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PREDICTIVE MAINTENANCE DEEP LEARNING FRAMEWORK FOR IOT-ENABLED FOOD PROCESSING EQUIPMENT

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Abstract :The development of smart manufacturing and Industry 4.0 has emphasized the utilization of intelligent manufacturing tools, techniques, and methods such as Predictive Maintenance (PM). The predictive maintenance function facilitates the early detection of failure and errors in machinery before they reach critical phases. Proper maintenance keeps the life cycle cost down and guarantees proper operations and good order internal logistics. This dissertation proposes a data-driven predictive maintenance framework tailored for IoT-enabled smart companies. Unlike existing research that focuses on anomaly detection through simulations, our study presents an end-to-end PM framework evaluated with real-world manufacturing data. The framework comprises five layers: Data Preprocessing and Feature Extraction, Feature Ranking and Selection, Clustering for Anomaly Pattern Mining, Supervised Anomaly Detection, and Anomaly-triggered Remaining Useful Life (RUL) Prediction. Combining unsupervised clustering with supervised deep learning, the framework effectively identifies anomalies and estimates equipment RUL. Testing revealed significant accuracy in tool wear and RUL prediction using LSTM variants, demonstrating the framework's effectiveness across various use cases.

IndexTerms - Predictive Maintenance, Anomaly-Onset Aware RUL Estimation, LSTM Variants, Data driven Model

I. INTRODUCTION

The Internet of Things (IoT) and Intelligent Production and Manufacturing are transforming various industrial sectors in the current century. This evolution emphasizes the strategic importance of predictive structural health monitoring and management technologies to meet the service demands of advanced manufacturing and safety-critical infrastructures. Industry 4.0, characterized by the integration of intelligent robotic systems and cyber-physical systems (CPS), is revolutionizing industrial processes by enhancing efficiency, monitoring, control, and automation.

Prognostic Health Management (PHM) is crucial in engineering and industrial sectors, focusing on improving maintenance techniques, machine performance, and operational efficiency. PHM includes predictive maintenance, which uses AI to analyze historical data and perform maintenance proactively, reducing costs and increasing productivity. The study aims to determine the most cost-effective maintenance strategies for small and micro companies using Multi Criteria Decision Making Tools. It explores the evolution of maintenance strategies from reactive to predictive maintenance and the integration of IoT in equipment monitoring and management, emphasizing the shift towards predictive maintenance in the food processing industry.Predictive maintenance leverages data analytics, machine learning, and sensor technology to proactively detect equipment issues, minimizing downtime and optimizing maintenance schedules. The study's objectives include extracting machine monitoring sensor data, designing a deep learning framework for anomaly detection, applying the technique in smart manufacturing, and analyzing its performance on real-world data.

II. LITERATURE REVIEW

2.1 General

Performing a literature review facilitates the research process by providing guidance through potential challenges and establishing a foundation based on previous studies. This review examines existing research on food dryers and IoT-based real-time monitoring solutions, focusing on the behavior of food within dryers, their monitoring systems, and the drying and value addition of green leaves. It also addresses critical findings and remarks from various researchers, highlighting significant factors pertinent to the research undertaken.

2.2 Applications of IoT

IoT technology offers numerous applications in agriculture, enhancing precision and efficiency through real-time monitoring and intelligent systems.

1.Soil and Crop Monitoring:

IoT sensors enable real-time monitoring of soil temperature, moisture, and nutrient content, optimizing crop management practices such as irrigation and fertilization (Pramanik et al., 2022).

2.Livestock Management:

Using body area sensors, temperature sensors, heart rate monitors, and GPS modules, IoT systems optimize feeding, breeding, and health management of livestock (Arshad et al., 2022).

3.Weather Monitoring:

IoT sensors track meteorological parameters like temperature, humidity, and rainfall, improving crop management and reducing crop loss due to adverse weather conditions (Mohapatra et al., 2022).

4.Crop Prediction and Yield Optimization:

IoT sensors in agricultural fields monitor environmental factors affecting crop growth. Data analysis reveals patterns and correlations for yield forecasting and informed decisions on planting, fertilizing, and harvesting (Phasinam et al., 2022).

5.Smart Irrigation:

IoT sensors monitor soil moisture levels, adjusting irrigation systems to provide the right amount of water at the right time, enhancing water use efficiency (Lima, 2019).

6. Food Supply Chain:

IoT-based Food Supply Chain Management (FSCM) systems track food safety, quality, and lifespan from production to sale. These systems help manage food safety procedures, monitor food storage and transportation, and ensure high-quality food products for consumers (Wei et al., 2023).

Overall, IoT has the potential to transform agriculture into a more productive, environmentally friendly, and financially viable industry.

2.3 Uses of Microcontroller in Agricultural Technology

Microcontrollers play a crucial role in IoT applications for agriculture, enabling the development of efficient monitoring and control systems.

Temperature and Humidity Monitoring System:

Roy et al. (2017) developed a system using the ATmega 328 microcontroller and C/OS-III embedded operating system to monitor industrial storage room conditions. The system utilized various access technologies (Wi-Fi, GPRS, Ethernet) for real-time monitoring, enhancing the accuracy of temperature and humidity detection in storage rooms. Their findings demonstrated the potential for extending the lifespan of stored fruits by maintaining optimal temperature and humidity levels.

White Copra Dryers:

Aror et al. (2018) used solar cells to power heating and fan systems in white copra dryers. The system, controlled by an Arduino Uno, maintained temperatures between 60°C and 80°C, activating the heater and fan as needed to ensure high-quality copra production.

Smart Refrigerator:

Nasir et al. (2018) designed a smart refrigerator with sensor modules (load cell, odour sensor), control modules (Arduino UNO, power supply), and transmission modules (LCD, Wi-Fi). The system monitored food quantity and condition, alerting users via text message and email. Gas sensors detected emissions from organic foods, maintaining cleanliness and freshness, while temperature and humidity sensors ensured optimal storage conditions.

Freezer Temperature Monitoring:

Budijono and Felita (2020) created a system using the ESP32 microcontroller, DS18B20 temperature sensor, and OLED SSD1306 display. The system monitored freezer temperature, comparing it to set thresholds and transmitting data to the cloud for remote analysis. This enabled users to address temperature issues promptly, preventing freezer malfunctions.

Grain Storage Monitoring:

Ekuewa et al. (2021) developed a system to monitor temperature, humidity, and moisture content in grain silos. Security systems (flame sensor, passive infrared sensor) provided alerts for high temperatures and intrusions. Data was transmitted to the cloud via GSM, allowing real-time status updates and management decisions through a mobile application.

Biomass Dryer Temperature Control:

Muhammad and Krisman (2021) designed a system with an Arduino microcontroller, LM35 temperature sensors, buzzer, and LCD screen to regulate temperature in a biomass dryer. The system maintained consistent drying temperatures by automatically opening windows to release excess heat, ensuring product quality.

2.4 Predictive Maintenance in Agriculture

Predictive maintenance is a critical aspect of modern smart manufacturing and agriculture, offering proactive solutions to machinery failures and operational inefficiencies. The implementation of predictive maintenance frameworks enables early detection of equipment failures, thus preventing critical malfunctions and reducing life cycle costs.

Data-Driven Predictive Maintenance:
In the context of IoT-enabled smart agriculture, data-driven models are essential for predictive maintenance. These models leverage data collected from various sensors to predict equipment failures accurately. The integration of predictive maintenance within agricultural IoT systems allows for controlled system shutdowns, avoiding emergency shutdowns and reducing associated costs.

Anomaly Detection Techniques:
Existing literature has focused extensively on developing anomaly detection techniques using simulations. However, there is a growing need for end-to-end predictive maintenance frameworks that can be evaluated using real-world data. Combining unsupervised clustering methods with supervised deep learning techniques enhances the detection of anomalies and the estimation of equipment remaining useful life (RUL).

Effectiveness of LSTM Variants:
The use of Long Short-Term Memory (LSTM) networks and their variants has shown significant promise in predictive maintenance applications. LSTM networks are particularly effective in handling time-series data, capturing temporal dependencies, and providing accurate predictions of tool wear and RUL. This effectiveness has been demonstrated through the application of LSTM variants to real-world datasets, yielding substantial accuracy in predictive maintenance tasks.

In summary, microcontrollers and IoT technologies significantly enhance agricultural monitoring and control systems, leading to improved efficiency, product quality, and management capabilities. Furthermore, the integration of predictive maintenance frameworks into these systems offers a comprehensive solution for early anomaly detection and accurate RUL estimation, contributing to the reliability and cost-effectiveness of smart agricultural operations.

III. Methodology for Anomaly-Onset Aware Remaining Useful Life Estimation (AOA-RUL)

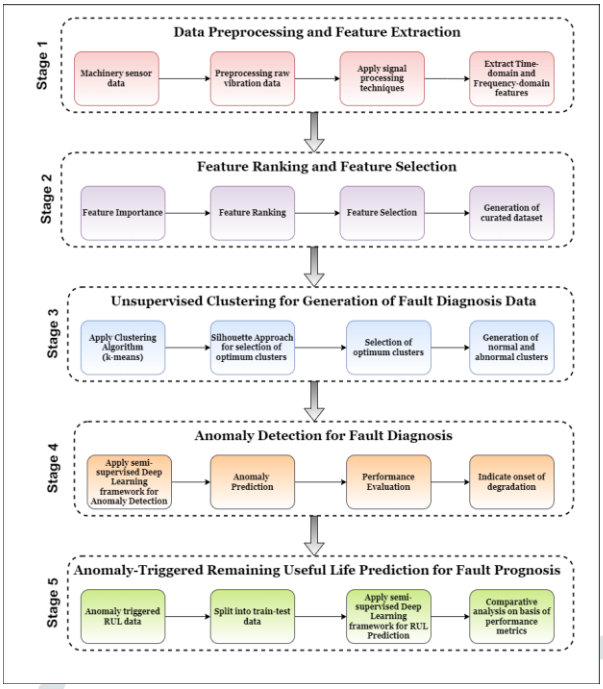
This chapter covers the combined technique for anomaly detection and remaining usable life prediction, referred to as "Anomaly-Onset Aware Remaining Useful Life Estimation (AOR-RUL)" from this point forward. The remaining life prognosis starts after the knowledge of the onset of the abnormality, which allows for the avoidance of calculations that are not essential prior to the beginning of the deterioration process. Using signal processing methods, unsupervised and supervised machine learning, and deep learning methodologies, this chapter provides a description of the five basic phases that comprise the AOA-RUL framework.

3.1 Anomaly-Onset Aware Remaining Useful Life Estimation (AOA-RUL) Methodology

Figure illustrates the architecture of the proposed Anomaly-Onset Aware RUL Prediction. One distinctive characteristic of this framework is that it allows for the development of a uniform method for fault diagnosis and prognosis. Unsupervised clustering methods are utilized for anomaly trend analysis, while supervised deep learning techniques are used for determining the incidence of anomalies and estimating RUL. There are five stages that make up the AOA-RUL estimation framework:

1. Data Preprocessing and Feature Extraction
2. Feature Ranking and Feature Selection
3. Clustering for Anomaly Pattern Mining
4. Supervised Anomaly Detection for the detection of the onset of anomaly
5. Anomaly-triggered RUL prediction for Fault Prognosis

Each step is broken down into its component parts in further detail in the next subsections.



3.1.1 Data Preprocessing and Feature Extraction

For estimating the lifespan of any piece of equipment, vibration data is a critical element. The magnitude and dispersion of the vibration signal change as the equipment approaches breakdown. The Pronostia bearings process involves collecting 2,560 data points over ten seconds, processed as a single signal. The total intensity level of these points shifts with fault severity. Feature extraction is used to convert raw machine data into more relevant information for model input. Features that correlate strongly with the target variables are selected, improving the model's predictive performance. Time-domain and frequency-domain features are particularly useful for monitoring equipment status from normal to failure.

3.1.1.1 Time-Domain Features

Time-domain features reflect characteristics associated with the progression of equipment deterioration. They help in identifying transient or atypical information in the time series of incoming data. Table 3.1 lists the time-domain features derived from the vibration signal used in this research.

3.1.1.2 Frequency-Domain Features

Frequency-domain features represent the quantity of information in each vibration signal. Different equipment flaws have distinct frequencies, making frequency-domain characteristics useful for fault identification.

3.1.2 Feature Ranking and Feature Selection

Time-domain and frequency-domain features indicate equipment degradation. Random feature selection can lead to overfitting, where the model performs well during training but poorly during testing. Feature selection identifies essential characteristics, removing those with minimal impact on model output. This improves model accuracy and performance. Feature selection methods used in this study include:

1. Linear Regressor: Uses recursive elimination for feature selection.
2. Random Forest Regressor: Computes average impurity scores for feature importance.
3. Mutual Information Regressor: Ranks feature relevance based on mutual information with the target variable.

The top five features from accelerometer sensors X and Y are selected for clustering to mine anomalous patterns.

3.1.3 Clustering for Anomaly Pattern Mining

Predictive maintenance datasets are often unlabeled or unannotated. Anomalies can occur at any time, leading to atypical vibrations. Unsupervised clustering is necessary for anomaly pattern mining, grouping representative samples based on distance measures. K-means clustering, used in this study, generates normal and anomalous clusters. The silhouette coefficient determines the appropriate number of clusters, indicating the clustering strategy's effectiveness.

3.1.4 Anomaly Detection for Onset of Anomaly

Anomaly detection identifies events that deviate from normal data. It is critical for predictive maintenance, providing insights into machine health. Anomaly detection techniques can be supervised, unsupervised, or semi-supervised. Supervised techniques require instance labels, while unsupervised and semi-supervised methods handle outliers as anomalies using pattern mining. Autoencoders, semi-supervised models, detect anomalies based on reconstruction loss. Sequential data in machine degradation can be effectively modeled using recurrent neural networks (RNNs) like long-term memory models (LSTM).

A hybrid AE-LSTM (Autoencoder-Long Short Term Memory) model is developed for anomaly detection in this research. The feature vector from previous steps is input to the hybrid model, trained on normal and pathological clusters. The model encodes data into LSTM features, capturing temporal correlations. Reconstruction loss is calculated at each step, with significant loss indicating anomalies. Figure 1. illustrates this hybrid model.

3.1.5 Anomaly-Onset Aware RUL Estimation

The final phase of the predictive maintenance framework is RUL estimation. Accurate RUL predictions are crucial for industrial equipment based on degradation data. The onset of the first abnormality is identified in the previous step. The AOA system prevents RUL estimation during normal operations, focusing on the deterioration phase. The RUL estimator trains and tests as soon as deterioration is detected. Sequential prediction, distinct from other supervised learning methods, retains the order of data for accurate forecasts. LSTM models, designed for sequential input, predict RUL by capturing temporal relationships.

Different LSTM variations are used for RUL estimation, including:
- Vanilla LSTM:Basic LSTM model with a hidden state and prediction layer.
- Bidirectional LSTM: Processes input sequences in both forward and backward directions.
- Stack LSTM:Includes multiple hidden memory layers for deep learning.
- CNN_LSTM: Combines CNNs for feature extraction with LSTM for sequence prediction.
- Conv_LSTM:Similar to CNN_LSTM but includes convolutional interpretation within LSTM units.
- AE-LSTM:Hybrid model using autoencoders and LSTM for anomaly detection and RUL estimation.

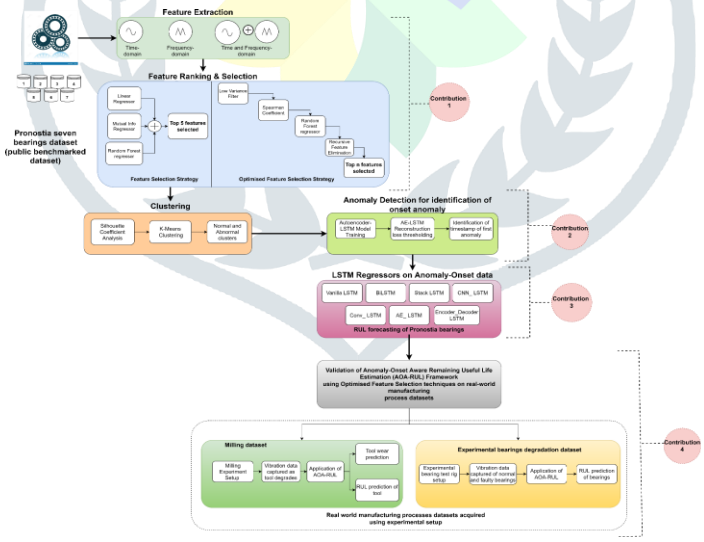


Figure 1: System Overview of the research study.

Formally, RUL estimation is a sequential problem-solving process. The sliding window method segments continuous time-series data into segments, each labeled with a decreasing RUL value. This method improves the model by capturing dynamic aspects over time. The sequence length and window size parameters significantly impact model performance and should be carefully analyzed.

IV. Implementation of the Proposed Methodology

4.1 Introduction

The Anomaly-Onset Aware Remaining Useful Life (AOA-RUL) Prediction framework integrates unsupervised clustering methods and supervised deep learning techniques to identify anomalies and predict the Remaining Useful Life (RUL) of machinery. This chapter details the implementation of the AOA-RUL framework, focusing on the technical procedures, algorithms, and tools used to achieve accurate anomaly detection and RUL estimation.

4.2 Framework Overview

The AOA-RUL framework involves a multi-step process designed to enhance the prediction accuracy of RUL by leveraging both time-domain and frequency-domain features. The framework's primary components include:

1. Data Collection and Preprocessing: Gathering raw sensor data and preprocessing it to extract relevant features.
2. Feature Selection: Utilizing advanced algorithms to select the most significant features for the prediction tasks.
3. Clustering and Anomaly Detection: Employing clustering techniques to identify normal and abnormal patterns in the data.
4. RUL Prediction: Applying deep learning models to predict the remaining useful life based on the detected anomalies.

4.3 Data Collection and Preprocessing

For the implementation, data is collected from different sensors installed on the equipment. The primary datasets include:
- Pronostia Bearings Dataset: A public dataset used for initial testing and validation.
- Milling Tool Wear Dataset: Vibration data collected from sensors on a milling machine.
- Bearing Machinery Dataset: Vibration data from journal bearings to simulate real-world operational conditions.

4.3.1 Pronostia Bearings Dataset

The Pronostia dataset contains vibration measurements from bearings under various operating conditions. It serves as a benchmark for testing the efficacy of the AOA-RUL framework.

4.3.2 Milling Tool Wear Dataset

In the milling tool wear experiment, vibration sensors are attached to the spindle and table of a Vertical Machining Control (VMC) system. Data is collected at a sampling rate of 1000 Hz during a milling process with a motor speed of 1000 RPM, a feed rate of 25 mm/revolution, and a cut depth of 0.25 mm.

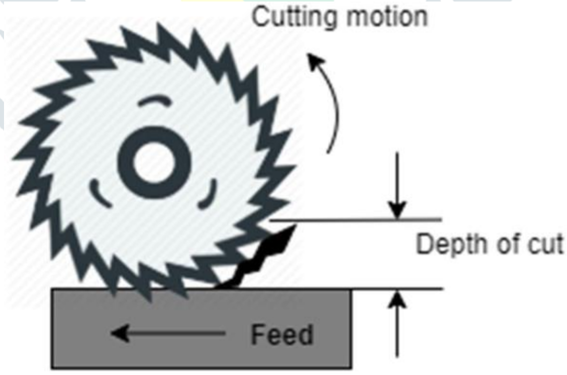


Figure 2: Diagrammatic representation of typical milling procedure

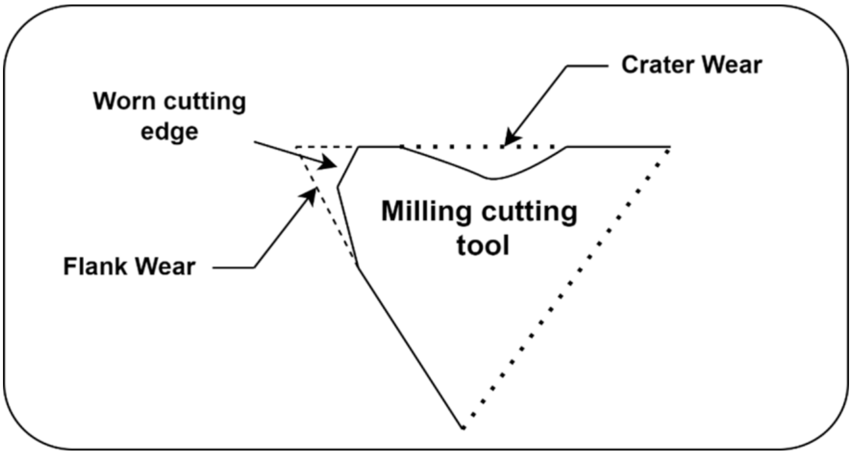


Figure 3: Types of tool wear faults in milling process [182]

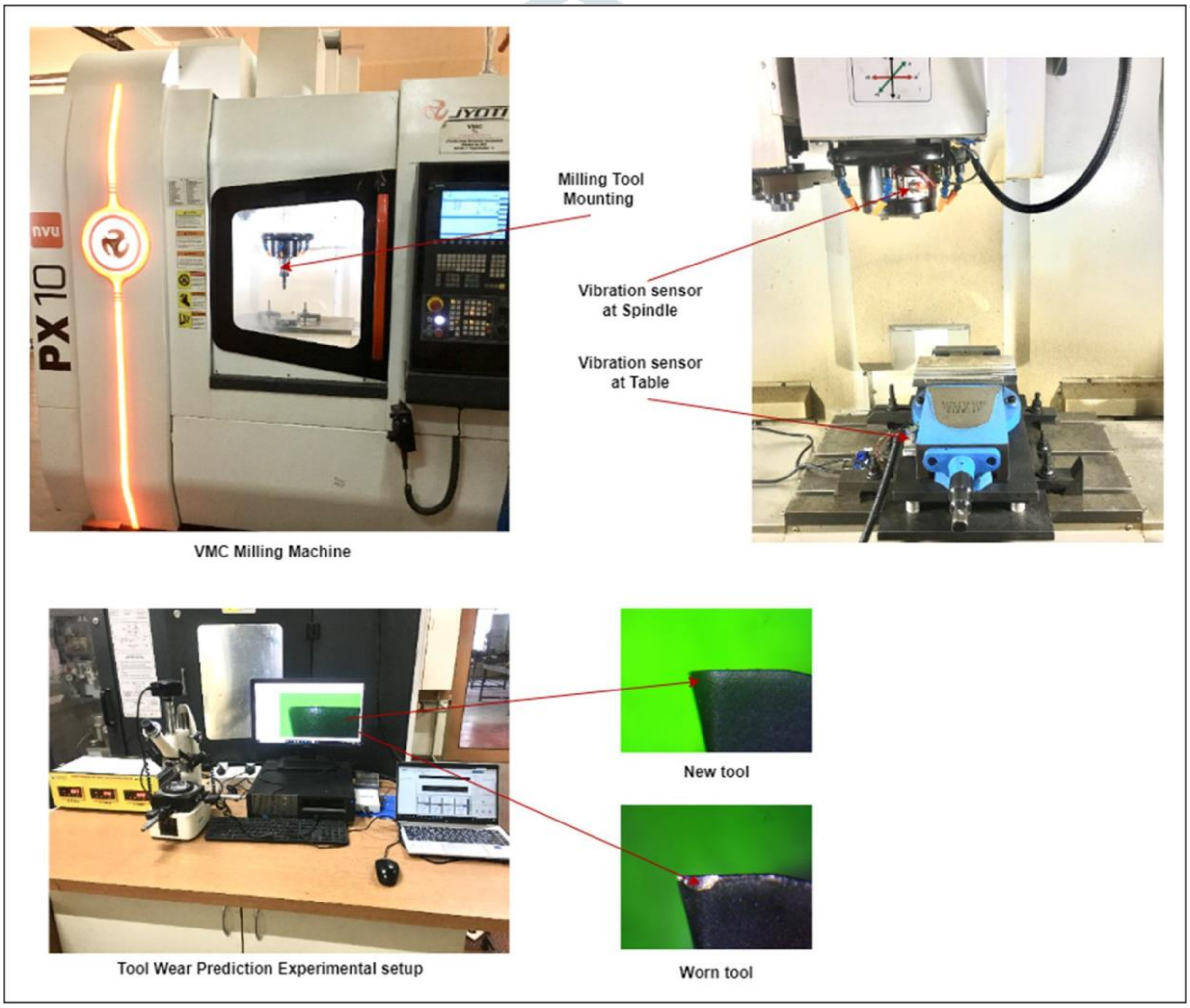


Figure 4: Milling Process Experimental Setup for Tool Wear Prediction

Table 1: Tool Wear prediction experimental setup operating characteristics

Milling cutter:	End-mill Coated carbide inserts
Workpiece:	H13 (Die steel)
Operating Conditions:	Speed: 1000rpm Feed rate:25mm/rev Depth_of_cut:0.25mmSampling rate:1000Hz Time duration: Approx 5 minutes (456,000 milliseconds)

4.3.3 Bearing Machinery Dataset

A bearing test rig with accelerometer sensors records vibration data at a motor speed of 1200 RPM and a sampling frequency of 1 kHz. Artificial defects are introduced to the bearings to simulate degradation, and the system runs continuously for 11 hours to collect failure data.

4.4 Feature Extraction and Selection

The framework extracts a comprehensive set of features from both time-domain and frequency-domain data.

4.4.1 Time-Domain Features

Time-domain features include statistical measures such as mean, standard deviation, skewness, kurtosis, peak-to-peak value, and root mean square (RMS).

4.4.2 Frequency-Domain Features

Frequency-domain features are derived using Fast Fourier Transform (FFT) and include measures like spectral centroid, bandwidth, and peak frequencies.

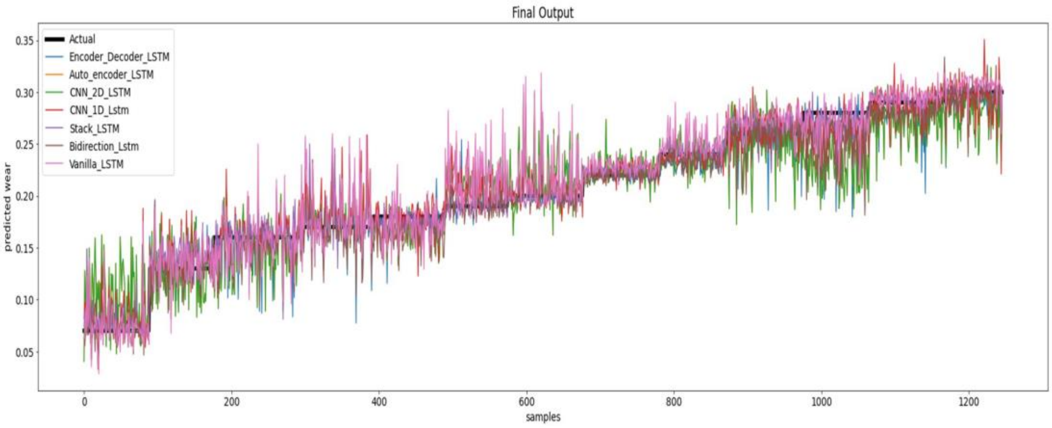


Figure 5: Tool wear prediction for test set over time

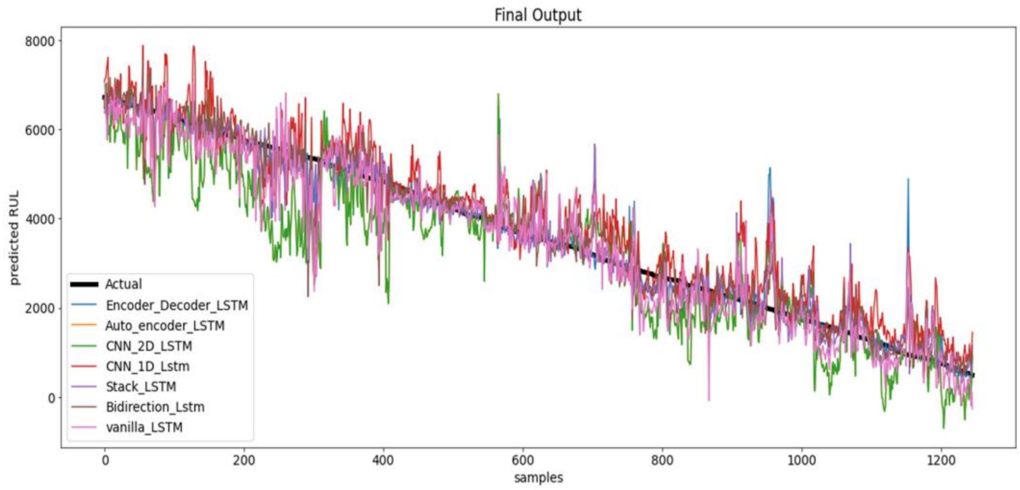
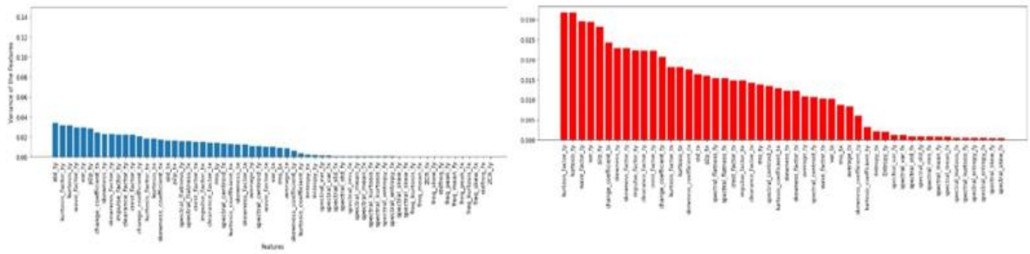


Figure 6 : Remaining useful life prediction of tool over test samples

4.4.3 Feature Selection Algorithms

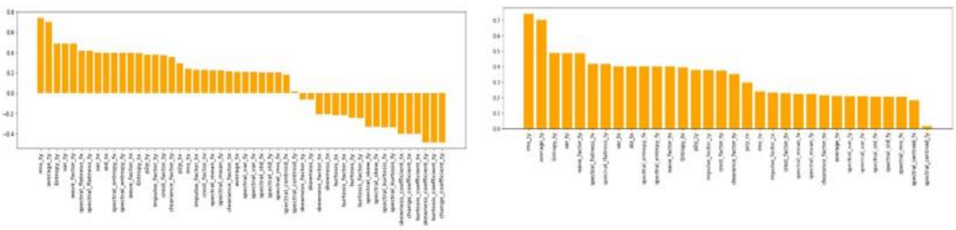
To enhance the prediction accuracy and reduce computational complexity, the following feature selection algorithms are applied:

- Low Variance Filter: Removes features with low variance.
- Spearman Correlation Coefficient: Identifies and removes highly correlated features.
- Random Forest Regressor: Selects features based on their importance scores.



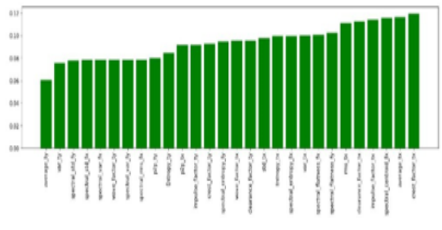
Original Features: 64 Selected features: 50

Feature Ranking before and after application of Low Variance Filter

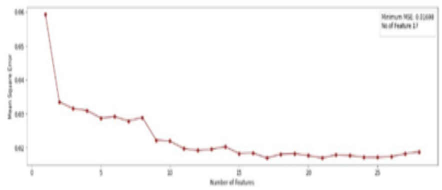


Positive and Negative Features Selected Positive Features: 32

Feature Ranking before and after application of Spearman Coefficient



28 ranked features



17 Features chosen having lowest MSE

Feature Ranking before and after application of Random Forest Regressor

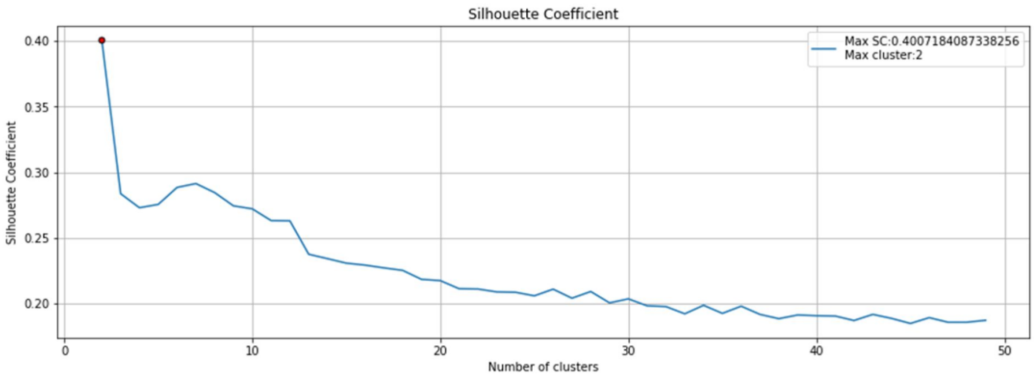
Figure 7: Optimized Feature selection framework applied on time and frequency-domain

4.5 Clustering and Anomaly Detection

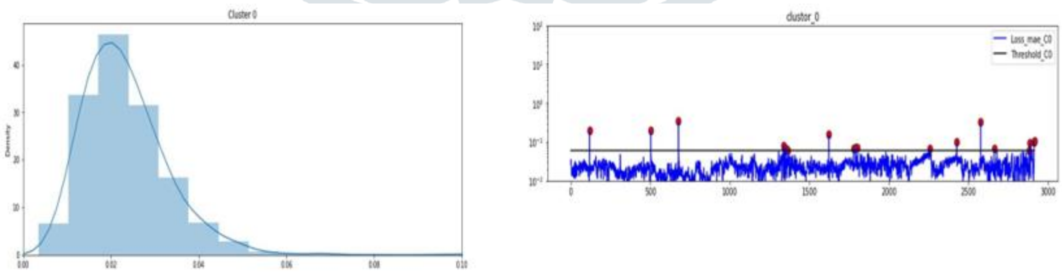
After feature selection, the data is clustered to distinguish between normal and abnormal operating conditions.

4.5.1 Clustering Analysis

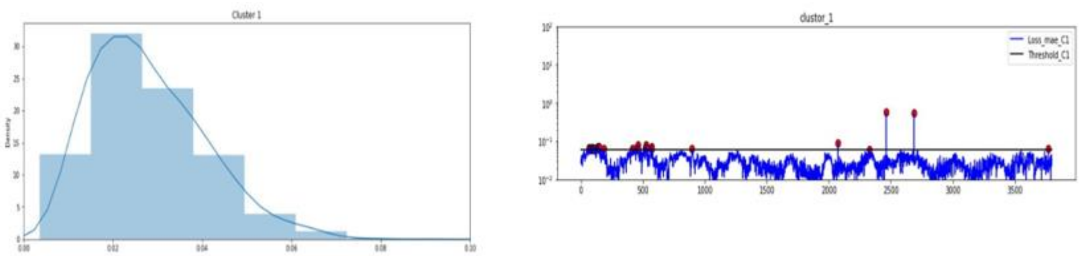
Clustering is performed using algorithms such as K-means, and the quality of the clusters is assessed using the silhouette coefficient. This step helps in identifying distinct patterns that indicate the onset of anomalies.



Silhoutte Coefficient indicating two optimum number of clusters for tool wear dataset



Cluster 0 threshold function for anomaly mining in cluster 0



Cluster 1 threshold function for anomaly mining in cluster 1

Figure 8: K-Means clustering for anomaly pattern mining using time and frequency domaininformation for tool wear dataset

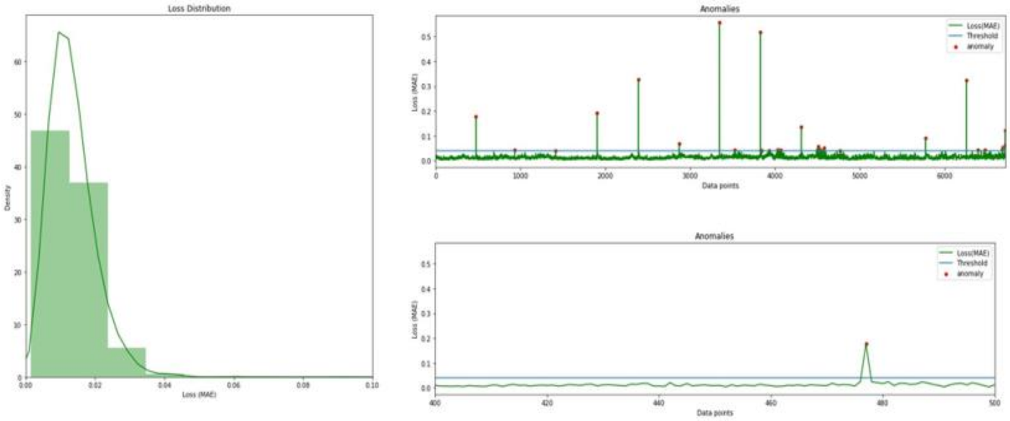


Figure 9: Autoencoder-LSTM reconstruction loss threshold for tool wear onset detection based

4.5.2 Supervised Anomaly Detection

Anomalies are detected using an Autoencoder-LSTM model that learns the normal operational patterns and identifies deviations indicating potential failures. The reconstruction loss probability distribution function is used to determine the anomaly threshold.

4.6 RUL Prediction

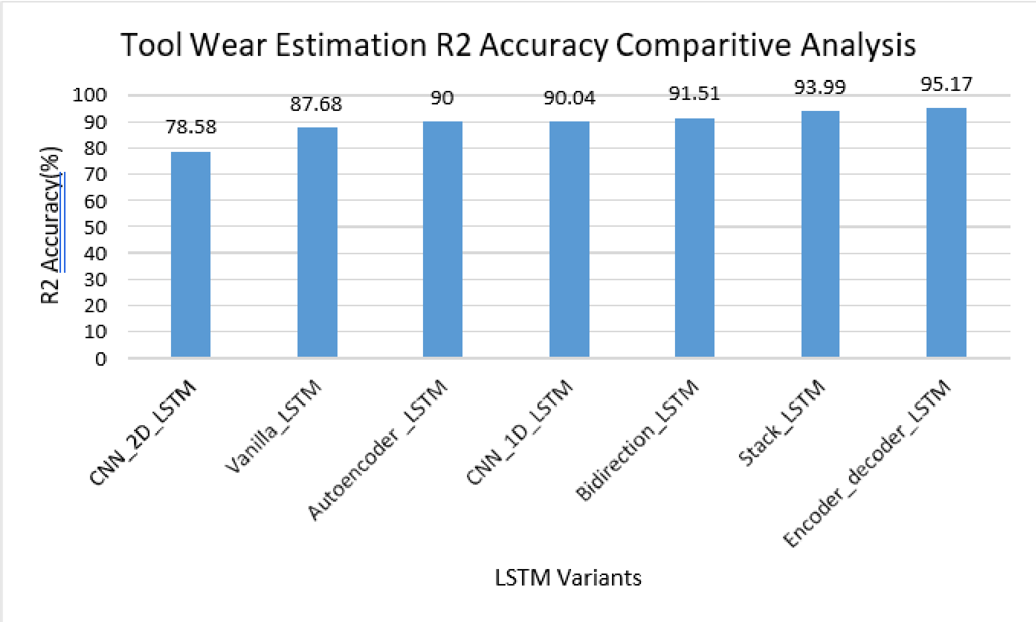
Once anomalies are detected, the RUL is estimated using various LSTM-based models. The performance of different LSTM variants, including Vanilla LSTM, BiLSTM, Stacked LSTM, CNN-1D LSTM, CNN-2D LSTM, and Encoder-Decoder LSTM, is evaluated to determine the most effective model for RUL prediction.

Table 2: Tool Wear and RUL prediction results for tool wear prediction dataset usingLSTM variants

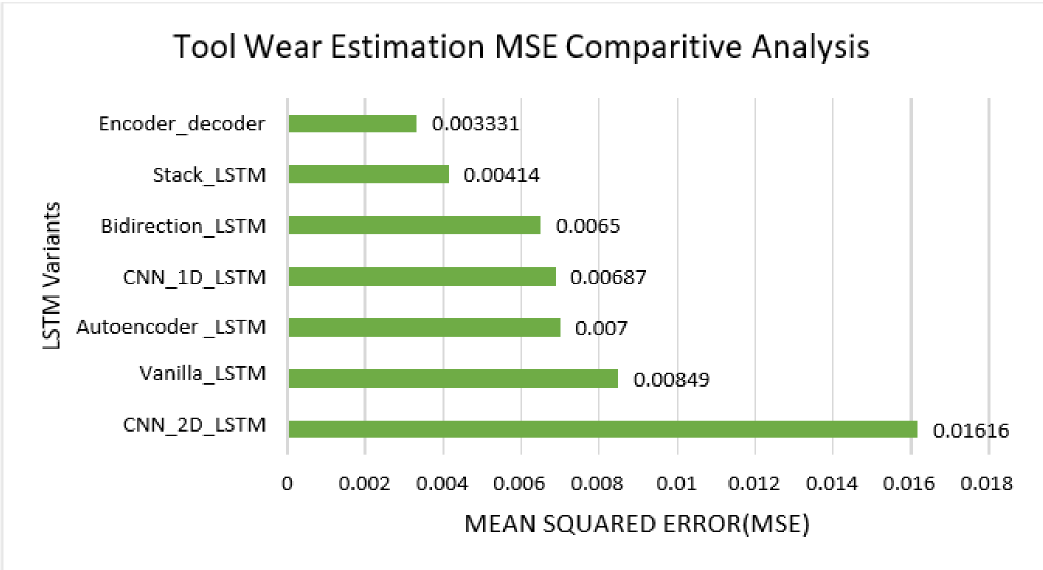
Prediction Results		**Vanilla LSTM**	**Bi LSTM**	**Stack LSTM**	**CNN 1D LSTM**	**CNN 2D LSTM**	**AE LSTM**	**Encode Decode LSTM**
Tool Wear Prediction	**R2 Accuracy (%)**	87.68	91.51	93.99	90.04	78.58	90.00	95.17
	MSE loss	0.0084	0.0065	0.00414	0.0068	0.0161	0.0070	0.00333
RUL Prediction	**R2 Accuracy (%)**	91.42	94.42	95.42	86.47	88.57	93.33	97.29
	MSE loss	0.0093	0.0059	0.00400	0.0171	0.0101	0.0069	0.00375

4.6.1 Performance Metrics

The models' performance is assessed using metrics such as R^2 accuracy and Mean Squared Error (MSE). The Encoder-Decoder LSTM consistently demonstrates the highest accuracy and lowest MSE, making it the preferred model for RUL estimation.



R2 accuracy comparison



Mean Squared Error loss comparison

Figure 10: Comparative performance analysis of LSTM variants for Tool wear prediction

4.7 Conclusion

This chapter has provided a detailed account of the implementation of the AOA-RUL framework. By integrating advanced feature selection, clustering, and deep learning techniques, the framework effectively predicts the onset of anomalies and estimates the RUL of machinery, thus supporting proactive maintenance and minimizing unexpected downtime.cal analysis and discussion in the appropriate sub-headings below.

V. CONCLUSIONS

The Anomaly-Onset Aware Remaining Useful Life (AOA-RUL) Prediction Framework demonstrated substantial improvements in the prediction of the Remaining Useful Life (RUL) of machinery, specifically using the Pronostia bearings dataset and real-world manufacturing processes datasets. The research focused on accurately diagnosing the onset of anomalies and subsequently predicting the RUL, leveraging deep learning techniques and optimized feature selection methodologies.

1. Enhanced Prediction Accuracy: The AOA-RUL framework achieved superior performance in RUL estimation, notably by combining time-domain and frequency-domain features. This combination improved the R2 accuracy and reduced the Mean Squared Error (MSE) across various LSTM models. The Encoder-Decoder LSTM variations particularly excelled in accuracy and reliability.

2.Optimized Feature Selection: Implementing a sequential feature selection technique further optimized the prediction accuracy. This approach, involving Low Variance, Spearman Coefficient, Random Forest Regressor, and Recursive Feature Elimination (RFE), proved more effective than the previous method of manually selecting the top five features.

3. Efficiency in Real-World Applications: The framework was validated using two real-world manufacturing datasets: the tool wear dataset from a milling process and an experimental bearing degradation dataset. The results indicated a significant reduction in computational training time, especially as the dataset sizes increased. For instance, a 14% reduction in training time was observed in the milling process dataset, and a 32% reduction was noted in the experimental bearing dataset.

4. Comparative Superiority: When compared to other data-driven strategies such as the Kalman filter and Interacting Multiple Model with Fuzzy systems (IMMF), the AOA-RUL framework, particularly the Encoder-Decoder LSTM model, demonstrated better performance metrics (e.g., R2 accuracy and MAPE).

Discussion

The findings from this research underline the efficacy of the AOA-RUL framework in addressing key challenges associated with RUL prediction. Several critical insights and implications can be drawn:

1.Importance of Anomaly Detection: Identifying the onset of anomalies is crucial for accurate RUL prediction. Traditional methods often overlook the period before degradation begins, leading to less precise estimations. The AOA-RUL framework's ability to start prognosis after anomaly onset ensures more accurate and relevant predictions.

2. Feature Selection Strategy: The shift from a static top-five feature selection to a dynamic, optimized method significantly improved prediction outcomes. This highlights the importance of an adaptive feature selection process tailored to the specific characteristics of the dataset and the machinery's operational context.

3.Time-Domain and Frequency-Domain Synergy: The combined use of time-domain and frequency-domain features capitalized on the strengths of both, capturing both transient and sustained changes in machinery conditions. This synergy is essential for a comprehensive understanding of machinery health.

4.Scalability and Efficiency: The framework's ability to reduce training time while maintaining high prediction accuracy is particularly beneficial for real-world applications, where large datasets are common. This efficiency not only saves computational resources but also enables more timely maintenance decisions.

5. Broader Applicability: While the study focused on bearings and milling tools, the principles and methodologies of the AOA-RUL framework can be extended to other types of machinery and industrial applications. This adaptability makes it a valuable tool across various sectors, including aviation, nuclear, pharmaceutical, and automotive industries.

6.Future Research Directions: Future work could explore further optimization techniques, integration with other advanced machine learning models, and application to more diverse datasets. Additionally, real-time implementation and continuous learning models could enhance the practical utility of the framework.

In conclusion, the AOA-RUL framework represents a significant advancement in predictive maintenance, offering precise, efficient, and scalable RUL estimation capabilities. Its application can lead to better maintenance planning, reduced downtime, and substantial cost savings in industrial operations.

VI. Acknowledgment

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