Developing an artificial intelligence quality control framework. A case study of rail industry in South Africa.

By

MK Mushi

Submitted in partial fulfilment of the requirement for the degree

MASTER'S DEGREE: ENGINEERING MANAGEMENT

in the

Department of Industrial Engineering

FACULTY OF ENGINEERING AND THE BUILT ENVIRONMENT

TSHWANE UNIVERSITY OF TECHNOLOGY

Co-supervisor: Mr T Mokgokong

Supervisor: Professor Mpofu

May 2022

DECLARATION

I hereby declare that the dissertation submitted for the degree MEng: Industrial Engineering at the Tshwane University of Technology is my own original work and has not been previously submitted to any other institution of higher education. I further declare that all sources cited or quoted are indicated and acknowledged by means of a comprehensive list of references.

M.K. Mushi

Signature:......[redacted]..........................

ACKNOWLEDGEMENTS

To God be the glory!

I want to extend my deepest gratitude to my supervisor, Prof Mpofu and Co-supervisor, Mr T Mokgokong, for their guidance throughout my dissertation. Department of Industrial Engineering and the Tshwane University of Technology for providing all the necessary tools for my research.

I am extremely grateful to my mother, Mrs Lizer Mushi, for the love, prayers and preparation for my future since childhood. Finally, and above all, I cannot begin to express my unfailing gratitude and love to my dear husband, Matodzi Mukhuba, and my children, Thendo, Hulisani, Dakalo and the late Ndimuhulu.

Thank you.

ABSTRACT

Quality control has become a critical parameter for competitiveness in manufacturing organisations. Although technology and automation have made a difference, many quality issues are still not managed by manual inspection. Due to poor quality control, approximately 20% of the commodity parts from the suppliers to Company X are received with defects. The objective was to develop an Artificial Intelligence (AI) quality control framework using Orange Anaconda 3.4 software. A literature review showed that factors such as fatigue, skills development and quality awareness could contribute to quality issues. Data collected from Company X consisted of historical defects of commodity parts used to train the machine learning (ML) algorithms for more accurate classification with supervised learning.

The quantitative results obtained from the ML algorithm simulation with trained data were used to compare Adaboost, CN2 rule inducer, Random Forest and Neural Network Algorithms, revealing the inspection efficiency and accuracy of the classification. Furthermore, the findings indicate that the existing model from Company X could integrate easily with AI to produce a better quality control system, production improvement, optimal efficiency, reduction of defects and greater financial growth within the business. In conclusion, the AI-based quality control framework is recommended to Company X's suppliers and other OEMs.

Table of Contents

LIST OF FIGURES

LIST OF TABLES

CHAPTER ONE - INTRODUCTION

1 Chapter Overview

This chapter addresses the background of product quality in manufacturing and outlines the problem being considered so that a specific aim, questions, and objectives are established. A problem statement was created, and the researcher provided a rationale for why this study was being conducted by pointing to the value of the analysis. The goals and objectives the researcher set out to accomplish were met, and the research questions listed in the subsections below were answered.

1.1 Background

The fast development of the economic environment and market factors requires increasingly more companies to have a more flexible quality control system. Product quality control is an essential aspect of any sector in which a product is generated because it allows reducing the variability of products and, consequently, the reduction of production costs. This control enables possible defects to be detected and appropriate measures taken, allowing the companies to offer a final product design (Blanco-Encomienda, 2021). Lombard (2014), describes quality as an essential aspect of every manufacturing environment affected by many factors between organisations and advises on the importance of the factors affecting product quality. Product quality is one of the critical factors influencing customers' purchases (Šugrová *et al*., 2017). Additionally, customers can easily distinguish high-quality products and make better decisions related to their purchases. Product quality is the ability to satisfy the customer and the market. It is often divided into eight dimensions, performance, features, reliability, conformity, durability, serviceability, aesthetics, and perceived quality. Companies with good product quality are more likely to attract higher customer value, thus improving their competitiveness (Yu Lin *et al*., 2018). Generally, a product is high quality when it meets or exceeds customers' expectations. Product quality is the most important factor in choosing a particular brand in a highly competitive market environment (Hanaysha, Abdullah & Ghani, 2016).

To this end, the thesis presents the localisation of urban rail commuter's railcar products by Tier 1 manufacturing alongside suppliers in the rail industry in South Africa. The localisation mandate is to boost the South African economy by creating jobs and empowering small businesses. The challenges are achieving on-time delivery (OTD) in manufacturing the railcars and poor-quality products received from suppliers following all the supply chain processes. The aim of this study is to develop an AI quality control framework to reduce human intervention by integrating a much smarter and more efficient framework incorporating existing quality frameworks and AI technologies. A literature review of other quality frameworks made it interesting to explore three research questions.

1.2 Problem Statement

About 20% of parts commodities are defective when received from Company X's suppliers. Most parts received from the suppliers undergo inspection by humans. This implies missed detection during quality control, which could have occurred on a significant percentage of parts, causing production line disruption and affecting the on-time delivery of trains to its customer (Company X database, 2021). Defective parts are then recalled from inventory to the supplier for root cause analysis and repairs suggesting a significant financial expense due to non-quality (CONQ). Unfortunately, with only human inspection, many errors are guaranteed due to fatigue and other emotional disruption factors human beings undergo. Therefore, an AI framework is proposed to accomplish 100% inspection with close to zero misdetection.

1.3 Research Aim and Objectives

1.3.1 Aim

The development of an AI quality control framework for purchased parts alongside a supplier in the rail industry.

1.3.2 Research objectives

I. To evaluate the existing quality control frameworks using the literature to document and analyse gaps.

II. To identify the relevance of AI in quality control in manufacturing by analysing existing literature.

III. To develop an intelligent AI quality control framework that combines key elements of existing quality control frameworks and the relevance of AI technologies.

1.4 Research Questions

(i) What factors affect visual product quality control efficiency?

(ii) What are the best practices for maximising efficient product quality control?

(iii) What key features should be considered when developing an intelligent AI quality control framework?

1.5 Significance of the Study

The research findings will reveal how quality control systems can be strengthened by ML technologies while improving efficiency and financial outcomes in the business environment. The results would be important in manufacturing sectors, such as Company X and other OEMs that adopt the framework, as quality control is fundamental. The intelligent quality control framework will assist engineers with improved analytic skills. The focus will motivate analysing root causes and corrective actions for the problem and finding solutions from inspection data provided by the intelligent AI quality control framework.

Business is guaranteed to improve production output with greater inspection efficiency.

1.6 Delimitation

The study only deals with the theoretical aspects. We did not simulate the physical setup of the quality control framework; however, we experimented with or simulated the features to be used in the framework. This AI technology model does not address the standards of quality management.

1.7 Summary

This chapter introduced the problem, aim and objectives of the study. The following chapter will address the analysis of reviewed literature.

CHAPTER TWO - LITERATURE REVIEW

2.0 Introduction

This chapter consists of the following literature reviews with various theories. The study focused on four major themes (i) product quality risks within the supply chain, (ii) factors influencing product quality, (iii) factors affecting visual quality control, and the (iv) the relevance of AI in quality control. Many recent studies have focused on product quality as a crucial aspect of manufacturing, hence a need to research this topic.

2.1 Product Quality Risk in the Supply Chain

Most theories of product quality are concerned with operational efficiency about efficient quality control. Tse *et al*. (2011), argued that product recalls indicate that companies with poor visibility in a supply chain are particularly vulnerable to product quality concerns. Li (2018), added that quality formation mechanism and quality-affecting factors are the origin of product quality and the basis for evaluating it. Saqib and colleagues *(*2019), saw value in getting the right supply chain visibility to meet customer expectations and ensure operational efficiencies. In recent studies outlined by Sankhye and Hu (2020), a lack of quality control led to issues with logistics, including reworks, reverse logistics, and production plan interruptions because of defective items. The authors refer back to poor quality control impacting supply chain efficiency throughout manufacturing.

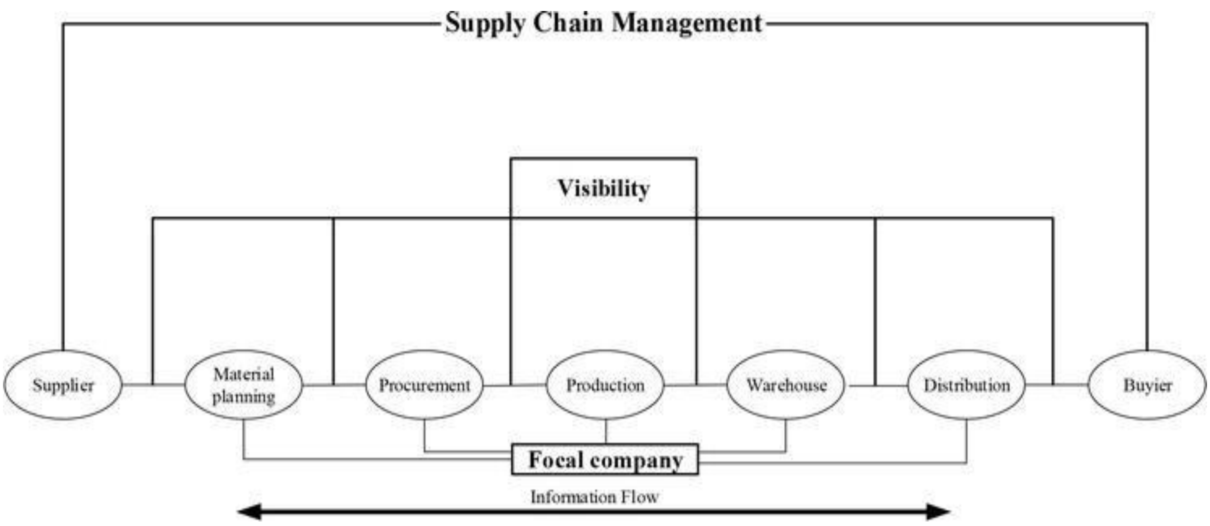


Figure 2.1: Product life cycle management (Saqib, 2011).

Positive relationships between quality and supply chain management exist, such that quality management improvements in reducing process variation impact several supply chain deliverables directly (Fish, 2011). The authors recognised the connection between the supply chain and the quality of the final product. Another author claimed poor supply chain visibility could affect the final product's quality. These authors concur that good product quality depends on having a proper or visible supply chain. Although Saqib (2011), demonstrated the framework for supply chain visibility, the emphasis was on the manufacturing line. This is debatable because supply chain visibility should cover all part flows from the supplier to the warehouse and production to the client. Unfortunately, Saqib's framework only allows for production-level supply chain visibility, which means the information flow is not sufficiently observable. More research on this topic was done to uncover the impact that supply chain visibility has on product quality.

2.1.2 Impact of supply chain visibility on product quality

Many other studies have confirmed that, without supply chain visibility, the company would not run efficiently. Saqib (2019), suggests that supply chain visibility is essential for the company's success, considering the entire product life cycle chain. He further classified factors contributing to the benefit of supply chain visibility (Table 2.1). Lofti and colleagues (2013) assert that companies that collaborate or cooperate with others in making supply chain visibility clear to each other have better competitive advantages than those that do not. The author further developed a framework with two dimensions, supply chain integration and product quality. Ahmed *et al*. (2021), suggested using the Internet of Things (IoT) in SC to have clear visibility in the supply chain. It is a digital technology that has provided immense business opportunities in industry, manufacturing, and service provision, restructuring the entire supply chains and enabling transparency in the product life cycle. Ahmed *et al.* (2021), concluded that supply chain planning, collaboration, traceability, flexibility, transparency, performance management, and order management are the key benefits of integrating IoT to achieve supply chain visibility (SCV) and explain that lack of standardisation, security, and misread information poses a threat to attaining SCV through IoT. Kalaiarasan *et al*. (2022), defined SCV as “the degree to which players within a supply chain have access to or share information that they believe to be key or valuable to their operations and that they consider to be of mutual value". In addition to affecting business performance, low visibility in the supply chain causes a restricted ability to achieve flexibility. Thus, managing supply chain disruption in a network of global suppliers, operations, and markets has increased attention to SCV to attain sustainable and competitive business performance. Visibility has become one of the most highlighted concerns of manufacturing companies. Kalaiarasan *et al*. (2022), further designed the ABCDE framework of SCV in Figure 2.2, highlighting all key factors contributing to SCV. The framework is divided into four categories: drivers of the supply chain (suppliers, internal metiers and customers), antecedents, barriers and effects. In another study, the author recognised the gap in addressing the implications of technologies that target SCV systems from other authors, which can provide insights into the possibilities and limitations of improving visibility in practice. He introduced a design science approach text-intervention-mechanism-outcome (CIMO) logic to map and analyse material and information flows, ensuring less deviation; however, the author limited the research study to logistics.

Table 2. 1: Supply chain visibility factors (Saqib, Saqib & Ou, 2019).

Reduce risk and costs	Risks such as defective products will be minimised by the visibility of the entire supply chain; return on investment is guaranteed.
Identify problems	Visibility of the entire supply chain can detect errors beforehand and mitigate time before a significant impact on the whole value chain.
Improve performance	Where there is visibility within the supply chain, performance is guaranteed, and businesses operate efficiently with substantial financial benefits.

Overall, various authors' findings on supply chain visibility agree.

Saqib, Saqib and Ou (2019), highlighted the key benefits of SCV. (1) reduce risk and costs, as a visible supply chain would mean products and information flow status are made available and clear, having no or less risk to production flow. (2) Identify problems; problems are easily and quickly identified as the supply chain remains visible, which also entails less or no risk to production flow. (3) Performance improvement will mean the business will operate at its optimal best with visibility in the supply chain. Cross-functional departments will work towards a common goal without bottlenecks, implying financial benefit. Lofti, Sanharan and Mukhtar (2013) encourage companies to collaborate to have a clear and flexible supply chain. Our study agrees with Lofti's idea, as collaboration would imply teamwork and communication, resulting in good information flow.

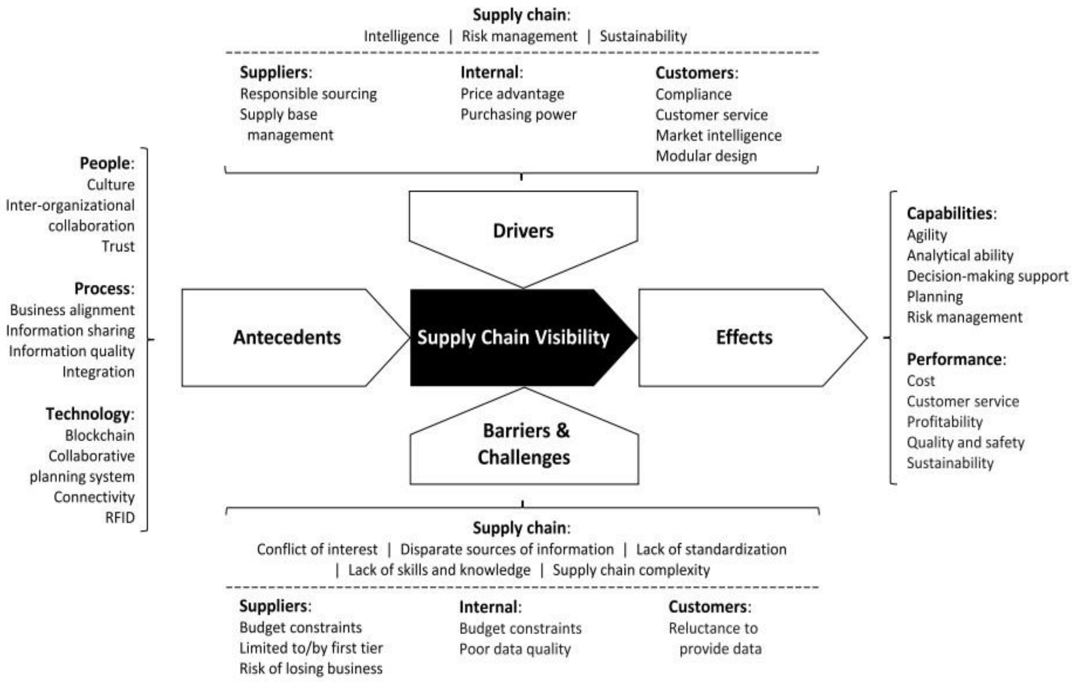


Figure 2. 2: The ABCDE framework of supply chain visibility (Kalaiarasan et al., 2022).

We consider coordinating the ABCDE supply chain framework and the IoT to have a transparent and visible supply chain.

2.1 Factors Affecting Product Quality

According to Lotfi, Sahran and Mukhtar (2013), product quality is crucial to operational performance in supply chain management. However, prior studies in this area neglected to consider the relationship between supply chain integration and aspects of product quality. Because of this, research on the impact of supply chain integration on quality performance has received less attention. These authors also explain that design quality impacts conformance quality and that each aspect of supply chain integration affects an aspect of product quality. Finally, they note that design quality (DQ) and conformance quality (CQ) are two such dimensions of supply chain integration and product quality and that research has paid little attention to them (Lofti, Sharan &

Mukhtar, 2013). According to Lofti's study, concentrating on supply chain integration management can also improve product quality within organisations.

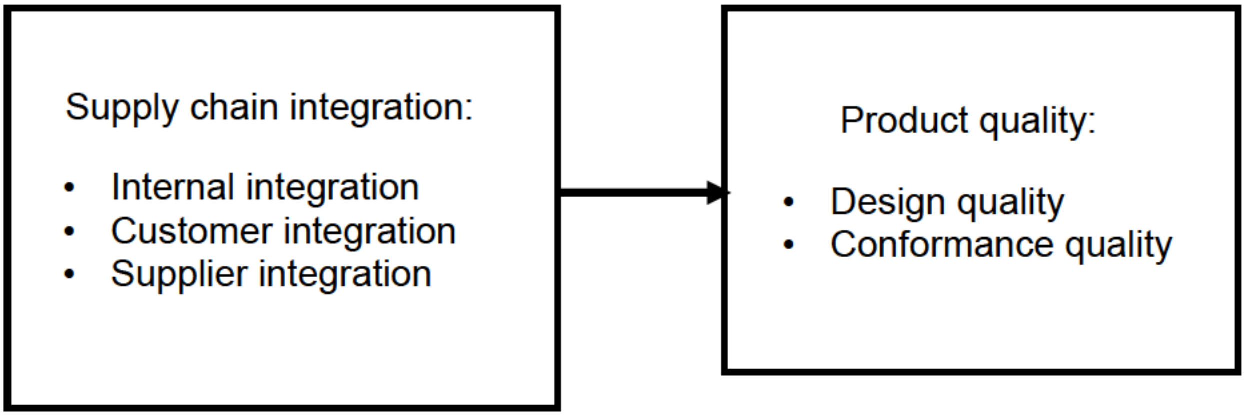


Figure 2.3: Supply chain integration and product quality framework (Lofti, Sanharan & Mukhtar, 2013).

Nguyen (2014), stated that most components used in the finished product are made from raw materials using various production techniques (cutting, grinding, forging, etc). The designed product bears the danger of falling short of customer expectations. As a result, the author put forth a technique enabling product quality management throughout its life cycle from the design stage. The method is explained in Figure 2.4 of the geometric variation model, showing how conceptual design (functional, behavioural and embodiment design) and conceptual process planning (manufacturing process, resource selection, time/cost estimation) are related. In general, the framework or model created by the author depicts that greater emphasis should be put on quality at the design and manufacturing process stages to produce good product quality. Before the design could be frozen, crucial issues, including comprehending the criteria or standards, the functionality of the part, and performance validation, were addressed in the conceptual design step. The discussion then turned to conceptual process planning in his framework, emphasising operations such as manufacturing, assembly, and inspection.

Figure 2. 4: The geometric variation model (Nguyen 2014).

Managing product quality throughout the entire life cycle is an essential task for businesses such that high-quality products will not only satisfy the requirements of both manufacturing companies and different users but will also improve user experience and provide better social and environmental benefits to our society, aiding businesses in remaining globally competitive amidst fierce market competition (Niu *et al*., 2018). The author continued by saying that product design is a crucial activity in contemporary life because it may originate and develop ideas through a process resulting in new goods to achieve the constantly shifting demands and expectations of users (Niu *et al*., 2018). Product design is the crucial factor determining product quality. The product lifecycle consists of four stages: design, manufacturing, maintenance, and recycling and the relationship among these terms is shown in Figure 2.5.

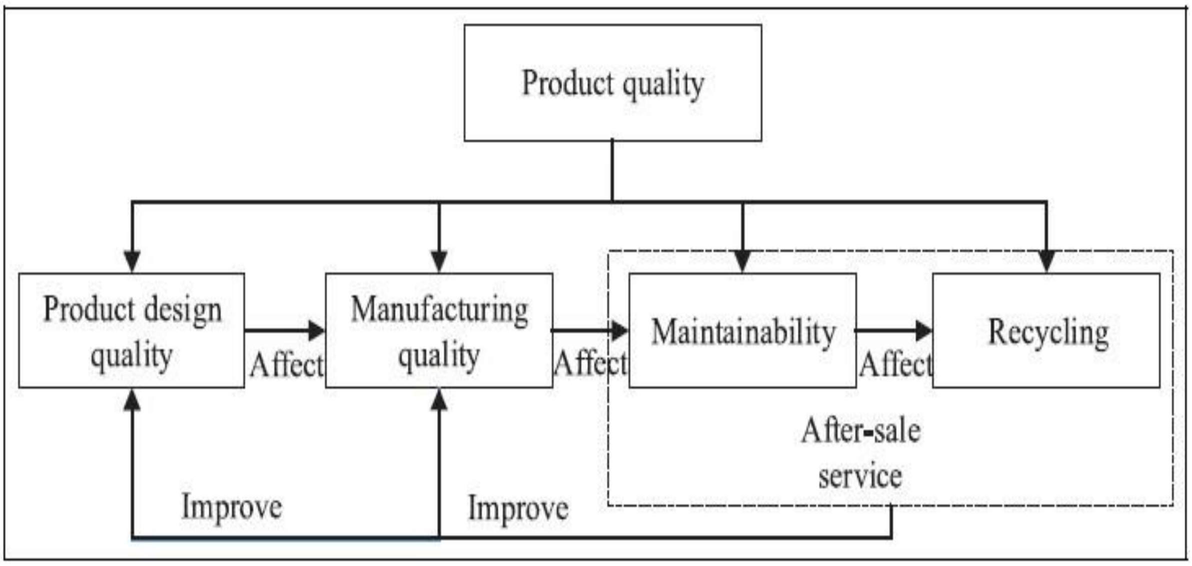


Figure 2.5: The relationship among quality-related terms throughout the product life cycle (Niu et al., 2018).

According to Duan and Yan (2020), one of the critical links of quality control is quality prediction. They also mentioned how quickly manufacturing process data has expanded, enabling predictions of product quality based on a real-time manufacturing process.

By mapping the manufacturing resources and the product quality characteristics, Duan and Yan (2020) introduced a real-time quality control system (RTQCS) that enables real-time prediction of the quality of the product production process. The authors say that every step of the production process impacts product quality. According to Duan and Yan (2020), by comparing the similarity of the product quality feature fluctuations in the manufacturing process, the essential quality characteristics of the product were found. These include man, machine, materials, method, measurement, and environment. In their analysis, as illustrated in Figure 2.6, the focus was mainly on manufacturing resources and their impact on product quality.

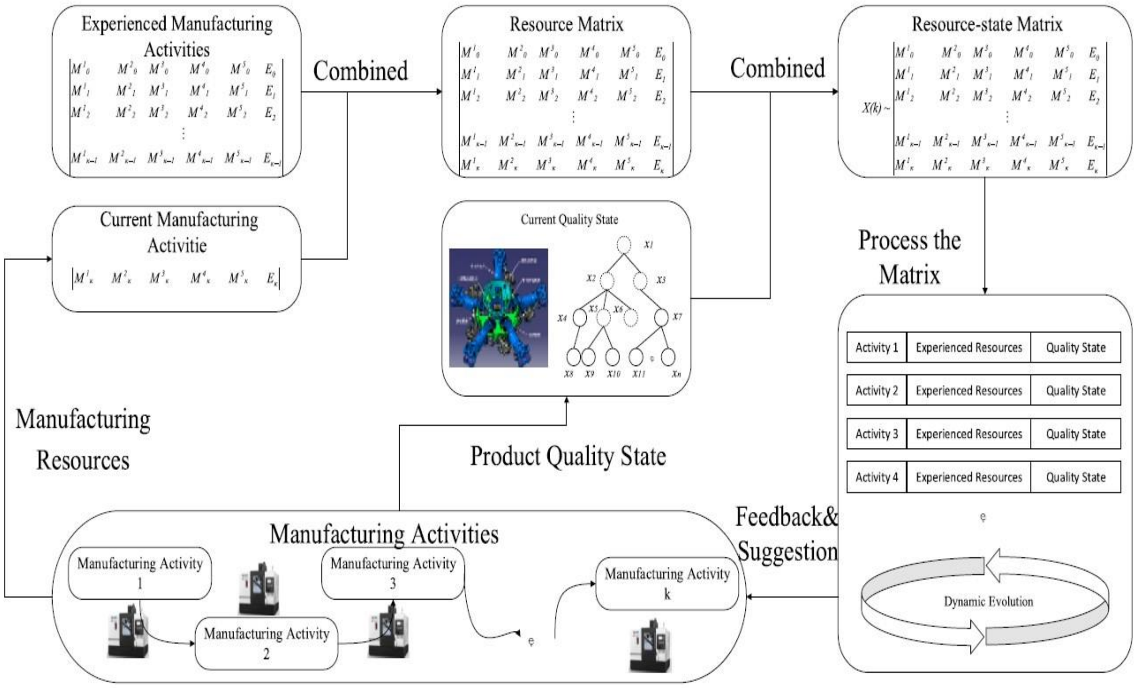


Figure 2.6: Framework of the RTQCS (Duan & Yan, 2020).

Although several authors built extensive research on factors affecting product quality over time, their findings were comparatively close. When examining the work of the first authors, Lotfi, Sahran and Mukhtar (2013), it is clear that their emphasis was on the integrative aspects of the supply chain (internal, supplier, and customer integration) to product quality (design and conformance quality). However, they did not provide a specific framework for what the user should consider enhancing in the design and manufacturing processes, highlighting a gap. Nguyen (2014), however, bridged the gap by introducing the geometric model that emphasises the significance of planning for the design and manufacturing processes. The geometric model highlights all elements to be performed during the product's design phase before the design can be frozen and during the manufacturing phase, giving specific process steps that must be validated. This concept can be used and would work in any state-of-the-art manufacturing plant. Niu *et al*. (2018) proposed a four-tiered product quality framework to improve the two components of product and manufacturing design quality resulting in a recyclable and maintainable product. On the other hand, Duan and Yan (2020) developed a real-time quality system model that helps the production system highlight essential factors that affect product quality in conjunction with the manufacturing process. Their study focused solely on manufacturing systems and did not provide comprehensive information about the product life cycle. The thorough geometric variation model of Nguyen (2014) was found to be pertinent in analysing the effects of product quality after extensive analysis by many authors.

2.2 Factors Affecting Visual Quality Control

In most studies, product quality is a critical parameter for the competitiveness of manufacturing organisations. Kujawińska and Vogt (2015) suggest that, at the beginning of the 20th century, human visual inspection was regarded as one of the most trustworthy alternative quality control techniques and the most reliable. However, the view was challenged between the 1950s and 1970s, when it was understood that man is the weakest link in the quality control process. Kujawińska and Vogt (2015) further explain factors affecting visual inspection efficiency (Table 2.2), mainly leading to the psychological behaviour of a human being. Neumann, Kolus and Wells (2016) argued that, although technology and automation have made a difference, there are still many quality issues caused by the shortcomings of human operators. As a result, human factors (HF) are crucial for lowering production-related errors and raising quality standards. These authors introduced a quality risk factor (QRF) framework that identifies stages in which HF problems emerge. These quality risk factors (QRF) are divided into three design stages: 1) product design, in which the assembly task characteristics are determined; 2) process design, which sets the stage for the performance of assembly defining flows, task division and materials supply strategies and 3) workstation.

All these aspects incorporate human intervention, and effects such as fatigue could cause quality losses in production. Figure 2.4 depicts a conceptual QRF framework. In addition, Gruszka and Gašpar (2018) suggest that HF is responsible and significantly impacts the quality of each manufacturing stage. Humans are the decision-makers and bear all the consequences of any actions taken because of human psychological factors. The authors recommended that companies invest financial resources in modern technologies that allow for streamlining processes, modernising production lines, and implementing innovative quality control methods that facilitate eliminating production errors.

It is clear from this comprehensive study on factors influencing visual control that the psychological component of the human element was the common denominator

throughout the writers' descriptions of the factors influencing visual quality control. Kujawińska’s analyses in 2015 were limited to HF and addressed other elements such as technical, psychological, organisational, workplace environment and social. He did not give further recommendations for solutions, limiting the study. However, Neumann's study in 2016 was far more comprehensive since he went beyond simply focusing on the human factor as the root of the problem. Instead, he went further to understand other factors or processes that impact the administration of visual control. He conducted a more thorough investigation of the three stages of product and process design and workstation distribution. In doing so, it is appropriate also to take other effects outside HF into account. The study also complied with Gruszka's advice that companies invest in cutting-edge technology systems and procedures. In conclusion, all these elements affecting effective visual inspection cannot be ignored. Therefore, it is essential to consider automated quality control methods that can close the gap.

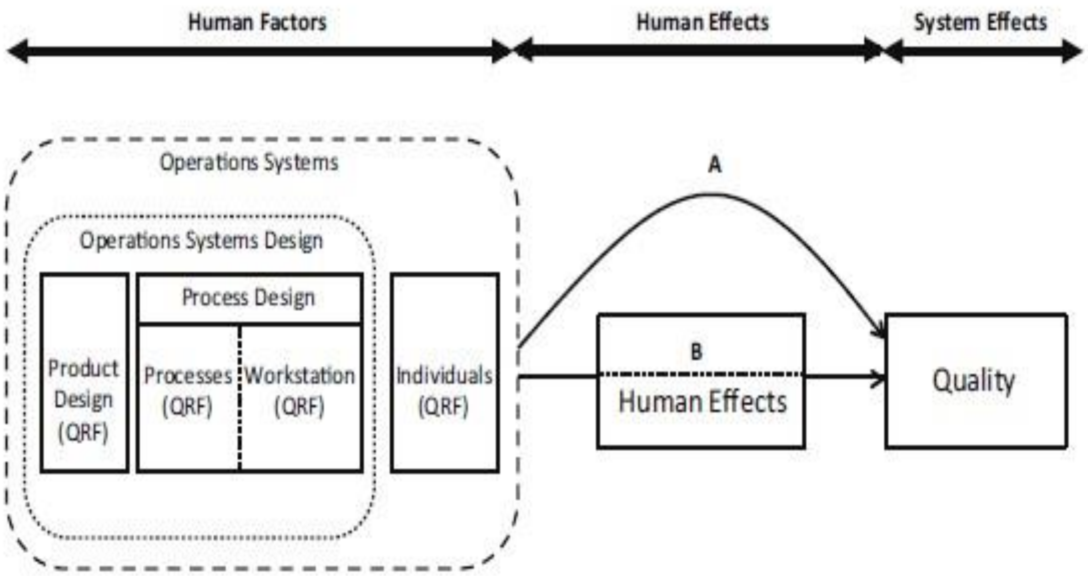


Figure 2.7: Conceptual model illustrating the main pathways identified in the literature of how HF quality risk factors affect production quality (Neumann, Kolus & Wells, 2016).

Table 2.2: Factors affecting visual inspection efficiency (Kujawińska & Vogt, 2015).

Factors	Examples
Technical	Type of defects, defect visibility, quality level, skills, other.
Psychophysical	Age, sex, observation skills, experience, temperament, creativity.
Organisational	Training, decision-making, feedback, precise instructions, other.
Workplace environment	Light, noise, temperature, work time, workstation organisation, other.
Social	Team communication, pressure, isolation, other.

2.4 Artificial Intelligence (AI) Quality Control

AI-based systems (also called AI-enabled systems) refer to software-based systems containing AI components besides traditional software components. However, there are different definitions of what AI means, varying in scope and level of detail.

AI is human intelligence demonstrated by machines, which denotes the automation of tasks that typically require human intelligence (Felderer & Ramler, 2021). The authors added that it is meaningful to account for various parameters, such as the artefact type, process and quality characteristics, to characterise AI-based systems for quality assurance, as shown in Figure 2.7.

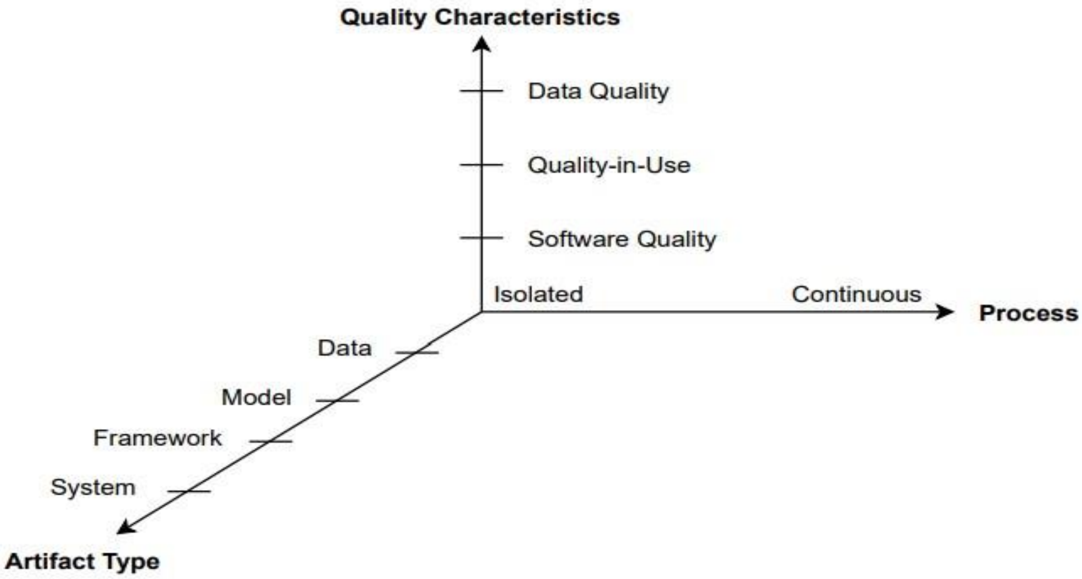


Figure 2.8: Dimensions of AI-based systems and quality assurance (Felder & Ramler, 2021).

Kersting (2018) describes AI as specifically intelligent computer programmes defined as “the science and engineering of producing intelligent machines.” Although it is connected to the same aim of using computers to comprehend human intellect, AI should not be limited to techniques that can be observed biologically. Schmitt *et al.* (2020) explain how excessive inspection volume causes manufacturing bottlenecks. Using machine-learning techniques and edge cloud computing technologies, they investigated a new integrated solution for predictive model-based quality inspection in industrial manufacturing. They added that predictive models are implemented on local edge devices after being trained in the cloud using historical data sets. Parameters are recorded during manufacturing and transferred to the edge device, where data processing and model application are handled in almost real-time. The prediction findings are assessed and compiled to a manageable level, and the outcomes demonstrate that the proposed strategy can dramatically reduce inspection volumes, leading to economic gains (Schmitt *et al*., 2020). Hamada *et al.* (2020) noted that AI systems, a kind of industrial innovation, are driven mainly by machine learning (ML). Because their components (models) are built by inductive data training, ML-based AI systems continuously exhibit distinctive qualities in engineering. However, they tend to be inaccurate since they are trained systems, particularly in deep learning. They are black-box systems since the taught behaviour is difficult to comprehend or explain rationally. Testing is the most significant aspect of the guidelines and the most significant activity in practice. The guidelines provide insights from quality assurance and test engineers.

Qazi *et al*. (2022) consider software quality assurance (SQA) techniques by applying AI-based tools and methods to overcome debugging issues and other software industry challenges. The authors designed survey questions to determine the software industry's awareness of AI efficiency in SQA-based evaluations. They found that most software houses have not implemented AI-based tools for SQA. They concluded that the software business might benefit from introducing AI-based tools by producing higher-quality software (Qazi *et al*., 2022). The study will aid in advancing context identification, human-caused error classification, behavioural detection and analysis, recognition and profiling, behavioural detection and analysis, and behavioural detection and classification in software development. Additionally, this will support the development of interpreting and anticipatory skills, decision-making and systems integration, suggestion and data gathering, and intelligent direction and behaviour. Almost all aspects were considered in the study as per each author. Felderer and Ramler (2021), modelled a framework consisting of three aspects of AI systems in quality control. These dimensions are vital parameters to consider. Schmitt *et al.* (2020), proposed a newly integrated predictive model-based quality inspection focused mainly on reducing volumes by making inspection processes more economical. However, other parameters, such as quality output in the model, were not discussed. Every process requires a guideline; therefore, Hamada *et al. (2020),* proposed a guideline for training and testing data on AI systems to help engineers or technicians. These guidelines are essential as clarity of AI technologies and skills is important. The guidelines alone cannot be of benefit if the software is not efficient in working hand-in-hand with the AI systems, as there cannot be one without the other, Qazi *et al*. (2022) considered software quality assurance system that will boost AI performance while overcoming debugging problems and other software challenges. These will allow quality control to transition easily from data training to faster systemwide decision-making.

Zhang *et al*. (2020), go beyond Table 2.3 to address all parameters that need to be considered for an AI-based quality control system to be as effective as possible. The factors considered include correctness, model relevance, robustness, security, data privacy, efficiency, fairness, and interpretability. Therefore, it is reasonable to say that the author has considered nearly all significant factors. Combining this with the recommendations made by Hamada *et al*. (2020), will benefit the entire AI system regarding quality control and the software quality assurance aspect informed by Qazi *et al.* (2022).

Table 2.3: Addresses the additional quality elements that an AI component or AI-based system must consider (Zhang et al., 2020).

Correctness	**The probability that an AI component gets things right.**
Model relevance	Measures how well the AI component fits the data.
Robustness	The flexibility of AI components to perturbations.
Security	Measures the resilience against potential harm, danger or loss by manipulating or illegally accessing AI components.
Data privacy	The ability of an AI component to preserve private data information.
Efficiency	Measures the prediction speed of an AI component.
Fairness	Ensures that decisions made by AI components are for the right way and right reason to avoid problems in human rights, discrimination, law, and other ethical issues.
Interpretability	

Artificial intelligence (AI) is an area of computer science that focuses on creating computer systems that simulate problem-solving processes and copy human brain functions. According to Avvari (2021), because human quality inspection is a constant, demanding, and repetitive procedure, research reveals that it is prone to errors caused by fatigue. Human inspection efficiency is approximately 80%, a persistent challenge in safety-critical and high-value production situations (DevTeam.Space, 2022). It would, therefore, be beneficial to use AI systems in quality control in manufacturing, as what was identified from other frameworks is that the process depends mainly on human beings.

Table 2.4: The benefits of AI for defect detection (Avvari, 2021).

Fast identification of material at risk	Due to the efficiency of AI technologies, a risky quality batch can be identified before parts are integrated into production compared to human quality control.
Product optimisation	Key variables that cause defects can be automatically analysed by patterns in the AI quality control, thus minimising defects and product waste.
Precise defect root cause analysis	AI tracks the sequence and reveals what parts of the value chain need changes, allowing engineers to improve yield and reduce manufacturing defects.

2.5 Machine Learning (ML) with Quality Control

Machine learning (ML) and artificial intelligence (AI) are becoming dominant problem-solving techniques in many areas of research and industry, not least because of the recent successes of deep learning (DL). Data is becoming more meaningful and contextually relevant, breaking new ground for ML, DL and AI, moving them out of research labs into production (Kersting, 2018).

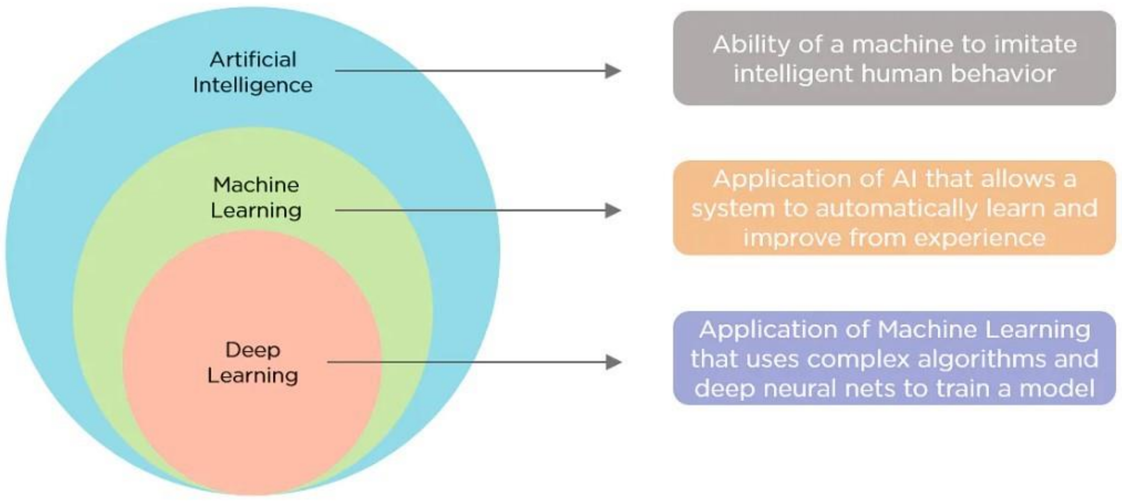


Figure 2.9: AI vs ML diagram (simplilearn.com).

2.5.1 Classification in ML

Several machine learning classifiers were trained and assessed on different metrics to forecast dimensional problems in an actual multistage assembly process. According to Peres *et al*. (2019), the line consists of two automated inspection stages, two human-operated assembly stages, and many human-operated pre-alignment stages.

The findings demonstrate that non-linear models, such as XGBoost and Random Forests, can simulate the complexity of such a setting, achieving a high true positive rate and showing promise for the advancement of current quality control techniques, allowing for the earlier identification of flaws and deviations and thereby assisting in lowering scrap and repair costs. Tan (2021), compared five traditional machine learning classifiers - GMM, Random Forest, SVM, XGBoost, and Naive Baye according to their accuracy, recall and F-score. In this study, the different classifiers performed similarly when applied to the various datasets or specific classification tasks. However, the SVM-based classifier had the lowest accuracy when processing text data to perform the text classification task. This outcome demonstrates that the accuracy would not be high if the classification task were challenging. According to Sankhye and Hu (2020), ML is used to aid in completing specific activities rather than extracting knowledge from data. Classification is an example of machine learning since its methods create classification models for predicting discrete response variables. ML is the software research area that enables algorithms to improve by self-learning from data without human intervention (Escobar & Morales-Menendez, 2018). According to Postindu (2022), the global market for AI-based services will reach $130 billion by 2025, and machine learning (ML) will be the dominant methodology. He added that adopting AI-powered technologies is a necessity for Industry 4.0. Already 64% of manufacturers rely on AI in their day-to-day operations, and quality control is where AI is employed most. Morán-Fernández, Bólon-Canedo, and Alonso-Betanzos (2022) advised that, if a good feature selection method is used before classification, the choice of a classifier is less critical. Additionally, feature selection not only eases the choice but also increases predictive accuracy and decreases the complexity of machine learning models, especially on high-dimensional datasets. The authors added that feature selection techniques could be roughly divided into three category filters. These are independent of the induction algorithm and determine the significance of the features using metrics such as mutual information or statistics like Chi2, wrappers, which rely on the induction algorithm's accuracy to assess the significance of subsets of features, and embedded methods, which carry out feature selection during the induction algorithm's training process. Filter methods assess the goodness of data subsets by observing intrinsic data features and comparing a single feature or data subset to the class label.

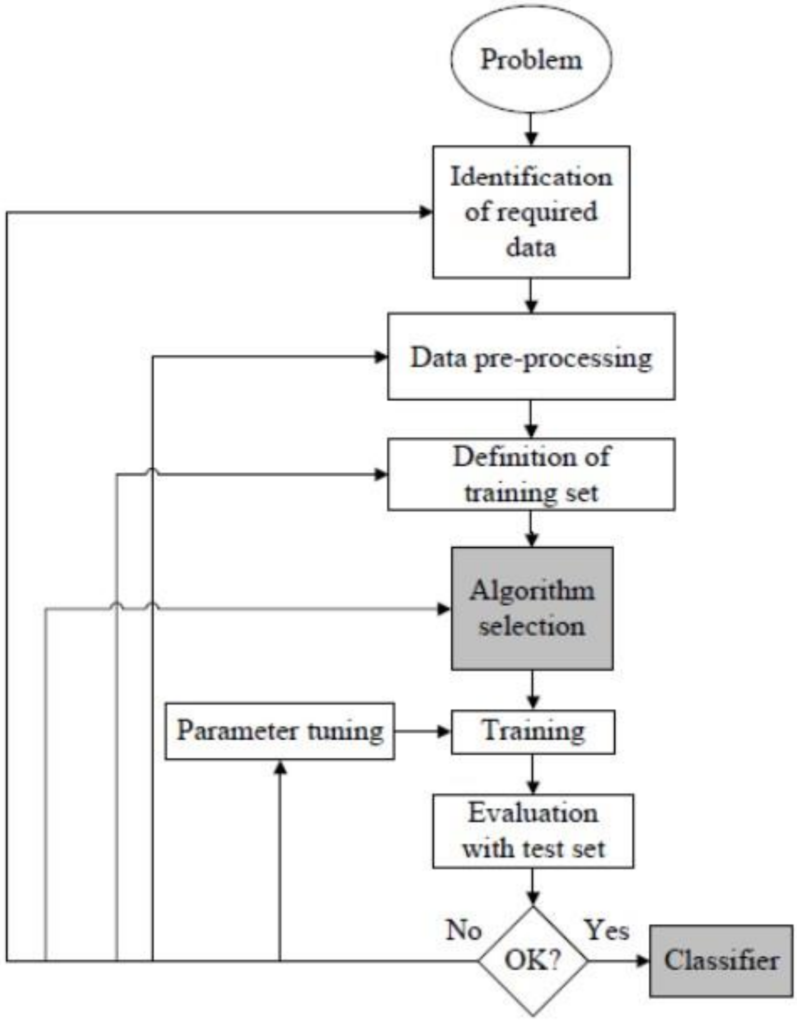


Figure 2.10: Flow chart of classification (Granstedt, 2017).

Tan and Peres' studies on classification found that some of the classifiers tested for accuracy performed quite similarly, with both identifying the XGboost algorithm and Random Forest as having high performance in accuracy and F-score. However, MoránFernández advised that a good feature selection process should be followed before classification to increase predictive accuracy and reduce ML model complexity.

The industrial revolution brought many changes to how various manufacturing processes operate. The techniques and means of working have expanded dramatically with the deployment of advanced technology such as computers.

2.6 Quality Control Tools

2.6.1 Statistical process control

Neyestani (2017) discussed seven fundamental quality tools to help companies solve issues and enhance processes. Dr Kaoru Ishikawa published a book named "Gemba no QC Shuho" in 1968 for Japanese businesses that dealt with controlling quality through methodologies and procedures. His research revealed the seven quality control tools that might cooperate in tracking, gathering, and analysing data for identifying and resolving issues with production processes, making it easier for enterprises to attain performance excellence. According to Memon *et al*. (2019), SPC, also known as statistical process control, is a crucial tool for reducing variances in any production and service environment. The SPC problem-solving instruments are referred to as traditional management techniques and include the 'management seven': checklists, histograms, Pareto charts, cause-and-effect diagrams, control charts, scatter diagrams, and diagrams. This equipment is very popular and often referred to as the Seven QC Tools. Their application for enhancing quality can be found in nearly all organisations that provide goods and services. Many scientists successfully incorporated these technologies into their work. Statistical process control (SPC) is a powerful quality control method for realising process stability and reducing variability in manufacturing. Control charts are the most significant tools in SPC for monitoring process performance (Date & Tanaka, 2021).

Understanding and identifying key product attributes relevant to customers or major process variations is crucial for SPC applications (Figure 2.8).

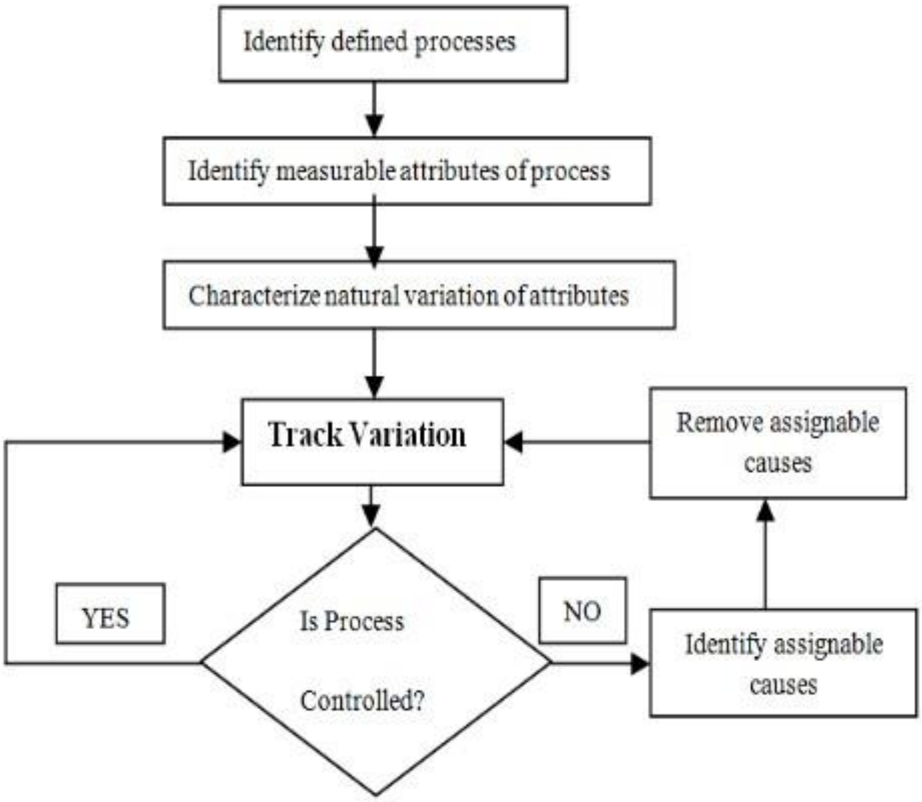


Figure 2.11: SPC application step (Madanhire & Mbohwa, 2016).

These quality control tools must be integrated to comprehend the various causes of defects, the ease with which processes can be managed given past and present conditions, and the best way to identify likely root causes before tackling each with the right quality control tool. Businesses that employ high-quality equipment and systematically resolve issues will undoubtedly see continuous quality improvement. The application phases of SPC in the process depicted in Figure 2.8 were made easy to define by Madanhire and Mbohwa (2016). If successfully applied, using quality control instruments will be much more advantageous and result-driven for the entire business.

2.6.2 Control Chart

Riaz and Muhammed (2012) define a control chart as a quality tool that shows the value of the quality characteristic of interest as a function of time or sample number. Generally, a control chart is made of a centreline which represents the mean value for the in-control process, and two horizontal lines, the upper control limit (UCL) and the lower control limit (LCL), detecting out-of-control signals in the statistical quality control (SQC). Aunali and Venkatesan (2019) added that quality is constantly checked using control charts. The two primary forms of control charts depend on the process characteristics that need to be tracked. The first is a chart of a single quality attribute known as a univariate control chart. The second is a multivariate control chart, a graphic that encapsulates or symbolises multiple quality traits. The control chart displays the value of the quality characteristic as a function of the sample size or time when just one quality characteristic has been evaluated from a sample. The chart's central line, which indicates the mean value for the in-control process, can be seen overall. The other two are the lower control limit (LCL) and upper control limit (UCL). A survey was done to investigate the most recent advances in control charts from the univariate, multivariate, and Bayesian approaches. Their versatility, ease of use, and complexity were found, along with the optimal times to use them. The author addressed the need for further research.

Quality control charts are simple for practitioners to use and interpret despite being sequential graphs of process data. These charts enhance conventional approaches by offering additional longitudinal data that could otherwise go undetected, aiding users in understanding the performance of a process and evaluating any advantages or drawbacks of process modifications.

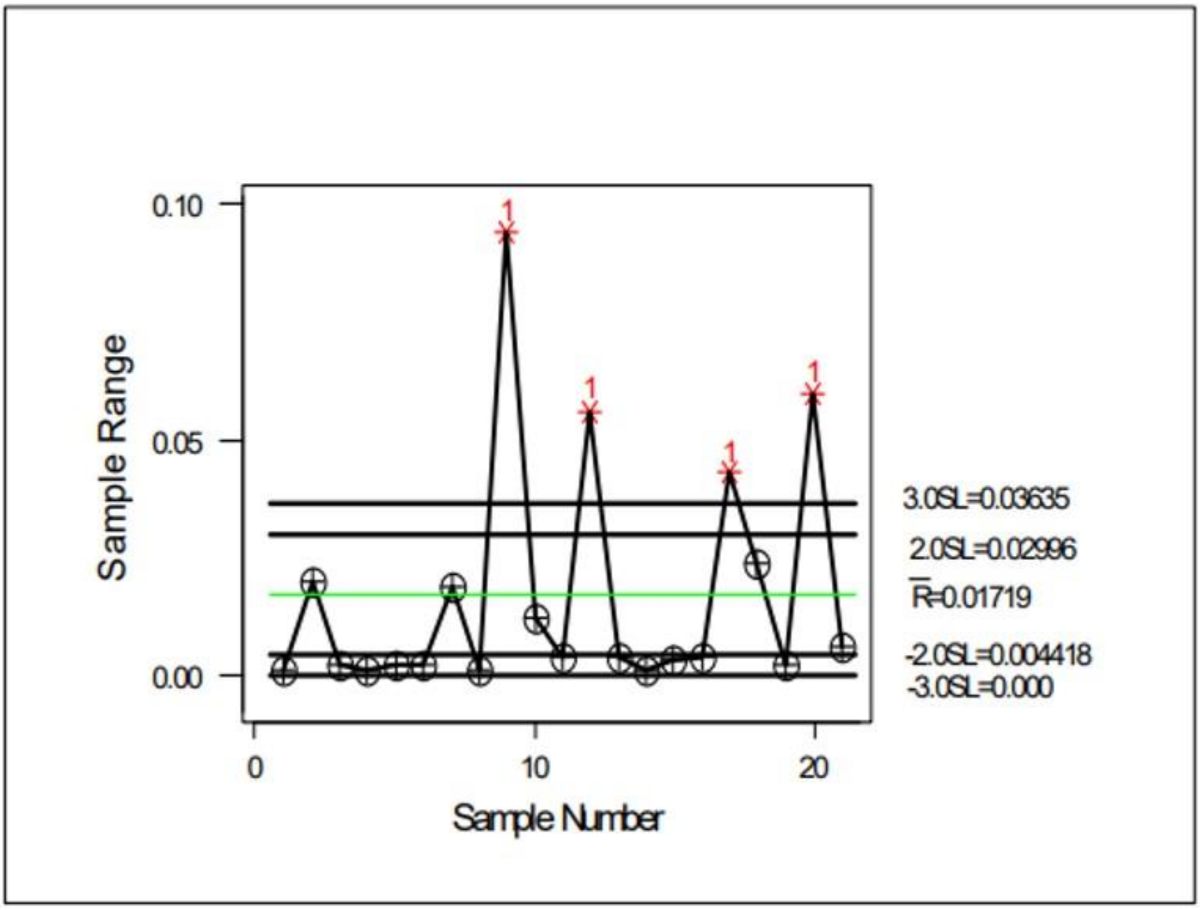


Figure 2.12: Quality control chart (Riaz & Muhammed, 2012).

2.6.3 Pareto chart

Joshi and Jugulkar (2014) addressed analysis from Pareto charts used to pinpoint the primary flaws responsible for most rejections. Pareto provides accurate identification. Joshi and Jugulkar (2014) integrated the Pareto principle and the cause-effect diagram to identify and evaluate different defects and causes for these defects responsible for the rejection of components at different stages. Using these statistical tools to analyse the defects and root causes, the authors concluded that methodical investigation demonstrates it is possible to control the defects by effective tool and process analysis. Nicolae, Nedelcu and Dumitrascu (2015) advised that a Pareto chart allows the examination of defects within the manufacturing process. The authors collected two months of data to investigate the point of focus in the faults detected in the manufacturing process. The study of evaluated problems and the use of corrective and preventive measures constitute prioritising, which implies Pareto analysis can be used to raise the standard of industrial goods. This helps to reduce flaws and enhance production methods and has the following advantages:

• Effectively resolving issues by identifying and ranking root causes according to significance;

• Establishing priorities for several practical applications, such as process improvement efforts, customer needs, supplier opportunities, and investment opportunities;

• Illustrating the direction in which process/product improvement efforts should be focused;

• Resolving issues efficiently by determining and prioritising the leading causes according to their significance.

Raman and Basavaraj (2019) suggested the simultaneous use of a Pareto chart and a fishbone diagram for major defects that occur frequently. They suggested that a cause-and-effect diagram be used to find the core reason and then a Pareto chart to investigate that cause further. After using a fishbone and a Pareto diagram, the outcomes are listed below:

1. Problems are identified, and the major cause is effectively prioritised.

2. Establishing the needs of various practical applications such as improving the process level, customer needs and satisfaction, suppliers' needs, investment opportunities, etc.

3. Improving the process/product by applying effort in the right direction. The Pareto approach can be used in production to evaluate the effectiveness of a product or a process. This study can be strengthened with the aid of fishbone analysis.

Figure 2.13: Pareto chart (support.microsoft.com, 2022).

Pareto analysis charts are often interpreted following Joshi and Jugulkar (2014) and Nicolae, Nedelcu and Dumitrascu (2015). However, their true intent is to help the manufacturing industries understand the defect or point of focus rather than the root cause, as Raman and Basavaraj (2019) suggested. However, it is crucial to begin by performing a Pareto analysis on the point of emphasis before using a fishbone diagram to identify any potential underlying causes of the issue. This is contrary to Raman and Basavaraj's (2019) suggestion.

2.6.4 Cause and effect diagram

Ilie and Ciocoiu (2010), identified a cause-and-effect diagram as a simple way of calculating the overall risk of an event with numerous significant causes. In addition to constructing treatment measures on vulnerability areas, mainly directed to the causes that establish high-risk values, the application allows for determining the risk of secondary and primary causes, cause categories, and global risk. The treatment of risks can be completed with further representation and hierarchy elements in addition to the analysis of the causes sequence, which can be as simple as referring to the many causes and their sequence. The technique is also used to model the dynamics of the process under study. Liliana (2016), realised the advantages of a cause-and-effect diagram, such as indicating potential reasons for variance, using an organised, understandable structure, encouraging group participation, increasing process understanding, and identifying places for data collection. Liliana (2016), proposed a new formula for the Ishikawa diagram (5MA + 5MB + 5 MC), which thoroughly represented all likely reasons for the failures. He concludes that using control and quality assessment procedures demonstrates the significance of the customer's needs. In many businesses where enhancing quality is required, the classic quality management instruments constitute the foundation and must be understood and used. Coccia (2018), suggests that using a fishbone, also known as an Ishikawa diagram or a cause-and-effect diagram, you can visually display the various factors contributing to a specific occurrence or phenomenon. A prominent tool for cause-and-effect analysis is the fishbone diagram, which has a structure resembling a fish skeleton and is used to show the intricate interactions of causes for a particular issue or event. A comprehensive theoretical framework to describe and examine the sources of innovation may be found in the fishbone diagram. A fishbone diagram is used to locate, investigate, and analyse any potential fundamental causes of the origin and development of general-purpose technologies (GPTs). Overall, fishbone diagrams appear to be a suitable and widely used method of graphical representation.

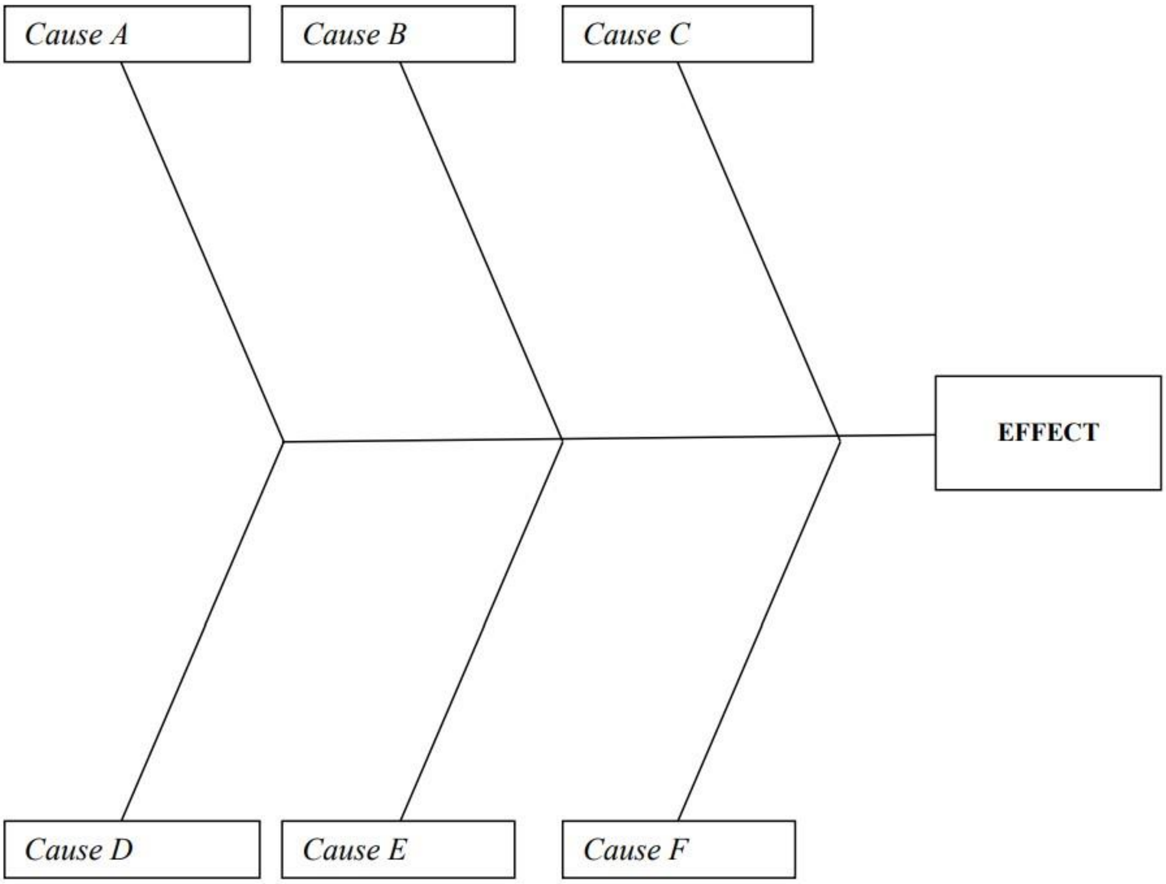
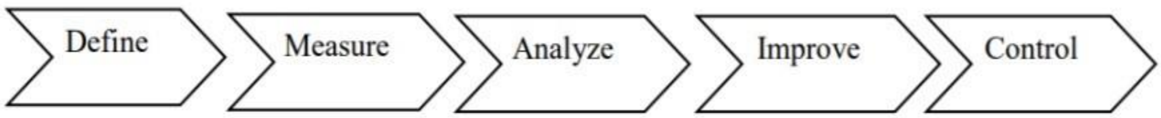


Figure 2.14: Cause and effect diagram (Coccia, 2018).

A cause-and-effect diagram is another crucial component of quality control tools. It enables businesses to concentrate on all facets of their operations, including people, machines, methods, materials, and the environment. This satisfies the need for the team to strategise and comprehend the gaps or potential fundamental causes of the issue that the Pareto chart had identified, allowing for the successful installation of controls and quality management.

2.7 Continuous Improvement

Motivation for continuous improvement is built on commonly understood goals and engaged leadership. It is necessary to have a long-time perspective with an underlying understanding of people's natural need to achieve goals or goal orientation (Holtskog, 2013). Gejdoš (2015), confirmed that capability indexes and histograms could achieve variation control in the procedure to fill the customer's requirements. Tools such as the capability index, histogram, model DMAIC, control chart, and others can reliably determine the anomalous variability in the process and contribute to quality improvement. Furthermore, he declares that one highly powerful instrument for assuring process stability is statistical process control (SPC). Using SPC with the DMAIC improvement methodology is ideal for accomplishing the intended quality improvement goals, and using it effectively can help with all the duties and issues that arise during the process. Smętkowska and Mrugalska (2018) explain that the two critical tools used in the Six Sigma concept are DMAIC and DMADV, among the many quality management techniques that can be thought of as quality improvement methods. The letters DMAIC stand for Define-Measure-Analyse-Improve-Control. This approach is based on the Deming cycle for process improvement and can increase effectiveness while adequately reacting to the appearing problem.



What is the problem?	What data is available?	What are the root causes of the problem?	Do we have the right solutions?	What do we recommend?
What is the scope?	Is the data accurate?	Have the root causes been verified?	How will we verify the solutions work?	Is there support for our suggestion?
What key metric is important?	How should we stratify the data?	Where should we focus our efforts?	Have the solutions been piloted?	What is our plan to implement?
Who are the stakeholders?	What graphs should we make?	What clues have we uncovered?	Have we reduced variation?	Are result sustainable?

Figure 2.15: Essential steps to consider in DMAIC (Nowotarski, Szymanski & Rzepecka, 2019).

DMAIC can be interfaced with supply chain processes. Mishra and Sharma (2014) introduced an intelligent framework for supply chain management (suppliers, inputs, process, output, and customers, SIPOC, and define, measure, analyse, improve and control, DMAIC) aimed at improving supply chain management (SCM) in a supply chain (SC) network. The proposed framework comprises three phases: design, implementation, and results. A brief introduction to the phases is presented below:

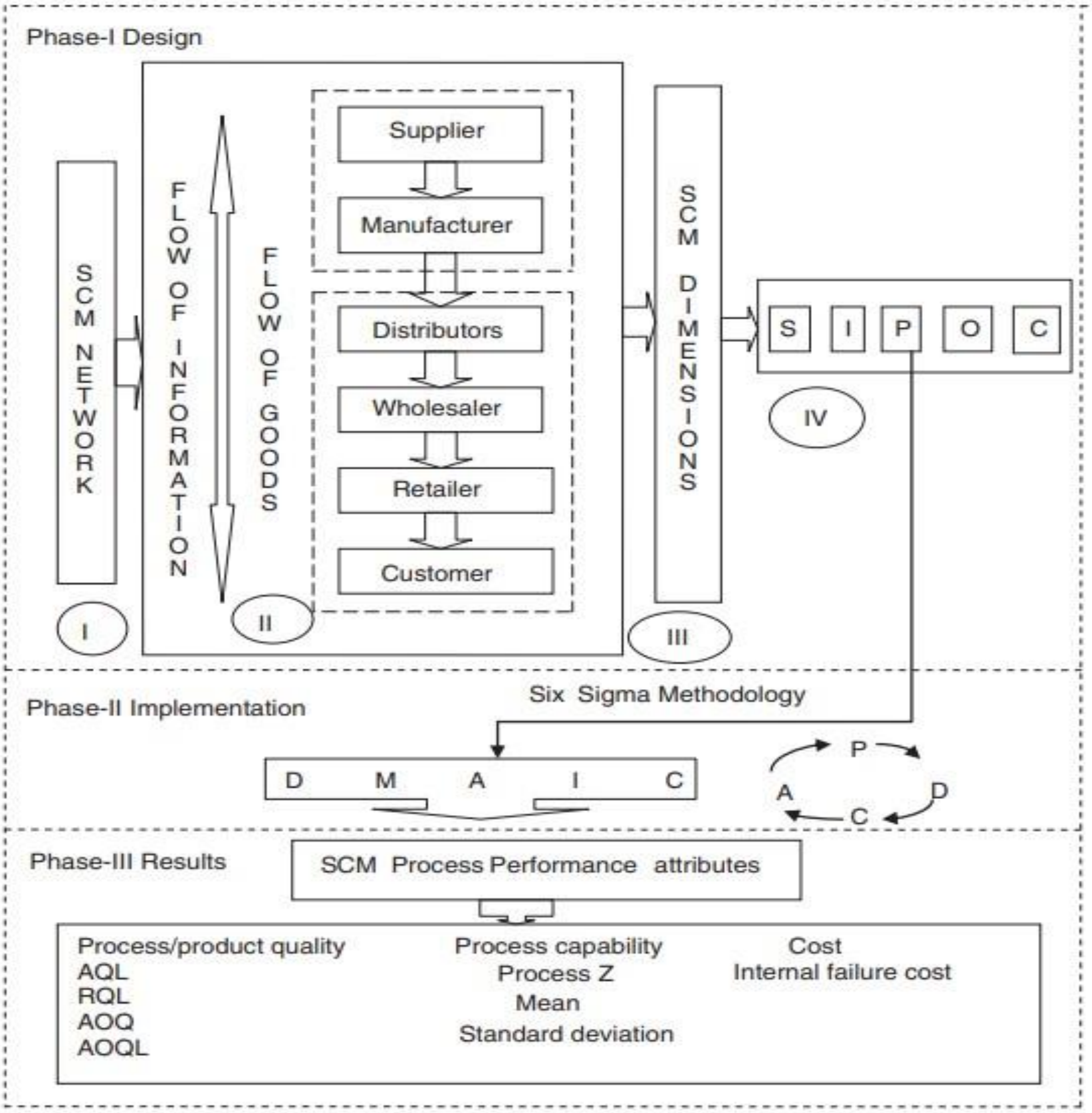


Figure 2.16: Hybrid SIPOC + DMAIC framework by (Mishra &Sharma, 2014).

2.7.1 Continuous improvement with ML

According to Poth, Beck and Riel (2019), lean methods emphasise effectively completing only necessary tasks. ML and AI present fresh possibilities for process optimisation. The method described here shows an improvement in employing machine learning as a support tool for test management to streamline the testing procedure. The selection of regression tests is under the purview of semi-automation. The suggested lean testing approach keeps the human test manager in control of selecting the appropriate test cases while using ML as support.

Figure 2.17: Lean workflow flow of regression test selection (Poth, Beck & Riel, 2019).

2.8 Conclusion

The conclusions closely matched the issue, addressing a potential solution that adds value. Among the objectives accomplished in the study, sources of information were reading journals. The journal study evaluated existing quality control frameworks and identified the relevance of AI in quality control. A better understanding of the study and its application was gained.

CHAPTER THREE - METHODOLOGY

3.0 Introduction

This chapter describes the methodological approaches, data collection, data analysis and experiments with machine learning algorithms. Furthermore, it explores the system used to address the core of the study and outlines the in-depth methodological approach. The outcome is to test the dataset with the nine ML algorithms and achieve the closest accurate algorithm possible. In conclusion, a simulation of the nine algorithms was evaluated and selected. The best algorithms were the Adaboost, Neural Network, CN2 inducer and Random forest.

3.1 Data Collection Methods

The research methodology used was quantitative. The quantitative research approach emphasises numbers and figures in the collection and analysis of data (Eyisi, 2016). The framework is implemented after analysing the defects per commodity from Company X's products and studying several models that define product quality and life cycle. Apuke (2017) explains that quantitative research deals with quantifying and analysing variables to get results. It involves using and analysing numerical data using specific statistical techniques to answer questions such as who, how much, what, where, when, how many, and how?

According to Ajayi (2017), data collection is crucial in statistical analysis. Different methods are used to gather information, which falls into two categories, primary and secondary data. This study used secondary data, as it was historical/already produced.

3.2 Data Sources

Secondary data was used in this study. According to Ajayi (2017), secondary data is easily accessible but is not pure, as it has undergone many statistical treatments. Secondary data sources are government publications, websites, books, journal articles and internal records.

3.2.1 Data Analysis

Secondary data analysis extracted from the existing database of Company X reported the frequency of defects per each commodity. The frequency of defects was presented graphically.

3.2.2 Document Analysis

Document analysis is a systematic procedure for reviewing or evaluating documents, which can provide context, generate questions, supplement other types of research data, track change over time and corroborate other sources (Bowen, 2009). Two major types of documents were reviewed: quality control frameworks and AI in quality control. Document analysis was used as a systematic procedure for collecting records and gaining information in the context of quality control studies at any level. The steps consisted of (1) reading materials, (2) data or keyword extraction, and (3) analysing data. Corpus analysis was done on the final selected documents using the keyword approach to compare the major aspects of existing quality control frameworks. The keyword counts were presented graphically, indicating critical aspects from both existing frameworks and suggested AI models which can be incorporated into an intelligent quality control framework.

3.3 Experiment with Machine Learning Algorithms

3.3.1 Supervised machine learning

In supervised algorithms, the classes are predefined by humans and created in a finite set, which in practice means that a particular segment of data will be labelled with these classifications (Nasteski, 2017:2). The purpose of the machine learning algorithm is to find patterns and construct mathematical models, whereby the models are evaluated based on the predictive capacity concerning measures of variance in the data itself (Nasteski, 2017). Granstedt (2017) states that supervised machine learning solves the type of problems where there is historical input data and corresponding solutions, which are mainly two types: classification and regression problems.

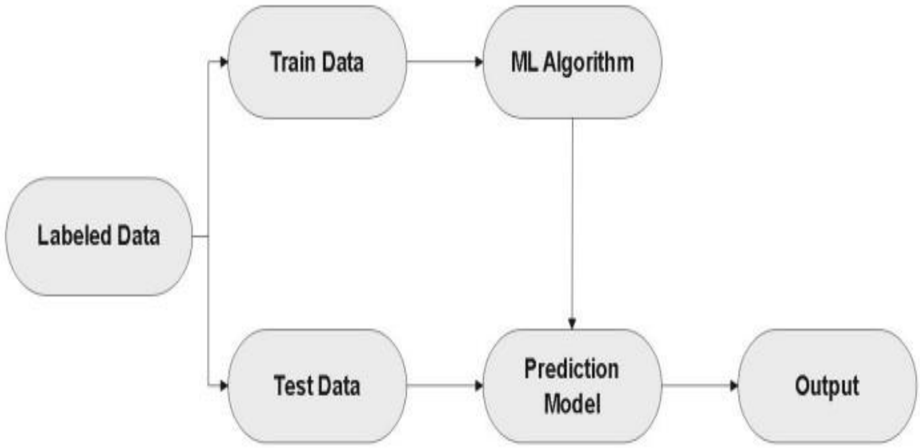


Figure 3.1**:** Basic architecture of supervised learning (Dridi, 2021).

The study followed supervised machine learning as the data set was used to pre-train the model on a labelled dataset, entailing classification and regression. According to Dridi (2021), regression is used when the output is continuous, and classification is used when the output is variable or categorical.

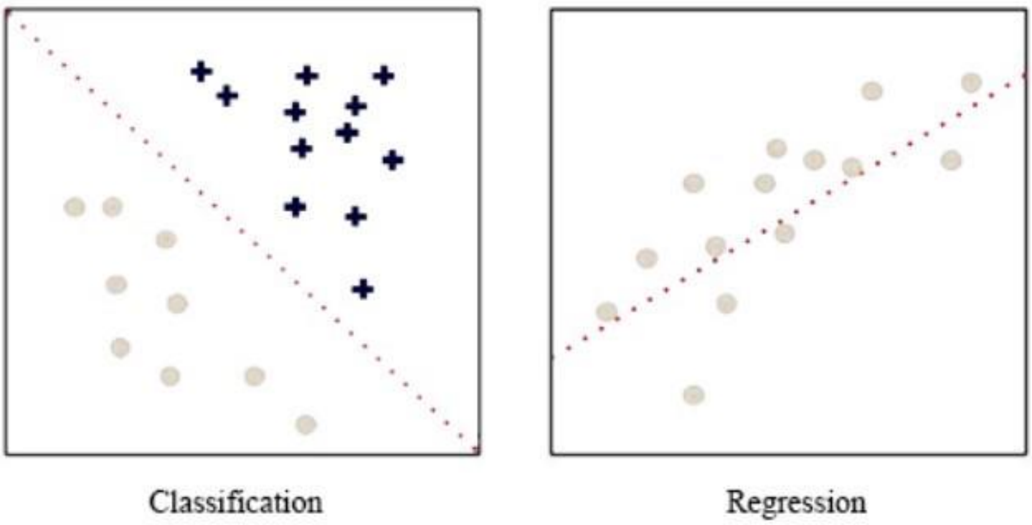


Figure 3. 2**:** Difference between classification and regression in visual form **(**Granstedt, 2017).

3.3.2 Data collection

Data was collected from Company X's quality portal (Figure 3.3). The collected set of data was for four years. The dataset contained different parts and commodity types, such as metallics and interiors, and the number of defects per part and supplier.

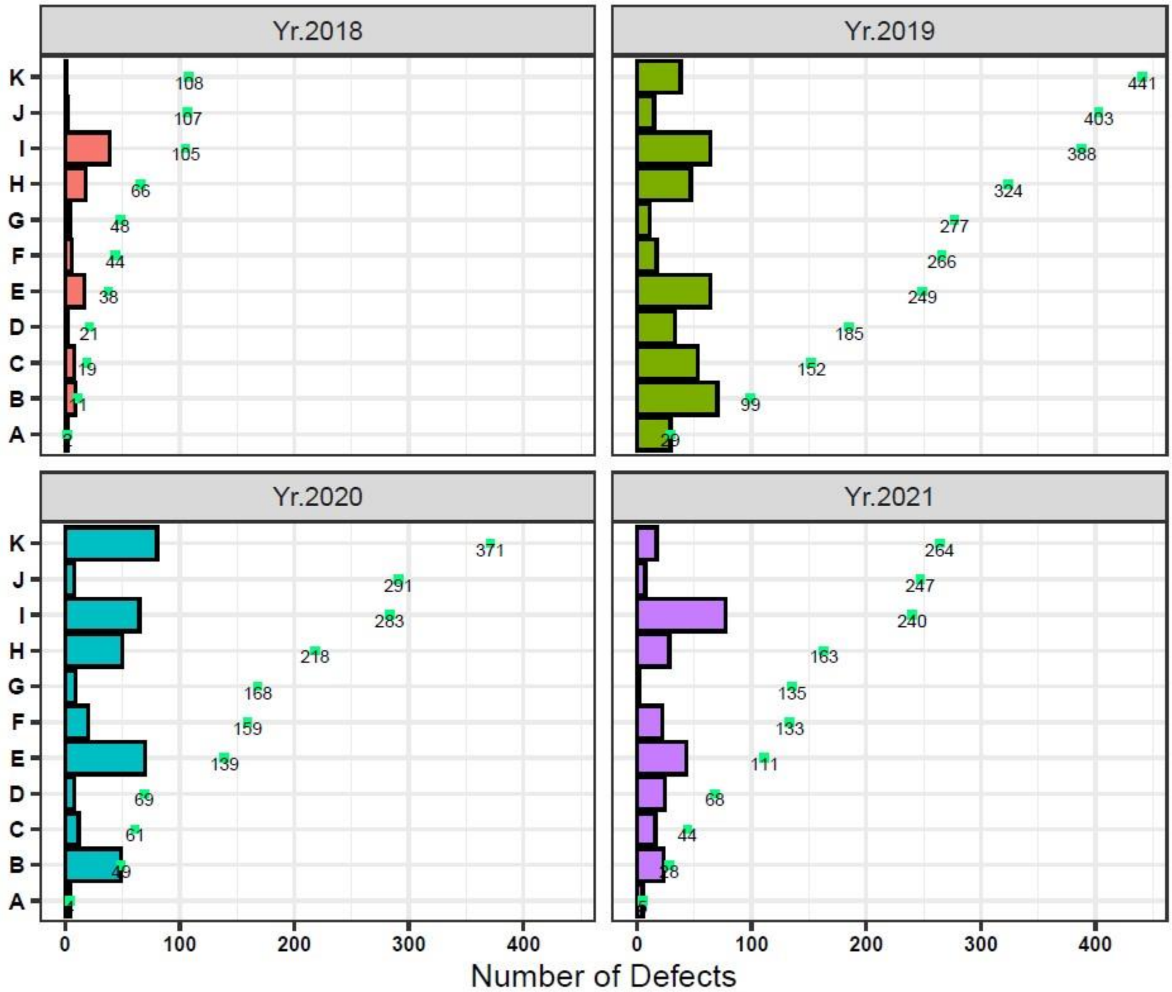


Figure 3.3**:** Dataset from Company X database (Portal, 2021).

3.3.3 Data preparation

Data preparation is a crucial step that assists in ensuring the accuracy, relevance, and security of the data (Ghareeb *et al.*, 2022). Data was prepared by combining the outputs, removing irrelevant features, and locating critical and minor defects. Excel filtering was used to clean the data, equating the instances to their categories. Data were categorised into the following subgroups:

- Commodities,
- Specifications,
- Number of supplied commodities,
- Supplier,
- Type of defects,
- Number of defects.

3.3.4 Training data set

During this phase, the algorithm was fed with historical data; 1925 hold-out datasets were used and returned the function which maps input to output data. During the second phase, data input was fed to the algorithm, and it returned categories for classifiers and numerical values for regression. Accuracy is commonly used to evaluate how well a classification algorithm performs. It is a measure of the proportion of correctly classified entries (Granstedt, 2017). This is achieved using input data with known output data on which the algorithm has not been trained. According to Escobar and Morales-Menendez (2018:3), a classifier is a supervised learning algorithm that analyses the training data (for example, data with classification class) and fits a model. The training dataset trains a set of candidate models using different tuning parameters.

3.3.5 Algorithm selection

Nine supervised machine learning algorithms were experimented with to detect and classify the commodity defects status of company X. ML algorithms include:

- Logistic regression (LR),
- Neural network (NN),
- Support vector machine (SVM),
- AdaBoost (ADB),
- Classification tree (CART),
- CN2 rule inducer,
- Random Forest,
- Naïve Bayes,
- Stochastic Gradient Descent (SGD),
- K-Neighbour (KNN).

3.3.6 Training algorithm

The software used for this experiment was Orange 3.24, an extension of Python, as it provides a better interface for running machine learning algorithms. The figure below shows how the experimentation was done. Since the defects can be easily classified as critical and minor based on defined specifications in the interactive database of supplied commodities, the supervised ML approach becomes a better method for quantitative evaluation. As ML methods are good at analysing big data, in this case, 1925 hold-out datasets were used to train and test the suggested techniques for integration with existing quality control techniques. The algorithms' performance was evaluated using:

- Area under the curve (AUC),
- Classification accuracy,
- F1-score,
- Precision,
- Recall,
- Confusion matrix.

As a rule of thumb, the best ML algorithm is the one which minimises classification and prediction errors. The best-performing algorithms were suggested and recommended as part of the intelligent quality control framework. The significant advantage of this approach is that it can be easily integrated with the company's existing systems.

The extracted important features include:

- Commodities,
- Specifications,
- Number of supplied commodities,
- Supplier,
- Type of defects,
- Number of defects.

.

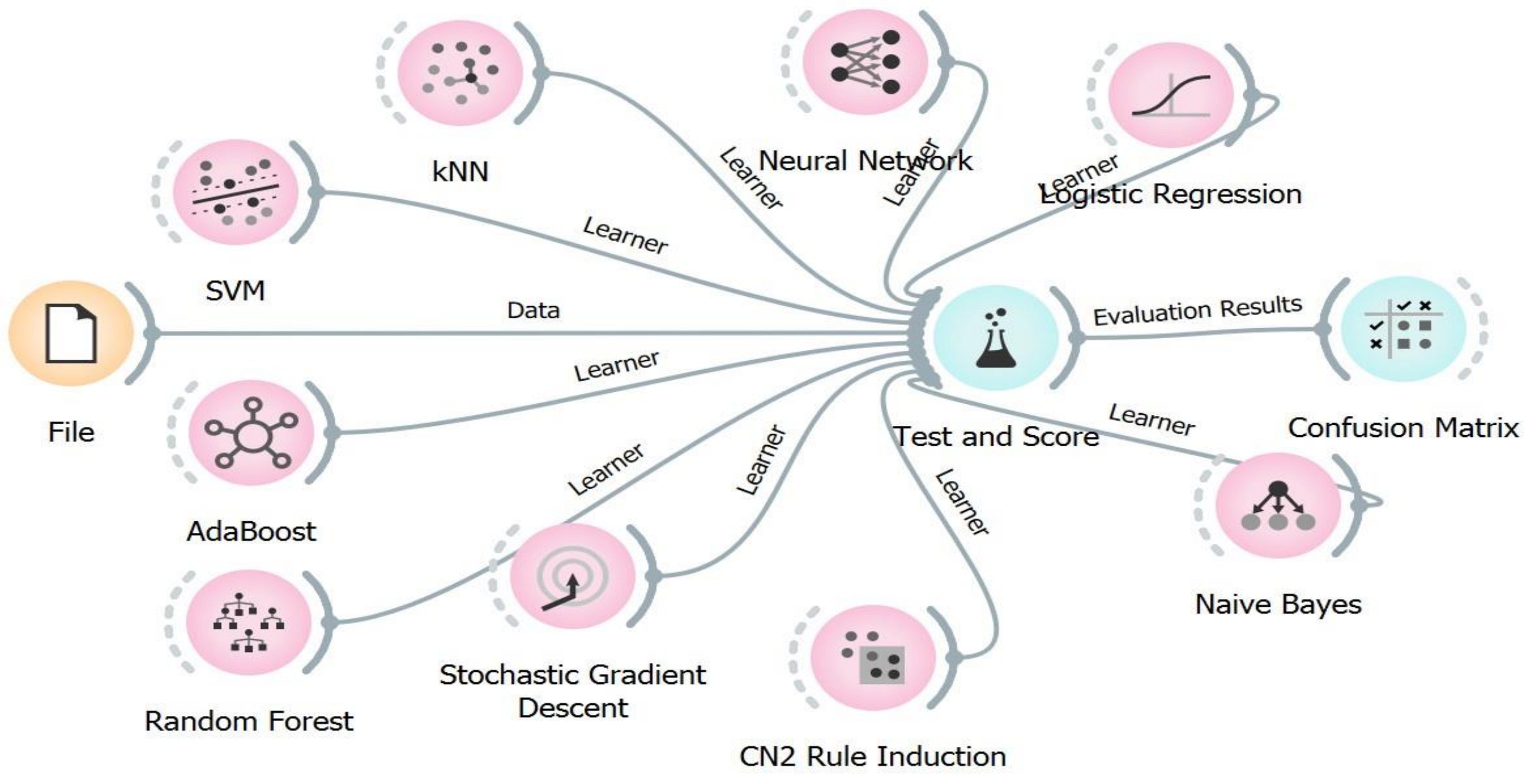


Figure 3. 4: The machine learning algorithm evaluation architecture using connected widgets, logistic regression (LR), neural network (NN), support vector machine (SVM), AdaBoost (ADB), classification tree (CART), CN2 rule inducer, Random Forest, Naïve Bayes, Stochastic Gradient Descent (SGD), and K-Neighbour (KNN).

3.3.7 Evaluation with a test set

According to Granstedt (2017), the test set evaluates the training. Compared to training, it is quick and simple. The success of the algorithm should be evaluated using appropriate performance metrics to distinguish between type I and type II errors. The outcome may serve as a guide for how to continue adjusting or whether to take a step back.

The experiment used a confusion matrix to evaluate the training, considering two variables, critical and minor.

3.4 Conclusion

In conclusion, secondary data analysis was used to test the performance of the nine algorithms. The collected data from Company X was used to train the model with nine algorithms to obtain an accurate prediction of labelled data. Based on the historical input data, the following problems were resolved: classification and regression. The outcome results from the simulation revealed the best ML algorithm is the one which minimises classification and prediction errors.

The following chapter introduces the results and discussion.

CHAPTER FOUR – RESEARCH RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents historical data collected from non-conformities of various items supplied to Company X. There were 108 defects in 2018, 441 in 2019, 371 in 2020 and 264 in 2021. These defects are cumulatively coming from different commodities. Corpus analyses considered several articles on key benefits and core elements of quality control and key benefits of AI in quality control. The confusion matrix was used to summarise the classification accuracy of the algorithms. In the end, it was noted that Adaboost, Neural Network, CN2 inducer and Random Forest minimise the prediction or misclassification error.

4.2 Defects data analysis

Figure 4.1 displays the number of part defects found at Company X. The non-functional product commodities were manually unwrapped, put on an inspection table, and visually inspected, whereas the functional parts were returned from production line after failing functional tests on a train-level. Products were either passed or failed during inspection; passed products went to the warehouse inventory flow, while failing products were sent to a non-conformity management area to be returned to the supplier. The data analysis per the graphs was recorded for four consecutive years and extracted from the Company X's quality portal.

Each year's total defects displayed was cumulative. Products commodities A, D, F, G, and J were found to be less defective, as seen on the graph. These are functional items, such electrical components, which only need to be tested functionally rather than visually. Product commodities B, C, E, H, I, and K were found to have the highest percentage of flaws in their non-functional parts, which are the train's exterior and interior sections, with aesthetic defects accounting for the majority of defects.

Following 2018, Company X ramped up because of the high production demand. In 2018, approximately two trains were produced monthly; in 2019, approximately three trains were produced monthly; in 2020, four trains were produced monthly; and in 2021, Company X ramped up to five trains per month. The number of defects reported in the parts that were received from suppliers was impacted by the ramp-up. The demand for parts increased as Company X ramped up. Most issues picked, were detected at the incoming inspection of Company X, which could have been missed at the suppliers' final inspection. This data was used to check what caused the misdetection during the inspection.

4.2.1 Effects of production ramp-up to product quality .

According to Dombrowski et al. (2018), during the ramp-up phase; there is a corresponding rise in the degree of product innovation, a rapid increase in the overall number of complex production ramp-ups, and a seamless integration of ramp-up activities into regular business operations. Ramp-up management is a crucial component of the manufacturing industry's performance when one considers that today's customers demand items with the best quality and lowest prices, delivered in the shortest amount of time. According to Dombrowski et al. (2018), there is evidence from multiple studies that the quality, time, and cost targets set during production ramp-ups are frequently unachievable. Figure 4.1 indicates that there was an increase in quality defects found from supplier's product commodities throughout the manufacturing ramp-up, which also influenced low production capacity of the rail-cars.

Production ramp-up is one of the most expensive stages of the product lifecycle, according to Glock and Grosse (2015). Typical ramp-up phase characteristics include low production rates, machine malfunctions, slow setup times, and the manufacturing of defective items, among other things. According to Glock and Grosse (2018), there is still a lack of understanding of the manufacturing process throughout the ramp-up stage, which means that a lot of the process development work is bound to go wrong. Possible problems to be found include: equipment malfunctions or is purposefully stopped to fix errors or modify material flow. Christensen (2018) contends that a variety of factors, including suppliers' delays or poor quality, contribute to delayed setups and unpredictable cycle time planning. Unique operations and tools are desired to correct product defects and process oversights, among other factors that prevent the desired output.

There are similarities among the issues that the many authors have tackled, pointing to the ramp-up influence on operational efficiency and the guarantee of defective product quality. The study's findings are supported by the data displayed on Company X's quality portal.

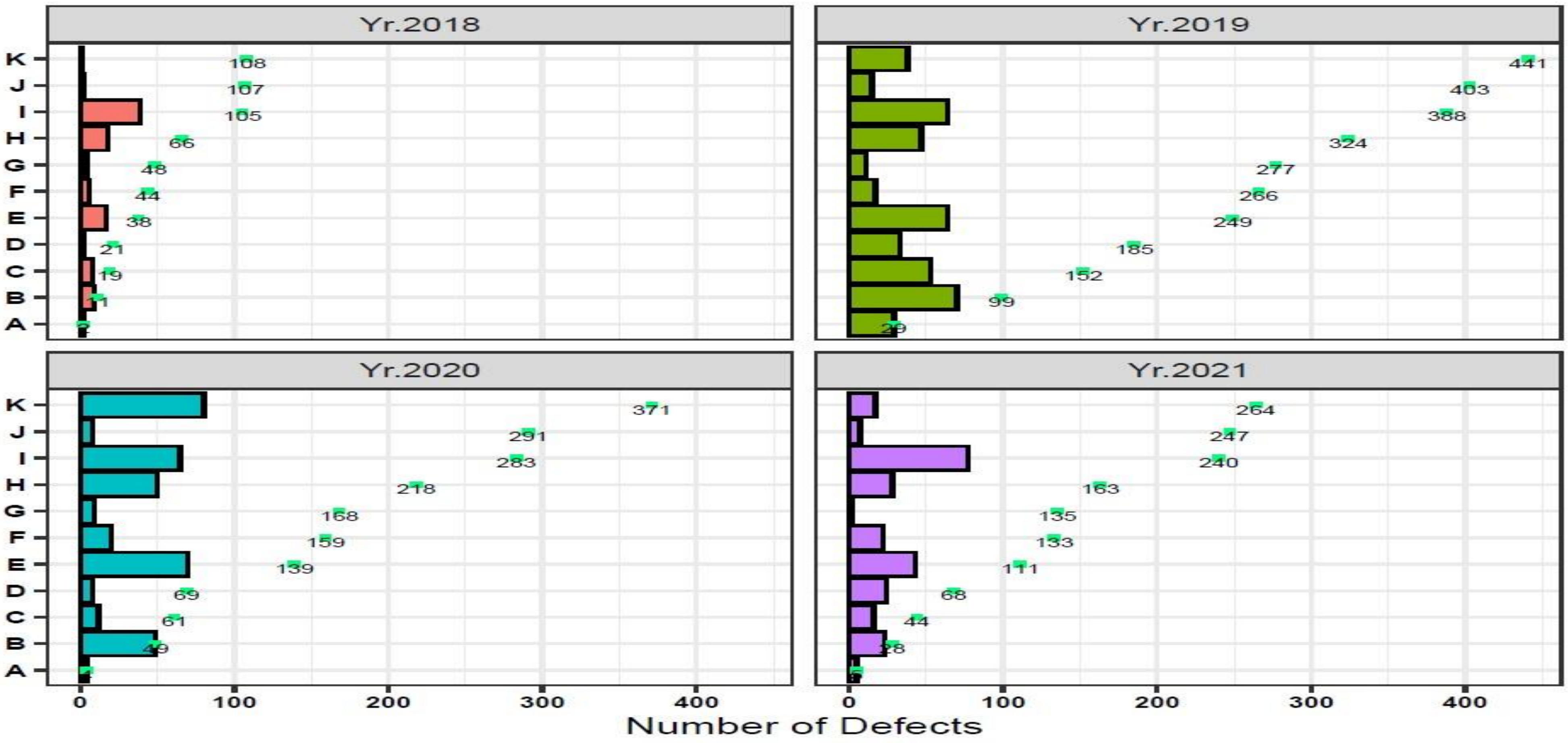


Figure 4. 1: Defects extracted from Company X's database (Portal, 2021).

4.3 Defective product commodity analysis

In Figure 4.2 considering the non-functional products B, C, E, H, I and K; product commodities B, K and I show the highest in year 2019, 2020 and 2021 respectively. Whereas product commodities A, D, F, G and J being the functional products present the least defective compared to non-functional product commodities. However the increase of defects on the non-functional products is noted particularly on product G in 2019, A in 2020 and yet again G in 2021. Overall high rejection rate was observed from the year 2019-2020.

Why was there a high rejection rate of products in 2019-2020? According to the supply-demand, based on the high volume increase of Company X’s production, suppliers were informed about boosting supply, thus increasing their production rate, which had an impact as more resources were required. As a result, new operators with lower competency levels were hired to execute the task. The outcome was that suppliers needed to train the newly hired production and final inspection operators for upskilling to the expected competency level. However, it was difficult for new employees to perform such a complex task during the high demand. Figures 4.1 and 4.2 demonstrate that visual inspections carried out at Company X’s suppliers were ineffective, putting Company X at risk of production line disruption and increasing the CONQ, thus impacting delivery. Additional risks were anticipated as Company X is expected to boost production annually.

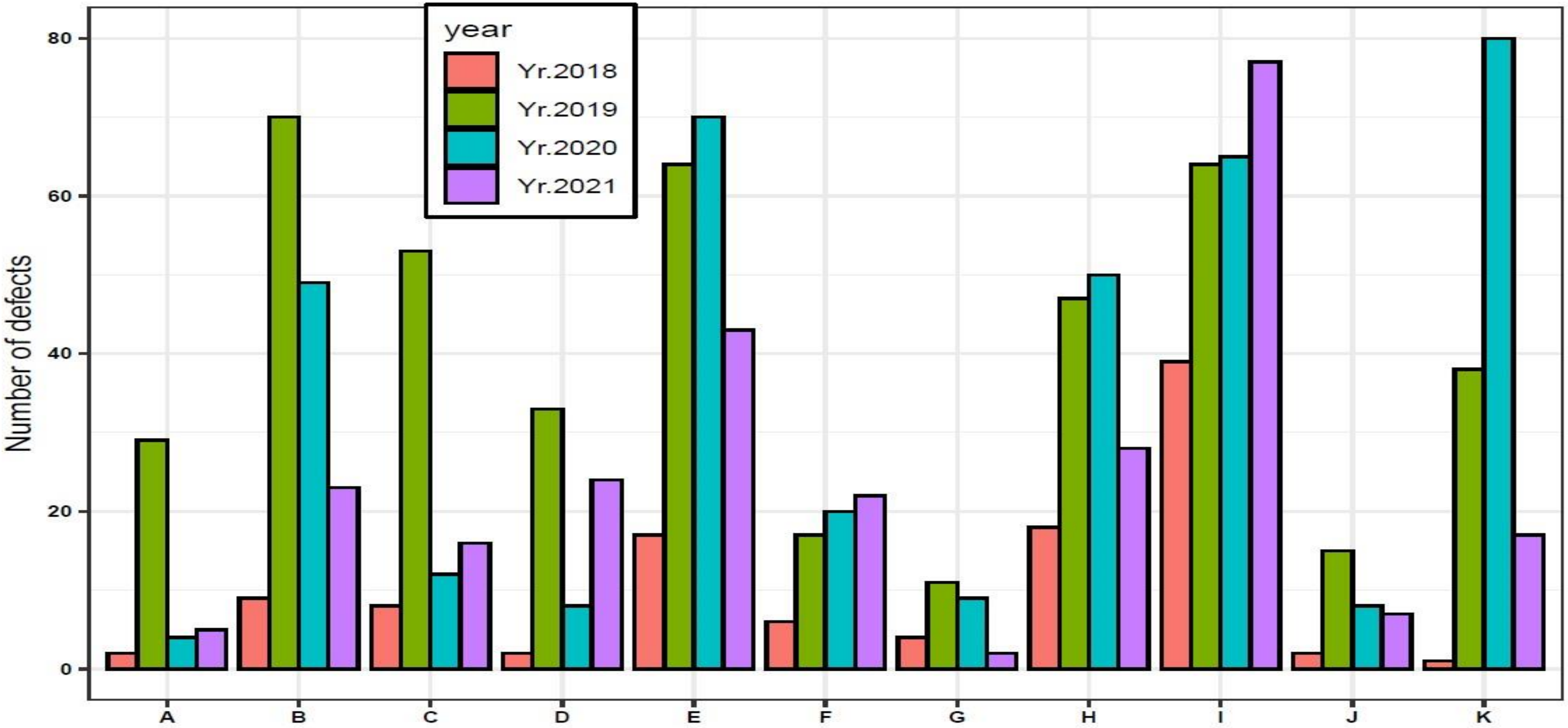


Figure 4. 2: Defects extracted from Company X’s database comparing commodities (Company X portal, 2021).

4.4 Key benefits of quality control

Figure 4.3 (A) illustrates the key benefits of quality control, encouraging quality consciousness (EQA). EQA aspect is the highest noted in Figure 4.3 and was recorded in over 50 articles. This key aspect promotes quality awareness and is human-conscious. Furthermore, over 46 articles mention that reduction in inspection costs (RIC) is a crucial element in quality control. This result summarises the need to improve quality control with fewer resources and high output for cost reduction. In addition, the reduction in production cost (RPC) was the third most mentioned and was recorded in about 41 articles. If quality control is effective, there will be lower production costs relating to line stoppages and non-quality, implying less waste such as over-processing, waiting, over-production and defects that can cause non-productivity. Any activity relating to quality control in the production line requires employees to have a competency skill level. Improved Techniques and Methods of Production (ITMP) addresses this. About 39 reviewed articles mention the need for operators to have improved skills and techniques to carry out tasks necessary to produce a much higher-quality product. Satisfaction of the customer (SOC) was mentioned in 23 articles. Although stated in fewer articles, the SOC is fundamental to a happy customer, and a sound quality-control system benefits customer satisfaction. Improved employer-employee relationships (IEER) were mentioned in 20 articles. This aspect is important; it encourages the psychological part of humans. If employer-employee relationships are positive, the job becomes enjoyable, and quality becomes a goal. Seventeen articles mentioned that increased goodwill (IGW) becomes apparent if employer-employee relationships are positive. The most effective utilisation of resources (MEUR) was considered crucial in three articles. It was not frequently mentioned, but it is part of what makes an activity more effective. It aligns with channelling competency in the correct direction driving the higher morale of employees (HME), which is another valuable aspect as motivated employees can produce good quality products. All these aspects matter in quality control.

4.5 Core elements of quality control

Figure 4.3 (B) shows the core elements of quality control. Forty-nine articles examined data management (DMA). This aspect is essential in quality control management as it supports analysis of defects trends and defective commodities that guide the company to make decisions and understand the performance metrics within quality. Processes (PRO) should have well-defined activities with defined task time, a person(s) in charge to perform each task with necessary skills and knowledge, and work instructions properly described to produce good product quality. Quality policy and objectives (QPO) should be the first driver of quality control. The first concept in making a good quality-controlled environment is to have well-defined quality policies and objectives to carry out all quality aspects in a controlled manner. Quality instrument (QIN) resources to carry out quality activities are beneficial to the quality output of the product, which is a core element of quality control. Organisational structure and responsibilities (OSR) for a well-structured organisation, responsibilities that align to activities should be well defined and addressed to carry out a well-balanced organisation; well-defined responsibilities on tasks encourage good quality practice as it becomes the person(s) in charge's responsibility to perform such tasks at their best. Continuous improvement (COIMP) was studied in about 33 articles and correlates with quality control. Every production system requires continuous improvement across the entire value chain. Another core element of quality control is a quality manual (QMA) which provides operators with crucial guidance for quality processes, which makes the job easier and more quality focused. Customer satisfaction with product quality (CSPQ) – a good quality product implies a satisfied customer. A quality control system should be well monitored to maintain a happy customer. A better process requires document control; document control and management (DCM) was one of the core quality control elements addressed in fewer records.

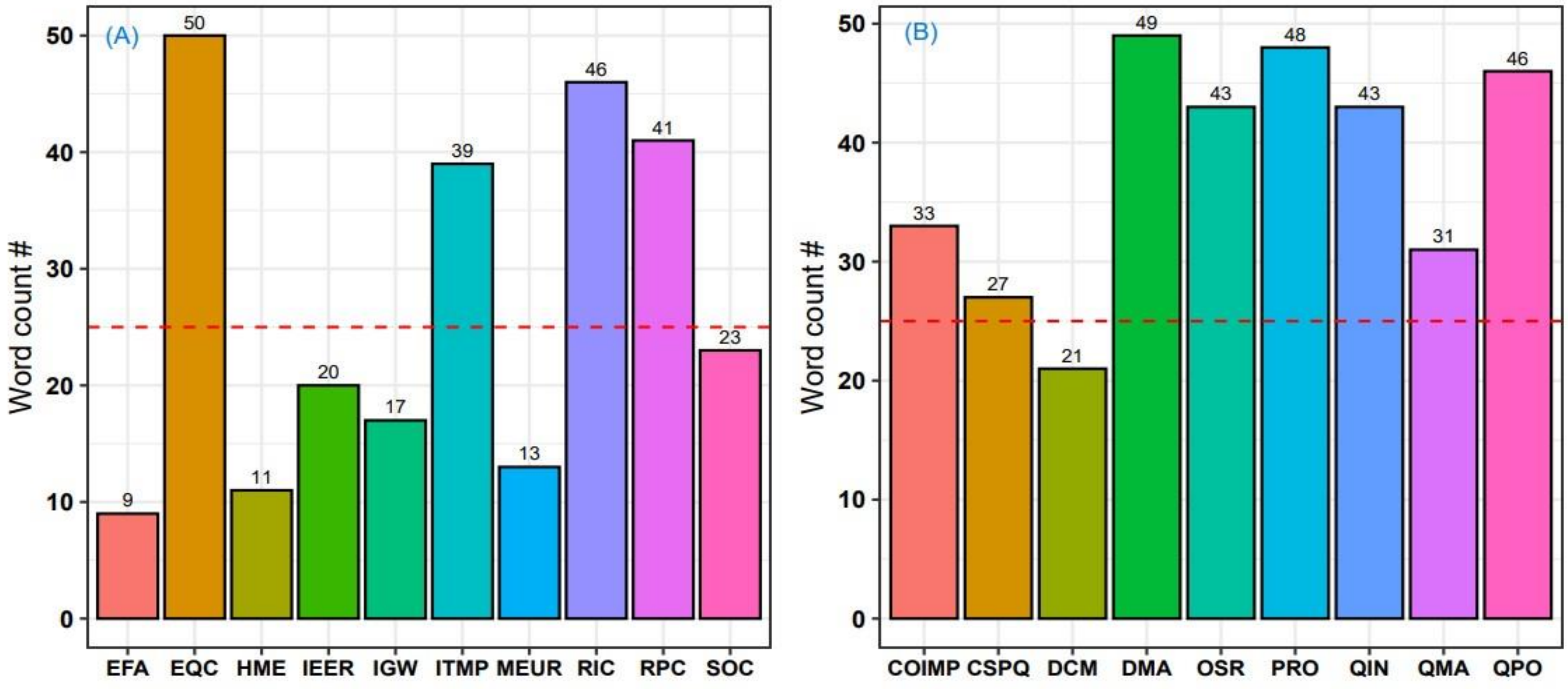


Figure 4.3**:** Key benefits (A) and core elements (B) of quality control.

4.6 Key benefits of AI in quality control.

Figure 4.4 highlights the key benefits of AI in quality control. The various factors that influence this process were evaluated. One of the features of AI technologies that makes them significantly more useful for quality control is their ability to perform tasks like humans. The automation (Auto) systems are also programmed to be smart decision-making (SDM), and 39 articles confirmed this. Data is automatically analysed and categorised to the correct defect pattern, which then directs to the root cause of the defect. In essence, handling repetitive jobs (HRJ) is one of the critical benefits of the AI quality control system. AI has become faster and more accurate compared to human operations. A reduction of error (REDE) is guaranteed when the AI system performs quality control as the system is programmed and does not get tired as an employee would. REDE is considered a key element in the benefits of AI within quality control and is mentioned in 49 articles. As noted in the research and data analysis (RDA) in Figure 4.4, AI quality control in manufacturing can identify the ideal operating conditions, which increases yield. It is possible to automatically identify the critical variables for such situations by examining various production data. Defects and product waste are reduced as a result. According to Automate.org (2022), predictive maintenance (PRM) and AI-based predictive maintenance can increase availability by up to 20% while decreasing inspection expenses by 25% and annual maintenance costs by up to 10%. This enables quality control by detecting defects before products (DDBP) reach the market. Using AI for asset fault detection eliminates the issue of fatigue or distraction, as those are human emotions, making predictive fault detection (PFD) in AI technology more effective. Hence the aspect of AI technologies speeding up fault detection (SFD) in quality control is categorised as a critical aspect. Scaling up quality control processes (SUQCP) with AI technology becomes easier as training is set on a system, which makes it faster and more effective than manual scaling.

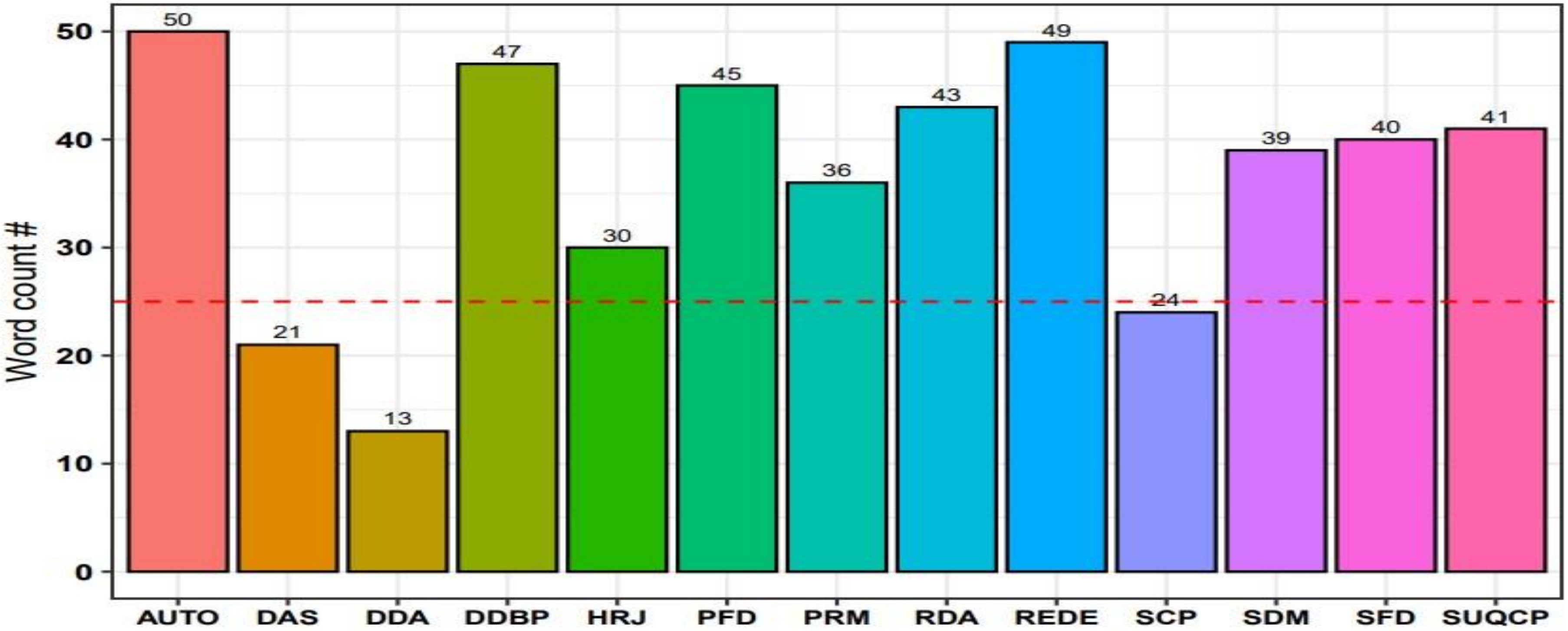


Figure 4. 4**: Key benefits of AI in quality control:** Day-to-day application = DDA, Digital assistance = DAS, Handling repetitive jobs =HRJ, Reduction of error = REDE, Automation = AUTO, Smart decision-making = SDM, Research and data analysis = RDA, Solving Complex problems = SCP, Predictive maintenance = PRM, Detecting defects before products reach the market = DDBP, Predictive fault detection = PFD, Speeding up fault detection = SFD, Scaling up quality control process = SUQCP

4.7 Evaluation of the algorithms in ML.

Table 4. 1: The evaluation metrics of all the tested binary classification algorithms derived from the confusion matrix. Logistic regression (LR), neural network (NN), support vector machine (SVM), AdaBoost (ADB), classification tree (CART), CN2 rule inducer, Random Forest, Naïve Bayes, Stochastic Gradient Descent (SGD), and K-Neighbour (KNN).

Model	AUC	CA	F1	Precision	Recall
SVM	0.551	0.504	0.506	0.535	0.504
Logistic Regression	0.743	0.685	0.679	0.680	0.685
SGD	0.671	0.687	0.685	0.685	0.687
Naive Bayes	0.739	0.689	0.686	0.686	0.689
KNN	0.767	0.707	0.706	0.705	0.707
Neural Network	0.804	0.739	0.737	0.736	0.739
Random Forest	0.855	0.769	0.769	0.769	0.769
CN2 rule inducer	0.865	0.795	0.794	0.794	0.795
AdaBoost	0.893	0.802	0.802	0.801	0.802

Table 4.1 illustrates the evaluation matrices used to assess the performance of the nine algorithms. In this assessment, an experiment was done with nine supervised machine learning algorithms to recommend the best ML algorithms that can be used as part of AI technologies needed to build an intelligent framework. The critical features used in the assessment were suppliers, types of commodities, defects and quantities to classify or predict the defect status and whether they are critical or minor. In the end, this will help the study to decide on which algorithm to use.

In this case, the evaluation matrices used were area under the curve (AUC), classification accuracy (CA), F1 score, precision score and recall. The table simplifies the evaluation process; however, this matrix can be derived from the confusion matrix. The results in terms of the algorithm performance in the above table show the Adaboost and the CN2 ruler inducer performed very well because, as a rule of thumb, an accuracy closer to 100% is far better. Therefore, the higher the classification accuracy, the better the algorithm.

Table 4. 2: The confusion matrix summarising the classification accuracy, precision, and specificity for all the experimented binary classification algorithms based on 10-fold cross-validation. Logistic regression (LR), neural network (NN), support vector machine (SVM), AdaBoost (ADB), classification tree (CART), CN2 rule inducer, Random Forest, Naïve Bayes, Stochastic Gradient Descent (SGD), and K-Neighbour (KNN).

Random Forest

Actual \ Predicted	Critical	Minor	Σ
Critical	80.7 %	28.5 %	1140
Minor	19.3 %	71.5 %	785
Σ	1133	792	1925

KNN

Actual \ Predicted	Critical	Minor	Σ
Critical	74.5 %	35.3 %	1140
Minor	25.5 %	64.7 %	785
Σ	1174	751	1925

SVM

Actual \ Predicted	Critical	Minor	Σ
Critical	61.3 %	57.7 %	1140
Minor	38.7 %	42.3 %	785
Σ	826	1099	1925

Neural Network

Actual \ Predicted	Critical	Minor	Σ
Critical	76.5 %	30.5 %	1140
Minor	23.5 %	69.5 %	785
Σ	1203	722	1925

SGD

Actual \ Predicted	Critical	Minor	Σ
Critical	72.6 %	37.5 %	1140
Minor	27.4 %	62.5 %	785
Σ	1192	733	1925

AdaBoost

Actual \ Predicted	Critical	Minor	Σ
Critical	83.2 %	24.3 %	1140
Minor	16.8 %	75.7 %	785
Σ	1142	783	1925

CN2 Rule Inducer

Actual \ Predicted	Critical	Minor	Σ
Critical	81.6 %	23.8 %	1140
Minor	18.4 %	76.2 %	785
Σ	1180	745	1925

Logistic Regression

Actual \ Predicted	Critical	Minor	Σ
Critical	70.9 %	36.1 %	1140
Minor	29.1 %	63.9 %	785
Σ	1280	645	1925

Naïve Bayes

Actual \ Predicted	Critical	Minor	Σ
Critical	72.4 %	37.1 %	1140
Minor	27.6 %	62.9 %	785
Σ	1205	720	1925

Furthermore, in evaluating the performance of the experimented algorithm, a

confusion matrix (CM) compares the actual vs the predicted. In predictive analytics, a CM is a contingency table with two dimensions, actual and predicted. In this case, the binary outcome was predicted in two dimensions, whether the defects were critical or minor. Considering the random forest model in Table 4.2 above, the total defects were 1925, 1140 were critical, and 785 were recorded as minor. In this case, the random forest correctly predicted 81.7% as critical and misclassified 28.5% as minor in the critical dimension when they were supposed to be critical. Moreover, 71.5% of defects were correctly predicted as minor in the minor dimension, whereas 19.3% were misclassified as critical. In the Adaboost, 1925 defects were recorded, and 83.2% were correctly predicted as critical, and 24.3% were misclassified as minor when they should have been critical. Altogether, 75.7% of minor defects were correctly predicted, and 16.8% were detected as critical when they should have been minor. Overall, the Adaboost, Neural Network, CN2 inducer and Random Forest minimised the prediction or misclassification error; therefore, this algorithm can be recommended for predicting and classifying the different commodities defects and can be implemented or deployed in quality control frameworks.

4.8 Conclusions

Four consecutive years of data for rejected parts were analysed. Corpus analysis in Figure 4.3 suggests the key benefits and core elements of quality control are addressed. Quality awareness and improved employee skills were considered in several articles, indicating awareness of quality control systems and competency skill levels as critical benefits to quality control. Reduction in inspection (RIC) and production costs (RPC) are fundamentally important and included in many other studies that motivate quality control. In essence, the core elements in quality control are the DMA and the PRO, enabling data management within the organisation to increase the effectiveness of quality control and making processes easier to follow. The key aspect of AI being able to handle repetitive jobs is one of the highly considered benefits to quality control, thus implying less human intervention with AI saved costs of hiring inspectors. In the end, ML algorithms were evaluated with the evaluation matrices, and the most accurate algorithms were the Adaboost, Neural Network, CN2 inducer and Random Forest since they minimise the prediction or misclassification

error.

The next chapter derives the proposed intelligent framework.

CHAPTER FIVE - PROPOSED INTELLIGENT FRAMEWORK

5.0 Introduction

This chapter presents the proposed intelligent framework and how it is incorporated with AI technologies into the existing quality control process of Company X. The processes outlined in the intelligent framework are before, during and after inspection. The computer-based system records all the characteristics of the commodity or part during the pre-inspection process. During the inspection, AI, such as camera sensors, are introduced, and the dataset is classified using any of the four algorithms considered accurate, Adaboost, CN2 rule inducer, Random Forest and the Neural Network. In conclusion, algorithms are classified to carry out validation, after which decisions about pass or fail are made.

5.1 Development of the intelligent quality control framework

Figure 5.1 shows the proposed intelligent quality control framework. The framework comprises three stages: before, during and after inspection. Characterisation takes place before inspection; product names, specifications and descriptions are recorded. At this point, a computer-based system that labels the dataset receives information from human input, which is called training. There are two steps in the inspection stage: qualitative inspection based on feature capturing of parts or commodities and quantitative inspection. Supervised machine learning algorithms classify the labelled features using camera sensors via an image-processing technique to perform inspection, which then detects the defective items according to the trained specifications. The simultaneously trained data is carried through a quantitative inspection evaluated by the defined ML algorithms by classifying the dimensions as pass or fail. In step 3, a decision is made by quantitative inspection and establishing a final decision with pass or fail criteria. In this study, AI is defined as a combination of technologies implemented to automate quality assessment at every stage, minimising manual work by humans. Before inspections, products are received from various suppliers, and all the specifications are captured and automated in an interactive database. This improves the process as similar products can easily skip this stage because specifications are already captured in the database. Moreover, if new commodities are supplied, they can easily be entered into the system or structured database, and the specifications can be revised and updated at any time. Once the products specifications and standards database exist, a qualitative inspection can be easily done by implementing natural language processing and deep learning algorithms. Product pictures can be captured, processed, analysed and categorised based on the specifications in the database. When the products are correctly defined and labelled, machine learning algorithms have the power to identify defects automatically.

5.1.2 Stages within the proposed framework

There are three stages within the proposed framework. Before the inspection, data must be labelled in categories; the collected data is analysed and labelled by the data engineer and sorted in a computer-based system. Data is then classified into two categories to align the ML algorithms to classify what is expected at the end. On the other end, there is an extensive job in categorising the product name and recording specifications such as dimensional attributes. The second stage of qualitative inspection has three categories. Inspection can be worded with automated natural language processing (NLP), where the application of computational techniques to the analysis and synthesis of natural language and speech is executed. According to Khurana *et al*. (2022), NLP has drawn much interest for its ability to represent and analyse human language computationally. It has expanded the range of industries in which it is used, including machine translation, email spam detection, information extraction, and summarization. There are two critical functions in the NLP system: natural language understanding and generation (Figure 5.2).

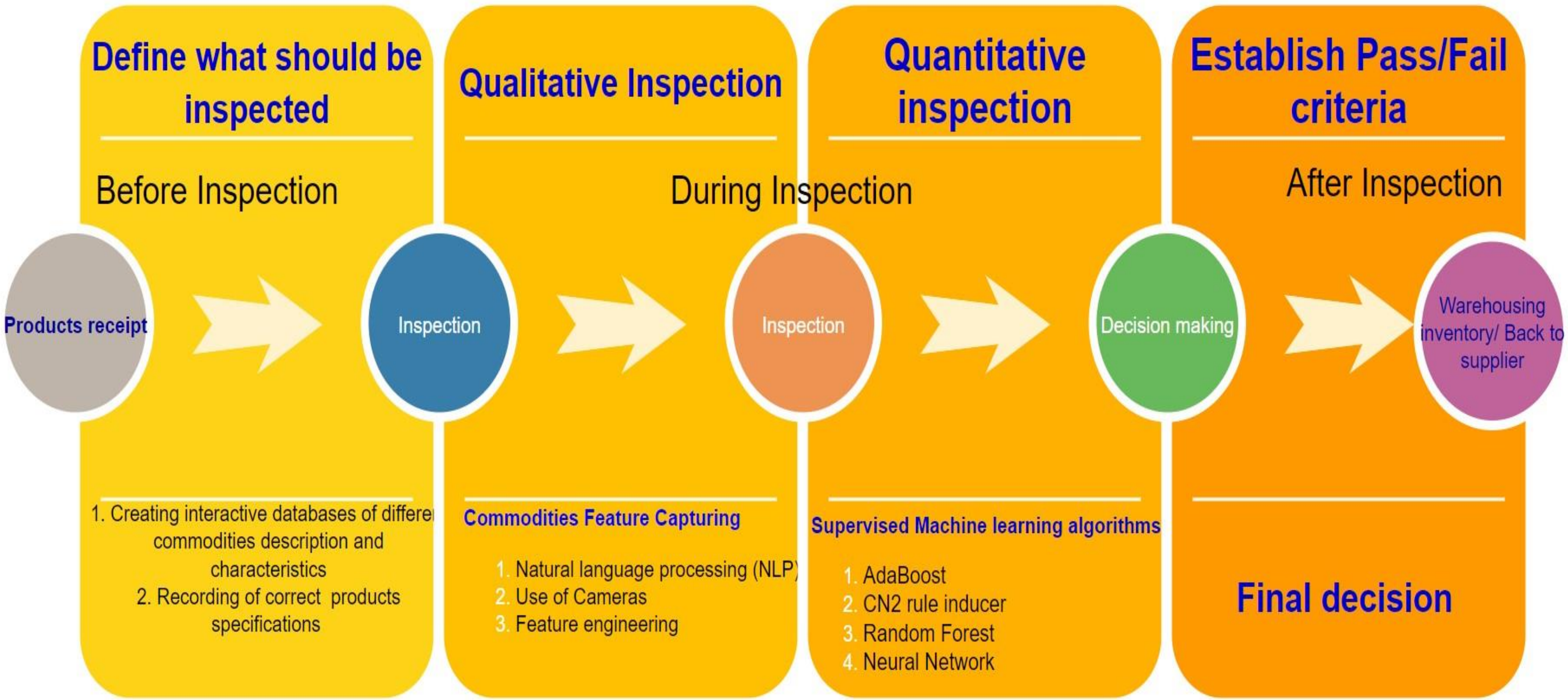


Figure 5.1: The proposed intelligent quality control framework.

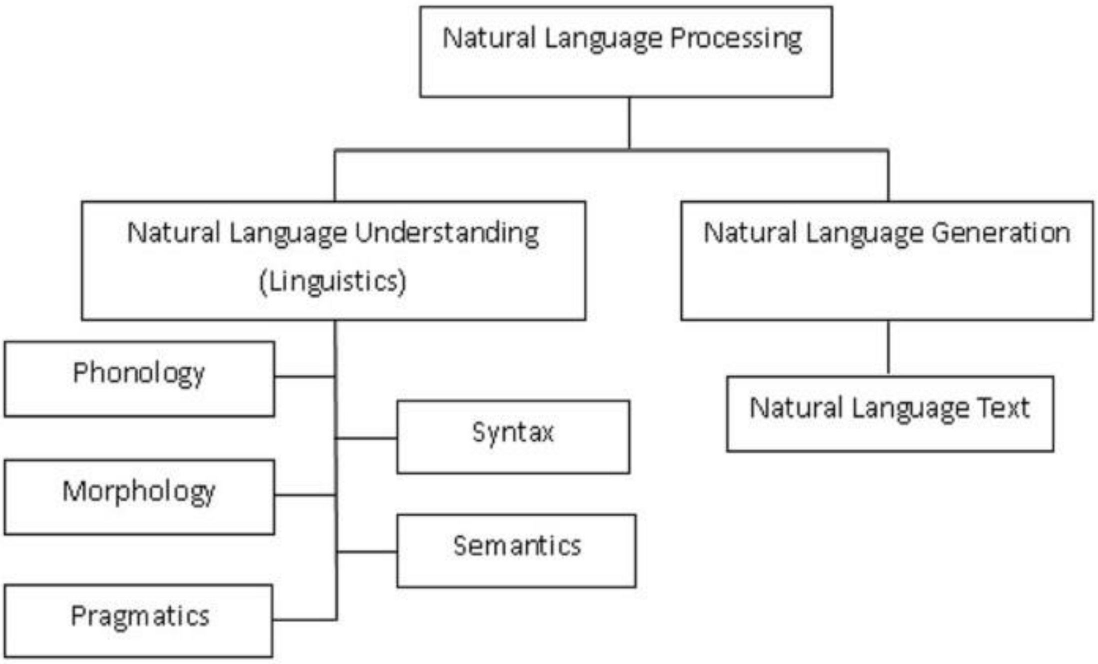


Figure 5.2: Broad classification of NLP (Khurana et al., 2022)

In the third stage of quantitative inspection of the intelligent quality control framework, any ML algorithm such as Adaboost, CN2 ruler, Random forest and Neural network are used as part of the quantitative inspection. These inspections lead to a decision

as to whether the defect has been detected. The nature of the defect is well-classified. If the intelligent quality control framework deems the part defective at the final decision-making stage, it returns to the supplier.

5.2 Conclusions

The framework is open-minded and considers all parties. It makes up for trained inspectors by shifting them to a more analytical role where they look for trends and collaborate with suppliers to find solutions to problems rather than just reporting to errors.

The following chapter contains the conclusion.

CHAPTER SIX - CONCLUSIONS

6.0 Introduction

This chapter concludes the study by summarising the main research findings concerning the research aims and questions and discussing their value and contribution. It will also review the limitations of the study and propose opportunities for future studies.

The study aimed to develop an intelligent quality control framework for purchased parts alongside suppliers in the rail industry. A literature analysis was performed on the existing quality control frameworks, and the relevance of AI in quality control in manufacturing was assessed. The current literature suggests that much of the quality framework/quality control process is human-dependent and prone to errors. The AI models developed AI quality control that substitutes for human intervention.

Several articles explored the impact of product quality within the supply chain, and various authors have indicated that poor visibility in the supply chain has a significant impact on product failures. Recently, the use of IoT integration to have a much more visible supply chain has been proposed. This study considered collaborating IoTs to the ABCDE framework that advocates communication of metiers within the entire value chain. One author, who agreed that the design and manufacturing processes were the problem, bridged the gap by introducing a geometric model, emphasising the importance of planning for the design and manufacturing process. More studies were considered on factors influencing product quality, with many focusing on design and manufacturing processes. The geometric model identifies each step that must be completed throughout the product's design phase before it can be frozen and during the manufacturing phase. It outlines particular actions that must be confirmed, including resources. The key elements from the geometric model are essential for this study. When discussing the psychological aspect of the human factor and factors impacting visual quality control, all authors agreed that this issue could not be ignored and that the study should instead focus on automated quality control techniques. The relevance of AI in quality control key benefits were addressed, highlighting higher financial output to the business.

6.1 Overall contribution of the study of product quality with AI

In Figure 4.3, the corpus analysis addressed the critical benefits of AI in quality control. Common elements were noted: AI is fast in identifying material at risk, product optimisation and precise defect root cause analysis and its ability to handle repetitive jobs. These benefits have far greater efficiency than manual quality control. An intelligent quality control was developed that summarises the three sections in the existing quality framework of Company X. The sections were before, during and after inspection. We conclude that all objectives were met.

The results obtained from experimenting with ML algorithms indicated that algorithms such as Adaboost, CN2 rule inducer, Random Forest and Neural network could be used for quantitative inspection of the framework as they were rated more precise or accurate. Further findings show that, in an intelligent framework, the existing framework of Company X could integrate easily with AI for a better quality control system. Camera sensors were considered qualitative attributes during inspection where images will be classified.

An intelligent quality control framework will benefit the organisation in economically beneficial inspection strategies, saving time on inspection and handling and generating an attractive business case. AI allows labour cost reduction and greater inspection efficiency compared to human checks. The system improves the analytical strategy by engineers as the focus will be analysing and correcting the root cause.

What are the factors affecting visual product quality control efficiency?

Factors affecting the efficiency of product quality control by human or visual inspection were addressed in Table 2.2. The technical aspects are attached, such as defect visibility to the inspector and skills development. The social aspect also ponders team communication, fatigue, and pressure.

What are the best practices for maximising efficient product quality control?

In the literature, AI technologies were considered to obtain a much more efficient quality control process Table 2.4. There is a significant financial gain in the business as AI is much faster and more reliable compared to visual quality control. The framework is open-minded and considers all parties. It makes up for trained inspectors by shifting them to a more analytical role where they look for trends and collaborate with suppliers to find solutions to problems rather than just reporting errors.

6.2 Recommendation

There are a few gaps in our knowledge about making the intelligent quality framework alive with actual cameras, sensors, and jigs that would benefit from further research, including realistic evaluation to extend and further tests. The intelligent quality framework will also be extended to Company X's supplier and other OEMs. A detailed proposal will be sent out.

BIBLIOGRAPHY

AJAYI, V.O., 2017. Primary sources of data and secondary sources of data, vol1: Benue State University: 1-6.

AUNALI, A.S. and VENKATESAN, D. 2019. Recent Developments in Control Charts Techniques, *Universal Review Journal*: 8 (4): 746-756.

AHMED, S., KALSOOM, T., RAMZAN, N., PERVEZ, Z., AZMAT, M., ZEB, B. and UR REHMAN, M. 2021. *Towards supply chain visibility using internet of things: A dyadic analysis review*, 21(12): Sensors : 4158.

AVVARI, D., 2021. *A Literature Review on Differences Between Robotic and Human In-Line Quality Inspection in Automotive Manufacturing Assembly Line*.

BLANCO-ENCOMIENDA, F.J., 2021. *Importance of quality control implementation in the production process of a company.*

MAGUIRE, J., 2022. How to Use Artificial Intelligence to Improve Quality Control. Available from: https://www.devteam.space/blog/how-to-use-artificial-intelligence-to-improve-quality-control/ [Accessed: 20/07/2022].

ESCOBAR, C.A. AND MORALES-MENENDEZ, R., 2018. Machine learning techniques for quality control in high conformance manufacturing environment. *Advances in Mechanical Engineering*, *10*(2): 1687814018755519.

FELDERER, M. AND RAMLER, R. 2021. Quality Assurance for AI-Based Systems: Overview and Challenges. In : *International Conference on Software Quality*, Springer, Cham, Jan. : 33-42.

GREENFIELD, D., 2020. How Artificial Intelligence Works in Quality Control. Available from: https://www.automationworld.com/factory/sensors/article/21198005/how-artificialintelligence-works-in-quality-control. [Accessed: 18/11/2020].

COCCIA, M. 2018. The Fishbone diagram to identify, systematize and analyze the sources of general-purpose Technologies, *Journal of Social and Administrative Sciences*, 4(4): 291-303.

Christensen, I. 2018. New Product Fumbles-Organizing for the Ramp-up Process. *Frederiksberg: Copenhagen Business School (CBS).*

DRIDI, S., 2021. Supervised Learning-A Systematic Literature Review.

DUAN, G.J. AND YAN, X., 2020. *A Real-Time Quality Control System Based on Manufacturing Process Data*, vol 8: IEEE Access : 208506-208517.

DATE, K. AND TANAKA, Y. 34th. 2021. Quality-Oriented Statistical Process Control Utilizing Bayesian Modeling, vol 3 : *IEEE Transactions on Semiconductor Manufacturing*: 307-311.

DEZHI, L., 2010. Robust design based on model of product design quality.: In : IEEE, *2010 International Conference on Logistics Systems and Intelligent Management (ICLSIM)* : vol 2, : 1190-1192.

DOMBROWSKI, U., WULLBRANDT, J. AND KRENKEL, P., 2018. Industrie 4.0 in production ramp-up management. *Procedia Manufacturing*, *17*:1015-1022.

FISH, L.A., 2011. Supply chain quality management. *Supply chain Management Pathways for research and practice*, 25.

Glock, C.H. and Grosse, E.H., 2015. Decision support models for production ramp-up: a systematic literature review. *International Journal of Production Research*, *53*(21) : 6637-6651.

GRUSZKA, S. AND GAŠPAR, Š., 2018. Effect of Human Factor on Product Quality in Manufacturing Activities. *Multidisciplinary Aspects of Production Engineering*, *1*.

GEJDOŠ, P., 2015. Continuous quality improvement by statistical process control. *Procedia Economics and Finance*, *34* : 565-572.

GRANSTEDT MÖLLER, E., 2017. The use of machine Learning in industrial quality control.

HOLTSKOG, H., 2013. Continuous improvement beyond the lean understanding. *Procedia Cirp*, *7* : 575-579.

HAMADA, K., ISHIKAWA, F., MASUDA, S., MYOJIN, T., NISHI, Y., OGAWA, H., TOKU, T., TOKUMOTO, S., TSUCHIYA, K., UJITA, Y. AND MATSUYA, M., 2020. Guidelines for Quality Assurance of Machine Learning-based Artificial Intelligence. *In SEKE*, July. : 335-341.

HANAYSHA, J., ABDULLAH, H.H. AND GHANI, N.H.A., 2016. Importance of product quality and service quality in developing brand equity. *Journal for Global Business Advancement*, 9(4) : 390-401.

JIANG, R., 2009. A product quality index derived from product lifetime distribution. In : IEEE, Vol 1. *2009 International Conference on Measuring Technology and Mechatronics Automation*: 573-577.

JOSHI, A. AND JUGULKAR, L.M., 2014. Investigation and analysis of metal casting defects and defect reduction by using quality control tools. *International journal of mechanical and production engineering. ISSN* : 2320-2092.

KUJAWIŃSKA, A. AND VOGT, K., 2015. Human factors in visual quality control. *Management and Production Engineering Review : 6*.

LIN, Y., LIANG, B. AND ZHU, X., 2018. The effect of inventory performance on product quality*. International Journal of Quality & Reliability Management* .

LOMBARD, R., VAN WAVEREN, C.C. AND CHAN, K.Y., 2014. Factors affecting quality in a manufacturing environment for a non-repairable product. In: *IEEE* , *2014 IEEE International Conference on Industrial Engineering and Engineering Management* , Dec.:137-142.

KERSTING, K., 2018. Machine learning and artificial intelligence: two fellow travelers on the quest for intelligent behavior in machines. *Frontiers in big Data*, *1* : 6.

KALAIARASAN, R., OLHAGER, J., AGRAWAL, T.K. AND WIKTORSSON, M., 2022. The ABCDE of supply chain visibility: A systematic literature review and framework. *International Journal of Production Economics*,108464.

KHURANA, D., KOLI, A., KHATTER, K. AND SINGH, S., 2022. Natural language processing: State of the art, current trends and challenges. *Multimedia Tools and Applications*,1-32.

KALAIARASAN, R., AGRAWAL, T.K., OLHAGER, J., WIKTORSSON, M. AND HAUGE, J.B., 2022. Supply chain visibility for improving inbound logistics: a design science approach. *International Journal of Production Research*, 1-16.

ILIE, G. AND CIOCOIU, C.N., 2010. Application of fishbone diagram to determine the risk of an event with multiple causes. *Management research and practice*, *2*(1) : 1-20.

LOTFI, Z., SAHRAN, S. AND MUKHTAR, M., 2013. A product quality—Supply chain integration framework. *Journal of Applied Sciences*, *13* : 36-48.

LOTFI, Z., SAHRAN, S., MUKHTAR, M. AND ZADEH, A.T., 2013. The relationships between supply chain integration and product quality. *Procedia Technology*, 11: 471-478.

MEYER, K., (2020). Bombardier woes reflect Canada's failed infrastructure policy. The Conversation [online], Available from :

https://theconversation.com/bombardier-woes-reflect-canadas-failed-infrastructure-policy-131019 [Accessed: 08/06/2020].

LILIANA, L., 2016. A new model of Ishikawa diagram for quality assessment. In: *IOP, Conference Series: Materials Science and Engineering*, IOP Publishing, Nov. :161(1) : 012099.

MÂNDRU, L., HÂRLAB, A. AND CAMARDA, A.L., 2009. Indicators used to measure the quality of products. *Retrieved June*. : 2019.

MACHAC, J., STEINER, F. AND TUPA, J., 2017. Product life cycle risk management. *Risk Management Treatise for Engineering Professionals*, 51-72.

MEMON, I.A., JAMALI, Q.B., JAMALI, A.S., ABBASI, M.K., JAMALI, N.A. AND JAMALI, Z.H., 2019. Defect reduction with the use of seven quality control tools for productivity improvement at an automobile company. *Engineering, Technology & Applied Science Research*, *9*(2) : 4044-4047.

MADANHIRE, I. AND MBOHWA, C., 2016. Application of statistical process control (SPC) in manufacturing industry in a developing country. *Procedia Cirp*, *40* : 580-583.

MORÁN-FERNÁNDEZ, L., BÓLON-CANEDO, V. AND ALONSO-BETANZOS, A., 2022. How important is data quality? Best classifiers vs best features. *Neurocomputing*, *470*: 365-375.

NIU, X., QIN, S., ZHANG, H., WANG, M. AND WONG, R., 2018. Exploring product design quality control and assurance under both traditional and crowdsourcing-based design environments. *Advances in Mechanical Engineering*, *10*(12) : 1687814018814395.

NICOLAE, R., NEDELCU, A. AND DUMITRASCU, A.E., 2015. Improvement The Quality of Industrial Products By Applying The Pareto Chart. *Review of the Air Force Academy*, (3) : 169.

NOWOTARSKI, P., SZYMANSKI, P. AND RZEPECKA, P., 2019. DMAIC method of quality improvement of ground works processes: case study. In *IOP Conference Series: Earth and Environmental Science*,221 (1) : 012002 . IOP Publishing.

NEUMANN, W.P., KOLUS, A. AND WELLS, R.W., 2016. Human factors in production system design and quality performance–a systematic review. *Ifac-Papersonline*, *49*(12) : 1721-1724.

POTH, A., BECK, Q. AND RIEL, A., 2019. Artificial Intelligence helps making Quality Assurance processes leaner. In : *European Conference on Software Process Improvement* .Springer, Cham, Sep. : 722-730.

PERES, R.S., BARATA, J., LEITAO, P. AND GARCIA, G., 2019. Multistage quality control using machine learning in the automotive industry. *IEEE Access*, *7* : 79908-79916.

RAMAN, R.S. AND BASAVARAJ, Y., 2019. Quality improvement of capacitors through fishbone and pareto techniques. *International Journal of Recent Technology and Engineering*, *8*(2) : 2248-2252.

SCHMITT, J., BÖNIG, J., BORGGRÄFE, T., BEITINGER, G. AND DEUSE, J., 2020. Predictive model-based quality inspection using Machine Learning and Edge Cloud Computing. *Advanced engineering informatics*, *45* : 101101.

SAQIB, Z.A., SAQIB, K.A. AND OU, J., 2019. Role of Visibility in Supply Chain Management. In *Modern Perspectives in Business Applications*. IntechOpen .

ŠUGROVÁ, M., ŠEDÍK, P., KUBELAKOVÁ, A. AND SVETLÍKOVÁ, V., 2017. Impact of the product quality on consumer satisfaction and corporate brand. *Economic annals-XXI*, (165) : 133-137

SMĘTKOWSKA, M. AND MRUGALSKA, B., 2018. Using Six Sigma DMAIC to improve the quality of the production process: a case study. *Procedia-Social and Behavioral Sciences*, *238*: 590-596.

TAN, H., 2021. Machine Learning Algorithm for Classification. In *Journal of Physics: Conference Series,* IOP Publishing, Aug, 1994(1) : 012016.

NASTESKI, V., 2017. An overview of the supervised machine learning methods. *Horizons, 4* : 51-62.

NGUYEN, D.S., 2014, DECEMBER. Total quality management in product life cycle. In: IEEE *, 2014 IEEE International Conference on Industrial Engineering and Engineering Management,* 754-758.

PRASAD, R.K., JHA, M.K. AND VERMA, S., 2019. A Comparative study of product life cycle and its marketing applications. *Journal of Marketing and Consumer Research*, 63: 62-69.

QAZI, S., MEMON, M.S., ALI, A. AND NIZAMANI, S., 2022. ROLE OF ARTIFICIAL

INTELLIGENCE (AI) TOOLS FOR ASSURING QUALITY IN SOFTWARE. *Journal of Southwest Jiaotong University*, *57*(2).

RIAZ, M. AND MUHAMMAD, F., 2012. An application of control charts in manufacturing industry. *Journal of Statistical and Econometric Methods*, 1(1) : 77-92.

TSE, YING K., TAN, AND KIM H., 2011 . Managing product quality risk in a multi-tier global supply chain*. International Journal of Production Research*, 49(1) : 139158.

TANNOCK, J.D., BALOGUN, O. AND HAWISA, H., 2007. A variation management system supporting six sigma. *Journal of Manufacturing Technology Management*.

YANMEI, Z., ALARD, R. AND SCHÖNSLEBEN, P., 2007. Design quality: a key factor to improve the product quality in international production networks. *In Advances in Production Management Systems*. Springer, Boston, MA : 133-14.

ZHANG, J.M., HARMAN, M., MA, L. AND LIU, Y., 2020. Machine learning testing: Survey, landscapes and horizons. *IEEE Transactions on Software Engineering*.