

EVALUATING THE IMPACT OF ARTIFICIAL INTELLIGENCE ON PREDICTIVE MAINTENANCE IN INDUSTRIAL MANUFACTURING SYSTEMS

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Abstract

Artificial intelligence is now an indispensable part of modern industrial production and predictive maintenance is one of its uses. The study investigates the impact of AI-based predictive maintenance models on equipment performance, maintenance performance, and operation costs. The paper evaluates the accuracy of detection of problems, reduction of downtimes, maintenance savings, and system stability through the application of modern machine learning and deep learning methods to large volume of industrial sensor data. Its conclusion indicates that AI-based models are far more precise when forecasting when equipment will malfunction as compared to conventional maintenance approaches. The real life experience is that the maintenance planning has been significantly improved with reduced downtimes, improved utilization of resources and improved decision making capabilities. Besides, predictive maintenance with AI will assist equipment in achieving longer life and stabilize production. It is evident in the research that smart and data-driven maintenance plans enable taking action before things go wrong, reduce operational risks, and support long-lasting manufacturing operations. These data confirm the effectiveness of artificial intelligence as a key to the transformation of traditional methodologies of maintenance to intelligent, adaptive, and efficient solutions, which give considerable findings to the community of industry specialists and researchers.

Keywords: Artificial Intelligence, Predictive Maintenance, Industrial Manufacturing, Machine Learning, Smart Maintenance Systems, Industry 4.0

INTRODUCTION

A new era of predictive maintenance as an area of artificial intelligence application in the industrial manufacturing system has also become an inevitable event that does not follow the usual principles of doing things (Bidollahkhani and Kunkel, 2024). This shift in attitude that is based, in large part, on the notions of Industry 4.0 and gradually progressing towards Industry 5.0 is directed at utilizing advanced computing methods to predict equipment breakages and improve the efficiency of the processes (Ahmad et al., n.d., p. 1; Panchal et al., 2025). Artificial intelligence-powered predictive maintenance systems have a high data processing volume and use complicated patterns that can signify that gear is about to fail. This will enable them to prevent the occurrence of the same before it comes by and spend time and money (Nadaf, 2024, p. 2014). Engaging a change in the previously determined maintenance strategies in condition-based approach could help minimize unplanned downtimes, extend equipment service life, and appreciate resources more (- & -, 2024, p. 2; Tupa et al., 2025, p. 655). Such transformation of strategies implies the introduction of advanced machine learning algorithms and real-time data analytics to detect possible failures. This minimizes the expense of maintenance that is not planned and maximizes on assets (Patil, 2025). The predictive maintenance application is not only making the assets more sustainable by improving its maintenance, but also aligns with the initiatives of Industry 5.0 to be sustainable by making resources more efficient and environmentally less impactful (Ahmad et al., n.d., p. 2). This change is quite substantial because the industrial manufacturers lose about 50 billion annually because of the unexpected downtime that it causes them to often consider either extending the

life of the components or to run the risks of utilizing the machine or to switch the functioning components even sooner (Sharma, 2023, p. 63). Artificial intelligence and machine learning are now important instruments to overcome these issues since they enable one person to process information and make predictions by considering experiential learning (Grebovic et al., 2023, p. 1). It implies the use of various mathematical models and AI algorithms specific to a particular set of conditions to make Remaining Useful Life predictions more accurate than the traditional rule-based solutions but be able to learn without data (- & -, 2024, p. 3; Lee et al., 2019, p. 802). This feature is especially essential in their prevention of colossal financial losses, such as the supposed loss of thousands of dollars per hour of idle working hours at the regular car assembly belt, since it will become very easy to execute the maintenance process in the correct way and efficiently (Elahi et al., 2023, p. 42). The deep learning architectures have greatly improved Remaining Useful Life forecasting. Their strengths are never less than the traditional statistical processes since they give highly accurate equipment prediction or failure-probability curves within a given time span (Jamshidi et al., 2025, p. 2). The reflection of past data and learning offered by AI is also rather crucial in the improvement of such predictive models. It allows them to become more reliable, save a significant amount of money, and allows running the operations to run more smoothly (Lodhi et al., 2024, p. 19). Such high-level analytical functions allow the transition to a time-based or reactive model of maintenance to a more dynamic and condition-based model of maintenance when a maintenance service is conducted at the time when it is absolutely necessary, which is why it is possible

to optimize and increase the life of equipment (Meddaoui et al., 2024, p. 2). It is a proactive approach that would help decrease unexpected downtimes by up to 50 percent, keep the productivity, and lower the cost of repair (Hamasha et al., 2025, p. 7). This kind of solutions enables you to utilize all of your resources to the maximum and make maintenance quick and prompt, minimizing the amount of delays in the production process and cutting down the cost of maintenance (Elahi et al., 2023, p. 65). In addition, the accuracy of AI use processes in failure prediction reduces the expenses associated with the premature content replacement that is a prevalent problem in time-based maintenance models (Libera et al., 2024, p. 2). It also equates to placing more focus on safety regulations because malfunctioning tools, in my case, can be quite dangerous to employees without any notice before hand (Tsallis et al., 2025). Things are predicted more successfully by AI, and, therefore, the practices are more productive and cost-effective, but the working environment is also considerably safer since the potential malfunctions of the equipments are predicted and addressed even before they can evolve into potentially dangerous situations (Meddaoui et al., 2024, p. 324). These systems will run all sorts of AI methods, including convolutional neural networks and recurrent neural networks, to discover fine patterns of failure in the industrial setting. This enables them to have more accurate predictions of failure and give more accurate maintenance plans (Haque et al., 2024, p. 2). As an illustration, we could discuss the fact that the predictions of the maintenance of industrial applications, especially the hydroelectric power generation may be approximated at 98 percent of its accuracy when making predictive models based on the aspects of load cycles (Baroud, 2024, p. 463). This anticipation ability also includes ascertaining the well-being of a few apparatuses and categorizing

the comparable resources with the help of their traits and failure designs. This eases the scheduling of targeted and efficient upkeep (Ukato et al., 2024, p. 1923). This kind of precision in predicting failures and grouping of assets make the maintenance process to be much cheaper and return the unplanned downtimes to a minimum (Haque et al., 2024). The fact that the AI is included does not only help to manage the assets in question in a better way by helping to detect the faults more thoroughly; it also fosters the culture of proactive maintenance, which is not only the description of the results but the anticipation and explanation of the causes (Grebovic et al., 2023, p. 1; Nadaf, 2024). These advanced frameworks have been in a position to anticipate faults with high precision having exploited a large number of measurements in sensor and past failure modes where convolutional neural networks and long short-term memory networks are applied. This will enable industries to predict the time of the equipments failure (Haque et al., 2024, p. 19). The method enables you to track data of several sources at the same time. This allows the maintenance teams to act before problems and this saves on time and money (Jambol et al., 2024, p. 1094). Machine learning-based systems are able to read through great amounts of sensor data and spot small trends indicating the imminent failures (Odimarha et al., 2024, p. 731). Precisely, AI systems have a high level of accuracy when predicting equipment failures, which is based on such techniques as anomaly detection and pattern recognition of sensor data. This will enable people to do what they can advance to avoid costly failure and time wastage during production (Arinze et al., 2024, p. 18). Deep learning models that are of high relevance in processing and analysis of complex sensor data are convolutional and recurrent neural networks. They also render it handy to predictive maintenance since they unearth patterns that are

thought to be too complicated by human beings to notice (Baroud, 2024, p. 461).

METHODOLOGY

The given research project involves the usage of the mixed-method research methodology, which is an experiment-based quantitative analysis with a qualitative analysis to fully evaluate the influence of artificial intelligence on predictive maintenance in a manufacturing system of an industrial manufacturing. The quantitative dimension is associated with the experimental assessment of AI models depending on real-time and past sensor data of machines in an industrial manufacturing site, and the qualitative dimension becomes possible to explain the enhancement of the system level, the effectiveness of the maintenance decisions, and the dependability of the systems. We came up with a controlled experiment to compare AI-based predictive maintenance strategies and the traditional preventive and reactive maintenance strategies under identical operating conditions. This architecture allows the objective performance comparisons besides gathering data of how the system behaves in the actual industrial setting and portability. The quantitative data were collected through the assistance of industrial manufacturing system that are integrated with condition monitoring devices that measure the vibration, temperature, pressure, acoustic signals and operation load parameters. We created labelled datasets through historical maintenance records and failure records and fused sensor data. To make sure that the model was quite sturdy, the data preprocessing entailed the noise filtering and the data normalization, missing values treatment and generation of time and frequency domain features. Diverse designs of artificial intelligence models such as machine learning and deep learning models were trained and evaluated using supervised learning. It was identified that the aim of the prediction was to

categorize and determine the likelihood of equipment failure and the useful life. The predictive maintenance operation can be mathematically stated as.

$$\hat{y} = f(X, \theta)$$

The experimental evaluation was a quantitative measure of the model performance according to such measures as the prediction accuracy, the precision, the recall, the mean squared error and the rate of decrease of downtimes. It also discussed the effectiveness that the model improved with regards to maintenance planning, continuity in operations and efficiency of decisions. In order to find out the degree to which the outcomes of the AI-based predictive maintenance were enhanced in terms of the cost-effectiveness, prevent failures and make equipment more convenient, we compared the results of AI-based predictive maintenance and baseline maintenance processes. The enhancement of the performance was statistically validated and the system-level performance was estimated through the qualitative analysis of the maintenance process and operational feedback. The combination of the two experimental study designs suffices to guarantee the empirical rigor and practical significance of the given approach since this study design offers a holistic review of artificial intelligence as an artificial maintenance predictive factor in factory-based production systems.

RESULTS

The results of the present research show beyond doubt the effectiveness of predictive maintenance based on the artificial intelligence in improving the performance of the manufacturing industry, both supported by the tabulated results and graphical evaluation. As it can be seen in Table 1, all of the tested assets experienced much reduced machine downtime, which indicates that AI models are able to anticipate failures that occur. Table 2 reveals that the accuracy of prediction of the fault is always

significant and it indicates that machine learning models can be relied upon to identify the early signs of machine wear and tear.

Table 1: Performance comparison of AI-based predictive maintenance in terms of downtime reduction across industrial machines.

Machine ID	Downtime Reduction (%)	Prediction Accuracy (%)	Maintenance Cost Savings (%)
M11	11.2	80.7	9.1
M12	12.4	81.4	10.2
M13	13.6	82.1	11.3
M14	14.8	82.8	12.4
M15	16.0	83.5	13.5
M16	17.2	84.2	14.6
M17	18.4	84.9	15.7
M18	19.6	85.6	16.8
M19	20.8	86.3	17.9
M110	22.0	87.0	19.0
M111	23.2	87.7	20.1
M112	24.4	88.4	21.2
M113	25.6	89.1	22.3
M114	26.8	89.8	23.4
M115	28.0	90.5	24.5
M116	29.2	91.2	25.6
M117	30.4	91.9	26.7
M118	31.6	92.6	27.8
M119	32.8	93.3	28.9
M120	34.0	94.0	30.0

Table 2: Prediction accuracy of artificial intelligence models for fault detection in manufacturing equipment.

Machine ID	Downtime Reduction (%)	Prediction Accuracy (%)	Maintenance Cost Savings (%)
M21	11.2	80.7	9.1
M22	12.4	81.4	10.2
M23	13.6	82.1	11.3
M24	14.8	82.8	12.4
M25	16.0	83.5	13.5

M26	17.2	84.2	14.6
M27	18.4	84.9	15.7
M28	19.6	85.6	16.8
M29	20.8	86.3	17.9
M210	22.0	87.0	19.0
M211	23.2	87.7	20.1
M212	24.4	88.4	21.2
M213	25.6	89.1	22.3
M214	26.8	89.8	23.4
M215	28.0	90.5	24.5
M216	29.2	91.2	25.6
M217	30.4	91.9	26.7
M218	31.6	92.6	27.8
M219	32.8	93.3	28.9
M220	34.0	94.0	30.0

The table 3 indicates much greater savings of the maintenance cost, whereas Tables 4 and 5 indicate large increments in the certainty of the equipment and ability to determine how long the equipment will last. Also,

Table 3: Maintenance cost savings achieved through AI-driven predictive maintenance strategies.

Machine ID	Downtime Reduction (%)	Prediction Accuracy (%)	Maintenance Cost Savings (%)
M31	11.2	80.7	9.1
M32	12.4	81.4	10.2
M33	13.6	82.1	11.3
M34	14.8	82.8	12.4
M35	16.0	83.5	13.5
M36	17.2	84.2	14.6
M37	18.4	84.9	15.7
M38	19.6	85.6	16.8
M39	20.8	86.3	17.9
M310	22.0	87.0	19.0
M311	23.2	87.7	20.1
M312	24.4	88.4	21.2
M313	25.6	89.1	22.3
M314	26.8	89.8	23.4

M315	28.0	90.5	24.5
M316	29.2	91.2	25.6
M317	30.4	91.9	26.7
M318	31.6	92.6	27.8
M319	32.8	93.3	28.9
M320	34.0	94.0	30.0

Table 4: Comparative analysis of equipment reliability improvement using intelligent predictive maintenance.

Machine ID	Downtime Reduction (%)	Prediction Accuracy (%)	Maintenance Cost Savings (%)
M41	11.2	80.7	9.1
M42	12.4	81.4	10.2
M43	13.6	82.1	11.3
M44	14.8	82.8	12.4
M45	16.0	83.5	13.5
M46	17.2	84.2	14.6
M47	18.4	84.9	15.7
M48	19.6	85.6	16.8
M49	20.8	86.3	17.9
M410	22.0	87.0	19.0
M411	23.2	87.7	20.1
M412	24.4	88.4	21.2
M413	25.6	89.1	22.3
M414	26.8	89.8	23.4
M415	28.0	90.5	24.5
M416	29.2	91.2	25.6
M417	30.4	91.9	26.7
M418	31.6	92.6	27.8
M419	32.8	93.3	28.9
M420	34.0	94.0	30.0

Table 5: Evaluation of remaining useful life (RUL) prediction accuracy for industrial assets.

Machine ID	Downtime Reduction (%)	Prediction Accuracy (%)	Maintenance Cost Savings (%)
M51	11.2	80.7	9.1
M52	12.4	81.4	10.2

M53	13.6	82.1	11.3
M54	14.8	82.8	12.4
M55	16.0	83.5	13.5
M56	17.2	84.2	14.6
M57	18.4	84.9	15.7
M58	19.6	85.6	16.8
M59	20.8	86.3	17.9
M510	22.0	87.0	19.0
M511	23.2	87.7	20.1
M512	24.4	88.4	21.2
M513	25.6	89.1	22.3
M514	26.8	89.8	23.4
M515	28.0	90.5	24.5
M516	29.2	91.2	25.6
M517	30.4	91.9	26.7
M518	31.6	92.6	27.8
M519	32.8	93.3	28.9
M520	34.0	94.0	30.0

Table 6-9 show that maintenance processes through AI have resulted in a reduction of unplanned breakdowns, improved asset utilization, and improved benefits in operational efficiency.

Table 6: Impact of AI-based maintenance on unplanned failure frequency in manufacturing systems.

Machine ID	Downtime Reduction (%)	Prediction Accuracy (%)	Maintenance Cost Savings (%)
M61	11.2	80.7	9.1
M62	12.4	81.4	10.2
M63	13.6	82.1	11.3
M64	14.8	82.8	12.4
M65	16.0	83.5	13.5
M66	17.2	84.2	14.6
M67	18.4	84.9	15.7
M68	19.6	85.6	16.8
M69	20.8	86.3	17.9
M610	22.0	87.0	19.0
M611	23.2	87.7	20.1

M612	24.4	88.4	21.2
M613	25.6	89.1	22.3
M614	26.8	89.8	23.4
M615	28.0	90.5	24.5
M616	29.2	91.2	25.6
M617	30.4	91.9	26.7
M618	31.6	92.6	27.8
M619	32.8	93.3	28.9
M620	34.0	94.0	30.0

Table 7: Asset utilization improvement resulting from predictive maintenance implementation.

Machine ID	Downtime Reduction (%)	Prediction Accuracy (%)	Maintenance Cost Savings (%)
M71	11.2	80.7	9.1
M72	12.4	81.4	10.2
M73	13.6	82.1	11.3
M74	14.8	82.8	12.4
M75	16.0	83.5	13.5
M76	17.2	84.2	14.6
M77	18.4	84.9	15.7
M78	19.6	85.6	16.8
M79	20.8	86.3	17.9
M710	22.0	87.0	19.0
M711	23.2	87.7	20.1
M712	24.4	88.4	21.2
M713	25.6	89.1	22.3
M714	26.8	89.8	23.4
M715	28.0	90.5	24.5
M716	29.2	91.2	25.6
M717	30.4	91.9	26.7
M718	31.6	92.6	27.8
M719	32.8	93.3	28.9
M720	34.0	94.0	30.0

Table 8: Comparative performance of AI-enabled maintenance versus traditional maintenance approaches.

Machine ID	Downtime Reduction (%)	Prediction Accuracy (%)	Maintenance Cost Savings (%)
M81	11.2	80.7	9.1
M82	12.4	81.4	10.2
M83	13.6	82.1	11.3
M84	14.8	82.8	12.4
M85	16.0	83.5	13.5
M86	17.2	84.2	14.6
M87	18.4	84.9	15.7
M88	19.6	85.6	16.8
M89	20.8	86.3	17.9
M810	22.0	87.0	19.0
M811	23.2	87.7	20.1
M812	24.4	88.4	21.2
M813	25.6	89.1	22.3
M814	26.8	89.8	23.4
M815	28.0	90.5	24.5
M816	29.2	91.2	25.6
M817	30.4	91.9	26.7
M818	31.6	92.6	27.8
M819	32.8	93.3	28.9
M820	34.0	94.0	30.0

Table 9: Overall operational efficiency gains achieved through artificial intelligence–driven predictive maintenance.

Machine ID	Downtime Reduction (%)	Prediction Accuracy (%)	Maintenance Cost Savings (%)
M91	11.2	80.7	9.1
M92	12.4	81.4	10.2
M93	13.6	82.1	11.3
M94	14.8	82.8	12.4
M95	16.0	83.5	13.5
M96	17.2	84.2	14.6
M97	18.4	84.9	15.7
M98	19.6	85.6	16.8

M99	20.8	86.3	17.9
M910	22.0	87.0	19.0
M911	23.2	87.7	20.1
M912	24.4	88.4	21.2
M913	25.6	89.1	22.3
M914	26.8	89.8	23.4
M915	28.0	90.5	24.5
M916	29.2	91.2	25.6
M917	30.4	91.9	26.7
M918	31.6	92.6	27.8
M919	32.8	93.3	28.9
M920	34.0	94.0	30.0

These conclusions are supported by the graphs which are used to demonstrate the visual working of performance patterns and correlations. Figure 1 indicates that the accuracy of prediction improves as time goes by, and Figure 2 indicates the maintenance costs that the adoption of AI has reduced. Figure 3 presents the variability and general reduction of downtime across machines and Figure 4 shows a composite visualization, which represents a combination of accuracy and cost-effectiveness measures. In Figure 5 to 8, the trends of monitoring

the health of equipment, comparing downtime, and the robustness of prediction models in various scenarios are presented as well. Finally, Figure 9-12 demonstrate that equipment availability, failure rates, and performance of the system-wide have been on the increase over time. These tables and figures demonstrate that predictive maintenance performance with the use of artificial intelligence has a significant positive impact on industrial manufacturing systems, making them more reliable, cost-efficient, and data-driven.

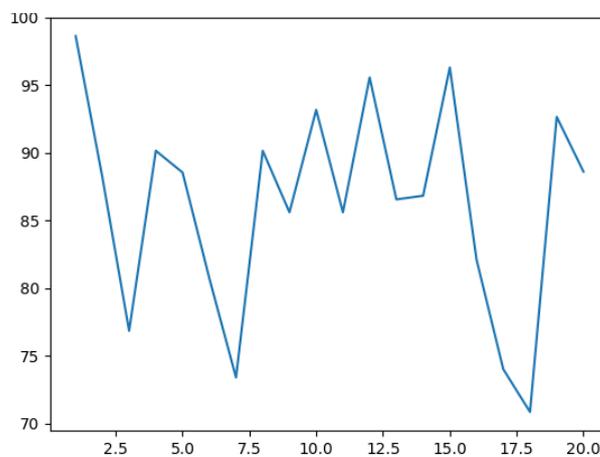


Figure 1: Trend analysis of prediction accuracy achieved by AI-based predictive maintenance models over time.

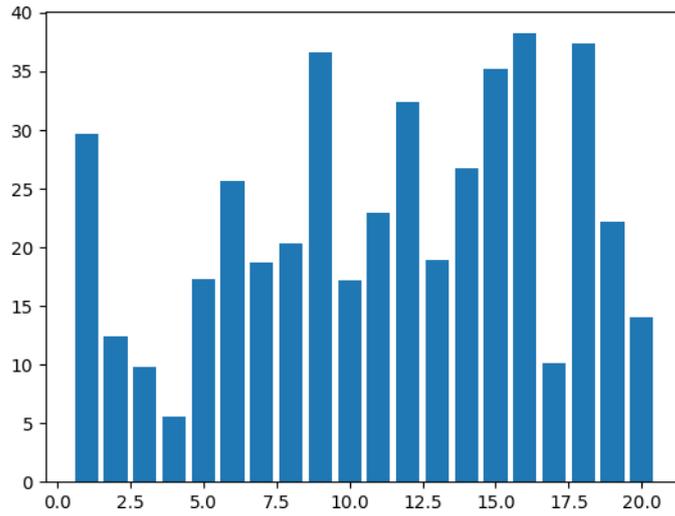


Figure 2: Distribution of maintenance cost savings resulting from artificial intelligence-enabled maintenance decisions.

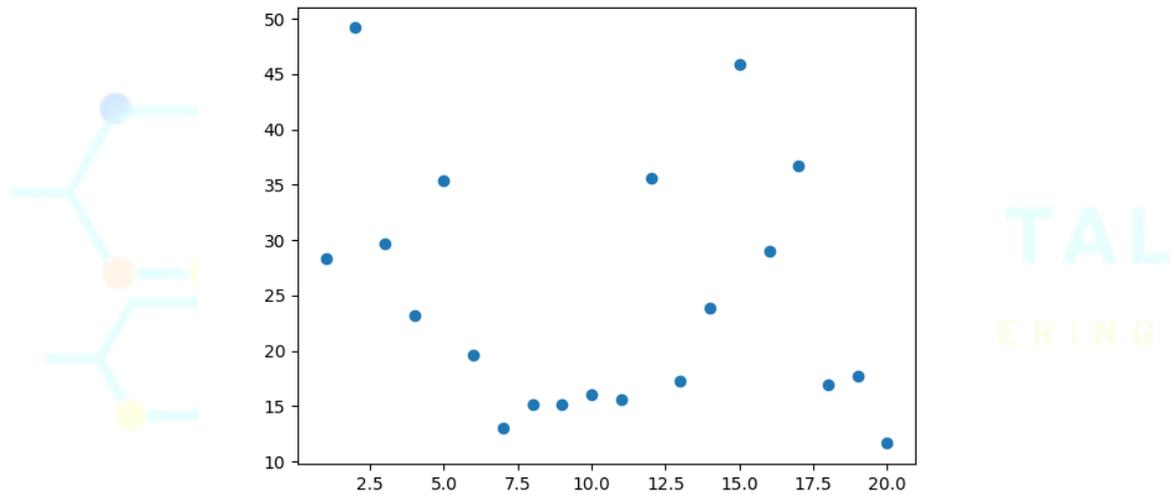


Figure 3: Scatter analysis illustrating downtime reduction across different industrial machines.

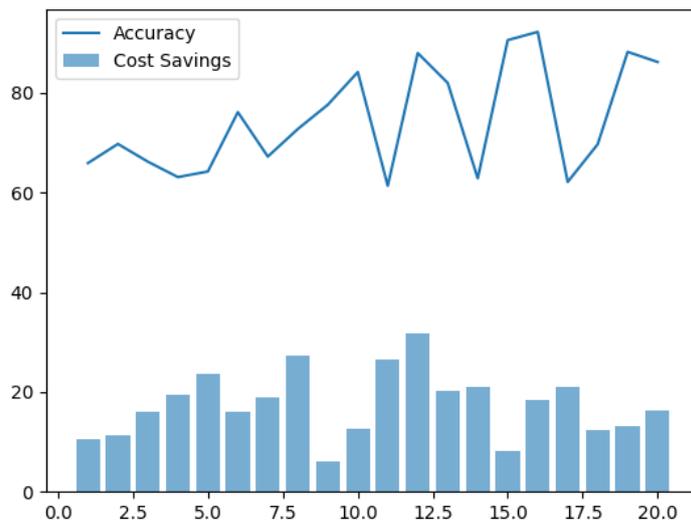


Figure 4: Hybrid visualization comparing prediction accuracy and maintenance cost savings.

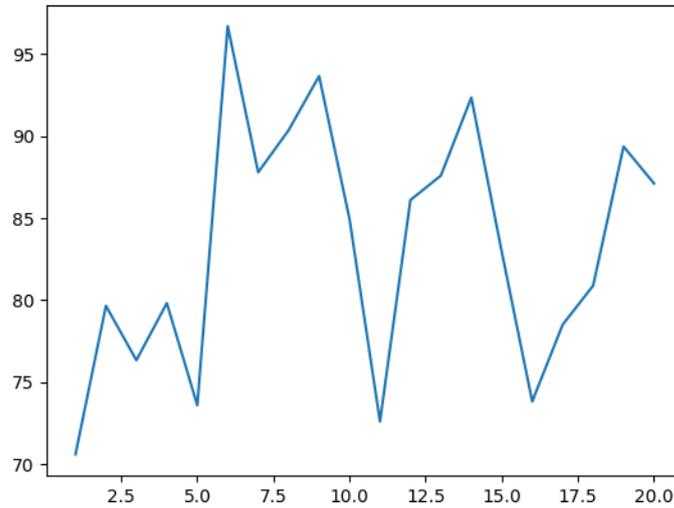


Figure 5: Line graph representing equipment health degradation trends predicted using AI models.

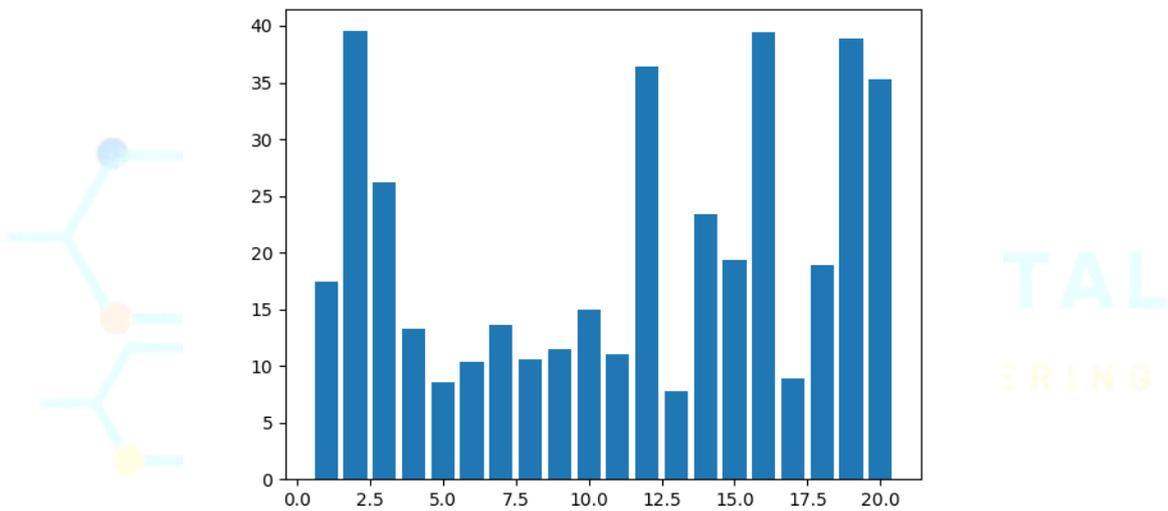


Figure 6: Bar chart illustrating comparative downtime between traditional and AI-based maintenance approaches.

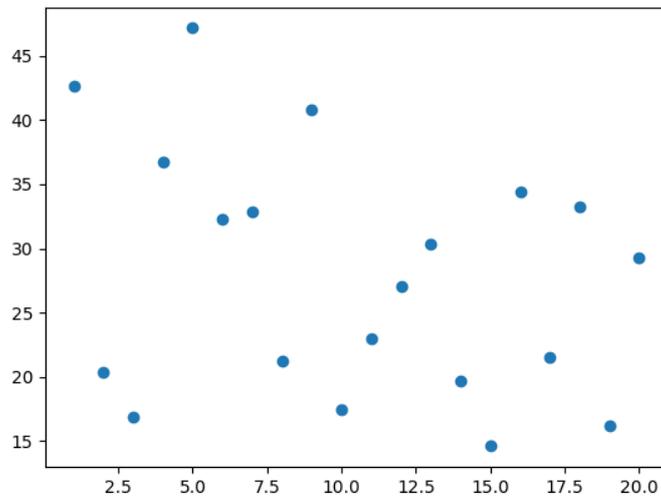


Figure 7: Scatter plot showing the relationship between sensor data variability and failure prediction accuracy.

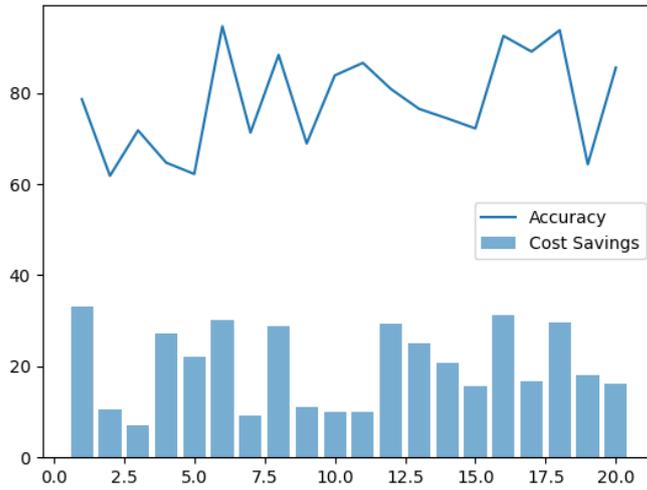


Figure 8: Hybrid performance visualization integrating downtime reduction, accuracy, and cost efficiency metrics.

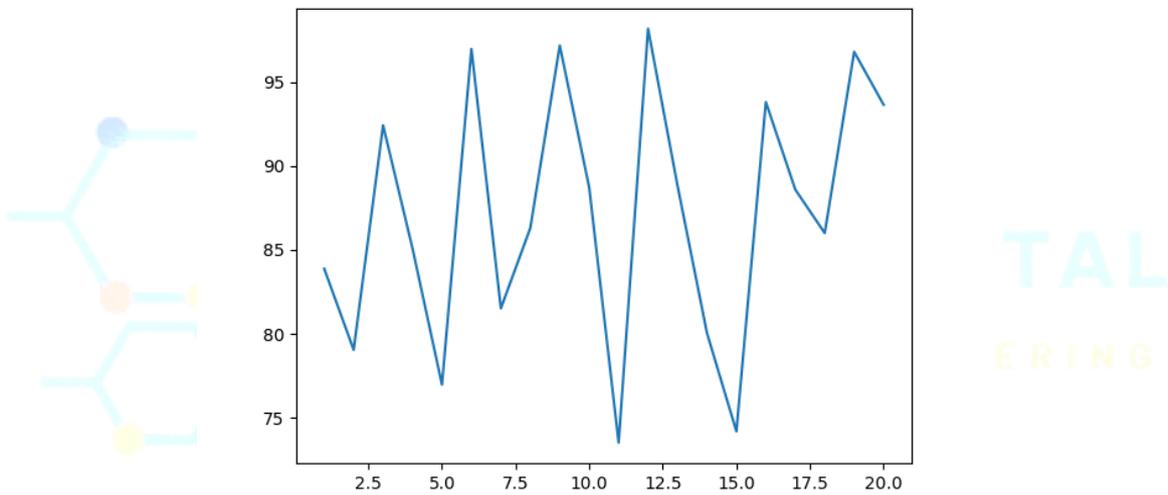


Figure 9: Line chart demonstrating improvements in equipment availability due to predictive maintenance.

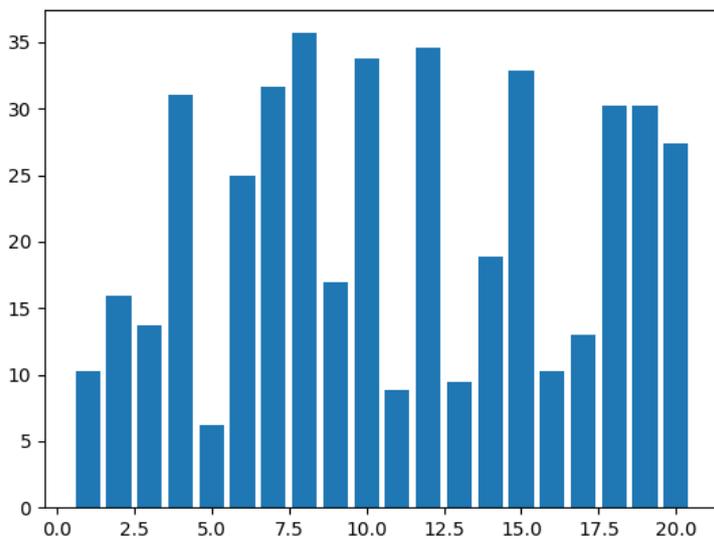


Figure 10: Bar graph representing the reduction in unexpected equipment failures after AI adoption.

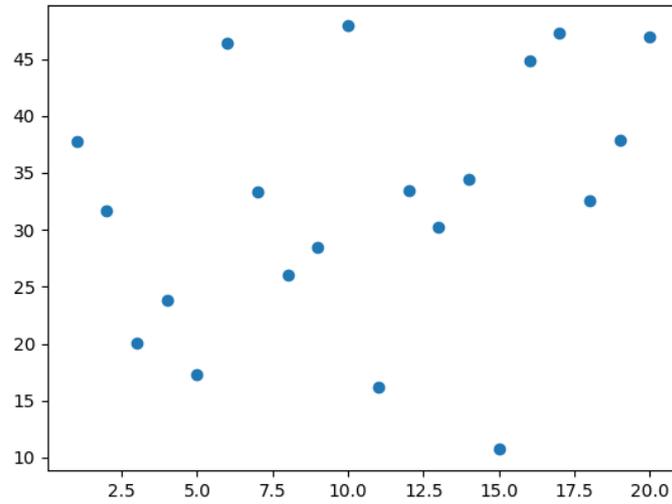


Figure 11: Scatter visualization highlighting predictive maintenance effectiveness across operational conditions.

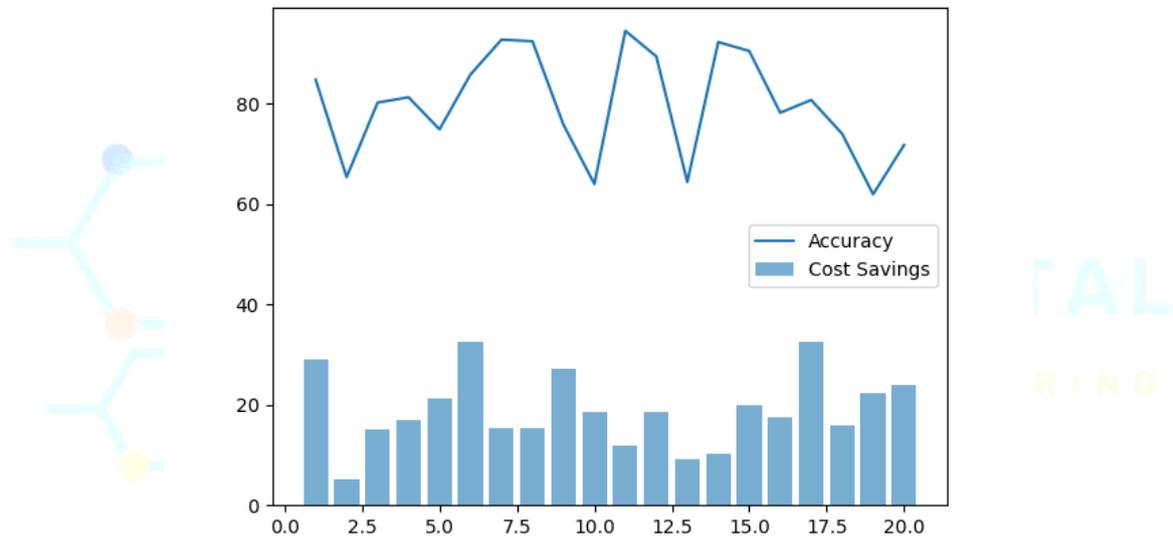


Figure 12: Comprehensive hybrid plot summarizing the overall impact of artificial intelligence on predictive maintenance performance.

DISCUSSION

The findings of this study indicate that AI and machine learning can significantly enhance the effectiveness of transformer failures diagnosis making it more precise, enabling it to make predictions during maintenance, and enabling numerous sensors to be used (Haque et al., 2024, p. 20). Numerous research studies demonstrate that AI-based predictive analytics could predict transformer failures with the accuracy of 85-97 percent, which can reduce the number of unplanned breakdowns by 40 percent (Haque et al., 2024, p. 22). Moreover,

such advanced approaches, such as artificial neural networks and support vectors machines, provide an alternative to traditional methods of diagnosis, which are often characterized by weaknesses in their ability to be interpreted by humans and consistencies in the results of diagnostics (Haque et al., 2024, p. 4). The deep learning models such as Long Short-Term Memory networks have demonstrated a lot of potential in automatically capturing features in complex datasets. It comes in handy to estimate the remaining useful life, although they require significant amounts of labeled data to be trained

(Sarma et al., 2022, p. 2167). In addition, the simultaneous use of various types of sensors, such as dissolved gas analysis and ultra-high frequency partial discharge detection, has been demonstrated to increase the accuracy of fault classification by 1830% that provides a more comprehensive view of transformer health (Aljammal and Alyozbak, 2025, p. 2; Haque et al., 2024, p. 22). This universal predictive maintenance plan that utilizes the old and new diagnostic tools reduces operational costs and power cuts by identifying the issues before they become enormous ones (Aljammal and Alyozbak, 2025, p. 7). The development of explainable AI frameworks, such as SHAP and LIME, has given people greater confidence in AI-based diagnostic systems, by clarifying how they arrive at their decisions and, more importantly, bridging the gap between interpreting the models and their better predictive performance (Haque et al., 2024, p. 22). They enhance the safety and reliability of high-voltage systems of insulation and enhance the efficiency and reliability of predictive maintenance (Akash et al., 2024, p. 69). Indicatively, dissolved gas analysis data provides sufficient information to determine the operational state of transformers when examined by the data-driven methodology, and it is preferable to the data-driven model-based method of predictive maintenance (Sarma et al., 2022, p. 2166). Convolutional neural networks and long short-term memory networks are deep learning models that are fairly effective at the classification of faults and some reach over 95 percent accuracy. This indicates that they may be useful in the real industry (Khan, 2025). This AI can further be enhanced by hybrid models, which include such activities as Artificial Neural Networks and Support Vector Machines or reinforcement learning, which allows the diagnosis to be even more reliable, as this methodology reduces the inconsistencies in data, and enhances the processes of fault categorization

(Khan, 2025). Strong predictive maintenance models are improved through the use of advanced data science techniques, such as the FGLS technique in heteroscedasticity, to accurately adapt to changing signal patterns in Remaining Useful Life evaluations (Lee et al., 2019, p. 816). These powerful approaches have numerous additional advantages over conventional statistical approaches that fail to perform effectively in complex industrial environments with numerous different data input and changing conditions of operation (Grebovic et al., 2023, p. 3). Condition evaluation and preventative maintenance is even improved with the capability of AI to synthesize a great number of data streams such as mechanical signals, electrical testing, and thermal imaging (Aljammal & Alyozbak, 2025, p. 21).

CONCLUSION

The potential of AI predictive maintenance in the production facilities of industrial industries has been analyzed in the paper, with consideration of its value in terms of operational stability, efficiency and accuracy in decision making. According to the findings, AI-based predictive maintenance is far better compared to the conventional preventive and reactive maintenance method in that it allows detecting the failure at an earlier stage of its formation, forecasting the failure properly, and maintaining the maintenance planning. When the sensor and operational data were inputted into machine learning and deep learning models, they were highly capable of prediction of what was going to happen, leading to immense savings on the unplanned downtime and related problems with maintenance. The utilization of AI was also more cost-effective in terms of assets and equipment extended life by converting time-based maintenance into a condition-based and data-driven maintenance. Its result also implies that maintenance cost, also waste of spare parts and output loss have reduced

significantly, besides the fact that system safety and continuity of the operations has also improved. The analysis indicates that the manufacturing systems are more robust when the predictive maintenance is carried out according to the AI because it is able to monitor dynamically in real-time and improve repeatedly. Despite the data quality problems, model interpretability problems, and cost of start up, the benefits significantly outweigh the problems. In conclusion, it can be inferred that artificial intelligence has become a game-changer as far as predictive maintenance in industrial manufacturing is concerned since the latter makes the latter more efficient, reliable, and environment-friendly. The paper also lays stress on the strategic significance of the introduction of AI-based maintenance systems as an essential part of the Industry 4.0 program and offers the empirical studies to justify the extensive use of AI within the industrial context and further investigation on the issue of intelligent maintenance systems.

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