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Development of Thermographic Image-Based Tool Wear Monitoring System: A Literature Review

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Abstract

Tool wear prediction is a critical aspect of modern manufacturing processes, influencing productivity, quality, and maintenance costs. Traditional methods for predicting tool wear are often limited by their reliance on empirical data and manual intervention, which can lead to inefficiencies and inaccuracies. This review paper explores the application of Artificial Intelligence (AI) and Machine Learning (ML) techniques in the prediction and monitoring of tool wear in various manufacturing industries. By synthesizing recent research and advancements, we examine the potential of AI/ML algorithms- such as neural networks, support vector machines, decision trees, and deep learning models- in improving the accuracy, reliability, and real-time capabilities of tool wear prediction systems. The paper also discusses the challenges associated with data acquisition, model training, and generalization, while highlighting successful case studies where AI/ML techniques have been effectively implemented. Finally, we propose future directions for integrating these technologies into smart manufacturing systems to enhance tool life, reduce downtime, and optimize the overall production process.

Major Findings: *AI and ML, particularly DNNs, have shown promise in improving tool wear prediction accuracy. This is due to their ability to process large datasets and identify patterns that traditional methods might miss. However, challenges like data quality, model interpretability, and real-time implementation need to be addressed to fully realize the potential of AI and ML in this field.*

Keywords: *Artificial Intelligence, Machine Learning, Mechanical, Tool Wear Prediction*

1.0 Introduction

Tool wear monitoring is considered to play a central role in intelligent manufacturing processes as a critical tool in maintaining high surface quality, reducing production costs, improving efficiency, and enabling continuous automated machining. Consequently, several researchers have thus applied extensive efforts toward the development of approaches related to tool wear monitoring[1–8]. The rapidly evolving fields of Artificial Intelligence (AI) and Machine Learning (ML) are significantly reshaping numerous industries, particularly in predictive maintenance and tool wear assessment. As the need for efficient manufacturing processes and cost-effective production becomes increasingly critical, the integration of advanced technologies like AI and ML offers unprecedented opportunities to enhance operational effectiveness. This review paper aims to explore how these innovative tools can improve tool wear prediction, thereby reducing downtime and extending the life cycle of manufacturing equipment. By synthesizing existing literature and case studies, the paper will critically analyse

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the methodologies employed in AI and ML, highlighting their advantages, limitations, and future potential. Ultimately, the discussion will underscore the importance of adopting these technologies for achieving greater precision and reliability in manufacturing environments, thereby contributing to the advancement of smart manufacturing solutions.

1.1 Overview of Tool Wear Prediction and its Importance in Manufacturing

In the realm of manufacturing, predicting tool wear has emerged as a critical factor for enhancing operational efficiency and product quality. As tools are subjected to varying loads and environmental conditions, accurate assessment of wear over time is essential to minimize downtime and prevent costly production interruptions. Implementing advanced predictive maintenance strategies not only optimizes tool usage but also extends their lifespans, which can lead to significant cost savings. The integration of machine learning algorithms into wear prediction models allows for real-time data analysis, enabling manufacturers to respond rapidly to tool degradation. Such methodologies harness vast datasets generated during production processes, allowing for precise forecasting of wear patterns and better planning of maintenance schedules. Ultimately, a robust tool wear prediction system is indispensable for modern manufacturing, as it contributes to operational excellence amidst increasing competition and technological advancements.

Tool wear remains a significant challenge across industries, impacting product quality, increasing costs, and posing safety risks, particularly in the context of Industry 4.0 and smart manufacturing. Traditional monitoring methods, including manual inspection and sensor-based techniques, often suffer from limitations like human error, complex setups, and sensitivity to environmental factors[9]. These systems aim to increase process efficiency, improve quality, and reduce tool maintenance costs[10]. The handling these challenges, a novel tool-wear monitoring system based on thermographic imaging is proposed. This technique offers several advantages, non-contact measurement eliminates the need for physical contact with the tool, reducing wear and potential damage. Real-time monitoring enables continuous observation of tool condition, facilitating early detection of wear and timely intervention. Remote monitoring allows for monitoring of hard-to-reach or hazardous areas, improving safety and efficiency[10,11].

By capturing thermal images of the tool during operation, the system can identify temperature variations associated with wear. This information can be used to accurately estimate tool life and predict potential failures, optimizing maintenance schedules and minimizing downtime. This innovative approach has the potential to significantly improve the accuracy and efficiency of tool wear monitoring, leading to enhanced product quality, reduced costs, and increased workplace safety. Cutting tool wear is a critical concern in the manufacturing industry, as it can lead to increased production costs, reduced product quality, and even unexpected downtime[12,13]. To address this issue, researchers have explored various techniques for monitoring tool wear, including the use of artificial intelligence and machine learning methods[13,14]. For instance, researchers have demonstrated the effectiveness of deep learning models in extracting valuable insights from sensor data to enable more accurate detection and prediction of tool wear[15,16]. These data-driven models have the potential to overcome the challenges associated with traditional monitoring methods, such as poor signal-to-noise ratios and the varying nature of the machining process. Various AIML techniques have been employed for tool condition monitoring, including Artificial Neural Networks (ANN), fuzzy logic, Support Vector Machines (SVM), Self-Organizing Maps (SOM), Hidden Markov Models (HMM), and Convolutional Neural Networks (CNN)[17].

The integration of AIML techniques with multi-sensor systems has demonstrated significant potential for accurate tool wear monitoring. Studies have shown that sensor fusion approaches, combined with novelty detection algorithms and neural networks, can effectively detect and predict tool wear in turning processes[18]. Furthermore, the use of two-dimensional data, such as infrared images, has shown superior capability compared to traditional one-dimensional signals for tool wear detection[19]. As sensor costs continue to decrease and AIML algorithms improve, the development of more reliable and efficient tool wear monitoring systems is expected to advance, contributing to the realization of fully automated and IoT-enabled manufacturing setups[10,11,20]. The primary focus lies on three prominent

machine learning models. While these machine learning models hold significant promise for accurate tool wear prediction, their effectiveness is still subject to ongoing research and validation. Factors such as data quality, feature engineering, and model hyperparameter tuning play crucial roles in determining the final prediction accuracy.

2.0 Artificial Intelligence Techniques in Tool Wear Prediction

The integration of Artificial Intelligence (AI) techniques in tool wear prediction represents a significant advancement in manufacturing processes, enabling improved efficiency and product quality. By employing machine learning algorithms, researchers have demonstrated the ability to accurately forecast tool degradation, thereby facilitating timely interventions that prolong tool life and minimize production downtimes. These techniques leverage various data inputs, such as cutting forces and tool wear metrics, to create predictive models that adapt and improve over time. For instance, the application of machine learning can enhance the accuracy of predicted cutting forces and tool wear, as documented in recent studies that showcase optimized machining parameters derived from such predictive analytics[21]. Moreover, the impact of AI extends beyond performance metrics; it also aids in energy consumption prediction and management during the machining process, aligning with sustainable manufacturing practices[22]. This multifaceted approach underscores the transformative potential of AI in revolutionizing tool wear prediction in CNC machining environments.

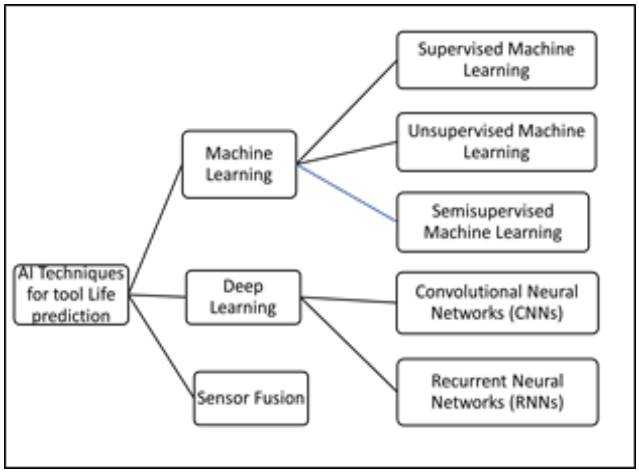


Figure 1. Classification of machine learning algorithms used in Artificial Intelligence.

The advent of Artificial Intelligence (AI) has revolutionized the field of tool monitoring, offering more accurate, efficient, and proactive solutions Various AI techniques have been employed to monitor tool wear.

There are many techniques that are used by different researchers and scholars for predicting different parameters related to the tool. AI-based predictive models, however, can process vast amounts of data from sensors embedded in machines, including temperature, vibration, force, and acoustic signals, to analyse tool performance in real time. By applying appropriate techniques, AI models can identify patterns and correlations between process variables and tool degradation that might not be immediately obvious through traditional methods. The chart shown in Figure 1 shows broad distinguishing of techniques in Artificial intelligence (AI).

2.1 Role of Neural Networks in Predicting Tool Wear

Neural networks have emerged as a powerful tool for predicting tool wear by analysing complex datasets that reflect various operational conditions as shown in Table 1. These networks excel in identifying patterns within large volumes of data generated during machining processes, enabling more accurate predictions of tool degradation over time. By employing deep learning techniques, researchers can train models on historical data that includes variables such as cutting speed, feed rate, and material properties. This capability offers significant advantages over traditional prediction methods, as it can account for the intricate interactions among multiple factors affecting tool life. Importantly, similar AI applications in fields such as hepatology demonstrate the potential of machine learning to handle diverse data types and provide actionable insights, thereby indicating that the integration of neural networks into tool wear prediction may lead to enhanced efficiency and reduced operational costs[23]. Ultimately, the continued development and application of these advanced algorithms promise to transform precision machining practices[24].

Table 1. Details of different research gap for different application in AI domain

Sr. No	Authors	Research Outcome	Research Gap
1	Daniel Yu. Pimenov *et al.*[26]	This article discusses modern approaches to tool condition monitoring using sensors and AI, including dynamometers, accelerometers, and image sensors.	The article mentions AI methods but does not extensively address the interpretability of AI models for tool condition monitoring.
2	Mehmet Erdi Korkmaz *et al.*[27]	This review explores online detection systems for machining processes, including sensors and signal processing software, to improve performance, reduce human effort, and meet Industry 4.0 requirements.	The review discusses various sensors for online detection but often in isolation. There is a research gap in exploring the integration of multiple sensors to provide a holistic view of the machining process.
3	Ayman Mohamed *et al.*[28]	This article reviews state-of-the-art tool condition monitoring (TCM) systems, focusing on sensing, data acquisition, signal conditioning, and monitoring models.	The review investigated how feature engineering and selection can help reduce data complexity and enhance the efficiency of TCM algorithms.
4	Prashant J. Bagga *et al.*[29]	A novel tool wear prediction system using an artificial neural network (ANN) is proposed for intelligent manufacturing. The system uses images of worn tools to predict tool life.	Not Considered the quality and consistency of the images used for tool wear assessment. Variations in image quality, lighting conditions, and camera angles can affect the accuracy of the prediction model.
5	Pei Chin Sim *et al.*[30]	This study uses Artificial Neural Network (ANN) prediction models and machine vision systems to predict flank wear in turning operations using machined surface texture images.	The study focuses on predicting flank wear in turning operations, but machining conditions can vary significantly in industrial settings.
6	Nika Brili *et al.*[31]	The paper presents a Tool Condition Monitoring (TCM) system that classifies tool wear into four classes using infrared thermography, computer vision, and deep learning. The system, which uses a temperature distribution based on image features, improves product quality and reduces costs.	Not investigated how the TCM system can facilitate human-machine collaboration in machining operations.
7	Lorenzo Colantonio *et al.*[32]	This literature review examines the use of Artificial Intelligence (AI) in monitoring tool conditions in stable turning operations. The review focuses on six AI techniques: Artificial Neural Network (ANN), fuzzy logic, Support Vector Machine (SVM), Self-Organizing Map (SOM), Hidden Markov Model (HMM), and Convolutional Neural Network (CNN).	Research is not focused on developing AI models that can adapt to changing machining conditions and maintain prediction accuracy under varying circumstances.
8	Qun Wang *et al.*[33]	This paper discusses the application of convolution neural networks in tool wear monitoring, highlighting their feasibility and reliability. It suggests that these networks can improve prediction accuracy, paving the way for future technology advancements in manufacturing.	The overview does not investigate the generalizability of CNN-based tool wear monitoring methods to a broader range of machining processes.

9	Munish Kumar Gupta *et al.*[34]	This experimental research used five sensors to monitor the cutting area, analyzing cutting forces, vibration, acoustic emission, temperature, and current. Results showed temperature and acoustic emission sensors were effective in detecting flank wear and tool breakage ensuring reliable machining.	Research is not focused on developing signal preprocessing and noise reduction techniques to ensure robust monitoring, especially when dealing with variations in cutting conditions and environmental factors.
10	Thorsten Augspurger *et al.*[35]	This publication presents a model extended measuring approach to monitor heat flow distribution in the milling process under dry conditions. The approach measures cutting power, tool temperature, and time response, revealing a decreasing heat partition with increasing cutting velocity, enabling economic and ecological process potentials.	The research has not developed and validated thermal models that can predict heat flow distribution in machining processes. Such models can serve as predictive tools for optimizing machining parameters and assessing heat-related effects on tool wear and workpiece quality.
11	Mustafa KuntoÄŸlu *et al.*[36]	This study reviews the literature on indirect tool condition monitoring systems in turning, focusing on the relationship between heat, vibration, cutting forces, and motor current.	Evaluate advanced signal processing techniques, such as wavelet analysis, time-frequency analysis, and envelope analysis, to extract valuable information from sensor data for tool condition monitoring.
12	Gokberk Serin *et al.*[37]	Tool condition monitoring is crucial for manufacturing efficiency and economics. Advanced sensors and computational intelligence detect undesirable conditions, such as chatter, wear, and breakage.	Research not focused on the scalability and adaptability of deep learning-based monitoring systems across different manufacturing industries, workpiece materials, tool geometries, and machining conditions.
13	Arash Zaretalab *et al.*[38]	This research presents a hybrid methodology for estimating cutting tool life using Weibull distribution parameters. Using Box-Behnken design, TTT transform, and GSS, the method is compared with well-known techniques like the least square method and maximum likelihood estimation.	Explore the integration of multi-objective optimization techniques into the hybrid methodology. Consider optimizing not only tool life but also other important machining objectives, such as surface finish, cutting forces, and energy consumption, to achieve a holistic machining process improvement.
14	PaweÅ, Twardowski *et al.*[39]	Predicting tool wear during machining is crucial for diagnostics and tool replacement. Artificial neural networks, MLP, were used to monitor cutting forces and mechanical vibrations.	Feature selection and dimensionality reduction methods can help improve the efficiency of the predictive models.
15	Munish Kumar Gupta *et al.*[40]	This study focuses on optimizing machining parameters to reduce tool wear and breakage, aiming to improve workpiece quality and reduce production costs. The Taguchi method and ANOVA analysis reveal cutting speed and tooltip as most effective in reducing tool wear.	Not developed advanced data collection and monitoring techniques to accurately capture and quantify progressive tool wear over time. This may involve the integration of multiple sensors, image processing, and real-time data acquisition systems.
16	Tadeusz Mikolajczyk *et al.*[41]	A two-step method for automatic tool life prediction in turning operations is presented, using Neural Wear software and Artificial Neural Networks. The complete-automated solution, with slightly higher error than direct measurements, meets industrial requirements for low-cost estimation.	More advanced neural network architectures, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), or deep learning models, for tool life prediction can be used.

17	Alessandra Caggiano[42]	A machine learning procedure monitors tool conditions during dry turning of Ti-6Al-4V alloy using cutting force, acoustic emission, and vibration sensor signals. Principal Component Analysis (PCA) is used to extract sensorial features, achieving accurate tool flank wear diagnosis.	Methods like autoencoders can be considered for sensor data, which can capture high-dimensional relationships in the data without relying on predefined features.
18	Tadeusz Mikolajczyk *et al.*[43]	This study presents an artificial neural network-based system for estimating tool wear using image analysis. The system uses the Single Category-Based Classifier neural network, resulting in a method for determining tool wear rate and evaluating errors.	This research is unable to investigate transfer learning techniques that allow models trained on one dataset to be adapted for wear analysis in different machining environments or with limited labeled data.
19	Qi Wang, *et al.*[44]	The article introduces a tool wear prediction and monitoring method using power signals for machining difficult materials, enhancing efficiency, cost control, and workpiece safety.	The paper presents a tool wear prediction model using power signals in mechanical processing, suggesting its extension to other machining processes and integration with advanced technologies.
20	Bing-Syun Wan, *et al.*[45]	The study demonstrates the impact of sensor location on micro tool wear monitoring, showing differing energy distribution and signal changes over time. Spindle	The study highlights research gaps in micro tool wear monitoring, including sensor placement, feature selection, HMM parameter optimization, generalization, and multimodal sensor data integration.
21	Rui Silva *et al.*[46]	The study demonstrates that combining an Expert System and two neural networks effectively monitors tool wear, allowing for quick retraining. Multiple sensors, including tangential and feed forces, are crucial for tool wear evaluation.	The current tool wear monitoring system's effectiveness is limited due to frequent retraining and noisy sensors, necessitating further research for robust, adaptive algorithms and improved sensor fusion techniques.
22	Wei Wang *et al.*[47]	The study suggests a static tool wear monitoring method for robotic belt grinding but suggests future research should focus on dynamic data acquisition and online monitoring.	The study suggests a static tool wear monitoring method for robotic belt grinding but suggests future research should focus on dynamic data acquisition and online monitoring.
23	Shan Fan *et al.*[48]	This chapter explores a new tool wear assessment technique using the GPR model for accurate tool back face monitoring during machining. It highlights its high prediction accuracy, small calculation time, and potential for online monitoring.	The paper highlights the need for advanced signal processing methods and predictive models to extract reliable information from time series signals for online tool wear monitoring.
24	Prashant J. *et al.*[49]	The tool wear measurement algorithm measures maximum flank wear on CNC lathe machines, using image capture and edge detection. The algorithm is similar to manual measurements, with a maximum variation of 4.98%.	In addition to showing the possibilities of digital image processing techniques for automated measurement, the article emphasizes the need for effective ways to monitor tool wear in the metal-cutting business.

25	Kunpeng Zhu *et al.*[50]	This study develops a single-image super-resolution method for tool condition monitoring, utilizing multi-scale dictionaries and sparse representation for faster and more accurate reconstruction, validated through experimental studies and future development.	The study proposes a single image super-resolution (SISR) approach for direct tool wear estimation in micro-milling, addressing the limitations of conventional machine vision-based TCM approaches due to micro-scale cutting parameters and spindle rotation speed.
26	Cornie Scheffer *et al.*[51]	The paper emphasizes the use of AI to monitor crater and flank wear during hard turning, focusing on minimizing training data and integrating it into CNC machines.	The study proposes an AI-based force monitoring system for hard turning, addressing the inadequacy of conventional wear-monitoring systems in hard turning processes due to unique tool and material characteristics.
27	Ruitao Peng *et al.*[52]	The paper introduces an automatic tool wear monitoring system using machine vision, structural similarity, and Harris corner detection algorithms, proving reliable and accurate in milling processes.	A machine vision-based tool wearing automatic monitoring system faces research gaps, including validation, integration, and cost-effectiveness, necessitating further exploration and comparison with existing methods.
28	Nika Brili *et al.*[53]	The research developed a real-time IR camera-based system for detecting cutting tool wear during machining, achieving classification accuracy of 95.00% and 99.39%, thereby reducing costs and improving product quality.	The article presents a cutting tool condition supervision control system using an infrared camera and CNN, but further research is needed to validate its effectiveness and economic feasibility.
29	R. Jegadeeshwaran *et al.*[54]	A thick film sensor and tool wear detection system were designed and tested, proving accurate tool wear detection in turning processes with a 0.02 mm error. Improvements include tooltip profile, rotating tool usage, and cost reduction.	The paper presents a silver-polyester thick film sensor system for detecting wear-out in single-point cutting tools, but further research is needed to evaluate its performance, durability, and integration with real-time control mechanisms.
30	Jing Yang *et al.*[55]	This article proposes a new tool wear monitoring framework using deep learning technology, focusing on fine-grained categorization and local features. The model is effective in monitoring tool wear levels but requires large training data for machined surface-based monitoring.	ECADCL, a fine-grained image classification method, has shown promise for tool wear monitoring, but research gaps remain in its robustness, generalizability, and real-time industrial performance.
31	German Herrera Granados *et al.*[56]	The paper proposes a multi-sensor monitoring system for estimating and classifying tool wear progression on a flat-end mill. It uses image recognition, force and vibration sensors, and surface roughness measurements to improve tool wear classification accuracy. The dynamometer is the best sensor for detecting tool wear.	The proposed method for tool wear detection combines direct and indirect monitoring techniques, but further research is needed to ensure its applicability, integrate image recognition, and evaluate its efficiency and economic feasibility.

3.0 Machine Learning Algorithms for Tool Wear Analysis

The integration of machine learning algorithms into tool wear analysis represents a transformative approach to enhancing the accuracy and efficiency of predictive maintenance in industrial applications. By utilizing various data-driven methods, these algorithms analyse complex datasets that capture real-time measurements related to tool performance. For instance, recent studies have demonstrated the effectiveness of Convolutional Neural Networks (CNNs) in accurately predicting tool wear by processing data from inertial sensors, thus enabling continuous monitoring and timely interventions to prevent tool failures[22]. Additionally, the use of random forest regression algorithms has shown significant promise in estimating battery life within IoT networks, suggesting that similar techniques could optimize energy use in machining operations[25]. Consequently, the synergistic application of machine learning not only improves predictive accuracy but also promotes operational sustainability, ultimately leading to cost savings and increased productivity in manufacturing environments.

Machine Learning (ML) is a subset of Artificial Intelligence (AI) that enables systems to learn and make decisions without explicit programming. It focuses on developing algorithms that allow computers to learn from data and improve their performance over time

3.1 Supervised Machine Learning (ML)

Supervised Machine Learning refers to a type of machine learning where the algorithm is trained on labelled data, i.e., input-output pairs, to learn a mapping from inputs to outputs. The goal is for the algorithm to generalize from the training data to make predictions on new, unseen data. In the context of tool life Prediction, supervised learning can be used to predict the lifespan of manufacturing tools (e.g., cutting tools, drills, etc.) based on historical data such as operational conditions, material properties, and machine settings.

Linear regression approach is to model the relationship between a dependent variable (tool life) and one or more independent variables (cutting speed, feed rate, temperature, etc.). Evaluation Metrics are method outperformed traditional models across three critical evaluation metrics:

Root Mean Square Error (RMSE) indicates the average magnitude of the prediction errors. The results show a lower RMSE for the proposed method, suggesting more accurate predictions. Mean Absolute Error (MAE) is similar to RMSE, MAE measures the average absolute errors between predicted and actual values. The lower MAE indicates that the proposed model consistently predicts tool wear more accurately than traditional methods. The coefficient of Determination (R^2) provides insight into how well the predicted values explain the variability of the actual values. A higher R^2 value for the proposed method indicates a better fit to the data, confirming its effectiveness in capturing the underlying patterns of tool wear.

3.1.1 Linear Regression

IEEE NUAA Idea house tool wear dataset[57] contains various sensor readings. Using TSFEL (Time Series Feature Extraction Library), automatic feature extraction was performed in the temporal, spectral, and statistical domains. Subsequently, PCC (Pearson's Correlation Coefficient) was employed to select features with a significant impact on tool wear. The dataset encompasses diverse features such as tool specification, tool material, feed rate in the z-direction (mm/r), RPM (r/min), ap (mm), and workpiece material. Accurate tool wear prediction can enhance product quality and reduce operational costs, making this research highly relevant to real-world applications[58].

3.1.2 Logistic Regression

Logistic Regression (LR) is a statistical method commonly used for binary classification problems, where the goal is to predict the probability of a binary outcome (e.g., tool wear worn vs. not worn). In the context of tool wear prediction, logistic regression can be employed to model the likelihood of tool degradation based on various input features such as cutting conditions (speed, feed rate), material properties, vibration signals, or sensor data from the machining process. Logistic Regression can be used to estimate the probability of tool failure or excessive wear occurring within a certain period, which helps manufacturers make informed decisions about tool

replacement or maintenance. The model typically takes sensor data (e.g., force, temperature, acoustic signals) as input variables and outputs a probability score that can be threshold to classify the tool's wear status (e.g., worn or not worn)[59].

3.1.3 Decision Tree Regression

A Decision Tree Regressor is a machine learning model commonly used in tool wear prediction to estimate the Remaining Useful Life (RUL) or the degree of wear of cutting tools during machining operations. It works by splitting the data into subsets based on feature values, creating a tree-like structure where each node represents a decision based on a specific feature, and the leaves contain the predicted output (tool wear). Decision Tree Regressor takes input features as sensor readings (e.g., temperature, vibration, acoustic emissions), machine parameters (e.g., cutting speed, feed rate), and other relevant factors, and produces a continuous output value representing the tool wear state or RUL[57]. The Gradient Boosting Decision Tree (GBDT)[58] algorithm and novel hybrid XGBoost-SDA[59] improve tool wear prediction accuracy and the flank wear of a drilling process by optimizing parameters through grid search and integrating downscaled features from t-SNE, enhancing the model's ability to identify tool wear status effectively in machining processes.

3.1.4 Random Forest Algorithm

The Random Forest algorithm is a powerful machine-learning technique used for this purpose. It works by creating an ensemble of decision trees, each trained on a subset of the data, and then aggregating their predictions to improve accuracy and robustness[60]. An image processing technique is employed to determine the tool wear area. A tailored misclassification cost matrix is utilized to train the random forest algorithm, enhancing the classification accuracy of tool conditions. This model can accurately classify tool conditions from 0.5-second vibration signals with a precision of 97%[61]. A decision tree uses the information gain method to determine the placement of features within the tree. In contrast, a random forest gives each tree an equal chance by building multiple trees. If the dataset contains n features, this algorithm constructs or trains n trees, ensuring all features are equally considered[62].

3.2 Unsupervised Machine Learning (ML)

Unsupervised machine learning involves training models on data without labelled responses. The primary goal is to explore the data and find hidden patterns or structures within it. Unlike supervised learning, where the algorithm learns from labelled data to predict outcomes, unsupervised learning deals with unstructured data to identify inherent groupings or distributions. Unsupervised learning is widely used in various applications, from customer segmentation in marketing to gene expression analysis in bioinformatics. Following are the classifications of the techniques:

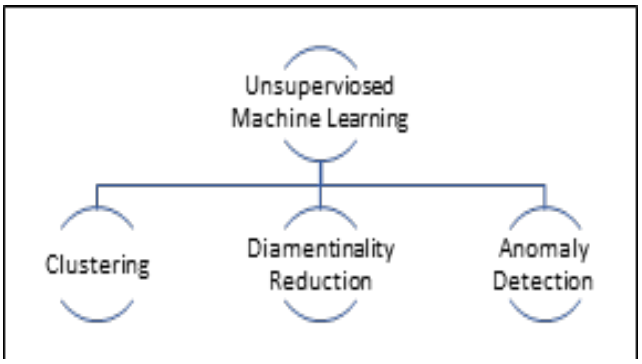


Figure 2. Classification of unsupervised machine learning.

3.3 Comparison of Supervised and Unsupervised Learning Approaches

In the realm of machine learning, distinguishing between supervised and unsupervised learning approaches is crucial for effective tool wear prediction. Supervised learning methods rely on labelled datasets, wherein the algorithm learns from input-output pairs to make predictions. This approach is particularly beneficial in scenarios where historical data is available, allowing for accurate predictions of tool wear based on previous experiences. On the other hand, unsupervised learning techniques work with unlabelled data, identifying patterns and structures within datasets without explicit guidance. Such methods, while less common in direct wear prediction, can uncover hidden relationships between variables that may not be evident through supervised learning alone. The integration of both approaches can enhance model accuracy and robustness, as reflected

in the predictive analyses seen in applications like wind power forecasting and smart grid security assessments[63-65]. By understanding the strengths and limitations of each method, researchers can optimize their strategies for predicting tool wear in various industrial contexts.

4.0 Deep Learning Algorithms for Tool Wear Analysis

Deep learning is a subset of machine learning that focuses on using neural networks with many layers (hence "deep") to model complex patterns in data. These networks, known as deep neural networks, are inspired by the structure and function of the human brain. Deep learning has revolutionized tool wear prediction in manufacturing by leveraging advanced neural network architectures to analyse complex data and predict tool conditions accurately. Deep learning has transformed many fields by providing tools to tackle complex problems and make intelligent predictions. It continues to evolve, driven by advancements in algorithms, computing power, and data availability. There are three main types of deep learning as shown in Figure 4.

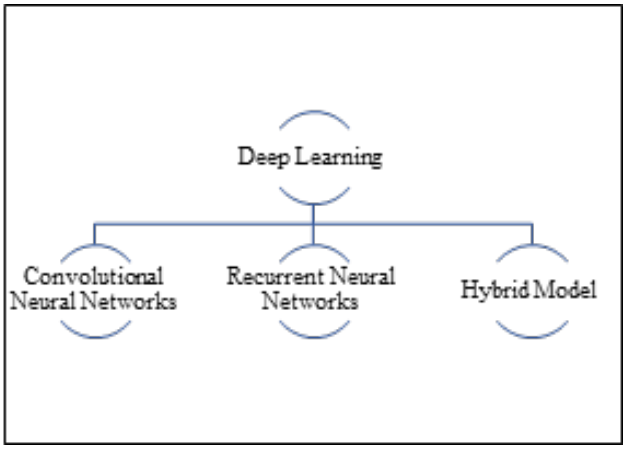


Figure 4. Classification of deep learning algorithms.

4.1 Convolutional Neural Networks (CNN)

A CNN is a type of feedforward network and is one of the key models in deep learning[66]. Commonly used in image recognition, video classification, and various other applications[67], CNNs excel at representation learning. They can automatically perform feature extraction and reduce the spatial dimensionality of feature maps through convolution and pooling operations. As illustrated in Figure 1, a typical CNN architecture consists of an input layer, a convolutional layer, a pooling layer, an activation function, and a fully connected layer as shown in Figure 5.

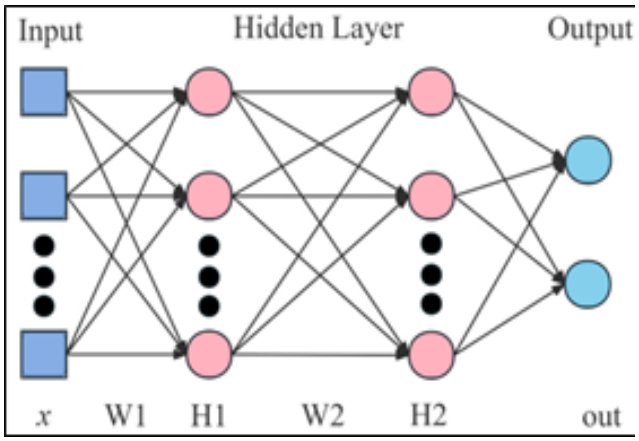


Figure 5. The architecture of a convolutional neural network[69].

Convolutional Neural Networks (CNNs) are a class of deep learning algorithms that are commonly used for image recognition and classification. In the context of tool wear prediction, CNNs have shown significant promise, primarily in their ability to analyse sensor data (such as vibration, acoustic emissions, or images) to predict tool condition and wear levels during manufacturing processes. The different techniques such as residual connections and auxiliary inputs enhance the model's ability to capture intricate patterns in wear data[68,69].

4.2 Recurrent Neural Networks

Recurrent Neural Networks (RNNs) are a class of artificial neural networks designed for sequential data processing. Unlike traditional feedforward networks, RNNs have connections that form cycles within the network, allowing them to maintain a form of memory. This enables RNNs to effectively process sequences of data, such as time series, text, or speech, where the current input depends on previous inputs. The digital shadow was created using the industrial edge device and the predictive AI model to minimize costs by reducing the need for expensive multi-sensors, manufacturing downtime, and tool underuse or overuse in a smart manufacturing system[70].

Recurrent Neural Networks (RNNs) are a class of artificial neural networks designed for processing sequences of data. Unlike traditional feedforward neural networks, RNNs have connections that form cycles, allowing information to be passed from one step of the network to the next. This cyclic structure enables RNNs to retain memory of previous inputs, making them particularly well-suited for tasks where context or temporal dependencies are important, such as time-series forecasting, speech recognition, language modelling, and machine translation. The key feature of RNNs is their ability to maintain hidden states, which capture information from earlier steps in the sequence. This allows the network to "remember" previous inputs and use this information to influence future predictions. However, standard RNNs suffer from issues like vanishing and exploding gradients, which can make training difficult, especially for long sequences.

5.0 Sensor Fusion AI Technique

Sensor techniques play a crucial role in monitoring and predicting tool wear in machining processes. Tool wear, which affects the precision, quality, and cost of manufacturing, can be effectively predicted using various sensors that provide real-time data for proactive maintenance and process optimization. Common sensor techniques for tool wear prediction include Vibration sensors which are used to detect changes in the vibrations of the cutting tool, with tool wear causing alterations in vibration patterns. These changes can be analysed to predict the progression of wear. Acoustic emission sensors capture high-frequency sound waves emitted during the cutting process, with the intensity and frequency of these emissions changing as the tool wears. This provides valuable insights into the tool's condition. Force sensors measure cutting, radial, and axial forces during machining, and as the tool wears, these forces typically increase due to higher friction and greater material removal resistance. Monitoring these forces can help predict tool wear. Temperature sensors, such as thermocouples or infrared cameras, monitor the heat generated during cutting. Excessive temperatures can accelerate tool degradation, and these sensors help track temperature changes that correlate with wear. Vision systems, using high-resolution cameras or laser scanning, monitor the physical condition of both the tool and the workpiece, with image processing techniques detecting wear, cracks, or material buildup. Finally, machine learning and data fusion techniques combine data from multiple sensors—such as force, vibration, and temperature—to predict tool wear more accurately and reliably[71,72].

6.0 Conclusion

The integration of AI and ML in tool wear prediction has shown significant potential in improving the accuracy of predictions and, consequently, operational efficiency. Deep neural networks, for instance, have outperformed traditional statistical methods, as is the case with other industries like finance and healthcare. This is a testament to how AI and ML are gaining acceptance in various fields for handling large datasets and recognizing patterns that the human eye may miss. Future research will be important for optimizing these technologies for practical application in tool wear prediction. This could eventually lead to better decision-making and increased productivity in manufacturing. Challenges and future directions related to AI and ML applications in tool wear prediction involve developing more complex algorithms that could process multimodal data and implementing real-time monitoring systems using edge computing. Acquiring good, diverse datasets and developing the interpretability of AI models to create trust among the stakeholders will be the key obstacles that will need to be overcome for advancing AI and ML applications in tool wear prediction. This will eventually lead to more efficient and sustainable manufacturing practices.

7.0 References

1. Liu MK, Tseng YH, Tran MQ. Tool wear monitoring and prediction based on sound signals. Int J Adv Manuf Technol. 2019; 103(14):3361-73. https://doi.org/10.1007/s00170-019-03686-2
2. Aghazadeh F, Tahan A, Thomas M. Tool condition monitoring using spectral subtraction and convolutional neural networks in milling process. Int J Adv Manuf Technol. 2018; 98(9-12):3217-27. https://doi.org/10.1007/s00170-018-2420-0
3. Xie Z, Li J, Lu Y. Feature selection and a method to improve the performance of tool condition monitoring. Int J Adv Manuf Technol. 2019; 100(9-12):3197-206. https://doi.org/10.1007/s00170-018-2926-5

4. Nouri M, Fussell BK, Ziniti BL, Linder E. Real-time tool wear monitoring in milling using a cutting condition independent method. Int J Mach Tools Manuf. 2015; 89:1-13. https://doi.org/10.1016/j.ijmachtools.2014.10.011
5. Towsyfyan H, Gu F, Ball AD, Liang B. Modelling acoustic emissions generated by tribological behaviour of mechanical seals for condition monitoring and fault detection. Tribol Int. 2018; 125:46-58. https://doi.org/10.1016/j.triboint.2018.04.021
6. Hocheng H, Tseng HC, Hsieh ML, Lin YH. Tool wear monitoring in single-point diamond turning using laser scattering from machined workpiece. J Manuf Process. 2018; 31:405-15. https://doi.org/10.1016/j.jmapro.2017.12.007
7. Ambhore N, Kamble D, Chinchanikar S, Wayal V. Tool condition monitoring system: A review. Mater Today Proc. 2015; 2:3419-28. https://doi.org/10.1016/j.matpr.2015.07.317
8. Shi C, Panoutsos G, Luo B, Liu H, Li B. Using multiple feature-space-based deep learning for tool condition monitoring in ultra precision manufacturing. IEEE Trans Ind Electron. 2019; 66:3794-803. https://doi.org/10.1109/TIE.2018.2856193
9. Pimenov DY, Bustillo A, Wojciechowski S, Sharma VS, Jamil M, Gupta MK, *et al*. Artificial intelligence systems for tool condition monitoring in machining: analysis and critical review. J Intell Manuf. 2023; 34:2079-121. https://doi.org/10.1007/s10845-022-01923-2
10. Korkmaz ME, Gupta MK, Li Z, Krolczyk GM, Binali R, Yaşar N, *et al*. Indirect monitoring of machining characteristics via advanced sensor systems: a critical review. Int J Adv Manuf Technol. 2022; 120:7043-78. https://doi.org/10.1007/s00170-022-09286-x
11. Mohamed A, Hassan MO, M'Saoubi R, Attia MH, Attia H. Tool condition monitoring for high-performance machining systems- A review. Sensors. 2022; 22(6):2206. https://doi.org/10.3390/s22062206
12. Sayyad S, Kumar S, Bongale A, Kotecha K, Abraham A. Remaining useful-life prediction of the milling cutting tool using time-frequency-based features and deep learning models. Sensors. 2023; 23:5659. https://doi.org/10.3390/s23125659
13. Han D, Yu J, Tang D. An HDP-HMM based approach for tool wear estimation and tool life prediction. Qual Eng. 2021; 33(2):208-20. https://doi.org/10.1080/08982112.2020.1813760
14. Ostasevicius V, Jurenas V, Augutis V, *et al*. Monitoring the condition of the cutting tool using self-powering wireless sensor technologies. Int J Adv Manuf Technol. 2017; 88:2803-17. https://doi.org/10.1007/s00170-016-8939-z
15. Yuan Y, Ma G, Cheng C, Zhou B, Zhao H, Zhang HT, Ding H. A general end-to-end diagnosis framework for manufacturing systems. Nat Sci Rev. 2020; 7(2):418-29. https://doi.org/10.1093/nsr/nwz190
16. Li Z, Meurer M, Bergs T. Deep learning-based tool wear estimation considering cutting conditions. 57th CIRP Conf Manuf Syst; 2024. p. 1-6. https://doi.org/10.48550/arXiv.2407.01199
17. Colantonio L, Equeter L, Dehombreux P, Ducobu F. A systematic literature review of cutting tool wear monitoring in turning by using artificial intelligence techniques. Machines. 2021; 9(12):351. https://doi.org/10.3390/machines9120351
18. Al-Azmi A, Al-Habaibeh A, Abbas J. Sensor fusion and the application of artificial intelligence to identify tool wear in turning operations. Int J Adv Manuf Technol. 2023; 126:429-42. https://doi.org/10.1007/s00170-023-11113-w
19. Elgargni MA, Al-Habaibeh A. A comparative study of signal and image processing systems for condition monitoring of milling processes using artificial intelligence. 2013 IEEE Jordan Conf Appl Electr Eng Comput Technol; 2013. p. 1-6. https://doi.org/10.1109/AEECT.2013.6716474
20. Patel ZB, Muthuswamy S. A machine learning scheme for tool wear monitoring and replacement in IoT-enabled smart manufacturing. In: Deepak B, Parhi D, Jena P, editors. Innovative Product Design and Intelligent Manufacturing Systems. Lecture Notes in Mechanical Engineering. Springer, Singapore; 2020. https://doi.org/10.1007/978-981-15-2696-1_43
21. Soori M, Arezoo B, Dastres R. Machine learning and artificial intelligence in CNC machine tools: A review. Smart Sustain Manuf Syst. 2023; 100009. https://doi.org/10.1016/j.smse.2023.100009
22. Maddikunta PKR, Srivastava G, Gadekallu TR, Deepa N, Boopathy P. Predictive model for battery life in IoT networks. Intelligent Transportation Systems in Smart Cities for Sustainable Environments. 2020; 1388-95. https://doi.org/10.1049/iet-its.2020.0009
23. Su T-H, Wu C-H, Kao J-H. Artificial intelligence in precision medicine in hepatology. J Gastroenterol Hepatol. 2021; 569-80. https://doi.org/10.1111/jgh.15415 PMID:33709606

24. Sigcha L, Borzì L, Amato F, Rechichi I, Ramos-Romero C, Acosta Cardenas AJ, Gascó L, Olmo G. Deep learning and wearable sensors for the diagnosis and monitoring of Parkinson's disease: A systematic review. 2023; 120541. https://doi.org/10.1016/j.eswa.2023.120541
25. Sigcha L, Borzì L, Amato F, Rechichi I, Ramos-Romero C, Acosta Cardenas AJ, Gascó L, Olmo G. Deep learning and wearable sensors for the diagnosis and monitoring of Parkinson's disease: A systematic review. 2023; 120541. https://doi.org/10.1016/j.eswa.2023.120541
26. Pimenov DY, Bustillo A, Wojciechowski S, Sharma VS, Jamil M, Gupta MK, Kuntoğlu M. Artificial intelligence systems for tool condition monitoring in machining: Analysis and critical review. J Intell Manuf. 2023; 34:2079-2121. https://doi.org/10.1007/s10845-022-01923-2
27. Korkmaz ME, Gupta MK, Li Z, Krolczyk GM, Binali R, Yaşar N, Pimenov DY. Indirect monitoring of machining characteristics via advanced sensor systems: A critical review. Int J Adv Manuf Technol. 2022; 120:7043-78. https://doi.org/10.1007/s00170-022-09286-x
28. Mohamed A, Hassan MO, M'Saoubi R, Attia MH, Attia H. Tool condition monitoring for high-performance machining systems- a review. Sensors. 2022; 22(6):2206. https://doi.org/10.3390/s22062206 PMID:35336377 PMCID:PMC8950983
29. Bagga PJ, Makhesana MA, Darji PP, Patel KM, Pimenov DY, Giasin K, Khanna N. Tool life prognostics in CNC turning of AISI 4140 steel using neural network based on computer vision. Int J Adv Manuf Technol. 2022; 123:3553-70. https://doi.org/10.1007/s00170-022-10485-9
30. Sim PC, Lee W, Abdullah H, Talib N, Ong P, Saleh A, Ahmad SA, Sung AN. Prediction of tool wear using machine vision approach. Acad J Manuf Eng. 2022.
31. Brili N, Ficko M, Klancnik S. Tool condition monitoring of the cutting capability of a turning tool based on thermography. Sensors. 2021; 21(19):6687. https://doi.org/10.3390/s21196687 PMID:34641006 PMCID:PMC8512854
32. Colantonio L, Equeter L, Dehombreux P, Ducobu F. A systematic literature review of cutting tool wear monitoring in turning by using artificial intelligence techniques. Machines. 2021; 9(12):351. https://doi.org/10.3390/machines9120351
33. Wang Q, Haoren W, Hou L, Yi S. Overview of tool wear monitoring methods based on convolutional neural network. Appl Sci. 2021; 11(24):12041. https://doi.org/10.3390/app112412041
34. Gupta MK, Kuntoğlu M, Saglam H. Investigation of signal behaviors for sensor fusion with tool condition monitoring system in turning. Measurement. 2020; 173:108582. https://doi.org/10.1016/j.measurement.2020.108582
35. Augspurger T, Da Silva G, Schraknepper D, Mattfeld P, Bergs T. Model-based monitoring of temperatures and heat flows in the milling cutter. Int J Adv Manuf Technol. 2020; 107:4231-8. https://doi.org/10.1007/s00170-020-05237-6
36. Kuntoğlu M, Aslan A, Pimenov DY, Usca ÜA, Salur E, Gupta MK, Mikolajczyk T, Giasin K, Kapłonek W, Sharma S. A review of indirect tool condition monitoring systems and decision-making methods in turning: Critical analysis and trends. Sensors. 2020; 21(1):108. https://doi.org/10.3390/s21010108 PMID:33375340 PMCID:PMC7794675
37. Serin GB, Sener B, Ozbayoglu AM, Ozbayoglu AM, Unver HO. Review of tool condition monitoring in machining and opportunities for deep learning. Int J Adv Manuf Technol. 2020; 109:953-74. https://doi.org/10.1007/s00170-020-05449-w
38. Zaretalab A, Sharifi M, Taghipour S. Machining condition-based stochastic modeling of cutting tool life. Int J Adv Manuf Technol. 2020; 111:3159-73. https://doi.org/10.1007/s00170-020-06225-6
39. Twardowski P, Wiciak-Pikuła M. A prediction of tool wear using artificial neural networks during turning of hardened steel. Materials (Basel). 2019; 12(19):3091. https://doi.org/10.3390/ma12193091 PMID: 31546732 PMCID: PMC6804216
40. Gupta MK, Kuntoğlu M, Saglam H. Investigation of progressive tool wear for determining optimized machining parameters in turning. Measurement. 2019; 140:427-36. https://doi.org/10.1016/j.measurement.2019.04.022
41. Mikolajczyk T, Nowicki K, Bustillo A, Pimenov DY. Predicting tool life in turning operations using neural networks and image processing. Mech Syst Signal Process. 2018; 104:503-13. https://doi.org/10.1016/j.ymssp.2017.11.022
42. Caggiano A. Tool wear prediction in Ti-6Al-4V machining through multiple sensors monitoring and PCA features pattern recognition. Sensors (Basel). 2018; 18(3):823. https://doi.org/10.3390/s18030823 PMID: 29522443 PMCID: PMC5876750
43. Mikolajczyk T, Nowicki K, Odowski AK, Pimenov DY. Neural network approach for automatic image analysis

of cutting-edge wear. Mech Syst Signal Process. 2017; 88:100-10. https://doi.org/10.1016/j.ymssp.2016.11.026
44. Wang Q, Chen X, An Q, Chen M, Guo H, He Y. A tool wear prediction and monitoring method based on machining power signals. Int J Adv Manuf Technol. 2023. https://doi.org/10.1007/s00170-023-12656-8
45. Wan BS, Lu MC, Chiou SJ. Analysis of spindle AE signals and development of AE-based tool wear monitoring system in micro-milling. J Manuf Mater Process. 2022.
46. Silva R, Wilcox SJ, Reuben RL. Development of a system for monitoring tool wear using artificial intelligence techniques. Dyn Syst Control. 2006.
47. Htun O, Wang W, Liu Z. Tool wear monitoring system in belt grinding based on image-processing techniques. Int J Adv Manuf Technol. 2020.
48. Fan S, Yi H, Zeng H. Research on on-line tool wear monitoring technology based on GPR. E3S Web Conf; 2021.
49. Bagga PJ, Makhesana MA, Patel KM, Patel K. Tool wear monitoring in turning using image processing techniques. Mater Today Proc. 2020.
50. Zhu K, Zhu K, Guo H, Guo H, Li S, Li S, Lin X, Lin X. Online tool wear monitoring by super-resolution-based machine vision. Comput Ind. 2023.
51. Scheffer C, Kratz H, Heyns PS, Klocke F. Development of a tool wear-monitoring system for hard turning. Int J Mach Tools Manuf. 2003. https://doi.org/10.1016/S0890-6955(03)00110-X
52. Peng R, Liu J, Fu X, Liu C, Zhao L. Application of machine vision method in tool wear monitoring. Int J Adv Manuf Technol. 2021.
53. Brili N, Ficko M, Klančnik S. Automatic identification of tool wear based on thermography and a convolutional neural network during the turning process. Sensors. 2021. https://doi.org/10.3390/s21051917 PMID: 33803442 PMCID: PMC7967223
54. Jegadeeshwaran R, Jakkamputi L, Mohanraj T, Patange AD, Gnanasekaran S. Development of online tool wear-out detection system using silver-polyester thick film sensor for low-duty cycle machining operations. Sensors. 2022.
55. Yang J, Duan J, Li T, Hu C, Liang J, Shi T. Tool wear monitoring in milling based on fine-grained image classification of machined surface images. Sensors. 2022. https://doi.org/10.3390/s22218416 PMID: 36366114 PMCID: PMC9658698
56. Granados GH, Misaka T, Herwan J, Komoto H, Furukawa Y. An experimental study of multi-sensor tool wear monitoring and its application to predictive maintenance. Int J Adv Manuf Technol. 2024. https://doi.org/10.1007/s00170-024-13959-0
57. Yingguang L, Changqing L, Dehua L, Jiaqi H, Peng W. Tool wear dataset of NUAA_Ideahouse. IEEE Dataport. 2021 Mar 20. https://dx.doi.org/10.21227/3aa1-5e83
58. Misal A, Karandikar H, Sayyad S, Bongale A, Kumar S, Warke V. Milling tool wear estimation using machine learning with feature extraction approach. 2024. https://doi.org/10.1109/MITADTSoCiCon60330.2024.10575626
59. Parisi G. Improving tool wear prediction with synthetic features from conditional generative adversarial networks. IEEE Sens J. 2022. https://doi.org/10.36227/techrxiv.21253308.v1
60. Misal A, Karandikar H, Sayyad S, Bongale A, Kumar S, Warke V. Milling tool wear estimation using machine learning with feature extraction approach. 2024 MIT Art, Design and Technology School of Computing International Conference (MITADTSoCiCon); 2024; 1-7. https://doi.org/10.1109/MITADTSoCiCon60330.2024.10575626
61. Xie Y, Gao S, Dai Y, Liu J. Tool wear status identification method based on t-distributed stochastic neighbor embedding and gradient boosting decision tree integrated model. 2023 3rd International Conference on Electrical Engineering and Mechatronics Technology (ICEEMT); 2023; 384-7. https://doi.org/10.1109/ICEEMT59522.2023.10262914
62. Alajmi MS, Almeshal AM. Predicting the tool wear of a drilling process using novel machine learning XGBoost-SDA. Materials. 2020; 13(21):4952. https://doi.org/10.3390/ma13214952 PMID: 33158099 PMCID: PMC7663048
63. Ghazal TM, Hasan MK, Alshurideh M, Alzoubi HM, Ahmad M, Akbar SS, *et al*. IoT for smart cities: Machine learning approaches in smart healthcare- A review. 2021; 218. https://doi.org/10.3390/fi13080218
64. Hallmann M, Pietracho R, Komarnicki P. Comparison of artificial intelligence and machine learning methods used in electric power system operation. 2024. https://doi.org/10.20944/preprints202404.0445.v1
65. Albahra S, Gorbett T, Robertson SA, D'Aleo G, Kumar SVS, Ockunzzi S, *et al*. Artificial intelligence and machine learning overview in pathology and laboratory medicine: A general review of data preprocessing and basic supervised concepts. 2023. https://doi.org/10.1053/j.semdp.2023.02.002 PMID: 36870825

66. Gu J, Wang Z, Kuen J, Ma L, Shahroudy A, Shuai B, *et al*. Recent advances in convolutional neural networks. Pattern Recognit. 2018; 77:354-77. https://doi.org/10.1016/j.patcog.2017.10.013
67. Krizhevsky A, Sutskever I, Hinton GE. Imagenet classification with deep convolutional neural networks. Adv Neural Inf Process Syst. 2017; 60:84-90. https://doi.org/10.1145/3065386
68. Li Z, Lei X, You Z, Huang T, Guo K, Li D, *et al*. Tool wear prediction based on residual connection and temporal networks. Machines. 2024. https://doi.org/10.3390/machines12050306
69. Shen B. Auxiliary input-enhanced siamese neural network: A robust tool wear prediction framework with improved feature extraction and generalization ability. Mech Syst Signal Process. 2024. https://doi.org/10.1016/j.ymssp.2024.111243
70. Chehrehzad M, Kecibas G, Besirova C, Uresin U, Irican M, Lazoğlu İ. Tool wear prediction through AI-assisted digital shadow using industrial edge device. J Manuf Process. 2024. https://doi.org/10.1016/j.jmapro.2024.01.052
71. Hamdi M, Mestiri S, Arbi A. Artificial intelligence techniques for bankruptcy prediction of Tunisian companies: An application of machine learning and deep learning-based models. 2024. https://doi.org/10.3390/jrfm17040132
72. Rescinito R, Ratti M, Payedimarri AB, Panella M. Prediction models for intrauterine growth restriction using artificial intelligence and machine learning: A systematic review and meta-analysis. 2023.