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Artificial Intelligence in Turning Operations: A Review of Experimental and Analytical Methods for Cutting Forces, Vibrations, and Surface Roughness Optimisation

Jadhav Sachin Zambar* and Rahul Kumar

Department of Mechanical Engineering, School of Science and Technology, Sandip University, Nashik - 422213, Maharashtra, India; sj0857614@gmail.com

Abstract

The integration of Artificial Intelligence (AI) in turning operations has revolutionised the optimisation of key machining outcomes, including cutting forces, vibrations, and surface roughness. This review comprehensively examines experimental and analytical methods leveraging AI techniques, such as machine learning, neural networks, and genetic algorithms, to enhance process efficiency and product quality. AI-driven models have demonstrated remarkable capabilities in predicting and optimising cutting parameters, reducing vibrations, and improving surface finish by analysing complex relationships between input variables and output responses. Experimental studies highlight the effectiveness of AI in real-time monitoring and adaptive control, while analytical approaches provide deeper insights into the underlying mechanics of machining processes. The synergy between AI and traditional methods offers a robust framework for addressing challenges in turning operations, paving the way for smarter, more sustainable manufacturing. This review underscores the transformative potential of AI in advancing precision machining and identifies future research directions for further innovation.

Major Findings: *AI-driven models have significantly improved turning operations by optimising cutting forces, reducing vibrations, and enhancing surface roughness. Experimental and analytical approaches leveraging machine learning, neural networks, and genetic algorithms enable real-time monitoring and adaptive control, leading to greater efficiency in machining processes. Integrating AI with traditional methods provides a robust framework for smarter, more sustainable, and precise manufacturing.*

Keywords: *Artificial Intelligence, Cutting Force, Machine Learning, Roughness Prediction, Surface Roughness*

1.0 Introduction

Artificial Intelligence (AI) has become a pivotal tool in optimising turning operations, particularly in predicting and enhancing surface roughness, cutting forces, and vibrations. Machining is a crucial industrial process that involves shaping metal by strategically removing material. This fundamental technique, while proven and relied upon for centuries, remains indispensable in modern manufacturing and is expected to continue playing a vital role for decades to come. However, the machining process inherently presents significant challenges, primarily centred around the cutting tools employed, Tool Wear, and Tool Failure[1]. The continuous contact between the cutting tool and the workpiece inevitably leads to gradual wear and tear on the tool's edges. This wear not only diminishes the tool's effectiveness but also increases the risk of producing inaccurate or defective parts. In more

**Author for correspondence*



Figure 1. Algorithms used in tool life prediction.

severe cases, excessive wear or unforeseen circumstances (such as collisions) can result in catastrophic tool failure. This not only halts the machining process abruptly but also can damage the workpiece, the machine, and potentially injure operators[2]. This synthesis reviews the application of AI techniques, focusing on experimental and analytical methods for optimising these parameters in turning operations.

Tool wear is widely recognised for its negative impact on machined surface quality and its ability to introduce unpredictable inaccuracies in work geometry. It also significantly influences tool life and production costs[2].

From both a technical and economic perspective, it is crucial to develop a smart system capable of monitoring tool wear progression during the machining process. Such a system would enable the identification of a worn tool, prompting timely replacement. This would enhance the cutting process's accuracy and ensure the machined components meet the required technical specifications for the desired geometry[3,4].

Modelling techniques are essential for improving machining effectiveness, reducing manufacturing time, and cutting costs, which benefits the manufacturing industry[5]. Since machining models are nonlinear, analytical models are often simplified or assumed. Recently, AI-based models have gained popularity, with researchers using them to develop near-optimal conditions for metal cutting, as shown in Figure 1.

There are a lot of different algorithms used to predict cutting force, tool life, vibration, and other prominent factors affecting tool life, as shown in Figure 2. Artificial Intelligence, particularly Artificial Neural Networks (ANN), is increasingly used for real-time applications and has proven to be reliable and effective[6]. Several studies have successfully implemented ANN-based models, yielding satisfactory results. For instance, Nalbant *et al.*[7] used ANN to predict surface roughness in CNC turning of AISI 1030 steel, while Özel and Karpat[8] applied ANN to predict surface roughness and tool flank wear during the finish dry hard turning of AISI H13 steel. Additionally, Leo and Varadarajan[9] used an ANN model to simulate surface milling of hardened AISI 4340 steel with minimal fluid application. A majority of the proposed

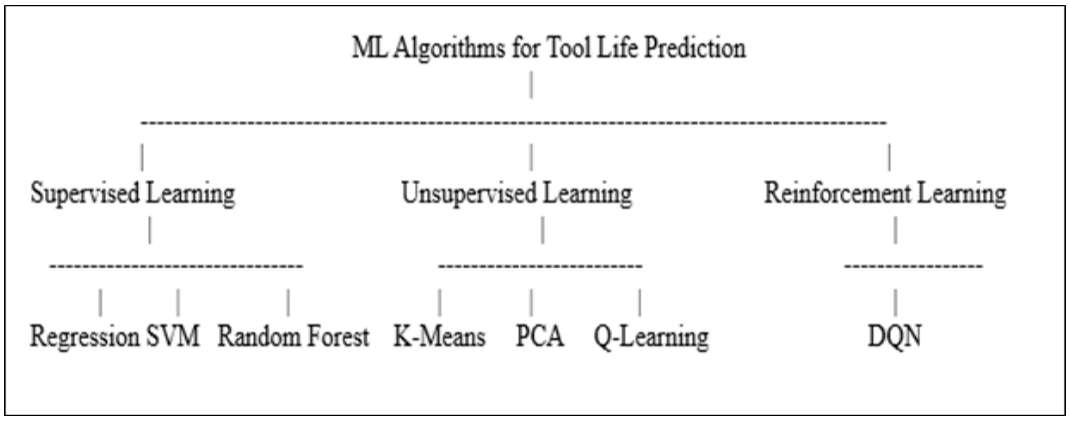


Figure 2. Different algorithms are used in tool life prediction using Machine Learning models.

approaches rely on data from diverse independent sensors[10-12], including acoustic emission (AE) sensors, force sensors, acceleration sensors, and sensors designed to measure contact resistance between the tool and the workpiece[9].

2.0 AI Techniques for Surface Roughness Prediction

Predicting surface roughness accurately is crucial for improving product quality and optimising machining conditions. AI can model complex relationships between input parameters and surface roughness, which traditional methods may struggle to handle effectively.

2.1 Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) have been widely used to predict surface roughness in turning operations. Studies have shown that ANN models provide higher accuracy in estimating surface roughness than traditional regression models. Surface roughness is a critical parameter in various industrial applications, as it directly impacts the performance and lifespan of manufactured components. The analysis and prediction of surface roughness in Computer Numerical Control milling processes is a challenging task due to the complex interplay of various machining parameters[13].

In this research paper, a Convolutional Neural Network model is proposed to predict surface roughness in CNC milling operations accurately. This approach is motivated by the need for robust and reliable predictive models that can account for the non-linear relationships between machining parameters and surface roughness[13-15]. The proposed CNN model aims to address the limitations of traditional statistical and empirical models, which often fail to capture the intricate dependencies between input variables and the surface quality outcome[13]. A comprehensive dataset was compiled to develop the CNN model, including various machining parameters such as spindle speed, feed rate, depth of cut, and tool geometry. The dataset was used to train and validate the CNN model, to minimise the mean squared error between the predicted and actual surface roughness values. Wenkler *et al.*[16] introduce a Convolutional Neural Network model to predict surface roughness in CNC milling processes. This is motivated by the limitations of traditional methods in capturing the complex relationships between machining parameters and surface roughness. The CNN is trained and validated on a dataset encompassing various machining parameters (spindle speed, feed rate, depth of cut, tool geometry) to minimise the mean squared error between predicted and actual surface roughness values[17-24].

Tool life prediction in CNC (Computer Numerical Control) machining is critical for ensuring manufacturing processes' optimal performance and efficiency[25,26]. By accurately predicting tool wear and failure, manufacturers can reduce machine downtime, minimise production costs, and enhance overall productivity[27]. Tool life prediction allows for more effective planning of tool replacements and maintenance schedules, thus contributing to enhanced operational efficiency[28].

Recent advancements in ML have significantly contributed to developing predictive models for tool life, offering a promising alternative to traditional approaches such as wear models and empirical methods[29,30]. These ML models can analyse large datasets obtained from various sensors, providing real-time predictions of tool wear and failure, thus improving the accuracy of tool life forecasting[30,31]. Key parameters such as cutting force, surface roughness, vibration, and temperature have been identified as crucial for predicting tool life[32,33]. These parameters can be measured using advanced sensors integrated into CNC machines, which continuously monitor the machining process and provide valuable data for predictive modeling[34,35].

The prediction models typically employ various machine learning techniques, including regression algorithms, Support Vector Machines (SVM), Artificial Neural Networks (ANN), and decision trees[36,37]. These algorithms are trained on historical data to develop a model that can predict future tool wear based on real-time input. By incorporating multiple process parameters and machining conditions, researchers have achieved high levels of prediction accuracy[37,38]. In addition, hybrid models that combine different machine-learning techniques have been explored to improve the robustness and reliability of tool life predictions[39,40].

Despite the significant progress made, challenges remain in tool life prediction, including the difficulty of obtaining accurate and high-quality data, the complexity of integrating real-time sensor data, and the need for

generalised models that can adapt to different machining conditions and tool materials[29,35]. Furthermore, the interpretability of machine learning models remains a key issue, as manufacturers need models that not only offer accurate predictions but also provide insights into the underlying factors affecting tool wear[28,31].

This literature review aims to provide an overview of the current state of tool life prediction in CNC machining, with a focus on machine learning techniques and the critical process parameters used in the prediction models. The review also explores the challenges and future directions for improving tool life prediction models, especially in the context of real-time monitoring and industrial applications.

2.2 Fully Convolutional Network (FCN)

Bergs *et al.*[17] explore the use of deep learning for automated tool wear analysis in metal cutting. A CNN achieved 95.6% accuracy in classifying cutting tool types. Subsequently, an FCN was trained on various datasets to segment worn areas on microscopic tool images, achieving an IoU of around 0.7. This research advances the potential for fully automated tool wear analysis using machine tool-integrated microscopes, offering significant benefits like reduced downtime and improved productivity in manufacturing.

FCNs excel at pixel-level image segmentation, crucial for applications like disaster management and precision agriculture[23]. Their architecture allows them to handle images of various sizes and types, including infrared and visible spectra[24]. Demonstrated superior performance compared to other models like Deep Lab when trained on small datasets, making them efficient in data-constrained scenarios[25]. Zhang[26] developed a novel intelligent image recognition scheme that utilises a Fully Convolutional Neural Network (FCNN) to improve classification accuracy. Leverages CNN by incorporating AlexNet, Optimised Loss Function, and Image Pre-processing are key performance parameters. The proposed scheme demonstrated superior recognition accuracy compared to traditional methods like KNN, SVM, and PSO, highlighting its effectiveness in image recognition tasks.

2.3 Multi-Scale Convolutional Neural Networks (MSCNN)

The Multi-Scale Convolutional Neural Networks (MSCNNs)[16,17] are employed to enhance tool wear information extraction by analysing features across various scales and types. For instance, Xu *et al.*[20] employed a multi-scale convolution-gated recurrent neural network to monitor tool state by processing and learning vibration signals. Zhu *et al.*[21] improved RUL prediction accuracy using time-frequency representation and MSCNN. Jiang *et al.*[22] utilised a bidirectional long short-term memory network and MSCNN for data-driven RUL estimation,

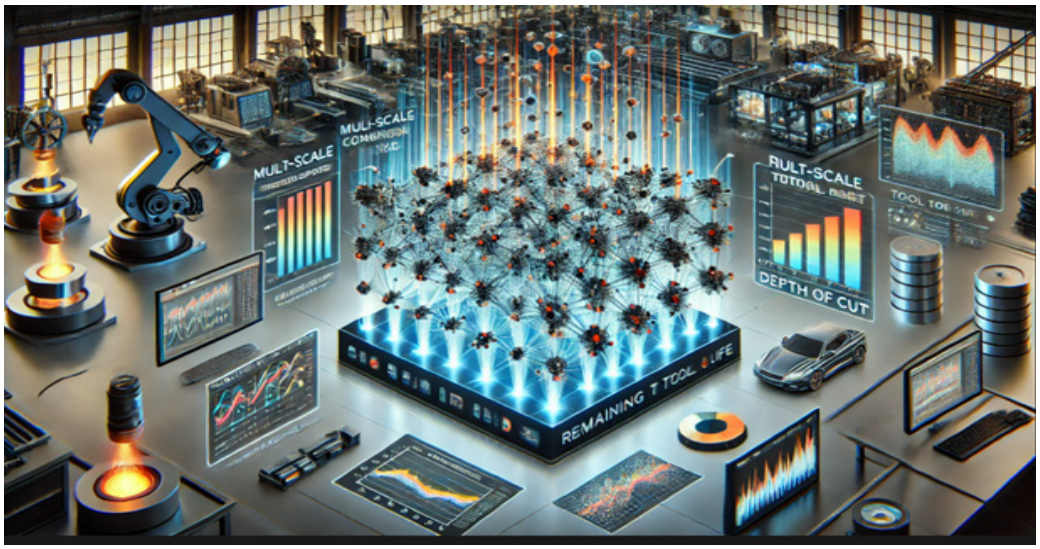


Figure 3. Multi-scale convolutional neural networks are used in the algorithm, considering input parameters.

achieving strong predictive performance. While these methods effectively extract multi-sensor information through MSCNNs, limitations exist. Firstly, MSCNNs often simply concatenate extracted features, potentially overlooking crucial information. Secondly, they do not consider the varying importance of different features for the prediction task, potentially hindering predictive performance. Multi-Scale Convolutional Neural Networks (MSCNN) are a class of deep learning models designed to capture features at multiple scales within an image. Traditional CNNs typically use fixed-size convolutional filters, which may struggle to capture both fine-grained and coarse-grained features simultaneously. MSCNNs address this limitation by incorporating multiple pathways or branches, each processing the input at different scales. This allows the network to learn hierarchical representations, improving performance in tasks such as object detection, segmentation, and classification. Consequently, further improvements in tool wear prediction accuracy through multi-scale networks are necessary.

MSCNNs are designed to capture features at various scales by employing convolutional kernels of different sizes as shown in Figure 3. This architecture enables the network to learn both fine-grained and coarse-grained features, which is essential for modelling the complex patterns associated with tool wear. For instance, Huang *et al.*[41] proposed a tool wear prediction method based on an MSCNN with attention fusion. Their approach utilised convolutional kernels of varying sizes to extract degradation information from multi-sensor data, followed by an attention mechanism to fuse these multi-scale features effectively. The model demonstrated superior performance in predicting tool wear compared to traditional CNNs. Similarly, Xu *et al.*[42] introduced a Multi-Scale Convolutional Gated Recurrent Unit (MCGRU) network for tool wear prediction. By integrating multi-scale convolutional layers with gated recurrent units, the model effectively captured temporal dependencies and multi-scale features from raw sensory data, leading to improved prediction accuracy.

2.4 Comparative Studies of AI Techniques

Comparative studies have been conducted to evaluate different AI techniques for predicting surface roughness. Techniques such as canonical genetic algorithms, particle swarm optimisation, and differential evolution have been compared, with differential evolution showing effectiveness in predicting surface roughness classes from vibration signals[8]. Moreover, Bayesian optimisation has been applied to enhance machine learning models like Extreme Gradient Boosting Regression (XGB) and Cat Boost Regression (CAT), significantly improving their predictive performance for surface roughness[8].

3.0 Optimisation of Cutting Forces and Vibrations

3.1 Influence of Cutting Force

Optimising cutting forces and vibrations is crucial for improving machining performance. Studies have

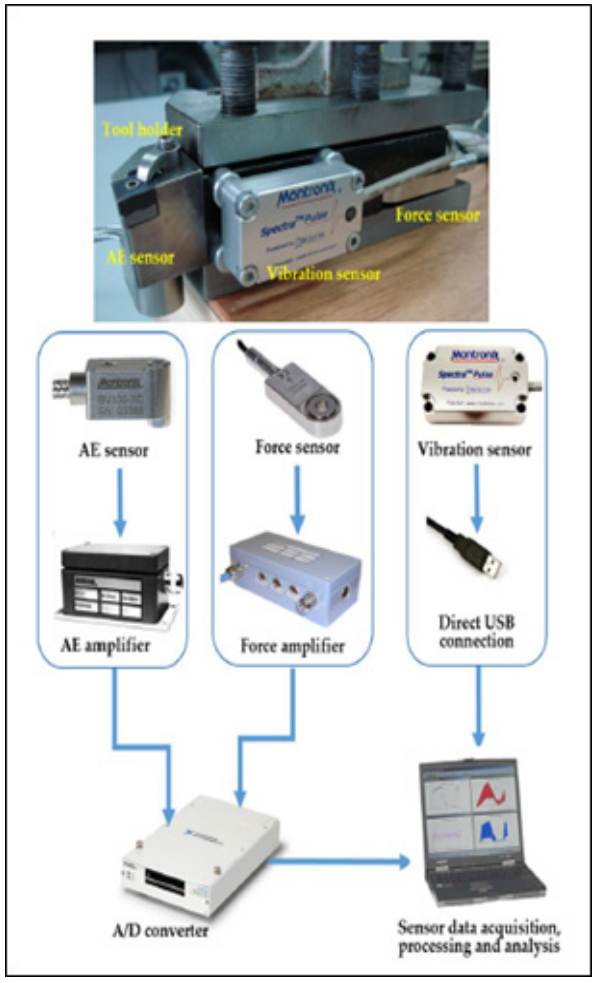


Figure 4. Multiple sensor systems comprising the cutting force, vibration, and acoustic emission sensors are mounted on the tool holder[48].

identified that feed rate significantly affects surface roughness, while depth of cut has a major influence on cutting forces and power consumption [24,25]. ANN models have been used to predict cutting forces and vibrations, demonstrating reliability and accuracy in forecasting these parameters based on inputs like cutting speed, feed rate, and tool noise radius[26].

Cutting forces are pivotal indicators of tool wear, as variations in these forces often correlate with the tool's condition. Incorporating cutting force data into predictive models enhances their accuracy. Li *et al.*[43] proposed a deep learning approach that integrates cutting conditions, including cutting forces, as additional inputs to a CNN. This method improved tool wear estimation accuracy and demonstrated robustness across varying cutting parameters.

Furthermore, a study by Huang *et al.*[41] emphasised the significance of cutting force signals in tool wear prediction. Their experiments revealed that models incorporating cutting force data achieved lower mean absolute errors compared to those that did not, underscoring the importance of this parameter in predictive modelling. The multiple sensor system is used in the data acquisition from the tool holder of the Lathe machine is as shown in Figure 4.

3.2 Influence of Vibration

Vibration signals are crucial indicators of tool wear, as changes in vibration patterns often correlate with the tool's condition. AI models utilising vibration data can enhance predictive accuracy by identifying patterns associated with tool degradation. Vibration monitoring provides real-time data reflecting tool conditions during machining processes[44]. Excessive vibrations indicate tool instability and can lead to premature wear, reducing tool life[45]. Advanced AI models leverage vibration signals to detect early-stage tool wear, offering real-time decision-making[46].

Studies have shown that frequency-domain features extracted from vibration signals, such as Fast Fourier Transform (FFT) and wavelet transforms, provide valuable indicators of tool wear[47]. Additionally, time-domain features such as Root Mean Square (RMS) and kurtosis help in understanding tool degradation patterns. Recent advancements integrate AI with signal processing techniques. For example, deep learning-based models using CNNs and LSTMs effectively capture spatial and temporal dependencies in vibration data, improving wear prediction accuracy[43]. Additionally, ensemble learning techniques combining multiple AI models enhance robustness in tool wear detection[26]. Another approach involves unsupervised learning techniques, such as autoencoders and clustering methods, to identify anomalies in vibration signals, leading to early detection of unexpected tool failures[41]. Hybrid AI models that integrate vibration data with other sensor signals, including acoustic emissions and cutting forces, further improve reliability and predictive capability[36].

Furthermore, the deployment of AI models in edge computing environments allows for real-time monitoring and adaptive tool wear prediction, minimising downtime and improving efficiency in machining operations[42]. Future research should explore AI-driven adaptive control systems that dynamically adjust machining parameters based on real-time vibration feedback.

3.3 Multi-Objective Optimisation

Multi-objective optimisation approaches have been employed to simultaneously minimise surface roughness and cutting forces while maximising productivity. Techniques such as the desirability function have been used to optimise machining parameters, achieving a balance between quality and efficiency[3,4].

The multi-scale convolutional network with attention fusion processes various pre-processed sensor data to capture tool wear degradation information across different time scales, as shown in Figure 4. By integrating an attention fusion module, it filters and prioritises features strongly correlated with tool wear, minimising irrelevant or redundant data while preserving key degradation information through residual connections. This approach enriches feature extraction, mitigates gradient issues, and enhances model robustness. Ultimately, a fully connected layer predicts tool wear values, leveraging the fused and refined sensor data for accurate results. These methods have shown that AI models, particularly ANN, can effectively guide the optimisation process by accurately predicting the outcomes of different parameter settings. Zhang *et al.*[27] reviewed multi-objective optimisation algorithms specifically in chemotherapy optimisation, highlighting their role in balancing treatment efficacy and toxicity. It discusses popular tumour models for growth

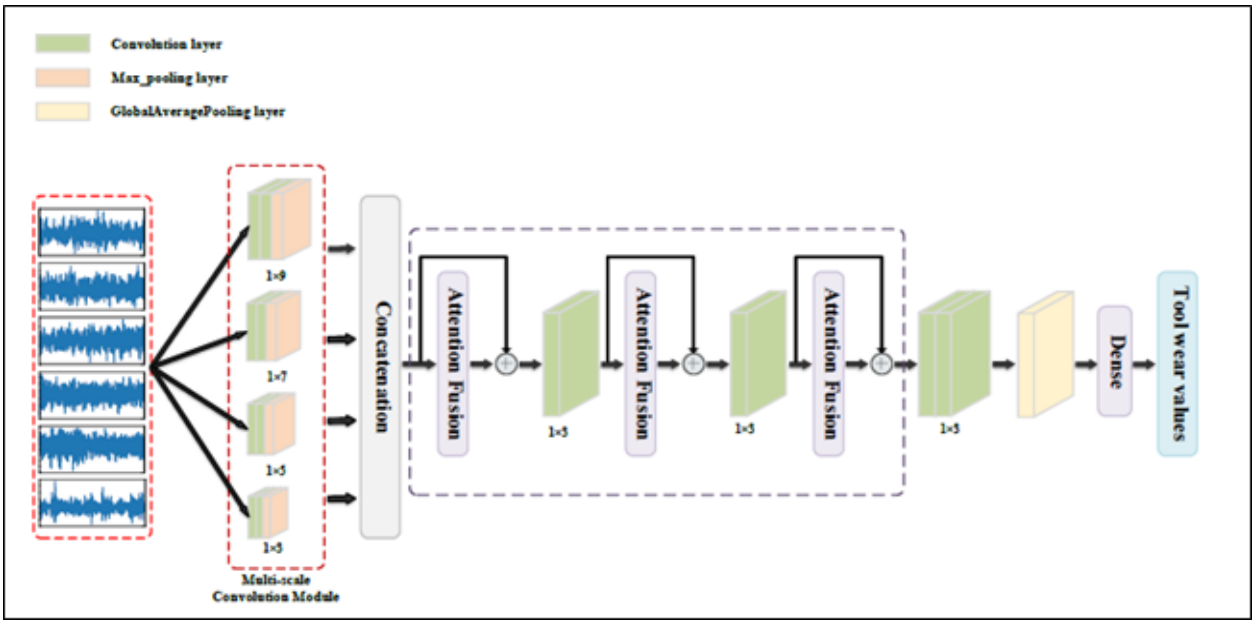


Figure 4. Network structure diagram of tool wear prediction[41].

description, outlines the requirements for multi-objective problem formulation, and identifies frequently used algorithms in this field.

4.0 Comparison of Product Quality

A Wearer Tool, due to its prolonged use, may exhibit signs of degradation such as blunting, surface roughness, and micro-cracks. These defects can lead to inconsistencies in the manufacturing process, affecting the dimensional accuracy and surface finish of the product. Studies have shown that the wear on tools can introduce variations in cutting forces, which in turn affect the stability of the machining process[48]. Additionally, the thermal properties of a worn tool may change, leading to increased heat generation and potential damage to the workpiece[49].

A Fresh Tool, on the other hand, is characterised by its pristine condition, with sharp edges and uniform surface properties. This ensures consistent performance in terms of cutting efficiency, dimensional accuracy, and surface finish. Research indicates that fresh tools provide better control over the machining process, resulting in higher-quality products with fewer defects[50]. The absence of wear also means that the tool maintains its thermal and mechanical properties, reducing the risk of workpiece damage[51].

The comparison of product quality between wearer tools and fresh tools reveals significant differences in various aspects of manufacturing performance. Fresh tools consistently produce parts with higher dimensional accuracy compared to wearer tools, primarily due to their uniform cutting edges and stable performance, which ensure precision in machining operations[52]. Additionally, products manufactured using fresh tools exhibit superior surface finish, as the sharp edges of the tool minimise surface irregularities, resulting in smoother and more refined outputs[53]. While fresh tools offer superior initial performance, their lifespan is inherently limited. In contrast, wearable tools, despite their degraded condition, can still be utilised for less critical operations, albeit with a higher risk of producing defective products[54]. From a cost perspective, the use of wearable tools may reduce tooling expenses in the short term. However, the potential for producing defective products can lead to increased costs associated with rework and scrap, offsetting any initial savings[55]. Furthermore, fresh tools contribute to greater process stability, reducing the likelihood of unexpected tool failures and production downtime, which is critical for maintaining efficient manufacturing

workflows[56]. Thermal management is another area where fresh tools outperform wearer tools. Fresh tools dissipate heat more effectively, minimising thermal damage to the workpiece, whereas wearer tools may cause localised overheating, potentially compromising the integrity of the product[57,58].

5.0 Conclusion

Artificial Intelligence (AI) has demonstrated significant potential in optimising turning operations by improving cutting forces, reducing vibrations, and enhancing surface roughness. The integration of AI with experimental and analytical methods provides a powerful approach to predict and control key machining parameters, leading to better process efficiency, higher product quality, and reduced costs. AI-based models, particularly Artificial Neural Networks (ANN), have been successfully applied in various studies to optimise machining conditions for diverse materials, making them valuable tools in modern manufacturing. Additionally, AI's ability to handle complex, nonlinear relationships in machining processes allows for real-time adjustments and predictive maintenance, ensuring more consistent and accurate outcomes. However, further advancements in AI techniques, particularly in terms of data quality, real-time monitoring, and hybrid models, will continue to enhance their applicability and effectiveness in turning operations. As AI technology evolves, its role in transforming machining processes will likely become even more critical, paving the way for smarter, more efficient manufacturing practices.

6.0 Challenges and Future Directions

The selection of appropriate kernel sizes for multi-scale feature extraction is crucial, as inappropriate choices can lead to information loss or redundant features. Additionally, the integration of attention mechanisms, as seen in some studies, adds complexity to the model but can enhance performance by focusing on relevant features. Future research should explore adaptive methods for selecting convolutional kernel sizes and further investigate the fusion of multi-sensor data, including cutting forces, vibrations, and acoustic emissions. Developing models that can generalise across different machining conditions and tool types will also be essential for broader industrial applications.

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8.0 References

1. Gouarir A, Kurokawa S, Sajima T, Murata M. In-process tool wear detection of uncoated square end mill based on electrical contact resistance. Int J Auto Technol. 2016; 10(5):767-72. https://doi.org/10.20965/ijat.2016.p0767
2. Lin SC, Yang RJ. Force-based model for tool wear monitoring in face milling. Int J Mach Tool Manuf. 1995; 35(9):1201-1211. https://doi.org/10.1016/0890-6955(94)00115-Z
3. Wilcox SJ, Reuben RL, Souquet P. The use of cutting force and acoustic emission signals for the monitoring of tool insert geometry during rough face milling. Int J Mach Tool Manuf. 1997; 37(4):481-494. https://doi.org/10.1016/S0890-6955(96)00069-7
4. Chen J. Development of in-process tool wear prediction systems in end milling operations with dynamometer, Dissertation, Iowa State University; 2003.
5. van Luttervelt CA, Childs THC, Jawahir IS, Klocke F, Venuvinod PK, Altintas Y, *et al.* Present situation and future trends in modelling of machining operations progress report of the CIRP working group Modelling of Machining Operations. CIRP Ann. 1998; 47(2):587-626. https://doi.org/10.1016/S0007-8506(07)63244-2
6. Chryssolouris G, Guillot M. A comparison of statistical and AI approaches to the selection of process parameters in intelligent machining. J Eng Ind. 1990; 112(2):122. https://doi.org/10.1115/1.2899554
7. Nalbant M, Gökkaya H, Toktaş İ, Sur G. The experimental investigation of the effects of uncoated, PVD- and CVD-coated cemented carbide inserts and cutting parameters on surface roughness in CNC turning and its prediction using artificial neural networks. Nat Prod Commun. 2009; 25(1):211-223. https://doi.org/10.1016/j.rcim.2007.11.004
8. O'zel T, Karpat Y. Predictive modeling of surface roughness and tool wear in hard turning using regression and neural networks, Int J Mach Tool Manuf.

2005; 45(4-5):467-479. https://doi.org/10.1016/j.ijmachtools.2004.09.007
9. Wins KLD, Varadarajan AS. Prediction of surface roughness during surface milling of hardened AISI4340 steel with Minimal cutting fluid application using Artificial Neural Network. Int J Adv Prod Eng Manag. 2012; 7(1):51-60. https://doi.org/10.14743/apem2012.1.130
10. Kumar CHRV, Ramamoorthy B. Performance of coated tools during hard turning under minimum fluid application, J Mat Process Technol. 2007; 185(1-3):210-216. https://doi.org/10.1016/j.jmatprotec.2006.03.148
11. Kumar CHRV, Nair PK, Ramamoorthy B. Performance of TiCN and TiAlN tools in machining hardened steel under dry, wet and minimum fluid application. Int J Mach Mach Mater. 2008; 3(1/2). https://doi.org/10.1504/IJMMM.2008.017630
12. Varadarajan AS, Philip PK, Ramamoorthy B. Investigations on Hard Turning with Minimal cutting Fluid application (HTMF) and its comparison with dry and wet turning. Int J Mach Tool Manuf. 2002; 42(2):193-200. https://doi.org/10.1016/S0890-6955(01)00119-5
13. Kumar A, Paswan MK. Optimization of surface topography for hard material machining with CNC end milling. Int J Inn Res Sci Eng Tech. 2014; 3(1):8889-8896.
14. Maher I, Eltaib MEH, Sarhan AAD, El-Zahry RM. Investigation of the effect of machining parameters on the surface quality of machined brass (60/40) in CNC end milling—ANFIS modeling. Int J Adv Manuf Technol. 2014; 74(1-4):531-537. https://doi.org/10.1007/s00170-014-6016-z
15. Karthikeyan R, Kumar VS, Punitha A, Chavan UM. An integrated ANN - GA approach to maximize the material removal rate and to minimize the surface roughness of wire cut EDM on titanium alloy. Adv Mat Process Technol. 2020; 8(1):22-32. https://doi.org/10.1080/2374068X.2020.1793267
16. Wenkler E, Arnold F, Hänel A, Nestler A, Brosius A. Intelligent characteristic value determination for cutting processes based on machine learning, Procedia CIRP. 2019; 79:9-14. https://doi.org/10.1016/j.procir.2019.02.003
17. Bergs T, Holst C, Gupta P, Augspurger T. Digital image processing with deep learning for automated cutting tool wear detection. Procedia Manuf. 2020; 48:947-958. https://doi.org/10.1016/j.promfg.2020.05.134
18. Cui Z, Wenlin C, Yixin C. Multi-scale convolutional neural networks for time series classification. arXiv. 2016.
19. Li T, Yu Y, Huang C, Yang J, Zhong Y, Hao Y. Method for predicting cutter remaining life based on multi-scale cyclic convolutional network. Int J Dist Sensor Net. 2022; 18(5):155013292211020. https://doi.org/10.1177/15501329221102077
20. Xu W, Miao H, Zhao Z, Liu J, Sun C, Yan R. Multi-scale convolutional gated recurrent unit networks for tool wear prediction in smart manufacturing. Chin J Mech Eng. 2021; 34:53. https://doi.org/10.1186/s10033-021-00565-4
21. Zhu J, Chen N, Peng W. Estimation of bearing remaining useful life based on multiscale convolutional neural network. In IEEE Transactions on Industrial Electronics. 2019; 66:3208-3216. https://doi.org/10.1109/TIE.2018.2844856
22. Jiang Y, Lyu Y, Wang Y, Wan P. Fusion network combined with bidirectional LSTM network and multiscale CNN for remaining useful life estimation. 2020 12th International Conference on Advanced Computational Intelligence (ICACI); 2020; p. 620-627. https://doi.org/10.1109/ICACI49185.2020.9177774
23. Sadeghi N, Mahdavi-Nasab H, Zeinali M, Pourghasem H. Comparing the semantic segmentation of high-resolution images using deep convolutional networks: SegNet, HRNet, CSE-HRNet and RCA-FCN. J Inf Sys Telecomm. 2023; 11(44):359-367. https://doi.org/10.61186/jist.39680.11.44.359
24. Hu H, Wang X, Li T. Infrared and visible image fusion method based on Full Convolutional Network (FCN). J Intell Fuzzy Sys. 2023; 46(1):2825-2834. https://doi.org/10.3233/JIFS-236094
25. Yang H. Efficiency in constraint: A comparative analysis review of FCN and DeepLab models on small-scale datasets. Appl Computat Eng. 2024; 75(1):19-30. https://doi.org/10.54254/2755-2721/75/20240501
26. He K, Zhang X, Ren S, Sun J. Spatial pyramid pooling in deep convolutional networks for visual recognition. IEEE Trans Pattern Anal Mach Intell. 2015; 37(9):1904-1916. https://doi.org/10.1109/TPAMI.2015.2389824 PMid:26353135
27. Zhang H, Jiang S, Gao D, Sun Y, Bai W. A Review of Physics-Based, Data-Driven, and Hybrid Models for Tool Wear Monitoring. Machines. 2024;12(12):833.
28. Lee J, Ni J, Singh J, Jiang B, Azamfar M, Feng J. Intelligent maintenance systems and predictive manufacturing. J. Manuf Sci Eng. 2020 Nov 1;142(11):110805.

29. Kumar R, Sharma A. Predictive models for tool life based on machine learning techniques in CNC machining. J Manufact Proc. 2019; 40:153-161.
30. Srivastava AK, Srivastava, Gupta S. Prediction of tool wear using machine learning approaches for machining on lathe machine. EVERGREEN Joint Journal of Novel Carbon Resource Sciences and Green Asia Strategy. 2023; 10(03):1357-1365.
31. Yang P, Guo Z, Kong Y. Plane kinematic calibration method for industrial robot based on dynamic measurement of double ball bar. Precision Engineering. 2020; 62:265-272. https://doi.org/10.1016/j.precisioneng.2019.12.010
32. Ghorbani M, Movahhedy MR. Extraction of surface curvatures from tool path data and prediction of cutting forces in the finish milling of sculptured surfaces. J Manuf Process. 2019; 45:273-289, https://doi.org/10.1016/j.jmapro.2019.07.008
33. Yang J, Roa JJ, Odén M, Johansson-Jõesaar MP, Llanes L. 3D FIB/FESEM tomography of grinding-induced damage in WC-Co cemented carbides. Procedia CIRP. 2020; 87:385-390. https://doi.org/10.1016/j.procir.2020.02.070
34. Zhang F, Xu F, Zhou X, Ding K, Shao S, Du C, Leng J. Data-driven and knowledge-guided prediction model of milling tool life grade. Int J Comput Integr Manuf. 2024; 37(6):669-84.
35. Zhang Y, Xu X. Machine learning cutting force, surface roughness, and tool life in high speed turning processes. Manufacturing Letters. 2021; 29:84-9.
36. Patange AD, Jegadeeshwaran R, Bajaj NS, Khairnar AN, Gavade NA. Application of machine learning for tool condition monitoring in turning. Sound Vib. 2022; 56(2):127–145. https://doi.org/10.32604/sv.2022.014910
37. Chen N, Li HN, Wu J, Li Z, Li L, Liu G, He N. Advances in micro milling: From tool fabrication to process outcomes. Int J Mach Tools Manuf. 2020; 160. https://doi.org/10.1016/j.ijmachtools.2020.103670
38. Soori M, Arezoo B, Dastres R. Machine learning and artificial intelligence in CNC machine tools, a review. Sustainable Manufacturing and Service Economics. 2023; 2:100009. https://doi.org/10.1016/j.smse.2023.100009
39. Sotubadi SV, Liu R, Neguyen V. Explainable ai for tool wear prediction in turning. arXiv preprint arXiv:2308.08765. 2023 Aug 17.
40. Hao C, Mao X, Ma T, He S, Li B, Liu H, Peng F, Zhang L. A novel deep learning method with partly explainable: Intelligent milling tool wear prediction model based on transformer informed physics. Advanced Engineering Informatics. 2023; 57. https://doi.org/10.1016/j.aei.2023.102106
41. Huang Q, Wu D, Huang H, Zhang Y, Han Y. Tool wear prediction based on a multi-scale convolutional neural network with attention fusion. Information. 2022; 13(10):504. https://doi.org/10.3390/info13100504
42. Li J, Zhou K, Zhang H. Deep learning approach integrating cutting conditions for tool wear prediction. ArXiv preprint arXiv:2407.01199. 2024.
43. Cao X, Chen B, Yao B, Zhuang S. An intelligent milling tool wear monitoring methodology based on convolutional neural network with derived wavelet frames coefficient. Applied Sciences. 2019; 9(18):3912.
44. Jianfei D. Feature-based tool condition monitoring for milling, Lee SY. In-process tool condition monitoring systems in CNC turning operations. Iowa State University; 2004.
45. Sick, B. Online and indirect tool wear monitoring in turning with artificial neural networks: A review of more than a decade of research. Mech Sys Signal Process. 2002; 16(4):487-546. https://doi.org/10.1006/mssp.2001.1460
46. Al-Habaibeh A, Gindy NN. A new approach for systematic design of condition monitoring systems for milling processes. J Mat Process Technol. 2000; 107(1-3):243-251. https://doi.org/10.1016/S0924-0136(00)00718-4
47. Segreto T, Doriana D'Addona, Teti R. Tool wear estimation in turning of Inconel 718 based on wavelet sensor signal analysis and machine learning paradigms. Prod Eng. 2020; 14(5-6):693-705. https://doi.org/10.1007/s11740-020-00989-2
48. Chiou YS, Chung ES, Liang SY. Analysis of tool wear effect on chatter stability in turning. International Journal of Mechanical Sciences. 1995; 37(4):391-404.
49. Wang JY, Liu CR, Wang KK. The effect of tool flank wear on the heat transfer, thermal damage and cutting mechanics in finish hard tuning. CIRP annals. 1999; 48(1):53-8.
50. Zhang X, Peng Z, Li Z, Sui H, Zhang D. Influences of machining parameters on tool performance when high-speed ultrasonic vibration cutting titanium alloys. Journal of Manufacturing Processes. 2020; 60:188-99.
51. Rodriguez A, Yanamandra K, Witek L, Wang Z, Behera RK, Iovita R. The effect of worked material hardness on stone tool wear. Plos One. 2022; 17(10):e0276166.

52. Yousefi S, Zohoor M. Experimental studying of the variations of surface roughness and dimensional accuracy in dry hard turning operation. The Open Mechanical Engineering Journal. 2018; 12(1):175-91.
53. Sata T, Li M, Takata S, Hiraoka H, Li CQ, Xing XZ, Xiao XG. Analysis of surface roughness generation in turning operation and its applications. CIRP annals. 1985; 34(1):473-6.
54. Iqbal A, Al-Ghamdi KA, Hussain G. Effects of tool life criterion on sustainability of milling. Journal of Cleaner Production. 2016; 139:1105-17.
55. Kim DM, Kim HI, Park HW. Tool wear, economic costs, and CO_2 emissions analysis in cryogenic assisted hard-turning process of AISI 52100 steel. Sustainable Materials and Technologies. 2021; 30:e00349.
56. Hajdu D, Insperger T, Stepan G. Robust stability analysis of machining operations. The International Journal of Advanced Manufacturing Technology. 2017; 88:45-54.
57. Yang Y, Bilgin B, Kasprzak M, Nalakath S, Sadek H, Preindl M, Cotton J, Schofield N, Emadi A. Thermal management of electric machines. IET Electrical Systems in Transportation. 2017; 7(2):104-16.
58. Pawar DM, Jagtap HP. Development of thermographic image-based tool wear monitoring system: A literature review. J Mine Metal Fuel. 2025; 73(3):621-635. https://informaticsjournals.co.in/index.php/jmmf/article/view/47464