Data Mining for Quality Prediction in Software-as-A-Service Concept: A Case Study in Offset Printing Company

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ABSTRACT

Purpose: This research aims to design a model of a quality prediction system using data mining methods in the software-as-a-service (SaaS) environment in order to facilitate manufacturers' ability to analyse process and product quality without software investment.

Methodology/Approach: To develop the quality prediction model, this study utilised a data mining methodology to extract knowledge from historical data collected from the offset printing industry, focusing on manufacturing parameters. Four classification algorithms (Decision Tree, k-NN, Naive Bayes, Random Tree) were employed and compared to identify the most precise model specifically tailored for offset printing. Subsequently, the prediction model was integrated into a web-based system to enable quality prediction.

Findings: This study demonstrates the practicality of integrating quality prediction into the SaaS framework, specifically for offset printing. This integration is designed to predict how manufacturing control parameters, such as printing slope angle, engine temperature, paper size, ink density, and roller speed, relate to the occurrence of product defects such as crumpled paper and imprecise printing.

Research Limitation/implication: Generalizability is constrained by its focus on the offset printing industry, and prediction accuracy relies on historical data, which can vary across manufacturing sectors, affecting model performance.

Originality/Value of paper: This article presents the concept and practical implementation of utilising data mining in a SaaS environment to enhance the quality of manufacturing, with a particular emphasis on the offset printing sector.

Category: Case study

Keywords: data mining; offset printing; quality prediction; software as a service

Research Areas: Quality 4.0, Quality Engineering

1 INTRODUCTION

Offset printing is a modern printing technique that is used for the commercialisation of printing products such as newspapers, magazines, and others (Shankar, Ravi and Zhong, 2003; Lundström and Verikas, 2013). Quality and reliability are two important aspects that must be prioritised in the printing process because every company engaged in printing does not want print materials, such as paper, that are wasted due to defects (Shankar, Ravi and Zhong, 2009). Paper, ink, colour management, printing angle, ink-water balance, roller speed, machine temperature, and size of paper are several factors that can affect the quality of printing results (Ng, Conners and Araman, 1992; Kim and Koivo, 1994; Shankar, Ravi and Zhong, 2009).

Some defects that can occur from the results of printing are crumpled paper, rough paper surface, piling, mottling, imprecise printing, etc. (Ejnarsson, Verikas and Nilsson, 2009; Lundström and Verikas, 2013). Based on factors and defect results in offset printing processes, several companies began to prioritise identifying these two aspects in order to improve the quality of products.

In the digital era, characterised by easier access to vast data, manufacturers are actively seeking to leverage data for enhanced quality management systems (Efimova and Briš, 2021). One of the initiatives involves conducting an in-depth analysis to uncover how process parameter data can influence product quality using data mining. Data mining methods have already been shown to be an efficient tool to improve manufacturing product and process quality in semiconductor industry, bio-chemical process, or plastic production (Jemwa and Aldrich, 2005; Chien, Wang and Cheng, 2007; Charaniya et al., 2010). Data mining in a quality management system is a method that can be used to identify hidden patterns in manufacturing control parameters that aim to improve product quality (Harding et al., 2006). Previous research shows that data mining can produce patterns and association rule from parameter control as a factor that affect the quality of product, and it can be used for predictive analysis in manufacturing processes (Da Cunha, Agard and Kusiak, 2006; Kusiak, 2006; Köksal, Batmaz and Testik, 2011).

The greatness of data mining is sometimes not applicable to companies because of high investment prices or the high complexity of the design and implementation of this method. (Medvedev et al., 2017) build a new web-based solution for modelling data mining processes called DAMIS. DAMIS is a data mining method that is implemented in cloud technologies. This web-based data mining show capabilities in data classification, clustering, and dimensionality reduction problems. With this solution, an organisation can analyse their data by using the web without having to build software investment. Another example of implementing web-based data mining is the Apromore software developed by (La Rosa et al., 2011). Apromore can do the analysis, management, and usage of large sets of process models. Apromore can do the process mining to build a business process model. Web-based data mining concept developed by (Medvedev et al.,

2017) and (La Rosa et al., 2011) can be called as software-as-a-service (SaaS) concept. This concept provides services to clients to use data mining software in a web-based or online manner. SaaS is a prevalent software delivery model in the cloud (Elsayed and Zulkernine, 2019).

2 USING SAAS IN QUALITY MANAGEMENT SYSTEM

Manufacturing companies, both large or small and medium enterprise industries, face the challenge of delivering high-quality products while minimising the use of resources (Song et al., 2017; Colledani, Tolio and Yemane, 2018; Sahoo and Yadav, 2018; Khourshed and Gouhar, 2023). Hence, companies will implement and prioritise a quality management system in each manufacturing process. In a conventional quality management system, manufacturing data is obtained from the flow of material during the production process. After that, manufacturing data that has been obtained will be analysed using offline statistical-based analyser software such as SPSS or RapidMiner. (Gao et al., 2011) shows an example implementation of SPSS in processing manufacturing data, specifically to analyse the relationship between soy sauce composition as a manufacturing control parameter on the quality of product taste. Besides the statistical-based approach, in manufacturing data analysis, RapidMiner can be used as a data mining tool to get knowledge from historical data. Gröger, Schwarz and Mitschang, 2014 use RapidMiner to mine manufacturing data to evaluate production processes and improve the quality of products. After the process of data analysis, if the output of analysis shows that data is still in-control, so there is no corrective action. But, if there is out-of-control data, corrective action will be taken to improve manufacturing processes. Conventional quality management systems can be seen in Figure 1.

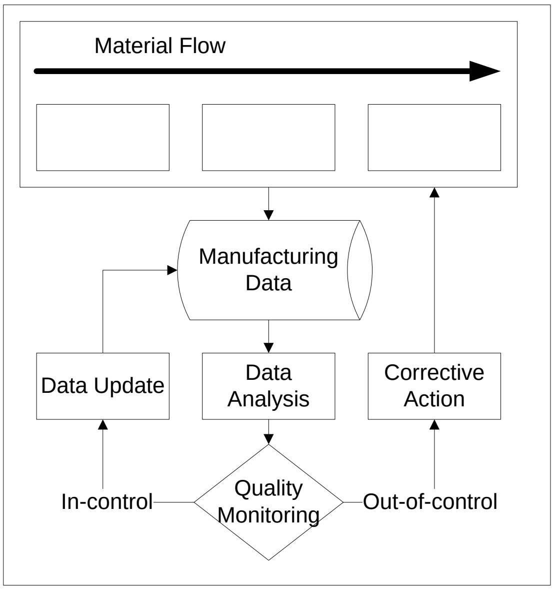

Figure 1 – The conventional quality system

In quality management systems, SaaS can be used to analyse and predict the quality of products and manufacturing processes. With web-based quality prediction systems, companies do not need to invest in quality software because they are only asked to import the data quality on the web. Quality control analyser processes in SaaS concept flow can be seen in Figure 2.

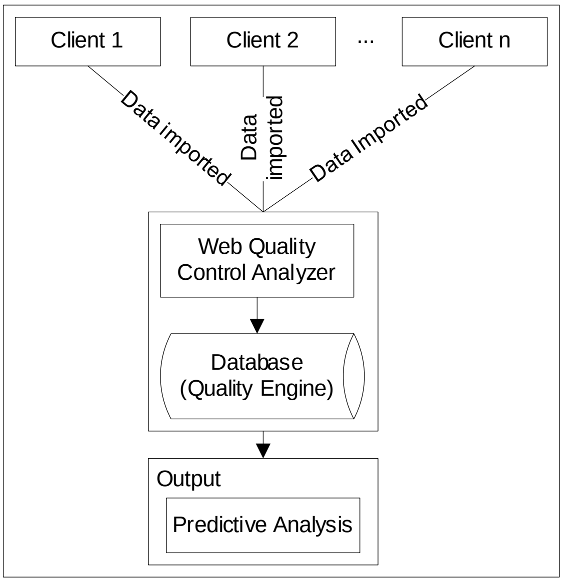

Figure 2 – The SaaS concept for quality prediction

As shown in Figure 2, several clients can access the web-based quality engine. A quality engine processes data imported by a client into an output. The processing can be performed in the form of statistical-based or data-mining approaches to produce predictive analyses.

Association rule or decision tree can be used as a result of data mining processing. This approach produces a quality prediction of product and manufacturing processes. This concept can be implemented in SaaS. After the association rule or decision tree is obtained, the predictive rule is implemented in web-based programming code. With this concept, the client imports data in a certain format to an online-database, and then the engine will process raw data with a data mining approach. The results of processing will be immediately seen or downloaded online by the client in a short time.

3 METHOD

The method focused on data mining methodology, which will be implemented in the SaaS concept. The stages in processing raw data into predictive analysis will be explained and continued with the stages of designing web-based quality prediction that are used as validation stages. In general, this research method is divided into five stages, namely data collection and selection, data preprocessing, knowledge extraction, knowledge presentation, and SaaS prototype implementation.

3.1 Data Collection

Data collection is an important stage in the data mining approach. Relevant data must be obtained from the material flow in manufacturing plants. Several data collection methods were developed by (Lin, Yan and Fu, 2019) to determine relevant data from raw data. This research object is one of the offset printing companies in Indonesia that produces novels (storybooks). This company has manufacturing data control parameters and product defect data from production results. The manufacturing parameters in this offset printing company are as follows:

- Printing slope angle: This parameter is related to the angle position in the printing device for each type of product, which can vary in terms of the angle value (300 ℃, 350 ℃, 400 ℃, 450 ℃, and 500 ℃).
- Roller speed: This parameter is related to the printing device speed, which can be set depending on the production target (5000 rpm and 9000 rpm).
- Printing engine temperature: This parameter is the temperature parameter of the machine, which can increase due to continuous processes on a scale of 260 ℃–280 ℃.
- Paper size: This parameter consists of three types of paper size: S (small), M (medium), and L (large).
- Ink density: This parameter is related to the ink-water balance, which can be different from one production to another production (60%, 70%, and 80%).

All of these manufacturing parameters will predict the effect of the two types of defective paper, namely, crumple defects in the paper cover and imprecise printing. An example of datasets of the relationship between the manufacturing parameter control and paper defects for each novel is presented in Table 1.

There are 1,491 instances in the datasets that will be identified based on the manufacturing plant. Each of the 1,491 titles has a different number of production units. Aside from the difference in the number of productions, five manufacturing control parameters vary for each novel book, accompanied by the percentage of defects produced. Based on this data, data processing will be conducted using a control chart to measure the defective proportion of the production of each type of product. This raw data format can be used as an example of an imported data template from clients in uploading processes on web-based systems that will be designed.

Table 1 – An example of datasets from manufacturing parameter control

No.	Title	Prod. Unit	Parameter					Defect (unit)		Defect (%)	
			Slope Angle (degree)	Roller speed (rpm)	Engine Temperature	Paper Size	Ink Density (%)	Crumpled Paper	Imprecise Printing	Crumpled Paper	Imprecise Printing
1	Title-1	2,000	45	8,000	26.8	S	80	8	10	0.40	0.50
2	Title-2	2,000	50	5,000	26.4	S	80	2	4	0.10	0.20
3	Title-3	2,000	45	5,000	27.4	S	80	3	2	0.15	0.10
4	Title-4	5,000	50	6,000	28.2	S	70	6	24	0.12	0.48
5	Title-5	2,000	45	5,000	27.8	S	80	9	9	0.45	0.45
6	Title-6	2,000	30	5,000	26.4	S	80	8	9	0.53	0.60
…	…	…	…	…	…	…	…	…	…	…	…
1491	Title-1491	750	45	5m000	27.5	S	80	5	5	0.67	0.67

3.2 Data Preprocessing

Data preprocessing is an essential aspect in the data mining approach to obtain final data sets, and one of the tools that can be used in the preprocessing stage is the control chart (García, Luengo and Herrera, 2016). An attribute control chart is usually used to control the process using attribute data, e.g., reject number. There are several types of control charts, i.e.,., np-chart, p-chart, c-chart, and u-chart (Chen and Cheng, 1998; Amirzadeh, Mashinchi and Parchami, 2009; Chong, Khoo and Castagliola, 2014). A p-chart is a type of control chart used to measure the reject proportion of the production, and it can be used when the number of samples collected is not constant (Chukhrova and Johannssen, 2019). This research used p-chart to make valid category limits for each defect, and the equation models are as follows:

$$\bar{n} = \frac{\sum_{i=1}^{k} x_i}{k} \tag{1}$$

$$\bar{p} = \frac{\sum_{i=1}^{k} a_i}{\bar{n}\ x\ k} \tag{2}$$

$$UCL = \bar{p} - 3\sqrt{\frac{\bar{p}(1-\bar{p})}{\bar{n}}} \tag{3}$$

where $\bar{\boldsymbol{n}}$ – sample mean; k – number of observations, $\boldsymbol{x_i}$ – number of productions for title i, $\bar{\boldsymbol{p}}$ – defect proportion, $\boldsymbol{a_i}$ – number of defects for product *i*; and UCL –

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Upper Control Limit. Based on equations 1 to 3, this research obtained a UCL value of 0.003459 (crumpled paper) and 0.003286 (imprecise printing).

3.3 Knowledge Extraction

Knowledge extraction is the stage of extracting information from data to be used as knowledge (Gangemi *et al.*, 2016; Yang *et al.*, 2018). All stages of this extraction are using RapidMiner Studio software. RapidMiner is open-source software for analysing data mining. Processing data using RapidMiner was aimed at obtaining knowledge from databases that do not yet have entities (Ristoski, Bizer and Paulheim, 2015). The mining process focused on the slope angle, roller speed, engine temperature, paper size, and ink density. It led to assessments of defects, determining whether they were considered acceptable or unacceptable. The layout design for knowledge extraction in the RapidMiner software is presented in Figure 3.

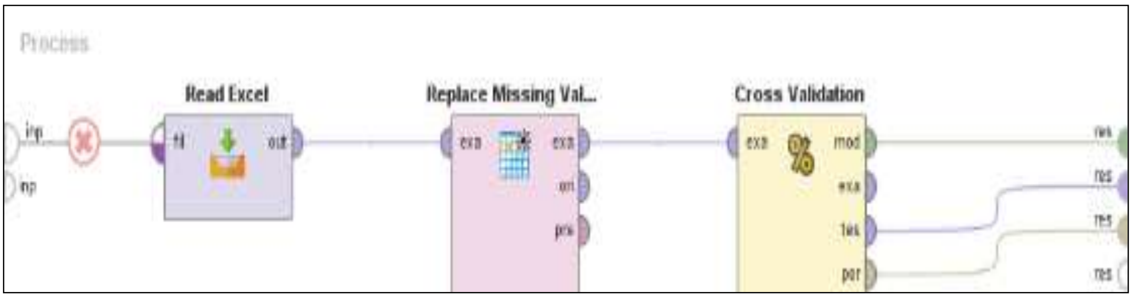


Figure 3 – Knowledge extraction processes in RapidMiner

As shown in Figure 3, there are three steps in the knowledge extraction process:

(1) Read Excel: This research performed the extraction processes using an import database method with an Excel file.

(2) Error minimising process: The replacement missing value technique and data value removal were used at this stage to complete existing data or make existing data available for processing.

(3) Cross-validation: This is a statistical method that evaluates and compares the algorithm by dividing data into two types of data, namely, training data (used for training models) and testing data (data that are used after training models). This last step is presented in Figure 4.

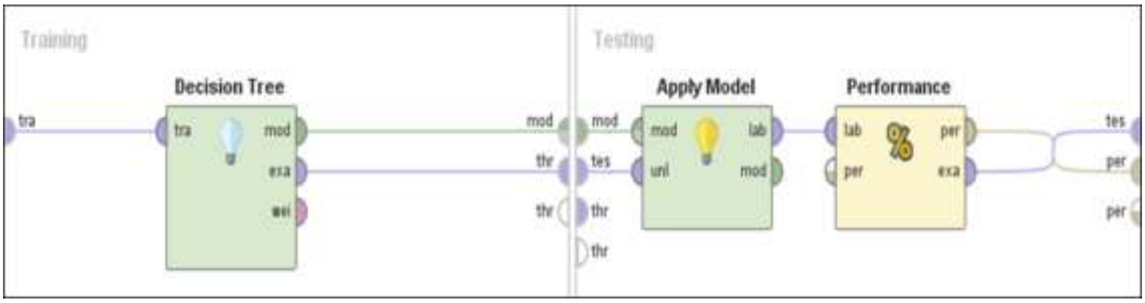


Figure 4 – Process view cross-validation in RapidMiner

As shown in Figure 4, a decision tree is used to describe the structure of the model. This structure can be used for prediction processes from a set of inputs to be the desired output. Table 2 shows that the decision tree has the highest accuracy value. Using these findings, the decision tree functions as a forecasting method, generating outcomes for quality prediction. The outcomes from the decision tree display predictions linked to manufacturing control factors (such as printing slope angle, roller speed, paper size, engine temperature, and ink density) related to defects, illustrated in Figures 5 and 6.

Table 2 – Predictive algorithms accuracy

No.	Predictive Algorithms	Crumple Paper	Imprecise Printing
1	Decision Tree	95.64%	95.48%
2	k-NN	91.41%	92.42%
3	Naïve Bayes	81.15%	80.81%
4	Random Tree	75.45%	75.51%

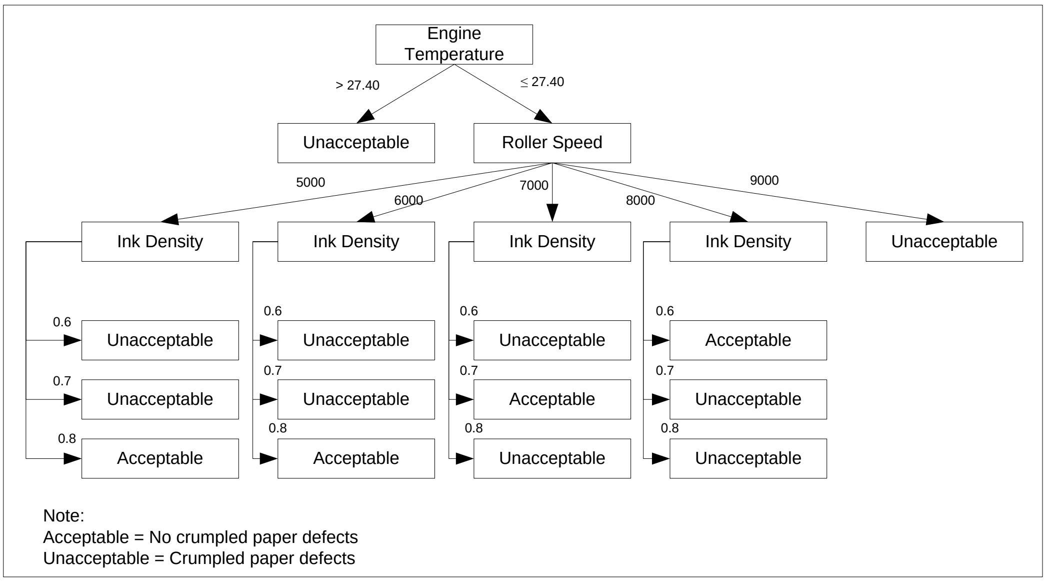


Figure 5 – Decision tree for crumpled paper defect

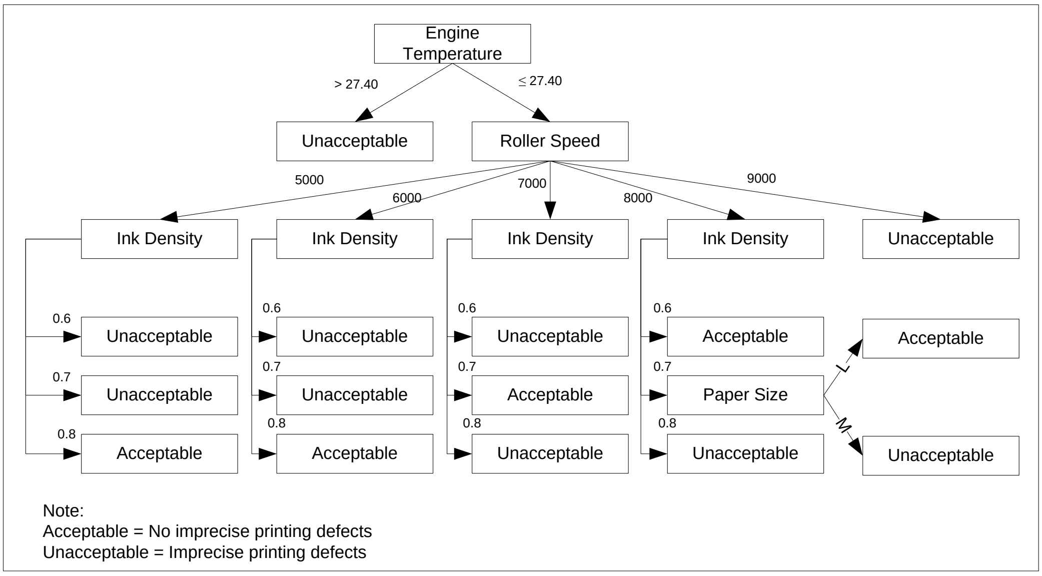


Figure 6 – Decision tree for imprecise printing defect

3.4 SaaS Prototype Implementation

After obtaining the decision tree models, the next step is implementing the model into a web programming code. This programming code acts as a data processing tool for quality prediction in the SaaS concept. The proposed algorithm for the crumpled paper defect and imprecise printing defect model as a result of the decision tree is presented in Figures 7 and 8.

```
Quality prediction algorithm (crumple paper defect)

Step 1
Importing excel data from client about manufacturing parameter control
and product defect for each type to database.
Step 2
Get the data from database, then the data is entered into a variable for
processing.
Step 3
Data is processed based on the results of the decision tree to determine the
acceptable or unacceptable product:
if Engine Temperature > 27.40, then Product = Unacceptable;
else go to rollerSpeedFunction
rollerSpeedFunction:
if Roller Speed = 5000 or 6000, then go to inkDensityFunction1;
else if Roller Speed = 7000, then go to inkDensityFunction2;
else if Roller Speed = 8000, then go to inkDensityFunction3;
else Product = Unacceptable
inkDensityFunction1:
if Ink Density = 0.6 or 0.7, then Product = Unacceptable;
else Product = Acceptable
inkDensityFunction2:
if Ink Density = 0.6 or 0.8, then Product = Unacceptable;
else Product = Acceptable
inkDensityFunction3:
if Ink Density = 0.7 or 0.8, then Product = Unacceptable;
else Product = Acceptable
Step 4
The output will be exported for download
```

Figure 7 – The proposed quality prediction algorithm (crumpled paper defect)

Quality prediction algorithm (imprecise printing defect)	
	Step 1
1:	Importing excel data from client about manufacturing parameter control and product defect for each type to database.
	Step 2
2:	Get the data from database, then the data is entered into a variable for processing.
	Step 3
3:	Data is processed based on the results of the decision tree to determine the acceptable or unacceptable product:
4:	if Engine Temperature > 27.40, then Product = Unacceptable;
5:	else go to rollerSpeedFunction
6:	rollerSpeedFunction:
7:	if Roller Speed = 5000 or 6000, then go to inkDensityFunction1;
8:	else if Roller Speed = 7000, then go to inkDensityFunction2;
9:	else if Roller Speed = 8000, then go to inkDensityFunction3;
10:	else Product = Unacceptable
11:	inkDensityFunction1:
12:	if Ink Density = 0.6 or 0.7, then Product = Unacceptable;
13:	else Product = Acceptable
14:	inkDensityFunction2:
15:	if Ink Density = 0.6 or 0.8, Product = Unacceptable;
16:	else Product = Acceptable
17:	inkDensityFunction3:
18:	if Ink Density = 0.6, then Product = Unacceptable;
19:	else if Ink Density = 0.7; go to paperSizeFunction;
20:	else Product = Unacceptable
21:	paperSizeFunction:
22:	if Paper Size = L, then Product = Acceptable;
23:	else Product = Unacceptable
	Step 4
24:	The output will be exported for download

Figure 8 – The proposed quality prediction algorithm (imprecise printing defect)

Two algorithms in Figures 7 and 8 will be implemented in web programming code (PHP code). This research builds a prototype SaaS concept for quality prediction with localhost server (using XAMPP software). The user interface of this web-based quality prediction can be seen in Figures 9 to 11.

Figure 9 – Home user interface

Figure 10 – The user display for upload data

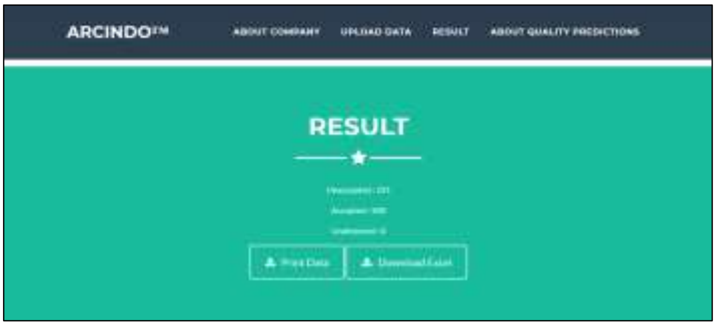


Figure 11 – The user display for download data

The prototype web quality prediction is the ARCINDO beta version (as in the home user interface shown in Figure 9), which in the future will be developed into a full version and can be accessed by all manufacturing companies. An example of the user display for uploading product and process quality data (in Excel format) is shown in Figure 10, and the display for downloading data by the user is presented in Figure 11. Users can download the product and process prediction results in a PDF or MS Excel format.

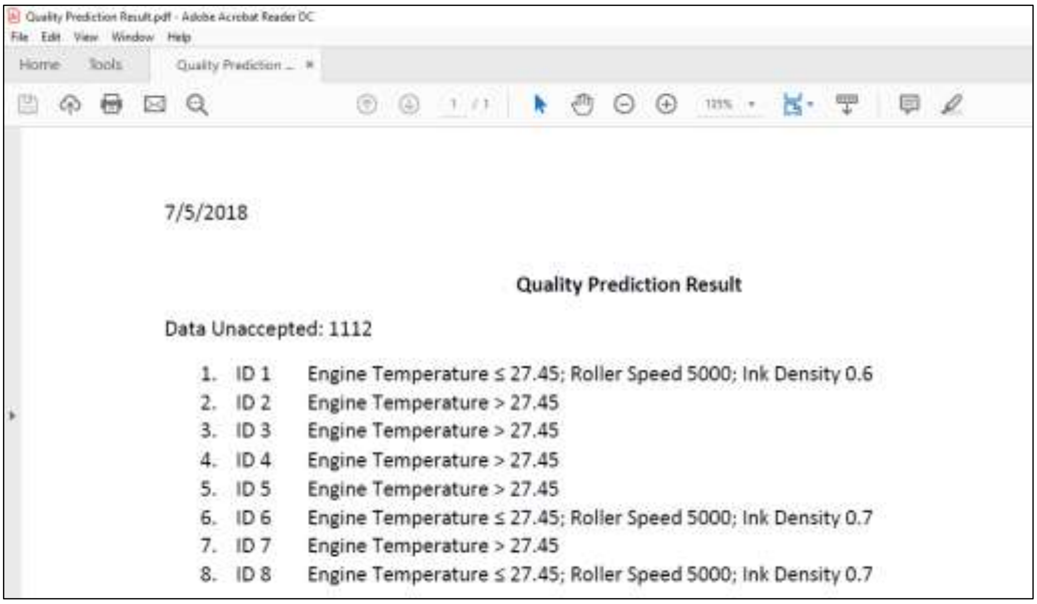
4 CONCLUSION

In this part, the system will be tested by generating random data (manufacturing parameter control and defect data) to be inputted into the web-based quality prediction ARCINDO software, and it will test the prediction results in the system. MATLAB is used for generating parameter control and defect data. The random number generator method is used in MATLAB for generating data. An example of random data in the Excel format is presented in Figure 12.

	A	B	C	D	E	F	G
1	No.	Product ID	Slope Angle	Roller Speed	Engine Temperature	Paper Size	Ink Density
2	1	ID 1	35	9000	27.35	S	0.8
3	2	ID 2	30	6000	27.97	M	0.8
4	3	ID 3	40	6000	26.03	S	0.7
5	4	ID 4	30	7000	27.51	S	0.7
6	5	ID 5	30	7000	27.25	M	0.8
7	6	ID 6	50	6000	26.48	S	0.7
8	7	ID 7	40	8000	26.89	L	0.6
9	8	ID 8	50	9000	27.26	M	0.7
10	9	ID 9	50	5000	27.31	S	0.7
11	10	ID 10	30	5000	26.33	S	0.6
12	11	ID 11	45	7000	27.09	M	0.8
13	12	ID 12	45	9000	27.01	M	0.8
14	13	ID 13	45	9000	27.89	M	0.7

Figure 12 – An example of excel input format

After generating random data, the Excel data (1500 data) will be uploaded in the ARCINDO system to predict product defects for each ID. The processing time of this system is quite fast. For example, the processing for 1500 data only takes less than 5 s. The results of the processing data are presented in Figure 13.


7/5/2018

Quality Prediction Result

Data Unaccepted: 1112

1. ID 1 Engine Temperature ≤ 27.45; Roller Speed 5000; Ink Density 0.6
2. ID 2 Engine Temperature > 27.45
3. ID 3 Engine Temperature > 27.45
4. ID 4 Engine Temperature > 27.45
5. ID 5 Engine Temperature > 27.45
6. ID 6 Engine Temperature ≤ 27.45; Roller Speed 5000; Ink Density 0.7
7. ID 7 Engine Temperature > 27.45
8. ID 8 Engine Temperature ≤ 27.45; Roller Speed 5000; Ink Density 0.7

Figure 13 – An example of PDF output format

Based on the implementation results, the data mining process in the SaaS concept was successfully performed. The output can be presented in two formats, i.e., PDF, which can be used as a reporting material, and Excel, which can later be further processed by clients from the quality prediction systems.

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5 CONCLUSION

This research aims to build a quality prediction using the model in the SaaS concept prototype using a data mining method. Based on a case study in the offset printing manufacturing industry, quality prediction using the SaaS concept is feasible in companies. In the processing stage, data mining methods can be used as tools for prediction. In this case, the use of decision trees can provide a conclusion for acceptable or unacceptable products from the manufacturing parameter control. Nonetheless, many developments can still be done from this research, including applying the SaaS concept to prototypes and implementing it continuously in manufacturing companies, using other data mining algorithms to achieve higher accuracy, and using other methods in preprocessing data to produce acceptable and unacceptable determinations.

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CONFLICTS OF INTEREST

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