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THE USE OF ARTIFICIAL INTELLIGENCE TECHNOLOGIES FOR THE DETECTION AND PREVENTION OF NONCONFORMITIES IN QUALITY PROCESSES

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Abstract - The management of nonconformities represents a critical component of modern quality management systems, especially in industrial environments characterized by complex processes, high data volumes and increasing requirements for traceability. This paper explores the use of artificial intelligence technologies for the early detection and prevention of nonconformities in quality processes. The proposed approach is based on the systematic collection of operational data from production, inspection, audit and corrective-action activities, followed by data preparation, predictive modelling and continuous monitoring of risk patterns. Classification techniques are used when historical labels are available, while anomaly detection methods are applied to identify rare, unknown or emerging deviations. The paper proposes a scalable integration model that connects artificial intelligence outputs with existing quality assurance routines, including nonconformity reports, risk registers, root-cause analysis and corrective actions. An illustrative evaluation framework is presented to show how key performance indicators such as nonconformity rate, detection lead time, false alarm rate and corrective-action closure time may be measured before and after implementation. The results indicate that artificial intelligence can increase organizational responsiveness by prioritizing high-risk process conditions and by supporting preventive action before defects become customer-visible failures. The study contributes a practical model for integrating artificial intelligence into quality assurance processes while emphasizing data governance, human oversight, explainability and continuous improvement.

Keywords: Artificial Intelligence, Nonconformity, Quality Management, Anomaly Detection, Predictive Analytics, Corrective Action, Process Improvement.

1. Introduction

Quality management systems are increasingly expected to operate in environments characterized by high product variety and strict customer requirements. In such conditions, the management of nonconformities becomes more than an administrative activity. A nonconformity indicates that a product, or a management-system activity has failed to meet a specified requirement. When nonconformities are not detected quickly, they may generate rework or compliance risks. For this reason, organizations need mechanisms that do not only record deviations after occurrence but also support early identification of quality risks before they become visible failures. Traditional quality management practices are based on inspection, statistical process control, corrective action and preventive action. These practices remain essential because they provide discipline, documentation and accountability.

Many traditional methods are reactive or periodic. Inspection may take place after a batch has already been produced, audits are often scheduled at fixed intervals, and root-cause analysis is initiated only after a problem has been formally registered.

In a manufacturing or service environment that produces large volumes of operational data, this reactive logic is no longer sufficient. The quality

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function must increasingly transform data into predictive information that can guide preventive action. The emergence of Industry 4.0 and Quality 4.0 creates an opportunity to redesign nonconformity management as a data-driven and evidence-based process. Quality 4.0 emphasizes the integration of quality management with digital technologies, and intelligent systems [1], [19]. In this context, quality professionals are expected to work with data from sensors, inspection equipment, enterprise systems, maintenance records, customer feedback, audit reports and supplier performance databases. The challenge is not only to collect data, but to interpret it in a way that supports decisions, prioritization and continual improvement.

Artificial intelligence technologies can support this transformation because they are able to identify complex patterns that are difficult to detect through manual analysis. Machine learning models can classify records according to the probability of nonconformity, anomaly detection methods can identify unusual process behaviour, natural language processing can extract patterns from textual quality reports, and computer vision can automate visual inspection tasks. Prior research on predictive quality in manufacturing shows that machine learning can use process and quality measurement data to estimate product quality before final inspection [3], [4]. It can analyse multivariate interactions and detect weak signals across multiple data sources. This is why anomaly detection, predictive quality analytics and automated visual inspection are increasingly studied in manufacturing and industrial contexts [5], [6], [8].

Nonconformity management also requires prioritization. Quality teams often face multiple open issues, audit findings and corrective actions at the same time. Treating all deviations with the same level of urgency can waste resources and delay attention to high-risk events. The concept proposes the use of risk-based tools to prioritize nonconformity events and improve decision-making in a data-rich quality environment [2]. Artificial intelligence can strengthen this logic by calculating risk scores, grouping similar events, identifying recurrent patterns and highlighting the factors that contribute most to potential failure. In addition to structured numerical data, many quality processes generate unstructured data. Nonconformity reports, audit observations, customer complaints, reports, corrective-action descriptions and supplier responses often contain important information written in natural language. These records may reveal repeated root causes, unclear requirements, ineffective corrective actions or recurring process weaknesses.

Natural language processing can help transform such textual information into analysable categories and trends. Manual visual inspection is widely used, but it can be inconsistent, time-consuming and affected by fatigue or subjective judgement. Recent literature shows that deep learning, convolutional neural networks and industrial visual anomaly detection methods are increasingly applied to detect surface defects, assembly errors and other abnormal visual patterns [9], [10], [11]. These methods are particularly useful when defects are subtle, rare or visually complex. However, their implementation also requires careful control of image acquisition, dataset quality, model validation and human oversight. A prediction has value only if it leads to an appropriate action, such as additional inspection, process adjustment, containment, supplier follow-up or preventive maintenance. Moreover, models must be explainable enough to support trust, auditability and learning. For this reason, human-in-the-loop governance is a central requirement when AI is used in quality processes [16], [17]. The objective of this paper is to propose a practical and scalable model for integrating artificial intelligence technologies into the detection and prevention of nonconformities in quality processes. The contribution of the study consists in connecting AI analytics with existing quality routines such as nonconformity reporting, root-cause analysis, corrective action and continual improvement.

2. Conceptual Background

ISO 9001:2015 specifies requirements for a quality management system intended to support consistent delivery of conforming products and services, while ISO 9000:2015 defines the fundamental vocabulary used for quality management. In practical terms, a quality management system is a structured way to establish processes, responsibilities and controls that enable consistent delivery of conforming products and services. Quality management is therefore not limited to final inspection. It includes leadership, planning, operational control, performance evaluation and improvement. Artificial intelligence is a broad field that includes machine learning, computer vision, expert systems and optimization techniques. In quality processes, artificial intelligence is particularly useful when historical or real-time data can be used to identify patterns. A supervised learning model may classify process records as conforming or nonconforming when labelled examples exist.

The integration of AI into quality management does not remove the need for human judgement.

AI should be understood as a decision-support capability. Quality engineers remain responsible for interpreting alerts, validating causes, approving containment decisions and verifying corrective-action effectiveness.

3. Proposed AI-Enabled Model for Nonconformity Prevention

The proposed model contains five interconnected layers: data acquisition, data preparation, AI analytics, quality action and continuous learning. Data acquisition collects information from enterprise resource planning systems, manufacturing execution systems, inspection records, audit reports, supplier quality records, maintenance systems and customer feedback. Data preparation transforms raw data into a usable analytical base. This includes cleaning missing values, aligning timestamps, standardizing defect codes, extracting features from text descriptions and validating the traceability of records. Poor data preparation is one of the main reasons why AI projects fail in operational environments. The AI analytics layer uses classification to estimate the probability that a record or process state will lead to a nonconformity. It also uses anomaly detection to identify unusual combinations of variables even when there is no previous example of that exact failure. The output should generate risk scores, explanations, contributing factors and recommended next steps.

Figure 1 illustrates the proposed process architecture. The model is intentionally designed to be compatible with existing management systems. Rather than replacing nonconformity reports or corrective action records, it enriches them with predictive signals and evidence-based prioritization.

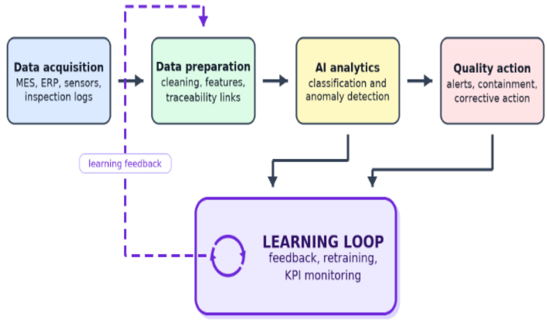

Figure 1: AI-enabled model for the detection and prevention of nonconformities

4. Case Study

The effectiveness of the proposed model depends on the relevance and reliability of data. In many organizations, quality information is distributed across several tools and departments. Inspection results may be stored in spreadsheets, audit findings in document repositories, machine parameters in production systems and customer complaints in service platforms. These variables help the AI model to understand not only whether a nonconformity occurred, but also under what conditions it occurred.

Supervised classification models are appropriate when the organization has sufficient historical labels. Examples include clustering, isolation forests, one-class support vector machines and autoencoders [13], [14], [15].

Image-based models may detect scratches, missing parts, dimensional deviations or incorrect assemblies [9], [10], [11], [12].

Table 1. Artificial intelligence techniques applicable to nonconformity detection

Technique	Typical input	Quality use	Main limitation
Classification	Labelled historical records	Predict probability of nonconformity	Requires representative labels
Anomaly detection	Normal process behavior	Detecting rare or unknown deviations	Threshold selection can be difficult
NLP text mining	Audit findings and complaints	Identify recurrent themes and similar events	Depending on text quality
Computer vision	Images or video streams	Detect visual defects automatically	Needs stable image acquisition
Optimization	Process constraints and targets	Recommend preventive controls	Requires validated business rules

4.1 Implementation Scenario and Practical Example

A phased implementation approach is recommended. The first phase should focus on defining the quality problem and selecting a limited pilot area. The second phase should consolidate and clean historical data. The third phase should develop a baseline model and compare it with existing quality controls. The fourth phase should perform controlled deployment through alerts that are reviewed by quality specialists.

In an illustrative pilot scenario, the organization may use twelve months of historical production and inspection data to train a model that predicts the risk of nonconformity for production batches.

The model generates a risk score at batch release and during production.

Batches above a defined threshold receive additional inspection or process adjustment.

4.2 Practical Example: Dimensional Nonconformity in an Assembly Process

The practical example considers an assembly line that produces mechanical subassemblies with one critical-to-quality dimensional characteristic. The allowed tolerance is defined by the engineering drawing, and the final inspection normally detects deviations only after a production batch has already been completed. The objective of the AI system is to identify high-risk batches earlier, using process and inspection signals collected during production. The historical dataset contains production batches from the previous twelve months. Each record combines information from the manufacturing execution system, inspection reports, maintenance records and supplier quality files. The target variable is binary: conforming batch or batch with dimensional nonconformity.

The model is trained to generate a risk score between 0 and 100. A score below 40 is considered low risk, a score between 40 and 69 is medium risk, and a score of 70 or higher is high risk. Table 2 presents the main categories of input data that can be used for an artificial intelligence model designed to detect and prevent nonconformities in quality processes. The table shows that an effective predictive model should not rely on inspection data alone, because nonconformities are often influenced by multiple operational factors. Product characteristics, process parameters, maintenance history, supplier information and shift-related context can all contribute to the probability of a quality deviation. Inspection values provide direct evidence about product conformity. First-piece inspection results, in-process measurements and measurement trends allow the model to identify whether the process is stable or moving toward a nonconforming condition. Maintenance status is included because equipment condition can significantly influence process variation.

Table 2. Input variables used in the practical AI pilot

Data group	Example variables	Reason for inclusion
Product and batch	Product family, batch size, order priority	Different product families and urgent batches may have different risk patterns
Process parameters	Machine temperature, cycle time, torque value, line speed	Process drift can appear before the measured dimension becomes nonconforming
Inspection values	First-piece result, in-process measurement, measurement trend	Early measurements provide direct evidence of dimensional stability
Maintenance status	Time since last maintenance, tool-change event, downtime history	Equipment conditions may influence dimensional variation
Supplier information	Supplier batch, material lot, incoming inspection status	Material variation may contribute to recurring process deviations
Human and shift context	Shift, operator group, training status	Context variables help identify where additional support may be needed

The first version of the model may use a random forest classifier because it can handle nonlinear relationships and interactions between variables. After validation, the model is not deployed as an automatic decision-maker, but as a decision-support tool. The quality engineer receives a ranked list of batches with the risk score and the most influential contributing factors. This information is reviewed during the shift quality meeting before preventive action is approved.

Table 3 shows a simplified example of how the model output can be translated into operational decisions. Batch A104 is classified as low risk and continues under the standard control plan. Batch A107 is medium risk because the measurement trend is approaching the upper warning limit. Batch A112 is high risk because several factors occur together: a recent tool change, a supplier lot with previous deviations and increasing cycle-time variation.

Table 3. Example AI risk scores for production batches

Batch	AI risk score	Main contributing factors	Recommended quality decision
A104	22 - Low	Stable measurements; no maintenance event; approved supplier lot	Continue standard inspection plan
A107	58 - Medium	Measurement trend close to warning limit; higher cycle-time variation	Increase in-process measurement frequency
A112	84 - High	Recent tool change; supplier lot with prior deviations; torque variation	Stop batch release, perform containment check and adjust process
A118	46 - Medium	New operator group; minor first-piece deviation	Supervisor review and additional first-piece confirmation
A121	76 - High	Machine temperature drift; repeated similar cases in history	Preventive maintenance review before continuing production

The action logic must be defined before deployment to avoid inconsistent reactions to AI alerts. A score by itself does not prevent nonconformity. Prevention occurs only when the organization has a clear rule for converting risk information into quality action. Table 4 proposes a practical alert matrix that can be included in the quality procedure for the pilot process.

In this example, the high-risk alert for batch A112 prevents a potential nonconformity because the batch is contained before final inspection. The process owner verifies the tool-change setup, the supplier quality engineer checks the material lot history, and the quality engineer performs additional dimensional measurements. If the measurements confirm drift, the batch is adjusted or stopped before nonconforming parts reach the customer. If the alert is false, the reviewer documents the reason, and the case is used to improve the model threshold.

Table 4. Alert levels and preventive actions in the practical example

Alert level	Risk score	Action owner	Preventive action	Evidence retained
Low	0-39	Production operator	Continuing normal production and standard inspection	Standard inspection record
Medium	40-69	Quality engineer	Increase sampling, review recent process changes and monitor trend	AI alert, additional measurements and reviewer decision
High	70-100	Quality engineer and process owner	Contain batch, verify setup, check material lot and approve restart only after review	Containment record, root-cause note and restart approval

Table 5. Example before-and-after indicators for the AI pilot

Indicator	Before AI	After AI pilot	Interpretation
Dimensional nonconformity rate	4.8%	3.5%	Earlier detection reduces the number of completed nonconforming batches
Average detection lead time	0 hours	16 hours	Risk is visible before final inspection
False alarm rate	Not applicable	12%	Acceptable for a first pilot if alerts are reviewed by experts
Corrective-action closure time	31 days	24 days	Better evidence supports faster investigation
Repeated root-cause categories	7	4	The organization focuses on systemic causes instead of isolated events

5. Results and Discussion

The link between AI alerts and corrective action is essential. An alert by itself does not prevent a nonconformity. Prevention occurs only when the organization responds with appropriate action. Therefore, the proposed model should define alert levels. A low-risk alert may require monitoring, a medium-risk alert may trigger additional inspection, and a high-risk alert may require containment or escalation. When a nonconformity is confirmed, the AI system can support root-cause analysis by retrieving similar historical cases and comparing process conditions before and after the event. This reduces the time spent searching for evidence and helps the team avoid superficial corrective actions. The operational workflow starts with the definition of a quality event. Each event should be connected to a requirement because quality management requires evidence of the gap between the expected and actual result.

After the event structure is defined, the organization can develop features used by the analytical model. Features are measurable attributes that describe the process context. Feature engineering is decisive because it translates quality knowledge into mathematical inputs.

The model should be trained and tested on separated datasets to avoid overly optimistic results. During validation, the organization should not evaluate only general accuracy. Precision and false alarm rate are more relevant for many quality applications.

Deployment should begin with a shadow mode in which the model produces alerts but does not influence decisions. After this learning period, the organization can move to assisted mode, where alerts are reviewed during daily quality meetings. The proposed approach changes the role of nonconformity management. In traditional systems, a nonconformity report is often opened after a defect, complaint or audit finding has already appeared. In an AI-supported system, quality data is continuously monitored to identify precursors. This is especially useful for complex processes where many small factors interact. Multivariate AI methods can identify combinations more effectively than isolated manual checks. Nevertheless, successful implementation requires realistic expectations, continuous communication and integration with existing quality culture.

5.1. Performance Indicators and Continuous Improvement

Performance measurement is necessary to prove that the AI-supported quality process creates value. Detection indicators include recall, precision and false alarm rate. Operational indicators include reduction of scrap, rework, customer complaints, containment time and corrective-action closure time. System-health indicators include data completeness, percentage of records with standardized defect codes, number of overridden alerts, number of false alarms, time since last model validation and number of process changes not yet reflected in the model.

Continuous improvement should be built into the monitoring cycle. Each confirmed nonconformity should be used as a learning opportunity for both the quality team and the analytical model..

5.2. Managerial and Practical Implications

The practical value of the proposed model is that it translates artificial intelligence from a technical concept into an operational quality-management instrument. For managers, the model supports better allocation of resources because investigation effort can be directed toward process conditions with the highest predicted risk. For quality engineers, the model provides evidence that can accelerate containment, root-cause analysis and verification of corrective action.

A second implication concerns organizational learning. Nonconformity records are often treated as isolated events, but AI can connect events across time, product families, suppliers and processes. This makes it easier to identify systemic weaknesses, recurrent causes and repeated ineffective actions. AI adoption should be accompanied by competence development. Quality professionals should understand the meaning of model outputs, false positives, false negatives and validation indicators. Data specialists should understand nonconformity logic, process constraints and the audit requirements.

5.3. Risks and Limitations

The adoption of artificial intelligence in quality processes introduces several risks. The first risk is poor data quality. If nonconformity records are incomplete, inconsistent or incorrectly coded, the model will learn unreliable patterns. The second risk is overreliance on automated outputs. The third risk is lack of explainability. AI models are sensitive to changes in the process environment. New products, equipment upgrades, supplier changes and revised specifications may reduce model accuracy. Governance rules should define who owns the model, how often it is retrained, how changes are approved and how model decisions are documented. The success of AI depends on organizational maturity. A company that does not have disciplined reporting, clear process ownership and effective corrective-action routines will not obtain sustainable value from AI. Data governance is a critical condition for the responsible use of artificial intelligence in quality management. Quality data may contain information about suppliers, customers, employees, proprietary production parameters and product performance. Therefore, access rights, retention rules, anonymization practices and cybersecurity controls should be defined before model deployment.

Ethical considerations are also relevant because AI-supported decisions can influence operational priorities and employee workload. The purpose of the system is to understand process conditions, not to assign blame. The quality culture should therefore emphasize learning, prevention and evidence-based improvement. Explainability is another governance requirement. In practical quality environments, a risk score is rarely sufficient. Engineers, auditors and managers need to understand why a model produced a specific alert. The expected benefits of the proposed model can be grouped into preventive, operational and strategic benefits. Preventive benefits include earlier identification of process drift, improved detection of weak signals and reduced probability of repeated nonconformities. Operational benefits include faster prioritization, better use of inspection resources, shorter investigation time and improved corrective-action evidence. However, these benefits depend on several success conditions. The first condition is process discipline. The second condition is cross-functional collaboration. The third condition is incremental implementation. A pilot project should be selected where the business problem is clear and where results can be measured with existing key performance indicators. Artificial intelligence models should not be treated as one-time software installations. They are analytical assets that require monitoring, recalibration and periodic review.

6. Conclusions

This paper proposed a practical model for using artificial intelligence technologies to detect and prevent nonconformities in quality processes. The model combines data acquisition, data preparation, AI analytics, quality action and continuous learning.

The practical example showed how AI can be applied to a dimensional nonconformity risk in an assembly process. By combining production data, inspection trends, maintenance status and supplier-lot information, the model can generate risk scores that support earlier containment and preventive action. The main point is the integration of AI outputs with existing quality assurance routines.

In future research should validate the proposed model using real industrial datasets from different sectors and additional work should investigate explainable AI methods for auditor acceptance, cost-benefit models and integration of AI alerts with enterprise quality management software.

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