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REAL-TIME TOOL CONDITION MONITORING AND SURFACE ROUGHNESS PREDICTION IN SMART MANUFACTURING

Lucas Bennett
Research Scholar

ABSTRACT

The increasing demand for high-quality products, reduced production losses, improved machine availability, and adaptive process control has accelerated the adoption of intelligent monitoring technologies in modern manufacturing environments. Tool degradation and surface-quality variation are among the most significant challenges in machining operations because progressive tool wear can increase cutting forces, vibration, temperature, dimensional deviations, energy consumption, and surface irregularities while also creating unexpected production interruptions. Conventional tool inspection methods frequently depend on scheduled manual measurements or offline quality inspection, which may identify deterioration only after defective components have already been produced. This paper proposes a real-time tool condition monitoring and surface roughness prediction framework for smart manufacturing that integrates Industrial Internet of Things sensing, multi-source process data acquisition, edge preprocessing, feature extraction, machine-learning analytics, tool-health assessment, surface-quality prediction, Digital Twin-based operational context, secure API integration, adaptive decision support, and continuous model lifecycle management. The framework collects heterogeneous machining information including vibration, cutting force, acoustic emission, spindle current, temperature, spindle speed, feed rate, depth of cut, machining duration, tool history, and contextual production variables. Edge-level processing performs signal validation, noise reduction, synchronization, segmentation, and feature generation before relevant observations are transferred to analytical services. The proposed methodology develops continuously updated tool-condition profiles and predicts surface roughness using combined sensor and process information rather than relying on isolated measurements. A Digital Twin layer maintains contextual representations of machine state, tool usage, process settings, predicted wear condition, and expected quality behavior. The decision-support component generates recommendations for tool inspection, parameter adjustment, maintenance intervention, and controlled tool replacement when predicted risks exceed acceptable operational limits. Secure OpenAPI-oriented interfaces enable interoperable communication among sensors, edge gateways, Digital Twin services, analytical models, manufacturing applications, and quality-management platforms. A representative analytical evaluation compares conventional periodic monitoring with the proposed real-time framework using tool-wear detection accuracy, surface roughness prediction quality, defect rate, unplanned downtime, tool utilization, false alarm rate, response time, energy consumption, and overall equipment effectiveness. The results indicate that the proposed framework can substantially improve early wear detection, surface-quality consistency, production continuity, and tool-resource utilization. The study concludes that integrated multi-sensor analytics, contextual Digital Twins, and continuously managed predictive models provide a practical foundation for real-time intelligent machining supervision in smart manufacturing environments.

Keywords: Tool Condition Monitoring, Surface Roughness Prediction, Smart Manufacturing, Machine Learning, Industrial Internet of Things, Predictive Maintenance, Digital Twin, Machining Analytics, Tool Wear, Multi-Sensor Fusion, Industry 4.0.

I. INTRODUCTION

Smart manufacturing has significantly transformed conventional machining by integrating Industrial Internet of Things (IIoT), cyber-physical systems, machine learning, Digital Twins, cloud computing, and intelligent manufacturing analytics. Modern production facilities continuously generate large volumes of heterogeneous sensor data from CNC machines, vibration sensors, cutting-force sensors, acoustic emission sensors, spindle current sensors, temperature sensors, and production control systems. Effective utilization of these data enables real-time monitoring of machining performance, improves product quality, reduces unexpected machine failures, and supports predictive maintenance. Among various machining challenges, progressive tool wear remains one of the primary factors influencing machining accuracy, production efficiency, surface finish, and manufacturing cost. Consequently, real-time tool condition monitoring has become an essential requirement for next-generation smart manufacturing systems **[1], [2]**.

Tool degradation occurs continuously because of abrasion, adhesion, diffusion, oxidation, thermal fatigue, and mechanical stresses acting on the cutting edge during machining operations. Progressive wear modifies cutting forces, vibration characteristics, spindle load, temperature distribution, acoustic emissions, and power consumption, eventually leading to deteriorated surface quality and unexpected tool failure. Traditional monitoring approaches generally depend on periodic manual inspection, scheduled tool replacement, or fixed threshold values, which often fail to detect early-stage degradation under varying machining conditions. Therefore, intelligent monitoring systems capable of continuously evaluating tool health have gained increasing importance in modern manufacturing environments **[3], [4]**.

Surface roughness is another critical indicator of machining quality because it directly affects component functionality, dimensional accuracy, fatigue strength, friction characteristics, corrosion resistance, and product reliability. Surface finish depends not only on machining parameters such as cutting speed, feed rate, and depth of cut, but also on evolving tool condition, workpiece material properties, thermal behavior, machine rigidity, and environmental disturbances. Machine learning techniques can effectively model these complex nonlinear relationships by integrating multiple process variables and sensor measurements to accurately predict machining quality during production **[5], [6]**.

Recent developments in edge computing, Digital Twins, cloud-native manufacturing, and predictive analytics further enhance intelligent machining by enabling continuous process monitoring, contextual equipment representation, adaptive decision-making, and scalable deployment of machine learning models. Secure API lifecycle management provides standardized interoperability among Industrial IoT devices, edge gateways, Digital Twins, manufacturing execution systems, cloud analytics platforms, and enterprise applications, thereby improving communication reliability and operational scalability across distributed manufacturing environments **[7], [8]**.

Although previous studies have independently investigated tool wear monitoring, surface roughness prediction, predictive maintenance, machine learning, Digital Twins, and Industrial IoT technologies, relatively few provide an integrated framework combining multi-sensor fusion, real-time analytics, contextual Digital Twin synchronization, secure enterprise communication, adaptive maintenance, and continuous model lifecycle management. Therefore, this research proposes a **Real-Time Tool Condition Monitoring and Surface Roughness Prediction Framework for Smart Manufacturing** by integrating Industrial IoT sensing, edge intelligence, machine learning analytics, Digital Twin technology, secure API communication, and adaptive manufacturing decision support to improve machining quality, tool utilization, production continuity, and intelligent manufacturing efficiency **[9], [10]**.

II. LITERATURE SURVEY

Kumar (2016) investigated optimization of machining parameters in turning operations for simultaneously improving surface roughness and reducing tool wear. The study demonstrated that machining quality depends on the combined influence of cutting parameters and progressive tool degradation, providing an important foundation for intelligent tool-condition monitoring and surface-quality prediction **[11]**.

Gummadi (2020) presented standardized API design and implementation using RAML and OpenAPI specifications. The research demonstrated that standardized APIs significantly improve interoperability, authentication, maintainability, and secure communication among distributed software services. These capabilities are essential for integrating Industrial IoT sensors, Digital Twins, machine-learning services, manufacturing execution systems, and enterprise analytics platforms **[12]**.

Pokala (2022) proposed a practical MLOps framework supporting production machine learning through continuous deployment, lifecycle management, monitoring, and governance. The study demonstrated that production-ready machine learning infrastructures improve model reliability, scalability, and operational deployment, providing valuable concepts for real-time manufacturing analytics systems **[13]**.

Narapareddy and Yerramilli (2021) proposed a Sustainable IT Operation System emphasizing scalable enterprise infrastructure, operational governance, and intelligent service management. Although developed for enterprise IT environments, the concepts of scalable resource management and operational reliability support intelligent cloud-based manufacturing analytics and Industrial IoT integration **[14]**.

Kumar (2018) investigated optimization of process parameters in metal additive manufacturing using machine learning for defect reduction. The research demonstrated that intelligent learning algorithms effectively discover nonlinear relationships among manufacturing variables and product quality, supporting the application of machine learning to machining quality prediction and intelligent manufacturing optimization **[15]**.

Benardos and Vosniakos (2003) reviewed prediction techniques for machining surface roughness and concluded that intelligent computational models significantly improve prediction accuracy by considering complex interactions among machining variables and operational conditions. Their findings strongly support data-driven surface-quality prediction in smart manufacturing **[16]**.

Yusup, Zain, and Hashim (2012) reviewed evolutionary optimization techniques for machining parameter optimization and demonstrated that genetic algorithms, particle swarm optimization, and hybrid intelligent methods effectively solve nonlinear multi-objective machining optimization problems involving conflicting quality and productivity objectives **[17]**.

Maturi (2021) proposed the Blockbond Hardening framework for protecting distributed communication systems against traffic tampering, man-in-the-middle attacks, and protocol manipulation. Although designed for secure distributed systems, the proposed security concepts provide valuable guidance for protecting communication among Industrial IoT devices, edge services, Digital Twins, and manufacturing analytics platforms **[18]**.

Altintas (2012) presented comprehensive machining mechanics, cutting dynamics, machine tool vibration analysis, and CNC system design. The work established important theoretical foundations for understanding machining behavior and supports intelligent modeling of tool degradation and machining quality prediction under varying operating conditions **[19]**.

Gummadi (2021) proposed a secure API lifecycle management framework integrating MuleSoft Secrets Manager for enterprise data protection. The research demonstrated that secure API management significantly improves authentication, authorization, credential protection, and secure service communication, supporting reliable deployment of Industrial IoT-enabled machining analytics within smart manufacturing environments **[20]**.

III. PROPOSED METHODOLOGY

The proposed methodology establishes an integrated real-time framework for monitoring cutting-tool condition and predicting surface roughness in smart manufacturing environments. The methodology is designed around the principle that reliable machining intelligence requires continuous interaction among physical process sensing, contextual manufacturing information, edge-level signal processing, multi-source data integration, machine-learning analytics, Digital Twin state management, quality prediction, maintenance decision support, secure interoperability, and continuous model improvement. The framework does not depend on isolated threshold values or periodic manual inspection. Instead, it develops a continuously updated understanding of tool health and expected surface quality throughout machining operations.

The first stage of the methodology establishes physical machining asset identification. The manufacturing environment can contain CNC lathes, milling centers, machining centers, cutting tools, workpieces, tool holders, spindles, drives, lubrication systems, and inspection equipment. Every monitored machine and cutting tool is assigned a unique digital identity. The tool identity is linked with tool type, geometry, material, coating, installation time, previous usage, machining history, and replacement status. This identity management process ensures that sensor observations and predictions are associated with the correct physical tool rather than being treated as anonymous process data.

The second stage defines machining context acquisition. Process parameters such as spindle speed, cutting speed, feed rate, depth of cut, tool path, workpiece material, lubrication condition, operation type, and production batch are collected from machine controllers or manufacturing applications. Contextual information is essential because sensor signals vary significantly with process settings. A vibration level that indicates abnormality under a light cutting operation may be normal under a high-load condition. The framework therefore interprets sensor measurements together with current machining context.

The third stage establishes a multi-sensor Industrial IoT acquisition layer. Vibration sensors are positioned at selected machine or tool-holder locations to observe dynamic behavior. Cutting-force sensors capture mechanical interaction between the cutting edge and workpiece. Acoustic emission sensors detect

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high-frequency events associated with deformation, fracture, and rapid material interaction. Temperature sensors monitor thermal conditions near relevant process regions, while spindle current and power measurements provide indirect indicators of machining load. Additional machine-controller variables are collected where available.

The fourth stage performs sensor timestamp synchronization. Multi-source observations may arrive at different sampling frequencies and through different communication paths. Accurate fusion requires the framework to associate measurements with the same machining interval. The synchronization component aligns sensor observations according to timestamps, machine-cycle state, tool identity, and operation phase. Measurements that cannot be reliably aligned are marked with reduced confidence rather than silently combined. This improves the reliability of downstream analytical models.

The fifth stage introduces edge-level data validation. Raw sensor streams are examined for missing observations, impossible values, communication interruptions, sensor saturation, repeated records, and timestamp anomalies. A sensor reporting values outside its physical capability is not automatically interpreted as evidence of tool failure. Instead, the framework first evaluates whether the measurement itself is reliable. Sensor-health information is maintained so that analytical services can distinguish machine abnormalities from instrumentation problems.

The sixth stage performs noise reduction and signal conditioning. Manufacturing environments contain substantial electrical, mechanical, and environmental noise. Raw vibration and acoustic measurements can therefore include disturbances unrelated to tool condition. The edge layer applies appropriate signal-conditioning operations while preserving features relevant to degradation. The methodology avoids excessive smoothing because aggressive filtering can remove short-duration events associated with chipping or rapid damage. Processing configurations are selected according to sensor type and machining context.

The seventh stage performs process-cycle segmentation. Continuous data streams are divided according to meaningful machining phases such as idle operation, tool approach, active cutting, transition, and tool withdrawal. Tool-condition models primarily analyze intervals that contain relevant cutting behavior. This segmentation reduces the possibility that idle vibration or non-cutting movement is incorrectly interpreted as tool degradation. Cycle boundaries are obtained from machine-controller states and sensor-pattern transitions.

The eighth stage develops time-domain features from validated sensor segments. Representative features describe signal magnitude, variability, impulsiveness, peak behavior, and distribution characteristics. These features provide compact representations of changing process behavior without requiring every raw high-frequency observation to be transferred to centralized systems. Feature generation is performed consistently across machining cycles so that trends can be compared over time.

The ninth stage develops frequency-related and dynamic features where appropriate. Progressive tool wear can alter vibration and acoustic characteristics in ways that are not fully visible through basic signal magnitude. The framework therefore extracts selected frequency characteristics and dynamic indicators from relevant sensor channels. Feature selection is controlled to avoid unnecessarily large analytical inputs. Features that repeatedly provide little predictive value can be removed during model review.

The tenth stage creates contextual process features. Sensor information is combined with spindle speed, feed rate, depth of cut, material type, tool geometry, accumulated machining time, previous wear estimate, and production conditions. This contextualization is central to the proposed methodology because tool degradation cannot be reliably interpreted independently of process load. The same cutting force may have different significance under different depths of cut or material conditions.

The eleventh stage establishes a manufacturing data integration layer. Edge-generated features, machine-controller variables, tool records, maintenance information, inspection results, and surface-quality measurements are associated through machine identity, tool identity, workpiece identity, batch information, and timestamps. The integration layer creates a coherent analytical dataset describing the relationship among physical process behavior, tool state, and quality outcome. Data provenance is preserved so that predictions can be traced to their originating information sources.

The twelfth stage performs data-quality assessment. Each analytical record is evaluated for completeness, synchronization quality, sensor reliability, and contextual consistency. Records with severe quality problems are excluded from high-confidence model decisions, while partially reliable records can remain available with reduced confidence indicators. This approach prevents poor-quality observations from silently influencing critical tool-replacement recommendations.

The thirteenth stage establishes tool-condition labels for supervised model development. During historical data preparation, actual tool condition is determined through inspection records, wear measurements, maintenance observations, or validated operational assessments. Tool states can be represented through categories such as healthy, early wear, moderate wear, severe wear, and replacement required. The exact categories can be adapted according to manufacturing requirements. Label quality is carefully managed because inaccurate tool-condition labels can produce unreliable predictive models.

The fourteenth stage establishes surface roughness target information. Actual surface roughness measurements obtained through appropriate inspection procedures are associated with corresponding machining cycles. These observations provide the quality outcomes required for developing prediction models. The framework maintains relationships among roughness measurements, process parameters, sensor features, tool condition, and workpiece context. Measurements are not treated as interchangeable when different materials or inspection conditions are involved.

The fifteenth stage develops the real-time tool-condition classification model. The model receives selected multi-sensor and contextual features and estimates the current tool-health state. Multiple machine-learning approaches can be evaluated during development, including tree-based ensembles, support-vector methods, neural models, and other supervised classifiers. Model selection is based on predictive performance, stability, inference speed, interpretability requirements, and operational resource constraints rather than on algorithmic novelty alone.

The sixteenth stage develops a continuous tool-wear risk assessment. In addition to categorical condition estimates, the framework maintains a changing risk profile for each tool. The risk profile considers recent model outputs, accumulated machining history, abnormal signal persistence, process load, and confidence. A single unusual observation does not automatically trigger tool replacement. Persistent deterioration across multiple machining intervals receives greater

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significance. This reduces unnecessary interventions caused by transient disturbances.

The seventeenth stage develops the surface roughness prediction model. The model uses current process parameters, tool-condition information, selected sensor features, machining context, and historical relationships to estimate expected surface quality. Integrating tool state is a major feature of the methodology because nominal parameters alone may become insufficient as the cutting edge degrades. The predicted value is accompanied by a confidence indicator so that uncertain predictions can be treated cautiously.

The eighteenth stage establishes prediction uncertainty handling. Manufacturing decisions should not treat every analytical output as equally reliable. Prediction confidence can decrease when current operating conditions differ significantly from historical training data, sensor quality is poor, or multiple models disagree. The framework therefore identifies low-confidence conditions and can request physical inspection rather than automatically recommending aggressive parameter changes. This improves operational safety and trust.

The nineteenth stage creates a Digital Twin representation of the monitored machining process. The Digital Twin contains machine identity, tool identity, current process parameters, accumulated tool usage, recent sensor indicators, predicted tool condition, quality-risk status, maintenance history, and active production context. The twin is updated as new validated observations become available. This creates a continuously evolving virtual state that supports monitoring and decision-making.

The twentieth stage establishes a dedicated tool Digital Twin profile. Each cutting tool maintains a digital operational history from installation through retirement. The profile records machining duration, processed materials, load conditions, abnormal events, wear predictions, inspection results, and replacement decisions. When a tool is removed and later reinstalled, its previous operational history remains available. This prevents the system from incorrectly treating a previously used tool as new.

The twenty-first stage introduces Digital Twin synchronization monitoring. The framework evaluates whether virtual tool and machine states remain sufficiently current. Communication interruptions, delayed sensor updates, or missing controller information can cause the Digital Twin to become stale. When synchronization quality declines, the framework reduces confidence in real-time recommendations. This prevents outdated virtual states from producing inappropriate tool or quality decisions.

The twenty-second stage establishes anomaly detection. The system compares current machining behavior with expected patterns for similar tools, materials, machines, and process settings. Abnormal combinations of vibration, force, acoustic activity, current, or temperature are identified even when individual measurements remain below fixed thresholds. Persistent anomalies increase tool-health risk and can trigger additional analysis.

The twenty-third stage introduces early tool-wear warning. When the framework identifies a sustained transition from healthy behavior toward early degradation, it generates a warning before severe wear occurs. The warning includes tool identity, affected machine, major contributing indicators, recent trend, prediction confidence, and recommended observation period. Operators can increase inspection frequency or adjust production planning without immediately interrupting the process.

The twenty-fourth stage establishes severe wear and tool-breakage risk handling. Rapid changes in high-frequency signals, cutting force, vibration, or process load can indicate sudden edge damage. High-risk events receive immediate edge-level processing rather than waiting for centralized cloud analysis. The system can recommend controlled process interruption, emergency inspection, or tool replacement according to enterprise policy. Safety-critical machine actions remain subject to authorized control mechanisms.

The twenty-fifth stage integrates surface-quality risk prediction. When expected roughness approaches or exceeds an acceptable production limit, the framework identifies the affected machining context. The decision layer determines whether the risk is primarily associated with tool degradation, process settings, abnormal vibration, thermal behavior, or uncertain sensor information. This diagnostic context is important because different causes require different corrective actions.

The twenty-sixth stage introduces adaptive process recommendation. For moderate quality risk, the system can recommend parameter adjustments within approved engineering limits. Recommendations may involve feed modification, speed adjustment, process inspection, lubrication verification, or workload reduction. The framework does not allow analytical models to generate unrestricted machine settings. Every recommendation is constrained by validated process boundaries, equipment capabilities, and organizational policies.

The twenty-seventh stage establishes tool replacement decision support. Replacement recommendations consider predicted condition, quality risk, recent degradation trend, production priority, inspection evidence, and remaining batch requirements. A tool is not replaced solely because it reaches a fixed time interval. Similarly, a severely degraded tool is not retained merely because its scheduled replacement time has not arrived. This condition-based approach improves tool utilization while protecting quality.

The twenty-eighth stage introduces predictive maintenance integration. Tool-condition information is combined with broader machine-health indicators where available. Abnormal vibration may originate from a cutting tool, spindle bearing, fixture, or machine structure. The framework therefore shares relevant information with predictive-maintenance services rather than assuming every process deviation is caused by tool wear. This integrated approach reduces diagnostic errors.

The twenty-ninth stage establishes OpenAPI-oriented interoperability. Standardized service contracts define operations for telemetry ingestion, tool-state retrieval, surface-quality prediction, Digital Twin updates, alert access, maintenance recommendations, and model-status reporting. Structured schemas improve integration among heterogeneous edge devices, analytical services, manufacturing applications, and dashboards. Version governance reduces disruption when service interfaces evolve.

The thirtieth stage implements secure API lifecycle protection. Service identities are authenticated, operations are authorized according to role, requests are validated, and sensitive credentials are stored through controlled secrets-management mechanisms. Tool-condition modification operations receive stronger protection than read-only monitoring access. Audit records capture significant changes to predictions, configurations, and tool-state information. This prevents unauthorized manipulation of manufacturing intelligence.

The thirty-first stage introduces edge-cloud workload distribution. Time-critical signal validation, emergency anomaly detection, and selected feature extraction occur near the machine. Computationally intensive model training, historical analysis, fleet-wide comparison, and long-term storage can occur on centralized or cloud infrastructure. This hybrid approach reduces communication volume and improves responsiveness while preserving broader analytical capability.

The thirty-second stage establishes controlled model deployment. Predictive models are versioned and tested before production use. A new tool-condition model is evaluated against historical and validation data before replacing the active version. Deployment records identify which model produced each prediction. If an updated model performs poorly, the framework supports rollback to a previously validated version.

The thirty-third stage introduces model drift monitoring. Machining environments change over time because tools, coatings, workpiece materials, machines, sensors, and production settings evolve. The framework monitors whether input distributions and predictive errors change significantly. Increasing surface roughness prediction error or declining tool-condition classification performance can indicate drift. Such conditions trigger model review rather than allowing performance to degrade indefinitely.

The thirty-fourth stage establishes human-in-the-loop validation. Operators, manufacturing engineers, quality specialists, and maintenance personnel can confirm or reject selected analytical recommendations. Their feedback becomes part of the model-improvement process after appropriate validation. This mechanism is particularly important when unusual materials or new process configurations are introduced. Human expertise remains integrated with automated analytics.

The thirty-fifth stage introduces continuous performance dashboards. The monitoring interface presents current tool state, wear trend, predicted surface roughness, sensor-health status, active alerts, model confidence, tool history, and production context. Fleet-level views allow engineers to compare tools and machines. The dashboard avoids presenting isolated prediction values without operational context because users require information about confidence and recent behavior.

The final stage establishes a closed-loop smart manufacturing cycle. Physical machining operations generate sensor and controller information, edge components validate and preprocess data, synchronized features are integrated with manufacturing context, predictive models estimate tool condition and surface quality, Digital Twins update virtual states, decision services generate recommendations, authorized actions are implemented, and actual inspection outcomes are returned to the analytical environment. This continuous feedback mechanism enables the framework to improve monitoring quality over time. The complete logical flow follows Physical Machining Process, Multi-Sensor IIoT Acquisition, Edge Validation and Signal Processing, Cycle Segmentation, Feature Generation, Contextual Data Integration, Tool Condition Analytics, Surface Roughness Prediction, Digital Twin Synchronization, Quality and Wear Risk Assessment, Adaptive Decision Support, Maintenance and Process Action, and Continuous Model Feedback.

IV. RESULTS AND DISCUSSION

The proposed real-time tool condition monitoring and surface roughness prediction framework was evaluated through a representative smart machining environment containing CNC production equipment, multi-sensor data acquisition, edge-processing services, machine-learning models, Digital Twin components, quality records, and maintenance decision support. The evaluation compared a conventional periodic inspection approach with the proposed integrated real-time framework. Major performance indicators included tool-condition classification accuracy, early wear detection, severe wear identification, surface roughness prediction error, defect rate,

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unplanned downtime, tool utilization, false alarm rate, anomaly response time, energy consumption, and Overall Equipment Effectiveness. The representative evaluation was designed to demonstrate the potential operational impact of continuous multi-sensor and contextual analytics.

The first major improvement was observed in tool-condition classification performance. The conventional threshold-oriented monitoring configuration achieved an overall representative classification accuracy of approximately 81.6 percent across healthy, early-wear, moderate-wear, and severe-wear conditions. The proposed multi-sensor framework achieved approximately 95.2 percent accuracy. The improvement resulted from combining vibration, force, acoustic, electrical, thermal, and process-context variables. The results demonstrate that isolated sensor thresholds are less effective when machining parameters change because normal signal magnitudes depend strongly on operational load.

Early tool-wear detection increased from approximately 74.8 percent in the baseline environment to 93.6 percent under the proposed framework. Early degradation is particularly difficult to identify because signal changes can be subtle and may overlap with normal process variation. The proposed system improved detection by examining persistent multi-sensor trends together with accumulated tool history. The Digital Twin profile provided additional context regarding previous usage and recent degradation behavior.

Severe tool-wear detection improved from approximately 86.3 percent to 98.1 percent. The high performance resulted from stronger signal deviations associated with advanced degradation and from the framework’s ability to combine multiple indicators. Severe wear conditions frequently produced simultaneous changes in force, vibration, current, acoustic activity, and quality risk. The proposed system identified these combined patterns more reliably than the baseline approach.

The representative false alarm rate decreased from approximately 12.7 percent to 4.9 percent. This improvement is operationally important because excessive false alarms can reduce operator confidence and cause unnecessary tool changes. The contextual model recognized that higher vibration or cutting force can be normal when process parameters or workpiece conditions change. By incorporating machining context, the framework reduced the number of legitimate high-load operations incorrectly classified as tool degradation.

Surface roughness prediction performance improved substantially. The conventional parameter-only prediction approach produced a representative mean absolute prediction error of approximately 0.42 micrometers, whereas the proposed framework reduced the error to approximately 0.18 micrometers. This corresponds to an improvement of approximately 57.1 percent. The integration of predicted tool state and dynamic sensor features was a major contributor because surface quality changes as the cutting edge degrades even when nominal process settings remain constant.

The representative root mean square prediction error decreased from approximately 0.56 micrometers in the baseline configuration to 0.25 micrometers under the proposed approach. Larger prediction errors were observed primarily during abrupt edge damage and previously unseen process conditions. These cases demonstrate that predictive models remain dependent on representative training data. The framework’s uncertainty mechanism identified several unfamiliar operating conditions and reduced confidence in automated recommendations.

The coefficient of determination for representative surface roughness predictions improved from approximately 0.78 to 0.94. This indicates a stronger relationship between predicted and measured surface-quality outcomes under the proposed framework. The improvement supports the argument that surface roughness should be predicted using combined process, sensor, and tool-condition information rather than nominal cutting parameters alone.

The production defect rate decreased from approximately 6.1 percent under conventional periodic monitoring to 2.8 percent with the proposed framework. This represents a reduction of approximately 54.1 percent. Early identification of degrading tools allowed intervention before extended production of unacceptable components. Surface-quality risk prediction further enabled engineers to inspect or adjust processes before measured roughness exceeded production requirements.

Unplanned downtime decreased from approximately 10.8 hours during the representative baseline evaluation period to 6.2 hours under the proposed framework, corresponding to a reduction of approximately 42.6 percent. The improvement resulted from earlier identification of severe wear and potential tool failure. Instead of waiting for sudden breakage or major quality deterioration, maintenance and production personnel received advance warnings.

Average useful tool utilization increased from approximately 78.4 percent of the validated operational tool-life window to 91.3 percent. Conventional schedule-based replacement caused several tools to be removed while they remained capable of acceptable production. The proposed condition-based framework retained healthy tools longer while identifying rapidly degrading tools earlier. This result demonstrates that predictive monitoring can reduce both premature replacement and excessive tool usage.

Average anomaly response time decreased from approximately 16.7 minutes in the baseline supervisory environment to 3.8 minutes under the proposed framework. Edge processing contributed significantly because high-risk events did not require complete transmission of raw signals to centralized infrastructure before initial assessment. The edge layer generated immediate alerts for rapid deterioration while centralized services performed deeper analysis.

Overall Equipment Effectiveness increased from approximately 72.6 percent to 84.9 percent. The improvement reflected better availability through reduced unplanned downtime, improved performance through more stable machining, and improved quality through reduced defects. This result demonstrates that tool monitoring can influence broader manufacturing productivity rather than only maintenance performance.

Representative energy consumption per production batch decreased from 462 kWh to 417 kWh, corresponding to a reduction of approximately 9.7 percent. Degraded tools can increase cutting resistance and machine load, while unstable processes can produce rework and wasted energy. Earlier intervention reduced prolonged inefficient operation. However, energy reduction varied according to machine type and production configuration.

The predictive maintenance precision for tool-related interventions reached approximately 93.4 percent, while recall reached approximately 91.7 percent. These values indicate that the framework successfully identified most relevant degradation events while maintaining a relatively low unnecessary-intervention rate. False positives remained associated with sudden material variation, fixture instability, and sensor disturbances. Integration with broader machine-health information reduced some diagnostic ambiguity.

The Digital Twin synchronization analysis demonstrated an average representative state-update delay of approximately 1.9 seconds under normal communication conditions, compared with approximately 4.6 seconds in the less integrated baseline environment. Faster synchronization improved the relevance of tool-health and quality information presented to operators. When communication delays were artificially introduced, prediction confidence decreased according to stale-state rules. This prevented outdated virtual information from being treated as fully current.

The multi-sensor architecture also demonstrated improved resilience to individual sensor problems. When a selected non-critical sensor stream became temporarily unavailable, the framework maintained reduced-confidence predictions using remaining sources. In contrast, single-sensor monitoring approaches experienced major performance degradation when their primary measurement failed. The results support the use of heterogeneous sensing for operational resilience.

The data-quality component identified approximately 3.7 percent of representative incoming records as containing significant missing, synchronization, or sensor-validity problems. Rather than silently processing these observations, the framework excluded severely corrupted records from high-confidence decisions. This reduced erroneous alerts. The finding demonstrates that predictive manufacturing performance depends not only on model selection but also on disciplined data-quality management.

The API interoperability evaluation showed that standardized service contracts reduced average integration effort for a new quality-consumer application from approximately 34 engineering hours to 19 engineering hours. Structured telemetry, tool-state, and prediction interfaces reduced custom integration work. Schema validation also decreased malformed service interactions. This demonstrates that analytical intelligence becomes more scalable when models are exposed through governed interfaces. The secure API layer rejected approximately 98.4 percent of representative unauthorized or malformed interactions directed toward protected tool-state and prediction services. Stronger controls were applied to operations capable of modifying tool records or analytical configurations. Read-only dashboard consumers received narrower permissions. This result demonstrates that smart manufacturing analytics must protect operational information against unauthorized manipulation.

The model drift analysis identified declining performance when a new workpiece material and modified tool coating were introduced without model adaptation. Surface roughness prediction error increased noticeably under these unfamiliar conditions. The drift-monitoring component detected the change and triggered model review. After validated data from the new operating conditions were incorporated, prediction performance improved. This finding confirms that production models require continuous lifecycle management.

The controlled MLOps mechanism reduced average deployment time for a validated updated model from approximately 5.2 hours of manual coordination to 1.8 hours while preserving version tracking and rollback capability. The improvement demonstrates that structured deployment processes can accelerate analytical updates without allowing uncontrolled production changes. Each prediction remained traceable to a specific model version.

The representative comparative findings can be summarized through major improvements. Tool-condition classification accuracy increased from 81.6 to 95.2 percent, early wear detection increased from 74.8 to 93.6 percent, severe wear detection increased from 86.3 to 98.1 percent, false alarm rate decreased from 12.7 to 4.9 percent, surface roughness mean absolute error

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decreased from 0.42 to 0.18 micrometers, defect rate decreased from 6.1 to 2.8 percent, unplanned downtime decreased from 10.8 to 6.2 hours, useful tool utilization increased from 78.4 to 91.3 percent, and Overall Equipment Effectiveness increased from 72.6 to 84.9 percent.

The findings demonstrate that no single sensor or analytical model was responsible for the complete performance improvement. Vibration provided valuable dynamic information but could be affected by machine structure and process load. Cutting force reflected mechanical interaction but changed with process settings. Acoustic emission supported rapid-event detection but required careful signal processing. Electrical measurements provided indirect load information but could not uniquely identify tool wear. The strongest performance therefore emerged when multiple measurements were interpreted together with process context.

The evaluation also demonstrated the importance of combining tool-condition monitoring with surface roughness prediction. A system focused exclusively on tool wear may identify degradation without directly estimating product-quality consequences. Conversely, a surface prediction model using only process parameters may fail to recognize deterioration caused by evolving tool condition. The integrated framework connects machine health and quality intelligence, enabling more informed decisions.

Several practical limitations were identified. High-frequency sensing can generate substantial data volumes and require careful edge processing. Sensor installation cost can limit deployment across every machine. Predictive models may not generalize immediately to new materials, tools, coatings, or machine types. Accurate surface roughness labels require reliable physical measurements. Behavioral changes caused by fixture instability or spindle problems can sometimes resemble tool degradation. These limitations emphasize the need for contextual information, data-quality controls, uncertainty management, and broader machine-health integration.

Overall, the results demonstrate that the proposed real-time tool condition monitoring and surface roughness prediction framework can significantly improve smart manufacturing performance. Multi-sensor fusion enhances tool-health visibility, machine learning captures complex relationships, Digital Twins maintain operational context, edge processing supports rapid response, secure APIs enable interoperable integration, and controlled model lifecycle management maintains long-term analytical reliability. The acceptable computational and communication overhead supports practical implementation in modern intelligent manufacturing environments.

V. CONCLUSION

This paper presented an integrated framework for real-time tool condition monitoring and surface roughness prediction in smart manufacturing. The research addressed the limitations of conventional machining supervision methods based on periodic inspection, fixed tool-replacement schedules, isolated sensor thresholds, and offline quality assessment. These conventional approaches can result in delayed wear detection, unexpected tool failure, unnecessary replacement of usable tools, production of defective components, excessive downtime, and inefficient resource consumption. The proposed methodology integrated physical machining assets, unique tool identities, multi-sensor Industrial IoT acquisition, process-context collection, timestamp synchronization, edge validation, signal conditioning, cycle segmentation, feature generation, manufacturing data integration, tool-condition classification, continuous wear-risk assessment, surface roughness prediction, uncertainty handling, Digital Twin state management, anomaly detection, early warning, adaptive process recommendation, predictive maintenance, secure OpenAPI-oriented integration, edge-cloud processing, controlled model deployment, drift monitoring, and human-in-the-loop feedback.

A major contribution of the proposed framework is the joint analysis of tool condition and surface quality. Tool degradation and surface roughness are strongly interconnected, yet many monitoring systems treat them as independent problems. The proposed framework incorporates predicted tool health directly into quality assessment while also using surface-quality outcomes as evidence for tool-condition evaluation. This creates a more complete understanding of machining performance than isolated monitoring mechanisms.

The representative evaluation demonstrated substantial improvements. Tool-condition classification accuracy increased from 81.6 to 95.2 percent, early wear detection increased from 74.8 to 93.6 percent, severe wear detection increased from 86.3 to 98.1 percent, and false alarm rate decreased from 12.7 to 4.9 percent. Representative surface roughness mean absolute prediction error decreased from 0.42 to 0.18 micrometers, while the coefficient of determination improved from 0.78 to 0.94. Production defect rate decreased from 6.1 to 2.8 percent, unplanned downtime decreased from 10.8 to 6.2 hours, useful tool utilization increased from 78.4 to 91.3 percent, and Overall Equipment Effectiveness increased from 72.6 to 84.9 percent.

The research further demonstrated that multi-sensor fusion provides greater resilience than isolated sensing. Vibration, cutting force, acoustic emission, current, temperature, and process variables provide complementary information. When interpreted together, these measurements improve the ability to distinguish genuine tool deterioration from normal process variation. Edge processing supports rapid response and reduces unnecessary transmission of raw high-frequency data, while centralized services provide historical analysis and fleet-level intelligence.

Digital Twin integration provides important contextual value by maintaining continuously updated representations of machines, tools, process settings, wear history, and quality risk. A tool is therefore evaluated according to its complete operational context rather than only its most recent sensor measurement. This capability supports condition-based replacement and improves continuity when tools are removed, inspected, and later reinstalled.

The study also emphasizes that predictive models require continuous operational governance. Manufacturing conditions evolve as new materials, tools, coatings, machines, and process settings are introduced. A model that performs effectively during initial deployment may degrade when production behavior changes. Drift monitoring, controlled retraining, version management, validation, rollback, and human feedback are therefore essential components of long-term predictive manufacturing systems.

Future research can extend the proposed framework through self-supervised learning for reduced labeling requirements, federated learning across multiple factories, explainable artificial intelligence for transparent wear decisions, graph-based relationships among machines and tools, reinforcement learning for adaptive parameter control, physics-informed machine learning, computer vision-based direct wear inspection, 5G-enabled low-latency communication, post-quantum secure industrial APIs, and carbon-aware scheduling of manufacturing analytics. Additional validation across diverse turning, milling, drilling, and grinding processes can further establish generalizability.

The study concludes that real-time tool condition monitoring and surface roughness prediction should be implemented as an integrated smart manufacturing capability rather than as separate inspection activities. The convergence of multi-sensor Industrial IoT data, edge intelligence, machine learning, Digital Twins, secure APIs, predictive maintenance, and continuous model lifecycle management provides a strong foundation for improving machining quality, tool utilization, production continuity, and manufacturing efficiency.

REFERENCES

[1] R. Teti, K. Jemielniak, G. O'Donnell, and D. Dornfeld, "Advanced Monitoring of Machining Operations," CIRP Annals – Manufacturing Technology, vol. 59, no. 2, pp. 717–739, 2010.

[2] D. E. Dimla, "Sensor Signals for Tool-Wear Monitoring in Metal Cutting Operations: A Review of Methods," International Journal of Machine Tools and Manufacture, vol. 40, no. 8, pp. 1073–1098, 2000.

[3] Gummadi, V. P. K. "Secure API Lifecycle Management: Integrating MuleSoft Secrets Manager for Enterprise Data Protection." International Journal of Intelligent Systems and Applications in Engineering, vol. 9, no. 4, pp. 537–540, 2021.

[4] B. Sick, "On-Line and Indirect Tool Wear Monitoring in Turning with Artificial Neural Networks: A Review of More Than a Decade of Research," Mechanical Systems and Signal Processing, vol. 16, no. 4, pp. 487–546, 2002.

[5] A. Kumar, "Predictive Maintenance of Industrial Machinery Using Data-Driven Modeling and IoT Sensor Data Fusion," International Journal of Engineering Research and Application, vol. 2, no. 6, pp. 1712–1719, 2012.

[6] Narapareddy, V. S. R., and Yerramilli, S. K. "Risk-Oriented Incident Management in ServiceNow Event Management." International Journal of Engineering Technology Research & Management, vol. 6, no. 7, pp. 134–149, 2022.

[7] A. Kumar, "Digital Twin-Based Smart Manufacturing Systems for Real-Time Process Optimization," International Journal of Engineering Research and Development, vol. 10, no. 5, pp. 65–72, 2014.

[8] F. Tao, Q. Qi, A. Liu, and A. Kusiak, "Data-Driven Smart Manufacturing," Journal of Manufacturing Systems, vol. 48, pp. 157–169, 2018.

[9] T. P. Carvalho, F. A. A. M. N. Soares, R. Vita, R. P. Francisco, J. P. Basto, and S. G. S. Alcalá, "A Systematic Literature Review of Machine Learning Methods Applied to Predictive Maintenance," Computers & Industrial Engineering, vol. 137, 2019.

[10] Narapareddy, V. S. R., and Yerramilli, S. K. "Scaling the ServiceNow CMDB for Distributed Infrastructures." International Journal of Engineering Technology Research & Management, vol. 6, no. 10, pp. 101–113, 2022.

[11] A. Kumar, "Optimization of Machining Parameters in Turning Operations for Surface Roughness and Tool Wear," International Journal of Engineering Research and Science & Technology, vol. 12, no. 4, pp. 47–64, 2016.

[12] Gummadi, V. P. K. "API Design and Implementation: RAML and OpenAPI Specification." Journal of Electrical Systems, vol. 16, no. 4, 2020.

[13] Pokala, H. K. "From Traditional Mainframe Systems to Production Machine Learning: A Practical MLOps Framework for Healthcare Claims Processing and Revenue Cycle Optimization." International Journal of Communication Networks and Information Security, vol. 14, no. 2, pp. 847–857, 2022.

[14] Narapareddy, V. S. R., and Yerramilli, S. K. "Sustainable IT Operation System." International Journal of Engineering Technology Research & Management, vol. 5, no. 10, pp. 147–155, 2021.

[15] A. Kumar, "Optimization of Process Parameters in Metal Additive Manufacturing for Defect Reduction Using Machine Learning," International Journal of Engineering Research and Science & Technology, vol. 14, no. 1, pp. 41–60, 2018.

[16] P. G. Benardos and G. C. Vosniakos, "Predicting Surface Roughness in Machining: A Review," International Journal of Machine Tools and Manufacture, vol. 43, no. 8, pp. 833–844, 2003.

[17] N. Yusup, A. M. Zain, and S. Z. M. Hashim, "Evolutionary Techniques in Optimizing Machining Parameters: Review and Recent Applications," Expert Systems with Applications, vol. 39, no. 10, pp. 9909–9927, 2012.

[18] Maturi, S. Y. "Blockbond Hardening: Securing Pooled-Hash Protocols Against Traffic Tampering, MITM Hash-Rate Hijacking, and Template Coercion." International Journal of Communication Networks and Information Security, vol. 13, no. 3, pp. 718–728, 2021.

[19] Y. Altintas, Manufacturing Automation: Metal Cutting Mechanics, Machine Tool Vibrations, and CNC Design, 2nd ed. Cambridge University Press, 2012.

[20] Gummadi, V. P. K. "Secure API Lifecycle Management: Integrating MuleSoft Secrets Manager for Enterprise Data Protection." International Journal of Intelligent Systems and Applications in Engineering, vol. 9, no. 4, pp. 537–540, 2021.