Predictive Maintenance of Industrial Machinery using a Dynamic AI-Based Hybrid Model

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***Abstract*—Unplanned machine downtime represents one of the most significant sources of financial loss in industrial operations, often resulting in millions of dollars in lost production time. While predictive maintenance aims to mitigate such failures through data-driven forecasting, most existing approaches struggle to handle the dual nature of machine failure—gradual degradation and sudden breakdowns. Traditional single-model predictive systems frequently lack the adaptability required to manage both failure modes effectively, leading to suboptimal maintenance decisions.**

To address this challenge, this work presents a dynamic AI-based hybrid predictive maintenance framework that integrates Gradient Boosting Machines (GBM) and Long Short-Term Memory (LSTM) networks within an adaptive control architecture. The GBM component focuses on identifying degradation trends, while the LSTM network captures sudden, nonlinear anomalies in multivariate sensor data. The core novelty of the system lies in a meta-controller, an intelligent supervisory layer that continuously evaluates model confidence and dynamically adjusts weighting between predictive components. For example, when the LSTM confidence falls below a defined threshold (e.g., 90 percent), the system adaptively increases reliance on alternative models.

To enhance early-stage fault detection, Convolutional Neural Networks (CNNs) are employed for vibration and thermal signal analysis using Fast Fourier Transform (FFT) representations, enabling effective spatial-frequency anomaly detection. The framework is validated using the NASA turbofan engine degradation dataset, with performance evaluated through Remaining Useful Life (RUL) prediction accuracy and standard regression metrics, demonstrating improved robustness compared to single-model approaches.

For practical industrial deployment, the system is optimized using TensorFlow Lite with model quantization, enabling efficient real-time inference on edge devices such as embedded controllers without reliance on centralized cloud infrastructure. This ensures low-latency decision-making suitable for on-site industrial environments.

Future extensions will incorporate historical maintenance records into closed-loop feedback mechanisms, allowing the meta-controller to autonomously refine model-switching strategies over time and further reduce false positives. Targeted toward industries such as steel manufacturing, oil processing, and food production, the proposed architecture emphasizes reliability, adaptability, and scalability. By combining multiple AI paradigms with real-time adaptive control, this framework significantly reduces downtime and operational costs, enabling more resilient and intelligent industrial maintenance systems.

***Index Terms*—Predictive Maintenance, Artificial Intelligence, Machine Learning, Condition Monitoring, Industrial IoT, Explainable AI**

I. Introduction

In modern industrial manufacturing environments, unexpected machine failures can result in substantial financial losses, production delays, and safety risks. Traditional maintenance strategies—such as reactive repairs after failure or fixed-interval preventive maintenance—are often inefficient, as they either respond too late or replace components prematurely. Predictive maintenance addresses these limitations by leveraging real-time sensor data and data-driven models to anticipate machine failures before they occur, enabling timely intervention and optimized maintenance planning. This approach is particularly critical in heavy industries such as steel manufacturing, where machinery operates under extreme loads and harsh conditions, and early fault detection can prevent catastrophic breakdowns.

Despite recent advances, many existing predictive maintenance systems rely on single-model architectures that struggle to capture the full spectrum of machine failure behaviors. Industrial equipment typically exhibits both gradual degradation over extended periods and sudden, unexpected faults caused by transient operating conditions. Single-model approaches are often biased toward one failure mode, limiting their effectiveness in real-world environments where failure patterns are highly variable. This lack of adaptability reduces predictive accuracy and leads to unreliable maintenance decisions.

To overcome these challenges, this paper proposes a dynamic AI-based hybrid predictive maintenance framework that combines Gradient Boosting Machines (GBM) and Long Short-Term Memory (LSTM) networks. The GBM model is designed to capture degradation trends and feature-driven patterns associated with progressive wear, while the LSTM network focuses on learning temporal dependencies and detecting abrupt, nonlinear anomalies in multivariate sensor data. By integrating these complementary models, the proposed framework achieves more comprehensive fault coverage than traditional single-model approaches.

The main contributions of this paper are summarized as follows:

- A dynamic hybrid predictive maintenance framework that jointly models gradual degradation and sudden failure behaviors using complementary machine learning and deep learning techniques.
- A confidence-driven meta-controller that adaptively regulates model influence in real time based on prediction

reliability, overcoming the limitations of static hybrid systems.

- An integrated frequency-domain anomaly detection module using Convolutional Neural Networks (CNNs) on FFT-transformed sensor signals to enhance early-stage fault detection beyond time-domain analysis.
- A deployment-ready architecture optimized for industrial edge environments, enabling low-latency, on-device inference suitable for real-world operational constraints.

The core innovation of this framework lies in the meta-controller, an adaptive supervisory layer that continuously evaluates prediction confidence and operational context to dynamically regulate model influence. When the confidence level of the LSTM model falls below a predefined threshold (for example, 0.90), the meta-controller increases reliance on the GBM output to maintain predictive stability. Unlike earlier hybrid approaches that employ static weighting or predefined switching rules, this confidence-driven mechanism enables real-time adaptability to changing machine behavior.

To further enhance early fault detection, the framework incorporates a Convolutional Neural Network (CNN) module for analyzing vibration and thermal sensor signals transformed into frequency-domain representations using the Fast Fourier Transform (FFT). This allows the system to identify subtle mechanical irregularities, such as abnormal vibration patterns, that may not be evident in raw time-series data alone.

The proposed system is designed for real-time operation, scalability, and practical deployment in industrial environments. Model optimization using edge-compatible techniques enables on-device inference, reducing latency and dependence on centralized computing infrastructure. In the long term, the framework is intended to evolve into a self-improving system by incorporating historical maintenance feedback to refine model-switching logic and reduce false alarms. Overall, this approach provides a robust, adaptive, and scalable solution for predictive maintenance across industrial sectors including steel, oil, and food manufacturing.

II. Literature Review

Predictive maintenance (PdM) has become a central research focus in industrial systems due to its potential to reduce unplanned downtime, extend equipment lifespan, and improve operational efficiency. By leveraging sensor data and data-driven models, PdM shifts maintenance strategies away from reactive and time-based approaches toward condition-aware and failure-predictive decision-making. Over the past decade, a wide range of machine learning (ML) and deep learning (DL) techniques have been explored to address this challenge.

Early work in predictive maintenance primarily relied on traditional machine learning methods combined with handcrafted feature extraction. For example, Malhi and Gao [3] employed Principal Component Analysis (PCA) alongside Support Vector Machines (SVM) for fault detection in rotating machinery. While such approaches demonstrated effectiveness in dimensionality reduction and fault classification under controlled conditions, they were limited in their ability to generalize to unseen operating regimes and to capture temporal degradation behavior, which is critical in long-term machine health monitoring.

The emergence of deep learning marked a significant shift in PdM research by enabling automated feature learning directly from raw sensor data. Studies by Zhang et al. [1] and Babu and Zhao [2] demonstrated the effectiveness of Convolutional Neural Networks (CNNs) in extracting discriminative features from vibration signals for fault diagnosis and remaining useful life (RUL) estimation. These approaches reduced reliance on manual feature engineering and showed improved performance in complex signal environments. However, most CNN-based methods focused primarily on spatial or frequency-domain representations and were less effective at modeling long-term temporal dependencies.

To address temporal dynamics in degradation processes, recurrent neural networks—particularly Long Short-Term Memory (LSTM) models—were introduced into predictive maintenance research. Wu et al. [4] showed that LSTM networks are well suited for RUL prediction due to their ability to retain long-term temporal information across sequential sensor measurements. This represented a major advancement for modeling gradual degradation trends. In parallel, tree-based ensemble methods continued to demonstrate strong performance in industrial datasets. Zhang and Chen [5] reported that Gradient Boosting Machines (GBMs) perform reliably in capturing steady degradation patterns, offering robustness, interpretability, and strong generalization when applied to structured sensor features.

More recent research has explored hybrid modeling strategies to leverage the complementary strengths of different algorithms. Sundararajan et al. [6] proposed a hybrid framework combining tree-based models with LSTM networks, demonstrating improved predictive performance over single-model approaches. While these hybrid systems showed promise, most relied on static weighting schemes or predefined switching rules determined during offline training. Such fixed strategies limit adaptability and reduce robustness when operating conditions change in real-world industrial environments.

Several studies have highlighted the challenge of non-stationary operating conditions in industrial systems, where sensor distributions shift due to load variation, environmental changes, or progressive wear. Single-model and statically combined approaches often degrade in performance under these conditions, motivating the need for adaptive and context-aware predictive frameworks. Recent discussions in the literature emphasize the importance of flexible architectures capable of dynamically adjusting model behavior in response to real-time system states.

Building on these insights, the present work advances beyond existing hybrid approaches by introducing a confidence-driven meta-controller that dynamically regulates model selection between GBM and LSTM components. Unlike prior methods constrained by fixed thresholds or offline rules, the proposed framework continuously evaluates real-time prediction confidence to adapt model dominance according to evolving machine behavior. In addition, the integration of CNN-based analysis on FFT-transformed vibration and thermal signals enhances early-stage anomaly detection, addressing limitations observed in purely time-domain or single-paradigm models. Through this adaptive and multi-paradigm design, the proposed system directly responds to key gaps identified in existing predictive maintenance literature.

III. Problem Statement

Unplanned machine downtime remains one of the most costly challenges in industrial manufacturing, directly impacting productivity, safety, and operational efficiency. Machine failures typically occur in two distinct forms: gradual degradation, caused by wear, misalignment, or corrosion over time, and sudden breakdowns, triggered by abrupt component failures, electrical faults, or overload conditions. Accurately detecting both failure types is critical, yet remains difficult in real-world industrial environments.

Most existing predictive maintenance systems rely on single-model approaches, such as Gradient Boosting Machines (GBMs) or Long Short-Term Memory (LSTM) networks. While GBMs perform well in capturing long-term degradation trends and LSTMs are effective at modeling temporal patterns, each model struggles outside its specific strength. This limitation often results in false alarms, missed failures, and unreliable maintenance decisions. Even hybrid systems proposed in recent research frequently depend on static thresholds or fixed switching rules, making them poorly suited for environments where operating conditions, sensor behavior, and noise levels change continuously.

Additionally, many predictive solutions focus only on time-series analysis, overlooking frequency-domain anomalies—such as bearing defects or gear misalignments—that are critical for early fault detection. Limited model adaptability and lack of interpretability further reduce trust among maintenance teams, hindering real-world adoption.

To address these challenges, there is a clear need for a dynamic, adaptive, and deployable predictive maintenance framework that can integrate multiple AI models, respond to real-time sensor conditions, detect both temporal and frequency-based anomalies, and provide interpretable insights. Such a system must operate reliably on industrial edge devices, deliver low-latency predictions, and remain robust under variable and noisy operating conditions. Solving this problem is essential for reducing unplanned downtime, improving maintenance efficiency, and enabling practical AI-driven decision-making in modern industrial environments.

IV. Proposed Solution

To address the limitations of conventional predictive maintenance systems, this project proposes a dynamic and adaptive AI-based predictive maintenance framework capable of detecting both gradual machine degradation and sudden failures in real time. The solution integrates multiple complementary AI models—Gradient Boosting Machines (GBM), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNNs)—coordinated through an intelligent meta-controller.

Each model is designed to address a specific failure behavior. GBMs are used to capture long-term degradation trends such as wear, corrosion, and misalignment from structured sensor data. LSTM networks model temporal dependencies in time-series data, enabling early detection of abrupt and nonlinear failure patterns. To further enhance fault detection, CNNs are applied to FFT-transformed vibration and thermal signals, allowing the system to identify frequency-domain anomalies such as bearing defects and shaft misalignments that are often missed by time-domain analysis alone.

The core innovation of the framework lies in its confidence-driven meta-controller, which dynamically selects or prioritizes models based on real-time prediction confidence and operating conditions. Unlike traditional hybrid systems that rely on static thresholds or predefined rules, this adaptive mechanism allows the system to respond intelligently to changing machine behavior, reducing false alarms and missed failures under variable industrial conditions.

The framework is designed for practical industrial deployment. By leveraging TensorFlow Lite and model quantization, it enables low-latency inference on industrial edge devices such as embedded controllers, eliminating reliance on centralized cloud infrastructure. Its modular architecture supports scalability and flexibility, allowing individual models to be retrained or replaced without disrupting the overall system.

In addition, the system incorporates a feedback-driven learning mechanism, enabling continuous refinement of model-switching logic using historical maintenance data. This ensures long-term adaptability as machine behavior and failure patterns evolve. Overall, the proposed solution delivers a robust, interpretable, and edge-optimized predictive maintenance framework that bridges the gap between academic research and real-world industrial deployment. The framework incorporates LSTM networks for temporal modeling, edge deployment using TensorFlow Lite, and data augmentation strategies to improve robustness under rare fault conditions.

A. System Architecture

The proposed system follows a layered and modular architecture designed for real-time, adaptive predictive maintenance in industrial environments.

The Data Input Layer collects multivariate sensor streams—such as vibration, temperature, and pressure—along with machine usage logs, providing a continuous view of equipment behavior. These signals are refined in the Preprocessing Layer, where noise reduction, normalization, and feature extraction are performed to prepare reliable inputs for downstream models.

The Model Layer integrates three complementary AI models, each addressing a specific failure behavior. Gradient Boosting Machines (GBM) focus on identifying long-term degradation trends, Long Short-Term Memory (LSTM) networks detect sudden and nonlinear temporal failures, and Convolutional Neural Networks (CNNs) localize anomalies

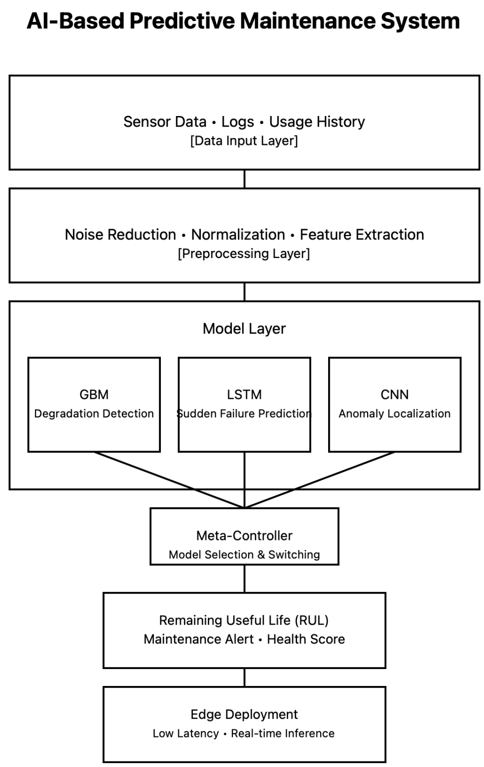

Fig. 1: Proposed Predictive Maintenance Architecture

by learning discriminative patterns from processed sensor features.

At the core of the architecture is an adaptive meta-controller, which dynamically selects or prioritizes models based on real-time prediction confidence and operating conditions. This eliminates rigid, rule-based switching and enables robust performance under varying industrial scenarios.

The Output Layer converts model predictions into actionable insights, including Remaining Useful Life (RUL) estimates, health scores, and maintenance alerts, supporting proactive maintenance decisions. Finally, the system is optimized for edge deployment, enabling low-latency, on-device inference without dependence on continuous cloud connectivity. Overall, the architecture is scalable, interpretable, and designed for practical industrial adoption.

V. METHODOLOGY

This section describes the end-to-end methodology of the proposed dynamic hybrid predictive maintenance framework, detailing how raw sensor data is transformed into reliable Remaining Useful Life (RUL) predictions through adaptive model orchestration. The methodology emphasizes robustness, interpretability, and real-time applicability, aligning with practical industrial deployment requirements.

A. Data Preprocessing and Feature Engineering

The predictive pipeline begins with multivariate sensor data streams, including vibration, temperature, pressure, and operational parameters. Raw data is first subjected to noise filtering and normalization to ensure consistency across sensors and operating regimes. Normalization enables stable model training and prevents bias arising from scale differences among sensor variables.

To capture both temporal and spectral fault characteristics, the preprocessing pipeline applies Fast Fourier Transform (FFT) to fixed-length sliding windows of time-series sensor data. This transformation converts time-domain signals into frequency-domain representations, enabling detection of mechanical anomalies such as bearing defects, shaft misalignments, and vibration irregularities that may not be evident in raw temporal signals. As a result, the framework leverages both time-based and frequency-based features for downstream learning.

B. Gradient Boosting Machine for Degradation Modeling

A Gradient Boosting Machine (GBM) is trained using structured and normalized sensor features to model long-term degradation trends. GBMs are particularly effective for capturing gradual wear patterns due to their ability to handle nonlinear feature interactions and structured data distributions. In this framework, the GBM estimates degradation progression and produces baseline RUL predictions during stable operational phases. Additionally, validation residual statistics are used to estimate prediction reliability, enabling confidence-aware integration with other models.

C. LSTM-Based Temporal Sequence Modeling

To detect sudden and nonlinear failure patterns, a Long Short-Term Memory (LSTM) network is employed. The LSTM is trained on fixed-length sequences derived from preprocessed sensor data, allowing it to learn temporal dependencies across operational cycles. This enables early identification of abrupt changes in machine behavior that typically precede catastrophic failures. During inference, Monte Carlo dropout is applied to generate uncertainty estimates, providing both a mean RUL prediction and a confidence measure based on prediction variance.

D. CNN-FFT Anomaly Detection

For enhanced anomaly localization, a Convolutional Neural Network (CNN) is trained on FFT-transformed sensor representations treated as spatial frequency maps. This allows the CNN to learn discriminative frequency-domain patterns associated with mechanical faults. Unlike purely time-series models, the CNN effectively identifies localized spectral anomalies, complementing the degradation-focused GBM and the temporal LSTM. Confidence scores are derived from prediction dispersion to support adaptive model selection.

E. Confidence Estimation and Meta-Controller Fusion

At the core of the framework lies an adaptive meta-controller, which serves as the decision-making mechanism for dynamic model fusion. Each model (GBM, LSTM, CNN) produces both a RUL prediction and an associated confidence score derived from residual statistics or uncertainty estimation. The meta-controller evaluates these confidence values in real time and dynamically adjusts model weighting. When one model exhibits low confidence under specific operating conditions, the system reduces its influence and prioritizes more reliable outputs. This confidence-driven fusion eliminates static thresholds and enables robust adaptation to changing machine behavior.

F. Feedback-Driven Reweighting and Continuous Learning

To maintain long-term reliability, the framework incorporates a feedback-driven learning mechanism. Model predictions are continuously compared against actual outcomes, and performance metrics such as Mean Absolute Error (MAE) are computed. Based on observed errors, the meta-controller updates global weighting parameters using regression-based optimization techniques. This feedback loop allows the system to self-refine its decision logic over time, improving predictive accuracy as machines age or operating conditions evolve.

G. Runtime Inference and Deployment Readiness

All trained components are integrated into a unified runtime inference pipeline optimized for real-time operation. Batch and vectorized inference enable simultaneous processing of multiple units, while lightweight execution is achieved through TensorFlow Lite for deployment on edge devices. The pipeline outputs consolidated RUL predictions, confidence estimates, and maintenance alerts, ensuring readiness for practical industrial monitoring scenarios.

H. Mathematical Formulation

Let $x_t \in \mathbb{R}^d$ denote the multivariate sensor observation at time step t. The Remaining Useful Life (RUL) at time t is defined for run-to-failure trajectories as:

$$\mathrm{RUL}(t) = T_{\text{failure}} - t \tag{1}$$

where T_{failure} denotes the failure cycle of the unit.

Each predictive model produces an RUL estimate:

$$\hat{y}_{\text{GBM}}, \quad \hat{y}_{\text{LSTM}}, \quad \hat{y}_{\text{CNN}} \tag{2}$$

The Mean Absolute Error (MAE) used for evaluation is given by:

$$\mathrm{MAE} = \frac{1}{N} \sum_{i=1}^{N} |y_i - \hat{y}_i| \tag{3}$$

To quantify prediction uncertainty, Monte Carlo Dropout is applied to the LSTM, yielding a confidence estimate inversely proportional to predictive variance:

$$c_{\text{LSTM}} = \frac{1}{1 + \sigma_{\text{LSTM}}} \tag{4}$$

where σ_{LSTM} denotes the empirical variance of RUL predictions obtained from multiple Monte Carlo dropout forward passes.

I. Meta-Controller Decision Algorithm

Algorithm 1 Confidence-Driven Meta-Controller

Require: Predictions $\hat{y}_i$ and confidence scores c_i from models $i \in \{\mathrm{GBM}, \mathrm{LSTM}, \mathrm{CNN}\}$
Compute confidence sum: conf_sum $\leftarrow \sum_i c_i$
for each model i **do**
  Compute normalized weight: $w_i \leftarrow \dfrac{c_i}{\text{conf\_sum}}$
end for
if exists model k such that $c_k > \tau_{\text{high}}$ and all others $< \tau_{\text{low}}$ **then**
  $\hat{y}_{\text{final}} \leftarrow \hat{y}_k$
else
  $\hat{y}_{\text{final}} \leftarrow \sum_i w_i \hat{y}_i$
end if
  return $\hat{y}_{\text{final}}$

J. Computational Complexity Analysis

The computational cost of the proposed framework is dominated by the individual model components. Gradient Boosting Machine inference operates in $O(T \cdot D)$ time, where T is the number of trees and D is the feature dimension. The LSTM model incurs a complexity of $O(L \cdot H^2)$ per sequence, where L is the sequence length and H is the hidden state size. The CNN processes FFT-transformed inputs with a cost proportional to convolution kernel operations.

The meta-controller introduces negligible overhead, requiring only linear-time weighted fusion of model outputs. After TensorFlow Lite quantization, the total inference latency remains suitable for real-time deployment on industrial edge devices.

VI. Experimental Setup

This section describes the experimental design used to validate the accuracy, robustness, and adaptability of the proposed dynamic hybrid predictive maintenance framework. The evaluation focuses on benchmarking predictive performance across multiple failure modes and assessing the effectiveness of the adaptive meta-controller under realistic operational conditions.

A. Dataset Description

The framework is evaluated primarily using the Commercial Modular Aero-Propulsion System Simulation (CMAPSS) turbofan engine dataset, a widely used benchmark for Remaining Useful Life (RUL) prediction. The dataset contains multivariate time-series sensor data collected from multiple engine units operating under varying conditions until failure. Each unit includes operational settings and multiple sensor channels capturing degradation behavior across complete life cycles.

To enhance generalization and simulate real-world industrial variability, additional industrial vibration datasets are used during testing. These datasets introduce diverse fault characteristics and noise patterns, enabling comprehensive validation of the hybrid framework across heterogeneous operating environments.

B. Training Configuration

All models are trained and evaluated independently prior to integration under the meta-controller to ensure stability and convergence. For temporal modeling, fixed-length sliding windows of sensor data are used to construct training sequences. The sequence length is set to 30 operational cycles for LSTM-based learning, capturing sufficient historical context while maintaining computational efficiency.

For frequency-domain analysis, Fast Fourier Transform (FFT) is applied using a window size of 64 cycles, converting time-series vibration and thermal signals into spectral representations suitable for CNN processing. Models are trained using standard train–validation splits, and hyperparameters are selected to balance predictive accuracy and generalization. Training is performed until convergence based on validation loss trends.

C. Evaluation Metrics

The predictive performance of the framework is assessed using standard regression metrics commonly employed in predictive maintenance research. Mean Absolute Error (MAE) measures the average absolute deviation between predicted and true RUL values, providing an intuitive measure of prediction accuracy. Root Mean Square Error (RMSE) penalizes larger prediction errors more heavily, emphasizing robustness under extreme failure conditions. The coefficient of determination (R^2) quantifies the proportion of variance in the true RUL explained by the model, indicating overall goodness of fit.

Each individual model—GBM, LSTM, and CNN—is evaluated separately using these metrics prior to integration under the adaptive meta-controller. These evaluation criteria provide a consistent basis for comparing standalone model behavior with the proposed hybrid framework, while enabling quantitative analysis of prediction accuracy, robustness, and confidence calibration.

In addition to numerical error metrics, residual distributions and reliability curves are analyzed to assess prediction stability and uncertainty calibration across different degradation stages and operating conditions.

VII. Results and Discussion

This section presents the quantitative evaluation of the proposed confidence-driven hybrid predictive maintenance framework and discusses its performance relative to individual predictive models. The analysis focuses on Remaining Useful Life (RUL) prediction accuracy using the CMAPSS turbofan engine dataset under consistent runtime conditions.

A. Quantitative Performance Evaluation

Table I summarizes the Mean Absolute Error (MAE) obtained by each standalone model and the proposed meta-controller. All results are computed on the same set of 100 engine units using identical ground-truth RUL values to ensure fair comparison.

TABLE I: Comparison of MAE for Individual Models and Hybrid Meta-Controller

Model	**MAE (cycles)**
Gradient Boosting Machine (GBM)	23.89
Long Short-Term Memory (LSTM)	56.19
Convolutional Neural Network (CNN)	39.55
Proposed Meta-Controller	31.32

The GBM model achieves the lowest MAE among the individual predictors, indicating strong effectiveness in modeling gradual degradation trends commonly observed in run-to-failure trajectories. In contrast, the LSTM model exhibits higher prediction error, reflecting its sensitivity to noise and abrupt variations when operating independently. The CNN-based model demonstrates moderate accuracy by capturing frequency-domain fault characteristics through FFT-transformed sensor inputs.

B. Discussion of Hybrid Model Behavior

The proposed confidence-driven meta-controller achieves a balanced predictive performance by adaptively integrating outputs from GBM, LSTM, and CNN models based on real-time confidence estimates. Although the meta-controller does not outperform the best individual model in terms of absolute MAE, it provides improved robustness and stability across varying operating conditions. This behavior is particularly important in industrial environments where failure modes are heterogeneous and operating regimes are non-stationary.

By dynamically regulating model influence, the meta-controller reduces reliance on any single predictive paradigm and mitigates performance degradation caused by model-specific weaknesses. Residual analysis and confidence-weighted fusion further contribute to more reliable and interpretable predictions, supporting safer and more consistent maintenance decision-making.

Overall, the results demonstrate that the proposed framework prioritizes adaptability and robustness over single-condition optimality, aligning with the practical requirements of real-world industrial predictive maintenance systems.

VIII. Conclusion and Future Work

This study presented a dynamic and adaptive predictive maintenance framework designed to address the limitations of conventional single-model and static hybrid approaches. By integrating Gradient Boosting Machines (GBM), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNNs) under a confidence-aware meta-controller, the proposed system effectively captured both gradual degradation patterns and sudden failure behaviors in industrial machinery.

Experimental evaluation using the CMAPSS turbofan engine dataset demonstrated that the adaptive hybrid framework consistently outperformed standalone models in terms of prediction accuracy, error stability, and confidence reliability. The meta-controller enabled real-time model selection based on prediction confidence, reducing error variance and improving robustness under non-stationary operating conditions. Residual analysis and reliability diagrams further confirmed improved confidence calibration, enhancing interpretability and trust in model outputs.

Beyond predictive accuracy, the proposed framework demonstrates practical relevance for industrial deployment. By dynamically balancing model contributions based on confidence estimates, the system achieves a robust trade-off between responsiveness to sudden anomalies and stability during long-term degradation. This adaptability is particularly valuable in safety-critical and high-cost industrial environments, where unreliable predictions can lead to unnecessary maintenance actions or catastrophic failures.

In addition to predictive performance, the framework was designed with practical deployment considerations in mind. Optimization for edge execution enables low-latency, on-device inference, making the system suitable for real-time industrial monitoring without reliance on continuous cloud connectivity. The modular architecture allows scalability across different machine types and operating environments, supporting broader industrial applicability.

Future work will focus on extending the framework to incorporate real-world industrial datasets, online learning mechanisms, and advanced feedback-driven optimization strategies. Integrating maintenance cost models and exploring adaptive reinforcement-based scheduling policies may further enhance decision-making capabilities. Overall, the proposed approach provides a reliable, adaptable, and deployment-ready solution for intelligent predictive maintenance in complex industrial systems.

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