## CHAPTER 4 ANALYSIS AND DESIGN

## 4.1. Analysis

The data was collected from public data *Wisconsin Breast Cancer Database UCI Repository Machine Learning (http://archive.ics. uci.edu/ml/machine-learning-databases/breastcancer-wisconsin/*). The following is an image snippet of the raw data that will be used. Before the dataset is processed it will look like this.



Figure 4.1 Example of Original Dataset Snippet

Starting from the left, the attributes in the database consist of: Sample code number, clump thickness, uniformity cell size, uniformity cell shape, marginal adhesion, single epithelial cell size, bare nucleoli, bland chromatin, normal nucleoli, mitoses, and class.

To simplify data processing, we need to extract the .DATA file as shown in *Illustration 4* into CSV. After the conversion, it will look like this.

	Sample code number	Clump Thickness	Uniformity of Cell Size	Uniformity of Cell Shape	Marginal Adhesion	Single Epithelial Cell Size	Bare Nuclei	в
0	1000025	5	1	1	1	2	1	_
1	1002025	5	4	4	5	7	10	
2	1015425	3	1	1	1	2	2	
3	1016277	6	8	8	1	3	4	
4	1017023	4	1	1	3	2	1	
94	776715	3	1	1	1	3	2	
95	841769	2	1	1	1	2	1	
96	888820	5	10	10	3	7	3	
97	897471	4	8	6	4	3	4	
98	897471	4	8	8	5	4	5	
0.0	rowe x 11 columns							
551	lows × 11 columns							3
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Figure 4.2 After Convertion Dataset

At this stage, pre processing is carried out on the data. First, we do data cleaning for the incomplete, empty or null data, as well as deleting attributes that are not used in the classification process. This process is carried out after the data selection process and will reduce the amount of data. The amount of data before cleaning was 699, 16 data deleted along with 1 attributes, resulting in 683 final data. The omitted attribute was the Sample\_code\_number.

Below are some of the results of the independent variables in the training data. The value on the independent variable is the cause of the value on the dependent variable. The independent variable in this study is all the attribute except sample\_code\_number and class. The dependent variable in this study is the "Class" column. After we define it, we can implement it into a train/test split function.

	Clump_ Thickne ss	Uniform ity_of_C ell_Size	Uniform ity_of_C ell_Sha pe	Margina I_Adhes ion	Single_E pithelial _Cell_Si ze	Bare_ Nuclei	Bland _Chro matin	Normal _Nucleo li	Mitoses
293	10	4	4	6	2	10	2	3	1
651	1	2	1	3	2	1	2	1	1
687	3	1	1	1	2	1	2	3	1
659	1	1	1	1	2	1	1	1	1
197	5	1	1	4	2	1	3	1	1
370	4	3	2	1	3	1	2	1	1
573	1	1	1	1	2	1	2	1	1
215	8	7	8	7	5	5	5	10	2
527	4	1	1	1	2	1	3	1	1
627	2	1	1	1	2	5	1	1	1
622	7	1	2	3	2	1	2	1	1

Table 4.1. Data Training

593	5	1	2	1	2	1	1	1	1
129	1	1	1	1	10	1	1	1	1
95	1	1	1	1	2	1	3	1	1
76	1	1	4	1	2	1	2	1	1
34	3	1	2	1	2	1	2	1	1
193	1	1	1	1	2	1	3	1	1
525	3	1	1	2	2	1	1	1	1
394	1	2	3	1	2	1	2	1	1
358	8	10	5	3	8	4	4	10	3

Then, we calculate the probability of each class in the population in the training data. In this stage, the data is divided using the train test split function with the distribution of data: 205 for testing data and 478 for training data. Produces the probability calculation value as follows:



After getting the prior probability, next step is to calculate the mean of each attribute. For the example we calculate the mean of Clump Thickness :

• Mean for Benign

$$\mu = \frac{\text{Total values of the Clump Thickness attribute in the Benign Class}}{\text{Total Benign Class}}$$
(4)

$$\mu = \frac{Value \ 1 + Value \ 2 + \dots + Value \ 315}{Total \ Benign \ Class}$$

$$\mu = \frac{4+5+\dots+3}{314}$$

Mean 
$$=\frac{955}{314}$$
 = 3,04140

• Mean for Malignant

 $\mu = \frac{Total \ values \ of \ the \ Clump \ Thickness \ attribute \ in \ the \ Malignant \ Class}{Total \ Malignant \ Class}$ 

(5)



The mean value of each attribute can be seen in this table:

C	Clump Thickness			Clump Thickness Uniformity of Cell Size				Unifo	ormity of C	ell Shape
	Benign	Malignant			Benign	Malignant		Benign	Malignant	
Mean	3,04140	7,18292		Mean	1,33439	6,64634	Mean	1,41401	6,53048	

 Table 4.2. Mean of Each Attribute

Marginal Adhesion			Single Epithelial Cell Size				Bare Nuclei			
	Benign	M <mark>aligna</mark> nt		Benign	Malignant	1	5	Benign	Malignant	
Mean	1,35987	5,60975	Mean	2,07324	5, <mark>48</mark> 780		Mean	<mark>1,308</mark> 91	7,54268	
		D						ス		

Bland Chromatin			Normal Nucleoli					Mitosis			
	Benig <mark>n</mark>	Malignant		1	Benign	Malignant			Benign	Malignant	
Mean	2,09235	6,03658		Mean	1,24840	6,07317		Mean	<mark>1,07</mark> 324	2,53048	

## 4.2. Desain

. The following flow is used to carry out a data cleaning procedure using jupyter notebook tools as a medium for data processing.



Figure 4.1 Flowchart of Data Cleaning

From the results of data cleaning, then the dependent and independent variables are determined. Then the data separation is done to get training data and test/validation data. Then, the model is evaluated by measuring accuracy using a confusion matrix.

	Clump	Uniformity	Uniformity	Marginal	Single	Bare	Bland	Normal	Mitoses
	Thickness	of Cell Size	of Cell	Adhesion	Epithelial	Nuclei	Chromatin	Nucleoli	
			Shape		Cell Size				
465	10	9	8	7	6	4	7	10	3
633	8	7	4	4	5	3	5	10	1
513	3	1	1	1	1	1	2	1	1
677	5	1	1	1	2	1	1	1	1
67	5	3	4	1	8	10	4	9	1
270	8	4	7	1	3	10	3	9	2
356	5	3	3	1	3	3	3	3	3
340	10	3	3	1	2	10	7	6	1
156	1	2	2	1	2	1	2	1	1
550	3	1	1	1	2	1	2	1	1
38	5	4	4	9	2	10	5	6	1
182	6	1	1	1	2	1	3	1	1
557	5	1	1	3	2	1	1	1	1
509	2	1	1	1	2	1	1	1	1
655	3	1	1	1	2	1	2	1	1
17	4	1	1	1	2	1	3	1	1
146	3	4	5	2	6	8	4	1	1
674	1	1	1	1	2	1	2	1	1
230	7	94	7	4	3	7	7	6	1
468	4	1	1	1	2	1	1	1	1

 Table 4.3. Data Testing

Confusion matrix is described as a table with four different combinations of the actual value and the predicted value. From the results of the classification can be represented in the Confusion Matrix table, as True Positive, True Negative, False Positive, False Negative.

	FALSE	TRUE
FALSE	True Negative (TN)	False Positif (FP)
TRUE	False Negative (FN)	True Positive(TP)

Table 4.4. Confusion Matrix Rules

From the Table 4.2 it can explained that True Positive is positive data that is predicted to be true, True Negative is negative data that is predicted to be negative, False Positive is negative data that is predicted to be positive, False Negative is positive data that is predicted as negative data. From the confusion matrix table, we can use to measure the level of accuracy, precision, recall, and the value of the F1 score. Equation to calculate it as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$
(6)

$$Precision = \frac{TP}{TP + FP}$$
(7)

$$Recall = \frac{TP}{TP + FP}$$
(8)

Accuracy is decribing how accurate the model is in classifying correctly. Precision describes the accuracy between the requested data and the prediction results. Recall / sensitivity describes the success of the model in retrieving information.

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