

Explainable Machine Learning Framework for Production Quality Prediction and Energy Optimization in Intelligent Manufacturing Machines

Parul Berwal¹, Narender Singh²

¹*Skill Assistant Professor, Shri Vishwakarma Skill University, Palwal, Haryana*

²*Plant Head, VN Sunrise, Faridabad, Haryana*

Abstract—Artificial Intelligence (AI), Machine Learning (ML), and Explainable Artificial Intelligence (XAI) are increasingly becoming an integral part of intelligent manufacturing systems and their adoption rate has grown significantly as a result of Industry 4.0 technologies. Recent developments in the area of explainable ML frameworks for production quality predictions and energy optimization in manufacturing environment are discussed. This study combines the results of the latest predictive maintenance, process optimization, energy forecasting, production scheduling, and sustainable manufacture publications. The reviewed papers have shown that the use of advanced ML models like RF, XGBoost, Cat Boost, GBM, LSTM, and deep learning methods in predicting electricity consumption accuracy, efficiency of operations, and energy management are significantly enhanced. Moreover, explainability approaches like SHAP and LIME increase transparency by uncovering key variables of the process in order to boost interpretability of the model and trust in industrial applications. The combination of Industrial Internet of Things (IIoT), digital twins, collaborative robotics and Agentic AI facilitates data-driven and autonomous manufacturing in line with the aims of Industry 5.0. While there are encouraging advances, there are still issues with data quality, interoperability, cyber-security and scalability of models. The study on robust, explainable and human-centric AI systems for sustainable, reliable and intelligent manufacturing systems is recommended for future studies.

Index Terms—Explainable Artificial Intelligence (XAI), Machine Learning, Intelligent Manufacturing, Production Quality Prediction, Energy Optimization, Industry 4.0, Industry 5.0, Predictive Maintenance, Industrial Internet of Things (IIoT), Sustainable Manufacturing.

I. INTRODUCTION

The manufacturing industry is witnessing a fundamental change due to the adoption of these new technologies, such as the Industrial Internet of Things (IIoT), Artificial Intelligence (AI), cloud computing, cyber-physical systems, digital twins and advanced data analytics, in particular [1]. The technologies have helped to build intelligent manufacturing systems that are able to gather, process and analyse large amounts of real-time operational data. A data-driven decision-making approach that uses data to enhance product quality, boost operational efficiency and lower operational costs is gradually replacing the traditional approach to production as manufacturing environments become increasingly interconnected and automated. Machine learning (ML) is one of these technologies that has proven to be a powerful weapon to predict production results, detect equipment faults, optimise variables and energy efficiency [2]. But, even though the prediction may be quite awesome with many ML models making little or no explanation of the decisions made, function as "black boxes". This lack of clarity is a problem especially when it comes to important manufacturing situations, where clear and easy to understand information is needed before making decisions based on AI suggestions. One of the important uses of machine learning in smart manufacturing is predicting how good the products will be. Day to day production lines collect a massive amount of data from various sources including sensors, programmable logic controls (PLCs), the machine vision system, quality control equipment and more [3]. These data are useful for understanding

the condition of the machines, processing parameters, environmental conditions, material properties, and the amount of process variability. Hidden correlations between these variables could be uncovered with the help of machine learning algorithms and used for prediction of product defects, quality grading, process capability analysis, and predictive maintenance. Quality prediction is crucial for manufacturers to identify defects early, reduce waste, limit rework, enhance customer satisfaction, and guarantee product quality. However, if the production engineers could not figure out why the model is predicting a defect or suggests that need to make some changes, It may not feel comfortable using or trusting the model in actual industrial settings [4]. As a result, for applications in manufacturing, interpretable and transparent systems are vital traits of a successful AI system.

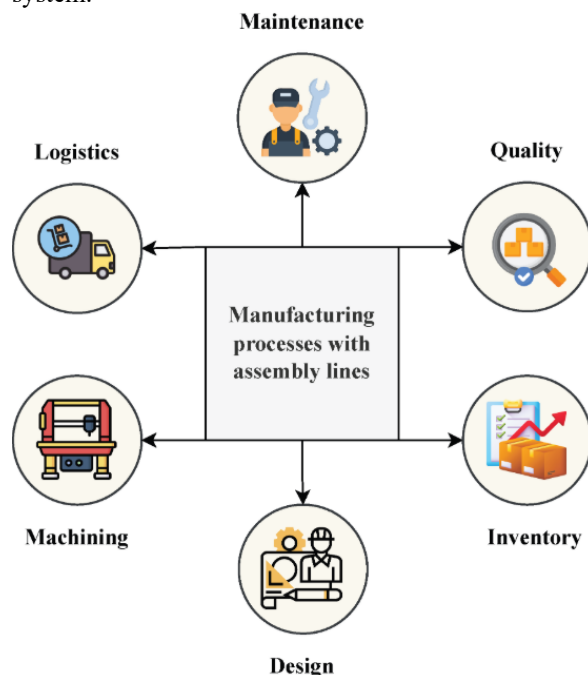


Figure 1: Manufacturing sub-processes with assembly lines for AI and ML applications [11]

At the same time, energy use is an increasingly important issue in manufacturing industries as energy costs increase; the environmental regulatory standards are getting tighter and the global efforts towards sustainability. Energy optimisation is of great importance for economic and environmental reasons, particularly for manufacturing as this sector consumes a considerable fraction of global industry's energy. Electrical energy is continuously being used

by intelligent manufacturing machines via motors, pumps, compressors, heating systems and automated production equipment [5]. By combining a machine's production data with historical energy consumption, machine learning could detect operating conditions that are not optimum, forecast future energy usage, schedule machines to run more efficiently and suggest operating parameters that would save energy without reducing quality of the product. Combining a production quality prediction system with energy optimisation allows manufacturers to accomplish two goals: quality products and lesser energy usage and carbon emissions. This optimized balance is becoming more widely acknowledged as a major factor in achieving sustainable smart manufacturing.

1.1 Explainable Machine Learning in Intelligent Manufacturing

Recognizing the need to address the shortcomings of black-box learning models, scientists and researchers are looking for ways to make machine learning models explainable. In response to this challenge, the concept of Explanatory Machine Learning (XML) or Explainable Artificial Intelligence (XAI) has been introduced. Explainable ML is about creating algorithms and interpretation that allow for human comprehension of the reasons behind model predictions and recommendations. Instead of just giving very accurate outputs, explainable models explain which input variables have most strongly influenced a prediction, how the performance of a production is affected by the various process parameters, and why certain decisions about the running of the process are suggested. Engineers could leverage popular approaches like SHAP (SHapley Additive explanations), LIME (Local Interpretable Model-Agnostic Explanations), feature importance analysis, decision rules and attention mechanisms to gain insight into the behavior of complex models without affecting their predictive accuracy [6].

In intelligent manufacturing, explain ability helps production managers, quality engineers, machine operators and maintenance staff find more confidence. For instance, when an ML model is used to predict higher chances of product defects, explainable methods could reveal if spindle speed, cutting temperature, vibration, feed rate, tool wear, humidity, or material properties were the most significant factors in predicting the defect. These

explanations enable engineers to confirm that the recommendations are consistent with their expertise and experience in the field. Additionally, explainability enables adherence to industrial quality standards, safety standards, and ethical guidelines for AI usage by providing transparency, traceability, and auditability of automated decisions. Manufacturing systems being more autonomous and increasingly explainable, explainable ML would become an essential key in supporting human expert decisions and not replacing them.

The combination of Machine Learning and the setup of Industrial Internet of Things makes manufacturing systems even smarter. Industrial Internet of Things devices are always checking the condition of machines how things are being made what is happening in the environment and how much energy is being used. It does with sensors and communication networks that are all connected. The information from these sensors is sent through the special computers that could handle a lot of data. These computers use Machine Learning to look at the data, in real time and make predictions.

Study could make this process better by using frameworks. These frameworks help us understand what the data is telling us by using easy to understand pictures and giving us ideas on what to do. This helps engineers make decisions quickly. Industrial Internet of Things and Machine Learning are important here. As a result, explainable ML has the potential to boost predictive effectiveness and at the same time foster transparency, accountability, reliability, and efficiency in the manufacturing system.

1.2 Framework for Production Quality Prediction and Energy Optimisation

The intelligent manufacturing explainable machine learning system consists of multiple interdependent elements, such as data collection, data pre-processing, feature engineering, predictive modelling, explainability analysis, optimisation methods, and decision support system. The first part of the framework involves gathering diverse data from various manufacturing systems, quality inspection systems, environmental sensors, enterprise resource planning systems and energy monitoring systems. Prior to model development, effective data pre-processing techniques are applied, like data cleaning, normalisation, feature selection and dimensionality

reduction, since industrial datasets are typically incomplete, include noisy measurements, have redundant features, and unevenly distributed class distributions. The processed data is then fed into the powerful machine learning models, including: Random Forest, Gradient Boosting, Extreme Gradient Boosting (XGBoost), Support Vector Machines, Artificial Neural Networks, Deep Learning architectures, and ensemble learning methods. These models estimate production quality characteristics like accuracy surface roughness, product classification, process deviations, defect occurrence and energy consumption of the machine during different operating modes. Based on this information multi-objective optimization algorithms could be used to find the combinations between process parameters that could produce the highest quality products with the lowest energy consumption and production costs. The key innovation of the proposed framework is the use of an explainability layer [8]. The framework is not a predictor of quality and energy results it also provides detailed descriptions of how individual process variables affect quality and energy outcomes. For engineers visual interpretation methods such as rankings of feature importance plots of dependence distributions of SHAP values and local explanation graphs help to better understand complex relationships, between manufacturing parameters and predicted outcomes. These explanations help optimize processes conduct root cause analysis, plan maintenance and create continuous improvement efforts.

Manufacturers use a kind of machine learning called explainable ML in smart factories. This helps reduce energy waste and makes production better. It also helps the equipment longer and makes better use of resources. This is good for the environment. Helps the industry in the long run. Manufacturers could make decisions about how to run their factories because it could see how the artificial intelligence is making its decisions. This helps them make production more efficient and reduces the harm to the environment. Nowadays factories are getting smarter. Could work on their own. So it is very important to have machine learning that people could understand. This helps build trust in the intelligence systems. These systems could predict what will happen and are reliable and good for the environment. Using machine learning to predict the quality of production and use

less energy is a big improvement for smart factories. This kind of solution is trustworthy and good for the environment. It is what the industrial sector needs. Intelligence that is reliable and easy to understand and good, for the environment. Explainable machine learning is very important for the industry to be sustainable. It give engineers insight into how the model behaves, optimize manufacturing, cut down on operational costs, enhance product quality, and enable efficient production of energy [10]. The ability to work with intelligent automation and have humans in the loop would be a central part of Industry 5.0, and explainable machine learning would be a key enabler for trustworthy, resilient and sustainable manufacturing systems.

II.LITERATURE REVIEW

2.1 Artificial Intelligence in Modern Manufacturing Artificial Intelligence (AI), Machine Learning (ML) and Explainable Artificial Intelligence (XAI) have been observed to have significant transformative potential in energy efficiency, process optimisation, predictive maintenance and sustainability in smart manufacturing. Thapaliya et al. (2024) [11] have developed ML models to predict energy consumption during CNC milling and have the maximum energy model as processing time. found that the most effective model was the Random Forest model. The main energy consumers from energy usage analysis (EUA) tools such as SHAP and LIME were found to be axis rotation and fast traverse movements. In CNC marble machining, Saruşik et al. (2026) [12] predicted the Specific Energy (SE) values by CatBoost, LightGBM, and XGBoost with high accuracy and Material Removal Rate (MRR) was defined as most important feature. To demonstrate the advantages of AI in PV manufacturing, Lee et al. 2026 [13] have proposed an AI-based manufacturing

framework with more than 100,000 industrial PV samples to achieve high precision, able to accurately predict PV efficiency and enhance PV manufacturing performance by optimizing.

Lamdjad et al. (2026) [14] proposed a carbon foot print-based Overall Equipment Effectiveness (OEE) model which showed that equipment availability and carbon emissions were the major influences on the sustainable production efficiency. Zaman et al., 2026 [15] summarized the Artificial Intelligence (AI) supported Additive Manufacturing (AM) technologies and distinguished three new technologies for autonomous AM systems to be: Deep Learning; Reinforcement Learning; Physics-informed ML. Prayogi et al. [16] presented an IoT based framework of Long Short-Term Memory (LSTM) for prediction based energy scheduling to minimize energy usage in industrial applications. A hybrid Reinforcement Learning–Genetic Algorithm scheduling model was introduced by Shaikat et al. (2025) [17] to enhance the production efficiency, machine reliability, resource utilisation, delivery performance, operational efficiency, and reduce energy consumption and machine downtime.

To enhance the prediction and interpretation of machine energy consumption, Daha et al. (2024) [18] used Explainable Machine Learning models such as Lasso Regression, Linear Regression and Decision Tree models. In a similar fashion, Aboulhosn et al. (2024) [19] improved the efficiency and trustworthiness of CNN-based U-Net and Feature Pyramid Network (FPN) models for the detection of steel surface defects. AI, ML, and XAI are proven technologies for intelligent and sustainable manufacturing, with AI predictive analytics playing a critical role as Ojadi et al. [20] showed in predicting carbon emissions, detecting anomalies, predictive maintenance, process optimisation and carbon assessment.

Ref.	Author (Year)	Dataset	Result (Numeric Value)
[11]	Thapaliya et al. (2024)	CNC milling machine operational dataset (power consumption and processing time)	Random Forest produced the best prediction performance. SHAP and LIME identified axis rotations and rapid traverse movements as the most influential variables. (No numerical performance metric reported).
[12]	Saruşik et al. (2026)	CNC marble machining energy consumption dataset	Cat Boost ($R^2 = 0.983$), LightGBM ($R^2 = 0.983$), XGBoost ($R^2 = 0.982$); Material Removal Rate (MRR) feature importance = 96.05%; Feed rate–cutting depth correlation (R^2

			= 0.70); MRR correlation ($R^2 = 0.16$); Gradient Boosting accuracy = 0.75.
[13]	Lee et al. (2026)	100,000+ photovoltaic wafer manufacturing samples	Extra Trees achieved $R^2 = 0.936$, RMSE = 0.0259%, MAPE = 0.109%; Tree-structured Parzen Estimator improved normalized efficiency by 0.0681.
[14]	Lamdjad et al. (2026)	Carbon-adjusted Overall Equipment Effectiveness (COEE) manufacturing dataset	Gradient Boosting Regressor achieved $R^2 = 0.920$ for sustainable production prediction.
[15]	Zaman et al. (2026)	Review of AI-enabled additive manufacturing literature	Review paper; no experimental dataset or numerical performance values reported.
[16]	Prayogi et al. (2026)	IoT-based industrial energy consumption dataset	LSTM achieved MAE = 0.84 kWh, RMSE = 2.13 kWh, $R^2 = 0.987$; industrial energy consumption reduced by 14.8%.
[17]	Shaikat et al. (2025)	Smart manufacturing production scheduling dataset (1,000 production tasks)	Production efficiency increased by 39%; Resource utilization = 91% (14% improvement); Machine downtime reduced by 34%; Delivery success improved from 78% to 94%; Energy consumption per task reduced by 17%; Operational efficiency exceeded 96%.
[18]	Daha et al. (2024)	Smart manufacturing machine energy management dataset	Explainable ML using Lasso Regression, Linear Regression, and Decision Tree improved energy prediction and interpretability. No numerical performance values reported.
[19]	Aboulhosn et al. (2024)	Steel surface defect image dataset	CNN-based U-Net and Feature Pyramid Network with XAI improved defect detection and segmentation robustness. No numerical performance values reported.
[20]	Ojadi et al. (2023)	Industrial manufacturing carbon emission dataset	AI-based predictive analytics enabled carbon emission forecasting, anomaly detection, predictive maintenance, and process optimization. No numerical performance values reported.

Figure 2 shows the benefits of AI in manufacturing, including an operational efficiency of 96%, a delivery success rate of 94% and a resource utilization of 91%, an operational efficiency of 39%, reduction of downtime by 34% and reduction of energy by 17%.

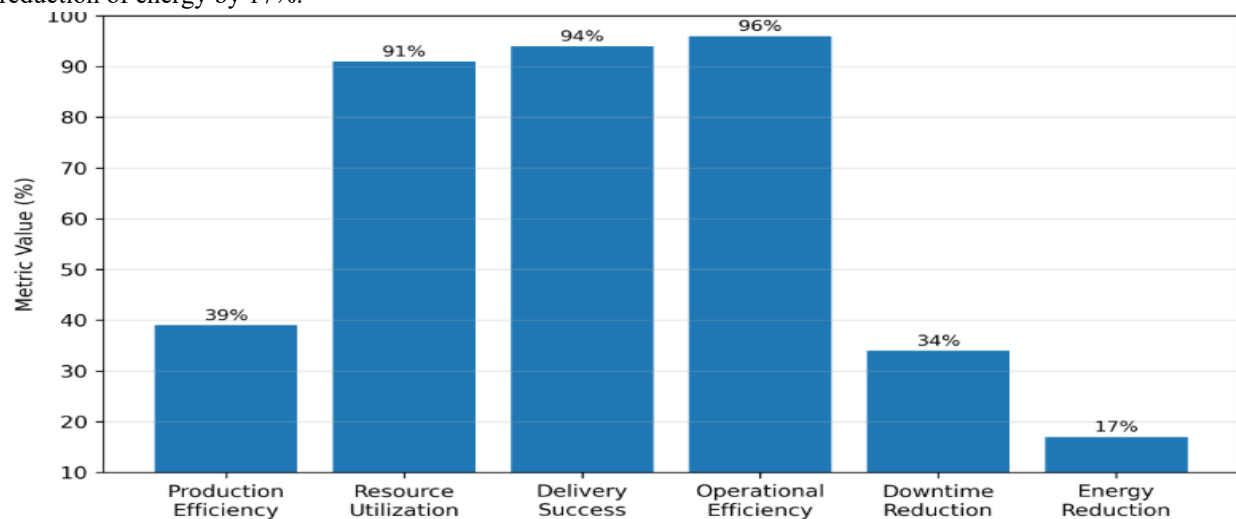


Figure 2: Manufacturing Efficiency Comparison

2.2 Technological Frameworks Supporting Intelligent Manufacturing

There have been extensive conceptual and technological frameworks of intelligent manufacturing that enable the evolution of this concept. Comprehensive conceptual and technological frameworks have also facilitated the evolution of intelligent manufacturing. To address these challenges, Tang et al. [21] proposed a four level industrial intelligence architecture that combines data analytics and optimization for planning, scheduling and resource management. Zhang et al., 2021 [22] highlighted that data denoising, imputation, the balancing of data, semantic annotation, and explainable deep learning are critical for the trustworthy industrial AI system. Sharma et al., 2021 [23] presented the Interpretive Model of Manufacturing which consists of five steps of scanning, storing, interpreting, executing and learning, to successfully implement ML models in manufacturing applications. Lins et al. [24] analysed IoT-enabled collaborative robotics and RAMI 4.0

architectures, and also, Shahbazi et al. [25] showed that IoT monitoring using Random Forest had a significant effect on the improvement of manufacturing fault detection. For the prediction of quality in injection molding processes, Jet et al., 2021 [26] reported better performance of auto encoder models compared to tree-based and regression models, and proposed that temperature and processing time are the main quality factors. Farahani et al. (2026) [27] introduced an Agentic AI and Multi-Agent System framework which automatically executed schema detection, schema pre-processing, model optimization, and explainable prescriptive maintenance. However, Abbas et al. (2025) [28] found that for predictive maintenance and smart factories, supervised, unsupervised, reinforcement learning, and deep learning could be used, and Vijay Kumar et al. (2025) [29] found that AI-based energy optimization, predictive maintenance, waste reduction, and circular economy practices are essential for intelligent, sustainable, and Industry 5.0-ready manufacturing systems.

Ref.	Author (Year)	Dataset	Result (Numeric Value)
[21]	Tang et al. (2021)	Industrial data analytics and smart manufacturing framework	Proposed a four-level industrial intelligence architecture integrating planning, scheduling, and resource optimization. No experimental dataset or numerical results reported.
[22]	Zhang et al. (2021)	Smart manufacturing data curation framework	Introduced data denoising, imputation, balancing, semantic annotation, and explainable deep learning for industrial AI. No numerical performance values reported.
[23]	Sharma et al. (2021)	Manufacturing machine learning conceptual framework	Proposed the Interpretive Model of Manufacturing comprising 5 stages: Scan, Store, Interpret, Execute, and Learn. No predictive performance metrics reported.
[24]	Lins et al. (2021)	Review of IIoT-enabled collaborative robotics and RAMI 4.0 architectures	Survey paper discussing collaborative robotics and IIoT platforms. No experimental dataset or numerical results reported.
[25]	Shahbazi et al. (2021)	IoT-enabled smart manufacturing monitoring dataset	Random Forest-based monitoring improved manufacturing fault detection and real-time analysis. No numerical performance metrics reported.
[26]	Jung et al. (2021)	Injection molding quality prediction dataset	Auto encoder outperformed Decision Tree, Random Forest, Support Vector Regression, and Linear Regression for quality prediction. Temperature and processing time were identified as dominant quality factors. No numerical performance values reported.
[27]	Farahani et al. (2026)	Smart manufacturing predictive maintenance framework	Proposed an Agentic AI and Multi-Agent System for autonomous schema detection, pre-processing, optimization, and explainable prescriptive maintenance. No quantitative performance metrics reported.

[28]	Abbas et al. (2025)	Review of predictive maintenance and advanced manufacturing studies	Reviewed supervised, unsupervised, reinforcement, and deep learning approaches for predictive maintenance and smart factories. No experimental dataset or numerical performance values reported.
[29]	Vijay Kumar et al. (2025)	Review of AI-enabled sustainable manufacturing studies	Highlighted AI applications in energy optimization, predictive maintenance, waste reduction, and circular economy for Industry 5.0. No experimental dataset or numerical performance values reported.

The figure 3 illustrates that there were studies in the field of intelligent manufacturing and Zhang and Sharma made five contributions, Tang, Farahani, Abbas and Vijay Kumar made four contributions, Jung made three and Lins and Shahbazi made two contributions.

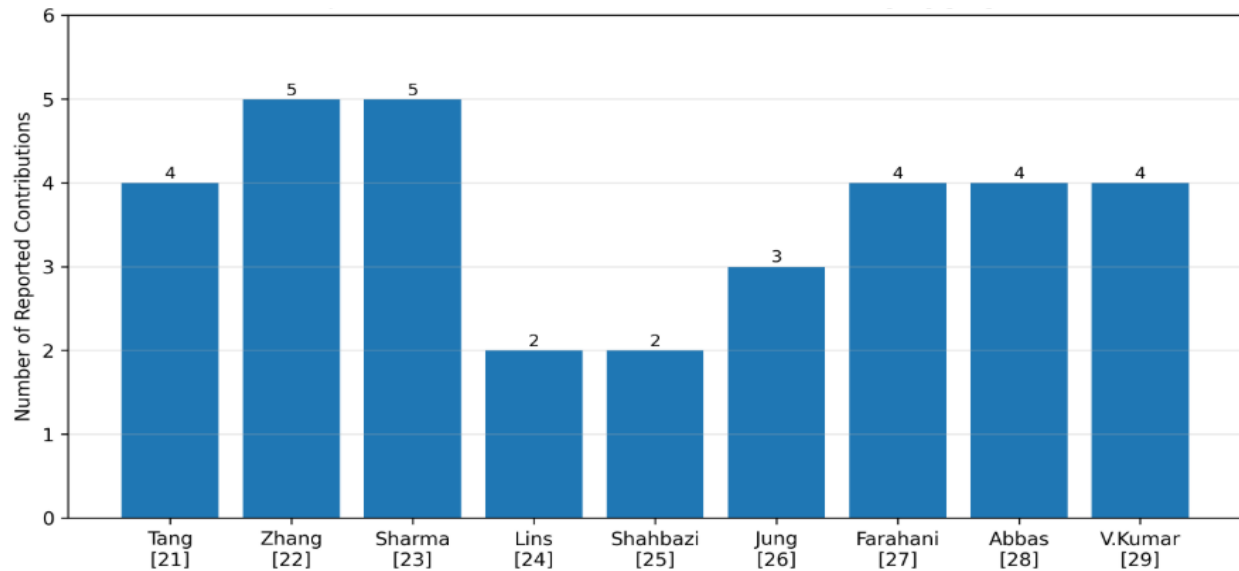


Figure 3: Intelligent Manufacturing Contributions

III. DISCUSSION

Overall, the studies have shown that Artificial Intelligence (AI), Machine Learning (ML), and Explainable Artificial Intelligence (XAI) are already essential technologies to boost smart manufacturing. It is shown that ensemble-based learning models like Random Forest, Cat Boost, XGBoost and Gradient Boost provide high predictive accuracy (R^2 up to 0.987) and significantly improve the accuracy of energy prediction, process optimization and production scheduling, compared to traditional algorithms. Energy forecasting and energy quality prediction are further enhanced by the deep learning methods such as LSTM and Auto encoder model that could model complex manufacturing patterns which are basically nonlinear. Furthermore, XAI methods, such as SHAP and LIME, improve the transparency of the models, highlighting key operating conditions,

improving end-to-end industrial trust and assisting in the decision-making process. The use of IoT, internet of things, digital twins, digital copies, collaborative robotics and AI systems that act on their own contributes to making manufacturing systems that could work on their own change when needed and last a time. With these improvements problems, with the quality of data making different systems work together connecting old systems and understanding how models make decisions are still big problems. In the future solutions that are easy to scale easy to explain and focused on people should be an area of study to help reach the goals of Industry 5.0 and green manufacturing systems.

IV. CONCLUSION

The importance of Artificial Intelligence (AI), Machine Learning (ML), and Explainable Artificial

Intelligence (XAI) in intelligent manufacturing, this review investigates the progress are making in the domain of manufacturing quality in terms of increased energy efficiency, predictive maintenance, and sustainable practice. The surveyed approaches indicate that advanced machine learning algorithms such as random forest, XGBoost, Cat Boost, gradient boosting, LSTM, and deep learning models have achieved superior predictive accuracy of the product quality, process optimization, and energy forecasting. Besides, explain ability methods like SHAP and LIME help make the model more transparent, making the users more confident, and aiding in better informed decision making for the industrial use. The Industrial Internet of Things (IIoT), Digital Twins, Collaborative Robots, and Agentic AI technologies also facilitate autonomous, adaptive and data-driven manufacturing systems that meet the goals of Industry 5.0. Although these developments have taken place, issues of data quality, interoperability, cybersecurity, model scalability and real-time implementation still exist. For industrial sustainability, the focus of future study should be on building strong and interpretable AI models that could effectively incorporate intelligent decision-making support and sustainable manufacturing methods to achieve higher productivity, lower environmental footprint, and long-term competitiveness.

REFERENCE

- [1] Leng, Jiewu, Kaiwen Zuo, Caiyu Xu, Xueliang Zhou, Shuai Zheng, Jiawen Kang, Qiang Liu et al. "Physics-informed machine learning in intelligent manufacturing: a review." *Journal of Intelligent Manufacturing* 37, no. 6 (2026): 2215-2257.
- [2] Ahangar, M. Nadeem, Z. A. Farhat, Aparajithan Sivanathan, N. Ketheesram, and S. Kaur. "Explainable AI-driven quality and condition monitoring in smart manufacturing." *Sensors* 26, no. 3 (2026): 911.
- [3] Champa, Shalina Sultana, and Richard S. Segall. "Artificial Intelligence and Machine Learning Framework for Smart Manufacturing Optimization: A Computational Intelligence Approach for Process Enhancement." *International Journal of Artificial Intelligence (AI) in Business and Management (IJAIBM)* 2, no. 1 (2026): 1-46.
- [4] Madathil, Abhilash Puthanveetil, Xichun Luo, Qi Liu, Charles Walker, Rajeshkumar Madarkar, and Yi Qin. "A review of explainable artificial intelligence in smart manufacturing." *International Journal of Production Research* (2025): 1-44.
- [5] Sumi, Sayeda Sufia. "Development of a Hybrid Machine Learning Model for Predictive Performance Optimization in Lean Manufacturing and Industry 4.0." *Review of Applied Science and Technology* 4, no. 03 (2025): 68-108.
- [6] Champa, Shalina Sultana. "A Unified AI and Machine Learning Framework for Decision Support and Operational Optimization in Smart Manufacturing." Available at SSRN 5800343 (2025).
- [7] Naqvi, Muhammad Raza, Linda Elmhahdhi, Arkopaul Sarkar, Bernard Archimede, and Mohamed Hedi Karray. "Survey on ontology-based explainable AI in manufacturing." *Journal of Intelligent Manufacturing* 35, no. 8 (2024): 3605-3627.
- [8] Moosavi, Sajad, Maryam Farajzadeh-Zanjani, Roozbeh Razavi-Far, Vasile Palade, and Mehrdad Saif. "Explainable AI in manufacturing and industrial cyber-physical systems: A survey." (2024).
- [9] Oyucu, Saadin, Betül Ersöz, Şeref Sağıroğlu, Ahmet Aksöz, and Emre Biçer. "Optimizing Lithium-ion battery performance: Integrating machine learning and explainable AI for enhanced energy management." *Sustainability* 16, no. 11 (2024): 4755.
- [10] Kumar, Sachin, T. Gopi, N. Harikeerthana, Munish Kumar Gupta, Vidit Gaur, Grzegorz M. Krolczyk, and ChuanSong Wu. "Machine learning techniques in additive manufacturing: a state of the art review on design, processes and production control." *Journal of Intelligent Manufacturing* 34, no. 1 (2023): 21-55.
- [11] Hijry, Hassan. "Advancing Sustainable Smart Manufacturing: A Comprehensive Review of Machine Learning Techniques in Assembly Lines." *Sustainability* 18, no. 1 (2025): 348.

- [12] Thapaliya, Suman, Omid Fatahi Valilai, and Hendro Wicaksono. "Power consumption and processing time estimation of CNC machines using explainable artificial intelligence (XAI)." *Procedia Computer Science* 232 (2024): 861-870.
- [13] Saruşıık, Gencay, and Ahmet Sabri Öğütü. "Machine Learning-Driven Optimization of Energy Efficiency in Marble Computer Numerical Control Machining for Sustainable Manufacturing." *Journal of Tribology* 148, no. 1 (2026): 014205.
- [14] Lee, Seungtae, Donghwan Kim, Yoonmook Kang, and Sungho Hwang. "Industrial data-driven machine learning framework for wafer quality-based decision making toward smart solar-cell manufacturing." *Energy and AI* (2026): 100700.
- [15] Lamdjad, Bouzidi. "Towards explainable and sustainable production: Integrating carbon metrics into overall equipment effectiveness using gradient boosting and SHAP." *Next Sustainability* 7 (2026): 100357.
- [16] Zaman, Saqlain, Md Shahjahan Mahmud, Ali Akber Mollick, Tenzin Lhaden, Joshua Dantzler, Sabina Arroyo, Nithin K. Goona, Maisha Mesbah, Md Ariful Ahsan, and Yirong Lin. "Artificial intelligence in additive Manufacturing: Advances in smart materials, lattice optimization, and process intelligence." *The International Journal of Advanced Manufacturing Technology* (2026): 1-55.
- [17] Prayogi, Soni, and Wahyu kunto Wibowo. "Intelligent Energy Prediction in Smart Manufacturing Using Deep Learning Techniques." *G-Tech: Jurnal Teknologi Terapan* 10, no. 3 (2026): 1359-1370.
- [18] Shaikat, Faisal Bin, Rafiqul Islam, Asma Tabassum Happy, and Shown Ahmed Faysal. "Optimization of production scheduling in smart manufacturing environments using machine learning algorithms." *Lett High Energy Phys* 12, no. 1 (2025): 1-15.
- [19] Daha Belghiti, Imane. "Enhancing and explaining energy management in smart manufacturing production via ml within the context of industry 4.0." Available at SSRN 4897106 (2024).
- [20] Aboulhosn, Zeina, Ahmad Musamih, Khaled Salah, Raja Jayaraman, Mohammed Omar, and Zeyar Aung. "Detection of manufacturing defects in steel using deep learning with explainable artificial intelligence." *IEEE Access* 12 (2024): 99240-99257.
- [21] Ojadi, Jessica Obianuju, E. Onukwulu, C. Odionu, and O. Owulade. "AI-driven predictive analytics for carbon emission reduction in industrial manufacturing: a machine learning approach to sustainable production." *International Journal of Multidisciplinary Research and Growth Evaluation* 4, no. 1 (2023): 948-960.
- [22] Tang, Lixin, and Ying Meng. "Data analytics and optimization for smart industry." *Frontiers of Engineering Management* 8, no. 2 (2021): 157-171.
- [23] Zhang, Jianjing, and Robert X. Gao. "Deep learning-driven data curation and model interpretation for smart manufacturing." *Chinese journal of mechanical engineering* 34, no. 1 (2021): 71.
- [24] Sharma, Ajit, Zhibo Zhang, and Rahul Rai. "The interpretive model of manufacturing: a theoretical framework and research agenda for machine learning in manufacturing." *International Journal of Production Research* 59, no. 16 (2021): 4960-4994.
- [25] Lins, Romulo Gonçalves, and Sidney N. Givigi. "Cooperative robotics and machine learning for smart manufacturing: platform design and trends within the context of industrial internet of things." *IEEE access* 9 (2021): 95444-95455.
- [26] Shahbazi, Zeinab, and Yung-Cheol Byun. "Smart manufacturing real-time analysis based on blockchain and machine learning approaches." *Applied Sciences* 11, no. 8 (2021): 3535.
- [27] Jung, Hail, Jinsu Jeon, Dahui Choi, and Jung-Ywn Park. "Application of machine learning techniques in injection molding quality prediction: Implications on sustainable manufacturing industry." *Sustainability* 13, no. 8 (2021): 4120.
- [28] Farahani, Mojtaba A., Md Irfan Khan, and Thorsten Wuest. "Hybrid agentic ai and multi-agent systems in smart manufacturing."

Journal of Manufacturing Systems 86 (2026): 612-623.

- [29] Abbas, Kiran. "Machine Learning Approaches for Predictive Analysis in Advanced Manufacturing Technologies." International Research Journal of Advanced Science 6, no. 2 (2025): 51-61.
- [30] Vijay Kumar, Vishnu, and Khaled Shahin. "Artificial intelligence and machine learning for sustainable manufacturing: current trends and future prospects." Intelligent and sustainable manufacturing 2, no. 1 (2025): 10002.