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Artificial Intelligence for Tool Condition Monitoring: A Comprehensive Review

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Abstract: Artificial Intelligence (AI) has gained considerable interest and is increasingly being applied in various aspects of Manufacturing Engineering. In manufacturing, the metal-cutting process is complex and nonlinear due to known and unknown disturbances. Monitoring the condition of the cutting tool is a crucial task. Incorporating AI-based approaches is the best way to monitor tool conditions. This paper presents a comprehensive study on the application of AI-based techniques for tool condition monitoring. AI typically includes machine learning, expert systems, and rule-based systems for analyzing sensor data collected during machining operations. These techniques leverage AI models' knowledge and reasoning capabilities to accurately assess tool condition and predict the remaining useful life of the tool. The findings of this study demonstrate that the experimental results show the effectiveness of the AI- and Machine Learning (ML)- based tool condition monitoring system in accurately detecting tool wear and predicting tool failure. Moreover, the AIML approach provides flexibility for incorporating new knowledge and adapting to changing machining environments. The paper also discusses the online trend of contemporary methods for tracking tool status during various machining operations. The benefits, drawbacks, and future possibilities of applying various AI techniques for tool wear monitoring are examined, along with the limitations and potential directions of the primary processing techniques. Overall, this study emphasizes the significant contributions of AIML-based tool condition monitoring systems in enhancing productivity, dimensional accuracy, and cost-effectiveness in machining operations.

Keywords: artificial intelligence; manufacturing; condition monitoring.

1. Introduction

Condition monitoring is the process of monitoring the health of a machine or piece of equipment in real time to detect anomalies or defects [1]. This process helps predict machine failures before they occur, thus reducing downtime and maintenance costs [2]. In recent years, AIML techniques for tool condition monitoring have gained significant attention due to their ability to analyze large volumes of data and provide accurate, reliable results [3,4]. AIML tools are used across industries, including manufacturing, transportation, healthcare, and energy

[5,6]. In industrial automation, machines are at the heart of manufacturing processes. Therefore, their proper functioning is crucial for the efficient and effective production of goods. However, machines are prone to wear and tear due to prolonged use, leading to breakdowns and downtime [7]. To avoid such failures, preventive maintenance is performed periodically. However, preventive maintenance is based on a fixed schedule, and there is no guarantee that it will detect all faults. Additionally, preventive maintenance may result in unnecessary maintenance and, therefore, increased costs [8,9].

Condition monitoring (CM) is an alternative to preventive maintenance that aims to detect faults before they cause machine failure. CM involves monitoring machinery condition and identifying anomalies that could indicate an impending fault. Traditionally, CM has been done manually through visual inspections or vibration analysis. However, these methods are labor-intensive, time-consuming, and may not detect early-stage faults. AIML-based CM techniques offer a better alternative to traditional CM methods. AIML-based CM techniques use algorithms that learn from machine data to detect and predict faults in machinery. AIML-based CM techniques provide real-time monitoring and analysis of machine data and can detect faults at an early stage, reducing downtime and maintenance costs [10,11].

In modern manufacturing processes, tool condition monitoring plays a critical role in ensuring optimal performance and productivity [12]. The ability to detect and predict tool wear or failure allows for timely maintenance, preventing unexpected breakdowns, reducing production downtime, and improving overall efficiency [13]. Traditional methods of tool condition monitoring often rely on manual inspections or fixed-threshold approaches, which can be time-consuming, subjective, and less effective at capturing subtle changes in tool condition. However, with recent advancements in artificial intelligence and machine learning, new opportunities have emerged to revolutionize tool condition monitoring through the application of Artificial Intelligence Markup Language [14-16].

AIML is a powerful tool that combines the capabilities of artificial intelligence and markup language, enabling the development of intelligent systems capable of reasoning, learning, and decision-making. By leveraging AIML techniques, manufacturers can automate the analysis of sensor data collected during machining operations, enabling real-time monitoring of tool conditions and accurate predictions of tool life [17]. This proactive approach to tool condition monitoring enables predictive maintenance, allowing tools to be replaced or serviced before failure, reducing downtime and maximizing production efficiency [18].

The use of AIML in tool condition monitoring offers several advantages over traditional methods. Firstly, AIML models can process and analyze large volumes of sensor data in real time, providing immediate feedback on tool conditions [19]. This enables manufacturers to identify potential issues early on and take corrective actions promptly, thereby minimizing the impact on production. Secondly, AIML models can learn from historical data and adapt to changing machining environments, continuously improving their accuracy and predictive capabilities [20,21]. This adaptability is particularly valuable in manufacturing settings where tool conditions can vary due to factors such as different workpiece materials, cutting parameters, or tool geometries.

AIML-based tool condition monitoring systems typically consist of three main stages: data acquisition, data preprocessing, and tool condition evaluation. During data acquisition, sensors embedded in the machining environment measure various parameters, including cutting forces, vibrations, temperature, and acoustic emissions. This sensor data serves as input for the AIML model, providing valuable information about the tool's performance and condition [22]. The data preprocessing stage involves filtering, feature extraction, and normalization techniques to enhance the quality and relevance of the sensor data. These preprocessing steps ensure that the AIML model receives clean, meaningful input, thereby improving the accuracy of the subsequent tool-condition evaluation stage [23].

The tool condition evaluation stage is where the true power of AIML is harnessed. Various AIML techniques, such as machine learning algorithms, expert systems, and rule-based systems, can be employed to analyze preprocessed data and assess tool condition. Machine learning algorithms, such as support vector machines, decision trees, or neural networks, can be trained on historical data to identify patterns and relationships between sensor data and tool conditions. Expert systems, on the other hand, can leverage domain knowledge and predefined rules to reason about the tool condition based on specific sensor data patterns. The selection of the AIML technique depends on the specific requirements of the manufacturing process, the available data, and the desired level of accuracy and interpretability [24,25].

Experimental results have demonstrated high accuracy, sensitivity, and specificity in detecting various tool conditions, including normal wear, excessive wear, and tool breakage. By accurately predicting the remaining useful tool life, manufacturers can plan maintenance activities, optimize tool usage, and reduce costs associated with tool replacements [26,27]. Moreover, integrating AIML techniques into machining processes provides flexibility to incorporate new knowledge and adapt to changing conditions, ensuring long-term sustainability and improved performance. By automating sensor data analysis and employing intelligent algorithms, manufacturers can proactively monitor tool conditions, predict failures, and optimize maintenance strategies. Given the increasing demand for smart manufacturing and Industry 4.0 integration, there is a growing need to review the application of AI in tool condition monitoring comprehensively. Understanding the current state of research, challenges, and future opportunities in this area will provide valuable insights to researchers, engineers, and industry professionals seeking to enhance manufacturing systems with AI-driven TCM solutions. This paper provides a brief overview of the AI techniques used to monitor tool conditions in various machining processes. It also summarizes the various sensors used in AI for real-time process monitoring.

2. AI Methods

2.1. Neural networks (NN).

NN is a biologically inspired algorithm that aims to resemble how the brain might function closely. It consists of a large number of units (nodes or neurons) linked to one another to allow communication. These neurons carry information about input signals and are connected to each other [28,29]. The signals are excited by these weights during communication. Each neuron has an internal condition known as an activation signal. At each neuron, the output signal is generated by summing the input and activation signals. The output neurons are the ANN's final layer; in a regression problem, there is just one output neuron that may accept any continuous value, whereas, in a classification problem, there is one output neuron for each class that might be represented by an output The number of input parameters utilized in the model to define the design factors is represented by the input layer in this instance. Depending on how complicated the structures are, this layer may have a large number of neurons, which is required to accurately estimate the output parameter [30,31]. Figure 1 shows a typical ANN model.

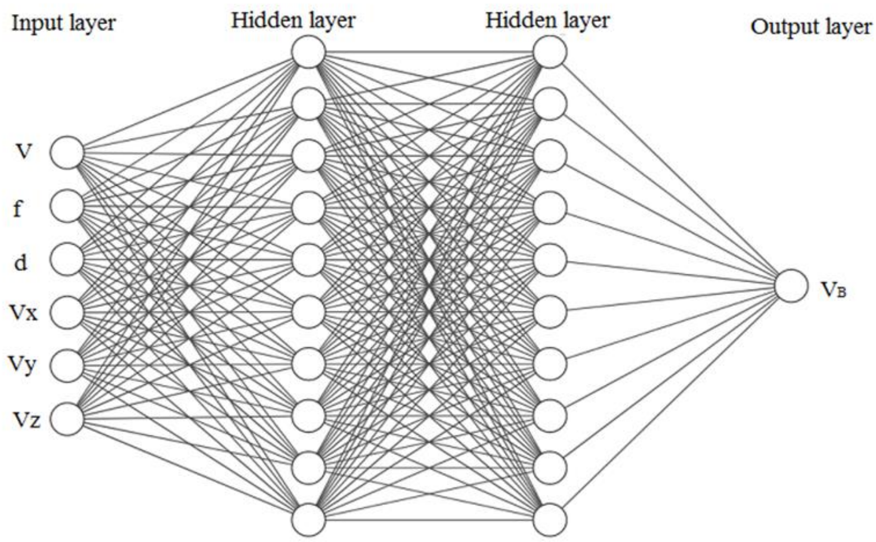

Figure 1. Neural network.

Drouillet *et al*. [32] predicted the remaining useful life (RUL) of tools based on the machine spindle power values using the NN technique. Results showed good agreement between the predicted and true RULs of the tools. The suggested approach was shown to be practical and computationally affordable, and it can be used to provide real-time RUL forecasts while milling.

Thangarasu *et al*. [33] evaluated and forecasted tool wear based on cutting force and surface roughness using an ANN. Three algorithms, such as Levenberg Marquardt, BFGS quasi-Newton, and Gradient Descent with Momentum and Gradient Descent with adaptive learning rate, have been analyzed. The network performance has been evaluated based on the mean square error and computation time of the three algorithms. The analysis showed that the BFGS quasi-Newton backpropagation algorithm produced the least mean squared error value with the shortest computation time.

Historical data is typically used to train a neural network for tool condition monitoring. This data includes sensor readings from previous machining operations, along with corresponding labels indicating the tool's condition at that time. The network learns from this data by adjusting the weights and biases of its neurons through a process called backpropagation. During training, the network iteratively updates its parameters to minimize the difference between its predictions and the actual tool conditions in the training data.

Once the neural network is trained, it can be deployed to predict the tool's condition in real-time. New sensor data is fed into the network, and it produces a prediction based on the learned patterns. This prediction can then be used to determine optimal maintenance actions, such as replacing or servicing the tool before failure. Ambhore *et al*. [34] developed an ANN model for predicting tool wear during turning hard steel. The model is found to be accurate and suitable. Neural networks offer several advantages for tool condition monitoring. They can handle large volumes of sensor data and capture complex relationships that may not be apparent through traditional analytical approaches. Moreover, they can adapt and generalize well across different machining conditions, enabling robust predictions across varying environments.

Neural networks are a valuable tool in AIML for tool condition monitoring. By leveraging their learning and prediction capabilities, manufacturers can achieve proactive maintenance strategies, reduce downtime, and optimize tool usage. However, it is important to consider factors such as data quality, network architecture selection, and training methodologies to ensure neural networks are effective in tool condition monitoring applications.

2.2. Genetic algorithms.

Multi- and single-objective optimization issues can both be solved successfully using genetic algorithm (GA) techniques. It is an adaptive heuristic search algorithm inspired by biology. GA algorithms are influenced by Charles Darwin's idea of evolution [35]. The population (chromosomes), which is a random collection of solutions, is where the algorithm starts. A new population is generated by applying these solutions from one population to another. As a result, the newly developed solutions have to be superior to the previous ones. The new solutions are chosen from the new population (offspring) based on fitness levels. This indicates that there is a greater chance of them having better children if they are more suitable. This occurs again. GAs can be used to optimize the performance of AIML models by fine-tuning their parameters or selecting the most relevant features from the sensor data. This optimization process helps improve the accuracy and effectiveness of the tool condition monitoring system [36].

The basic principle of a GA involves generating, evaluating, and selecting a population of potential solutions (individuals) through a series of iterations, or generations. Each individual represents a set of parameters or features that determine the behavior or performance of the AIML model. The individuals are evaluated using a fitness function that measures their performance in terms of tool condition-monitoring accuracy or other relevant metrics [37].

The GA process starts with an initial population of randomly generated individuals. These individuals undergo genetic operations such as selection, crossover, and mutation, simulating the natural process of evolution. During the selection process, individuals with higher fitness values are more likely to be selected as parents. Crossover involves combining the genetic material of selected parents to produce offspring, while mutation introduces random changes in offspring to maintain population diversity. After the genetic operations, the newly created offspring form the next generation, which is then evaluated and selected again. This iterative process continues for a predefined number of generations or until a termination criterion is met (e.g., convergence of fitness values). The goal is to find an individual or set of individuals that achieves the best performance in terms of tool condition monitoring accuracy or other defined objectives [38]. Figure 2 shows the flowchart of the genetic algorithm.

GAs have several advantages in the context of AIML for tool condition monitoring. They can efficiently explore a large search space and handle non-linear relationships between the parameters or features and the tool condition. Moreover, GAs are robust to noisy or incomplete data and can handle multi-objective optimization problems, allowing for the simultaneous optimization of multiple criteria [39].

It is important to note that the success of GAs in tool condition monitoring depends on various factors, such as the selection of appropriate fitness functions, the representation of individuals, the choice of genetic operators, and the size of the population. These aspects should be carefully considered and tailored to the specific requirements of the tool condition monitoring problem at hand [40].

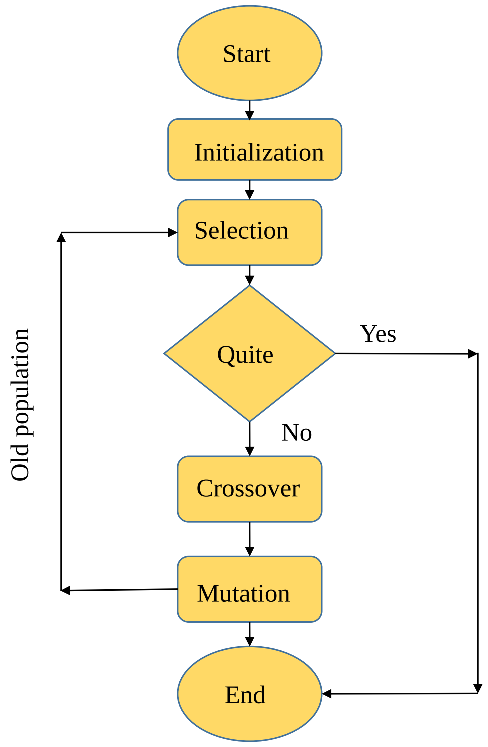

Figure 2. Flow chart of the Genetic algorithm.

2.3. Fuzzy logic.

The fuzzy logic (FL) algorithm accepts many-valued logic, allowing any real number between 0 and 1 to represent the value of a variable. It becomes challenging to determine whether the statement is true or incorrect in real-world conditions. Therefore, FL offers considerable reasoning flexibility in cases like this. The FL algorithm resolves a problem after considering all the information available. The FL, in the end, offers the optimal choice for any input values. Tool condition monitoring and fuzzy logic provide a framework for modeling and reasoning about tool condition using linguistic variables and fuzzy rules. Linguistic variables represent subjective terms or concepts, such as good, fair, or bad, which are used to describe the tool's condition. Fuzzy rules define the relationship between the input variables (e.g., sensor data) and the output variable (e.g., tool condition) [41].

The fuzzy logic process begins with fuzzification, in which crisp input data, such as sensor readings, are converted into fuzzy sets using membership functions. These membership functions assign degrees of membership to each fuzzy set based on the input values. The degree of membership indicates the level of relevance or similarity of the input to the linguistic terms [42]. After fuzzification, fuzzy rules are applied to determine the output fuzzy sets or fuzzy values representing the tool condition. These rules typically take the form of If input is A and input is B, then output is C. The fuzzy rules are defined based on expert knowledge or extracted from historical data through data-driven approaches [43]. The fuzzy logic controller is shown in Figure 3.

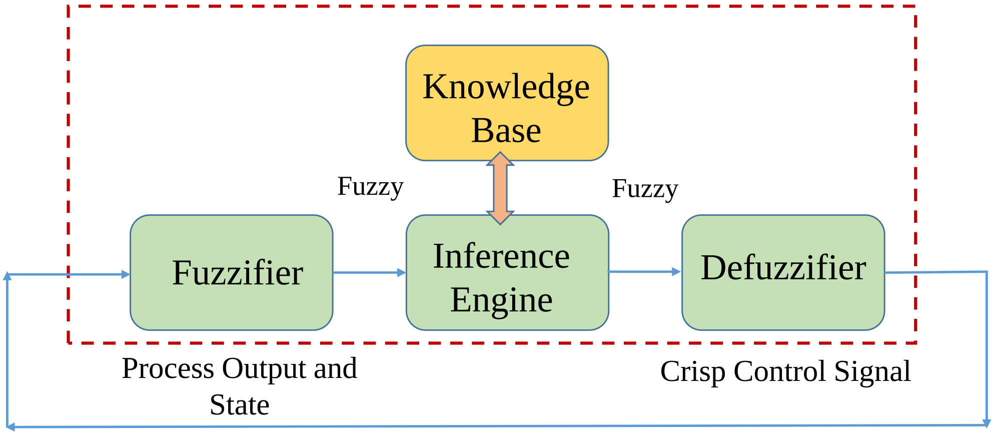

Figure 3. Block diagram of a fuzzy logic controller.

The next step is inference, in which the fuzzy rules are used to derive a fuzzy output set from the fuzzy input sets. This process involves combining the fuzzy sets and applying appropriate inference methods, such as fuzzy logic operators (e.g., AND, OR) and implication methods.

Once the fuzzy output set is obtained, it is defuzzified to yield a crisp output value or decision. Defuzzification methods include centroid calculation, maximum membership value, or weighted average, depending on the specific requirements of the tool condition monitoring system. Fuzzy logic in AIML for tool condition monitoring offers several advantages. It can handle imprecise or incomplete data, making it suitable for situations where sensor readings may have noise or uncertainties. Fuzzy logic also allows the incorporation of expert knowledge and linguistic terms, enabling intuitive, interpretable decision-making in tool condition assessment. Furthermore, fuzzy logic systems are flexible and adaptable, as they can easily incorporate new rules or modify existing ones to accommodate changes in the machining environment. Fuzzy logic provides a powerful computational framework for tool condition monitoring in AIML. By capturing and reasoning with imprecise information, fuzzy logic models can effectively assess and classify tool conditions based on linguistic variables and fuzzy rules. Integrating fuzzy logic with other AIML techniques can enhance the accuracy and robustness of tool condition monitoring systems, ultimately leading to improved maintenance strategies and manufacturing efficiency [44-46].

2.4. Support vector machine(SVM).

SVM are methods for regression, classification, and supervision. It looks for a hyperplane that divides the dataset into two classes. In SVMs, the goal is to find an optimal hyperplane that separates different classes or conditions of the tool based on the input sensor data. The margin, or the distance between the hyperplane and the closest data points from each class, is determined such that the hyperplane maximizes it. This margin maximization seeks to improve the model's robustness and generalizability [47].

The SVM algorithm maps the input data to a higher-dimensional feature space via a kernel function. This transformation allows for nonlinear decision boundaries in the original input space. Popular kernel functions used in SVMs include linear, polynomial, radial basis function (RBF), and sigmoid kernels. The choice of the kernel depends on the specific characteristics of the tool condition monitoring problem and the complexity of the data.

Labeled data, which consists of sensor readings and corresponding tool condition labels, is required to train an SVM model for tool condition monitoring. The SVM algorithm learns the optimal hyperplane by solving a convex optimization problem that minimizes classification errors while maximizing the margin. This optimization is typically achieved using techniques such as quadratic programming. During the prediction phase, the trained SVM model can classify new, unseen sensor data into different tool conditions based on the learned decision boundaries. The model assigns new data points to the appropriate class based on their position relative to the hyperplane [48].

SVMs offer several advantages in AIML for tool condition monitoring. They can handle high-dimensional and complex data, capturing intricate relationships between sensor data and tool conditions. SVMs are also less prone to overfitting compared to some other machine learning algorithms, leading to better generalization and improved performance on unseen data. Moreover, SVMs have a solid theoretical foundation, allowing for rigorous analysis of their performance and interpretability. They provide clear decision boundaries and can identify support vectors, which are the data points closest to the hyperplane and critical for classification [49]. However, SVMs have some considerations to keep in mind. They can be sensitive to the selection of hyperparameters, such as the kernel type and regularization parameter. Choosing appropriate hyperparameters via techniques such as cross-validation is crucial for optimal model performance. SVMs can also be computationally expensive, especially when dealing with large datasets or complex feature spaces [50].

In conclusion, SVMs are a powerful machine-learning technique for tool condition monitoring in AIML. Their ability to handle non-linear relationships and generalize well to unseen data makes them well-suited for capturing complex tool conditions. By leveraging SVMs in tool condition monitoring systems, manufacturers can improve maintenance strategies, reduce downtime, and optimize tool usage for enhanced productivity and efficiency. The summary of the AI Technique is reported in Table 1.

Table 1. Summary of AI techniques used for tool condition monitoring.

Techniques	Applications	Ref.
Neural network	Prediction of surface roughness, tool wear, or cutting forces, and optimization of the cutting process	[2,10,12,]
Genetic algorithms	Prediction of tool wear using image processing, surface roughness, cutting forces, and optimization of cutting processes such as grinding, milling	[19;20,24,30]
Fuzzy logic	Prediction of spindle power, surface roughness, tool wear, or cutting forces, and optimization of the cutting process using spindle power	[36,41,45
Markov models	Prediction of surface roughness, tool wear, or cutting forces, and optimization of the cutting process	[47,48,49]
Support vector machine	Useful for modeling the complex manufacturing process, such as Milling, Hard Turning	[68,74]

2.5. Markov models.

In this method, the observed event and the states are connected through a probability distribution rather than through a direct one-to-one relationship. This doubly stochastic process makes use of the Markov chain. States cannot be seen from the observer's perspective, but the observed values can. A stochastic process is used to determine whether the states exist and what makes them unique. Consequently, it is known as a hidden Markov model. Statistical techniques are used to produce state transitions in HMM and identify trends in the surveillance data. Markov models can be employed to capture the dynamic behavior of the tool's condition over time. The tool condition is represented as a series of discrete states, such as good, fair, or bad. The transitions between these states are probabilistic, and the model estimates the likelihood of moving from one state to another based on historical data [51]

To construct a Markov model for tool condition monitoring, labeled data consisting of sequential sensor readings and corresponding tool condition labels is required. The data is analyzed to estimate the transition probabilities between different tool condition states. These transition probabilities can be computed by counting the occurrences of state transitions in the data or by using more advanced estimation techniques, such as maximum likelihood estimation. Once the Markov model is built, it can be used for prediction and monitoring. Given the current tool condition state, the model can estimate the probabilities of transitioning to different future states. This information can be used to make predictions about tool conditions and plan maintenance actions accordingly. The model can also be used for real-time monitoring, where the current state is continually updated based on incoming sensor data.

Markov models offer several advantages in AIML for tool condition monitoring. They can capture the temporal dependencies and dynamics of the tool's condition, enabling more accurate predictions and proactive maintenance strategies. Markov models are particularly useful when the tool condition transitions have a memoryless property, meaning that they depend only on the current state and are independent of the history [52]. Figure 4 shows the general outline of the Markov model.

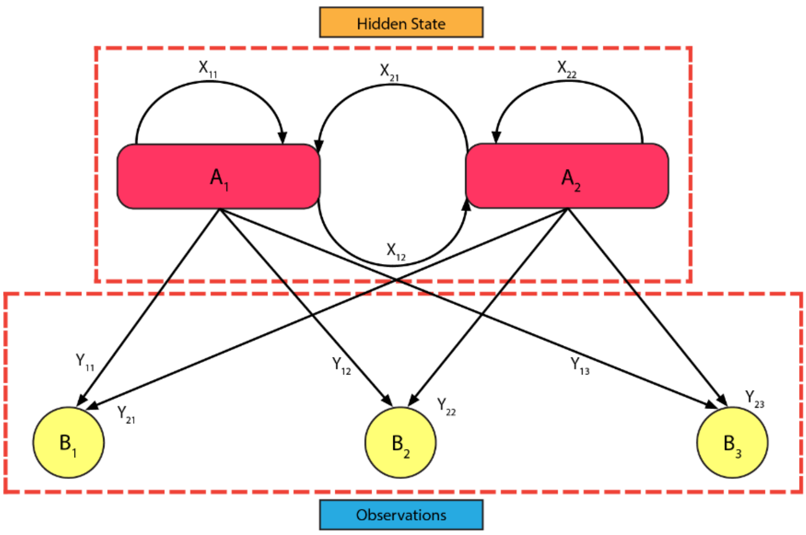

Figure 4. A general outline of HMM.

However, there are considerations when using Markov models for tool condition monitoring. These models assume that the tool condition transitions are stationary, meaning that the transition probabilities remain constant over time. If the tool condition behavior changes significantly, the model may need to be updated or modified accordingly. Markov models are also limited in their ability to capture long-term dependencies or complex patterns in the data [53].

2.6. Decision and regression trees.

This approach splits the dataset into smaller subsets and builds a decision tree iteratively at the same time. The method divides the dataset into smaller, more manageable subsets as it iteratively builds a decision tree. The outcome is a tree with decision nodes and leaf nodes. A decision regarding the target is represented by the node leaf. Decision trees are used for classification tasks, where the goal is to assign a label or class to a given input based on its feature values. Each internal node of the tree represents a decision based on a specific feature, and each leaf node represents a class label or decision outcome. The tree structure is built by recursively splitting the data based on feature thresholds to maximize the purity (homogeneity) of the resulting subsets [54]. Regression trees, on the other hand, are used for regression tasks, where the goal is to predict a continuous numerical value based on the input features. Similar to decision trees, regression trees split the data based on feature thresholds, but the leaf nodes contain predicted numerical values instead of class labels. The construction of decision and regression trees involves selecting the most informative features and determining the optimal splitting criteria at each node. Various algorithms, such as ID3, C4.5, or CART (Classification and Regression Trees), can be used to build these tree models.

Once the tree is constructed, it can be used for prediction by traversing the tree based on the input feature values. At each node, the decision or regression rule determines the path to follow until a leaf node is reached, where the corresponding class label or predicted value is assigned. Decision and regression trees offer several advantages in AIML for tool condition monitoring. They are interpretable models, as their decision rules are easily understood and visualized. These models can handle both categorical and numerical input features and are robust to outliers or missing data. Additionally, decision and regression trees can handle non-linear relationships between features and tool conditions, capturing complex patterns that may not be easily captured by traditional statistical models [55,56].

However, decision and regression trees have some considerations. They can be prone to overfitting, especially if the tree grows too deep or if the training data is limited. Overfitting occurs when the tree captures noise or irrelevant patterns in the data, leading to a poor generalization of unseen data. Techniques like pruning or regularization can be applied to mitigate overfitting. Ensemble methods, such as random forests or gradient boosting, can be employed to enhance the performance of decision and regression trees. These methods combine multiple trees to improve prediction accuracy and robustness [57].

2.7. Adaptive neuro-fuzzy inference systems (ANFIS).

A hybrid computational technique called ANFIS blends fuzzy logic's linguistic interpretability with neural networks' adaptive learning capabilities. Because ANFIS can effectively model complex, nonlinear interactions between sensor data and tool conditions, it has been widely employed in AIML for tool condition monitoring [58].

ANFIS integrates fuzzy logic concepts with neural network structures to create a hybrid model that can quantitatively capture and represent domain experts' linguistic knowledge. The model consists of interconnected layers of nodes, each performing a specific computation. The ANFIS design typically includes five layers: input, fuzzification, rule, defuzzification, and output layers [59]. Figure 5 represents the fuzzy inference system. The input layer of the ANFIS model receives sensor data, representing the features or variables relevant to tool condition monitoring. The fuzzification layer transforms the crisp input values into fuzzy sets using membership functions. These functions define the relevance of the input data to specific linguistic terms or variables.

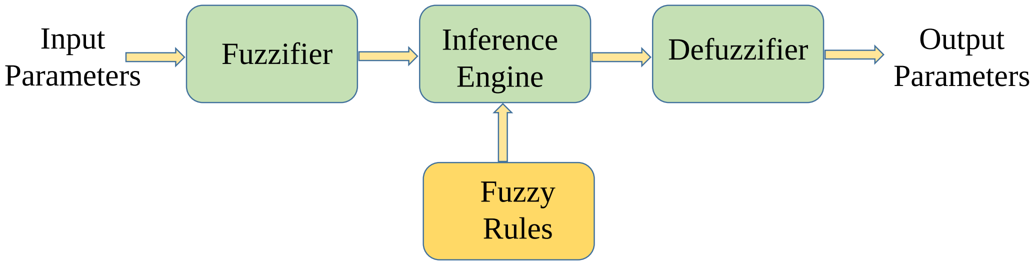

Figure 5. Fuzzy inference system.

The ruling layer of ANFIS determines the firing strength of each fuzzy rule based on the membership values obtained from the fuzzification layer. These fuzzy rules capture the expert knowledge or heuristics about the relationship between the sensor data and the tool condition. The rules are typically defined in the form of IF-THEN statements, where the antecedent describes the input conditions, and the consequent specifies the predicted tool condition. The defuzzification layer of ANFIS combines the outputs of the fuzzy rules to compute the crisp output, or the predicted tool condition. This layer involves calculating the weighted average or centroid of the fuzzy sets to obtain a crisp value representing the tool condition.

The output layer of ANFIS provides the final predicted tool condition based on the crisp value obtained from the defuzzification layer. The model is trained using an adaptive learning algorithm, such as backpropagation or gradient descent, to adjust its parameters and optimize performance. The training process involves minimizing the error between the predicted and actual tool condition labels in the training data [60].

ANFIS offers several advantages in AIML for tool condition monitoring. It combines the strengths of fuzzy logic, such as linguistic interpretability and handling imprecise data, with the learning and generalization capabilities of neural networks. ANFIS models can effectively capture and represent expert knowledge and heuristics in tool condition monitoring, enabling intuitive decision-making and transparency.

However, there are considerations when using ANFIS for tool condition monitoring. The performance of ANFIS heavily depends on the quality and representativeness of the training data. Adequate and diverse training data is crucial to ensure accurate modeling of complex tool-condition relationships. Additionally, ANFIS models may require longer training times and more computational resources compared to simpler models [61].

3. Sensors with AI

Sensors play a critical role in AI for AIML tool condition monitoring. They provide the necessary input data that enables the AI system to monitor and analyze tool condition in real time. Sensors capture various physical parameters and tool performance metrics, such as vibration, temperature, sound, current, voltage, and more. These measurements serve as valuable indicators of tool condition and can help identify abnormalities or deviations from normal operating conditions [62].

In tool condition monitoring, sensors act as the interface between the physical world and the AI system. They collect raw data from the tool or its environment, which is then processed and analyzed by AI algorithms to extract meaningful insights about the tool's condition. The choice of sensors depends on the specific tool and monitoring requirements, including the tool type, the critical parameters to be measured, and the desired level of accuracy and precision. AI models utilize sensor data to detect patterns, trends, and anomalies that signify changes in tool conditions. By continuously monitoring sensor data, AI systems can identify early warning signs of tool degradation, wear, or faults, allowing for timely maintenance interventions and preventing costly failures or production disruptions [63].

The integration of AI and sensors in tool condition monitoring offers several advantages. Firstly, it enables real-time and continuous monitoring of tool conditions, providing up-to-date information for maintenance decision-making. Secondly, sensors capture objective, quantitative data, eliminating human bias and subjective interpretation. Thirdly, AI algorithms can process and analyze large volumes of sensor data more efficiently and accurately than manual inspection, thereby improving the detection of subtle changes or deviations.

Different types of sensors can be employed based on the specific tool and monitoring requirements. For example, accelerometers can measure vibration, providing insights into tool stability, wear, or imbalances. Temperature sensors can detect overheating or thermal abnormalities in tools, indicating potential issues with lubrication or cooling systems. Force sensors can monitor cutting forces, helping detect tool wear or breakage. Other sensors, such as acoustic or optical sensors, can be used to capture sound or visual cues related to tool conditions [64-66].

The selection and placement of sensors require careful consideration to ensure accurate and representative measurements. Factors such as sensor calibration, signal processing techniques, and data acquisition systems must be considered to ensure the reliability and quality of sensor data. Additionally, sensor fusion techniques that combine data from multiple sensors can enhance the accuracy and robustness of tool condition monitoring systems.

3.1. Dynamometer.

A dynamometer is a specialized instrument used in AIML for tool condition monitoring to measure and analyze the cutting forces experienced during machining operations. It provides valuable data about the forces exerted on the tool during cutting processes, which can be utilized to monitor tool condition, assess tool wear, and detect anomalies or deviations from normal machining behavior. Dynamometers are typically integrated into the machining setup, either as a separate device or as part of a machine tool system. They consist of sensors that measure cutting forces in different directions, including axial (thrust), radial, and tangential. These sensors capture the dynamic forces acting on the tool during machining, enabling real-time monitoring and analysis [67]. The measured cutting forces are influenced by various factors, including tool wear, cutting parameters, material properties, and machining process stability. By analyzing the cutting force data, AIML algorithms can extract valuable insights and patterns that indicate changes in tool conditions. Machine learning techniques, such as neural networks or support vector machines, can be employed to develop models that correlate cutting force patterns with specific tool conditions, such as wear levels or breakage [68].

The integration of dynamometers with AIML enables the development of intelligent tool condition monitoring systems. These systems continuously monitor and analyze cutting force data, providing real-time information on the tool's condition and performance. By comparing the measured forces to established thresholds or reference models, the system can identify abnormal force patterns or deviations from expected behavior, indicating potential tool wear or faults [69].

Dynamometer-based tool condition monitoring offers several advantages. Firstly, it provides direct, quantitative measurements of cutting forces, enabling an accurate, objective assessment of tool conditions. Secondly, the real-time nature of the measurements allows for proactive maintenance interventions, minimizing the risk of tool failures and production disruptions. Thirdly, dynamometer data can be combined with other sensor data, such as vibration or temperature, to create comprehensive, multimodal tool condition monitoring systems [70].

However, there are considerations when utilizing dynamometers for tool condition monitoring. Proper calibration and installation of the dynamometer sensors are crucial to ensure accurate and reliable measurements. The selection of appropriate cutting force thresholds or reference models requires comprehensive data analysis and validation. Additionally, dynamometers add complexity and cost to the machining setup, and their integration may require modifications to the machine tool or cutting processes [71]. Figure 6 shows the application of acoustic emission and a dynamometer.

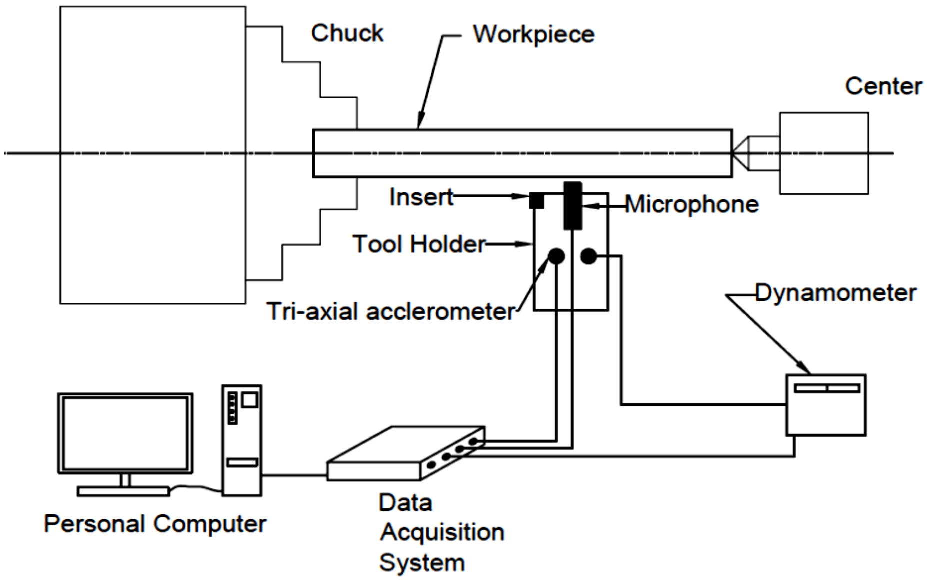

Figure 6. TCM method uses an AE sensor and a dynamometer.

By calculating the present tool's health factors and comparing the results with prior health factor data, the model can estimate how long the tool will remain useful by averaging the weighted data. Sensors collected substantial information on vibration, power, and machine tool stability to represent the relationship between the monitoring signal and tool life. The tool's remaining useful life was predicted with 94.35% accuracy after extracting signal characteristics from the original data and establishing an SVR model that accounted for various signal lengths. Six characteristic quantities were retrieved from the signals produced by the tool's cutting operation after 14 characteristic values were extracted [72].

3.2. Accelerometer.

Accelerometer sensors play a crucial role in AIML for tool condition monitoring as they provide valuable insights into the dynamic behavior of tools during machining operations.

These sensors measure the acceleration experienced by the tool or the surrounding machinery, allowing for real-time monitoring, analysis, and prediction of tool conditions [73].

Accelerometers are commonly used to capture vibrations generated during machining processes. Tool vibrations are indicative of various conditions, such as tool wear, tool breakage, cutting instability, and other anomalies [74]. By monitoring and analyzing the accelerometer data, AIML algorithms can detect patterns and changes in the vibration signals, enabling the identification of tool condition variations.

Accelerometer sensors are typically attached to the tool or the machine tool structure to measure acceleration along the X, Y, and Z axes. The sensors convert the mechanical vibrations into electrical signals, which are then processed and analyzed by AI algorithms. The accelerometer sensors provide information about the amplitude, frequency, and direction of vibrations, which can be used to assess tool condition. AIML techniques, such as signal processing algorithms, neural networks, or support vector machines, can be employed to extract meaningful features from the accelerometer data and develop models for tool condition monitoring. These models can learn the relationships between the vibration patterns and specific tool conditions, enabling the prediction of tool wear levels, breakage, or other abnormal conditions [75].

The integration of accelerometer sensors with AIML allows for real-time monitoring of tool conditions during machining operations. By continuously monitoring the vibration signals, the system can detect deviations from normal behavior and identify potential tool issues before they lead to catastrophic failures or poor-quality products. This proactive approach to tool condition monitoring enables timely maintenance interventions, reducing downtime and increasing productivity. Accelerometer-based tool condition monitoring offers several advantages. Firstly, accelerometers provide direct, objective measurements of tool vibrations, offering insights into the tool's dynamic behavior. Secondly, accelerometer data can be collected and processed in real time, enabling immediate responses and interventions. Thirdly, accelerometers are non-intrusive and can be easily integrated into existing machining setups, making them practical for industrial applications.

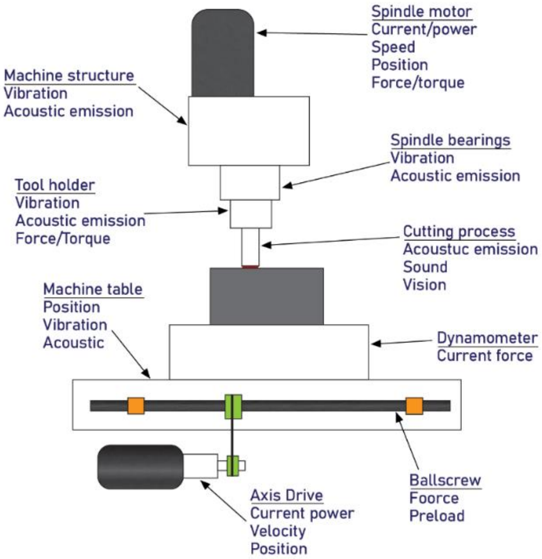

Figure 7. Approaches of tool breaking monitoring for end milling operations.

However, there are considerations when utilizing accelerometer sensors for tool condition monitoring. Proper sensor placement and calibration are critical to ensure accurate and reliable measurements. Selecting appropriate signal processing techniques and feature extraction methods requires careful analysis and validation. Additionally, interpreting accelerometer data may require domain expertise to distinguish normal vibrations from abnormal or undesirable conditions [76].

Accelerometer sensors are essential in AIML for tool condition monitoring as they provide valuable information about tool vibrations and dynamic behavior. By leveraging accelerometer data and combining it with advanced AI techniques, manufacturers can develop proactive tool condition monitoring systems, optimize maintenance strategies, and enhance overall machining performance [77]. The integration of accelerometers with AIML enables real-time monitoring and analysis, leading to improved productivity, reduced downtime, and enhanced tool utilization. Figure 7 shows the application of an accelerometer for a milling operation.

3.3. Temperature sensors.

Temperature sensors play a crucial role in tool condition monitoring within the realm of artificial intelligence and machine learning. They are commonly used to monitor the thermal behavior of tools during manufacturing processes. Here is a detailed overview of temperature sensors in AIML for tool condition monitoring [78]. Temperature sensors are employed to measure and monitor the temperature of tools or workpieces during machining, cutting, or other industrial processes. The temperature data collected by these sensors provides valuable insights into the condition and performance of the tools, enabling the detection of anomalies or deviations from normal operating conditions.

3.4. Thermocouples.

Thermocouples are made of two different metal wires joined at one end. They generate a voltage proportional to the temperature difference between the two ends. Thermocouples are widely used due to their simplicity, ruggedness, and wide temperature range [79,80]. Resistance Temperature Detectors (RTDs) are temperature sensors that change resistance with temperature variations. They are typically made of pure metals such as platinum and exhibit high accuracy and stability over a wide temperature range. Thermistors are temperature-sensitive resistors whose resistance changes with temperature. They are typically made of ceramic or semiconductor materials. Thermistors offer high sensitivity but are more prone to self-heating and nonlinear behavior. Infrared (IR) Sensors: Infrared sensors measure temperature remotely by detecting thermal radiation emitted by objects. They are non-contact sensors that can measure the temperature of tools or workpieces without direct physical contact [81,82].

3.5. Laser sensors.

Laser sensors are widely used in various artificial intelligence (AI) applications to gather precise, detailed information about the surrounding environment. These sensors utilize laser technology to measure distances, detect objects, capture 3D point clouds, and enable AI systems to understand and interact with the physical world. Laser sensors are designed to emit laser beams and measure the properties of the light reflected or scattered. They are employed in AI applications for tasks such as object detection, localization, mapping, gesture recognition, robot navigation, and autonomous vehicles [83]. Laser sensors generate raw data in the form of distance measurements or point clouds. This data is collected by the sensor and processed using AI algorithms. The processing involves filtering, segmentation, feature extraction, and data fusion techniques to extract meaningful information from the raw laser measurements [84-86].

4. Future Scope

In the future, AIML for tool condition monitoring will involve integrating data from multiple sensors, such as temperature, vibration, acoustic, and image sensors. By combining data from different sources, AIML models can gain a comprehensive understanding of tool conditions, leading to more accurate predictions and fault detection. Future advancements will focus on leveraging advanced machine learning techniques, such as deep learning and reinforcement learning. Deep learning architectures such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) can automatically extract complex features from sensor data, thereby improving the accuracy of tool condition predictions. The integration of AIML algorithms with edge computing devices and systems will enable real-time tool condition monitoring. By processing sensor data locally on edge devices, latency can be reduced, enabling faster decision-making and immediate responses to tool condition changes or faults. Apart from this, AIML models will play a crucial role in predictive maintenance strategies. By analyzing historical data and sensor readings, these models can predict the remaining useful life of tools and identify when maintenance or replacement is required. Predictive maintenance minimizes downtime, optimizes production schedules, and reduces costs associated with tool failure. Unsupervised learning techniques will be utilized for anomaly detection in tool condition monitoring. These techniques can identify abnormal behavior and detect unknown patterns without relying on labeled training data. Unsupervised learning enables the detection of emerging tool condition issues and enhances the robustness of monitoring systems. As AIML models become more complex, there will be a need for explainability and interpretability. Future research will focus on developing techniques to understand and explain the decisions made by AIML models in tool condition monitoring. This will enhance trust, facilitate collaboration between AI systems and human experts, and enable the identification of model limitations and potential biases.

5. Conclusions

In this comprehensive review, we explored the significant advancements in AI for tool condition monitoring for various machining processes. AI techniques have proven highly effective for predicting tool wear, identifying tool failures, and optimizing machining parameters in real time. Recently developed machine learning ensembles have proven highly accurate for tracking tool conditions. They exhibit insensitivity to training dataset size and do not require a wide range of complex parameter tuning like ANNs. SVMs and ANNs are both sophisticated machine learning algorithms that produce precise wear-prediction models for tools. The field of machine learning research is expected to put in significant effort to adapt conventional methods to the constraints of industrial datasets created under the Industry 4.0 paradigm. The integration of AI with sensor technologies, such as acoustic emission, vibration analysis, and image-based monitoring, has opened new avenues for accurate and reliable tool condition assessment. Future research should improve AI models' adaptability across diverse manufacturing settings, enhance data-acquisition systems, and explore more efficient, lightweight AI algorithms.

Author Contributions

Conceptualization, N.A., S. S., and D.W.; methodology, A.D., V.G.; validation, N.A., O.B., and A.ZD; resources, N.S., A.D., O.B.; data curation, N.A., S.S., D.W.; writing—original draft preparation, N.A., S. S.; writing—review and editing, S.S., D.W., A.D.; visualization, N.A., V.G.; All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

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Conflicts of Interest

The authors declare no conflict of interest.

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