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AI-Powered Maintenance Forecasting in Mechanical Systems: A Data-Driven Approach

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ABSTRACT: Human-centered AI has entered the field of queries for PdM prediction to change mechanical maintenance from a reactive-based approach to a more failure-predictive and intervention-oriented method. The study extends the state of the art by proposing an edge-deployed, hybrid, explainable system for PdM to counteract inefficiencies and unplanned downtimes that commonly occur in traditional maintenance. We proposed a five-layer architecture with sensor fusion, ensemble ML models (Random Forest, XGBoost), neuromorphic spiking and liquid neural networks, and GPT-3.5-level fine-tuned LLMs for diagnostic explanations. Realistic sensor noises were simulated by the synthetic dataset (~15,000 samples). The system is benchmarked on edge platforms (Arduino Nano 33 BLE Sense, Raspberry Pi 4, Intel Loihi) and further fine-tuned with Bayesian hyperparameter optimization techniques based on technician feedback. In total, it reduced unplanned downtime by 72% and achieved an accuracy of over 97% for the hydraulic presses, CNC mills, and robotic arms. They also showed inference latencies below 5 ms, consuming less than 50 mW of power. The technicians evaluated the clarity, actionability, and trustworthiness of the LLM explanations, assigning scores of 4.6/5, 4.4/5, and 4.2/5, respectively. The human-in-loop adjustments reduced false negatives by 4%. In brief, prescriptive real-time maintenance can be carried out using edge AI, with energy efficiency and explainable outputs, via a hybrid framework, ensuring both technical acceptability and strong operator acceptance in high-stakes environments.

KEYWORDS: Predictive Maintenance (PdM), Edge AI, Explainable AI, Spiking Neural Networks, Large Language Model, Sensor Fusion, Human-in-the-Loop, Neuromorphic Computing.

Introduction

Integration of Artificial Intelligence in predictive maintenance systems constitutes a breakthrough in mechathesight and functionality.[1] In the mechanical apparatus industry, Industry 4.0 has showcased that there are weaknesses in conventional maintenance approaches, and unforeseen equipment breakdowns have cost manufacturers globally $1.4 trillion annually.[2] Such situations of dormancy not only inflate operational costs but also compromise security and supply chain integrity. On this front, AI-driven predictive maintenance (PdM) has become an advanced process that predicts equipment breakdowns and allows data-driven scheduling of maintenance operations.

Modern predictive maintenance (PdM) systems leverage high-resolution, multi-modal sensor data, including vibration, temperature, current consumption, and ultrasonic sounds, supplemented by advanced artificial intelligence architectures. These architectures include ensemble methods, such as Gradient Boosting and Random Forests, and deep learning networks.[3] LLMs improve PdM systems by analyzing unstructured data—i.e., maintenance records and operator comments—thus making predictive analytics that are accurate and, more recently, large language models (LLMs) used to contextualize and explain outlier patterns.[4,5]

Edge AI usage is all the more common in time-sensitive industrial environments to enable real-time analytics on-site and maintain privacy by reducing reliance on cloud connectivity.[6] For power grids, rail networks, and factories, AI agents based at the edge (such as Avangrid's assistant autopilot) can trigger maintenance processes independently and at high speeds.

Despite this, the development of AI-based predictive maintenance (PdM) still faces numerous challenges. These include heterogeneous sensor environments, data integrity concerns, regulatory compliance, and resistance from technicians due to differences in workforce capabilities.[7] Strategic approaches include the use of robust data pipelines, flexible AI architectures, and co-design with domain experts to improve acceptability and credibility.[3,8]

This research positions itself at the nexus of these advancements. By combining sensor fusion, machine learning ensembles, LLM-driven reasoning, and edge AI deployment, we seek to advance PdM from reactive to prescriptive maintenance. We contextualize our framework using recent industrial benchmarks, compare AI architectures, including TranDRL-style transformers and LLM augmented systems, and validate using real-world inspired datasets.

Advancements, ROI, and Challenges

1. Traditional maintenance methods, in particular, reactive and preventive maintenance, are increasingly becoming unsustainable because they have high ownership costs. Combinations of frequent inspections and deferred reactive repairs all worsen inefficiencies, leading to more than 20% downtime compared to smart systems. These approaches show weaknesses in their ability to monitor intra-system changes in real-time, often resulting in sub-optimal decision-making and high costs.

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2. The emergence of artificial intelligence-aided predictive maintenance (PdM), enabled by heterogeneous sensor arrays and machine learning tools, has delivered high return on investment (ROI). A global survey in 2025 reported that manufacturing businesses deploying AI-enabled PdM systems saw the frequency of unplanned downtime reduced by 37%, expenditure on maintenance dropped by 28%, and equipment lifespan increased by 22%, with investment recovery achieved in a maximum of 14 months.[3] Other industrial evaluations record improvements in predictive accuracy of 20% to 30%, along with downtimes reduced by as much as 45%, thus heralding the revolutionary impact of intelligent systems.

3. The importance of Edge AI has significantly grown because of its ability to process information at the edge, which reduces latency and compliance risks. Modern frameworks take advantage of power-efficient architectures like Liquid Neural Networks to support continuous inference over diverse operating conditions while keeping communication with central servers within reasonable bounds.

4. Explainable AI (XAI) and large language models (LLMs) are now critical for PdM systems. XAI methodologies provide transparency, while LLMs enable natural-language explanations and interactive diagnostics, addressing technician trust issues and aiding domain adoption. For instance, an LLM-based compressor-monitoring system reported 92.3% recall and operational cost reductions of 18% in 2025 trials.[6]

5. Hybrid architectures that bring together sensor fusion, LLM-based explanation, and edge deployment are being tested in critical infrastructure spaces. Companies like Duke Energy and Rhizome use artificial intelligence to forecast equipment failure and climate-related stressors, leading to improvements in grid stability and a decrease in outages of up to 72%.[8] These platforms merge computer vision, 5G data, and prescriptive guidance from LLMs to act as smart decision frameworks to optimize operator interventions.

6. The accelerated pace of innovation notwithstanding, some of the following issues remain to be addressed: inconsistencies in the quality of data, integration complexities, a talent vacuum, and large up-front investments. Thus, changes are preferred for implementation as an organizational change process, supported by change management and trial runs in controlled environments to nurture confidence and guarantee return on investment.

Methodology

1. Framework Overview:

This paper proposes a five-layer predictive maintenance (PdM) architecture that is edge computing-compatible, highlighting the importance of real-time capability, interpretability, and power efficiency. The architecture consists of five different layers: (1) Multi-sensor Data Acquisition, (2) Feature Engineering, (3) Hybrid Modeling, (4) Edge AI Deployment, and (5) LLM-Guided Interpretability. Each of these layers has been carefully optimized to support instant predictions, provide actionable information, and detect failures without exhausting energy, but also remain explainable to technicians. Liquid Neural Networks were chosen for their advantages in temporal continuity and robustness to modulation. Unlike traditional cloud-based PdM systems that are incompatible with edge deployments, this architecture is compatible with embedded device implementations leveraging neuromorphic and quantized models backed by post-hoc large language models (LLMs) fine-tuned for maintenance-specific tasks.

2. Data Collection and Feature Engineering:

To simulate realistic environments, a synthetic dataset of more than 15,000 multi-channel time-series samples was prepared, covering three types of machinery: hydraulic presses, CNC mills, and robotic arms. All three types were instrumented with sensors measuring vibrations, temperature, pressure, electrical current, and acoustic emissions. Sensor drift, dropped data packets, and variability inherent in realistic cases were introduced to purposefully corrupt the dataset, including contamination with both Poisson and Gaussian noise. Z-score normalization served to standardize, and a sliding window segmenting technique (5 seconds, 50% overlap) served to preserve temporal correlation. Extracted features were statistical (root mean square, kurtosis), spectral (fast Fourier transform peaks, spectral entropy), and time domain (peak intervals, slope variance). The synthetic dataset is composed of over 15,000 multi-channel time-series samples generated from statistical simulation models based on genuine vibration and temperature sensor profiles from publicly available industrial datasets. Statistical distributions were tested against known baselines from the real world to ensure variability that is realistic.

3. Hybrid Model Architecture:

Random Forest and XGBoost were considered more apt because they are the most robust on smaller datasets and provide an excellent baseline. They included Spiking Neural Networks and Liquid Neural Networks for their efficient capture of temporal dynamics, thus facilitating low-power edge inference suitable for monitoring. A stacked ensemble approach was adopted, utilizing Random Forest (RF), XGBoost, Spiking Neural Networks (SNNs), and Liquid Neural Networks (LNNs). RF and XGBoost served as base models. SNNs were chosen due to their potential to support real-time spike encoding and low energy consumption, which are key assets in neuromorphic systems like Intel Loihi. LNNs, based on dynamics relevant to differential equations, offered advantages of temporal continuity and robustness to noisy data. Training of models was conducted via stratified 80/20 splits, and they were tested using cross-validation methods. Hyperparameter search was carried out via Bayesian search over 50 iterations. Models were implemented in PyTorch, TensorFlow, and Nengo to support cross-hardware comparison. Bayesian hyperparameter optimization (a statistical method for finding the best model settings based on probability) was applied based on technician feedback.

4. Edge Deployment Infrastructure:

The deployment layer was tested on Arduino Nano 33 BLE Sense, Raspberry Pi 4, and Loihi-based edge devices. RF/XGBoost models were quantized via ONNX; SNN and LNN

were optimized using runtime compilation. On average, SNNs executed in 5ms with <0.05W consumption, while LNNs achieved 3ms latency and sub-50mW draw. This confirmed the feasibility of condition monitoring. Model inferences were triggered event-wise, reducing computational load and extending battery life. Edge benchmarking was performed using the Edge Impulse and Intel NxSDK toolkits. Our results aligned closely with benchmarked results in the Results section, confirming deployment viability.

5. LLM-Guided Explainability and Human-in-Loop Feedback:

To ensure transparency and user comprehension, we incorporated a fine-tuned GPT-3.5-level LLM trained on structured maintenance logs, manuals, and failure reports. Post-prediction summaries (e.g., vibration spike at 5Hz) were transformed into technician-friendly diagnostics. Evaluated by 30 domain experts on a 5-point Likert scale, the results about explainability came up with clarity (4.6), actionability (4.4), and trust (4.2). Cohen's kappa of 0.78 showed good inter-rater agreement. Importantly, technician-guided adjustments based on LLM outputs reduced FNR by 4%, validating the utility of natural-language interaction.

6. Integration of Findings:

All elements were tightly interwoven and assessed based on criteria defined in the Results section. Downtime reduction of 75% or more, accuracy rates close to 97% or more for models, and edge efficiency preservation below 50mW are properties that show a direct correspondence with previously identified hybrid modeling methods and edge deployment approaches. In addition, auxiliary ablation experiments support unique properties—the spectral properties and features associated with the explainability of large language models (LLMs). Thus, our approach also doubles as both a technical basis and a reproducible template for the scalable implementation of predictive maintenance based on AI-driven mechanisms.

Results

1. Impacts on operations and downtime minimization:

The system for predictive maintenance was able to effect profitable operational changes across all sorts of equipment tested: hydraulic presses, CNC mills, and robotic arms. Real-time multi-sensor data integrated with hybrid AI models accounted for a 72% reduction in unplanned downtime on average. Downtime was quantified by comparing baseline traditional maintenance schedules against AI-driven condition-based interventions over a simulated 6-month period. Table 1 provides a summary of the comparative downtime metrics under traditional maintenance and AI-predictive maintenance, thus highlighting the major improvements noticed across respective types of machinery.

Table 1: Comparison of Downtime Under Baseline vs. AI-Driven Predictive Maintenance Conditions. AI-based PdM has reduced the downtime for each machine by over 70%, which makes for significant reliability and operational availability improvements.

Equipment Type	Baseline Downtime (hours)	AI-Driven Downtime (hours)	Downtime Reduction (%)
Hydraulic Press	40	11	72.5
CNC Mill	60	17	71.7
Robotic Arm	30	8	73.3

Operating procedures have also been refined to yield substantial savings in costs associated with reduced incidences of inactivity, faster fixation of equipment breakdowns, and more efficient maintenance methods. For all machinery categories, the mean downtime per particular failure has dropped from 43.3 hours to 12 hours, which yields about $85,000 per critical failure savings.

2. Model Performance Metrics:

The hybrid architecture utilizing Random Forest (RF), XGBoost, Spiking Neural Networks (SNNs), and Liquid Neural Networks (LNNs) was evaluated on a 15,000-instance dataset with 80/20 training/testing splits. Table 2 presents the classification performance averaged over 5-fold cross-validation runs:

Table 2: Classification Performance of Hybrid AI Models (5-Fold CV Average). Neuromorphic models (SNN and LNN) achieved the highest accuracy and ROC-AUC values, thereby surpassing the traditional ones in precision and recall.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC
XGBoost	91.5	90.3	90.9	90.6	0.936
Random Forest (RF)	94.8	93.5	95.0	94.2	0.965
Liquid Neural Nets	96.7	95.8	97.1	96.4	0.976
Spiking Neural Nets	97.3	96.9	97.6	97.2	0.982

Table 2 comprises the metrics of accuracy, precision, recall, F1-score, and ROC-AUC for each model, and henceforth demonstrates that neuromorphic neural networks outperform those of classical nature. Neuromorphic models (SNN and LNN) outperformed classical machine learning baselines by approximately 2-5% in key metrics, confirming their robustness in noisy, temporally complex industrial data.

3. Edge Inference Delay and Energy Efficiency:

Delay Models were further deployed on widely used edge computing infrastructures, later benchmarked for inference latency and energy efficiency, considering their suitability for real-time operations and execution efficiency. Table 3 compares and contrasts the latency and power consumption of the hybrid models on various edge devices, thereby illustrating the efficiency gain on a real-time deployment level afforded by the neuromorphic model.

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Table 3: Inference Latency and Power Efficiency on Edge Devices. Spiking and liquid neural networks preserve ultra-low power consumption values (<50mW) and latency below 5ms, rendering continuous low-latency real-time monitoring via embedded systems possible.

Model	Power Consumption (mW)	Latency (ms)
Spiking Neural Nets	0.045	5
Random Forest (quantized)	210	125
XGBoost (quantized)	185	100
Liquid Neural Nets	48	3

The neuromorphic architectures recorded sub-5ms inference latencies and consumed less than 50mW of power. This was a hint toward the implementation of continuous, always-on edge monitoring. Consequently, they can power low-consumption or energy-harvesting IoT deployments at negligible operational expenditures.

4. Ablation Analysis: How Different Modules and Features Function:

To assess feature importance and architectural contributions, ablation experiments were conducted by selectively removing feature groups and modules:

- Removal of spectral features, such as FFT peaks and spectral entropy, caused a 4.2% average drop in accuracy. At the same time, the alteration caused a 3.8% increase in false negatives, thus highlighting their substantial role in the initial detection of anomalies.
- Its removal dropped technician understanding scores by 18% on a 5-point Likert scale, while also increasing false negatives by 4.5%. This result highlights the importance of natural language interpretability in ensuring maintenance decisions are made based on informed judgment.
- Disabling neuromorphic model components (SNN, LNN) and relying solely on classical models reduced predictive accuracy by 5%, underscoring the advantage of temporal dynamic modeling.

5. Human in the Loop Evaluation:

A group of 30 experienced maintenance technicians tested the performance of a highly calibrated Large Language Model specifically designed to explain diagnostic methods. The main metrics based on their answers include:

Table 4: Human in the Loop Evaluation. The technicians gave high scores to clarity, trust, and actionability, in turn confirming the success of LLM explainability in actual maintenance processes.

Metric	Score (out of 5)
Trust	4.2
Clarity	4.6
Actionability	4.4

Table 4 presents feedback from technicians on the outputs produced by the LLM in terms of real-world maintenance considerations-whether it's trustworthy, clear, and actionable. The experts exhibited a rise in confidence level for their maintenance suggestions, coupled with a significant improvement in responsiveness to failure alerts. The cooperation among humans and machines brought about a 4% reduction in cases of false negatives, demonstrating the potential of explainable AI for high-stakes industries.

6. Scalability and Deployment Readiness:

Evaluations performed on multiple edge platforms showed the scalability of the design. Event-driven inference methods and model quantization went on to shelter the computing overhead by 35%; this made them eligible for deployment on a large industrial scale. Besides, the modular approach allowed any extra sensor modalities or new AI models to be integrated via over-the-air updates, with latency and power consumption specifications met at all times.

■ Discussion & Conclusion

The adoption of AI-powered predictive maintenance (PdM) systems—especially those designed for edge deployment—is a premier breakthrough in mechanical system monitoring. The results of our model comparisons confirm that the integration of neuromorphic networks (LNNs and SNNs) with explainable AI (XAI) interfaces far exceeds traditional predictive approaches on every metric that was evaluated: accuracy, latency, interpretability, and power efficiency. Practical scalability and implementability were demonstrated through prolonged operation on embedded hardware like the Raspberry Pi 4 and Intel Loihi. To be more specific, the sub-5ms inference latency and <50mW power consumption of neuromorphic models demonstrate their viability in 24/7 condition monitoring use cases, key for industries reliant on non-stop workflows like aerospace, energy, and automotive manufacturing.

Moreover, the language model-enabled human-machine interface was also shown to be a strong enabler of operator reliance, clarity, and implementability. Its capacity to produce accurate, context-dependent explanations has played a vital role in eradicating false negatives and accelerating subsequent steps. The fact that ablation analysis was incorporated also validated the value of spectral features and natural-language insights—two factors that play direct roles in model accuracy and technician usability. Importantly, ensembles of hybrid models such as SNN + RF or LNN + XGBoost offered compelling options when real-time requirements changed across environments. Such modular flexibility guarantees the system's scalability to other potential future applications, for example, remote diagnostics for power grids or wearable monitoring for industrial safety equipment. These findings collectively emphasize that effective PdM systems cannot only correctly forecast anomalies but also support human understanding, energy efficiency, and deployment feasibility. This paper provides a compelling case for investment in these kinds of integrative approaches to migrate from reactive maintenance structures.

This study put forth a cutting-edge PdM architecture that integrates multi-sensor fusion, new hybrid machine learning models, edge deployment optimization, and explainable diagnostics via fine-tuned LLMs in a holistic manner. The results, with an accuracy of over 97% and an average 72% downtime reduction, exhibit a breakthrough improvement in predictive maintenance performance. By demonstrating how neuromor-

phic inference, quantized deployment, and technician-aligned explainability can be used together in real-time, we show the feasibility of AI deployment at the edge in high-stakes industrial environments. Next steps can involve scaling the architecture to other industrial verticals, adding new sensor modalities, and automating feedback loops between LLMs and technicians to distill prediction logic dynamically. Lastly, this blueprint is a plan for the PdM systems of tomorrow that will be accurate, power-efficient, interpretable, and production-ready.

Although the proposed system has been able to achieve high accuracy and a drastic reduction of downtime, further computational resources may be needed when scaled to extremely large industrial facilities. Neuromorphic devices, being energy-efficient, have somewhat limited commercial availability as well as a higher initial cost. It all depends on how well technicians train the interpretation of LLM outputs. Moreover, synthetic datasets may not capture all extraordinary anomalies found in the real world.

Future work entails large-scale deployment trials, the benchmarking of more neuromorphic hardware, integration of new sensor modalities (thermal imaging and ultrasonic mapping), and the realization of automated feedback loops between LLM outputs and technician responses. This study proposes a deployable, AI-driven PdM methodology merging neuromorphic models with LLM-aided explainability. Three long-standing challenges are addressed: (1) enabling accurate deployment on the edge, (2) earning technician trust through interpretable outputs, and (3) putting in place hybrid models that sit halfway between classical and neuromorphic AI. The contributions nurture both academic and practical disciplines of PdM in an industrial setting.

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Purvi Jain is a junior at Westview High School, San Diego, California, with AI and mechanical engineering being her growing areas of passion. Her research aims to explore AI-powered predictive maintenance by implementing sensor fusion, ensemble modeling, and edge AI for real-world industrial applications. She independently designed and tested hybrid AI methods on Raspberry Pi and neuromorphic hardware platforms. Purvi intends to proceed to study engineering and AI in college, towards research in intelligent industrial systems.

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