

Development of an Integrated Quality Control Model for Outer Gear Couplings Based on Six Sigma DMAIC and J48 Decision Tree

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Abstract: Producing precision components like outer gear couplings requires high geometric and surface quality to maintain mechanical transmission performance in machinery. However, CV Adi Makmur Metalindo experiences recurring quality issues with these specific components. Between July and October 2025, the overall defect rate reached 16.94% (62 defective units out of 366 total units). These issues are primarily geometric defects (62.90%) and surface defects (37.10%). This comprehensive study evaluates production quality performance, identifies dominant process attributes triggering defects, and develops a robust decision support model for quality control. The methodology utilizes a quantitative case study approach, integrating the Six Sigma DMAIC framework with the J48 decision tree algorithm to reinforce the Analyze stage. Results indicate a Defect Per Million Opportunities (DPMO) value of 169,399 and a Defect Per Unit (DPU) of 0.1694, confirming an unstable production process with a high probability of defects. The J48 algorithm modeling clearly identified rough turning RPM (rpm_bubut_kasar) as the dominant predictor classifying product quality. Extracted decision rules reveal that setting machine RPM too low (under 53.9 RPM) or too high (over 65.5 RPM) heavily correlates with geometric defects, whereas the intermediate range triggers surface defects. Consequently, the Improve phase proposes standardizing operational parameters within an optimal range of 55 to 65 RPM. For the Control phase, a mockup of a smart monitoring dashboard interface was designed to efficiently support targeted quality control decisions. Ultimately, integrating Six Sigma DMAIC and the J48 algorithm successfully transforms manufacturing process data into practical decision rules, effectively supporting product quality optimization.

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INTRODUCTION

Quality is one of the elements that determines the competitiveness of manufacturing companies because it is directly related to the process's ability to produce products that meet specifications, reduce waste, maintain cost efficiency, and consistently meet customer needs (Saputra et al., 2025). Quality in the manufacturing context cannot be understood solely as the end result of inspection activities, but rather as the output of a process system influenced by the interaction between humans, machines, work methods, materials, and operating conditions (Köksal et al., 2011). Quality problems in the manufacturing industry generally do not arise singly, but are formed from a combination of various interrelated process attributes. This condition causes quality analysis to require an approach that is not only able to describe the level of defects but also able to read the relationships between process attributes more systematically (Ait-el-cadi et al., 2021).

Quality control in the industrial sector is moving towards an increasingly data-driven approach. A systematic analysis of defect detection and classification research in the industry shows that data-driven analytics has been widely used to support defect pattern identification, quality classification, and attribute tracking associated with process failures (Elbany et al., 2024). A study by Elbany et al. (2024) on the integration of machine learning and Six Sigma in the plastics industry demonstrated that data-driven analytical approaches can be combined with process improvement frameworks to strengthen quality decision-making. This confirms that quality control is no longer solely supported by final inspections and manual assessments, but requires analytical models capable of interpreting the relationships between process attributes in a more structured manner.

CV Adi Makmur Metalindo is a fabrication company engaged in the production of precision components for the palm oil processing industry. One of the products produced is the outer gear coupling, namely a mechanical transmission element used to transmit rotary motion and torque and accommodate certain misalignments between components connected to a screw press machine. The condition of tooth contact, load distribution, torque and misalignment greatly affect the performance of the coupling, so the quality of geometry and surface conditions are very important aspects (Guo et al., 2016). The outer gear coupling can be seen in Figure 1.1.



Source: Literature

Figure 1.1 Outer Gear Coupling

Figure 1.1 shows the physical form of the outer gear coupling which has a diameter of 400 mm and a length of 310 mm. The manufacturing process of the outer gear coupling is as follows: The gear coupling process at CV Adi Makmur Metalindo begins with the roughing of the component using a lathe to achieve the desired diameter and alignment of the component's base axis. This process is then continued with a scraping process to form a precision tooth profile or key slot. Each process consists of two stages: roughing, the initial product formation stage, and finishing, the surface smoothing stage. Based on the product's function and the process characteristics, a product is considered good if it meets the acceptance standards, which include geometric aspects and surface conditions, as shown in Table 1.1.

Table 1.1 Outer Gear Coupling Product Specification Standards

Indicator	Nominal Size	Tolerance/Acceptance Criteria
Outer diameter	400.00 mm	±0.20 mm
Total length	310.00 mm	±0.20 mm
Tooth profile length	55.00 mm	±0.10 mm
Tooth profile height	37.00 mm	±0.10 mm
Tooth profile width	48.00 mm	±0.10 mm
Scratch	No scratch	No dominant scratch is allowed
Tool marks / chisel marks	Normal chisel marks	Excessive tool marks are not allowed.
Burr / sharp residue	No burrs	No burrs or sharp remains are permitted.
Surface uniformity	Uniform surface	Non-uniform/wavy surfaces are not permitted.

Source: CV. Adi Makmur Metalindo

Table 1.1 shows the acceptance standards for outer gear coupling products used as a reference to determine whether the product meets specifications or experiences non-conformity. Geometric indicators include the outer diameter, total length, and tooth profile size consisting of length, height, and profile width. Meanwhile, surface indicators include the presence of scratches, tool marks, burrs or sharp residue and surface uniformity. A product is declared to meet the standard if all geometric indicators are within the tolerance limits and all surface indicators meet the acceptance criteria. This standard serves as the operational basis in determining Critical to Quality at the Define stage in the DMAIC framework, specifically to distinguish between non-defect products, geometric defects, and surface defects. A recapitulation of production volume and defect rate during the period July 2025 to October 2025 is shown in Table 1.2.

Table 1.2 Disability Rate for the Period July 2025 to October 2025

Month	Outer Gear Coupling Production Quantity (Pcs)	Defect Outer Gear Coupling (Pcs)	Percentage (%)
July 2025	94	16	17.02%
August 2025	88	15	17.05%
September 2025	94	16	17.02%
October 2025	90	15	16.67%
Amount	366	62	16.94%

Source: CV. Adi Makmur Metalindo

Table 1.2 shows the production data of outer gear couplings for the period July 2025 to October 2025 with a production volume of 366 units and a number of defective products of 62 units, so that the defect rate reached 16.94%. At the monthly level, the number of defects is relatively consistent, namely 16 units in July 2025, 15 units in August 2025, 16 units in September 2025 and 15 units in October 2025. These data indicate that quality problems in outer gear couplings are not incidental events, but tend to appear repeatedly. The defect percentage of 16.94% not only indicates that the product does not comply with acceptance standards.

Study of the application of Six Sigma in the manufacturing context conducted by (Siregar & Elvira, 2020) on support products assy shows that an average defect of just 9.49% is considered to exceed the manufacturing company's tolerance limit of 5% and is treated as a quality problem requiring corrective action. The 16.94% defect rate in the outer gear coupling can be considered a serious problem from both a company and academic perspective. The types of defects focused on in this study fall into two main categories: geometric defects and surface defects. The types of defects in the outer gear coupling product can be seen in Figure 1.2.



Figure 1.2 Types of Defects
Source: CV. Adi Makmur Metalindo

Based on Figure 1.2, defects found in outer gear coupling products can be grouped into two main categories, namely geometric defects and surface defects. Geometric defects relate to deviations in product dimensions or shape from predetermined specifications, including outer diameter, total length, tooth length, tooth height, and tooth profile width. Meanwhile, surface defects relate to substandard machining quality, such as the appearance of scratches, excessive tool marks, burrs, and surface non-uniformity. This grouping is based on the characteristics of the outer gear coupling manufacturing process, which is greatly influenced by the stability of the turning and scrap processes, and is supported by the availability of relevant process attribute data. This finding is in line with research by Qehaja et al. (2015) which shows that the quality of machining results is greatly influenced by the consistency of process parameters and cutting tool conditions, especially regarding the geometric accuracy and surface quality of the product.

According to Bártová et al. (2022), quality control in the manufacturing sector still relies heavily on conventional descriptive methods, such as cause-and-effect analysis, field discussions, and the use of basic quality tools. Although useful for early problem identification, these approaches are unable to comprehensively describe the complex relationships between process variables. In the production of outer gear couplings, product quality is influenced by various interacting factors, including operator characteristics, turning and scrap parameters, cutting tool conditions, workpiece clamping stability, and inspection activities during the process. Therefore, this study integrates the DMAIC-based Six Sigma framework with the J48 algorithm in the Analyze stage to identify defect patterns, classify products into non-defect, geometric defect, and surface defect categories, and generate easily interpretable decision rules. The results of this analysis are then used as a basis for developing improvement strategies in the Improve stage and developing a control system in the Control stage to support continuous quality improvement .

The general objective of this research is to design a model to support quality control of outer gear couplings based on Six Sigma Integration (DMAIC) and the J48 algorithm. Specifically, this research aims to:

1. Analyze the quality performance of the outer gear coupling production process using the Six Sigma (DMAIC) approach.
2. Identify the dominant process attributes in the classification of outer gear coupling defects using the J48 algorithm.
3. Develop decision rules and quality improvement proposals based on the results of the Six Sigma analysis and the J48 classification.
4. Design an interface mock-up to visualize the model supporting quality decision-making in the outer gear coupling production process.

RESEARCH METHOD

This applied quantitative research is structured as an in-depth case study at CV Adi Makmur Metalindo, a palm oil machine component manufacturer located in Medan, specifically targeting the production quality of their Gear Coupling Screw Press Machine components. Rather than implementing physical interventions on the production line, the study focuses on systematically analyzing recurring product defects to develop a comprehensive quality control support model. By examining the unique characteristics of the production process and operational conditions, the research aims to measure current quality performance, identify the root causes of defects, and design a practical visual mock-up to support future decision-making.

To achieve these objectives, the study utilizes a thorough data collection strategy encompassing both primary and secondary sources. Primary data was gathered directly from the shop floor through planned observations of the manufacturing processes and direct interviews with workers, capturing real-time operational challenges and accurate insights into existing defect phenomena. This is complemented by secondary data extracted from internal company documents—such as historical defect rates and product specifications—and an extensive literature review of relevant scientific publications to build a strong theoretical foundation for the proposed quality control solutions.

The collected data is systematically analyzed using the Six Sigma DMAIC (Define, Measure, Analyze, Improve, Control) framework integrated with the J48 decision tree algorithm. The Define and Measure stages establish a clear baseline by identifying Critical to Quality (CTQ) characteristics and quantifying process performance through metrics like DPMO and overall Sigma Level. In the core Analyze stage, the J48 algorithm processes operational variables to construct a robust classification model that extracts actionable decision rules and pinpoints the dominant attributes driving defects. Finally, the Improve and Control phases translate these empirical insights into targeted corrective recommendations, ultimately visualizing them through an interactive dashboard mock-up designed to sustain continuous, data-driven quality management.

RESULTS AND DISCUSSION

Identify Quality Problems

Problem identification is marked as an important initial stage in understanding the actual condition of the quality of the products produced by the company. This stage is intended to provide a

systematic overview of the level of defects that occur in the outer gear coupling production process at CV. Adi Makmur Metalindo, as well as to identify recurring problem patterns as a basis for designing a quality control model.

Based on historical production data from July 2025 to October 2025, information was obtained regarding the production volume and the number of defective products that occurred during the outer gear coupling production process. The data indicates that out of a total production of 366 units, 62 units were found to have defects. This results in a defect rate of 16.94%. This value indicates that the proportion of defective products is relatively high and is above the general tolerance limit in the manufacturing industry, which is generally around 5%. Table 4.1 below presents a distribution of the number of defects based on the type of defect that occurred during the observation period.

Table 4.1 Distribution of Number of Defects

Month	Production	Disabled geometric	Disabled surface	Total disabled	Non defect	Percentage disabled
July 2025	94	10	6	16	78	17.02
August 2025	88	9	6	15	73	17.05
September 2025	94	10	6	16	78	17.02
October 2025	90	10	5	15	75	16.67

Source: CV. Adi Makmur Metalindo, 2026

Based on Table 4.1, the defect rate for outer gear coupling products during the four months of observation ranged from 16.67% to 17.05%. This value indicates that the proportion of defects is relatively stable from month to month, although production volumes experience slight variations. Geometric defects are the most frequently occurring type of defect, with 9–10 units per month, while surface defects are in the range of 5–6 units. This pattern indicates that quality issues are not transient, but rather recurrent in the production process. The data is then visualized in Figure 4.1 as follows:

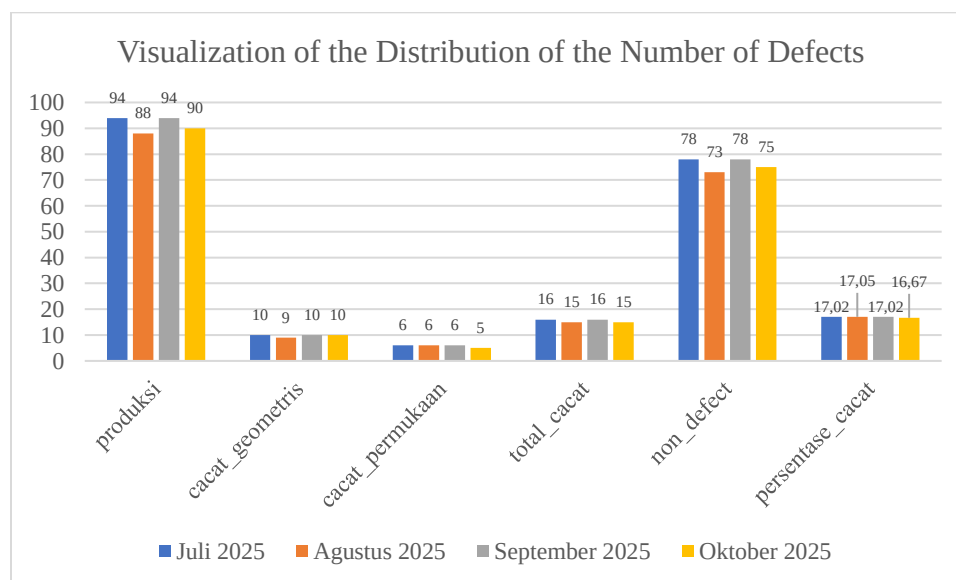


Figure 4.1 Visualization of the Distribution of the Number of Defects

Source: CV. Adi Makmur Metalindo, 2026

Figure 4.1 shows that the production volume of outer gear couplings during the period from July to October 2025 was relatively stable, ranging from 88 to 94 units per month. Although the number of defect-free products was greater than that of defective products, the defect percentage of around 16–17% still indicates the presence of quality problems. Geometric defects were more dominant than surface defects throughout the entire production period. This condition reinforces the indication that geometric defects need to be a top priority in quality control analysis, without ignoring surface defects, which also still contribute to the total defect rate.

Define Phase

define stage aims to identify the primary requirements for designing a quality control model based on the actual production process conditions (Zulkhulaifah & Apriliani, 2024). Critical to Quality (CTQ) is positioned as the primary quality characteristic that must be met by the outer gear coupling product . The CTQ is structured based on the relationship between defect types, product quality characteristics, and process attributes that potentially affect production results. The formulation of this CTQ is important because it serves as the basis for determining the focus of quality measurement and selecting attributes to be used in the classification model. Details of the CTQ for the outer gear coupling product are presented in Table 4.2.

Table 4.2 CTQ of Outer Gear Coupling Products

No	Main CTQ	Sub Types of Defects	Quality Characteristics	Related Process Attributes	Explanation
1	Outer Gear Coupling Product Defects	Geometric Defects	Accuracy of product dimensions and shape	rpm_rough_lathe, rpm_finish_lathe, depth_of_cut, condition_of_the_cut , operator skill	Dimensional mismatches can occur due to unstable cutting parameters, poor tool conditions, or suboptimal machine settings.
		Surface Defects	Surface finishing quality	feed_rate, lathe_rpm, tool_edge_condition, inspection process, operator skill	Rough surfaces or finishing defects tend to be related to cutting parameters, tool conditions, and the precision of the machining process.

Source: CV. Adi Makmur Metalindo, 2026

Table 4.2 shows that the main CTQ in this study is the outer gear coupling product defect , which is divided into two subtypes of defects, namely geometric defects and surface defects. Geometric defects are related to the accuracy of the dimensions and shape of the product, while surface defects are related to the quality of the machining finish . Both types of defects are related to process parameters, cutting tool conditions, process stability, and operator skills. The Pareto principle approach is used as to reveal that the majority of quality problems that occur are generally caused by a number

of small but still dominant factors. The results of the Pareto analysis are explained in more detail in Figure 4.2:

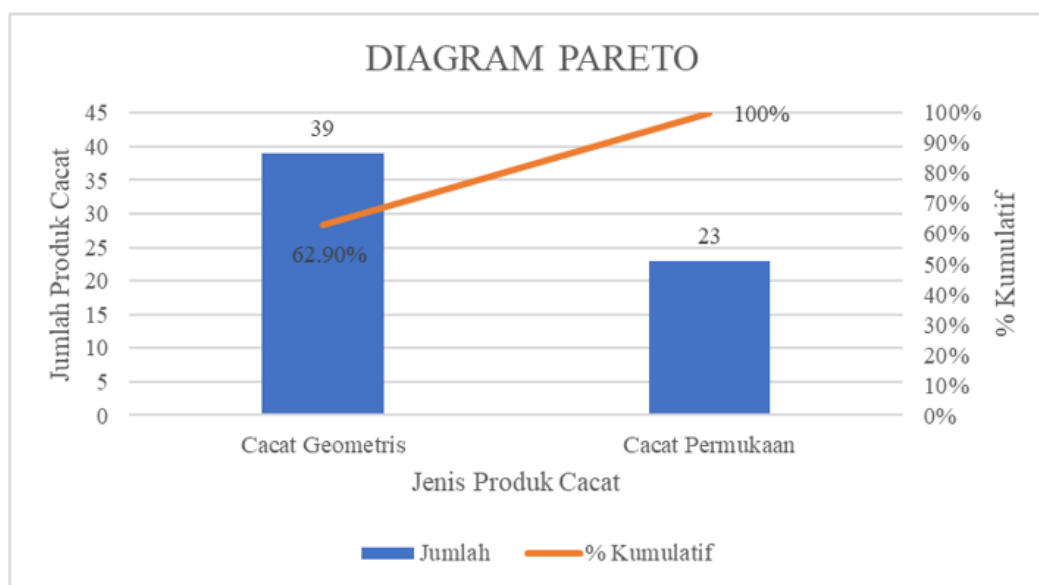


Figure 4.2 Pareto Analysis of Defects

Source: Excel Output , 2026

The Pareto analysis in Figure 4.2 reveals that geometric defects are the most dominant type of defect, contributing 62.90% of the total defects. Surface defects contribute 37.10%. Although both types of defects contribute significantly, geometric defects are prioritized because they account for the largest proportion of all defects. In accordance with the Pareto principle, most quality problems are generally caused by a small number of dominant factors (Selviani & Mahariani, 2025). Surface defects are still considered in the study because their contribution is still quite large and has the potential to affect overall product quality.

Measure Phase

measure stage aims to quantitatively measure the quality performance of the outer gear coupling production process as a basis for designing a quality control model. Measurements are carried out using several main indicators in Six Sigma , namely defect rate, Defects Per Unit (DPU), Defects Per Opportunity (DPO), Defects Per Million Opportunities (DPMO), to determine the sigma level . Then, a defect distribution analysis process is also carried out to present a visual picture of the defect patterns that occur. The more complete DPMO value is presented in Table 4.3 as follows:

Table 4.3 Calculation of DPMO Value

Month	Production	Total Defects	CTQ	DPO	DPMO
July 2025	94	16	1	0.1702	170,213
August 2025	88	15	1	0.1705	170,455
September 2025	94	16	1	0.1702	170,213
October 2025	90	15	1	0.1667	166,667
Total	366	62	1	0.1694	169,399

Source: CV. Adi Makmur Metalindo, 2026

Based on Table 4.3, the monthly DPO value ranged from 0.1667 to 0.1705. This value indicates that the probability of defective products occurring was relatively consistent throughout the observation period. The highest DPMO value occurred in August 2025 at 170,455, while the lowest DPMO value occurred in October 2025 at 166,667. Overall, the total DPMO value of 169,399 indicates that the production process still produces a fairly high level of defects. Although there was a slight decrease in October 2025, the change was not strong enough to indicate significant process improvement.

The outer gear coupling production process has a sigma level value of 2.46 sigma. This value indicates that the process capability is still at a relatively low level and is still quite far from the six sigma quality standard. This condition indicates that process variation is still quite large and the production process is not yet fully controlled consistently. In relation to distribution practices, production processes with a sigma level below 3 generally still have a high level of variation and are not yet able to guarantee optimal product quality consistency (Alfiansyah et al., 2024). This low sigma value also means that the production system is still dominated by process variations whose causes have not been fully identified (Firmansah, 2025).

Analyze Phase

Analyze stage is intended to build a classification model to identify patterns of relationships between production process attributes and product defect occurrences.

The formation of a classification model using the J48 algorithm begins with determining predictor attributes relevant to the production process and the potential for defects in outer gear coupling products. The attributes used are grouped into several categories, namely operator factors, turning process parameters, scrap process parameters, cutting tool conditions, workpiece clamping stability, work environment factors, inspection activities, and target attributes in the form of quality status and types of defects. The selection of these attributes is based on their relationship to the quality of dimensions, tooth profiles, and surface conditions of products produced during the machining process.

The dataset used in this study consists of 366 data units (instances) representing the production conditions of each outer gear coupling. Based on the results of processing using WEKA, the dataset contains 27 attributes consisting of identity attributes, predictor attributes, and target attributes. The distribution of production data is relatively even in the period from July to October 2025. Operator factors are one of the important attribute groups that include age, work experience, number of trainings, and operator codes in the turning and scrap processes. Operator profiles show variations in levels of experience and competence, where operators P1 and P2 have the highest experience in the turning process, while operators P5 and P6 are more dominant in the scrap process with a greater number of trainings.

The results of the exploration of human resource attributes indicate variations in characteristics between operators. Lathe operators have an age range of 26–45 years with an average of around 31 years and work experience between 12–84 months. Meanwhile, scrap operators have a more homogeneous age range, namely 26–35 years with an average work experience of around 14 months. The number of trainings for lathe operators ranges from 0–2 times with an average of less than one training, while scrap operators have a higher average training. In addition, the overtime attribute shows

an average additional working time of 1,126 hours, which indicates variations in workload during the production period.

Exploration of process attributes shows that machining parameters have quite a wide variation. In the turning process, the rough rpm value is in the range of 39.9–83.2 rpm and the finishing rpm is 76.1–143.6 rpm. Feed rate and depth of cut in both turning and scrap processes are relatively more controlled compared to the machine speed parameters. In the scrap process, the stroke speed has an average of 32.744 spm with quite visible variation, while the scrap feed rate shows a more consistent distribution. The condition of the tool blade in both processes is predominantly in the good category, although there are still some tools that are starting to wear or have worn. In addition, most of the production process is carried out with stable clamping conditions, but there are still a number of samples that show unstable to unstable conditions.

Process supporting factors were also analyzed through in-process inspection attributes, fan usage, quality status, and product defect types. The exploration results showed that only a small portion of samples underwent inspection during the process, while the majority did not receive inspection between processes. The use of fans also showed a relatively balanced distribution between conditions using and not using fans. In terms of product quality, 304 samples were categorized as non-defective and 62 samples were defective. When viewed by defect type, there were 39 cases of geometric defects and 23 cases of surface defects. This distribution became the basis for developing the J48 classification model to identify the dominant attributes related to the occurrence of each type of defect.

Improve Phase

Unlike the conventional approach that directly implements improvements in the field, the improve stage focuses on interpreting model results and formulating data-based recommendations as part of the quality control model design. According to the rule extraction results from the J48 algorithm, it is known that the `quality_status` and `rough_turning_rpm` attributes are the main factors in determining product quality classification. The `rough_turning_rpm` value plays a particular role in distinguishing the types of defects that occur, thus indicating that turning process parameters have a significant influence on product quality variations. Therefore, the priority of the problem is focused on controlling technical parameters that are direct and measurable.

The model interpretation results are then used as a basis for formulating proposed corrective actions aimed at minimizing potential defects and improving production process consistency. The proposed improvements take into account the influence of each factor in the model, placing greater emphasis on attributes that are proven to be dominant. A summary of the interpretation results, problem priorities, and proposed corrective actions based on the J48 model is presented in Table 4.8.

Table 4.8 Interpretation Results, Problem Priorities, and Improvement Proposals

Aspect	Results / Findings	Implications	Proposed Improvements	Reason for Selection
Rule Interpretation	Quality status is the main separator between defect and non-defect	Non_defect products are stable and easy to classify	Focus control on defect conditions	Because quality variations occur when defects occur

Dominant Factor	rpm_lathe_rough as the most influential attribute	Process parameters greatly determine the type of defect	Standardization of the value of rough lathe rpm	The most dominant technical attributes in the model
Defect Pattern	≤ 53.9 = geometric	RPM too low causes dimensional mismatch	Avoid too low rpm	Reducing geometric defects
	53.9 – 65.5 = surface	RPM is triggering finishing defects	RPM range optimization	Maintain surface quality
	> 65.5 = geometric	Too high RPM causes deformation	Limit maximum rpm	Avoiding defects
Problem Priority	Turning process parameters (rpm)	Major sources of quality variation	Focus control on the machine, not other factors	Based on the results of the J48 model
Supporting Factors	Operator, tool, environment is not dominant	Smaller influence in classification	Remain controlled as a supporting factor	Maintaining system stability
Action 1	RPM standardization	Reducing process variation	Establishing optimal rpm range SOP	Production consistency
Action 2	Monitoring engine parameters	Prevent deviations	Regular monitoring (manual/system)	Early detection of errors
Action 3	Operator training	Improve process understanding	Parameter setting training	Support SOP implementation
Action 4	Evaluation of machines & cutting tools	Ensure engine performance	Periodic maintenance	Avoiding technical glitches
Improvement Approach	Focus on measurable technical factors	More effective repairs	Data-driven implementation	According to the model results
Feasibility of Implementation	Realistic in the field	Easy to apply	Integration with production systems	Supporting sustainability

Source: Research Output , 2026

The analysis results show that products in the non-defect category can be classified consistently with a good level of accuracy. Meanwhile, for products with defects, the rough turning rpm parameter is the main factor that differentiates the types of defects that appear. Rough turning rpm values that are too low (≤ 53.9) tend to trigger geometric defects, while values in the range of 53.9–65.5 more often produce surface defects. On the other hand, rough turning rpm values exceeding 65.5 again increase the potential for geometric defects to appear. These findings indicate that inaccurate rotational speed settings during the turning process are one of the dominant causes of product quality variations. Therefore, improvement efforts are focused on controlling process parameters, especially

rough turning rpm, because it has proven to be the most influential attribute compared to other factors such as operators, equipment conditions, and work environments that do not appear as primary factors in the classification model.

Based on these results, the proposed improvement step is to standardize the rough lathe rpm value by establishing an optimal operating range to minimize the risk of product defects. The recommended rotational speed range is in the range of 55–65 rpm because in this interval product quality tends to be more stable and the defect rate is relatively lower compared to conditions where the speed is too low or too high. Implementation of this control is the responsibility of the lathe operator, while the monitoring function is carried out by the quality control department and the production manager to ensure that process parameters remain within standards. Measurement and verification of the rpm value are carried out before production begins, periodically during the process, and after changes in machine settings or operator changes. Monitoring activities are supported by the use of a machine display panel, a digital tachometer, and a process parameter recording form that contains the actual rpm data, inspection time, operator identity, and machine condition.

The success of implementing rpm parameter control can be measured by the stability of the rpm value within the specified range, a reduction in the number of geometric and surface defects, and an increase in the proportion of products meeting quality standards. If deviations in the rpm value are found outside the recommended limits, the operator must immediately adjust the machine settings. If deviations occur repeatedly, further action is required, including checking the machine condition, evaluating cutting parameters, checking the tool condition, and conducting retraining for the operator. Furthermore, improving operator competency in understanding process parameter settings and their impact on product quality is also necessary on an ongoing basis. Periodic evaluation of the machine and cutting tools is essential to ensure that all parameters are running optimally. The selection of corrective actions is based on the results of the analysis that shows that process parameters are the most determining factor in the occurrence of defects, so that a measured and realistic approach is expected to improve product quality while supporting the sustainability of the company's quality control system.

Control Phase

The Control phase focuses on designing a model-based monitoring system to ensure that the analysis results of the J48 algorithm can be applied practically and sustainably in the quality control process. Unlike conventional Six Sigma approaches that generally use tools such as Fishbone Diagrams or Failure Tree Analysis (FTA) to identify root causes of problems, this study positions the J48 algorithm as a key component in developing a quality control system. The resulting decision rules not only serve as analysis output but also serve as the basis for the monitoring and decision-making process. Through the rule extraction process, attributes that have a significant influence on product quality can be identified, with `quality_status` and `rough_lathe_rpm` as the main variables that need to be monitored continuously. The analysis results show that `rough_lathe_rpm` is the most dominant attribute in determining the type of product defects, so controlling this parameter becomes the main focus to maintain consistent production quality.

To support the monitoring process, a monitoring system is designed to display important information such as production volume, number of defective products, defect percentage, rough lathe rpm value, and defect type classification results based on the J48 model. In addition, the resulting

decision rules are presented in a simple form to make it easy for users to understand in identifying the relationship between process conditions and potential product defects. The system is also equipped with a corrective action recommendation feature that is integrated with the classification results, so that each detected condition can be immediately followed by appropriate handling suggestions, such as adjusting the rpm parameters to the range that is at risk of causing defects. Thus, the designed system not only functions as a means of quality monitoring, but also as a decision support system that helps operators and management in making data-based decisions to improve and maintain the quality of the production process.

In order to clarify the implementation of the model results into the monitoring and decision-making system, the decision rules generated by the J48 algorithm are translated into the form of monitoring requirements, risk indicators, and action recommendations that can be implemented operationally, as presented in Table 4.9.

Table 4.9 Translation of Rule J48 to the Monitoring and Decision-Making System

Rule J48	Monitored Parameters	Condition	Risk Status	Information Displayed	Recommended Actions
IF quality_status = non_defect	Quality status	<i>Non-defective</i>	Safe	Normal production quantity	Maintain process conditions
IF defect AND rpm $\leq$ 53.9	RPM rough lathe	Too low	Tall	Geometric defect warning	Increase the RPM to the optimal range
IF defect AND rpm 53.9–65.5	RPM rough lathe	Medium range	Currently	Indication of surface defects	Optimize RPM settings
IF defect AND rpm $>$ 65.5	RPM rough lathe	Too high	Tall	Geometric defect warning	Lower the RPM to a safe limit

Source: Research Output, 2026

The translation results of the decision rules generated by the J48 algorithm show that each rule can be systematically converted into monitoring requirements, risk identification, and recommendations for corrective actions. In non-defect conditions, the system indicates that the production process is under control and can run according to standards without requiring special actions. Conversely, in defect conditions, the rpm_lathe_rough parameter is the main indicator in determining the level of risk and the type of defects that could potentially occur. RPM values that are too low (≤ 53.9) or too high (> 65.5) both increase the likelihood of geometric defects, while the rpm range of 53.9–65.5 tends to be associated with the risk of surface defects. These findings indicate that controlling the rpm value within the optimal range is a critical factor in maintaining product quality. Through this rule mapping, the monitoring system not only functions to display process conditions in real-time but also is able to provide risk interpretation and appropriate action recommendations based on the results of the model classification.

The quality control concept is then visualized in the form of a dashboard mock-up that integrates production information, defect rates, J48 model classification results, decision rules, and corrective action recommendations in one structured display. This dashboard is designed as a conceptual prototype that illustrates how production data, process parameters, and analysis results can be used in an integrated manner to support data-driven decision-making. In addition to displaying the final

results in the form of quality information, the dashboard design also shows the overall system flow from the data input stage, the model analysis process, monitoring, decision support, to evaluation and control. Thus, the developed mock-up serves as an initial design that can become the basis for developing a quality monitoring system in the next implementation stage, while also helping users understand the relationship between process parameters, classification results, and corrective actions needed to improve production quality.

In the initial stage, users enter the production quality control monitoring system by logging in with a username and password . The initial display displays the J48 algorithm-based quality control system identity and an access menu to the main dashboard . This stage aims to ensure that only relevant parties, such as production operators, quality control , and supervisors, can access the system. who can access the system. The mockup display is represented in Figure 4.34 as follows:

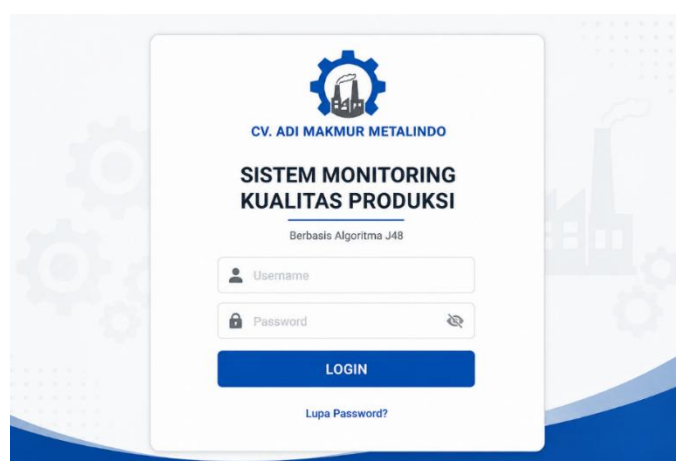


Figure 4.34 Monitoring System Login Page Mockup
Source: Research Output, 2026

After successfully logging in , users are directed to the main menu page, which contains several of the system's key features. This menu serves as the navigation center for inputting production data, running J48 analysis, viewing classification results, and opening the quality monitoring dashboard . This is shown in Figure 4.35.

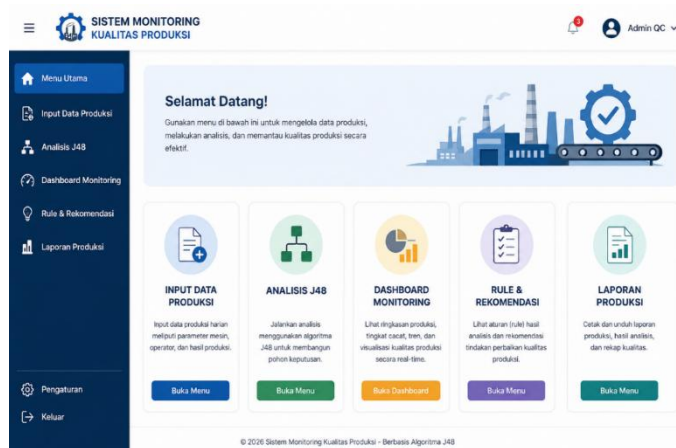


Figure 4.35 Mockup Main Menu Dashboard Monitoring System

Source: Research Output , 2026

Next, production data is inputted. At this stage, the operator or quality control department enters production data to be analyzed by the system. The data entered includes production process parameters and product conditions , which are attributes in the J48 algorithm. This is shown in Figure 4.36:

SISTEM MONITORING KUALITAS PRODUKSI

Admin QC

Input Data Produksi
Masukkan data produksi untuk dianalisis oleh sistem

1. Bulan Produksi Mai 2026	7. Feed Rate (mm/rev) Contoh: 0.25
2. Kode Pekerja Bubut Contoh: BB-012	8. Depth of Cut (mm) Contoh: 1.2
3. Umur Pekerja (tahun) Contoh: 28	9. Kondisi Mata Pahat -- Pilih Kondisi --
4. Pengalaman Kerja (tahun) Contoh: 5	10. Status Kualitas -- Pilih Status --
5. RPM Bubut Kasar (rpm) Contoh: 120	11. Jenis Cacat -- Pilih Jenis Cacat --
6. RPM Bubut Finish (rpm) Contoh: 180	

Reset Simpan Data Proses Analisa

Figure 4.36 Production Data Input Menu Mockup

Source: Research Output , 2026

Before data is processed, the system displays a summary of the data entered by the user. This step allows the user to double-check to ensure there are no errors in the production data input. This is shown in Figure 4.37:

SISTEM MONITORING KUALITAS PRODUKSI

Admin QC

Ringkasan & Validasi Data Input
Periksa kembali data yang telah Anda masukkan sebelum diproses

RINGKASAN DATA INPUT PRODUKSI

No.	Bulan Produksi	Kode Pekerja Bubut	Umur (tahun)	Pengalaman Kerja (tahun)	RPM Kasar (rpm)	RPM Finish (rpm)	Feed Rate (mm/rev)	Depth of Cut (mm)	Kondisi Mata Pahat	Status Kualitas	Jenis Cacat
1	Mai 2026	BB-012	28	5	120	180	0.25	1.2	Baik	Defect	Geometris

INFORMASI DATA
Jumlah Data yang Dimasukkan : 1 record
Tanggal Input : 10 Mei 2026 10:15
Input Oleh : Admin QC

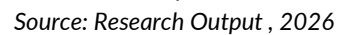
STATUS VALIDASI
Status Data : Valid
Data input telah berhasil divalidasi.
Tidak ditemukan kesalahan pada data.

Edit Data Lanjut Analisa

Figure 4.37 Production Input Data Summary Mockup

Source: Research Output , 2026

After clicking "continue analysis," the J48 analysis will be performed. This screen shows the model training process, data preprocessing, and decision tree formation. This is shown in Figure 4.38 as follows:



```

graph TD
    A(status_kualitas) -->|non_defect| B(non_defect [104.0])
    A -->|defect| C(rpm_bubut_kasar)
    C -->|≤ 52.2| D(geometri [22.0])
    C -->|> 52.2| E(rpm_bubut_kasar)
    E -->|≤ 65.5| F(rpm_bubut_kasar)
    E -->|> 65.5| G(kondisi_mata_pahat_bubut)
    F -->|≤ 53.9| H(kode_pemeriksaan_serap)
    F -->|> 53.9| I(permukaan [20.0])
    H -->|P6| J(geometri [2.0])
    H -->|P5| K(permukaan [1.0])
    H -->|P4| L(geometri [0.0])
    H -->|P3| M(geometri [0.0])
    G -->|baik| N(lambung_kerja_jam)
    G -->|mulut_aus| O(geometri [8.0])
    G -->|aus| P(geometri [8.0])
    N -->|≤ 0| Q(geometri [1.0])
    N -->|> 0| R(permukaan [2.0])
  
```

Source: Research Output , 2026

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Figure 4.40 Mockup Dashboard Production Quality Monitoring

Source: Research Output , 2026

The dashboard displays the monthly and daily defect counts , along with a bar chart showing the daily movement data over time. It also displays the percentage of geometric and surface defects. This is followed by the results of the previously performed J48 rules analysis. This is followed by recommendations for implementation, such as adjusting the roughing lathe RPM to the optimal range or conducting operator training on RPM adjustments and quality control procedures.

CONCLUSION

The integration of Six Sigma DMAIC and the J48 algorithm at CV Adi Makmur Metalindo reveals that the outer gear coupling production process operates at a suboptimal quality level. Production data from July to October 2025 shows a 16.94% defect rate (62 defective units out of 366), resulting in a DPU and DPO of 0.1694, and a DPMO of 169,399. These metrics confirm that the manufacturing process is unstable and prone to recurring failures, which are heavily dominated by geometric defects (62.90%) and surface defects (37.10%). To diagnose these systemic issues, the J48 algorithm successfully strengthens the DMAIC "Analyze" stage by structuring and interpreting how key manufacturing variables—such as turning parameters, cutting tool conditions, clamping stability, and in-process inspections—are strongly associated with these specific quality deficiencies.

Furthermore, the actionable decision rules generated by the J48 decision tree provide an empirical foundation for targeted quality improvements, eliminating reliance on generalized assumptions. These rules outline clear parameters for standardizing machine settings, enhancing operator precision, evaluating tool degradation, and securing workpiece stability during machining. To operationalize these findings, the study introduces a quality control support model visualized through an interface dashboard mock-up. This mock-up serves as a conceptual tool that aggregates real-time production metrics, defect classifications, and explicit corrective recommendations into an intuitive layout, establishing a systematic, data-driven workflow from initial performance measurement to visual decision support.

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