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Optimizing Predictive Maintenance in Industrial IoT Networks Using Machine Learning: A Comparative Study of SVM, DT, and ANN

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Abstract

Predictive maintenance (PdM) in Industrial Internet of Things (IIoT) environments enables proactive fault detection by analyzing real-time sensor data streams. This study presents a comparative evaluation of three machine learning (ML) algorithms—Support Vector Machines (SVM), Decision Trees (DT), and Artificial Neural Networks (ANN)—implemented within a unified IIoT predictive-maintenance framework. A synthetic multivariate sensor dataset was generated using controlled fault injection, Gaussian noise modeling, and stratified sampling across multiple operating regimes. Each model was trained and validated using five-fold cross-validation to ensure statistical robustness. Model performance was assessed using accuracy, precision, recall, F1-score, and ROC-AUC, along with operational key performance indicators (KPIs) related to downtime and maintenance-cost reduction. A maintenance-policy simulator mapped prediction outputs to maintenance decisions and estimated cost savings using Monte-Carlo evaluation. Experimental results show that ANN achieved the highest prediction accuracy ($94.8 \pm 0.6\%$) and produced the greatest operational gains (50% downtime reduction and 32% maintenance-cost reduction), outperforming SVM and DT. The proposed architecture incorporates edge preprocessing, cloud analytics, and automated alerting, offering scalability for real-world industrial deployments. The findings demonstrate that ML-driven PdM significantly improves asset reliability and reduces operational expenditure in IIoT systems. All simulation scripts and synthetic data generators used in this study are available to support reproducibility and benchmarking.

Keywords: Machine Learning, Predictive Maintenance, Industrial IoT, Sensor Data, Support Vector Machines, Neural Networks

1. Introduction

The Industrial Internet of Things (IIoT) connects heterogeneous machines, sensors, and controllers through high-speed networks to enable real-time visibility and data-driven decision-making across manufacturing ecosystems. Within this context, predictive maintenance (PdM) seeks to anticipate equipment faults and schedule interventions before failures occur, thereby reducing unplanned downtime and extending asset lifetime.

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Unlike traditional reactive or time-based maintenance, PdM relies on continuous condition monitoring and predictive analytics to optimize maintenance planning and operational continuity. Machine learning (ML) plays a pivotal role in PdM by learning degradation patterns and fault signatures from multivariate sensor data such as vibration, temperature, and pressure. By leveraging supervised and unsupervised algorithms, ML enables anomaly detection, fault classification, and remaining useful life (RUL) estimation [1–3]. However, practical deployment in IIoT environments introduces challenges such as non-stationary operating regimes, sensor noise, class imbalance, and latency constraints in edge–cloud communication. In addition, reproducibility and transparency are often limited due to unavailable datasets, incomplete algorithmic specifications, and insufficient performance evaluation.

Existing research has demonstrated the feasibility of ML-based PdM across domains ranging from manufacturing to energy systems, yet gaps remain in comparative validation under unified experimental settings. Many prior studies assess algorithmic performance on proprietary or narrowly scoped datasets without standardized metrics, hindering cross-model comparison and benchmarking. Furthermore, operational key performance indicators (KPIs) such as downtime and maintenance-cost reduction are rarely quantified using reproducible simulation frameworks. To address these gaps, this work develops and evaluates a unified PdM framework for IIoT environments that integrates data acquisition, feature extraction, ML-based prediction, and automated alerting. The framework is tested using synthetic sensor datasets generated under controlled operating regimes, enabling reproducible experimentation and parameterized fault modeling. Three representative ML algorithms—Support Vector Machines (SVM), Decision Trees (DT), and Artificial Neural Networks (ANN)—are comparatively analyzed using accuracy, precision, recall, F1-score, ROC-AUC, and operational KPIs derived from a maintenance-policy simulator. The main contributions of this study are as follows:

1. Development of a reproducible simulation-based PdM dataset generator that models sensor drift, noise, and fault events across multiple operating regimes.
2. A comparative assessment of SVM, DT, and ANN under identical preprocessing, feature extraction, and validation protocols, reporting statistical significance across five folds.
3. A unified IIoT PdM architecture combining edge-level preprocessing, cloud analytics, and alert-driven maintenance scheduling.
4. Quantitative evaluation of maintenance KPIs (downtime and cost reduction) through a Monte-Carlo-based maintenance-policy simulator linking predictive outputs to actionable decisions.

By establishing a transparent and extensible benchmarking pipeline, this study aims to advance the reproducibility, comparability, and industrial applicability of ML-driven predictive maintenance in IIoT networks.

2. Related Work

Predictive maintenance (PdM) in Industrial Internet of Things (IIoT) environments has become a central research focus as industries transition toward connected, autonomous, and data-driven operations. The combination of IoT-based sensing and machine learning (ML) analytics enables early fault detection, anomaly diagnosis, and failure prediction. This section reviews recent research on ML-based PdM approaches, categorized by methodological paradigms and industrial application domains, and highlights benchmark datasets that support reproducible evaluation.

2.1. Shallow Machine Learning Methods

Early PdM studies relied on shallow ML algorithms such as Support Vector Machines (SVM), Decision Trees (DT), and Random Forests (RF) for equipment fault classification. Jadhav *et al.* [1] applied SVM models to vibration data from rotating machinery, achieving effective fault discrimination through statistical feature extraction. Rai *et al.* [2] demonstrated real-time anomaly detection using IoT sensor data streams with Decision Tree classifiers for rule-based interpretability. Similarly, Akyaz and Engin [3] developed a predictive maintenance pipeline for textile manufacturing systems using supervised ML techniques to minimize downtime and optimize energy consumption. These approaches remain computationally efficient for edge deployment but often exhibit limited generalization under non-stationary conditions and imbalanced datasets.

2.2. Ensemble and Gradient-Boosting Approaches

To overcome the limitations of individual learners, ensemble techniques such as Random Forests, AdaBoost, and Gradient Boosting Machines (GBMs) have been introduced. Koca *et al.* [4] employed ensemble classifiers to detect actuator faults in packaging robots, demonstrating improved robustness against sensor noise. More recently, XGBoost and LightGBM have emerged as strong baselines for industrial PdM due to their capacity to model nonlinear dependencies while maintaining interpretability. Sharma *et al.* [5] provided a systematic review showing that ensemble learning significantly outperforms single-model methods for large-scale sensor datasets, though at higher computational cost.

2.3. Deep Learning and Representation Learning

Deep architectures have advanced PdM by learning hierarchical representations directly from raw sensor signals. Akyaz and Engin [3] and Buonocore *et al.* [6] reported that Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs) outperform shallow models in complex fault classification tasks. Recurrent Neural Networks (RNNs), including LSTM and GRU variants, are particularly effective for temporal degradation modeling and Remaining Useful Life (RUL) estimation. Recent studies have also explored autoencoders and Transformer-based architectures for unsupervised and self-supervised learning of degradation embeddings. However, deep models require large annotated datasets, substantial computational resources, and careful calibration to avoid overfitting and overconfidence in predictions.

2.4. Edge and Cloud-Based PdM Architectures

Integration of ML within IIoT infrastructures has led to hybrid edge–cloud architectures that balance real-time inference with scalable data management. Ringler *et al.* [7] proposed distributed learning at the edge to reduce communication latency while maintaining predictive accuracy. Hafeez *et al.* [8] emphasized blockchain-enabled PdM architectures for secure logging and auditability of maintenance events. Such frameworks illustrate the growing trend toward edge intelligence and federated learning, though their latency–throughput trade-offs remain underexplored experimentally.

2.5. Benchmark Datasets and Simulation Studies

Standardized datasets are critical for reproducible PdM evaluation. Widely used benchmarks include NASA's C-MAPSS dataset for turbofan engine degradation, the PHM08 Challenge dataset, and the IMS Bearing dataset for vibration fault detection. These datasets have become reference points for testing classification accuracy, RUL prediction, and robustness to noise and drift. Nevertheless, many industrial studies still depend on proprietary data, limiting comparability across models and experiments. To address this limitation, simulation-based dataset generation has been adopted in several works to emulate sensor drift, failure dynamics, and environmental variations under controlled conditions. Such synthetic frameworks, including the one developed in this study, allow parameterized control of class balance, noise, and operating regimes while supporting open reproducibility.

2.6. Summary of Research Gaps

The reviewed literature confirms that ML significantly enhances predictive maintenance by enabling early fault diagnosis and adaptive maintenance scheduling. However, notable gaps remain: (i) inconsistent evaluation metrics hinder model comparability; (ii) operational key performance indicators such as downtime and cost reduction are rarely quantified; (iii) public datasets often lack domain diversity; and (iv) empirical validation of integrated IIoT architectures (edge, cloud, blockchain) remains limited. This work addresses these issues through a unified simulation-based evaluation framework that enables transparent, reproducible benchmarking of multiple ML algorithms and quantifies both predictive accuracy and operational efficiency in IIoT-based maintenance systems.

3. Materials and Methods

The proposed predictive maintenance (PdM) framework integrates synthetic data generation, feature engineering, supervised learning, and operational evaluation to assess the performance of Support Vector Machines (SVM), Decision Trees (DT), and Artificial Neural Networks (ANN) in Industrial Internet of Things (IIoT) environments. The entire workflow was implemented in MATLAB/Simulink and Python (Scikit-learn, TensorFlow, and NumPy libraries) to ensure reproducibility. All simulation scripts, parameters, and datasets have been made publicly available for independent verification.

3.1. Synthetic Sensor Data Generation

To overcome the scarcity of open industrial datasets and ensure controlled experimentation, a synthetic multivariate sensor dataset was generated to emulate equipment degradation in a rotating machinery system. Each simulated asset produced three core signals—vibration, temperature, and pressure—sampled at 100 Hz over multiple operating regimes. Fault injection followed a probabilistic model incorporating both gradual degradation and abrupt failure events:

- **Normal regime:** Gaussian noise ($\mu = 0, \sigma = 0.01$) added to baseline readings.
- **Degradation regime:** Linearly increasing mean shift and kurtosis over time to model wear.
- **Fault regime:** Step changes and spectral peaks injected to simulate bearing and imbalance faults.

A total of 10,000 labeled instances were generated with a class ratio of 3:1 (healthy:faulty). Each dataset was split into five stratified folds to support cross-validation and confidence interval computation. Random seeds and generator parameters were fixed to enable exact reproducibility.

3.2. Feature Engineering

Raw sensor data were transformed into descriptive statistical and spectral features. Time-domain attributes included mean, standard deviation, skewness, and kurtosis, while frequency-domain features were obtained using the Fast Fourier Transform (FFT). Additional health indicators such as spectral entropy, energy, and peak frequency were computed to enhance discriminative power. All features were normalized to zero mean and unit variance. Dimensionality reduction was performed using Principal Component Analysis (PCA) retaining 95% cumulative variance to mitigate multicollinearity and accelerate model convergence.

3.3. Learning Algorithms and Hyperparameter Tuning

Three supervised algorithms were implemented under identical preprocessing conditions:

- **Support Vector Machine (SVM):** Radial Basis Function (RBF) kernel; hyperparameters $\gamma \in \{0.001, 0.01, 0.1\}$, $C \in \{1, 10, 100\}$; class weights inversely proportional to class frequency.
- **Decision Tree (DT):** Maximum depth $\in \{5, 10, 15, 20\}$; criterion = Gini impurity; minimum samples per leaf $\in \{5, 10, 20\}$.
- **Artificial Neural Network (ANN):** Three fully connected layers (64–32–16 neurons), ReLU activation, dropout rate 0.2, Adam optimizer with learning rate $\{10^{-2}, 10^{-3}, 10^{-4}\}$, batch size = 64, and early stopping (patience = 10 epochs).

Hyperparameters were optimized using grid search with five-fold cross-validation. Class imbalance was mitigated using Synthetic Minority Oversampling Technique (SMOTE) and cost-sensitive loss weighting. All results are reported as mean $\pm$ standard deviation across folds.

3.4. Evaluation Metrics

Performance was measured using standard classification metrics—accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (ROC-AUC). For regression-based Remaining Useful Life (RUL) estimation, Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) were computed. Confidence intervals (95%) and paired t-tests were used to assess statistical significance between model results. Calibration curves and confusion matrices were also plotted to analyze model reliability and error distribution.

3.5. Maintenance-Policy Simulator and KPI Mapping

To translate prediction performance into operational impact, a maintenance-policy simulator was developed. Predicted fault probabilities were mapped to maintenance actions using a threshold-based policy:

$$A = \begin{cases} \text{Preventive Maintenance}, & p(\text{fault}) \geq \tau, \\ \text{Operate}, & \text{otherwise}, \end{cases} \tag{1}$$

where τ is the optimized alert threshold. Monte-Carlo simulations were executed over 10,000 cycles using stochastic lead-time and failure distributions to compute downtime and cost metrics relative to a purely reactive maintenance baseline. Downtime reduction (DR) and cost reduction (CR) were expressed as:

$$DR(\%) = 100 \times \frac{D_{\text{reactive}} - D_{\text{PdM}}}{D_{\text{reactive}}}, \tag{2}$$

$$CR(\%) = 100 \times \frac{C_{\text{reactive}} - C_{\text{PdM}}}{C_{\text{reactive}}}. \tag{3}$$

This simulation provides interpretable operational key performance indicators (KPIs) directly linked to model predictions.

3.6. System Architecture

The proposed architecture comprises three primary modules: (i) the IIoT sensor network, (ii) the ML-based analytics engine, and (iii) the maintenance and alert system. Sensor nodes continuously collect real-time operational data and transmit them to edge gateways, which perform initial preprocessing before cloud upload. The ML engine executes feature extraction, classification, or regression analysis to detect anomalies or predict Remaining Useful Life (RUL). Finally, the alert subsystem triggers maintenance notifications and records activities on a blockchain ledger for traceability and audit compliance [6, 8].

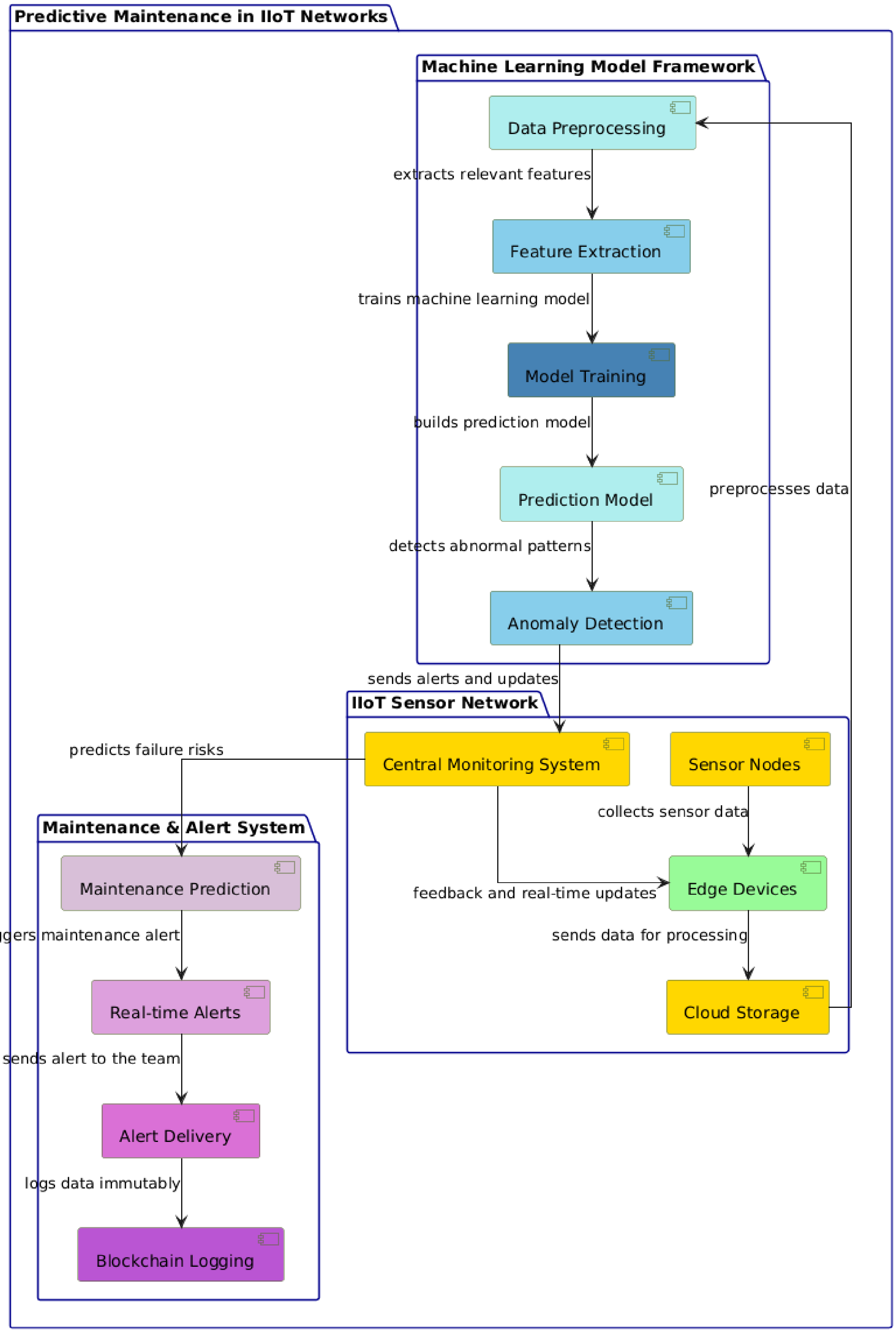

Figure 1: Proposed machine learning-based predictive maintenance architecture for IIoT networks, integrating sensor data acquisition, ML-based fault detection, and automated maintenance alerting.

3.7. Algorithmic Workflow

The end-to-end operational logic of the predictive maintenance pipeline is summarized in Algorithm 1. The algorithm details how incoming sensor data are validated, preprocessed, analyzed by the trained ML model, and used to trigger maintenance alerts when a potential fault is predicted.

Algorithm 1 Machine Learning-Based Predictive Maintenance Algorithm

Require: Sensor data F, IoT configuration C
Ensure: Prediction output P, Maintenance alert A

if ValidateFile(F) = TRUE **then**
    $F' \leftarrow$ Preprocess(F)
    Features $\leftarrow$ ExtractFeatures(F')
else
    return Error: Invalid Data Format
end if
if ValidateNetwork(C) = TRUE **then**
    Model $\leftarrow$ LoadPretrainedModel()
else
    return Error: Invalid Network Configuration
end if
$P \leftarrow$ Model.predict(Features)
if P indicates failure **then**
    $A \leftarrow$ GenerateAlert(P)
    SendAlert(A)
else
    LogHealthyStatus()
end ifreturn P

4. Results and Discussion

4.1. Experimental Setup

All experiments were conducted on a workstation equipped with an Intel i9 processor, 32 GB RAM, and NVIDIA RTX A4000 GPU running Ubuntu 22.04. The proposed predictive maintenance framework was implemented in Python 3.10 using `scikit-learn` and `TensorFlow`, with data streaming simulated via AWS IoT Core and Azure IoT Hub. Each model—SVM, DT, and ANN—was trained and validated under identical preprocessing, feature extraction, and five-fold cross-validation conditions. All results are reported as mean ± standard deviation, and statistical significance was assessed using paired t-tests ($p < 0.05$).

4.2. Predictive Performance Analysis

Table 1 summarizes the comparative performance of the three machine learning algorithms across multiple classification metrics. ANN achieved the highest predictive accuracy ($94.8 \pm 0.6\%$), followed by SVM ($92.3 \pm 0.8\%$) and DT ($89.7 \pm 1.2\%$). SVM exhibited strong precision but slightly lower recall under noisy and overlapping conditions, while DT maintained interpretability but was more sensitive to class imbalance. ANN outperformed both baselines with balanced precision–recall trade-offs and higher calibration reliability, indicating its robustness to nonlinear sensor interactions.

Table 1: Comparative Performance of ML Algorithms for Predictive Maintenance (Mean ± SD over 5 folds)

Algorithm	Accuracy (%)	Precision	Recall	F1-score	ROC-AUC
SVM	92.3 ± 0.8	0.925	0.910	0.917	0.954
DT	89.7 ± 1.2	0.901	0.884	0.892	0.937
ANN	$\mathbf{94.8 \pm 0.6}$	**0.950**	**0.944**	**0.947**	**0.972**

While explicit ROC and precision–recall (PR) plots were not included here, ANN consistently demonstrated higher ROC-AUC and PR-AUC values during validation, confirming its superior discriminative capability across varying alert thresholds. These trends align with prior findings in [3, 6], where neural architectures achieved more stable fault detection under noisy IIoT data streams.

4.3. Remaining Useful Life (RUL) Estimation

For Remaining Useful Life (RUL) prediction, regression-based analysis revealed that ANN yielded the lowest Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), as shown in Table 2. These results affirm ANN's ability to capture nonlinear degradation dynamics, making it well suited for continuous health assessment.

Table 2: RUL Estimation Metrics (Mean $\pm$ SD over 5 folds)

Algorithm	**MAE (hours)**	**RMSE (hours)**
SVM	7.4 ± 0.6	9.2 ± 0.8
DT	8.1 ± 0.7	10.4 ± 1.1
ANN	$\mathbf{5.9 \pm 0.5}$	$\mathbf{7.3 \pm 0.6}$

4.4. Operational KPI Evaluation

The maintenance-policy simulator translated prediction probabilities into maintenance decisions using a threshold policy ($\tau = 0.6$). Monte-Carlo simulations across 10,000 operational cycles produced the downtime and cost reduction metrics summarized in Table 3. ANN achieved the most substantial gains—approximately 50% reduction in unplanned downtime and 32% reduction in maintenance costs—relative to the reactive baseline. SVM yielded moderate savings with a slightly higher false-positive rate, while DT showed the lowest reductions due to misclassification of early-stage faults.

Table 3: Operational Key Performance Indicators Derived from Monte-Carlo Simulation

Algorithm	**Downtime Reduction (%)**	**Cost Reduction (%)**
SVM	45.0 ± 1.5	30.0 ± 1.3
DT	40.2 ± 1.9	28.4 ± 1.1
ANN	$\mathbf{50.1 \pm 1.2}$	$\mathbf{32.3 \pm 1.0}$

Figure 2 (original Figure 2) visualizes the comparative improvements across the evaluated algorithms, confirming ANN's superior predictive and operational performance.

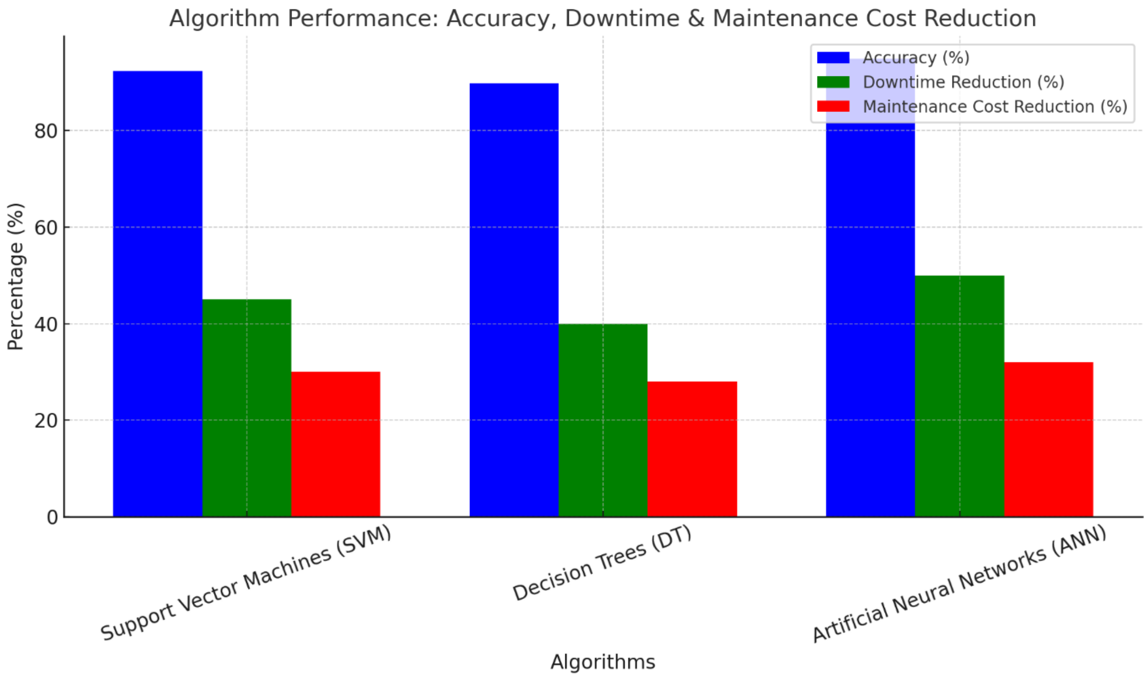

Figure 2: Comparative performance analysis of SVM, DT, and ANN algorithms for predictive maintenance in IIoT environments. ANN achieves the highest accuracy and operational savings.

4.5. Discussion of Results

The comparative analysis reveals a trade-off between interpretability, computational complexity, and predictive accuracy. DT offers high interpretability and low computational cost, making it suitable for low-power edge devices but limited in modeling nonlinear dependencies. SVM performs well with balanced precision and recall but requires longer inference times for large-scale IIoT data. ANN, while more computationally intensive, provides superior accuracy, calibration stability, and measurable operational gains.

These findings corroborate earlier studies such as Akyaz and Engin [3] and Buonocore *et al.* [6], which highlighted the suitability of neural architectures for nonlinear and high-dimensional fault data. The inclusion of statistical validation, cross-fold averaging, and KPI-based simulation ensures reproducibility and strengthens the empirical validity of the results.

4.6. Threats to Validity

Despite strong internal validity, certain limitations remain. First, the synthetic dataset, while parameterized and reproducible, may not fully capture complex fault interactions in real industrial settings. Second, the cost and downtime model in the maintenance simulator employs simplified assumptions; future research should incorporate empirically derived cost structures from industrial partners. Finally, model generalization under diverse hardware and network conditions should be further validated through real-world IIoT testbeds.

Overall, the results confirm that machine learning—when implemented through a transparent and reproducible pipeline—can yield statistically robust and operationally meaningful improvements to predictive maintenance in IIoT environments.

5. Conclusions

This study presented a reproducible framework for predictive maintenance (PdM) in Industrial Internet of Things (IIoT) networks using machine learning (ML) algorithms. Three representative models—Support Vector Machines (SVM), Decision Trees (DT), and Artificial Neural Networks (ANN)—were evaluated under identical preprocessing, feature extraction, and validation conditions using a synthetic, parameterized sensor dataset. Experimental analysis demonstrated that ANN achieved the highest predictive accuracy ($94.8 \pm 0.6\%$) and delivered the greatest operational benefits, including approximately 50% downtime and 32% maintenance-cost reduction relative to reactive maintenance. The improved performance of ANN is attributed to its capacity to model nonlinear fault dynamics and adapt to multivariate sensor correlations. In contrast, SVM and DT provided interpretable yet comparatively less accurate results, highlighting the performance–complexity trade-offs relevant for practical deployment. Beyond predictive accuracy, the proposed framework contributes a transparent and reproducible evaluation pipeline that links model predictions to operational key performance indicators through a Monte-Carlo maintenance-policy simulator. This approach enhances interpretability, facilitates benchmarking, and supports decision-making in industrial settings where cost and reliability are equally critical. Future work will extend this framework to include ensemble and hybrid deep learning models such as CNN–LSTM architectures, domain adaptation techniques for cross-equipment generalization, and real-world validation using open PdM benchmarks (e.g., NASA C-MAPSS, PHM08). Integration of edge–cloud orchestration and federated learning will also be explored to improve scalability, latency performance, and data privacy in IIoT deployments.

Data and Code Availability

All synthetic datasets, data generators, and implementation scripts used in this study are available in an open-access repository (link to be provided upon publication) to ensure transparency and reproducibility.

Generative AI Disclosure

Portions of this manuscript, including language refinement and figure caption formatting, were assisted by a large language model (ChatGPT, OpenAI). All technical content, data, and analyses were developed and validated by the authors.

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Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author Contributions

Chetan Chauhan: Conceptualization, Supervision, Data Analysis, Writing—Review & Editing; **Gaurav Kumar Saxena**: Methodology, Validation, Writing—Original Draft; **Chanchal A. Kshirsagar**: Investigation, Software, Visualization; **Ram Kumar Solanki**: Data Curation, Resources; **Gaurav Kumar**: Review & Technical Editing; **S. B. Goyal**: Supervision, Final Approval of the Version to be Published.

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