Interdisciplinary School of Management and Technology
Institut Teknologi Sepuluh Nopember

JURNAL TEKNOBISNIS
2022 Vol. 8(1), 44-55

Received 20 Jan, 2022; Revised 3 Mar, 2022; Accepted 24 Mar, 2022 | DOI: 10.12962/j24609463.v8i2.1405

Classification Modeling using Methods Cross Industry Standard Process for Data Mining to Improve Product Quality

Pravitasari Anjar Pratiwi[1,2*], Ahmad Saikhu[3]

ABSTRACT

The purpose of this research is to develop a classification model and measure the effect of changes in production inputs on product quality at PT. XZY. This study uses an analytical method adopting the CRISP-DM framework (Cross Industry Standard Process for Data Mining). At the modeling stage, the development of a classification model framework is carried out using the method Random Forest and Logistic Regression. Research results show that by applying the technique oversampling k-Mean SMOTE produces a product classification model with better predictive performance. on models Random Forest with k- Mean SMOTE was able to increase the AUC value from 0.810 to 0.944, while in Logistic Regression there was an increase in the AUC value from 0.690 to 0.724. An increase in the AUC value shows that with k-Mean SMOTE is able to produce a model with very good sensitivity in predicting data classes with low false positive/negative rates. Changes in tow, adhesive, and triacetin materials have a significant effect on the quality of the resulting product. Based on the odds ratio respectively, using adhesive, triacetin, and tow materials with SA/TRIAL status creates a higher chance of producing a product that does not meet the company's quality standards.

KEYWORDS: Cigarette Filter, Data Mining, Logistic Regression, Product Quality, Random Forest

[1]CoE Kretek Engineer, PT HM Sampoerna Tbk, Surabaya, Indonesia
[2]Business Analytics, Interdisciplinary School of Management and Technology, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia
[3]Department of Informatics, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia
*Corresponding author: pravita.anjar@gmail.com

1. INTRODUCTION

Process manufacture can define as activity of where material base changed become so product. From field manufacture, process production is regularly widely defined as something process Where product made from material base through various process, usage equipment and machine, as well as usage energy work based on planning production which careful. Objective production not only makes product, but product the must own mark add, cost production must effective and efficient, so that profitable company. In meaning which wider, production interpreted as something system Which accepted and flexible, capable offer quality the best in accordance with need customer (Scallan, 2003).

According to (Đokić et al., 2012), there is a concept used by world leaders in the manufacturing business namely World Class Manufacturing (WCM). WCM is a synthesis of various concepts, principles, guidelines, and techniques for managing and operating manufacturing companies. The main objectives are constant quality improvement, cost efficiency, production time, flexibility and customer service. Quality is one of the 10 pillars that must be considered by companies because when there is a product quality problem, it will affect other important aspects such as additional costs due to poor quality, high waste, product delivery schedules and others. In addition, if the products produced are not in accordance with customer specifications, this has a long-term impact on the sustainability of the company.

PT. XYZ is one of the manufacturing companies engaged in the production of cigarette filters. The business scheme of PT. XYZ is B2B because the resulting products will be marketed to the cigarette industry. In managing the production process, product quality is an important aspect that must be considered because when defective goods are sent to customers it can be a potential problem in the customer's business process. From the data obtained from the company that during 2018 to September 2022 it is known that the quality of filter products produced by PT. XYZ is not good enough, besides that there has been an increase in production volume over the last 5 years (2018 to 2022). However, the increase was also followed by an increase in the number of customer complaints. Customer complaints received by PT. XYZ had 12 complaints out of a target of 11 complaints for one year. Another criterion that shows customer complaints is the number of Complaints per Billion rods (CPB), which is the number of complaints received by PT. XYZ of every trillion filter rods produced. The CPB value until September 2022 was 1.79, up 17% from the previous year. The value is also lower than the annual target of PT. XYZ is determined by the Group at 1.5 so that it can be concluded that the quality of cigarette filters produced by PT. XYZ in 2022 did not meet the target.

Customer complaints are an indicator that product quality is achieved externally. The high number of customer complaints indicates that defective products cannot be identified and delivered to customers. The second indicator is an external quality indicator. This can be seen from the many anomalies during the production process marked by NCR (Non-conformity Report) and QAN (Quality Alert Notice). NCR or internal complaints during QAN or internal quality problems during the production or inspection process. Achievement of product quality PT. XYZ on the number of internal issues and internal complaints over the past 5 years shows that in 2022 there has been an increase in the number of NCRs and also the projected number of QAN by the end of the year is estimated to reach 1,460 QAN as the highest achievement of the number of internal issues over the last 5 years. NCR is basically sourced from QAN which is major and critical in nature meaning that it has a high number of defects and has the potential to cause serious problems when it comes to customers, so in 2022 an increase in the number of linear QANs with the number of NCRs issued.

The quality of PT. XYZ is determined by the Quality Assurance (QA) Inspector based on criteria or Acceptance Quality Level (AQL). AQL filter products are divided into two parts, namely parameters and visual attributes. Parameters are criteria that can be followed by instruments, such as Circumference, Finish Weight, Hardness, Pressure Drop, Roudness, and others. The filter attribute checked is a visual filter whose AQL is determined from the visual defect guidance book owned by PT. XYZ. Products that do not meet one of the various standard parameters or filter attributes specified will be categorized as defective products that will eventually be rejected. The percentage of defective products produced by PT. XYZ until September 2022 amounted to 8% of the total products produced. This figure indicates that there is a potential data imbalance between quality-qualified passing product categories and defective products.

The business challenges faced by PT. XYZ in 2022 are not only related to product quality. But also, the issue of material availability. Availability of main ingredients vizcellulose acetate (tow) experienced scarcity and significant price increases. The demand for cigarette filters for the mono type with high tow consumption shows a positive trend, resulting in an imbalance between demand and supply. PT. XYZ must remain capable of implementing business processes and meeting revenue targets which were agreed at the beginning of the year, so various changes had to be made to the materials used. High material usage in 2022 has increased significantly, especially in tow materials. The tendency of other materials such as plugwrap, adhesive and triacetin is almost the same from year to year. In addition to the influence of material changes, the high demand in the domestic market led to the allocation of machines for the consumption of certain products and was diverted to other machines with different operators. Changes in important factors of production indirectly affect the quality of manufactured products or lead to possible errors and lead to defective products.

Corrective measures owned by PT. XYZ related to product quality improvement are not yet comprehensive and can be classified as a temporary corrective action. Some improvements are made only to respond to problems that have occurred (corrective action) and not to prevent the same problem from happening again (preventive action). This is evidenced by the combination of the same SKU and engine, there are still many recurring quality problems. Based on the description above, it is necessary to conduct a comprehensive predictive analysis of the quality and available production process data to determine potential errors in the production process and prevent product defects. In order to perform predictive and prescriptive analytics, manufacturing companies must digitize diverse and unstructured information from various sources. This must be done so that the analysis process is more efficient.

According to (Clancy et al., 2023), Cross Industry System Process for Data Mining (CRISP- DM) is an approach to data mining that helps digitize data in the production process to create analytics that can help reduce the number of defective products through predictive and prescriptive analytics. In addition, CRISP-DM can be combined with Machine Learning to optimize production processes to detect or even be able to prevent defects at the beginning of the production process that are related to each process. The binary classification model is used by (Buschmann et al., 2021), for defect prediction using decision trees equipped with several Machine Learning models such as Gradient Boosting, Random Forests, Extra Tree Classification, Stacked Decision Trees, and Logistic Regression with L1- regularization. The same thing was also done by (Kumari et al., 2022), to formulate predictive and perscriptive models of parameters that affect the quality of car bumpers using Logistic Regression because the problem analyzed is a type of binary classif ication.

The CRISP-DM framework is relevant enough to help PT. XYZ in formulating prediction models in product classification because it is quite often used in the field of quality assurance. The method will be combined with various classification models to be able to predict potential product defects during the production process with high predictive accuracy. Based on the description above, it is necessary to conduct research on the classification model of cigarette filter products at PT. XYZ with the CRISP-DM method to assist companies in formulating quality improvement strategies that are significantly able to improve the quality of cigarette filter products produced.

Based on the explanation above, it can be formulated the problems that underlie the need for research, namely as follows; development of a classification model framework to determine the quality of cigarette filter products at PT. XYZ and measure the impact of input changes on the quality of cigarette filter products at PT. XYZ

2. LITERATURE REVIEW

Product Quality

Quality can be measured in various ways, it can be in the form of physical metrics, aesthetic attributes, or functional characteristics attached to a product or service offered. In general, quality includes several attributes such as: (1) conformity to specifications, (2) as close as possible to zero defects, (3) reliability and durability, (4) serviceability if it is customer service, or (5) customer preference which is good. Quality measurement is very specific to the product produced. In the manufacturing process, the focus of quality is on physical characteristics such as defects, reliability, or consistency of the products produced (Doane & Seward, 2009).

The term quality is inseparable from quality management which studies every area from operations management from product line and facility planning, to scheduling and monitoring results. Quality is part of all other business functions (marketing, human resources, and finance). In reality, quality inquiry is a natural common cause for unifying business functions. There are seven quality factors, namely management support, quality information, process management, product design, workforce management, supplier involvement, and customer involvement (Ariani, 2020).

A good quality product or service allows an organization to attract and retain customers. Poor quality leads to customer dissatisfaction. One of the causes of poor product quality is the occurrence of product defects or defective products that pass to customers. Defective products can be found in every product manufacturing process, especially in the production process itself (Kim-Soon, 2012).

Cigarette Filter

The initial concept of filters in cigarettes began to be introduced in 1860 to 1920 with the aim of keeping tobacco particles from entering the mouth. The filter was originally a potted cigarette holder and contained cotton as a blockage. In 1952 cigarette filter products began to be launched using celulose acetate which was used as a cigarette filter industry standard afterwards, until in 1977 it was confirmed that 93% of cigarettes marketed had filters while the rest were unfiltered. In 2002 began to develop filters containing activated carbon as a form of response to filter development to health, then PMI (Phillip Moris International) began to develop cigarette filters with flavor in 2003 and was quite popular among youth. Five years later a cigarette filter with flavor was developed and equipped with a capsule which when broken (crushed) will produce a liquid that makes cigarettes taste like menthol or other flavorings (Pauly et al., 2009).

According to (Figlar et al., 2004), cigarette filters are made from fibrous materials such as cellulose acetate or paper to eliminate cigarette smoke particulates produced through mechanical processes. As for (Mohsen et al., 2018) explained that cigarette filters are specifically designed to absorb vapor and accumulate particulate smoke components generated through the combustion process of cigarettes. The material used to make cigarette filters consists of 81.6% cellulose acetate, 10.18% plugwrap, 7.4% triacetin, 0.46% hotmelt glue, and 0.34% polyvinyl glue. Cigarette filters can be produced using KDF2 type filter machines.

Cross Industry Standard Process for Data Mining (CRISP-DM)

The Cross Industry Standard Process for Data Mining (CRISP-DM) was designed in 1996 as a complete and well-documented data mining method. The use of these methods often also uses several statistical methods so that the results obtained are more accurate. The CRISP-DM method is very suitable for processing large data and is quite widely used in various scientific fields with a clear and easy-to-understand explanation of data mining steps (Abdurachman et al., 2022). CRISP- DM is a comprehensive data mining methodology with a process model that can be used by everyone, even those who are not experts in the field of data mining (Shearer C, 2000). CRISP-DM breaks down the data mining life cycle into 6 phases, namely (1) Business Understanding, (2) Data Understanding, (3) Data Preparation, (4) Modelling, (5) Evaluation, (6) Deployment.

According to the Data (Saltz, 2023) Cross Industry Standard Process for Data Mining or known as CRISP-DM is one of the most popular frameworks used in executing data science projects. Based on the DSPA Poll in 2020, it can be seen that CRISP-DM is most in demand by data science project practitioners as much as 49% of the total sample surveyed. This method can provide a work process or workflow that is easy to understand and focuses on the data needed for a specific project but needs to be combined with other frameworks in order to achieve the expected data mining goals.

Cross Industry Standard Process for Data Mining (CRISP-DM)

The Classification Model is one of the prediction analyses with response variables in the form of categorical data (discrete, not sequential). Classification is the process of defining models (or functions) that describe and differentiate classes or concepts of data. The model is derived based on analysis from training data (data label objects whose categories are known). A model used to predict data whose category is not yet known. Classification models can be derived using several methods such as decision trees, mathematician formulas, or neural networks. A decision tree is a flowchart-like tree structure where each node represents a test on an attribute value, each branch represents a test result, and a leaf of the tree represents a class category. Decision trees can be easily turned into classification models. Neural networks can also be used for classification models, which are collections of processing units such as human neural networks (Han et al., 2012).

According to (Tufféry, 2011), classification (discriminant) is one of the predictive analysis techniques in data mining along with Regression (prediction). The purpose of the two techniques is to estimate the value of the response/dependent/target variable of an individual object or function of a value against the independent variable/control/predictor. Classification is an operation that places each individual of the population under study in one category or class based on the characteristics of that individual or determined according to a particular algorithm. In practice there will be two predicted classes or categories. There are two types of methods that can be used in classification techniques or models, namely inductive technique and transudative technique.

Model Selection

Model Selection is the process of selecting the best statistical model from a set of candidate models resulting from the processing of the given data. The best models can be obtained easily when using effective methods or tools. The method or tool that is considered to determine the best classification method is the collaboration between values in the confusion matrix, Receiver Operating Characteristic (ROC) chart and Area Under the Curve (AUC)

3. METHODS

In order to achieve the research objectives to develop a classification model framework as well as the effect of changes in main production inputs on the quality of the products produced requires data mining techniques based on production and quality checking databases. The analysis method adopts the CRISP-DM (Cross Industry Standard Process for Data Mining) framework. The steps taken by researchers to formulate a product classification model for the quality produced. The first stage is to answer the formulation of the first problem using a data mining framework with the Cross Industry Standard Process for Data Mining (CRISP-DM) method. Data that has gone through the preparation phase and has become the final dataset is ready to be analyzed and formulated as a classification model. Before modeling, the final dataset can be analyzed first with descriptive analytics to perform descriptive and diagnostic analysis of the data. In addition, at this stage also requires pre-processing in the form of data balancing to prevent biased results by doing SMOTE and Label Encoder (replacing string data into numeric).

The data used in the study is secondary data. The data is obtained from the results of checking the quality of cigarette filter products in the form of checking parameters and attributes along with production process data that is consolidated thoroughly in the Manufacturing Software of PT. XYZ. The data collection period is June 2020 to September 2022 considering that the historical data available in the software is until June 2020 and in October 2022 there was a change in quality checking procedures, so that the attributes owned by the data are not uniform. The process of formulating a classification model is carried out with the identification of relevant variables for research purposes

4. RESULTS

Classification Model Framework for Determining Product Quality

The framework of the cigarette filter product quality classification model has been obtained using two algorithms, namely Random Forest and Regerei Logistics. Both algorithms produce different matrices. To determine the best classification model in predicting product quality, it is necessary to compare these metrics. In addition, there are other parameters that can be used to compare classification models, namely ROC and AUC. AUC or Area Under Curve is the measurement of the entire two-dimensional area under the entire curve of the Receiver Operating Characteristic (ROC). ROC (Receiver Operating Characteristic) Curve is a commonly used performance evaluation tool for binary classification models. The ROC Curve maps the sensitivity of the model to false positive rates. The ROC Curve comparing the two models can be seen in Figure 1:

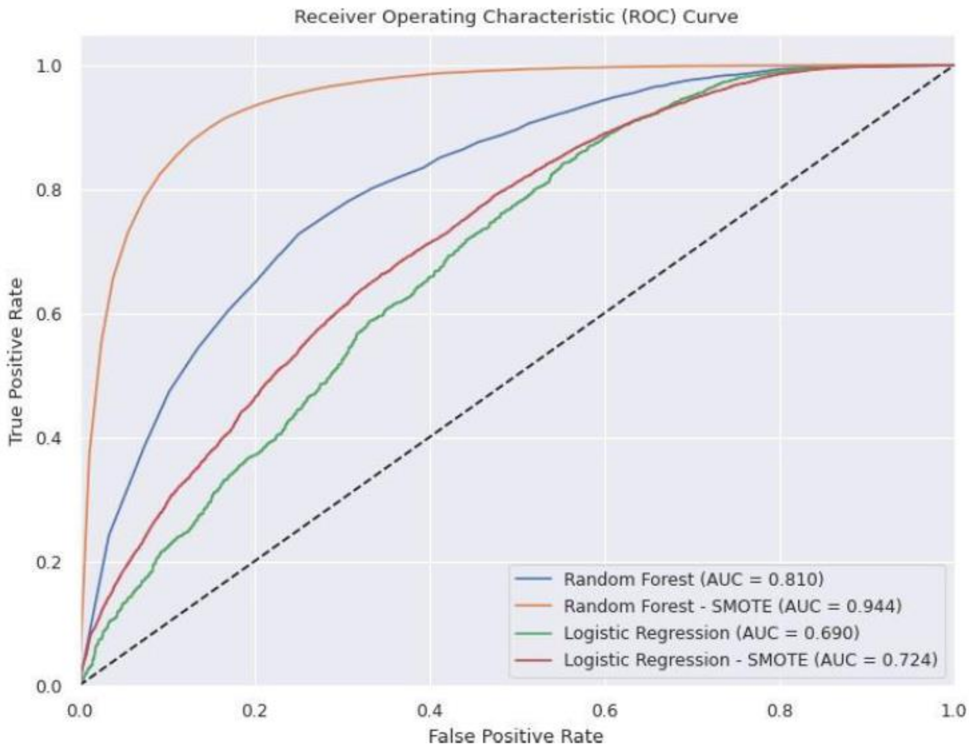

FIGURE 1. ROC Curve

The AUC graph illustrated in Figure 1 shows that with the application of k-Means SMOTE is able to increase the AUC value for both models. The random forest model with SMOTE gives an AUC value of 0.944 greater than the normal random forest model with an AUC value of 0.810. The application of SMOTE to logistic regression gives an AUC value of 0.724 better than the original logistic regression model with an AUC value of 0.690. Overall, SMOTE is able to provide a greater true positive rate value than without over sampling. A comparison of AUC values after SMOTE between Random Forest and Logistic Regression shows that random forests have higher AUC values. An AUC Random Forest value of 0.944 means that the model shows Outstanding Discrimination, indicating that the model has excellent sensitivity to class differences and does not produce many false positives. Logistic Regression gives an AUC value of 0.724 giving acceptable discrimination, meaning that the model has a fairly good sensitivity to class differences, but can still produce some false positives.

In determining the best classification model, it is necessary to compare thoroughly the results of confusion matrix calculations in Tables 1 and AUC values in Figure 1. Based on several parameters that have been obtained, there are five parameters that can be compared to determine the best product classification model. Considering that there is an imbalance d ata condition in class 0 (NOK), the comparison of metrix in the confusion matrix focuses on class 0 and compares the effectiveness of the application of oversampling techniques with k-Means SMOTE. The following is a comparison of the analysis metrics obtained along with the AUC value as an additional parameter to determine the best model:

TABLE 1. Parameter in Classification Models

Parameter	Random Forest		Regresi Logistik	
	Original	SMOTE	Original	SMOTE
Precision	0.67	0.94	0.77	0.70
Recall	0.22	0.96	0.12	0.54
F1 Score	0.60	0.95	0.21	0.61
Accuracy	0.93	0.95	0.93	0.66
AUC	0.810	0.944	0.690	0.724

Table 1 shows that there are several parameters that can be used to compare two classification models. Thus, it can be concluded that the random forest model with SMOTE provides the highest accuracy, precision, recall, F1 Score, and AUC. The existence of SMOTE with k-Means clustering is able to improve Precision, Recall, and F1 Score values in Random Forest and Logistic Regression models. In modeling product classification against the quality produced, the random forest model is the best model for problems in cigarette filter products at PT. XYZ.

Impact of Input Changes on Product Quality

Changes in production inputs that often occur in the last 2 years are challenges faced by PT. XYZ and allegedly has an influence on the quality of the products produced. High customer complaints and the high potential for product defects are thought to be the impact of frequent changes in production inputs. In order to answer problems related to the impact of changes in production inputs, logistic regression analysis was carried out with Minitab 19.

The logistic regression model was built with four predictor variables, namely Tow Material Status (X13), Plugwrap Material Status (X14), Adhesive Material Status (X15), and Triacetin Material Status (X16) with each having three categories, namely, FINAL, SUB, and SA/TRIAL. FINAL is the main material status and has been validated through various trials and long-term use, so that it is ensured from the material aspect that it meets the standards to produce products with appropriate quality. SUB is an alternative material that can be used, but not a priority use. SUB type materials have been validated for long-term use. Material with SA / TRIAL status is material that should not be used because it does not meet the standards or criteria determined by the customer or PT. XYZ so that it has the potential to produce prod ucts whose quality is not appropriate.

Analysis of the relationship between 19 predictor variables was performed with Minitab 19 using the Logit function. There are several statistical tests conducted to determine the influence between predictor and response variables, including Goodness of Fit test, Overall Parameter Test, Individual Parameter Test, and Odd Ratio Interpretation. The following are the results of logistic regression model analysis to measure the impact of material changes on product quality.

Based on testing logistic regression models to measure the impact of material changes on product quality, there are three materials that significantly affect the quality of the products produced, namely, tow, adhesive, and triacetin. Successive material changes that have the highest impact on the chances of obtaining products with quality that are not in accordance with standards (NOK) are:

1. Change of adhesive material to SA / TRIAL with odds ratio 0.1853
2. Substitution of triacetine material to SA/TRIAL with odds ratio 0.2847
3. Change of tow material to SA/TRIAL with odds ratio 0.4891
4. Substitution of triacetin material to SUB with odds ratio 0.6046
5. Change of tow material to SUB with odss ratio 0.7661
6. Change of adhesive material to SUB with odds ratio 1.0889

Thus PT. XYZ can allocate its materials better, especially to key materials that have an impact on quality. FINAL and SUB adhesive materials both have relatively equal opportunities to produce products with appropriate quality, while if using materials with SA / TRIAL status have the highest chance to produce defective products. Triacetine and tow materials for SA/TRIAL and SUB status have a higher chance of producing products of inappropriate quality. Therefore PT. XYZ can anticipate related to validation criteria when using adhevise materials with trial status, such as tightening the Quality Plan, increasing sampling frequency, increasing long-term validation such as durability tests, as well as projecting the use of adhesive, tow, and triacetin materials with SA / TRIAL status not for some categories with the risk of producing inappropriate products.

The risks that can be avoided to use materials with SA / TRIAL status are when production is carried out for new products with low order sequences, products with high waste process indications, problematic machine conditions are indicated by the amount of down time and the number of rejected products. This is because the odds ratio value listed in Appendix 2 shows that the chance to produce a product of suitable quality is less than 1. Moreover. The use of trial material is not recommended for products on High Speed machines and MNC customers because it has a lower odss ratio value than other classes. If there is a back log and these conditions cannot be avoided, it is better to use inappropriate materials that can be used for low speed machines with not so much output in the production period, so that checks can be more intense, as well as products for local customers with quality standards that are not so strict.

5. CONCLUSIONS

Quality classification model of cigarette filter products at PT. XYZ developed using k- Means SMOTE was able to provide better results in predicting minority classes, random forest models with k-Mean SMOTE were able to increase AUC values from 0.810 to 0.944 and logistic regression increased AUC values from 0.690 to 0.724 showing that with k-Mean SMOTE was able to produce models with very good sensitivity in predicting data classes with low false positive/negative rates.

Changes in the input production of tow, adhesive, and triacetine materials have a significant influence on the quality of cigarette filter products produced by PT. XYZ, especially when using materials with SA / TRIAL status respectively, increases the chances of producing products with non-standard quality, namely 0.1853 times for adhesives, 0.2847 times for triacetin, and 0.4891 for tow.

REFERENCES

Abdurachman, E., Thoyyibah, T., Heryadi, Y., & Zahra, A. (2022). CRISP-DM Method for Mood Classification in Indonesian Music 70 and 80 eras. *International Journal of Applied Engineering and Technology (London)*, *4*(1).

Ariani, D. W. (2020). Manajemen Kualitas. In *Jurnal Managemen* (2nd ed.). Universitas Terbuka.

Buschmann, D., Enslin, C., Elser, H., Lütticke, D., & Schmitt, R. H. (2021). Data-Driven Decision Support for Process Quality Improvements. *Procedia CIRP*, *99*, 313–318. https://doi.org/10.1016/j.procir.2021.03.047

Clancy, R., O'Sullivan, D., & Bruton, K. (2023). Data-Driven Quality Improvement Approach to Reducing Waste in Manufacturing. *TQM Journal*, *35*(1), 51–72. https://doi.org/10.1108/TQM-02-2021-0061

Doane, D., & Seward, L. (2009). *Applied Statistics in Business and Economics* (5th ed.). McGraw-Hill Education.

Đokić, I., Arsovski, S., & Pešić-Đokić, S. (2012). Quality and World Class Manufacturing. *International Quality Conference*, *6*, 605–610.

Figlar, J. N., Tucker, B. E., & Charles, K. St. (2004). *Cigarette Filter* (Patent 6779529).

Han, J., Kamber, M., & Pei, J. (2012). Data Mining : Concepts and Techniques. In *Data Mining* (3rd ed.). Elsevier.

Kim-Soon, N. (2012). Quality Management System and Practices. In *Quality Management and Practices* (1st ed.). In Tech. https://doi.org/10.5772/2346

Kumari, R., Saini, K., & Anand, A. (2022). Predictive Analytics to Improve The Quality of Polymer Component Manufacturing. *Measurement: Sensors*, *24*, 1–10. https://doi.org/10.1016/j.measen.2022.100428

Mohsen, S. M., Saleh Ammar, A. alla, & Ateya, A. F. (2018). Effect of Cigarette Filter Components on Its Efficiency and Smoking Characteristics of Cigarettes. *Bioscience Research*, *15*(1), 325–336.

Pauly, J. L., O'Connor, R. J., Paszkiewicz, G. M., Cummings, K. M., Djordjevic, M. V., & Shields, P. G. (2009). Cigarette Filter-Based Assays as Proxies for Toxicant Exposure and Smoking Behavior - A Literature Review. *Cancer Epidemiology Biomarkers and Prevention*, *18*(12), 3321–3333. https://doi.org/10.1158/1055-9965.EPI-09-0925

Saltz, J. (2023, June 1). *Agile, Life Cycle, Project Management*. Data Science Process Alliance.

Scallan, P. (2003). Process Planning: The Design/Manufacture Interface. In *Process Planning: The Design/Manufacture Interface* (1st ed.). Butterworth Heinemann. https://doi.org/10.1016/B978-0-7506-5129-5.X5000-4

Shearer C. (2000). The CRISP-DM Model: The New Blueprint for Data Mining. *Journal Data Warehousing*, *5*(4), 13–22.

Tufféry, S. (2011). Data Mining and Statistics for Decision Making. In S. Tufféry (Ed.), *Data Mining and Statistics for Decision Making*. John Wiley & Sons, Ltd. https://doi.org/10.1002/9780470979174

How to cite this article:

Pratiwi, P. A., Saikhu, A. (2022). Classification Modeling Using Methods Cross Industry Standard Process For Data Mining To Improve Product Quality. *Jurnal Teknobisnis*, 8(2): 44 - 55. DOI: 10.12962/j24609463.v8i2.1405