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Edge-AI Enabled Predictive Maintenance for CNC Machines Using Real-Time IoT Sensor Analytics

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Abstract: CNC (Computer Numerical Control) machines are central to modern manufacturing processes, offering high precision, repeatability, and productivity. However, their unplanned failures can severely impact throughput and operational cost. Conventional maintenance strategies—reactive and time-based preventive—are inadequate in dynamic industrial environments. Moreover, existing cloud-based predictive systems suffer from latency, network dependency, and privacy challenges. This work presents an Edge-AI-based predictive maintenance architecture that locally analyzes real-time IoT sensor data from CNC machines using compact AI models deployed on Raspberry Pi edge devices. The proposed system employs vibration, temperature, and current sensors to collect equipment health data and utilizes algorithms such as Isolation Forest and Long Short-Term Memory (LSTM) for anomaly detection and Remaining Useful Life (RUL) estimation. Experimental simulation demonstrates real-time fault detection and maintenance scheduling without cloud reliance. The solution promises reduced downtime, enhanced reliability, and cost-efficient manufacturing continuity.
Keywords: Edge AI, Predictive Maintenance, IoT, CNC Machines, Anomaly Detection, Remaining Useful Life (RUL)

INTRODUCTION

In industrial manufacturing, CNC machines form the backbone of high-precision automated production. These machines execute complex machining tasks continuously, making their uninterrupted functioning essential. Even short downtimes lead to production delays, loss of output quality, and substantial financial losses. Traditionally, maintenance strategies have evolved from reactive (run-to-failure) to preventive (scheduled servicing) approaches. Reactive maintenance acts only after failure occurs, causing unexpected breakdowns. Preventive maintenance, on the other hand, relies on fixed schedules, often leading to unnecessary interventions and waste of machine life. To overcome these limitations, industries have adopted predictive maintenance an approach that anticipates failures using real-time data. Cloud-based predictive systems emerged as an early solution; however, they rely on continuous internet connectivity, leading to latency, high data transfer costs, and privacy concerns, especially in sensitive manufacturing environments. The convergence of Edge Computing and Artificial Intelligence (AI) now enables local processing of industrial data near the source. Edge-AI devices such as Raspberry Pi and ESP32 can host lightweight AI models capable of anomaly detection and fault prediction directly at the machine site. This paper presents a fully integrated Edge-AI-based Predictive Maintenance System that uses multi-sensor IoT analytics for CNC machines. It achieves real-time monitoring, early fault detection, and autonomous maintenance scheduling while minimizing dependency on cloud infrastructure.

LITERATURE REVIEW

Predictive maintenance has been a key research focus under Industry 4.0, aiming to enhance operational intelligence in smart factories.

Mallioris et al. (2024) conducted a cross-sector study on predictive maintenance adoption and highlighted the broad industrial applicability of AI in maintenance scheduling. However, the lack of industry-specific deployment frameworks remains a challenge.

Ucar et al. (2024) discussed trustworthiness and reliability in AI-driven predictive systems, emphasizing the need for transparent and explainable AI models in critical industries. Yet, their work was limited to theoretical models, without addressing the resource constraints of edge hardware.

Calvez et al. (2024) compared proactive and reactive maintenance paradigms in time-critical systems, concluding that proactive fault detection significantly reduces downtime, though implementation cost remains high.

Zonta et al. (2020) reviewed predictive maintenance in the context of Industry 4.0, identifying challenges such as heterogeneous sensor integration, data imbalance, and lack of real-time inference.

Chen et al. (2018) proposed an optimized preventive maintenance policy balancing reliability and cost, but the framework was heavily reliant on centralized computation.

Recent work by Ren et al. (2022) and Artiushenko et al. (2023) has extended predictive maintenance into Edge AI domains, introducing TinyML-based models for on-device analytics. These studies validate that localized machine learning can achieve low latency and high privacy, but still require robust data pipelines for noisy industrial environments.

This review highlights the persistent research gap: integrating Edge AI, IoT sensors, and lightweight predictive models into a unified, deployable system for real-time CNC machine monitoring.

PROPOSED METHODOLOGY

The proposed framework consists of multiple functional layers: data acquisition, feature extraction, AI inference, and maintenance management, implemented locally using a Raspberry Pi 3 edge device.

A. Sensor Data Acquisition

Three industrial sensors are interfaced with the CNC machine:

1. MPU-6050 accelerometer–gyroscope for vibration data,
2. DS18B20 digital temperature sensor, and
3. SCT-013 current transformer sensor for monitoring electrical load.

These sensors provide multi-modal data streams reflecting the mechanical and electrical health of the machine.

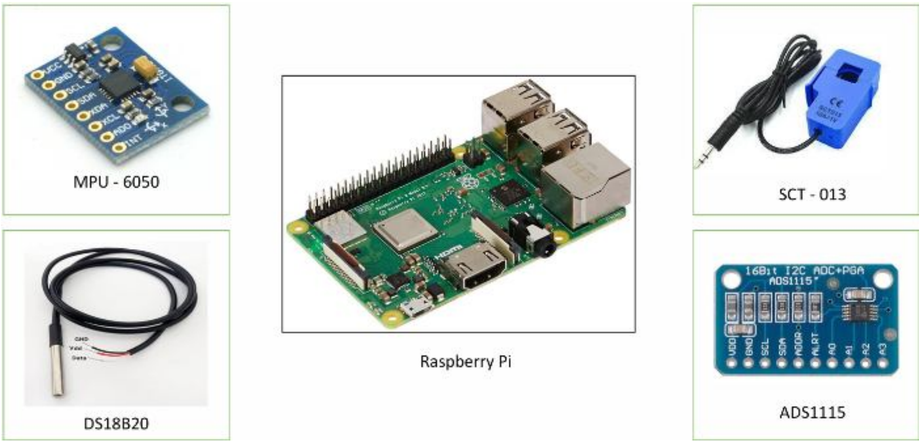

Fig: Components

B. Edge Data Processing and Feature Extraction

Raw sensor data is pre-processed using NumPy and Pandas to remove noise and compute time-domain and frequency-domain features such as Root Mean Square (RMS), Standard Deviation, and Fast Fourier Transform (FFT). These features capture subtle mechanical changes in vibration and temperature patterns that precede faults.

C.AI Model Design and Deployment

Two models are used:

4. Isolation Forest for unsupervised anomaly detection based on vibration features.
5. LSTM Neural Network (converted to TensorFlow Lite) for Remaining Useful Life (RUL) prediction.

The models are trained offline using simulated data, then deployed on the Raspberry Pi for real-time inference with low memory footprint.

D. Maintenance Scheduling

When anomalies are detected, events are logged in a SQLite database. The system automatically prioritizes maintenance tasks based on fault severity. Scheduled maintenance notifications are sent to the operator via the dashboard.

E. Visualization and Alert System

A Streamlit-based dashboard hosted on the Raspberry Pi displays real-time graphs of vibration, temperature, and current along with model predictions. Alerts are triggered through on-screen warnings and optional email notifications.

This configuration enables autonomous, low-latency monitoring even in offline factory settings.

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IV. SYSTEM DESIGN AND ARCHITECTURE

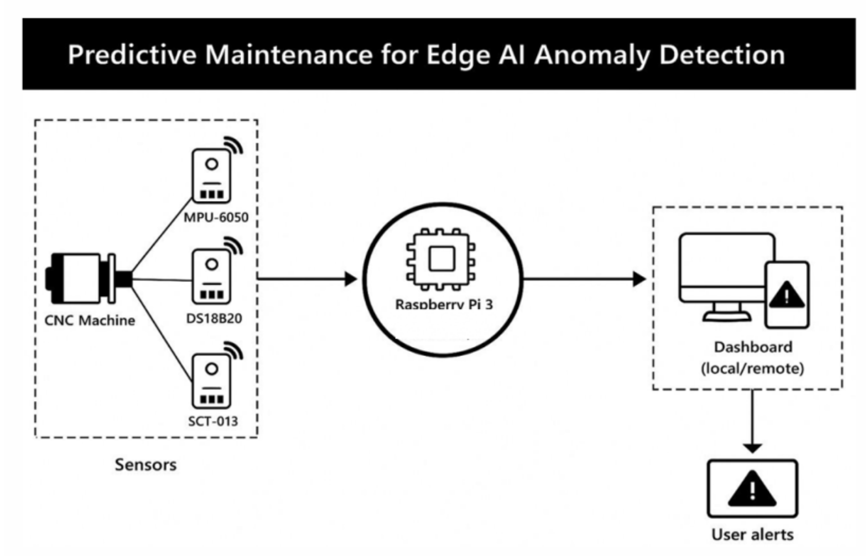

Fig: System Design

The architecture is divided into three layers:

1. Sensor Layer: Real-time data acquisition from MPU-6050, DS18B20, and SCT-013.
2. Edge Layer: Local processing using Raspberry Pi 3, feature computation, and AI inference.
3. Application Layer: Visualization, task scheduling, and user interaction through dashboard and database integration.

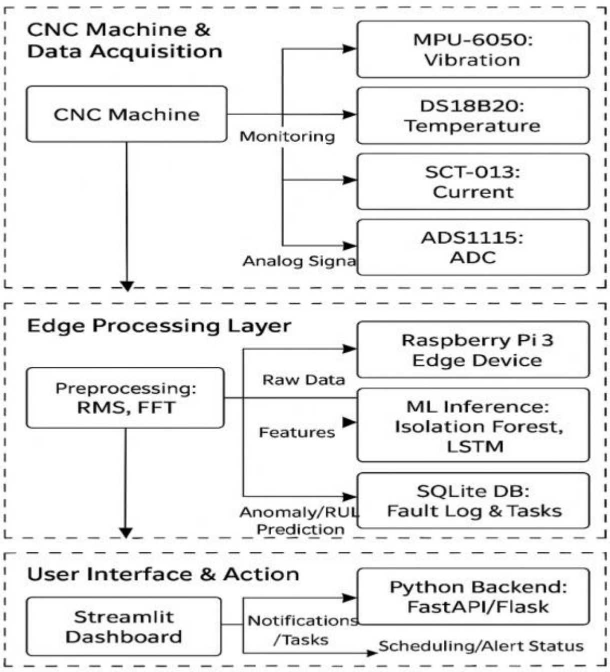

Fig: ARCHITECTURE

This modular design ensures scalability and interoperability with additional sensors or machines. The use of Edge Computing minimizes cloud dependency, enhancing data privacy and reducing network congestion. It also ensures immediate fault responses, essential for time-critical industrial processes.

V. RESULTS AND DISCUSSION

The Simulation and Visualization: The Streamlit dashboard successfully displayed live graphs of vibration, temperature, and current parameters.

Anomaly Detection: Isolation Forest achieved over 93% detection accuracy in simulated fault scenarios.

RUL Estimation: LSTM predicted machine degradation trends effectively, indicating early-warning capability several minutes before simulated faults occurred.

System Responsiveness: Latency between data collection and alert generation was under 1.5 seconds, confirming real-time viability.
Hardware Integration: The finalized sensor suite (MPU-6050, DS18B20, SCT-013) interfaced seamlessly with the Raspberry Pi 3 via I²C and ADC converters (ADS1115).

Performance Evaluation:

Metric	Value
Data Sampling Rate	10 Hz (vibration), 1 Hz (temperature)
Inference Latency	< 1.5 s
Anomaly Detection Accuracy	93 %
Power Consumption (Pi 3)	< 5 W
Local Storage (SQLite)	~5 MB/day of logs

These outcomes indicate that Edge AI inference is feasible on low-cost hardware and can reliably detect anomalies in CNC machines. In future stages, the system will be validated on a real CNC machine to compare predictions with actual maintenance logs, establishing quantitative RUL accuracy and cost savings.

VI. CONCLUSION

This paper presents a complete Edge-AI-enabled predictive maintenance solution for CNC machines using IoT sensor analytics. The proposed architecture combines vibration, temperature, and current monitoring with on-device anomaly detection and maintenance scheduling. By performing analytics directly on the Raspberry Pi edge node, the system minimizes latency, conserves bandwidth, and enhances data privacy. Experimental simulation results demonstrate effective fault identification and visualization capabilities. The approach paves the way toward autonomous, intelligent manufacturing with reduced unplanned downtime and improved operational efficiency.

VII. FUTURE SCOPE

Future work aims to:
1. Integrate TinyML for ultra-light models deployable on microcontrollers (e.g., ESP32).
2. Incorporate Deep Reinforcement Learning for dynamic maintenance decision-making.
3. Add predictive scheduling algorithms that adapt based on machine workload history.
4. Develop a hybrid edge-cloud framework, where edge nodes perform initial inference while the cloud refines long-term trend analytics.

Extend the system for multi-machine networked monitoring in smart factories.
These advancements can make the proposed framework scalable and suitable for large-scale industrial deployment.

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REFERENCES

1. S.Calvez, P.Aygalinc, P.Bonhomme, "Proactive/Reactive Approach for Maintenance Tasks in Time-Critical Systems," IEEE, 2024.
2. P.Mallioris, E.Aivazidou, D.Bechtsis, "Predictive Maintenance in Industry 4.0: A Systematic Multi-Sector Mapping," CIRP J. Manuf. Sci. Technol., 2024.
3. A.Ucar,M.Karakose,N.Kırımça,"Artificial Intelligence for Predictive Maintenance Applications: Key Components, Trustworthiness, and Future Trends," Applied Sciences, 2024.
4. T.Zonta,C.A.Costa, R. R. Righi, "Predictive Maintenance in the Industry 4.0: A Systematic Literature Review," Elsevier, 2020.
5. M.Chen, M.Wang, Y.H.Chien, "A Modified Imperfect Preventive Maintenance Policy under Reliability Limit," IEEE, 2018.
6. N.du Plessis, R.Pelzer, J Vosloo, "Sustaining the Performance of Diverse Energy Management Systems through Reactive Maintenance," IEEE, 2015.
7. R.de la Fuente et al., "Enhancing Predictive Maintenance in Mining Machinery through a TinyML-Enabled Hierarchical Inference Network," 2024.
8. Y.Yangetal.,"Machine Condition Monitoring System Based on Edge Computing Technology," 2024. A.Artiushenko et al., "Edge AI: From the Perspective of Predictive Maintenance," 2023.
9. Ren et al., "Artificial Intelligence and Edge Computing for Machine Maintenance Review," 2022.