ESKİŞEHİR TECNICAL UNIVERSITY

Engineering Faculty

Artificial Intelligence

Master's Degree

BIL539 – Artificial Intelligence

Term Project Proposal

Predictive Maintenance Agent for Machine Downtime Forecasting

Sevda ERGÜN

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1. Problem Statement and Task Definition

Unexpected machine downtimes in production lines cause time loss and high costs at the same time. Traditional maintenance strategies are usually time-based, meaning maintenance is performed at fixed intervals. This approach may cause unnecessary maintenance or problems in detecting and preventing sudden errors in a timely manner.

In this project, I aim to develop a predictive maintenance tool that uses historical sensor data such as temperature, vibration, and current to predict potential machine failures before they occur. I aim to detect early warning signs in the sensor data and provide notifications before the error occurs.

2. Input/Output Behavior

Type	Description	Example
Input	Last 24-hour sensor readings (temperature, vibration, current, rpm, load, etc.)	[68.2, 0.35, 5.4, 1450, 0.80]
Output	Probability of downtime in the next 24 hours (0–1)	0.83 → Alarm

The created agent will continuously monitor sensor values and will warn when the predicted failure probability exceeds a certain threshold.

3. Data Plan

At the beginning of the project, I will use publicly available datasets. If I can later access any real-life data, the model will also be tested on that. Missing values will be handled with interpolation, and time windows will be created for feature extraction.

Possible datasets:

- NASA Turbofan Engine Degradation Dataset (CMAPSS)
- SKF Bearing / CWRU dataset
- AI4I 2020 Dataset

4. Evaluation Metrics

System performance will be measured primarily by Precision-Recall AUC (PR-AUC) and Recall@k, rather than overall accuracy, because predictive maintenance datasets are typically unbalanced. In these datasets, normal operating records appear much more frequently than fault records. A higher PR-AUC and Recall@k mean the system can detect most faults early (high recall) and keep false alarms low (high precision). Mean Lead Time will also be measured to see how early the model can predict a fault before it occurs. These metrics reflect both the model's accuracy and its practical utility in a real-world production environment.

5. Baseline Plan & Methodology

There will be two stages in the project:

1. **Baseline model:** A simple Logistic Regression trained on basic statistical features like rolling mean, rolling standard deviation, and short-term changes (deltas).
2. **Main approach:** An XGBoost classifier using more advanced statistical and frequency-domain features.

Feature engineering will include moving averages, variation measures, and rate-of-change calculations for each sensor. If the dataset is imbalanced (few failure samples), I plan to use class weighting or limited oversampling. For interpretability, SHAP (SHapley Additive Explanations) will be used to explain which sensors contribute most to the model's decisions.

6. Challenges and Risks

Challenge	**Risk**	**Mitigation**
Imbalanced data	Low recall	Use weighted loss or sampling
Sensor noise	False alarms	Apply smoothing or rolling filters
Threshold tuning	Too many / few alerts	Optimize threshold using PR curve
Data privacy	Confidentiality issues	Use anonymized datasets only

8. References

- Russell, S., & Norvig, P. (2020). *Artificial Intelligence: A Modern Approach* (4th ed.). Pearson.
- Ahmad, R., & Kamaruddin, S. (2012). An overview of time-based and condition-based maintenance. *Procedia Engineering*, 38, 150–157.
- Zhao, R., Yan, R., Chen, Z., Mao, K., Wang, P., & Gao, R. X. (2019). Deep learning and its applications to machine health monitoring. *Mechanical Systems and Signal Processing*, 115, 213–237.
- Saxena, A., Goebel, K., Simon, D., & Eklund, N. (2008). Damage propagation modeling for aircraft engine run-to-failure simulation. *IEEE Aerospace Conference.*
- Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. *NIPS.*