Predictive Maintenance System for Industrial Equipment

Term Project Proposal

1. **Introduction and Problem Statement**

Industrial machinery failures lead to costly downtime, emergency repairs, and safety hazards. Current approaches rely on reactive maintenance (fixing after failure) or scheduled maintenance (based on time intervals), both being inefficient. This will be a system that predicts when industrial machinery is likely to fail. By analyzing the machine's operational data, temperature, vibrations, and other metrics, the system could notify engineers or technicians to conduct maintenance before a critical failure occurs.

1. **Project Objectives and Hypothesis**

* Deploy sensors to collect real-time equipment operational data
* Develop algorithms to analyze multivariate sensor time-series data
* Build ML models to predict failures and recommend maintenance actions
* Create an alert system and monitoring dashboard

**Hypothesis**: Equipment failures exhibit detectable degradation patterns before catastrophic failure. We believe sensor data (vibration, temperature, power consumption) can predict failures with at least 85% accuracy and 72-hour advance warning, significantly outperforming threshold-based monitoring systems.

**3. Proposed Models and Methodology**

**3.1 Models to Build**

1. Remaining Useful Life (RUL) Prediction Model: Regression model estimating time before failure
2. Failure Mode Classification Model: Identifying specific types of potential failures
3. Anomaly Detection Model: Identifying unusual equipment behavior patterns

**3.2 Prediction Targets**

* Remaining operational hours before failure
* Probability of failure within time horizons (24hrs, 7 days, 30 days)
* Specific failure mode classification (bearing failure, gear wear, etc.)

**3.3 Features**

* Time-domain features: Statistical measures of vibration signals
* Frequency-domain features: Spectral power, dominant frequencies
* Operational context: Load, speed, ambient temperature, runtime cycles
* Historical maintenance: Time since last maintenance, previous failures

**3.4 Algorithms**

* RUL Prediction: Random Forest Regression, LSTM Networks
* Failure Classification: Support Vector Machines and possibly XGBoost
* Anomaly Detection: Isolation Forests, Autoencoders

**3.5 Dataset Sources**

* NASA Prognostics Data Repository (Bearing and Turbofan Engine datasets)
* MIMII Dataset (industrial machine sound recordings)
* PHM Society Data Challenge Datasets
* Supplementary data collection from available industrial equipment

1. Significance and Expected Outcomes

The economic impact is substantial—industrial equipment failures cost manufacturers approximately $50 billion annually, with potential reduction of 30-40% through predictive maintenance.

The completed system will demonstrate significantly improved maintenance efficiency, reduced downtime, and extended equipment lifespan compared to traditional approaches, while providing an interpretable framework that maintenance teams can trust and implement effectively.