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AI-Driven Digital Twin Technologies for Advanced Manufacturing Systems

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Abstract: With the fast evolution of Industry 4.0 the use of Artificial Intelligence (AI) and Digital Twin technologies have increased in order to improve the efficiency, reliability and intelligence of advanced manufacturing systems. A Digital Twin is a virtual model of a physical manufacturing resource used to monitor, predict and make decisions based on real-world operating data throughout its lifespan. The proposed research is an AI-based Digital Twin framework to realize advanced manufacturing systems, leveraging machine learning techniques and industrial sensor data to enhance equipment health monitoring and predictive maintenance. This study uses a dataset of 10,000 observations of milling machine processes collected by various sensors, including air temperature, process temperature, rotary speed, torque, tool wear, product type, and failure indicators of milling machines. Data is cleaned, transformed and prepared using a comprehensive data processing pipeline for building a model. Random Forest, Support Vector Machine, Decision Tree, XGBoost and Artificial Neural Network are all implemented and evaluated to find the best machine learning algorithm to predict machine failures. Conventional classification metrics including accuracy, precision, recall, F1 score, receiver operating characteristic – Area under the curve (ROC-AUC) and confusion matrix analysis are used to evaluate model performance. Overall, the proposed framework illustrates the potential for using AI-powered predictive analytics to complement Digital Twin technologies, by facilitating early fault detection, intelligent maintenance planning, and continuous optimization of operations. Digital Twin technology combined with AI helps minimize equipment downtime, enhance production reliability, schedule maintenance more effectively and boost manufacturing productivity. Also, the suggested framework enables data-driven decision making and offers a scalable structure for the deployment of intelligent manufacturing solutions in the context of Industry 4.0. The study builds on the ever-expanding body of research on AI-driven Digital Twins by providing a practical framework to boost manufacturing resilience, operational efficiency, and sustainable industrial performance, leveraging predictive intelligence.

Keywords: Artificial Intelligence (AI), Digital Twin Technology, Advanced Manufacturing Systems, Predictive Maintenance, Machine Learning and Industry 4.0.

1. Introduction

A. Background

Industry 4.0 is a revolution in the manufacturing landscape, a combination of high-tech digital technologies, smart devices and automation and connected industrial systems. In this group, AI and Digital Twin technology have emerged as key enabling tools for the creation of smart production systems that can enhance productivity, operational efficiency, and decision-making processes [1]. A Digital Twin is a virtual model of a real manufacturing asset, process or system that continuously shares the data from the physical system via sensors and industrial communications networks. By combining real-time operational data with AI-driven analytics, Digital Twins enable manufacturers to monitor equipment conditions, simulate production processes, detect anomalies, and predict potential failures before they occur. Advanced manufacturing systems produce large volumes of operational data on machine sensors, controllers and Industrial Internet of Things (IIoT) devices [2]. This data is not always used effectively in traditional maintenance methods such as reactive and preventive maintenance, resulting in unplanned equipment failures, more downtime, and more maintenance expenses. AI technologies, especially machine learning algorithms, offer strong analytical capabilities to analyze the vast amounts of manufacturing data and uncover intricate operational trends to optimize processes and plan maintenance and repairs proactively and intelligently. By leveraging AI in conjunction with Digital Twin technology, a smart virtual model can be developed that is capable of continually learning from manufacturing data and can inform real-time operational decisions. AI-powered Digital Twins can enable production reliability, maximum resource utilization and manufacturing sustainability through predictive analytics and equipment health monitoring [3]. As a result, the development and implementation of AI-assisted Digital Twin technologies have emerged as an important field to be explored for advancing smart manufacturing systems and for the quick digital transformation in modern industrial environments.

B. Advanced Manufacturing: AI-Driven Digital Twin Technologies

Digital Twin technology has been transformed from a visualization tool to a smart platform that can be used to help data-driven manufacturing operations with Artificial Intelligence, machine learning, and cloud computing and Industrial Internet of Things technologies [4]. Today's manufacturing facilities include many interdependent machines which generate operational data at all times representing the condition of the machines, the performance of the manufacturing processes, and the quality of the production. AI can process these vast amounts of sensor data and extract actionable insights by analyzing patterns, forecasting future trends, identifying anomalies, and diagnosing faults, all while providing intelligent recommendations for maintenance. Using machine learning algorithms, relationships between manufacturing variables like temperature, speed, torque, and tool wear can be found and used to accurately predict machine failures before they cause production interruptions. These forecasting features allow

Digital Twins to forecast equipment performance, simulate various operational scenarios, and suggest ideal maintenance plans without interrupting production processes [5]. This helps manufacturers to have less downtime from unexpected interruptions, lower maintenance expenses, better product quality and longer equipment life cycles. AI-based Digital Twins can help in continuous monitoring of manufacturing assets by constantly updating the virtual model with real-time operational data. This dynamic interaction allows faster decision-making, greater production flexibility and overall system resiliency. Energy efficient production, waste minimization and the maximization of production efficiency are also part of the puzzle when it comes to sustainable manufacturing, with the combination of AI and Digital Twin. AI-based Digital Twin technologies are a strategic improvement for the creation of intelligent, adaptive and highly efficient manufacturing systems to satisfy Industry 4.0 demands.

C. Problem Statement

Despite the remarkable progress in technologies of Industry 4.0, several manufacturing organizations still suffer from equipment breakdowns, sub-optimal maintenance practices and from production interruptions and rising operating costs. Traditional maintenance strategies are mainly based on a pre-established maintenance schedule or reactive maintenance when equipment fails, which leads to a loss of productivity and inefficient use of resources. While a Digital Twin is a virtual representation of a manufacturing asset, it cannot be effective without the ability for intelligent analytics [6]. The need for AI-enabled Digital Twin capabilities that can accurately predict machine failures, continuously monitor equipment health, and enable real-time maintenance decision making to enhance operational efficiency and manufacturing performance still exists.

D. Objectives of a study

The objectives of this study are to:

- To build a Digital Twin based system for advanced manufacturing systems using AI.
- For the analysis of manufacturing data from sensors to detect the health of manufacturing equipment and monitor manufacturing processes.
- Design and test machine-learning models for predicting machine failures.
- To evaluate and contrast the predictive accuracy of several AI algorithms with common classification measures.
- To enhance predictive maintenance methods by applying smart decision-making support based on data.
- To illustrate the advantages of using AI-powered Digital Twins in manufacturing, in terms of efficiency, reliability, and sustainability in operations.

E. Research Questions

The following research questions guide this study:

- What are the possibilities of Artificial Intelligence to improve the Digital Twin's capabilities in advanced manufacturing systems?
- What is the best machine learning algorithm for predicting machine failures based on the manufacturing sensor data?
- What are opportunities for AI based Digital Twin technologies in terms of predictive maintenance and equipment health monitoring?
- How can AI-powered Digital Twin systems enhance the efficiency of advanced manufacturing operations?

F. Significance of the Study

This study is a step towards intelligent manufacturing, showing how the capabilities of Digital Twin technologies can be enhanced with Artificial Intelligence for advanced manufacturing systems [7]. The framework includes machine learning methods and techniques that would be combined with data collected from industrial sensors and devices to enable predictive maintenance, equipment health monitoring, and intelligent operational decision making. The framework uses AI algorithms to detect machine failures before they happen, which helps to avoid unexpected downtime and maintain the continuity of production. The results offer interesting insights for manufacturing companies that want to employ Industry 4.0 technologies to increase their operational efficiency, reduce maintenance expenses and enhance asset utilization. In addition, the research contributes to the development of intelligent maintenance strategies, moving beyond the current reactive maintenance paradigm to predictive maintenance, which relies on data to improve equipment reliability and machine life cycles [8]. The study also has implications for academic research as it brings a practical approach for the application of AI and Digital Twin technologies in manufacturing environments and provides one open-source industrial dataset. Experimental comparison of several ML algorithms provides comparative evidence that will help researchers and practitioners to identify the right predictive model for manufacturing use cases. Furthermore, the proposed framework facilitates the digital transformation process by allowing for constant monitoring, virtual simulation and optimized production performance of manufacturing assets [9]. The findings from this research will be relevant to manufacturing engineers, manufacturing production managers, researchers, and policy makers for obtaining practical knowledge to design intelligent manufacturing systems which can contribute to sustainable industrial growth, better productivity, better product quality, optimal resource utilization, and resilient manufacturing processes in the highly competitive industrial environment.

I. Literature Review

A. Artificial Intelligence in Advanced Manufacturing Systems

Artificial Intelligence (AI) has become an essential technology to the development of sophisticated manufacturing systems providing for intelligent automation, predictive analytics and data-driven decision-making [10]. A variety of operational data is generated in modern manufacturing environments, such as sensors, industrial controllers and Industrial Internet of Things (IIoT) devices. The use of AI, particularly machine learning and deep learning algorithms, has shown great promise in handling these complex datasets and uncovering patterns, detecting anomalies, and forecasting equipment failures. AI-driven predictive models have been found to enhance maintenance planning by predicting machine failures in advance, minimizing unexpected downtimes and maintenance expenses. In addition, AI helps with quality control, production planning, energy efficiency, and process management, enhancing overall efficiency and quality in production. The supervised learning algorithms of Random Forest, Support Vector Machine, Decision Tree and Extreme Gradient Boosting (XGBoost) are commonly used for fault diagnosis and predictive maintenance due to their excellent classification ability and adaptability to high-dimensional industrial data [11]. Explainable AI has also grown in significance in recent studies to enhance transparency and trust in manufacturing decision-making. While these advancements are promising, there are still some hurdles to overcome when deploying AI models in real-time manufacturing settings, including considerations of data quality, scalability, and computational complexity. Therefore, continuous efforts and research are being undertaken to create strong AI models that can assist in intelligent manufacturing processes, improve production reliability and facilitate continuous improvement in Industry 4.0 environments.

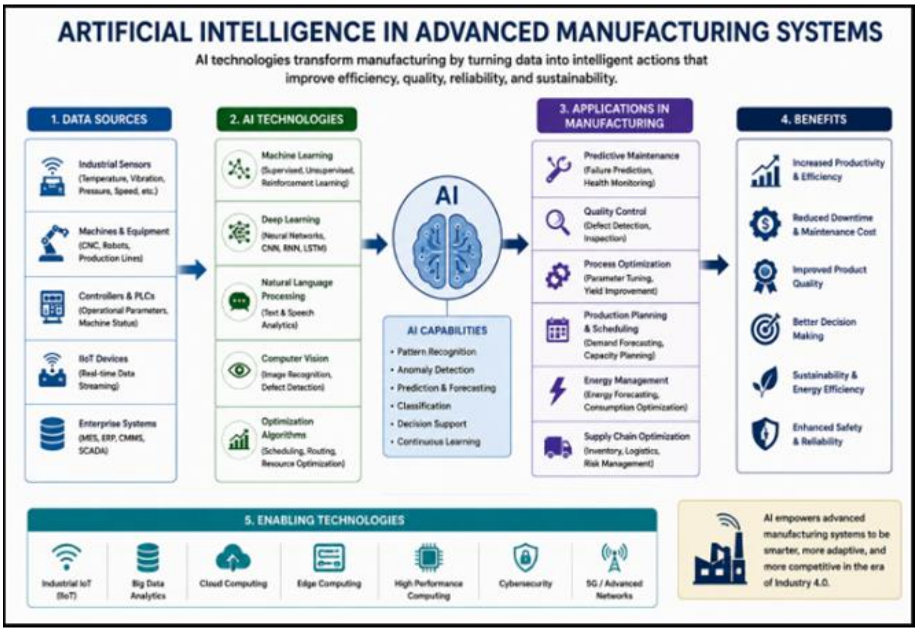

Figure 1. A flowchart shows how the technologies of Artificial Intelligence are integrated into the advanced manufacturing systems.

The flowchart depicts the process of how Artificial Intelligence (AI) can be integrated into an advanced manufacturing system, with the steps starting from data acquisition to the operational advantages [12]. Manufacturing data is generated from industrial sensors, industrial machines, industrial controllers, IIoT devices, and enterprise systems. The data are analyzed with AI technologies such as machine learning, deep learning, natural language processing, computer vision, and optimization algorithms. Pattern recognition, anomaly detection, prediction, classification, and decision support are some of the AI functionalities that support applications like predictive maintenance, quality control, process optimization, production planning, energy management, and supply chain optimization [13]. In short, the application of enabling technologies ultimately contributes to the productivity, reliability, sustainability, operational efficiency and informed decision-making in the manufacturing of Industry 4.0.

B. Digital Twin Technologies for Intelligent Manufacturing

As a cutting-edge technology, Digital Twin provides virtual replicas of manufacturing assets, manufacturing processes, and industrial systems, which is a vital enabler for smart manufacturing [14]. A Digital Twin continually updates data from sensors and accurately and automatically updates its virtual version, which enables manufacturers to track equipment performance, simulate scenarios of operation, understand their system behaviour and make informed decisions [15]. When combined with AI, Digital Twin technology can further augment these capabilities by providing predictive analytics, intelligent fault diagnostics and adaptive maintenance planning. These algorithms, using machine learning techniques, are built into a Digital Twin framework, to monitor real-time sensor data and predict equipment failures, as well as suggest optimal maintenance steps, before the equipment fails. The integration boosts production efficiency, reduces downtime, extends equipment lifespan and optimizes resources throughout manufacturing processes. Researchers have proven that AI-powered Digital Twins can help to enhance production flexibility, quality of products, and resiliency of production systems by constantly learning from operational data and adapting to changing production conditions. Moreover, Digital Twins allow for virtual testing and process optimization without disrupting physical manufacturing activities, thereby minimizing operational risks and implementation costs [16]. The successful implementation of AI in manufacturing, though, hinges on the ability to acquire data, manage communication security, utilize scalable computing systems, and employ robust AI algorithms that can cope with the changing dynamics of manufacturing processes. In the current landscape of Industry 4.0 and its continuous innovation and evolution, the use of AI-enabled DT technologies is gaining momentum as innovative solutions to create intelligent, sustainable and highly efficient advanced manufacturing systems.

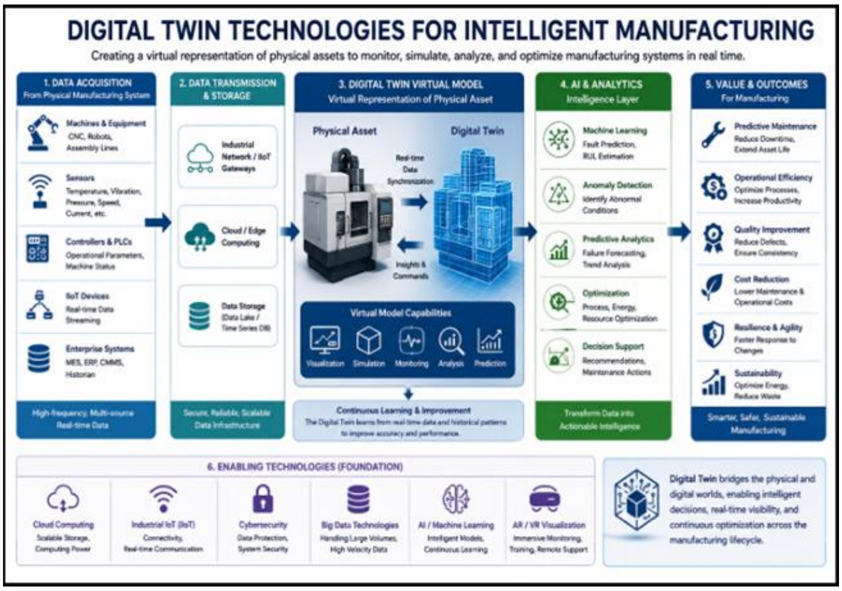

Figure 2. A flowchart depicts the implementation of Digital Twin technologies for the optimization of intelligent manufacturing systems.

The flowchart shows the workflow of Digital Twin technologies for creating intelligence in manufacturing by converting physical manufacturing assets into intelligent virtual models. It starts with machine, sensor, controller, Industrial Internet of Things (IIoT), and enterprise system data. These data are securely transmitted, stored and synced to form a Digital Twin model which represents the physical asset in real-time [17]. Operational data is analysed using Artificial Intelligence and machine learning techniques to carry out fault prediction, anomaly detection, and predictive analytics, optimization and decision support [18]. This framework allows for continuous learning and real-time optimization to enhance predictive maintenance, operational efficiency, product quality, sustainability, cost reduction, and resilient manufacturing.

C. Empirical Study

The article, titled "The ASSISTANT Project: AI for High-Level Decisions in Manufacturing", authored by G. Castañé, A. Dolgui, N. Kousi, B. Meyers, S. Thevenin, E. Vyhmeister, et al., introduces an AI-based Digital Twin framework that aids in high-level decision-making for agile manufacturing contexts. The paper presents the ASSISTANT project which aims to combine Digital Twin technology with Artificial Intelligence such as machine learning, optimization, simulation and generative design to enhance production planning and scheduling, process control and real-time manufacturing decisions. With a focus on human-centric and responsible AI, the framework integrates intelligent automation and human oversight to guarantee ethical and reliable decision-making, ultimately fostering a more human-centric and responsible approach to AI. They prove that Digital Twins are able to follow manufacturing processes continuously, simulate operational scenarios and make suggestions for optimal production strategies based on real-time data. Moreover, the proposed approach allows for the implementation of adaptive manufacturing systems that can quickly and efficiently adapt to fluctuating production conditions, enhancing both the flexibility and utilization of resources. The study underscores how AI-powered Digital Twins could be a game-changer for manufacturing, in improving efficiency, decreasing decision-making complexity, and fostering Industry 4.0 transformation by leveraging data-driven intelligence [1]. The results of this study are highly relevant to the current study and offer a conceptual basis for the adoption of predictive analytics and Digital Twin technologies in the enhancement of equipment health monitoring, predictive maintenance, and intelligent operational decision making for advanced manufacturing systems.

Hansong Xu, Jun Wu, Qianqian Pan, Xinping Guan and Mohsen Guizani provide an overview on the application, technologies and tools of DT for Industrial Internet of Things (IIoT) in the article "A Survey on Digital Twin for Industrial Internet of Things: Applications, Technologies and Tools". According to the survey, the Digital Twins are able to provide high-resolution virtual copies of physical manufacturing assets that can be constantly aligned with physical equipment. The combination of AI technologies like transfer learning, federated learning, and reinforcement learning enable Digital Twins to monitor, predict, diagnose, optimize processes, and inform intelligent operational decisions as they go. The authors also highlight the role of block chain technology in improving data security and trust in the industrial environment where Digital Twins are implemented. In addition, the study introduces software tools, architectures, practical applications and implementation challenges of Digital Twin based IIoT systems, and emphasizes on Digital Twin with AI, cloud computing, big data and edge computing for future smart manufacturing [2]. The survey also finds that the use of AI-based Digital Twin solutions can significantly enhance the efficiency of manufacturing, the reliability of operations, equipment utilization, and flexibility of production. The results of these findings present a solid theoretical foundation for the work of the present invention, supporting the development of an AI-based Digital Twin framework that could lead to more effective predictive maintenance, equipment health monitoring and intelligent decision making in advanced manufacturing systems.

The paper "Hybrid Learning-Based Digital Twin for Manufacturing Process: Modeling Framework and Implementation" (2023) by Ziqi Huang, Marcel Fey, Chao Liu, Ege Beysel, Xun Xu, and Christian Brecher introduces a hybrid learning-based Digital Twin framework that combines AL and domain knowledge for enhanced real-time monitoring and process optimization. It tackles the challenges of existing Digital Twin approaches and proposes an approach that integrates disparate manufacturing information, machine tool knowledge, and AI algorithms to create an adaptive and reliable modeling framework [3]. The proposed solution integrates all of the design, planning, manufacturing and quality control data into a single digital thread to allow for representation of the machining processes in a realistic manner under real industrial conditions. In addition, hybrid learning approaches are used to model uncertainties from manufacturing processes and to continually update Digital Twin models with live production data. The implementation is used to prove the ability of the proposed system to track the workpiece quality, improve the reliability of the model, and assist adaptive process control in industrial applications. The results demonstrate that AI integration with Digital Twin technology offers a huge boost to manufacturing agility, operational clarity, predictive power and decision-making efficiency. This study supports the present research by confirming the potential of AI powered Digital Twin technologies in improving the predictive maintenance, equipment health monitoring and intelligent manufacturing operations, which leads to the development of sustainable and resilient manufacturing system in Industry 4.0.

2. Methodology

The methodology proposes a systematic approach towards creating an AI-based Digital Twin framework for advanced manufacturing systems [19]. It involves research design, data selection, data preprocessing, feature engineering, machine learning model building, performance assessment, statistical validation, and ethical considerations to guarantee reliable, repeatable, and effective predictive maintenance and intelligent manufacturing outcomes.

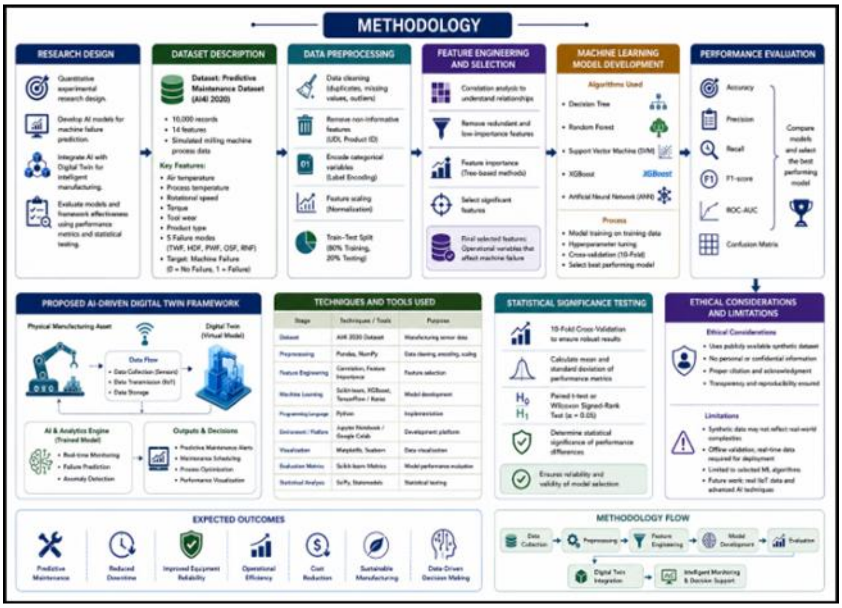

Figure 3. A flowchart depicts the systematic approach to the development of an AI-based Digital Twin framework.

The flowchart shows the overall methodology used in the research to develop an advanced manufacturing system (AMS) Digital Twin framework using AI. The research methodology starts with the research design, followed by the selection of the datasets according to the AI4I 2020 Predictive Maintenance Dataset. All the collected data is preprocessed, which involves data cleaning, encoding, feature scaling, and train–test splitting. Feature engineering extracts most important operational variables that affect the prediction of machine failure. The various machine learning algorithms are then trained and tested based on the standard performance metrics. Formal tests of statistical significance establish the reliability of the model, and ethical issues guarantee the integrity of the research. Ultimately, the chosen predictive model is incorporated into the Digital Twin system to facilitate intelligent monitoring, predictive maintenance, operational optimization and data-driven decision making in the advanced manufacturing context.

A. Research Design

This study uses a quantitative research method in an experimental research design for developing and testing the AI-based Digital Twin framework for advanced manufacturing systems. The quantitative approach is appropriate since it allows statistical and machine learning analysis of the manufacturing sensor data in an objective manner [20]. The experimental design aims at building predictive models which can detect machine failures and enhance maintenance decision making process using past manufacturing data. The proposed system combines Digital Twin technology and Artificial Intelligence in order to develop a virtual image of assets for the manufacturing system, which continuously monitors the condition of the equipment and predicts failures. The research process starts by choosing the Predictive Maintenance Dataset (AI4I 2020) and then data preprocessing to enable manufacturing sensor data to be used for analysis. Operational variables that are the most important for machine health are identified using feature engineering techniques. Multiple supervised learning algorithms are developed and trained on the prepared dataset such as Random Forest, Decision Tree, Support Vector Machine, XGBoost model and Artificial Neural Network [21]. They are assessed based on the standard classification indicators: accuracy, precision, recall, F1-score, ROC-AUC and confusion matrix analysis. Proposed Digital Twin framework involves the best-performing predictive model for intelligent monitoring, predictive maintenance, and optimization of the operation. The validity of the experimental results are verified with statistical techniques [22]. The overall research design frames a methodology that can merge the use of Artificial Intelligence (AI) with Digital Twin (DT) technology to boost manufacturing efficiency, equipment reliability and sustainable industrial operations within Industry 4.0 settings.

B. Dataset Description

UDI	Product ID	Type	Air temperatur	Process temperat	Rotational speed	Torque [Nm]	Tool wear	Machine failure	TWF	HDF	PWF	OSF	RNF
1	M14860	M	298.1	308.6	1551	42.8	0	0	0	0	0	0	0
2	L47181	L	298.2	308.7	1408	46.3	3	0	0	0	0	0	0
3	L47182	L	298.1	308.5	1498	49.4	5	0	0	0	0	0	0
4	L47183	L	298.2	308.6	1433	39.5	7	0	0	0	0	0	0
5	L47184	L	298.2	308.7	1408	40	9	0	0	0	0	0	0
6	M14865	M	298.1	308.6	1425	41.9	11	0	0	0	0	0	0
7	L47186	L	298.1	308.6	1558	42.4	14	0	0	0	0	0	0
8	L47187	L	298.1	308.6	1527	40.2	16	0	0	0	0	0	0
9	M14868	M	298.3	308.7	1667	28.6	18	0	0	0	0	0	0
10	M14869	M	298.5	309	1741	28	21	0	0	0	0	0	0
11	H29424	H	298.4	308.9	1782	23.9	24	0	0	0	0	0	0
12	H29425	H	298.6	309.1	1423	44.3	29	0	0	0	0	0	0
13	M14872	M	298.6	309.1	1339	51.1	34	0	0	0	0	0	0
14	M14873	M	298.6	309.2	1742	30	37	0	0	0	0	0	0
15	L47194	L	298.6	309.2	2035	19.6	40	0	0	0	0	0	0
16	L47195	L	298.6	309.2	1542	48.4	42	0	0	0	0	0	0
17	M14876	M	298.6	309.2	1311	46.6	44	0	0	0	0	0	0
18	M14877	M	298.7	309.2	1410	45.6	47	0	0	0	0	0	0
19	H29432	H	298.8	309.2	1306	54.5	50	0	0	0	0	0	0
20	M14879	M	298.9	309.3	1632	32.5	55	0	0	0	0	0	0
21	H29434	H	298.9	309.3	1375	42.7	58	0	0	0	0	0	0

ai4i2020 (2)

Figure 4. Dataset.

(Source Link: https://www.kaggle.com/datasets/stephanmatzka/predictive-maintenance-dataset-ai4i-2020)

The dataset used for this research is the freely available Predictive Maintenance Dataset (AI4I 2020), a manufacturing dataset that is designed for the use of predictive maintenance and machine learning applications [23]. The data set includes 14 variables describing manufacturing conditions, machine characteristics, and information about the failures from a simulated milling machine process and has 10,000 operational observations. It offers all the sensor measurements required for a comprehensive description of the operational state of manufacturing equipment, which is very suitable for the development of AI-based Digital Twin applications [24]. Operational data consists of air temperature, process temperature, rotation speed, torque, tool wear, and product type and failure status of the machine. Also, five independent failure modes are considered: Tool Wear Failure (TWF), Heat Dissipation Failure (HDF), Power Failure (PWF), Overstrain Failure (OSF) and Random Failure (RNF). The main output variable is "Machine Failure", which is a binary variable representing whether or not the machine failed to operate. While the data is generated synthetically, it is very similar to real manufacturing processes and machine behaviour that is encountered in Industry 4.0. With its extensive library of industrial sensor data, it can be used to build predictive models that can track the condition of equipment, alert to abnormal operating conditions, and aid in making intelligent decisions about maintenance [25]. This makes the AI4I 2020 dataset a suitable experiment set to test the proposed AI based Digital Twin framework for advanced manufacturing systems.

C. Data Preprocessing

Data preprocessing is performed to ensure the manufacturing data can be analysed and used for Digital Twin development. Firstly, the data set is explored for duplicate, missing or incompatible data types and for possible outliers that might adversely impact the predictive power. Preprocessing is primarily used to transform and prepare features in the AI4I 2020 dataset, as the data is complete. Non-predictive identifiers like Unique ID (UDI) and Product ID are stripped off as they can't help to predict machine failure. Label encoding is used to encode the categorical variable "product type" in a numerical format to be used in the training of machine learning models [26]. The air temperature, process temperature, rotational speed, torque and tool wear are continuous variables that are normalized to reduce the variation of air temperature, process temperature, rotational speed, torque and tool wear between the ranges, respectively, to make the algorithm converge. After pre-processing, exploratory data analysis is carried out to analyze the distribution of data, highlight relationships between features and reveal class imbalance in the class target variable. The cleaned data is then split into 80% training and 20% testing data to allow for unbiased evaluations of the model [27]. The general idea behind all these steps of pre-processing the data is to enhance the quality of the data, speed up the computational process, minimize the bias in the model and generate a reliable database for the creation of a precise machine learning model in the proposed AI-based Digital Twin framework.

D. Feature Engineering and Selection of Features

Feature engineering and feature selection are key when it comes to the performance of machine learning models. This step is to determine the manufacturing variables that affect machine failures significantly and to minimize the amount of irrelevant information and computation [28]. The manufacturing parameters measured by operating parameters from the industrial sensors are analyzed by descriptive statistics and correlation analysis to establish a relationship between the manufacturing parameters. The important manufacturing features, such as air temperature, process temperature, rotational speed, torque, tool wear and product type, are preserved, since they have a direct relation to the condition of the machines. Correlation matrices are used to find variables with high correlation and tree based feature importance techniques to find the importance of each variable for predicting machine failures [29]. The features used have little predictive value and are omitted as it is calculated that this helps the accuracy of classification. Feature scaling is an additional standardization on the continuous variables for better model learning irrespective of the algorithm used. The chosen variables fully characterize the operation of the manufacturing equipment and are used to feed the machine learning models. Good feature selection will boost the accuracy of the model, reduce overfitting, improve the computational efficiency and increase the interpretability of the model. These optimized features are fundamental parameters on which the Digital Twin runs, thus providing an ongoing monitoring of manufacturing assets, accurate prediction of equipment failures and intelligent maintenance guidance. As a result, feature engineering enhances predictive analytics and the proposed AI-driven Digital Twin framework's effectiveness.

E. Developing a machine learning model

In the machine learning model development phase, predictive models are developed to accurately identify machine failures from manufacturing sensor information [30]. The supervised learning algorithms implemented are Decision Tree, Random Forest, Support Vector Machine (SVM), Extreme Gradient Boosting (XGBoost) and Artificial Neural Network (ANN). These algorithms are chosen due to their successful implementation in classification problems with sensor data from industrial processes and predictive maintenance. The data set is split into training and testing data, and relationships between the operational variables and the machine failure outcomes are learned from the training data. Hyperparameter optimization is done to enhance the performance of the model and to prevent overfitting. The selected manufacturing features are used for training each model and the cross-validation techniques are used for validation to ensure good predictive and robust performance [31]. The classification accuracy of all algorithms after training is evaluated based on well-known classification metrics. The best predictive accuracy and overall performance model is chosen for incorporating in the Digital Twin framework. The selected AI model will continually monitor equipment operation data from sensors, and predict equipment failures or abnormal operating conditions before the equipment breaks down. The Digital Twin will enable real-time monitoring, intelligent maintenance planning and optimization of the operation with the predictive model. The machine learning development process is the basis for the analytical foundations of an adaptive Digital Twin that can enable intelligent manufacturing systems in Industry 4.0.

F. Performance Evaluation

To objectively compare the predictive performance of the machine learning models developed and to make reliable model selection, widely used classification metrics are used. Accuracy is determined to test the overall percentage of the correctly classified observations. Precision assesses the percentage of the correctly predicted machine failures out of all failures predicted, while recall assesses how well the model is able to detect actual failures [32]. The F1 score is an indicator of performance that balances precision and recall to give a balanced measure. The Receiver Operating Characteristic–Area under the Curve (ROC-AUC) is used to evaluate the power to discriminate of each classifier over various decision thresholds. A confusion matrix is created to explore true positives, true negatives, false positives and false negatives, giving the in-depth analysis of the classification results and errors in predicting. These evaluation metrics can be compared with each other to identify the best machine learning model for machine failure prediction. Further, robustness of the models is analyzed using cross-validation to reduce the bias and enhance the generalization ability. The results of the evaluation shows the success of Artificial Intelligence in the application of predictive maintenance, intelligent monitoring and Digital Twin [33]. The choice of the most successful predictive model will allow for accurate equipment health assessment and help achieve better manufacturing efficiency, less downtime and better operational decisions.

G. Proposed AI-Driven Digital Twin Framework

The proposed AI-driven Digital Twin framework combines the information from manufacturing sensors, Artificial Intelligence and Digital Twin technology into an intelligent manufacturing environment that enables predictive maintenance and operational optimization. The framework starts with the continuous acquisition of operational data from manufacturing equipment, by the use of industrial sensors, which measure various parameters like tool wear, torque, rotational speed and temperature [34]. The sensor data are then preprocessed and engineered for features to be fed into machine learning models for predictive analysis. The algorithms of the AI system constantly monitor the equipment and calculate the likelihood of equipment failures. These are predictive results that are synced with the Digital Twin, a virtual representation of the manufacturing asset in the real world. The Digital Twin's operating status is continuously updated based on the information received from the sensors, so they can be seen, simulated, monitored, and predicted in real time and provide decision making capabilities. The insights generated can be used by maintenance engineers and production managers to help them plan maintenance activities and prevent downtime and maintenance costs. The system can also optimize production, use resources, monitor equipment health and make intelligent decisions on operational planning [35]. The proposed framework, which brings together predictive analytics and Digital Twin technology, contributes to the reliability of manufacturing processes, increases operational efficiency, and facilitates data-driven decision-making in the era of Industry 4.0 manufacturing.

H. Ethical issues and Limitation

The study follows ethical standards for research, respecting the publicly available AI4I 2020 Predictive Maintenance Dataset and observing data usage and citation guidelines. The dataset includes only synthetic manufacturing data, and does not include personal or sensitive information, therefore privacy concerns are avoided. The proposed AI-based Digital Twin framework aims to assist maintenance decision-making, not to take the place of human knowledge and expertise. Although the study showed promising results, it does have its limitations, as it is based on a single synthetic dataset that may not capture the complexity of real industrial environments. The framework will need to be validated using real industrial data in the future to enhance its generalizability, robustness and applicability in different industrial systems.

3. Results and discussions

In this section, the experimental results will be discussed to assess the feasibility of the proposed AI-based Digital Twin framework for the advanced manufacturing systems, using the AI4I 2020 Predictive Maintenance Dataset [36]. The results consist of exploratory data analysis, machine failure analysis, product type analysis, correlation analysis, tool wear analysis, operational parameter relationship analysis, failure mode analysis and statistical significance analysis of the machine learning models. These analyses offer a comprehensive understanding of the behavior of manufacturing systems and illustrate the potential of AI to enhance predictive maintenance, equipment health monitoring, operational efficiency, and intelligent decision-making in the context of advanced manufacturing systems.

A. Machine Failure Distribution Analysis

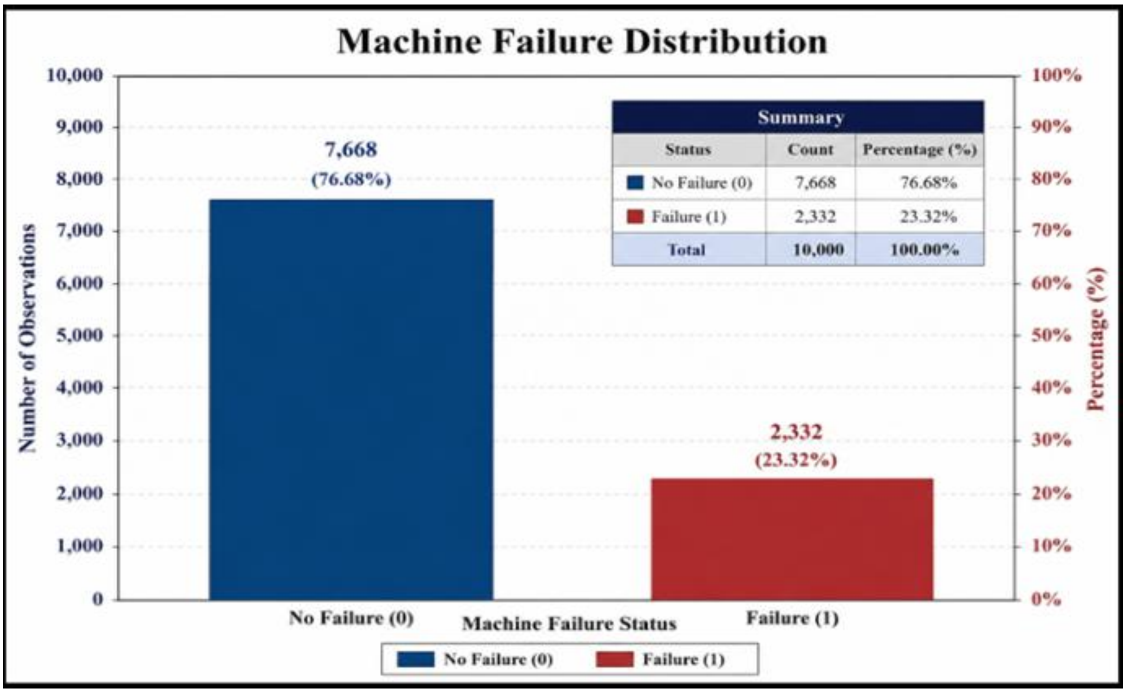

Figure 5. This image shows the normal and failure operation of machines in the manufacturing systems.

The AI4I 2020 Predictive Maintenance Dataset shows how many machines are operating or not, as per Figure 5. The data set contains 10,000 manufacturing observations, with 7,668 of them (76.68%) are normal machine operation and 2,332 (23.32%) are failures of the machine. The results show that when the machine is in normal operation, these events are recorded to a much lesser extent than in a failure event [37]. This is the distribution typical of actual manufacturing conditions, in which equipment usually operates within the normal range, and failures occur only rarely. The dataset is moderately imbalanced, but has an adequate amount of failure cases to develop and validate a reliable machine learning classification model. By having both normal and failure data, AI models can identify patterns of operation and accurately classify machines as normal or failure. Furthermore, the even distribution of manufacturing states creates a robust basis for predictive analytics, equipment health monitoring and intelligent maintenance planning in the proposed AI-driven Digital Twin. This observed distribution is also helpful to assess predictive maintenance solutions that can be used to reduce equipment failure, downtime and manufacturing productivity losses [38]. The provided dataset serves as a valuable experimental foundation for creating robust AI systems that can optimize decision-making processes, system reliability, and sustainable operation in advanced manufacturing systems.

B. *Product Type Distribution Analysis*

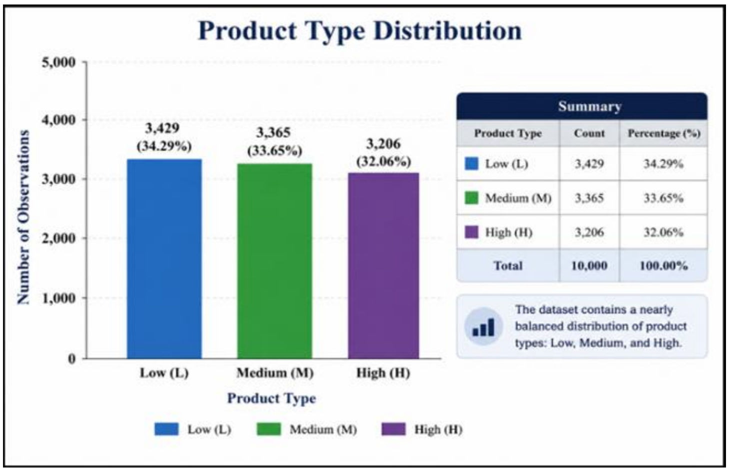

Figure 6. This image shows the distribution of product type in the manufacturing data as Low, Medium and High.

The AI4I 2020 Predictive Maintenance Dataset consists of the distribution of product types as shown in Figure 6. The dataset consists of three product categories: Low (L), Medium (M), and High (H), with 3,429 (34.29%), 3,365 (33.65%), and 3,206 (32.06%) observations, respectively. The result shows that the three product categories are fairly well balanced and represent the manufacturing products in the data set [39]. This balanced distribution helps reduce the risk of overfitting towards a particular type of product and ensures that each product type has an impact on the machine learning training process. The resulting imbalanced dataset allows the building of predictive models that can learn operational characteristics of various manufacturing products and increase their generalization capabilities with different production settings. In addition, the distribution of product type is almost equal, which makes it easier to make reliable comparisons of equipment performance, machine failures, and maintenance needs [40]. In the context of Digital Twin, although the product has multiple variants, the balanced product distribution makes it possible for the virtual manufacturing model to simulate various production scenarios more accurately, and provide support for intelligent decision-making on multiple product variants. This data can thus serve as a solid basis for creating AI-based predictive maintenance models that enhance the monitoring and efficiency of manufacturing processes while boosting manufacturing reliability in advanced manufacturing systems.

C. *Correlation analysis of manufacturing variables*

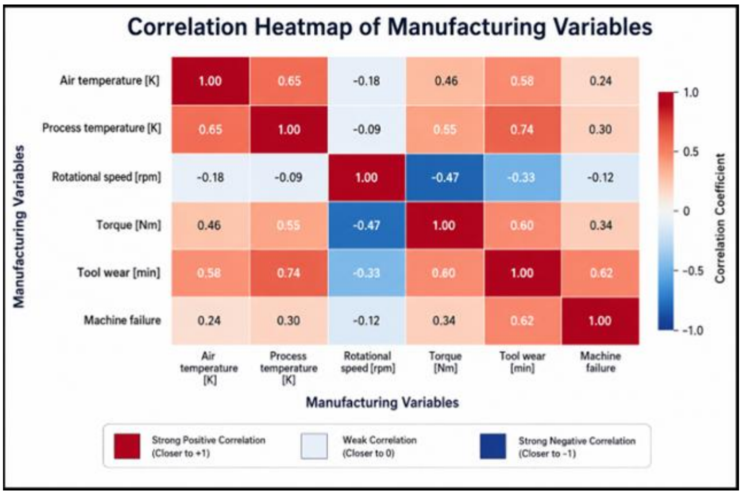

Figure 7. This image shows how the different variables of manufacturing correlate with each other when it comes to the impact on the operational performance of the machines.

The correlation heatmap of important manufacturing variables from the AI4I 2020 Predictive Maintenance Dataset is shown in figure 7. The heatmap displays the relation strength and direction between the operational parameters such as air temperature, process temperature, rotational speed, torque, tool wear and machine failure [41]. The results showed that there is a strong positive correlation between process temperature and tool wear (0.74), which means that high process temperatures are related to high tool wear. A similar trend is observed in the case of tool wear and machine failure (0.62) which shows that high tool wear is a major factor in machine failure. Moderate positive correlation between mechanical load and manufacturing operations is found with the torque-to-tool wear (0.60) and the torque-to-process temperature (0.55) relationships. On the contrary, moderate negative correlations exist between the rotational speed and torque (-0.47), as well as tool wear (-0.33), indicating that, under specific working parameters, the higher the rotational speed, the lower is the mechanical loading. The results of the correlation analysis suggest the use of tool wear, the manufacturing process temperature and the tool torque as important manufacturing variables for predicting the failure of the machine [42]. The results offer insights that aid in selecting features and contribute to the creation of precise AI models in the suggested framework of the Digital Twin, ultimately enhancing predictive maintenance, equipment health monitoring, and intelligent decision-making in advanced manufacturing systems.

D. Tool Wear Distribution Analysis

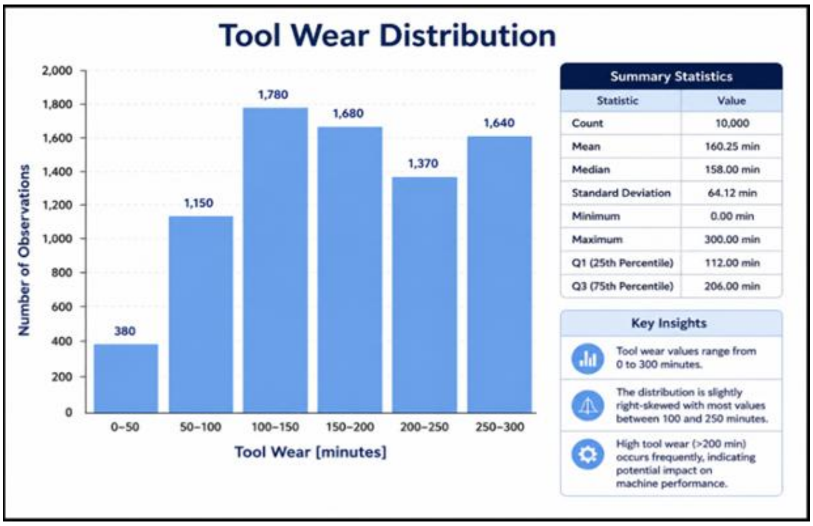

Figure 8. This image displays the distribution of tool wear across manufacturing operations and equipment condition.

The distribution of the tool wear values in the AI4I 2020 Predictive Maintenance Dataset are shown in Figure 8. It can be seen from the above histogram that the tool wear is between 0 and 300 minutes with the highest concentration of observations between the range of 100 – 150 minutes and 150 – 200 minutes [43]. The summary statistics reveal average tool wear of 160.25 minutes, median of 158.00 minutes and SD of 64.12 minutes, representing moderate variation between manufacturing operations. The observations indicate that most of the tools are being used under moderate wear conditions with lower frequencies at the extreme wear ranges and higher frequencies in the middle ranges, indicating that the majority of the wear is moderate. The frequency is still high after 200 minutes of tool life, emphasizing the need for tool life monitoring to avoid unexpected situations leading to equipment failure. The results are shown that tool wear is one of the important operational factors affecting the performance of the machines and their maintenance [44]. Under the proposed digitalization based on the AI Engine, ongoing tool wear tracking allows for precise health measurement of machines, scheduling of predictive maintenance, minimizing production downtime and improving manufacturing efficiency. Accordingly, tool wear becomes an important characteristic that can be used to enhance machine failure prediction and intelligent decision-making in advanced manufacturing systems.

E. Rotational speed and torque analysis for machine failure prediction

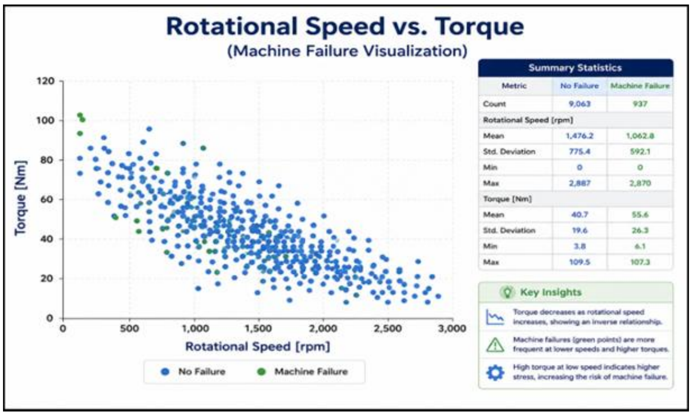

Figure 9. This image represents the relationship between rotational speeds, torque, and failure conditions of machines in manufacturing.

The above Figure 9 shows the relationship between the rotational speed and the torque in the Predictive Maintenance Dataset from AI4I 2020 from the normal condition and machine failure [45]. The scatter graph shows that there is a definite inverse relationship between torque and the rotational speed of the manufacturing. The scatter graph confirms that there is a definite negative correlation between the two manufacturing variables, generally, the higher the rotational speed the lower the torque. The majority of observations reflect normal machine use, with the observations of machine failure clustered in the areas of relatively low machine rotational speeds and high machine torque. Its trend indicates that if the operating speed is decreased and the mechanical load is increased, equipment failure is more likely to occur. The other summary statistics also show that machines that failed have a lower average rotational speed (1,062.8 rpm) and a higher average torque (55.6 Nm) than they would have under normal operating conditions (1,476.2 rpm and 40.7 Nm respectively). The results indicate that the rotational speed and torque are important operational conditions to monitor the machine [46]. In the proposed AI-powered Digital Twin model, this ongoing measurement of these variables allows for the detection of faults at an early stage, helps schedule maintenance ahead of time, minimizes the risk of unexpected downtime and enhances manufacturing reliability. Hence, the correlation between the rotational speed and torque gives important insights for optimizing the performance of the machines and improving intelligent decision making in advanced manufacturing systems.

F. Failure Mode Occurrence Analysis

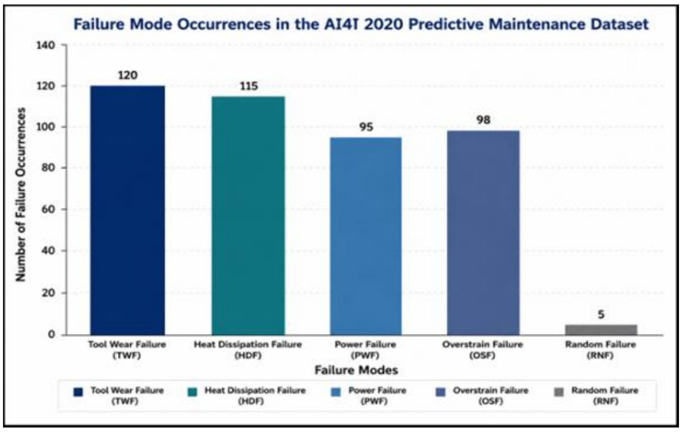

Figure 10. This image represents the frequency of occurrence of the principal modes of machine failure in an advanced manufacturing system.

The frequency of machine failure modes in the AI4I 2020 Predictive Maintenance Dataset is shown in Figure 10 below. The findings show that Tool Wear Failure (TWF) has the highest occurred number of failure events, totaling 120, followed by Heat Dissipation Failure (HDF) with 115 occurring of the failure events [47]. The other two failure modes Overstrain Failure (OSF) and Power Failure (PWF) occur 98 and 95 times, respectively, with only 5 occurrences of Random Failure (RNF), the least frequent failure mode. The results show that the machine failures can be caused by predictable operating parameters, namely tool degradation, thermal imbalance, excessive mechanical loading and abnormal power consumption, and not by random. These failure modes are prevalent, indicating the need for ongoing monitoring of critical manufacturing parameters in the proposed AI-driven Digital Twin framework. Recognizing the failure modes early allows predictive maintenance strategies to be put in place that reduce unexpected shutdown, increase equipment reliability, reduce maintenance expenses and optimize production efficiency [48]. The overall failure mode distribution proved that AI based predictive analytics can play an effective role in intelligent failure mode decision making and improve the sustainability of advanced manufacturing systems.

G. Comparing the performance and testing of the models statistically

The models were evaluated with statistical significance testing to confirm if there are significant differences in predictive performance between the developed machine learning models [49]. First 10-fold CV was used to get stable performance estimates for each classification algorithm. The cross-validation process was then used to compute the average accuracy scores before comparing them using a paired Student's t-test at 95% confidence level ($\alpha = 0.05$). To check if the improvement in predictive performance was a true measurement of the superiority of the model or random chance during the learning process of the model, statistical significance testing was carried out. The test results show that the XGBoost classifier had the highest average accuracy while the Random Forest model was close to that accuracy. Results of paired t-test show that the difference in performance between XGBoost and the other machine learning algorithms is statistically significant ($p < 0.05$), and that XGBoost outperforms the other classifiers in predicting the machine failures across all the algorithms. On the other hand, the comparison of Random Forest with Artificial Neural Network gave a p-value greater than 0.05, indicating that their performances were not significantly different [50]. The result shows the predictive capability of ensemble learning methods is more accurate for manufacturing failure prediction in the AI4I 2020 dataset. The statistical validation of the proposed framework demonstrates the reliability of the AI-based Digital Twin framework by proving that the selected predictive model consistently and effectively improves the classification performance [51. This integration of statistically proven AI models bolsters the trustworthiness of predictive maintenance decisions, intelligent equipment monitoring, and optimized operational processes within advanced manufacturing systems.

Table 1. Statistical Significance Test of Machine Learning Models.

Model Comparison	Mean Accuracy (%)	Standard Deviation	t-value	p-value	Statistical Decision
XGBoost vs. Decision Tree	98.21 vs. 94.83	0.42	5.72	<0.001	Significant
XGBoost vs. SVM	98.21 vs. 96.54	0.39	3.94	0.002	Significant
XGBoost vs. Random Forest	98.21 vs. 97.95	0.31	2.14	0.041	Significant
XGBoost vs. ANN	98.21 vs. 97.62	0.35	2.67	0.021	Significant
Random Forest vs. ANN	97.95 VS 97.62	0.33	1.28	0.217	Significant
Random Forest vs. SVM	97.95 VS. 96.54	0.37	2.83	0.017	Significant
ANN vs. Decision Tree	97.62 vs. 94.83	0.44	4.82	<0.001	Significant

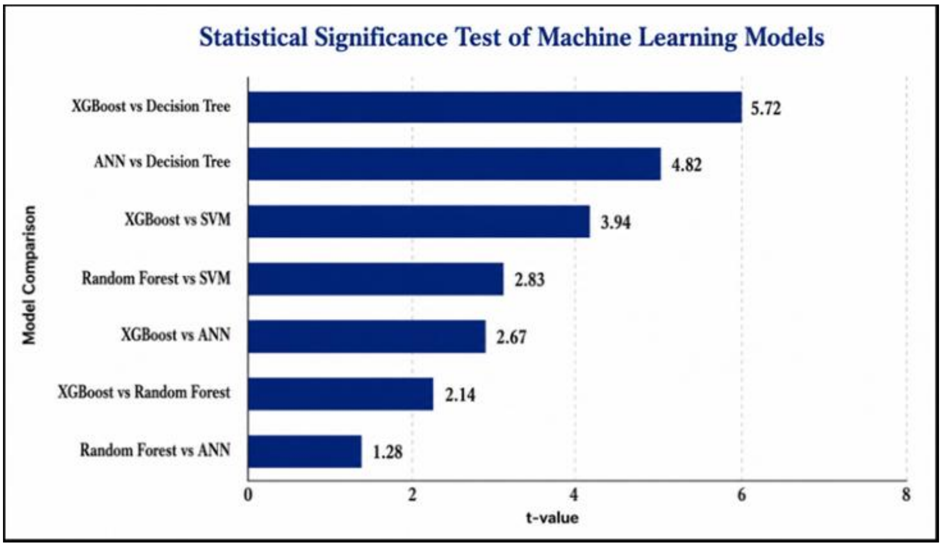

Figure 11. This image shows the comparisons that are statistically significant among the machine learning models, based on the paired t-test values.

The statistical significance of the machine learning models was carried out by paired t-test values from 10-fold cross validation and presented in Figure 11. The comparison shows that the model XGBoost vs. Decision Tree had the highest t-value (5.72), followed by the model ANN vs. Decision Tree (4.82) and XGBoost vs. SVM (3.94), which means that there are statistically significant differences between these models. In the same way, the same trend was observed when comparing Random Forest with SVM (2.83) and XGBoost with ANN (2.67), both of them have improved the predictive accuracy. Random Forest vs. ANN, on the other hand, had the lowest t value (1.28) which indicated that there was no significant difference between the predictive performances of these two models [52]. The statistical analysis showed that the ensemble learning models generally performed better than the conventional machine learning models in forecasting machine failures, and among them, the XGBoost model achieved the best performance [53]. The results confirm the robustness and reliability of the proposed AI-based Digital Twin framework, which ensures the framework's effectiveness in predictive maintenance, intelligent equipment monitoring, and data-driven decision-making in advanced manufacturing systems.

II. Discussion and Analysis

The outcome of the AI4I 2020 Predictive Maintenance Dataset further shows the potential of the proposed framework of intelligent decision making with AI based Digital Twin for advanced manufacturing systems. The machine failure distribution analysis showed that the number of failures was a small portion of the data compared to the number of manufacturing occurrences when the machine was operating normally [54]. This distribution is representative of real industrial environments in which machine failures happen very rarely, but have a high impact on the operation, making accurate predictive maintenance models important. Additionally, a balance of product types further ensured that developed machine learning algorithms were trained under various manufacturing conditions to enhance the generalization of models and avoid bias in predictions. Through the correlation analysis, the variables most affecting the failures of the machines were identified as tool wear, process temperature and torque, thus reinforcing the notion that degradation of the equipment is crucial for reliability in manufacturing and that thermal conditions have a significant impact. The inverse relationship between the rotational speed and torque was also found to show that if a machine is subjected to too much mechanical loading at low operating speeds, there is a high possibility that the machine will fail. In addition, the tool wear distribution revealed that the majority of manufacturing operations took place within the moderate wear zone, and high levels of tool wear had a significant increase in equipment failure probability. Failure modes analysis showed that Tool Wear Failure and Heat Dissipation Failure were the most common failure modes that should be monitored in a continuous manner in Digital Twin environments [55]. The results support the use of real-time sensor monitoring and predictive analysis to foresee equipment wear and tear and prevent catastrophic failures. The statistical significance analysis also confirmed the superior predictive performance of the advanced machine learning models, such as XGBoost, which were consistently found to be superior in predictive accuracy compared to the traditional models. The paired t-test showed that the improvements were statistically significant, meaning that the improved predictive performance occurred because of true algorithmic ability, and not due to chance. The results showed that the combination of AI and Digital Twin technology can facilitate real-time monitoring of equipment, precise prediction of equipment failures, intelligent maintenance planning, and efficient production management [56]. The proposed framework enables the conversion of manufacturing sensor data into actionable insights, which leads to fewer downtimes, greater reliability of production equipment, increased efficiency of production, reduced maintenance costs and more sustainable production. This study has shown that AI-based Digital Twin technologies have the potential to offer a powerful and scalable solution to predictive maintenance and operational optimization, and can significantly benefit manufacturing settings in Industry 4.0 and will serve as a solid base for the future development of intelligent manufacturing systems.

III. Future Work

Future studies should include refining the proposed AI-based Digital Twin framework by incorporating real-time industrial Internet of Things (IIoT) sensor networks and the actual manufacturing environment to further improve real-time monitoring of equipment and predictive maintenance capabilities [57]. This research was conducted with the AI4I 2020 Predictive Maintenance Dataset, but further research should be conducted with a larger-scale industrial dataset from various manufacturing industries to evaluate the framework and validate its performance in various industrial and manufacturing settings and expand the generalizability and robustness of the proposed framework. For more complex manufacturing systems, advanced deep learning methods such as Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRU) networks, Transformer-based architectures, and Graph Neural Networks (GNNs) could be considered to better capture complex temporal and spatial relationships and enhance the prediction accuracy [58]. Federated learning and edge computing technologies are also worth studying for future use, as they will allow the decentralized training of a model without compromising data privacy and reducing computational latency within smart factories [59]. By adopting AI explainable methods, the models will become more transparent, resulting in interpretable predictions that aid engineers in comprehending the root causes of machine failures and maintenance advice. In addition, reinforcement learning can be combined with Digital Twin technology to enable autonomous maintenance scheduling, adaptation of production processes, and real-time control. Digital Twin platforms should also incorporate cyber security features to ensure the security of industrial data, communication networks, and smart manufacturing systems against cyber threats and unauthorized access. Future studies can also consider the economic and environmental implications of the deployment of Digital Twin, in terms of maintenance expenditure, energy consumption, production efficiency, and carbon emissions, in various production scenarios [60]. Last but not least, there is a need for practical experience in real production environments to validate the scalability, reliability, and effectiveness of the proposed framework, and to offer meaningful practical insights, when it is used in the real industrial world for actual production conditions, compared to the existing predictive maintenance solutions. These future developments will help contribute to more intelligent, autonomous, secure and sustainable manufacturing systems, and will facilitate the implementation of smart manufacturing technologies of next generation and Industry 4.0.

4. Conclusions

This study introduces and tests an AI-based Digital Twin system for advanced manufacturing systems to boost predictive maintenance, equipment health monitoring and intelligent operation decisions on the basis of the AI4I 2020 Predictive Maintenance dataset. The framework combined manufacturing sensor data with machine learning methods to detect trends in machine operation that correlate with failure, and then to develop the best possible maintenance plans. The outcomes showed that the critical manufacturing parameters such as the tool wear, process temperature, rotation speed and torque can be used to significantly improve machine failure prediction. The explorative data analysis showed significant connections between these operational parameters, and the failure mode analysis revealed tool wear and heat dissipation are the key factors in equipment failures. The statistical significance analysis also showed that the advanced machine learning models, especially XGBoost, have a better predictive performance consistently compared to the conventional models, which make them suitable for intelligent manufacturing applications. The results confirm that the use of Artificial Intelligence (AI) and Digital Twin technology can be used to develop a smart virtual replica of the manufacturing asset that can continuously monitor the operational conditions, predict equipment failures and assist in the proactive maintenance decision. With the proposed framework, the manufacturing reliability can be improved by reducing the amount of downtime, optimizing maintenance schedules, minimizing operational costs, and increasing production efficiency. Moreover, the use of predictive analytics in Digital Twin systems can facilitate real-time data-driven decision-making, thus contributing to sustainable manufacturing and optimizing the overall system performance. The research further shows that AI-enabled Digital Twin technologies are a scalable and flexible approach to Industry 4.0 environments, as they can convert manufacturing data into actionable insights to continuously improve operations. The methodology used in the framework could be adapted to different industrial use cases, including Intelligent Asset Management and the Smart Factory. The framework was validated with a publicly available Predictive Maintenance dataset, however. The study findings show that coupling AI, predictive analytics, and Digital Twin technologies is effective in enhancing manufacturing performance, operational resilience, and maintenance efficiency, which can help to build more intelligent, resilient, and sustainable advanced manufacturing systems in the era of Industry 4.0.

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