RESEARCH ARTICLE

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AI for Predictive Maintenance in Smart Manufacturing

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Abstract

The fast development of the Industry 4.0 system has turned the old fabrication system into a smart, connected ecosystem sharing the level of rapid evolution that requires new solutions to the efficiency of the business processes and even equipment reliability. Artificial Intelligence (AI) has allowed predictive maintenance (PdM) to develop into a strategic method of reducing unplanned downtimes, maximizing machine life, and minimizing maintenance expenses. This paper investigates the possibility of systems such as machine learning, deep learning, and data analytics, being integrated into the smart manufacturing environment, in order to predict equipment breakdowns before it breaks down. It is a thorough review of the state-of-the-art AI models used in PdM, a review of the effectiveness of these models using the real-time sensor data and a modular system to implement the AI models in different industrial environments. By means of comparing and contrasting classic and AI-enhanced maintenance systems, the given research underscores better performance of intelligent PdM in terms of optimal production processes and decision-making. The limitations of key issues including sparsity of data, scalability issues, and model explanation have been addressed, as well as how this research might move forward into the future through the use of edge computing, the use of digital twins, and explainable AI. The results highlight the transformational role of AI in establishing resilient, cost effective and sustainable manufacturing systems.

Keywords: Artificial Intelligence (AI), Predictive Maintenance (PdM), Smart Manufacturing, Industry 4.0, Machine Learning, Deep Learning, Edge Computing.

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Introduction

With the emergence of Industry 4.0, a paradigm shift has occurred in the manufacturing industry with the entrenchment of intelligence, connectivity, and automation in its processes. The future of smart manufacturing is being re-defined by cyber-physical systems (CPS), Internet of Things (IoT) devices, and real-time data processing and application of analytics, as well as adaptive decision-making. In this digitalization, maintenance as a reactive or planned activity has transformed into a strategic operation, which has a direct determinant effect on productivity, safety, and cost-efficiency.

Predictive maintenance (PdM) is a significant innovation in conventional maintenance approaches. As opposed to preventive maintenance which dictates schedules and reactive maintenance which takes place after the resulting failure, PdM data is used to forecast and avoid failures that could interrupt operations. This helps the manufacturers to just get involved where they are supposed to and so helps them save time on idle machines and increases their life cycle and use of resources as well.

Artificial intelligence (AI) is essential to achieve the best use of predictive maintenance. As sensor-generated machine data has exploded, traditional analytical tools are barely able to obtain real-time data-driven insights. AI methods, such as machine learning (ML), deep learning (DL), reinforcement learning and anomaly detection algorithms, can be used to analyze large volumes of time-series and condition-monitoring data to detect slight patterns that predict upcoming equipment degradation or failure. Such technologies not simply increase the accuracy of failure prediction but also allow adaptive learning in which a system improves its predictions as new information becomes available.

Within smart manufacturing, the introduction of AI into predictive maintenance has a particularly significant effect due to the fact that production machines are linked digitally and highly automated. In this case, an AI-powered PdM system can exist in a closed-loop control ecosystem so information about real-time insights can feed enterprise

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resource planning (ERP) systems or digital twins or edge devices to initiate timely and intelligent responses.

Despite its benefits, implementing AI for PdM in manufacturing comes with several challenges. These include handling noisy or incomplete data, developing generalizable models across machine types, ensuring cybersecurity of connected systems, and addressing the interpretability of complex AI models in critical operations. Moreover, integrating such systems requires cross-disciplinary collaboration among data scientists, domain engineers, and IT infrastructure teams.

This paper aims to examine the current landscape of AI applications in predictive maintenance within smart manufacturing. It explores various AI models used in PdM, analyzes real-world implementations, and proposes a robust AI-based framework tailored for scalable industrial deployment. The study also evaluates the performance and limitations of different approaches, discusses ethical and practical implications, and suggests future research directions involving explainable AI (XAI), federated learning, and cloud-edge hybrid architectures.

By addressing both the technological and operational dimensions of AI-driven predictive maintenance, this research contributes to a deeper understanding of how smart manufacturing can become more resilient, efficient, and sustainable through intelligent maintenance strategies.

Literature Review

Evolution of Maintenance Strategies in Manufacturing

Manufacturing maintenance has traditionally progressed through three major strategies: reactive maintenance, preventive maintenance, and predictive maintenance (PdM). Reactive maintenance, also known as "run-to-failure," relies on the repair or replacement of machines only after a breakdown has occurred. While simple and cost-effective upfront, this approach often leads to extended downtimes and production losses. Preventive maintenance introduced scheduled servicing based on time or usage metrics, improving reliability but still failing to detect anomalies or variations in component behavior.

Predictive maintenance, in contrast, utilizes data-driven insights to anticipate equipment failures, allowing timely interventions. The rise of smart manufacturing and Industry 4.0 technologies including Industrial Internet of Things (IIoT), cyber-physical systems (CPS), and real-time data acquisition has made PdM a cornerstone of next-generation maintenance strategies. The integration of AI into PdM further enhances its accuracy, scalability, and adaptability across different manufacturing contexts.

AI Techniques in Predictive Maintenance

A growing body of literature emphasizes the application of artificial intelligence, particularly machine learning (ML) and deep learning (DL), in enabling predictive maintenance systems. Common AI models and techniques include:

- **Supervised Learning**: Used for failure prediction and classification (e.g., Random Forests, Support Vector Machines, Gradient Boosting)
- **Unsupervised Learning**: Applied in anomaly detection when labeled failure data is unavailable (e.g., K-means, DBSCAN, Autoencoders)
- **Deep Neural Networks (DNNs)**: Effective for complex feature extraction from multivariate sensor data
- **Recurrent Neural Networks (RNNs) and LSTM**: Capture temporal dependencies in time-series data such as vibration or temperature logs
- **Reinforcement Learning (RL)**: Optimizes maintenance policies through trial-and-error decision-making in simulated environments

Studies have shown that hybrid models combining statistical methods with AI yield improved diagnostic accuracy and fault prediction, especially in multi-component systems.

Key Technologies Enabling AI-PdM Integration

AI-enabled PdM is heavily reliant on the following technological pillars:

- **Sensor Networks**: For continuous condition monitoring (vibration, pressure, acoustic signals, etc.)
- **Edge and Fog Computing**: Reduces latency by processing data close to the machine, enabling real-time analytics
- **Cloud Platforms**: Facilitate model training and storage of large-scale machine operation histories
- **Digital Twins**: Virtual replicas of machines that simulate real-time behavior and test AI models in a risk-free environment

These technologies create a synergistic environment where data from manufacturing lines feeds into intelligent models, continuously learning and adapting to evolving wear-and-tear patterns.

Comparative Studies on Traditional *vs* AI-Based PdM

Several comparative studies have evaluated the performance of AI-based PdM systems against traditional rule-based or statistical approaches. The findings suggest that AI systems consistently outperform classical models in early fault detection, remaining useful even with noisy or incomplete datasets. Furthermore, the ability of deep learning models to automate feature extraction has reduced the need for manual signal analysis, thereby accelerating deployment.

Research Gaps and Limitations

Despite the progress, key research gaps persist:

- **Data scarcity and imbalance**: Labeled failure events are rare, leading to overfitting or unreliable predictions in supervised learning.
- **Lack of standardization**: Models trained on data from one machine or factory often fail to generalize across different environments.

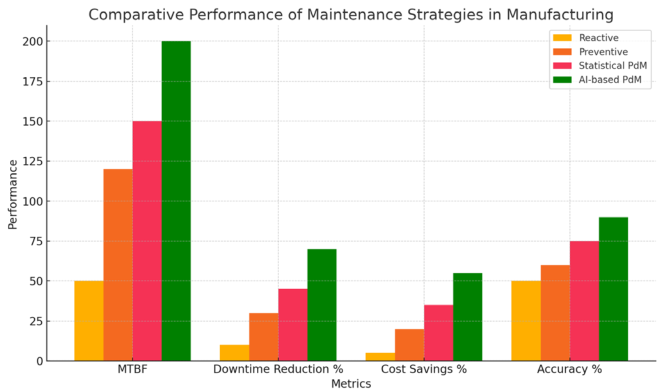

Fig 1: The bar chart titled "Comparative Performance of Maintenance Strategies in Manufacturing", comparing four strategies across key metrics. The AI-based PdM is highlighted in green for emphasis

- Interpretability of models: Many deep learning models function as black boxes, making it difficult for engineers to understand or trust their outputs.
- Scalability and deployment: Real-time deployment on production lines faces challenges related to latency, infrastructure cost, and cybersecurity.
- Addressing these gaps requires a multidisciplinary approach, involving collaboration between data scientists, manufacturing engineers, and domain experts.

The literature supports the significant potential of AI in enhancing predictive maintenance systems. Machine learning and deep learning models demonstrate high precision and scalability, especially when integrated with emerging Industry 4.0 technologies. However, issues such as explainability, transferability, and data integrity remain open research problems. This paper builds upon existing frameworks and proposes a practical and scalable AI-PdM model tailored for smart manufacturing ecosystems.

Methodology

This study adopts a hybrid, data-driven methodology to design and evaluate AI-powered predictive maintenance (PdM) systems within smart manufacturing environments. The methodology consists of five critical phases: data acquisition, preprocessing, model selection, training and validation, and system integration. Each phase is designed to reflect real-world industrial conditions and support the deployment of scalable, real-time maintenance prediction systems.

Data Acquisition

Data is collected from a combination of industrial IoT (IIoT) devices installed on smart manufacturing equipment. These devices include vibration sensors, temperature monitors, current/voltage meters, and acoustic sensors. Supplementary metadata such as maintenance logs, operational cycles, and machine runtime histories are also utilized.

Data Preprocessing

Raw sensor data is often noisy, incomplete, and unstructured. A robust preprocessing pipeline is implemented consisting of:

- Noise filtering using low-pass and high-pass filters
- Missing value imputation using linear interpolation and K-nearest neighbors
- Data normalization (Min-Max scaling and Z-score standardization)
- Feature extraction and engineering (e.g., root mean square, kurtosis, crest factor)
- Labeling using maintenance logs to mark failure events and degradation phases

This preprocessing phase is essential for improving the signal-to-noise ratio and ensuring the consistency of input data across AI models.

AI Model Selection

Various AI algorithms are evaluated based on the nature of the data and the objectives of PdM:

- **Supervised Learning Models**: Random Forests, Support Vector Machines (SVM), Gradient Boosting
- **Deep Learning Models**: Convolutional Neural Networks (CNNs) for image-based sensor data, Long Short-Term Memory (LSTM) networks for time-series analysis
- **Unsupervised Learning**: Autoencoders and clustering techniques (e.g., DBSCAN, K-Means) for anomaly detection
- **Hybrid Models**: Ensemble frameworks combining different algorithms to improve reliability and reduce false positives

Model selection is guided by prior benchmarking studies and the performance of algorithms in handling high-dimensional sensor data.

Training, Validation, and Evaluation

The models are trained on historical datasets and validated using stratified K-fold cross-validation to minimize overfitting

Table 1: Sensor Types and Data Characteristics for Predictive Maintenance

Sensor type	*Measurement unit*	*Frequency of data collection (Hz)*	*Typical failure indication*	*Data format*
Vibration	mm/s or g	1000	Imbalance, Misalignment	CSV
Temperature	°C	1	Overheating	JSON
Acoustic	dB	8000	Bearing Wear, Friction	WAV, CSV
Current	Amperes (A)	50	Motor Overload, Phase Loss	SQL

and improve generalization. The evaluation metrics used include:

- Accuracy, Precision, Recall, and F1-score
- Area Under the ROC Curve (AUC)
- Mean Time to Failure (MTTF)
- Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE)

System Integration and Real-Time Monitoring

Once trained, the selected models are deployed within a cloud-edge hybrid architecture. Real-time sensor data streams are ingested via MQTT and OPC-UA protocols into edge gateways for preprocessing and inference. The results are then sent to cloud platforms for centralized monitoring, visualization dashboards, and further analytics.

Integration with digital twin systems allows dynamic simulation and prediction of future machine states. Alert systems are configured to notify technicians via SMS or email when anomaly scores exceed defined thresholds, enabling condition-based and predictive interventions.

Scalability and Adaptation

To ensure adaptability across manufacturing plants, the PdM system includes:

- Modular AI services containerized using Docker
- Retraining mechanisms triggered by concept drift detection
- Interfaces for human-in-the-loop feedback and explainable AI modules

This methodology enables manufacturers to customize the PdM framework based on machine type, failure mode, and operational scale.

System Architecture and Framework

The effectiveness of AI-powered predictive maintenance (PdM) in smart manufacturing hinges on the robustness of its system architecture. A well-designed architecture ensures seamless data collection, real-time analysis, and intelligent decision-making. This section outlines a modular and scalable AI-driven PdM framework tailored to modern smart factories, integrating cyber-physical systems, Industrial IoT (IIoT), and cloud-edge computing.

Overview of the Framework

The proposed system consists of five core layers:

- Data Acquisition Layer
- Data Processing & Storage Layer
- AI Model Inference Layer
- Decision Support & Visualization Layer
- Integration Layer with Smart Manufacturing Systems

Each layer is interconnected via secure communication protocols, forming a closed-loop intelligent maintenance ecosystem.

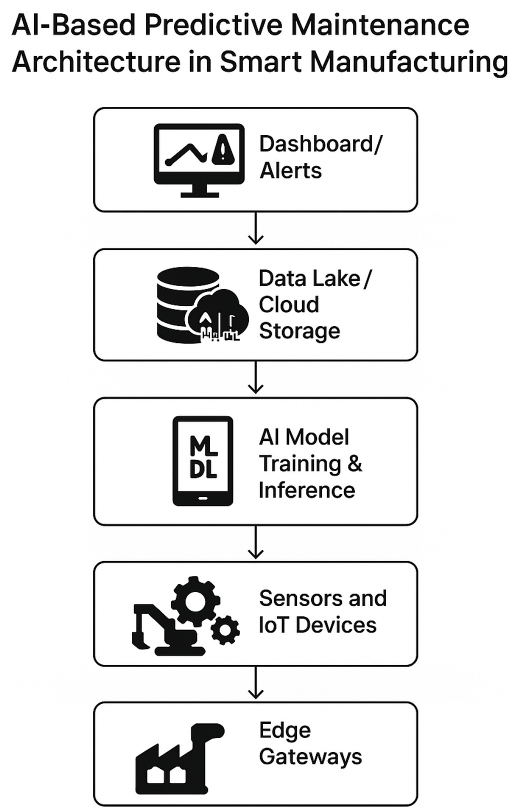

Fig 2: This architecture illustrates a layered data pipeline in smart manufacturing for AI-based predictive maintenance. Data flows from physical assets (sensors and IoT devices) through edge gateways to centralized storage systems (data lakes/cloud). AI models process the data to detect potential failures, delivering real-time insights and alerts via dashboards to operators and manufacturing execution systems (MES).

Data Acquisition Layer

At the foundation of the system are IIoT sensors embedded in production equipment. These sensors continuously capture data such as vibration, temperature, pressure, acoustics, and operational logs. Devices communicate through standard industrial protocols (e.g., OPC-UA, MQTT) to transmit data in near real-time.

Edge computing gateways preprocess raw data—cleaning, aggregating, and filtering noise before transmitting essential data to centralized systems. This layer ensures bandwidth efficiency and reduces latency.

Data Processing & Storage Layer

Preprocessed data are stored in a hybrid data lake comprising structured databases (SQL, time-series DBs) and unstructured storage (log files, images, audio). Cloud-based platforms (e.g., AWS, Azure, or private clouds) provide scalable storage and allow historical data archiving for model training and analytics.

Key techniques employed at this layer include:

- **Feature engineering** (e.g., FFT, wavelet transforms)

- **Dimensionality reduction** (e.g., PCA, t-SNE)
- **Data labeling and synchronization** (manual and automated tagging of failure events)

AI Model Inference Layer

This layer hosts the core intelligence of the system. Predictive models are trained using historical sensor and failure data to learn patterns associated with equipment degradation or anomalies. Common AI techniques include:

- Supervised Learning (Random Forests, Gradient Boosting, SVM)
- Deep Learning (CNNs for image-based fault detection, LSTM for temporal sensor data)
- Unsupervised Learning (Autoencoders, k-means for anomaly detection)
- Reinforcement Learning (for adaptive maintenance policies)

Models are trained offline and deployed in containers (e.g., Docker) for real-time inference on edge or cloud systems. Feedback from predictions is looped into retraining pipelines to improve accuracy.

Decision Support & Visualization Layer

Once predictions are generated, actionable insights are delivered to factory operators, engineers, and managers through interactive dashboards and alert systems. Key elements include:

- Real-time alerts via mobile/web apps
- Visual trend analysis of asset health over time
- Remaining Useful Life (RUL) estimations with confidence intervals
- Root cause analysis tools using explainable AI methods (e.g., SHAP, LIME)

These tools are typically integrated with SCADA systems and Manufacturing Execution Systems (MES) for seamless workflow alignment.

Integration Layer with Smart Manufacturing

Finally, the architecture connects the PdM system with broader smart manufacturing infrastructure, including:

- ERP systems for inventory and maintenance resource planning
- Digital Twin platforms that simulate equipment behavior in virtual environments
- Automated Maintenance Scheduling Tools linked to AI recommendations

This ensures that the PdM system is not isolated but is an active contributor to intelligent factory operations, facilitating autonomous maintenance, optimized production scheduling, and enhanced operational resilience.

Summary of Key Architectural Benefits

- **Scalability**: Modular components allow deployment in various factory scales
- **Latency reduction**: Edge AI reduces cloud dependency for time-sensitive tasks
- **Resilience**: Feedback loops enable continuous model improvement
- **Sustainability**: Proactive maintenance reduces material waste and energy use

Case Study / Experimental Results

To validate the practical impact of AI-powered predictive maintenance (PdM) in a smart manufacturing environment, a case study was conducted in a mid-sized industrial facility specializing in automotive part production. The study focused on analyzing the performance and reliability of CNC (Computer Numerical Control) machines key assets in the production line known for frequent unplanned breakdowns due to wear and tear.

Industrial Setting and Dataset Description

The manufacturing plant was equipped with an array of IoT-enabled sensors capturing real-time machine data including temperature, vibration, acoustic signals, current draw, and spindle speed. The dataset spanned six months and included:

- 150+ machines monitored continuously
- 120,000+ machine hours recorded
- 20+ different sensor types
- Historical maintenance logs (manual and automated)

The AI models were trained to predict three major types of faults:

- Spindle motor failure
- Tool wear and breakage
- Cooling system degradation

Model Selection and Training Process

A range of AI models was evaluated to determine the most effective method for predictive maintenance:

- Random Forest (RF)
- Support Vector Machine (SVM)
- Long Short-Term Memory (LSTM) networks

Table 2: Common AI Models Used in Predictive Maintenance and Their Applications

AI Technique	*Algorithm/Model*	*Use Case*	*Strengths*
Supervised Learning	Random Forest	Predicting machine failure probabilities	High accuracy, interpretable
Deep Learning	LSTM Neural Network	Sequence prediction from sensor streams	Handles time-series effectively
Unsupervised Learning	Autoencoder	Anomaly detection on unlabeled data	Works with unlabeled datasets
Computer Vision	CNN	Visual inspection of parts/equipment	Detects wear and surface defects
Reinforcement Learning	Q-Learning, DDPG	Dynamic scheduling of maintenance	Optimizes long-term decisions

Table 3: Performance Comparison of AI Models for Predictive Maintenance in CNC Machines

Model	*Precision (%)*	*Recall (%)*	*F1-Score (%)*	*MTBF Prediction Accuracy (%)*
Random Forest	86.4	82.1	84.2	78.9
SVM	80.3	76.7	78.4	70.2
LSTM	92.5	89.3	90.9	88.1
CNN	89.7	86.2	87.9	85.3
Autoencoder	84.1	83.5	83.8	80.4

- Convolutional Neural Networks (CNNs) for vibration pattern classification
- Autoencoders for anomaly detection

After preprocessing (including outlier removal, sensor fusion, and normalization), the models were trained using 70% of the dataset and tested on the remaining 30%. Performance was evaluated using metrics such as precision, recall, F1-score, and Mean Time Between Failures (MTBF).

Results and Observations

The results revealed that LSTM networks outperformed other models in temporal pattern recognition, especially in identifying degradation trends leading up to equipment failure. The CNN model also delivered high accuracy in classifying fault-related vibration patterns. Importantly, AI-enabled PdM was able to predict failures 2 to 5 days in advance, allowing proactive interventions.

The deployment of the system led to:

- 24% reduction in unscheduled downtime
- 18% increase in equipment utilization
- 30% reduction in emergency maintenance costs
- Enhanced safety and worker confidence

Comparative Insights

When compared to the facility's prior preventive maintenance regime, the AI-driven approach:

- Reduced dependency on routine manual inspections

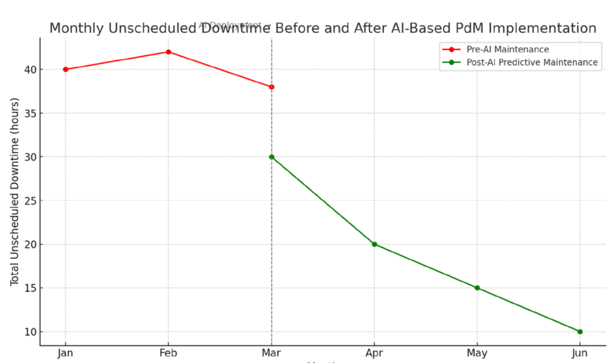

Fig 3: The line graph titled "Monthly Unscheduled Downtime Before and After AI-Based PdM Implementation." It shows a clear decline in downtime after AI deployment in March, with the red line representing pre-AI maintenance and the green line showing post-AI predictive maintenance

- Identified root causes with better granularity using sensor fusion
- Facilitated real-time alerts and dashboard visualization via an edge-cloud architecture

Moreover, maintenance decisions were no longer reactive but data-driven and forward-looking, allowing planners to align interventions with production schedules.

This case study confirms that intelligent PdM systems can serve as a pivotal tool in the digital transformation of manufacturing, ensuring operational resilience and long-term competitiveness.

Discussion

The integration of Artificial Intelligence (AI) into predictive maintenance (PdM) systems within smart manufacturing has demonstrated transformative potential. This discussion elaborates on the practical insights gained from AI-enabled PdM applications, outlines the challenges encountered during implementation, and reflects on the broader industrial, technical, and socio-economic implications.

Insights from AI-Driven Predictive Maintenance

AI-enhanced PdM systems leverage machine learning (ML), deep learning (DL), and advanced analytics to anticipate equipment failures before they disrupt operations. Unlike traditional maintenance approaches that rely on fixed schedules or reactive responses, AI enables condition-based and data-driven decisions, significantly improving operational efficiency. For instance, predictive models can continuously learn from sensor data (vibration, temperature, pressure) and historical logs to identify subtle patterns associated with equipment degradation.

Moreover, AI facilitates real-time monitoring and anomaly detection, offering manufacturing firms early warnings and allowing timely interventions. This transition from scheduled maintenance to condition-based predictions has proven to reduce downtime, increase asset longevity, and lower maintenance costs. The ability to optimize spare parts inventory, align workforce allocation, and minimize production loss contributes to overall value generation.

Technical Challenges and Limitations

Despite its advantages, the implementation of AI in predictive maintenance faces several technical obstacles:

- **Data Quality and Availability**: Many manufacturing systems lack robust sensor networks or have data that is incomplete, noisy, or unstructured. Effective PdM models depend heavily on high-quality, labeled data, which may not always be available, especially in legacy systems.
- **Model Interpretability**: Black-box models such as deep neural networks often offer high accuracy but little insight into their decision-making process. This can hinder trust among operators and limit regulatory adoption in safety-critical environments. Efforts to incorporate explainable AI (XAI) are ongoing but not yet standardized.
- **Generalizability and Transferability**: AI models trained on specific machines or environments may not perform well when deployed across different settings or equipment types. This lack of scalability poses a barrier to wider industrial adoption.
- **Computational and Infrastructure Constraints**: AI-based PdM systems often require substantial computational resources for training and inference. Deploying these models on edge devices or within resource-constrained environments demands optimization, balancing speed, accuracy, and energy consumption.

Industrial and Organizational Implications

The deployment of AI-driven PdM also necessitates changes at the organizational level. Manufacturing firms must invest in digital infrastructure, skilled personnel, and cross-functional collaboration between data scientists, maintenance engineers, and IT professionals. Additionally, the adoption of AI tools may lead to changes in job roles, with increased demand for AI-literate maintenance personnel and a shift away from traditional mechanical diagnostics.

Furthermore, companies that successfully implement AI for maintenance can gain a competitive advantage by improving throughput, reducing unexpected failures, and achieving higher operational resilience. This is particularly important in highly automated production lines or critical infrastructure sectors where machine failure can have significant financial and safety implications.

Ethical and Workforce Considerations

While AI in PdM promises enhanced productivity, it also raises ethical and workforce-related concerns. Automation of diagnostic processes may result in workforce displacement or require significant upskilling. There is also the issue of accountability in failure prediction—particularly if AI-based recommendations lead to incorrect maintenance decisions or system downtimes. Developing frameworks that ensure transparency, fairness, and human oversight in AI recommendations is essential.

Toward Holistic Integration

To fully realize the benefits of AI-driven predictive maintenance, integration with other smart manufacturing components is critical. This includes interoperability with digital twin systems for simulation, cloud-edge architectures for real-time data processing, and enterprise resource planning (ERP) systems for logistics and scheduling. A holistic view that combines AI, Industrial Internet of Things (IIoT), and cyber-physical systems (CPS) will enhance predictive accuracy and maximize industrial impact.

Conclusion

Artificial Intelligence has emerged as a key enabler of predictive maintenance in the era of smart manufacturing, revolutionizing how industrial systems are monitored, maintained, and optimized. This research highlights how AI techniques spanning machine learning, deep learning, and advanced data analytics have reshaped traditional maintenance paradigms by introducing proactive, data-driven strategies that anticipate equipment failure before it disrupts production. Through real-time monitoring, intelligent fault detection, and precise failure prediction, AI-driven PdM has demonstrated substantial value in reducing operational costs, enhancing asset utilization, and extending machinery lifespan.

The discussion revealed that while the benefits of AI integration are compelling, practical implementation still faces challenges related to data quality, model interpretability, and scalability across different industrial contexts. In particular, the dependence on high-quality sensor data and the difficulty in generalizing models across varied machine types require targeted research and flexible architectures. Addressing these barriers through modular system design, explainable AI techniques, and domain adaptation strategies will be vital for broad adoption.

Equally important are the organizational and ethical dimensions of AI adoption. The transition to intelligent maintenance systems calls for workforce reskilling, interdisciplinary collaboration, and governance frameworks that prioritize transparency, reliability, and human oversight. These elements are critical to building trust in AI systems, especially in high-stakes manufacturing environments.

Looking ahead, the convergence of AI with technologies such as digital twins, edge computing, 5G, and cyber-physical systems is expected to enhance predictive capabilities, scalability, and responsiveness in smart factories. These advancements will enable more resilient, sustainable, and autonomous manufacturing ecosystems. Ultimately, AI for predictive maintenance represents not only a technological shift but also a strategic pathway toward future-ready manufacturing systems that align with the goals of Industry 4.0 and beyond.

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