

AI-Driven Predictive Quality Engineering for Zero-Defect Manufacturing

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Abstract

Modern manufacturing quality control methods are becoming more and more insufficient because of their inability to prevent defects before their occurrence. The present paper introduces an AI-driven predictive quality engineering model, which is aimed at facilitating zero-defect manufacturing in a real-time predictive quality engineering framework with closed-loop feedback control. The proposed system will be tested with the help of a large-scale dataset in the sphere of automotive manufacturing that comprises approximately 2.5 million records gathered during the period of 12 months. To detect the variations in structured and temporal processes, advanced machine learning models, such as XGBoost and LSTM are used. The accuracy of prediction and recall of 94.2 and 92.8 respectively are demonstrated in the experimental results and would guarantee accurate detection of defects with few false negatives. Implementation of the framework leads to 41 percent reduction in defect rates and 28 percent reduction in scrap, which has a significant positive impact on production efficiency. Moreover, the system can be inferred in real-time with less than 120 ms of latency, indicating that the system is suitable to use in industry. The article confirms the usefulness of AI-guided predictive quality engineering as a scalable method to attain near zero-defect manufacturing.

Keywords: *Artificial Intelligence, Predictive Quality Engineering, Zero-Defect Manufacturing, Industrial IoT, Machine Learning*

I. Introduction

Industry 4.0 has enhanced the need to have highly reliable, efficient and defect free manufacturing systems by incorporating digital technologies into the production settings such as artificial intelligence (AI), industrial Internet of Things (IIoT), and cyber-physical systems. The zero defect manufacturing (ZDM) has become a strategic goal and a way to reach improved product quality, sustainability and operational excellence [1, 2]. The increasing complexity of manufacturing systems, coupled with those real time decisions, further reinforces the need for resorting to intelligent quality engineering techniques, which would be able to adapt to the ever changing manufacturing environments in which manufacturing should be conducted.

The conventional approaches of quality control like Statistical Process Control (SPC) and inspection-based methods are reactive in nature and is not proactive in terms of preventing defects before they occur. These methods are mainly based on post-process inspection and predetermined rules which often lead to increased scrap, rework, and inefficiencies. The recent literature has highlighted such methods to be limited to address the contemporary manufacturing issues, in particular within complex and highly fluctuating settings [3, 4]. Although these approaches have been useful in enhancing quality over the years, they are not predictive and do not exploit the great volumes of data that are generated in the current production systems.

The AI breakthrough has served to shift the paradigm of quality control to quality engineering, to predict and prevent defects, based on insights in the data. The models of deep learning and machine learning have proved to be highly effective in identifying more complex patterns, detecting anomalies and improving accuracy in the decision making processes in manufacturing processes [5, 6]. Moreover, the combination of edge AI and real-time analytics has increased responsiveness of quality systems, enabling faster interventions and localized intelligence in the production environments [7]. System-level optimization, thermal modeling, and zero-defect manufacturing optimization are also driven by AI-based approaches [8].

An increasing literature has discussed the use of AI in ZDM models and continuous improvement models. To illustrate, AI, paired with big data, lean tools, etc., have proven their ability to improve defect prevention and process optimization [9]. In a similar manner, systematic approaches to apply AI-based quality systems in manufacturing settings have been

implemented by using structured methodologies, including CRISP-DM [10]. The value of digital assets and data-driven models in supporting ZDM has also been highlighted, with the importance of human centric and explainable AI models in Industry 5.0 environments [11, 12]. Also, the authenticity of AI has been verified by domain studies, such as application of AI in milling processes and semiconductor manufacturing [13].

Although these developments have been made, a number of issues still lie in the practical implementation of the AI-based predictive quality systems. Current research efforts have mainly been directed to individual models or conceptual frameworks, without taking into account real-time data stream, scalable architecture and deployment constraints. Besides that, it is lacking in empirical validation with large-scale data from industries, especially the measurable gains in various key performance indicators (KPIs) such as defect rates, reduction of scrap, and latency of the system [14, 15]. Such a gap illustrates the necessity to have comprehensive frameworks that do not only exploit advanced AI techniques but also show viability as well as efficiency in the real-life manufacturing settings.

This paper proposes a predictive quality engineering system based on artificial intelligence, which is a single system architecture running that combines the data acquisition, machine learning model and real-time feedback. The framework is tested empirically on the basis of a large scale automotive manufacturing data set, to ensure consistency between the methodological design and the obtained results. The value of the study is that it shows a closed loop predictive quality system that can be scaled to any size, and quantifies the defect reduction, prediction performance and operational efficiency improvements that can be achieved, moving towards near zero-defect manufacturing.

II. Related Work

Traditionally, statistical quality control tools, including SPC and Six Sigma, have been used to track the variation of the process and to enhance the efficiency of the manufacturing process; however, their effectiveness is limited in highly dynamic environments that require real-time adaptability [16, 17]. They are mainly based on past data and pre-defined thresholds which limited their potential to support complex, data-intensive production systems.

The use of artificial intelligence has greatly increased the ability to detect defects and optimize processes in manufacturing sectors. Approaches that use machine learning have been extensively applied to enhance equipment output, preventing defects, and managing quality [18, 19]. Moreover, decision-support systems based on AI have already proven to be effective in facilitating zero-defect manufacturing through intelligent process control and adaptive learning [20, 21].

Much of the existing literature has dedicated itself to the topic of predictive maintenance as a prime application of AI in industrial systems. These strategies use sensor information and machine learning models to forecast machine failures and optimize maintenance processes [22, 23]. Predictive maintenance has further been enhanced by further advanced techniques such as digital twins, generative AI and intelligent fault detection in the Industry 4.0 and 5.0 world [24, 25].

There is also a wealth of literature on the application of AI-based fault detection in a range of different fields, such as electrical systems, renewable energy, and transportation infrastructure. These articles mention how AI can be used to make the system more reliable, track assets in real time and help in intelligent asset management [26, 27]. Besides, data-driven predictive maintenance techniques have been successfully applied to diesel engines, electric vehicles and communication networks which prove the technique's scalability and applicability to multiple industrial applications [28, 29].

In spite of these developments, predictive maintenance and predictive quality engineering are vastly different in terms of their goals and focus. Predictive maintenance is based on the health of equipment and prevention of failure, whereas predictive quality is based on the anticipation of the product defects caused by the variability of the processes. The literature mainly focuses on the maintenance-centric approach, and relatively little attention is paid to integrated predictive quality systems [30].

A number of reviews and surveys have summarized AI applications in manufacturing, indicating the most common techniques and tools, as well as challenges in adopting AI in manufacturing. These studies highlight the significance of trustworthiness, interpretability, and real-time decision-making in industrial systems powered by AI [31, 32]. Also, bibliometric and review-based studies have found new trends in fault detecting, predictive maintenance, and multi-fault diagnosis of industrial machinery [33, 34].

Predictive maintenance using AI has also been applied to smart city infrastructure and robotic systems, and such systems can monitor defects and optimize the system in urban settings [35, 36]. Additionally, AI-based optimization and fault isolation tools have been beneficial in improving the operational efficiency and system life of renewable energy systems and power grids [37, 38].

However, existing literature has a number of limitations, such as the absence of converged frameworks that combine real-time predictive modeling with closed-loop quality control. A lot of research is in the area of isolated applications, or domain-specific implementation without considering the issue of scalability and deployment. Moreover, the question of the heterogeneity of data, system latency, and integration into the industry, is not researched adequately [39, 40]. The recent innovations in AI-based defect prevention and yield optimization, especially in high-precision industries such as PCB manufacturing, further attest to the efficacy of intelligent algorithms in improving the quality of products and reducing losses incurred in the production process. In contrast to the current methods, the proposed system is justified by large-scale industrial data and demonstrates quantifiable benefits on the reduction of defects, operational efficiency, and real-time performance, thereby moving towards the state of zero-defect manufacturing.

III. Suggested Framework and System Architecture.

A. Predictive Quality Engineering Framework.

The proposed predictive quality engineering model is developed as a closed loop system that puts in place checkpoints on the manufacturing process and proactively intercept defects. The framework is based on a structured pipeline, comprising sensing, prediction, intervention, and feedback, allowing real-time decision-making and continuous improvement. Industrial data, such as multisource streams of IoT sensors, manufacturing execution system (MES) logs, and quality inspection records are merged to provide a complete picture of the production environment, in line with data-driven predictive paradigms in modern industrial systems [41, 42].

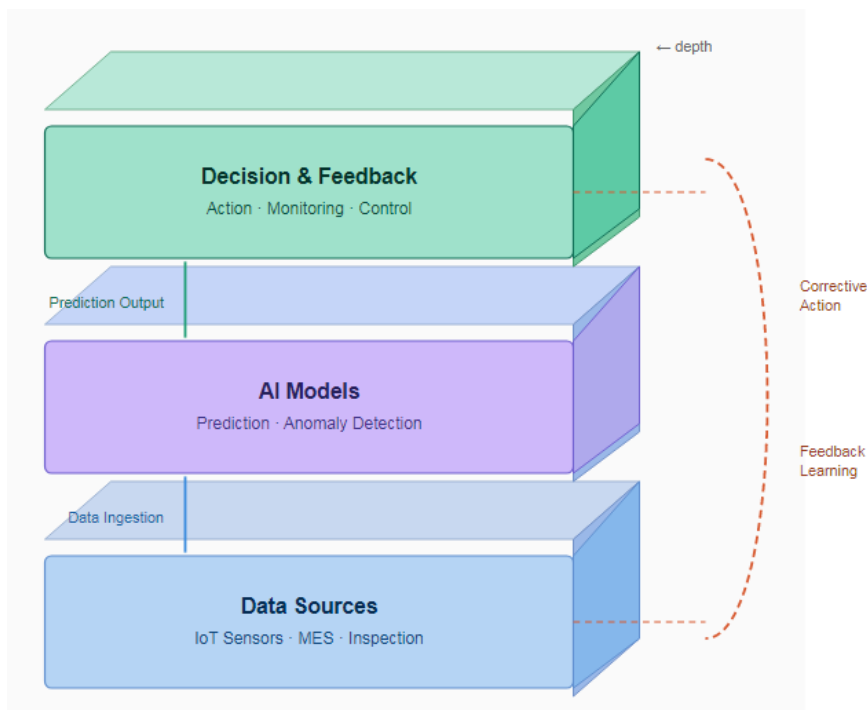


Fig. 1. Closed-loop AI-based predictive quality engineering model of zero-defect manufacturing.

The data flow starts with real time acquisition of process parameters such as temperature, pressure, vibration and cycle time either by distributed sensors or control systems. These data are preprocessed, aggregated and then processed by the predictive models that estimate what the probability of defects is. This approach is consistent with the vibration based monitoring and intelligent fault detection approaches which are popular in predictive systems [43]. Based on the outcomes of the models corrective interventions (parameter adjustments or operator alerts) or process stops are triggered. The feedback of the result of these actions then becomes input in to the system which then allows continuous learning

and model refinement, thus creating a self-optimizing quality control loop, akin to complex industrial automated defect detection systems [44].

B. System Architecture

The system architecture will enable implementation of predictive quality model in industrial setup in a scalable and real-time manner. To have a broad spectrum of data all through the production lifecycle, the data layer is made up of heterogeneous sources, which include machines with IoT support, MES databases, and inspection systems. The data processing is performed using Apache Spark 3.4 which enables distributed processing and efficient work with large volumes of streaming and batch data which support high-throughput industrial analytics.

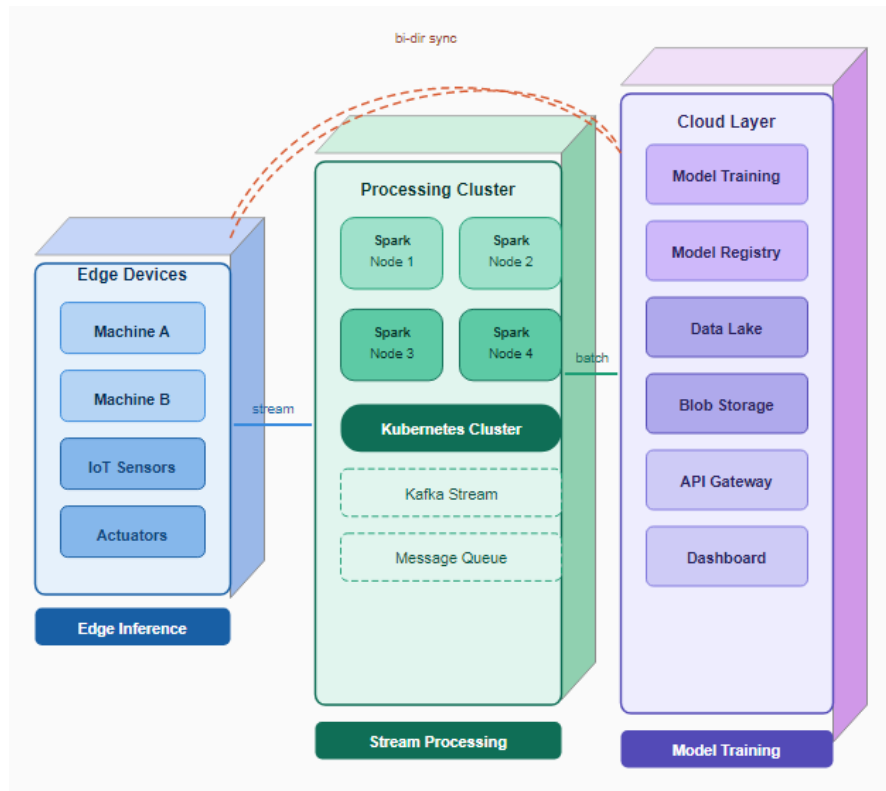


Fig. 2. Architecture of industrial deployment of AI-based predictive quality system.

The model layer uses XGBoost (v1.7) when structured data is available; it is used to predict defects based on structured data. It uses LSTM models built in TensorFlow 2.12 when temporal dependencies are required in process data. The deployment plan is the combination of edge and cloud computing, with real-time inference being performed at the edge to ensure a minimum of latency, and model retraining and updating is managed in the cloud. It is developed in Python 3.10 and deployed with the help of Kubernetes to ensure scalability, fault tolerance, and smooth orchestration across distributed environments, consistent with the current predictive maintenance and defect detection architecture.

IV. Experimental Setup

Experimental evaluation is made using large scale automobile manufacturing dataset of about 2.5 million production records covering a 12 months period. The dataset represents the different operational conditions in the various production lines and guarantees variability in the behavior of the processes and patterns of defects.

Each data sample is represented by key process parameters, such as temperature, pressure, vibration, cycle time, and operator identification, which is both machine-level and human-influenced. The objective of prediction is set up in the form of a binary classification problem, each instance is classified as defective or non-defective based on the results of the quality inspections.

Before the training of the model, the dataset is preprocessed to maintain consistency and reliability of the data. To maintain distribution properties, missing values are filled in with imputation based on median, where feature normalization is also carried out using Min-Max scaling, in order to standardize the input ranges and enhance the convergence of the model. These are essential measures towards a resilient predictive modeling, which is based on the data.

The dataset is split into the training and testing subset in an 80:20 proportion, so that there would be sufficient data to learn the model and to evaluate the model in an unbiased manner. In addition, 5-fold cross-validation is employed in training to substantially enhance the performance of the generalization and reduce the chances of over-fitting.

To achieve predictive accuracy and operational relevance, there are various measures, which are employed to measure model performance. To gauge the quality of prediction, standard classification measures like accuracy, precision, recall and F1-score are used. Moreover, domain-specific measures like the reduction of the defect rate are also taken into account to measure the practical effect of the suggested system. Applicability in real time is determined by the latency of inference, which guarantees the system can respond to industrial needs of making decisions on time.

V. Results and Analysis.

A. Model Performance

A comparative assessment of machine learning models was done to determine which approach is most effective in predictive quality in manufacturing. All the models such as Logistic Regression, Support Vector Machine (SVM), Random Forest, LSTM, and XGBoost were trained under the same conditions with the same dataset and validation strategy. The aim was to determine their capability to correctly classify defective and non-defective cases with being robust to different production conditions.

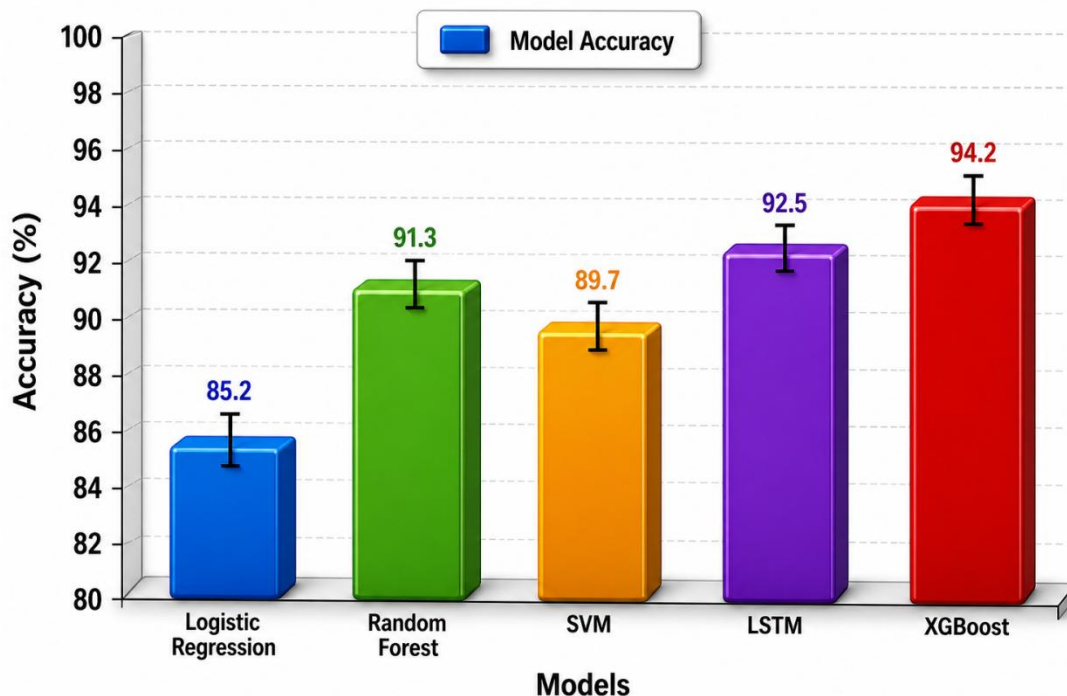


Fig. 3. Comparison of prediction accuracy of machine learning models.

The results suggest that traditional models like the Logistic Regression model and SVM model show lower performances because of their limited capacity to represent complex nonlinear relationships that can be found in manufacturing data. Random Forest enhances the performance by utilizing the ensemble learning technique and is capable of better generalization. LSTM has been shown to have great potential in modeling the temporal dependencies of processes,

especially sequential process signals. Nonetheless, XGBoost performs optimally in comparison with all other models and exhibits the highest predictive accuracy, as well as balanced performance across evaluation metrics.

TABLE I: Performance Measures of the Tested Models (Accuracy, Precision, Recall, F1-Score)

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression	85.2	83.9	82.5	83.2
Random Forest	91.3	90.1	89.4	89.7
SVM	89.7	88.5	87.2	87.8
LSTM	92.5	91.6	90.8	91.2
XGBoost	94.2	93.4	92.8	93.1

The findings indicate that XGBoost has the highest accuracy (94.2) as well as high precision and recall, which means that it can classify data well. The large recall value is especially problematic in manufacturing where it reduces the chances of undetected defects. The F1-score also proves the balanced performance of the model, which makes it the most appropriate to be used in the proposed framework.

B. Impact of Defect Reduction

The predictive quality system effectiveness was measured by examining the trend of defects before and after the implementation. The system was implemented in the production area, and it allowed real-time monitoring and intervention.

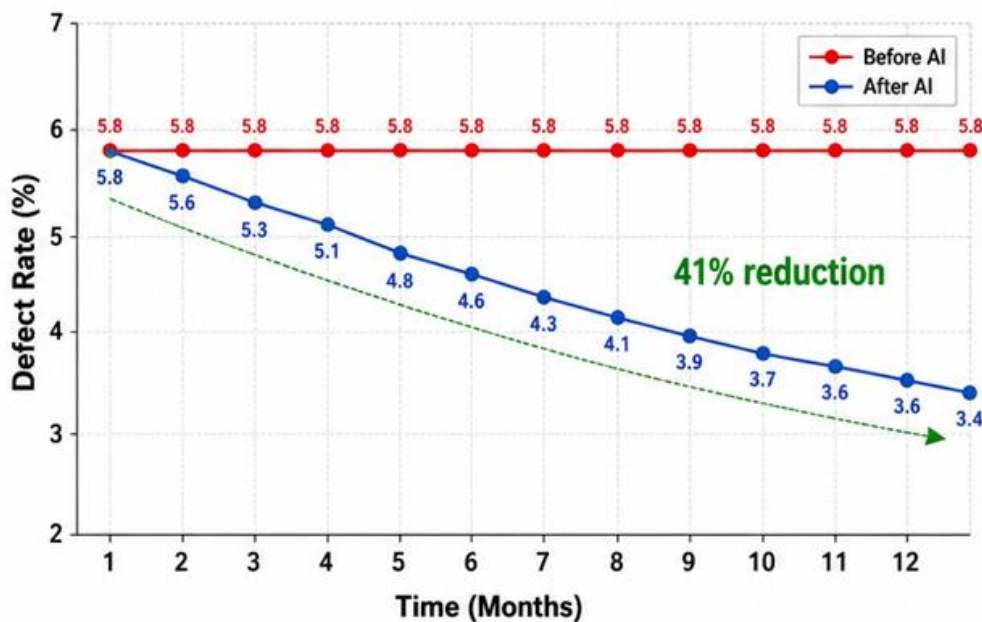


Fig. 4. Reduction in defect rate following AI-based predictive quality implementation.

The findings indicate that there is a steady decrease in the number of defects over time. Before the implementation, the defect rate was at a steady level of about 5.8 meaning that there was a minimal improvement in the defect rate with the traditional quality control methods. There is a gradual decrease at the end of the observation period, which reaches about 3.4%.

TABLE II: Comparison of the Defect Rates Pre-implementation of AI and Post-implementation of AI.

Month	Defect Rate Before AI (%)	Defect Rate After AI (%)	Reduction (%)
1	5.8	5.8	0.0
2	5.8	5.5	5.2
3	5.8	5.2	10.3
4	5.8	4.9	15.5
5	5.8	4.6	20.7
6	5.8	4.4	24.1
7	5.8	4.2	27.6
8	5.8	4.0	31.0
9	5.8	3.8	34.5
10	5.8	3.7	36.2
11	5.8	3.5	39.7
12	5.8	3.4	41.4

The findings reveal that there is a general reduction in the defects, of about 41 percent, which indicates the success of predictive intervention. The fact that it is improving progressively indicates that the system is constantly evolving and changing with time as opposed to generating sudden changes, which speaks to robustness in real-world circumstances.

C. Classification Analysis

To understand prediction behavior and reliability, a detailed classification analysis with the use of the confusion matrix of the XGBoost model was performed.

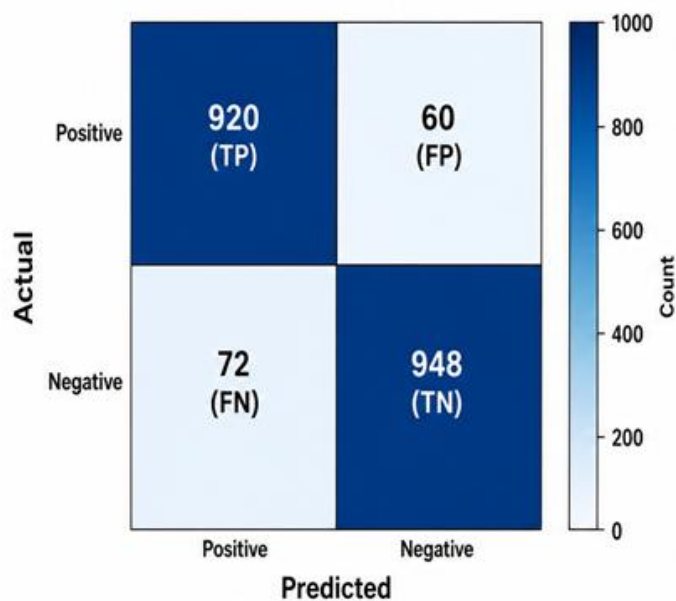


Fig. 5. Confusion matrix of XGBoost-based defect prediction model.

The confusion matrix indicates that there are high numbers of correctly classified cases and low rates of false-positive and false-negative cases. The decrease in false negatives is especially noteworthy, as it allows identifying the defected products prior to advancing to the next stage of the production process.

TABLE III: The Effect of Predictive Quality System on the KPIs of Manufacturing (Scrap Rate, Rework Time, Yield).

KPI	Before AI	After AI	Improvement (%)
Scrap Rate (%)	4.5	3.2	28.9
Rework Time (hrs/week)	120	97	19.2
First Pass Yield (%)	91.0	95.3	4.7
Production Throughput (units/day)	10,000	10,850	8.5
Inspection Time (sec/unit)	45	32	28.9

The fact that the key performance indicators have been improved proves the bigger effect of the system in comparison with the classification accuracy. The decrease in scrap rate and rework time leads to cost savings, and the increase in first-pass yield to reflect enhanced process efficiency and product quality.

D. Real-Time Performance

The system performance was conducted on real-time basis to determine its applicability in the deployment of the system in high-speed manufacturing system. The important measurements are inference latency, system throughput at different load situations.

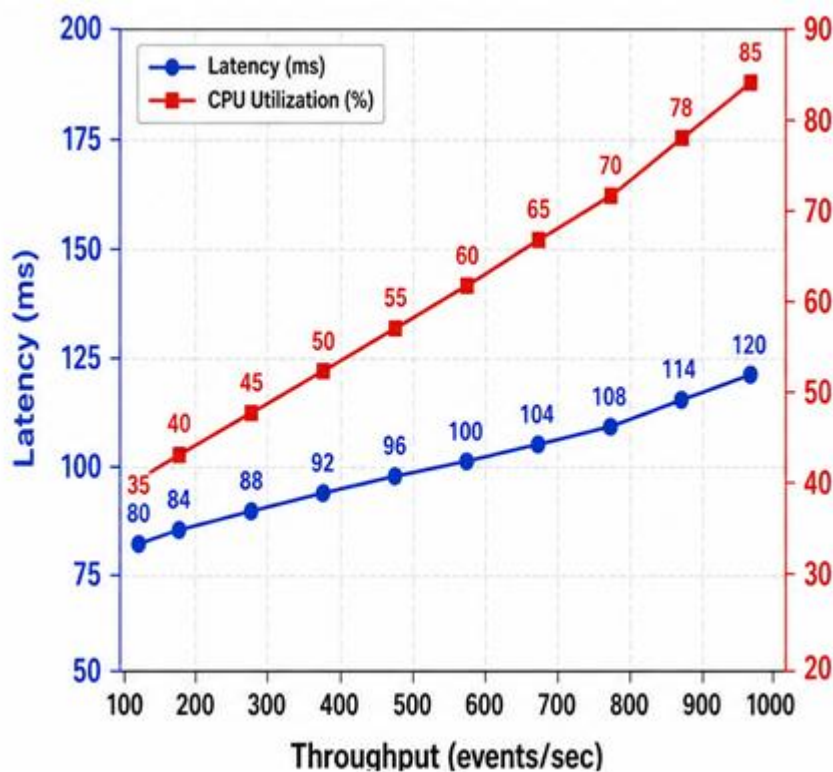


Fig. 6. Predictive quality system in real-time Latency and throughput.

The system has consistent performance with throughput growth, and a slight increase in latency. Mean latency of inference is still below 120 ms, which meets the real-time decision-making demands of an industry. The distributed processing and edge-based inference makes the system scalable to allow the efficient processing of large amounts of data.

VI. Discussion and Conclusion

The experimental findings are good evidence of the efficacy of the suggested AI-based predictive quality engineering paradigm in real-world manufacturing performance improvements. With the results carefully interpreted, it is possible to identify the strengths of the chosen modeling approach, as well as the overall implications of the chosen modeling approach to the zero-defect manufacturing systems.

The high performance of XGBoost that is evident in the model evaluation phase can be explained by the fact that it is capable of handling structured industrial data with complex feature interactions. Manufacturing datasets can often be non-linear in nature, in terms of process parameters that are hard to capture by traditional linear models such as temperature, pressure and vibration. The XGBoost gradient boosting mechanism allows the model to learn progressively, based on residual errors to enable the model to refine predictions and increase accuracy. Moreover, its intrinsic ability to address missing values and to address features importance, also contributes to its resilience in real-life scenarios of industry.

The fact that the model has been able to attain a high recall value is especially important on a manufacturing basis. False negatives in quality engineering refer to the unidentified defects that can be spread by downstream processes and cause huge financial and reputational losses. The confusion matrix shows that the model has a low false-negative rate, indicating that the model is very reliable in detecting defective cases. Though a slight increase in false positives can result in more inspections, this trade-off is reasonable in manufacturing environments that are safety-critical and highly precise in that false positives are not a concern.

The trend of reduction of defects after system deployment can be seen as evidence of the practical effects of predictive quality engineering. The fact that the percentage of defects decreases over time implies that the system is enjoying the advantages of continuous learning and adaptation. The proposed framework is dynamic and can adapt to any change in process conditions, thus allowing continuous enhancement, unlike the case with the static rule-based systems. Such practice is consistent with the idea of closed-loop quality control, according to which the feedback of past outcomes is applied to the new predictions and interventions.

The fact that key performance indicators have improved further supports the effectiveness of the system. The high decline in scrap rate means improved material utilization and less wastage, directly relating to the cost-saving and sustainability objectives. Similarly, the decrease in the duration of the rework time can be taken as a measure of the process stability and the minimization of the need to carry out correctional measures. It is a measure of how well a manufacturing system can ensure the quality of the products created during the first production cycle – the first pass yield is a key element of a high efficiency manufacturing system.

Operationally, real time exhibition of how the system works is a key-facilitator of the practical applicability of the system. The capability of sustaining inference latency of less than 120 ms, makes sure that predictions are realized within the stipulated time frame to intervene immediately. This is important in cases where a high speed production line is used, and where there is a risk of defect build-up if there is a delay in decision making. The system has been able to scale its use because it has shown its scalability through the amount of data it produces, as it can handle the volume of data produced by large scale industrial use without having to compromise the performance of the system.

The other important discovery is that multi-source data integration would be applicable to enhancing the accuracy of predictions. The framework takes into account information collected via sensors, MES system and inspection logs to demonstrate the complete picture of the manufacturing process. This integration makes it possible for the model to highlight delicate relationships and links that may become apparent when using stand-alone data source. As a result, the performance of the system in predicting the result is significantly improved.

There are some shortcomings that should be considered in the performance although it is of good quality. The quality and consistency of inputs data is important for the model effectiveness. Noise, missing values and sensor inaccuracies may affect the accuracy of prediction if not properly taken care of in the preprocessing. Also, although XGBoost can be very

high performance, its interpretability relative to simpler models may be a challenge in settings where explainability is needed to make decisions.

Although this has its advantages, there are a number of challenges that have to be addressed in order to achieve success in implementation and scalability. Data imbalance is one of the main challenges because flawed cases are usually significantly less than non-defective cases, which may bias the model training process and can influence the performance of predictions. Resampling and cost-sensitive learning are some of the techniques that can be used to reduce this problem. The other issue is that it is difficult to integrate AI-driven systems with the existing legacy infrastructure, such as MES or ERP systems, which might not be designed to support real-time data exchange. To achieve smooth interoperability, it is necessary to carefully design the system, as well as to standardize data interfaces.

The other important issue is model interpretability, especially in the industrial environment where the decision-making process should be transparent and explainable. Although recent models like XGBoost can have a high predictive performance, it tends to act as a black-box system. This may restrict user confidence and adoption, particularly in safety-critical applications. To overcome this issue, it is necessary to add explainability methods that will give information about model predictions and the contribution of features.

To sum up, the suggested AI-powered predictive quality engineering model has a great potential in allowing near zero-defect production. It's all three factors – high predictive accuracy, high defect reduction, real-time operation – that prove its ability to function in the context of today's modern manufacturing environment and to be a scalable solution. The research has been able to fill the gap between theoretical and practical models of AI, and offer a comprehensive approach to predictive quality management.

The research directions in the future will be the incorporation of explainable AI methods to increase the model transparency and user trust. The benefits of predictive can be enhanced through the use of Digital Twins and the ability to optimise and analyse situations through simulation. Moreover, federated learning can be considered to be able to conduct collaborative model training in a number of manufacturing sites without losing data privacy. These will assist in developing smarter, safer and bigger predictive quality systems and even easier to realize zero-defect manufacturing.

References

- [1] F. Psarommatis, J. Sousa, J. P. Mendonça, and D. Kiritsis, “Zero-defect manufacturing: The approach for higher manufacturing sustainability in the era of Industry 4.0: A position paper,” *International Journal of Production Research*, vol. 60, no. 1, pp. 73–91, Jan. 2022.
- [2] M. A. Mateo-Casali, A. Boza, and F. Fraile, “Digital assets in zero-defect manufacturing: Literature review and proposed framework,” *International Journal of Production Research*, 2025.
- [3] K. Shivani, M. A. Sharma, and S. Jain, “A review of defect reduction, quality improvement, and process optimization strategies for enhancing manufacturing efficiency,” *International Journal of Engineering Science & Humanities*, vol. 15, no. 3, pp. 315–324, Sep. 2025.
- [4] M. M. Hasan, M. Kasedullah, M. B. Ripon, and M. M. Khan, “AI-driven quality control in manufacturing and construction: Enhancing precision and reducing human error,” *Applied IT & Engineering*, vol. 3, no. 1, 2025.
- [5] O. Morales Matamoros, J. G. Takeo Nava, J. J. Moreno Escobar, and B. A. Ceballos Chávez, “Artificial intelligence for quality defects in the automotive industry: A systemic review,” *Sensors*, vol. 25, no. 5, p. 1288, Feb. 2025.
- [6] M. Shenoy, S. Sahasrabudhe, and F. Ameri, “Neurosymbolic AI-driven zero-defect manufacturing in semiconductor assembly: A hybrid framework,” in *Proc. 36th Annual SEMI Advanced Semiconductor Manufacturing Conf. (ASMC)*, 2025, pp. 1–6.
- [7] Y. B. Kariyappagowda, G. Manjunatha, T. T. Sabin, and K. Prabhavathi, “Edge AI-driven vision systems for zero-defect manufacturing in 6G-enabled Industry 5.0: The factory of the future,” in *Proc. Int. Conf. Sustainability, Innovation & Technology (ICSIT)*, 2025, pp. 1–7.
- [8] G. Deepak *et al.*, “AI-enhanced thermal modeling for integrated process-product-system optimization in zero-defect manufacturing chains,” *Thermal Science and Engineering Progress*, vol. 55, p. 102945, Oct. 2024.

- [9] M. F. Hossain and A. Dhanekula, "Smart continuous improvement with artificial intelligence, big data, and lean tools for zero defect manufacturing systems," *American Journal of Scholarly Research and Innovation*, vol. 2, no. 1, pp. 254–282, Dec. 2023.
- [10] M. Getachew, B. Beshah, A. Mulugeta, and D. Kitaw, "Application of artificial intelligence to enhance manufacturing quality and zero-defect using CRISP-DM framework," *International Journal of Production Research*, 2024.
- [11] V. Fani, I. Bucci, R. Bandinelli, and M. Rossi, "Advancing human-centric zero defect manufacturing: A theoretical framework and practical insights," *International Journal of Production Research*, 2025.
- [12] P. Catti *et al.*, "Human-centric proactive quality control in Industry 5.0: The critical role of explainable AI," in *Proc. IEEE Int. Conf. Engineering, Technology, and Innovation (ICE/ITMC)*, 2024, pp. 1–7.
- [13] I. Cascón-Morán *et al.*, "Towards zero-defect manufacturing based on artificial intelligence through the correlation of forces in 5-axis milling process," *Machines*, vol. 12, no. 4, p. 226, Mar. 2024.
- [14] N. Leberuyser, M. Ahlskog, and J. Bruch, "Addressing challenges when adopting AI-driven zero defect manufacturing: Insights from industry," *Procedia CIRP*, vol. 130, pp. 112–119, 2024.
- [15] J. Sharma, M. L. Mittal, and G. Soni, "Predictive maintenance of industrial assets: A fault detection and diagnosis approach with explainable AI," *International Journal of Reliability, Quality and Safety Engineering*, vol. 32, no. 2, 2025.
- [16] E. P. Bhaskaran, H. Pallathadka, and S. B. Sethupathy, "The technical efficiency on zero effect and zero-defect in Chennai automotive components cluster," *International Journal of Scientific Research & Engineering Trends*, vol. 11, no. 3, 2025.
- [17] M. M. Kabeer, "AI in manufacturing quality management: A review of techniques, tools, and industrial adoption," *Global Journal of Multidisciplinary Sciences and Arts*, vol. 1, no. 2, pp. 46–64, Dec. 2024.
- [18] R. C. Palsaniya, "AI-driven machine learning for enhancing nanomanufacturing equipment output," in *Proc. IEEE Nanotechnology Materials and Devices Conf. (NMDC)*, 2025, pp. 237–242.
- [19] H. Ghelani, "Advanced AI technologies for defect prevention and yield optimization in PCB manufacturing," *International Journal of Engineering and Computer Science*, vol. 13, no. 10, 2024.
- [20] E. Pereira *et al.*, "A zero-defect manufacturing decision-support system for the decorative surfaced panels industry," in *Proc. IEEE Int. Conf. Emerging Technologies and Factory Automation (ETFAs)*, 2025, pp. 1–7.
- [21] M. T. Islam *et al.*, "A meta-analysis of machine learning-enhanced lean quality control practices in manufacturing," *ASRC Procedia*, vol. 1, no. 1, pp. 166–192, Apr. 2025.
- [22] A. Hosseinzadeh, F. F. Chen, M. Shahin, and H. Bouzary, "A predictive maintenance approach in manufacturing systems via AI-based early failure detection," *Manufacturing Letters*, vol. 35, pp. 1179–1186, Aug. 2023.
- [23] A. H. Juliet, "AI-driven predictive maintenance for industrial IoT with real-time fault detection and prediction," in *Proc. Int. Conf. Electronics, Materials Engineering & Nano-Technology (IEMENTech)*, 2025, pp. 1–6.
- [24] E. Mikołajewska *et al.*, "Generative AI in AI-based digital twins for fault diagnosis," *Applied Sciences*, vol. 15, no. 6, p. 3166, Mar. 2025.
- [25] L. Rojas, Á. Peña, and J. Garcia, "AI-driven predictive maintenance in mining: A systematic literature review," *Applied Sciences*, vol. 15, no. 6, p. 3337, Mar. 2025.
- [26] S. Rana, "AI-driven fault detection and predictive maintenance in electrical power systems," *American Journal of Advanced Technology and Engineering Solutions*, vol. 1, no. 1, pp. 258–289, Feb. 2025.
- [27] A. M. Suci *et al.*, "Artificial intelligence in renewable energy: A review of predictive maintenance," *Journal of Clean Technology*, vol. 2, no. 1, pp. 29–44, Jun. 2025.

- [28] A. A. Soomro *et al.*, “Data-driven predictive maintenance of diesel engines,” *Spectrum of Engineering Sciences*, pp. 408–429, Jul. 2025.
- [29] M. Cavus, D. Dissanayake, and M. Bell, “Next generation of electric vehicles: AI-driven predictive maintenance,” *Energies*, vol. 18, no. 5, p. 1041, Feb. 2025.
- [30] A. Ucar, M. Karakose, and N. Kırımça, “Artificial intelligence for predictive maintenance applications,” *Applied Sciences*, vol. 14, no. 2, p. 898, Jan. 2024.
- [31] T. V. A. Johanesa *et al.*, “Survey on AI applications for product quality control and predictive maintenance,” *Electronics*, vol. 13, no. 5, p. 976, Mar. 2024.
- [32] A. T. Keleko *et al.*, “Artificial intelligence and real-time predictive maintenance in Industry 4.0,” *AI and Ethics*, vol. 2, no. 4, pp. 553–577, Nov. 2022.
- [33] D. Divya, B. Marath, and M. B. Santosh Kumar, “Review of fault detection techniques for predictive maintenance,” *Journal of Quality in Maintenance Engineering*, vol. 29, no. 2, pp. 420–441, Apr. 2023.
- [34] S. Gawde *et al.*, “Multi-fault diagnosis of industrial rotating machines,” *Engineering Applications of Artificial Intelligence*, vol. 123, p. 106139, Aug. 2023.
- [35] M. A. Khedr and M. Abdelaziz, “AI-driven robotic system for predictive maintenance,” in *Proc. Int. Conf. Computer and Applications (ICCA)*, 2024, pp. 1–6.
- [36] A. Abbas, “AI for predictive maintenance in industrial systems,” *International Journal of Advanced Engineering Technologies and Innovations*, vol. 1, no. 1, pp. 31–51, 2024.
- [37] S. Bello *et al.*, “AI-driven predictive maintenance and optimization of renewable energy systems,” *International Journal of Science and Research Archive*, vol. 13, no. 1, pp. 2823–2837, Oct. 2024.
- [38] S. J. Soundappan, “AI-based fault detection and isolation for reliability in modern power systems,” *IJRPETM*, vol. 5, no. 4, pp. 7106–7110, Jul. 2022.
- [39] S. A. Farabi, “AI-driven predictive maintenance model for DWDM systems,” *Preprints*, 2025.
- [40] S. Smaoui and M. Baklouti, “ML-based failure detection approach for predictive maintenance,” in *Proc. IEEE ATSIP*, 2024, pp. 426–431.
- [41] M. Drakaki *et al.*, “Machine learning and deep learning methods for predictive maintenance in induction motors,” *Journal of Industrial Engineering and Management*, vol. 15, no. 1, pp. 31–57, 2022.
- [42] X. Wang *et al.*, “Data-driven and knowledge-based predictive maintenance for industrial robots,” *Expert Systems with Applications*, vol. 234, p. 121136, Dec. 2023.
- [43] M. Romassini *et al.*, “A review on vibration monitoring techniques for predictive maintenance,” *Eng.*, vol. 4, no. 3, pp. 1797–1817, Jun. 2023.
- [44] U. Hijjawi *et al.*, “A review of automated solar photovoltaic defect detection systems,” *Solar Energy*, vol. 266, pp. 112186, Dec. 2023.