ABBREVIATIONS

Terminologies	**Definition**
ANN	Artificial Neural Network
FNN	Feedforward Neural Network
PCA	Principal Component Analysis
BBK	*Balai Besar Keramik*
ASAKI	*Asosiasi Aneka Industri Keramik Indonesia*
RGB	Red, Green, Blue

CHAPTER I INTRODUCTION

I.1 Background

Contributing 3.0% of the total world ceramic production, Indonesia is considered as the seventh largest ceramic manufacturers (Stock, 2016). This position has given a significant value as it had contributed to the development of Indonesia infrastructure (ASAKI, 2017). Thus, maintaining and improving the competitive advantage of this sector is an important issue which needs a considerable attention. To evaluate the performance of Indonesian ceramic commodities, Figure I.2 provide the comparisons of the import ceramic tile and the exported ceramic tiles from 2011 – 2015. The chart in Figure I.1 reveals how the trend of the import ceramic products volume increasing which was in contrast with the declining trend of the domestic exported ceramic product. Thus, this study concludes that there is an indication of the lack of competitiveness in Indonesian ceramic commodities.

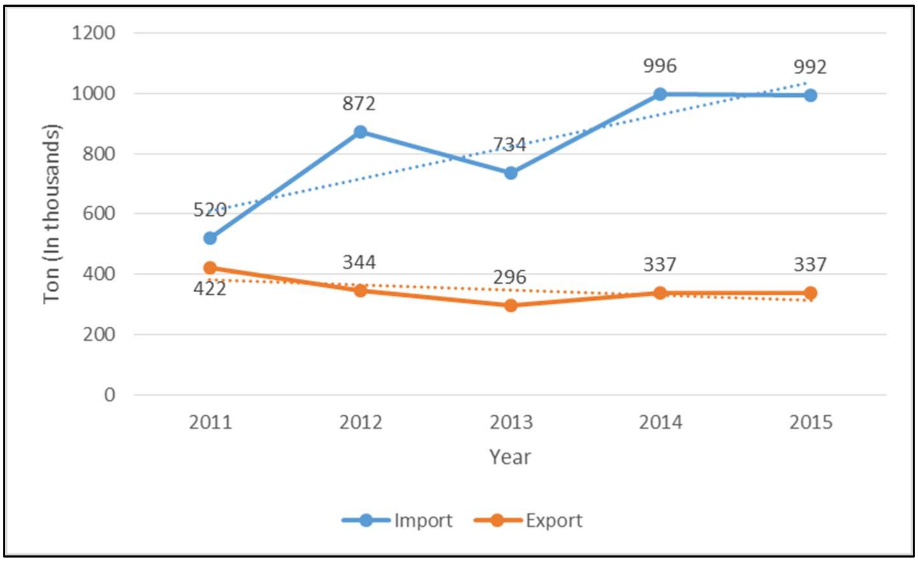

Figure I.1. Ceramic Export and Import Volume (BI, 2016)

One of the underlying factor which determine the competitive advantage of an organization is quality (Ehmke, 2008). In the case of ceramic tile industry, the surface quality of ceramic may affect the perceived quality of the customer (Callarisa Fiol *et al.*, 2011). Therefore, to prevent or minimize the occurrence of the unwanted quality being received to customers, assessing quality inspection techniques becomes an important issue.

Observations and studies related to the ceramic quality inspection has been conducted in the previous researches which use *Balai Besar Keramik* (BBK) as the case study (Atmaja and Herliansyah, 2015; Luthfil *et al.*, 2016; Lestari *et al.*, 2017; Putri *et al.*, 2017). It was found that the quality inspection process conducted in BBK was done manually and repeatedly by operators which in a long run, may cause fatigue. Consequently, Yeow *et al* (2014) found that stress, repetition, fatigue and work environment are major factors which significantly contributes to human errors. Francis (as cited in Brosnan and Sun, 2004) also states that human perception which play role in activities could be easily deceived. From these studies, one could conclude that manual quality inspections may possess several disadvantages regarding the human errors.

One other concern that can be mentioned was the inspection time of the operator. An operator assessment of quality inspection of tile surface defect had been studied using an eye tracker to see how an operator might perform in ceramic tile surface defect detection task (Ozkan and Ulutas, 2016). The study found that an average fixation count (average inspection time) of workers to detect an Area of Interest (AOI) i.e. surface defects was 13.60 seconds for novice worker and 11.39 seconds for expert worker (Ozkan and Ulutas, 2016). Note that ceramic tiles industries are mass production industries which in case study conducted by Septiani and Anne (2013) can produce an average of 145,014 tiles per month. In the case where manual inspection was conducted, it was laborious to inspect each tile for surface quality inspection. Therefore sampling methods using Military Standards 105E was conducted for inspection of the study (Septiani and Anne, 2013). In this case, one disadvantage is the risk of letting defected product to pass through inspection (Montgomery, 2009).

To address the issues arise from the manual inspection, several studies have attempted to automate this process by using computer vision and image processing techniques (Brosnan and Sun, 2004; Masci *et al.*, 2012; Patel *et al.*, 2012). Particularly in the field of ceramic tiles quality inspection, computer vision techniques have been extensively studied in order to detect defects features which a ceramic tiles might possess (Atmaja and Herliansyah, 2015; Luthfil *et al.*, 2016; Lestari *et al.*, 2017; Putri *et al.*, 2017).

In order to appropriately inspect the surface of ceramic tiles images, an optimal parameters settings related with the environment is needed to obtain a desirable inspection results. One of the attempts of optimizing these parameters was conducted by Atmaja and Herliansyah (2015) which examines two parameters that may affect the accuracy of ceramic inspection: light intensity (300 lx, 600 lx, and 900 lx) and distance between camera and object (50 cm, 75 cm, and 100 cm). With these parameters, an optimization to minimize the errors is then carried out using the method of full factorial design. The study found that with the light intensity of 300 lx and camera distance of 50 cm, the inspection were able to obtain 0.0675% and 2.30% of errors for surface area and dry spots inspection respectively. In the current study, the parameters discovered by Atmaja and Herliansyah (2015) will be taken as a consideration since it provides an appropriate justification on how the parameters are set.

Another important consideration in tiles visual inspection is feature extraction techniques which employed to extract a set of different numerical representation that one ceramic sample image might possess (Elbehiery *et al.*, 2007; Rahaman and Hossain, 2009). Elbehiery *et al* (2007) proposed a morphological techniques in order to visually detect surface defects of ceramic tiles. Specifically, the study used different sets of morphological techniques were used to detect different detects: Long Crack, Crack, Blob, Pin-Hole, and Spot Detectors algorithms. The study were found to be successful at extracting images that were easier to comprehend visually by human perception. One limitation of this research is that the final judgements of whether a particular ceramic is considered as normal or defect which involve classification task were still taken by operator rather than automatically by computer. Therefore, another concern would be how to create a system which can automatically create such decision given an input image.

In contrast with the morphological techniques, several studies have attempted to automate the classification task for visual inspection by employing Artificial Intelligence (AI) and Machine Learning techniques (Luiz, Flavio and Paulo, 2010; Mishra and Shukla, 2014; Lestari *et al.*, 2017; Putri *et al.*, 2017). In the case of binary classification, an AI system i.e. fuzzy logic with Gray-Level Co-Occurrence Matrix (GLCM) feature extraction was utilized by Putri et al. (2017) to detect ceramic tile surface defect. The study was able to correctly classify 12 out of 13 test images and thus giving an accuracy rate of 92.31%. Sharma and Kaur (2012) employed several machine learning techniques i.e. K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Bayesian Classifier to detect defect of ceramic tiles. Using 24 samples of test set, the study was able to get 70.84% of accuracy for each model. Bayesian machine learning classification system have also been utilized in industrial products particularly for classifying cork stopper defects (Radeva *et al.*, 2002). Given 2000 test images, the system were able to correctly classify 98% of the image examples.

Among Machine Learning algorithms, one of the models which capable of drawing complex non-linear decision boundaries is Artificial Neural Networks (ANN) (LeCun *et al.*, 2015). This model was inspired by the interconnected biological neurons which learn by changing the connection weights between neurons (Glorot *et al.*, 2011). Due to this property, this model has been applied in wide range of image classification tasks such as remote sensing images (Giacinto and Roli, 1997), face detection (Shende and Patel, 2013), and medical imaging (Wang *et al.*, 2014).

Given the capability of ANN, extensive studies on the utilization of ANN approach on visual inspection system can be found in several literatures and researches (Hocenski and Nyarko, 2002; Lim, Ratnam and Khalid, 2007; Mirapeix *et al.*, 2007; Bhuvaneswari and Sabarathinam, 2013; Mishra and Shukla, 2014; Lestari *et al.*, 2017). One of the early studies was the application of ANN and one of unsupervised learning methods i.e. Principal Component Analysis (PCA) for industrial welding seam inspection which yields a favorable error of 0.817% false inspection rate (Liao *et al.*, 2004). Another weld defect classification system using ANN was employed by Lim *et al.* (2007) using 49 for testing examples. The study were able to obtain an accuracy of 97.96%. In the case of ceramic tiles inspection, ANN has been utilized for surface defect detection by using GLCM feature extraction as preprocessing techniques (Lestari *et al.*, 2017). Given 32 samples as a training set and 13 samples for test set, an accuracy of 92.3% was obtained during the real time testing. Furthermore, Mishra and Shukla (2014) have employed Probabilistic Neural Network (PNN) to ceramic tile inspection by trying to model the probability distribution of each class. With 50 tiles samples, the model was capable of reaching the average accuracy of 98.20 %.

While several studies found that ANN was a capable model for ceramic tile defects detection and classifier, it was possible to improve the architecture of the network further. While log-sigmoid activation function was often used in the previous studies as an activation function of the hidden layer (Liao *et al.*, 2004; Lim *et al.*, 2007; Lestari *et al.*, 2017), it was found that a rectified linear unit (ReLU) can improve the performance and training time of the network (Glorot *et al.*, 2011).

One other improvement to the network can be achieved by adding an unsupervised learning to find a lower dimensional representation of the image while still keeping the important information consisted within the dataset (Goodfellow *et al.*, 2016). This can be achieved by one of the dimensionality reduction techniques called Principal Component Analysis (PCA) (Abdi and Williams, 2010). While reducing the dimensionality of the data, PCA can extract important features consisted in the dataset and compress the data size to reduce computational cost (Abdi and Williams, 2010). Several studies have employed PCA as a feature extraction technique for visual inspection (Mirapeix *et al.*, 2007; Kumari and Soni, 2014; Zuber and Bacjric, 2016). In one of the studies in leaf classification, PCA was found to outperformed the GLCM feature extraction with the accuracy of 98% and 78% respectively (Ehsanirad and H, 2010).

Given the justification for utilizing automation in ceramic tile surface defection, an attempt to create a system which enables a real time detection for the visual inspection was made. This real time detection system was constructed by combining an unsupervised learning algorithm i.e. PCA and a supervised learning technique to classify instances called ANN. By using PCA as representation learning for ceramic images feature extraction and ANN capability to form multi-class output layer, this study aims to create a multi-class classification system to classify defects of ceramic tile surface.

I.2 Problem Formulations

The issues described on the research background can be formulated as how to optimize ceramic defect classification using Principal Component Analysis and Artificial Neural Network model?

I.3 Research Objectives

Based on the problem formulations, the objectives can be summarized as the optimizing ceramic defect classification using Principal Component Analysis and Artificial Neural Network model.

I.4 Research Constraints

Constraints of the research are listed as follow:

1. Plain white ceramic tiles with the size of 30 x 30 cm are used as research object.
2. Images were taken by camera at the distance of 50cm above the sample.
3. Gradient descent, RMSprop, Adam optimization, and Momentum are considered in the optimization scheme.
4. Dry spots, Crack, Chip off, and scratch are considered as the defect types to classify.
5. Real time detection was conducted in the automation model designed in the lab.
6. Image acquisition and real time inspection were conducted using camera with the specification of Full HD 1080p at 30 fps and 720p at 60fps.

I.5 Research Benefits

Research benefits are listed as follow:

1. Reduces labor cost by relying automation to inspect ceramic quality.
2. Provide an alternative technique to address ceramic tile visual inspection problem.
3. Reduces inspection time carry out by operator to inspect ceramic quality.

I.6 Writing Systematics

The research shall be written following the systematics as follow:

Chapter I Introduction

This chapter discusses the problems in ceramic industries and quality inspection conducted manually, the need for enhancing the quality inspection, and the importance of computer vision in quality inspection.

Chapter II Literature Review

The following chapter discusses the previous researches conducted in order to enhance quality inspection system using computer system and the methods conducted by previous studies. The chapter also discusses the theoretical overview of automation system, Principal Component Analysis, and Artificial Neural Network model.

Chapter III Research Method

In this chapter, the research method is explained. The chapter includes the conceptual model of the study and the problem solving systematics that will be conducted in the study.

Chapter IV Data Processing

The chapter shall discuss the implementation details on several techniques used to pre-process the image, Automation Design, Graphic User Interface Design, hyperparameter search and training steps of the PCA and ANN.

Chapter V Analysis and Results

The following chapter discussed the results of cross validation. Error analysis via F1-score, determination of the model selection for real time inspection. A comparative inspection time performance of the system and the manual inspection shall also be discussed.

Chapter VI Conclusions and Suggestions

The following chapter consist of the conclusions regarding the results of the study. Suggestion regarding potential future works regarding the improvement of the system are also presented.

CHAPTER II THEORITICAL BASIS

II.1 Ceramic Tile Defects

In this study, three types of ceramic tile defect according to the definition of SNI ISO 10545-2: 2010 standard shall be inspected using the model. The defects are mentioned as follows.

1. Cracks, a type of surface defect which defined as the fracture visible on the body of the tile.
2. Dry spots, a type of surface defect which the area of the face of the glazec tile does not appear to have glaze.
3. Chip off: Chipping in the corner of the ceramic.
4. Scratch: Typical scratch that may appear on the surface.

II.2 Digital Image Representations

Different from how the eyes perceive image, computer perceives image as an array or matrix which consist of numerical representation. Each element in the matrix is called pixel where it corresponds to the brightness intensity value of the given element of the image (Fukunaga, 2013).

II.2.1 RGB Images

To represents image with "true colors", three color channels i.e. red, green, and blue are used to create a 3-dimensional array. For a given image, the size can be expressed as Width x Height x 3. In this notation, the value of 3 corresponds to three color channels Red, Green, and Blue (Karpathy, 2016).

II.2.2 Grayscale Images

The grayscale images consist of black, white, and shades of gray in between. This type of image has only one channel. Therefore the image of grayscale does not represents the true color of an image. The value of the grayscale image ranges from 0 to 255, where the higher the pixel value represents the brighter the colour in the image (Fukunaga, 2013). Due to having one channel of matrix intensities withing the image, processing a grayscale image is computationaly cheaper than RGB which consist of three colour channel. Due to this property, a grayscale image was often preferred in some cases of image processing task. Figure II.2 shows a simple example of greyscale image in a form of 10x10 matrix.

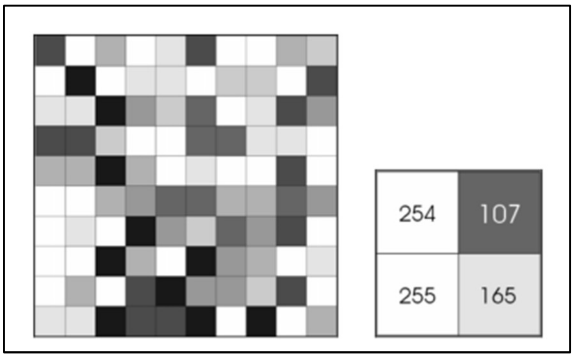

Figure II.1. 10x10 greyscale image (Fukunaga, 2013)

II.3 Artificial Neural Networks

Artificial Neural Networks (ANN) are computational models which inspired by biological neurons. This model takes input vectors and send these information to an interconnected artificial neurons to make a prediction (Shea and Nash, 2015). The basic model of ANN is also called Feedforward Neural Networks (FNN) (Shea and Nash, 2015) shown in Figure II.4. This architecture consist of L number of layers and where every number of n_l units in layer *l* are fully connected with every units in layer *l+1*.

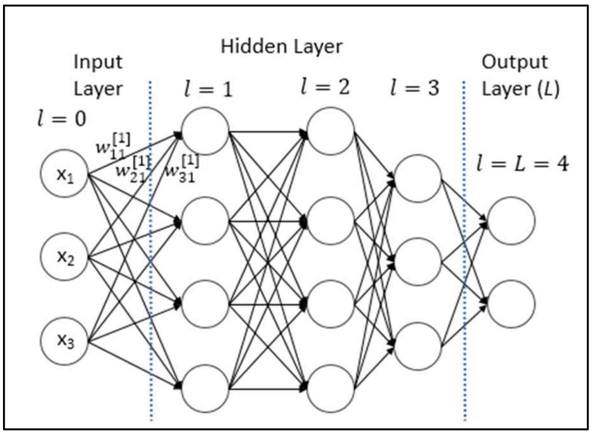

Figure II.2. Feedforward Neural Network Architecture (LeCun *et al.*, 2015)

II.3.1 Activation Functions

In order to send the information from one layer to the next, ANN models send the sum of their weighted input into an activation function which add nonlinearity (LeCun *et al.*, 2015) as shown in equation (2) . These functions are used to solve problem which has nonlinear property (Karlik and Olgac, 2010). One of the most widely used activation function are rectified linear unit (ReLU) activation function which can be defined as the half wave rectifier (LeCun *et al.*, 2015) as in

$$ReLU(z) = \max(z, 0). \tag{1}$$

Another commonly used activation functions (LeCun *et al.*, 2015) are logistic sigmoid (2) and tan hyperbolic function (3) as expressed in:

$$\sigma(z) = \frac{1}{1 + \exp(-z)} \tag{2}$$

and (3)

$$tanh(z) = \frac{\exp(z) - \exp(-z)}{\exp(z) + \exp(-z)}.$$

II.3.2 Softmax for Multi-class Classification

Instead of using multiple log-sigmoid function in the output layer to make multi-class prediction, one can used the generalization of the function called softmax function (Goodfellow *et al.*, 2016). Softmax function can be defined as the normalized probability of the prediction as in

$$softmax(z_{y_k}) = \frac{\exp(z_{y_k})}{\sum_{k=1}^{K} \exp(z_k)}. \tag{4}$$

Where z_{y_k} corresponds to one of the output pre-activation and $\sum_{k=1}^{K} \exp(z_k)$ is the sum of all the pre-activation of the output classes. Given the property of the function, the sum of all $softmax(z_{y_k})$ therefore should sum into 1 (Goodfellow *et al.*, 2016).

II.3.3 Forward Propagation

In ANN, the way it maps the input into prediction is by implementing forward propagation from the input layer to the output layer (LeCun *et al.*, 2015). Given an input vector of $x \in \mathcal{R}^{nx1}$ consisting of *n* features, the procedure for forward propagation (Hagan *et al.*, 1995) is given as follows.

1) Compute the pre-activation for each of the k-th unit of neuron in layer l as in:

$$z_k^{[l]} = (w_k^{[l]})^T a_k^{[l-1]} + b_k^{[l]} \tag{5}$$

where $w_k^{[l]}$and $b_k^{[l]}$are the weight and bias vectors respectively,$a_k^{[0]}$ is equal to input vector x, and for $l = \{1,2, \dots L\}$ is $a_k^{[l]}$ defined as the activation term.

2) Compute the activation term in layer l as in:

$$a_k^{[l]} = g(z_k^{[l]}) \tag{6}$$

where $g(z)$ is the activation function which adds nonlinearity to the pre-activation z.

3) Repeat the step 1 and 2 for $l = \{1,2, \dots L\}$. Thus, in the output layer, the hypothesis or prediction can be formulated as:

$$\hat{y} = a^{[L]} \tag{7}$$

Where in the case classification problem, $a^{[L]}$ can be a softmax activation function (4) which output a probability of input vector x classified as target class y. Therefore the predicted class is the class with the largest value of probability.

II.3.4 Cost function

In order for prediction to be accurate, each training example predicted value needs to be close to the target labeled data as in $\hat{y}^{(i)} \approx y^{(i)}$.To mathematically express the measure of how close the prediction to the target $y^{(i)}$, the cost function (Ng, 2012) is formalized as

$$E(w, b) = \frac{1}{m}\sum_{i=1}^{m} L(\hat{y}^{(i)}, y^{(i)}) \tag{8}$$

Where m is the number of examples and $L(\hat{y}, y)$ is the loss function formulated as

$$L(\hat{y}, y) = -\sum_{k=1}^{K}(y_k^{[l]} log(\hat{y}_k)). \tag{9}$$

The loss function in (9) is considered when the output activation is softmax (4) The given the cost function (7), objective of the learning algorithm is therefore to minimize the $E(w, b)$ by using w and b as a control variables (Ng, 2012).