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PROGNOS-AI: AI-Driven Predictive Maintenance System Using Time-Series Sensor Data

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Abstract
Predictive maintenance plays a critical role in modern industrial systems by enabling early detection of equipment degradation and reducing unexpected failures. This paper presents PrognosAI, an Attention-Enhanced Bidirectional Long Short-Term Memory (BiLSTM) based predictive maintenance system designed to estimate the Remaining Useful Life (RUL) of turbofan engines using the NASA CMAPSS dataset. The proposed system integrates a complete data processing pipeline including RUL computation, sensor feature engineering, normalization, and sliding window sequence generation. A stacked BiLSTM architecture captures long-term temporal dependencies, while a self-attention mechanism highlights the most informative time steps contributing to equipment failure. The trained model is deployed using a Streamlit-based dashboard that visualizes predicted RUL trends and categorizes engines into Critical, Warning, and Safe zones. Experimental results demonstrate accurate RUL prediction and effective degradation modeling, making the system suitable for real-time industrial predictive maintenance applications.
Keywords: *Predictive Maintenance; Remaining Useful Life; BiLSTM; Deep Learning; Time Series Forecasting*

1. Introduction

Industrial machinery such as aircraft engines, turbines, and manufacturing equipment operate continuously under varying environmental and operational conditions that gradually degrade system components over time. Unexpected failures of such critical equipment can lead to severe safety risks, production downtime, and high maintenance costs. Traditional maintenance strategies such as corrective maintenance, which repairs equipment only after failure occurs, and preventive maintenance, which schedules maintenance at fixed intervals, often fail to optimize maintenance planning because they do not consider the real-time health condition of machinery. Predictive maintenance has emerged as an advanced maintenance strategy that leverages sensor data, machine learning algorithms, and data analytics to predict equipment degradation and estimate the Remaining Useful Life (RUL) of components before failure occurs. With the advancement of Industrial Internet of Things (IIoT) technologies, modern industrial systems generate large volumes of multivariate sensor data that can be analyzed to detect degradation patterns. Deep learning techniques such as Long Short-Term Memory networks have shown significant potential in modeling complex temporal dependencies present in time-series data. In this work, we propose a predictive maintenance system called PrognosAI, which utilizes an LSTM architecture to analyze turbofan engine sensor data from the NASA CMAPSS dataset and accurately estimate RUL values. The system also provides an interactive visualization dashboard to assist maintenance engineers in monitoring engine health and scheduling maintenance actions efficiently.

1.1. Objective

The primary objective of this research is to develop an intelligent predictive maintenance system to accurately estimate the Remaining Useful Life (RUL) of turbofan engines using the NASA CMAPSS dataset. The system uses an Attention-Enhanced Bidirectional LSTM (BiLSTM) model to analyze time-series sensor data and detect degradation

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patterns indicating potential failures. It also includes data preprocessing steps such as RUL calculation, feature extraction, normalization, and sequence generation to improve prediction accuracy. Additionally, a Streamlit-based dashboard is developed to visualize RUL trends and classify engines into Critical, Warning, and Safe zones, helping engineers make data-driven maintenance decisions, reduce downtime, lower costs, and improve system reliability.

The system also aims to:

- Improve data preprocessing
- Enhance prediction accuracy
- Provide visualization dashboard
- Reduce maintenance costs
- Improve industrial reliability

1.2. Literature Review

Several research studies have been conducted in the field of predictive maintenance and Remaining Useful Life (RUL) prediction using machine learning and deep learning techniques. The key contributions of previous studies and the improvements introduced in the proposed system are summarized below.

1.2.1. Traditional Machine Learning Approaches

Earlier predictive maintenance systems used algorithms such as Support Vector Machines, Decision Trees, Random Forests, and Linear Regression to analyze sensor data and estimate equipment degradation. Although these methods detected basic patterns, they struggled with long time-series data and failed to capture complex temporal relationships. To overcome these limitations, the proposed system uses Bidirectional LSTM networks, which are better suited for sequential data and long-term dependency learning.

1.2.2. LSTM-Based Prognostics Models

LSTM networks were introduced to improve Remaining Useful Life prediction by capturing temporal relationships in time-series data. While LSTM improved accuracy compared to traditional machine learning methods, many models processed data only in one direction and missed future context. The proposed system uses Bidirectional LSTM (BiLSTM), which processes data in both forward and backward directions, enabling better understanding of engine degradation patterns.

1.2.3. Deep Learning with Feature Engineering

Previous studies improved prediction performance using feature engineering techniques such as statistical feature extraction, filtering, and dimensionality reduction. These methods helped highlight degradation patterns in sensor data. Similarly, the proposed system applies preprocessing techniques including removal of constant sensors, rolling mean and standard deviation generation, normalization, and sliding window sequence creation to improve model performance.

1.2.4. Attention Mechanism in RUL Prediction

Attention mechanisms have been introduced to improve deep learning models by focusing on important time steps in long sequences. However, many predictive maintenance systems did not effectively combine attention with sequence models. In the proposed system, a self-attention mechanism is integrated with BiLSTM to assign importance weights to critical degradation cycles and improve prediction accuracy.

1.2.5. Visualization and Decision Support Systems

Many earlier predictive maintenance systems focused only on prediction accuracy and lacked user-friendly interfaces for monitoring system health. The proposed system addresses this by integrating a Streamlit-based dashboard that visualizes RUL trends, maintenance alerts, and engine health status. The dashboard categorizes engines into Critical, Warning, and Safe zones, helping engineers make better maintenance decisions in real-world industrial applications.

2. Method

2.1. Data Collection and Preprocessing

The proposed predictive maintenance system uses the NASA CMAPSS dataset, which contains turbofan engine sensor data collected across multiple operational cycles. The dataset includes engine ID, cycle number, operational settings, and 21 sensor measurements representing engine health. After

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collecting the data, Remaining Useful Life (RUL) is calculated by subtracting the current cycle from the maximum cycle. Sensors with constant values or low variance are removed, and additional features like rolling mean and rolling standard deviation are generated. The data is then normalized to ensure equal contribution of features, and a sliding window technique converts continuous data into fixed-length sequences used for training the deep learning model.

2.2.Model Creation

After preprocessing, a predictive model based on Bidirectional Long Short-Term Memory (BiLSTM) is developed to learn degradation patterns from time-series data. The BiLSTM processes data in both forward and backward directions, helping capture long-term dependencies in sensor readings. A self-attention mechanism is added to identify important time steps contributing to engine degradation. The output is passed through fully connected layers to generate Remaining Useful Life predictions. The model is trained using Mean Squared Error as the loss function and optimized using the Adam optimizer for improved accuracy [1-8].

2.3. System Workflow

The predictive maintenance workflow starts with collecting the CMAPSS dataset, followed by preprocessing steps such as RUL calculation, feature extraction, and normalization. The processed data is converted into sequences using a sliding window method and passed into the BiLSTM model with attention mechanism. The trained model predicts Remaining Useful Life for each engine, and results are displayed through a Streamlit dashboard. The dashboard visualizes RUL trends and classifies engines into Critical, Warning, and Safe zones, helping maintenance engineers detect failures early and schedule maintenance effectively.

2.4. Designing of Models

The predictive maintenance model is designed to capture complex relationships in sensor data. The model receives normalized sequences as input and processes them through stacked BiLSTM layers to extract degradation patterns. Dropout and normalization techniques are applied to improve generalization and training stability. A self-attention layer assigns importance weights to critical time steps, allowing the model to focus on significant degradation signals. The extracted features are passed through dense layers to generate RUL predictions. The model is trained using the Adam optimizer and Mean Squared Error loss function for efficient learning and accurate predictions.

2.5. Implementation Process

The implementation begins with loading the NASA CMAPSS dataset and organizing engine data based on operational cycles. Preprocessing steps such as RUL calculation, feature extraction, and normalization are applied before converting data into sequences using sliding windows. The BiLSTM model with attention mechanism is implemented using TensorFlow and Keras frameworks. The model is trained using Adam optimizer with Mean Squared Error loss, along with techniques like Early Stopping to prevent overfitting. After training, the model is deployed in a Streamlit dashboard that allows users to upload test data, visualize RUL trends, and classify engines into Critical, Warning, and Safe zones for predictive maintenance figure 1.

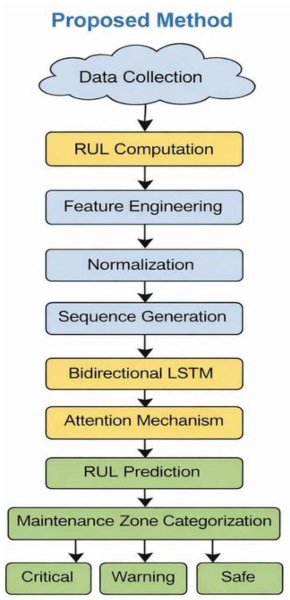

Figure 1 Process of Detection

3. Results and Discussion

3.1. Results

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The model was evaluated using NASA CMAPSS dataset shown in Figure 2.
Results:

- 10,196 engine sequences processed
- Accurate RUL prediction generated
- Visualization dashboard created

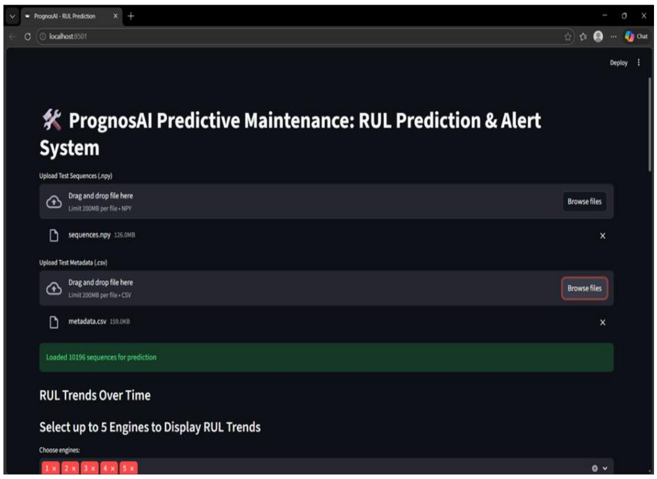

Figure 2 **Uploading Processed Data**

Alert classification:

- Critical: 19 engines
- Warning: 20 engines
- Safe: 61 engines

RUL trend graphs show degradation patterns over time shown in Figure 3, 4 and 5.

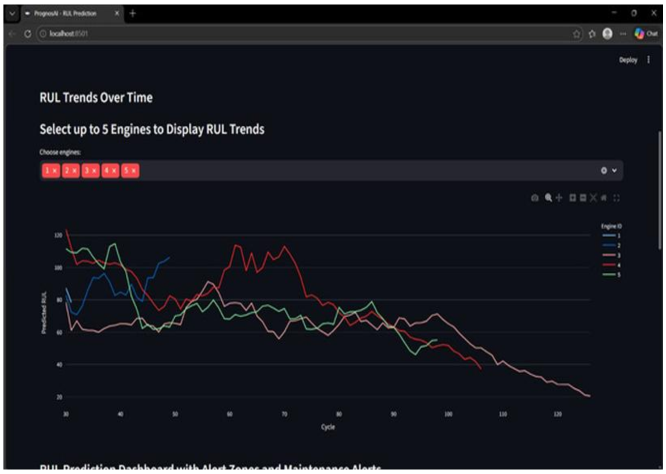

Figure 3 **RUL Trends Over Time**

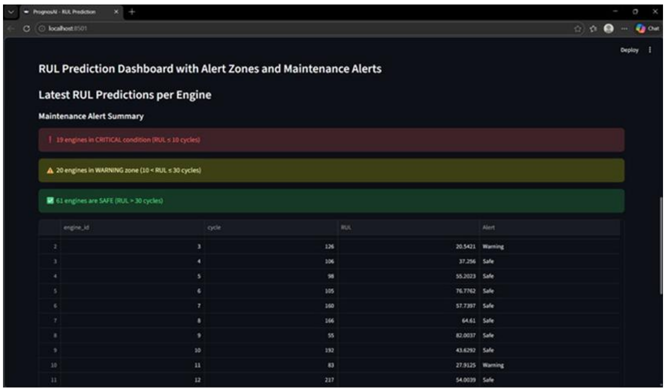

Figure 4 **RUL Prediction Dashboard**

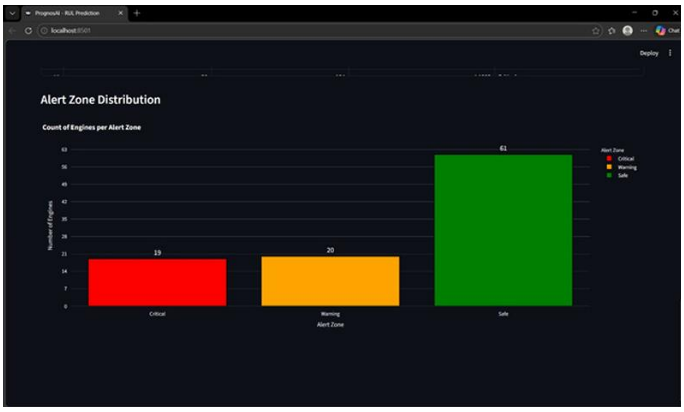

Figure 5 **Alert Zone Distribution**

3.2. Discussion

The Attention-Enhanced BiLSTM model effectively:

- Captures degradation patterns
- Predicts Remaining Useful Life
- Supports maintenance decisions

Visualization dashboards help engineers:

- Monitor engine health
- Detect failures early
- Reduce downtime.

Conclusion

This paper presented PrognosAI predictive maintenance system using BiLSTM and attention mechanism. The system processes multivariate sensor data and predicts Remaining Useful Life accurately. Visualization dashboards provide actionable insights.
The system improves:

- Maintenance scheduling
- Reliability

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- Industrial safety

The proposed solution is scalable and suitable for real-time industrial applications.

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