Ph.D. Research Proposal

Title:

AI-Enabled Predictive Maintenance for Industrial Systems Using Intelligent Data Analytics and Edge Computing

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1. Introduction

In recent years, the fourth industrial revolution—commonly known as **Industry 4.0**—has dramatically reshaped the way industries operate. The integration of **Artificial Intelligence (AI)**, **Internet of Things (IoT)**, and **cyber-physical systems** has opened new possibilities for improving efficiency, reducing downtime, and optimizing operations. One of the most significant and transformative applications of these technologies is **Predictive Maintenance (PdM)**.

Traditional maintenance strategies, such as reactive or preventive maintenance, are often inefficient. They either wait for failures to occur or rely on fixed schedules that may not reflect the actual condition of machinery. Predictive maintenance, in contrast, leverages data from sensors and smart devices to predict failures **before** they happen—saving both time and resources.

However, despite its potential, predictive maintenance still faces key challenges. These include **high data transmission latency**, **limited computational resources at the edge**, and the **lack of transparency** in AI models, which often function as "black boxes." This research proposes an **AI-enabled predictive maintenance framework** that combines **edge computing**, **machine learning**, and **explainable AI (XAI)** to make industrial maintenance smarter, faster, and more reliable.

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2. Research Problem

While many predictive maintenance systems rely heavily on cloud-based computation, this approach is not always feasible for real-time applications. High latency, connectivity issues, and privacy concerns often limit performance. Moreover, deep learning models, though powerful, are complex and difficult to interpret, leading to low trust among engineers and operators.

The proposed research seeks to address these gaps by:

- Reducing **latency** and **network dependency** through **edge-based analytics**.
- Enhancing **model generalization** across diverse industrial environments.

- Improving **explainability** to help maintenance teams understand and trust AI-driven decisions.

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3. Objectives

The primary goal of this research is to develop and validate a **real-time, explainable, and edge-deployable AI framework** for predictive maintenance in industrial systems.

Specific Objectives

1. Design an IoT-based data acquisition and preprocessing pipeline for real-time equipment monitoring.
2. Develop robust AI and machine learning models for **fault detection** and **Remaining Useful Life (RUL)** prediction.
3. Implement optimized models on **edge devices** for low-latency, real-time inference.
4. Integrate **Explainable AI (XAI)** techniques to ensure transparency and trust in AI predictions.
5. Validate the system using **benchmark datasets** (e.g., NASA C-MAPSS) and **real-world industrial data**.

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4. Literature Overview

Recent advances in deep learning, such as **Convolutional Neural Networks (CNNs)** and **Recurrent Neural Networks (RNNs)**, have shown strong potential in fault diagnosis and health monitoring. Additionally, **edge AI** technologies—such as NVIDIA Jetson and TensorFlow Lite—allow models to operate close to the data source, reducing latency and bandwidth consumption.

However, most existing systems focus either on high accuracy or low latency, not both. Furthermore, very few studies have explored combining **edge AI** with **explainable models** for predictive maintenance. This research aims to fill that gap by creating a balanced and practical framework.

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5. Methodology

The research will proceed through five major phases:

Phase 1: Data Acquisition and Preprocessing

- Collect sensor data (vibration, temperature, current, etc.) from industrial equipment or publicly available datasets.
- Apply data cleaning, feature extraction, and normalization techniques.

Phase 2: Model Development

- Design hybrid deep learning models (e.g., CNN-LSTM) for fault diagnosis and RUL estimation.
- Apply transfer learning to generalize across different equipment types.

Phase 3: Edge Deployment

- Optimize trained models through quantization and pruning for edge deployment.
- Integrate with IoT hardware (e.g., Raspberry Pi, Jetson Nano).

Phase 4: Explainability Integration

- Apply tools like **LIME** and **SHAP** to interpret model predictions.
- Develop a dashboard for engineers to visualize health indicators and AI reasoning.

Phase 5: Validation and Evaluation

- Evaluate the proposed system based on accuracy, latency, interpretability, and reliability.
- Conduct pilot testing in collaboration with industry or KARE research labs.

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6. Expected Outcomes

- A **fully functional AI-edge predictive maintenance system** that can detect faults and predict failures in real time.
- Improved **trust and interpretability** in AI-based industrial systems through XAI integration.
- Academic contributions in the form of **publications in peer-reviewed journals**.
- A **prototype solution** ready for deployment in manufacturing, energy, or transportation industries.

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7. Research Timeline (3 Years)

Year	Focus Areas
Year 1	Literature review, data collection, initial model design
Year 2	Model training, edge optimization, explainability integration
Year 3	System validation, prototype development, publication, and thesis submission

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8. Required Resources

- Edge computing devices: Raspberry Pi, Jetson Nano
- IoT sensors (vibration, temperature, current)
- Python-based AI frameworks: TensorFlow, PyTorch
- Access to **KARE's AI and Robotics Laboratory** for model validation

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9. References (Selected)

1. Lee, J., Bagheri, B., & Kao, H.A. (2015). *A cyber-physical systems architecture for industry 4.0-based manufacturing systems.* Manufacturing Letters.
2. Zhang, W., et al. (2020). *Deep learning-based prognostics and health management: A review.* IEEE Transactions on Instrumentation and Measurement.
3. Miao, Y., et al. (2022). *Edge intelligence for industrial predictive maintenance.* IEEE Internet of Things Journal.
4. Ribeiro, M.T., et al. (2016). *"Why should I trust you?": Explaining predictions of any classifier.* KDD Conference.

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10. Applicant Details

- **Name:** RATHIKAA SRE RM
- **Academic Background:** B.E. in Electronics and Communication Engineering
- **Proposed Institution:** Kalasalingam Academy of Research and Education (KARE)
- **Proposed Field of Study:** Artificial Intelligence and Predictive Maintenance