■ Milestone 3 Report: Remaining Useful Life (RUL) Prediction using GRU

This report summarizes the implementation and evaluation of a GRU-based Remaining Useful Life (RUL) prediction model developed using the NASA Turbofan Engine Degradation Simulation Dataset (FD001). The project aims to predict the remaining operational life of engines to enable predictive maintenance, preventing failures and optimizing maintenance scheduling.

Data Preprocessing

The dataset used was preprocessed to handle time-series degradation patterns for multiple engine units. Key steps included: - Normalization of sensor readings - Sequence generation with a fixed time window - Splitting into training and testing datasets The processed dataset was saved as *processed_fd001.csv*.

Model Architecture

A Gated Recurrent Unit (GRU) neural network was built using TensorFlow/Keras. The model architecture included: - Two stacked GRU layers (64 and 32 units) - Dropout layer to prevent overfitting - Dense output layer with one neuron for RUL regression The model was trained using the Mean Squared Error (MSE) loss function and Adam optimizer.

Model Training & Evaluation

The model was trained on the processed FD001 dataset for 50 epochs with a batch size of 64. After training, performance was evaluated on the test set using RMSE and MAE metrics. Key Observations: - The GRU effectively captured temporal dependencies in sensor data. - The loss curves indicated stable convergence.

Risk Thresholding & Alert System

A maintenance alert system was implemented using predicted RUL values. Thresholds: - CRITICAL (≤10 cycles): Immediate maintenance required - WARNING (≤30 cycles): Schedule inspection - NORMAL (>30 cycles): Engine health is stable Example alert distribution (from Milestone 4 analysis): - NORMAL: 75.3% - WARNING: 12.4% - CRITICAL: 12.3%

Insights

- GRU models are well-suited for time-series degradation forecasting. - Early detection of declining RUL enables cost-efficient maintenance. - Most test samples fall under the NORMAL category, indicating model stability.

Conclusion

The GRU-based RUL prediction system successfully demonstrates the use of deep learning for predictive maintenance. With clear alert thresholds, it provides actionable insights to prevent

unexpected equipment failures and improve operational reliability.