Remaining Useful Life (RUL) Prediction using Bi-LSTM

1. Project Overview

This project focuses on predicting the Remaining Useful Life (RUL) of machinery components using deep learning, specifically a Bidirectional LSTM (Bi-LSTM) model. The dataset ('train_FD001_processed.csv') contains sensor readings collected from multiple engines over their operational life. The goal is to estimate how many cycles remain before a failure occurs, enabling predictive maintenance and reducing downtime.

2. Objectives

• Develop an end-to-end pipeline for RUL prediction using Bi-LSTM.
• Capture temporal dependencies in sensor data using sequential models.
• Evaluate model accuracy using metrics like RMSE, MAE, and R^2.
• Visualize model performance and error distributions for interpretability.

3. Tools and Technologies

- Programming Language: Python
- Libraries: TensorFlow, Keras, Pandas, NumPy, Matplotlib, Scikit-learn
- Environment: Google Colab
- Dataset: NASA CMAPSS FD001 (processed version)

4. Methodology

1. **Data Loading and Preprocessing**: The dataset is loaded, and RUL values are clipped to a maximum threshold (100 cycles) to handle extreme outliers.
2. **Sequence Generation**: A sliding window approach (sequence length = 50) is used to create time-series input sequences.
3. **Train-Test Split**: Data is split using GroupShuffleSplit to ensure units from the same engine are not shared between sets.
4. **Model Architecture**: A Bidirectional LSTM network with dropout layers, dense layers, and an output regression node is implemented.
5. **Model Training**: The model is trained for up to 150 epochs with EarlyStopping and ModelCheckpoint callbacks.
6. **Evaluation**: Performance metrics include RMSE, MAE, and R^2. Visualization includes line, scatter, and histogram plots.

5. Model Architecture

The optimized Bi-LSTM model consists of:
• Bidirectional LSTM (128 units) with dropout 0.3
• Bidirectional LSTM (64 units) with dropout 0.3
• Dense (32 units, ReLU)
• Dense (10 units, ReLU)
• Output Layer: Dense(1) for RUL regression
The model uses Adam optimizer with a learning rate of 0.0005 and Mean Squared Error (MSE) as

the loss function.

6. Model Evaluation and Results

The model performance is measured using:
- **Mean Squared Error (MSE)**
- **Root Mean Squared Error (RMSE)**
- **Mean Absolute Error (MAE)**
- **R^2 Score (Coefficient of Determination)**

Final Evaluation Results:
• Test RMSE: 7.9447
• Test MAE: 5.3960
• Test R^2: 0.9438
• Mean Bias: 0.0178
• Error Std: 7.9447

7. Visualization Summary

The following plots were generated to interpret model performance:
1. Predicted vs Actual RUL (line plot)
2. Scatter plot showing correlation between true and predicted values
3. Error distribution histogram
4. Bias and residual analysis for under/over-prediction trends

8. Interpretation

The model demonstrates excellent predictive performance with a high R^2 value (0.94), low RMSE (7.94), and minimal bias. These results indicate that the Bi-LSTM model effectively captures temporal dependencies in sensor data. Residual analysis confirms minimal systematic bias, suggesting strong generalization to unseen test units.

9. Conclusion

This project successfully developed a robust Bi-LSTM-based model for RUL prediction. The framework can be extended to other industrial datasets for predictive maintenance applications. Future improvements could involve hyperparameter tuning, attention mechanisms, or hybrid CNN-LSTM architectures for enhanced feature extraction.