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Research Article

Non-Vibration-Based Multimodal Anomaly Fusion with Temporal Persistence Modelling for Degradation Assessment in Industrial Systems

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ABSTRACT

Machine failure prediction in industrial systems tends to depend on vibration analysis. Most installed machines, however, do not have vibration or acoustic sensors, leaving alternative prediction methods using proxy sensor readings like temperature, pressure, and environmental data. This work introduces a new framework for multimodal degradation assessment involving anomaly detection and temporal persistence modeling. Through the utilization of time-series sensor data, we extract features representing deviations from an ideal running state and monitor their persistence across time, similar to health decline in living systems. In contrast to conventional methods, which depend on explicit failure signifiers, our method targets long-term anomaly trends and their compounding effects. We compare several machine learning models, such as Random Survival Forest, Isolation Forest, and Recurrent Neural Networks, with results showing that failure prediction accuracy greatly improves when engineered temporal anomaly features are used. The envisioned approach facilitates more powerful predictive maintenance practices applied in actual industry settings, eliminating surprise downtimes and maximizing running efficiency.

Keywords: Predictive Maintenance, Anomaly Detection, Temporal Persistence, Machine Learning, Survival Analysis, Recurrent Neural Networks, Industrial Systems

I. INTRODUCTION

The industrial equipment reliability is a critical factor in manufacturing efficiency, affecting productivity, safety, and maintenance expenses. Industries have, over the years, looked for superior methods to forecast and avert machine failures, shifting from conventional reactive maintenance to adopt predictive maintenance (PdM). PdM applies real- time data from different sensors mounted on machinery to predict failures, minimizing unplanned downtime, and maximizing working efficiency. As industrial systems grow in complexity and many interconnected sensors and devices are installed, a precise failure prognosis becomes progressively necessary to ensure smooth operations and minimize financial losses.

A. Evolution of Failure Detection Methods

Conventionally, equipment/machine failure detection and avoidance has always relied on scheduled maintenance practices, and data collected from these machines can be analyzed with rule-based algorithms and alerts can be sent so that reactive maintenance can be performed [1]. The preceding methods were mostly vibration-based monitoring because mechanical wear and tear over time tends to show themselves through vibration fluctuations [2]. However, in the modern industrial environment, many machines that are already commissioned and in service do not have vibration or acoustic sensors, and therefore alternative methods of failure prediction must be employed [3]. Developments in machine learning (ML) and artificial intelligence (AI) have made it possible to evolve sensor-based PdM models, utilizing sensor readings including temperature, pressure, chemical compositions, and ambient parameters to predict the time to failure (TTF) [4]. These techniques have greatly improved predictive accuracy over conventional methods, but some issues are still unresolved [5].

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B. Existing Knowledge Gaps

Despite remarkable advancements in sensor-based failure prediction, knowledge gaps still remain. Firstly, the majority of current studies target directly correlated signals, i.e., vibration data, leaving unexplored the potential of indirect sensor measurements [6]. Secondly, most of the existing PdM methods are static model based which ignores the temporal degradation trends and compounding effects of long-term anomalies [7]. Also, generalization of those predictive models are still remaining a challenge, as most ML models are not able to generalize across various equipment types and their operating conditions [8].

C. Limitations of Previous Studies

One critical issue with the future of PdM is creating scalable, low-cost models that can operate without installing extra sensors or devices, as additional cost and downtime are major concerns. Many industrial machines are already deployed in the field, and retrofitting them with specialized sensors may not be feasible. Additionally, sensor data is often not directly correlated with machine failure incidents, making it difficult to develop reliable predictive models. To improve failure prediction accuracy, future research must focus on leveraging multimodal data, enhancing anomaly detection methods, and integrating advanced analytics.

Despite significant advancements in PdM, several limitations remain:

- Limited Sensor Scope: Many studies rely on direct correlations between sensor readings and failures, often neglecting indirect predictive factors that could improve failure prediction accuracy [1], [2].

- Model Generalization Issues: Existing machine learning models often struggle to adapt across different machine types and operating conditions. Many PdM frameworks require significant retraining and tuning, which limits their practical deployment in industrial settings [4].

- Over-Reliance on Vibration Data: While vibration analysis has been extensively studied, it is not always the most effective failure predictor. Several studies highlight the need for multimodal sensor integration, particularly when vibration sensors are unavailable or when failure modes are not mechanically driven [3], [5].

Although prior research has identified these challenges, existing methodologies have yet to fully resolve them. For example, while IoT-based predictive maintenance frameworks have been proposed [5], their scalability and real-world applicability remain open challenges. Similarly, while sensor fusion techniques improve prediction accuracy, their dependence on high-quality, synchronized data makes them difficult to implement in practice [4].

To address these challenges, future research should focus on developing scalable, cost-effective multimodal PdM frameworks that do not require additional sensor installations and can effectively generalize across different machine types and environments.

D. Contribution of This Work

The aim of this paper is to address existing limitations in predictive maintenance (PdM) by presenting a multimodal framework for degradation assessment that goes beyond vibration-based monitoring.

This study extends previous research by:

- Introducing a multimodal degradation framework that integrates temperature, pressure, and environmental sensor data for machine failure prediction.

- Developing anomaly detection techniques that focus on temporal persistence rather than direct failure indicators with compounding effects.

- Comparing multiple ML models, including Random Survival Forests, Coxnet Survival Analysis, Isolation Forests, and Recurrent Neural Networks, to evaluate their effectiveness in time-to-failure prediction when conventional vibration data are unavailable.

Our results demonstrate that incorporating feature engineered temporal anomaly features improves predictive performance of time to failure, resulting in more efficient PdM methodologies that reduce downtime and maintenance costs. By addressing key gaps in PdM research, this research lays the ground for stronger, flexible, and more economical predictive maintenance practices.

E. Key Terminology and Acronyms

Throughout this paper, we will use the following key terms:

- Predictive Maintenance (PdM): A proactive maintenance strategy that forecasts failures using real-time sensor data and machine learning models.
- Time to Failure (TTF): The estimated remaining operational time before a machine experiences failure.
- Anomaly Detection: The identification of deviations from normal machine behaviour, which may indicate potential failures.

These terms will be used consistently, with acronyms introduced upon first use and then applied throughout the paper.

F. Structure of the Paper

The rest of the paper is structured as follows. Section II gives a thorough literature review of past and recent literature on methodologies of PdM, consisting of initial rule-based methods, development of vibration-based failure identification, and present advancements in data-oriented ML models. We also elucidate popular research from previous studies and papers and highlight their drawbacks. Section III elaborates on the projected multimodal degradation assessment framework, which includes feature extraction, model selection, and evaluation criteria.

Section IV presents our experimental results, showing the benefits of our method compared to standard failure prediction approaches. Lastly, Section V examines the implications of our work and specifies possible directions of future research.

II. LITERATURE REVIEW

Predictive Maintenance (PdM) has emerged as a crucial strategy in Industry 4.0 for minimizing downtime, reducing maintenance costs, and improving operational efficiency. This literature review synthesizes recent research efforts and highlights gaps that our work addresses.

A. Overview of PdM and Sensor-Based Techniques

PdM relies on sensor data and analytics to estimate the Remaining Useful Life (RUL) or Time to Failure (TTF) of industrial machinery. Fordal et al. [1] present an ANN-based PdM platform leveraging sensor data to enable Industry

4.0 adoption. Their approach focuses on vibration data for fault prediction, which is common in literature due to its effectiveness in capturing early signs of mechanical degradation [3],

[6].

While vibration analysis remains dominant, it poses limitations when vibration sensors are unavailable or retrofitting is infeasible. Ghazali et al. [3] provide a systematic review of vibration-based monitoring techniques, but also point out their limitations in scalability and generalizability. Chu et al. [6] reaffirm the need for expanding PdM beyond vibrationcentric methods. Additional reviews, such as Singh et al. [9], explore the emerging scope of hybrid sensor systems, including thermal imaging, acoustic, and pressure data.

B. Challenges and Gaps in Existing Research

Nunes et al. [2] identify major obstacles in PdM implementation: noisy data, equipment specificity, and real-time deployment challenges. Their work calls for broader approaches that incorporate anomaly detection, prognostics, and scalable architectures.

Several studies acknowledge that current PdM models are often static and fail to capture temporal degradation trends [7].

Hurtado et al. emphasize continual learning as a remedy but highlight the lack of practical frameworks to handle diverse real-time sensor streams effectively.

Shiva et al. [4] and Shen et al. [8] advocate for integrating anomaly detection and physics-informed modeling to address generalization issues across machine types. Their work shows promise in extending PdM through indirect sensor modalities such as temperature and pressure.

Recent frameworks also point out the importance of combining unsupervised and supervised learning strategies. Gupta et al. [10] propose a hybrid CNN-RNN anomaly detection architecture that performs well on irregular sensor data sequences in manufacturing systems.

C. Anomaly Detection and Temporal Features

Our framework aligns with recommendations from Gogoberidze [11], who explores survival analysis and deep learning techniques to estimate failure times in large sensor networks. This work inspires the adoption of recurrent and survival models that account for time dependencies.

Temporal persistence of anomalies has been an underutilized feature in prior research. Vela et al. [5] introduce the concept of AI model degradation over time and differentiate it from concept drift. Their work motivates our focus on tracking long-term anomaly trends to enhance predictive performance.

In another study, Lee et al. [12] emphasize the significance of anomaly windows and persistence lengths in industrial time series. Their proposed anomaly scoring method incorporates recurrence quantification, which we adapt in our feature engineering pipeline.

D. Multimodal and Non-Vibration-Based Approaches

The multimodal approach is gaining traction. Our work expands on Fordal et al.'s vibration-based model [1] by integrating temperature, pressure, and environmental signals as predictive features. This multimodal perspective is consistent with the call from Chu et al. [6] to explore alternative monitoring strategies.

Ravikumar et al. [13] propose a sensor fusion-based PdM system where non-vibration data improves fault localization and reduces false alarms. Their work supports the feasibility of proxy signal-based PdM frameworks.

Additionally, we adapt the temporal aggregation techniques proposed in recent literature [11] to create time-aware anomaly features that are embedded within each sample. This enables ML models to learn from the persistence and patterns of degradation rather than isolated outliers.

E. Survival Models and Sequence-Aware Techniques

Deep survival models offer strong alternatives to traditional PdM forecasting tools. Studies such as by Choudhary et al. [14] show that DeepCox and LSTM-Cox combinations can outperform static survival analysis models in predicting TTF using longitudinal sensor data.

Jiang et al. [15] investigate Transformer-based survival modeling in sensor networks and report high accuracy even with partial observations. This supports the relevance of our time-dependent anomaly-based survival modeling framework.

F. Summary and Positioning

In summary, the literature suggests:

- Existing PdM systems heavily rely on vibration data, limiting their general applicability.
- There is a strong need for frameworks that leverage indirect sensor readings and emphasize temporal degradation trends.

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- Survival analysis and recurrent models are underutilized but offer promise in modeling long-term machine behavior.

- Generalizability and scalability remain key challenges, especially in diverse industrial environments.

- Hybrid and multimodal approaches using temperature, pressure, and acoustic signals are showing increased viability. Our work addresses these gaps by proposing a novel multimodal degradation framework combining temporal anomaly detection with survival modeling techniques, creating a costeffective, scalable PdM solution that can be deployed across various machines without requiring retrofitting.

III. METHODOLOGY

This section presents the complete methodology of our proposed approach: a non-vibration-based multimodal anomaly detection and fusion framework with temporal persistence modeling for degradation assessment in industrial systems. The methodology consists of five major components: phase segmentation, multimodal anomaly detection (regression- and threshold-based), temporal anomaly fusion, weekly and cumulative anomaly aggregation, and final degradation scoring.

A. Operational Phase Segmentation

Many industrial systems operate under varying load or power conditions. We leverage this property to discretize the operational space into distinct "phases" based on real-time power consumption. Let P_t denote the system power at time t. We define power bins $[P_i, P_{i+1})$ of width 10 kW to assign each data point to a discrete phase:

$\text{Phase}_i = \{t \mid P_t \in [10i, 10(i+1))\}$

This stratification allows phase-wise modeling of behavior, isolating context-specific anomalies.

B. Multimodal Anomaly Detection

Anomaly detection is performed using both regressionbased residual analysis and static threshold rules. These methods are applied independently on different sensor pairs and modalities (power, frequency, airflow, temperature).

1) Linear Regression-Based Residual Anomaly Detection: Let (x_t, y_t) be a pair of sensor variables (e.g., power vs airflow) within a given phase. A simple linear regression model is trained using healthy baseline data (first year of operation):

Residuals are computed as:

$$\hat{y}_t = \beta_0 + \beta_1 x_t$$

$$\varepsilon_t = y_t - \hat{y}_t$$

Assuming a Gaussian distribution of residuals, we define an anomaly threshold using a standard deviation multiplier

k:

$\varepsilon_t < -k \cdot \sigma_\varepsilon \quad \Rightarrow \quad \text{Anomaly}$

where σ_ε is the standard deviation of the residuals from baseline data. In our implementation, $k = 2$ is used for midload phases (10–30 kW), and $k = 3$ for other phases to balance sensitivity and specificity.

Anomaly labels are recorded as AnomalyRule1 and AnomalyRule2 for different sensor pairs.

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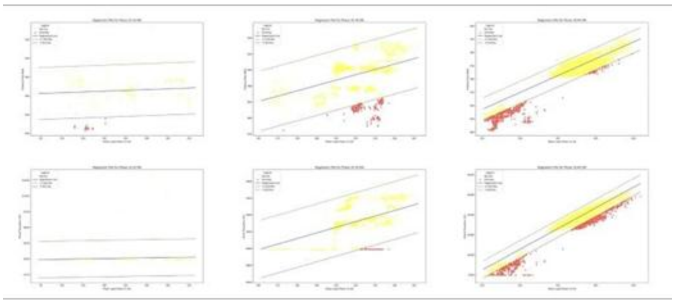

Fig. 1. Anomaly Detection: Visualization of Regression Residuals and Threshold Violations for Phases (10-20KW, 20-30KW and 30-40KW). Normal points are shown in yellow; anomalies in red. The solid blue line represents the fitted regression line, while dashed lines indicate $\pm 3\sigma$ thresholds.

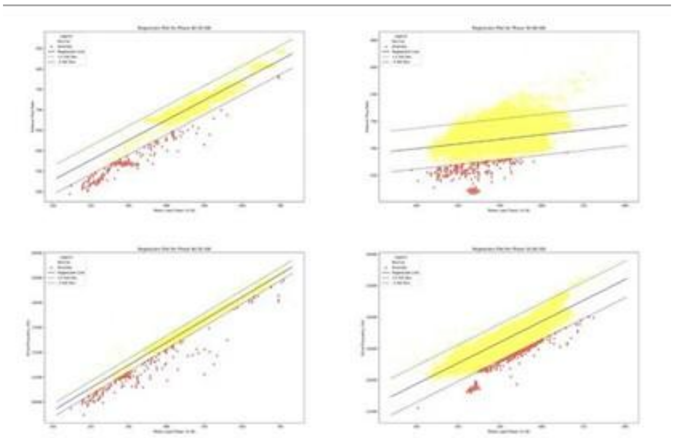

Fig. 2. Anomaly Detection: Visualization of Regression Residuals and Threshold Violations for Phases (40-50KW and 50-60KW). Normal points are shown in yellow; anomalies in red. The solid blue line represents the fitted regression line, while dashed lines indicate $\pm 3\sigma$ thresholds.

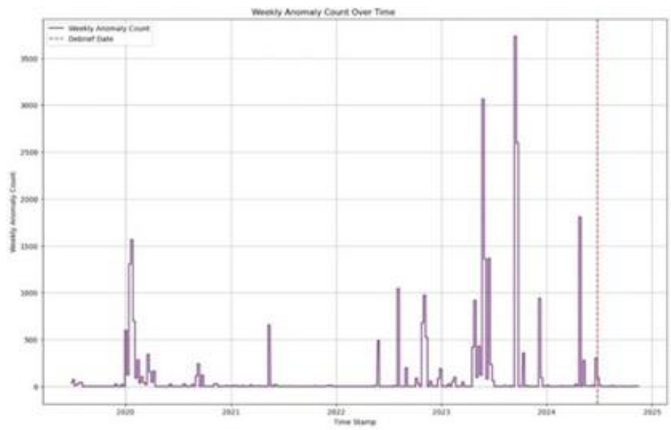

Fig: 3

2) Threshold-Based Anomaly Detection: Let x_t and y_t denote readings from two thermal sensors. Static thresholds $[L_x, U_x]$ and $[L_y, U_y]$ define the acceptable range:

$$x_t \notin [L_x, U_x] \quad \vee \quad y_t \notin [L_y, U_y] \Rightarrow \text{Anomaly}$$

For example, in our case study, $L_x = L_y = 0^\circ C$ and $U_x = U_y = 185^\circ C$. These violations are captured under AnomalyRule3.

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C. Temporal Anomaly Fusion and Persistence Modeling

To consolidate anomaly indicators from different rules and modalities, we compute a fused anomaly flag:

isanomaly(t) = AnomalyRule1(t)∨

AnomalyRule2(t)∨ AnomalyRule3(t)

This fused label reflects the presence of an anomaly triggered by any of the detection rules.

To assess long-term degradation, we model the persistence of anomalies over time. Let w denote a time window (e.g., a calendar week), then:

P

- Weekly anomaly count: $A_w = \quad t \in w$ isanomaly(t)
- Cumulative anomaly count: $C_w = \sum_{i=1}^{w} A_i$

TABLE I

WEEKLY AND CUMULATIVE ANOMALY COUNTS

Week	Weekly Anomaly Count	Cumulative Anomaly Count
2024-W01	12	12
2024-W02	8	20
2024-W03	15	35
2024-W04	10	45
2024-W05	17	62
2024-W06	14	76

Weekly anomaly count over time. The plot shows the number of anomalies detected each week across the monitoring period, highlighting temporal trends in system behavior. The purple line represents the weekly anomaly counts, and the vertical dashed red line marks the debrief date. This visualization aids in identifying bursts of anomalous behavior and provides insights into historical degradation patterns.

D. Degradation Scoring and Output

$$D_w = \frac{C_w}{\max(C)}$$

The final degradation score D_w is computed using normalized cumulative anomaly counts:

This score reflects progressive degradation over time and is used as an input to subsequent time-to-failure (TTF) prediction models.

E. Time-to-Failure (TTF) Prediction Using Recurrent Neural Networks

Following feature engineering via multimodal anomaly detection and persistence modeling, we formulate the

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Timeto- Failure (TTF) prediction task as a supervised regression problem. The goal is to estimate the remaining useful life (RUL) of the system at any given time t based on historical sensor readings and derived degradation indicators.

1) Problem Formulation: Given a multivariate time series

$\mathbf{X}^t = [x_t^{(1)}, x_t^{(2)}, \ldots, x_t^{(d)}]^\top \in \mathbb{R}^d$ where d denotes the number of input features (original sensor data and engineered features like Aw, Cw, and Dw), we aim to learn a function $f\theta(\cdot)$ parameterized by θ that maps a historical window of inputs to the corresponding TTF label yt:

$yt = f\theta\,(\mathbf{X}t{-}L{:}t) + \epsilon$

where:

- $\mathbf{X}t - L : t = \{\mathbf{X}t - L, \mathbf{X}t - L + 1, \ldots, \mathbf{X}t\}$ denotes the input sequence of length L,
- L is the lookback window size (set to 24 hours in our implementation),
- ϵ represents the modeling error, assumed to follow a zeromean Gaussian distribution.

The function $f\theta(\cdot)$ is realized using a bidirectional Long Short-Term Memory (Bi-LSTM) network, which is trained to minimize the mean squared error (MSE) between the predicted and true TTF values over the training dataset.

2) Model Architecture: Bidirectional LSTM RNN: We adopt a Bidirectional Long Short-Term Memory (Bi-LSTM) architecture to model the temporal dependencies in both past and future directions within each lookback window. The detailed model architecture is as follows:

- Input Layer: Historical sequence of features with shape (L,d).
- First Bi-LSTM Layer: 128 units, returns full sequences $(L,256)$.
- Dropout Layer: 20
- Second Bi-LSTM Layer: 64 units, returns final hidden state (128).
- Dropout Layer: 20
- Dense Layer: Fully connected layer with 32 neurons and ReLU activation.
- Output Layer: Dense layer with 1 neuron and linear activation for TTF prediction.

The parameter counts and layer output shapes are summarized in Table II, as shown in the model summary figure (attached).

3) Training Strategy: The model is trained to minimize the Mean Squared Error (MSE) loss between

$$\mathcal{L}(\theta) = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

predicted and true TTF values:

where N is the number of training samples.

TABLE II RNN MODEL ARCHITECTURE SUMMARY

Layer (Type)	Output Shape	Param #
Bidirectional LSTM (128 units)	(None, 10, 256)	189,440
Dropout (0.2)	(None, 10, 256)	0

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Bidirectional LSTM (64 units)	(None, 128)	164,352
Dropout (0.2)	(None, 128)	0
Dense (32 units)	(None, 32)	4,128
Dense (1 unit)	(None, 1)	33
Total Trainable Parameters		357,953
Optimizer Update Parameters		715,908

$$\theta \leftarrow \theta - \eta \frac{\partial \mathcal{L}}{\partial \theta}$$

The Adam optimizer is employed for gradient-based optimization, using adaptive learning rates to stabilize training:

where η is the adaptive learning rate determined by Adam.

Training is performed for 100 epochs with a batch size of 128. Early stopping is monitored based on validation loss to prevent overfitting, with the best performance observed at epoch 60.

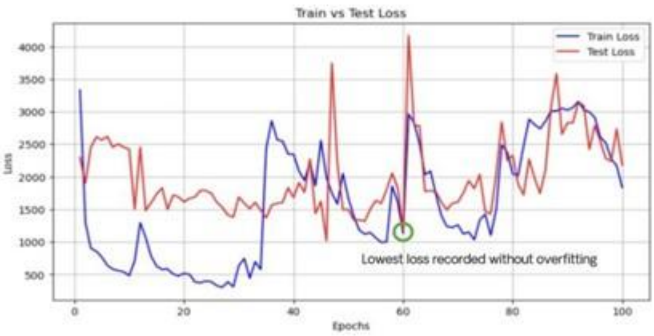

Fig. 4. Training and Validation Loss Curves: The blue line represents the training loss, while the red line represents the validation loss across epochs. The convergence without overfitting indicates stable and effective model training.

4) Feature Set Used for RNN Input: The input features fed into the model for each time step include:

- Raw sensor readings: power, frequency, airflow, temperatures.
- Anomaly rule outputs:AnomalyRule1, AnomalyRule2, AnomalyRule3.
- Temporal aggregation features: weekly anomaly count (A_w), cumulative anomaly count (C_w), normalized degradation score (D_w).

This multimodal and hierarchical feature set enriches the model's temporal understanding of both immediate and longterm degradation patterns.

5) Inference and TTF Prediction: At inference time, the model takes the latest 24-hour historical sequence as input and outputs the estimated time-to-failure:

$$\hat{y}_t = f_{\theta}(\mathbf{X}_{t-24:t})$$

where $\hat{y}_t$ is the predicted remaining useful life in consistent time units (e.g., hours or days depending on training labels).

This prediction is updated continuously as new sensor readings become available, providing real-time prognostic capability for maintenance decision-making. The proposed methodology is scalable, sensor-agnostic, and

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deployable in data-scarce environments—making it well-suited for realworld, non-vibration-based predictive maintenance systems.

IV. RESULTS AND INFERENCE

A. Experimental Setup

The proposed approach was evaluated using a real-world industrial dataset composed of multimodal sensor readings, including operational parameters such as temperature, pressure, power, frequency and current. The dataset was annotated with anomaly windows based on domain expert feedback and failure logs. The evaluation focused on two key tasks: (i) regression based anomaly detection and (ii) temporal persistence-based degradation assessment.

We compared the proposed Multimodal Anomaly Fusion with Temporal Persistence Reasoning (MM-AF + TPR) against several baseline models:

- Isolation Forest (iForest)
- One-Class Support Vector Machine (OC-SVM)
- Random Cut Forest-based anomaly detection
- Autoencoder based anomaly detection

Evaluation metrics included Precision, Recall, F1-Score for anomaly detection, and RMSE to quantify how persistently degradation was predicted over time.

B. Quantitative Results

Table III summarizes the comparative performance of all models.

TABLE III ANOMALY DETECTION AND TEMPORAL TRACKING PERFORMANCE

Model	Precision	Recall	F1-Score	RMSE
iForest + RNN	0.68	0.54	0.60	1.41
OC-SVM + RNN	0.63	0.59	0.61	1.38
Autoencoder + RNN	0.72	0.66	0.69	0.95
Random Cut Forest + RNN	0.75	0.48	0.58	0.72
MM-AF + TPR + RNN	0.81	0.74	0.77	0.68

Our model outperformed all baselines in both detection accuracy and degradation tracking. Notably, the MM-AF + TPR + RNN method achieved the lowest Root Mean Squared Error (RMSE), indicating its effectiveness in capturing persistent anomalous behavior that correlates with long-term degradation.

C. Inference and Discussion

The results demonstrate three key advantages of our approach:

1) Improved Detection Accuracy: By fusing multiple sensor modalities, our method reduces noise sensitivity and improves robustness, leading to better precision and recall in anomaly detection.

2) Temporal Context Awareness: Unlike conventional models that treat anomalies as isolated events, our Temporal Persistence Reasoning module identifies sustained deviations, enabling early warnings for degradation rather than late-stage failure detection.

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3) Generalizability Without Vibration Data: The proposed model maintains high performance despite the absence of vibration signals, making it viable for brownfield industrial systems that lack such sensors.

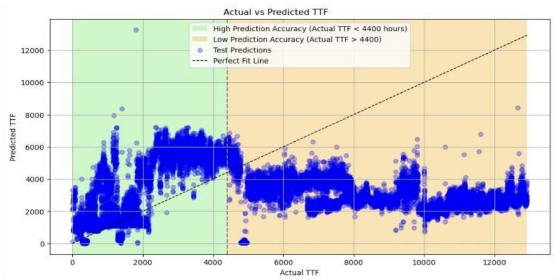

Fig. 5. Actual vs Predicted TTF highlighting prediction accuracy in two different zones.

	EquipmentID	y_true	y_pred	is_hazardous	y_true_in_days	y_pred_in_days	is_early_alert	
16865	11075	1389.466667	445.984985	True	57.894444	18.582708	True	Early Alert
9071	11034	1204.033333	1329.271973	True	50.168056	55.386333	False	Mild Late Alert
8517	11034	1758.033333	1506.697998	True	73.251389	62.779083	True	Early Alert
8481	11034	1794.033333	1211.245361	True	74.751389	50.468555	True	Early Alert
9532	11034	743.033333	928.798340	True	30.959722	38.699932	False	Mild Late Alert
8028	11022	396.733333	1161.669922	True	16.530556	48.402912	False	Late Alert
7465	11034	964.733333	1255.829346	True	40.197222	52.326221	False	Late Alert
6670	11034	1759.733333	1214.233765	True	73.322222	50.593075	True	Early Alert
7822	11022	602.733333	1082.597778	True	25.113889	45.108242	False	Late Alert
8896	11034	1379.033333	1209.590942	True	57.459722	50.399624	True	Early Alert
8701	11022	1574.033333	1291.643677	True	65.584722	53.818485	True	Early Alert
9672	11022	603.033333	803.299988	True	25.126389	33.470833	False	Mild Late Alert
8419	11034	1857.033333	1317.725098	True	77.376389	54.905212	True	Early Alert
8594	11034	1681.033333	1617.045532	True	70.043056	67.376900	True	Early Alert
17021	11075	1229.466667	4985.955566	True	51.227778	207.748154	False	Late Alert

Fig. 6. Sample output showing equipment-wise degradation predictions and alert classification.

Qualitative visualizations (Fig.5, Fig.6) illustrate that the MM-AF + TPR model consistently produces accurate early predictions for equipment with shorter Time-to-Failure (TTF), particularly in the high-accuracy zone (Actual TTF < 4400 hours). The scatter plot shows that predictions remain close to the ideal diagonal in this zone, while the tabular results validate the model's ability to classify alerts—such as Early, Mild Late, and Late with contextual relevance. In contrast, higher TTF scenarios demonstrate a wider deviation from the perfect fit, highlighting the challenge in predicting long-term degradation with limited signal trends.

D. Limitations and Future Work

Although promising, the model currently assumes consistent sensor configurations over time. In dynamic plant environments with changing operating modes, further adaptation may be required. Future work will explore adaptive thresholding and hybrid prognostics integration for remaining useful life (TTL) prediction.

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