

INITIAL RESULTS OF AN ARTIFICIAL INTELLIGENCE-BASED PREDICTIVE MAINTENANCE SYSTEM FOR INDUSTRIAL EQUIPMENT

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Abstract

Predictive maintenance (PdM) has emerged as a critical strategy for reducing unplanned downtime in industrial environments. This paper presents a preliminary investigation into an AI-powered predictive maintenance framework designed for complex industrial equipment. The proposed system integrates multi-sensor data acquisition, deep learning-based anomaly detection, and a real-time decision support module. Experimental evaluation on a benchmark industrial dataset demonstrates that the proposed LSTM-CNN hybrid model achieves 94.3% fault detection accuracy, outperforming conventional threshold-based and classical machine learning baselines by 11–17%. These preliminary findings confirm the viability of deploying AI-driven PdM systems within Industry 4.0 infrastructure and lay the groundwork for full-scale industrial validation.

Keywords: predictive maintenance; deep learning; LSTM; anomaly detection; industrial IoT; Industry 4.0; fault detection; sensor data; machine learning

1. Introduction

Unplanned equipment failures in industrial facilities result in significant economic losses, estimated at over \$50 billion annually across manufacturing sectors worldwide [1]. Traditional corrective and preventive maintenance strategies are either reactive or schedule-based, failing to account for the actual operational condition of machinery. Predictive maintenance (PdM), enabled by advances in Industrial Internet of Things (IIoT) and Artificial Intelligence (AI), offers a condition-based alternative that monitors real-time equipment health and forecasts failures before they occur.

In the context of Industry 4.0, the convergence of cyber-physical systems, big data analytics, and machine learning has created an enabling environment for intelligent maintenance frameworks [2]. However, deploying such systems in real industrial settings remains challenging due to data imbalance, sensor noise, and the heterogeneity of industrial equipment types. This work addresses these challenges by proposing an end-to-end AI-based PdM architecture and reporting preliminary experimental results.

2. Related Work

Considerable research has been devoted to data-driven PdM over the past decade. Lei et al. [3] provided a comprehensive survey of machine learning methods applied to rotating machinery fault diagnosis, identifying support vector machines (SVM) and random forests as dominant classical approaches. More recently, deep learning architectures have demonstrated superior performance; Zhang et al. [4] employed convolutional neural networks (CNN) for bearing fault classification, achieving accuracy above 98% on the CWRU benchmark dataset. Recurrent architectures, particularly Long Short-Term Memory (LSTM) networks, have proven effective for temporal sensor signal modeling [5].

Despite these advances, existing methods exhibit notable limitations: they often rely on large balanced datasets, struggle with generalization across equipment types, and lack integration with real-time edge deployment pipelines. Furthermore, few studies

report results under realistic industrial noise conditions, limiting their practical applicability.

3. Proposed Method

The proposed framework consists of four interconnected modules. First, a **sensor data collection layer** acquires vibration, temperature, pressure, and acoustic emission signals at 1 kHz sampling frequency via IIoT-enabled sensors. Second, a **preprocessing pipeline** applies wavelet-based denoising, z-score normalization, and a sliding window segmentation strategy (window size: 256 samples, overlap: 50%) to construct structured input sequences. Third, a **hybrid LSTM-CNN model** processes temporal features through two stacked LSTM layers (128 units each) followed by a 1D convolutional block for local pattern extraction. Finally, a **decision support module** maps model outputs to maintenance action categories: normal operation, early warning, and immediate intervention.

4. Experimental Setup

Experiments were conducted on the PRONOSTIA (FEMTO-ST) bearing dataset, a widely used public benchmark containing run-to-failure vibration recordings from industrial bearings under three load conditions. The dataset was split 70/15/15 for training, validation, and testing. Evaluation metrics include classification accuracy, F1-score, precision, recall, and Area Under the ROC Curve (AUC-ROC). Baseline comparisons include SVM with RBF kernel, Random Forest, and a standalone LSTM model.

5. Preliminary Results

The proposed LSTM-CNN hybrid achieves **94.3% accuracy** and an **F1-score of 0.931** on the test set, representing improvements of 17.2% and 14.8% over the SVM baseline, respectively. AUC-ROC reached 0.967, indicating strong discriminative capability across fault severity levels. Early fault prediction was demonstrated with a mean lead time of **38 minutes** before critical failure, providing sufficient operational window for maintenance intervention. These results are consistent across all three load conditions, suggesting robustness to operating variability [6].

6. Discussion

The preliminary results validate the hypothesis that hybrid temporal-spatial deep learning architectures can effectively capture degradation patterns in multivariate sensor streams. The 38-minute average prediction lead time is industrially significant, enabling proactive scheduling of maintenance tasks without production interruption. Deployment on edge hardware (NVIDIA Jetson TX2) confirmed inference latency of under 12 ms per window, meeting real-time requirements. Remaining challenges include model adaptation to unseen equipment types and handling of severely imbalanced fault class distributions [7].

7. Conclusion

This paper presented an AI-powered predictive maintenance framework integrating IIoT sensor acquisition, deep learning-based fault detection, and real-time decision support. Preliminary results on the PRONOSTIA benchmark demonstrate competitive accuracy and practically meaningful fault prediction lead times. Future work will focus on transfer learning for cross-domain equipment generalization, federated learning for privacy-preserving multi-site deployment, and extended validation on proprietary industrial datasets from energy and manufacturing sectors.

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