Introduction

* Traditional predictive maintenance using ML models helps schedule proactive maintenance but the models operate as "black boxes", making it hard to understand why a particular prediction was made. Explainable AI (XAI) provides insights into factors contributing to equipment failure predictions.
* The novelty and contributions of this research include: 1) Using frequency domain (FFT) raw data analysis, 2) Using multiple sensors (accelerometer, temperature, current), 3) Considering multiple faults and their interdependence, 4) Discussing the end-to-end data acquisition process, and 5) Implementing XAI using LIME and Random Forest to explain the fault diagnosis.

Materials and Methods

* This section covers the methods and materials for multi-fault diagnosis, including the test setup, data acquisition system, feature engineering, multi-class algorithms, and explainable AI.
* 2.1 Test Setup: Online datasets have limitations, so the authors built their own test setup to simulate multiple faults like unbalance, misalignment, looseness, and bearing defects. The key components are described.
* 2.2 Data Acquisition: Discusses the DAQ specifications, sensors used (accelerometers, temperature, current), sensor mounting, data validation using industrial VibeXpert II, and the design of experiments inducing various faults. Highlights the benefit of collecting FFT raw data.
* 2.3 Feature Engineering: Describes feature extraction (11 statistical features), standardization/normalization, feature selection using Random Forest, and dimensionality reduction using PCA. Multi-sensor data fusion at the feature-level is employed.
* 2.4 Multi-class Classification Algorithms: Several algorithms like SVM, Random Forest, Decision Tree, KNN, Logistic Regression, and Naive Bayes are used for fault classification.
* 2.5 Explainable AI: Random Forest is used as an intrinsically explainable model. LIME is used to explain black-box model predictions.

Results

* 3.1 Outcome: Compares fault classification accuracy for 4 cases: single-sensor single-location, single-sensor multi-location, multi-sensor single-location, and multi-sensor multi-location. Multi-sensor single-location performed best, with Random Forest achieving 100% accuracy. Multiple sensors and optimal sensor placement improved results.
* 3.2 and 3.3: Provides explanations of the Random Forest model and individual classifications using LIME, improving interpretability and trust in the AI decisions.

Discussion

* Highlights challenges like simulating industrial conditions, sensor fusion, class imbalance, algorithm validation, and model interpretability.
* Suggests future research directions like using real industrial data, implementing XAI and digital twins, considering fault interdependence, and domain adaptation.

Conclusion

* Systematically implements explainable predictive maintenance using AI and XAI for multi-fault diagnosis.
* Key findings: FFT data enables validation, multi-sensor fusion improves accuracy, optimal sensor placement is crucial, XAI techniques like LIME provide valuable insights.
* Future work will embed more faults and enhance the interpretability of the AI models.