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Optimization Design of Mechanical Manufacturing Quality Control System Based on Machine Learning

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Abstract. With the rise of intelligent manufacturing, the mechanical manufacturing industry faces challenges such as stringent quality requirements and complex production processes. Traditional quality control methods, relying on manual experience and basic statistics, struggle to handle the large and diverse data in modern manufacturing. Machine learning, with its powerful data analysis and pattern recognition capabilities, has become a crucial solution to enhance the intelligence of quality control systems. This paper explores the optimization design of quality control systems in mechanical manufacturing using machine learning to improve monitoring efficiency and product quality. It addresses issues like incomplete data collection and insufficient prediction accuracy. By integrating algorithms like support vector machines and neural networks, the proposed system architecture enhances model training and prediction through efficient data preprocessing. Real-time monitoring and dynamic feedback strategies are implemented to achieve online quality monitoring and anomaly detection. Practical cases validate the system's effectiveness in improving quality and reducing costs. This study offers valuable insights for the intelligent transformation of the manufacturing industry.

Keywords: machine learning, mechanical manufacturing, quality control system, system optimization, real-time monitoring

1. Introduction

As a crucial pillar industry of the national economy, mechanical manufacturing is closely linked to industrial development and national competitiveness. However, traditional quality control methods, which rely on manual experience and static inspection, struggle to meet the complex demands of modern manufacturing. These methods are slow, inaccurate, and cannot adjust dynamically, hindering quality improvement [1].

The integration of machine learning technology enables full utilization of the massive volumes of data generated during the manufacturing process. Through automated data analysis and pattern recognition, this technology facilitates early warning of quality issues and precise quality control. Machine learning models are capable of continuous self-optimization, adapting to changes in the production environment, improving the accuracy and efficiency of quality inspection, and reducing the risks of human intervention and misjudgment. This not only contributes to enhancing the

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consistency and reliability of products but also effectively lowers production costs and resource waste, thereby promoting the development of green manufacturing [2].

The study focuses on developing advanced machine learning algorithms tailored for real-time quality monitoring and predictive maintenance in mechanical manufacturing environments. It provides robust support for driving the high-quality development of the manufacturing industry and the transformation and upgrading of intelligent manufacturing.

2. Analysis of the current state of quality control systems in mechanical manufacturing

2.1. Fundamental concepts of quality control in mechanical manufacturing

Quality control in mechanical manufacturing refers to the management activities undertaken throughout the entire process of mechanical product design, machining, assembly, and inspection. Through scientific methods and technical means, it ensures products meet predetermined quality standards and performance requirements. Its core objectives are to achieve product quality stability and consistency, reduce defect rates, and enhance production efficiency, thereby strengthening the enterprise's market competitiveness. Quality control encompasses not only the testing of final products but also the monitoring and optimisation of production processes, emphasising prevention as the primary approach to minimise the occurrence of quality issues.

Mechanical manufacturing quality control involves stages like raw material inspection, process parameter control, equipment condition monitoring, in-process quality testing, and finished product inspection. Each stage requires effective quality control measures to ensure the production process remains under control. Traditional quality control methods, often reliant on manual expertise and rudimentary statistical techniques, struggle to address the complex, dynamic production environments and massive data processing demands of modern mechanical manufacturing.

2.2. Issues with the existing quality control system

Existing quality control systems in mechanical manufacturing still face numerous challenges in practical application, primarily manifested in incomplete data collection, insufficient model prediction accuracy, and the absence of real-time feedback mechanisms. The data collection phase suffers from issues such as unreasonable sensor placement, data transmission delays, and noise interference, resulting in missing or anomalous quality data that compromises the accuracy of subsequent analysis. Traditional quality control models predominantly rely on empirical rules and statistical methods, proving ill-suited to complex and dynamic manufacturing environments. Their limited generalissimo capabilities and predictive precision fail to effectively capture potential quality fluctuations during production. Existing systems generally lack real-time monitoring and dynamic feedback mechanisms, meaning quality anomalies are often only detected retrospectively [3]. This misses the optimal window for promptly adjusting process parameters and preventing defect propagation. Table 1 summarises the principal issues currently affecting quality control systems in mechanical manufacturing and their consequences:

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Table 1. Principal issues and their impacts in current mechanical manufacturing quality control systems [4-6]

Problem category	Specific manifestations	Scope of impact	typical case	Impact degree
Data collection problem	Sensor layout is not reasonable, data loss	Production process	Key dimensions measurement data missing	high
Data quality issues	Noise interference, abnormal values	Data analysis phase	Sensor signal fluctuations lead to misjudgment	middle
Model predictions are inadequate	Rely on empirical rules and lack adaptability	Quality prediction and control	Traditional statistical models cannot accurately predict defect rates	high
Lack of real-time feedback	Lack of online monitoring and dynamic adjustment	industrial control	Quality anomalies are detected late, resulting in batch rework	high
System integration challenges	Multiple system data islands, information sharing is limited	Enterprise information management	Quality data can not be effectively linked with production scheduling system	middle

2.3. Current applications of machine learning technology in quality control

With the rapid advancement of Industry 4.0 and intelligent manufacturing, machine learning technology is increasingly applied in quality control within mechanical manufacturing. By analysing and mining vast quantities of production data, machine learning enables anomaly detection, defect prediction, and quality assessment during manufacturing processes, thereby effectively enhancing product quality and production efficiency. Machine learning technology is primarily applied in the following areas: Machine learning is employed for the automatic identification of quality defects. By collecting multi-source information such as sensor data and image data, classification algorithms are utilised to automatically identify surface defects and dimensional deviations in products, thereby reducing the subjective errors and labour intensity associated with manual inspection. The application of Convolutional Neural Networks (CNNs) in visual inspection has significantly improved the accuracy of defect recognition. Machine learning plays a vital role in optimising manufacturing process parameters [6]. By learning from historical production data, it establishes mappings between process parameters and product quality, enabling dynamic adjustment of critical parameters to ensure production stability and consistency. Machine learning is also applied to predictive maintenance and fault diagnosis. Through analysing equipment operational data, it forecasts potential failures, allowing proactive maintenance scheduling to prevent quality issues and production downtime caused by equipment malfunctions [7]. Table 2 presents typical applications and advantages of several commonly used machine learning algorithms in quality control for mechanical manufacturing.

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Table 2. Typical applications and advantages of common machine learning algorithms in quality control for mechanical manufacturing [8]

Algorithm Type	Application fields	superiority	typical case
Support Vector Machine	Classification of defects	High dimensional data processing power	Automatic identification of surface defects
Neural Network	Image Recognition	Strong nonlinear modeling capability	Defect recognition in visual inspection
Decision Tree	Process parameter optimization	Strong interpretation, easy to understand	Process parameter adjustment
ensemble learning	Quality prediction	Improve model stability and accuracy	Product qualification rate forecast
Clustering Algorithm	Anomaly detection	Unsupervised learning to detect potential anomaly patterns	Equipment operating status monitoring

3. Design of a machine learning-based quality control system

3.1. System architecture design

The architecture design of a machine learning-based quality control system for mechanical manufacturing aims to establish an intelligent platform integrating data acquisition, model training, real-time monitoring, and feedback for efficient quality management throughout the manufacturing process. It comprises four primary components: the data layer, algorithm layer, application layer, and interaction layer. The data layer is responsible for real-time collection of multidimensional quality-related data from production equipment, sensors, and inspection instruments, ensuring data integrity and accuracy. The algorithm layer employs machine learning techniques, utilising multiple models for feature extraction, pattern recognition, and anomaly detection to enhance the accuracy and robustness of quality predictions [9]. The application layer implements quality control strategy formulation and execution, including automated production parameter adjustment and anomaly alert mechanisms. The interaction layer provides a user-friendly interface supporting visualisation of quality data and operational feedback, facilitating managerial decision-making.

The design emphasizeseffective inter-module coordination and seamless data flow. The data layer uses edge computing for preliminary data cleansing, reducing backend load. The algorithm layer utilises a distributed computing framework, supporting parallel training and online updating of multiple models to ensure adaptability to dynamic production environment changes. The application layer integrates rule engines with model outputs to achieve intelligent quality control decision-making. The interaction layer integrates diverse visualisation tools—including trend charts, heatmaps, and anomaly alert dashboards—to enhance user experience and response velocity. Table 3 outlines the primary functions and key technologies across each system layer:

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Table 3. Primary functions and key technologies of each system layer [9]

System level	Main functions	Key technologies	Data type	Processing mode
Data layer	Data collection and preprocessing	Sensor networks, edge computing	Sensor data, images	Cleaning, compression and fusion
Algorithm layer	Feature extraction and model training	Support vector machine, neural network	Structured and unstructured data	Model training, prediction
Application Layer	Implementation of quality control strategy	Rule engine, automatic adjustment system	Model outputs	Decision implementation, feedback
Alternation of bed	Data visualization and user interaction	Visual tools, alarm systems	Statistical data, alarm information	Graphic display, interactive operation

3.2. Key technologies and algorithm selection

In the design of machine learning-based quality control systems for mechanical manufacturing, the selection of key technologies and algorithms directly impacts system performance and application effectiveness. Given the diversity and complexity of data in mechanical manufacturing processes, algorithms capable of handling high-dimensional, multi-sample datasets must be employed. Support Vector Machines (SVMs), owing to their excellent classification capabilities and robust generalisation performance, are well-suited for defect detection and classification tasks. Neural networks, particularly deep learning models, can automatically extract complex features, making them suitable for processing manufacturing data exhibiting pronounced non-linear relationships. Ensemble learning methods such as random forests and gradient-boosted trees enhance model stability and accuracy by combining multiple weak classifiers, rendering them applicable for multi-class quality assessment.

For data preprocessing and feature selection, techniques like Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) effectively reduce dimensionality, eliminate redundant information, and enhance model training efficiency. To meet real-time monitoring demands, incremental learning algorithms continuously update models within streaming data environments, ensuring rapid system response to novel defects.

3.3. Data acquisition and pre-processing methods

In machine learning-based quality control systems for mechanical manufacturing, data acquisition and preprocessing are critical stages for ensuring model accuracy and system stability. Data collection must encompass multiple key nodes throughout the manufacturing process, including equipment operational status, workpiece dimensions, environmental parameters, and inspection results. To achieve comprehensive, high-quality data acquisition, the system employs multi-sensor fusion technology. This integrates visual sensors, force sensors, and temperature/humidity sensors to capture multidimensional data in real time, guaranteeing information completeness and diversity.

Raw collected data frequently exhibits noise, missing values, and outliers. If unaddressed, these issues severely compromise the training efficacy of machine learning models. The preprocessing stage primarily encompasses data cleansing, missing value imputation, anomaly detection, and data normalisation. Data cleansing employs reasonable thresholds and rules to eliminate obviously erroneous or invalid records; Missing value imputation employs interpolation or nearest neighbour

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estimation methods to guarantee data continuity and completeness. Outlier detection utilises statistical analysis and clustering algorithms to identify anomalous samples, preventing their misleading influence on the model. Data normalisation converts measurements with different units to a unified scale, enhancing the convergence speed and stability of model training.

4. Conclusion

This research focuses on the optimised design of a machine learning-based quality control system for mechanical manufacturing. It analyses current challenges and shortcomings in mechanical manufacturing quality control, proposing an innovative architecture that leverages the strengths of machine learning. The study explores the characteristics and applicable scenarios of various machine learning algorithms, designing an efficient data collection and pre-processing workflow to ensure accurate and stable model training. Practical case studies demonstrate that this system improves product pass rates, reduces costs, and elevates manufacturing intelligence, providing a technological foundation for traditional manufacturing transformation. Machine learning possesses a robust theoretical framework and practical solutions for quality control applications.

As the mechanical manufacturing industry advances and becomes more intelligent, machine learning-based quality control systems will have broader application prospects. Improvements in sensing technology and the Internet of Things will facilitate comprehensive and precise data collection, providing high-quality training data for machine learning models, thereby enhancing predictive accuracy and response speed. The development of advanced algorithms, such as deep learning, will enable better handling of complex nonlinear relationships and multidimensional data, improving understanding of manufacturing processes and anomaly detection. Additionally, integrating edge and cloud computing will allow flexible and efficient deployment of quality control systems, supporting real-time monitoring and remote decision-making. Future research should also focus on enhancing the systems' adaptive capabilities and robustness, improving their stability and reliability under varying operating conditions and unexpected events. Cross-disciplinary convergence and innovation will further emerge as a key driver for advancing quality control systems.

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