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Research Article

AI-Driven Predictive Maintenance for Smart Manufacturing Systems: A Case Study Using Deep Learning on Sensor Data

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Abstract
The rapid advancement of Industry 4.0 has catalyzed the integration of artificial intelligence (AI) into smart manufacturing, with predictive maintenance emerging as a crucial application to reduce downtime and optimize operational efficiency. This study aims to develop and evaluate a deep learning-based predictive maintenance model by leveraging real-time sensor data from a smart factory environment. A convolutional neural network (CNN) architecture was implemented to detect anomalies and predict machinery failures in advance. The dataset, consisting of multivariate time-series signals from industrial sensors, was preprocessed and used to train, validate, and test the model's predictive performance. Results indicate that the proposed deep learning model achieved a prediction accuracy of 94.6%, outperforming traditional statistical and machine learning methods in both precision and recall. The implementation of this AI-driven system enables proactive maintenance strategies, minimizing production losses and extending equipment lifespan. In conclusion, the research demonstrates the feasibility and effectiveness of deep learning in predictive maintenance applications for smart manufacturing systems and offers a scalable solution adaptable to diverse industrial settings.

Keywords: Deep Learning, Predictive Maintenance, Smart Manufacturing

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INTRODUCTION

The ongoing transformation in manufacturing industries, driven by Industry 4.0, has significantly altered traditional production paradigms through the integration of cyber-physical systems, Internet of Things (IoT), and artificial intelligence (Chang dkk., 2025; Kiangala & Wang, 2025). Smart manufacturing has emerged as a revolutionary model that emphasizes automation, real-time data utilization, and system-wide interconnectivity. In such highly dynamic and data-intensive environments, the efficiency and reliability of machinery play a pivotal role in sustaining operational continuity and competitiveness.

Conventional maintenance approaches, such as reactive and scheduled maintenance, often fall short in addressing the complexity and variability present in modern industrial settings. Reactive maintenance leads to unplanned downtime and costly disruptions, while scheduled maintenance may result in unnecessary part replacements and excessive operational costs. Predictive maintenance (PdM), by contrast, leverages real-time monitoring and data analytics to anticipate failures before they occur, allowing for informed decision-making and timely intervention (Cană dkk., 2025; Pydikalva dkk., 2025). The transition to AI-enabled PdM has thus become increasingly indispensable in contemporary manufacturing systems.

The advent of AI, particularly deep learning, has expanded the frontier of predictive maintenance by enabling the modeling of non-linear, high-dimensional sensor data patterns that were previously difficult to capture with conventional statistical methods (Boareto dkk., 2025; Guidotti dkk., 2025). This capability opens up new possibilities for fault detection, remaining useful life (RUL) estimation, and autonomous decision support systems. The role of deep learning in this context is to empower smart factories with scalable, adaptive, and accurate predictive tools that enhance equipment reliability, reduce costs, and increase productivity.

Despite the growing interest in AI applications for predictive maintenance, many manufacturing systems still rely on rule-based or threshold-based monitoring techniques that offer limited adaptability to complex, real-world conditions (Boareto dkk., 2025; Massaro dkk., 2025). These methods are often insufficient in detecting subtle or compound fault patterns, especially in environments with noisy, incomplete, or non-stationary sensor data. This inadequacy leads to either missed detections or false alarms, both of which negatively impact operational efficiency and maintenance planning.

Industrial sensor networks continuously generate large volumes of time-series data that are underutilized in conventional maintenance systems due to the lack of robust, intelligent analytics frameworks (Massaro dkk., 2025; D. Singh & Singh, 2025). While the data hold valuable indicators of equipment health, the extraction of meaningful insights requires advanced machine learning algorithms capable of learning from complex data distributions. The absence of such mechanisms in many implementations has created a performance bottleneck, hindering the predictive capabilities needed for modern manufacturing reliability management.

There is also a practical challenge in designing models that are generalizable across different types of machinery and operating conditions. Many existing models are either too domain-specific or fail to adapt when deployed in real factory environments. As a result, manufacturers are confronted with a gap between the theoretical promise of AI-driven PdM and its effective real-world application (Vijayachitra dkk., 2025; Yorston dkk., 2025). This research seeks to address that gap by developing a deep learning model tailored for high-dimensional sensor data in a smart manufacturing context.

This study aims to develop and validate a deep learning-based predictive maintenance framework specifically designed for sensor-driven smart manufacturing systems. The primary objective is to construct a model capable of accurately predicting machinery failures by learning from multivariate time-series data collected from industrial sensors (Namboodri & Felhő, 2025; Park dkk., 2025). This framework seeks to bridge the gap between raw data acquisition and actionable maintenance decisions.

In addition to model construction, the research evaluates the performance of the deep learning system in terms of predictive accuracy, precision, recall, and robustness under variable operational conditions. By applying real-world sensor datasets from a smart factory environment, the study provides empirical evidence of the model's effectiveness and reliability in detecting early signs of equipment degradation (Martínez-Mireles dkk., 2025; Voshart, 2025). These evaluation metrics are intended to measure the practical feasibility of deploying such a model in industrial scenarios.

Another critical objective of this study is to demonstrate the scalability and transferability of the proposed model (Bakirci & Bayraktar, 2025; Renukhadevi dkk., 2025). The research explores how the model can be adapted across different machine components or production systems with minimal retraining, thereby offering a generalized solution that supports the broader goals of intelligent, data-driven maintenance in Industry 4.0 frameworks.

The existing body of literature on predictive maintenance reveals an increasing reliance on machine learning algorithms; however, much of the focus remains limited to shallow learning methods such as decision trees, support vector machines, or basic neural networks. These approaches often struggle with the volume, velocity, and variability of sensor data typically encountered in industrial settings. There is a clear need for more sophisticated models that can capture temporal dependencies and abstract representations inherent in multivariate sensor streams.

Several studies have explored deep learning for predictive maintenance, yet many lack rigorous validation using real-world datasets or fail to integrate end-to-end frameworks applicable to industrial contexts. In some cases, models are trained on simulated data that do not reflect the noise, anomalies, and complexity of live production systems (Bakirci & Bayraktar, 2025; Prabu dkk., 2025). This restricts their usefulness when applied in practice and underscores the need for empirical case studies based on authentic sensor data from actual manufacturing environments.

Furthermore, prior research has generally overlooked the deployment perspective, including system integration, interpretability, and operational constraints in manufacturing systems. While algorithmic accuracy is vital, the usability and transparency of the model also play a crucial role in industrial adoption (Negru dkk., 2025; S. Singh dkk., 2025). This study addresses these gaps by providing not only a performant deep learning model but also a deployment-ready architecture tested within a real factory setting.

The contribution of this research lies in the implementation of a novel deep learning architecture that effectively processes high-dimensional, temporal sensor data to predict equipment failures in advance. Unlike traditional models, the proposed framework incorporates both spatial and temporal features using a convolutional neural network (CNN) combined with long short-term memory (LSTM) units, enabling the system to capture both static patterns and sequential behaviors over time (Chen, 2025). This hybrid approach enhances the model's sensitivity and specificity in fault detection.

In addition to methodological innovation, the study provides practical insights into the end-to-end application of AI in smart manufacturing systems. By using real industrial datasets and deploying the model within an operational environment, the research offers a holistic perspective that bridges theoretical development with engineering implementation (Kodumuru dkk., 2025; Meena dkk., 2025). The validation process includes system-level evaluation and scenario-based testing, ensuring the model's relevance to real-world operational challenges.

The novelty of this work also extends to its interdisciplinary significance. The findings contribute to the fields of AI, industrial engineering, and data science by offering a scalable and transferable predictive maintenance solution (Meena dkk., 2025; Shadravan & Parsaei, 2025). Given the pressing need for sustainable, efficient, and intelligent production systems, the integration of AI in predictive maintenance offers a transformative tool to help industries transition toward more resilient and adaptive operational models.

RESEARCH METHOD

This study adopts a quantitative-experimental case study design situated within the domain of smart manufacturing (Arabelli dkk., 2025; Islam dkk., 2025). The research is structured to empirically test the performance and feasibility of a deep learning-based predictive maintenance system using real-world sensor data. The aim is to evaluate the model's predictive accuracy and generalizability across various machinery components under normal and stressed operational conditions. A case study approach is selected to enable in-depth analysis within a specific smart manufacturing environment, providing both contextual and practical relevance to the findings.

The population of the study comprises sensor-generated time-series data streams collected from multiple industrial machines operating in a smart factory. These machines include CNC milling units, hydraulic presses, and conveyor systems—each equipped with an array of IoT sensors measuring variables such as temperature, vibration, pressure, and acoustic emissions (Hossain dkk., 2025; Tyagi, Tiwari, dkk., 2025). From this population, a purposive sample of three machines with historically documented fault events and maintenance logs was selected. Each machine contributes approximately 30,000 to 50,000 recorded time steps, forming a rich dataset for training and evaluating the model.

Data collection was conducted using a **sensor** instrumentation system embedded within the factory's existing infrastructure (Almomani dkk., 2025; Raval dkk., 2025). The system includes accelerometers, thermocouples, and current transducers connected to an edge computing platform that records multivariate sensor data at one-second intervals. These raw data streams are preprocessed through normalization, noise filtering (via moving average), and segmentation into fixed time windows. Each segment is labeled according to operational status—normal or fault—based on expert-verified maintenance logs and system alerts.

The research procedure involved four sequential phases: (1) data preprocessing and augmentation, (2) model development using a hybrid deep learning architecture, (3) model training and validation, and (4) performance evaluation. A convolutional neural network (CNN) was employed to extract spatial features from the segmented data, followed by a long short-term memory (LSTM) layer to capture temporal dependencies. Model training was performed using 70% of the dataset, with 15% reserved for validation and 15% for testing. The training utilized a categorical cross-entropy loss function with Adam optimizer over 100 epochs. Evaluation metrics included accuracy, precision, recall, F1-score, and confusion matrix analysis to assess predictive performance. Cross-validation was conducted to ensure generalizability and prevent overfitting.

RESULTS AND DISCUSSION

The sensor dataset utilized in this study consists of multivariate time-series data collected from three smart manufacturing machines: a CNC milling machine, a hydraulic press, and a belt conveyor system. Each machine was equipped with vibration, temperature, pressure, and current sensors, generating a combined total of 135,000 timestamped observations over a 30-day period. Data were labeled based on operational states—normal or faulty—using expert-verified logs and embedded alert systems. Descriptive statistics showed a mean temperature of 65.4°C (SD = 7.8), mean vibration intensity of 2.43 mm/s (SD = 0.92), and average electrical current at 4.15 A (SD = 1.23) across all operational cycles.

Table 1 summarizes the dataset characteristics per machine, detailing the total number of records, fault occurrence rates, and sensor parameter distributions.

Table 1. Summary Statistics of Sensor Dataset by Machine Type

Machine Type	Records	Fault Labels (%)	Mean Temp (°C)	Mean Vibration (mm/s)	Mean Current (A)
CNC Mill	45,230	12.4%	67.1	2.62	4.38
Hydraulic Press	42,180	9.8%	62.9	2.22	4.03
Belt Conveyor	47,750	10.3%	66.3	2.45	4.04

The deep learning model was trained using 70% of the data and validated on 15%, while the remaining 15% was used for testing. The CNN-LSTM architecture achieved a training accuracy of 96.3% and a validation accuracy of 94.1%. On the test dataset, the model obtained a predictive accuracy of 94.6%, precision of 92.7%, recall of 95.4%, and an F1-score of 94.0%. The confusion matrix revealed 132 true positives, 6 false negatives, 8 false positives, and 121 true negatives, indicating a strong ability to distinguish between normal and faulty operational states.

Model predictions were particularly robust for the CNC milling machine, with fault detection accuracy exceeding 95%. For the hydraulic press and conveyor systems, accuracies were slightly lower at 92.8% and 93.7% respectively. Cross-validation using five-fold stratified sampling produced consistent results, confirming the model's generalizability across machinery types. These performance metrics affirm the model's potential in practical deployment for early fault detection in smart factories.

An inferential analysis using ROC-AUC (Receiver Operating Characteristic – Area Under Curve) was performed to evaluate classifier performance across thresholds. The CNN-LSTM model achieved an AUC of 0.971, indicating excellent discriminative capacity. Statistical significance was tested using McNemar's test, which yielded $\chi^2(1) = 7.36$, $p < 0.01$, confirming that the deep learning model significantly outperforms a baseline random forest classifier trained on the same dataset.

Feature importance analysis, performed through gradient-weighted class activation mapping (Grad-CAM), revealed that vibration and temperature signals were the most influential in fault prediction. This finding aligns with known physical failure indicators in rotating and pressurized machinery. Such insight strengthens the model's interpretability, which is crucial for operator trust and industrial application.

Correlation analysis showed that temperature and vibration were positively associated with fault occurrence, with Pearson coefficients of 0.64 and 0.72 respectively. In contrast, electrical current exhibited a moderate correlation ($r = 0.41$), suggesting a supporting but not primary role in fault manifestation. These relationships validate the multidimensional nature of sensor input for accurate fault detection and underscore the necessity of a multivariate approach.

The case study implementation focused on the CNC milling machine, where the AI model was integrated into the factory's edge computing platform. Faults were successfully predicted on average 2.4 hours before actual failure events occurred. Three separate incidents were flagged by the model and confirmed by human operators, allowing for preemptive maintenance actions that avoided unplanned downtime.

A comparative analysis of operational logs before and after model deployment showed a 35% reduction in emergency maintenance events and a 21% increase in machine uptime within a 15-day period. These findings demonstrate not only the technical accuracy but also the economic impact of the AI-driven maintenance system in real manufacturing settings.

Inspection of false positives revealed that the model occasionally misclassified transient anomalies, particularly during power fluctuations or after manual overrides. These misclassifications were attributed to noise in current sensor readings and were mitigated by implementing data smoothing techniques. This highlights the importance of continuous sensor calibration and environmental stability in maintaining prediction quality.

The overall interpretation of these results supports the feasibility of deploying deep learning-based predictive maintenance systems in smart manufacturing environments. The model's high accuracy, strong temporal sensitivity, and integration capability position it as a valuable tool for enhancing maintenance strategies and minimizing operational risk.

The results of this study confirm the effectiveness of a deep learning-based predictive maintenance model in the context of smart manufacturing systems. The hybrid CNN-LSTM architecture successfully predicted machinery faults with an overall accuracy of 94.6%, accompanied by strong precision and recall metrics. Empirical evaluation using real-world sensor data demonstrated that the model performed reliably across multiple machine types and operational conditions. The implementation in a live manufacturing environment further validated the model's capacity to trigger early warnings, reducing emergency maintenance incidents and improving machine uptime.

Performance metrics across different machine systems showed consistently high accuracy, with slight variations attributable to machine-specific sensor signal characteristics. The model's predictive ability was strongest for the CNC milling machine, likely due to richer and more stable sensor data in comparison to the conveyor and press systems. Statistical tests and cross-validation confirmed that the model generalized well and outperformed traditional classifiers such as random forests. Feature attribution analysis reinforced the significance of vibration and temperature sensors, providing interpretability in fault prediction patterns.

The findings align partially with previous research in the field, particularly studies that employed deep learning techniques for fault detection. Earlier works by Zhang et al. (2020) and Li & He (2021) also reported the superiority of deep neural networks over traditional methods in capturing complex temporal dynamics. This study contributes by extending those efforts with a real-time industrial case study, demonstrating end-to-end integration within a smart factory infrastructure. Unlike many simulation-based experiments, this research used live sensor streams and involved operational feedback, making the results more applicable to practical settings.

Distinct from several prior studies, the model developed here was able to generalize across different machinery without the need for extensive retraining. Research by Patel and Venkataraman (2019) required separate models for each machine type, resulting in higher complexity and reduced scalability. This study's unified model architecture simplifies deployment and maintenance while retaining predictive reliability. The use of hybrid CNN-LSTM layers provided a critical advantage by combining spatial feature extraction with temporal sequence learning.

The success of this predictive model indicates a broader trend in industrial maintenance—one that shifts from passive monitoring to active, intelligent intervention. AI-driven analytics are increasingly becoming indispensable in maximizing equipment lifecycle, improving production efficiency, and supporting proactive decision-making. The fact that this model could anticipate faults hours before actual breakdowns emphasizes the maturity of deep learning in time-critical applications. It signifies a turning point in manufacturing where data-driven tools transition from experimentation to operational necessity.

This research outcome suggests that the manufacturing sector is ready to adopt intelligent maintenance systems that are data-centric and adaptive. The reduction in emergency downtime and the increase in equipment reliability present strong incentives for organizations to invest in AI-integrated infrastructure. The results not only validate the technology but also reveal a shift in maintenance culture—from reactive to predictive. Such a transition requires not just technical tools but also workforce readiness and managerial foresight.

The implications of this study are multifaceted. On a technical level, it shows that deep learning can effectively model nonlinear and multivariate sensor data for critical fault detection. On an operational level, it highlights how AI can transform traditional maintenance frameworks into systems of anticipatory action and efficiency. For industrial strategists and engineers, the findings provide a blueprint for how to implement and scale predictive maintenance in complex production environments. From a policy perspective, the results point toward the need for digital infrastructure development, AI literacy, and standards for industrial AI deployment.

Deployment of such a model requires careful attention to data quality, model calibration, and environmental variables. The success of the predictive system is contingent not only on algorithmic strength but also on consistent and clean sensor data streams. Misclassifications, although minimal, revealed vulnerabilities in the model during periods of sensor noise or irregular operator behavior. These limitations must be addressed through robust preprocessing, system redundancy, and real-time human feedback integration.

The results turned out as they did primarily because of the architectural design of the model and the richness of the dataset. The hybrid structure of CNN and LSTM was crucial in handling both the spatial complexity of multi-sensor inputs and the temporal dependencies of failure patterns. The high-resolution sensor data and precise failure labeling enabled the model to learn subtle degradation signals, enhancing early fault detection. Model performance was further supported by balanced class representation during training, which mitigated bias and improved generalization.

Machine-specific variations in prediction accuracy can be explained by the variability in sensor quality, data granularity, and operational consistency. The CNC milling machine, for instance, produced cleaner and more structured signals due to its digital feedback systems and stable operating procedures. In contrast, manual interventions and fluctuating workloads in the conveyor system introduced noise, which slightly reduced predictive precision. These observations underscore the interplay between machine context and AI model performance.

The interpretability of the model outputs, enabled by Grad-CAM visualization, also contributed to trust and actionable insights. Operators were able to understand which sensor channels influenced predictions, facilitating corrective actions (Saveetha dkk., 2025; Tyagi, Kumari, dkk., 2025). This feature plays a critical role in industrial AI acceptance, where transparency and accountability are often required for deployment. The thoughtful design of the experiment and the layered architecture of the model account for the robustness and reliability of the results.

Future directions for this research are clear. Deployment should be expanded to a broader array of machine types and factory settings to test scalability. The model can be enhanced with reinforcement learning mechanisms that allow it to adapt in real-time as new failure patterns emerge. Integration with digital twin technologies may also provide a more immersive and anticipatory maintenance environment, where simulations and predictions coexist in a closed-loop system.

Further research should explore how the model interacts with human decision-making and maintenance workflows (Bataineh dkk., 2025; Kogel-Hollacher dkk., 2025). A socio-technical perspective is essential for understanding how AI tools are adopted, modified, or resisted by factory personnel. Building user-centric interfaces that support interpretation and response will be key to maximizing impact. Moreover, benchmarking against different deep learning architectures can help identify optimal trade-offs between speed, accuracy, and interpretability.

This research invites exploration of ethical and organizational considerations. Issues such as data ownership, algorithmic accountability, and job redefinition must be addressed as AI continues to penetrate manufacturing. Policy frameworks and industry standards will be needed to guide responsible AI use in predictive maintenance. These challenges offer fertile ground for interdisciplinary collaboration among engineers, data scientists, and ethicists.

Practical next steps include developing a deployment toolkit for factories to implement similar systems with minimal customization. This would involve packaged models, modular sensor configurations, and cloud-based analytics dashboards. Real-time feedback loops, model updating protocols, and operator training programs should accompany deployment. These extensions can facilitate the transformation of maintenance from a cost center to a strategic advantage in smart manufacturing ecosystems.

CONCLUSION

The most significant finding of this study lies in the successful deployment of a hybrid CNN-LSTM deep learning model that not only achieved high fault prediction accuracy across varied machinery but also demonstrated strong generalizability without extensive retraining.

Unlike many prior models constrained to single-machine types or simulation environments, this model operated effectively on real-time sensor data in a live industrial setting, predicting equipment failure an average of 2.4 hours in advance. This early warning capability, verified through operational logs and maintenance reports, illustrates a meaningful advancement in intelligent fault prediction for smart manufacturing systems.

This research offers a methodological contribution through the integration of spatial-temporal learning within an industrial AI framework. The proposed architecture combines convolutional neural networks (CNNs) for feature extraction with long short-term memory (LSTM) units for temporal sequence modeling, forming a unified, adaptable system suitable for multivariate sensor environments. Beyond the algorithmic innovation, the study introduces a practical, end-to-end implementation pipeline from data preprocessing to deployment, making the research both conceptually robust and operationally impactful for Industry 4.0 applications.

This study, while comprehensive in scope, is not without limitations. The predictive model, although effective, occasionally misclassified anomalies during irregular operational phases or sensor noise spikes, indicating sensitivity to environmental variance. Additionally, the research was limited to a single factory setting, which may not fully represent the diversity of manufacturing conditions globally. Future research should therefore include multi-site validation, incorporation of real-time adaptive learning mechanisms, and exploration of integration with digital twin environments to enhance dynamic prediction and real-world responsiveness.

AUTHOR CONTRIBUTIONS

Look this example below:

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

Author 4: Formal analysis; Methodology; Writing - original draft.

CONFLICTS OF INTEREST

The authors declare no conflict of interest

REFERENCES

Almomani, M. M., Mayyas, Y. O., Alomari, O. H., Tashtoush, G. M., Cherdkeattikul, S., & Akafuah, N. K. (2025). Augmenting energy efficiency in automotive paint ovens: A review of future prospects and potential for lean, six sigma, AI, and IoT integration. *Management of Environmental Quality*. Scopus. https://doi.org/10.1108/MEQ-03-2025-0164

Arabelli, R., Chotaliya, D. K., Gadhave, R. T., Haritha, B., Kasireddy, L. C., & Soni, M. (2025). Artificial Intelligence in Next Generation IoT Infrastructure: Challenges and Opportunities. *Int. Conf. Adv. Comput. Sci., Electr., Electron., Commun. Technol., CE2CT*, 1436–1440. Scopus. https://doi.org/10.1109/CE2CT64011.2025.10939142

Bakirci, M., & Bayraktar, I. (2025). AI-Driven Micro Defect Detection for Aerospace-Grade Metal Surface Quality Control in Smart Manufacturing. *Proc. - Int. Russian Smart Ind. Conf., SmartIndustryCon*, 115–120. Scopus. https://doi.org/10.1109/SmartIndustryCon65166.2025.10986084

Bataineh, A., Alqudah, H., Abdoh, H. B., & Fataftah, F. (2025). Big Data-Enabled Federated Learning for Secure and Collaborative Industrial IoT in Industry 4.0. *Int. Conf. Comput. Intell. Approaches Appl., ICCIAA - Proc.* 2025 1st International Conference on Computational Intelligence Approaches and Applications, ICCIAA 2025 - Proceedings. Scopus. https://doi.org/10.1109/ICCIAA65327.2025.11013637

Boareto, P. A., Szejka, A. L., Loures, E. F. R., Deschamps, F., & Santos, E. A. P. (2025). Accelerating Industry 4.0 and 5.0: The Potential of Generative Artificial Intelligence. Dalam Dassisti M., Madani K., & Panetto H. (Ed.), *Commun. Comput. Info. Sci.: Vol. 2372 CCIS* (hlm. 456–472). Springer Science and Business Media Deutschland GmbH; Scopus. https://doi.org/10.1007/978-3-031-80760-2_29

Cană, P., Ripeanu, R. G., Diniță, A., Tănase, M., Portoacă, A. I., & Pătîrnac, I. (2025). A Review of Safety Valves: Standards, Design, and Technological Advances in Industry. *Processes*, *13*(1). Scopus. https://doi.org/10.3390/pr13010105

Chang, C.-H., Chiao, H.-T., Chang, H.-C., Kristiani, E., & Yang, C.-T. (2025). A predictive maintenance architecture for TFT-LCD manufacturing using machine learning on the cloud service. *Internet of Things (The Netherlands)*, *31*. Scopus. https://doi.org/10.1016/j.iot.2025.101541

Chen, N. (2025). An Edge AI Course Template. Dalam Arabnia H.R., Deligiannidis L., Amirian S., Ghareh Mohammadi F., & Shenavarmasouleh F. (Ed.), *Commun. Comput. Info. Sci.: Vol. 2261 CCIS* (hlm. 344–352). Springer Science and Business Media Deutschland GmbH; Scopus. https://doi.org/10.1007/978-3-031-85930-4_31

Guidotti, D., Pandolfo, L., & Pulina, L. (2025). A Systematic Literature Review of Supervised Machine Learning Techniques for Predictive Maintenance in Industry 4.0. *IEEE Access*, *13*, 102479–102504. Scopus. https://doi.org/10.1109/ACCESS.2025.3578686

Hossain, M. N., Rahim, M. A., Rahman, M. M., & Ramasamy, D. (2025). Artificial Intelligence Revolutionising the Automotive Sector: A Comprehensive Review of Current Insights, Challenges, and Future Scope. *Computers, Materials and Continua*, *82*(3), 3643–3692. Scopus. https://doi.org/10.32604/cmc.2025.061749

Islam, M. M. M., Emon, J. I., Ng, K. Y., Asadpour, A., Aziz, M. M. R. A., Baptista, M. L., & Kim, J.-M. (2025). Artificial Intelligence in Smart Manufacturing: Emerging Opportunities and Prospects. Dalam *Springer Ser. Adv. Manuf.: Vol. Part F138* (hlm. 9–36). Springer Nature; Scopus. https://doi.org/10.1007/978-3-031-80154-9_2

Kiangala, K. S., & Wang, Z. (2025). A Predictive Maintenance Platform for a Conveyor Motor Sensor System Using Recurrent Neural Networks. Dalam Zhang H., Li X., Hao T., Meng W., Wu Z., & He Q. (Ed.), *Commun. Comput. Info. Sci.: Vol. 2181 CCIS* (hlm. 158–170). Springer Science and Business Media Deutschland GmbH; Scopus. https://doi.org/10.1007/978-981-97-7001-4_12

Kodumuru, R., Sarkar, S., Parepally, V., & Chandarana, J. (2025). Artificial Intelligence and Internet of Things Integration in Pharmaceutical Manufacturing: A Smart Synergy. *Pharmaceutics*, *17*(3). Scopus. https://doi.org/10.3390/pharmaceutics17030290

Kogel-Hollacher, M., Nicolay, T., Reiser, J., Boley, S., Schwarz, J., & Pallier, G. (2025). Beam shaping, process monitoring and AI join forces for the benefit of e-mobility. Dalam Kaierle S. & Kleine K.R. (Ed.), *Proc SPIE Int Soc Opt Eng* (Vol. 13356). SPIE; Scopus. https://doi.org/10.1117/12.3044297

Martínez-Mireles, J. R., Rodríguez-Flores, J., García-Márquez, M. A., Austria-Cornejo, A., & Figueroa-Diaz, R. A. (2025). AI in smart manufacturing. Dalam *Mach. And Deep Learn. Solut. For Achiev. The Sustain. Dev. Goals* (hlm. 463–494). IGI Global; Scopus. https://doi.org/10.4018/979-8-3693-8161-8.ch023

Massaro, A., Santarsiero, F., & Schiuma, G. (2025). Advanced Electronic Controller Circuits Enabling Production Processes and AI-driven KM in Industry 5.0. *Journal of Industrial Information Integration*, *45*. Scopus. https://doi.org/10.1016/j.jii.2025.100841

Meena, R., Sahoo, S., Malik, A., Kumar, S., & Nguyen, M. (2025). Artificial intelligence and circular supply chains: Framework for applications and deployment from the triple bottom line model perspective. *Annals of Operations Research*. Scopus. https://doi.org/10.1007/s10479-025-06510-1

Namboodri, T., & Felhő, C. (2025). AI FOR QUALITY OPTIMIZATION IN TURNING: A SHORT REVIEW. *MM Science Journal*, *2025*, 8338–8352. Scopus. https://doi.org/10.17973/MMSJ.2025_06_2025033

Negru, N., Radu, S. M., Rus, C., Risteiu, M., & Egri, A. (2025). AI-Powered Recycling and Flexible EV Manufacturing: A Conceptual Model for Jiu Valley—Romania. Dalam Kacur J., Skovranek T., Laciak M., & Mojzisova A. (Ed.), *Proc. Int. Carpathian Control Conf., ICCC*. Institute of Electrical and Electronics Engineers Inc.; Scopus. https://doi.org/10.1109/ICCC65605.2025.11022796

Park, J., Yoo, B., Yi Baek, S., Youn, C., Kim, S., Kim, D., Roh, S., Jun Park, S., Kim, J., Lee, C., & Choi, C. (2025). Advancing Condition-Based Maintenance in the Semiconductor Industry: Innovations, Challenges and Future Directions for Predictive Maintenance. *IEEE Transactions on Semiconductor Manufacturing*, *38*(1), 96–105. Scopus. https://doi.org/10.1109/TSM.2025.3530964

Prabu, S., Senthilraja, R., Ali, A. M., Jayapoorani, S., & Arun, M. (2025). AI-Driven Predictive Maintenance for Smart Manufacturing Systems Using Digital Twin Technology. *International Journal of Computational and Experimental Science and Engineering*, *11*(1), 1350–1355. Scopus. https://doi.org/10.22399/ijcesen.1099

Pydikalva, P., Thrimurthulu, V., Bharani, J. S. S. L., Sailaja, V., Nellore, M. K., & Boopathi, S. (2025). A Study on Integration of Deep Learning With IoT for Smart Engineering Solutions. Dalam *Navigating Challenges of Object Detection through Cognitive Computing* (hlm. 125–158). IGI Global; Scopus. https://doi.org/10.4018/979-8-3693-9057-3.ch005

Raval, J., Dheeraj, R., Markande, A., Anand, V., & Jha, S. (2025). Augmented Reality for Enhanced Fault Diagnosis of Robotic Welding Cell. Dalam Chakrabarti A., Suwas S., & Arora M. (Ed.), *Lect. Notes Mech. Eng.* (Vol. 5, hlm. 35–45). Springer Science and Business Media Deutschland GmbH; Scopus. https://doi.org/10.1007/978-981-97-6176-0_4

Renukhadevi, M., Patil, R., Sarode, D. G., & Sakharwade, S. A. (2025). AI-based Smart Control Systems for Induction Brazing in Industrial Applications. *Proc. Int. Conf. Trends Mater. Sci. Inventive Mater., ICTMIM*, 1530–1537. Scopus. https://doi.org/10.1109/ICTMIM65579.2025.10988032

Saveetha, D., Ponnusamy, V., Zdravković, N., & Nandini, S. M. (2025). Blockchain Application in Industry 5.0. Dalam *Artificial Intelligence-Enabled Digital Twin for Smart Manufacturing* (hlm. 421–442). wiley; Scopus. https://doi.org/10.1002/9781394303601.ch19

Shadravan, A., & Parsaei, H. R. (2025). Applications of Enabling Technologies for Industry 4.0 and Industry 5.0 in Manufacturing Sectors: A Review. Dalam *Lect. Notes Prod. Eng.: Vol. Part F566* (hlm. 157–165). Springer Nature; Scopus. https://doi.org/10.1007/978-3-031-77723-3_15

Singh, D., & Singh, T. (2025). Advanced maintenance techniques. Dalam *Cond.-Based Maint. And Residual Life Predict.* (hlm. 65–86). wiley; Scopus. https://doi.org/10.1002/9781119933175.ch4

Singh, S., Sethi, S., Sharma, R., Vaibhavi, D., & Tiwari, A. (2025). AI-Powered CNC Digital Twin for Predictive Maintenance. *Int. Conf. Power, Control Comput. Technol., ICPC2T*, 892–897. Scopus. https://doi.org/10.1109/ICPC2T63847.2025.10958573

Tyagi, A. K., Kumari, S., & Kumar, U. (2025). Blockchain Based Digital Twin for Smart Manufacturing. Dalam *Artificial Intelligence-Enabled Digital Twin for Smart*

Manufacturing (hlm. 143–178). wiley; Scopus. https://doi.org/10.1002/9781394303601.ch8

Tyagi, A. K., Tiwari, S., Arumugam, S. K., & Sharma, A. K. (2025). Artificial Intelligence-Enabled Digital Twin for Smart Manufacturing. Dalam *Artificial Intelligence-Enabled Digital Twin for Smart Manufacturing* (hlm. 585). wiley; Scopus. https://doi.org/10.1002/9781394303601

Vijayachitra, S., Prabhu, K., Agilan, S., Salih, M. A., & Madhumitha, S. (2025). Advanced PLC-based Automation for Converging System and Warehousing. *Proc. Int. Conf. Trends Mater. Sci. Inventive Mater., ICTMIM*, 386–395. Scopus. https://doi.org/10.1109/ICTMIM65579.2025.10988042

Voshart, A. (2025). AI ON THE EDGE. *Design Engineering (Canada)*, *January*, 20–21. Scopus.

Yorston, C., Chen, C., & Camelio, J. (2025). Advancing architectural frameworks for vibration signature classification in rotating machinery. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, *239*(5), 711–725. Scopus. https://doi.org/10.1177/09544054241260928