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RESEARCH ARTICLE

A Comparative and Hybrid Machine Learning Framework for IoT-Based Predictive Maintenance of Rotating Machinery

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Abstract

Predictive Maintenance (PdM) has emerged as a critical application of Industrial Internet of Things (IIoT) and artificial intelligence for improving reliability and reducing unplanned downtime in industrial rotating machinery. While existing studies demonstrate high predictive accuracy using either classical machine learning (ML) or deep learning (DL) techniques, most approaches are evaluated in isolation and fail to address deployment feasibility, interpretability, and computational constraints inherent in industrial IoT systems. This paper proposes a comparative and hybrid predictive maintenance framework that integrates feature-based machine learning models and convolutional neural network (CNN)–based deep learning models within a unified IIoT architecture. Building upon prior work on ML-based classification and vibration-based CNN time-series learning, the proposed framework systematically evaluates both paradigms across predictive performance, computational complexity, and deployment suitability. Extensive experiments using IoT-derived sensor datasets demonstrate that ensemble ML models provide efficient and interpretable solutions for edge-level deployment, whereas CNN-based models achieve superior fault sensitivity for high-frequency vibration signals. Based on quantitative analysis, a hybrid decision algorithm is introduced to guide model selection under practical industrial constraints. The results confirm that decision-oriented hybrid PdM architectures offer superior scalability and industrial applicability compared to standalone modeling approaches.

Keywords: Predictive maintenance, Industrial IoT, Rotating machinery, Machine learning, Deep learning, Convolutional neural networks, Hybrid framework.

Introduction

Rotating machinery such as induction motors, pumps, compressors, turbines, fans, and gearboxes constitutes the operational backbone of modern industrial systems. Failures in these assets result in significant production losses, increased maintenance costs, and safety risks. In recent years, the convergence of automation and digital technologies under the Industry 4.0 paradigm has intensified the need for intelligent asset health management (Lee et al., 2015), (S. Wang et al.,2016).

Traditional maintenance strategies, including reactive and time-based preventive maintenance, are inadequate for modern industrial environments due to their inability to adapt to dynamic operating conditions (Carvalho et al.,2019), (R. K. Mobley et al.,2002). These limitations have driven the adoption of predictive maintenance (PdM), which aims to anticipate failures by continuously monitoring machine health using sensor data and intelligent analytics (Carvalho et al.,2019).

The emergence of the Industrial Internet of Things (IIoT) has enabled large-scale deployment of sensors that generate continuous streams of operational data, including vibration, temperature, torque, and rotational speed (Lee et al., 2015), (J. Wan et al., 2011). When combined with artificial intelligence techniques, this data facilitates early fault detection and condition-based maintenance decision-making (S. Yin et al.,2015).

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Classical machine learning (ML) techniques such as Logistic Regression, Support Vector Machines, Random Forests, and gradient boosting methods have been widely applied for predictive maintenance using engineered features derived from sensor signals (A. Widodo et al.,2007), (T. K. Ho, 1995), (G. Susto et al., 2015). These models are computationally efficient and interpretable, making them attractive for industrial deployment, particularly in resource-constrained environments.

More recently, deep learning (DL) models have demonstrated superior capability in learning hierarchical and temporal representations directly from raw sensor data. Convolutional neural networks (CNNs) have shown strong performance in vibration-based fault diagnosis of rotating machinery (Wei et al.,2019), (W. Zhang et al.,2017), (M. Ince et al., 2016), (L. Wen et al., 2018). However, deep learning models often incur higher computational cost and lack interpretability, limiting their widespread industrial adoption.

Despite these advances, most existing studies evaluate ML and DL models in isolation and primarily emphasize predictive accuracy (Wei et al.,2019), (S. Zhang et al., 2020). Limited attention is paid to deployment feasibility, scalability, and interpretability under heterogeneous IIoT infrastructures. This motivates the need for a decision-oriented hybrid predictive maintenance framework that integrates multiple modeling paradigms while accounting for industrial constraints.

This paper addresses these gaps by proposing a comparative and hybrid predictive maintenance framework that unifies ML and CNN-based DL models within a single IIoT architecture. Rather than introducing a new learning algorithm, the contribution lies in systematic evaluation, integration, and decision-oriented deployment of existing models to enhance industrial applicability.

The main contributions of this paper are as follows:

- A comprehensive comparative analysis of classical ML and CNN-based DL models for IoT-enabled predictive maintenance.
- Quantitative evaluation of predictive performance, computational complexity, and deployment feasibility.
- A hybrid decision algorithm that guides model selection based on data characteristics and system constraints.
- A scalable IIoT-oriented framework suitable for real-world industrial deployment.

Related Work

Predictive maintenance (PdM) has gained substantial research attention due to its potential to improve asset reliability, reduce unplanned downtime, and optimize maintenance costs in industrial environments. With the advent of Industrial Internet of Things (IIoT), PdM systems increasingly rely on large-scale sensor data combined with intelligent data analytics. Existing research in this domain can broadly be categorized into three streams: (i) feature-based machine learning approaches, (ii) deep learning–based time-series models, and (iii) emerging hybrid and system-level frameworks.

Feature-Based Machine Learning Approaches for PdM

Early PdM research predominantly relied on classical machine learning models combined with handcrafted feature extraction. Vibration, temperature, current, torque, and acoustic signals were transformed into statistical, frequency-domain, or time–frequency features, which were then used for supervised classification or regression tasks. Signal preprocessing and frequency-domain analysis remain fundamental in vibration-based fault diagnosis (C. R. Berger et al., 2010)

Algorithms such as Support Vector Machines (SVM), Random Forest (RF), Logistic Regression (LR), and Gradient Boosting have demonstrated strong performance in fault detection and diagnosis of rotating machinery.

Random Forest–based approaches are particularly popular due to their robustness to noise and ability to handle nonlinear relationships. Several studies reported high classification accuracy using RF models for bearing and motor fault diagnosis, emphasizing their interpretability through feature importance analysis. Similarly, gradient boosting methods such as XGBoost have shown improved generalization and robustness when dealing with high-dimensional sensor data.

Despite these advances, most existing studies evaluate ML and DL models in isolation and primarily emphasize predictive accuracy (Wei et al.,2019), (S. Zhang et al., 2020). Limited attention is paid to deployment feasibility, scalability, and interpretability under heterogeneous IIoT infrastructures. This motivates the need for a decision-oriented hybrid predictive maintenance framework that integrates multiple modeling paradigms while accounting for industrial constraints.

However, these approaches rely heavily on domain-specific feature engineering and are limited in capturing complex temporal dependencies inherent in vibration signals (R. B. Randall, 2011), (J. G. Proakis, 2007). Class imbalance further degrades fault detection performance unless explicitly addressed using resampling techniques such as SMOTE (N. V. Chawla et al., 2002)

The authors' prior work demonstrated that ensemble ML models can achieve high predictive accuracy when combined with systematic feature engineering and imbalance handling. However, the reliance on handcrafted features and limited temporal modeling capability restricts their applicability in complex and evolving industrial environments.

Deep Learning–Based PdM Using Time-Series Data

Deep learning techniques have significantly advanced vibration-based predictive maintenance by enabling automated feature learning from raw time-series data (I. Goodfellow et al.,2016), (Y. LeCun et al.,2019). CNN-based architectures, particularly one-dimensional CNNs, have shown superior fault detection performance for rotating machinery (Wei et al.,2019), (W. Zhang et al.,2017), (M. Ince et al., 2016). Recent advances in deep learning have significantly influenced PdM research by enabling automated feature learning directly from raw sensor data. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and hybrid CNN–RNN architectures have been extensively explored for vibration-based fault diagnosis.

CNN-based models are particularly effective in extracting local and hierarchical features from vibration signals. One-dimensional CNNs (Conv1D) have been widely adopted for PdM tasks due to their ability to process raw time-series data with reduced preprocessing. By applying convolutional filters, these models learn frequency and temporal patterns associated with different fault conditions.

Hybrid architectures combining CNNs with LSTM or BiLSTM layers have further improved fault detection by capturing both spatial and long-term temporal dependencies. These models have demonstrated superior recall and fault sensitivity, especially for early-stage degradation patterns that are difficult to detect using traditional ML models.

However, deep learning–based PdM approaches introduce new challenges. High computational complexity, longer training times, and increased memory requirements limit their feasibility for deployment on edge or resource-constrained IoT devices. Moreover, deep models are often criticized for their lack of interpretability, which poses challenges for maintenance engineers who require explainable insights for decision-making. Hybrid CNN–RNN models have also been explored to capture long-term temporal dependencies (S. Hochreiter et al., 1997), (P. Malhotra et al., 2015). Despite improved fault sensitivity, deep learning models suffer from high computational complexity and limited interpretability, which restricts their deployment in industrial IoT systems (S. Zhang et al., 2020).

The authors' previous work on CNN-based vibration analysis confirmed the superior fault sensitivity of deep models but also highlighted their deployment constraints and limited transparency.

Hybrid and System-Level Predictive Maintenance Frameworks

Recent studies have explored hybrid predictive maintenance frameworks and edge–cloud collaborative architectures to address deployment challenges (S. Wang et al.,2016), (O. B. Sezer et al., 2018). Some studies propose combining physics-based models with data-driven learning to enhance robustness and interpretability. Others explore ensemble learning strategies that integrate ML and DL outputs for improved performance.

Edge–cloud collaborative PdM architectures have also been investigated, wherein lightweight models operate at the edge for real-time monitoring, while complex deep learning models are deployed in the cloud for advanced diagnostics. These architectures acknowledge the heterogeneous nature of industrial IoT systems but often lack formal decision mechanisms for model selection.

Despite these advancements, existing hybrid approaches remain largely model-centric, focusing on algorithmic fusion rather than decision-oriented deployment strategies. There is limited guidance on when to use classical ML versus deep learning based on data characteristics, computational constraints, and operational requirements.

Prior work by the authors demonstrated the effectiveness of feature-based machine learning models for IoT-based predictive maintenance (Bisht et al., 2025) and subsequently explored CNN-based vibration time-series modeling for fault diagnosis (Bisht et al., 2025). Building upon these works, the present study focuses on system-level integration and deployment-aware decision-making, which has not been adequately addressed in existing literature.

Research Gap and Motivation

Based on the literature review, the following gaps are identified:

- Most PdM studies evaluate ML and DL models independently, offering limited comparative insights.
- Accuracy is often treated as the primary evaluation metric, while computational cost, interpretability, and deployment feasibility are overlooked.
- Existing hybrid frameworks lack systematic decision logic aligned with industrial IoT constraints.
- There is insufficient emphasis on translating model-level performance into deployable system-level solutions.

To address these gaps, this paper proposes a comparative and hybrid predictive maintenance framework that unifies feature-based machine learning and CNN-based deep learning within a decision-oriented IIoT architecture. Unlike prior studies, the focus is not on introducing new algorithms but on enabling context-aware model selection and integration, thereby improving industrial applicability and scalability.

System Architecture and Problem Formulation

This section outlines the proposed system architecture for IoT-enabled predictive maintenance and presents the mathematical formulation of the fault detection problem. The formulation establishes a common basis for evaluating machine learning and deep learning approaches under practical deployment constraints.

IIoT-Based Predictive Maintenance Architecture

The proposed predictive maintenance system follows a layered Industrial IoT architecture designed to support scalable data acquisition, processing, and analytics. The architecture consists of four primary layers: sensing, preprocessing, analytics, and decision support.

The sensing layer comprises IoT-enabled sensors mounted on rotating machinery to continuously capture vibration, temperature, torque, and rotational speed data. The preprocessing layer performs signal conditioning, normalization, segmentation, and feature extraction. The analytics layer hosts both feature-based machine learning models and CNN-based deep learning models. Finally, the decision support layer translates model outputs into actionable maintenance insights and alerts.

Problem Formulation

Let

$\mathbf{X} = \{x_1, x_2, \ldots, x_n\}$ denote multivariate sensor observations collected over time. The predictive maintenance task is formulated as a supervised classification problem:

$f(\mathbf{X}) \rightarrow y, y \in \{0,1\}$ where $y=0$ represents normal operation and $y=1$ represents a faulty condition.

For vibration-based deep learning models, the input is represented as a time-series:

$\mathbf{V} = \{v_1, v_2, \ldots, v_T\}$ The objective is to learn a function $f(\cdot)$ that maximizes fault detection performance while satisfying computational and deployment constraints.

Feature-based Machine Learning Models For Predictive Maintenance

This section describes the feature-based machine learning (ML) models employed for predictive maintenance of rotating machinery. These models constitute the first analytical pillar of the proposed hybrid framework and are designed to deliver efficient, interpretable, and resource-aware fault classification, making them suitable for deployment in edge and gateway layers of Industrial IoT systems.

Feature Representation and Engineering

Let the multivariate sensor signals acquired from rotating machinery be denoted as:

$\mathbf{X}(t) = \{x_1(t), x_2(t), \ldots, x_m(t)\}$ where $x_i(t)$ represents the i^{th} sensor measurement at time t, including vibration, temperature, torque, and rotational speed.

Since classical ML models operate on fixed-length feature vectors, the raw time-series data is transformed into a structured feature representation:

$\mathbf{F} = [f_1, f_2, \ldots, f_k]$ Feature engineering is performed in both time and operational domains to capture degradation-related characteristics.

Time-domain Statistical Features

For vibration and operational signals, the following statistical features are computed over segmented windows of length N:

Mean

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$$

Standard deviation

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$$

Root Mean Square (RMS)

$$\text{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$$

Skewness and kurtosis, which capture asymmetry and impulsiveness of vibration signals.

These features are sensitive to mechanical defects such as imbalance, misalignment, and bearing wear.

Operational and Engineered Features

To incorporate domain knowledge, additional engineered features are derived:

Temperature difference

$$\Delta T = T_{\text{process}} - T_{\text{ambient}}$$

Mechanical power:

$$P = \tau \cdot \omega$$

where τ is torque and ω is angular speed.

Such features enhance fault separability by linking sensor data to physical operating conditions.

Handling Class Imbalance

Predictive maintenance datasets are inherently imbalanced, with fault instances occurring far less frequently than healthy observations. To mitigate this issue, the Synthetic Minority Oversampling Technique (SMOTE) is applied exclusively to the training data (N. V. Chawla et al., 2002).

Given a minority class sample $\mathbf{F}_i$, synthetic samples are generated as:

$$\mathbf{F}_{\text{new}} = \mathbf{F}_i + \lambda\left(\mathbf{F}_j - \mathbf{F}_i\right), \lambda \in (0,1)$$

This approach improves fault recall while preserving the original data distribution in the test set.

Machine Learning Models

Logistic Regression

Logistic Regression models the probability of failure as:

$$P(y=1 \mid \mathbf{F}) = \frac{1}{1 + e^{-\left(\mathbf{w}^T \mathbf{F} + b\right)}}$$

Although linear, Logistic Regression serves as a baseline due to its interpretability and low computational cost.

Support Vector Machine (SVM)

SVM constructs an optimal separating hyperplane by solving:

$$\min_{\mathbf{w},b} \frac{1}{2} || \mathbf{w} ||^2 + C\sum_i \xi_i$$

subject to margin constraints. The Radial Basis Function kernel is employed to model nonlinear decision boundaries.

Random Forest

Random Forest is an ensemble of decision trees:

$$\hat{y} = \text{mode}\{h_1(\mathbf{F}), h_2(\mathbf{F}), \ldots, h_n(\mathbf{F})\}$$

Each tree is trained using bootstrap sampling and random feature selection, reducing overfitting and improving generalization. Random Forest ensembles improve robustness through bootstrap aggregation and random feature selection (T. K. Ho, 1995).

Extreme Gradient Boosting (XGBoost)

XGBoost minimizes the regularized objective:

$$\mathcal{L} = \sum_i l(y_i, \hat{y}_i) + \sum_k \Omega(f_k)$$

where $\Omega(\cdot)$ penalizes model complexity. Its sequential learning mechanism makes it effective for structured industrial datasets. Extreme Gradient Boosting optimizes a regularized objective function to improve generalization performance (T. Chen et al., 2016).

ML Training and Selection Algorithm

Algorithm 1: Feature-Based ML Training and Selection

Input: Feature matrix F, labels y
Output: Best-performing ML model M
1: Normalize F using Z-score scaling
2: Apply SMOTE to training subset
3: Train LR, SVM, RF, and XGBoost models
4: Evaluate using cross-validation
5: Select model maximizing F1-score and ROC–AUC
6: Return selected model M

Computational Characteristics

Feature-based ML models exhibit:

- Training complexity: $O(n\log n)$ for tree-based models
- Inference latency: typically < 10 ms
- Memory footprint: low

These properties make them ideal for edge-level continuous monitoring.

Cnn-Based Deep Learning Model for Vibration Time-Series Analysis

This section describes the CNN-based deep learning model used for vibration-based predictive maintenance. Unlike classical ML models, the CNN architecture learns discriminative features directly from raw time-series data, enabling superior modeling of complex temporal fault patterns. One-dimensional CNNs are particularly suitable for vibration-based predictive maintenance due to their ability to learn local temporal patterns directly from raw signals (W. Zhang et al.,2017), (M. Ince et al., 2016).

Vibration Signal Representation

Let the vibration signal segment be represented as:

$$\mathbf{V} = \{v_1, v_2, \ldots, v_T\}, \mathbf{V} \in \mathbb{R}^{T\times 1}$$

Each segment corresponds to a fixed-length window capturing dynamic machine behavior.

One-Dimensional Convolution Operation

The 1D convolution is defined as:

$$y(t) = \sum_{i=0}^{k-1} w(i) \cdot v(t+i) + b$$

where k is kernel size and $w(i)$ are learnable parameters. Multiple filters extract diverse fault-related patterns.

CNN Architecture Design

The CNN model consists of:

Conv1D Block 1

- 64 filters, kernel size 3
- ReLU activation
- Batch normalization
- Max pooling

Conv1D Block 2

- 128 filters, kernel size 3
- ReLU activation
- Batch normalization
- Max pooling

Fully Connected Layers

- Dense layer with 64 neurons
- Dropout (0.3)
- Sigmoid output layer

This architecture balances expressive power with computational feasibility. The adopted CNN architecture is inspired by prior studies that demonstrated robust fault diagnosis performance on rotating machinery vibration data (Wei et al.,2019), (L. Wen et al., 2018).

Loss Function and Optimization

Binary cross-entropy loss is used:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)]$$

The Adam optimizer updates network parameters using adaptive learning rates.

Table 1: CNN Hyperparameters

Parameter	*Value*
Optimizer	Adam
Learning rate	0.001
Loss function	Binary cross-entropy
Epochs	100
Batch size	32
Dropout rate	0.3

CNN Training Algorithm

Algorithm 2: CNN-Based PdM Training

Input: Vibration segments V, labels y
Output: Trained CNN model D
1: Normalize vibration segments
2: Initialize CNN parameters
3: for epoch = 1 to N do
4: Forward propagation
5: Compute loss
6: Backpropagate gradients
7: Update parameters using Adam
8: end for
9: Return trained model D

Computational Considerations

CNN-based models exhibit:

- Higher training time (GPU recommended)
- Inference latency of 20–40 ms
- Larger memory footprint

They are therefore best suited for cloud or centralized analytics layers.

Proposed Hybrid Predictive Maintenance Framework

This section presents the proposed hybrid predictive maintenance (PdM) framework, which constitutes the core contribution of this paper. The framework integrates feature-based machine learning (ML) models and CNN-based deep learning (DL) models within a unified Industrial Internet of Things (IIoT) architecture and introduces a decision-oriented deployment strategy tailored to industrial constraints.

Unlike conventional hybrid approaches that focus on model fusion or ensemble prediction, the proposed framework emphasizes context-aware model selection, ensuring that predictive performance is balanced with computational efficiency, interpretability, and scalability.

Rationale for Hybridization

The experimental analysis of Sections IV and V demonstrates that ML and CNN-based models exhibit complementary strengths:

- ML models provide fast inference, low computational cost, and interpretability, making them suitable for edge-level monitoring.
- CNN-based models offer higher fault sensitivity, particularly for complex vibration patterns, but incur higher computational overhead.

Industrial environments typically involve heterogeneous assets, varying sensor configurations, and distributed computing resources. Deploying a single modeling paradigm across all scenarios leads to either underutilization of predictive capability or excessive computational cost. Therefore, a hybrid PdM framework is required to dynamically adapt predictive strategies based on operational context. Edge–cloud collaborative predictive maintenance architectures have been increasingly advocated to balance computational efficiency and fault sensitivity (S. Wang et al.,2016), (O. B. Sezer et al., 2018). The proposed hybrid framework extends these concepts by introducing decision-oriented model selection aligned with industrial constraints.

Hybrid Framework Architecture

The proposed framework consists of five logical layers:

Sensing layer

IIoT sensors continuously acquire vibration, temperature, torque, and rotational speed data from rotating machinery.

Preprocessing and representation layer

Signal conditioning, normalization, segmentation, and feature extraction are performed. Structured feature vectors are generated for ML models, while raw time-series segments are prepared for CNN models.

Model repository layer

Stores trained ML and CNN models, enabling modular updates and scalability.

Hybrid decision layer

Evaluates data characteristics, computational constraints, and operational requirements to select the appropriate predictive model.

Decision support layer

Converts model outputs into actionable maintenance insights, alarms, and condition-based maintenance schedules.

This layered architecture supports deployment across edge, gateway, and cloud infrastructures.

Decision Criteria for Model Selection

Model selection within the hybrid framework is governed by three primary criteria:

Data Characteristics (D_c)

- Structured, low-dimensional sensor features → ML models
- High-frequency, sequential vibration signals → CNN models

Computational Constraints (C_c)

- Resource-limited edge or gateway devices → ML models
- Cloud or centralized infrastructure with GPU support → CNN models

Operational Requirements (O_c)

- High interpretability and rapid response → ML models
- Early fault detection and sensitivity → CNN models

These criteria are jointly evaluated to enable context-aware decision-making.

Hybrid Model Selection Algorithm

The decision logic is formalized as follows.

Algorithm 3: Hybrid Predictive Maintenance Decision Logic

Input: Sensor data D, computational constraints C, operational requirements O
Output: Selected predictive model M
1: Analyze data characteristics Dc
2: Analyze computational constraints Cc
3: Analyze operational requirements Oc
4: if Dc == structured_features AND Cc == resource_limited then
5: M ← Feature-Based ML Model
6: else if Dc == time_series_vibration AND Cc == cloud_enabled then
7: M ← CNN-Based Model
8: else
9: M ← ML Model for monitoring + CNN Model for diagnostics
10: end if
11: return M

This strategy supports parallel deployment, where ML models perform continuous monitoring and CNN models are selectively activated for detailed diagnostics.

Mathematical Representation of the Hybrid Decision Function

The hybrid decision process can be expressed as:
$M = \mathcal{H}(D_c, C_c, O_c)$ where $\mathcal{H}(\cdot)$ maps data and system constraints to an appropriate predictive model or model combination.

Deployment Scenarios

The framework supports multiple industrial deployment scenarios:

Edge-centric deployment

ML models perform real-time monitoring with minimal latency.

Cloud-centric deployment

CNN models perform advanced diagnostics using high-performance computing resources.

Edge–cloud collaborative deployment

ML models detect anomalies at the edge, triggering CNN-based diagnostics in the cloud.

This flexibility ensures scalability and cost-effective deployment.

Novelty and Contribution

The proposed framework introduces novelty through:

- Decision-oriented hybridization rather than algorithmic fusion
- Explicit consideration of deployment constraints
- Practical alignment with industrial IoT architectures

Experimental Setup and Datasets

This section details the experimental design adopted to evaluate the proposed hybrid predictive maintenance framework, ensuring reproducibility, fairness, and industrial relevance. The evaluation metrics and experimental protocol follow standard practices in predictive maintenance literature (Carvalho et al.,2019), (G. Susto et al., 2015).

Datasets Description

Two categories of datasets were used:

Structured Sensor Dataset

This dataset includes:

- Air temperature
- Process temperature
- Rotational speed
- Torque
- Tool wear

Each instance is labeled as healthy or faulty, reflecting real-world class imbalance.

Vibration Time-Series Dataset

The vibration dataset consists of high-frequency accelerometer signals acquired from rotating machinery components. Signals are segmented into fixed-length windows to create independent samples for CNN training.

Data Preprocessing

Data cleaning

- Removal of invalid readings
- Handling missing values through statistical imputation

Feature scaling

Z-score normalization is applied:

$$x' = \frac{x - \mu}{\sigma}$$

Signal Segmentation

Vibration signals are segmented into windows of length T, preserving temporal fault characteristics.

Class Imbalance Mitigation

SMOTE is applied to training data for ML models. Test data remains untouched to preserve realistic class distribution.

Train–Test Strategy

- 80% training, 20% testing

Table 2: ML Model Hyperparameters

Model	*Key Parameters*
LR	C, max_iter
SVM	Kernel, C, γ
RF	n_estimators, max_depth
XGBoost	learning_rate, n_estimators

- Stratified sampling
- 10% validation split for CNN training

Model Training Configuration

ML Model Hyperparameters asshown in Table 2

CNN Training Parameters

- Epochs: 100
- Batch size: 32
- Learning rate: 0.001
- Early stopping patience: 10

Evaluation Metrics

Performance is evaluated using:

- Accuracy
- Precision
- Recall
- F1-score
- ROC–AUC
- Training time
- Inference latency

Experimental Environment

- Language: Python
- Libraries: NumPy, Pandas, Scikit-learn, TensorFlow/Keras
- Hardware: Intel i5 CPU, 16 GB RAM, GPU-enabled system

Results and Comparative Analysis

This section presents a comprehensive evaluation of the feature-based machine learning models, the CNN-based deep learning model, and the proposed hybrid predictive maintenance framework. The objective is not only to compare predictive accuracy, but also to assess fault sensitivity, robustness under class imbalance, computational efficiency, and deployment feasibility, which are critical for industrial IoT applications.

Table 3: Performance of Feature-Based Machine Learning Models

Model	*Accuracy (%)*	*Precision (%)*	*Recall (%)*	*F1-Score (%)*	*ROC–AUC*
Logistic Regression	96.9	73.7	20.0	31.5	0.949
SVM (RBF)	95.3	41.8	87.1	56.5	0.972
Random Forest	98.2	69.4	84.3	76.1	0.983
XGBoost	98.4	69.1	82.9	75.3	0.983

Performance of Feature-Based Machine Learning Models

Feature-based machine learning models were evaluated on the structured sensor dataset using the test split described in Section VII. Table III summarizes the predictive performance of individual ML models after applying SMOTE to the training data.

The results indicate that ensemble-based models outperform linear classifiers in terms of recall and F1-score. Logistic Regression achieves high accuracy but exhibits extremely low recall, demonstrating its inability to reliably detect rare failure events. SVM achieves high recall but suffers from low precision, resulting in an increased number of false alarms.

Random Forest and XGBoost provide the most balanced performance, achieving high accuracy while maintaining strong recall and F1-scores. These results confirm the suitability of ensemble ML models for edge-level predictive maintenance, where interpretability and computational efficiency are essential.

Impact of Class Imbalance Handling

To quantify the impact of imbalance mitigation, ML models were evaluated with and without SMOTE. Without imbalance handling, all models exhibited inflated accuracy but poor fault recall. After applying SMOTE, recall improved by 20–40% across models, particularly for ensemble classifiers.

This result highlights a critical insight: accuracy alone is a misleading metric in predictive maintenance, as it fails to capture a model's ability to detect failures. Recall and F1-score are more representative of industrial usefulness.

Performance of CNN-Based Deep Learning Model

The CNN-based deep learning model was evaluated on vibration time-series data under both imbalanced and balanced training conditions. Table IV presents the results.

The CNN model demonstrates significantly higher recall than ML models, particularly after class balancing. This confirms the effectiveness of CNNs in learning complex temporal fault patterns directly from vibration signals. However, this improvement comes at the cost of reduced precision, indicating a higher false-positive rate.

These results suggest that CNN-based models are highly effective for fault-sensitive diagnostics, but may not be optimal as standalone solutions for continuous monitoring due to their computational cost and false alarm behavior.

Comparative Analysis: ML vs. CNN Models

A direct comparison between the best-performing ML model (XGBoost) and the CNN model is shown in Table V.

The comparison clearly demonstrates complementary strengths. ML models offer fast inference, interpretability, and low resource consumption, while CNN models deliver superior fault sensitivity at higher computational cost.

Table 4: Performance of CNN-Based Deep Learning Model

Training condition	*Accuracy (%)*	*Precision (%)*	*Recall (%)*	*F1-Score (%)*	*Loss*
Without SMOTE	98.2	79.3	65.7	71.9	0.060
With SMOTE	94.8	39.4	90.0	54.8	0.140

Evaluation of the Hybrid Framework

The proposed hybrid framework integrates ML and CNN models using decision-oriented deployment logic. ML models perform continuous monitoring, while CNN models are selectively invoked for detailed diagnostics. Table VI summarizes the performance of the hybrid framework.

The hybrid framework achieves a balanced trade-off, improving recall over ML-only deployment while significantly reducing computational cost and false positives compared to CNN-only deployment. Similar trade-offs between accuracy, recall, and computational cost have been reported in prior predictive maintenance studies (S. Zhang et al., 2020).

Table 5: Comparative Analysis of ML and CNN Models

Criterion	*XGBoost*	*CNN*
Accuracy (%)	98.4	94.8
Recall (%)	82.9	90.0
F1-Score (%)	75.3	54.8
Training Time (s)	18	210
Inference Latency (ms)	6	28
Interpretability	High	Low

Table 6: Hybrid Framework Performance

Metric	*ML only*	*CNN only*	*Hybrid framework*
Accuracy (%)	98.4	94.8	97.9
Recall (%)	82.9	90.0	88.1
False Positives	Low	High	Moderate
Inference Cost	Low	High	Moderate

Summary of Results

The results confirm that:

- Ensemble ML models are well-suited for efficient, interpretable monitoring.
- CNN models excel at detecting complex and early-stage faults.
- Hybrid deployment offers superior overall performance under industrial constraints.

Discussion and Industrial Implications

This section interprets the results from an industrial deployment perspective, emphasizing practical applicability rather than algorithmic performance alone.

Deployment-oriented Insights

Industrial predictive maintenance systems must operate across heterogeneous infrastructures. The results demonstrate that deploying deep learning models indiscriminately across all assets is impractical. Conversely, relying solely on classical ML models may limit fault sensitivity.

The proposed hybrid framework addresses this challenge by enabling context-aware deployment, aligning predictive capability with resource availability.

Interpretability and Trust

Interpretability is a key requirement for industrial adoption. Feature-based ML models provide transparency through feature importance analysis, allowing maintenance engineers to relate predictions to physical phenomena. CNN models, while powerful, lack inherent explainability.

Interpretability and trust remain critical barriers to industrial adoption of deep learning–based predictive maintenance systems (S. Yin et al.,2015), (S. Zhang et al., 2020). The hybrid framework mitigates this limitation by positioning CNN models as diagnostic enhancers rather than primary decision-makers, preserving trust and accountability.

Scalability and Cost Efficiency

As the number of monitored assets increases, computational scalability becomes critical. The hybrid framework reduces operational cost by:

- Limiting CNN inference to critical events
- Enabling incremental deployment
- Supporting edge–cloud collaboration

Limitations

The study uses representative but limited datasets and evaluates inference latency qualitatively. Future work should incorporate live plant data, sensor drift, and energy consumption metrics.

Conclusion and Future Work

This paper presented a comparative and hybrid predictive maintenance framework for rotating machinery in Industrial IoT environments. Unlike conventional studies that focus on isolated modeling paradigms, this work systematically evaluated feature-based machine learning and CNN-based deep learning models across predictive performance, computational complexity, and deployment feasibility.

Experimental results demonstrated that ensemble ML models provide efficient and interpretable solutions suitable for edge deployment, while CNN-based models offer superior fault sensitivity for vibration time-series data.

To reconcile these strengths, a decision-oriented hybrid framework was proposed, enabling context-aware model selection and scalable deployment.

The proposed framework bridges the gap between academic predictive maintenance research and industrial implementation by emphasizing deployment realism alongside predictive performance.

Key Contributions

- Comparative evaluation of ML and CNN models for IoT-based predictive maintenance.
- Quantitative assessment beyond accuracy, incorporating recall, latency, and computational cost.
- A novel decision-oriented hybrid framework aligned with IIoT constraints.
- Practical guidance for scalable and trustworthy industrial deployment.

Future Work

While the proposed framework demonstrates strong potential, several avenues remain for future exploration. The integration of real-time streaming IoT data and online learning mechanisms would enhance adaptability under changing operating conditions. Edge-focused optimization techniques, such as model compression and lightweight deep learning architectures, could further improve deployment feasibility in resource-limited environments.

Additionally, incorporating explainable AI (XAI) techniques would improve model transparency and foster trust among maintenance engineers and decision-makers. Extending the framework to include transfer learning and cross-domain generalization could enable predictive maintenance models to adapt across different machines, plants, and operating regimes. Finally, large-scale industrial validation using live plant data would further strengthen the applicability and robustness of the proposed approach.

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