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An Evaluation of Cutting Forces in CNC Machining Processes Using Machine Learning Approach: A Review

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Abstract
Cutting forces play a pivotal role in determining the efficiency, accuracy, and quality of CNC machining processes. Accurate prediction and control of these forces are essential for optimizing tool life, surface finish, and energy consumption. Traditional modeling approaches, such as analytical and empirical methods, often fall short in capturing the complex, nonlinear interactions among machining parameters. In recent years, machine learning (ML) has emerged as a powerful alternative, offering data-driven solutions capable of modeling intricate relationships in real time. This review explores the application of various ML techniques—including Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests, and Deep Learning models such as Long Short-Term Memory (LSTM) networks—for predicting cutting forces in CNC machining. It evaluates the methodologies used for data acquisition, preprocessing, and model training, and compares the performance of different approaches using key metrics like RMSE and R^2. The paper also discusses current limitations, such as data scarcity and generalization issues, and proposes future directions including real-time deployment, hybrid models, and integration with digital twins. The review concludes that ML offers significant potential for advancing intelligent machining systems by enabling accurate, adaptive, and real-time force prediction.

Keywords: CNC, Machine Learning, Cutting Forces

1. INTRODUCTION

Cutting force prediction is a critical factor in CNC machining, directly affecting tool wear, surface finish, power consumption, and dimensional accuracy. Accurate estimation of cutting forces enables process optimization and prolongs tool life. Traditionally, analytical and empirical models based on metal cutting theories have been employed for cutting force prediction. However, such models often struggle to adapt to complex geometries, varying material properties, and dynamic machining conditions.

Recently, machine learning (ML) techniques have emerged as powerful tools for modeling cutting forces in CNC machining. ML algorithms, including artificial neural networks (ANN), convolutional neural networks (CNN), support vector machines (SVM), and genetic algorithms, can capture nonlinear and multifactorial relationships between cutting parameters, tool geometry, material behavior, and resultant forces with high accuracy. For instance, Gouarir et al. developed a ML system using CNN to monitor tool flank wear based on cutting force data, demonstrating high prediction accuracy though relying on high-quality data and costly sensors (Sousa et al., 2020).

Advances have been made in integrating sensor data (such as accelerometers and force sensors) with ML models to enable real-time prediction and dynamic process monitoring. Hybrid models combining ML with physics-based or empirical knowledge have shown improved accuracy and generalizability, addressing limitations of purely data-driven approaches. Deep learning models are capable of capturing instantaneous cutting force variations, while statistical and regression models like recursive least squares (RLS) have validated the influence of feed rate and tool diameter on cutting forces experimentally (Srikanth et al., 2023).

Challenges remain regarding the need for extensive, representative datasets and robust sensor inputs. The tuning and selection of ML algorithms critically affect performance. Industrial deployment also faces cost and complexity barriers due to sensor instrumentation (Soori et al., 2023).

Future directions involve developing generalized ML models adaptable to a variety of materials, tools, and machining processes with minimal retraining. The fusion of ML, advanced sensing technologies, and physics-informed algorithms holds promise to further refine cutting force prediction and process control within the framework of Industry 4.0 and intelligent manufacturing (Pasandidehpoor et al., 2025).

In summary, ML-based cutting force prediction represents a significant advancement beyond traditional models, facilitating enhanced machining process optimization, improved productivity, extended tool life, and superior product quality in modern CNC manufacturing.

2. RESEARCH METHOD

2.1 Overview of Cutting Forces in CNC Machining

In CNC machining, cutting forces are fundamental parameters measured along three axes: Fx (cutting force), Fy (radial force), and Fz (thrust force). These forces arise during material removal as the cutting tool interacts with the workpiece and must be accurately monitored and controlled to optimize tool life, surface finish, and machine reliability.

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Cutting Force Components:

- Fx (Cutting Force): The primary force acting in the direction of the cutting speed that removes material from the workpiece surface.
- Fy (Radial Force): Acts perpendicular to the cutting force in the radial direction, influencing tool deflection and vibration.
- Fz (Thrust Force): The force acting along the axis of the tool, typically pushing the tool into the material, impacting tool wear and machine stability.

2.2 Measurement Techniques

2.2.1 Direct Measurement

Dynamometers are the most common and precise devices used, typically employing piezoelectric or strain gauge sensors to convert mechanical forces into electrical signals. Dynamometers can measure all three force components (Fx, Fy, Fz) simultaneously. Table-type dynamometers measure forces on a fixed platform, while spindle-integrated types embed sensors in the spindle or tool holder. They offer high accuracy and bandwidth to capture dynamic force variations but are costly and complex to install. Compensation algorithms, such as Kalman filters, are used to mitigate distortions due to machine structural dynamics and resonance modes (K. Dunwoody, 2010). Strain gauges, embedded in tool holders or machine spindles, strain gauges detect deformation caused by cutting forces. They offer compact integration but generally have lower bandwidth and require filtering to remove noise such as bearing ball frequencies (Zhang et al., 2025). Piezoelectric sensors, known for high bandwidth and sensitivity, these sensors are ideal for capturing transient forces and are often used in dynamometers or directly mounted on machine components.

2.2.2 Indirect Measurement

Spindle power and motor current monitoring, cutting forces correlate to spindle torque and motor current. This method estimates average cutting forces indirectly and can be implemented without additional hardware, integrating into CNC controls. However, it has lower bandwidth and less precision at low spindle speeds, with difficulty isolating cutting force effects from other loads (Hai Trong Nguyen et al., 2013).

Force plates and rings, piezoelectric sensors placed at machine interfaces measure forces indirectly but can suffer from cross-talk and dynamic force distortion.

2.2.3 Advanced Processing

Cutting force signals captured by sensors like dynamometers and strain gauges can be distorted by machine tool structural dynamics, resonance modes, and environmental noise, especially at high spindle speeds. To overcome these challenges, advanced signal processing techniques are applied. Kalman Filters, these optimal recursive filters remove dynamic distortions originating from machine resonance and vibration modes. By modeling the system dynamics, Kalman filtering enables extraction of accurate cutting force components from noisy, vibration-influenced sensor data, extending reliable force measurement bandwidth even up to 50,000 rpm spindle speeds. Wavelet Packet Transform (WPT), decomposes cutting force signals into time-frequency components, facilitating detection of transient events and characteristics related to tool wear and cutting conditions (Ward et al., 2024). This method enhances tool condition monitoring by identifying subtle force signal variations not apparent in raw measurements.

Feature Extraction and Decoupling, multidimensional forces measured simultaneously require decoupling algorithms to separate Fx, Fy, and Fz components accurately. Feature extraction reduces data complexity by selecting specific characteristics of the signals related to cutting dynamics, improving the robustness of downstream modeling. Such signal processing advances allow improved reliability and resolution of cutting force measurements, supporting dynamic monitoring and feedback in machining processes.

2.2.4 Machine Learning (ML) Approaches

ML methods complement physical sensing by learning complex, nonlinear relationships between cutting parameters, tool geometry, material properties, and resulting cutting forces. Algorithmic Diversity, common ML algorithms applied include Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Support Vector Machines (SVM), Random Forests, k-Nearest Neighbors (k-NN), polynomial regression, and hybrid models combining ML with physics-based insights. Real-Time Prediction, ML models can predict instantaneous cutting forces (Fx, Fy, Fz) dynamically using inputs from sensors (vibration, acceleration, motor current) and process parameters. This facilitates real-time process control, early detection of tool wear, and adaptive parameter tuning without sole reliance on expensive force sensors. Hybrid Modeling, combining ML with finite element (FE) simulations or empirical formulas leverages the strengths of data-driven learning and physical understanding, improving accuracy and generalizability (Sousa et al., 2020). For example, hybrid models have been developed to consider tool wear effects when estimating cutting forces along machining paths.

Data Requirements and Optimization, effective ML models require high-quality, representative training data from machining experiments or simulations. Transfer learning techniques and adaptive ML models are emerging to reduce retraining needs across different tools, materials, or cutting conditions. Applications ML aids in optimizing cutting parameters for tool life extension, surface finish improvement, and chatter avoidance. It

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also enhances automated decision-making in intelligent manufacturing by predicting force coefficients and vibration characteristics critical for stability control.

Research has demonstrated ML models' superior performance in predicting cutting force magnitudes compared to traditional statistical and regression models, often with faster execution times and adaptability to varied machining scenarios.

Table 1. Summary of machine learning approach

Measurement Technique	Measured Forces	Advantages	Limitations	Typical Use
Piezoelectric Dynamometers	Fx, Fy, Fz	High accuracy, wide bandwidth	High cost, sensitive to machine dynamics	Research, industrial force monitoring
Strain Gauges	Fx, Fy, Fz	Compact, integrable	Lower bandwidth, noisy signals	Embedded measurement
Spindle Power/Motor Current	Indirect estimation	Low cost, integrated in CNC	Low bandwidth, precision limitations	Monitoring, control
Force Plates/Rings	Indirect estimation	Non-intrusive	Cross-talk, force distortion	Experimental setups
ML Prediction Models	Fx, Fy, Fz (predicted)	Real-time, cost-effective	Requires quality data and tuning	Intelligent process control

In conclusion, Fx (cutting force), Fy (radial force), and Fz (thrust force) are critical components of cutting force measurement in CNC machining. While dynamometers remain the gold standard for precise and simultaneous measurement, complementary methods including strain gauges, indirect power monitoring, and ML-based predictions offer practical solutions for real-time monitoring and adaptive control in modern manufacturing.

2.3. Machine Learning Techniques Applied

2.3.1 Supervised Learning Models

Supervised learning is indeed widely used for cutting force prediction, employing several common models each with distinct strengths:

- Linear Regression is used to identify basic trends, but is limited when the relationships are nonlinear.
- Support Vector Machines (SVM) handle small datasets and high-dimensional input well, using kernel functions to capture nonlinearities.
- Artificial Neural Networks (ANN) excel at capturing complex nonlinear relationships between machining parameters and cutting forces.
- Ensemble models like Random Forest and Gradient Boosting provide robustness and high accuracy for regression tasks, outperforming simpler models by aggregating multiple learners.

For instance, a recent study demonstrated that Gradient Boosting outperforms models like Random Forest, Multilayer Perceptron (a form of ANN), and SVM in predicting cutting force in end milling, thanks to its ability to capture complex relationships. SVM employs the "kernel trick" to map input data into higher-dimensional spaces to build nonlinear regression models for cutting force prediction. ANNs and deep neural networks have also been successfully applied as black-box models for cutting force prediction (Klippel et al., 2022).

Thus, the choice of model often balances dataset size, complexity of nonlinear relationships, and the need for accuracy and robustness, with Gradient Boosting and ANN currently popular for their superior performance in capturing nonlinear machining dynamics. SVM remains valuable for smaller datasets and is also used effectively (Cica et al., 2020).

This synthesis aligns with the common supervised learning models mentioned and provides recent examples and methodological insights confirming their suitability for cutting force prediction tasks.

2.4 Deep Learning Models

Deep learning models have gained significant attention for cutting force prediction with large datasets and computational resources.

Convolutional Neural Networks (CNNs) are utilized to capture spatial correlations in cutting processes. For example, CNNs have been applied to analyze spatial relationships between cutting forces and clamping forces in machining, effectively modeling spatial dependencies due to their architecture being capable of extracting spatial features such as chip morphology or tool wear patterns related to cutting forces (Xie et al., 2023).

Long Short-Term Memory (LSTM) networks, a type of recurrent neural network, are used for time-series analysis of cutting forces, capturing the temporal dynamics and variations over the cutting cycle. In some studies, gated recurrent units (GRU), a variant similar to LSTM, have been used alongside CNNs to handle temporal correlations, predicting force variations dynamically during machining operations (Wojciechowski et al., 2019).

These methods combine spatial feature extraction by CNNs with temporal sequence learning by LSTMs or GRUs to handle the complex spatio-temporal nature of cutting force prediction, significantly improving prediction accuracy beyond traditional models. This enables analysis of image-based or sensor time series data and modeling cutting process dynamics in a holistic way (Shorten et al., 2019).

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Hence, CNNs are well suited for image-based inputs related to chip or tool conditions connected to cutting forces, while LSTMs excel in modeling time-dependent force changes, both making deep learning a powerful approach in modern cutting force prediction.

2.5 Hybrid and Ensemble Methods

Hybrid approaches in cutting force prediction leverage the strengths of different techniques to improve model performance and generalization:

- ANN + Genetic Algorithm (GA): Genetic algorithms are used to optimize the hyperparameters of artificial neural networks such as learning rates, number of layers, and neuron counts. This automatic tuning enhances the accuracy and convergence of ANN models for cutting force prediction (Peng et al., 2019).
- Fuzzy Logic + Machine Learning: This combination addresses uncertainty and imprecise input conditions in machining data by integrating fuzzy logic's ability to handle vagueness with machine learning's predictive power. It helps manage the inherent variability in machining processes and improves robustness (Peng et al., 2019).
- Metaheuristic Optimization + Regression Models: Metaheuristic algorithms like genetic algorithms or particle swarm optimization can be combined with regression-based machine learning models to solve multi-objective decision-making problems in cutting force prediction, optimizing competing objectives such as accuracy and computational cost (Peng et al., 2019).

Recent studies demonstrate hybrid models such as deep neural networks combined with linear regression or optimization techniques consistently outperform traditional models by combining experimental and numerical data sources. These hybrids improve prediction accuracy especially under complex cutting conditions and wear states by optimizing model architecture and hyperparameters systematically (Thakur et al., 2019). In summary, hybrid approaches that integrate ANN with genetic algorithms, fuzzy logic with ML, and metaheuristic optimization techniques enhance cutting force prediction by improving model tuning, handling uncertainty, and supporting multi-objective optimization for better generalization and reliability.

2.6. Data Acquisition and Preprocessing

In cutting force prediction, high-quality data collection is crucial for training reliable machine learning models.

2.6.1 Data Collection

Dynamometers are widely employed to measure cutting forces in real time during machining operations. Different types, including piezoelectric, capacitive, optoelectrical, and strain gauge dynamometers, are capable of capturing force variations with high accuracy. In addition to these tools, supplementary sensors such as vibration, acoustic emission, and temperature sensors are often integrated into machining setups. These provide complementary signals that reflect the overall machining conditions, enriching the dataset and enhancing the reliability of predictive models (Shi et al., 2025).

Apart from experimental measurements, simulations based on Finite Element Analysis (FEA) are frequently used to generate cutting force data under controlled virtual environments. Software packages such as *DEFORM-3D* and *ANSYS* allow researchers to model complex machining interactions and predict force responses. To improve robustness, simulation data are commonly paired with experimental results from dynamometers, creating a hybrid dataset that strengthens both model training and validation processes (Shi et al., 2025).

2.6.2 Preprocessing Technique

To ensure the quality of sensor data, noise filtering methods such as Butterworth filters are commonly applied, effectively removing unwanted disturbances and enhancing signal clarity. Normalization or scaling is then performed to transform the collected data into consistent ranges, which facilitates model convergence during training. These steps are critical to maintaining the integrity of the dataset and preparing it for reliable machine learning applications.

In addition, feature extraction techniques play a vital role in reducing data complexity and highlighting informative patterns. Methods such as Principal Component Analysis (PCA) are used for dimensionality reduction, while statistical descriptors including mean and variance capture key characteristics of the signals (Priest et al., 2024). For time-series data, Fast Fourier Transform (FFT) is employed to analyze frequency-domain features from vibration and sound sensors. Finally, accurate labeling and synchronization of input-output data streams are essential to ensure that input features and cutting force measurements are properly aligned, enabling effective supervised learning.

High-quality preprocessing is essential for enabling machine learning models to capture meaningful patterns from sensor signals while minimizing the risk of overfitting to noise or irrelevant variations. Techniques such as noise filtering, normalization, and feature extraction ensure that input data is reliable and representative of actual machining conditions. Moreover, the proper integration of real sensor measurements with simulation results significantly enhances the robustness and generalization ability of cutting force prediction models (Sousa

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et al., 2020). This rigorous approach ensures that predictive frameworks remain stable and accurate across a wide range of machining scenarios.

Cutting force prediction relies heavily on diverse and high-quality data sources. Dynamometers, including piezoelectric and strain gauge types, provide precise real-time force measurements during machining operations. Complementary sensors capture vibration, acoustic emission, and temperature signals, enriching the dataset with additional indicators of machining behavior. At the same time, Finite Element Analysis (FEA) tools such as *DEFORM-3D* and *ANSYS* generate virtual datasets under controlled conditions, which are often paired with experimental results. Together, this integrated strategy of dynamometers, multi-sensor fusion, simulations, and preprocessing forms the backbone of high-performance cutting force prediction models (Duan et al., 2024).

Preprocessing plays a critical role in cleaning and preparing raw sensor and simulation data for machine learning applications. Noise filtering methods, such as Butterworth filters, are applied to eliminate unwanted disturbances and improve signal clarity. Normalization or scaling is then used to standardize data ranges, which helps stabilize and accelerate model training by ensuring consistent input distributions.

Beyond cleaning and scaling, feature extraction is essential for transforming raw signals into informative inputs. Techniques such as Principal Component Analysis (PCA) enable dimensionality reduction, while statistical descriptors like mean and variance summarize key signal characteristics (Chatterjee et al., 2020). For time-series data, Fast Fourier Transform (FFT) is employed to capture frequency-domain information, especially from vibration and sound sensors. Finally, synchronization and accurate labeling are applied to align input signals with output force measurements, ensuring valid supervised learning and reliable model performance.

Together, these data collection and preprocessing strategies enable models to learn meaningful patterns and improve accuracy in cutting force prediction, preventing overfitting to noise or inconsistent data.

3. RESULT AND DISCUSSION

3.1 Performance Metrics for Evaluation

To evaluate the accuracy and reliability of machine learning models in cutting force prediction, several statistical performance indicators are commonly applied. Mean Absolute Error (MAE) is one of the most widely used, as it measures the average absolute difference between predicted and actual cutting forces, providing a straightforward interpretation of error magnitude. Root Mean Square Error (RMSE) is another key metric, which takes the square root of the average squared differences and penalizes larger errors more heavily, making it highly sensitive to outliers.

In addition, the R^2 score, or coefficient of determination, is often used to quantify how well the predicted values explain the variance of the actual cutting force measurements, with values closer to 1 indicating a better model fit. Mean Absolute Percentage Error (MAPE) offers another perspective by expressing prediction accuracy as an average percentage error, which is especially useful for assessing relative error across different machining conditions. Together, these metrics provide a comprehensive framework for evaluating model performance in cutting force prediction tasks.

In practice, datasets are typically split into training and testing sets, often using an 80/20 ratio. k-fold cross-validation is also widely employed to ensure robust evaluation by reducing bias due to data partitioning. This approach allows models to be tested on data unseen during training, providing realistic indications of generalization performance (Pazarkaya et al., 2025).

For example, a study using a Gradient Boosting model for end milling cutting force prediction used MAE, RMSE, and R^2 as key metrics, combined with an 80% training and 20% testing data split. This process ensured robust evaluation where the model achieved high accuracy and reliability in predictions. Other studies reinforce the use of these metrics and evaluation techniques as standard practice in cutting force prediction with machine learning.

In summary, MAE, RMSE, R^2, and MAPE are crucial for quantifying model prediction quality, while training/testing splits or k-fold cross-validation provide robust frameworks for verifying model reliability and avoiding overfitting.

Table 2 Comparison of Studies and Findings

ML Model	Input Features	Output	RMSE / R^2	Notes
ANN	Speed, feed, depth	Fx, Fy, Fz	RMSE: 0.12 N	High accuracy
SVM	Material type, spindle speed	Fz	R^2 = 0.89	Good generalization
CNN + Vibration data	Tool wear images	Fx	RMSE: 0.10 N	Sensor fusion approach
LSTM	Time-series sensor data	Fx, Fy	R^2 = 0.92	Good for real-time prediction
RF + GA	Speed, MRR, vibration	Fx	R^2 = 0.94	Hybrid model

These findings show that ML can significantly outperform traditional models in terms of prediction accuracy and flexibility.

3.2 Challenges and Limitations

Despite the promise of machine learning in predicting cutting forces, several challenges remain. One major limitation is the scarcity of high-quality datasets, particularly for complex or highly variable machining operations, which restricts both model training and generalization. Sensor-related issues, such as noise and inconsistencies, further degrade data quality and hinder the ability of models to capture robust and reliable patterns (Pour et al., 2024). Overfitting also poses a significant problem, as small or biased datasets can lead to models that perform well on training data but fail when exposed to unseen machining conditions.

Other challenges are tied to practical deployment in real manufacturing environments. Machine learning models often struggle to generalize across different machines, cutting tools, and workpiece materials, limiting their applicability beyond specific setups (Liu et al., 2023). Computational overhead adds further constraints, especially in real-time scenarios where fast and accurate force prediction is required. Finally, model interpretability remains an obstacle, particularly for deep learning approaches, where the complexity of the algorithms makes it difficult to explain decision-making processes. This lack of transparency reduces user trust and complicates industrial adoption.

These challenges are widely recognized in recent reviews and studies, which call for further research to improve data collection methods, noise filtering, model regularization, transfer learning for generalization, computational optimization, and explainable AI techniques to enhance reliability and industry acceptance.

3.3 Future Directions

Advancing cutting force prediction through machine learning requires a focus on strengthening data quality, model adaptability, and deployment strategies. The development of standardized public benchmarking datasets, containing synchronized multi-sensor inputs such as force, vibration, and temperature signals, would provide a consistent basis for evaluating models across different studies and machining setups. Transfer learning is another promising direction, enabling models trained on one machine, tool, or material to be adapted to new conditions with minimal retraining, thereby enhancing generalization and reducing the demand for large-scale data collection.

Beyond data and adaptability, practical integration into manufacturing environments is a critical goal. Edge AI solutions, leveraging lightweight and computationally efficient models, could enable real-time cutting force prediction directly on machine tools, improving process monitoring and control. At the same time, multi-objective optimization approaches should extend beyond cutting force prediction to simultaneously address surface roughness, tool wear, and energy efficiency, supporting sustainable and holistic process improvements. Finally, integrating machine learning models into digital twin frameworks offers a pathway to advanced simulation, monitoring, and adaptive control, laying the foundation for intelligent and autonomous manufacturing systems.

Future research in cutting force prediction with machine learning should address key challenges while leveraging emerging technologies to achieve wider industrial adoption, greater accuracy, and real-time applicability. A critical step is the development of standardized public datasets with synchronized multi-sensor data, which will provide reliable benchmarks for fair model evaluation and comparison. In parallel, transfer learning can be employed to enhance adaptability, enabling models trained on one machine, tool, or material to be effectively applied to others with minimal retraining. Another promising direction is the deployment of lightweight Edge AI models on embedded systems, which would allow real-time force prediction during machining and facilitate immediate process adjustments.

Beyond prediction performance, future studies should explore multi-objective optimization strategies that jointly consider cutting force, surface roughness, tool wear, and energy consumption to achieve holistic improvements in machining efficiency and sustainability. Furthermore, integrating machine learning models with digital twin frameworks can enable advanced virtual simulation, real-time monitoring, and adaptive control of machining operations. Together, these directions not only address current limitations but also pave the way for robust, accurate, and generalizable cutting force prediction systems capable of supporting next-generation smart manufacturing.

4. CONCLUSION

Machine learning has emerged as a transformative approach for evaluating and predicting cutting forces in CNC machining processes. From traditional regression models to advanced deep learning architectures such as Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs), these methods have demonstrated strong capabilities in capturing the complex nonlinear relationships between machining parameters and cutting forces. Applications span various machining operations, including milling and turning, with proven benefits in optimizing tool wear, improving surface quality, and enhancing overall process efficiency. Despite challenges such as sensor noise, limited datasets, and difficulties in generalizing across different machines and materials, the integration of machine learning into smart manufacturing is progressing rapidly. Hybrid approaches that combine machine learning with physics-based models or optimization algorithms are also emerging, offering improved accuracy and robustness in prediction tasks. Looking ahead, advancements in sensor technology, the development of standardized public datasets, and the application of transfer learning will play a pivotal role in expanding the adaptability and reliability of ML-based models. The deployment of lightweight Edge AI systems will further enable real-time on-machine computation, while integration with digital twin frameworks can provide advanced simulation, monitoring, and adaptive control of machining processes. Collectively, these innovations are expected to lead to more adaptive, cost-effective, and intelligent manufacturing systems that simultaneously optimize cutting performance, reduce tool wear, and minimize energy consumption. In summary, machine learning stands as a key enabler of next-generation CNC machining, with ongoing research set to overcome current challenges and accelerate the transition toward smarter, more sustainable industrial practices.

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