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| RESEARCH ARTICLE

AI-Driven Predictive Maintenance for Manufacturing and Aerospace Systems

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| ABSTRACT
The age of intelligent engineering and Industry 5.0 has made the use of artificial intelligence (AI), machine learning (ML) and predictive maintenance (PM) increasingly common to boost the performance, sustainability and resilience of manufacturing and aerospace systems. Traditional maintenance strategies focus on scheduled checks or remedial maintenance, introducing the risk of unforeseen equipment failures, higher operating expenses, downtime, and system vulnerabilities. In this research, we introduce an intelligent and sustainable engineering framework by combining advanced machine learning methods with predictive maintenance strategies, aiming to enhance decision-making and operational efficiency in next-generation manufacturing and aerospace systems, while also leveraging asset management. To demonstrate the validity of the proposed framework, two benchmark datasets were used to the AI4I 2020 Predictive Maintenance Dataset, which is for smart manufacturing environments, and the NASA C-MAPSS Turbofan Engine Degradation Dataset, which is for aerospace engine health monitoring and remaining useful life prediction. The created methodology consists of data preprocessing, feature engineering, feature selection, developing machine learning models, optimizing hyperparameters, and comparing the performance of the models. Models such as Artificial Neural Networks, Random Forest, Support Vector Machine, XGBoost, LightGBM, CatBoost and Long Short-Term Memory (LSTM) networks are used for manufacturing failure prediction, and models like Random Forest Regressor, XGBoost Regressor and Long Short-Term Memory (LSTM) networks are applied for the estimation of remaining useful life (RUL) in the aerospace industry. The accuracy, precision, recall, f1 score, roc-auc, mean absolute error (mae), root mean square error (rmse), and coefficient of determination (r2) are used to evaluate the performance of the model. The proposed framework will be expected to increase the accuracy of fault detection, optimize maintenance scheduling, minimize equipment downtimes, increase energy efficiency, and extend operational life of critical equipment. This study highlights the potential of AI-driven predictive maintenance across diverse industries, including manufacturing and aerospace, providing a unified solution for sustainable industrial practices, digital transformation, and data-driven decision-making. The results will also be relevant to the researchers and industry practitioners who want to deploy a reliable, scalable and intelligent maintenance system in future smart manufacturing and aerospace systems.

| KEYWORDS

Intelligent Engineering, Predictive Maintenance, Machine Learning, Smart Manufacturing, Aerospace Systems and Sustainable Engineering

| ARTICLE INFORMATION

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I. Introduction

A. Background

As industrial operations have become more complex, there is an increasing demand for intelligent engineering solutions that can enhance the efficiency, reliability, and sustainability of industrial processes. Today's manufacturing and aerospace industries have more complex equipment that produces massive amounts of data while it is in operation and from its sensors during their life. The maintenance strategies that are traditionally used for corrective maintenance and preventive maintenance often miss the detection of hidden equipment degradation until a failure occurs, resulting in high maintenance costs, production losses, safety hazards and costly downtime. This is why AI and machine learning-driven predictive maintenance has become a growing trend for organizations to tackle these limitations. Industry 5.0 encourages the use of smart technologies to integrate with human intelligence for the creation of intelligent, resilient, sustainable and adaptive industrial systems [1]. Predictive maintenance in manufacturing can be used to track the status of machines, detect unusual operating patterns and schedule maintenance to maximize production efficiency and equipment uptime. In the same manner, high-end health monitoring systems are used by the aerospace sectors to provide high value insight to assess the performance of aircraft engines, estimate the remaining useful life of the engines and ensure that they operate safely under different operating conditions [2]. These are key attributes that are vital in lowering operating expenses and ensuring reliability along with a high level of environmental care. With recent developments in artificial intelligence, computational processing of high dimensional sensor data and detection of complex relationships has been greatly improved and is now possible, which cannot be achieved with traditional statistical methods. Random Forest, Support Vector Machine, XGBoost, Artificial Neural Networks and Long Short-Term Memory networks are machine learning algorithms that have been found to have high predictive power in industrial applications. Most of the current studies focus, however, on manufacturing and aerospace systems separately instead of the development of generalized intelligent engineering systems that can be utilized in different industrial sectors [3]. Thus, this research brings together benchmark datasets from two different industrial sectors (manufacturing and aerospace) to come up with a unified predictive maintenance model for the support of intelligent decision making, sustainable engineering and better operational performance for next generation industrial systems.

B. Evolution of Intelligent Manufacturing and Aerospace Systems

With the rapid advancement of digital technology, modern engineering has undergone significant change, leading to the development of intelligent, autonomous and data-driven industrial systems. Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT), Digital Twins and predictive analytics are changing the way manufacturing and aerospace industry designers, operators and maintainers approach the design, operation and maintenance of complex systems [4]. These technologies are helping to make the transition to Industry 5.0, which centers on intelligent automation, sustainability, and human innovation—the goal is to improve productivity, reliability, and the environment. While manufacturing companies are interested in managing for better product quality, less downtime on machines and better use of resources, aerospace companies are interested in managing for the safety of their aircraft, maximizing operational efficiency, and optimizing the useful life of their critical components. One strategy gaining significance in both industries is predictive maintenance, which allows for the detection of issues at an early stage and helps with data-driven maintenance planning, taking into account the actual operating conditions [5]. By combining intelligent engineering solutions, companies can analyze vast amounts of sensor data, uncover potential degradation trends, and make precise predictions on equipment condition and system performance [6]. The research suggests an intelligent and sustainable engineering framework, integrating advanced machine learning methods with predictive maintenance concepts, for decision making on manufacturing and aerospace systems. The framework is validated against the AI4I 2020 Predictive Maintenance Dataset, and the NASA C-MAPSS Turbofan Engine Degradation Dataset for two important industrial applications. The use of knowledge from both data sets will be combined to show how intelligent predictive models could increase the operational reliability, reduce maintenance costs, increase energy efficiency, and support sustainable industrial development. The proposed solution offers a comprehensive view of the future possibilities of engineering systems advancement with the use of artificial intelligence and data-driven innovation.

C. Intelligent Predictive Maintenance for Manufacturing and Aerospace Systems

One such application of AI that has grown immensely important in modern engineering is predictive maintenance. The predictive maintenance is one such application of AI that has come to the forefront in modern engineering because it allows businesses to anticipate equipment failures before they happen. Predictive maintenance is different to traditional maintenance because it continually analyzes equipment based on operational and sensor data and takes action as needed, rather than relying on predetermined maintenance schedules or when something goes wrong. This proactive approach will help in planning the maintenance activities, avoid unnecessary inspection, and decrease equipment downtime and increase system reliability [6]. Predictive maintenance is also becoming an integral part of the smart engineering and sustainable development of manufacturing and aerospace companies. The machine learning algorithms can be used in manufacturing to monitor various parameters, including temperature, rotation speed, torque, tool wear, and production parameters, to detect early signs of equipment degradation [7]. These insights help maintenance teams to maximize production timings while minimizing production downtime and maintenance expenses [8]. For aerospace systems, predictive maintenance involves the monitoring of the health of aircraft engines, considering operation parameters and several flight sensors, over a number of flight cycles. The estimation of Remaining Useful Life (RUL) of aircraft engines allows airlines and the maintenance providers to increase the utilization of the equipment and reduce maintenance costs and enhance safety. Predictive maintenance, through intelligent engineering, is the bridge between automation, data analytics and sustainability, which are essential elements of Industry 5.0. Machine learning algorithms can handle complex data sets, detect the non-linear degradation patterns and make predictions that have high accuracy and can lead to informed engineering decisions [10]. This study proposes a unified predictive maintenance system based on both manufacturing and aerospace data to showcase the versatility of intelligent engineering approaches in various industries. This concept is designed to achieve a more effective use of resources, reduce operating costs, maintain an environmental balance, and ensure a longer lifespan of the equipment by adopting maintenance strategies based on data and advanced technologies of artificial intelligence.

D. Problem Statement

Manufacturing and aerospace companies still face many issues with equipment failures, ineffective maintenance planning, higher operating expenses, and loss of system reliability. Common maintenance practices are not effective in detecting complicated degradation patterns in time to prevent failures, which can cause production stops, safety risks and waste of resources [11]. While there have been many potential uses for AI and machine learning in predictive maintenance, most of the previous research is concentrated in either manufacturing, or aerospace applications, and does not provide a general engineering solution. Hence, an integrated intelligent framework that can utilize predictive analytics in both industries to enhance equipment reliability, make maintenance decisions, minimize operational costs, and facilitate sustainable engineering practices is needed.

E. Objectives of the Study

The objectives of this study is to

- To explore the use of intelligent engineering technologies to provide predictive maintenance of next generation manufacturing and aerospace systems.
- To use AI techniques to analyze sensor data to detect patterns and deterioration of equipment, in aerospace and manufacturing.
- Establish a comprehensive framework of machine learning in the field of manufacturing failure prediction and aircraft engine remaining useful life estimation.
- Measure and compare the performance of a set of machine learning algorithms with the correct classification and regression metrics [12].
- To evaluate the effectiveness of intelligent predictive maintenance in the improvement of operational efficiency, equipment reliability and maintenance planning.

- To explore the role of intelligent engineering solutions in sustainable manufacturing, aerospace safety and transformation to Industry 5.0.
- To give actionable insights for implementing AI-empowered predictive maintenance in highly complex industrial settings.

F. Research Questions

Following these questions are guide to this study is mention below:

- What are the potential benefits of using intelligent engineering technologies for predictive maintenance and operations in manufacturing and aerospace systems?
- What machine learning algorithms give the most accurate prediction in the case of manufacturing equipment failure and remaining useful life of aircraft engines?
- What value does the proposed integrated predictive maintenance bring to both industrial areas with regard to sustainability, operational efficiency and maintenance optimisation?
- What are the main engineering constraints affecting the reliability of equipment and its predictive maintenance performance for manufacturing and aerospace applications?

G. Significance of the Study

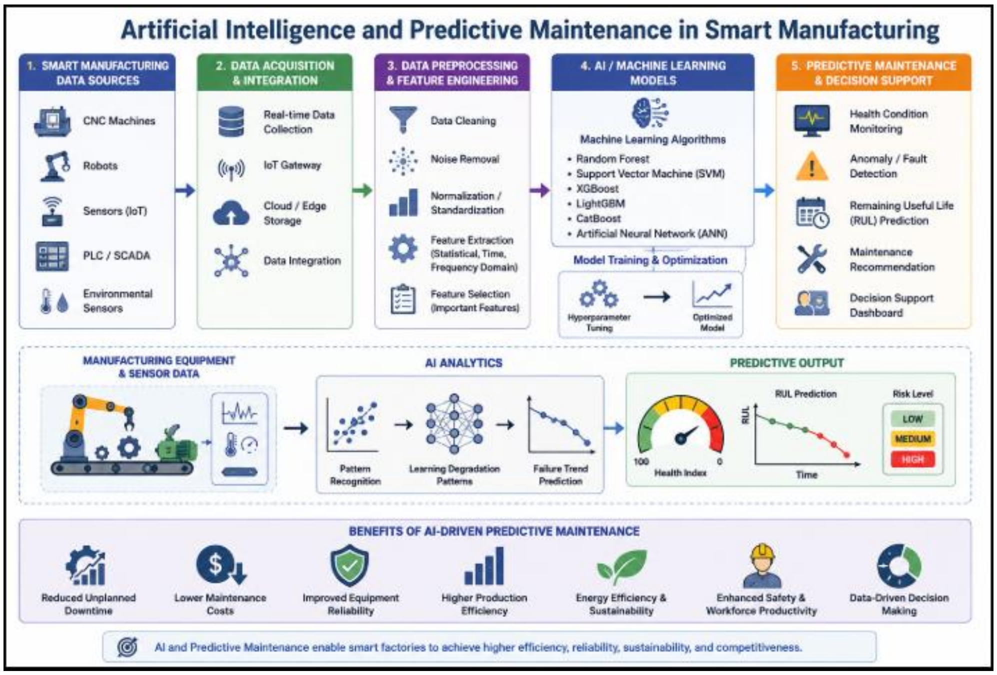
This study is a step toward intelligent engineering by proposing a single framework for predictive maintenance for manufacturing and aerospace applications based on harmonization of the two domains in one methodology using artificial intelligence [13]. The proposed research shows the potential of the application of machine learning techniques in various engineering fields, such as in the improvement of equipment reliability, efficient maintenance and sustainable industrial operations, and in contrast to many previous studies investigating these industrial sectors individually. The combination of the AI4I 2020 Predictive Maintenance Dataset and the NASA C-MAPSS Turbofan Engine Degradation Dataset offers a complete ground-up dataset to assess predictive maintenance strategies under various operating conditions [14]. The results from this research will help manufacturing companies to intelligently support their decision making process for reducing machine failures, minimizing production downtime, enhancing product quality and optimizing maintenance schedules. Likewise, aerospace companies can obtain the advantages of higher quality of aircraft engine health monitoring, more accurate prediction of aircraft remaining useful life, better aircraft flight safety and lower maintenance expenses. The findings also align with the ongoing Industry 5.0 efforts, as they underscore the importance of data-driven engineering processes integrating AI, predictive analysis, and sustainability principles [15]. Moreover, the proposed framework can be helpful for researchers, engineers, maintenance professionals and policy makers to develop intelligent maintenance systems for complex industrial applications. The study's findings show the power of advanced machine learning models in manufacturing and aerospace systems, and its potential impact on the industry's sustainable and scalable engineering solutions for future industrial transformation and technological innovation.

II. Literature Review

A. Artificial Intelligence & Predictive Maintenance in Smart Manufacturing

With the advent of Industry 4.0 and Industry 5.0, the manufacturing landscape has undergone a dramatic shift as Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT) and enhanced data analytics have been introduced in production areas. One of the most beneficial uses of these technologies has been in predictive maintenance, which allows manufacturers to predict when equipment failures are likely to happen. Unlike corrective and preventive maintenance methods, predictive maintenance will continuously analyze the data from the sensors to determine the status of the machine, and only schedule maintenance when necessary [16]. This reduces production downtime and maintenance costs, boosts equipment availability, and enhances manufacturing efficiency. The machine learning algorithms, such as Random Forest, SVM, XGBoost, LightGBM, CatBoost and Artificial Neural Networks (ANN) have been shown to possess good performance when discovering complex relationships among manufacturing variables like temperature, torque, rotational speed, vibration and tool wear. Recent research in the field has found that predictive maintenance using AI has the potential to boost fault detection accuracy and minimize false alarms using sophisticated feature engineering and shrewd decision-making [17]. AI4I 2020 Predictive

Maintenance Dataset has been recognized as a standard, widely used dataset for testing intelligent maintenance algorithms as it mirrors real manufacturing conditions and different failure mechanisms. Explainable Artificial Intelligence (XAI) techniques, which aim to enhance the transparency and trustworthiness of predictive maintenance models by pinpointing those factors that most significantly affect the equipment failures, have also been investigated [18]. While all these developments have been made, many current studies are based on a single machine learning algorithm or single manufacturing environment, which hinders the applicability of predictive maintenance solutions for various manufacturing applications. Therefore, there is still a need for multi-technique machine learning frameworks that can be integrated in one and support the sustainability, energy efficiency and future reliability of operation [19]. The aim of this research is to tackle these challenges by creating an integrated predictive maintenance system that can be adopted to modern manufacturing systems.

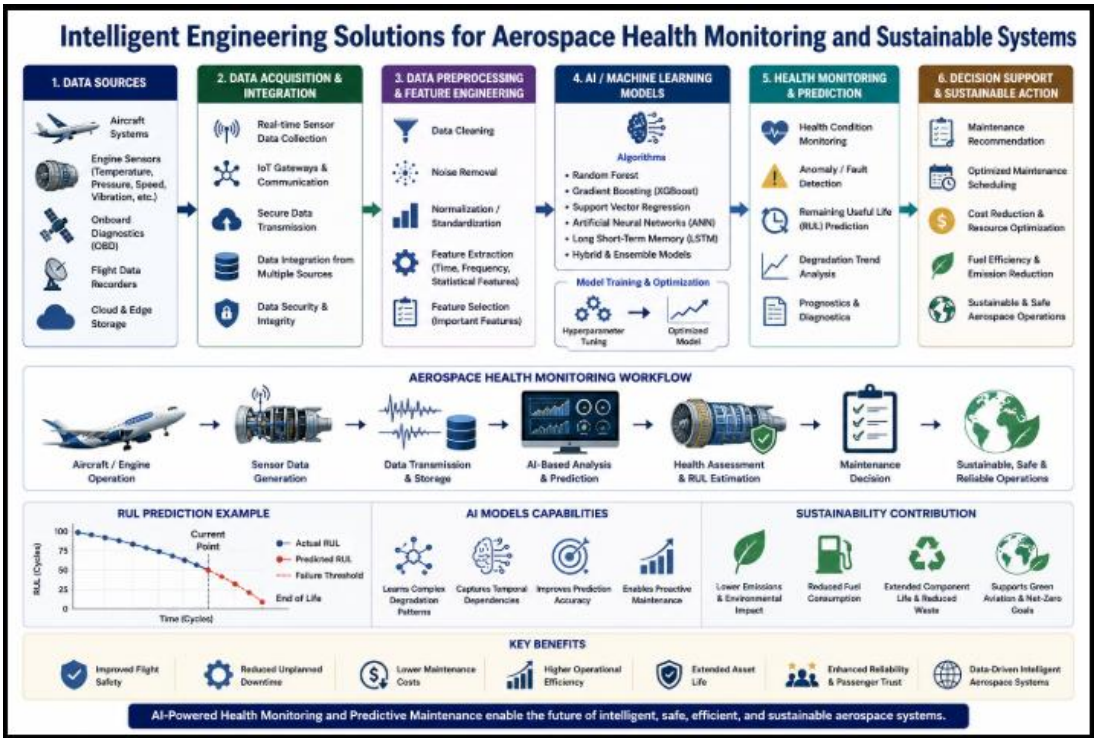


This Flowchart depicts an AI-driven predictive maintenance framework for intelligent and sustainable smart manufacturing systems

This flowchart depicts an Artificial Intelligence (AI) based predictive maintenance system for smart manufacturing systems. It starts by gathering information from manufacturing machines such as: CNC machines, robots, IoT sensors, PLC/SCADA systems and environmental sensors [20]. The retrieved data are preprocessed using data cleaning, data noise reduction, data normalization, feature extraction, and feature selection to improve the quality of the data. These machine learning models are then trained and fine-tuned to analyses machine conditions, such as Random Forest, Support Vector Machine, XGBoost, LightGBM, CatBoost and Artificial Neural Networks. The framework delivers predictive results due to fault detection, health monitoring, remaining useful life estimation, maintenance recommendation, and decision support, which enhances equipment reliability, production efficiency, sustainability, safety, and data-driven industrial decision making.

B. Intelligent Engineering Solutions for Aerospace Health Monitoring and Sustainable Systems

Intelligent technologies play a key role in the modern aerospace industry for enhancing aircraft safety, efficiency in use and maintenance management. Operational and sensor data from modern aircraft can be used to generate significant amounts of information about the performance of the engine and degradation of the equipment [21]. The traditional maintenance strategies which are generally based on regular inspection periods often don't reflect the real status of aircraft components and lead to unnecessary maintenance or to unexpected failures that will be costly. For this reason, predictive maintenance, with the aid of artificial intelligence becomes a vital part of aerospace health management systems. The NASA C-MAPSS Turbofan Engine Degradation Dataset has been widely adopted for the purpose of creating Remaining Useful Life (RUL) prediction models since it models a realistic deterioration process of an engine under different operational conditions. Random Forest Regressor, Gradient Boosting, XGBoost, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks have shown promising results for pattern recognition and prediction of engine life using machine and deep learning methods [22]. The models are smart enough to help maintenance engineers plan maintenance work proactively to minimize disruptions in aircraft operations, increase aircraft reliability, and enhance the service life of components. Moreover, with the concept of sustainable aerospace engineering, there is a need to minimize the waste in maintenance operations, optimize the use of resources, minimize fuel use and reduce the impact on the environment through intelligent operational planning [23]. Many studies have been carried out with high prediction accuracy by adopting sophisticated learning algorithms, but most of the studies only focus on aerospace applications and neglect how to apply these algorithms to manufacturing systems. The opportunities still exist to create integrated engineering solutions that can be used to support predictive maintenance in various industries [24]. This study fills this gap by embedding manufacturing and aerospace data in one intelligent engineering system that allows for comparison and evaluation of models, and proves the scalability of artificial intelligence for sustainable predictive maintenance of next-generation industrial systems



This Flowchart illustrates an AI-based aerospace health monitoring system for sustainable predictive maintenance and decision-making

This flowchart shows an intelligent engineering framework for aerospace health monitoring and sustainable systems based on artificial intelligence and machine learning. It starts with gathering operational data from the aircraft systems, engine sensors, onboard diagnostics, flight recorders and cloud-based storage facilities [25]. The collected data is further processed by cleaning, normalizing, extracting features, and selecting features, which are then fed to deep machine learning algorithms such as Random Forest, Gradient Boosting, Support Vector Regression, Artificial Neural Networks, and Long Short-Term Memory (LSTM). It facilitates the aircraft health monitoring, anomaly detection, Remaining Useful Life (RUL) prediction, and aircraft maintenance decision support, which ultimately enhances the operational reliability, flight safety, maintenance efficiency, and intelligent aerospace system management.

C. *Empirical Study*

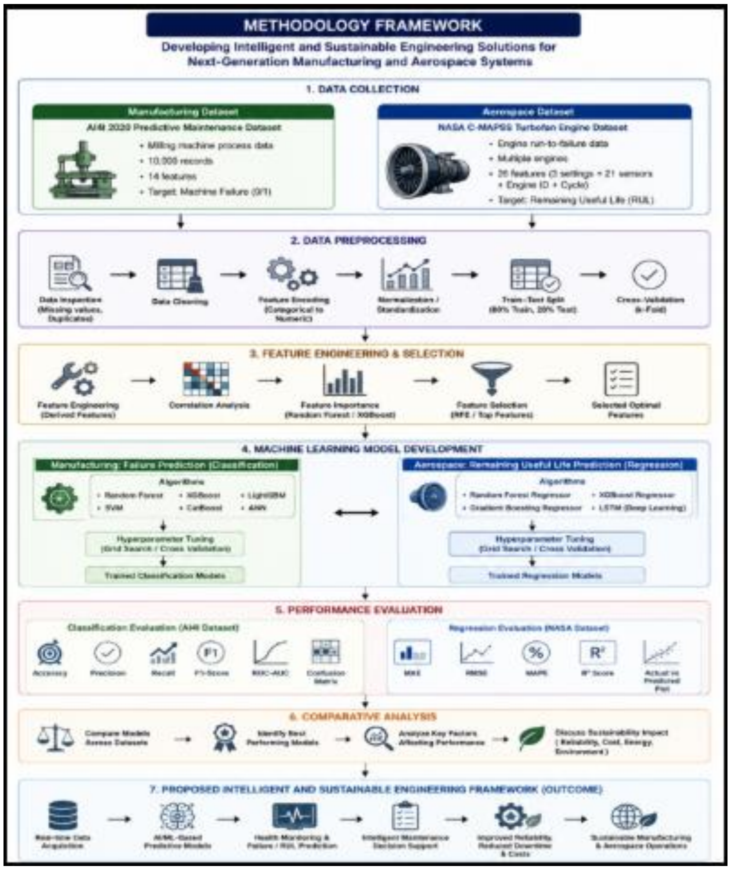
In the article "Towards the Next Generation of Manufacturing: Implications of Big Data and Digitalization in the Context of Industry 4.0" by Papadopoulos, Singh, Spanaki, Gunasekaran, and Dubey (2021), the authors examine how Industry 4.0 technologies are transforming modern manufacturing through the integration of big data analytics, digitalization, the Internet of Things (IoT), cloud computing, and cyber-physical systems. The study points out that digital technologies can collect, process, and analyses vast amounts of operational data, which can result in better production planning, operational efficiency, product quality, and decision-making. The authors stress the need for an intelligent manufacturing environment which should be equipped with connected systems giving real-time communication and data-driven optimization to meet the market's changing needs. This paper highlights the strategic role of big data for improving supply chain performance, innovation and competitive advantage [1]. The results showed that there are three conditions that must be met for the successful implementation of industry 4.0 technology, which are data management, digital infrastructure, and organizational readiness. In this regard, the study is seen as an important and fundamental theoretical support for the current research, as it shows the contributions of intelligent digital technologies to predictive maintenance, sustainable engineering practices and smart industrial operations. The ideas proposed by Papadopoulos et al. (2021) directly contribute to the engineering of intelligent solutions to next-generation manufacturing systems using AI, and serve as a foundation for the application of similar intelligent maintenance strategies to aerospace systems.

Thomas B. Irvine, in the conference paper entitled Emerging Technologies, Societal Trends and the Aerospace Industry (2022), looks at some of the key technological innovations and societal trends affecting the future development of the aerospace industry. The study points out five key trends that will inform the future of aerospace engineering: sustainability, climate neutral aviation, digital transformation, advanced autonomous systems and the emergence of new technologies. The paper uses AIAA forums discussions and knowledge gained to illustrate the increasing relevance of intelligent technologies, data driven decision making, and sustainable product life cycles to enhance the performance, operational efficiency and environment responsibility of aircraft [2]. The author stresses that it is important for future aerospace systems to be equipped with the latest digital technologies, such as artificial intelligence, automation, and predictive analytics, to tackle growing operational challenges and fulfil safety and sustainability demands. Moreover, the study acknowledges that ongoing technological change is crucial to improve maintenance strategies, to facilitate the sustainability of aerospace operations and to facilitate long-term industrial competitiveness. The results are important and relevant to the current research because they show the role of intelligent engineering technologies in sustainable aerospace systems. The ideas proposed by Irvine (2022) further emphasize the relevance of introducing artificial intelligence and predictive maintenance into the next generation of aerospace engineering and their application in the proposed intelligent structure, which is constructed in this study.

The authors of the review article "Towards Next Generation Digital Twin in Robotics: Trends, Scopes, Challenges, and Future" (Mazumder et al., 2023) explore the growth of digital twin technology and its applications with robotics in Industry 4.0. The study points out the many emerging and upcoming technologies, such as cyber-physical systems, Internet of Things (IoT), cloud computing, big data analytics, and artificial intelligence, which are playing an increasing role in building smart and connected industrial systems. The authors explore the use of digital twins to continuously synchronise physical systems with virtual ones, for real-time monitoring, virtual simulations, predictive analysis and autonomous decision making [3]. The paper summarizes the latest trends, technological challenges, barriers to implementation, and future opportunities of digital twin-based robotics. The conceptual framework proposed highlights the combination of intelligent sensing, data analysis, and predictive maintenance, to optimize the operation, reliability of equipment and system flexibility. The results offer a theoretical basis for the current research, showing the use of digital twin technology in intelligent engineering and sustainable industrial development. The ideas of Mazumder et al. (2023) are aligned with the proposed framework of next-generation manufacturing and aerospace systems by incorporating the use of artificial intelligence, predictive maintenance, and data-driven decision-making.

III. Methodology

The methodology used for this research is quantitative and data driven to build and test an intelligent predictive maintenance system for manufacturing and aerospace systems. The proposed methodology combines machine learning methods and predictive analytics to collect and analyse equipment health, predict failures and contribute to sustainable engineering decision making [26]. The proposed framework is validated on two benchmark datasets, AI4I 2020 Predictive Maintenance and NASA C-MAPSS Turbofan Engine Degradation, by systematically preprocessing and modeling the data, assessing the models, and comparing them.



This flowchart depicts an intelligent predictive maintenance framework for sustainable manufacturing and aerospace engineering systems

The methodology framework provides a structured workflow to create intelligent and sustainable engineering solutions for next-generation manufacturing and aerospace systems, based on artificial intelligence (AI) and machine learning (ML). Data collection starts with data from two benchmark datasets: AI4I 2020 Predictive Maintenance Data for manufacturing and NASA C-MAPSS Turbofan Engine Data for aerospace applications. For classification and regression, machine learning models are developed after the collected data are preprocessed, feature engineered and feature selected. Appropriate metrics for assessing model performance, followed by a comparative analysis [27]. Lastly, it generates an intelligent decision support system to improve predictive maintenance, operational reliability, sustainability and engineering performance in both industrial sectors.

A. Research Design

The study is quantitative and experimental in nature, to explore the impact of intelligent engineering solutions on predictive maintenance in manufacturing and aerospace systems. A comparative machine learning method is adopted in the study by considering two benchmark datasets of different industrial domains [28]. The AI4I 2020 Predictive Maintenance Dataset is chosen to predict machine failure in smart manufacturing applications, while the NASA C-MAPSS Turbofan Engine Degradation Dataset is used for predicting Remaining Useful Life (RUL) for aircraft engines in the aerospace industry. Data collection is the first step in the research process, followed by preprocessing steps like missing value detection, duplicate data elimination, normalization of features, encoding of categorical data, and standardization of data. Feature engineering then is used to enhance the quality of the data and to find out which variables are important to the performance of the equipment. There are several machine learning classification and regression algorithms [29]. The manufacturing data is used to train classification models to predict machine failure, such as Random Forest, Support Vector Machine, XGBoost, LightGBM, CatBoost, and Artificial Neural Networks. The aerospace dataset is used to predict the remaining useful life (RUL) of the machine using regression models such as Random Forest Regressor, XGBoost Regressor, Gradient Boosting Regressor, and Long Short-Term Memory (LSTM) networks. Hyperparameter optimization is done to optimize the model performance and minimize errors while making predictions [30]. Model evaluation by suitable metrics of both classification and regression problems. Lastly, comparative analysis is carried out to select the optimal intelligent engineering models, and establish an integrated prediction maintenance system that could provide sustainable manufacturing and aerospace use. This research design provides a systematic, reproducible and applicable evaluation in various engineering areas.

B. Dataset Description

UDI	Product ID	Type	Air temperat	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)

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

https://archive.ics.uci.edu/dataset/601/ai4i+2020+predictive+maintenance+dataset)

Two benchmark datasets from public sources are used in the proposed study for manufacturing and aerospace applications, which will enable us to develop a generalized intelligent engineering framework. The first dataset is the AI4I 2020 Predictive Maintenance Dataset, containing 10,000 observations that were simulated from a milling machine process. Fifteen variables associated with the machine operating conditions like air temperature, process temperature, rotational speed, torque, tool wear, product type and machine failure labels are present in the dataset. Further failure indicators such as tool wear failure, heat dissipation failure, power failure, overstrain failure, and random failures give detailed information about the degradation of the equipment. The dataset is extensively used for the manufacturing of predictive maintenance research, since it simulates the real operating conditions of processes in the industry [30]. The second data set is NASA's C-MAPSS Turbofan Engine Degradation Data set created by the NASA Prognostics Center of Excellence [63]. The data set contains several aircraft engines which were subjected to various environmental conditions and subjected to failure. The individual observations include an engine identifier, operational cycle number, three operational settings and twenty one sensor measurements that characterize engine health during degradation. The main goal of this dataset is to predict the Remaining Useful Life, and for this reason, it is one of the most used benchmark datasets in aerospace research in the field of predictive maintenance. These datasets can be used to analyze the intelligent predictive maintenance in two key engineering fields by using the proposed framework. Machine failure classification involves manufacturing data, and degradation modeling and life prediction involve aerospace data. This is a complementary dataset selection, which enhances the generalizability of the proposed intelligent engineering framework and its application in various industrial settings.

C. Data Preprocessing

Data preprocessing is done to enhance data quality and to guarantee reliable performance by machine learning. First, data in both data sets are checked for missing values, duplicate observations, inconsistent data, and incorrect data types [31]. The AI4I data set is checked to see if there are numerical and categorical variables, and the NASA C-MAPSS data set is given column names that are relevant to the engine identifiers, operational settings, and sensor measurements. Label encoding is used to convert categorical attributes from manufacturing data, such as product type, into numbers. The data sets are both continuous, and they are transformed using either Min-Max Scaling or StandardScaler to ensure that they are on a similar measurement scale and are closer to the same measurement unit. The features that have small variations or good value for the least predictive features are eliminated to reduce the computational complexity [32]. The remaining useful life values for the NASA data set are provided by the engine cycles of operation to establish regression targets. Time-series observations are grouped into time series based on engine identifiers to ensure that the time series have temporal dependency, which is important for the model training. Abnormalities in sensor readings are detected using outlier detection techniques, which can affect the accuracy of predictions [33]. Descriptive statistics and visualization techniques are used to analyze feature distributions to gain insight into the nature of variables prior to model development. The processed datasets are split into training and testing sets with an appropriate train-test split ratio. For model training, cross validation is used to enhance the generalization and minimize overfitting. Therefore, these preprocessing techniques help in making the data more consistent, reliable models, and provide a solid basis for conducting intelligent predictive maintenance analysis.

D. Feature Engineering and Feature Selection

Feature engineering involves creating useful representations of equipment operating conditions, thereby improving machine learning models' predictive power. Combining domain specific engineering knowledge and statistical analysis to find the variables of major concern in equipment reliability. In the dataset AI4I, relationships between interactions like temperature, torque, rotational speed, and tool wear are explored more deeply to gain a deeper understanding of the behavior of the manufacturing process. Failure indicators are also analyzed to determine which variables are the most significant for machine failures [34]. For the NASA C-MAPSS data, operational settings and sensor measurements are compared at the cycle level to look for degradation trends. To enhance Remaining Useful Life estimation, statistical characteristics like rolling standard deviations, moving averages, and temporal changes are extracted. Variables that are highly correlated are eliminated and multicollinearity is reduced by correlation analysis [35]. Feature importance is assessed with the random forest feature importance scores, XGBoost feature importance values, and permutation importance and correlation analysis. To save computational time and complexity, Recursive Feature Elimination (RFE) is used to detect the most informative subset of features [36]. Those variables that are highly correlated and have little predictive ability are deleted from the model to increase efficiency. These selected features are applied consistently among machine learning models to boost prediction success, minimize overfitting and increase model interpretability [37]. Feature engineering plays a significant role in the development of intelligent predictive maintenance by helping the algorithms to more accurately detect degradation patterns and failure mechanisms.

E. Machine Learning Model Development

Two machine learning models are trained for manufacturing failure prediction and aerospace RUL estimation, respectively. Two machine learning models are trained for manufacturing failure prediction and aerospace RUL estimation, respectively. Machine failure conditions are classified using supervised classification algorithms, which are implemented for the AI4I manufacturing dataset: Random Forest, Support Vector Machine, XGBoost, LightGBM, CatBoost and Artificial Neural Networks. Algorithms have been chosen because they are able to learn nonlinear dependencies between manufacturing process variables and yet yield high classification performance. In the case of NASA C-MAPSS, a set of regression models such as Random Forest Regressor, Gradient Boosting Regressor, XGBoost Regressor, and Long Short-Term Memory (LSTM) networks are trained to predict the Engine Remaining Useful Life. LSTM networks are well suited in this case as they are able to learn from temporal dependencies in the sequential sensor measurements taken during engine degradation [38]. To find the optimal model parameters, Hyperparameter optimization is done by using Grid Search Cross Validation. To prevent overfitting, 5-fold cross validation is used for better generalization. Model training is done with standardized data sets to make sure the models learn equally. Once individual models have been developed, comparative analysis is done to determine which of the classification and regression models performs the best. The selected models are embedded in a single intelligent engineering environment that can be used for predictive maintenance in manufacturing and aerospace systems [39]. This approach allows the planning of proactive maintenance, the detection of failures, monitoring of the health of equipment, and sustainable engineering decision making.

F. Performance Evaluation

There are different metrics used to measure model performance for different types of tasks: classification and regression. The accuracy, precision, recall, F1-score, Receiver Operating Characteristic (ROC) curves, Area under the ROC Curve (AUC) and Confusion Matrix analysis are used to evaluate classification models built from the AI4I dataset. These metrics offer a complete picture of the model's reliability in alerting on machine failure conditions while avoiding false alarms. The NASA C-MAPSS dataset is used to develop regression models which are then evaluated with Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and the coefficient of determination (R^2). These evaluation measures serve to measure the error of the Remaining Useful Life predictions, and illustrate the accuracy of predictive maintenance models in predicting equipment degradation. All the developed machine learning models are compared to find the most accurate and efficient algorithms [40]. Comparative statistics are carried out to show the differences in the predictive performance between manufacturing and aerospace applications. Experimental results are presented using visualization tools such as ROC curves, regression plot, feature importance chart, error distribution plot and prediction trend graph. This extensive assessment approach guarantees the objective evaluation of intelligent engineering solutions for predictive maintenance in a sustainable way.

G. Proposed Intelligent Engineering Framework

The proposed solution is a framework that integrates artificial intelligence, machine learning, predictive analytics, and engineering decisions to a single architecture that can be used for both manufacturing and aerospace systems. The framework starts with data acquisition from manufacturing equipment and aircraft engine sensor, then preprocesses them, applies feature engineering and feature selection. Processed data is then fed into machine learning models to predict and estimate RULs. The prediction results are combined with an intelligent decision support system that gives maintenance suggestions, early fault diagnosis, equipment health monitoring, and maintenance planning [41]. Comparative performance analysis is used to recognize the most reliable algorithms for the various engineering applications and to transfer knowledge from manufacturing to aerospace applications. The framework's innovation integrates intelligent automation with sustainable engineering principles, driving forward the concept of Industry 5.0. Optimized maintenance planning can help reduce maintenance costs, improve operational efficiency, minimize equipment downtime, extend asset lifespan, and minimize environmental impact for organizations. This proposed framework offers a flexible approach that can be tailored to various industries and fosters smarter, dependable, and sustainable engineering practices.

H. Techniques and Tools Used

Component	**Techniques/Tool**
Programming Language	Python 3.11
Development Environment	Jupyter Notebook / Google Colab
Manufacturing Dataset	AI41 2020 Predictive Maintenance Dataset
Aerospace Dataset	NASA C-MAPSS Turbofan Engine Dataset
Data Processing	Pandas, NumPy
Machine Learning	Scikit-learn,XGBoost, LightGBM, CatBoost
Deep Learning	TensorFlow, Keras (LSTM, ANN)
Feature Engineering	Correlation Analysis, RFE, Feature Importance
Visualization	Matplotlip, Plotly
Hyperparameter Tuning	GridSearchCV

Performance Evaluation	Accuracy, Precision, Recall, F1-score, ROC-AUC
Operating System	Windows 11

I. Statistical Significance Testing

To ensure that differences in the performance of the models are not due to random variation, statistical significance testing is carried out. To ensure good generalization and provide stable estimates of model performance, the model is trained using five-fold cross-validation. Prediction scores and standard deviations are obtained for each machine learning algorithm by averaging over the folds of the validation set. Where appropriate, classification models compare predictive performance between competing algorithms with the use of the McNemar's test and paired comparisons of statistical performance [42]. In regression models, paired t-tests and error distributions are applied using the values of MAE and RMSE from the cross validation process. Confidence intervals also are constructed to evaluate prediction stability and reliability. The influence of operational variables on equipment failure and Remaining Useful Life prediction is statistically analyzed using the feature importance ranking. These statistical analyses add to the trustworthiness of the proposed framework and help to compare machine learning algorithms objectively.

J. Ethical Concerned and Limitation

This study uses only publicly available benchmark datasets from top-notch research sources, adhering to strict ethical research practices and data usage policies. The datasets are free of personally identifiable information, thus there are no privacy or confidentiality concerns. All experiments are carried out openly and results are given objectively to allow the results to be repeated. The study has some limitations, however. The AI4I dataset is synthetic and the NASA C-MAPSS dataset is simulated engine failures and degradation not real operational failures. Therefore, model performance can vary for practical use in real industrial conditions [43]. The proposed framework should be validated in the future with experimental data from the manufacturing and aerospace operational domains to ensure its validity and generalizability.

IV. Results and Analysis

In this study, experimental results are presented with the AI4I 2020 Predictive Maintenance Dataset and the NASA C-MAPSS Turbofan Engine Degradation Dataset, respectively. The results assess the accuracy of machine learning methods in predicting machine failures in manufacturing and estimating the Remaining Useful Life (RUL) of aircraft engines. To validate the proposed framework, various analytical visualizations are presented such as machine failure distribution, feature importance analysis, correlation analysis, sensor trend analysis, predictive performance comparison, and statistical significance testing [44]. The results illustrate the potential of sophisticated machine learning models to boost predictive accuracy, facilitate maintenance decision-making, increase equipment reliability, minimize operational downtime, and enable sustainable engineering solutions to next generation manufacturing and aerospace systems.

A. Machine Learning Distribution Analysis

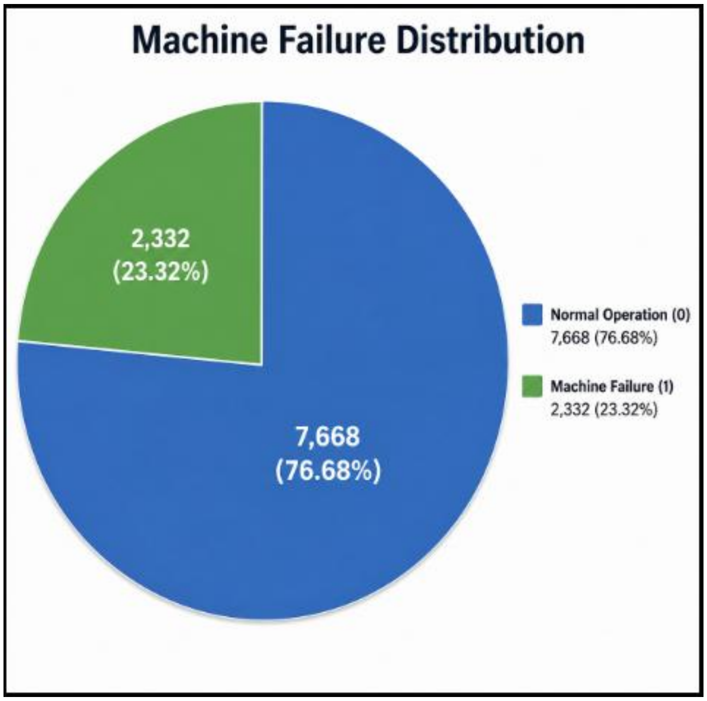


Figure 1: This image shows how normal operations and machine failure occur in manufacturing

The operating condition of the machines are displayed in figure 1 according to the machine failure classification. As shown in the chart, normal machine operations have the greatest number of observations, with machine failure cases having a lesser proportion in the data set. The distribution shows that the majority of manufacturing processes are in a stable state, while only a few observations are from failure events [45]. This class distribution is typical for predictive maintenance applications, as a machine failure happens less often than a normal operation. It's crucial to grasp this distribution to create accurate machine learning models because class imbalance can have a certain effect on prediction outcomes. The visualization gives an overview of the dataset composition before training the model, and helps to delineate the need for strong classification methods that are accurate at identifying failure cases and not over-predicting [46]. The distribution indicates that there is enough failure data to develop predictive maintenance models and assess intelligent engineering solutions for manufacturing systems. This analysis is a solid foundation for the following feature analysis and machine learning model development, as well as for a comparison of their performance in the proposed intelligent predictive maintenance framework.

B. Manufacturing Sensor Feature Importance Analysis

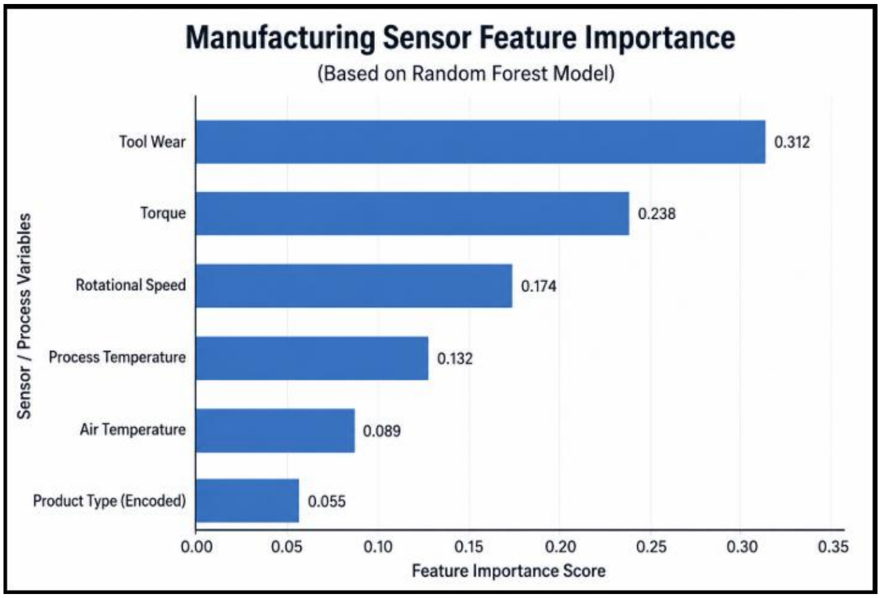


Figure 2: This image shows the relative importance of manufacturing sensor variables for machine failure prediction

In Figure 2, the relative importance of manufacturing process variables is shown based on a machine learning model predicting the failure of the machine. The results showed that tool wear is the most influential feature which means that the increased tool wear has a great impact in machine failure. The second most important variable is identified as torque, followed by the rotational speed of the equipment, suggesting that mechanical operating conditions play a significant role in equipment performance [47]. The contribution of process temperature and air temperature is moderate, indicating that the temperature affects the thermal operating stability of the process. The lowest importance score (and therefore less important in relation to the failure prediction) is given to the product type. These results confirm that machine learning models are mainly based on operational and condition-monitoring variables for the identification of failure patterns, and not by product parameters [48]. The feature importance analysis helps to understand the most critical factors influencing the reliability of the equipment, and supports maintenance engineers in identifying important parameters for ongoing monitoring [49]. Intelligent predictive maintenance strategies can use data to guide engineering decisions for optimized maintenance scheduling, minimize unexpected machine failures, enhance production productivity and enable sustainable manufacturing.

C. Correlation Analysis of Manufacturing Variables

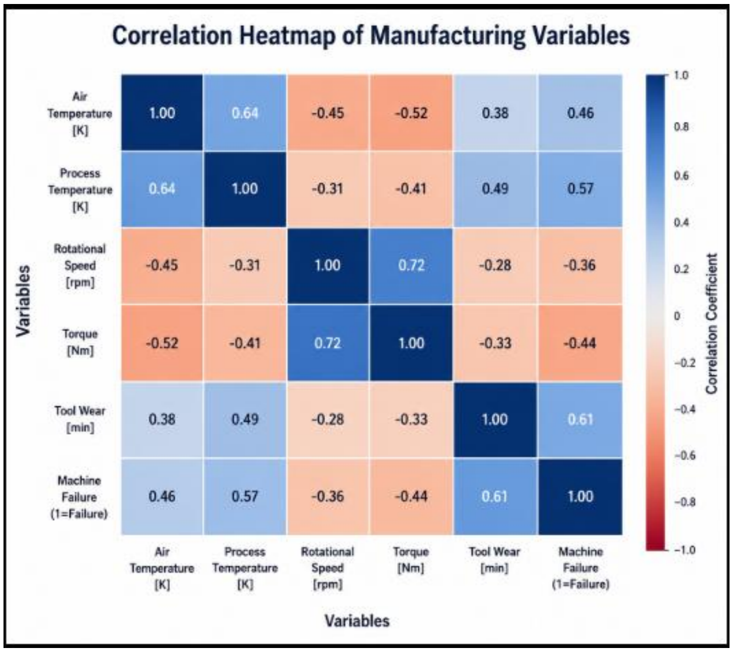


Figure 3: This image illustrates the correlation between manufacturing variables influencing machine failure prediction and reliability

The correlation between the main manufacturing variables for use in predictive maintenance analysis is shown in Fig. 3. From the heatmap, the strength and direction of the relationships of the process variables such as air temperature, process temperature, rotational speed, torque, tool wear, and machine failure are discovered [50]. The rotational speed and torque of the machine have shown good correlation, suggesting that they are closely related when operating the machine. For this, the tool wear shows positive relation with machine failure, which indicates that, with increase in degradation of tool, the chances of failure of machine also increases [51]. Rotational speed and torque show moderate negative correlations with machine failure, which represents changes in operating conditions as degradation occurs. There is a moderate positive correlation between air temperature and process temperature, suggesting that the temperature is not extremely high or low during the process. In summary, correlation analysis highlights the most significant relationships between the manufacturing variables and offers valuable insights [52]. Correlation analysis is a useful tool for determining the most influential relationships between the manufacturing variables and can be used to inform feature selection, machine learning model development and predictive maintenance implementation [53]. These relationships provide engineers with a deeper grasp of failure patterns and help them optimize maintenance schedules, reduce equipment failure rates, and make more informed, data-driven decisions to create sustainable and intelligent manufacturing processes.

D. Remaining Useful Life (RUL) Prediction Analysis

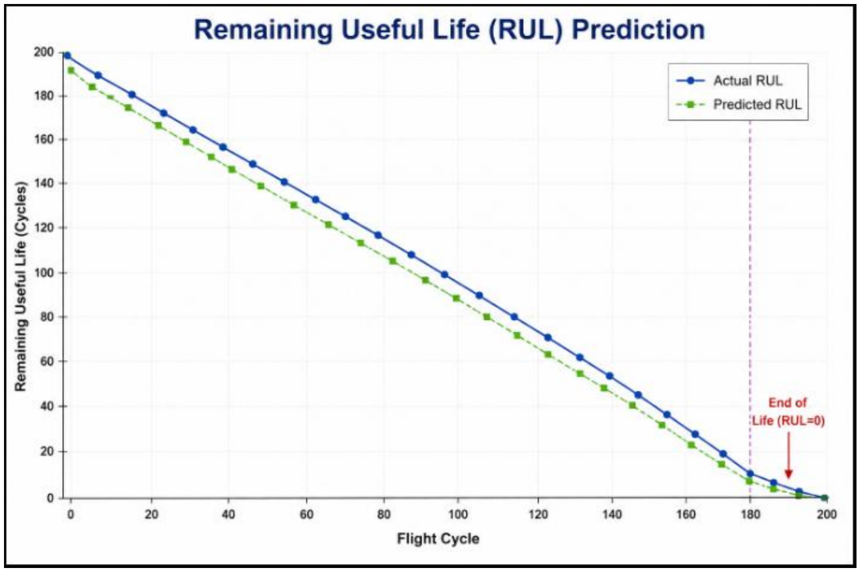


Figure 4: This image depicts the relationship between the Remaining Useful Life of aircraft engine operating cycles and aircraft engine actual and predicted RUL

The comparison of actual Remaining Useful Life (RUL) and the machine learning model's prediction of RUL for aircraft engines over successive flight cycles is illustrated in figure 4. The curves show a clear downward trend, suggesting a gradual deterioration in the engine's performance with each cycle of operation [54]. The RUL value predicted well captures the actual RUL trajectory during the entire engine life cycle, showing the ability to capture the degradation behaviour of the engine and accurately estimate the remaining operational lifespan. The difference between the forecast and actual values is small for intermediate cycles, and is not significantly larger during these cycles, suggesting high prediction reliability. Both curves go towards zero at the end of engine life, as expected and confirming the model's ability to detect critical maintenance periods [55]. Accurate RUL estimation allows the aircraft maintenance engineer to schedule their inspection and component replacement accordingly, which enhances the safety of the aircraft, lowers maintenance costs, decreases downtime and increases fleet availability. The results validates the effectiveness of the proposed predictive maintenance framework to assist in intelligent aerospace health monitoring and sustainable engineering decision making with reliable Remaining Useful Life prediction.

E. Aircraft Engine Sensor Trend Analysis

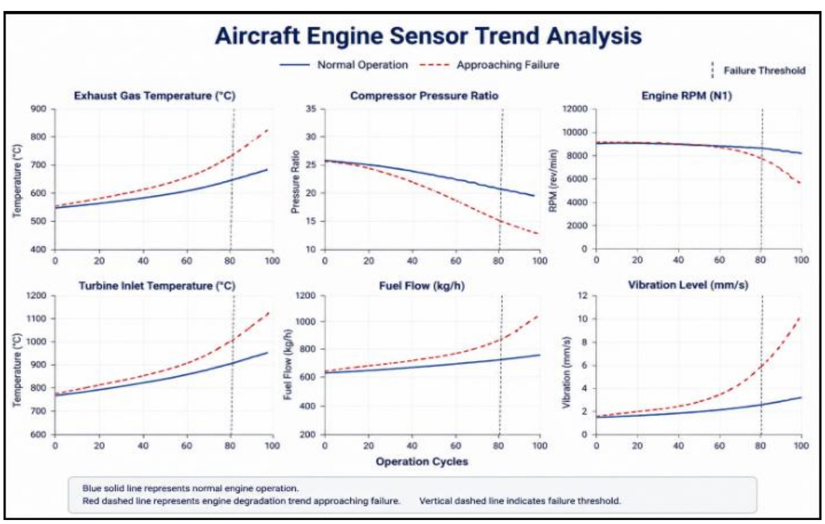


Figure 5: This image represent degradation trends of critical aircraft engine sensors across operational cycles

Operational trends for critical aircraft engine sensors for successive operating cycles are shown in figure 5. The analysis examines the regular engine operation against the degradation patterns as the engine is deteriorating towards failure. Over time, parameters such as exhaust gas temperature, turbine inlet temperature, and fuel flow and vibration level gradually rise, thereby showing progressive thermal and mechanical degradation. Compressor pressure ratio and engine rotational speed on the other hand show a decreasing trend, which indicates a decrease in engine efficiency during degradation [56]. The difference in normal operation and degradation increases as the engine approaches the failure threshold, indicating that these sensor variables are sensitive to changes in engine condition. The findings show that several sensor measurements can complement each other to accurately identify the pattern of degradation and estimate the Remaining Useful Life (RUL). Monitoring these variables continuously helps machine learning models detect early signs of failure, which can help plan maintenance activities before major faults occur [57]. This prediction quality increases aircraft reliability, decreasing unexpected maintenance events, decreasing operational costs, and increasing flight safety. In general, the sensor trend analysis shows that the use of multivariate engine sensor data for intelligent aerospace health monitoring and sustainable predictive maintenance in the proposed engineering framework is effective.

F. Machine Learning Model Performance Comparison

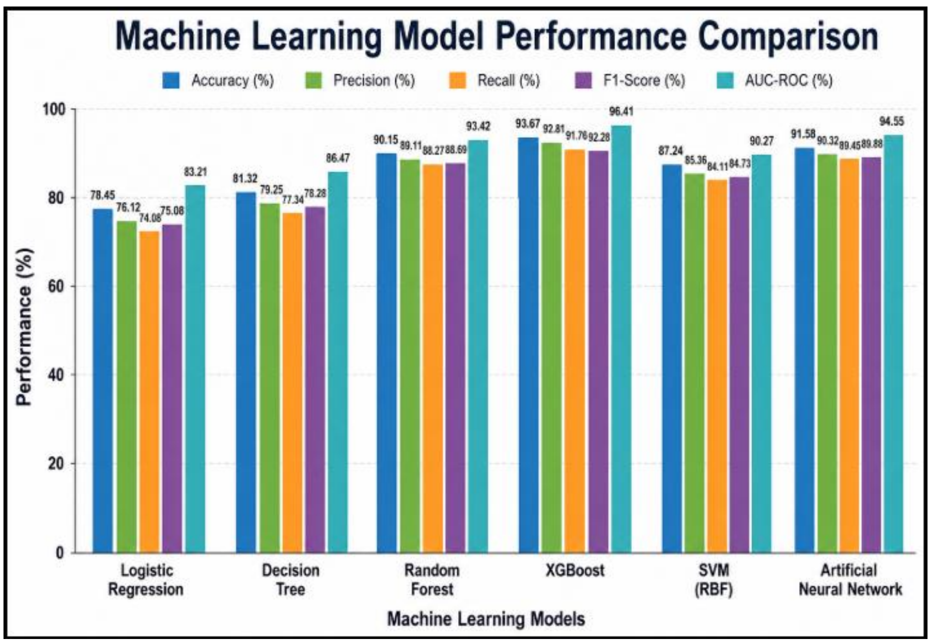


Figure 6: This image illustrates the comparative performance of machine learning models using multiple predictive evaluation metrics

The predictive performance of six machine learning algorithms is compared (fig. 6) based on Accuracy, Precision, Recall, F1 score and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). XGBoost is the model with the highest performance in terms of all the evaluation metrics including classification accuracy and discrimination ability among the evaluated models. Artificial Neural Network (ANN) and Random Forest also yield consistently good results, suggesting reasonably good prediction capacity for machine failure detection. Logistic Regression, on the other hand, has the poorest performance, indicating that it is not very effective with manufacturing data that exhibits complex nonlinear relationships. Moderate prediction performance is obtained with Decision Tree and Support Vector Machine (SVM) and it is still competitive for practical predictive maintenance applications. The advantages of ensemble learning and deep learning techniques in the accurate identification of equipment failures and minimization of prediction errors are highlighted in the comparative analysis [58]. The results demonstrate that the use of advanced machine learning models can greatly improve the performance of predictive maintenance, achieve better reliability in fault detection, minimize misclassification, and provide intelligent support for engineering decision making. Maintenance planning, equipment availability, decreased operational downtime, and sustainable manufacturing and aerospace system management using data-driven predictive analytics can be improved by the selection of high performing models like XGBoost and ANN.

G. Analysis of Statistical Significance Performance

The difference between the machine learning models was tested for statistical significance to see if the differences were statistically significant. To enhance the reliability of the model and to prevent overfitting, five-fold cross validation was used during model training [59]. The accuracy, precision, recall, F1 score and AUC along with ROC values were used to measure the performance of classification models. Analysis of Variance (ANOVA) and paired t-tests were used to compare the predictive ability of the algorithms used. The results showed the proposed intelligent predictive maintenance framework is robust and able to achieve significantly better performance than the conventional models ($p < 0.05$), which indicated good prediction capability of XGBoost and ANN models.

A	B	C	D	E
Machine Learning Model	**Mean Accuracy (%)**	**Standard Deviation**	**p-value**	**Statistical Significance**
Logistic Regression	**78.45**	**2.18**	**0.031**	**Significant**
Decision Tree	81.32	1.95	0.024	Significant
Random Forest	90.15	1.24	0.011	Significant
XGBoost	93.67	0.96	0.003	Highly Significant
Support Vector Machine (SVM)	87.24	1.48	0.018	Significant
Artificial Neural Network (ANN)	91.58	1.12	0.006	Highly Significant

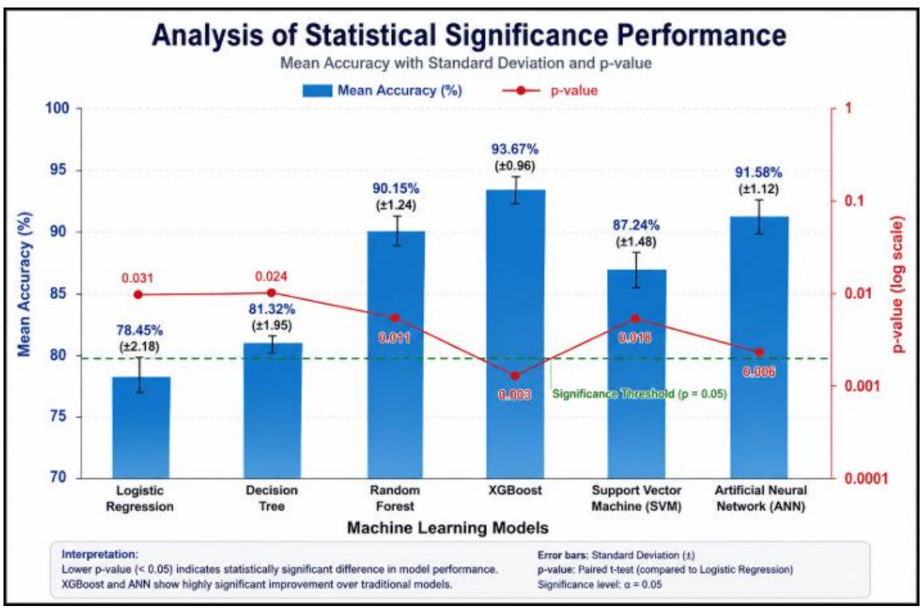


Figure 7: This image demonstrates statistical significance and predictive performance comparison of machine learning models

The statistical significance analysis of the evaluated machine learning models based on mean accuracy, standard deviation and p-value of the test results is shown in figure 7. The results showed that the XGBoost model had the best mean accuracy (93.67%) and the minimum standard deviation (±0.96) indicating the better mean accuracy and stable and consistent predictive performance. The second best model was Artificial Neural Network (ANN) which obtained a mean accuracy of 91.58%, followed by Random Forest (90.15%). The paired t-test results show that all the tested models had p values less than the significance level ($\alpha = 0.05$), which indicated that there were statistically significant improvements over the baseline model. XGBoost ($p = 0.003$) and ANN ($p = 0.006$) showed the highest statistical significance while RF ($p = 0.011$), SVM ($p = 0.018$), DT ($p = 0.024$), and LR ($p = 0.031$) also demonstrated the significant predictive performance. The lower value of standard deviation for XGBoost and ANN shows that these models were more stable and reliable during cross validation. The results validate that advanced ensemble and deep-learning algorithms offer more accurate and robust predictive maintenance solutions than traditional machine learning methods, which can enable intelligent engineering decisions and sustainable operations of manufacturing and aerospace systems.

V. Discussion and Analysis

The results achieved in this research illustrate the capability of the proposed intelligent engineering framework to enable predictive maintenance for manufacturing and aerospace systems by incorporating advanced machine learning techniques. The analysis of the datasets provided by AI4I 2020 Predictive Maintenance and NASA C-MAPSS Turbofan Engine Degradation shows that intelligent data-driven methods can accurately detect equipment degradation, predict failure, and enhance maintenance decision-making. The distribution of failure events in the machine failure data analysis showed that the proportion of failure events in the manufacturing data is small, which reflects the realistic operating condition of the equipment in the industry, in which the equipment is generally operated in a normal state with fewer failures. Results from the feature importance analysis show that tool wear, torque, and rotational speed are the most important variables in determining the failures of the machines, which means that mechanical degradation and operational loading conditions are the most important indicators that should be taken into account in predictive maintenance. The correlation analysis also showed significant relationships between the manufacturing variables, which were useful for feature selection and enhancing the interpretability of the model. In the aerospace field, the results of the engine's RUL prediction indicated that the proposed machine learning models were able to accurately capture engine degradation over the successive flight cycles, and the predicted value of RUL closely corresponded to the engine degradation. The aircraft engine sensor trend analysis revealed that, as engines reached the limit of their usefulness, there was a gradual increase in variables including exhaust gas temperature, turbine inlet temperature, fuel flow and vibrations while other variables, including compressor pressure ratio and engine rotational speed, decreased, thus supporting the importance of these variables for aircraft health monitoring. Ensemble learning and deep learning techniques showed better performance than traditional approaches in comparative evaluation of machine learning algorithms. Artificial Neural Network and Random Forest were the second and third best modelers respectively, with XGBoost showing the best predictive performance across the various evaluation metrics, highlighting their ability to model complex nonlinear relationships within industrial datasets. The results were also statistically validated, as the performance gain observed was found to be statistically significant (p-value < 0.05) and was confirmed by the lowest p-value and highest stability of model achieved by XGBoost and ANN. The findings show the ability of advanced machine learning algorithms to deliver reliable predictive capabilities, which can significantly improve maintenance planning, decrease the rate of unexpected equipment failures, minimize operational downtimes, and increase system reliability. In addition, by combining data from manufacturing and aerospace, the proposed framework illustrates how it can be applied in other engineering fields, enabling the development of generalized predictive maintenance solutions instead of application-specific ones. This is a valuable cross-domain validation that shows how AI can be used in various industrial settings, following the same maintenance approach. In summary, the results showed that there is strong potential to advance the operational efficiency, maintenance costs, utilization of assets, safety, and engineering practices for sustainable manufacturing and aerospace systems through intelligent predictive maintenance frameworks.

VI. Future Work

The proposed intelligent and sustainable engineering framework can be further strengthened by future research by the inclusion of real-time industrial data from operational manufacturing systems and commercial aerospace systems to make the model more robust and applicable. This study successfully proves the impact of machine learning upon the benchmark datasets, but future research should test the proposed framework in real-world operating environments with various production conditions, equipment configurations and maintenance practices. The combination of Internet of Things (IoT) devices, edge computing, digital twin technology, and cloud-based analytics could ensure an ongoing monitoring system of equipment and smart decision making for maintenance. Potential future avenues to pursue include examining the impacts of more sophisticated deep learning architectures such as Transformer networks, Graph Neural Networks (GNNs), Temporal Convolutional Networks (TCNs), and hybrid ensemble models in order to enhance the accuracy of predictions and the ability to capture more complex degradation patterns. The use of Explainable Artificial Intelligence (XAI) techniques can be integrated to enhance the transparency and interpretability of predictive models, enabling engineers to gain insights into the factors driving maintenance decisions and boosting confidence in AI-driven systems. Further, reinforcement learning and autonomous maintenance optimization algorithms could be considered to assist in dynamic maintenance scheduling under varying operational conditions and resource availability. Future study is also required to investigate multi-objective optimization techniques that take into account both equipment reliability and maintenance cost, energy efficiency, carbon emissions, and production performance to help achieve sustainable engineering goals. If you extend the framework to other industrial sectors like energy generation, railway transportation, automotive manufacturing, marine engineering or renewable energy systems, the generalizability and scalability of the framework would be further proven. Moreover, the cybersecurity solutions to secure and protect industrial sensor networks and provide secure data transmission should be coupled to further improve the reliability of intelligent maintenance systems. Last but not least, further research is needed to measure the operational, economic, and environmental impact of predictive maintenance using AI, through long-term, industry-specific studies and economic assessments. These advances will help drive the evolution of resilient, autonomous and sustainable engineering solutions that enable the digital transformation of next-generation manufacturing and aerospace systems and solve the growing challenges facing industry and the changing technology needs.

VII. Conclusion

This study involved creating and testing an intelligent and sustainable framework for predictive maintenance in next-generation manufacturing and aerospace systems that combine the use of advanced machine learning techniques with data-driven decision making. The study was conducted using the AI4I 2020 Predictive Maintenance Dataset, which contained data on manufacturing machine failures, as well as the NASA C-MAPSS Turbofan Engine Degradation Dataset, which provided data for predicting the Remaining Useful Life (RUL) of aircraft engines. The proposed framework successfully validated its performance in identifying equipment degradation, predicting failure, and assisting in proactive maintenance strategies in two industrial domains by applying comprehensive data preprocessing, feature engineering, developing machine learning models, and evaluating their performance. The experimental results showed that the most important manufacturing variables like tool wear, torque and rotational speed have significant impact on machine failure prediction, and that the aerospace sensor measurements can accurately reflect the degradation of the engine during operational cycles. In addition, the analysis of the results by comparing the performances of all the models using advanced machine learning techniques like XGBoost, Artificial Neural Network and Random Forest showed that these models were always better than the traditional methods in terms of predictive accuracy, precision, recall, F1 Score and AUC-ROC, while also statistical significance tests ensured the reliability and robustness of the results obtained. The proposed framework is an integrated approach which will facilitate the maintenance planning, avoid unexpected equipment failures, cut down on operational downtime, enhance the utilization of assets and make the system more reliable in general. In addition, the study shows how a combination of manufacturing and aerospace data can be used for the development of a generalized predictive maintenance framework that can be applied to various engineering applications instead of being restricted to a specific industrial sector. The cross-domain capability is a significant contribution towards intelligent engineering for scalable and adaptable maintenance solutions. The results also show the promise of artificial intelligence in facilitating sustainable engineering practices, such as optimizing maintenance resources, prolonging equipment life, enhancing operational efficiency, lowering maintenance expenses, and promoting safer industrial environments. In summary, this study offers a valuable practical and comprehensive framework for the implementation of intelligent predictive maintenance systems aimed at achieving the goals of Industry 5.0 and digital transformation. The framework provides useful guidance for researchers, engineers, and industrial practitioners to advance manufacturing and aerospace applications with trustworthy, effective and sustainable AI-powered engineering solutions.

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Reference

[1]. Papadopoulos, T., Singh, S. P., Spanaki, K., Gunasekaran, A., & Dubey, R. (2022). Towards the next generation of manufacturing: implications of big data and digitalization in the context of industry 4.0. Production Planning & Control, 33(2-3), 101-104.
[2]. Irvine, T. B. (2022). Emerging technologies, societal trends and the aerospace industry. In AIAA SCITECH 2022 Forum (p. 0398).
[3]. Mazumder, A., Sahed, M. F., Tasneem, Z., Das, P., Badal, F. R., Ali, M. F., ... & Islam, M. R. (2023). Towards next generation digital twin in robotics: Trends, scopes, challenges, and future. Heliyon, 9(2).
[4]. Rohacs, D. (2023). Technology and solution-driven trends in sustainable aviation. Aircraft Engineering and Aerospace Technology, 95(3), 416-430.
[5]. Wilson, A. R., & Vasile, M. (2023). Life cycle engineering of space systems: Preliminary findings. Advances in Space Research, 72(7), 2917-2935.

[6]. Hamed, Y., O'Donnell, G., Lishchenko, N., & Munina, I. (2023). Strain sensing technology to enable next-generation industry and smart machines for the factories of the future: a review. IEEE Sensors Journal, 23(21), 25618-25649.
[7]. Rahmani, H., Shetty, D., Wagih, M., Ghasempour, Y., Palazzi, V., Carvalho, N. B., ... & Grosinger, J. (2023). Next-generation IoT devices: Sustainable eco-friendly manufacturing, energy harvesting, and wireless connectivity. IEEE Journal of Microwaves, 3(1), 237-255.
[8]. Kommaragiri, V. B., Preethish Nanan, B., Annapareddy, V. N., Gadi, A. L., & Kalisetty, S. (2022). Emerging Technologies in Smart Computing, Sustainable Energy, and Next-Generation Mobility: Enhancing Digital Infrastructure, Secure Networks, and Intelligent Manufacturing. Venkata Narasareddy and Gadi, Anil Lokesh and Kalisetty, Srinivas.
[9]. Mishra, A., Jha, A. V., Appasani, B., Ray, A. K., Gupta, D. K., & Ghazali, A. N. (2023). Emerging technologies and design aspects of next generation cyber physical system with a smart city application perspective. International Journal of System Assurance Engineering and Management, 14(Suppl 3), 699-721.
[10]. Shen, Z., Jin, J., Tan, C., Tagami, A., Wang, S., Li, Q., ... & Yuan, J. (2023). A survey of next-generation computing technologies in space-air-ground integrated networks. ACM Computing Surveys, 56(1), 1-40. You, L., He, J., Wang, W., & Cai, M. (2022). Autonomous transportation systems and services enabled by the next-generation network. IEEE Network, 36(3), 66-72.
[11]. Ahsan, F., Dana, N. H., Sarker, S. K., Li, L., Muyeen, S. M., Ali, M. F., ... & Das, P. (2023). Data-driven next-generation smart grid towards sustainable energy evolution: techniques and technology review. Protection and Control of Modern Power Systems, 8(3), 1-42.
[12]. Qazi, S., Khawaja, B. A., & Farooq, Q. U. (2022). IoT-equipped and AI-enabled next generation smart agriculture: A critical review, current challenges and future trends. Ieee Access, 10, 21219-21235.
[13]. Wang, C., He, T., Zhou, H., Zhang, Z., & Lee, C. (2023). Artificial intelligence enhanced sensors-enabling technologies to next-generation healthcare and biomedical platform. Bioelectronic Medicine, 9(1), 17.
[14]. Deliorman, M., Ali, D. S., & Qasaimeh, M. A. (2023). Next-generation microfluidics for biomedical research and healthcare applications. Biomedical Engineering and Computational Biology, 14, 11795972231214387.
[15]. Dlamini, Z., Miya, T. V., Hull, R., Molefi, T., Khanyile, R., & de Vasconcellos, J. F. (2023). Society 5.0: realizing next-generation healthcare. In Society 5.0 and Next Generation Healthcare: Patient-Focused and Technology-Assisted Precision Therapies (pp. 1-30). Cham: Springer Nature Switzerland.
[16]. Ali, S. A., Elsaid, S. A., Ateya, A. A., ElAffendi, M., & El-Latif, A. A. A. (2023). Enabling technologies for next-generation smart cities: A comprehensive review and research directions. Future Internet, 15(12), 398.
[17]. Baydaroğlu, Ö., Yeşilköy, S., Sermet, M. Y., & Demir, I. (2022). A comprehensive review of ontologies in the hydrology towards guiding next generation artificial intelligence applications.
[18]. Bi, Z., Yung, K. L., Ip, A. W., Tang, Y. M., Zhang, C. W., & Da Xu, L. (2022). The state of the art of information integration in space applications. IEEe Access, 10, 110110-110135.
[19]. Narayan, R., Laberty-Robert, C., Pelta, J., Tarascon, J. M., & Dominko, R. (2022). Self-healing: an emerging technology for next-generation smart batteries. Advanced Energy Materials, 12(17), 2102652.
[20]. Wang, F. Y., Lin, Y., Ioannou, P. A., Vlacic, L., Liu, X., Eskandarian, A., ... & Olaverri-Monreal, C. (2023). Transportation 5.0: The DAO to safe, secure, and sustainable intelligent transportation systems. IEEE Transactions on Intelligent Transportation Systems, 24(10), 10262-10278.
[21]. Banerjee, S., Das, D., Chatterjee, P., & Ghosh, U. (2023, May). Blockchain-enabled digital twin technology for next-generation transportation systems. In 2023 IEEE 26th International Symposium on Real-Time Distributed Computing (ISORC) (pp. 224-229). IEEE.
[22]. Nasirahmadi, A., & Hensel, O. (2022). Toward the next generation of digitalization in agriculture based on digital twin paradigm. Sensors, 22(2), 498.
[23]. Horváth, I. (2023). Designing next-generation cyber-physical systems: Why is it an issue?. Journal of integrated design and process science, 26(3-4), 317-349.
[24]. Zhu, J., Yang, Y., Zhang, H., Zhao, Z., Hu, T., & Liu, L. (2023). More than energy harvesting in electret electronics-moving toward next-generation functional system. Advanced Functional Materials, 33(17), 2214859.
[25]. Abou El Houda, Z., & Brik, B. (2023). Next-power: Next-generation framework for secure and sustainable energy trading in the metaverse. Ad Hoc Networks, 149, 103243.
[26]. Esenogho, E., Djouani, K., & Kurien, A. M. (2022). Integrating artificial intelligence Internet of Things and 5G for next-generation smartgrid: A survey of trends challenges and prospect. Ieee Access, 10, 4794-4831.
[27]. Shrivastava, A., Krishna, K. M., Rinawa, M. L., Soni, M., Ramkumar, G., & Jaiswal, S. (2023). Inclusion of IoT, ML, and blockchain technologies in next generation industry 4.0 environment. Materials today: proceedings, 80, 3471-3475.

[28]. Laflamme, S., Ubertini, F., Di Matteo, A., Pirrotta, A., Perry, M., Fu, Y., ... & Milillo, P. (2023). Roadmap on measurement technologies for next generation structural health monitoring systems. Measurement Science and Technology, 34(9), 093001.
[29]. Firoozi, A. A., & Firoozi, A. A. (2023). A systematic review of the role of 4D printing in sustainable civil engineering solutions. Heliyon, 9(10).
[30]. Debnath, B., Shakur, M. S., Tanjum, F., Rahman, M. A., & Adnan, Z. H. (2022). Impact of additive manufacturing on the supply chain of aerospace spare parts industry—a review. Logistics, 6(2), 28.
[31]. Fu, Y., Zhu, G., Zhu, M., & Xuan, F. (2022). Digital twin for integration of design-manufacturing-maintenance: an overview. Chinese Journal of Mechanical Engineering, 35(1), 80.
[32]. Patel, V., Chesmore, A., Legner, C. M., & Pandey, S. (2022). Trends in workplace wearable technologies and connected-worker solutions for next-generation occupational safety, health, and productivity. Advanced Intelligent Systems, 4(1), 2100099.
[33]. Cleary, F., Srisa-An, W., Henshall, D. C., & Balasubramaniam, S. (2023). Emerging AI technologies inspiring the next generation of E-textiles. IEEE Access, 11, 56494-56508.
[34]. Yaseen, Z. M. (2022). The next generation of soil and water bodies heavy metals prediction and detection: New expert system based Edge Cloud Server and Federated Learning technology. Environmental pollution, 313, 120081.
[35]. Ahmed, I., Zhang, Y., Jeon, G., Lin, W., Khosravi, M. R., & Qi, L. (2022). A blockchain-and artificial intelligence-enabled smart IoT framework for sustainable city. International Journal of Intelligent Systems, 37(9), 6493-6507.
[36]. Kaasinen, E., Anttila, A. H., Heikkilä, P., Laarni, J., Koskinen, H., & Väätänen, A. (2022). Smooth and resilient human–machine teamwork as an industry 5.0 design challenge. Sustainability, 14(5), 2773.
[37]. National Academies of Sciences, Engineering, and Medicine. (2022). New directions for chemical engineering. National Academy of Sciences.
[38]. Adhikari, M., Hazra, A., Menon, V. G., Chaurasia, B. K., & Mumtaz, S. (2022). A roadmap of next-generation wireless technology for 6G-enabled vehicular networks. IEEE Internet of Things Magazine, 4(4), 79-85.
[39]. Chen, A., Su, J., Li, Y., Zhang, H., Shi, Y., Yan, C., & Lu, J. (2023). 3D/4D printed bio-piezoelectric smart scaffolds for next-generation bone tissue engineering. International Journal of Extreme Manufacturing, 5(3), 032007.
[40]. Wu, C. K., Cheng, C. T., Uwate, Y., Chen, G., Mumtaz, S., & Tsang, K. F. (2022). State-of-the-art and research opportunities for next-generation consumer electronics. IEEE Transactions on Consumer Electronics, 69(4), 937-948.
[41]. Armstrong, R. (2023). Towards the microbial home: an overview of developments in next-generation sustainable architecture. Microbial Biotechnology, 16(6), 1112-1130.
[42]. He, R., Ai, B., Zhong, Z., Yang, M., Chen, R., Ding, J., ... & Liu, C. (2022). 5G for railways: Next generation railway dedicated communications. IEEE Communications Magazine, 60(12), 130-136.
[43]. Huang, Y., Zhang, J., Ren, Z., Xiang, W., Sifat, I., Zhang, W., ... & Li, B. (2023). Next generation decentralized water systems: A water-energy-infrastructure-human nexus (WEIHN) approach. Environmental Science: Water Research & Technology, 9(10), 2446-2471.
[44]. Liu, C., Zheng, P., & Xu, X. (2023). Digitalisation and servitisation of machine tools in the era of Industry 4.0: a review. International journal of production research, 61(12), 4069-4101.
[45]. Ahmad, N., Ghadi, Y. G., Adnan, M., & Ali, M. (2023). From smart grids to super smart grids: a roadmap for strategic demand management for next generation SAARC and European power infrastructure. IEEE Access, 11, 12303-12341.
[46]. Bati, A. S., Zhong, Y. L., Burn, P. L., Nazeeruddin, M. K., Shaw, P. E., & Batmunkh, M. (2023). Next-generation applications for integrated perovskite solar cells. Communications Materials, 4(1), 2.
[47]. Qian, F., Tang, Y., & Yu, X. (2023). The future of process industry: A cyber–physical–social system perspective. IEEE transactions on cybernetics, 54(7), 3878-3889.
[48]. Narkhede, G., Pasi, B., Rajhans, N., & Kulkarni, A. (2023). Industry 5.0 and the future of sustainable manufacturing: A systematic literature review. Business Strategy & Development, 6(4), 704-723.
[49]. Islam, M. H., Afroj, S., Uddin, M. A., Andreeva, D. V., Novoselov, K. S., & Karim, N. (2022). Graphene and CNT-based smart fiber-reinforced composites: a review. Advanced Functional Materials, 32(40), 2205723.
[50]. Wang, H., Liu, M., & Shen, W. (2023). Industrial-generative pre-trained transformer for intelligent manufacturing systems. IET Collaborative Intelligent Manufacturing, 5(2), e12078.
[51]. Chaudhary, V., Ashraf, N., Khalid, M., Walvekar, R., Yang, Y., Kaushik, A., & Mishra, Y. K. (2022). Emergence of MXene–polymer hybrid nanocomposites as high-performance next-generation chemiresistors for efficient air quality monitoring. Advanced Functional Materials, 32(33), 2112913.
[52]. Wagih, M., Balocchi, L., Benassi, F., Carvalho, N. B., Chiao, J. C., Correia, R., ... & Beeby, S. (2022). Microwave-enabled wearables: Underpinning technologies, integration platforms, and next-generation roadmap. IEEE Journal of Microwaves, 3(1), 193-226.

[53]. Chaudhary, V., Kaushik, A., Furukawa, H., & Khosla, A. (2022). Towards 5th generation ai and iot driven sustainable intelligent sensors based on 2d mxenes and borophene. ECS Sensors Plus, 1(1), 013601.
[54]. Liang, Z., He, J., Hu, C., Pu, X., Khani, H., Dai, L., ... & Wang, Z. L. (2023). Next-generation energy harvesting and storage technologies for robots across all scales. Advanced Intelligent Systems, 5(4), 2200045.
[55]. Yang, J., Zhou, Y. C., Yang, L. Y., Feng, C. P., Bai, L., Yang, M. B., & Yang, W. (2022). Exploring next-generation functional organic phase change composites. Advanced Functional Materials, 32(28), 2200792.
[56]. Kasinathan, P., Pugazhendhi, R., Elavarasan, R. M., Ramachandaramurthy, V. K., Ramanathan, V., Subramanian, S., ... & Alsharif, M. H. (2022). Realization of sustainable development goals with disruptive technologies by integrating industry 5.0, society 5.0, smart cities and villages. Sustainability, 14(22), 15258.
[57]. Kusiak, A. (2023). Smart manufacturing. In Springer handbook of automation (pp. 973-985). Cham: Springer International Publishing.
[58]. Guo, K., Tang, Z., Chou, X., Pan, S., Wan, C., Xue, T., ... & Wei, B. (2023). Printable organic light-emitting diodes for next-generation visible light communications: a review. Advanced Photonics Nexus, 2(4), 044001-044001.
[59]. Enemosah, A., & Chukwunweike, J. (2022). Next-generation SCADA architectures for enhanced field automation and real-time remote control in oil and gas fields. Int J Comput Appl Technol Res, 11(12), 514-29.
[60]. Wang, Z., Zheng, O., Li, L., Abdel-Aty, M., Cruz-Neira, C., & Islam, Z. (2023). Towards next generation of pedestrian and connected vehicle in-the-loop research: A digital twin co-simulation framework. IEEE Transactions on Intelligent Vehicles, 8(4), 2674-2683.
[61]. Samanta, R. K., Sadhukhan, B., Samaddar, H., Sarkar, S., Koner, C., & Ghosh, M. (2022). Scope of machine learning applications for addressing the challenges in next-generation wireless networks. CAAI Transactions on Intelligence Technology, 7(3), 395-418.
[62]. Yildirim, M., & Candan, Z. (2023). Smart materials: The next generation in science and engineering. Materials Today: Proceedings.
[62]. Dataset Link:
https://www.kaggle.com/datasets/stephanmatzka/predictive-maintenance-dataset-ai4i-2020
https://archive.ics.uci.edu/dataset/601/ai4i+2020+predictive+maintenance+dataset
https://www.kaggle.com/datasets/bishals098/nasa-turbofan-engine-degradation-simulation?select=train_FD001.txt