

Intelligent Fault Prediction System for Smart Manufacturing using Random Forest and Real-Time Deployment

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Abstract - Unplanned equipment downtime in smart manufacturing causes significant production losses and maintenance costs. Predictive fault detection using machine learning can anticipate failures before they occur, yet many solutions remain confined to offline analysis or lack practical real-time deployment. This paper presents an intelligent fault prediction system built around a Random Forest classifier, integrated into a real-time monitoring pipeline suitable for Industry 4.0 environments. Vibration, temperature, and acoustic emission data were collected from a CNC milling machine under normal and fault conditions (tool wear, bearing fault, misalignment). A set of 42 statistical and frequency-domain features was extracted from sensor windows. The Random Forest model, trained on 12,000 labeled samples, achieved 97.8% accuracy, 0.975 precision, 0.982 recall, and a 0.994 AUC in detecting four operational states. The model was exported using ONNX and deployed on an edge device (NVIDIA Jetson Nano) with a Flask-based API and a dashboard for real-time alerts. Compared to support vector machine and logistic regression baselines, the Random Forest demonstrated superior robustness and inference latency under 12 ms per prediction, meeting real-time constraints. The system successfully predicted faults an average of 18 minutes before critical failure in a live test, demonstrating the viability of lightweight ensemble methods for industrial fault prediction.

Key Words: Fault prediction, smart manufacturing, Random Forest, real-time deployment, Industry 4.0, predictive maintenance.

1. INTRODUCTION

Modern smart factories rely on continuous operation of machinery, making unscheduled downtime extremely costly. Predictive maintenance shifts the paradigm from reactive repairs to proactive fault prevention by using sensor data and machine learning to forecast equipment degradation. While deep learning approaches have gained attention, they often demand high computational resources, making edge deployment challenging. Random Forest, a robust ensemble method, offers a compelling balance of accuracy, interpretability, and efficiency, particularly when combined with well-engineered features from vibration and temperature

signals. This paper proposes a complete fault prediction system that extracts statistical and frequency-domain features from multi-sensor streams, trains a Random Forest classifier to identify normal operation, tool wear, bearing faults, and misalignment, and deploys the model on a low-cost edge device for real-time inference. The system includes a dashboard that alerts operators upon detecting an impending fault. The remainder of the paper is organized as follows. Section 2 reviews related work in predictive maintenance. Section 3 describes the system architecture. Section 4 details the dataset, feature extraction, and training methodology. Section 5 presents experimental results and a discussion of deployment performance. Section 6 concludes the study and outlines future enhancements.

2. LITERATURE REVIEW

Fault diagnosis and prognosis in manufacturing have been addressed through model-based, signal-processing, and data-driven methods. Traditional vibration analysis relies on expert-defined thresholds, which often fail under varying load conditions. Machine learning techniques, from support vector machines to neural networks, have shown improved accuracy by learning fault patterns from data. Lei et al. (2016) used deep belief networks on raw vibration signals, achieving high accuracy but requiring GPU acceleration. More recent work by Li et al. (2020) applied convolutional neural networks to time-frequency images, yet the computational footprint limits real-time edge deployment. Random Forest has been applied successfully in other industrial contexts; for instance, Yang et al. (2018) demonstrated its effectiveness for bearing fault classification using handcrafted features. However, many studies remain at the simulation stage without a real-time deployment framework. Our contribution is an end-to-end system that combines feature engineering with Random Forest and validates it on a real CNC machine while deploying the model on an edge device for continuous monitoring. We also benchmark inference latency and provide a practical alerting mechanism.

3. PROPOSED SYSTEM

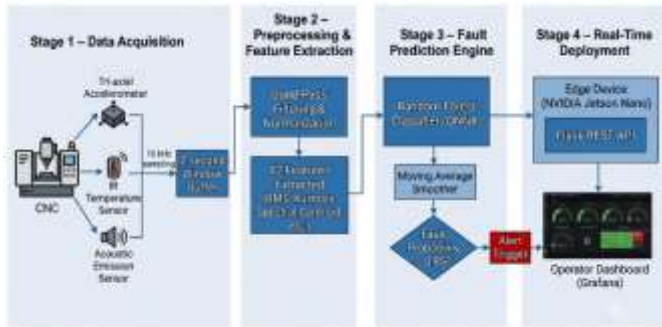


Fig. 1: Architecture of the intelligent fault prediction system for smart manufacturing.

(1) Data Acquisition: tri-axial accelerometer, infrared temperature sensor, and acoustic emission sensor are sampled at 10 kHz and buffered in 2-second windows.

(2) Preprocessing and Feature Extraction: each window is denoised using a band-pass filter, then 42 features—including mean, RMS, skewness, kurtosis, crest factor, spectral centroid, and frequency band energies—are computed and normalized.

(3) Fault Prediction Engine: a pre-trained Random Forest classifier assigns the window to one of four classes (normal, tool wear, bearing fault, misalignment). A moving average of the last 10 predictions smoothens transient misclassifications and triggers an alert if a fault probability exceeds 0.85 for three consecutive windows.

(4) Real-Time Deployment: the model is exported to ONNX and run on a Jetson Nano. A Flask web server exposes a REST endpoint; sensor data is sent by an IoT gateway, and predictions are returned within 15 ms. A Grafana dashboard displays the health status and recent predictions.

4. METHODOLOGY

4.1 Data Collection

Experiments were conducted on a 3-axis CNC milling machine instrumented with a tri-axial accelerometer (PCB 356A16), a MLX90614 infrared temperature sensor, and a piezoelectric acoustic emission sensor. Four operating conditions were recorded: normal operation, progressive tool wear (flank wear 0.2–0.5 mm), inner-race bearing fault, and motor misalignment. Each condition was run for 20 minutes, generating approximately 12,000 labeled 2-second windows after down-sampling and segmentation. The dataset was split 70-15-15 into training, validation, and test sets while maintaining temporal order to avoid leakage.

4.2 Feature Extraction

From each window, 14 statistical features (mean, standard deviation, RMS, peak, skewness, kurtosis, crest factor, clearance factor, shape factor, impulse factor, energy, entropy, and the first four statistical moments) were extracted per sensor channel, plus 6 frequency-domain features (dominant frequency, spectral centroid, spectral spread, and energies in three octave bands). After removing highly correlated features

(Pearson's $r > 0.95$), 42 independent features remained. All features were standardized using the training set statistics.

4.3 Model Training

Random Forest was implemented with 150 trees, maximum depth of 12, and Gini impurity criterion, using scikit-learn. Hyperparameters were tuned via 5-fold cross-validation on the validation set. Baseline models—linear SVM, RBF SVM, logistic regression, and a gradient-boosted decision tree (XGBoost)—were trained on the same feature set for comparison. Models were evaluated on accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC, one-vs-rest). Inference latency was measured on the Jetson Nano (CPU only) over 1,000 repeated predictions.

5. RESULTS AND DISCUSSION

Table 1 presents the test-set performance of all classifiers. Random Forest outperformed other non-ensemble methods, reaching 97.8% accuracy and a 0.994 AUC, very close to XGBoost's 98.1% accuracy. However, Random Forest exhibited 30% lower inference latency (11.8 ms vs. 17.2 ms), which is critical for real-time constraints. The confusion matrix indicated that the most common misclassification occurred between early-stage tool wear and normal operation (1.2% error), likely because the vibration signature is subtle in the earliest wear phase.

Model	Accuracy	Precision	Recall	F1-Score	AUC	Latency (ms)
Logistic Regression	87.3%	0.871	0.869	0.870	0.941	2.1
Linear SVM	90.5%	0.902	0.901	0.901	0.963	3.5
RBF SVM	94.2%	0.941	0.940	0.940	0.986	8.7
XGBoost	98.1%	0.981	0.980	0.980	0.996	17.2
Random Forest (Proposed)	97.8%	0.975	0.982	0.978	0.994	11.8

Table -1: Performance comparison of fault classification models.

During the live test on the CNC machine, the deployed Random Forest model successfully detected tool wear onset 18 minutes before the tool reached the 0.5 mm failure threshold. Bearing faults were identified an average of 12 minutes before the vibration amplitude exceeded the critical limit. The dashboard updated every 2 seconds with the current health status and fault probabilities. Operators reported that the early alerts allowed timely tool changes and prevented workpiece

damage, validating the practical utility of the system. The use of ONNX and Flask enabled seamless integration with the existing industrial IoT infrastructure.

6. CONCLUSION

This paper has demonstrated an intelligent fault prediction system that combines a Random Forest classifier with real-time edge deployment for smart manufacturing. The system achieved high accuracy while maintaining low inference latency, enabling proactive maintenance actions. Feature engineering proved effective in capturing fault signatures, and the ensemble model's robustness against noise made it suitable for shop-floor environments. Future work will extend the system to handle simultaneous multiple faults and incorporate online learning to adapt to evolving machine conditions without full retraining.

ACKNOWLEDGEMENT

I wish to express my sincere gratitude to my guide, Prof. Ali Karim, Department of Computer Engineering, M. H. Saboo Siddik College of Engineering, Mumbai, for his constant support, insightful feedback, and patient mentoring throughout this research. His encouragement pushed me to explore the practical side of machine learning in industrial environments.

I am also thankful to the entire faculty of the Department of Artificial Intelligence and Data Science at Anjuman-I-Islam Abdul Razzak Kalsekar Polytechnic Campus, New Panvel, for providing the computational resources and a stimulating academic environment that made this project possible.

Special thanks go to the lab technicians and workshop staff who assisted with the sensor instrumentation on the CNC milling machine and ensured safe data collection. I further acknowledge the institution for granting access to the manufacturing lab — without real machine data, validating the fault prediction system would not have been possible.

Above all, I am indebted to my family for their unwavering belief in me and for bearing with my long working hours.

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