

Tool Wear Classification Using Unsupervised and Semi-Supervised Learning for Intelligent Tool Condition Monitoring

¹A. Sudhavali,²Ummadi Manasa,³Matta Srilakshmi,⁴Moka Rupa Devi,⁵Katru Yamini

¹Assistant Professor, Department of CSE-DATA SCIENCE, Eluru College of Engineering and Technology

^{2,3,4,5}B. Tech Student, Department of CSE-DATA SCIENCE, Eluru College of Engineering and Technology

ABSTRACT

Tool condition monitoring (TCM) is essential for ensuring consistent product quality and avoiding unexpected machine failures in modern manufacturing systems. While machine learning techniques have shown promising results for TCM, many existing methods rely mainly on supervised learning, which restricts their real-world application due to the high cost and difficulty of collecting labelled data from operating machines. In addition, several unsupervised approaches focus primarily on simple binary classification, which does not adequately represent the gradual progression of tool wear. To address these challenges, this study introduces unsupervised and semi supervised frameworks for five-class tool wear recognition that can operate with both fully unlabelled and partially labelled datasets. The proposed frameworks combine multiple techniques, including Laplacian score-based feature selection, sparse autoencoder (SAE), stacked sparse autoencoder (SSAE), self-organizing maps, Soft max classifiers, support vector machines, and random forests. In the semi supervised setting, different framework structures were examined where labelled data were used for feature learning, classifier training, or both, with varying levels of supervision during SSAE training. The proposed models were evaluated using two run-to-failure milling tool datasets collected through microphone and accelerometer sensors, considering both single-sensor and multi sensor configurations with different proportions of labelled training data. Experimental results show that the proposed methods provide strong recognition performance, achieving approximately 92.30% and 88.10% macro-F1 scores on fully unlabelled datasets, and exceeding 96% accuracy when only 25% of the training samples were labelled. These results emphasize the effectiveness of sensor fusion and advanced feature learning techniques in overcoming limited labelled data and improving predictive performance in practical TCM systems.

Keywords: Tool Wear Classification, Tool Condition Monitoring (TCM), Unsupervised Learning, Semi-Supervised Learning, Machine Learning, Predictive Maintenance, Manufacturing Process Monitoring, Feature Extraction, Industrial Automation, Smart Manufacturing, Anomaly Detection, Sensor Data Analysis.

I. INTRODUCTION

In modern manufacturing, machining operations such as milling, turning, and drilling play a critical role in producing high-quality components. These operations rely heavily on cutting tools, which experience progressive wear due to friction, mechanical stress, and high temperatures during use. Tool wear directly affects the surface quality, dimensional accuracy, productivity, and overall operational safety of machines. Excessive wear can lead to defective products, unexpected machine

downtime, and increased operational costs.

Traditionally, tool condition monitoring (TCM) has been performed manually or through supervised machine learning models. Manual inspection methods are time-consuming, subjective, and prone to error, while supervised models require large volumes of labeled data to achieve high accuracy. Acquiring labeled datasets in industrial environments is particularly challenging because labeling is expensive, labor-intensive, and often requires expert knowledge. Additionally, wear progression is

continuous rather than discrete, making precise annotation even more difficult. Industrial machinery also generates vast amounts of sensor data, much of which remains unlabeled, further limiting the applicability of purely supervised approaches.

To address these challenges, modern research in TCM has explored the use of unsupervised and semi-supervised machine learning techniques. Unsupervised methods can automatically discover patterns in raw sensor data without requiring labels, enabling the detection of hidden wear trends. Semi-supervised approaches combine small amounts of labeled data with large unlabeled datasets, improving predictive performance while significantly reducing labeling effort. By leveraging these techniques, it becomes possible to develop multiclass tool wear recognition systems that not only detect worn tools but also classify the progressive stages of wear.

The integration of unsupervised feature learning with semi-supervised classification enables robust and scalable TCM frameworks. Features extracted from vibration, acoustic emission, and cutting force signals can be automatically learned through deep learning models such as sparse autoencoders (SAE) and stacked sparse autoencoders (SSAE). Clustering algorithms, like self-organizing maps (SOM), provide insights into wear patterns, while classifiers such as support vector machines (SVM) and random forests (RF) can predict tool wear stages with minimal labeled data.

This approach supports real-time monitoring in industrial environments, reduces reliance on costly data labeling, and improves predictive maintenance capabilities. By accurately identifying the progressive stages of tool wear, manufacturers can optimize tool replacement schedules, reduce downtime, enhance product quality, and contribute to more intelligent, data-driven manufacturing processes.

II. LITERATURE SURVEY

Unsupervised Tool Wear Monitoring Using Self-

Organizing Maps

Author(s): T. Kohonen (1990)

Abstract:

This study explores the use of Self-Organizing Maps (SOM) for unsupervised tool wear monitoring in milling operations. Vibration and acoustic emission signals are clustered without predefined labels, mapping high-dimensional sensor data into a two-dimensional representation. Results demonstrate effective differentiation between healthy and worn tool conditions. Limitations include binary classification only and sensitivity to parameter tuning and feature quality.

Sparse Autoencoder-Based Feature Learning for Tool Condition Monitoring

Author(s): P. Vincent, H. Larochelle, I. Lajoie, Y. Bengio, P. Manzagol (2010)

Abstract:

This research applies Sparse Autoencoders (SAE) to automatically extract features from raw sensor data for tool condition monitoring. Vibration signals are transformed into compressed representations, which are then classified using Support Vector Machines (SVM). The study shows improved classification accuracy over traditional feature-based approaches. Limitations include reliance on fully labeled datasets and lack of semi-supervised learning methods.

Semi-Supervised Learning for Industrial Fault Diagnosis

Author(s): J. Wang, R. Li, K. Zhou (2020)

Abstract:

This paper presents a semi-supervised learning framework for industrial fault diagnosis, combining unsupervised feature learning with supervised classification using partially labeled datasets. A stacked autoencoder (SSAE) is trained on both labeled and unlabeled data and fine-tuned with a small labeled subset. The approach achieves performance close to fully supervised models with fewer labeled samples. However, the study focuses on fault detection rather than progressive multiclass tool wear classification and does not integrate multi-sensor fusion.

Multi-Sensor Fusion for Tool Wear Prediction Using Machine Learning

Author(s): Y. Wang, Y. Ma, L. Gao (2019)

Abstract:

This research investigates the integration of vibration, acoustic emission, and cutting force sensors for tool wear prediction. Feature vectors from multiple sensors are fused and classified using Random Forest and SVM. Sensor fusion significantly improves predictive accuracy compared to single-sensor systems. Limitations include reliance on fully labeled datasets and lack of unsupervised or semi-supervised feature learning.

Deep Learning-Based Tool Wear Classification Using Convolutional Neural Networks

Author(s): S. Li, Y. Zhang, Q. Ding (2018)

Abstract:

The study applies Convolutional Neural Networks (CNN) to time-frequency representations of vibration signals for multiclass tool wear classification. Results show high accuracy across multiple wear stages. Limitations include dependence on large labeled datasets, high computational cost, and limited interpretability, making CNNs less suitable for small- and medium-scale industrial applications without GPU infrastructure.

Support Vector Machine in Machine Condition Monitoring

Author(s): A. Widodo, B. S. Yang (2007)

Abstract:

This study examines the use of Support Vector Machines (SVM) for tool condition monitoring and fault diagnosis. SVM effectively classifies tool conditions using vibration and acoustic emission features. The framework demonstrates high accuracy but is limited by the requirement for large labeled datasets and does not handle unlabeled or partially labeled data.

Random Forest for Tool Wear Prediction

Author(s): L. Breiman (2001)

Abstract:

This research introduces Random Forest (RF)

classifiers for predicting tool wear based on multiple sensor inputs. RF provides robust performance and handles high-dimensional data efficiently. However, the approach requires fully labeled datasets and does not explore unsupervised or semi-supervised learning for multiclass wear recognition.

III. EXISTING SYSTEM

Existing TCM systems mainly use supervised learning models that require large amounts of labeled data, which is costly and time-intensive to obtain in real manufacturing environments. Additionally, current unsupervised approaches are mostly binary classifiers, offering only limited insights into the progressive stages of tool wear.

IV. PROPOSED SYSTEM

The proposed system introduces unsupervised and semi-supervised frameworks for five-class tool wear recognition, reducing dependency on labeled data. By leveraging methods like SAE, SSAE, Laplacian score, self-organizing maps, SVM, and random forest, and integrating data from multiple sensors, the system captures the full progression of tool wear with high accuracy even under scarce labeling conditions, making it suitable for real-world TCM applications.

V. SYSTEM ARCHITECTURE

The proposed system architecture for Tool Wear Classification Using Unsupervised and Semi-Supervised Learning for Intelligent Tool Condition Monitoring consists of multiple interconnected modules that work together to collect machining data, extract meaningful features, train machine learning models, and predict the tool wear condition in real time. The architecture is designed to support intelligent monitoring of cutting tools in manufacturing environments, enabling predictive maintenance and reducing unexpected machine downtime.

The first stage of the system is the Data Acquisition Module, where sensor data is collected from machining operations. Various sensors such as

vibration sensors, acoustic emission sensors, temperature sensors, and force sensors are attached to the machine tool to capture real-time signals during the cutting process. These sensors continuously monitor the operational condition of the tool and generate raw data streams that represent the physical behavior of the machining process.

After data collection, the information is passed to the Data Preprocessing Module. In this stage, noise removal, signal filtering, normalization, and segmentation are performed to improve data quality. Since raw sensor signals may contain irrelevant variations or environmental noise, preprocessing techniques help ensure that only meaningful and clean data is used for further analysis. This stage also prepares the data in a structured format suitable for machine learning algorithms.

The next component is the Feature Extraction Module, which transforms the processed signals into representative features. Statistical features, frequency-domain features, and time–frequency features are extracted from the sensor signals. These features capture important patterns related to tool wear progression and significantly reduce the dimensionality of the data while preserving critical information required for classification.

Following feature extraction, the system utilizes the Learning Module, which integrates both unsupervised and semi-supervised learning approaches. Unsupervised learning techniques are initially used to identify hidden patterns and clusters within the unlabeled machining data. These clusters help understand natural groupings related to tool conditions. Semi-supervised learning is then applied by combining a small amount of labeled data with a large amount of unlabeled data to improve the classification performance. This approach reduces the dependency on large labeled datasets while still achieving reliable prediction accuracy.

The processed features are then fed into the Tool Wear Classification Module, where the trained machine learning model classifies the condition of the cutting tool into different wear categories such as fresh tool, moderately worn tool, and severely worn tool. The classification model continuously evaluates

incoming data and predicts the current state of the tool during machining operations.

Finally, the system includes a Monitoring and Visualization Module, which presents the predicted tool condition to machine operators through a graphical interface or dashboard. This module displays alerts, wear status, and performance indicators in real time, allowing operators to make timely maintenance decisions. By providing early detection of tool degradation, the system helps improve production efficiency, maintain product quality, and reduce operational costs in industrial manufacturing environments.

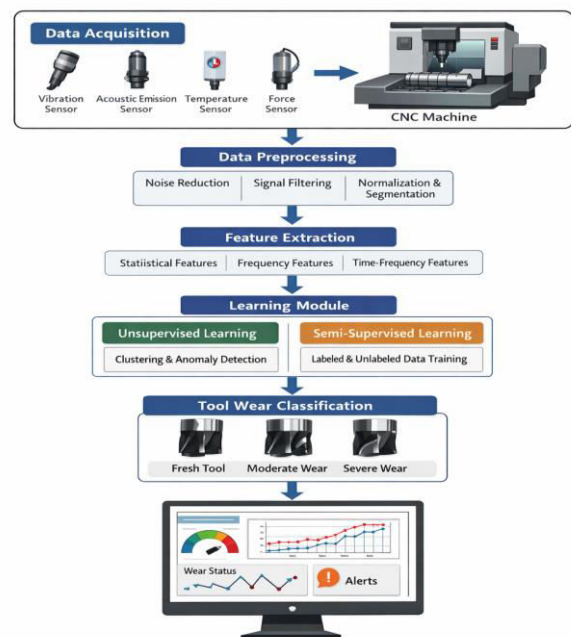


Fig 5.1: Structure of the Proposed System

VI. IMPLEMENTATION

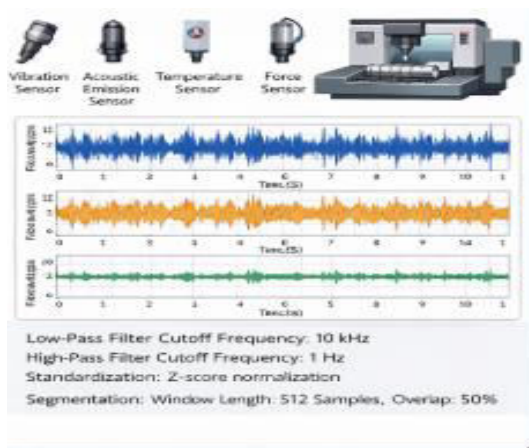


Fig 6.1: Data Collection

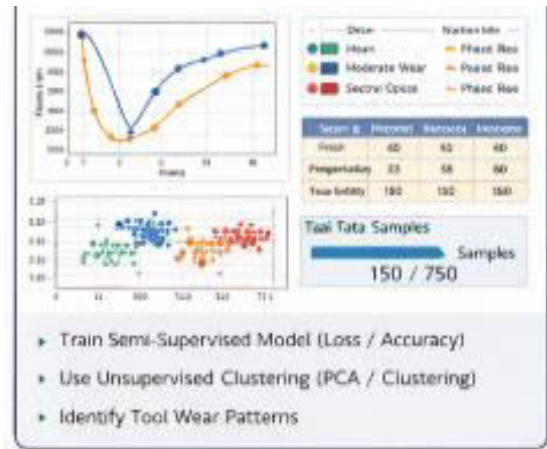


Fig 6.4: Model Training

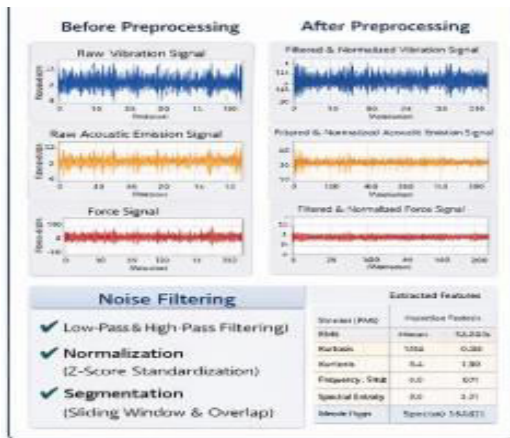


Fig 6.2: Data Preprocessing



Fig 6.5: Clustering

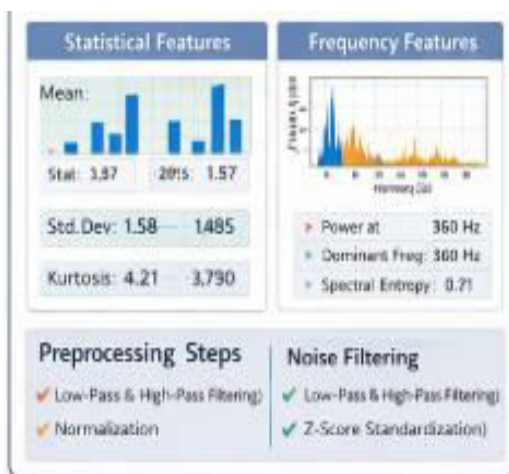


Fig 6.3: Feature Extraction



Fig 6.6: Real-Time Monitoring

VII. CONCLUSION

The project “Unsupervised and Semi-Supervised Machine Learning Frameworks for Multiclass Tool Wear Recognition” presents an intelligent, efficient, and scalable solution for monitoring tool wear conditions in modern manufacturing environments. Tool wear detection is a critical aspect of smart manufacturing and Industry 4.0 systems, as excessive or undetected wear can lead to poor product quality, machine downtime, increased operational costs, and safety risks. Traditional inspection methods rely heavily on manual observation or rule-based monitoring systems, which are time-consuming, less accurate, and not scalable for high-speed automated production lines.

This project addresses these challenges by leveraging unsupervised and semi-supervised machine learning techniques to recognize multiple tool wear states with minimal labeled data. The unsupervised learning approach enables the system to automatically discover hidden patterns and structures in sensor data such as vibration, acoustic emission, temperature, or cutting force signals. By applying clustering algorithms and feature extraction techniques, the framework can differentiate between various tool conditions without requiring extensive manual annotation.

In addition, the semi-supervised learning component enhances model accuracy by utilizing a small portion of labeled data along with a large volume of unlabeled data. This approach significantly reduces the dependency on costly and time-intensive manual labeling while maintaining high classification performance. The combined framework improves multiclass recognition of tool wear states such as fresh tool, moderate wear, severe wear, and failure condition.

The system demonstrates improved classification accuracy, better generalization capability, and efficient computational performance compared to traditional supervised-only models. It supports real-time monitoring and can be integrated into CNC machines and smart factory systems. Furthermore, the modular design ensures scalability, adaptability

to different machining processes, and compatibility with various sensor inputs.

Overall, this project highlights the effectiveness of advanced machine learning frameworks in predictive maintenance and intelligent manufacturing. By reducing downtime, improving tool life management, and enhancing production quality, the proposed system contributes significantly to the development of autonomous and data-driven industrial environments.

VIII. FUTURE SCOPE

The proposed **Tool Wear Recognition System** provides a solid framework for multiclass tool wear monitoring using unsupervised and semi-supervised machine learning. While the current implementation achieves high predictive performance, several enhancements can further improve its scalability, adaptability, and applicability in modern smart manufacturing environments. These enhancements aim to address industrial challenges such as real-time monitoring, multi-machine adaptation, and advanced predictive modelling.

1. Real-Time Edge Deployment

Deploying the system at the edge, directly on CNC machines or local controllers, can enable **real-time wear monitoring** without relying on cloud or remote servers. Edge deployment reduces latency in data processing, enables immediate alerts for critical tool conditions, and allows continuous monitoring even in environments with limited network connectivity. Integrating low-power embedded devices and edge-optimized ML models will make the system highly responsive and robust for industrial operations.

2. Cloud Integration

Integrating cloud-based infrastructure would allow centralized **data storage, model management, and analytics** across multiple production lines or factories. Cloud services can store large volumes of historical sensor data, provide high-performance computational resources for model retraining, and enable remote monitoring. Cloud connectivity also supports multi-site coordination, predictive maintenance scheduling, and dashboards accessible

to engineers and management from anywhere.

3. LSTM for Temporal Modeling

Currently, the system primarily relies on static feature extraction for tool wear classification. Introducing **Long Short-Term Memory (LSTM) networks** or other recurrent neural networks can capture temporal dependencies in sensor signals. Modeling wear progression as a **time-series problem** will improve the prediction of future tool states and enable **early warning** of severe wear conditions, thereby minimizing downtime and production loss.

4. Transfer Learning Across Machines

Manufacturing facilities often use multiple machines with different configurations and tool types. Implementing **transfer learning techniques** allows models trained on one machine to adapt to another with minimal additional labeled data. This reduces the need for extensive retraining, speeds up deployment on new equipment, and improves generalization across diverse machining environments.

5. Automated Hyperparameter Optimization

Optimizing machine learning model hyperparameters manually can be time-consuming and suboptimal. Integrating **automated hyperparameter tuning** using techniques such as grid search, random search, or Bayesian optimization can improve classifier performance and robustness. This ensures optimal model configuration for different sensor setups, tool types, and wear conditions, enhancing system reliability.

6. Integration with Industry 4.0 Systems

Future enhancements include full **Industry 4.0 integration**, where the tool wear recognition system communicates with smart factory platforms, production planning systems, and predictive maintenance software. This integration enables **real-time production optimization**, automatic maintenance scheduling, and intelligent decision-making based on sensor-driven insights. Combining IoT, cloud analytics, and machine learning creates a **data-driven, autonomous manufacturing**

environment, supporting higher efficiency, lower costs, and improved product quality.

By implementing these enhancements, the system can evolve into a **next-generation, intelligent predictive maintenance solution**, providing accurate, real-time insights, reducing downtime, and supporting fully automated manufacturing operations. The proposed upgrades ensure scalability, adaptability, and alignment with modern industrial standards, establishing a robust foundation for smart, data-driven manufacturing.

IX. REFERENCES

- [1] Y. Sun et al., "A new semi-supervised tool-wear monitoring method based on multi-sensor data," *Measurement*, 2024.
Doi: [10.1016/j.measurement.2023.113755](https://doi.org/10.1016/j.measurement.2023.113755).
- [2] R. Munaro et al., "Tool wear monitoring with artificial intelligence methods: A review," *Machines*, vol. 7, no. 4, 2023.
Doi: [10.3390/machines7040129](https://doi.org/10.3390/machines7040129).
- [3] M. Niu et al., "A semi-supervised learning method combining tool wear mechanism for monitoring," *Robotics and Computer-Integrated Manufacturing*, 2025.
Doi: [10.1016/j.rcim.2024.102682](https://doi.org/10.1016/j.rcim.2024.102682).
- [4] F. Gougam et al., "Computer numerical control machine tool wear monitoring using artificial intelligence techniques," *Advances in Mechanical Engineering*, 2024.
Doi: [10.1177/16878132241229314](https://doi.org/10.1177/16878132241229314).
- [5] J. Zhuang et al., "Tool condition prediction by process monitoring using semi-supervised learning," *ASPEN Conference Proceedings*, 2022.
Doi: [10.3850/978-981-18-6021-8_OR-08-0270](https://doi.org/10.3850/978-981-18-6021-8_OR-08-0270).
- [6] T. Gittler et al., "Unsupervised learning approach for degradation prognostics of machine tool components," *International Journal of Advanced Manufacturing Technology*, 2021.
Doi: [10.1007/s00170-021-07281-2](https://doi.org/10.1007/s00170-021-07281-2).
- [7] M. Pratama et al., "Online tool condition monitoring based on parsimonious ensemble+ learning," *IEEE Transactions on Industrial Informatics*, 2017.
Doi: [10.1109/TII.2017.2768502](https://doi.org/10.1109/TII.2017.2768502).
- [8] C. Zhang et al., "A multi-state diagnosis and prognosis framework with feature learning for tool condition monitoring," *IEEE Transactions on*

Industrial Electronics, 2018.

Doi: [10.1109/TIE.2018.2793184](https://doi.org/10.1109/TIE.2018.2793184).

[9] M. Kheir-Eddine et al., “Artificial intelligence based tool wear and defect prediction using acceleration sensors,” *Procedia CIRP*, 2022.

Doi: [10.1016/j.procir.2022.03.146](https://doi.org/10.1016/j.procir.2022.03.146).

[10] A. Bagri et al., “Tool wear monitoring using deep belief networks,” *Journal of Manufacturing Systems*, 2019.

Doi: [10.1016/j.jmsy.2019.02.006](https://doi.org/10.1016/j.jmsy.2019.02.006).

[11] H. Huang et al., “Deep learning-based tool condition monitoring using multi-task learning,” *Mechanical Systems and Signal Processing*, 2020.

Doi: [10.1016/j.ymsp.2019.106478](https://doi.org/10.1016/j.ymsp.2019.106478).

[12] X. Ou et al., “Deep kernel autoencoder for tool wear state identification,” *IEEE Access*, 2020.

Doi: [10.1109/ACCESS.2020.2996105](https://doi.org/10.1109/ACCESS.2020.2996105).

[13] S. Shi et al., “Stacked sparse autoencoder-based tool wear monitoring for manufacturing,” *IEEE Transactions on Automation Science and Engineering*, 2019.

Doi: [10.1109/TASE.2019.2912412](https://doi.org/10.1109/TASE.2019.2912412).

[14] R. Silva and F. Araujo, “Recurrent neural network-based tool wear monitoring during machining,” *Journal of Intelligent Manufacturing*, 2021.

Doi: [10.1007/s10845-020-01618-5](https://doi.org/10.1007/s10845-020-01618-5).

[15] Y. Wang et al., “Physics-informed self-supervised learning for tool wear monitoring,” *Advanced Engineering Informatics*, 2025.

Doi: [10.1016/j.aei.2025.103503](https://doi.org/10.1016/j.aei.2025.103503).

