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Predictive Maintenance for Industrial Machinery Using Sensor Data and Deep Learning

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Focus, Need, and Industrial Relevance

Focus

Developing deep-learning–based predictive maintenance frameworks that analyze sensor data from industrial machinery to detect anomalies, forecast component failures, and estimate Remaining Useful Life (RUL). The goal is to enable proactive maintenance actions that reduce downtime, extend equipment lifespan, and ensure continuous operational efficiency.

Need

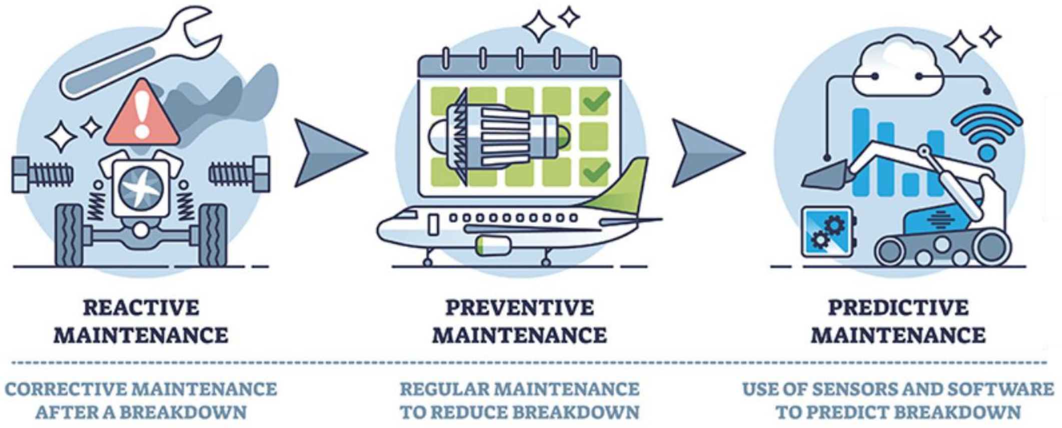
Industrial operations increasingly depend on continuous, high-throughput machinery whose unexpected failures lead to costly downtime, safety risks, and production delays. Traditional condition-monitoring approaches often rely on manual inspection or threshold-based methods that lack adaptability and accuracy. There is a clear need for advanced machine-learning systems capable of leveraging high-frequency sensor streams to perform early-stage fault detection, degradation modeling, and predictive diagnostics in a scalable, real-time manner.

Relevance

This work supports the mission of sustainable manufacturing systems. The resulting predictive maintenance models will provide value to manufacturers, equipment operators, maintenance teams, and system integrators by improving asset reliability, reducing unplanned outages, optimizing maintenance scheduling, and increasing overall productivity across industrial environments.

Project Goals

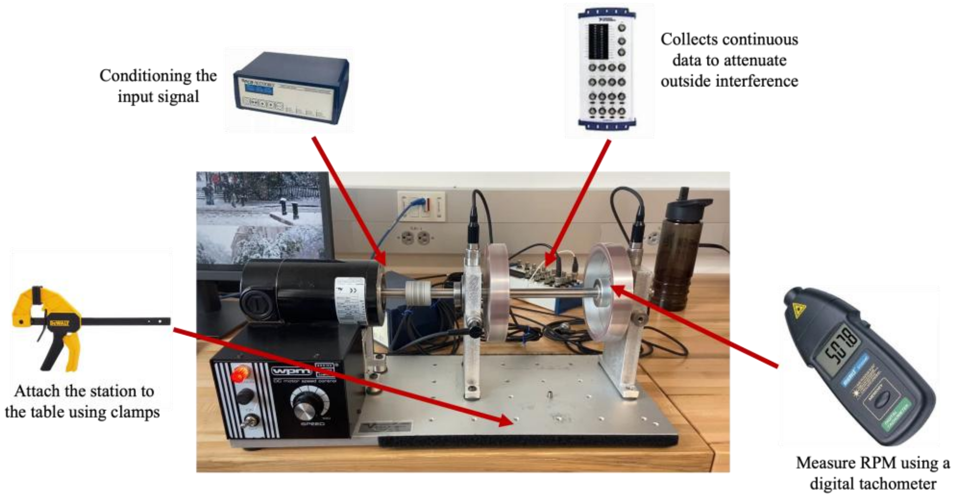
- Develop a scalable, deep-learning–driven predictive maintenance framework capable of analyzing multisensor machinery data to detect anomalies, forecast component failures, and estimate Remaining Useful Life.
- Enable continuous, real-time equipment health monitoring through advanced signal processing and machine-learning models that identify early <u>degradation patterns</u> and <u>operational abnormalities</u>.
- Improve equipment reliability and <u>reduce unplanned downtime</u> through data-driven maintenance scheduling, optimized asset utilization, and proactive failure prevention across industrial environments.



Evolution of Maintenance Paradigm

Objectives

- Develop a multi-sensor data acquisition and processing system that integrates vibration, acoustic, thermal, electric, and/or operational signals to continuously monitor machinery health in real-time.
- Design deep-learning models for anomaly detection, fault classification, and remaining useful life (RUL) prediction, leveraging spatiotemporal patterns in sensor data to identify early-stage degradation and deviations from normal operating conditions.
- Develop a lightweight, edge-deployable analytics platform that transforms raw sensor streams into actionable maintenance insights while maintaining computational efficiency for on-site industrial use.
- Validate the predictive maintenance framework through pilot testing on representative industrial machinery and quantify improvements in equipment reliability, downtime reduction, and maintenance planning efficiency.

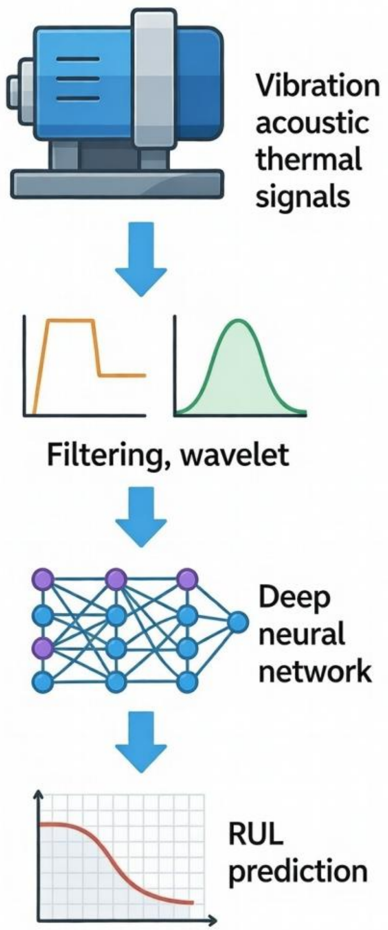


Pilot Test Setup for Data Collection and Rotating Machine Configuration

Approach / Research Methods (1)

1. Sensor Data Acquisition & Preprocessing
   - Integrate vibration, acoustic, thermal, electrical, and operational sensor feeds from industrial machinery.
   - Apply filtering, denoising, and feature extraction techniques (e.g., STFT, MFCCs, wavelets, statistical descriptors).
   - Synchronize multisensory time-series streams and segment them for real-time analysis.

- 2. Deep Learning Model Development
   - Develop neural network architectures for anomaly detection (autoencoders, CNNs, LSTMs, Transformers).
   - Train supervised and self-supervised models for fault classification and remaining useful life (RUL) prediction.
   - Employ domain adaptation and transfer learning to facilitate deployment across diverse machine types.



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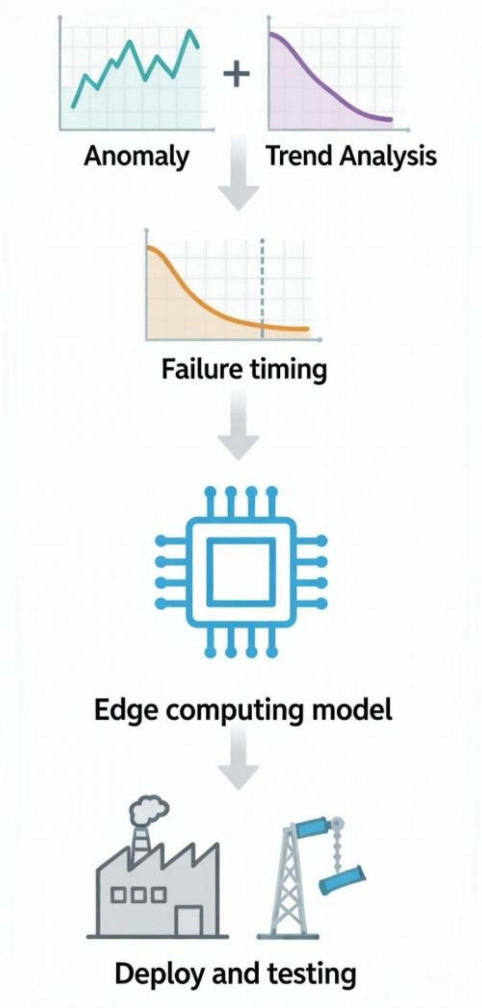
Approach / Research Methods (2)

- 3. Real-Time Predictive Diagnostics
  - Implement continuous inference pipelines that detect early degradation signatures.
  - Combine anomaly scores, trend analysis, and temporal prediction models to forecast failure likelihood and timing.
  - Generate automated alerts and recommended maintenance actions through rule-based or ML-driven decision engines.
- 4. Fog-Deployable Analytics Platform & Validation
  - Optimize models for resource-efficient edge deployment (quantization, pruning, lightweight architectures).
  - Integrate the predictive maintenance system into industrial control networks for live monitoring.
  - Validate performance through pilot deployments, evaluating accuracy, downtime reduction, and maintenance efficiency improvements.



Outcomes / Deliverables

- A deployable, sensor-driven predictive maintenance framework that integrates vibration, acoustic, thermal, and operational data streams and applies deep-learning models for real-time anomaly detection, fault classification, and remaining-useful-life (RUL) prediction.
- A validated multimodal analytics module that quantifies equipment health trends, identifies degradation patterns, characterizes operating anomalies, and detects early indicators of component failure using advanced time-frequency and deep learning–based feature representations.
- A real-time diagnostics and alerting system capable of forecasting imminent failures, generating automated maintenance recommendations, and supporting proactive interventions to reduce unplanned downtime and prevent critical equipment failures.
- A comprehensive performance evaluation report documenting model accuracy, inference latency, scalability, robustness across varying operating conditions, and measurable improvements in equipment reliability, maintenance efficiency, and downtime reduction based on pilot deployments.
- A software toolkit and technical documentation package including implementation guidelines, deployment workflows, sensor integration procedures, and instructions for applying the predictive maintenance system across diverse industrial machinery platforms.

Expected Impacts

- By enabling continuous monitoring of machinery health and operational performance, the proposed system will support data-driven maintenance planning, resulting in reduced unplanned downtime, improved equipment availability, extended asset lifespan, and more efficient use of maintenance resources across industrial environments.
- The development of a scalable predictive maintenance framework will lower deployment costs and technical barriers, accelerating adoption of intelligent maintenance systems among small- and medium-sized manufacturers seeking improved reliability and operational visibility.
- The project will advance AI-enabled smart manufacturing technologies, strengthening industrial competitiveness, supporting the transition toward more autonomous maintenance ecosystems, and contributing to safer, more resilient, and more sustainable production environments.

Project Administration

Budget

Item	Year 1	Year 2	Total
Salaries and Stipends			
Faculty – H. Yoon	3,000	3,000	6,000
Faculty – C. Chen	3,000	3,000	6,000
Graduate Research Assistant	31,200	31,200	62,400
Fringe Benefits			0
Faculty and Staff (32%)	1,920	1,920	3,840
Student Research Assistants	1,664	1,664	3,328
Other Direct Costs			
Supplies, Software, and Equipment			
Travel	3,416	3,416	6,832
Total Direct Costs	44,200	44,200	88,400
Indirect Costs (10% Request)	4,420	4,420	8,840
Items Not Charged F&A			
GRA Tuition	11,380	11,380	22,760
Budget Totals	**$60,000**	**$60,000**	**120,000**

Duration: 24 Months

Q1 | Q2 | Q3 | Q4 | Q5 | Q6 | Q7 | Q8

Q1. System setup and sensor data collection

Q2. Sensor data preprocessing

Q3. Prediction model development using deep learning

Q4. Deep learning model training

Q5. Refinement of model inference

Q6. Edge deployment of the prediction model

Q7. Integration with industrial control networks

Q8. Performance validation

Questions?

Selected References

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- O’Donnell, J. and Yoon, H.S., 2020. Determination of time-to-failure for automotive system components using machine learning. *Journal of Computing and Information Science in Engineering*, *20*(6), p.061003.
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