AI-Based Real-Time Tool Condition Monitoring System for CNC Lathe

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Abstract - *This paper presents an AI-based real-time tool condition monitoring system for CNC lathe operations. Tool wear and unexpected failures significantly affect machining accuracy, productivity, and maintenance cost. To address this issue, a multi-sensor monitoring system is developed using a temperature sensor (K-type thermocouple), vibration sensor (MPU6050), and acoustic emission sensor (INMP441). These sensors are interfaced with an ESP32 microcontroller to acquire real-time data during machining. The collected data is transmitted to a web-based monitoring interface for visualization and storage. A Random Forest machine learning algorithm is implemented to classify tool conditions into three categories: Good, Warning, and Replace. The dataset is generated using real-time machining data collected under different cutting conditions. The proposed model achieves an accuracy of approximately 95–96% in classifying tool conditions. The system enables early detection of tool wear, supporting predictive maintenance and reducing unexpected downtime. Experimental results demonstrate that the proposed system is effective and suitable for real-time industrial applications.*

***Key Words*: CNC Lathe, Tool Condition Monitoring, Machine Learning, ESP32, Random Forest, Sensor Data.**

1. INTRODUCTION

Computer Numerical Control (CNC) machines are widely used in modern manufacturing industries due to their high precision, automation, and productivity. They enable accurate and repeatable machining operations, making them essential in sectors such as automotive, aerospace, and tool manufacturing. However, tool wear and unexpected tool failure remain significant challenges that adversely affect machining accuracy, surface quality, and overall productivity.

Tool wear is an inevitable phenomenon in CNC machining processes due to continuous contact between the cutting tool and the workpiece. Factors such as high temperature, friction, and mechanical stress contribute to gradual tool degradation during machining. Excessive tool wear can lead to poor surface finish, dimensional inaccuracies, increased machining time, and, in severe cases, sudden tool failure. These issues result in increased maintenance costs and unplanned machine downtime. Therefore, continuous monitoring of tool condition is essential to ensure consistent machining performance and product quality.

Conventional tool condition monitoring methods, such as manual inspection and scheduled maintenance, are often time-consuming, subjective, and incapable of detecting early-stage tool wear. These traditional approaches do not provide real-time information about tool health, making them unsuitable for modern automated manufacturing environments. With advancements in sensor technology and artificial intelligence, it is now possible to develop intelligent monitoring systems that continuously analyze machining conditions. By integrating sensors such as temperature, vibration, and acoustic emission with machine learning algorithms, tool wear can be predicted effectively.

Despite the advancements in tool condition monitoring, many existing systems are limited by the use of single-sensor data, lack of real-time implementation, and dependence on offline analysis. These limitations reduce their effectiveness in practical industrial environments where continuous monitoring is essential. Additionally, existing methods often fail to integrate low-cost embedded systems with intelligent decision-making algorithms for real-time applications.

To overcome these limitations, this work proposes a multi-sensor, AI-based real-time tool condition monitoring system using a temperature sensor (K-type thermocouple), vibration sensor (MPU6050), and acoustic emission sensor (INMP441), integrated with an ESP32 microcontroller. A Random Forest machine learning algorithm is employed to classify tool conditions into Good, Warning, and Replace categories. The system provides real-time monitoring through a web-based interface and enables early detection of tool wear, thereby improving machining efficiency, reducing downtime, and supporting predictive maintenance in industrial applications.

1.1 TOOL WEAR IN CNC MACHINING

Tool wear is an inevitable phenomenon in CNC machining processes due to continuous contact between the cutting tool and the workpiece. During machining, factors such as high temperature, friction, and mechanical stress contribute to gradual degradation of the cutting tool. As the tool undergoes wear, its cutting efficiency decreases, leading to poor surface finish, dimensional inaccuracies, and increased machining time. Excessive tool wear can also result in sudden tool failure, causing unplanned machine downtime and increased production costs. The wear process is influenced by various machining parameters such as cutting speed, feed rate, material properties, and environmental conditions. Therefore, continuous monitoring of tool condition is essential to maintain machining quality, improve productivity, and reduce maintenance costs in modern manufacturing systems.

1.2 Need for AI-Based Tool Condition Monitoring

Conventional tool condition monitoring methods, such as visual inspection and scheduled maintenance, are often inaccurate and fail to provide real-time information about tool health. With advancements in sensor technology and artificial intelligence, it is possible to develop intelligent monitoring systems that continuously analyze machining conditions. By integrating sensors such as temperature, vibration, and acoustic emission with machine learning algorithms, tool wear can be predicted effectively. An AI-based monitoring system enables early detection of abnormal conditions, reduces unexpected failures, and improves overall machining efficiency and reliability.

2. LITERATURE REVIEW

Recent research in tool condition monitoring has focused on the use of sensor-based techniques and machine learning approaches to improve machining performance and reliability. Various sensing methods such as vibration analysis, acoustic emission monitoring, and temperature measurement have been widely used to detect tool wear during machining processes. Vibration-based monitoring is commonly used due to its high sensitivity to changes in cutting conditions. Studies have shown that vibration signals vary significantly with tool wear and can be effectively used for tool condition classification [1]. Acoustic emission (AE) techniques are also widely employed to detect high-frequency signals generated during machining, which are closely associated with tool wear and tool fracture [2]. Similarly, temperature-based monitoring methods have been explored, as cutting temperature increases with tool wear progression and directly affects tool life and machining quality [3]. With the advancement of artificial intelligence, machine learning techniques such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Decision Trees have been applied for tool wear prediction and classification [4][5]. Among these, the Random Forest algorithm has gained attention due to its high accuracy, robustness, and ability to handle complex and nonlinear datasets [6]. However, most existing systems are limited by the use of single-sensor data, lack of real-time implementation, and reliance on offline data analysis [7]. These limitations reduce their effectiveness in practical industrial environments where continuous and real-time monitoring is required.

Table-1: Comparison of Existing Tool Condition Monitoring Methods

Method	Technique	Limitation
Vibration-based methods	Signal analysis	Sensitive to noise
Acoustic emission methods	High-frequency monitoring	Requires complex processing
Temperature-based methods	Thermal analysis	Slow response to sudden wear
Machine learning models (SVM, ANN)	Data-driven prediction	Requires large data

Table 1 presents a comparison of existing tool condition monitoring approaches and their limitations. Based on the above analysis, it is evident that there is a need for a real-time, multi-sensor monitoring system integrated with machine learning algorithms. The proposed system addresses these limitations by combining temperature, vibration, and acoustic emission sensors with an ESP32 microcontroller and a Random Forest model to enable real-time tool condition prediction.

3. METHODOLOGY

The proposed system is an AI-integrated real-time tool condition monitoring system designed to monitor tool health during CNC lathe operations. The methodology involves multi-sensor data acquisition, real-time monitoring, and machine learning-based classification.

3.1 System Architecture

The system consists of temperature, vibration, and acoustic emission sensors connected to an ESP32 microcontroller. The sensors collect real-time machining data near the cutting zone. The ESP32 processes the data and transmits it through Wi-Fi to a web-based monitoring interface for visualization and storage. The processed data is used for tool condition prediction using a machine learning model. The overall system operates in a sequential manner involving data acquisition, processing, and prediction. Initially, sensor data is collected from the machining zone. The acquired signals are then processed and transmitted to a web-based interface. The processed data is further used as input for the machine learning model, which predicts the tool condition in real time. This integrated approach ensures continuous monitoring and timely detection of tool wear.

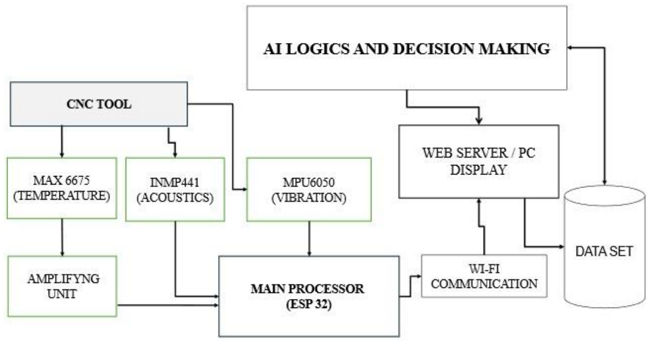

Figure 1: Block diagram of the proposed system
Figure 1 shows the overall block diagram of the proposed tool condition monitoring system**.**

3.2 Sensor Setup

A K-type thermocouple is used to measure temperature near the tool tip. An MPU6050 sensor is used to monitor vibration, and an INMP441 microphone is used to capture acoustic signals generated during machining. The sensors are placed close to the cutting zone to ensure accurate data acquisition. The vibration sensor is mounted inside the tool holder slot using epoxy adhesive for rigid attachment and stable signal measurement.

Table -2: Sensor Specifications

Sensor	Parameter Measured	Range	Purpose
K-type Thermocouple	Temperature	-200°C–1,260°C	Detect thermal variation
MPU 6050	Vibration	±16g	Monitor cutting vibrations
INMP441	Acoustic Emission	up to 120 dB	Capture machining sound

3.3 System Working Procedure

The working of the proposed system is carried out in the following steps:

1. Sensors are placed near the cutting zone to capture temperature, vibration, and acoustic signals.
2. The ESP32 microcontroller collects real-time sensor data during machining operations.
3. The collected data is processed and transmitted through Wi-Fi to a web-based interface.
4. The data is stored and used for dataset generation.
5. The machine learning model analyzes the input features and predicts the tool condition.
6. The predicted result is displayed in real time on the web-based monitoring interface.

3.4 Data Acquisition and Transmission

The sensor data is collected and processed by the ESP32 microcontroller in real time. The acquired data includes temperature (°C), vibration (g), and acoustic emission (dB). The ESP32 hosts a web server that displays real-time values and allows data logging. The collected data is stored and used for further analysis and dataset generation.

3.4 Machine Learning Model

A Random Forest algorithm is used for tool condition classification. Random Forest is an ensemble learning technique that constructs multiple decision trees and combines their outputs using majority voting to improve prediction accuracy and reduce overfitting. The input features for the model include temperature, vibration, and acoustic emission signals collected during machining. The dataset is divided into training and testing sets in an 80:20 ratio. The model is trained using labelled data categorized into Good, Warning, and Replace conditions. The trained model is capable of predicting tool condition based on real-time sensor inputs, enabling early detection of tool wear and supporting predictive maintenance.

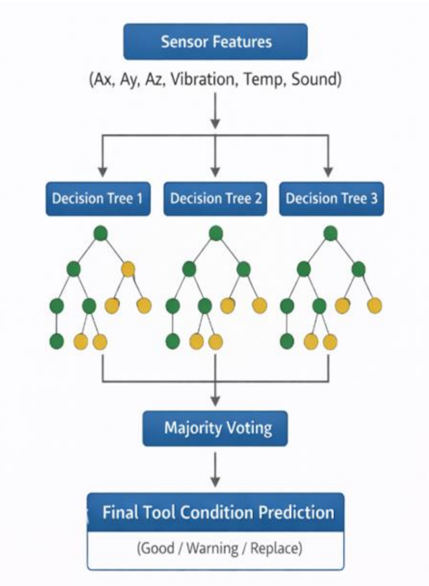

Figure-2: Machine learning model workflow for tool condition prediction

Figure 2 illustrates the workflow of the Random Forest model used for tool condition prediction.

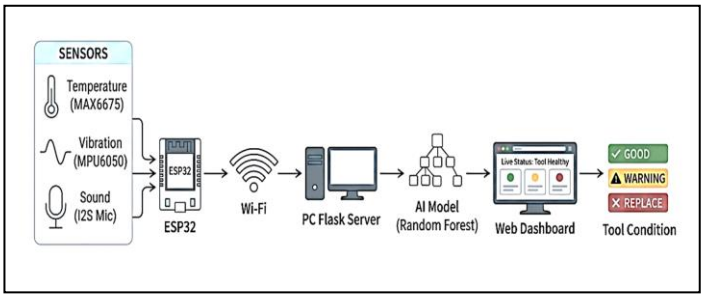

Figure-3: Architecture of the proposed system

Figure 3 represents the system architecture integrating sensors, ESP32, and web interface.

3.5 Dataset Collection and Preparation

The dataset used for tool condition prediction was generated using real-time sensor data collected during CNC machining operations. The system was tested under different cutting conditions using various workpiece materials such as aluminium, mild steel, and stainless steel. During machining, temperature, vibration, and acoustic emission signals were continuously measured using the respective sensors.

The data was collected over multiple machining cycles to ensure variability in operating conditions. The sensor readings were recorded at regular intervals and transmitted through the ESP32 microcontroller to a web-based monitoring system, where they were displayed and stored as a structured dataset.

An initial calibration process was performed to establish baseline sensor values under normal cutting conditions. Based on variations in sensor readings, the dataset was labelled into three categories: Good, Warning, and Replace.

The collected dataset was pre-processed to remove noise and ensure consistency. The dataset was then divided into training and testing sets in an approximate ratio of 80:20 for model development and validation. This process ensured reliable training of the machine learning model and improved prediction accuracy.

Figure 4: Web interface for data-set generation

Figure 4 shows the web interface used for dataset generation and monitoring.

4.SYSTEM IMPLEMENTATION

The proposed system is implemented using an integrated hardware and software approach for real-time tool condition monitoring. The system combines sensor data acquisition, embedded processing, and wireless communication to enable continuous monitoring during machining operations. The ESP32 microcontroller collects and processes sensor data and transmits it to a web-based interface through Wi-Fi. The system enables real-time visualization, data logging, and supports machine learning-based prediction for tool condition monitoring.

4.1 System Setup

The hardware setup consists of multiple sensors mounted near the cutting zone to capture machining parameters accurately. The ESP32 microcontroller is housed in a compact enclosure along with supporting components to ensure stable operation during machining. The system is designed to withstand machining conditions while enabling efficient data acquisition and communication.

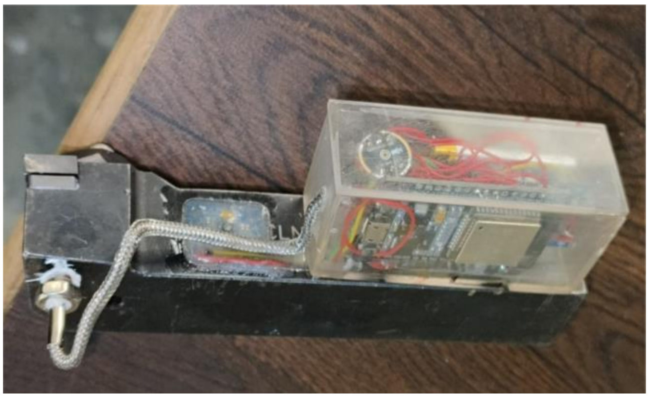

Figure-5: Hardware setup

Figure 5 shows the hardware setup mounted near the tool holder.

4.2 Machine Learning and Web-Based Monitoring

The collected sensor data is used for tool condition prediction using a Random Forest algorithm. The input features include temperature, vibration, and acoustic signals obtained during machining. The dataset is labelled into Good, Warning, and Replace categories based on sensor variations. The ESP32 transmits real-time sensor data through Wi-Fi to a web-based interface. The interface displays sensor values along with the predicted tool condition and supports data logging. This integration enables real-time monitoring and early detection of tool wear for improved machining performance

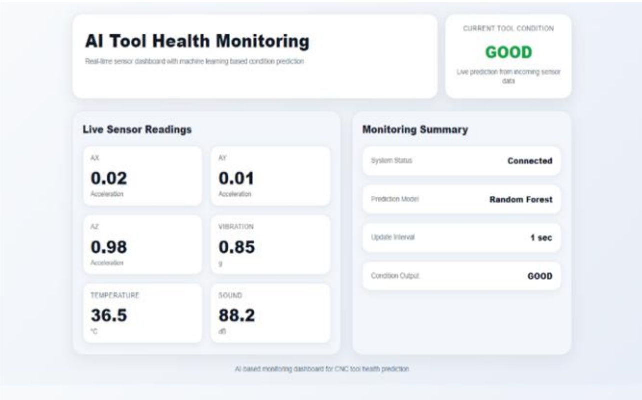

Figure-6: Prediction result web interface

Figure 6 displays the prediction result through the web interface.

5. RESULTS AND DISCUSSION

The performance of the proposed tool condition monitoring system was evaluated using real-time sensor data collected during CNC machining operations. The system successfully acquired temperature, vibration, and acoustic emission signals and processed them using the ESP32 microcontroller. The collected dataset was used to train and test the Random Forest machine learning model for tool condition classification. The model demonstrated high classification performance, achieving an overall accuracy of approximately 99%. The confusion matrix, as shown in Figure X, indicates that the majority of predictions are concentrated along the diagonal elements, representing correct classifications. The model correctly classified 476 instances of Good condition, 105 instances of Replace condition, and 513 instances of Warning condition. Only a single misclassification was observed, highlighting the robustness and reliability of the proposed system. Further analysis was carried out using feature importance evaluation, as illustrated in Figure Y. The results show that acoustic emission (sound) and vibration signals have the highest contribution to tool condition prediction, indicating their strong correlation with tool wear. Temperature provides moderate influence in identifying gradual wear progression, while acceleration components (Ax, Ay, Az) have minimal contribution to the prediction process. The integration of multiple sensor inputs significantly enhances the accuracy of the prediction model compared to single-sensor approaches. The real-time monitoring system successfully displays sensor values and predicted tool conditions through a web-based interface, enabling early detection of abnormal tool behavior. This capability helps prevent unexpected tool failure and supports predictive maintenance in CNC machining applications. Overall, the results confirm that the proposed multi-sensor AI-based monitoring system is effective, reliable, and suitable for real-time industrial implementation.

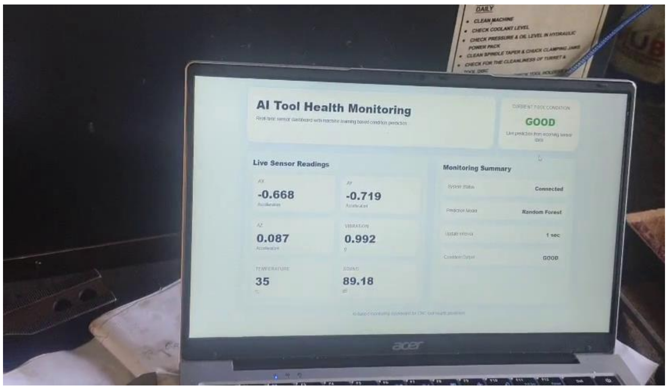

Figure-7: Real-time monitoring via web interface

Figure 7 shows real-time monitoring of tool condition using the web interface.

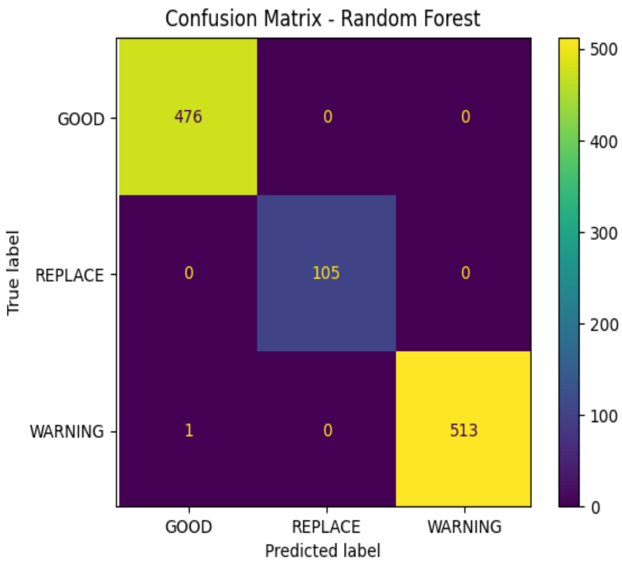

Figure-8: Confusion matrix of Random Forest model for tool condition classification

Figure 8 illustrates the classification performance of the Random Forest model, where the majority of predictions are concentrated along the diagonal elements, indicating high accuracy and minimal misclassification.

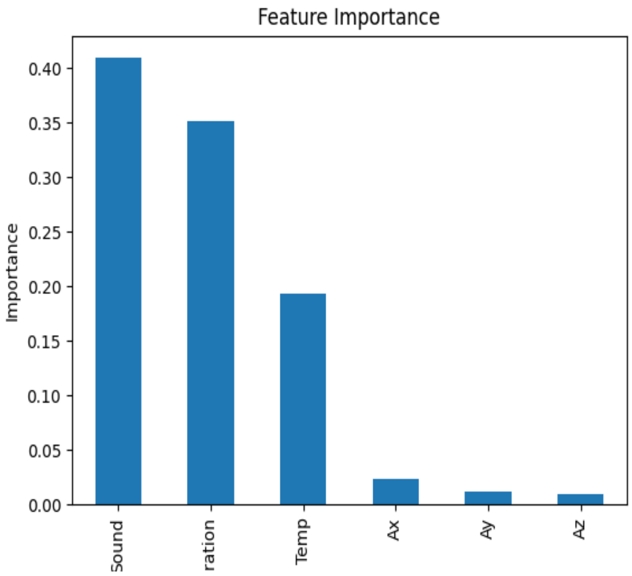

Figure 9: Feature importance of sensor parameters for tool condition prediction

Figure-9 Feature importance analysis shows that acoustic emission (sound) and vibration signals have the highest contribution to tool condition prediction, indicating their strong correlation with tool wear. Temperature provides moderate influence, while acceleration components (Ax, Ay, Az) contribute minimally. This demonstrates that vibration and acoustic signals are the most reliable indicators for detecting tool condition changes.

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REFERENCES

[1] T. Pfeifer and L. Wiegers, "Reliable tool wear monitoring by optimized image and signal processing," *CIRP Annals*, vol. 49, no. 1, pp. 275–280, 2000.

[2] Inasaki, "Application of acoustic emission sensor for monitoring machining processes," *Ultrasonics*, vol. 36, no. 1–5, pp. 273–281, 1998.

[3] S. Y. Liang and D. A. Dornfeld, "Tool wear detection using force and temperature signals," *ASME Journal of Manufacturing Science and Engineering*, vol. 111, no. 3, pp. 452–457, 1989.

[4] K. Jemielniak, "Commercial tool condition monitoring systems," *International Journal of Advanced Manufacturing Technology*, vol. 15, no. 10, pp. 711–721, 1999.

[5] G. Rehorn, J. Jiang, and P. E. Orban, "State-of-the-art methods and results in tool condition monitoring," *International Journal of Advanced Manufacturing Technology*, vol. 26, pp. 693–710, 2005.

[6] L. Breiman, "Random Forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.

[7] S. Dimla, "Sensor signals for tool wear monitoring in metal cutting operations," *International Journal of Machine Tools and Manufacture*, vol. 40, no. 8, pp. 1073–1098, 2000.

[8] S. Smith and J. Tlusty, "Monitoring tool wear using acoustic emission signals," *Journal of Manufacturing Science and Engineering*, vol. 120, no. 2, pp. 345–350, 1998.

[9] J. Brown, "Real-time monitoring of machining processes using IoT," *IEEE Transactions on Industrial Electronics*, vol. 66, no. 5, pp. 4002–4010, 2020.

[10] A. Gupta and R. Kumar, "Machine learning techniques for tool wear prediction," *Procedia Manufacturing*, vol. 20, pp. 231–236, 2019.

[11] M. Patel et al., "Application of Random Forest in predictive maintenance," *International Journal of Engineering Research*, vol. 9, no. 4, pp. 112–118, 2021.

[12] Y. Altintas, *Manufacturing Automation: Metal Cutting Mechanics, Machine Tool Vibrations, and CNC Design*, Cambridge University Press, 2012.

[13] S. Teti, K. Jemielniak, G. O'Donnell, and D. Dornfeld, "Advanced monitoring of machining operations," *CIRP Annals*, vol. 59, no. 2, pp. 717–739, 2010.

[14] J. Zhou, C. Li, and Y. Wang, "Tool wear monitoring using multi-sensor data fusion and machine learning," *Sensors*, vol. 20, no. 5, 2020.

[15] H. Shao, H. Jiang, H. Zhao, and F. Wang, "A novel deep learning approach for tool wear monitoring," *IEEE Access*, vol. 6, pp. 2123–2131, 2018.