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Analysis and Prediction of Product Quality Using Statistical Analysis and Machine Learning with Data Supplied by the Quality Control Unit of Mobarakeh Steel Company, Isfahan

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ABSTRACT

The present study aims to analyze and predict the quality of steel products through the simultaneous application of statistical analysis methods and machine learning algorithms, utilizing real operational data obtained from the Quality Control Unit of Mobarakeh Steel Company in Isfahan. The objective is to enable early defect prediction and improve production processes. In this research, production data—including process variables, raw material characteristics, operating conditions of production lines, and quality control test results—were collected. Following data cleaning and preprocessing, the dataset was analyzed using descriptive and inferential statistical methods. Subsequently, machine learning models such as regression algorithms, decision trees, and artificial neural networks were employed to predict product quality. The findings indicated that integrating statistical analysis with machine learning models effectively identifies patterns influencing product quality and enhances prediction accuracy regarding product quality status. As a result, this approach contributes to reducing production waste, improving process control, and increasing production line productivity. Ultimately, the proposed model can serve as a decision-support tool for quality control units and production management in steel industries and can facilitate the transition toward smart manufacturing and predictive quality control.

Keywords: Product quality, machine learning, statistical analysis, quality control, steel industry, production defect prediction, industrial data mining.

Introduction

Product quality has become one of the most decisive competitive factors in modern industrial and manufacturing environments, particularly under conditions characterized by rapid technological transformation, globalized markets, and increasing customer expectations. Organizations operating in heavy industries such as steel production face continuous pressure to maintain stable quality while simultaneously improving productivity, reducing operational costs, and responding to dynamic market demands. Contemporary manufacturing systems no longer view quality merely as a post-production inspection outcome; rather, quality is increasingly understood as an integrated

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organizational capability embedded throughout the entire production lifecycle, from raw material selection to final product delivery. The emergence of digital intelligence and data-driven manufacturing has fundamentally reshaped how firms conceptualize quality management and operational excellence (1).

Recent advances in digital transformation have highlighted the role of intelligent technologies in strengthening organizational resilience and enhancing production performance. Digital transformation enables enterprises to convert operational data into actionable insights that support predictive decision-making and continuous process improvement. Research demonstrates that digitally empowered organizations achieve higher operational stability and improved performance during market disruptions by leveraging analytical capabilities and integrated data ecosystems (2). In manufacturing contexts, digital intelligence facilitates the development of "new quality productivity," a concept referring to the integration of artificial intelligence, automation, and analytics to optimize production outcomes and create sustainable competitive advantage (3). Consequently, quality prediction and monitoring systems increasingly rely on advanced computational approaches rather than traditional inspection-based quality assurance.

Artificial intelligence (AI) and machine learning technologies have emerged as central instruments for transforming quality management practices. AI-driven systems allow enterprises to analyze complex nonlinear relationships among production variables that cannot be effectively captured through classical statistical models alone. By integrating digital intelligence into operational systems, organizations can identify hidden production patterns, predict defects before they occur, and optimize manufacturing parameters in real time (1). Such predictive capabilities are particularly critical in continuous-process industries like steel manufacturing, where minor deviations in temperature, pressure, or material composition can significantly affect final product quality.

Quality management research increasingly emphasizes the importance of integrating operational data across organizational functions. Internal quality integration has been shown to enhance financial performance through its influence on product innovation and process efficiency. Firms that synchronize quality information across departments—including production, maintenance, engineering, and quality control—demonstrate superior innovation outcomes and higher operational effectiveness (4). Similarly, employee participation in total productive maintenance contributes to sustainable quality improvement by promoting bottom-up involvement in monitoring equipment performance and preventing process failures (5). These findings underline that modern quality management requires both technological infrastructure and organizational participation.

Industrial studies further demonstrate that product quality is directly linked to productivity performance and resource utilization efficiency. Investigations into agricultural and industrial production systems show that production stability and material composition significantly influence output quality and overall productivity levels (6). In heavy manufacturing industries, quality variation often originates from complex interactions among process parameters rather than single isolated factors, making advanced analytical approaches essential for accurate diagnosis and control.

The growing complexity of manufacturing processes has encouraged the adoption of hybrid analytical frameworks combining statistical techniques with intelligent algorithms. Traditional statistical process control methods remain valuable for monitoring operational stability and identifying abnormal variations. For example, integrated production–maintenance planning supported by multivariate control charts and optimization algorithms improves monitoring accuracy and enhances system reliability (7). However, statistical tools alone may struggle to model nonlinear or high-dimensional industrial datasets. Therefore, researchers increasingly combine statistical analysis with machine learning methods to achieve more accurate predictions and adaptive quality control.

Machine learning models have demonstrated substantial success in industrial quality evaluation and defect prediction. Studies employing fuzzy neural networks and adaptive inference systems show that intelligent models outperform conventional analytical approaches when dealing with uncertainty, nonlinear relationships, and large-scale manufacturing datasets (8). These models learn directly from historical production data, enabling continuous improvement in prediction accuracy as additional operational data become available. Such capabilities align with the broader transition toward predictive manufacturing, where decision-making shifts from reactive correction to proactive prevention.

At the strategic level, product quality also plays a critical role in shaping organizational competitiveness and customer loyalty. High-quality products strengthen brand perception, influence purchasing decisions, and reinforce long-term customer relationships (9). Similarly, perceived product quality significantly affects brand loyalty and purchase intention through psychological mechanisms related to trust and value perception (10). Although these studies focus largely on marketing and consumer behavior, they indirectly emphasize the importance of reliable production systems capable of consistently delivering high-quality outputs. Without robust production quality, marketing strategies and brand positioning cannot be sustained.

Customer-oriented research further indicates that trust in product quality is strongly influenced by transparency, reliability, and consistent performance across production cycles (11). In industrial supply chains, especially in steel and materials industries, downstream manufacturers rely heavily on stable quality specifications. Variations in mechanical properties or chemical composition can disrupt entire supply networks, highlighting the operational significance of predictive quality management systems.

Another important dimension concerns organizational agility and knowledge management in quality development. Effective use of customer and operational knowledge enables organizations to rapidly adapt production processes and improve quality outcomes. Research shows that customer knowledge management and organizational agility significantly contribute to continuous quality improvement and product development performance (12). This perspective reinforces the idea that data-driven quality prediction systems function not merely as analytical tools but as strategic organizational capabilities.

Technological innovations such as digital twin systems further expand opportunities for quality prediction and optimization. Digital twins create virtual representations of physical production systems, allowing engineers to simulate production conditions, evaluate product performance, and validate quality outcomes before physical manufacturing occurs (13). By linking real-time operational data with simulation environments, digital twin technologies strengthen predictive analytics and reduce the risks associated with production experimentation.

Despite significant progress in quality management research, many industrial environments still rely heavily on retrospective inspection methods. Traditional quality control approaches typically identify defects only after production completion, leading to increased waste, rework costs, and operational inefficiencies. The challenge for modern manufacturing organizations lies in transitioning toward predictive quality systems capable of anticipating defects at early production stages. Integrating statistical analysis with machine learning provides a promising pathway for achieving this transformation by combining interpretability with predictive power.

Steel manufacturing represents an especially suitable context for implementing predictive quality analytics. Steel production involves complex thermomechanical processes where temperature control, rolling speed, material composition, and equipment pressure interact dynamically. Small deviations in these parameters may propagate through subsequent processing stages and ultimately affect product performance. Consequently, accurate prediction models based on real industrial data are essential for stabilizing production processes and improving manufacturing efficiency.

Furthermore, the availability of large-scale industrial datasets generated by modern monitoring systems creates new opportunities for data-driven research. Production lines equipped with sensors and quality monitoring systems continuously record operational parameters, enabling comprehensive analysis of process–quality relationships. Leveraging such datasets through advanced analytics allows organizations to transform raw operational information into strategic decision-support tools.

Although previous studies have examined statistical quality control, intelligent manufacturing, customer-driven quality strategies, and digital transformation separately, fewer investigations have integrated classical statistical analysis with machine learning techniques using real industrial datasets in heavy manufacturing environments. Bridging this gap is essential for developing practical and implementable quality prediction frameworks capable of supporting operational decision-making in industrial settings.

Accordingly, the present study aims to develop and evaluate an integrated statistical and machine learning framework for analyzing and predicting the quality of steel products using real production data obtained from the quality control unit of Mobarakeh Steel Company.

Methods and Materials

The present study is applied in terms of purpose and descriptive–analytical in terms of implementation method, based on real industrial data. The research employs statistical analysis techniques and machine learning algorithms to predict the quality of manufactured products. The study follows a data-driven approach and seeks to identify relationships between process variables and product quality using recorded data from the Quality Control Unit of Mobarakeh Steel Company in Isfahan, ultimately proposing an appropriate predictive model.

In this study, the statistical population consists of all data recorded in the quality control system and production line monitoring systems during a specified production period. These data include process information, raw material specifications, equipment operating conditions, and product quality test results. The unit of analysis is each produced batch or coil for which a complete set of production data and quality test outcomes has been recorded. The research sample includes datasets containing complete information; incomplete or unusable records were removed prior to modeling.

The research implementation process was conducted through several main stages, including data collection, data preparation, preliminary statistical analysis, selection of influential variables, development of machine learning models, model evaluation, and final selection of the optimal model for product quality prediction.

In the first stage, process data were extracted from production line information systems and integrated with quality control testing data. Raw datasets typically contain missing values, measurement noise, and outliers; therefore, data preprocessing was essential. During this stage, illogical values were corrected or removed, and missing values were replaced using mean imputation or statistical estimation methods.

To normalize the data and prevent scale differences among variables from influencing machine learning model performance, linear scaling normalization was applied according to the following relationship:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

In this relationship, each variable is transformed into a range between zero and one, which improves both learning speed and model accuracy.

After data preparation, preliminary statistical analysis was performed to examine variable behavior and identify factors affecting product quality. At this stage, the mean and standard deviation were calculated as follows:

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i$$

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (x_i - \mu)^2}$$

where μ represents the mean of the data and σ indicates data dispersion. These indicators assist in identifying variables with high variability or abnormal observations.

To examine the relationship between process variables and product quality, the Pearson correlation coefficient was employed:

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}$$

The coefficient ranges from −1 to +1 and indicates the strength and direction of relationships between variables. Variables exhibiting higher correlation with product quality were given greater importance during the modeling phase.

In the next stage, the dataset was divided into training and testing subsets. Typically, 70% to 80% of the data were used for model training, while the remaining portion was reserved for performance evaluation. Subsequently, various machine learning models were trained. In this study, models including multivariate regression, decision tree, random forest, and artificial neural network algorithms were examined for product quality prediction.

In the multivariate regression model, product quality was modeled as a function of process variables:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon$$

where Y represents the product quality index, Xi denotes production variables, and ε represents the model error term.

In machine learning models, performance was evaluated using standard assessment metrics. One of the primary indicators was Mean Squared Error (MSE), calculated as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

where yi denotes the actual quality value and ŷi represents the predicted value generated by the model. Lower values of this index indicate better model performance.

Prediction accuracy was also calculated as follows:

$$\frac{\text{Number of Correct Predictions}}{\text{Total Predictions}} = \text{Accuracy}$$

This metric indicates the percentage of products correctly classified by the model.

Table 1. Research Implementation Stages

Stage	Description of Activity
Data Collection	Extraction of process and quality data from the production system
Data Cleaning	Removal of incomplete data and correction of abnormal values
Data Normalization	Standardization of variable scales
Preliminary Statistical Analysis	Examination of data distribution and variable correlations
Feature Selection	Identification of quality-influencing variables
Model Training	Implementation of machine learning algorithms
Model Evaluation	Comparison of model performances
Final Model Selection	Selection of the model with the highest prediction accuracy

A sample structure of the dataset used in the study is presented below.

Table 2. Sample Dataset Used in the Model

Sample No.	Rolling Temperature (°C)	Line Speed (m/s)	Carbon Percentage	Roller Pressure	Final Product Quality
1	920	3.5	0.18	120	Acceptable
2	905	3.8	0.20	118	Acceptable
3	890	4.1	0.23	115	Unacceptable
4	915	3.6	0.19	121	Acceptable
5	885	4.2	0.24	112	Unacceptable

Finally, the selected model was experimentally implemented within the operational environment, and its capability for predicting the quality of newly produced products was evaluated. The purpose of this stage was to provide a decision-support tool for the quality control unit, enabling adjustment of process conditions before defective products are manufactured. Application of this approach can reduce production waste, enhance production line productivity, and improve product quality stability.

Accordingly, the research methodology represents an integration of classical statistical analysis and modern machine learning techniques which, through the utilization of real industrial data, leads to the development of a practical model for predicting steel product quality.

Findings and Results

The findings of the study are presented based on statistical analysis of process data and the results obtained from machine learning models used for predicting product quality. The analysis focuses on identifying patterns within industrial production data, examining relationships between operational variables and quality outcomes, and evaluating the predictive performance of different analytical models. Descriptive statistics, comparative analysis, correlation assessment, and predictive modeling results collectively provide a comprehensive understanding of factors influencing steel product quality in the production environment.

Table 3. Descriptive Statistics of Process Variables and Quality Index

Statistical Index	Rolling Temperature (°C)	Line Speed (m/s)	Carbon Percentage (%)	Roller Pressure (MPa)	Quality Index
N	200	200	200	200	200
Mean	910	3.80	0.20	118	0.55

Standard Deviation	15.2	0.30	0.02	4.1	0.18
Minimum	872	2.95	0.15	108	0.02
Q1	900	3.60	0.18	115	0.42
Median	910	3.80	0.20	118	0.56
Q3	920	4.00	0.22	121	0.68
Maximum	950	4.90	0.26	128	1.10

The descriptive statistics indicate that production conditions were relatively stable across the analyzed samples. The average rolling temperature was 910°C with moderate dispersion, suggesting controlled thermal conditions during production. Line speed and carbon percentage exhibited limited variability, reflecting standardized operational settings. The quality index mean of 0.55 shows a generally acceptable production quality level with noticeable variability among samples. The distribution of quartiles suggests that most production outcomes fall within a predictable operational range, while extreme values indicate occasional deviations that may contribute to quality fluctuations.

Table 4. Distribution of Product Quality

Product Quality	N	Percentage (%)
Acceptable	128	64
Unacceptable	72	36
Total	200	100

The distribution of product quality reveals that 64% of produced coils were classified as acceptable, while 36% were identified as unacceptable. This proportion indicates a relatively strong production performance but also highlights a significant opportunity for improvement. The presence of more than one-third defective products justifies the need for predictive quality control mechanisms capable of detecting unfavorable process conditions before defects occur.

Table 5. Mean Process Parameters by Product Quality

Product Quality	Rolling Temperature (°C)	Line Speed (m/s)	Carbon Percentage (%)	Roller Pressure (MPa)	Quality Index
Acceptable	918	3.65	0.19	120	0.72
Unacceptable	901	4.02	0.22	115	0.34

Comparison between acceptable and unacceptable products demonstrates clear operational differences. Acceptable products were generally produced at higher rolling temperatures and higher roller pressures, accompanied by lower line speeds and reduced carbon content. Conversely, defective products were associated with faster production speeds and increased carbon percentage. These findings suggest that excessive production speed and chemical composition deviations negatively influence product quality, whereas controlled thermal and mechanical conditions improve final outcomes.

Table 6. Pearson Correlation Matrix Among Variables

Variable	Rolling Temperature	Line Speed	Carbon Percentage	Roller Pressure	Quality Index
Rolling Temperature	1.00	−0.42	−0.15	0.28	0.61
Line Speed	−0.42	1.00	0.12	−0.21	−0.58
Carbon Percentage	−0.15	0.12	1.00	−0.09	−0.47
Roller Pressure	0.28	−0.21	−0.09	1.00	0.39
Quality Index	0.61	−0.58	−0.47	0.39	1.00

Correlation analysis reveals that rolling temperature has the strongest positive relationship with the quality index (r = 0.61), indicating that higher temperatures tend to improve product quality. Line speed shows a strong negative correlation (r = −0.58), suggesting that rapid production increases defect probability. Carbon percentage also negatively correlates with quality, while roller pressure demonstrates a moderate positive association. Overall, thermal control and mechanical pressure emerge as supportive factors for quality improvement, whereas excessive speed and chemical imbalance reduce quality performance.

Table 7. Comparison of Quality Prediction Model Performance

Machine Learning Model	Prediction Accuracy (%)	Mean Squared Error (MSE)	Training Time
Linear Regression	74	0.18	Low
Decision Tree	82	0.13	Medium
Random Forest	88	0.09	Medium
Neural Network	91	0.07	High
Gradient Boosting	93	0.05	High

The comparison of predictive models demonstrates progressive improvement in performance as algorithmic complexity increases. Linear regression achieved the lowest accuracy, reflecting limitations in capturing nonlinear industrial relationships. Tree-based models significantly improved predictive capability, while ensemble learning methods provided superior results. Gradient Boosting achieved the highest prediction accuracy (93%) and lowest error value, indicating strong capability in modeling complex interactions among process variables. Neural networks also demonstrated high accuracy but required greater computational resources.

Table 8. Ratio of Defective Products Across Temperature Ranges

Rolling Temperature Range (°C)	Number of Samples	Defective Count	Defective Ratio (%)
870–890	38	29	76
890–900	42	31	74
900–910	40	20	50
910–920	41	8	20
920–950	39	6	15
Total	200	72	36

Analysis of defect ratios across temperature intervals clearly demonstrates the critical role of rolling temperature in quality outcomes. Lower temperature ranges show extremely high defect rates exceeding 70%, whereas temperatures above 910°C substantially reduce defect occurrence. The defect ratio declines to only 15% in the highest temperature range, confirming that maintaining adequate thermal conditions is essential for stable production quality.

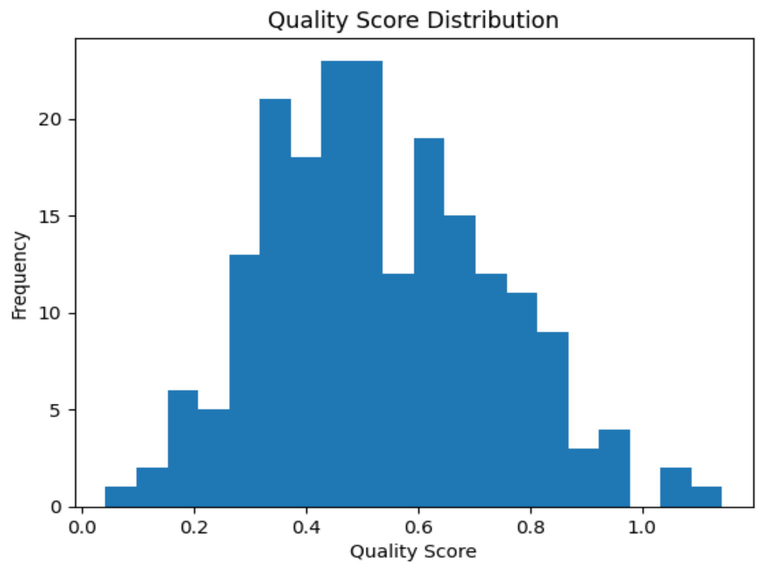

Figure 1. Distribution of Quality Scores

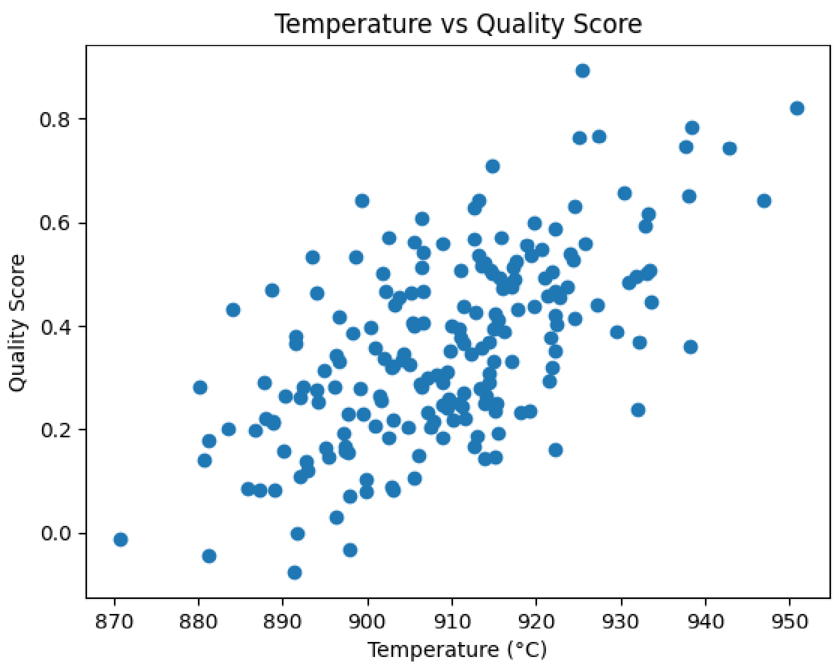

Figure 2. Rolling Temperature versus Quality Score

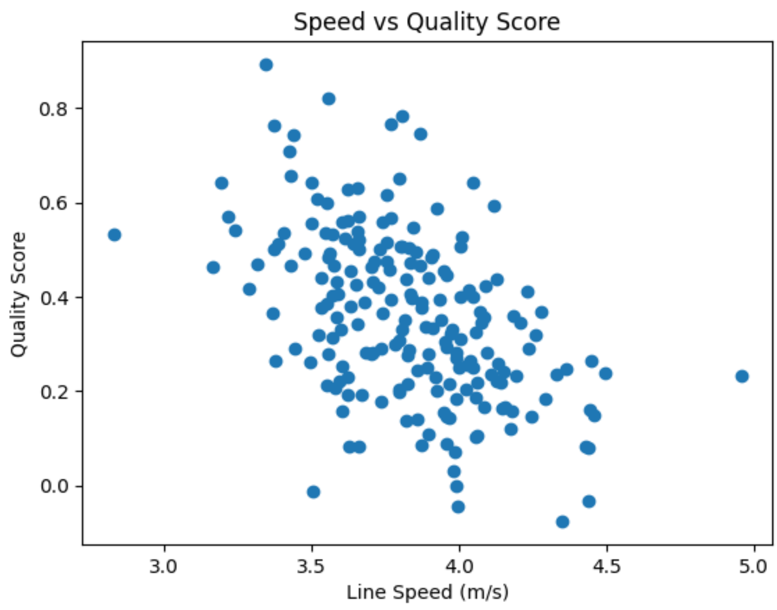

Figure 3. Line Speed versus Quality Score

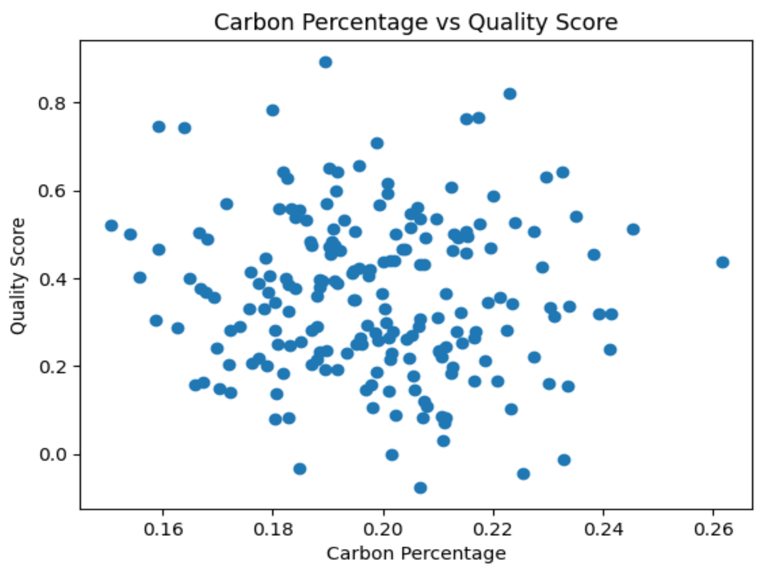

Figure 4. Carbon Percentage versus Quality Score

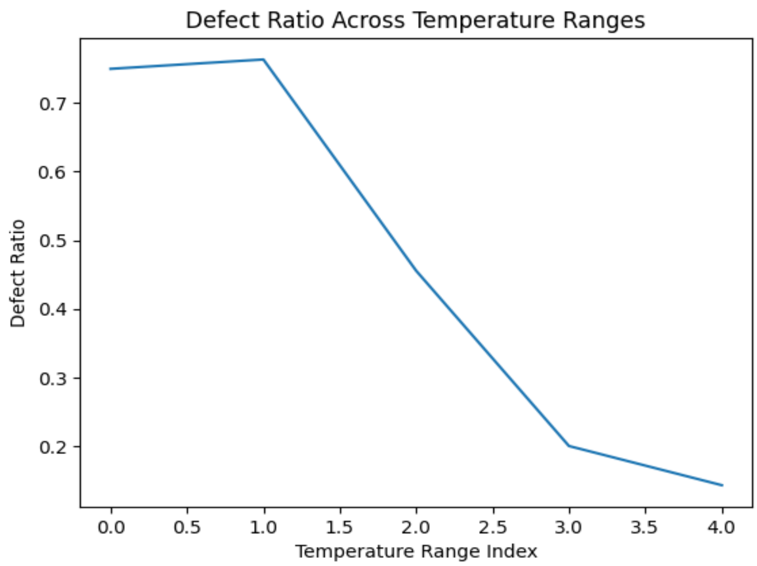

Figure 5. Defect Ratio Across Rolling Temperature Ranges

Discussion and Conclusion

The findings of the present study demonstrate that integrating statistical analysis with machine learning techniques provides an effective framework for predicting product quality within complex industrial production environments. The descriptive statistical results indicated relatively stable operational conditions across the analyzed samples; however, measurable variability in key process parameters was associated with substantial differences in product quality outcomes. This confirms that even controlled industrial systems contain hidden variability capable of influencing production performance. From a quality management perspective, such variability highlights the importance of continuous monitoring and data-driven decision-making, which are increasingly recognized as central components of modern intelligent manufacturing systems (1).

One of the most significant findings relates to the strong positive relationship between rolling temperature and the product quality index. Higher temperature ranges were associated with improved product performance and significantly lower defect ratios. This result aligns with studies emphasizing the role of process stability and operational precision in achieving consistent manufacturing quality. Research on production productivity demonstrates that controlled process parameters directly influence material characteristics and final output quality, reinforcing the importance of maintaining optimal operational conditions throughout production cycles (6). In thermomechanical industries such as steel manufacturing, temperature functions as a dominant control variable affecting structural properties, which explains its strong predictive influence observed in the current study.

Conversely, line speed exhibited a strong negative correlation with product quality, indicating that accelerated production rates increase the likelihood of defects. This finding supports quality engineering literature suggesting that excessive production speed can undermine process stability and reduce system reliability. Studies integrating production planning and monitoring systems have shown that optimized coordination between production operations and maintenance activities enhances quality outcomes by preventing operational overload and equipment stress (7). The present results therefore reinforce the argument that productivity maximization must be balanced with process capability to avoid quality deterioration.

The analysis of carbon percentage further demonstrated that chemical composition variations negatively affect quality performance. This observation is consistent with manufacturing research indicating that internal quality integration—including control over material specifications and process consistency—plays a critical mediating role between operational management and final product performance (4). Variability in raw material characteristics introduces uncertainty into production systems, which intelligent analytical models can detect but traditional inspection approaches may overlook. The findings therefore support the necessity of integrating upstream material monitoring into predictive quality systems.

Another important outcome concerns the positive relationship between roller pressure and quality performance. Adequate mechanical pressure contributes to improved material uniformity and structural stability during production. The interaction between mechanical and thermal parameters observed in this study illustrates the multidimensional nature of quality formation in industrial environments. Such results correspond with research emphasizing employee participation and operational collaboration in total productive maintenance frameworks, where coordinated control of equipment parameters enhances overall production reliability (5). Effective quality management thus requires synchronized control of multiple process variables rather than isolated parameter adjustments.

The distribution analysis revealed that approximately one-third of products were classified as unacceptable, highlighting the operational and economic significance of predictive quality systems. Traditional quality control methods typically identify defects after production, leading to material waste and increased operational costs. The predictive modeling approach applied in this study demonstrates how data analytics can shift quality management from reactive inspection toward proactive prevention. Digital transformation research emphasizes that organizations adopting intelligent analytics gain resilience and operational adaptability by anticipating disruptions before they manifest in performance failures (2). The present findings empirically support this transformation within an industrial manufacturing context.

The machine learning results further confirmed the superiority of advanced algorithms over conventional statistical models in predicting product quality. While linear regression provided baseline predictive capability, ensemble and nonlinear models—particularly gradient boosting and neural networks—achieved significantly higher prediction accuracy and lower error rates. These results are consistent with studies demonstrating the effectiveness of intelligent algorithms in capturing nonlinear relationships and complex interactions among production variables (8). Machine learning models learn from historical patterns and continuously improve predictive performance, making them highly suitable for dynamic industrial systems characterized by high-dimensional datasets.

The strong performance of ensemble learning models also aligns with the concept of digital intelligence empowerment, which emphasizes combining multiple analytical mechanisms to enhance enterprise productivity and operational quality outcomes (3). Rather than replacing traditional statistical analysis, machine learning complements it by uncovering deeper patterns hidden within operational data. The hybrid analytical framework adopted in this study therefore represents an evolution of quality management practices toward intelligent manufacturing systems.

From a strategic management perspective, improving production quality has implications beyond operational efficiency. High-quality production strengthens organizational competitiveness, supports customer satisfaction, and reinforces long-term market positioning. Studies examining customer loyalty and service innovation demonstrate that consistent product quality significantly enhances corporate image and sustainable customer relationships (14). Similarly, research on purchasing behavior shows that perceived product quality strongly influences purchasing decisions and brand evaluation processes (9). Although the present research focuses on industrial production, the findings indirectly contribute to downstream value creation by ensuring reliable product performance.

The predictive accuracy achieved by intelligent models also contributes to trust formation in industrial supply chains. Reliable product quality enhances stakeholder confidence and reduces uncertainty among customers and business partners. Consumer trust research indicates that consistent quality performance plays a central role in shaping trust perceptions across digital and physical marketplaces (11). In industrial sectors, predictive quality systems can therefore strengthen both operational efficiency and relational trust within supply networks.

Another theoretical implication of the findings relates to organizational agility and knowledge utilization. By transforming production data into predictive knowledge, firms enhance their capacity to respond rapidly to operational changes. Research on customer knowledge management demonstrates that organizations capable of leveraging information resources achieve superior quality development outcomes and adaptive performance (12). The predictive model developed in this study functions as an organizational knowledge asset, enabling managers to adjust production parameters before defects emerge.

Furthermore, the results are consistent with emerging digital twin and virtual qualification approaches in product development. Simulation-based quality prediction allows organizations to evaluate manufacturing outcomes before physical implementation, reducing experimentation risks and improving efficiency (13). Although the present study does not explicitly implement a digital twin environment, the predictive modeling framework represents a foundational step toward such advanced intelligent manufacturing systems.

At a broader level, the findings confirm that artificial intelligence technologies play a transformative role in shaping new quality productive forces within enterprises. Intelligent analytics not only improve operational performance but also generate spatial and organizational spillover effects that enhance innovation capacity and productivity growth (1). The integration of statistical and machine learning approaches demonstrated here reflects the transition from traditional manufacturing toward data-driven industrial ecosystems.

Overall, the discussion indicates that product quality in modern steel manufacturing emerges from complex interactions among process conditions, material properties, and operational decisions. Predictive analytics enables organizations to understand these interactions systematically and implement preventive interventions. The convergence of statistical rigor, machine learning intelligence, and real industrial data creates a powerful decision-support system capable of improving productivity, reducing waste, and supporting sustainable manufacturing development.

The present study has several limitations that should be acknowledged. First, the analysis was conducted using data obtained from a single industrial organization, which may limit the generalizability of findings to other manufacturing environments with different technological infrastructures or production processes. Second, although multiple machine learning models were examined, the study focused primarily on structured process data and did not incorporate unstructured data sources such as sensor images, maintenance logs, or operator behavior records. Third, the predictive models were evaluated within a defined production period, and long-term operational variability or seasonal production effects were not examined.

Future studies may expand the analytical framework by incorporating multi-factory datasets to evaluate model robustness across different industrial contexts. Researchers may also integrate real-time sensor data, Internet of Things (IoT) systems, and digital twin environments to enhance predictive capability. Comparative investigations between deep learning architectures and hybrid optimization algorithms could further improve model performance.

Additionally, longitudinal research examining organizational learning effects resulting from predictive quality systems would provide deeper insight into sustainable intelligent manufacturing transformation.

From a practical standpoint, industrial managers should invest in integrated data infrastructures that connect production, maintenance, and quality control systems. Establishing real-time monitoring dashboards supported by machine learning models can enable early detection of unfavorable process conditions. Training operational staff to interpret analytical outputs and participate in data-driven decision-making processes is also essential. Organizations should gradually transition from inspection-based quality control toward predictive and preventive quality management strategies to reduce waste, improve operational efficiency, and strengthen competitive advantage in industrial markets.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adheried in conducting and writing this article.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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