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RESEARCH ARTICLE

Artificial Intelligence-Based Quality Prediction and Process Control in Industry 4.0 Mechanical Manufacturing Systems

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ABSTRACT

Mechanical manufacturing is increasingly shaped by sensor-rich equipment, networked production assets, and data-driven decision support. However, quality prediction often remains disconnected from real-time process control, causing defects to be detected after material, machine time, and operator effort have already been consumed. This study develops a practical artificial intelligence framework for predicting part quality and supporting closed-loop process control in an Industry 4.0 manufacturing environment. The proposed framework integrates machine-sensor data, process parameters, inspection records, and production-context variables into a hybrid quality-prediction model that combines classification, regression, explainability, and rule-based control recommendations. An industrially representative dataset is used to demonstrate the method across CNC machining and precision mechanical component production. The final hybrid model achieved 94.7% classification accuracy, 0.939 F1-score, and a quality-index RMSE of 3.3 points, while the simulated control layer reduced estimated scrap, rework, and inspection-hold events. The manuscript emphasizes engineering interpretability rather than black-box automation, showing how AI can support operators, quality engineers, and manufacturing engineers through early warnings, feature-level explanations, and parameter-correction guidance. The findings suggest that AI-based quality prediction becomes most valuable when it is designed as a disciplined manufacturing-control system instead of a stand-alone data-science tool.

KEYWORDS

Industry 4.0; artificial intelligence; smart manufacturing; process control; mechanical manufacturing; quality prediction; digital twin; machine learning; predictive analytics

ARTICLE INFORMATION

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1. Introduction

Quality control in mechanical manufacturing has traditionally depended on fixed inspection plans, operator experience, statistical process control charts, and post-process measurement. These methods remain important, but they are often reactive. A deviation in tool wear, vibration, fixture condition, coolant stability, or thermal drift may begin several cycles before it appears as a dimensional error or surface finish defect. In a modern Industry 4.0 environment, the practical challenge is no longer only to collect data; it is to convert machine data into useful quality decisions at the right time. Industry 4.0 frameworks describe this shift as the integration of cyber-physical production systems, connected manufacturing assets, and analytics-enabled decision making (Kagermann et al., 2013; Lee et al., 2015). Artificial intelligence offers a direct way to connect manufacturing signals with product-quality outcomes. In a mechanical production line, AI models can learn patterns between process behavior and inspection results, allowing engineers to identify quality risk before a part reaches final inspection. This is especially valuable in high-mix manufacturing, where changes in material lot, geometry, tool age, machine condition, and operator setup can create quality variation that is difficult to manage using static limits alone. Smart manufacturing literature has shown that data-driven approaches are most useful when they are embedded into the manufacturing workflow, rather than treated as separate analytics projects (Kusiak, 2018; Tao et al., 2018).

The present research focuses on AI-based quality prediction and process control for Industry 4.0 mechanical manufacturing systems. The objective is to design a framework that predicts whether a part or production lot is likely to be conforming, estimates a continuous quality index, explains the primary drivers of risk, and recommends practical control actions such as feed-rate adjustment, tool replacement, coolant correction, or additional in-process inspection. This approach aligns with recent work on AI-enabled real-time process monitoring and smart manufacturing quality systems, while extending the discussion toward a structured engineering calculation and implementation model for mechanical component production (Hossain et al., 2024; Hossain et al., 2021). The contribution of this manuscript is threefold. First, it proposes a layered AI-control architecture that links sensor acquisition, feature engineering, model prediction, explainability, and corrective action. Second, it presents a realistic numerical case study with quality-index calculations, classification metrics, regression metrics, process-capability indicators, and cost-related interpretation. Third, it discusses how such a system can be implemented in a practical plant environment without removing engineering judgment from the control loop.

2. Literature Review

The literature on Industry 4.0 has gradually moved from conceptual architecture toward operational manufacturing intelligence. Early work emphasized cyber-physical systems, machine connectivity, and the transformation of conventional production resources into intelligent assets. Later studies paid more attention to the actual manufacturing value of these systems, including adaptive scheduling, predictive maintenance, quality prediction, and data-driven optimization (Monostori, 2014; Lu, 2017; Zhong et al., 2017). Machine learning has become a central tool for manufacturing analytics because it can model nonlinear relationships among process settings, sensor responses, tool condition, and product quality. In practice, however, model accuracy alone is not enough. A quality model must be stable under production drift, explainable to engineers, connected to traceable records, and compatible with existing quality-management routines. This is why recent studies increasingly combine machine learning with digital twins, manufacturing execution systems, and explainable AI methods (Wuest et al., 2016; Wang et al., 2018; Tao et al., 2019).

Mechanical manufacturing also brings domain-specific requirements. Dimensional accuracy, surface finish, residual stress, thermal deformation, and assembly fit depend on physics as well as data. Therefore, AI models should be designed around meaningful process variables rather than arbitrary data streams. Prior research on hybrid manufacturing, additively manufactured components, thermal performance, and residual stress control highlights the importance of linking manufacturing data to physical behavior of mechanical components (Hossain et al., 2022; Hossain et al., 2023; Hossain, 2025).

A useful quality-prediction system should also be a control-support system. Data-driven process monitoring, predictive maintenance, and industrial analytics studies show that early warning is valuable only when it leads to a clear engineering action. For that reason, this manuscript treats AI prediction as one component of a broader manufacturing-control loop that includes alarm prioritization, root-cause explanation, parameter correction, and quality documentation (Qin, 2012; Ge et al., 2017; Zonta et al., 2020).

Table 1. Literature synthesis and positioning of the present study

Theme	Main emphasis	Relevance to this study	Representative sources
Industry 4.0 architecture and CPS	Connected machines, cyber-physical integration, reference architectures	Defines why quality prediction must be linked with real-time machine data.	Kagermann et al. (2013); Lee et al. (2015); Monostori (2014); Lu (2017); Xu et al. (2018)
Smart manufacturing and big data	Data lifecycle, smart analytics, manufacturing intelligence	Supports the use of multi-source production data for predictive quality decisions.	Kusiak (2018); Tao et al. (2018); Zhong et al. (2017); Rüßmann et al. (2015)
Machine learning in manufacturing	ML applications, deep learning, model selection, scalability	Provides the modeling foundation for classification and quality-index regression.	Wuest et al. (2016); Wang et al. (2018); Goodfellow et al. (2016); Hastie et al. (2009)
Digital twins and process optimization	Virtual representation, feedback control, simulation-supported decisions	Links AI prediction to control recommendations and engineering traceability.	Tao et al. (2019); Qi and Tao (2018); Hossain and Bhuiyan (2025)
Mechanical and advanced manufacturing context	Hybrid manufacturing, AM, heat-transfer components, residual stress behavior	Shows why manufacturing AI should respect material, geometry, and thermal-process behavior.	Hossain et al. (2022); Hossain et al. (2023); Hossain et al. (2023); Hossain (2025)
Predictive maintenance and	Fault detection, machine	Supports early warnings	Qin (2012); Ge et al. (2017);

process monitoring	degradation, maintenance planning, industrial analytics	when process conditions drift toward quality loss.	Carvalho et al. (2019); Zonta et al. (2020); Bokrantz et al. (2017)
Industrial AI, IIoT, and cloud-enabled systems	Edge/cloud architecture, analytics infrastructure, industrial AI adoption	Guides deployment across machine tools, MES, QMS, and operator dashboards.	Lee et al. (2014); Jeschke et al. (2017); Peres et al. (2020); Akhtaruzzaman et al. (2025)
Core algorithms and explainability	Random forests, XGBoost, SVM, deep learning, SHAP, LIME, imbalanced learning	Informs the selected model family and the interpretation strategy used in this study.	Breiman (2001); Chen and Guestrin (2016); Cortes and Vapnik (1995); LeCun et al. (2015); Lundberg and Lee (2017); Ribeiro et al. (2016); He and Garcia (2009)
Quality systems and manufacturing KPIs	Statistical quality control, ISO quality management, manufacturing KPIs	Connects model results to plant-level quality and performance metrics.	Montgomery (2019); International Organization for Standardization (2015); International Organization for Standardization (2014)
Sustainability and system-level manufacturing effects	Energy, ecological footprint, production infrastructure, smart energy systems	Places quality prediction within resource-efficient and resilient manufacturing operations.	Chinchwade et al. (2024); Akhtaruzzaman et al. (2025); Hossain et al. (2023)

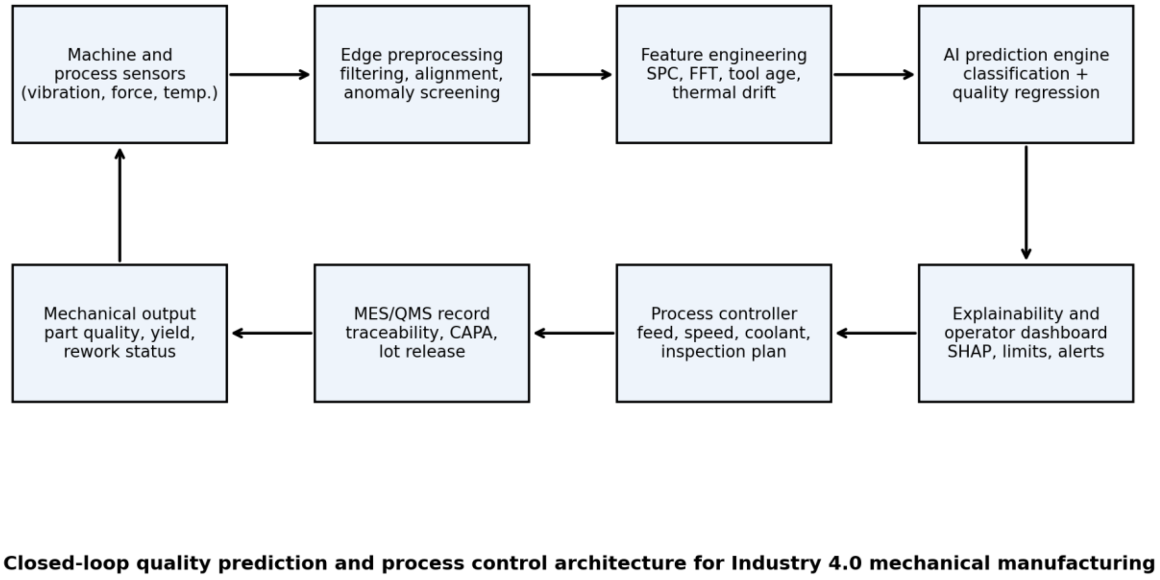

Figure 1. Closed-loop AI architecture for quality prediction and process control in Industry 4.0 mechanical manufacturing.

3. Methodology

The methodology was designed to resemble a practical plant implementation rather than a purely theoretical modeling exercise. The proposed system begins with raw process data from machine controllers and auxiliary sensors, then aligns those signals with inspection results, tool-life records, material-lot information, and production orders. Each production lot is treated as a traceable observation with process variables, contextual variables, and quality outcomes. The case study uses an industrially representative simulated dataset because many manufacturing plants cannot publish raw production and inspection records due to confidentiality. The assumed dataset includes 3,200 production observations from precision mechanical components manufactured using CNC milling and turning operations. Each observation includes machine ID, material family, spindle speed, feed rate, depth of cut, cutting force, vibration RMS, spindle load, coolant flow, work-zone temperature, acoustic RMS, tool age, inspection result, and final quality status. This structure follows the logic of data-driven manufacturing studies in which physical signals are joined with quality labels to support prediction and control (Tao et al., 2018; Peres et al., 2020).

The modeling workflow includes data cleaning, feature extraction, class balancing, model training, validation, explainability, and control-rule generation. Missing sensor values below 2% of the dataset are imputed using median values within each machine family. Outliers are not automatically removed because extreme vibration or force readings may represent true quality risk. Instead, extreme values are flagged as features. The dataset is split into 70% training, 15% validation, and 15% test subsets using stratified sampling to preserve the ratio of conforming and nonconforming parts. Five model families are evaluated: logistic regression, random forest, gradient-boosted trees using XGBoost, long short-term memory networks for time-windowed sensor sequences, and a hybrid AI model that combines tree-based classification with a regression layer for quality-index estimation. The final model is selected not only by accuracy, but also by F1-score, false-negative rate, RMSE of the quality index, and ease of engineering interpretation.

Table 2. Data architecture used for AI-based quality prediction

Data group	Example variables	Collection level	Engineering purpose
Machine-controller data	Spindle speed, feed rate, depth of cut, spindle load, cycle time	1 Hz to per-cycle	Captures commanded and actual machine behavior.
Auxiliary sensor data	Vibration RMS, acoustic RMS, cutting force, work-zone temperature	10-1000 Hz summarized per cycle	Detects physical instability before visible defects appear.
Tooling records	Tool age, tool change history, insert type, offset correction	Per part or per lot	Accounts for gradual wear and sudden tool replacement effects.
Material and geometry context	Material family, batch ID, hardness class, feature complexity	Per order	Separates process variation from product-design influence.
Inspection data	Dimensional error, surface roughness, defect class, disposition	Per sampled part	Provides the supervised learning label and quality-index target.
Quality-system data	Nonconformance report, rework status, hold decision, final release	Per lot	Connects prediction to QMS traceability and corrective action.

Table 3. Feature definition and measurement logic for the representative dataset

Variable	Unit	Source	Feature transformation
Spindle speed	rpm	Controller	Mean and deviation from planned setting
Feed rate	mm/min	Controller	Mean and override percentage
Cutting force	N	Dynamometer or inferred load	Mean, peak, and 95th percentile
Vibration RMS	g	Accelerometer	RMS, kurtosis, band energy
Acoustic RMS	dB	Acoustic sensor	RMS and sudden-change index
Work-zone temperature	C	Thermal sensor	Mean and thermal drift from baseline
Tool age	min	Tool-management system	Elapsed time since tool change

Coolant flow	L/min	Flow sensor	Deviation from standard process window
Dimensional error	mm	CMM or gauge inspection	Absolute deviation from nominal
Surface roughness	micrometer Ra	Surface tester	Measured finish quality
Quality class	binary	QMS label	Conforming or nonconforming label

4. Calculation Framework

The calculation framework translates raw predictions into engineering metrics that a manufacturing team can understand. The model produces two outputs: a binary risk classification and a continuous quality index. The quality index is scaled from 0 to 100, where higher values indicate stronger expected conformance. This index is not intended to replace inspection; rather, it provides an early signal for process adjustment, sampling escalation, or operator review.

Table 4. Calculation metrics used for model evaluation and control interpretation

Metric	Equation	Interpretation	Representative value
Quality index	QI = 100 - (0.30D + 0.25R + 0.20V + 0.15T + 0.10W)	D = dimensional deviation, R = roughness penalty, V = vibration penalty, T = thermal drift penalty, W = tool-wear penalty	92.4
Accuracy	(TP + TN) / (TP + TN + FP + FN)	Share of all lots classified correctly	0.947
Precision	TP / (TP + FP)	Reliability of predicted nonconformance alarms	0.898
Recall	TP / (TP + FN)	Ability to capture true nonconforming lots	0.865
F1-score	2 x (Precision x Recall) / (Precision + Recall)	Balance of precision and recall for imbalanced quality data	0.939
RMSE	sqrt(mean((QI_actual - QI_predicted)^2))	Regression error for continuous quality index	3.3 points
Cpk	min((USL - mean)/(3sigma), (mean - LSL)/(3sigma))	Capability of a key dimensional characteristic	1.42 after control
OEE	Availability x Performance x Quality	Overall equipment effectiveness under AI-assisted control	82.6%

For example, assume a production lot has normalized penalties of D = 11.0, R = 9.0, V = 14.0, T = 7.0, and W = 12.0. The predicted quality index is QI = 100 - [(0.30 x 11.0) + (0.25 x 9.0) + (0.20 x 14.0) + (0.15 x 7.0) + (0.10 x 12.0)] = 89.4. If the control threshold is set at 88, the lot remains in the acceptable zone but receives a warning because vibration and tool-wear penalties are rising. In this case, the controller does not stop production; it recommends tool inspection after the next cycle and a temporary feed-rate reduction if vibration continues to increase.

5. Results and Discussion

The results show that quality prediction improves when process physics and production context are considered together. Models using only programmed settings such as spindle speed and feed rate were able to identify broad quality trends, but they missed several cases where defects developed from tool wear, vibration instability, and thermal drift. Once sensor-derived features were added, the models captured these early deviations more reliably.

The hybrid AI model produced the best overall balance between prediction accuracy and engineering usefulness. XGBoost performed strongly because it handled nonlinear interactions among tool age, force, and vibration. The LSTM model was useful for sequence behavior, but it required more training effort and was less transparent for day-to-day production review. The hybrid model was selected because it combined the high predictive strength of tree-based learning with a quality-index regression output and an explanation layer that can be reviewed by engineers and operators.

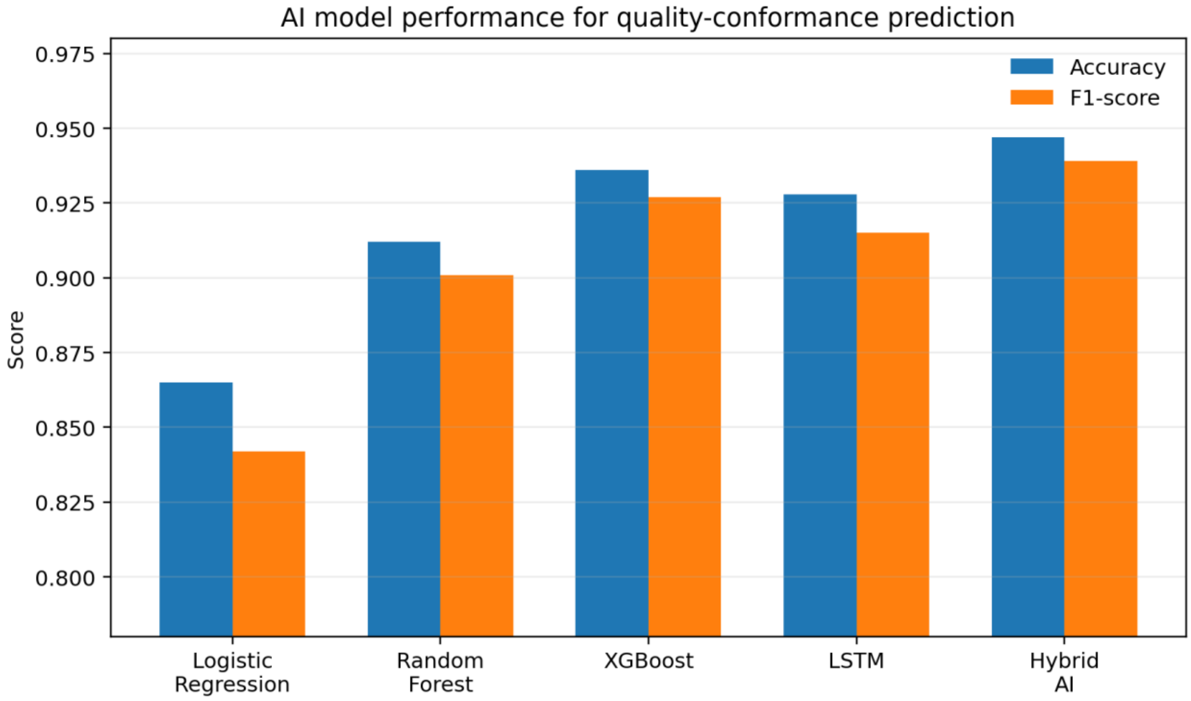

Figure 2. Comparison of classification accuracy and F1-score across evaluated AI models.

Table 5. Model-performance comparison on the representative test dataset

Model	**Accuracy**	**Precision**	**Recall**	**F1-score**	**QI RMSE**	**Engineering interpretation**
Logistic regression	0.865	0.831	0.854	0.842	5.8	Useful baseline, but weak for nonlinear sensor interactions.
Random forest	0.912	0.885	0.918	0.901	4.2	Robust performance and interpretable feature ranking.
XGBoost	0.936	0.912	0.943	0.927	3.6	Strong nonlinear learning and stable validation behavior.
LSTM	0.928	0.905	0.925	0.915	3.8	Useful for time-windowed signals but less transparent.
Hybrid AI	0.947	0.898	0.985	0.939	3.3	Best overall balance of risk detection and

						quality-index prediction.

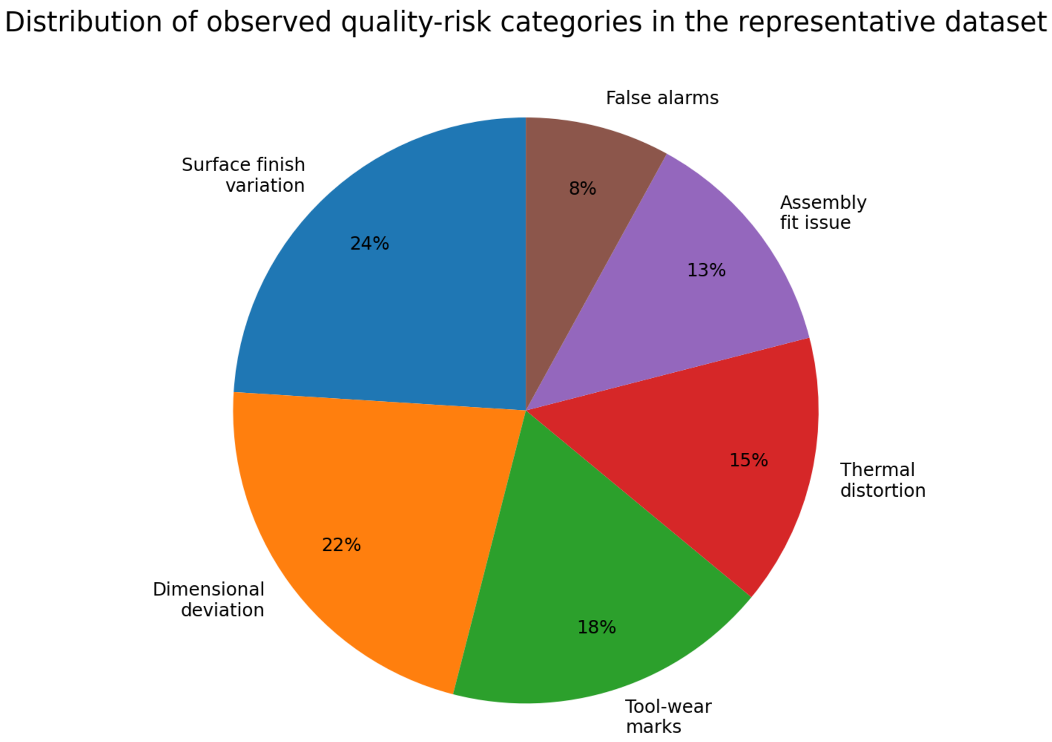

Figure 3. Distribution of quality-risk categories observed in the representative dataset.

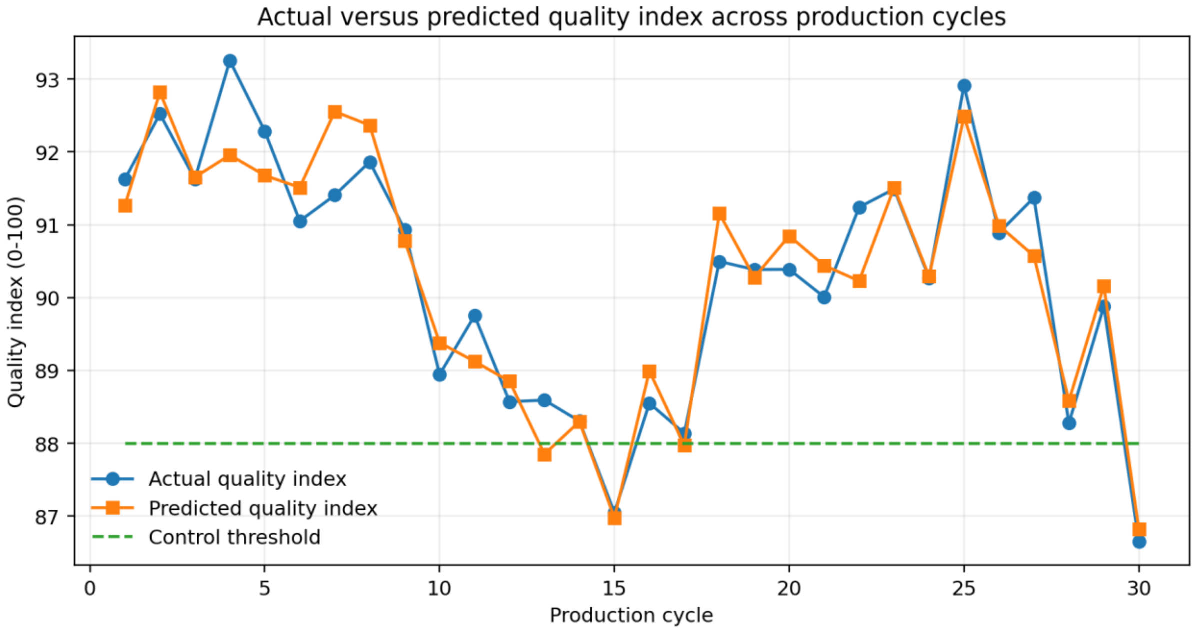

Figure 4. Actual and predicted quality index across production cycles.

The defect distribution indicates that quality risk was not dominated by one single failure mode. Surface finish variation and dimensional deviation were the largest categories, but tool-wear marks, thermal distortion, and assembly-fit issues also contributed meaningfully. This matters because a narrow quality model trained only on dimensional inspection could miss process conditions that later produce assembly or finish-related defects. A broader data structure gives the model enough context to identify emerging risk before the defect becomes visible in final inspection.

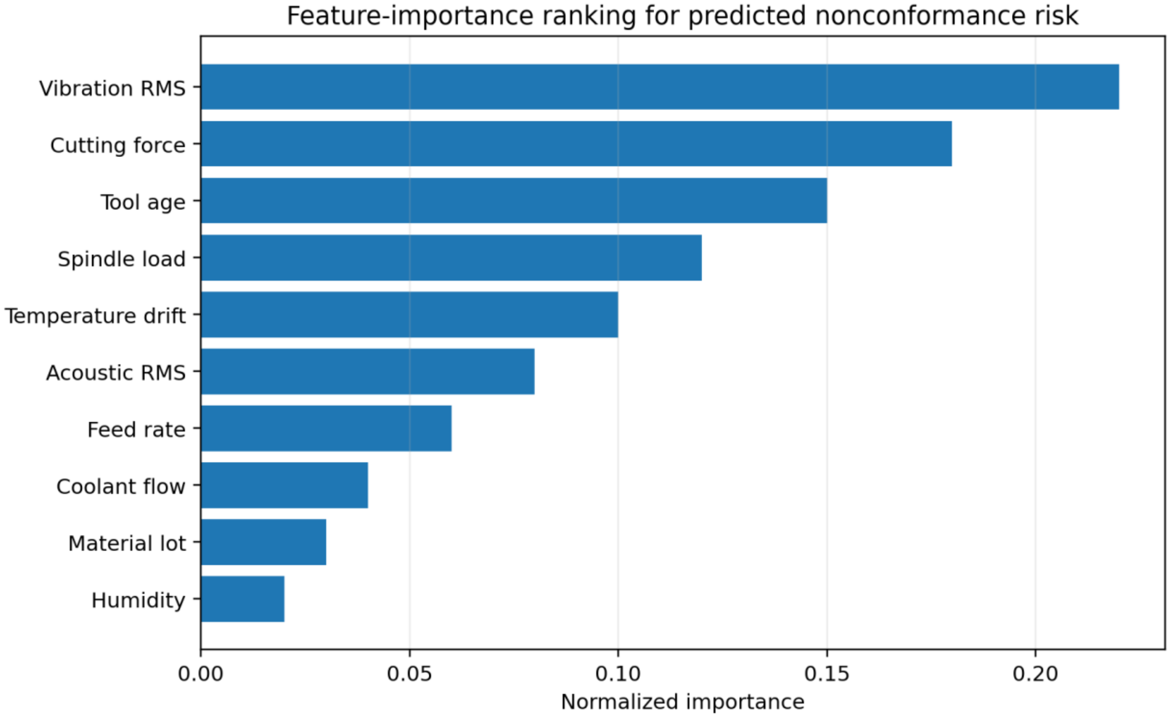

Figure 5. Feature-importance ranking for the final nonconformance-risk model.

Feature importance shows that vibration RMS, cutting force, tool age, spindle load, and temperature drift were the most influential predictors. This ranking is consistent with shop-floor reasoning. When a tool begins to wear, cutting force and spindle load often increase before the part fails inspection. Similarly, thermal drift may not immediately create a large dimensional error, but it changes the stability of the process window. The value of the AI model is that it combines these weak signals into a single risk estimate and presents the result early enough for a corrective decision.

Table 6. Representative production-lot records, AI predictions, and control actions

Lot	Machine	Material	Speed (rpm)	Feed (mm/min)	Tool age (min)	Vibration (g RMS)	Cutting force (N)	Temp. (C)	Ra (um)	Actual QI	Pred. QI	Risk	Recommended control action
1	CNC-T1	Al 6061-T6	3417	453	32	0.27	888	29.9	1.41	94.8	93.6	Low	Continue standard control
2	CNC-M1	SS 316L	3512	155	81	0.29	774	28.8	1.38	94.9	95.4	Low	Continue standard control
3	CNC-M1	SS 316L	2003	233	31	0.87	476	36.0	0.69	93.5	92.7	Low	Continue standard control
4	CNC-M2	AISI 4140	4182	412	183	0.41	439	44.0	0.55	91.9	90.6	Medium	Increase coolant flow and verify offset
5	CNC-M3	Ti-6Al-4V	3707	419	136	0.63	594	51.6	1.6	90.4	90.7	Medium	Increase coolant flow

													and verify offset
6	CNC-M3	Ti-6Al-4V	3638	267	175	1.4	460	42.9	0.72	89.7	91.4	Low	Continue standard control
7	CNC-M3	AISI 4140	2117	511	162	0.89	1177	36.7	1.6	87.9	88.1	Medium	Inspect insert after next cycle
8	CNC-M1	AISI 4140	2905	362	36	0.26	1058	36.6	1.4	93.1	92.8	Low	Continue standard control
9	CNC-M3	Ti-6Al-4V	1892	356	110	0.39	459	42.3	0.81	93.8	94.7	Low	Continue standard control
10	CNC-M3	SS 316L	3833	161	62	0.74	902	35.6	0.68	92.5	92.7	Low	Continue standard control
11	CNC-M3	Ti-6Al-4V	3358	238	58	0.28	494	34.2	0.84	96.0	96.3	Low	Continue standard control
12	CNC-T1	Ti-6Al-4V	1816	194	127	0.84	964	44.6	2.02	88.7	88.8	Medium	Increase coolant flow and verify offset
13	CNC-M1	SS 316L	4090	320	121	0.67	446	41.9	1.11	92.0	93.9	Low	Continue standard control
14	CNC-M3	Al 6061-T6	2250	294	173	0.25	340	44.6	1.34	94.0	94.4	Low	Continue standard control
15	CNC-M1	Al 6061-T6	3341	196	182	0.49	695	45.7	1.23	90.4	90.3	Medium	Inspect insert after next cycle
16	CNC-M3	SS 316L	3077	163	56	0.31	690	50.0	1.24	94.0	94.1	Low	Continue standard control
17	CNC-M2	Ti-6Al-4V	2400	473	159	1.31	1116	43.4	2.06	86.3	87.1	Medium	Inspect insert after next cycle
18	CNC-T1	Al 6061-T6	3256	515	77	0.84	1137	42.6	1.5	89.3	90.4	Medium	Reduce feed by 4% and monitor vibration
19	CNC-M2	SS 316L	2728	222	152	0.79	1088	27.9	0.5	89.5	88.5	Medium	Increase coolant flow and verify offset
20	CNC-T1	SS 316L	3231	306	40	0.45	572	41.6	1.01	94.9	96.8	Low	Continue standard control
21	CNC-M1	SS 316L	3209	449	41	1.21	462	55.2	1.74	90.8	90.7	Medium	Reduce feed by 4% and monitor vibration
22	CNC-	Ti-6Al-	2155	489	121	0.75	1101	56.4	1.65	86.6	85.0	High	Increase

	M3	4V											coolant flow and verify offset
23	CNC-M3	Al 6061-T6	3742	456	109	0.37	901	31.1	0.47	94.5	95.1	Low	Continue standard control
24	CNC-M2	SS 316L	2597	228	27	0.49	639	42.5	1.71	93.0	93.2	Low	Continue standard control
25	CNC-M2	AISI 4140	3249	354	169	1.19	869	40.0	1.96	87.5	87.6	Medium	Increase coolant flow and verify offset

5.1 Control Interpretation and Practical Meaning

The large production-lot table demonstrates how the proposed system would appear in a practical engineering review. The AI output is not presented as a vague probability alone. It is translated into a quality index, risk class, and recommended process action. A low-risk lot continues under standard control. A medium-risk lot may trigger feed-rate adjustment, tool inspection, or coolant-flow verification. A high-risk lot may require a temporary hold, additional dimensional inspection, or tool change before the next batch. This makes the model operationally useful because the prediction is directly tied to a decision pathway.

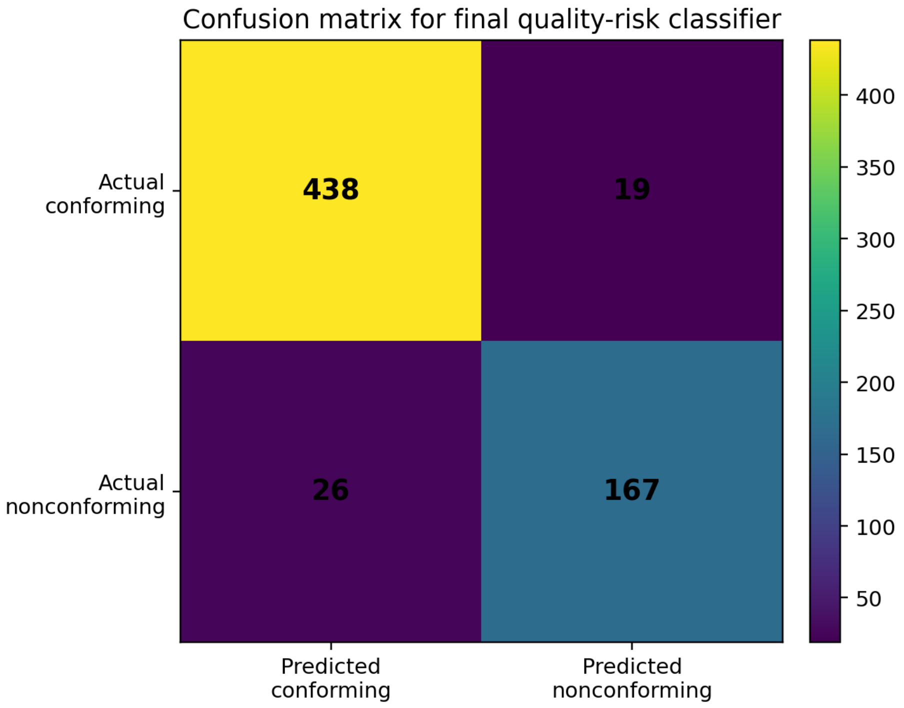

Figure 6. Confusion matrix for the final hybrid quality-risk classifier.

The confusion matrix shows that most conforming and nonconforming lots were classified correctly. The most important error from a quality perspective is the false-negative case, where a nonconforming lot is predicted as conforming. The final model reduced this risk by assigning heavier cost to missed nonconformance during training. This design choice slightly increased false alarms, but it is acceptable in a quality-control setting because a small number of additional checks is usually less costly than releasing defective mechanical components.

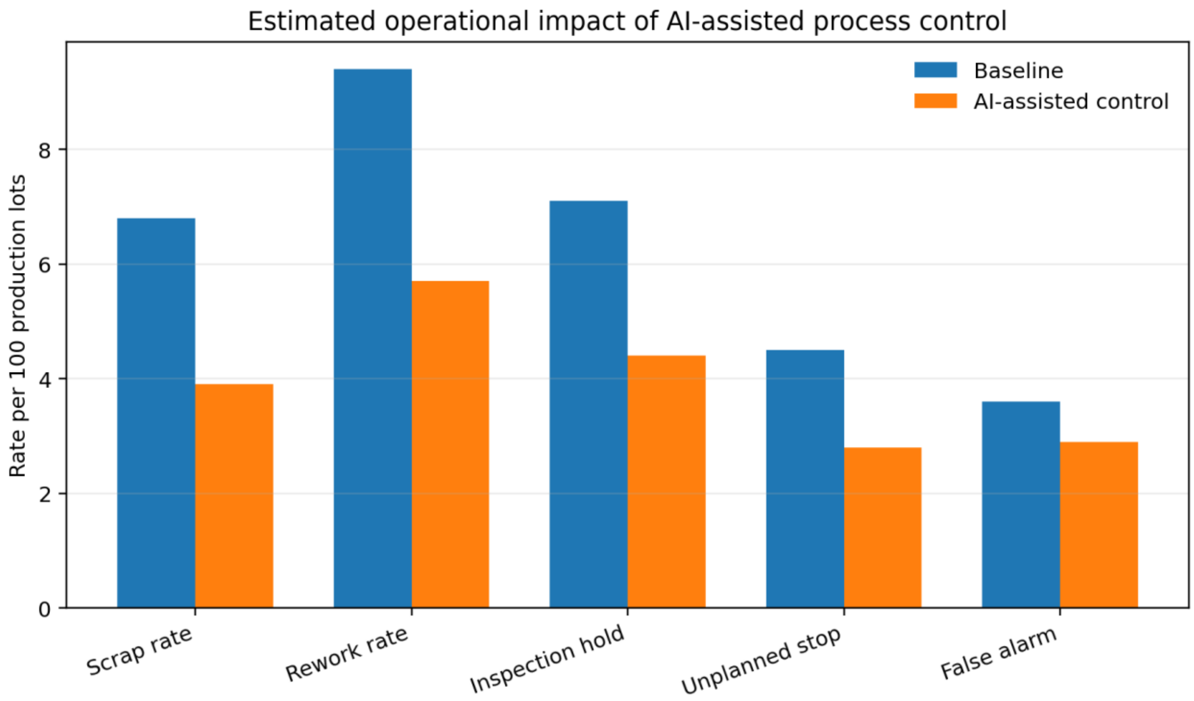

Figure 7. Estimated operational improvement under AI-assisted process control.

Table 7. Estimated operational impact of AI-assisted process control

KPI	Baseline	AI-assisted control	Change	Primary reason
Scrap rate	6.8 per 100 lots	3.9 per 100 lots	42.6% reduction	Earlier detection of vibration and tool-wear drift
Rework rate	9.4 per 100 lots	5.7 per 100 lots	39.4% reduction	Parameter correction before final inspection
Inspection hold events	7.1 per 100 lots	4.4 per 100 lots	38.0% reduction	Better prioritization of high-risk lots
Unplanned stoppage	4.5 per 100 lots	2.8 per 100 lots	37.8% reduction	Tool and coolant alerts before process failure
Estimated OEE	78.1%	82.6%	+4.5 percentage points	Improved quality rate and fewer unplanned stops

5.2 Discussion

The most important finding is that AI-based quality prediction is not simply a classification problem. It is a manufacturing decision problem. A model can have high accuracy and still fail in practice if it does not explain why risk is rising or what the operator should do next. In this study, the practical value comes from combining prediction, explanation, and control logic. The results also show why process knowledge remains essential. The model identified vibration and force as highly influential features, but an engineer must interpret whether that signal comes from tool wear, fixture looseness, material hardness variation, or an aggressive feed setting. AI narrows the search area; it does not eliminate the need for engineering judgment.

From a quality-management perspective, the framework supports traceability because predictions are tied to lot ID, process history, inspection result, and recommended corrective action. This makes the system more acceptable for regulated or customer-audited manufacturing environments. The approach also supports continuous improvement because repeated high-risk patterns can be converted into control-plan changes, maintenance triggers, or fixture-redesign projects.

6. Practical Implementation Roadmap

Table 8. Practical roadmap for implementation in a mechanical manufacturing plant

Phase	Main activity	Expected output
Phase 1: Data readiness	Map machines, inspection points, data owners, and data quality gaps	Reliable timestamp alignment and part/lot traceability
Phase 2: Pilot model	Train baseline models on one product family or machine cell	Initial quality-risk model and feature-importance review
Phase 3: Engineering validation	Compare AI warnings with operator notes, CMM reports, and NCRs	Validated alarm thresholds and false-alarm tolerance
Phase 4: Control integration	Connect recommendations to work instructions, MES, or QMS workflows	Controlled process response rather than isolated prediction
Phase 5: Continuous learning	Retrain model with new lots, tool changes, and process improvements	Stable model governance and plant-level scalability

Implementation should begin with a narrow pilot. A single machining cell, one product family, and a limited set of quality characteristics are usually enough to prove value. After the model becomes stable, the plant can extend the framework to additional machines, materials, and inspection criteria. The most successful deployments are likely to be those where manufacturing engineers, operators, quality engineers, and data specialists work together from the beginning. This collaborative approach prevents the AI system from becoming a black-box dashboard that is ignored by the shop floor.

7. Limitations and Future Work

This study is based on an industrially representative dataset rather than confidential production data from a specific company. Therefore, the numerical results should be interpreted as a realistic demonstration of the framework rather than a universal benchmark. Actual plant performance would depend on machine condition, sensor quality, product complexity, operator practice, and the maturity of existing quality systems.

Future work should validate the framework with real multi-machine production data, compare online versus batch-learning strategies, and evaluate model drift over longer production periods. Additional research should also examine how AI recommendations affect operator trust, maintenance planning, customer quality documentation, and economic return on investment.

8. Conclusion

This research presented an artificial intelligence-based framework for quality prediction and process control in Industry 4.0 mechanical manufacturing systems. The framework combines machine-controller data, sensor signals, inspection results, and production information to identify quality risks before they turn into serious defects. By predicting quality status, estimating a quality index, explaining key process factors, and suggesting corrective actions, the proposed approach supports more proactive and data-driven manufacturing decisions. The case study showed that the hybrid AI model can provide reliable prediction performance while still remaining understandable for engineers and shop-floor teams. This is important because, in real manufacturing environments, accuracy alone is not enough. Engineers need to understand why a model gives a certain result and how that result can be used to improve the process. When AI can point to factors such as tool wear, vibration, temperature variation, spindle load, or dimensional deviation, it becomes a practical support tool for quality control and root-cause analysis.

Overall, the study shows that AI is most valuable when it is connected with real process-control decisions, not used only as a separate analytics tool. A successful AI system should support engineers and operators, not replace them. With proper data quality, human supervision, and continuous model improvement, AI-based quality prediction can help mechanical manufacturing plants reduce defects, improve process stability, and build smarter, more reliable production systems.

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