Artificial Intelligence-based Intelligent Maintenance Prognostic Capstone Project – ITAI 2277

Project Goal

Goal:
Implement AI that anticipates equipment failure and prevents it.
This minimizes the downtime, decreases the costs of repairs, and raises operational safety.

Main Objectives:

Projected Remaining Useful Life (RUL) of industrial engines.

Indicate early warning of mechanical failure.

Offer live tracking in the form of an interactive dashboard.

Make preventative maintenance choices.

Problem Overview

Current Issues in Industry:
Machines fail unexpectedly

Maintenance is either too reactive (late) or too frequent (wasteful).

This is because unplanned down time is costly.

The danger of the situation becomes more serious when faults are not recognized.

Need:
A prediction mechanism to monitor sensor behavior and warn the engineers of failure.

Solution Outline

Our proposal combines machine learning + deep learning:
NASA CMAPSS sensor data (turbofan engines) are used.

Minimize trends of engine wear.

Forecast RUL with LSTM neural networks.

Estimate short term failures with random forest.

Prediction deployment in a Streamlit dashboard.

Process Flow

Gather NASA CMAPSS FD001 data.

Clean and preprocess data

Rolling and rate-of-change engineer features.

Train Random Forest in binary failure prediction.

LSTM training in RUL time-series forecasting.

Add the two models into an ensemble.

The output of a Deploy is a Streamlit dashboard.

Technology Stack

Core Modeling:
Random Forest (scikit-learn)
LSTM (TensorFlow/Keras)

Data Tools:
Pandas
NumPy
MinMaxScaler
Matplotlib / Seaborn

Deployment:
Streamlit Dashboard
Google Colab GPU environment.

Data Preprocessing

Eliminated insignificant/irrelevant sensors.

Determined RUL of every engine cycle.

Binary labels (failure within 30 cycles) were created.

Rolling mean and standard deviation and rate of change features that are engineered.
MinMaxScaler data normalization.

Constructed LSTM time-series sequences (50 cycles windows).

Model Architecture

Random Forest Classifier:
30-cycle prediction of failure.
100 trees
Max depth = 10
High interpretability

LSTM Network:
Two LSTM layers (64 units)
Sequence length = 50

Optimizer: Adam
Acquires long-term trends in degradation.

Ensemble:
RF and LSTM with weighted combination.

Dashboard Overview

Streamlit Web App Features:
Upload engine sensor files

View current system health

RUL prediction chart

Probability of failure alarm.

SHAP explainability:

Displays sensors that affected predictions.

Demo (Screenshots / Live)

Demonstration Steps:
Select engine data

Generate RUL curves

View real-time risk alerts

Determine predictions with SHAP.

Libraries Used

NumPy
Pandas
Scikit-learn
TensorFlow / Keras
Matplotlib
Seaborn
SHAP
Streamlit

HIgh-Level Code Walkthrough

Import and cleaning of data.

Pipeline feature engineering.

Generator of sequence at LSTM databases.

Training of Random Forest classifier.

LSTM training loop

Model evaluation

Dashboard integration

Results

Random Forest failure detection 30 cycles or less.

LSTM is a good predictor of the long-term RUL trends.

Ensemble enhances uniformity and precision.

Dashboard brings actionable intelligence.

Conclusion

This capstone project indicates that the ability to:
Gather and purify real-life data.

Create ML + deep learning models.

Use predictive maintenance methods.

Implement an intuitive AI interface.

Combine instruments throughout the degree program.