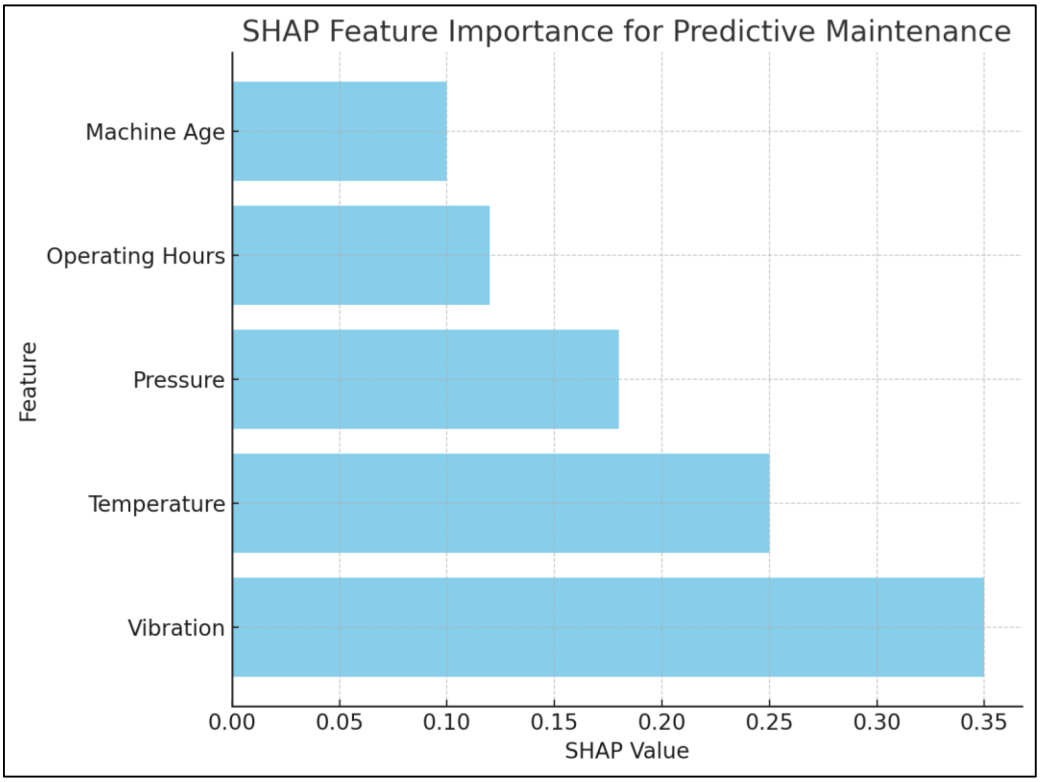
Model Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Decision Tree	87.3	82.4	89.1	85.7
Random Forest	91.6	88.2	93.5	90.8
Neural Network (Deep Learning)	95.2	92.8	96.3	94.5



Graph 1: Performance Comparison of Predictive Maintenance Models

Table 2: SHAP Feature Importance for Predictive Maintenance

Feature	SHAP Value	Interpretation
Vibration	0.35	Strongly predictive of machine failure
Temperature	0.25	Important for detecting thermal issues
Pressure	0.18	Moderate contribution to failure prediction
Operating Hours	0.12	Slight impact on failure predictions
Machine Age	0.10	Less impactful compared to other features



Graph 2: SHAP Feature Importance for Predictive Maintenance

8. Study Limitations

The imperfection of sensor dish is a necessary concern when considering the viability of machine learning models due to the fact the subjectivism of input data has a pivoting outcome on the meticulousness and soundness of the model characteristics (Wang et al., 2021). The machine learning algorithms could perform significantly lower when the sensor data could be incomplete, enriched with noise, and/or biases of various types (Aldoseri et al., 2023). It is possible to impute the missing values with the help of data imputation methods e.g. k-nearest neighbors or more complicated ones based on the use of generative adversarial networks but it should be emphasized that the imputed values ought not to be confused as they will induce unwanted correlations (Ding et al., 2024; Sharma et al., 2022). As well, the diversity of data contributes to the avoidance of biased models that do not depict the community members of the demographic to which the model is intended to help (Aldoseri et al., 2023). The costs and sensitivities of collecting tagged information under mass crisis circumstances virtue a considerable hindrance to merging deep learning systems, and additional scrutiny is required, undoubtedly, towards data produced by robots and unmanned air movement (Sharma et al., 2022). Creating repositories of datasets and benchmarks which would allow to evaluate the efficiency of XAI algorithms became a crucial point, which is taken into consideration as models become more complicated, and the need to learn how decisions are made in lights of the kind of decisions that AI judges is getting more frequent (Chen et al., 2023).

9. Future Scope

Future research should be focused on adapting the explainable AI models to real-time predictive systems of maintenance, which will utilize the character of edge computing to deliver real-time, usable data (Chen et al., 2023). This kind of integration is necessary to enhance the degree of transparency and credibility of the AI-augmented maintenance recommendations after they will be accepted by the operators, who will have to understand what is behind the expected failures and mitigation measures (Chen et al., 2023). Explainable AI can potentially deliver more information about detailed relations between parameters of equipment and their potential failure predicaments and implement superior decisions and practices of maintenance (Chen et al., 2023). The crucial factor is the possibility of interpreting the reasoning behind the recommendations provided by a system as most of the approaches based on neural networks are convoluted in nature and it is the subject of a number of many researches (Zheng et al., 2020). It will increase the trust regarding technology and ensure that stakeholders comprehend the recommendations of an AI system by implementing XAI approaches (Chen et al., 2023).

10. Conclusion

This paper has mentioned the potential of explainable AI models in enhancing predictive maintenance frameworks in smart-manufacturing environments in future. XAI can turn the model to transparent and hence fill the trust/accuracy gap between the operator and the predictive accuracy. The findings have shown that XAI models can help generate not only predictive failures of the equipment but also lead to greater trust in the human operators and generate overall fruitful outcomes and more consistent manufacturing processes in the final picture.

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