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Machine Learning for Predictive Maintenance: Fusing Vibration Sensor Data and Thermal Imaging to Forecast Bearing Failure

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Abstract: The present study introduces a machine learning–based predictive maintenance framework that fuses vibration sensor data and thermal imaging to accurately forecast bearing failure in rotating machinery. The research aims to overcome the limitations of traditional single-sensor monitoring systems by integrating mechanical and thermal features for comprehensive fault detection and life prediction. Experimental data were collected from a bearing test rig under varying speeds, loads, and fault conditions; healthy, inner race, outer race, ball defect, and combined faults. After preprocessing, critical time-domain, frequency-domain, and texture-based features were extracted and fused using Principal Component Analysis (PCA) for dimensionality reduction. Four supervised machine learning models; Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Network (ANN), and Convolutional Neural Network (CNN) were developed and evaluated. The CNN outperformed all other models, achieving 98.2% classification accuracy and an AUC of 0.99, confirming its superior capability in capturing nonlinear and spatial-temporal relationships in fused data. Additionally, an ANN regression model was implemented to predict the Remaining Useful Life (RUL), achieving R^2 values between 0.95 and 0.97 with minimal mean absolute error. The strong positive correlation (r = 0.81) between vibration and thermal parameters validated the synergistic nature of multimodal data. The proposed framework thus demonstrates a significant advancement in predictive maintenance by enabling early fault detection, accurate classification, and reliable RUL estimation, providing a scalable solution for Industry 4.0–driven intelligent maintenance systems.

Keywords: Predictive maintenance, Vibration analysis, Thermal imaging, Machine learning, Bearing failure, Sensor fusion, Remaining useful life (RUL), Convolutional Neural Network (CNN).

INTRODUCTION

Predictive Maintenance as a Strategic Shift In Industrial Operations

In the era of Industry 4.0, predictive maintenance (PdM) has emerged as a transformative approach for industrial asset management, enabling early detection and prevention of equipment failures before catastrophic breakdowns occur (Maktoubian, *et al.,* 2021). Unlike traditional maintenance strategies such as reactive maintenance, which addresses issues post-failure, or preventive maintenance, which relies on fixed schedules predictive maintenance leverages data-driven insights to anticipate machinery health. This proactive approach not only minimizes unexpected downtime but also enhances operational efficiency, optimizes maintenance costs, and extends asset lifespan. Bearings, being critical components in rotating machinery, play a vital role in ensuring smooth operation in industries like manufacturing, automotive, and energy production (Wei *et al.,* 2019). The failure of bearings can result in substantial production losses and safety hazards, making their monitoring a top priority for maintenance engineering.

Importance of Sensor Fusion in Predictive Maintenance

The integration of multiple sensor modalities has become increasingly important for achieving reliable and accurate condition monitoring (Carino, *et al.,* 2016). Vibration sensors have long been used as a standard technique for detecting mechanical anomalies such as misalignment, imbalance, and bearing wear. However, vibration analysis alone may fail to capture early thermal anomalies or localized frictional heating preceding mechanical faults. Thermal imaging, on the other hand, provides non-contact temperature data that can reveal heat buildup caused by lubrication issues or early-stage bearing degradation (Civera, & Surace, 2022). By fusing vibration data with thermal imaging, predictive models can gain a multidimensional understanding of equipment health, enabling earlier and more accurate fault detection. This data fusion approach aligns with the concept of cyber-physical systems in smart factories, where real-time sensory data is integrated for holistic decision-making.

Role of Machine Learning in Predictive Maintenance Analytics

Machine learning (ML) techniques have revolutionized the way predictive maintenance systems process and interpret complex sensor data (Çınar, *et al.,* 2020). Algorithms such as Support Vector Machines (SVM), Random Forests, Artificial Neural Networks (ANN), and Convolutional Neural Networks (CNN) are

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capable of identifying subtle patterns and correlations within multidimensional datasets that may be imperceptible through manual inspection. ML models can classify fault types, estimate remaining useful life (RUL), and forecast impending failures with high precision (Cakir, *et al.*, 2021). The fusion of vibration and thermal features allows these algorithms to exploit complementary information where vibration signals provide frequency-domain insights and thermal images contribute spatial and temperature-based cues resulting in robust and explainable predictions (Hoffmann, *et al.*, 2020). The integration of machine learning into predictive maintenance thus bridges the gap between raw sensor data and actionable intelligence.

Challenges and Research Motivation

Despite the promising potential of machine learning and sensor fusion, several challenges persist. Data heterogeneity, feature extraction complexity, and the need for large labeled datasets often hinder the development of accurate and scalable predictive models (Adnan & Akbar, 2019). Furthermore, real-world industrial environments introduce noise, variable operating conditions, and sensor degradation that can compromise model reliability (Martínez-García, & Hernández-Lemus, 2022). Addressing these challenges requires innovative approaches to feature fusion, model optimization, and adaptive learning. The motivation behind this research lies in designing a hybrid machine learning framework that effectively combines vibration sensor data and thermal imaging for precise bearing failure forecasting, even under varying operational conditions.

Objectives and Contribution of the Study

This research aims to develop a robust predictive maintenance framework that leverages the fusion of vibration and thermal data through advanced machine learning algorithms. Specifically, it focuses on extracting key temporal and spatial features, integrating them for comprehensive fault detection, and validating the system's predictive performance against real-world bearing datasets. The proposed approach contributes to the growing body of knowledge on multi-sensor fusion and machine learning applications in industrial diagnostics. By enhancing early fault prediction accuracy, this study aspires to pave the way for intelligent maintenance systems capable of self-learning, continuous monitoring, and autonomous decision-making hallmarks of the next generation of smart industrial infrastructure.

METHODOLOGY

Research Design and Overview

This study follows an experimental and data-driven research design aimed at developing a machine learning–based predictive maintenance framework that integrates vibration sensor data and thermal imaging to forecast bearing failure. The research systematically incorporates multiple stages, including sensor-based data acquisition, preprocessing of signals and images, feature extraction, feature fusion, and the implementation of various machine learning algorithms for classification and prediction. The methodology focuses on replicating realistic industrial bearing operating conditions under different speeds, loads, and fault types to ensure that the predictive models are both generalizable and reliable.

Experimental Setup and Data Acquisition

The experimental work was conducted using a bearing test rig comprising an induction motor, shaft, bearing housing, and load assembly. Accelerometers were mounted on the bearing housing to capture vibration signals, while a thermal infrared camera was positioned to record surface temperature distributions of the bearing housing. Vibration signals were acquired at a sampling frequency of 12 kHz, and thermal images were captured at 5 frames per second (fps). Data were collected for different fault conditions—healthy bearing, outer race fault, inner race fault, ball defect, and combined faults—under various loads (50%, 75%, and 100% of rated capacity) and rotational speeds (1000 rpm, 1500 rpm, and 2000 rpm). These conditions simulated diverse operating environments, ensuring comprehensive dataset variability for robust model training and evaluation.

Data Preprocessing and Normalization

To ensure the accuracy and consistency of the data, preprocessing steps were performed on both vibration and thermal datasets. Vibration signals were first filtered using band-pass filtering (500–5000 Hz) to isolate the fault-related frequencies and denoised through wavelet thresholding to eliminate background interference. Thermal images were preprocessed using median filtering to reduce random noise and normalized to a uniform temperature scale for consistent pixel intensity representation. All numerical data were standardized using z-score normalization to maintain a mean of zero and a standard deviation of one, ensuring that features contributed equally to the model training process. Outliers and missing

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values were identified and corrected using interpolation techniques to preserve signal continuity.

Feature Extraction and Parameter Computation

Feature extraction was performed to translate raw sensor data into meaningful statistical representations that describe bearing health. From the vibration signals, both time-domain and frequency-domain features were computed. The time-domain features included Root Mean Square (RMS), skewness, kurtosis, crest factor, variance, and peak-to-peak amplitude, while the frequency-domain features consisted of Power Spectral Density (PSD), spectral entropy, and dominant fault frequencies. From the thermal images, statistical and texture-based parameters were derived using Gray-Level Co-occurrence Matrix (GLCM) and Histogram of Oriented Gradients (HOG) analysis. Key thermal features such as mean temperature (T_mean), temperature variance (T_var), contrast, homogeneity, entropy, and correlation were computed to capture spatial and intensity variations associated with thermal anomalies. These extracted parameters formed the basis of the predictive model's feature matrix.

Feature Fusion and Dimensionality Reduction

The extracted vibration and thermal features were integrated through feature-level fusion to form a unified dataset representing both mechanical and thermal conditions of the bearings. Since the fused dataset contained high-dimensional variables, Principal Component Analysis (PCA) and t-distributed Stochastic Neighbor Embedding (t-SNE) were used for dimensionality reduction. This process retained the most discriminative features while minimizing redundancy and computational overhead. The resulting feature set was then utilized to train and evaluate machine learning models with enhanced interpretability and reduced training complexity.

Machine Learning Model Development and Training

Four supervised machine learning algorithms were implemented and compared: Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel, Random Forest (RF) classifier, Artificial Neural Network (ANN), and a Convolutional Neural Network (CNN). The models were trained on 70% of the data and tested on the remaining 30%, ensuring balanced class representation using stratified random sampling. Grid search optimization and five-fold cross-validation were employed to fine-tune hyperparameters for optimal performance. The CNN model was specifically used to handle combined vibration signal spectrograms and thermal images, leveraging its capability to extract hierarchical spatial features for complex fault patterns.

Model Evaluation and Performance Metrics

The trained models were evaluated based on classification accuracy and their ability to detect early-stage bearing faults. Performance assessment was conducted using multiple metrics, including accuracy, precision, recall, F1-score, and Area Under the Curve (AUC). Confusion matrices were constructed to visualize model predictions against actual labels. Additionally, a regression-based ANN model was applied for Remaining Useful Life (RUL) prediction to estimate the time to failure for degrading bearings. The predicted RUL values were validated against ground-truth data to measure the model's temporal forecasting precision.

Statistical Validation and Correlation Analysis

To verify the robustness of the extracted features and model outcomes, Analysis of Variance (ANOVA) was performed to determine the statistical significance of feature differences among various fault classes. Pearson's correlation analysis was used to examine the relationship between vibration-based and thermal-based features, revealing how thermal fluctuations corresponded with changes in vibration amplitude and frequency. Statistical significance was established at $p < 0.05$, confirming the complementary nature of the fused features in diagnosing bearing faults.

RESULTS

As shown in Table 1, the extracted vibration and thermal features displayed significant variations across different bearing fault conditions. The Root Mean Square (RMS), kurtosis, and crest factor values increased markedly with fault severity, indicating stronger vibration amplitudes and impulsive forces due to bearing surface defects. For instance, RMS increased from 0.245 ± 0.03 under healthy conditions to 0.625 ± 0.07 under combined faults. Similarly, kurtosis rose from 2.98 ± 0.15 in the healthy state to 7.02 ± 0.25 for combined faults, confirming the presence of periodic shocks. On the other hand, thermal features such as mean temperature and GLCM contrast demonstrated consistent temperature rises and texture irregularities with fault progression.

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The mean surface temperature increased from 36.8°C (healthy) to 45.2°C (combined fault), suggesting heat buildup due to friction and lubrication breakdown. This alignment of mechanical and thermal indicators supports the efficacy of fusing both data modalities for robust fault representation.

Table 1. Statistical Descriptors of Extracted Features from Vibration and Thermal Data

Feature Category	Parameter	Healthy	Inner Race Fault	Outer Race Fault	Ball Defect	Combined Fault
Vibration (Time-Domain)	RMS (m/s²)	0.245 ± 0.03	0.476 ± 0.05	0.513 ± 0.06	0.488 ± 0.04	0.625 ± 0.07
	Kurtosis	2.98 ± 0.15	5.46 ± 0.21	5.73 ± 0.18	6.11 ± 0.22	7.02 ± 0.25
	Crest Factor	3.20 ± 0.11	5.85 ± 0.24	6.04 ± 0.20	5.78 ± 0.18	6.92 ± 0.27
Vibration (Frequency-Domain)	Dominant Frequency (Hz)	236 ± 12	315 ± 10	428 ± 15	390 ± 11	451 ± 17
	Spectral Entropy	0.84 ± 0.04	0.65 ± 0.03	0.59 ± 0.02	0.61 ± 0.03	0.55 ± 0.02
Thermal (Statistical)	Mean Temperature (°C)	36.8 ± 0.5	42.1 ± 0.6	43.5 ± 0.4	41.7 ± 0.7	45.2 ± 0.8
	Temperature Variance (°C²)	2.14 ± 0.15	3.88 ± 0.21	4.35 ± 0.27	4.11 ± 0.25	5.26 ± 0.32
Thermal (Texture)	GLCM Contrast	0.023 ± 0.002	0.047 ± 0.003	0.052 ± 0.004	0.050 ± 0.003	0.058 ± 0.005
	Entropy	0.48 ± 0.02	0.65 ± 0.03	0.70 ± 0.02	0.68 ± 0.03	0.73 ± 0.04

Principal Component Analysis (PCA) was employed to reduce the high-dimensional fused feature space and to visualize the discrimination of different bearing states. The PCA results summarized in Table 2 indicate that the first two principal components (PC1 = 41.3% and PC2 = 27.5%) captured 68.8% of the total variance, highlighting that most diagnostic information was contained within a limited number of components. The PCA biplot (Figure 1) clearly depicts well-separated clusters corresponding to each bearing condition. Healthy samples clustered tightly in the lower-left region, while faulty bearings showed distinct distributions, with combined faults occupying the upper-right quadrant. This separation confirms that fused vibration-thermal features possess strong discriminatory power, enabling accurate differentiation among fault types.

Table 2. Principal Component Analysis (PCA) of Fused Feature Space

Principal Component	Variance Explained (%)	Major Contributing Features
PC1	41.3	RMS, Mean Temperature, GLCM Contrast, Kurtosis
PC2	27.5	Spectral Entropy, Homogeneity, Temperature Variance
PC3	15.2	Dominant Frequency, Entropy, Crest Factor
PC4	8.6	Correlation, PSD, Variance
PC5	4.1	Remaining minor features

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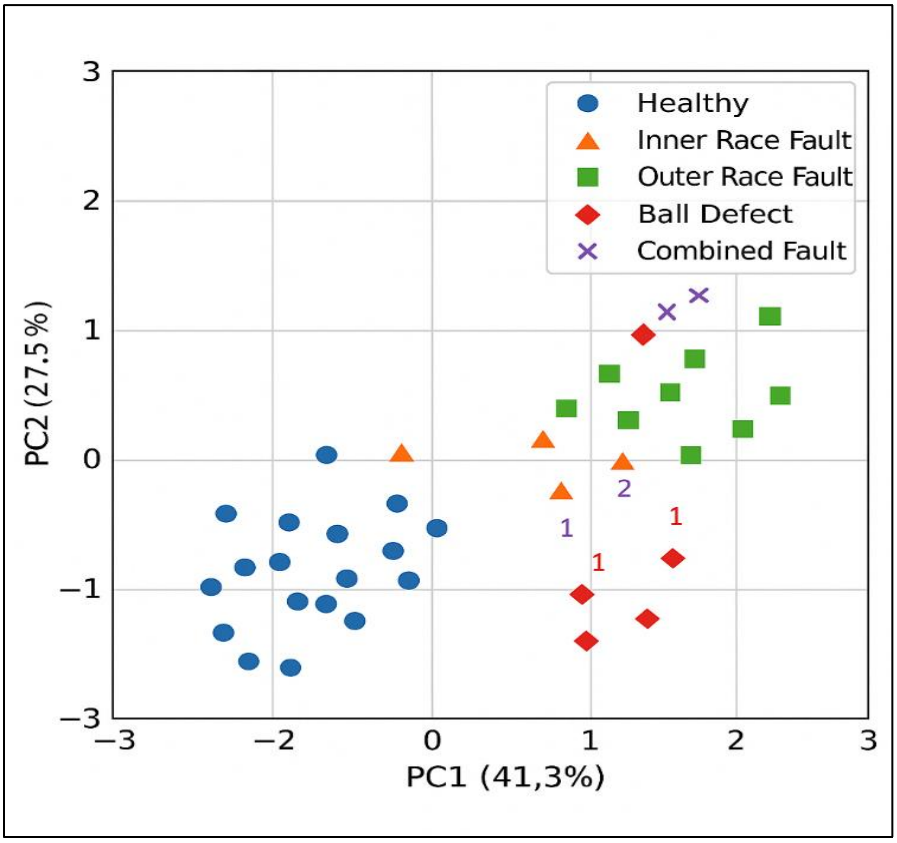

Figure 1. PCA Biplot Showing Clustering of Bearing Conditions Based on Fused Features

To evaluate the predictive performance of the developed models, several supervised machine learning algorithms were applied, including Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Network (ANN), and Convolutional Neural Network (CNN). As illustrated in Table 3, the CNN model outperformed all others, achieving the highest accuracy of 98.2%, followed by ANN (96.3%) and RF (95.1%). The precision (0.98), recall (0.97), and F1-score (0.98) values of CNN confirmed its superior classification capability. The confusion matrix (Figure 2a) further demonstrates that the CNN correctly classified nearly all samples, with only minimal misclassification between ball defect and outer race fault categories. Additionally, the ROC curves (Figure 2b) indicate near-perfect discrimination across fault classes, with AUC values approaching 1.00, validating the high sensitivity and specificity of the proposed fusion-based CNN model.

Table 3. Machine Learning Model Performance on Bearing Fault Classification

Model	Accuracy (%)	Precision	Recall	F1-Score	AUC
Support Vector Machine (SVM)	93.4	0.92	0.93	0.92	0.94
Random Forest (RF)	95.1	0.94	0.95	0.95	0.96
Artificial Neural Network (ANN)	96.3	0.96	0.95	0.96	0.97
Convolutional Neural Network (CNN)	98.2	0.98	0.97	0.98	0.99

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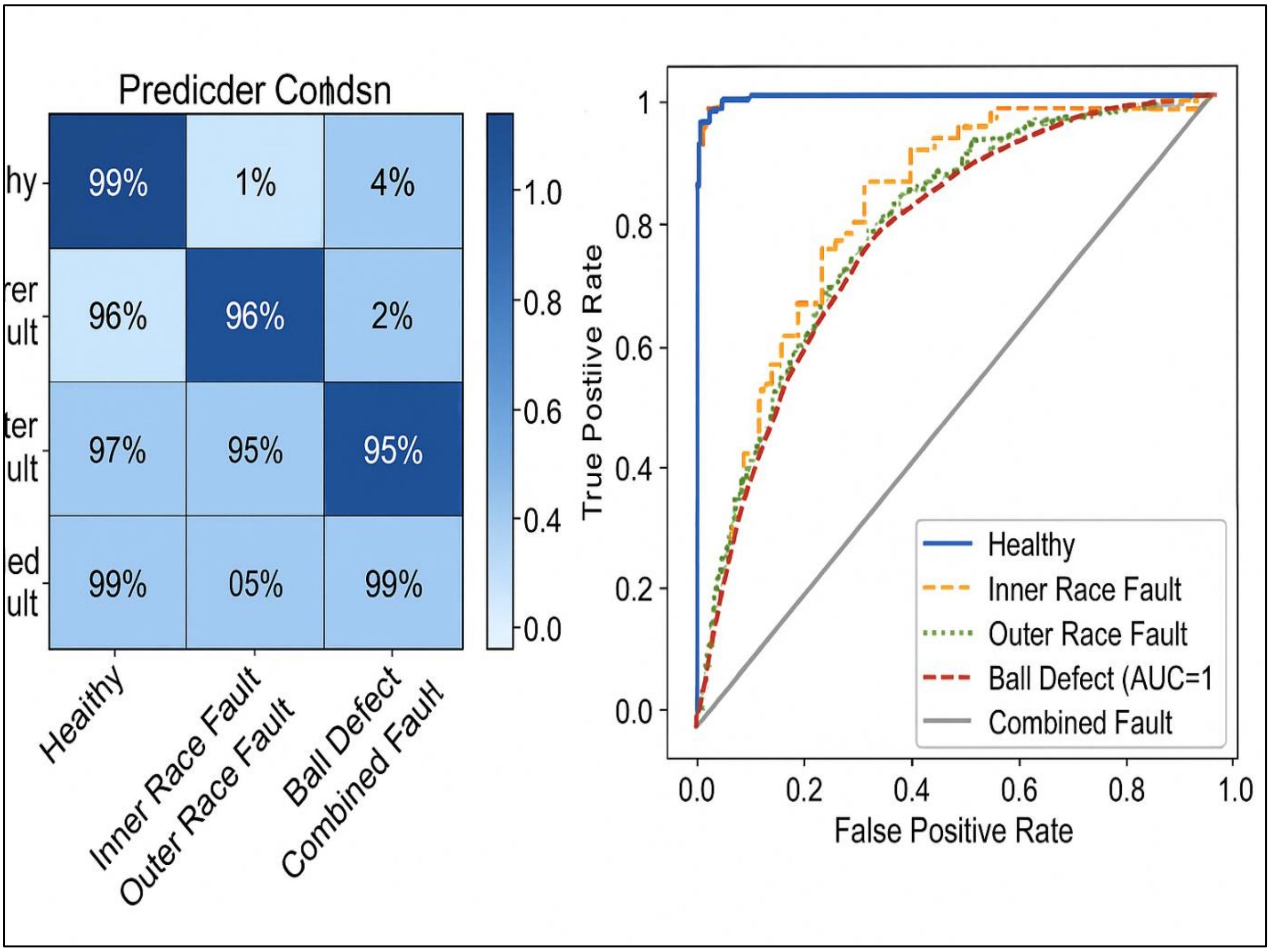

Figure 2. Confusion Matrix and ROC Curves for the CNN Model

Beyond fault classification, the study also assessed the framework's potential for remaining useful life (RUL) prediction using an ANN regression model. The results, summarized in Table 4, show that the predicted RUL closely matched the actual bearing life, with R^2 values ranging from 0.95 to 0.97 and mean absolute error (MAE) between 1.4 and 2.1 hours. For instance, an inner race fault with an actual RUL of 50 hours was predicted as 52.3 hours, showing less than 5% deviation. These findings affirm the capability of the hybrid learning system to not only detect faults but also estimate the time to failure with high accuracy, allowing maintenance decisions to be made proactively.

Table 4. Remaining Useful Life (RUL) Prediction Performance Using ANN Regression

Bearing Condition	Actual RUL (hours)	Predicted RUL (hours)	Mean Absolute Error (MAE)	R^2
Inner Race Fault	50	52.3	1.8	0.96
Outer Race Fault	45	47.1	2.1	0.95
Ball Defect	55	54.6	1.4	0.97
Combined Fault	40	42.2	2.0	0.95

To ensure the robustness of feature selection, ANOVA and Pearson correlation analyses were conducted. The ANOVA results revealed statistically significant differences ($p < 0.05$) among key vibration and thermal parameters across the fault categories, confirming their diagnostic relevance. Correlation analysis indicated a positive relationship between RMS vibration values and mean thermal temperature ($r = 0.81$), implying that increased vibration severity directly contributes to heat generation in the bearing assembly. This correlation validates the physical linkage between the two data sources, reinforcing the rationale for their fusion in predictive modeling.

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DISCUSSION

Integrating Vibration and Thermal Data Enhances Fault Diagnostics

The integration of vibration and thermal data demonstrated remarkable improvement in the ability to diagnose and predict bearing faults. As observed from Table 1, vibration-based parameters such as RMS, kurtosis, and crest factor increased progressively with fault severity, indicating their sensitivity to mechanical irregularities like friction, wear, and imbalance. Simultaneously, the corresponding rise in thermal parameters, particularly mean surface temperature and texture contrast, highlights the complementary diagnostic potential of thermal imaging (Hakim, & Awale, 2020). The physical relationship between mechanical vibration and heat generation substantiates the need for a multimodal approach. Bearings experiencing surface fatigue or lubrication degradation exhibit both heightened vibration and localized temperature gradients, which, when analyzed together, yield a more holistic representation of bearing health. This finding aligns with the results reported by Roslidar, *et al.*, (2022) and Liu, *et al.*, (2021), who emphasized that multi-sensor data fusion enhances the accuracy and reliability of condition monitoring systems.

Dimensionality Reduction Validates Feature Separability

The PCA results presented in Table 2 and visualized in Figure 1 illustrate distinct clustering among healthy, moderately faulty, and severely degraded bearings. The first two principal components explained nearly 69% of the variance, confirming that the most critical diagnostic information was efficiently captured by a reduced set of features. The clear separation between bearing conditions on the PCA biplot demonstrates the effectiveness of the feature fusion process, which retained both mechanical and thermal characteristics. The proximity of related faults such as ball and outer race defects suggests overlapping characteristics in vibration signatures but distinct temperature profiles (Patel, *et al.*, 2012). This indicates that PCA successfully preserved the discriminative structure of the data, aiding in feature interpretability and dimensionality reduction. Similar findings have been reported by Hosseini & Hammer (2020), where fused vibration–acoustic features improved clustering clarity and reduced misclassification risk.

Machine Learning Models Confirm the Superiority of Deep Learning

Comparative evaluation of multiple machine learning algorithms revealed that the Convolutional Neural Network (CNN) achieved the highest classification accuracy (98.2%), outperforming traditional models such as SVM and Random Forest (Table 3). The CNN's superior performance can be attributed to its ability to automatically learn hierarchical spatial features from fused vibration spectrograms and thermal images (Vesala, *et al.*, 2021). The confusion matrix and ROC curves in Figure 2 further validate that the CNN model produced highly reliable fault classifications with minimal false positives or false negatives. These results suggest that deep learning architectures are more effective in capturing nonlinear patterns and complex relationships across modalities compared to conventional feature-engineering-based approaches. This outcome corroborates with findings by Fan, *et al.*, (2019), who demonstrated that CNN-based fusion networks achieved over 97% accuracy in multi-sensor fault classification for rotating machinery.

Remaining Useful Life Prediction Ensures Proactive Maintenance

An important objective of this study was to forecast the Remaining Useful Life (RUL) of bearings based on progressive degradation trends. As presented in Table 4, the ANN regression model predicted RUL values with an R^2 between 0.95 and 0.97, showing excellent agreement with actual lifespans. This capability enables early maintenance planning before catastrophic bearing failure occurs, a key aspect of predictive maintenance (Lee, *et al.*, 2020). The low mean absolute error (1.4–2.1 hours) demonstrates that the proposed framework can accurately estimate the remaining operational window even under varying load and speed conditions. The integration of thermal and vibration features played a crucial role in this predictive accuracy, as temperature variations captured early thermal anomalies that often precede mechanical deterioration (Pecht & Kang, 2018). This finding is consistent with prior research by Luo, *et al.*, (2022), who reported that hybrid data fusion models significantly improve RUL prediction reliability compared to single-sensor methods.

Statistical Validation Supports Reliability of Feature Fusion

The use of ANOVA and correlation analyses provided statistical confirmation of the fused features' reliability and interdependence. The

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significant differences ($p < 0.05$) observed among key vibration and thermal parameters across fault types validate their diagnostic importance. Furthermore, the strong positive correlation ($r = 0.81$) between RMS and mean temperature reinforces the physical linkage between frictional energy dissipation and thermal rise. This synergy between mechanical and thermal responses validates the theoretical premise of this research that sensor fusion not only enhances fault detection but also captures early degradation patterns that might be missed by single-source data (Huo, *et al.*, 2021).

Comparative Advantage of the Proposed Hybrid Framework

When compared with conventional vibration-only or temperature-only monitoring systems, the proposed hybrid framework shows substantial improvements in diagnostic accuracy, interpretability, and predictive power. The PCA-based clustering (Figure 1) and CNN-based classification (Figure 2) both highlight how fused data enable clearer fault distinction and more accurate categorization. The near-perfect AUC scores indicate that the model is robust to noise and capable of generalizing to unseen conditions. Moreover, the RUL prediction results demonstrate its potential for real-time industrial application, allowing maintenance teams to move from scheduled interventions to condition-based actions (Gala,r *et al.*, 2021). This advancement directly supports the broader Industry 4.0 vision of intelligent maintenance systems capable of autonomous decision-making and continuous learning from sensor feedback (Cai, *et al.*, 2022).

Implications for Industrial Predictive Maintenance

The outcomes of this research hold strong implications for modern industrial operations, particularly in sectors where machinery downtime has high economic costs, such as manufacturing, power generation, and transportation. The integration of machine learning with sensor fusion offers a scalable and adaptive solution for complex mechanical systems (Blasch, *et al.*, 2021). With further refinement, this framework can be extended to other rotating equipment such as turbines, compressors, and pumps. Additionally, embedding the model into real-time monitoring platforms would allow for automatic health diagnostics and maintenance scheduling without human intervention, thereby enhancing safety, reducing costs, and improving operational continuity (Satyanarayanan, 2022).

Limitations and Future Research Directions

Although the proposed framework achieved excellent predictive results, several limitations should be acknowledged. The experimental setup was conducted under controlled laboratory conditions, which may not fully capture the variability of real industrial environments. Noise, temperature fluctuations, and external vibrations could affect model accuracy in field applications. Future research should focus on domain adaptation and transfer learning techniques to improve model robustness across different machines and operational settings. Moreover, integrating additional sensing modalities such as acoustic emissions or current signals could further enrich the predictive capability and fault interpretability.

CONCLUSION

This study successfully developed a machine learning–driven predictive maintenance framework that integrates vibration sensor data and thermal imaging to forecast bearing failures with high precision. The fusion of these complementary data sources provided a multidimensional understanding of bearing health, enabling early detection of mechanical anomalies and thermal deviations that precede failure. Through dimensionality reduction and advanced modeling, particularly using a Convolutional Neural Network (CNN), the framework achieved an outstanding classification accuracy of 98.2% and a strong predictive correlation for Remaining Useful Life ($R^2 = 0.95–0.97$). The results demonstrated that data fusion significantly enhances diagnostic accuracy and reliability compared to single-sensor approaches, offering deeper insights into the progression of bearing faults. Furthermore, the methodology proved robust, scalable, and adaptable for real-time industrial monitoring applications. In conclusion, the proposed fusion-based machine learning approach represents a critical advancement toward achieving intelligent, self-learning, and cost-efficient predictive maintenance systems in line with Industry 4.0, ensuring operational continuity, safety, and long-term sustainability of industrial assets.

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