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DEVELOPMENT OF AUTOMATED CERAMIC TILES SURFACE DEFECT DETECTION AND CLASSIFICATION SYSTEM

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ABSTRACT
This research presented the development of an automated system for ceramic tiles surface defect detection and classification. The production process of ceramic tiles is very fast through the use of automated system except the inspection process that is manually carried out. The fast rate of production and numerous amounts to be produced make it difficult to manually inspect the tiles defects. Currently many literatures have proposed various automated systems for detecting and classifying defects on ceramic tiles. In this research different defected and non-defected images of ceramic tiles were taking at the firing unit in a Ceramic Company with a Nikon D40 camera. A statistical method called Rotation Invariant Measure of Local Variance (RIMLV) operator was used for detection of the defects while morphological operator was used to fill and smooth detected regions. Then, the detected defects are labelled to extract the corresponding features vectors using Fourier descriptors. To categorize the defect, multi-class support vector machine classifier (SVM) was used. The proposed system recorded an accuracy of 98 percent for classification and 0.094939 seconds for classification using one-against all SVM classifier.

Keywords: Defects, RIMLV, Support vector machine (SVM), Fourier descriptor, Classifier.

1. INTRODUCTION
The production of Ceramic tile undergoes many processes and basically the process is composed of clay preparation by dry grinding, moulding of the tile by dry pressing, glaze preparation, drying, glazing and decoration of the tile, kiln firing, classification and packing (Meena, & Mittal, 2013).

Ceramic tile is a composition of clay mixed with other natural materials like sand, quartz and water. These compounds are properly mixed and pressed to obtain desired shape such as rectangle, squares or ovals under high pressure (Mishra & Shukla, 2014). The baking of these compound takes specific time under a regulated temperature and when done in large amount, sometimes there is possibility of the outcome not to be uniformly treated which result in flaws development (Islam & Sahriar, 2012). There are different types of flaws that may develop depending on the factors that have been compromised. These flaws is call defect and is as a result of chemical impurities in the material used and it could as well be as result of physical faults in the production process (Elbehiery, Hefnawy, & Elewa, 2005). The defects are usually identified and classified by the firing unit so as to effectively take decision for good quality control on the product that will come out of the factory (Hanzaei, Afshar, & Barazandeh, 2017). The defects are sometimes inconsistent and sometimes may not be easy to see, these makes CT industries to find a number of innovative means of production and automation to handle this challenge. Most factories still rely on the use of human for the detection of CT defects grading which is highly prone to error (Hanzaei et al., 2017).

The use of human to manually monitor the quality of CT production is labour intensive, prone to error and exposes the human operators to health related hazard associated with extreme temperature and humidity (Elbehiery et al., 2005). The inspection involves different measures such as surface defect detection, color analysis and dimension verification (Elbehiery et al., 2005). The limitation of this manual inspection done by human inspectors is that, human beings easily get tired within a limited time (Hanzaei et al., 2017). Fatigue could also affect the judgment of human beings, and also since production process runs continuously in the factories if inspection process does not match with the production process it could result in CTs omission (Meena & Mittal, 2013). There is need for automatic detection and classification system that is fast, accurate, repetitive and reliable to replace the existing system and should also be able to sort the tiles with defects for recycling. The accuracy of this system will be a means to improve quality control (QC) of ceramic tiles manufacturing companies (Hanzaei et al., 2017).

The first stage of the work is to be able to detect defects using statistical method known as Rotation Invariant Measure of Local Variance (RIMLV) operator with morphological operator. Then, the detected defects is labeled to extract the corresponding features vectors using Fourier descriptors. Then the second stage is to categorize the defects using multi-class support vector machine classifier (SVM).

Most of the defects in CT production process that have statistical interest are the one that are found in the firing stage (Hanzaei et al., 2017). Some data collected from firing unit by firing unit worker in a CT factory is shown in Table 1

Table 1: Major Defects in CT Firing Unit (Hanzaei et al., 2017)

Type	Diffused Glaze Crack (Crack I)	Capillary Crack (Crack II)	Pin-Hole	Hole
Ocured in the kiln	Occurred in pre-heating due to excessive increasing rate of temperature, and then the glaze diffuses inside it in cooking area.	Occurred in cooling area due to excessive decreasing rate of temperature.	Occurred in cooking area due to excessive cooking.	Occurred in pre-heating and cooking area due to excessive absorption of CT‘s body moisture.
Defective images				

2. METHODOLOGY

The CT surface detection and classification framework comprises the image acquisition section, the defect detection and classification section, and then the sorting unit. The image acquisition stage capture the images through a sensor and camera, the defect detection and classification stage is done in the computer and finally the sorting unit. The experimental setup of CT Defect Detection and Classification Framework is shown in figure 1

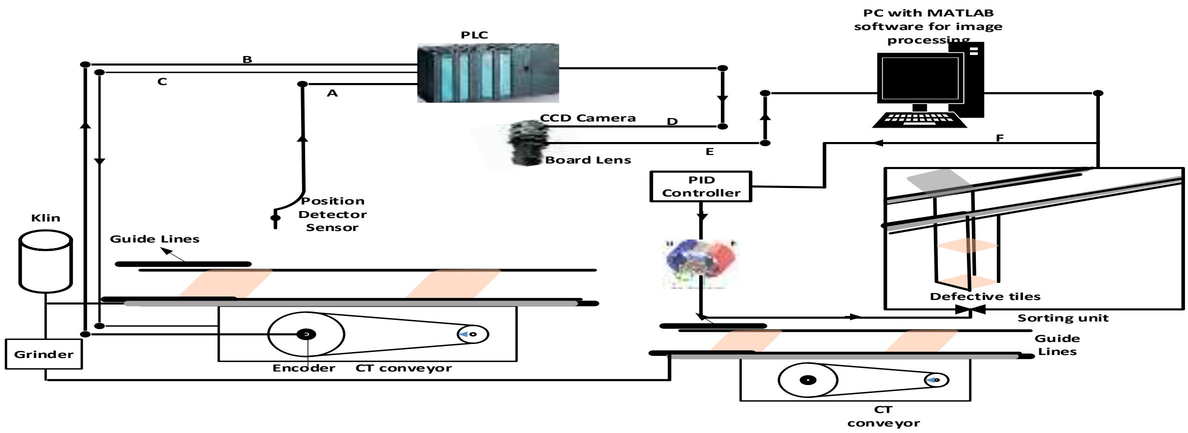


Figure 1. CTs' surface defects detection and classification experimental setup framework

2.1. Acquisition of Images

Figure 1 is a setup that explain the image capturing process CT been baked and tried coming out of the kiln fixed on the conveyor belt by guide lines. The position detector sensor will detect the edge of the tile then send a signal (A) to the programmable logic controller. The programmable Logic Controller (PLC) with the aid of the encoder on the rotor shaft of the motor begins to record the encoder numeration and mathematically. It relate the ratio to the distance of the tile on the conveyor when it received signal (B). The Conveyor motor will be stopped at predefined position under the camera when it received signal (C) and at that point the camera will receive signal (D) from the PLC to snap the surface of the CT. The analog signal of the captured image will be sent to the PC for processing and this is referred to as signal (E). The detection and classification scheme are achieved in the PC. In sorting unit, the classified CT is sorted using automatic systems such as Automatic Sorting Lines. The sorting line responds to the output of the classifier where the good tiles move for packaging, the defective tiles are dropped by the sorting unit for further decision. A total of 230 CTs' images were acquired with 180 of them having one defect on their surfaces, 20 numbers have several defects on their surfaces, and 30 images with no surface defects being used as templates

2.2. Defect Detection

The defect stage focuses on developing a system to be able to detect the defects on the CT. This is carried out on the Computer as shown in Figure 1 with the aid of software. Figure 2 shows a flow chart of CT defect detection and classification algorithm. It comprises the image pre-processing, defect detection, defect labelling, defect feature extraction and defect classification.

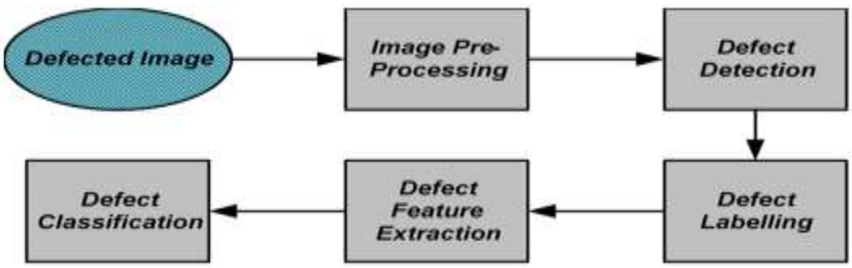


Figure 2: Flow chart of CT defect detection and classification algorithm.

2.2.1. Image pre-Processing

Image pre-processing is so fundamental in any image processing and computer vision process. It must be done on every ceramic tile coming out of the kiln to render the image for better processing. Image pre-processing steps includes varieties of operations such as noise reduction, contrast enhancement, image smoothing and sharpening. At this stage the images is trimmed into equal size in width and height ($m * n$ pixels) The captured images which in Red, Green and Blue (RGB) format is converted to gray-scale format for easy operation. This process renders the images better for processing and it involves gray scaling and de-noising

The RGB captured images are converted to gray-scale format based on NTSC conversion formula as in Equation (3.1), used in image processing toolbox of MATLAB. The lowest possible luminance intensities of Red (R). Green (G), and Blue (B) are identical to zero and the highest values are 255. It takes RGB images with three (3) dimension as input and outputs a 2-dimensional grey scale.

rgb2gray = 0.2989R + 0.5870G + 0.1140B

2.2.2 Noise Reduction

Figure 3 (a) and (b), shows how median filter and mean filter are applied in detecting noise. The median filter as seen in figure 3 (a) moves through the image pixel one after the other sorting through the windows by arranging the values into numerical order to find the median. The number of the pixel being considered will be replace. The number being consider is “102” and is being replaced by the “2” shown in red. The result is the application of median filter. Similarly the mean filter move through the pixels in the window and calculate the means value that will replace the pixel under consideration. In figure 3 (b), the mean value is “13” that is shown in red replacing the “102”. The wide disparity in the result and the existing pixel shows the limitation of mean filer.

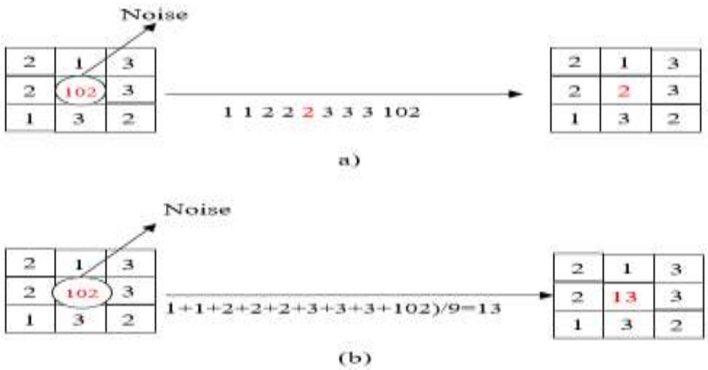


Figure 3. (a) Median filter application, (b) mean filter application

2.2.2. Defect Detection

Defects are areas on the surface of the ceramic tiles that do not conform to standard. The defective areas need to be clearly detected and deferent operations are carried out to achieve that, these operations are shown in Figure 4. The algorithm for detecting the defect in the CT consist of edge detection, thresholding, subtract of reference tile’s image, removing noise and morphological operation. The final product will be the binary matrix of the defect.

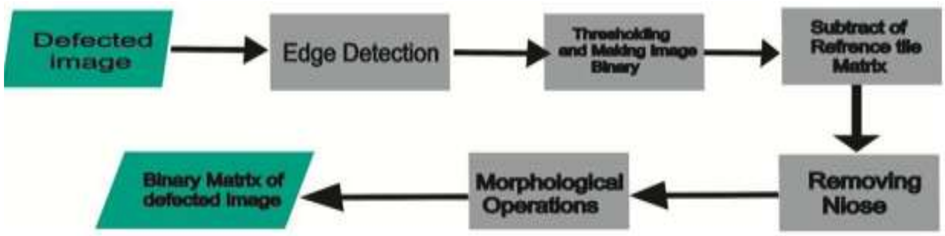


Figure 4: Defect detection algorithm

Edge detection is very key in the detection stage and is the boundary between two dissimilar regions. The defects have peculiarity when analyzing them. Rough and zigzag edges is associated with diffused glaze crack and are mostly concave and convex viewing the crack while hole and pin-hole defect also have concave, convex nature but with a disordered edge. This peculiar nature of the texture of the defect will require statistical texture analysis approach that could handle the distribution of colors or grey levels in the texture (Hanzaei et al., 2017). Rotation Invariant Measure of Local Variance (RIMLV) operator was adopted by (Hanzaei et al., 2017) for detection of the defect edge.

$$VAR_{P,R} = \frac{1}{p}\sum_{p=0}^{p-1}(g_p - \mu)^2 \qquad (1)$$

Where $$\mu = \frac{1}{p}\sum_{p=0}^{p-1} g_p \qquad (2)$$

R is the radius of neighborhood, P is the number of neighbor points, and g_p is the gray value of the P^{th} neighbour, g_c is the gray value of the center point, $VAR_{P,R}$ continuous values and it has to be quantized.
Morphological operators improve, smoothen, and reduce noise when the defect is detected. The closing of an image as shown in equation (4) is a combination of erosion and dilation operation. A is an image that is close by structuring element B results in erosion and dilation as expressed in Equation (4) and that shows the relationship of erosion and dilation have with closing. Closing dual operator is opening and is also based on how erosion and dilation are being used.

$$A.B = (A \oplus B) \ominus B \qquad (3)$$

The closing operator that is used here involves filling the internal borders of defect regions by applying dilation operator while the external borders of defective will be removed by applying erosion operator (Hanzaei et al., 2017).
Dilation and erosion are shown in equation (4) and (5) respectively

$$A \oplus B = \{Z \mid (\hat{B}_Z) \cap A \neq \varnothing\} \qquad (4)$$

While A is the image matrix, B is the mask matrix and z is the coordination of dilation matrix, $(\hat{B}_Z)$ is a subscript transformer of z being inverse form of B, while A is not empty.
The second part is called erosion as defined in Equation (5)

$$A\,!\;\; B = \{Z \mid (\hat{B}_Z) \subseteq A\} \qquad (5)$$

This is erosion of A by B; A being the image matrix, B being the supplement of mask matrix the operation, while z is the coordination of erosion matrix and $(\hat{B}_Z)$ subset of A.

2.3. Feature Extraction

Feature extraction is just the process through which we obtain information from the image, the features of interest in the image is usually highlighted then extracted. (D'Silva & Bhuvaneswari, 2015).
Fourier Descriptor is one of the best descriptors and it is used in this system**.** According to French mathematician Jean Baptiste Joseph Fourier in formulating Fourier transform states that any periodic function can be represented as the sum of sines and/or cosines of different frequencies, each multiplied by a different co-efficient. He further said that a periodic even function whose area under the curve should be finite can be represented as the integral of sines and/or cosines multiplied by the weighted function. The function can be recover or reconstructed by the inverse process without losing information (Singh, Gupta, & Hrisheekesha, 2015). Fourier descriptors have characteristics, like simple derivation, simple normalization and its robustness to noise, which have made them very popular in a wide range of applications. Fourier descriptors are obtained by applying Fourier transform to a shape signature. The Fourier transform on a complex vector derived from the shape boundary coordinates gives us the Fourier descriptors. The shape boundary coordinates can be given as (x_n, y_n), n=0, 1,.., N-1. (D'Silva & Bhuvaneswari, 2015)
The complex vector $\cup$ is given by the difference of the boundary points from the centroid (x_c, y_c), of the shape.

$$\cup = \begin{bmatrix} x_0 - x_c + i(y_0 - y_c) \\ x_1 - x_c + i(y_1 - y_c) \\ \vdots \\ x_n - x_c + i(y_n - y_c) \end{bmatrix}, \; n = 0,1,eN-1 \qquad (6)$$

Where, $x_c = \frac{1}{N}\sum_{n=0}^{N-1} x(n), y_c = \frac{1}{N}\sum_{n=0}^{N-1} y(n)$

The location of the shape from boundary coordinates gives the centroid subtraction, which makes the representation invariant to translation. The Fourier transformed coefficients are then obtained by applying One-dimensional Fourier transform on U in equation (6). These coefficients are given as

$F_k = FFT(U)$ =FFT (7)

For scaling invariance, the magnitudes of the Fourier transformed coefficients U are normalized by the magnitude of the first Fourier transformed coefficient. The obtained Fourier descriptor (FD) is translation, rotation and scale invariant. The high-frequency noise can be reduced to a large extent by limiting the number of coefficients k, leaving at the same time the main details of the patterns. However, this reduction also leads to loss of spatial information in terms of fine detail. (D'Silva & Bhuvaneswari, 2015)

2.4. Defect classification

After the feature vector is been determined, how to classify the defects will become the concern. There are different types of classifier such as K-nearest neighbor (K-NN), neural network, Decision tree etc. Appropriate choice of the classifier to use is important but anyone to selected should deal with non-linearity and eventually high dimensionality. Support Vector Machine (SVM) is used especially because of its ability to handle non-linear data point (Hanzaei et al., 2017). The SVM algorithms though initially developed to handle binary classification problem but could later solve multi-class problem. SVM aim at finding a hyper plane in an N-dimensional space that will classify the data point clearly. If the number of input features is more the One-Against-All SVM is used.

2.5. Confusion Matrix

The confusion matrix is a prediction outline used in statistical analysis in machine learning result, it describes the experimental performance evaluation of the classifier model on test set for which the true values are known.

The accuracy of the classification is assessed base on; calculating accurately the number of identified class examples i.e. true positive, also the number of accurate examples identified that does not belong to a class in question i.e. true negatives (TN) and, false positive (FP) which are class examples that are inaccurately allocated to a class example or false negative which are classes not identified as class example. These four enumeration make up the confusion matrix (Sokolova & Lapalme, 2009).

To analytically compute the performance measure equation (8) states the classifier effectiveness per-average class.

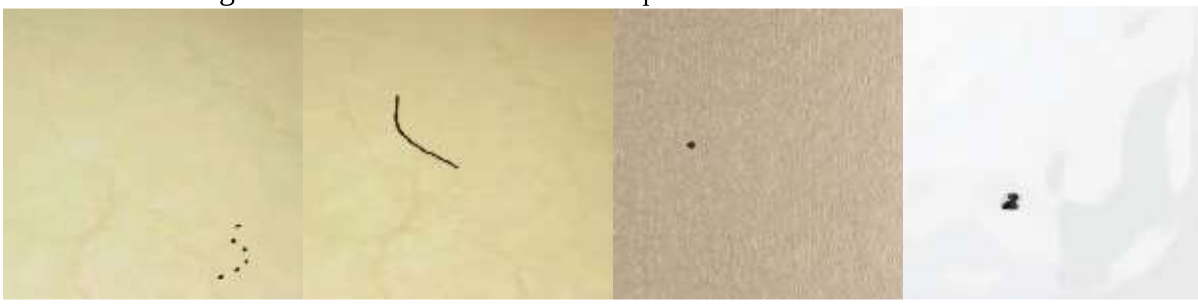
$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} * 100\% \quad (8)$$

3. RESULTS AND DISCUSSION

In this section, the result of the research beginning with image preprocessing of the dataset, followed by defect detection and classification using the multiclass SVM classification models for the training of different extracted feature vectors and, the generation of confusion matrix used to analyse the performance of the test dataset on the trained classifier (SVM) algorithm were discussed and relevant results reported comparing existing method. The algorithm was implemented in MATLAB as discuss in these sub-sections.

3.1.Test images of Defected CT

A dataset of 230 CT images with various defects were acquired.



a) Image I b) Image II c)Image III d) Image IV

Figure 6: Dataset of CT with different defects

Figure 6 presents the samples of the raw dataset with different defects, 50 data set were collected for each defect. Image I is Diffused Glaze Crack (crack I type), image II is Capillary Crack (crack II), image III is Pin-hole and image IV is Hole.

3.2 Result of Image Pre-processing

The acquired colored images were pre-processed to render them in grey scale and to also remove noise. Figure 7 shows each of the defect image with a corresponding pre-processed images result for the four types of defects.

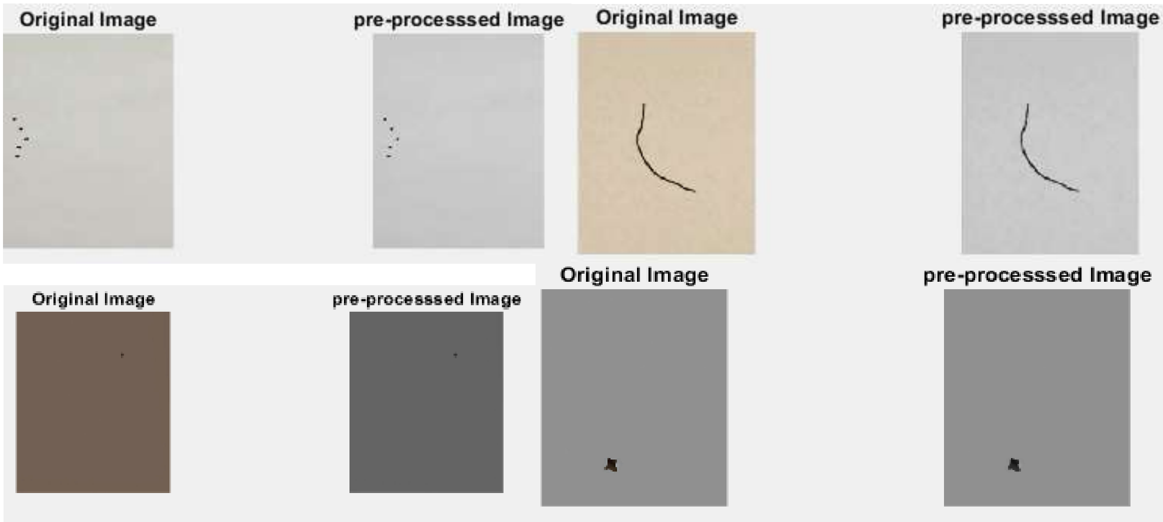


Figure 7: Results of Pre-processed images

3.3. Results of Edge Detection and Binary Closing

The RIMLV operator was used to detect the edges of the defect and the result is presented. To render the detected edge for better feature extraction morphological operator was in-cooperated. The result presented in figure 8 is edge detection using RIMLV and closing using morphological operation for Crack I, Crack II, Pin-hole and Hole defect type.

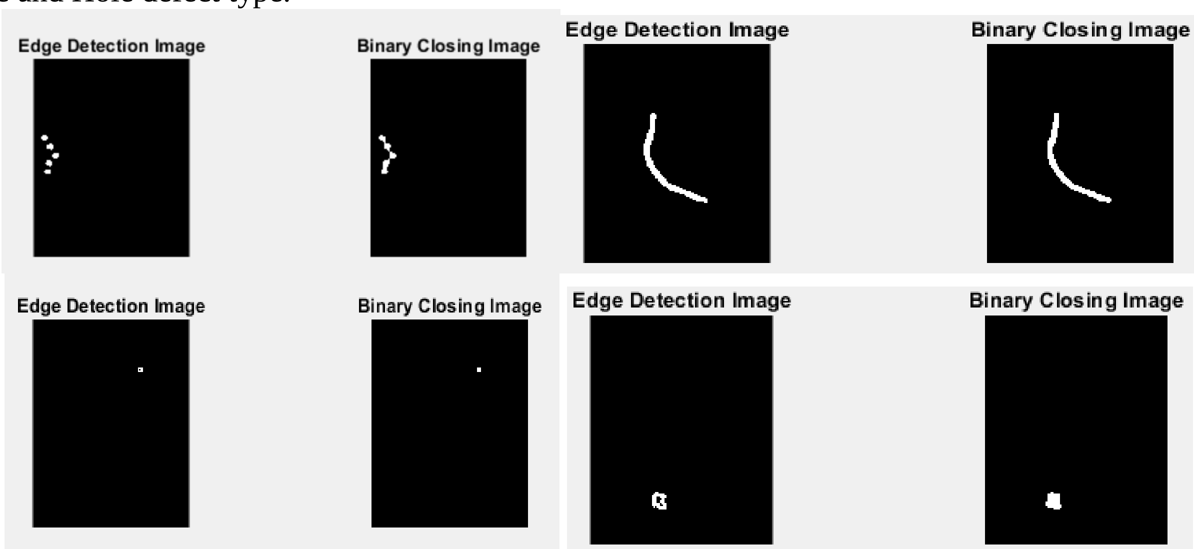


Figure 8: Defect Edge Detection and Closing

3.4 Training and Testing Dataset Model with SVM Classifier

70% of the images was used to train the SVM while 30% was used to test the system. Table 2 and 3 show the prediction when geometric and Fourier descriptor were used on SVM respectively for Crack I, Crack II, pin-hole and hole types of defect.

Table 2: Classification Prediction with Geometric Features

Defects	Crack I	Crack II	Pin-hole	Hole
Crack I	0.93	0.07	0.00	0.00
Crack II	0.00	1.00	0.00	0.00
Pin-hole	0.00	0.00	1.00	0.00
Hole	0.00	0.00	0.13	0.87

Table 2 shows the true positive prediction when Geometric feature is used for SVM classification on the test data for Crack I, Crack II, Pin-hole and hole with the following results were obtained in percentages 93%, 100%, 100% and 87% respectively. The result shows that the system recorded 100% accuracy for crack II type and Pin-hole while 93% for Crack I types and 87% for hole defect type.

Table 3: Classification Prediction with Fourier Features

Defects	Crack I	Crack II	Pin-hole	Hole
Crack I	0.93	0.07	0.00	0.00
Crack II	0.00	1.00	0.00	0.00
Pin-hole	0.00	0.00	1.00	0.00
Hole	0.00	0.00	0.00	1.00

Table 3 shows the true positive prediction when Fourier descriptor is used on SVM classification on the test data for Crack I, Crack II, Pin-hole and hole with the following result in percentage 93%, 100%, 100% and 100% respectively. This shows that the system records 100% prediction for Crack II, Pin-hole, and hole defect type while 93% was recorded for Crack I type defect. The system recorded 98% classification accuracy with Fourier Descriptor and 95% classification with Geometry descriptor on SVM.

Table 4: Comparing SVM Classifier using the two descriptors

	Proposed method (Fourier)	Existing method (Geometric)
Training Time (sec)	1.24	6.20
Classification time (sec)	0.095	0.28

The results show that it takes SVM less time to classify CT defects when Fourier descriptor is used than when geometric descriptor is employed. Higher training time of 6.2 seconds was recorded for geometric against the 1.24 seconds for Fourier descriptor. From the chart we can also see that SVM classify the defect within 0.094939s when Fourier descriptor is used compared with 0.286053s when geometric descriptor is used.

4. CONCLUSION

This research work has proposed, development of automated system for ceramic tiles surface defects detection and classification about 270 CT data were used for the experiment. The data were reprocessed and the RIMLV together with morphological operator were used for defect edge detection while Fourier descriptor was used for defect feature extraction before the one against all SVM was used for classification. Confusion matrix was developed and accuracy of 98% was recorded. The average time of 0.095s was achieved for classification. This shows an improved record over existing method.

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