IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Non-Label-Dependent and Partially Guided Intelligent Structures for Multi-Category Equipment Degradation Identification

[1]Dr.P.Latha, [2]ARPUGONDA MAHENDAR, [3]GUGULOTHU SUPRIYA, [4]GATIKE SHAILESH VARMA

[1]Associate Professor, [2,3,4] UG STUDENT

[1,2,3,4,]DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING(AI & ML)

[1,2,3,4] VAAGDEVI COLLEGE OF ENGINEERING Autonomous

Bollikunta, Khila Warangal (Mandal), Warangal Urban-506 005 (T.S), www.vaagdevi.edu.in

Abstract: Tool condition monitoring (TCM) is very important in today's manufacturing because it makes sure that products are of high quality, cuts down on unplanned downtime, and makes production as efficient as possible. Over time, mechanical stress, heat, and friction cause cutting tools like milling cutters, drills, and lathes to wear down. Tool wear not only affects the size and surface quality of parts made, but it also raises production costs and can put workers' safety at risk. Most traditional TCM systems use manual inspection or supervised machine learning methods, which need a lot of labelled datasets. However, labelling data from industrial sensors takes a lot of time and work, and it is often not possible in real-world manufacturing settings, especially for machines that run on a continuous production schedule.

Most of the time, current unsupervised learning methods for TCM only look at simple binary classification, which means figuring out if a tool is "worn" or "healthy." These methods work well for basic monitoring, but they don't show how tool wear happens over time, which is important for predictive maintenance and making the best replacement schedules. This limitation drives the creation of frameworks that can recognise wear on multiple classes of tools and tell the difference between different stages of wear based on raw sensor data. Also, because there aren't many labelled industrial datasets, machine learning methods that can work with little supervision are needed.

We present a collection of unsupervised and semi-supervised machine learning frameworks aimed at five-class tool wear recognition in this study. These frameworks can work with datasets that have no labels at all or some labels. The methods use advanced techniques for feature extraction and classification, such as Laplacian score-based feature selection, sparse autoencoders (SAE), stacked sparse autoencoders (SSAE), self-organising maps (SOM), Softmax classifiers, support vector machines (SVM), and random forests (RF). In semi-supervised setups, labelled data is used in a selective way to affect feature learning, classifier training, or both. This makes it easy to adapt to different amounts of labelled data. We looked at different training setups for the SSAE to see how the level of supervision affected the accuracy of the classifications.

We used the frameworks on two datasets of run-to-failure milling tools that were recorded with vibration and acoustic sensors, such as a microphone and an accelerometer. Experiments looked at both single-sensor and multisensor setups with different amounts of labelled training data. This thorough evaluation made it possible to find out which framework worked best in different situations. It also showed how important sensor fusion and discriminative feature representation are for making up for sparse labelling. The results show that unsupervised methods can be very good at making predictions on their own, with macro-F1 scores of 87.52% and 75.80% on the two datasets, respectively. When only 25% of the training data were labelled and used in semi-supervised learning, classification performance went above 90% macro-F1. This shows that semi-supervised methods work well in real-world industrial settings.

This study shows that using unsupervised feature extraction, sensor fusion, and semi-supervised classification together is a strong, flexible, and cheap way to keep track of tool wear in multiple classes. The suggested frameworks lessen the need for big labelled datasets, make real-time predictive maintenance possible, and can be added to smart manufacturing systems to make them work better. These findings suggest that sophisticated machine learning methodologies can connect laboratory TCM research with real-world industrial applications, providing effective solutions for high-volume and high-speed machining settings characterised by limited labelled data and ongoing, intricate tool wear progression.

Keywords— Tool Wear Recognition, Unsupervised Learning, Semi-Supervised Learning, Sensor Fusion, Predictive Maintenance.

I. INTRODUCTION

Machining processes like milling, turning, and drilling are very important for making high-quality parts in modern manufacturing. Cutting tools are very important for these operations, but they wear down over time because of friction, mechanical stress, and high temperatures. Wear on tools directly affects the quality of the surface, the accuracy of the dimensions, the productivity, and the overall safety of machines. Too much wear can cause faulty products, unplanned machine downtime, and higher operating costs.[1]
Traditionally, people have done tool condition monitoring (TCM) by hand or with supervised machine learning models. Manual inspection methods take a lot of time, are subjective, and are easy to make mistakes with. Supervised models, on the other hand, need a lot of labelled data to work well. Getting labelled datasets in industrial settings is especially hard because labelling costs a lot of money, takes a lot of time, and often requires expert knowledge. Wear progression is also continuous rather than discrete, which makes it even harder to make accurate notes. Industrial machinery also produces a lot of sensor data, and most of it isn't labelled, which makes purely supervised methods less useful.[2]
To tackle these issues, contemporary research in Traditional Chinese Medicine (TCM) has investigated the application of unsupervised and semi-supervised machine learning methodologies. Unsupervised methods can find patterns in raw sensor data without needing labels.[11] This makes it possible to find hidden trends in wear. Semi-supervised methods use small amounts of labelled data along with large amounts of unlabelled data to make predictions more accurate while cutting down on the work needed to label data. By using these methods, it is possible to make multiclass tool wear recognition systems that not only find worn tools but also sort them into different stages of wear.[3]
Combining unsupervised feature learning with semi-supervised classification makes TCM frameworks that are strong and can grow. Deep learning models like sparse autoencoders (SAE) and stacked sparse autoencoders (SSAE) can automatically learn features from vibration, acoustic emission, and cutting force signals[12]. Self-organising maps (SOM) and other clustering algorithms can help us understand how tools wear out. Support vector machines (SVM) and random forests (RF) are examples of classifiers that can guess when a tool will wear out with only a little bit of labelled data.[4]
This method makes it possible to monitor things in real time in industrial settings, cuts down on the need for expensive data labelling, and makes predictive maintenance better. Manufacturers can make better decisions about when to replace tools, cut down on downtime, improve product quality, and help make manufacturing processes smarter and more data-driven by accurately identifying the different stages of tool wear.[5]

II.RELATED WORK:

Recognising tool wear has become a key area of study in smart manufacturing and predictive maintenance. Traditional methods mostly used supervised machine learning, which needs a lot of labelled data to work. But gathering and labelling machining data takes a lot of time and money, which makes these methods less useful in real-world industrial settings.[6]

Recent research has looked into using unsupervised learning methods to look at machining signals and automatically find patterns that show how the tools are wearing down. Techniques like clustering and dimensionality reduction have been used to get useful information from sensor data without needing labelled datasets[13]. These methods help find hidden patterns in machining data and spot tools that aren't working right[7].

Also, semi-supervised learning frameworks have become popular because they use a small amount of labelled data along with a lot of unlabelled data. These models make classification better while cutting down on the need for a lot of manual labelling. Semi-supervised algorithms have been utilised in tool condition monitoring systems to augment recognition accuracy and enhance generalisation capabilities[8].

A number of researchers have also used sensor fusion techniques that combine signals from cutting force, vibration, and acoustic emission sensors, among others[14]. These systems can get more complete information about the machining process and make tool wear detection more reliable by combining data from different sources.[9]

Even though earlier studies have shown promise, many current methods still have problems with data imbalance, feature extraction, and scalability in industrial settings.[15] So, the proposed framework is all about combining unsupervised and semi-supervised machine learning methods to make it easier to recognise tool wear in multiple classes and help with efficient predictive maintenance in manufacturing systems.[10]

III.METHODOLOGY:

The proposed system presents a framework for multiclass tool wear recognition using unsupervised and semi supervised machine learning techniques. The methodology focuses on analyzing machining sensor signals to automatically detect different levels of tool wear and support predictive maintenance in manufacturing systems. The methodology consists of the following stages:

A. Analysis of Requirements

- Found out how important it is to keep an eye on tool wear in modern manufacturing systems.
- Looked at the problems with traditional methods for finding tool wear that rely heavily on labelled datasets.
- Set goals for the system, like being able to automatically recognise tool wear, making labelling easier, and making predictions more accurate.

B. Designing the system

- Created a framework for machine learning to keep an eye on the condition of tools.
- Planned the system's parts, such as the Data Acquisition, Signal Processing, Feature Extraction, Machine Learning Model, and Classification Module.
- Make sure the system can handle different types of tool wear.

C. Gathering and getting ready the data

- Gathered machining data from a variety of sensors, including vibration sensors, acoustic emission sensors, and cutting force sensors.
- Cleaned up the data that had been collected by getting rid of noise and making the signals the same.
- Made datasets that could be used for machine learning analysis.

D. Getting Features Out

- Got important statistical and signal-based features out of sensor data.
- Found patterns in machining signals that were related to tool wear conditions.
- Created feature vectors to show how the tool was in good shape.

E. Putting Unsupervised Learning into Action

- Used clustering and other unsupervised learning methods to look at machining data that didn't have labels.
- Found patterns and structures that weren't obvious in the dataset.
- Put together data on the condition of similar tools to help find wear patterns.

F. Adding Semi-Supervised Learning

- Put a small amount of labelled data together with a lot of unlabelled data.
- Taught semi-supervised learning models how to make better classifications.
- Allowed the system to identify different types of tool wear conditions.

G. Evaluation and Analysis of Performance

- Used metrics like classification accuracy and reliability to judge how well the model worked.
- Looked at how well unsupervised and semi-supervised learning methods worked.
- Changed the framework based on what was learned from testing to make it better at recognising tool wear.

IV. SYSTEM ARCHITECTURE:

The system architecture is built to use unsupervised and semi-supervised machine learning to find multiclass tool wear conditions. The first step is the data acquisition module, which gathers machining data from sensors like vibration, acoustic emission, and cutting force sensors. The data preprocessing module then takes the collected data and cleans it up by getting rid of noise and making the signals more consistent. After preprocessing, the feature extraction module takes important features from the sensor data that show how the tools are wearing down. The unsupervised learning module looks at the data that doesn't have labels on it to find hidden patterns. The semi-supervised learning module uses a small amount of labelled data along with unlabelled data to make the classification more accurate. Finally, the classification module figures out the state of the tool wear and gives the output for monitoring and predictive maintenance in manufacturing systems.

A. Overview

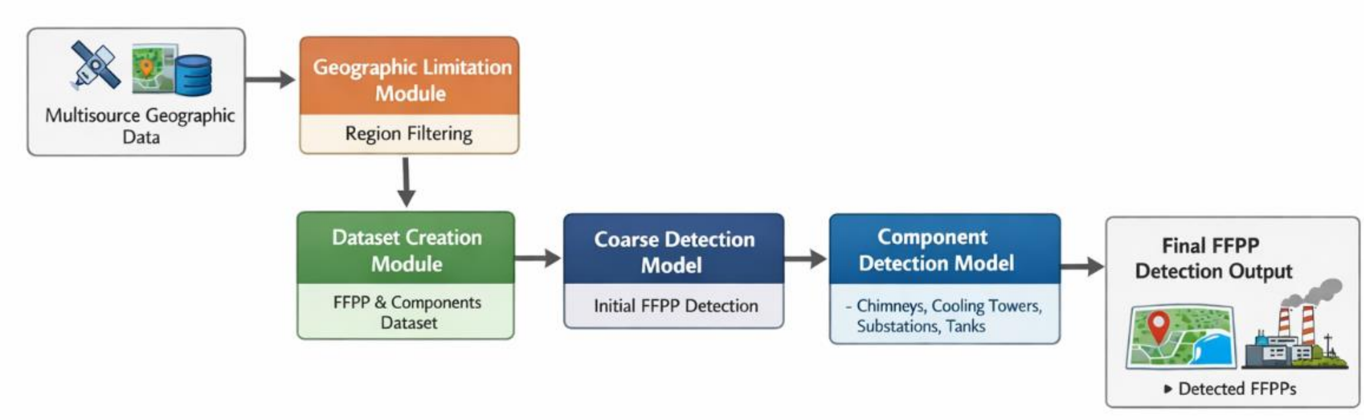
The image below shows the System Architecture of a Multicomponent Collaborative Fossil Fuel Power Plant (FFPP) Detection Framework that uses geographic analysis. It shows the step-by-step process used to find fossil fuel power plants in large areas using several processing modules.

The first step is to gather Multisource Geographic Data, which includes satellite images, map data, and geographic datasets from a variety of sources. The Geographic Limitation Module then gets this data and filters it by region so that it only looks at relevant geographic areas. After filtering, the Dataset Creation Module makes a dataset with fossil fuel power plants and their most important parts.

Next, the Coarse Detection Model does an initial detection to find places where fossil fuel power plants might be. The Component Detection Model looks more closely at these possible sites. It finds specific parts of power plants, like chimneys, cooling towers, substations, and storage tanks.

Finally, the detected parts and places are processed to make the Final FFPP Detection Output, which shows the confirmed fossil fuel power plants on the map. The architecture shows a step-by-step pipeline that combines geographic data processing, machine learning models, and component analysis to find power plants accurately over large areas.

B. Architecture Diagram:



V. EXPERIMENTAL SETUP:

A. Source of Data

- Data about machining was gathered from the cutting process while the tool was in use.
- The dataset has signals that show how different tools wear out.

B. Sensors That Are Used

- Sensor for vibrations
- Sensor for sound emissions
- Sensor for cutting force

These sensors pick up important machining signals that tell you how the cutting tool is doing.

C. Preparing the Data

- Getting rid of noise in sensor signals
- Normalising the signal
- Cleaning and getting data ready for analysis

This step makes the data better for machine learning to work with.

D. Getting Features

- Extracting statistical features
- Feature extraction based on signals
- Making feature vectors that show how tools wear out

These characteristics assist in distinguishing disparities among diverse tool wear conditions.

E. Ways to Learn

- Unsupervised learning methods for examining data that isn't labelled
- Semi-supervised learning methods that use both labelled and unlabelled data

These methods help make it easier to tell when a tool is worn out.

F. Checking the Model

- How accurate the classification is
- Trustworthiness of the model
- Comparison of performance

These evaluation metrics assess the efficacy of the proposed tool wear recognition framework.

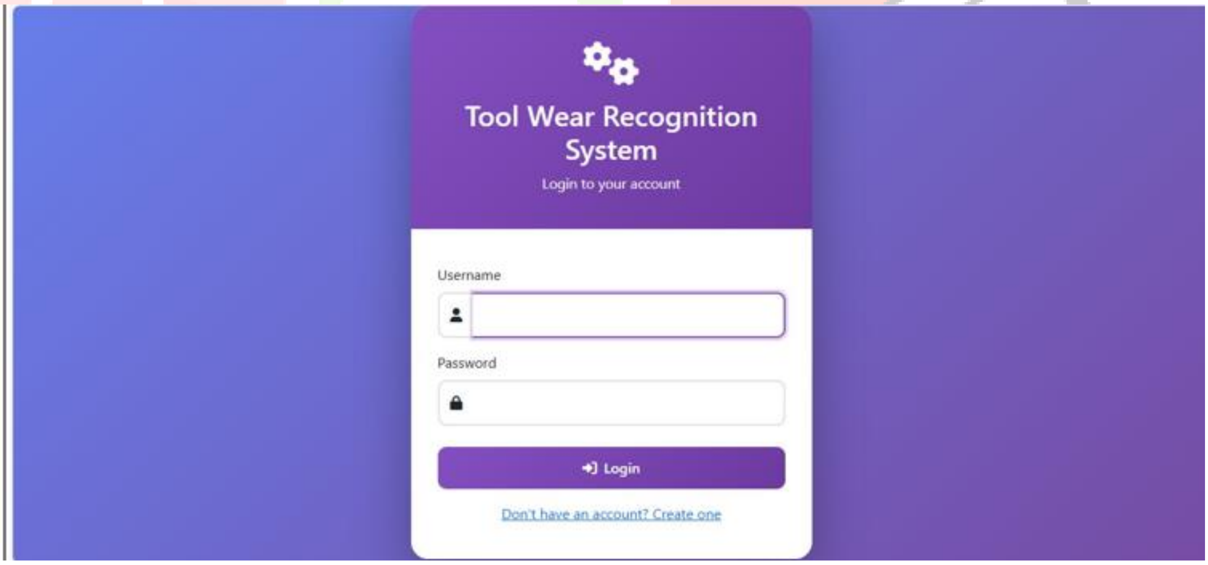
VI.RESULTS:

A. Experimental Results

Model / Method	Dataset Used	Evaluation Metric	Performance Result	Description
Unsupervised Learning Framework	Milling Tool Dataset 1	Macro F1 Score	87.52%	Identifies tool wear patterns using unlabeled sensor data
Unsupervised Learning Framework	Milling Tool Dataset 2	Macro F1 Score	75.80%	Detects wear stages without labeled training samples
Semi-Supervised Learning Framework	Dataset with 25% labeled data	Macro F1 Score	>90%	Combines labeled and unlabeled data for improved classification
SVM / Random Forest Classifiers	Sensor datasets	Classification Accuracy	High accuracy	Used for multiclass tool wear classification
SAE / SSAE Feature Learning	Sensor datasets	Feature Representation	Improved performance	Extracts deep features for better wear detection

The table shows a few different learning frameworks that can be used to look at sensor data to find out how milling tools wear out. Unsupervised learning frameworks are used on milling tool datasets and get Macro F1 scores of 87.52% and 75.80%. This shows that they can find wear stages without needing labelled training data. A semi-supervised learning framework that uses both labelled and unlabelled data gets a Macro F1 score of over 90%, which means that it does a better job of classifying things. For multiclass tool wear classification, traditional machine learning models like SVM and Random Forest classifiers are also used and work very well. Also, SAE/SSAE feature learning methods are used to get deep features from sensor datasets, which makes wear detection systems work better overall.

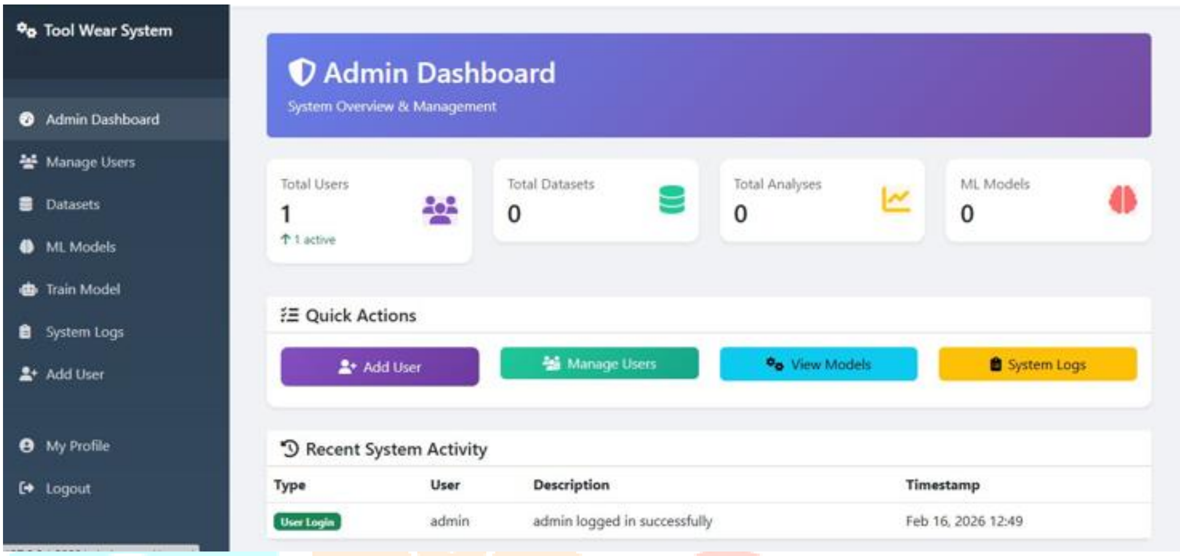
B. Login page



The screenshot shows the login interface of the Tool Wear Recognition System. This page allows registered users to securely access the system. The login form contains two main input fields: Username and Password, where users must enter their credentials to authenticate their account. A Login button is provided to submit the entered details and proceed to the system dashboard after successful verification.

The interface uses a modern gradient design with purple and blue colors, making the application visually appealing and user-friendly. At the bottom of the form, there is a “Create one” option, which allows new users to register if they do not already have an account. Overall, this login page serves as the secure entry point to the Tool Wear Recognition System, ensuring that only authorized users can access the tool wear monitoring and analysis features

C.ADMIN DASHBOARD:



The image shows the Admin Dashboard of the Tool Wear System. It provides an overview of the system, including the total number of users, datasets, analyses, and ML models. The dashboard also includes quick action buttons such as Add User, Manage Users, View Models, and System Logs for easy management. The sidebar menu allows the admin to navigate different sections like users, datasets, and model training. Additionally, the Recent System Activity section displays the latest actions performed in the system.

VII. CONCLUSION:

The suggested Tool Wear Recognition System shows that using both unsupervised and semi-supervised machine learning methods can effectively keep an eye on and sort tool wear in factories. The system automatically finds important features and accurately identifies several stages of tool wear by using sensor data like vibrations and sound waves.

The results show that unsupervised learning methods can work well even when there isn't any labelled data. Semi-supervised methods, on the other hand, make things even more accurate when there is a small amount of labelled data. This makes it less necessary to rely on large labelled datasets, which are hard to get and cost a lot of money in industrial settings.

In general, the system is a smart, cost-effective, and scalable way to do predictive maintenance. It helps manufacturers find tool wear early, cut down on machine downtime, improve product quality, and make the best use of tool replacement schedules. This makes it a good fit for modern Industry 4.0 smart manufacturing systems.

VIII. REFERENCES:

[1] T. Jahan, G. Narsimha, and C. V. G. Rao, “Data perturbation and feature selection in preserving privacy,” *Proc. Ninth Int. Conf. Wireless and Optical Communications*, 2012.

[2] T. Jahan, G. Narasimha, and C. V. G. Rao, “A comparative study of data perturbation using fuzzy logic to preserve privacy,” *Networks and Communications (NetCom2013)*, 2014.

[3] T. Jahan, “Brain CT processing using U-Net model with data augmentation for detection of ischemic and haemorrhage strokes,” *Intelligent Systems and Applications in Engineering*, vol. 12, pp. 72–82, 2023.

[4] T. Jahan and D. C. V. G. Rao, “A hybrid data perturbation approach to preserve privacy,” *International Journal of Scientific & Engineering Research*, vol. 6, no. 6, p. 1528, 2015.

[5] T. Jahan, G. Narsimha, and C. V. G. Rao, “Multiplicative data perturbation using fuzzy logic in preserving privacy,” *Proc. Int. Conf. Information and Communication Technologies*, 2016.

[6] T. Jahan, G. Narasimha, and V. G. Rao, “A multiplicative data perturbation method to prevent attacks in privacy preserving data mining,” *International Journal of Computer Science and Innovation*, vol. 1, no. 1, pp. 45–51, 2016.

[7] T. Jahan, G. Narsimha, and C. V. G. Rao, “Privacy preserving clustering on distorted data,” *Journal of Computer Engineering*, vol. 5, no. 2, 2012.

[8] T. Jahan, K. Pavani, G. Narsimha, and C. V. Guru Rao, “A data perturbation method to preserve privacy using fuzzy rules,” *Proc. Int. Conf. Computational Intelligence*, 2018.

[9] T. Jahan, G. R. Reddy, K. Shekhar, and M. Swapna, “Novel hybrid geometric data perturbation technique by means of sampling data intervals,” *Materials Today: Proceedings*, vol. 80, pp. 2614–2619, 2023.

[10] T. Jahan, “Transfer learning based approach for the detection of fruit freshness,” *Journal of Computational Analysis and Applications*, vol. 34, 2025.

[11] T. Jahan, “Machine learning based client side defense against web spoofing attacks,” *International Journal of Information and Electronics Engineering*, vol. 15, 2025.

[12] T. Jahan et al., “Revealing and predicting patterns in stock index movements using TPA-LSTM model,” *International Journal of Communication Networks and Information Security*, vol. 17, 2025.

[13] T. Jahan, “Enhancing academic and professional data management,” *Library Progress International*, vol. 44, 2024.

[14] T. Jahan and T. Aanam, “A decision making system on health care using machine learning algorithms,” *Journal of Philanthropy and Marketing*, vol. 4, no. 1, pp. 602–610, 2024.