

***DESIGN AND EVALUATION OF AN EXPLAINABLE
ARTIFICIAL INTELLIGENCE FRAMEWORK FOR PREDICTIVE
MAINTENANCE IN SMART MANUFACTURING USING
MACHINE LEARNING MODELS***



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Abstract

Industry 4.0 has been developing at a rapid pace, turning traditional manufacturing into smart, linked and data driven production environments. Smart factories increasingly depend on Industrial Internet of Things (IIoT) sensors, Artificial Intelligence (AI), cloud computing and cyber-physical systems to monitor equipment performance and support operational decision making. Predictive Maintenance (PdM) is an important paradigm in this context to minimise unplanned downtimes, improve machine dependability and optimise maintenance costs by anticipating equipment breakdowns before they occur. [1], [2]

Despite the strong predictive capability of Machine Learning (ML) models in maintenance applications, many high-performing models operate as black-box systems. This creates a huge challenge in manufacturing as maintenance engineers need to be able to understand before making decisions affecting safety, cost and production continuity. Hence, prediction accuracy alone is not sufficient for practical industrial use. [5], [6]

In this study we present an Explainable Artificial Intelligence (XAI) framework for predictive maintenance in smart manufacturing based on ML algorithms. The framework will contain algorithms like Random Forest, XGBoost, LightGBM, Decision Tree and Support Vector Machine along with explainability methods such as SHAP and LIME. The study will be conducted inside Design Science Research and will assess the framework with datasets and metrics for predictive maintenance, such as Accuracy, Precision, Recall, F1-score and ROC-AUC. The expected result is a transparent, reliable and trustworthy AI-based maintenance framework that supports better industrial decision making. [8], [10], [13]

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1. Introduction

1.1 Context and Background

Industry 4.0 is the integration of Artificial Intelligence, Industrial Internet of Things, cloud computing, cyber-physical systems and big data analysis that has transformed traditional industrial processes into intelligent, interconnected and data-driven production systems. The technologies provide manufacturers with real-time visibility into how their machines are performing, helping them to improve their production processes and make data-driven decisions. Smart manufacturing has therefore helped improve efficiency of operations, quality of products and utilisation of resources while lowering costs of production and downtimes of equipment. [2], [10], [13]

Among the most important Industry 4.0 applications is Predictive Maintenance (PdM), which combines sensor data and machine learning algorithms to predict equipment breakdown in advance. Predictive maintenance varies from reactive or preventive maintenance in that it is always checking the status of the machine. It does this by sensing characteristics including temperature, vibration, pressure, torque and tool wear. This means that maintenance measures can be performed exactly when they are needed. This proactive method contributes to reliability of equipment, cutting down unexpected breakdown and enhancing production continuity. [1], [5], [7]

Recent breakthroughs in Machine Learning (ML) further enable predictive maintenance through intelligent analysis of vast industrial data sets. In equipment defect diagnostics, various algorithms such as Decision Tree, Random Forest, Support Vector Machine (SVM), XGBoost and LightGBM offer strong predictive performance. However, many of these models are black box systems which make it difficult for maintenance engineers to grasp the logic behind the prediction results. The lack of transparency limits user trust and the practical implementation of AI-driven maintenance solutions. [5], [6], [11]

To overcome this problem, the Explainable Artificial Intelligence has become an important study area that enhances the transparency and interpretability of machine learning algorithms. To enable users to comprehend the aspects that influence the prediction results, explainability techniques such as SHAP and LIME are employed, thus facilitating more dependable maintenance decisions.

Hence, this research proposes Explainable Artificial Intelligence Framework for Predictive Maintenance in Smart Manufacturing utilising Machine Learning based Models to improve the prediction accuracy, model transparency and industry confidence. [8], [10], [13]

1.2 Research Problem

Despite the significant advances in Machine Learning for predictive maintenance, many current systems remain difficult to interpret as they are black-box models. These models can accurately predict the failure of equipment but do not provide information on how the prediction is made or which operational parameters affect the final decision most. The lack of transparency decreases the confidence of maintenance engineers in AI-supported decision making and hinders the deployment of intelligent maintenance systems in industrial environments. [5], [6], [10] Although Explainable Artificial Intelligence (XAI) techniques have recently gained popularity, most current research applies these methods as standalone interpretative tools, instead of integrating them into a comprehensive predictive maintenance framework. Hence, there still exists a big research gap to develop an explainable framework with higher transparency and predictive accuracy as well as reliable maintenance suggestions. [8], [10], [13]

1.3 Research Aim and Objectives

Research Aim

The goal of the project is to design, improve and assess an Explainable Artificial Intelligence (XAI) framework for Predictive Maintenance in Smart Manufacturing utilising standard Machine Learning algorithms. Specifically, the suggested framework enhances the accuracy of forecasts and the transparency of models and the decision-making process for maintenance in Industry 4.0 settings, combining advanced machine learning algorithms with SHAP and LIME explainability methodologies.

Research Objectives

The following aims are put forward to achieve the aim of the research:

- Perform a critical analysis of current literature on Industry 4.0, Predictive Maintenance, ML and Explainable Artificial Intelligence to identify recent developments and gaps in the research.

- Design and create a comprehensive Explainable Artificial Intelligence framework employing machine learning algorithms and interpretability techniques such as SHAP and LIME.
- To execute and evaluate Random Forest, Decision Tree, Support Vector Machine (SVM), LightGBM, and XGBoost utilising benchmark predictive maintenance datasets.
- To evaluate the proposed framework using predictive performance metrics and explainability analysis to determine its suitability for industrial maintenance decision-making.

1.4 Significance of the Research

This research addresses the need for transparent, interpretable, and trustworthy Artificial Intelligence in predictive maintenance. By integrating Explainable Artificial Intelligence with machine learning models, the proposed framework seeks to improve both prediction accuracy and decision transparency. [5], [8], [10]

Academically, the study contributes by integrating Predictive Maintenance, Machine Learning, and Explainable Artificial Intelligence into a unified framework while addressing current research gaps. Industrially, the framework is expected to support maintenance engineers through interpretable failure predictions, leading to reduced downtime, improved maintenance planning, and enhanced equipment reliability. Ultimately, the research proposes the deployment of trustworthy AI for smart manufacturing environments of Industry 4.0. [2], [10], [13]

2. Literature Review

2.1 Introduction to the Literature Review

In this literature study aims critically analyse the existing body of knowledge on Industry 4.0, Smart Manufacturing, Predictive Maintenance (PdM), Machine Learning (ML), and Explainable Artificial Intelligence (XAI). The aim of this chapter is to analyse existing studies, highlight major technical breakthroughs, appraise current methodologies and show research gaps that support the

proposed study. The review is not a descriptive account, but a critical comparison of prior studies to establish the theoretical and technological basis for the proposed research. [1], [2], [10]

The study primarily examines peer-reviewed journal articles and conference papers published between 2020 and 2025. Several seminal works that presented explainability methodologies, such SHAP and LIME, are also incorporated. The literature is structured thematically, encompassing Industry 4.0, predictive maintenance, machine learning algorithms, and explainable artificial intelligence, followed by an examination of the limitations of existing research. This framework allows the proposed research to be situated within the current body of knowledge while simultaneously showcasing its originality and scholarly contribution. [8], [10], [13]

2.1.1 Literature Search Strategy (PRISMA 2020)

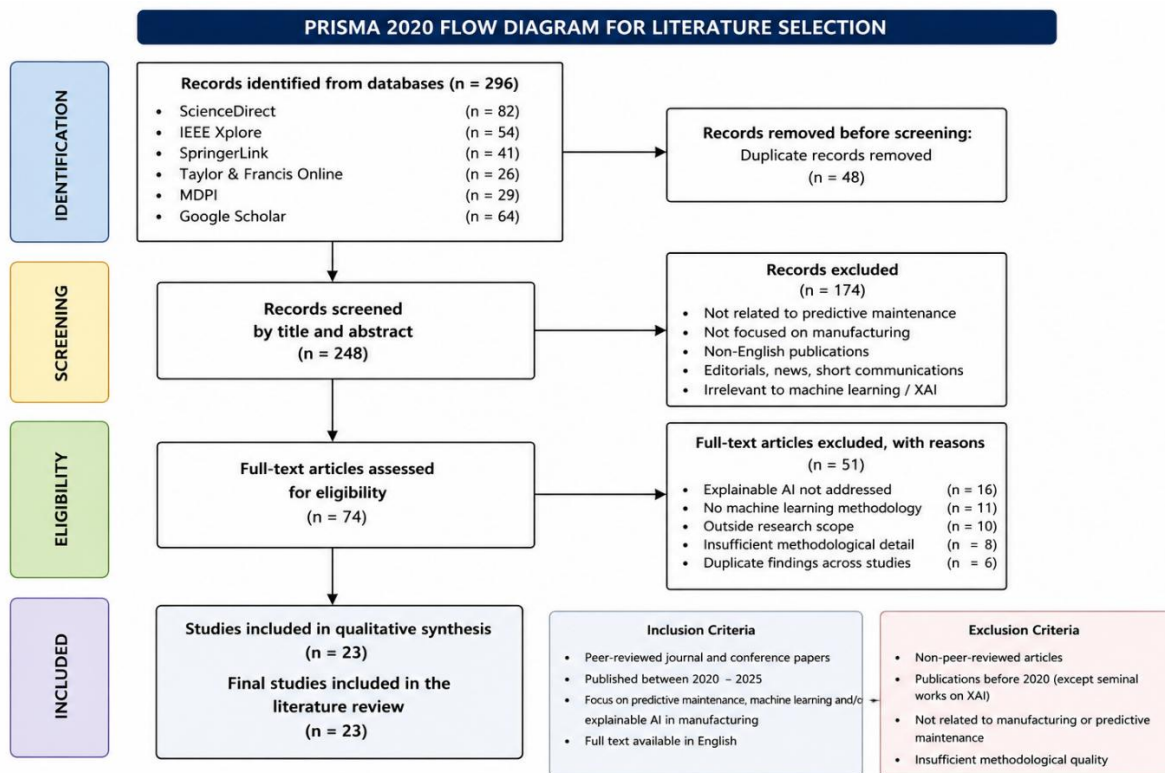


Figure 1. PRISMA 2020 flow diagram illustrating the systematic literature search and study selection process.

2.2 Industry 4.0 and Smart Manufacturing

Industry 4.0 has revolutionised the manufacturing industry by integrating advanced digital technologies, such as the Industrial Internet of Things (IIoT), Artificial Intelligence (AI), Cyber-Physical Systems (CPS), cloud computing, and big data analysis, into the production environment. These technologies enable real-time communication between information systems, sensors and machines, allowing manufacturers to improve operational efficiency, optimise resource utilisation and monitor production processes. Industry 4.0 has thus laid the basis for Smart Manufacturing, which enables the development of autonomous, intelligent and flexible production systems, able to adapt to the changing requirements of the industrial sector. [2], [10], [13]

Smart Manufacturing extends traditional automation, enabling manufacturing systems to continuously collect, process and analyse operational data. The proliferation of the IIoT sensors provides real-time information on the machine conditions like temperature, vibration, pressure, rotational speed, and energy consumption. This data enables the development of intelligent applications such as predictive maintenance, quality monitoring, process optimisation and production scheduling. Past research has shown that the combination of AI with Industry 4.0 technologies greatly improves productivity, equipment reliability, and maintenance efficiency. [1], [5], [8]

However, several researchers argue that cybersecurity, data quality, system interoperability, and the limited transparency of AI-based decision-making are still significant challenges for current smart manufacturing systems even with these improvements. As current research focuses primarily on the automation and prediction performance, relatively little effort is spent on the development of trustworthy and understandable AI solutions that support human decision making. Thus, Explainable Artificial Intelligence (XAI) integration into smart manufacturing is a vital research direction that can boost industrial trust and facilitate the adoption of responsible AI. [6], [10], [13]

2.3 Predictive Maintenance

Predictive Maintenance (PdM) is a major use of AI in Smart Manufacturing that enables to foresee equipment failures before they happen. Reactive Maintenance is repairing machinery after it has

broken down. Preventive Maintenance is a scheduled maintenance. Predictive Maintenance constantly monitors the status of the equipment utilising real time sensor data . This proactive strategy leads to better availability of equipment, less unplanned downtime, fewer maintenance costs, and longer machine life, making it an important part of Industry 4.0 manufacturing systems. [1], [2], [7]

In recent years, Machine Learning (ML) has significantly enhanced predictive maintenance by smartly analysing industrial sensor data, including vibration, temperature, pressure, rotational speed and tool wear. Machine learning algorithms can identify complex degradation patterns and find early indicators of equipment failure that are hard to detect using traditional statistical methods. The efficacy of AI-based predictive maintenance has been proved through different studies in enhancing the fault detection accuracy, maintenance scheduling, and operational efficiency of various manufacturing industries. [5], [6], [10]

Despite these advantages, existing predictive maintenance systems face many challenges. Many studies primarily focus on improving prediction accuracy, but do not sufficiently consider model transparency, interpretability, and user trust. High-performing machine learning algorithms are often black-box systems, which makes it hard for maintenance engineers to understand why they produce certain prediction results. This constraint leads to a loss of trust in AI-supported maintenance decisions and slows down the practical adoption of intelligent maintenance technologies. Thus, the integration of Explainable Artificial Intelligence (XAI) into predictive maintenance has become an important research focus in the development of transparent and trustworthy industrial decision-support systems. [8], [10], [13]

2.4 Machine Learning Models for Predictive Maintenance

Machine Learning (ML) has become the core technology to realise Predictive Maintenance (PdM) for the smart analysis of industrial sensor data to detect equipment deterioration and predict machine failures. Machine learning algorithms are able to handle large volumes of operational data and to identify complex relationships between machine states and failure events, improving and speeding up maintenance decisions, as opposed to traditional statistical methods. Therefore,

predictive maintenance in smart manufacturing has used a variety of supervised learning algorithms. [5], [6], [10]

Some of the most popular algorithms are: Decision Tree (DT): It is a simple and very interpretable model which represents decision rules using a tree structure. Decision tree models are easy to understand and implement, but they can overfit and lose predictive power on complex industrial datasets. To overcome this limitation, Random Forest (RF) combines multiple decision tree models to improve predictive accuracy, robustness and generalisation. Random forest is known for its ability to handle high dimensional industrial data with feature importance analysis that partially helps to interpret the model. [5], [11], [12]

The Support Vector Machine (SVM) has been widely used for predictive maintenance because of its ability to classify complex datasets with high precision, especially in cases with limited training data. However, SVM calls for careful tuning of parameters and is computationally expensive for large industrial datasets. In recent years, due to sophisticated ensemble learning algorithms, the predictive performance of Extreme Gradient Boosting (XGBoost) and LightGBM has been improved. The algorithms effectively handle nonlinear relationships, missing values, and large amounts of sensor data, resulting in high classification accuracy. Both algorithms are black-box models, which makes it difficult for the maintenance engineers to interpret the prediction process without additional explainability techniques. [6], [10], [13]

The literature shows that, although machine learning algorithms have a great predictive capacity, no single model can simultaneously achieve high predictive accuracy, computational efficiency and full interpretability. Therefore, the combination of advanced machine learning algorithms with Explainable Artificial Intelligence (XAI) methods is a feasible solution to boost transparency, user trust and industrial decision-making. This is the basis for the proposed research framework. [8], [10], [13]

2.5 Explainable Artificial Intelligence

The increasing use of Machine Learning (ML) for Predictive Maintenance (PdM) has significantly improved the ability to predict equipment failures using industrial sensor data. However, many

high performing machine learning algorithms are black-box systems, which makes it difficult for the users to understand how the models make predictions. The lack of transparency erodes user confidence and inhibits the real-world deployment of AI-powered maintenance systems in industrial environments where maintenance decisions have direct impact on production, costs, and operational safety. [6], [10], [13]

Explainable Artificial Intelligence (XAI) has become a powerful tool to improve the transparency, interpretability, and reliability of machine learning algorithms. XAI provides understandable explanations, so that maintenance engineers can understand factors affecting the prediction results rather than just the accuracy of the prediction. Current explainability techniques, such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME), are appreciated for their ability to explain local and global model behaviour. The techniques are used to assess the impact of input features including temperature, vibration, pressure, torque, and tool wear, which helps engineers validate AI-generated recommendations and make informed maintenance decisions. [8], [9], [13]

The benefits of XAI are shown in recent work but, in most of the existing literature, explainability techniques are used as stand-alone tools without being integrated in a holistic predictive maintenance framework. In addition, few studies have explored the combined effects of prediction accuracy, model interpretability and industrial applicability in an integrated way. Thus, the development of a unified Explainable Artificial Intelligence framework is a promising research opportunity for promoting maintenance decision support and the adoption of trustworthy AI in smart manufacturing. [8], [10], [13]

2.6 Research Gap

The literature review reveals that there is a significant progress in the use of ML for Predictive Maintenance (PdM) within the framework of Industry 4.0 environments. Previous studies have demonstrated increased predictive accuracy using algorithms such as Random Forest, Support Vector Machine, XGBoost and LightGBM. However, most of the research has mainly focused on improving predictive performance, while relatively little attention has been paid to model transparency, interpretability and trustworthiness. This results in many predictive maintenance

systems being black-box models, which is a barrier to their adoption in industrial settings where maintenance decisions require transparent and reliable explanations. [5], [6], [10]

While the development of techniques for Explainable Artificial Intelligence such as SHAP and LIME has been ongoing to enhance the interpretability of models, they are typically evaluated in isolation and not as part of an integrated predictive maintenance framework. A unique research gap is to develop a coherent framework that combines high predictive accuracy, model interpretability and industrial decision support. In this paper, an Explainable AI framework based on advanced machine learning algorithms integrated with explainability techniques is presented to support transparent, reliable, and trustworthy predictive maintenance in smart manufacturing. [8], [10], [13]

Research Question	Linked Objective	Evidence Required	Expected Output
RQ1: What are the key gaps in existing ML-based predictive maintenance research?	Objective 1	Q1/Q2 literature review, PRISMA screening and thematic synthesis	Clear research gap and justification
RQ2: Which ML model offers the best balance of predictive performance and industrial practicality?	Objective 3	Model comparison using F1-score, Accuracy, Precision, Recall & ROC-AUC	Baseline model is very best
RQ3: How can SHAP & LIME improve transparency of predictive maintenance decisions?	Objective 2 and 4	Global feature importance and local explanation analysis	Explainable decision-support layer
RQ4: How suitable is the proposed XAI framework for smart manufacturing decision-making?	Objective 4	Combined evaluation of performance, interpretability and usability criteria	Validated XAI-PdM framework

Table 1. Research Questions, Objectives and Evidence Alignment

2.7 Literature Summary

Literature review shows that Industry 4.0, Smart Manufacturing and Machine Learning have significantly improved predictive maintenance through better equipment monitoring and failure prediction. However, many machine learning algorithms are difficult to explain in existing studies, which reduces industrial trust and limits practical application. While Explainable Artificial

Intelligence (XAI) has great potential to increase model transparency, there is little work that integrates explainability into a unified predictive maintenance framework. To this end, this study proposes an Explainable Artificial Intelligence framework by integrating sophisticated machine learning algorithms together with SHAP & LIME to improve prediction accuracy, transparency, and maintenance decision-making in smart manufacturing environments. [8], [10], [13]

3. Research Design and Methodology

3.1 Research Design

This paper presents a Design Science Research (DSR) based approach for the design and evaluation of an Explainable Artificial Intelligence (XAI) framework for Predictive Maintenance (PdM) in Smart Manufacturing. The fundamental objective of this study is to build, implement and assess a practical framework that solves the identified research topic rather than analysing current phenomena. Therefore, Design Science Research is suitable for this study. The DSR methodology supports the systematic development of innovative artefacts such as software frameworks and intelligent decision-support systems with rigorous evaluation for effectiveness and practical applicability. [2], [10], [13]

The proposed research framework integrates Machine Learning (ML) algorithms with Explainable Artificial Intelligence (XAI) techniques to improve the transparency and reliability of predictive maintenance decisions. The framework will be developed in a systematic way that includes data collection, preprocessing of data, feature engineering, machine learning model development, model evaluation, and explainability analysis. This systematic process makes predictive performance and model interpretability are considered throughout the research. [5], [8], [10]

The research will use publicly available predictive maintenance datasets to train and evaluate machine learning models that are standardised. We will implement and evaluate algorithms such as Decision Tree, Random Forest, Support Vector Machine (SVM), XGBoost and LightGBM to choose the best model for predicting equipment failure. Then, SHAP and LIME are utilised as explainability techniques to give transparent explanations of the prediction results on the selected model. This comprehensive strategy enables maintenance engineers to understand the variables

affecting the equipment failure forecasts, and helps make better maintenance decisions. [6], [8], [11]

The proposed research design is appropriate as it combines theoretical analysis through a comprehensive literature review with the development and evaluation of a practical framework. Furthermore, the Design Science Research methodology is aligned with the goal of producing an innovative and practically applicable solution that improves both academic understanding and industrial application. The proposed framework is intended to improve the prediction accuracy, enhance the model transparency, and facilitate wide deployment of trustworthy Artificial Intelligence in smart manufacturing environments. [10], [13]

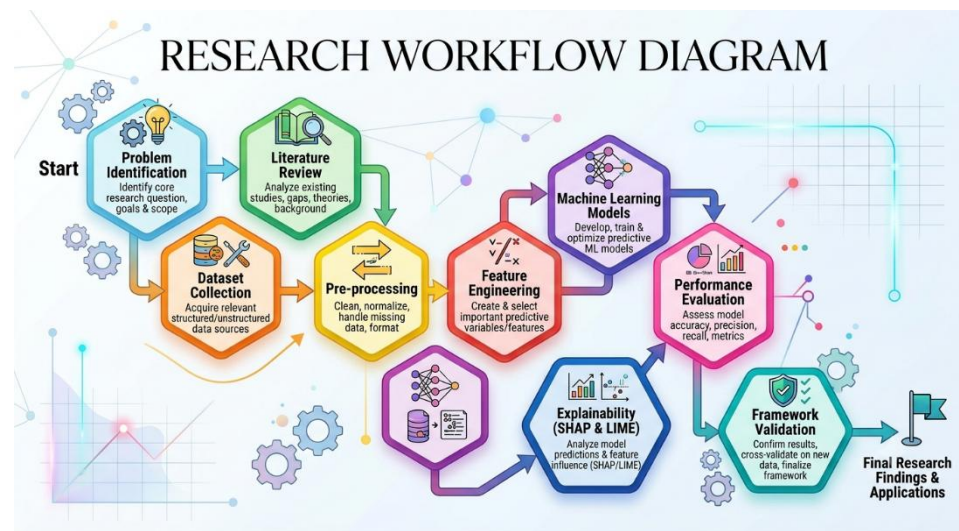


Figure 2. Research Workflow Diagram

3.2 Research Methods and Materials

3.2.1 Research Method

The research methodology used in this study is quantitative. It is based on the analysis of the numerical data from sensors to predict equipment failures using Machine Learning (ML) models. The quantitative approach makes it possible to subjectively evaluate the performance of the model by means of statistical evaluation metrics and the comparison of different machine learning algorithms. This method is appropriate since the research objective is to develop and validate an Explainable Artificial Intelligence (XAI) framework with structured industrial data sets, not to gather subjective opinions or qualitative data. [5], [10], [13]

3.2.2 Research Strategy

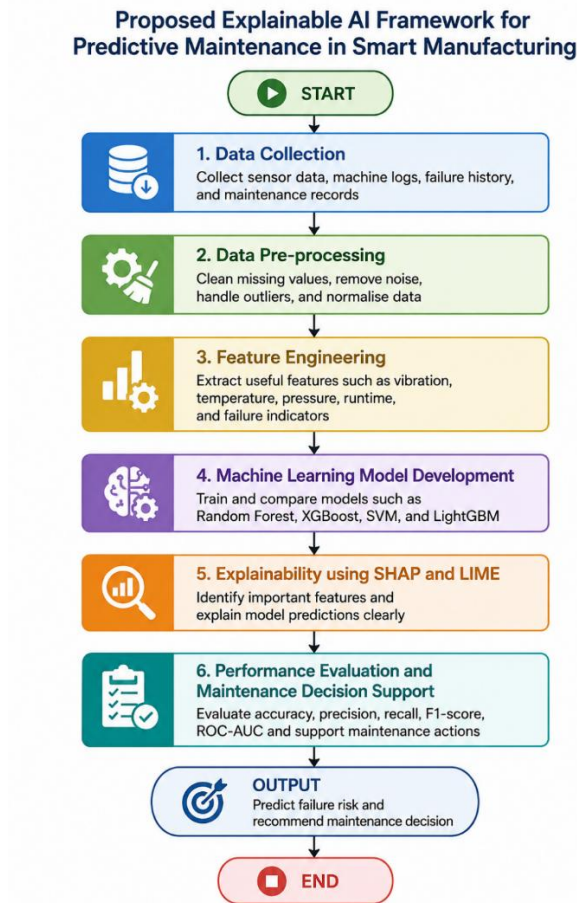
The research follows a software development and experimental strategy. Initially, industrial predictive maintenance datasets will be collected and preprocessed to remove missing values and improve data quality. We will then develop and train standard models for machine learning such as Decision Tree, Random Forest, Support Vector Machine (SVM), XGBoost, and LightGBM. The best-performing model will be integrated with SHAP and LIME explainability techniques to provide transparent explanations of prediction outcomes. Finally, the framework will be evaluated by standard metrics for performance to assess its effectiveness and industrial applicability. [6], [8], [10]

Stage	Method/Tool	Purpose	Quality Check	Distinction-Level Value
Literature Review	PRISMA-informed screening	Select high-quality papers	Q1/Q2 focus, keywords, inclusion/exclusion	Shows academic rigour
Data Preparation	Pandas, NumPy, Scikit-learn	Clean and transform sensor data	Missing values, scaling, imbalance check	Improves reproducibility
Model Development	DT, RF, SVM, XGBoost, LightGBM	Predict failure risk	Train/test split and parameter tuning	Provides comparative evidence
Explainability	SHAP and LIME	Explain global and local model behavior	Feature contribution consistency	Builds trust and transparency
Evaluation	Accuracy, Precision, Recall, F1 & ROC-AUC	Measure effectiveness	Confusion matrix & error analysis	Connects results to industrial decision-making

Table 2. Methodology and Evaluation Matrix

3.2.3 Proposed Framework Architecture

The proposed framework consists of six sequential stages:



This architecture enables accurate equipment failure prediction while providing interpretable explanations that improve maintenance engineers' understanding of AI-generated recommendations. [8], [10], [13]

3.2.4 Research Data

Data Set	Source	Records	Features	Target
AI4I 2020	UCI	10000	14	Machine Failure
NASA C-MAPSS	NASA	100+ Engines	26	Remaining Useful Life

The project will employ public predictive maintenance datasets, notably the AI4I 2020 Predictive Maintenance Dataset and NASA C-MAPSS Turbofan Engine Dataset. These files comprise sensor measurements such as air temperature, process temperature, rotational speed, torque, tool wear and machine failure data. Public datasets are sufficient because they are dependable, regularly used for predictive maintenance research, and allow for fair comparisons with earlier work. [3], [5], [10]

3.2.5 Data Analysis and Evaluation

The machine learning algorithms will be assessed with conventional classification metrics as Accuracy, Precision, Recall, F1-score, ROC-AUC. Moreover, SHAP and LIME will be used to explain the prediction results by finding out the effect of each feature on each prediction. This integrated assessment ensures that the proposed framework is evaluated for predictive effectiveness and model interpretability. [8], [10], [13]

3.2.6 Software and Hardware Requirements

The framework will be implemented in Python language utilising the Jupyter Notebook environment. Libraries we will be using for data pre-processing, model creation, explainability analysis and visualisation are Pandas, NumPy, Scikit-learn, XGBoost, LightGBM, SHAP, LIME, Matplotlib and Seaborn. The studies will be conducted on 16 GB RAM ,Intel core i7 processor, and Windows 11 machine. GPU resources are optional since the machine learning techniques selected can be efficiently trained on CPU-based computations. [5], [8], [10]

3.2.7 Ethical Considerations

This research utilises publically accessible datasets. This study does not engage human participants, personal data, or industrial property. Therefore, the ethical risk of the study is minimal. All datasets will be used in accordance with their licensing stipulations, and appropriate academic citations will be used throughout the research to ensure integrity, transparency and adherence to responsible research practices. [3], [10]

4. Expected Outcomes

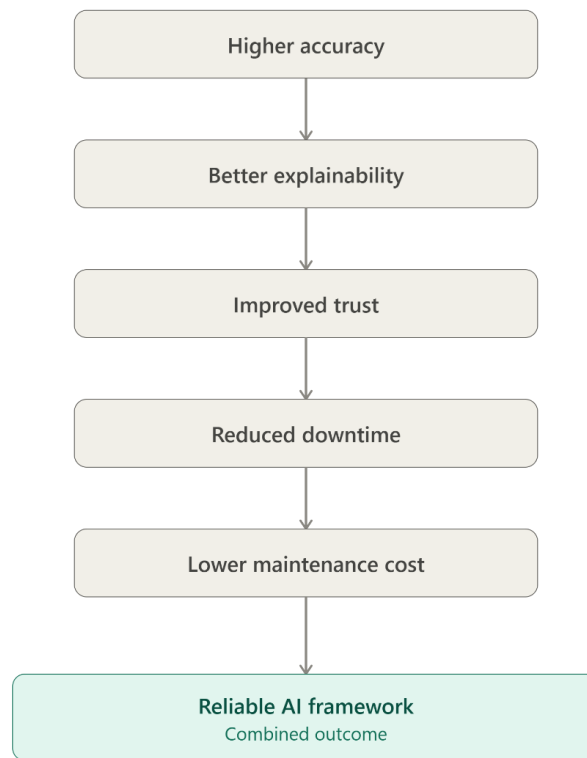


Figure 3. Expected Outcomes and Research Contribution Map

The proposed Explainable Artificial Intelligence framework aims to improve the effectiveness of Predictive Maintenance (PdM) by integrating accurate machine learning predictions with transparent and understandable decision support. The proposed framework is expected to offer more reliable equipment failure predictions than traditional predictive maintenance models and explain the factors affecting each prediction with SHAP and LIME explanation methodologies. This will enable maintenance engineers to better understand the machine behaviour and to make better choices on maintenance.

This research aims to contribute the state of the art in ML, Explainable Artificial Intelligence and Smart Manufacturing by proposing a comprehensive framework to overcome existing gaps in model transparency and industrial relevance. Based on an industrial perspective, the proposed framework is expected to reduce unexpected equipment failures, optimise maintenance

scheduling, increase equipment reliability, reduce maintenance costs, and improve production efficiency.

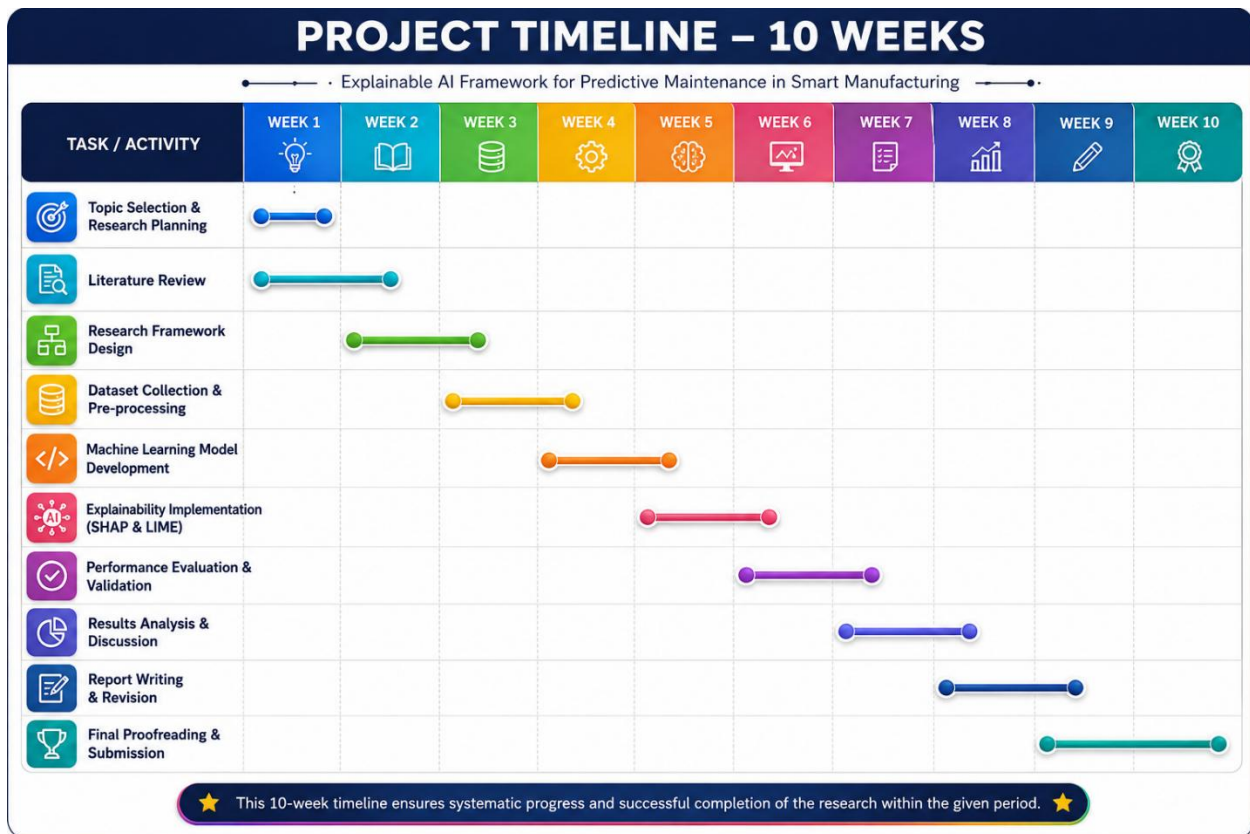
Despite these expected contributions, the research could face some limitations, such as dependence on the quality of publicly available datasets, computational constraints during model training, and potential variability in model performance across different industrial contexts. Nevertheless, the proposed framework is expected to provide a pragmatic and scalable approach for the deployment of trustworthy AI for predictive maintenance applications.

Outcome Area	Expected Result	Success Indicator	Assessment Strength
Predictive Performance	Reliable equipment failure prediction	High F1-score and ROC-AUC with balanced precision/recall	Evidence-based model evaluation
Explainability	Clear reasons behind model predictions	SHAP feature ranking and LIME local explanation plots	Transparency and trust
Decision Support	Actionable maintenance recommendations	Risk priority linked to sensor contribution	Industrial relevance
Research Contribution	Integrated XAI-PdM framework	Framework validated using benchmark datasets	Original academic value

Table 3. Expected Outcomes and Success Indicators

5. Timeline

The proposed research is expected to be completed over a 10 weeks period. The project will begin with an extensive literature review, followed by framework design, dataset preparation, model development, explainability implementation, performance evaluation, and final report writing.



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