

Integrating Artificial Intelligence and Six Sigma DMAIC Methodology Using CART for Predictive Defect Control and Process Optimization in Apparel Manufacturing

Khaj Mohammad Riyad

Department of Industrial Engineering
BGMEA University of Fashion & Technology
Dhaka 1230, Bangladesh
222-020-651@buft.edu.bd

Sadik Hossain Siam

Department of Industrial Engineering
BGMEA University of Fashion & Technology
Dhaka 1230, Bangladesh
222-010-651@buft.edu.bd

Md Ariful Ferdous

Department of Industrial Engineering
BGMEA University of Fashion & Technology
Dhaka 1230, Bangladesh
ariful.ferdous@buft.edu.bd

Abstract

The growing demand for high-quality production and fast delivery has pushed manufacturers to rethink the traditional quality control methods. Although Six Sigma and other quality control tools provide a systematic quality improvement framework, they often struggle with data generated in today's modern production environments because of its volume and complexity. This study responds to this challenge by integrating Artificial Intelligence (AI) with the Six Sigma DMAIC methodology. This study was conducted using production data of KAC Fashion Wear Ltd., a renowned garment manufacturer in Bangladesh. This work creates an adaptive model programmed to predict potential defects, track the root cause, and help in decision-making to improve quality. Prior work has generally considered AI and Six Sigma as distinct tools, one anchored on statistical control, the other on machine learning, thus leaving a distinct gap in predictive quality management. Applying production data from garments, the combined Six Sigma - AI model (CART) was able to ascertain the accuracy of prediction as 76.93%, holding promise towards quality issues forecasting before occurrence. The CART results also helped identify the key variables that contribute to defects, allowing more precise corrective actions to be taken. More broadly, the findings suggest that AI can extend the analytical reach of Six Sigma, turning it from a backward-looking framework into a practical, adaptive system for continuous improvement and sustainable quality control across all manufacturing environments.

Keyword

Six Sigma, DMAIC, AI, Classification and Regression Trees (CART), Six Sigma - AI.

1. Introduction

Businesses nowadays face strong competition for quality. Thus, the combination of AI technology and Six Sigma methodology is extremely important for contemporary business models that seek excellence in quality. Six Sigma describes the use of a set of statistical tools to eliminate variations in processes and improve their quality. On the other hand, AI technology uses algorithms and machine learning to make predictions and simulate human decisions. Together, they build a formidable combination for process optimization and quality management. (Srinivasu & Reddy, 2010).

This topic is important because there needs to be a well-defined strategy to forecast defects and enhance a given process. For this enhancement, businesses can synthesize information if sophisticated methods, such as CART (Classification and Regression Trees), a decision-based algorithm for classifying data and predicting outcomes, are employed. CART is useful in the garment, textile, and manufacturing industries where defect manifestations and their outputs need to be pinpointed. Six Sigma provides a methodology for removing these defects in a process, which ultimately improves the quality of the product and the efficiency of operations. (Van Driesche et al., 1998; Wahyuni et al., 2024)

This paper discusses the challenges associated with forecasting defects and enhancing processes in contexts where data are of high dimensionality. The objective of this research is to develop a straightforward and relevant method by merging selected artificial intelligence methods, like CART through Minitab's predictive analytical module with Six Sigma's DMAIC Techniques. The aim is to address the gaps in currently available methods and provide an approach that reduces waste and costs while improving the quality of the products and services offered. (Abed & Elmo'z Ibrahim, n.d.)

1.1 Six Sigma

Six Sigma is a disciplined, data-driven methodology for process improvement that aims to reduce variation and eliminate defects through the application of statistical tools. It is structured around the DMAIC framework Define, Measure, Analyze, Improve, and Control which provides a systematic protocol for diagnosing root causes of inefficiencies, implementing solutions, and sustaining enhanced performance to achieve operational excellence. (Linderman et al., 2003)

1.2 DMAIC

The DMAIC methodology is a structured, data-driven approach within Six Sigma that is designed to systematically improve processes by reducing defects, variability, and inefficiencies. It follows five phases. (Palawatta, 2015)

1.2.1 Define

In the define phase, stakeholders must clearly define the project objective, scope, and, if possible, the time frame. The stakeholders must agree on the project target and its duration. This may include a process map or other analysis to develop an aims statement.

1.2.2 Measure

This phase requires data collection to establish baseline metrics. Data extracted from aggregate databases should be analyzed for accuracy. Data should be able to be displayed visually for subsequent analysis. Box plots, pareto charts, control charts, or histograms may be used, which will subsequently be used in further steps. Exemption from the institutional review board can usually be obtained for data used for quality improvement.

1.2.3 Analyze

This phase merges the information about the process and baseline data to identify and validate the causes of errors, deviations, delays, waste, or other etiologies of defects in the process. Analysis may include pareto diagrams, histograms, pie charts, Ishikawa (fishbone) diagrams, a 5-whys analysis, or other tools to explore cause and effect.

1.2.4 Improve

In this phase, the team works to address the root cause and make changes to eliminate issues that lead to variability and waste. Communication with team members, team involvement, and commitment is essential. Stakeholders should be comfortable brainstorming and using clear and regular communication about potential solutions. Various stakeholders may disagree on who should be changed or what should be changed to achieve the objective

1.2.5 Control

The control phase is crucial to sustainable change and requires efficient tracking. A process control plan usually builds on an ideal process map that indicates who is responsible for each aspect of the new process. The team must be aware of new potential problems that could arise due to workarounds, design flaws, or resistance to process change. Ongoing control charts can be used to monitor variations. Team members must regularly be aware of the metrics so that “out of control” performance can be corrected and the control plan can be updated. The frequency at which team members are updated (daily, weekly, annually, etcetera) is dependent on the metric being tracked and the amount of time required to gather and verify the data.

1.3 Classification and Regression Trees (CART)

It is a Minitab function and a machine learning algorithm that is used to create decision trees to classify data (classification) or predict continuous values (regression). It splits the data recursively into subsets by the most relevant feature in each node and uses decision measures such as Gini impurity for classification and least squared error for regression. This process is iterated until the model meets a stopping requirement, such as a maximum depth or amount of improvement in accuracy. The terminal nodes (leaves) of the resulting structure constitute the predicted value or class and, therefore, CART is a powerful tool for handling difficult, high-dimensional data in many applications, such as defect prediction and process optimization. (Chandra Mukhopadhyay M Namal Arosha Senanayake P W Chandana Withana Editors, n.d.)

1.4 Six Sigma – AI

This Six Sigma - AI system is the combination of Artificial Intelligence (AI), in the form of the Classification and Regression Trees (CART) algorithm, and the Six Sigma DMAIC methodology for enhanced defect prediction and process improvement. With the combination of CART with the DMAIC framework, the system allows data-driven exploration to detect prevailing defect patterns, predict potential process failure, and implement specific improvements. This AI-driven approach takes the traditional Six Sigma process beyond the limitations of legacy statistical software to predict defects in real-time and make adaptive decisions. The Six Sigma - AI system thereby enables reducing process variability, waste elimination, and overall manufacturing efficiency optimization in a systematic as well as scalable manner.

2. Objectives

- Develop an AI-driven prediction model using Classification and Regression Trees (CART) with Six Sigma DMAIC methodology to improve defect detection and minimize process variances.
- Integrate AI with Six Sigma methods to efficiently analyse and manage large amounts of data, overcome the limitations of traditional process improvement tools to deal with structured data.
- Create a dynamic and scalable Six Sigma -AI model that can be applied across various industries in an effort to facilitate process optimization, reduce waste, and improve overall product quality.

3. Literature review

In today’s industrial era, with increasing changes and complexities in production systems, combining Artificial Intelligence (AI) with quality control tools is increasingly recognized as an effective approach to enhance quality and efficiency. A quality tool like Six Sigma is a methodology that aims to eliminate defects and reduce variations through data-driven analysis for identifying and removing causes of problems. On the contrary, artificial intelligence or machine learning methods such as classification and regression trees (CART) have been widely successful in predicting possible problems before they actually happen so that proactive measures can be taken by managers instead of just reactive measures in traditional business. Moreover, integration of artificial intelligence with Six Sigma will prove to be a smarter and highly efficient system in order to control manufacturing processes as well as take decisions. Recent studies have also analyzed how artificial intelligence can be integrated with IoT and blockchain technology in order to form more efficient and environmentally sound manufacturing systems (Chadha et al., 2024; Zheng et al., 2018)

Research carried out by (Fardan, 2023) and (Vargas et al., 2024) suggests that while it is true that AI is increasingly applied for predictive analysis, it is nonetheless the case that it has not yet been integrated in full as part of more traditional approaches to Six Sigma methodology. Traditional approaches of Six Sigma analysis have been shown to lack applicability when it comes to large and complex data. This is a strength of more modern approaches that incorporate increased data usage in an era of highly data-driven industries. In a similar manner, it would seem that

while current approaches to AI lack flexibility in terms of usage, they also specifically lack effectiveness when conveyed across different usage areas within an industrial setting. (Sood & Dhull, 2024) In this study, researchers believe that combining an understanding of AI with current approaches to Six Sigma could revolutionize how companies respond in terms of continuous improvement. On this foundation, (Muhammad et al., 2024) demonstrate that AI technology is capable of transforming Six Sigma methodology in terms of making possible predictive quality control and intelligent process optimization. Rather than waiting for a situation to go wrong before taking action, it is possible to anticipate and prevent problems before they arise. Other studies have also produced similar findings in that integrating Artificial Intelligence has been shown to decrease process variation, hasten decision-making, and enhance product reliability. Nevertheless, it is also a fact that integrating Artificial Intelligence with current systems of Six Sigma is not without its challenges, especially when large datasets become involved and when adapting models to fit manufacturing conditions. In this manner, an imperative of this proposed study is that CART's predictive analytics approach needs to be integrated with DMAIC by means of Minitab's predictive analytics component like CART (Table 1- Table 4). This is in order to make possible a flexible, data-driven model that is easily adjusted to fit different manufacturing conditions. In such a manner, a fusion of Artificial Intelligence and Six Sigma methodologies will make it possible for an organization to work in a more efficient, less wasteful, and more productive manner in a manner that will also pass muster in terms of product quality.(Palawatta, 2015; Radi, 2023)

Table 1. Comparison of Related Studies on Six Sigma and AI Integration

Research	Integration of AI with Six Sigma	Focus on Manufacturing	Predictive Analytics (CART/ML)	High-Dimensional Data Handling	Real-time Process Optimization	Scalability across Industries	Data-Driven Decision Support
Chadha et al. (2024)	✓	✓	✓	×	✓	✓	✓
Radi (2023)	✓	✓	✓	×	✓	✓	✓
Zheng et al. (2018)	×	✓	×	✓	✓	✓	✓
Fardan (2023)	✓	✓	✓	×	✓	✓	✓
Vargas et al. (2024)	✓	✓	✓	✓	✓	✓	✓
Sood & Dhull (2024)	✓	✓	✓	×	✓	✓	✓
Muhammad et al. (2024)	✓	✓	✓	×	✓	✓	✓
Palawatta (2015)	×	✓	×	×	×	×	✓
Proposed Study (AI-Six Sigma)	✓	✓	✓	✓	✓	✓	✓

4. Methods and Data Collection

Step 1: Collected seven working days of production data from 2 March to 9 March 2024, excluding Friday as a non-operational day, from Line 1 and Line 7 of KAC Fashion Wear Ltd. In total, 104 line and 11 type of production records were obtained.

Step 2: Used those datasets, consisting of 96 rows and 11 columns, to train the CART model in Minitab.

Step 3: Tested the model using real production data from 9 March 2024, comparing predicted defects with actual defects, which produced an accuracy of 76.93 percent.

Step 4: Lastly connected the model's analysis and findings with DMAIC framework to suggest solution and improve the production quality

Table 2. Sample data of the variables for predicting defects

Date	Hour	Inspector name	Line no	Product type	Colour	Size	Total Manpower	No. of M/c	Total inspection	Total defects
2-Mar	1	Roksana	7	T-shirt	black	L	24	15	209	9
2-Mar	2	Roksana	7	T-shirt	black	L	24	15	217	7
2-Mar	3	Roksana	7	T-shirt	black	L	24	15	217	12
2-Mar	4	Roksana	7	T-shirt	black	L	24	15	260	10
2-Mar	5	Roksana	7	T-shirt	black	L	24	15	300	13
2-Mar	6	Roksana	7	T-shirt	black	L	24	15	283	12
2-Mar	7	Roksana	7	T-shirt	black	XXXL	24	15	360	14
2-Mar	8	Roksana	7	T-shirt	black	MXL	24	15	351	16
2-Mar	1	Mousumi	1	T-shirt	black	M	27	18	166	16
2-Mar	2	Mousumi	1	T-shirt	black	M	27	18	160	10
2-Mar	3	Mousumi	1	T-shirt	black	M	27	18	163	11
2-Mar	4	Mousumi	1	T-shirt	black	M	27	18	215	15
2-Mar	5	Mousumi	1	T-shirt	black	L	27	18	266	16
2-Mar	6	Mousumi	1	T-shirt	black	L	27	18	269	19
2-Mar	7	Mousumi	1	T-shirt	black	L	27	18	212	10
2-Mar	8	Mousumi	1	T-shirt	black	L	27	18	213	11
Mean of all data used							25.5	16.5	279.26	14.43
Std of all data used							1.51	1.51	59.63	4.17
Range of all data used							3	3	265	15

6. Results and Discussion

6.1 Numerical Results

The accuracy of the prediction is 76.93%.

Table 3. Predicted defects and actual defects

Date	Hour	Inspector name	Line no	Product type	Colour	Size	Total Manpower	No. of M/c	Total inspection	Predicted defects	Actual defects
9-Mar	1	Mousumi	1	T-shirt	Black	M	27	18	270	20.5	17
9-Mar	2	Mousumi	1	T-shirt	Black	M	27	18	269	20.5	19
9-Mar	3	Mousumi	1	T-shirt	Black	M	27	18	322	21.333333	20
9-Mar	4	Mousumi	1	T-shirt	Black	M	27	18	321	21.333333	21
9-Mar	5	Mousumi	1	T-shirt	Black	M	27	18	319	17.333333	17
9-Mar	6	Mousumi	1	T-shirt	Black	M	27	18	320	17.333333	19
9-Mar	7	Mousumi	1	T-shirt	Black	XL	27	18	323	21.333333	21
9-Mar	8	Mousumi	1	T-shirt	Black	XL	27	18	352	19.444444	20

6.2 Graphical Results

WORKSHEET 1

16 Node Alternative CART® Regression: Total defects versus Hour, Line no, Total Manpower, No. of M/c, Total inspection, Product type, Inspector name, Colour, Size (Figure 1- Figure 3)

Method

Node splitting	Least squared error
Optimal tree	Within 1 standard error of maximum R-squared
Model validation	10-fold cross-validation
Rows used	96

Response Information

Mean	StDev	Minimum	Q1	Median	Q3	Maximum
14.4271	4.17195	7	10	14	18	22

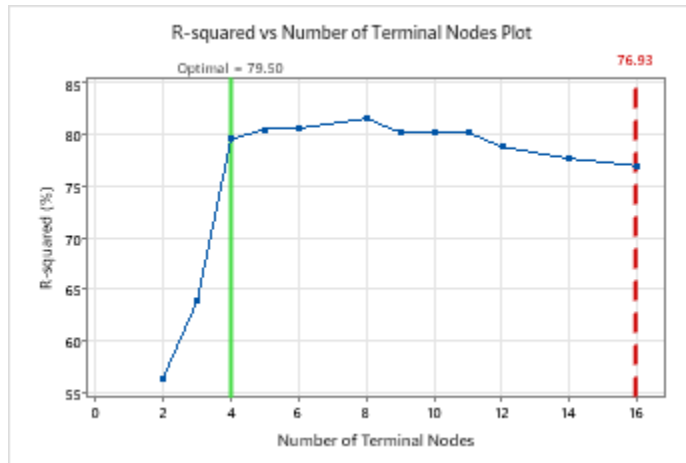


Figure 1. Regression

Alternative Tree Diagram:

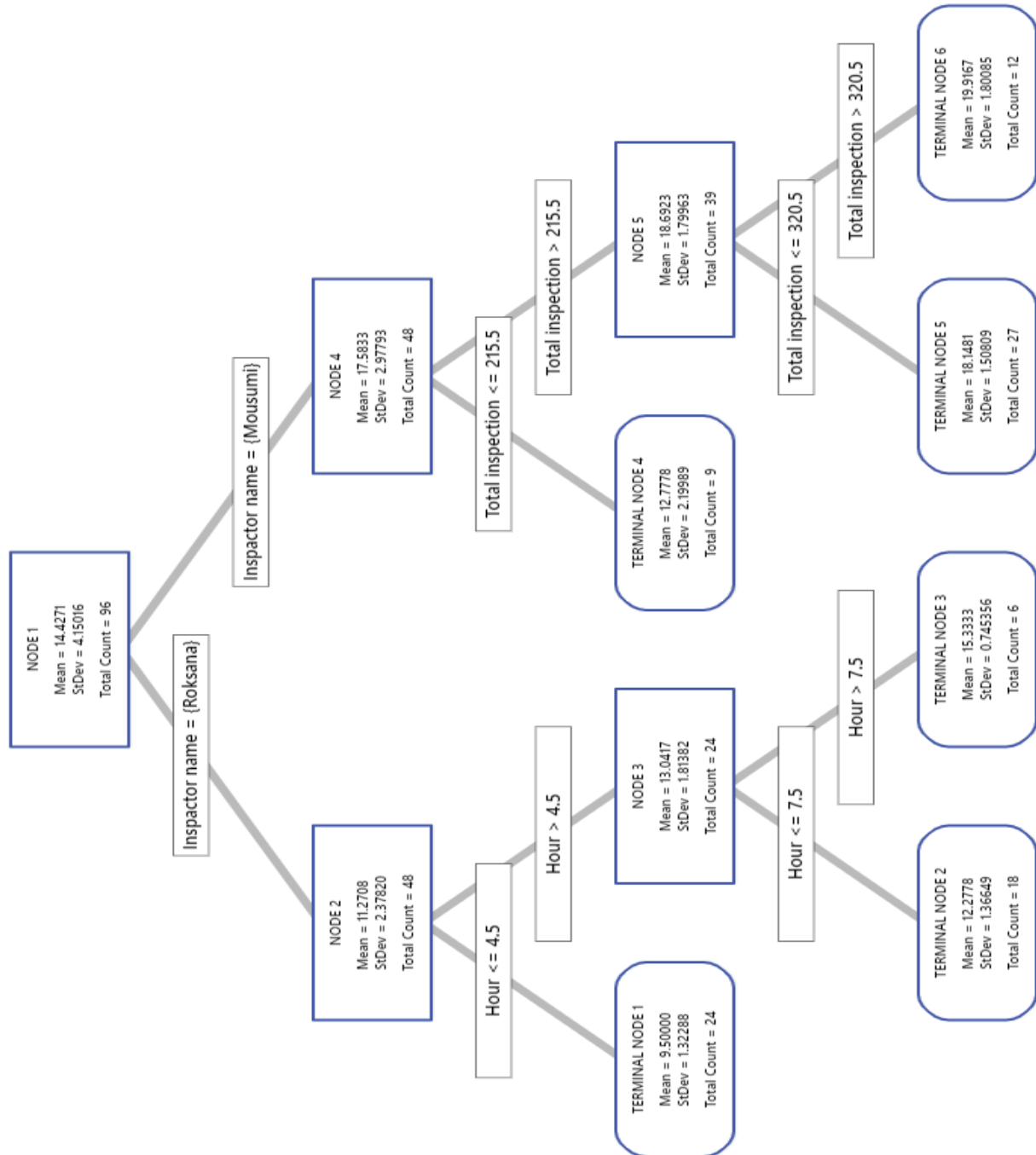
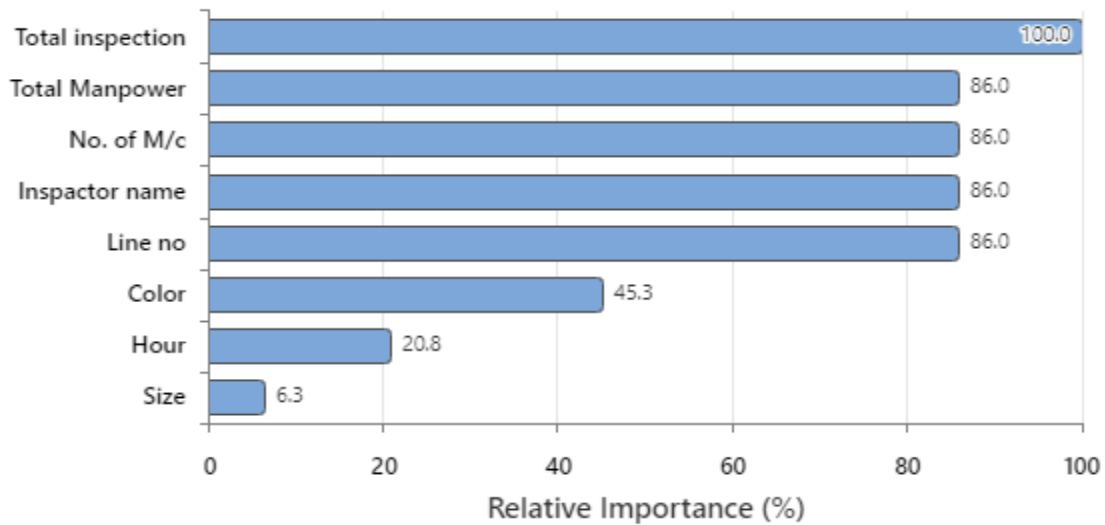


Figure 2. Tree Diagram

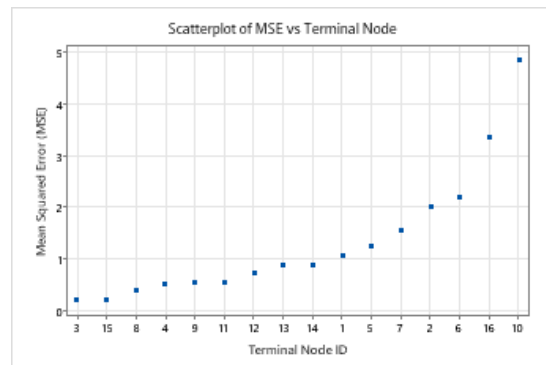
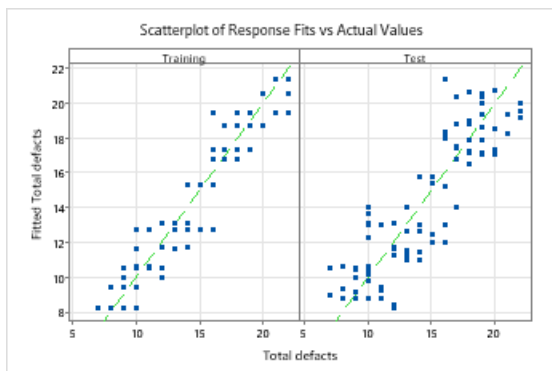
Model Summary:

Total predictors	9		
Important predictors	8		
Number of terminal nodes	16		
Minimum terminal node size	3		
Statistics		Training	Test
R-squared		91.08%	76.93%
Root mean squared error (RMSE)		1.2392	1.9935
Mean squared error (MSE)		1.5355	3.9740
Mean absolute deviation (MAD)		0.9917	1.6420
Mean absolute percent error (MAPE)		0.0761	0.1242

Relative Variable Importance



Variable importance measures model improvement when splits are made on a predictor. Relative importance is defined as % improvement with respect to the top predictor.



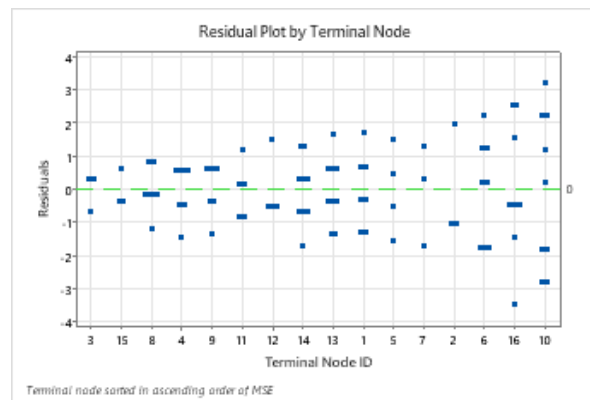


Figure 3. Various model

7. Proposed Improvements

To strengthen the process optimization, this study proposes an enhanced Six Sigma DMAIC framework by data generated through the Classification and Regression Trees (CART) model. Contrary to relying on CART for improvement processes, this work attempts to utilize CART's prediction capability for understanding influential variables concerning defects. Thus, by this integration, improvement activities are not assumption governed but instead are data-guided. This leads to systematic and proactive quality management.(De Mast & Lokkerbol, 2012)

7.1 Define Phase - Establishing Objectives for Defect Prevention

During the Define stage, it would be appropriate for the organization to rely on CART-generated insights to specify important categories of defects, for example, total inspection and total manpower etc. Based on this information, specific objectives can be developed concerning improvement in quality by focusing on the types of defects which can be predicted by CART. Specifically defined objectives with a focus on evidence-based information mean that improvement strategies will effectively address quality issues.

7.2 Measure Phase: Data Gathering and Augmentation

During the Measure stage, variables that reflect data relationships uncovered by CART, such as the effect of manpower, machine availability, and inspection volume, can be employed during this phase to improve measurement practices. Additional variables that could be used to improve measurement practices include operator performance, machine downtime, and environmental variables.

7.3 Analyze Phase: Identifying Root Causes Using CART Insights

In the Analyze phase, management can leverage the predictive strength of CART modelling to identify the primary factors driving defects. For instance, it might reveal how interactions among human resource challenges, specific production lines, and product dimensions contribute to defect rates.

7.4 Improve Phase: Implementing Targeted, Data-Informed

In this phase, it is necessary for the management to identify preventive actions based on the critical factors identified by CART. Methods like Poka Yoke and Jidoka can be adopted to avoid human errors that have been identified as critical to generating defects. Finally, AI alert systems or control boards can be put in place to alert operators for defects if probabilities breach acceptable limits.

7.5 Control Phase: Sustaining Data-Driven Improve

In this phase, management should focus on continuous observation and control of these critical variables, which have been identified by using CART modelling. The actual data collected by real-time manufacturing can be used for periodic improvement in the model's predictability. Six Sigma audits can then be done on a periodic basis to validate if the percentage of defects is low and if process optimizations made by CART insight are providing value.

7.6 Expected Outcome

Through structured incorporation of CART derived information and insights with the Six Sigma DMAIC model, it can be expected that:

- Development of a Six Sigma - AI model with flexibility for implementation in various manufacturing setups.
- Improved accuracy in identifying root causes for defects based on data analysis s given by CART.
- Minimize defect occurrences through effectively focused improvement and defect prevention activities.

8. Validation

To evaluate the effectiveness of our proposed Six Sigma - AI model, defect-based data were collected from Line 1 and Line 7 of KAC Fashion Wear Ltd., ready-made garment manufacturer in Bangladesh. For the training of the CART model, from 2nd March 2024 to 8th March 2024, data was used. However, for model validation, the real-time data of the 9th of March 2024 was used. Then the predicted output of the model was compared with the actual number of defects reported. Based on the results, the accuracy of the CART model was 76.93 percent, signifying that the predicted results matched the reported results. The validated CART predictions were subsequently applied within the DMAIC framework to guide improvement efforts, based on prior evidence that DMAIC contributes to measurable quality and process improvements in manufacturing environments (De Mast & Lokkerbol, 2012; Palawatta, 2015).

Table 4. Predicted defect vs actual defect

Total inspection	Predicted defects	Actual defects
270	20.5	17
269	20.5	19
322	21.333333	20
321	21.333333	21
319	17.333333	17
320	17.333333	19
323	21.333333	21
352	19.444444	20

9. Conclusion

This study was successful in achieving its objectives by developing an artificial intelligence-based predictive model through the Classification and Regression Trees (CART) algorithm within the Six Sigma DMAIC framework. With the combination of Six Sigma and artificial intelligence, this study could break the constraints of traditional process improvement approaches, thus enabling effective defect prediction and process optimization. The suggested Six Sigma - AI model performed with prediction accuracy of 76.93% and a mean absolute deviation (MAD) of 1.6420, meaning it is an efficient and useful method for defect prediction and enhancement of production quality.

One of the significant contributions of this study is that this is a one of the early studies to integrate CART-based prediction within Six Sigma DMAIC methodology to create a scalable and globally deployable framework for defect reduction and efficiency improvement. The application of CART not only allowed accurate predictions of defects but also promoted data-driven decision-making, which further contributed to better quality products and reduced waste. The study offers, apart from this, an organizational framework under which other organizations can introduce AI into their continuous improvement strategies and close the gap between predictive analysis and real industrial application.

Future research can advance these results by examining sophisticated machine learning methods to enhance the accuracy of defect prediction models and broaden their applicability across various manufacturing industries. In summary, this study offers valuable implications for artificial intelligence and DMAIC method collaboration, showing an effective strategy for quality control and operational excellence.

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Biographies

Khaj Mohammad Riyad is currently pursuing his Bachelor's in Industrial engineering at the BGMEA University of Fashion and Technology (BUFT), Dhaka, Bangladesh. He is also BUFT IEOM Student Chapter Director of Membership and Vice President of the BUFT Industrial Engineering Club (BUFTIEC) and is actively promoting research and innovation there amongst his peers to address real-world industrial cases.

Md. Sadik Hossain Siam is an undergraduate student in the Industrial Engineering Department at BGMEA University of Fashion and Technology (BUFT), Dhaka, Bangladesh. He is a member of the BUFT IEOM Student Chapter and is involved in various academic and extracurricular activities.

Md. Ariful Ferdous is a Faculty member of the Department of Industrial Engineering at BGMEA University of Fashion and Technology, Dhaka, Bangladesh. He completed his B.Sc. in Industrial and Production Engineering from Khulna University of Engineering and Technology. He then completed his Master's degree in Applied Statistics and Data Science at Jahangirnagar University. His academic and professional interests are data-driven decision-making in production and manufacturing, with a focus on Operations Research, supply chain optimization, supply chain data analytics, Machine Learning, and Lean manufacturing.