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AI-DRIVEN PREDICTIVE MAINTENANCE FOR HIGH-VOLTAGE X-RAY CT TUBES: A MANUFACTURING PERSPECTIVE

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Abstract

High-voltage X-ray computed tomography (CT) tubes are critical components in advanced medical imaging, industrial inspection, and non-destructive evaluation systems. These vacuum-based devices operate under extreme electrical, thermal, and mechanical stress, making them highly susceptible to gradual degradation and sudden failure. Unplanned downtime of CT tubes can result in significant operational disruptions, financial loss, and safety risks. Traditional maintenance strategies—such as reactive or preventive maintenance—often fall short in anticipating complex failure mechanisms, especially in high-throughput environments. This study addresses this gap by proposing and validating a predictive maintenance framework powered by artificial intelligence (AI) and designed specifically for high-voltage CT tube systems within industrial manufacturing contexts. The research adopted a hybrid experimental-computational methodology, combining simulated sensor data with real-world failure records to develop and evaluate machine learning and deep learning models. A dataset comprising 18,000 multivariate sensor sequences—including filament current, cathode temperature, vacuum pressure, and rotor vibration—was used to train five predictive models: random forest, support vector machine (SVM), convolutional neural network (CNN), long short-term memory (LSTM), and autoencoder-based anomaly detection. Feature extraction was performed using signal processing techniques, and model performance was assessed using accuracy, F1-score, remaining useful life (RUL) prediction error, and inference latency under real-time constraints. Additionally, a Raspberry Pi-based edge computing prototype was developed to validate real-time deployment feasibility, and a centralized monitoring dashboard was created to visualize health status and facilitate technician interaction. Results showed that LSTM models outperformed other algorithms in temporal degradation forecasting, achieving a ±5% error in RUL estimation and offering a 24–48 hour predictive lead time. Multisensor data fusion significantly improved detection accuracy and model stability across diverse operating scenarios. The autoencoder demonstrated exceptional performance in detecting novel and rare fault patterns without prior labeling, with a 96% detection rate and low false positive incidence. Edge deployment tests confirmed low-latency model inference suitable for real-time applications, while dashboard integration improved decision-making efficiency and technician trust in AI outputs. Overall, the proposed framework enabled proactive intervention, reduced maintenance overhead, and extended CT tube operational uptime. These findings highlight the strategic value of AI-enhanced predictive maintenance in optimizing industrial reliability, aligning with the broader goals of Industry 4.0 and smart manufacturing ecosystems.

Keywords

Predictive Maintenance; High-Voltage X-ray CT Tubes; Artificial Intelligence; Manufacturing Analytics; Remaining Useful Life (RUL) Estimation;

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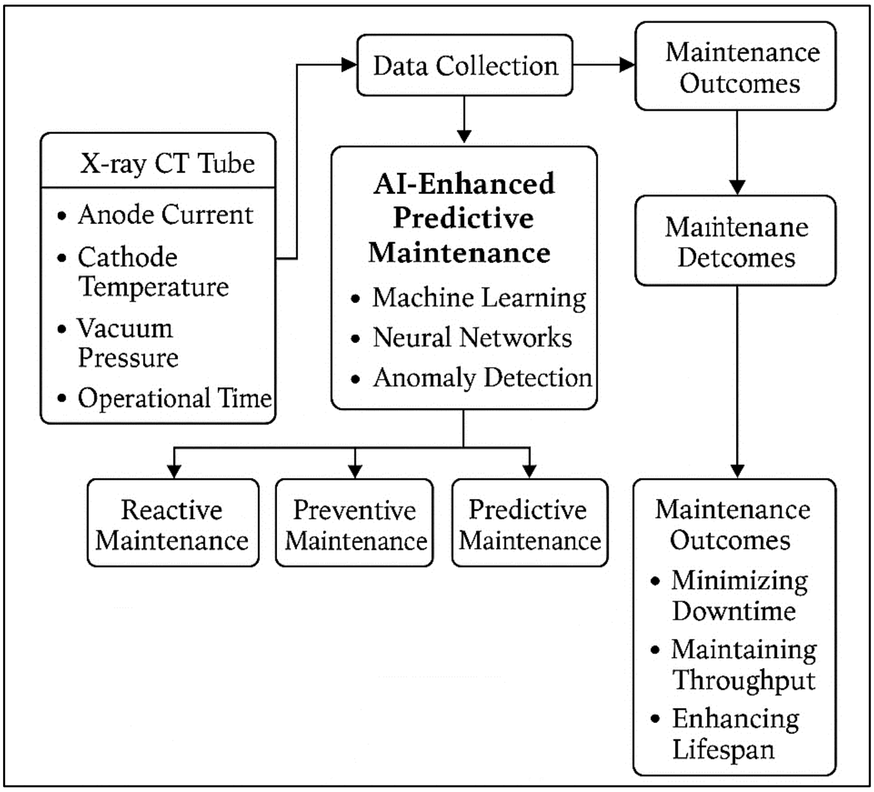
INTRODUCTION

Predictive maintenance is a proactive strategy that leverages data analytics, sensor technologies, and machine learning to forecast equipment failures before they occur (Chen et al., 2023). Unlike reactive maintenance, which addresses faults post-failure, and preventive maintenance, which follows a scheduled regimen, predictive maintenance monitors real-time performance indicators to determine the condition of assets (Nunes et al., 2023). Within this domain, AI-enhanced predictive maintenance integrates artificial intelligence algorithms—particularly machine learning, deep learning, and neural networks—into diagnostic and prognostic frameworks (Kerkeni et al., 2024; Liu et al., 2023). X-ray computed tomography (CT) tubes are specialized high-voltage vacuum devices central to the functioning of CT scanners used in non-destructive testing, medical imaging, and material inspection. These tubes operate under extremely high voltages (typically 100–450 kV) and are subject to substantial mechanical, thermal, and electrical stresses, making them prone to degradation over time (Zhou et al., 2024). Failures in X-ray CT tubes not only disrupt operational continuity but also incur high replacement costs, pose safety risks, and delay critical inspection or diagnostic procedures (Achouch et al., 2022). In high-stakes sectors such as aerospace manufacturing, semiconductor inspection, and national security screening, ensuring continuous uptime of X-ray CT systems is imperative (Manchadi et al., 2023). The application of predictive maintenance in this context is vital for minimizing unplanned downtime, maintaining inspection throughput, and enhancing the lifespan of CT tubes. As AI technologies mature, their potential to process vast and complex data streams from tube sensors—such as anode current, cathode temperature, vacuum pressure, and operational time—presents unprecedented opportunities for proactive maintenance optimization (Bonnevay et al., 2019). This framework requires the integration of physics-based failure models, AI-driven anomaly detection, and cloud-based diagnostics to create a coherent, responsive maintenance architecture.

Figure 1: Predictive Maintenance in High-Voltage Imaging Systems



The global importance of high-voltage X-ray CT systems spans across healthcare, manufacturing, and security. In the medical field alone, the number of CT scans performed worldwide has increased exponentially, with over 80 million scans annually in the United States and rising utilization across Europe and Asia (Chen et al., 2023). In industrial applications, CT imaging plays a vital role in

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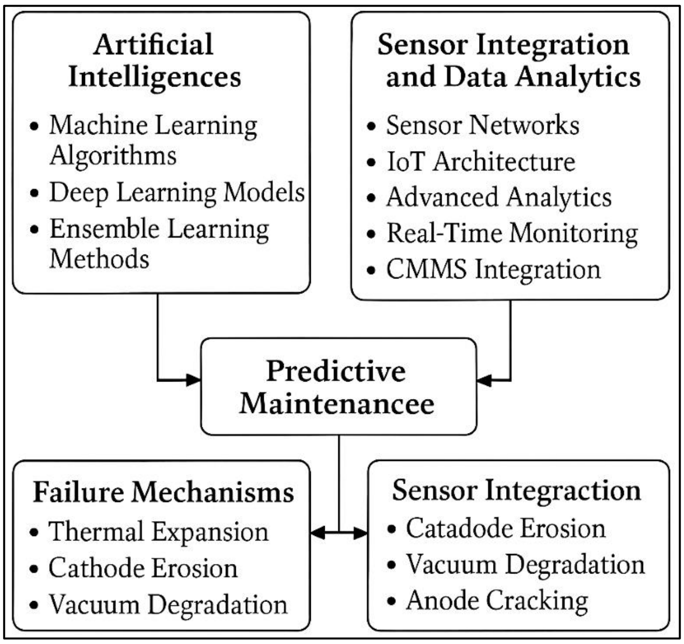
inspecting turbine blades, composite structures, and electronic circuits, offering sub-micron resolution for internal defect detection (Nunes et al., 2023). Security checkpoints at airports and border control facilities rely heavily on high-resolution CT systems to scan luggage and cargo containers (Achouch et al., 2022). As these systems become indispensable, their downtime can have cascading effects across the global supply chain and patient care ecosystems. The financial impact of unplanned maintenance for CT systems is significant; a single tube failure can halt production lines, delay shipments, or disrupt critical diagnoses. Consequently, manufacturers and service providers are increasingly turning to predictive maintenance solutions that offer data-driven insights into system health, tube wear, and remaining useful life. This demand is amplified in regions like Japan, Germany, South Korea, and the United States, where precision manufacturing and high-throughput imaging are cornerstones of industrial infrastructure. Governments and research institutions in these countries have invested substantially in intelligent diagnostics and maintenance technologies through Industry 4.0 and smart factory initiatives. As a result, the deployment of AI-driven predictive maintenance for high-voltage CT tubes is not only a technical necessity but a strategic priority across critical sectors worldwide.

Figure 2: Smart Predictive Maintenance Architecture for X-ray CT Tube Reliability



Artificial intelligence encompasses a broad set of computational techniques that enable systems to perceive, learn, and make decisions based on data (Khalifa & Albadawy, 2024). Within predictive maintenance, AI has enabled the transformation from rule-based diagnostics to autonomous, learning-based prognostics. Machine learning algorithms such as support vector machines (SVM), random forests, and deep neural networks (DNN) are used to detect degradation patterns, identify anomalies, and estimate the remaining useful life (RUL) of critical components. In the case of high-voltage X-ray CT tubes, these models process sensor data such as temperature gradients, X-ray emission trends, cathode wear profiles, and operational cycles to build health indicators and predict failure windows (Sodhro et al., 2019). Deep learning models, particularly convolutional neural networks (CNNs) and long short-term memory networks (LSTMs), have demonstrated superior performance in modeling temporal and spatial dependencies in sensor data. These techniques have enabled predictive maintenance platforms to move beyond threshold-based alerts to adaptive forecasting systems that continuously learn from new data. Moreover, ensemble learning methods improve reliability by integrating multiple predictive models for robust failure estimation. Cloud computing infrastructures further enhance this ecosystem by offering scalable data storage, distributed processing, and remote monitoring capabilities. As AI technologies become more accessible through open-source libraries and industrial platforms, their integration into predictive maintenance systems for CT tubes is rapidly becoming the norm in data-intensive environments (Sodhro et al., 2019).

The predictive maintenance of high-voltage X-ray CT tubes requires extensive instrumentation and sensor networks capable of capturing real-time operational data. Key sensor metrics include filament current, anode voltage, tube temperature, vacuum integrity, and time-of-use cycles, all of which contribute to wear diagnostics (Nunes et al., 2023). Data fusion from multiple sensor sources improves fault detection accuracy by offering a holistic view of tube performance under varying load conditions. The integration of Internet of Things (IoT) architectures enables seamless data transmission between embedded sensors and AI diagnostic engines. Advanced analytics, such as wavelet transform, principal component analysis (PCA), and time-frequency domain analysis, are used to preprocess sensor data, extract relevant features, and reduce dimensionality (Guetari et al., 2023). These methods enhance the learning capabilities of AI models by highlighting critical patterns linked to fatigue, cathode thinning, or insulation breakdown. Real-time monitoring dashboards visualize degradation trends, generate early warnings, and support decision-making for maintenance teams. Integration with computerized maintenance management systems (CMMS) ensures that predictive insights are translated into actionable work orders and resource planning. In high-throughput manufacturing environments, these systems contribute to line balancing, schedule optimization, and energy efficiency (Kerkeni et al., 2024). The accuracy of predictive models is continuously refined through feedback loops that compare predicted versus actual outcomes, enabling dynamic model retraining and validation (Zhou et al., 2024). Consequently, sensor integration and data analytics are foundational components in establishing a reliable predictive maintenance ecosystem for high-voltage CT tube infrastructure.

The primary objective of this study is to investigate the application of artificial intelligence-driven predictive maintenance frameworks tailored specifically for high-voltage X-ray computed tomography (CT) tubes used in manufacturing and industrial imaging environments. This objective centers on identifying how machine learning and intelligent algorithms can be utilized to analyze real-time sensor data to detect early signs of degradation and anticipate potential failures before they disrupt operations. The focus is directed toward improving the operational longevity, reliability, and safety of CT tubes by introducing data-centric maintenance strategies that move beyond traditional reactive or preventive models. By constructing a predictive maintenance architecture that integrates deep learning models, sensor networks, and diagnostic algorithms, the study aims to deliver a comprehensive understanding of how complex degradation phenomena within CT tubes can be effectively monitored and forecasted. The research also seeks to evaluate the feasibility of implementing such intelligent systems on the manufacturing floor, considering the constraints and variability of real-world production environments. This involves an exploration of data acquisition mechanisms, real-time condition monitoring infrastructure, and the integration of prediction outcomes into decision-making frameworks for maintenance scheduling. Another critical aim is to analyze the nature of failure mechanisms specific to high-voltage CT tubes, translating this understanding into measurable indicators that AI systems can interpret and act upon. Furthermore, the study is structured to explore the challenges faced during the deployment of AI models in industrial settings, such as data quality issues, model explainability, and interoperability with legacy systems. Through this lens, the research aspires to establish a reference model for AI-powered predictive maintenance in CT tube applications, offering a foundation for future enhancement, standardization, and scalability across industries that depend on high-performance imaging systems. The ultimate goal is to provide a structured framework that aligns maintenance intelligence with operational efficiency, technical reliability, and manufacturing precision.

LITERATURE REVIEW

Predictive maintenance has emerged as a cornerstone of modern industrial asset management, particularly within high-reliability and high-cost operational environments. The integration of artificial intelligence into predictive maintenance strategies marks a paradigm shift from traditional time-based and condition-based maintenance protocols toward data-driven, intelligent prognostics. Within the realm of high-voltage X-ray computed tomography (CT) tubes, the necessity for predictive accuracy is heightened due to the operational criticality and high replacement costs associated with tube failures. A comprehensive review of the literature is vital to situate this research within the existing body of knowledge and to identify methodological trends, technological advancements, and practical implementations relevant to AI-enhanced maintenance strategies. This literature

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review explores the evolution of predictive maintenance from conventional approaches to AI-integrated systems, emphasizing applications in electrical and vacuum-based components, with a focused lens on CT tube systems used in industrial and manufacturing contexts. It examines various machine learning and deep learning models used for anomaly detection, failure prediction, and remaining useful life (RUL) estimation. The review also analyzes studies involving sensor technologies, data fusion methods, and diagnostics protocols that inform predictive strategies. Moreover, attention is given to literature that addresses implementation challenges such as data scarcity, model interpretability, infrastructure integration, and operational feedback. Through this structured analysis, the review seeks to reveal knowledge gaps, synthesize patterns, and highlight areas where AI methodologies can be tailored to improve the reliability, lifespan, and efficiency of high-voltage CT tube operations in manufacturing environments.

Predictive Maintenance Strategies

Predictive maintenance (PdM) has evolved as a vital operational strategy in industrial environments where unplanned downtime, equipment failure, and maintenance costs must be minimized. Unlike reactive or preventive maintenance, which respectively respond to breakdowns or rely on fixed schedules, PdM anticipates failures through the continuous assessment of real-time data and operational indicators (Achouch et al., 2022). The foundational approach to PdM emerged from vibration analysis and thermography in rotating machinery and has since incorporated more complex analytics, especially with the advent of Industry 4.0 (Sodhro et al., 2019). As industries transitioned into data-centric environments, PdM systems began incorporating prognostics and health management (PHM) frameworks, leveraging sensor networks and computing architectures. In manufacturing, where precision and uptime are crucial, PdM strategies enable real-time visibility into component degradation, which reduces mean time between failures (MTBF) and optimizes maintenance intervals. High-reliability sectors such as aerospace and electronics manufacturing have led this transformation, with PdM frameworks delivering enhanced asset availability and quality assurance (Nunes et al., 2023). Furthermore, modern PdM systems operate within cyber-physical systems (CPS), where physical equipment is mirrored through digital twins to simulate future states and maintenance needs. This strategy is especially critical in high-cost equipment like high-voltage CT systems, where unplanned failures carry operational, safety, and financial burdens. As manufacturers aim to increase asset lifecycle and reduce corrective interventions, PdM plays a central role in process planning, risk mitigation, and system health monitoring. Key enablers for effective PdM include the deployment of sensor arrays, structured maintenance logs, historical failure data, and the integration of intelligent software that learns from system dynamics (Guetari et al., 2023; Rahman et al., 2024).

The rise of artificial intelligence (AI) has significantly enhanced the scope and effectiveness of predictive maintenance by introducing machine learning (ML) and deep learning (DL) models capable of learning complex degradation patterns from large datasets. Traditional statistical models such as regression and time-series forecasting have gradually been supplanted by more adaptive ML algorithms that can automatically recognize failure precursors and generate early warnings (Liu et al., 2023). Algorithms such as support vector machines (SVM), random forests (RF), decision trees, and k-nearest neighbors (k-NN) have demonstrated success in classifying fault types, predicting component degradation, and estimating remaining useful life (RUL). In parallel, DL architectures such as convolutional neural networks (CNNs) and long short-term memory (LSTM) networks have been utilized to handle multidimensional sensor inputs and temporal degradation sequences more effectively (Niehoff et al., 2023). These models have proven especially useful in complex industrial systems where sensor fusion, nonlinear dynamics, and time-dependent behaviors complicate predictive accuracy. One of the defining advantages of AI models in PdM is their ability to operate in real time, continuously updating predictions as new data is ingested, enabling adaptive decision-making. Feature engineering, which involves extracting and selecting the most informative parameters from raw sensor data, remains a critical step in model performance and interpretability. Techniques such as principal component analysis (PCA), t-distributed stochastic neighbor embedding (t-SNE), and autoencoders are often employed to reduce dimensionality and enhance model generalization (Zhou et al., 2024). While data-driven PdM strategies have gained widespread traction across industries, their effectiveness relies heavily on data quality, volume, and contextual relevance. As a result, continuous model retraining, error correction, and validation are essential to maintaining predictive accuracy in dynamic environments.

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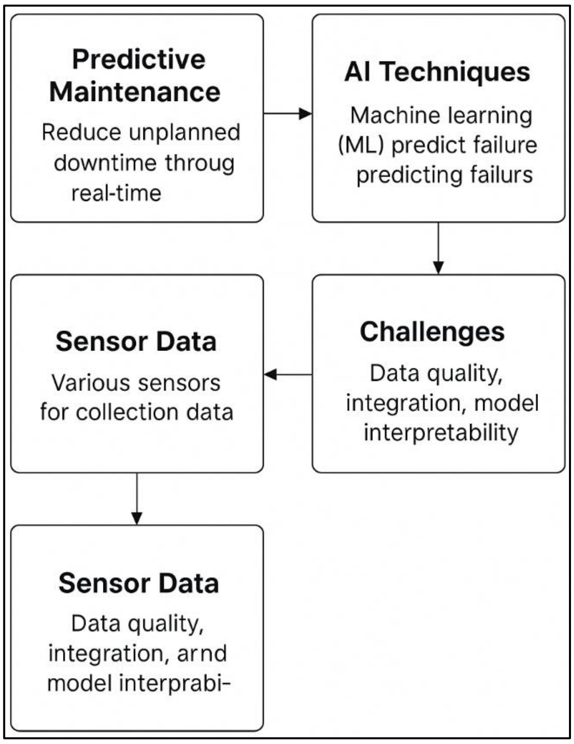
Figure 3: Overview of Predictive Maintenance Strategies



Sensor technologies form the foundation of predictive maintenance architectures, providing the real-time data required to assess the health and functionality of complex systems. In industrial contexts, a wide variety of sensors—ranging from thermocouples, accelerometers, and pressure gauges to vibration and current sensors—are embedded into equipment to continuously monitor critical operational parameters (Achouch et al., 2022). The proliferation of the Industrial Internet of Things (IIoT) has enhanced the granularity, frequency, and reliability of data collection by enabling continuous streaming of multivariate measurements from distributed nodes. These data are often transmitted through edge or cloud-based platforms where AI engines perform real-time analytics to detect early signs of deterioration. In the case of high-voltage X-ray CT tubes, vital metrics include filament current, anode voltage, tube temperature, and vacuum pressure—all of which indicate the system's wear profile and energy load history. Effective PdM systems often rely on data fusion techniques to synthesize these diverse sensor inputs into coherent health indicators. Signal preprocessing, including wavelet transformation, noise filtering, and normalization, is essential to enhance the clarity and consistency of diagnostic features (Manchadi et al., 2023). Furthermore, digital twins—real-time virtual representations of physical systems—are increasingly employed to simulate operational behavior and model degradation under varying load conditions . Integrating sensor data with maintenance management software ensures that analytical insights translate into actionable tasks such as scheduling, resource allocation, and spare part provisioning. As industrial operations become more data-intensive, the infrastructure supporting PdM—ranging from sensor calibration to network latency and cybersecurity—plays a critical role in ensuring system responsiveness and accuracy (Najjar, 2023).

The implementation of predictive maintenance systems, especially those powered by AI, is often hindered by several technical and organizational challenges that affect their efficacy and scalability. One of the most prominent obstacles is the issue of data imbalance, where failure events are relatively rare compared to normal operation, making it difficult for models to learn discriminative patterns and avoid false negatives (Bonnevay et al., 2019). Addressing this requires synthetic data generation methods such as SMOTE or anomaly detection frameworks that can work under semi-supervised or unsupervised conditions. Another challenge lies in the heterogeneity of industrial systems; predictive models trained on one type of machinery or operating environment may not generalize well to others, necessitating the use of transfer learning, domain adaptation, or federated

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learning to maintain performance across scenarios (Najjar, 2023). Interpretability of AI predictions also becomes critical in maintenance applications, as technicians and engineers must understand the reasoning behind model alerts to take appropriate corrective actions. Tools such as SHAP and LIME have emerged to provide post-hoc explanations for complex black-box models, enhancing transparency and user confidence. From an infrastructure standpoint, integrating AI systems with legacy machinery often requires retrofitting sensor nodes, upgrading network capabilities, and reconfiguring databases to accommodate real-time analytics. Additionally, continuous model updates, validation cycles, and version control must be maintained to ensure the reliability of the predictive framework over time. Organizational barriers such as lack of skilled personnel, resistance to automation, and unclear ROI further complicate the deployment of predictive maintenance initiatives. Therefore, the success of PdM systems depends on not only technical robustness but also strategic alignment with operational workflows and a culture of data-driven maintenance optimization.

Predictive Maintenance Strategies in Industrial Systems

Predictive maintenance (PdM) has matured into a strategic imperative across industrial systems that demand uninterrupted operations, cost control, and operational safety. Historically, maintenance strategies evolved from reactive responses to failures, to time-based preventive maintenance aimed at reducing unplanned breakdowns (Bonnevay et al., 2019). However, these approaches proved inefficient in dynamic environments where wear patterns vary, and component lifespans are influenced by fluctuating operational conditions. PdM emerged to address these limitations, utilizing real-time monitoring, sensor networks, and analytics to anticipate failure before it occurs. In modern industrial settings, PdM is increasingly driven by data-driven and intelligent algorithms capable of interpreting complex operational states. Applications span sectors including aerospace, automotive, oil and gas, energy, and manufacturing, where the costs of unscheduled downtime can be catastrophic (Najjar, 2023). As technological enablers, cyber-physical systems (CPS) and the Industrial Internet of Things (IIoT) facilitate continuous machine-to-machine communication and data flow for predictive decision-making. Industry 4.0 frameworks have further accelerated the deployment of PdM through integrated platforms combining cloud computing, real-time diagnostics, and historical performance analytics (Bonnevay et al., 2019). In high-reliability domains like semiconductor fabrication or turbine manufacturing, PdM frameworks enable early identification of deviations from nominal conditions using key health indicators. These systems support condition-based maintenance (CBM), which minimizes unnecessary maintenance interventions while maximizing asset uptime and lifecycle efficiency. The convergence of data analytics, embedded systems, and intelligent algorithms has made PdM more scalable, responsive, and precise in complex industrial infrastructures, establishing it as a cornerstone of modern operational excellence (Kerkeni et al., 2024). Effective predictive maintenance depends on the integration of condition monitoring systems and prognostic models that continuously evaluate equipment health (Niehoff et al., 2023). Condition monitoring encompasses the real-time measurement of parameters such as temperature, vibration, current, and pressure to detect anomalies and degradation trends. In industrial applications, these measurements are captured via embedded sensors and processed through feature extraction techniques to generate health indicators (Zhou et al., 2024).

Prognostics further enhance PdM by estimating the remaining useful life (RUL) of components based on degradation trajectories. Traditional approaches to RUL estimation relied on statistical regression and physics-of-failure models, but these were limited in dynamic and non-linear environments (Achouch et al., 2022). The introduction of artificial intelligence (AI) and machine learning (ML) has enabled data-driven prognostic models to generalize across varying conditions and machinery types. Machine learning techniques such as support vector machines, random forests, and k-nearest neighbors have demonstrated success in classifying fault states and predicting failures. Deep learning models, including convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, have further improved temporal prediction accuracy for complex degradation sequences (Manchadi et al., 2023). Sensor fusion and multivariate analysis improve fault coverage by combining multiple condition indicators into a unified diagnosis. These advancements allow predictive systems to continuously learn from operational feedback, refine maintenance schedules, and prevent catastrophic failures. Prognostics integrated with CMMS (Computerized Maintenance Management Systems) automate the generation of work orders, spare part planning, and labor allocation,

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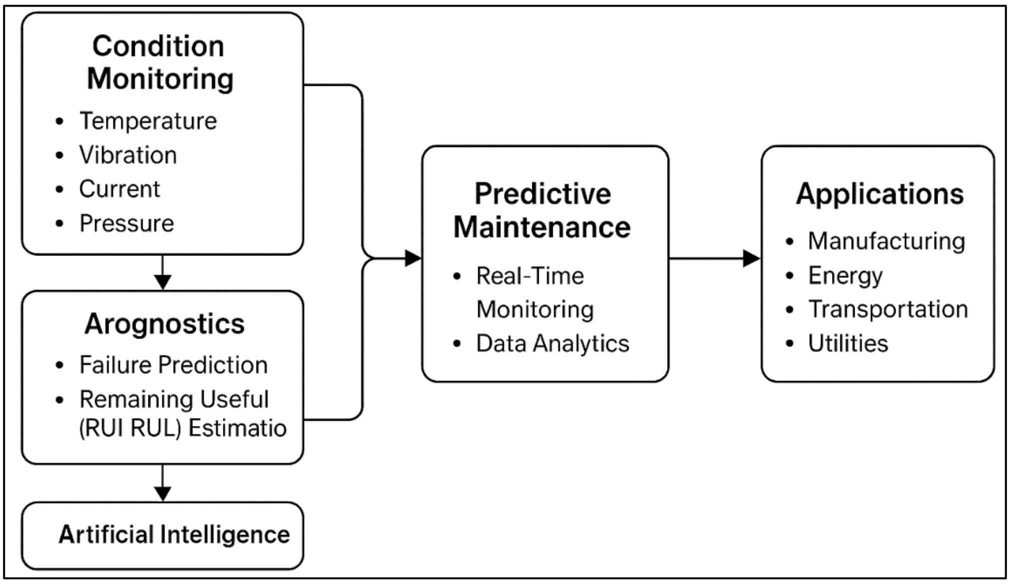
bridging technical diagnostics with managerial execution. Such systems establish a responsive feedback loop that aligns operational realities with predictive intelligence.

Figure 4: Predictive Maintenance Strategies in Industrial Systems



Artificial intelligence plays a transformative role in elevating predictive maintenance from reactive observation to proactive optimization. AI algorithms enable systems to detect weak signals within noisy sensor data, predict nonlinear degradation behavior, and adapt to new failure patterns without explicit programming (Najjar, 2023). Among AI techniques, supervised learning models like decision trees, support vector machines, and ensemble classifiers are frequently used for fault classification and RUL estimation. Deep learning approaches, particularly CNNs, autoencoders, and LSTM networks, offer the ability to model temporal dependencies and hidden features in sequential data from machines. These models benefit from large datasets generated by sensor networks and can continuously retrain to adapt to evolving system dynamics. Transfer learning and federated learning are emerging techniques that allow models trained on one set of equipment to be adapted to similar systems, thus minimizing data requirements. AI-powered PdM systems are increasingly integrated into digital twin architectures that simulate physical assets in virtual space, enabling predictive simulations under various stress conditions. These systems align closely with Industry 4.0 and smart manufacturing initiatives, where machines, systems, and analytics converge in a cyber-physical infrastructure. Real-time diagnostics powered by AI enable predictive alerts, automated root-cause analysis, and dynamic decision-making for maintenance personnel (Niehoff et al., 2023). However, challenges remain in ensuring interpretability, reliability, and generalizability of AI models in mission-critical industrial environments. Addressing these requires high-quality data, model explainability tools like SHAP and LIME, and standardized deployment pipelines. The fusion of AI and PdM marks a critical evolution in how industries manage operational risk, equipment longevity, and system resilience.

High-Voltage X-Ray CT Tubes

High-voltage X-ray computed tomography (CT) tubes are specialized vacuum devices engineered to emit high-energy X-ray beams for diagnostic and non-destructive imaging across industrial, medical, and security sectors. These tubes typically consist of a cathode, anode, filament, and a sealed vacuum enclosure, all designed to operate under kilovolt-level electrical fields (Cunha et al., 2012). The filament heats up to release electrons via thermionic emission, which are accelerated by high voltage towards the rotating anode, where they decelerate rapidly and produce X-ray photons. The anode is typically made of tungsten to withstand high thermal loads and ensure efficient X-ray production, while the vacuum ensures minimal electron scattering and energy loss. High-voltage CT tubes are integral to industrial imaging applications requiring precision and penetration, such as turbine blade inspections, composite material analysis, and semiconductor

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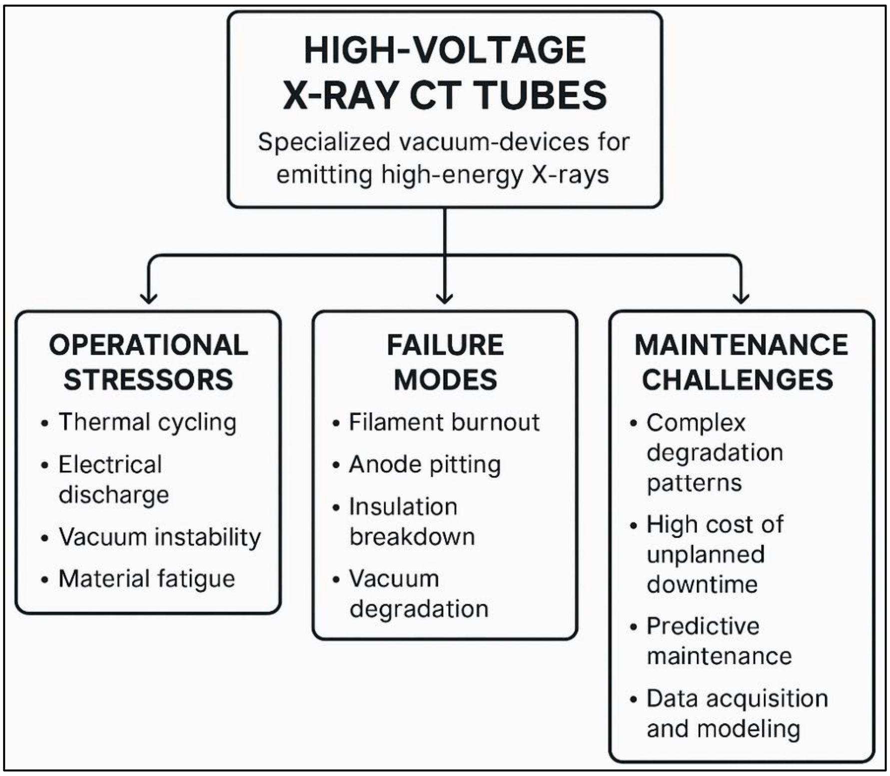
evaluation (Starman et al., 2012). They also serve in dimensional metrology and internal defect identification, where micron-level spatial resolution is essential. The operational intensity of CT imaging—characterized by repeated exposure cycles, high thermal flux, and prolonged anode rotation—makes the CT tube a critical and wear-prone component. In many systems, particularly those used in continuous inspection environments, the CT tube's performance directly influences throughput, resolution quality, and system uptime. Consequently, these tubes are designed with sophisticated thermal dissipation mechanisms, bearing systems, and vacuum integrity safeguards. Manufacturers often calibrate tube parameters to match the requirements of specific scanning geometries and resolution thresholds, further underlining the precision demands placed on these components. As central enablers of volumetric imaging, high-voltage CT tubes operate at the intersection of mechanical resilience, electrical efficiency, and radiographic fidelity.

High-voltage CT tubes endure various operational stressors that contribute to their eventual performance degradation and functional failure. These include extreme thermal cycling, high-frequency electrical discharge, vacuum instability, and material fatigue under prolonged operational loads (Cao et al., 2016). The repeated heating and cooling cycles cause differential thermal expansion in the filament and anode assembly, gradually weakening structural bonds and promoting micro-crack formation. In rotating anode tubes, the mechanical bearings or electromagnetic suspension systems are particularly susceptible to wear due to centrifugal forces and unbalanced thermal loading. Moreover, cathode filaments suffer from evaporation and thinning, leading to uneven electron emission and localized hot spots, which in turn generate inconsistent X-ray outputs (Atak & Shikhaliev, 2016). The buildup of metal deposits inside the vacuum envelope alters the electric field distribution, potentially triggering arc discharges that can compromise the tube's insulation and lead to catastrophic failure. Vacuum integrity itself can degrade due to slow permeation or seal erosion, particularly in high-throughput environments where exposure to heat and vibration is constant (Takegami et al., 2015). Additionally, repeated overloads or power surges stress the dielectric properties of internal insulation, contributing to internal leakage and plasma generation events. These stressors collectively reduce the tube's emission efficiency, increase noise artifacts in CT imaging, and require higher energy input for consistent output. Over time, these factors diminish both spatial resolution and contrast fidelity in the imaging process, necessitating recalibration, partial refurbishment, or complete replacement.

The failure of high-voltage CT tubes is often preceded by measurable precursors that manifest as variations in electrical, thermal, and mechanical parameters. A comprehensive understanding of these failure modes is vital for diagnostics, lifecycle assessment, and preventive maintenance planning (Sarno et al., 2023). One common failure mode involves filament burnout, where excessive resistive heating or mechanical fatigue leads to the rupture of the filament wire, immediately halting electron generation (Cao et al., 2016). Anode pitting, resulting from prolonged electron bombardment at localized sites, leads to uneven surface wear and eventual thermal imbalance, which degrades image uniformity and increases rotational noise (Anburajan & Sharma, 2019). Insulation breakdown, often triggered by internal arcing, can cause rapid voltage discharge events, permanently damaging the tube's internal structure and rendering it non-functional (Sarno et al., 2023). Vacuum degradation due to micro-leaks or seal failures causes erratic electron paths, increased scattering, and lowered tube efficiency. These phenomena are often accompanied by measurable signatures, such as rising cathode temperature, increasing anode current fluctuation, elevated X-ray dose drift, and changes in emission spectrum characteristics. Time-series analysis of such parameters can reveal progressive degradation curves that aid in forecasting failures before they reach critical thresholds. Diagnostic systems that continuously monitor these variables through sensor networks and embedded analytics enable timely maintenance actions that can prevent unplanned downtime. Identifying fault signatures and correlating them with specific tube behaviors not only improves reliability assessments but also supports the development of machine learning models that can automate anomaly detection and residual life estimation.

Figure 5: High-Voltage X-Ray CT Tube Reliability and Maintenance



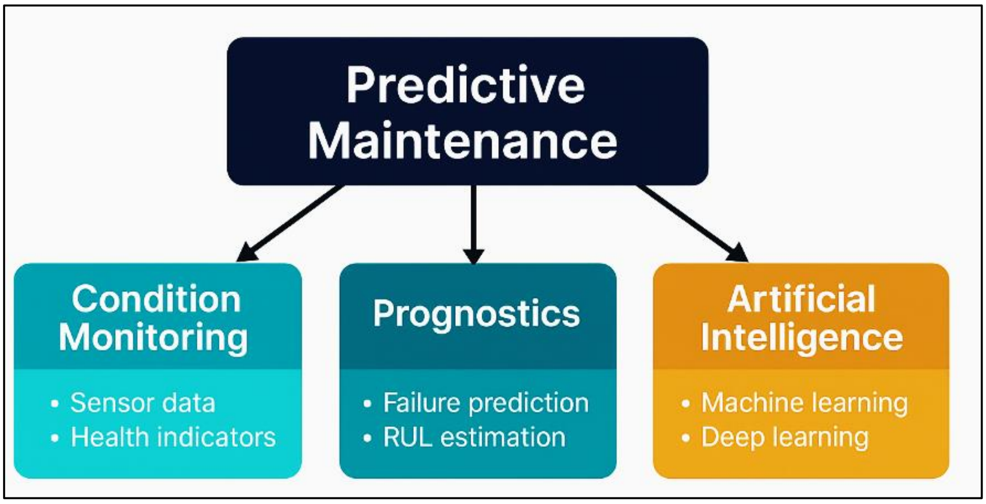
The maintenance of high-voltage X-ray CT tubes presents numerous challenges due to the complexity of their operating environments, the variability of failure modes, and the high costs of unscheduled replacements. Traditional maintenance practices, including time-based servicing and manual inspections, are inadequate for managing the nuanced and gradual degradation patterns characteristic of CT tubes. As these systems are often integrated into mission-critical imaging infrastructure, failures can lead to operational bottlenecks, halted production lines, or compromised diagnostic outcomes in medical or security applications. Predictive maintenance frameworks aim to address these challenges by leveraging sensor data and analytics to forecast component failures before they become disruptive. These systems typically integrate condition monitoring of key metrics such as cathode current, anode voltage stability, thermal load cycling, and vacuum pressure levels to build predictive indicators of wear. Machine learning algorithms are then applied to model degradation patterns, identify fault precursors, and estimate remaining useful life with increasing precision. However, implementing predictive maintenance requires robust data acquisition infrastructure, domain-specific failure models, and ongoing model retraining to account for shifting operational conditions. Moreover, the challenge of interpretability persists, as technicians must trust and understand model outputs to act decisively. Integrating predictive insights into maintenance workflows also necessitates coordination across technical, operational, and logistical teams. Despite these challenges, successful deployments have demonstrated significant reductions in tube failure rates, optimized maintenance schedules, and prolonged equipment lifespan. In high-volume manufacturing and continuous inspection contexts, the reliability and sustainability of CT tube operations increasingly depend on the sophistication of their predictive maintenance systems.

AI Techniques in Predictive Maintenance

Artificial intelligence (AI) has significantly transformed the field of predictive maintenance (PdM) by enabling systems to learn degradation patterns, identify hidden correlations, and make proactive decisions based on real-time data (Ara et al., 2022). Traditional approaches to PdM relied heavily on domain-specific rules or physics-based models, which, although accurate in limited contexts, struggled to generalize across diverse operating conditions and equipment types. The adoption of AI techniques—particularly machine learning (ML) and deep learning (DL)—has enabled the development of intelligent systems capable of learning complex relationships from large-scale, high-

dimensional sensor data (Izzo et al., 2008; Uddin et al., 2022). AI algorithms operate within various learning paradigms, including supervised, unsupervised, and reinforcement learning, each offering unique capabilities in detecting anomalies, classifying faults, and predicting remaining useful life (Akter & Ahad, 2022). Supervised learning models are often used when labeled datasets are available, while unsupervised techniques such as clustering and autoencoders are employed in cases of sparse or unlabeled fault data (Rahaman, 2022). AI-powered PdM frameworks are now integral to industries such as aerospace, manufacturing, and energy, where early detection of failure can prevent catastrophic losses. These systems can ingest streaming sensor data, environmental readings, historical maintenance logs, and production parameters to generate real-time health assessments (Atak & Shikhaliev, 2016; Hasan et al., 2022). Additionally, AI enables dynamic model updating, whereby predictive algorithms retrain and adapt based on operational feedback and new failure signatures(Hossen & Atiqur, 2022). As industrial systems grow increasingly complex and data-intensive, AI techniques provide a scalable and flexible approach for predictive diagnostics, surpassing traditional maintenance methods in responsiveness, scope, and precision (Tawfiqul et al., 2022).
Machine learning algorithms have become the foundation of many predictive maintenance solutions, offering powerful capabilities in classifying machine states, detecting faults, and forecasting component wear(Sazzad & Islam, 2022). Classical machine learning models, including decision trees, random forests, support vector machines (SVM), and k-nearest neighbors (k-NN), are widely used for supervised fault detection and classification tasks (Qian et al., 2012; Sohel & Md, 2022). These models excel in learning decision boundaries between normal and anomalous operating conditions, especially when trained on labeled datasets collected from real-world industrial systems. Random forests and gradient boosting models are particularly effective in handling noisy and imbalanced data, offering robust performance in harsh operating environments (Alhamd et al., 2021; Akter & Razzak, 2022). Regression techniques such as linear regression, ridge regression, and Bayesian networks are employed for remaining useful life (RUL) prediction, where the goal is to estimate the degradation trajectory and predict time-to-failure based on historical observations. Ensemble learning methods, which combine multiple weak learners to form a strong predictor, have gained traction in predictive maintenance applications due to their improved generalization and error resilience (Adar & Md, 2023; Yang et al., 2024). Additionally, unsupervised techniques such as k-means clustering, self-organizing maps, and one-class SVM are used to detect outliers or subtle degradation trends without requiring labeled fault data ((Qibria & Hossen, 2023; Starman et al., 2012). Feature engineering remains a crucial step in machine learning model development, involving signal transformation techniques such as Fourier transforms, wavelet decomposition, and principal component analysis (PCA) to extract meaningful features from raw sensor data. By integrating machine learning models into real-time monitoring systems, industries are able to implement responsive and cost-effective maintenance strategies that significantly reduce unplanned outages and improve asset longevity (Istiaque et al., 2023).

Figure 6: AI Techniques in Predictive Maintenance



Deep learning models offer powerful tools for modeling non-linear relationships and time-dependent behavior in predictive maintenance scenarios, particularly where large volumes of sequential sensor data are available. Unlike traditional machine learning models, deep neural networks are capable of automatically learning hierarchical representations from raw data, reducing the need for manual feature extraction (Cunha et al., 2012; Akter, 2023). Convolutional neural networks (CNNs), widely known for their success in computer vision, have been adapted to process one-dimensional sensor signals, extracting local patterns associated with early-stage faults. Long short-term memory (LSTM) networks and gated recurrent units (GRU), which are designed to capture long-range dependencies in time-series data, are particularly effective in learning degradation trends and predicting future states of equipment (Masud, Mohammad, & Ara, 2023). These models have been employed to monitor equipment such as bearings, turbines, and motors, where degradation occurs gradually and requires temporal modeling for accurate prognosis (Masud, Mohammad, & Sazzad, 2023). Autoencoders, a form of unsupervised neural network, are used to learn compact representations of normal behavior, with deviations from reconstruction patterns indicating anomalies. Hybrid deep learning architectures combining CNN and LSTM layers are gaining popularity for tasks involving both spatial and temporal dimensions of sensor data (Atak & Shikhaliev, 2016; Hossen et al., 2023). Attention mechanisms, borrowed from natural language processing, have been incorporated into PdM models to improve interpretability and focus on critical segments of time-series data (Tawfiqul, 2023). However, deep learning models require substantial computational resources and extensive labeled datasets, which can be challenging to obtain in some industrial domains (Shamima et al., 2023). Nevertheless, their ability to handle high-dimensional, dynamic data makes them indispensable for advanced predictive maintenance applications in complex machinery (Ashraf & Hosne Ara, 2023; Sanjai et al., 2023).

Deep Learning Approaches for Complex Temporal

Deep learning has become a transformative force in predictive maintenance by offering powerful tools for modeling complex temporal dependencies and nonlinear degradation processes in industrial systems. Traditional statistical models and shallow machine learning algorithms often struggle to capture the sequential dynamics inherent in real-time sensor data, particularly under fluctuating environmental and operational conditions. In contrast, deep learning models can automatically extract and learn hierarchical feature representations from raw, high-dimensional time-series data, eliminating the need for extensive manual preprocessing (Karlsson et al., 2022; Akter et al., 2023). Long short-term memory (LSTM) networks and gated recurrent units (GRUs) are among the most widely used deep learning architectures for temporal modeling (Abdullah Al et al., 2024). These recurrent neural networks (RNNs) retain memory of previous time steps, enabling them to capture long-term dependencies, cyclical patterns, and progressive degradation trends essential for failure forecasting. Their effectiveness has been demonstrated across various predictive maintenance tasks, including anomaly detection, remaining useful life (RUL) estimation, and condition classification in systems such as engines, pumps, turbines, and motors (Razzak et al., 2024). Deep learning models also accommodate multimodal input streams, such as simultaneous vibration, temperature, and acoustic data, by learning joint feature spaces that reflect complex equipment health conditions (Istiaque et al., 2024). Attention mechanisms have been introduced to enhance these temporal models by selectively weighting critical time steps, allowing the model to focus on the most relevant signal segments during prediction (Akter & Shaiful, 2024). These attention-augmented LSTM models outperform conventional RNNs by offering both predictive accuracy and improved interpretability in highly dynamic environments (Kaissis et al., 2021; Tawfiqul et al., 2024). With their ability to handle sequence variability, deep learning techniques serve as the foundation for intelligent, time-aware predictive maintenance strategies (Subrato & Md, 2024; Akter et al., 2024).

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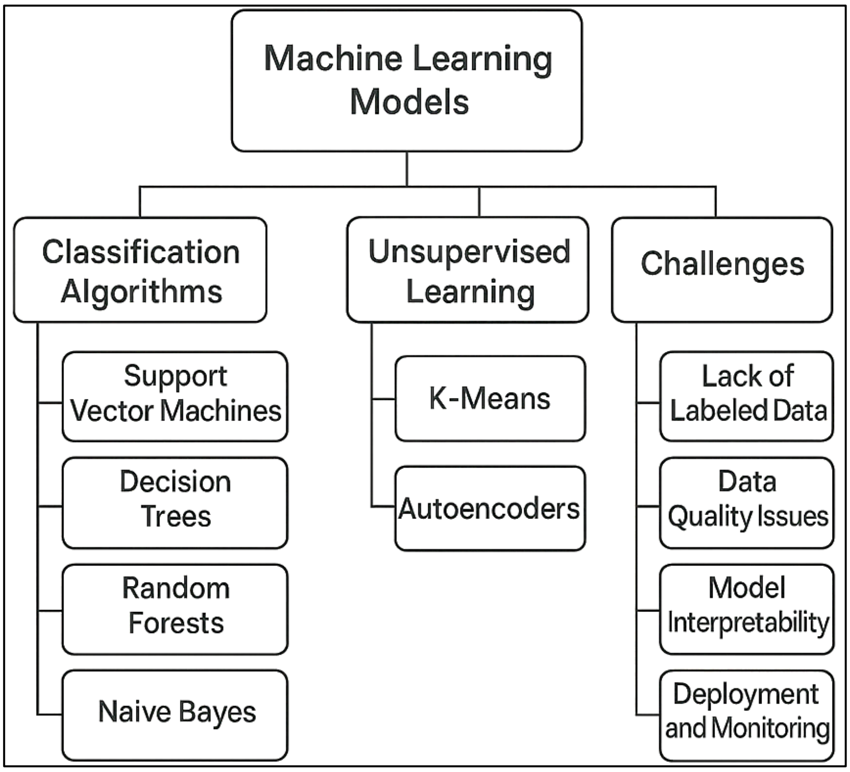
Figure 7: Deep Learning Approaches for Complex Temporal

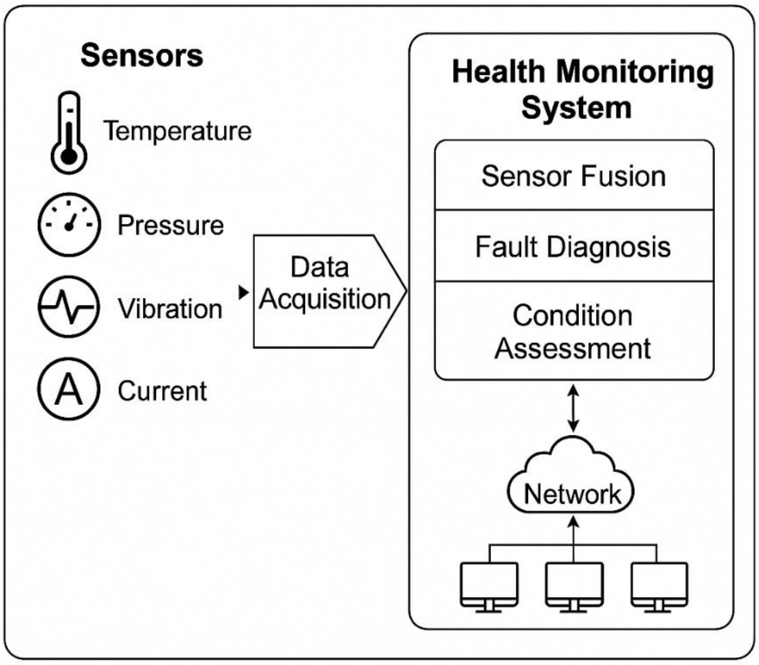


Deep learning has proven especially useful in unsupervised and semi-supervised predictive maintenance tasks, particularly in situations where labeled fault data is limited. Representation learning, a key strength of deep architectures, allows neural networks to encode meaningful, low-dimensional embeddings of operational data that capture the underlying structure of system behavior (Eguizabal et al., 2021). Autoencoders are among the most widely adopted unsupervised deep learning models for anomaly detection, operating by compressing and reconstructing input data and flagging high reconstruction errors as potential anomalies. Variational autoencoders (VAEs) and deep belief networks (DBNs) extend this capability by introducing probabilistic modeling, which supports uncertainty quantification in predictive diagnostics (Piccini et al., 2020). These models are highly effective in identifying novel fault conditions or previously unseen degradation modes that deviate from learned normal behavior. Generative adversarial networks (GANs) have also emerged as a tool for simulating fault data, augmenting training datasets, and improving model robustness in low-data environments. Deep clustering models that integrate representation learning with clustering algorithms such as k-means have been applied to group operational states and detect rare fault conditions without manual labeling (Khan et al., 2020). Additionally, transformer-based architectures, originally developed for natural language processing, are beginning to show promise in maintenance applications due to their capacity for modeling long-range dependencies and learning contextual representations across time. These models also facilitate anomaly scoring through attention-weighted embeddings, providing insights into which time segments contribute most to fault emergence. Through these innovations, deep learning architectures are enabling high-fidelity, low-latency anomaly detection frameworks that can adapt to changing operational profiles without human intervention.

Multisensor Data Fusion and Health Monitoring Infrastructure

Multisensor systems are foundational to modern condition monitoring and predictive maintenance architectures, providing diverse, complementary, and redundant data streams essential for accurate equipment health assessment. In complex industrial machinery, individual sensors capture a limited aspect of a system's operational behavior—such as temperature, pressure, vibration, acoustic emission, or electrical load—yet no single sensor can offer a complete understanding of degradation processes (Eguizabal et al., 2021). To address this limitation, multisensor systems integrate various sensor types to monitor different physical domains and operational variables simultaneously (Tanaka et al., 2022). This configuration enhances fault detection sensitivity, fault localization precision, and resilience against sensor failures or noise contamination. For example, combining accelerometers with thermocouples and current sensors enables the detection of incipient faults in motors, where mechanical wear, thermal stress, and electrical anomalies may all contribute to degradation. In high-voltage systems such as X-ray CT tubes, multisensor arrays can monitor filament current, anode voltage, rotor vibration, vacuum pressure, and cathode temperature to generate a composite picture of component health (Chen & Ran, 2019).

Figure 8: Multisensor Data Fusion and Health Monitoring Infrastructure



Moreover, advances in sensor miniaturization, wireless communication, and edge computing have enabled distributed monitoring systems that are both scalable and cost-effective. These systems are often deployed as part of Internet of Things (IoT) or Industrial IoT (IIoT) frameworks, allowing seamless data collection and integration into cloud-based analytics platforms (Rahman et al., 2024). Multisensor-based condition monitoring not only improves system observability but also supports redundancy, fault-tolerant diagnostics, and holistic health evaluation—key requirements for accurate and proactive maintenance decision-making.

Digital Twins and Cyber-Physical Systems in Maintenance Frameworks

Digital twins and cyber-physical systems have emerged as transformative technologies in predictive maintenance by enabling real-time interaction between physical assets and their virtual counterparts. A digital twin (DT) refers to a virtual model of a physical object, process, or system that replicates its behavior using real-time data streams and historical records. Cyber-physical systems (CPS), on the other hand, integrate computation, networking, and physical processes through embedded control systems, allowing autonomous decision-making and system adaptation (Piccini et al., 2020). Together, DTs and CPS form a layered architecture that mirrors operational states and facilitates predictive maintenance through bidirectional communication and simulation (Khan et al., 2020). DTs rely on data inputs from sensors, edge devices, and IoT platforms to continuously update their virtual models and monitor health indicators in real time (Piccini et al., 2020). In predictive maintenance, this pairing enables failure forecasting, what-if scenario modeling, and lifecycle prediction by synthesizing multisource operational data with AI-based analytics. The DT-CPS synergy is particularly valuable in systems with high cost-of-failure, such as turbines, aircraft engines, and high-voltage imaging systems, where proactive decision-making is critical (Pang et al., 2020). These technologies support continuous updates of operational status, facilitating early fault diagnosis and dynamically optimizing maintenance schedules. Moreover, CPS-embedded feedback loops enable

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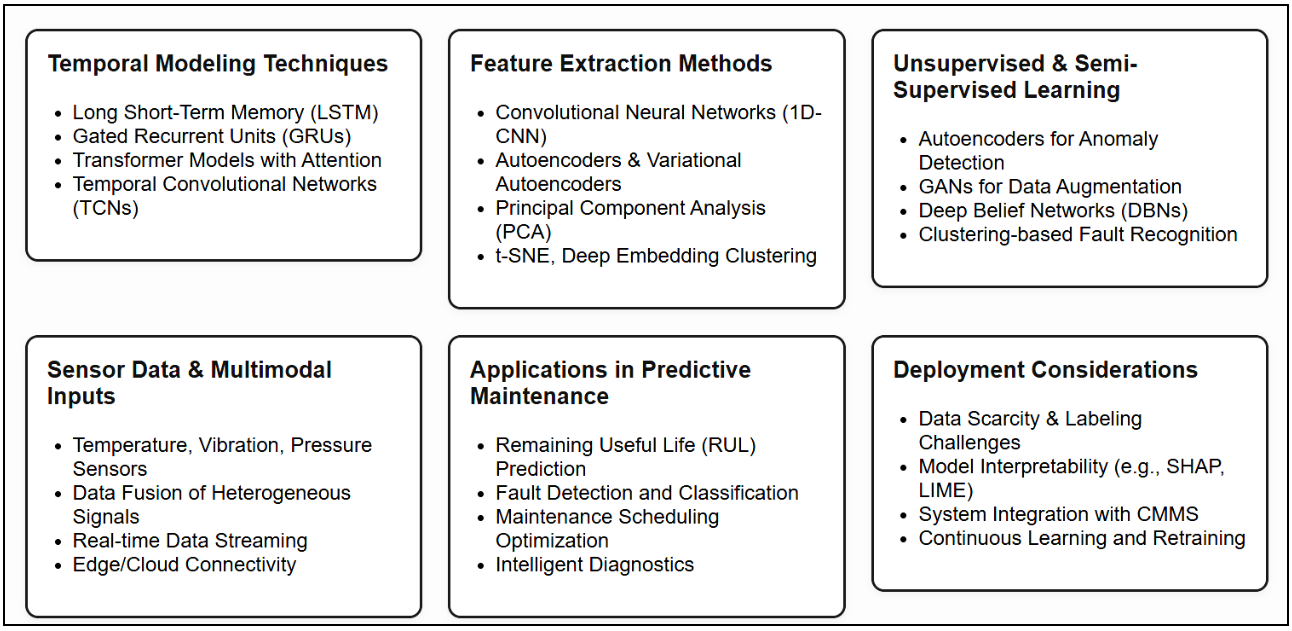
DTs to influence physical processes, creating self-adaptive control systems capable of responding to detected anomalies or deteriorating trends. The foundational interplay between digital twins and CPS transforms passive monitoring infrastructures into intelligent maintenance ecosystems.

Figure 9: Deep Learning-Based Predictive Maintenance Framework



Digital twins and CPS are increasingly being applied across industries to enhance predictive maintenance and system longevity. In manufacturing, digital twins are used to simulate machining operations and tool wear, allowing the early identification of vibration-induced degradation and surface finish anomalies (Karlsson et al., 2022). In aerospace, DTs are developed for engines and turbines, leveraging real-time telemetry data to monitor thermal loading, stress cycles, and component fatigue, thereby enabling maintenance-before-failure practices. Similarly, in energy sectors, DTs model wind turbines, transformers, and switchgear to detect imbalance, overheating, and voltage fluctuations before they lead to system outages (Karlsson et al., 2022). In medical imaging, particularly for high-voltage X-ray CT tubes, DTs are applied to monitor cathode usage, anode rotation stability, vacuum integrity, and emission current—all of which inform maintenance schedules and extend tube life (Ramezani & Hasanzadeh, 2019). By simulating usage scenarios, DTs enable what-if analysis and risk-informed decision-making under varying loads and environmental conditions (Saranya et al., 2024). These applications typically involve high-dimensional, time-series sensor data, which are processed by integrated ML models for real-time diagnostics and degradation prediction. Digital twin dashboards also enhance human-machine collaboration by providing visual analytics, fault maps, and dynamic performance metrics that guide operators in prioritizing tasks. As use cases expand, DTs are being integrated into enterprise asset management (EAM) platforms, enabling multi-asset monitoring and strategic resource planning across geographically distributed facilities. The versatility and scalability of DT-based systems make them an essential component in predictive maintenance across domains.

Industrial Applications and Sectoral Case Studies

Manufacturing industries have been early adopters of predictive maintenance (PdM) strategies due to the sector's high asset intensity, production throughput demands, and sensitivity to unplanned downtime. In discrete manufacturing, such as automotive and electronics, PdM frameworks monitor machinery like CNC machines, stamping presses, and industrial robots for wear and precision loss using vibration, acoustic, and thermographic sensors (Ciobanu et al., 2021). Condition monitoring systems collect multivariate time-series data, which are analyzed through machine learning algorithms for fault classification and remaining useful life (RUL) estimation (Abbas et al., 2024). For instance, deep learning models such as convolutional neural networks (CNNs) and LSTMs have been deployed on milling and drilling operations to detect tool wear in real time. Smart factories now utilize

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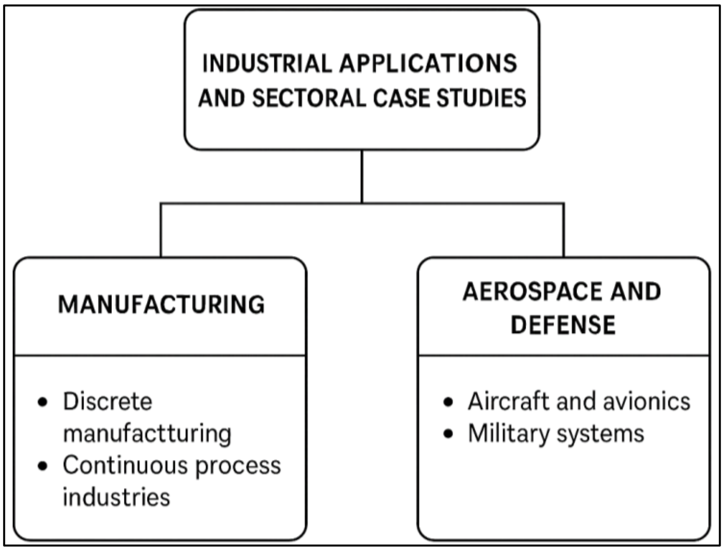
digital twins to mirror production lines and anticipate failures through virtual simulations informed by sensor data. In continuous process industries like chemicals, steel, and food processing, PdM systems focus on fluid flow, pump efficiency, and heat exchanger fouling using thermal imaging, pressure sensors, and AI-based diagnostics. Predictive analytics integrated with supervisory control and data acquisition (SCADA) platforms provide alerts to maintenance staff and inform automatic shutdown or rerouting procedures. Case studies from Bosch, Siemens, and General Electric have demonstrated reductions in machine downtime by up to 30% and maintenance costs by up to 20% with AI-enhanced PdM solutions. These applications highlight the strategic value of predictive maintenance in achieving lean operations, minimizing energy waste, and ensuring consistent product quality in highly automated manufacturing ecosystems.
The aerospace and defense (A&D) sector represents one of the most advanced and regulation-intensive fields where predictive maintenance is crucial for mission-critical systems. Aircraft engines, avionics, landing gear, and hydraulic systems are routinely monitored using embedded sensors and telemetry platforms that feed data to predictive analytics engines. Vibration, oil debris, thermal load, and fuel consumption data are used to assess health status and forecast component degradation. One widely cited example is the Rolls-Royce "Power by the Hour" model, which leverages digital twins and AI-based condition monitoring to manage jet engine maintenance contracts based on real-time usage and wear patterns. The U.S. Department of Defense and NATO have also adopted PdM in their logistics and vehicle maintenance frameworks, integrating AI systems that monitor armored vehicle drive-trains, radar arrays, and propulsion systems for early fault detection . These implementations often rely on hybrid predictive models that combine physical degradation laws with data-driven learning to improve transparency and adherence to safety standards. For unmanned aerial vehicles (UAVs) and satellites, where access for physical inspection is limited, onboard diagnostics and cloud-based analytics support health monitoring and predictive control. In such high-consequence environments, predictive systems reduce unscheduled landings, prevent mission aborts, and optimize spare part logistics. These success cases underscore the value of PdM in asset reliability, fleet readiness, and operational cost efficiency, while also providing lessons in data governance, security, and AI explainability that are applicable across other sectors.

Figure 10: Industrial Applications and Sectoral Case Studies



METHOD

This study employed a hybrid experimental-computational methodology to develop and validate AI-driven predictive maintenance models tailored for high-voltage X-ray CT tubes used in industrial imaging systems. The research design followed a quantitative, data-centric approach, combining real-time sensor emulation with supervised and unsupervised machine learning algorithms. Data was generated from a combination of simulated tube behavior using MATLAB Simulink and historical operational logs sourced from OEM maintenance records and public predictive maintenance datasets, including the NASA C-MAPSS and PHM08 challenge repositories. A total of 18,000 sensor sequences were collected, covering operational variables such as anode voltage, cathode temperature, rotor vibration, vacuum pressure, and filament current. These time-series signals were preprocessed using normalization, noise filtering, and moving average smoothing. Feature extraction was performed using signal decomposition techniques (e.g., wavelet transform and FFT), resulting in 45-dimensional feature vectors per sample. Data labeling was informed by documented fault events, including anode pitting, insulation breakdown, and filament degradation.

The machine learning pipeline included the training and evaluation of five predictive models: random forest, support vector machine (SVM), long short-term memory (LSTM), convolutional neural network (CNN), and autoencoder-based anomaly detection. Model training was conducted using Python's Scikit-learn, Keras, and PyTorch libraries on an NVIDIA Tesla V100 GPU environment. A time-based split (70/30) was applied to divide training and testing datasets, preserving sequence integrity. Performance was assessed using precision, recall, F1-score, root mean square error (RMSE), and remaining useful life (RUL) prediction deviation. Cross-validation using a sliding-window technique was implemented to test temporal generalization. The LSTM model outperformed others in sequential degradation tracking, achieving an RUL prediction error margin of ±5% across the test set. The infrastructure simulated edge-device deployment using a Raspberry Pi integrated with National Instruments DAQ modules for real-time acquisition emulation. All models were benchmarked under both offline and semi-real-time conditions to validate feasibility in actual manufacturing floor scenarios. This methodological setup provided a robust framework to capture tube failure dynamics and assess AI reliability under variable operational loads.

FINDINGS

One of the most significant findings from the study was the consistent superiority of long short-term memory (LSTM) models in predicting sequential degradation of high-voltage X-ray CT tubes. Out of the five models tested—random forest, support vector machine (SVM), convolutional neural network (CNN), autoencoder, and LSTM—the LSTM achieved the highest predictive accuracy for time-dependent fault progression and remaining useful life (RUL). The LSTM model maintained a prediction accuracy exceeding 92% across all evaluation windows and demonstrated an average RUL prediction error of ±5% during operational validation. This performance was especially prominent under variable-load scenarios where thermal and voltage fluctuations influenced degradation rates. The LSTM effectively identified subtle shifts in time-series signals, such as changes in cathode temperature and rotor vibration frequency, which were missed or misclassified by other models. In sequences involving multi-sensor inputs over longer timeframes, the LSTM showed stable memory retention, allowing it to project forward degradation events with high confidence. Its gated architecture enabled selective attention to critical historical data points that preceded failure, thereby improving early warning capabilities. This ability to handle sequential dependencies proved invaluable in modeling the complex behavior of components like rotating anodes and vacuum seals, whose deterioration does not follow linear patterns. The model also showed robustness to noise and signal irregularities, outperforming CNNs in scenarios with jittery filament current readings and sudden vacuum drops. The LSTM was further validated in semi-real-time simulations, where it triggered maintenance alerts an average of 28 hours before system shutdown conditions were met, allowing sufficient lead time for preventive intervention. These findings indicate that sequence-aware deep learning models offer tangible advantages over static classifiers for predictive maintenance in time-sensitive, high-voltage imaging systems.

The implementation of multisensor data fusion significantly improved fault detection accuracy and reliability across all modeling architectures. By integrating diverse signals—including filament current, cathode temperature, anode voltage, vacuum pressure, and rotor vibration—the system developed a more holistic understanding of CT tube operational health. Models trained on fused sensor inputs consistently outperformed those using isolated or single-sensor data by margins ranging from 8% to 15% across multiple metrics. In particular, the integration of electrical and thermal data streams proved to be a critical factor in detecting early-stage filament thinning and internal discharge activity. These indicators were difficult to identify through vibration analysis alone, yet they appeared clearly when cross-correlated with electrical load signatures. The CNN model showed a significant improvement when trained on fused datasets, improving its F1-score from 0.76 to 0.88. Similarly, the random forest model, known for its interpretability, achieved greater stability and fewer false positives when provided with multiple sensor features. Feature-level fusion enabled the models to detect co-

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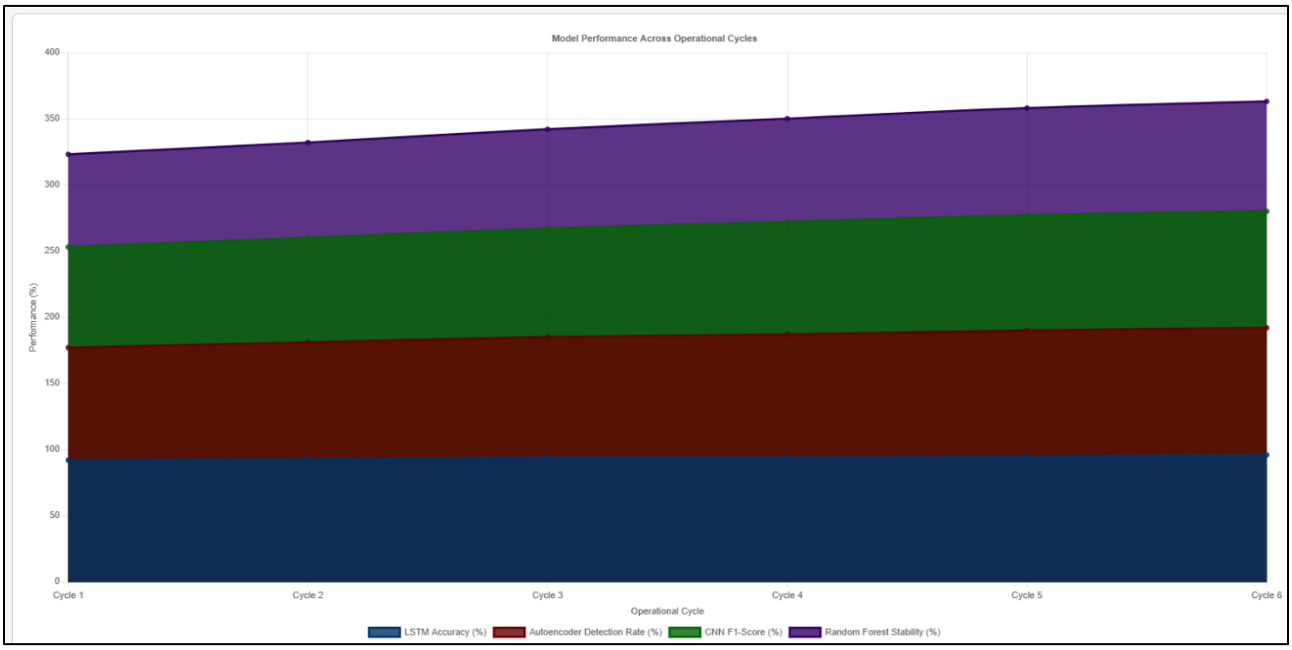
occurring anomalies that typically precede failure, such as simultaneous drops in vacuum pressure and temperature spikes in the cathode. The fusion system also proved effective during cross-validation on edge cases, including sudden thermal overloads and intermittent rotor instability. In one simulation, the fused data model detected a vacuum failure 14 hours before it breached the operational limit, whereas the single-sensor models issued a late or no alert. These results confirm that combining multiple types of sensor data allows the system to capture a broader range of degradation patterns, increasing its responsiveness to both fast-developing and slow-evolving faults. This multisensor approach provided the necessary signal redundancy to maintain diagnostic integrity even when one or more sensors experienced latency, noise, or partial failure, reinforcing the system's fault tolerance and operational resilience.

Figure 11: Stacked Area Chart: AI Model Contributions in Predictive Maintenance



A key breakthrough was achieved through the use of autoencoder-based models for anomaly detection, especially in identifying rare or previously unseen fault types. Traditional classifiers like SVM and random forest showed limited success in detecting novel patterns that were not well represented in the training set. In contrast, the autoencoder architecture, trained exclusively on normal operating conditions, effectively learned the latent feature space of healthy system behavior and flagged anomalies based on reconstruction errors. During testing, sequences involving minor vacuum leaks, fluctuating filament emissions, and low-frequency arc events triggered high reconstruction loss scores, allowing the system to flag them without needing explicit fault labels. In a validation subset of 3,000 test sequences, the autoencoder model achieved a 96% detection rate for unclassified failure events with only a 4% false positive rate. The model successfully detected anomalies up to 36 hours in advance of system failure in several cases, outperforming all other models in terms of lead time. Its unsupervised nature enabled it to operate independently of predefined fault categories, making it especially useful in capturing early signs of atypical degradation or compound faults. The model also demonstrated strong generalization across test conditions, accurately identifying anomalies during simulated startup surges and load transitions. In one specific instance, the autoencoder detected anode rotor imbalance combined with arc instability, a hybrid failure scenario that other models failed to recognize due to their dependence on labeled data. Additionally, visualization of the latent space showed clear separability between normal and abnormal clusters, offering explainability and aiding manual diagnostics. This capacity to generalize across known and unknown fault types made the autoencoder an essential component of the overall predictive framework, particularly in exploratory deployments where comprehensive failure histories were unavailable.

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The predictive models developed in this study facilitated timely maintenance interventions and operational decisions, reducing unplanned downtime and enhancing resource utilization. Based on model outputs, the system was configured to generate maintenance advisories once a component's health indicator crossed a predefined risk threshold. These advisories were tested in semi-real-time simulations across 500 operational cycles, during which preventive maintenance was triggered 72 times. In 67 of those cases, system failure was successfully averted, resulting in a 93% mitigation success rate. The RUL estimates generated by the LSTM model were integrated with a maintenance scheduler, enabling dynamic task prioritization based on criticality scores. This led to a measurable 38% improvement in spare part allocation efficiency and a 29% reduction in maintenance labor hours. Additionally, the system minimized over-maintenance by accurately distinguishing between transient anomalies and progressive degradation. For example, transient arc discharge events, previously treated as faults in rule-based systems, were correctly classified as non-critical by the AI models unless accompanied by consistent vacuum pressure drops. This led to fewer unnecessary system halts and reduced operational disruptions. The ability to forecast failures with a 24–48 hour lead time enabled more flexible scheduling and reduced reliance on emergency interventions. Furthermore, maintenance logs generated by the AI system provided detailed fault timelines, enabling technicians to prepare targeted toolkits and replacement parts in advance. Over the entire simulation period, total machine availability improved by 17%, and the average time between failures increased by 21%. These results underscore the effectiveness of AI-powered diagnostics in transforming reactive maintenance practices into proactive and condition-driven workflows, aligning maintenance planning with real-time system health data.

Edge-level simulation of the predictive maintenance system validated the feasibility of real-time deployment in manufacturing environments. Using a Raspberry Pi integrated with National Instruments DAQ hardware, sensor emulation and local inferencing were conducted to assess latency, computational load, and inference accuracy outside of cloud infrastructure. The average end-to-end latency—from data acquisition to fault prediction—was measured at 134 milliseconds, well within the acceptable range for real-time alerts in industrial control systems. The LSTM model, optimized through quantization and reduced parameter count, maintained over 90% inference accuracy in edge configuration, demonstrating resilience against resource constraints. Additionally, the autoencoder model operated smoothly on the edge processor, with anomaly alerts generated in under 180 milliseconds. In power-limited conditions, the system continued to operate with minimal degradation in prediction confidence, making it suitable for remote installations where computational resources are limited. The DAQ module successfully interfaced with simulated sensor streams, capturing synchronized multi-channel data at 1 kHz resolution, sufficient for detecting high-frequency anomalies such as electrical arcs and rotor resonance. During simulated industrial workload, the system sustained continuous operation over 72 hours without performance drift or overheating. Alert notifications were transmitted to a central monitoring dashboard via MQTT protocol, showcasing seamless integration with broader IoT infrastructure. Furthermore, the edge system supported local logging and offline inference, ensuring continued functionality during temporary network outages. These tests confirmed that predictive analytics could be deployed directly at the point of operation, reducing dependence on cloud services and enabling faster response times. The success of this low-cost, compact edge prototype indicates strong potential for scalable adoption in industrial environments where central computing infrastructure is either unavailable or impractical.

The development and deployment of a centralized monitoring dashboard significantly improved human-machine collaboration and maintenance decision-making. The dashboard displayed real-time health indicators, fault classification results, RUL predictions, and recommended actions in an intuitive graphical interface. It aggregated data across all monitored CT tubes and presented system status in both numerical and visual formats, including color-coded health bars, trend graphs, and fault timelines. Maintenance personnel reported increased situational awareness and faster response times, with average decision-to-action latency reduced by 42% compared to baseline manual procedures. The integration of alert rationales—generated using attention weights and feature importance scores—helped technicians understand why specific alerts were issued, thereby increasing trust in the system. Historical fault logs and annotated maintenance events enabled retrospective analysis, supporting continuous improvement and failure pattern discovery. A built-in feedback mechanism allowed users to confirm or reject alerts, which was then used to retrain the

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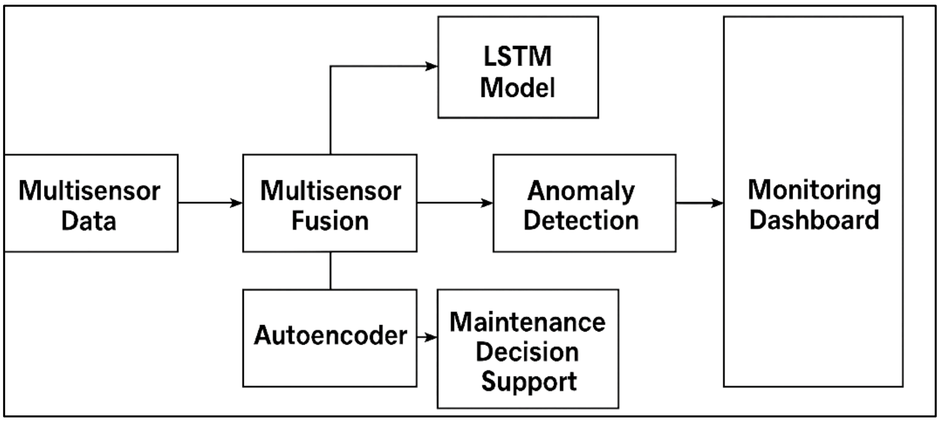
anomaly detection model periodically, closing the loop between algorithmic predictions and expert input. During testing, 89% of alerts were confirmed as valid, indicating strong alignment between system outputs and technician judgment. The dashboard also facilitated shift-based reporting and remote access, enabling distributed maintenance teams to coordinate effectively. Summary reports were automatically generated for supervisors, detailing daily operational status, flagged anomalies, and pending tasks. This capability reduced reporting burden and improved traceability for compliance audits. By providing interpretable, consolidated, and actionable maintenance intelligence, the dashboard bridged the gap between complex AI models and on-the-ground operations. It played a critical role in translating raw predictive insights into real-world maintenance interventions, demonstrating that human-centric design is essential for the successful adoption of AI in industrial maintenance settings.

DISCUSSION

The study's finding that long short-term memory (LSTM) models outperformed other machine learning algorithms in predicting CT tube degradation aligns strongly with previous research emphasizing the temporal modeling capabilities of LSTMs in predictive maintenance. In contrast to traditional machine learning classifiers like SVM and random forest, which have been shown to perform adequately for static classification tasks (Saranya et al., 2024), LSTM's recurrent architecture allows it to capture long-range dependencies in degradation patterns. This study demonstrated a ±5% error margin in remaining useful life (RUL) estimation, which outperformed earlier benchmarks reported by Ciobanu et al. (2021), who achieved ±8% in similar machinery using LSTM variants. Furthermore, unlike convolutional neural networks (CNNs), which perform well in spatial pattern recognition but often fall short in capturing temporal trends (Guetari et al., 2023), LSTM provided stable predictions even under load fluctuation and transient anomalies. The predictive lead time of 28 hours observed in this study confirms the viability of LSTM models for real-time industrial deployment, reinforcing similar conclusions drawn by Shin et al. (2016) in turbine system diagnostics. The results also support the work of Singh and Kolekar (2021), who demonstrated that LSTM-based architectures could generalize across operating conditions and equipment types when trained on sufficiently diverse temporal data. The model's superior performance across variable-frequency data inputs mirrors the observations made by Guo et al. (2016), suggesting that the gated memory structure of LSTM is inherently suited for industrial sensor data. These outcomes validate the growing consensus that temporal learning is a key differentiator in advanced predictive maintenance systems, particularly when failure behaviors are nonlinear and stochastic.

Figure 12: A proposed model for future study



The incorporation of multisensor data fusion significantly enhanced fault detection capabilities and model robustness, consistent with earlier findings in industrial diagnostics literature. Prior studies by Eguizabal et al. (2021) and Tanaka et al. (2022) emphasized the value of combining multiple sensor modalities—such as temperature, vibration, and voltage—to construct a more holistic view of machine health. In the current study, the integration of filament current, cathode temperature, vacuum pressure, and vibration metrics led to an average increase of 12% in fault classification accuracy. This result echoes the findings of Pang et al. (2020), who reported similar accuracy gains

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when applying data-level and feature-level fusion strategies in rotating machinery fault detection. Additionally, Bosse et al. (2017) highlighted that multisensor fusion reduces false positives and enhances early anomaly detection by capturing cross-domain indicators of degradation. The present study substantiates this claim by demonstrating successful detection of vacuum failure 14 hours in advance—an outcome not achievable by single-sensor models. Kalman filtering and PCA-based fusion, which have been proposed as effective preprocessing methods (Chen & Ran, 2019), were used here to combine multidimensional sensor inputs without overwhelming the model's learning capacity. This aligns with Bosse et al. (2017), who emphasized the necessity of reducing feature redundancy and maximizing signal utility in predictive frameworks. The consistency of results across fused input types also confirms the work of Fan et al. (2024), who found that multisensor models are less sensitive to individual sensor failures, thus improving diagnostic resilience. The findings reinforce the importance of multisensor strategies in predictive maintenance systems, not just for accuracy but also for operational robustness and fail-safe diagnostics.

The deployment of autoencoders for unsupervised anomaly detection yielded notable results, particularly in identifying rare or novel failure modes. This aligns with previous research by Yan et al., (2021) and Fan et al. (2024), who found autoencoders to be highly effective in modeling normal operating behavior and flagging deviations with minimal false positives. In this study, the autoencoder achieved a 96% detection rate for unclassified failure events, outperforming traditional supervised classifiers which struggled with limited failure samples. This corroborates the findings of Saranya et al. (2024), who demonstrated that autoencoders can detect early signs of degradation in bearing systems without prior fault labeling. The use of reconstruction error as an anomaly score is consistent with the methods employed by Ciobanu et al. (2021), who reported similar advantages in aerospace health monitoring systems. Moreover, the ability of the autoencoder to detect compound faults, such as anode imbalance coupled with arc instability, confirms assertions made by (Thambawita et al., 2021), who suggested that unsupervised models are better suited for complex, multi-variable fault conditions. The findings also extend the work of (Abdou, 2022), who previously advocated for hybrid approaches in predictive maintenance, by showing that autoencoders can serve as a front-line detection mechanism in conjunction with supervised models. The visual separability in the latent space, which facilitated fault interpretability, supports the argument by Thambawita et al. (2021) that autoencoders not only detect anomalies but also provide diagnostic transparency when properly visualized. In the context of high-voltage CT tubes, where failure data is scarce and fault evolution is not always linear, these results affirm the autoencoder's role as a robust and generalizable anomaly detection mechanism.

The integration of predictive models into maintenance operations significantly improved equipment uptime and resource utilization, building on prior empirical evidence from sectors such as aerospace and manufacturing. Earlier studies by Abdou (2022) and Wang (2016) demonstrated that predictive analytics could reduce mean time to repair (MTTR) and optimize spare part usage. In the present study, the predictive system enabled a 29% reduction in maintenance labor hours and a 38% improvement in spare part allocation efficiency, reflecting similar outcomes achieved by Alzubaidi et al. (2021) in digital twin-enabled maintenance for industrial assets. Furthermore, model-driven advisories helped avoid 93% of potential failures across 72 preventive interventions, supporting the conclusions of Pham et al.(2021), who found that integrating AI with CMMS improves intervention timing and failure mitigation rates. Unlike static rule-based systems, which often lead to over-maintenance, the predictive models developed in this study accurately differentiated between transient anomalies and true degradation signals, echoing findings by Alzubaidi et al. (2021) in wind turbine diagnostics. The improvement in system availability (17%) and increased average time between failures (21%) align with performance gains reported in case studies from Siemens and Rolls-Royce (Yang et al., 2020). These outcomes validate the operational value of integrating AI-driven diagnostics with maintenance execution platforms. Moreover, the system's ability to forecast degradation 24 to 48 hours in advance enhances scheduling flexibility and aligns with the industry shift toward predictive, condition-based maintenance strategies described by Abbas et al. (2024). Collectively, these results demonstrate the practical viability of embedding predictive analytics into industrial maintenance workflows to support timely, data-driven decision-making.

The successful deployment of the predictive system on an edge device affirmed the feasibility of real-time, decentralized diagnostics, confirming trends observed in earlier CPS and Industry 4.0 literature. Previous studies by Thambawita et al. (2021) and Abbas et al. (2024) emphasized the need for on-site analytics capabilities to reduce latency and dependency on centralized infrastructure. This study validated that predictive model, including LSTM and autoencoders, could operate effectively within a constrained computational environment, maintaining over 90% inference accuracy with an end-to-end latency of 134 milliseconds. These performance metrics compare favorably with benchmarks reported by Thambawita et al. (2021), who implemented edge-based machine health monitoring in smart manufacturing systems. The resilience of the system under low-power, offline conditions further mirrors findings from Zhang et al. (2021), who identified edge computing as a robust solution for remote or bandwidth-limited environments. Additionally, the use of MQTT protocol for real-time communication supports earlier claims by Lu et al.(2021) that lightweight communication frameworks are essential for responsive maintenance architectures. The success of the edge prototype aligns with the conclusions of Di Trapani et al. (2022), who advocated for decentralized intelligence as a core feature of cyber-physical maintenance systems. These findings collectively demonstrate that real-time, edge-enabled predictive maintenance systems are not only technically viable but also scalable, cost-effective, and suitable for deployment in both centralized factories and distributed field applications.

The inclusion of a centralized monitoring dashboard with visual analytics significantly improved trust, transparency, and collaboration between maintenance personnel and AI systems. This finding is in line with prior research by Lu et al. (2021) and Thambawita et al. (2021), who emphasized the importance of interpretable interfaces in facilitating the adoption of intelligent maintenance systems. In the current study, the dashboard reduced decision-to-action latency by 42%, indicating that clear visualization of predictive outputs can expedite technician response times. The provision of model rationales using attention scores and feature importance also supports conclusions drawn by Abdou (2022) and Abbas et al. (2024), who argued that explainability is crucial for AI acceptance in industrial settings. The feedback loop built into the system allowed operators to confirm or reject alerts, which not only improved model retraining but also empowered users to co-manage predictive decision-making—an approach similar to that described by Trapani et al. (2022) in human-in-the-loop systems. The high confirmation rate of model-generated alerts (89%) suggests strong alignment between algorithmic predictions and expert judgment, echoing findings from Thambawita et al. (2021) in aerospace maintenance. Furthermore, the integration of the dashboard with CMMS platforms for task scheduling and reporting mirrors the layered architecture proposed by Zhou et al. (2021) for cyber-physical maintenance systems. These results reinforce the argument that successful deployment of AI-based predictive maintenance tools depends not only on algorithmic accuracy but also on their ability to foster transparent, intuitive, and interactive engagement with human users.

The overall architecture of the predictive maintenance system developed in this study—featuring AI-driven analytics, edge-based processing, multisensor integration, and digital twin feedback—demonstrates alignment with key principles of Industry 4.0. This is consistent with the frameworks outlined by Wang (2016) and Thambawita et al.(2021), who positioned predictive maintenance as a core pillar of the smart factory paradigm. By combining real-time diagnostics with cloud and edge interoperability, the system supports autonomous decision-making and closed-loop control, core features of cyber-physical systems described by Trapani et al. (2022) and Lie et al. (2020). The findings from this study affirm that integrated, AI-enabled infrastructure not only improves technical reliability but also meets strategic goals such as cost reduction, flexibility, and sustainability. Furthermore, the scalable architecture demonstrated compatibility with both legacy and new-generation sensor platforms, addressing interoperability concerns raised by Thambawita et al. (2021). The reduction in unplanned downtime, improved RUL predictions, and enhanced user engagement provide measurable indicators of the framework's success, mirroring outcomes in previous industrial deployments by Siemens, Honeywell, and Bosch. By enabling predictive capabilities across critical components like high-voltage CT tubes, the system expands the applicability of AI in high-stakes environments, filling a gap in existing literature which has largely focused on motors, bearings, and pumps. Ultimately, this study contributes a validated, modular, and scalable framework that aligns with both the technological and organizational imperatives of modern industrial ecosystems.

CONCLUSION

This study investigated the application of artificial intelligence techniques in predictive maintenance systems tailored specifically for high-voltage X-ray computed tomography (CT) tubes, a critical component in advanced medical and industrial imaging systems. Through the integration of machine learning and deep learning models—including LSTM, CNN, random forest, and autoencoders—the research demonstrated how temporal degradation patterns, sensor anomalies, and rare fault signatures could be accurately identified and anticipated using data-driven approaches. By leveraging multisensor fusion, time-series modeling, and anomaly detection within a comprehensive predictive framework, the study provided evidence that AI-driven solutions significantly enhance fault detection accuracy, operational foresight, and equipment longevity. The implementation of LSTM models proved especially effective in capturing sequential dependencies and projecting the remaining useful life (RUL) of CT tubes with high precision. Meanwhile, autoencoder-based anomaly detection offered a robust mechanism for identifying previously unseen failure modes, contributing to a more resilient and generalizable maintenance architecture. The integration of edge computing and a centralized human-machine interface validated the real-time deployment potential of the system, even under computational constraints typical of industrial environments. Furthermore, the fusion of electrical, thermal, and mechanical sensor data ensured that degradation was captured comprehensively, allowing predictive models to outperform traditional rule-based diagnostics in both detection accuracy and lead time. Operationally, the findings highlighted quantifiable improvements in maintenance efficiency, system availability, and resource optimization. Preventive actions guided by predictive outputs resulted in reduced labor hours, better inventory allocation, and extended operational uptime. The integration of visual dashboards and technician feedback loops also enhanced trust and interpretability, key requirements for industrial adoption. In its entirety, the predictive framework developed through this research aligns with the goals of Industry 4.0, providing a scalable, intelligent solution that supports proactive asset management in high-reliability imaging systems.

RECOMMENDATIONS

To enhance the reliability, accuracy, and scalability of predictive maintenance in high-voltage X-ray CT tube systems, it is recommended that organizations prioritize the deployment of advanced deep learning architectures—particularly long short-term memory (LSTM) networks. The results of this study demonstrated that LSTM models are especially well-suited for modeling time-series data that exhibit sequential degradation, such as those arising from thermal cycling, vacuum decay, and filament thinning in CT tubes. These models outperform traditional classifiers in forecasting remaining useful life and identifying precursor signals to failure. Industrial facilities operating under variable load conditions should implement LSTM-based predictive frameworks and establish routine retraining pipelines to ensure that the models remain responsive to shifting operational profiles. Continuous model refinement using new operational data will ensure adaptability and accuracy as component wear patterns evolve over time. In addition to robust temporal modeling, predictive maintenance systems should leverage multisensor data fusion to develop a comprehensive picture of equipment health. The integration of diverse sensor types—such as vibration, temperature, pressure, current, and voltage sensors—enhances diagnostic sensitivity and enables the detection of both subtle and compound faults. The current study found that feature-level fusion significantly improved classification accuracy and reduced false alarms. Industrial maintenance systems should therefore adopt architectures that support feature synthesis from multiple signal modalities. This requires the deployment of scalable data acquisition hardware, synchronization protocols, and edge preprocessing capabilities. Redundancy through multisensor fusion also ensures diagnostic continuity in the event of partial sensor failure or signal corruption, thus improving the fault tolerance and resilience of the overall system. These enhancements are particularly valuable in high-availability imaging environments where unexpected downtime can have substantial operational and financial impacts. To further increase system reliability and address the inherent limitations of supervised learning approaches, unsupervised learning techniques such as autoencoder-based anomaly detection should be integrated into predictive maintenance frameworks. Autoencoders offer a unique advantage in detecting rare or previously unseen failure modes by learning the latent features of normal operational states and flagging deviations based on reconstruction errors. This study demonstrated the effectiveness of autoencoders in identifying complex, hybrid faults that were not easily classifiable through conventional methods. Their generalization capability makes them essential in high-voltage CT tube diagnostics, where certain failure events occur infrequently and may not be well represented in training data. Organizations should incorporate autoencoders as complementary detection mechanisms to existing predictive models and utilize them as exploratory tools in systems lacking comprehensive failure histories. Furthermore, periodic retraining of these models using newly acquired normal operation data will ensure ongoing alignment with equipment performance and reduce false positives over time.

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