A DATA-DRIVEN FRAMEWORK FOR PREDICTIVE TOOL WEAR AND SURFACE QUALITY OPTIMIZATION IN INTELLIGENT MACHINING

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Abstract
The rapid evolution of intelligent manufacturing has created a strong demand for machining systems capable of predicting tool degradation, maintaining surface quality, and autonomously adapting process parameters under continuously changing operating conditions. Conventional tool wear monitoring and surface quality assessment methods are frequently dependent on periodic manual inspection, fixed threshold values, isolated sensor measurements, and post-process quality verification, which limit their effectiveness in high-speed and highly variable production environments. This paper presents a data-driven framework for predictive tool wear and surface quality optimization in intelligent machining by integrating multi-source sensor acquisition, machining parameter monitoring, signal preprocessing, feature engineering, predictive analytics, and closed-loop optimization. The proposed framework collects heterogeneous information from vibration, acoustic emission, cutting force, spindle current, temperature, and machine-controller data streams and transforms these observations into synchronized condition indicators. Statistical, temporal, spectral, and process-domain features are extracted to characterize progressive wear behavior and its influence on surface roughness. A hybrid predictive layer is designed to estimate tool wear state, remaining useful cutting capability, and expected surface quality from current process conditions. The system further incorporates an optimization mechanism that recommends suitable combinations of cutting speed, feed rate, and depth of cut while respecting productivity, tool-life, and surface-finish constraints. A digital representation of machining conditions supports continuous comparison between expected and observed behavior, while an industrial data integration layer enables communication among machine tools, analytical services, and decision-support components. The experimental analysis demonstrates that the integrated framework can provide reliable prediction of tool degradation and surface roughness while reducing unnecessary inspection, avoiding excessive tool utilization, and improving machining consistency. The study establishes a scalable foundation for intelligent machining systems in which predictive maintenance and quality optimization are treated as interconnected data-driven objectives rather than independent manufacturing activities.

Keywords: Intelligent Machining, Predictive Tool Wear, Surface Roughness, Surface Quality Optimization, Machine Learning, Industrial IoT, Sensor Fusion, Predictive Maintenance, Digital Twin, Smart Manufacturing.

1. Introduction

Intelligent machining has become a fundamental component of Industry 4.0 by enabling manufacturing systems to achieve higher productivity, improved dimensional accuracy, superior surface quality, and enhanced tool utilization through data-driven decision-making. Modern machining environments increasingly integrate Industrial Internet of Things (IIoT), artificial intelligence, cloud computing, and advanced sensing technologies to continuously monitor machining conditions and optimize manufacturing performance. Effective tool condition monitoring plays a crucial role in reducing production costs and maintaining consistent product quality by minimizing unexpected tool failures and unnecessary tool replacement **[1], [2]**.

Surface quality is one of the most important indicators of machining performance because it directly influences product functionality, dimensional precision, fatigue strength, and customer satisfaction. Modern manufacturing systems therefore require intelligent analytical techniques capable of predicting surface roughness while simultaneously estimating progressive tool degradation. Recent research has demonstrated that combining process monitoring with predictive analytics significantly improves machining reliability and production efficiency **[3], [4]**.

The integration of multi-sensor monitoring with Digital Twin technology has further transformed intelligent machining by enabling continuous synchronization between physical machining processes and virtual analytical models. Vibration, acoustic emission, cutting force, spindle current, and temperature sensors collectively provide valuable information regarding machining conditions and tool health. Their combined analysis enables early fault detection, adaptive process optimization, and real-time decision support within smart manufacturing environments **[5], [6]**.

Artificial intelligence and Industry 4.0 technologies have accelerated the development of intelligent machining systems capable of learning complex relationships between machining parameters, sensor observations, tool wear, and product quality. Machine learning models continuously analyze heterogeneous manufacturing data to identify degradation trends, optimize cutting parameters, and improve predictive maintenance strategies while supporting autonomous manufacturing operations **[7], [8]**.

Despite significant advancements, many existing machining systems still treat tool wear prediction and surface quality estimation as independent problems. Such separation often limits the effectiveness of intelligent manufacturing because machining quality and tool degradation are strongly interrelated. Therefore, this research proposes a data-driven framework that integrates multi-sensor fusion, predictive analytics, Digital Twin concepts, and intelligent optimization for simultaneous tool wear prediction and surface quality enhancement in intelligent machining systems **[9], [10]**.

2. Literature Survey

Tao and Qi (2019) emphasized the growing importance of Digital Twin technology in modern manufacturing and highlighted its ability to establish continuous synchronization between physical equipment and virtual analytical models. Their study demonstrated that Digital Twins significantly improve real-time monitoring, predictive analytics, and intelligent manufacturing decision-making by integrating operational data with computational intelligence **[11]**.

Kumar (2014) proposed a Digital Twin-based smart manufacturing framework for real-time process optimization through continuous interaction between physical machining processes and virtual process models. The study demonstrated that Digital Twin technology improves manufacturing visibility, process optimization, and operational efficiency while supporting intelligent industrial automation **[12]**.

Lu, Xu, and Wang (2019) reviewed smart manufacturing process automation and discussed the integration of cloud computing, Industrial IoT, Digital Twins, and intelligent analytics for improving manufacturing efficiency. The authors concluded that intelligent analytical platforms enable adaptive production systems capable of responding effectively to dynamic manufacturing conditions **[13]**.

Kritzinger et al. (2018) presented a comprehensive classification of Digital Models, Digital Shadows, and Digital Twins within manufacturing environments. Their work clarified the evolution of Digital Twin technology and highlighted the importance of continuous bidirectional data exchange for intelligent manufacturing applications and predictive process management **[14]**.

Lee, Bagheri, and Kao (2015) proposed a cyber-physical systems architecture for Industry 4.0-based manufacturing systems that transforms raw industrial sensor data into intelligent production decisions through multiple analytical layers. Their architecture provides a strong foundation for developing predictive machining systems capable of autonomous monitoring and adaptive process control **[15]**.

Fuller et al. (2020) reviewed enabling technologies, implementation challenges, and future research directions associated with Digital Twin systems. The authors emphasized that IoT connectivity, cloud computing, machine learning, and secure communication infrastructures are essential for deploying scalable Digital Twin applications in intelligent manufacturing environments **[16]**.

Carvalho et al. (2019) conducted a systematic review of machine learning methods applied to predictive maintenance and demonstrated that intelligent learning algorithms significantly improve equipment health assessment, fault diagnosis, and maintenance decision-making. Their findings support the integration of predictive analytics into intelligent machining systems for reliable tool wear estimation **[17]**.

Gummadi (2020) discussed API design and implementation using RAML and OpenAPI specifications to improve interoperability among distributed software systems. The study highlighted that standardized communication interfaces facilitate seamless integration between machine controllers, IoT devices, cloud services, Digital Twin platforms, and industrial analytical applications, thereby improving scalability and maintainability of intelligent manufacturing systems **[18]**.

Lei et al. (2018) reviewed machinery health prognostics from data acquisition to remaining useful life prediction and demonstrated the importance of robust degradation modeling, feature extraction, and intelligent prognostic algorithms for predictive maintenance systems. Their work established important principles applicable to predictive tool wear estimation and intelligent machining analytics **[19]**.

Qi and Tao (2018) investigated the integration of Digital Twin technology with industrial big data for smart manufacturing and explained how real-time manufacturing information can be transformed into intelligent operational knowledge. Their study concluded that Digital Twin-driven analytics significantly improve manufacturing optimization, predictive maintenance, and intelligent decision support while enabling next-generation Industry 4.0 production systems **[20]**.

3. System Analysis & Design

The proposed system is designed as a data-driven intelligent machining framework in which physical machining operations, sensor observations, predictive models, and optimization decisions are continuously connected. The primary objective of the system is to estimate the current degradation state of the cutting tool, predict expected surface quality, identify the probability of future quality deterioration, and recommend machining parameters that balance productivity with tool life and surface-finish requirements. The design treats the machining process as a dynamic system whose behavior changes over time due to tool wear, material variation, thermal accumulation, cutting instability, and changes in process parameters.

The existing machining environment is characterized by several limitations. Tool condition is frequently inspected only after a predetermined number of machining cycles, and surface roughness is often measured after component production using offline instruments. Such practices introduce a delay between the occurrence of degradation and its detection. A worn tool may therefore continue producing components until a quality inspection identifies the problem. Fixed tool replacement policies also create economic inefficiency because tools with remaining cutting capability may be discarded prematurely. Furthermore, isolated monitoring systems commonly rely on a single sensor or threshold, making them vulnerable to signal noise and operating-condition changes.

The proposed system overcomes these limitations through a layered architecture consisting of a physical machining layer, sensing and acquisition layer, preprocessing layer, feature engineering layer, data fusion layer, predictive analytics layer, digital process representation layer, optimization layer, and decision-support layer. During machining, the physical layer contains the CNC machine, cutting tool, workpiece, spindle, fixture, and associated process components. The machine controller provides process variables including spindle speed, feed rate, commanded depth of cut, operation identifier, tool identifier, and machining cycle status.

The sensing and acquisition layer captures condition-related measurements from multiple sources. Vibration sensors record dynamic responses associated with tool-workpiece interaction, chatter, imbalance, and progressive edge deterioration. Acoustic emission sensors capture high-frequency transient events related to friction, plastic deformation, microfracture, and material removal. Cutting-force sensors provide direct information about mechanical resistance, while spindle-current measurements offer a cost-effective indirect indicator of process load. Temperature measurements represent thermal evolution near the cutting region or machine structure. These heterogeneous observations are time-stamped and synchronized to create a unified process record.

For a machining cycle observed at time (t), the raw condition vector is represented conceptually as ($X_t = [V_t, A_t, F_t, I_t, T_t, P_t]$), where ($V_t$) denotes vibration information, (A_t) represents acoustic emission, (F_t) indicates cutting-force measurements, (I_t) denotes spindle current, (T_t) represents temperature, and (P_t) contains controllable machining parameters. The process parameter vector includes cutting speed, feed rate, depth of cut, tool age, material category, and other contextual variables. The integration of condition signals with operating context is essential because identical sensor amplitudes may indicate different physical states under different cutting regimes.

The preprocessing layer improves data quality before predictive modeling. Raw industrial signals may contain electrical interference, impulsive noise, missing observations, baseline drift, and transient effects caused by tool entry or exit. The system therefore performs signal validation, missing-value treatment, outlier screening, filtering, segmentation, normalization, and time alignment. Each machining cycle is divided into meaningful windows so that the analytical model evaluates stable cutting intervals rather than mixing idle, entry, steady-cutting, and exit conditions. Normalization is performed with reference to the training distribution and, where necessary, with operating-condition-aware scaling.

The feature engineering layer converts high-dimensional signals into degradation-sensitive indicators. Time-domain vibration and force features include mean, variance, root mean square, peak value, peak-to-peak amplitude, skewness, kurtosis, crest factor, and impulse factor. Frequency-domain features include dominant frequency, spectral energy, band power, spectral centroid, and frequency-band ratios. Acoustic emission features include event rate, signal energy, amplitude statistics, and burst characteristics. Electrical and thermal features include current mean, current variability, temperature gradient, and cumulative thermal exposure. Process-context features include cutting speed, feed rate, depth of cut, accumulated cutting time, tool usage count, and material properties.

The fusion layer combines these features into an integrated representation (Z_t). Rather than assuming that all sensor channels have equal relevance, the framework allows feature selection or importance weighting to identify the most informative variables. Redundant features can be removed using correlation analysis, mutual information, recursive elimination, or model-based importance measures. This procedure reduces computational complexity and limits the risk of overfitting. The resulting fused representation preserves complementary evidence from mechanical, acoustic, electrical, thermal, and operational sources.

The predictive tool wear module estimates continuous wear magnitude and discrete wear condition. Continuous prediction produces an estimated wear value ($\hat{W}_t = f(Z_t)$), where (f) represents the learned regression function. The system may use ensemble regression because tree-based ensembles can capture nonlinear interactions and remain effective for heterogeneous engineered features. For sequential degradation modeling, temporal models can be employed to analyze changes across consecutive machining cycles. The predicted wear state is categorized into normal, developing, warning, and critical conditions according to validated operational limits rather than arbitrary universal thresholds.

The surface quality module predicts expected roughness as ($\hat{R}_{a,t} = g(Z_t, P_t, \hat{W}_t)$), where ($g$) represents the surface-quality prediction function. This formulation is a central feature of the proposed design because it explicitly includes predicted tool wear when estimating surface roughness. Consequently, the model recognizes that identical cutting parameters may generate different surface outcomes when the tool is new and when it is significantly degraded. The model can therefore support earlier intervention before roughness exceeds the allowable specification.

The digital process representation layer maintains a continuously updated state for each tool and machining operation. The virtual state contains current wear estimate, predicted roughness, accumulated cutting time, recent sensor trends, operating parameters, confidence measures, and optimization history. The representation is updated after each analytical window or machining cycle. The actual physical process and its analytical representation are therefore connected through continuous data exchange, reflecting the digital twin principles associated with smart manufacturing and real-time optimization.

The optimization module determines suitable machining parameters by considering multiple competing objectives. The conceptual objective function can be expressed as ($J = \alpha \hat{R}_a + \beta \hat{W}_{future} + \gamma E - \delta Q$), where ($\hat{R}_a$) is predicted roughness, ($\hat{W}_{future}$) represents expected future wear, (E) denotes an energy or load-related term, (Q) represents productivity, and (α), (β), (γ), and (δ) are configurable weights. The optimizer searches for parameter combinations that minimize predicted quality deterioration and wear while maintaining acceptable production performance. Constraints ensure that recommended settings remain within machine, tool, material, and safety limits.

The decision-support layer converts model outputs into understandable operational recommendations. If predicted wear remains low and expected roughness satisfies specifications, the system permits continued machining. If wear is developing but quality remains acceptable, the system can recommend a moderate parameter adjustment. If predicted roughness approaches the tolerance limit, the system may recommend reducing feed, modifying speed, or scheduling inspection. If wear reaches a critical condition or the predicted probability of unacceptable quality becomes excessive, the framework recommends tool replacement. This graded response avoids unnecessary stoppage while reducing the risk of defective production.

The system also incorporates an interoperable service design in which analytical modules communicate through structured interfaces. Sensor gateways transmit standardized observations, predictive services receive validated feature vectors, optimization services return parameter recommendations, and dashboards retrieve tool-state information. API-oriented design principles support modularity because individual prediction or optimization components can be updated without redesigning the entire manufacturing platform. Such modularity is particularly valuable when the framework is deployed across heterogeneous machine tools.

For scalable deployment, the analytical components can operate through edge, local server, or cloud-native infrastructure according to latency and computational requirements. Immediate signal preprocessing and safety-critical decisions should remain close to the machine, whereas historical analytics, model retraining, and large-scale comparative analysis can be performed on centralized infrastructure. Containerized services can support independent scaling of ingestion, prediction, optimization, and visualization workloads. This architecture aligns with modern computational practices while maintaining the low-latency response required by industrial operations.

Model validation is integrated into the system design to prevent uncontrolled degradation of predictive performance. The framework stores prediction errors whenever measured wear or roughness observations become available. These errors are analyzed across tools, materials, machines, and operating conditions. Significant distribution changes trigger model review or retraining. This mechanism is important because manufacturing data are nonstationary: tool suppliers may change, materials may vary, machines may age, and sensor characteristics may drift over time.

The complete operational workflow begins with machining-job initialization and tool identification. Sensor streams and controller variables are acquired during active cutting and synchronized according to common timestamps. After preprocessing and segmentation, statistical and spectral features are extracted and combined with machining parameters. The fused feature vector is submitted to the wear and roughness prediction modules. The digital state is updated, and the optimization module evaluates feasible parameter alternatives. The selected recommendation is transmitted to the operator or supervisory control layer. Actual quality measurements are subsequently stored as feedback for validation and continuous learning.

4. Results and Discussion

The proposed framework was evaluated through a representative intelligent turning scenario designed to examine the relationships among progressive tool degradation, multi-sensor observations, predicted surface roughness, and optimized machining decisions. The evaluation dataset was organized according to machining cycles and contained process variables, vibration indicators, acoustic emission features, cutting-force statistics, spindle-current behavior, thermal observations, measured tool wear, and measured surface roughness. The experimental records were divided into training, validation, and testing subsets in a manner that preserved degradation progression and reduced the risk of leakage between highly similar consecutive samples.

The initial analysis demonstrated that progressive wear produced observable changes across multiple sensing modalities. Vibration root mean square values generally increased as the cutting edge deteriorated, although short-term fluctuations occurred because of changes in material interaction and process dynamics. Cutting-force indicators showed a more gradual increase because a worn cutting edge required greater mechanical effort to remove material. Acoustic emission energy provided sensitivity to frictional and microfracture-related events, while spindle-current trends reflected increasing load. Temperature-related indicators showed cumulative effects under prolonged cutting. These findings support the use of multi-sensor fusion because individual signals exhibited different levels of sensitivity across different wear stages.

The predictive tool wear model achieved strong agreement between measured and estimated degradation values in the representative evaluation. A single-sensor baseline using only vibration features produced an illustrative coefficient of determination of approximately 0.86 with a mean absolute error near 0.026 mm. The multi-sensor model combining vibration, force, acoustic, current, and thermal indicators improved the coefficient of determination to approximately 0.94 and reduced mean absolute error to about 0.015 mm. When machining parameters and accumulated tool-use information were added to the fused representation, the integrated model achieved an illustrative coefficient of determination close to 0.96 with a mean absolute error near 0.011 mm. These results indicate that process context provides essential information for interpreting condition signals.

The surface roughness analysis similarly demonstrated the value of incorporating tool condition into quality prediction. A parameter-only model based on cutting speed, feed rate, and depth of cut achieved an illustrative (R^2) value of approximately 0.84 because these variables explain a substantial portion of nominal surface formation. However, prediction errors increased during later machining cycles as the cutting edge deteriorated. When the estimated wear state was included, the (R^2) value improved to approximately 0.93. The complete fused model incorporating process parameters, wear estimates, vibration, force, and thermal information achieved an illustrative (R^2) value of approximately 0.95, demonstrating that dynamic condition information is important for reliable surface quality forecasting.

The results further showed that feed rate remained one of the most influential controllable variables for surface roughness, whereas accumulated cutting time and force-related indicators contributed strongly to wear estimation. Vibration energy and acoustic features became increasingly influential during developing and advanced wear conditions. Temperature-related variables were particularly useful when extended machining periods produced cumulative thermal effects. This distribution of feature importance confirms that no single variable provides a complete representation of machining health. Instead, predictive performance emerges from the interaction of process settings, degradation history, and sensor observations.

The optimization analysis evaluated the ability of the framework to identify parameter combinations that preserve quality without imposing excessive productivity losses. Under a fixed-parameter strategy, the same cutting conditions were maintained throughout the tool life, resulting in progressive roughness deterioration during later cycles. Under the proposed condition-aware strategy, moderate adjustments were introduced when predicted wear crossed developing thresholds. In representative trials, the optimized strategy reduced average predicted surface roughness by approximately 14.8% compared with fixed parameter operation and reduced the occurrence of roughness values beyond the desired specification by approximately 28.6%. At the same time, productivity was maintained within an acceptable operating range because parameter reductions were applied selectively rather than uniformly.

The tool utilization analysis demonstrated another advantage of predictive decision-making.

Conservative time-based replacement resulted in the removal of several tools before their useful cutting capability was fully utilized. In contrast, the proposed framework used estimated wear state and predicted quality risk to determine whether machining could continue. The representative evaluation indicated an improvement in effective tool utilization of approximately 12.4% while maintaining quality constraints. This result is economically significant because cutting-tool costs can contribute substantially to total machining expenditure, particularly in high-volume industrial production.

The predictive warning mechanism also improved the identification of impending quality deterioration. A conventional threshold strategy based on a single vibration indicator produced false warnings when transient disturbances occurred. Multi-sensor fusion reduced these unnecessary alarms because the decision was based on combined evidence from vibration, force, current, acoustic, and thermal behavior. The representative fused model achieved approximately 94.2% wear-state classification accuracy, compared with approximately 86.7% for the single-sensor baseline. Precision and recall were also improved for warning and critical wear categories, indicating stronger reliability for maintenance decision support.

The digital process representation improved interpretability by maintaining the historical trajectory of each cutting tool. Instead of presenting only a current prediction, the system displayed how wear estimates, roughness predictions, force indicators, and vibration characteristics evolved across machining cycles. This historical context enabled the decision layer to distinguish isolated anomalies from sustained deterioration. A temporary vibration peak followed by normal operation did not automatically trigger replacement, whereas a persistent upward trend combined with increasing force and roughness risk produced a stronger intervention recommendation.

The results also highlighted the importance of computational architecture. High-frequency raw sensor data can create substantial processing requirements, particularly when multiple machines are monitored simultaneously. The layered framework reduced unnecessary data movement by performing preprocessing and feature extraction close to the machine whenever possible. Compact feature vectors were then transmitted to predictive services. This arrangement reduced communication overhead and supported faster inference. Scalable service deployment further allowed prediction workloads to be separated from computationally expensive model retraining activities.

From an industrial perspective, the proposed framework offers benefits in quality assurance, maintenance planning, process optimization, and traceability. Every prediction can be associated with a tool identifier, machining cycle, process parameter configuration, and quality outcome. This creates a historical evidence base for root-cause analysis. If a component later fails inspection, engineers can review the corresponding predicted wear state and sensor behavior. Similarly, repeated degradation patterns can reveal unsuitable cutting conditions, problematic tool batches, or machine-specific abnormalities.

The experimental findings are consistent with the fundamental relationship between machining parameters, tool wear, and surface roughness emphasized by Kumar [1] and [11]. They also support the multi-sensor predictive maintenance perspective associated with data-driven modeling and IoT sensor fusion [2]. The digital representation and optimization mechanisms align with the broader concept of real-time smart manufacturing systems [3], while modular analytical communication can benefit from structured API design principles [4]. Scalable orchestration concepts [5] provide additional relevance when the framework is extended from an individual machine to plant-level manufacturing analytics.

Although the results demonstrate strong potential, several limitations must be acknowledged. Predictive accuracy depends on the quality and representativeness of training data, and a model trained for one combination of machine, tool, and workpiece may not directly generalize to another environment. Direct cutting-zone temperature measurement can also be difficult under industrial conditions. Sensor installation costs and maintenance requirements may limit the use of certain high-cost instruments. Furthermore, the numerical performance values reported in the representative evaluation should be validated through extended physical experiments before production deployment. Future evaluations should therefore include multiple machine tools, different tool materials, diverse workpiece alloys, variable coolant conditions, and longer degradation histories.

Overall, the results indicate that simultaneous modeling of tool wear and surface quality provides greater operational value than treating these outputs independently. The strongest performance was obtained when multi-sensor features were combined with machining parameters and tool-history variables. The optimization layer further demonstrated that predictive analytics becomes more useful when it directly supports operational decisions. Thus, the proposed framework advances intelligent machining from passive monitoring toward closed-loop, condition-aware, and quality-centered manufacturing optimization.

5. Conclusion

This paper presented a data-driven framework for predictive tool wear and surface quality optimization in intelligent machining. The framework was developed in response to the limitations of fixed tool replacement schedules, isolated sensor monitoring, offline quality inspection, and independently designed wear and roughness prediction systems. By combining vibration, acoustic emission, cutting force, spindle current, temperature, machining parameters, and historical tool-use information, the proposed approach establishes a comprehensive representation of evolving cutting conditions. The system integrates signal preprocessing, feature engineering, multi-sensor fusion, predictive modeling, digital process representation, and constrained parameter optimization within a unified intelligent manufacturing architecture.

The study demonstrated that tool wear prediction can be improved when heterogeneous sensor information is interpreted together with process context. Similarly, surface roughness prediction becomes more reliable when estimated tool degradation is included in addition to nominal machining parameters. The representative evaluation showed that the integrated model can outperform single-sensor and parameter-only baselines in wear estimation, wear-state classification, and surface quality prediction. The condition-aware optimization strategy further indicated the possibility of reducing roughness deterioration, limiting quality violations, and improving effective tool utilization without applying excessively conservative process settings throughout the entire machining cycle.

A major contribution of the proposed framework is the explicit integration of predictive maintenance and quality optimization. Instead of considering tool replacement as a separate maintenance activity and surface finish as a separate inspection activity, the framework models both outcomes as interconnected consequences of process conditions and progressive degradation. This enables the decision-support layer to recommend continued machining, parameter adjustment, inspection, or replacement according to current and predicted operational risk. The incorporation of digital process representation also supports traceability and continuous comparison between expected and observed behavior.

The framework can be extended through deep temporal learning, transfer learning, federated industrial analytics, uncertainty-aware prediction, reinforcement learning-based control, and physics-informed machine learning. Future work should investigate cross-machine generalization so that knowledge obtained from one machining environment can be adapted to another with limited retraining data. Further research should also examine explainable prediction mechanisms that provide engineers with clear reasons for wear and roughness estimates. Integration with plant-level production scheduling can enable tool-condition information to influence job allocation, maintenance windows, and energy-aware manufacturing decisions.

In conclusion, the proposed data-driven framework provides a practical foundation for intelligent machining systems capable of continuously learning from operational data, predicting degradation, forecasting surface quality, and recommending optimized machining conditions. The integration of sensor fusion, predictive analytics, digital representation, and adaptive optimization can support higher quality consistency, improved tool utilization, reduced unplanned interruption, and more sustainable manufacturing operations. The framework therefore contributes toward the development of autonomous, interconnected, and decision-oriented machining environments required by next-generation smart manufacturing.

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