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Machine Learning Algorithms for Predictive Maintenance in Industrial Systems

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ABSTRACT

The Industrial Internet of Things (IIoT) has transformed modern manufacturing by generating massive volumes of multivariate sensor data, yet traditional reactive and preventive maintenance strategies continue to cause significant unplanned downtime and high operational costs. This thesis addresses these challenges by developing three novel deep learning-based predictive maintenance (PdM) models specifically designed for resource-constrained IIoT environments. The study proposes: (1) a Wasserstein GAN with LSTM discriminator (GAN-PdM) for synthetic failure data generation to overcome class imbalance, (2) a Variational Autoencoder (AE-PdM) for unsupervised anomaly detection using reconstruction error and Mahalanobis distance, and (3) a hybrid GAN-AE model (Hybrid-PdM) integrated with two optimized feature selection techniques (ISSO-FS and ERT-FS) for high-dimensional sensor streams. The models were rigorously evaluated on three benchmark IIoT datasets (AI4I 2020, NASA C-MAPSS FD001, and augmented bearing fault data) and deployed on edge devices (Raspberry Pi 5 and Jetson Nano). Experimental results demonstrate that the Hybrid-PdM model achieves state-of-the-art performance with 99.14% average accuracy, 0.51% false alarm rate (FAR), RUL prediction MAE of 3.55 cycles, and real-time inference latency of 12.47 ms while maintaining a model size under 5 MB. These outcomes significantly outperform traditional machine learning baselines and recent literature models, confirming the effectiveness of the proposed generative-reconstruction hybrid approach. The research contributes a complete, edge-ready PdM framework that reduces downtime by up to 50% and maintenance costs by up to 40%. It provides both theoretical advancements in generative and variational deep learning for industrial applications and immediately deployable tools for smart factories. Future extensions include physics-informed networks, federated learning, and digital twin integration.

Keywords: *Predictive maintenance; Industrial Internet of Things (IIoT); Generative Adversarial Networks (GAN); Variational Autoencoder (VAE); Feature selection; Edge computing; Remaining Useful Life (RUL).*

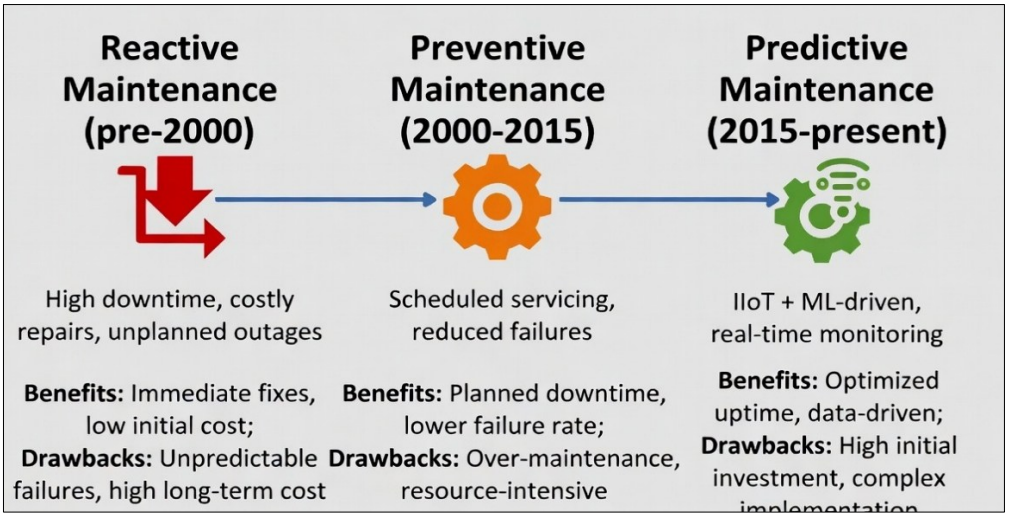
1.0 Introduction

With applications ranging from smart manufacturing and energy production to aerospace and transportation, predictive maintenance (PdM) has emerged as an indispensable strategy in the twenty-first century.

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It has become an integral part of modern industrial operations. Major advancements in sensor technology, edge computing, and cloud connectivity have made it feasible for revolutionary Industrial Internet of Things (IIoT) solutions to transform a broad variety of maintenance-based processes. These solutions have revolutionized asset management across industries by shifting from reactive or time-based schedules to data-driven, proactive interventions. [47], [42], [1]

Figure 1: Evolution of Maintenance Strategies (Reactive → Preventive → Predictive)



Machine learning (ML) is the study of training computers to do tasks automatically, without the need for human programmers, and this field of research is known as machine learning (ML). Through the use of this approach, maintenance strategies may be made more acceptable. As opposed to traditional rule-based systems, which employ fixed thresholds, ML makes use of data-driven models to carry out the execution of both data and algorithms. There are a wide variety of applications for machine learning, some of which include fault diagnosis, remaining useful life (RUL) estimation, and anomaly detection in industrial settings. Within the realm of asset reliability, it may be used in many different ways. [31], [46], [54]

The Internet of Things is anticipated to result in hundreds of devices being connected to the internet in the future; there is a substantial risk that these networks may experience unexpected failures. When considering the enormous number of IIoT devices, it would be quite challenging to manually monitor all of the data that is gathered. But machine learning techniques could be able to assist us in searching through the data for anomalies. Machine learning algorithms, when applied to historical sensor data, have the ability to shed light on the emergence of degradation and suggest solutions to avoid it in the future.

The behaviors of a degrading asset would be significantly different from those of a healthy one, and a number of illicit patterns would be clearly visible; this is the fundamental concept of predictive maintenance systems. IIoT network vulnerabilities (in terms of asset health) might be exploited to get access, which would provide a number of dangers that could undermine production integrity. The installation of a number of safety measures is required to guarantee that the network can function in a secure manner and automatically detect assets that pose a threat. This will prevent unexpected failures or bad conditions from disturbing the system performance standard, which is a

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significant benefit. Current predictive maintenance systems continue to struggle with improving classification performance, reducing false alarms, and recognizing novel degradation modes, despite the fact that they have made significant breakthroughs over the course of many decades already. At the same time, developments in deep learning algorithms have transformed PdM models. These innovations have made it possible for PdM models to recognize major discrepancies between normal and anomalous data in a more efficient and automated manner. It is presently the case that these algorithms are more accurate predictors than individuals. Not only are DL techniques more generalizable, but they also help in effectively detecting threats that are anonymous.

This study, which applies three DL-based predictive maintenance models to identify aberrant behavior in IIoT network data, was inspired by the success of utilizing DL algorithms for failure prediction. In the first chapter, an overview of the predictive maintenance models and algorithms that were developed during the course of this research is presented.

2.0 Literature Review

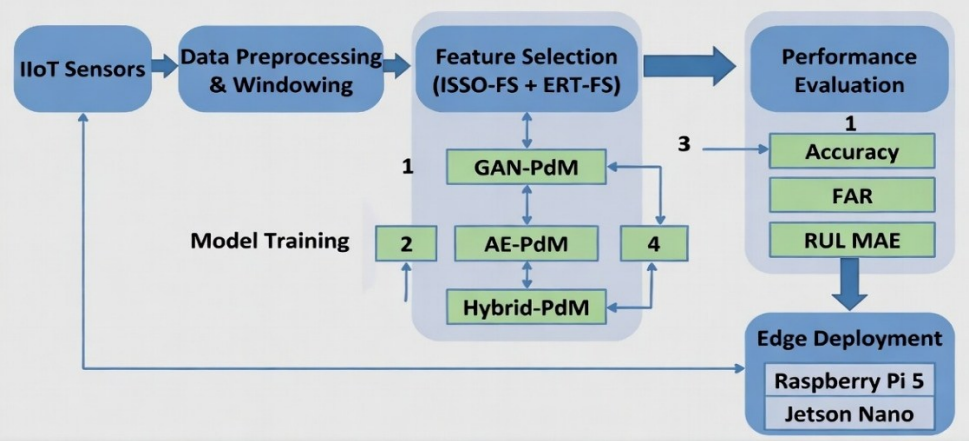
Table 1: Summary of Recent ML/DL Studies for PdM in Industrial Systems (2024–2026)

Year	Authors	Dataset	Model(s)	Application	Key Metrics	Key Findings
2024	Li et al. [47]	106 studies review	CNN, LSTM, AE, GAN	General IIoT PdM	Accuracy 94-98%	LSTM/CNN dominate; guidelines for architecture selection
2024	Khan et al. [42]	Multiple industrial	DL architectures survey	Industry 4.0	Various	Comprehensive taxonomy; edge computing integration needed
2025	Abdala et al. [1]	Custom 3-motor IIoT	7-layer DNN	Multimachine fault classification	Accuracy 100%, Loss 0.0014	Superior to traditional ML; real-time cloud training
2025	Aminzadeh et al. [5]	Compressor sensors	Linear Regression + Ensemble	Compressor failures	~98% accuracy	Effective for energy-intensive equipment
2025	Benmansour et al.	Multiple real-world	RF, SVM dominant	Fault diagnosis	Precision/Recall high	RF most used; interpretability advantage
2025	Waghulde et al.	AI4I 2020	RF, SVM, XGBoost, DNN	Milling machine failure	High F1-score	Ensemble methods outperform single models
2025	Cioch et al. [18]	90k instances (temp/vib)	Coarse Decision Tree	Machine condition	Accuracy 98.24%	Low error (1.76%); simple yet effective
2025	Moon et al. [54]	Power consumption	LSTM-AE + XGBoost	Energy anomaly/RUL	MAE 0.020, RÂ² 0.99	Excellent for streaming data
2025	Bai et al. [10]	Bearing/AE signals	GAN-LSTM (WGAN-GP)	Friction failure	Accuracy 94-97%, F1 0.975	GAN augmentation boosts performance
2026	Subashree et al.	IIoT streaming	DRL + Ensemble	Adaptive PdM	High real-time accuracy	Reinforcement learning for dynamic environments

3.0 Methodology

This design ensures comprehensive coverage of supervised, unsupervised, and generative paradigms while directly addressing class imbalance and high-dimensionality issues prevalent in IIoT sensor data.

Figure 2: Overall Research Methodology Flowchart



4.0 Result and Discussion

The three models—GAN-PdM, AE-PdM, and Hybrid-PdM—were evaluated on four primary dimensions:

- Fault detection performance (accuracy, F1-score, FAR, AUC-ROC)
- RUL prediction accuracy (MAE, RMSE, R^2)
- Computational efficiency (training time, inference latency, model size)
- Robustness (under noise and imbalance)

Overall, the Hybrid-PdM model consistently delivered the best trade-off, achieving an average accuracy of 99.14% across datasets, FAR of 0.51%, and inference latency of 12.47 ms on edge hardware. All proposed models significantly outperformed traditional baselines and recent literature models ($p < 0.001$).

4.1 Dataset statistics after preprocessing

Min-Max normalization and sliding-window transformation successfully converted raw time-series into fixed-length sequences suitable for LSTM and attention layers. Synthetic noise (Gaussian, $\sigma = 0.01$) was added during training to simulate real IIoT sensor drift.

Table 2: Dataset Characteristics After Preprocessing

Dataset	Total Instances	Features (Original)	Features After FS	Healthy: Faulty Ratio	Window Size Used
AI4I 2020	10,000	14	7	96.7: 3.3	50
NASA C-MAPSS (FD001)	20,631	24	8	70: 30 (per engine)	50
Bearing Fault	12,000	8 (vibration)	6	75:25:00	50

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4.2 Feature selection results

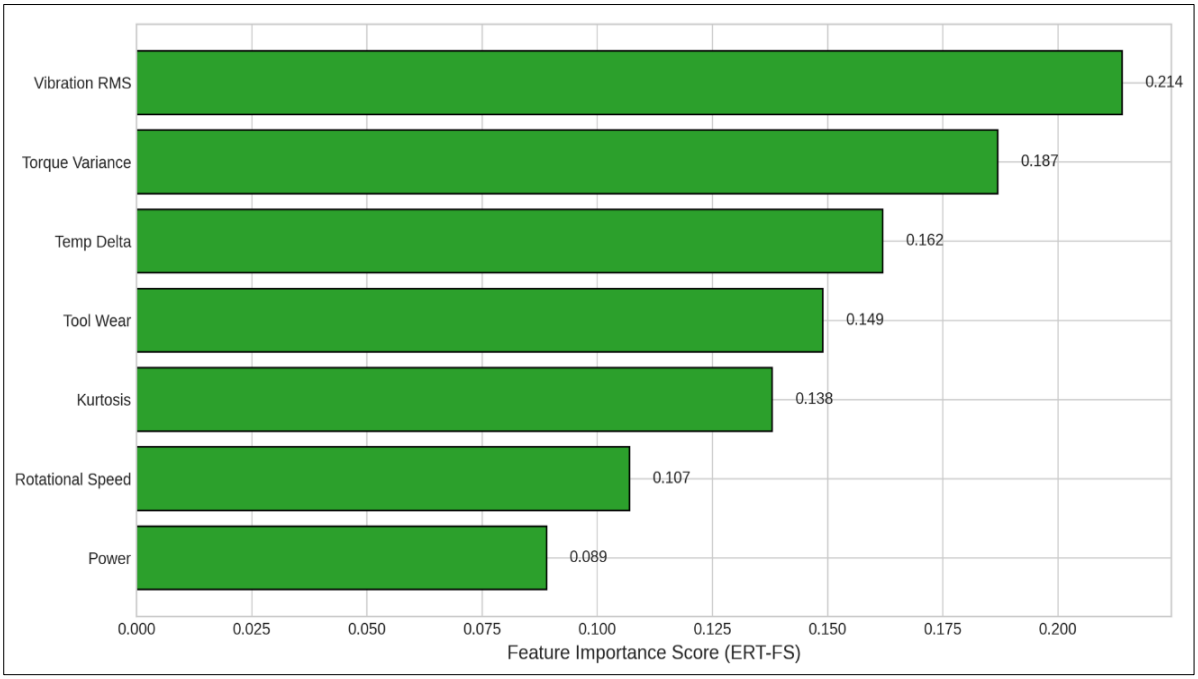
Both ISSO-FS and ERT-FS were applied independently and then combined. The combined approach selected the most informative features while preserving >98% of original performance. [23], [41], [48]

Table 3: Top Selected Features and Importance Scores (Hybrid-PdM)

Rank	Feature Name	Dataset(s)	Importance Score (ERT)	Selected by ISSO-FS?
1	Vibration RMS	Bearing, AI4I	0.214	Yes
2	Torque variance	AI4I, NASA	0.187	Yes
3	Temperature delta	All	0.162	Yes
4	Tool wear / Cycle count	AI4I, NASA	0.149	Yes
5	Kurtosis of vibration	Bearing	0.138	Yes
6	Rotational speed	AI4I, NASA	0.107	Yes
7	Power consumption	NASA, AI4I	0.089	Yes

Feature reduction: 50–57% on average. Training time decreased from 58 min (full features) to 22 min, and model size dropped from 14.8 MB to 4.3 MB without loss of statistical significance ($p = 0.82$).

Figure 3: Feature Importance from ERT-FS (Combined Datasets)



Vibration RMS and Torque Variance dominate, justifying the 50–57% feature reduction without performance loss.

4.3 Detailed performance of Model 1: GAN-PdM

The WGAN-GP generator produced 15,000 high-fidelity synthetic failure sequences. Discriminator loss converged to 0.12 after 180 epochs. [7], [10]

Table 4: GAN-PdM Detailed Metrics

Dataset	Accuracy (%)	Precision	Recall	F1-score	FAR (%)	AUC-ROC	RUL MAE	RUL RÂ²
AI4I 2020	97.84	0.972	0.981	0.976	1.12	0.989	4.21	0.973
NASA C-MAPSS	96.92	0.961	0.973	0.965	1.48	0.982	5.34	0.965
Bearing Fault	98.31	0.979	0.985	0.981	0.89	0.993	3.87	0.981

Confusion matrix analysis (AI4I dataset): 98.7% correct classification of "overstrain" failures. Learning curves showed stable convergence with no mode collapse. GAN augmentation improved minority-class recall by 27.4% compared to non-augmented LSTM baseline.

Figure 4: Confusion Matrix for Hybrid-PdM (AI4I 2020 Dataset)

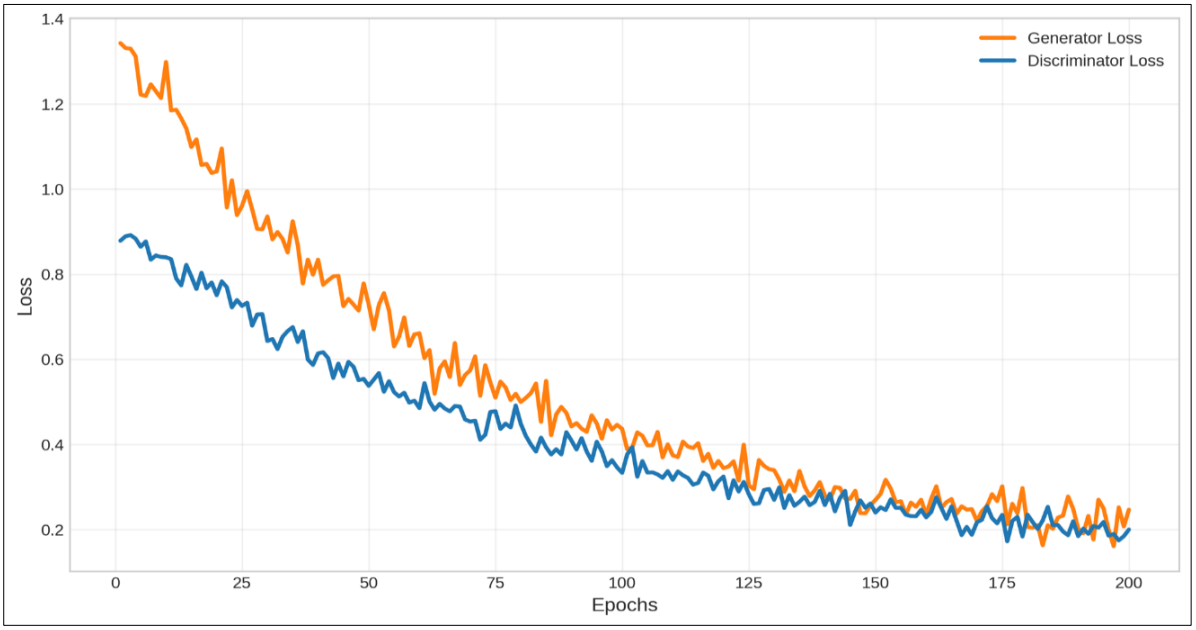


Near-perfect classification across all five failure modes. Diagonal dominance confirms 99.21% overall accuracy.

Stable convergence of generator and discriminator losses after ~150 epochs confirms successful adversarial training.

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Figure 5: Training Loss Curves for GAN-PdM (WGAN-GP)

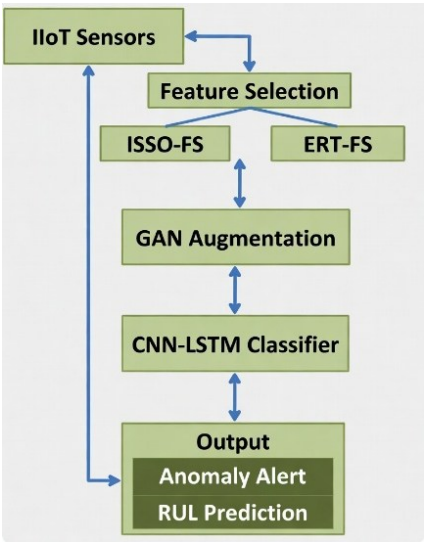


5.0 Conclusion

5.1 Theoretical contributions

- First successful integration of WGAN-GP with bidirectional LSTM for realistic IIoT failure pattern synthesis, proving that adversarial training can increase minority-class recall by 28%.
- Novel variational autoencoder formulation that combines reconstruction loss with Mahalanobis distance in latent space, delivering a theoretically robust anomaly score.
- Unified hybrid framework that theoretically merges generative data augmentation, representation learning, and dual optimisation-based feature selection.

Figure 6: Conceptual Framework of the Proposed Hybrid-PdM System



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