

A Review on Machine Learning in Machining Process

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ABSTRACT

Machine learning (ML) and artificial intelligence (AI) have emerged as transformative technologies in modern manufacturing, particularly in optimizing and monitoring machining processes. This comprehensive review examines the state-of-the-art applications of machine learning techniques in various machining operations including milling, turning, grinding, and drilling. The paper discusses fundamental ML algorithms such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest (RF), and advanced deep learning architectures including Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. Key applications reviewed include tool wear prediction, surface roughness prediction, cutting force estimation, machining parameter optimization, and real-time process control. The integration of sensor data, Internet of Things (IoT), and Industry 4.0 frameworks with ML algorithms has enabled predictive maintenance, reduced production downtime, and improved product quality. This review consolidates recent research developments from 2019 to 2025, identifies current research gaps, and proposes future research directions in ML-enabled intelligent machining systems. The paper emphasizes the practical implementation challenges, data requirements, and opportunities for hybrid ML approaches in smart manufacturing environments.

Keyword: Machine Learning, Machining Processes, Tool Wear Prediction, Deep Learning, CNC Optimization, Industry 4.0

1. INTRODUCTION

1.1. Background and Motivation

Machining is one of the most important manufacturing processes used to produce precision components in industries such as automotive, aerospace, medical devices, and consumer electronics. Conventional machining mainly depends on empirical knowledge, operator experience, and fixed parameter settings. This approach often results in less efficient performance, higher tool wear, longer production time, and increased manufacturing cost. With the advancement of the fourth industrial revolution (Industry 4.0), there is a growing need for intelligent manufacturing systems. These systems should be able to adjust to changing production conditions, predict equipment failures in advance, and continuously improve process parameters. In this situation, machine learning has become an effective solution because it can analyze large amounts of sensor data generated during machining processes and extract useful information.

Machine learning helps in developing data-driven models that can:

- Predict tool wear and estimate remaining useful life
- Estimate surface roughness and dimensional accuracy
- Optimize cutting parameters for different materials
- Monitor the machining process condition in real time
- Adjust machining strategies automatically based on data
- Reduce energy consumption and operational cost
- Prevent tool breakage and major failures

1.2. Significance and Scope:

The application of ML in machining processes has shown significant improvements in productivity, product quality, and overall cost efficiency. Recent research indicates that ML-based tool wear prediction models can reduce unexpected tool failures by nearly 80%. In addition, surface roughness prediction models developed using ML techniques have achieved accuracy levels higher than 95% [5][6].

This review comprehensively covers:

1. Fundamental machine learning algorithms applied to machining
2. Major machining technologies and their ML-enabled optimization

3. Real-time monitoring and adaptive control systems
4. Integration with Industry 4.0 and IoT infrastructure
5. Current challenges, limitations, and future research directions

2. MACHINE LEARNING TECHNIQUES

Machine learning algorithms can be broadly classified into three categories: supervised learning, unsupervised learning, and reinforcement learning[7]. In machining applications, supervised learning dominates because historical machining data with known outcomes (tool wear values, surface roughness measurements) are typically available.

2.1. Artificial Neural Networks

Artificial Neural Networks, particularly feedforward backpropagation neural networks (BPNNs), have been extensively applied to machining process modeling[8]. ANNs learn complex nonlinear relationships between input variables (cutting speed, feed rate, depth of cut, tool geometry) and output parameters (tool wear, surface roughness, cutting forces)[9].

Key advantages of ANNs in machining applications:

- High prediction accuracy (reported accuracies up to 99.85% for surface roughness prediction) [10]
- Ability to model complex, nonlinear relationships
- Capability to handle multi-dimensional input and output parameters
- Real-time prediction capabilities with minimal computational overhead However, ANNs suffer from limited interpretability and require substantial training data for robust generalization[11].

2.2. Support Vector Machines (SVM)

Support Vector Machines have been successfully applied to classification and regression problems in machining. SVMs are particularly effective for small to medium-sized datasets and excel at high-dimensional problems[12]. In machining, SVM has been used for:

- Tool condition classification (normal, wear, failure)
- Fault detection and diagnosis
- Parameter optimization and process control

SVMs use quadratic programming to find optimal hyperplanes that maximize the margin between classes or minimize prediction error[13]. The kernel trick enables SVMs to handle nonlinear relationships without explicitly transforming the data into higher dimensions[14].

2.3. Random Forest (RF)

Random Forests are ensemble methods that construct multiple decision trees and aggregate their predictions through averaging (for regression) or voting (for classification)[15]. In machining applications, Random Forests offer several advantages:

- Robust handling of mixed data types (continuous and categorical)
- Built-in feature importance ranking
- Reduced overfitting compared to single decision trees
- Good generalization with relatively modest training data requirements
- Reduced need for extensive data preprocessing and scaling

Research demonstrates that Random Forests achieve 98% accuracy in fault detection for machining systems when combined with feature extraction techniques[16].

2.4. Decision Trees and Gradient Boosting Methods

Decision Trees provide interpretable models suitable for real-time applications with limited computational resources. Gradient Boosting algorithms (Gradient Boosting Machines, XGBoost, LightGBM) sequentially build trees to correct errors made by previous trees, achieving superior prediction accuracy[17]. These methods have shown particular promise in:

- Tool condition monitoring
- Machining parameter optimization
- Real-time process adjustment

3. DEEP LEARNING ARCHITECTURES

3.1. Convolutional Neural Networks (CNN)

Convolutional Neural Networks have revolutionized the analysis of sensor signals in machining. CNNs automatically extract hierarchical features from raw vibration, acoustic, and electrical signals[18]. In machining applications, CNNs excel at:

- Processing multidimensional sensor data (vibration arrays, spectrograms)

- Detecting subtle patterns indicative of tool wear
- Real-time signal classification with minimal preprocessing

Recent studies comparing CNN with traditional machine learning algorithms demonstrate that CNN provides superior analytical efficiency for surface roughness prediction in stainless steel milling[19]. The convolutional layers reduce computational requirements while improving accuracy through automatic feature learning.

3.2. Long Short-Term Memory (LSTM) Networks

LSTM networks address the vanishing gradient problem of traditional recurrent neural networks, enabling learning of long-term dependencies in sequential machining data[20]. LSTM has been applied to:

- Temporal prediction of tool wear progression
- Time-series forecasting of machining quality parameters
- Adaptive control systems with state memory
- Detection of anomalous machining conditions

Research indicates that LSTM networks outperform traditional ANN models when processing continuous sensor streams during extended machining operations[21].

3.3. Vision Transformers and Hybrid Architectures

Emerging architectures combining Vision Transformers (ViT) with CNN models have demonstrated improved performance in tool wear prediction by 15-20% compared to conventional deep learning approaches[22]. These hybrid models leverage both local feature extraction (CNN) and global pattern recognition (ViT), creating robust predictive systems[23].

4. FEATURE ENGINEERING AND DATA PREPROCESSING

The quality of machine learning models directly depends on input data quality and appropriate feature selection[24]. In machining applications, feature engineering involves:

- **Signal preprocessing:** Filtering noise (Savitzky-Golay filters, low-pass filtering), removing outliers
- **Feature extraction:** Time-domain features (RMS, peak, mean), frequency-domain features (FFT), wavelet transforms
- **Feature selection:** Reducing dimensionality using Principal Component Analysis (PCA), wrapper methods, embedded methods
- **Normalization:** Scaling features to uniform ranges to improve model convergence and performance

The integration of Neighborhood Component Analysis (NCA) with Sparse Autoencoders (SAE) and particle swarm optimization has demonstrated 8-12% improvement in feature engineering effectiveness for machining applications[25].

5. MACHINING TECHNOLOGIES AND ML APPLICATIONS

5.1 Milling Operations

Milling represents one of the most extensively studied machining processes with ML applications due to its widespread industrial use and complex process dynamics[26].

5.1.1 Surface Roughness Prediction in Milling

Surface roughness is a critical quality parameter affecting component functionality, fatigue life, and aesthetic properties[27]. Traditional empirical models often fail to capture the complex relationships between machining parameters and surface finish across different materials.

Machine learning-based surface roughness prediction has achieved notable results:

- Neural network models: 99.85% accuracy in eco-friendly milling processes[10]
- Hybrid CNN-LSTM architectures: Superior performance for SUS304 stainless steel prediction[19]
- Integration of vibration, current, and acoustic sensor data improves prediction accuracy by 15-20%

The workflow involves collecting comprehensive sensor data from microphones, current transformers, and displacement sensors at 10 kHz sampling frequency, preprocessing with Savitzky-Golay filters, feature extraction, and training regression models[28].

5.1.2 Cutting Force Estimation

Cutting forces in milling operations depend on tool geometry, cutting conditions, material properties, and tool wear state. ML models effectively capture these complex relationships[29]. Force prediction enables:

- Tool breakage prevention through real-time monitoring
- Optimization of cutting parameters for specific materials
- Machine tool protection and damage prevention
- Adaptive feed rate control

5.1.3 Tool Wear Prediction and Monitoring

Tool wear is a gradual process affecting surface quality and production costs. Machine learning enables timely tool replacement strategies:

- Classification-based approaches: Determining tool condition states (normal, acceptable wear, failure)
- Regression models: Quantifying actual wear progression over time
- Remaining Useful Life (RUL) prediction: Forecasting tool replacement timing

Random Forest and SVM algorithms show 95-98% accuracy in tool wear classification when trained with comprehensive sensor datasets[30].

5.1.4 CNC Machining Efficiency Optimization

Recent advances in deep learning-based intelligent control console systems enable real-time optimization of:

- Cutting speed and feed rate adjustments
- Tool selection for specific operations
- Machining path optimization (Double-ResNet Local Smoothing DRLS algorithm)
- Thermal management and spindle speed control

These systems integrate reinforcement learning with deep neural networks to dynamically adjust parameters based on continuous feedback, reducing machining time by 12-18% while improving product quality[31].

5.2 Turning Operations

Turning is a fundamental machining process where ML applications focus on tool wear prediction, surface roughness control, and cutting force management.

5.2.1 Tool Wear in Turning Operations

The progressive flank and crater wear during hard steel turning has been successfully predicted using Artificial Neural Networks and self-organizing maps (SOM)[32]. Studies demonstrate that:

- ANN-based models achieve MLP prediction accuracy of 85-92% for hardened steel turning
- Multi-layer perceptron networks effectively filter process interference from actual wear signals
- Proper sensor placement and signal processing are critical for robust predictions

5.2.2 Surface Roughness in Turning

Wiper inserts in turning operations provide opportunities for precision surface finishing. ML models comparing wiper and conventional insert performance show:

- Root Mean Square (RMS) error of 0.745 for wiper inserts
- RMS error of 0.475 for conventional inserts
- Neural network models adapt well to different insert types and materials[33]

5.3 Grinding Operations

Grinding achieves superior surface finishes but involves complex interactions between grain wear, wheel dressing, coolant flow, and material removal rates.

5.3.1 ML Applications in Grinding

While less extensively studied than milling and turning, grinding processes benefit from ML:

- Wheel wear prediction through acoustic emission and vibration analysis
- Surface finish prediction incorporating wheel condition and dressing parameters
- Thermal damage detection in workpiece materials
- Energy consumption optimization

Advanced sensing and data fusion techniques enable effective ML model development for precision grinding operations[34].

5.4 Drilling Operations

Drilling is critical in aerospace and automotive manufacturing where hole quality directly impacts component reliability[35].

5.4.1 Tool Breakage Prediction

Drill bit breakage represents a major quality and productivity concern. ML algorithms applied to drilling include:

- Real-time torque and thrust force monitoring
- SVM classification for breakage prediction
- ANN-based thrust force estimation
- Adaptive speed and feed rate control

Deep learning models show promise in predicting hole diameter deviation and surface damage[36].

5.5 Emerging Machining Technologies

5.5.1 Precision Machining with Deep Learning

Recent advances in precision machining leverage:

- Power Spectral Density (PSD) analysis combined with CNN for tool wear detection
- Vision Transformer models for multi-scale feature learning
- Hybrid CNN-ViT architectures achieving 15-20% accuracy improvement[22]

5.5.2 Electrical Discharge Machining (EDM)

EDM processes benefit from ML for:

- Gap voltage control and servo-system optimization
- Surface quality prediction
- Tool electrode wear monitoring
- Energy efficiency enhancement

6. REAL-TIME PROCESS MONITORING AND ADAPTIVE CONTROL

6.1 IoT Integration and Industry 4.0 Implementation

The integration of Industrial Internet of Things (IIoT) sensors with machine learning models has enabled real-time monitoring and predictive maintenance[37]. Key components include:

- Wireless sensor networks capturing vibration, temperature, power, and acoustic signals
- Edge computing processing local data streams
- Cloud-based ML model deployment and updates
- Visualization dashboards for operator decision support

6.2 Intelligent Control Console Systems

Deep learning-based intelligent control systems dynamically adjust machining parameters based on real-time feedback[2]. These systems:

- Monitor cutting tool wear, machine health, and process performance
- Provide early fault detection and predictive maintenance alerts
- Implement multi-objective optimization for machining time, energy consumption, and tool life
- Offer operator warning mechanisms for potential failures and deviations

The integration of reinforcement learning enables autonomous parameter optimization, reducing human intervention and improving consistency[38].

6.3 Predictive Maintenance Frameworks

ML-enabled predictive maintenance transitions manufacturing from reactive maintenance (fixing failures) to proactive maintenance (preventing failures)[39]. This approach:

- Reduces unplanned downtime by 50-70%
- Extends machine tool lifespan
- Improves asset utilization rates
- Enables optimal spare parts inventory management

7. SENSOR DATA FUSION AND SIGNAL PROCESSING

7.1 Multi-Sensor Data Integration

Modern CNC machines generate diverse sensor signals: vibration (accelerometers), acoustic emission, cutting forces (dynamometers), spindle current, temperature, and displacement. Effective ML modeling requires intelligent integration of these heterogeneous data streams[40].

7.1.1 Signal Preprocessing Techniques

- Noise filtering: Savitzky-Golay filtering maintains signal characteristics while removing noise
- Outlier detection and removal: Isolating measurement errors and process disturbances
- Signal segmentation: Identifying active machining phases versus idle periods
- Synchronization: Aligning signals from multiple sensors with different sampling rates

7.1.2 Feature Extraction Methods

Time-domain features (RMS, peak-to-peak, skewness, kurtosis) capture signal amplitude characteristics[41]. Frequency-domain analysis via Fast Fourier Transform (FFT) reveals periodic patterns and harmonics indicative of specific wear modes[42]. Wavelet transforms enable simultaneous time-frequency analysis, effectively detecting transient events and progressive changes[43].

7.2 Advanced Signal Analysis for Tool Wear Detection

Power Spectral Density (PSD) analysis combined with deep learning has demonstrated superior performance in detecting subtle tool wear signatures embedded in noisy sensor signals[22]. The methodology involves:

1. Computing PSD from time-domain vibration or acoustic signals
2. Encoding PSD features for CNN processing
3. Combining CNN features with Vision Transformer global pattern recognition
4. Producing tool wear predictions with improved generalization

8. CURRENT CHALLENGES AND LIMITATIONS

8.1 Data Acquisition and Labeling

Obtaining high-quality, labeled training data for ML models remains challenging:

- Extensive experimental work required to generate diverse machining conditions
- Manual labeling of tool wear stages and failure modes is labor-intensive
- Domain variability (different machine tools, tool geometries, materials) limits model transferability
- Cost of comprehensive sensor instrumentation and data collection infrastructure

8.2 Model Generalization and Transfer Learning

ML models trained on specific machines or materials often fail when applied to different conditions[44]. Challenges include:

- Machine tool variability (stiffness, thermal characteristics, control systems)
- Material variation and material properties uncertainty
- Tool type and geometry differences
- Operating condition diversity

Transfer learning and domain adaptation techniques are emerging to address generalization challenges, but standardized approaches remain lacking[45].

8.3 Computational and Deployment Constraints

Real-time ML model inference on CNC machine controllers faces limitations:

- Legacy CNC systems have limited computational capacity
- Edge computing infrastructure requirements and costs
- Network latency and connectivity reliability concerns
- Model update and retraining logistics

8.4 Interpretability and Explainability

Deep learning models, while achieving superior accuracy, often function as "black boxes" lacking explainability[46]:

- Operators and maintenance personnel cannot understand model decisions
- Regulatory and quality assurance requirements demand transparency
- Debugging failed predictions becomes difficult
- Trust and adoption in manufacturing environments are hindered

Hybrid approaches combining interpretable models (decision trees) with high-accuracy deep learning show promise in addressing this challenge[47].

8.5 Industry Adoption Barriers

Despite technical advances, ML adoption in manufacturing remains limited:

- Initial investment costs for sensing infrastructure and software
- Requirement for cross-functional expertise (manufacturing, data science, software engineering)
- Risk aversion in production environments
- Lack of standardized best practices and guidelines
- Cybersecurity concerns with connected systems and cloud data transfer

9. EMERGING HYBRID AND ADVANCED APPROACHES

9.1 Hybrid Machine Learning Ensembles

Combining multiple ML algorithms leverages individual strengths while mitigating individual weaknesses[48]. Successful hybrid approaches include:

Random Forest + Support Vector Machine (RF-SVM): Initial RF classification extracts critical features and identifies fault types, then SVM maximizes classification accuracy. This approach achieved 98% accuracy in fault detection while significantly reducing sensor requirements[49].

Bayesian Regularized Artificial Neural Networks (BRANN): Incorporating Bayesian principles with ANN regularization improves predictions with limited training data by preventing overfitting. BRANN has

demonstrated superior performance in milling tool wear prediction with 12% better generalization compared to standard ANN[50].

CNN-LSTM Hybrid Architectures: Combining CNNs for local spatial feature extraction with LSTM for temporal dependency learning creates robust models for time-series machining data[51].

9.2 Physics-Informed Machine Learning

Integrating physical process models with data-driven ML creates hybrid frameworks achieving improved accuracy and generalization[52]:

- Embedding machining mechanics equations as constraints in neural networks
- Using symbolic regression to discover interpretable physical relationships
- Combining finite element models with ML for rapid predictions
- Implementing conservation laws (energy, momentum) as soft constraints

9.3 Reinforcement Learning for Autonomous Optimization

Reinforcement learning agents learn optimal machining strategies through interaction with simulated or real machining environments[53]:

- Multi-objective optimization of competing goals (time, cost, quality)
- Autonomous tool path planning and adjustment
- Adaptation to tool wear and thermal effects
- Learning from operator preferences and explicit rewards

10. CASE STUDIES AND PRACTICAL IMPLEMENTATIONS

10.1 Surface Roughness Prediction in Stainless Steel Milling

A comprehensive study compared multiple ML algorithms (Linear Regression, ANN, CNN, LSTM) for predicting surface roughness in SUS304 stainless steel milling[19]. Results demonstrated:

- CNN provided superior analytical efficiency
- Integration of vibration, current, and acoustic features improved accuracy by 18%
- Model generalization improved with careful feature selection and preprocessing
- Practical implementation requires careful sensor calibration and placement

10.2 Tool Wear Prediction with Limited Data

Bayesian Regularized ANNs successfully predicted milling tool wear with limited experimental data (50% less data compared to standard ANNs) while maintaining accuracy[50]. Implementation included:

- Feature extraction from cutting force and vibration signals
- Bayesian posterior distribution estimation for neural network weights
- Automatic regularization parameter optimization
- Superior generalization to unseen machining conditions

10.3 Real-Time CNC Control System Integration

An intelligent control console system integrated deep learning with reinforcement learning to enable real-time CNC optimization[2]:

- Processing real-time sensor data streams (>100 parameters)
- Updating cutting speed, feed rate, and tool selection every machining cycle
- Reducing machining time by 12-18%
- Improving surface quality by 10-15%
- Extending tool life by 20-25%

11. FUTURE RESEARCH DIRECTIONS

11.1 Advanced Sensing Modalities

Future machining systems should incorporate:

- Non-destructive sensing (thermal imaging, ultrasonic inspection)
- In-process dimensional measurement (laser, photonics)
- Material property identification through acoustic signatures
- Indirect measurement of unmeasurable phenomena (strain, stress)

11.2 Federated Learning and Collaborative Intelligence

Federated learning enables multiple CNC machines to collaboratively train ML models while preserving data privacy[54]:

- Decentralized model training across manufacturing networks
- Rapid knowledge transfer between facilities

- Improved generalization through diverse training data
- Reduced cybersecurity risks from centralized data storage

11.3 Few-Shot and Meta-Learning Approaches

Meta-learning enables rapid adaptation to new machining scenarios with minimal labeled examples[55]:

- Quick model recalibration for new machine tools or materials
- Transfer of learned strategies to different machining operations
- Reduction in data collection requirements
- Scalable deployment across diverse manufacturing environments

11.4 Uncertainty Quantification and Bayesian Methods

Probabilistic ML frameworks provide prediction confidence estimates essential for decision-making[56]:

- Bayesian neural networks quantifying prediction uncertainty
- Ensemble methods providing confidence intervals
- Risk-aware optimization incorporating confidence measures
- Adaptive sampling focusing on uncertain regions

11.5 Explainable AI (XAI) for Manufacturing

Developing interpretable ML models for manufacturing requires:

- SHAP (Shapley Additive explanations) values identifying influential features
- LIME (Local Interpretable Model-agnostic Explanations) for local interpretability
- Attention mechanisms highlighting critical signal regions
- Symbolic regression discovering mathematical relationships

11.6 Digital Twin Integration

Digital twins virtual replicas of physical machining systems combined with ML enable[57]:

- Continuous simulation-based optimization
- Safe testing of parameter adjustments before implementation
- Failure mode analysis and consequence assessment
- Rapid scenario evaluation and decision support

12. CONCLUSION

Machine learning has fundamentally transformed the optimization, monitoring, and control of machining processes. From predicting tool wear and surface roughness to enabling real-time adaptive control, ML techniques have demonstrated substantial improvements in manufacturing efficiency, product quality, and operational cost reduction.

The maturation of deep learning architectures, integration with IoT sensors, and advancement toward Industry 4.0 standards have created unprecedented opportunities for intelligent machining systems. Hybrid approaches combining multiple algorithms, physics-informed models, and reinforcement learning continue to push the boundaries of what is achievable.

However, significant challenges remain in data acquisition, model generalization, computational deployment, interpretability, and industry-wide adoption. Future progress depends on continued research in federated learning, meta-learning, explainable AI, and digital twin integration.

The convergence of machine learning with advanced machining technologies promises a future of fully autonomous, self-optimizing manufacturing systems. Organizations that successfully implement and adapt these technologies will gain substantial competitive advantages in precision manufacturing. Continued collaboration between academic research institutions, industrial practitioners, and technology providers is essential to realize the full potential of machine learning in transforming modern manufacturing.

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