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# Automated Defective Ceramic Tiles Classification using Image Processing Techniques

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**ABSTRACT**

Surface quality is one of the critical issues in the ceramic tile manufacturing industry. However, there are still large amounts of ceramic tiles manufacturers who use a manual inspection process to check the quality of the ceramic tiles' surfaces. The manual inspection is time-consuming and has low accuracy. Additionally, the slow inspection process could not keep up with the production rate. Therefore, this study presents a solution where image processing techniques are implemented to construct an automated defective ceramic tiles classification. The process consists of a few phases which include image enhancement, image segmentation, feature extraction, and classification. The input image which is the ceramic tiles image was enhanced using the histogram equalization technique. The segmentation was done using Sobel and the global thresholding technique before the feature extraction process is implemented. Three shape features of mean intensity, area, and perimeter were extracted in analyzing the characteristics of each ceramic tile defect type of crack, corner, and edge. Then, the image was classified using the K-Nearest Neighbor (k-NN) technique. A confusion matrix was used to assess the performance of the k-NN classification to 150 testing images. The overall mean accuracy, sensitivity, and specificity returned good performance at 93.34%, 89.93%, and 95% respectively. Thus, it can be inferred that the proposed automated defective ceramic tiles classification using image processing techniques was successful.

## 1. Introduction

Tiles are small, flat objects with a square or rectangular shape. A tile is a manmade component of tough substance, like ceramic, stone, metal, baked clay, and even glass, that is commonly used to cover roofs, floors, walls, or other objects such as tabletops. However, tiles tend to be defective considering certain aspects like their colour, texture, and many more [1,2]. The most common defect of tiles surface includes the presence of blob, corner, crack, edge, pinhole, and glaze [3].

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Surface quality is a critical issue in the ceramic tile manufacturing industry. In this modernized atmosphere, nearly every industry denotes automation to accomplish comparative benefits over manual procedures. Coskun *et al.,* [4] indicate that albeit this inspection stage was critical to maintaining quality and customer gratification, it was still done manually. The manual procedures were done by using human force or labor force during the inspection process of detecting defective ceramic tiles. Lu *et al.,* [5] rightly pointed out that staff in the ceramic tile industry would still work manually to locate flaws throughout the tile surfaces.

Additionally, the exhaustion among staff leads to a slow inspection process and made the inspection rate could not keep up with the production rate [6]. As Mohammad *et al.,* [7] perceptively stated perpetuation of the engendering process which was a tedious process did not equivalent to the engendering rate because the human had constrained time and facilely got tired. The noxious atmosphere in the manufacturing industry was also one of the factors that drove it to time-consuming and labor-intensive during the defects detection process [8]. Thus, the importance of a computerized defect detection system could not be disputed.

Image processing is used to evoke various information from images using a computer automatically, with or without human participation [9]. On another note, image processing is the process of converting an image into a digital medium and applying various operations to obtain useful information. There were a lot of image processing applications in various types of fields that had been developed before to ease the process to get a better view and information of the image. For instance, in the medical field, there were applications to enhance Magnetic Resonance Imaging (MRI) images and to detect brain tumors [10]. There were also applications for the agricultural field for instance herbs recognition, nutrient deficiency detection through the leaf, and to name a few [11-13] Due to the aptitudes that image processing techniques held which were available to proffer a high precision rate, high dependability, and utilizer-conviviality, it could avail to solve these issues. The outstanding advantages of image processing like having high reliability could help industries face many obstacles in the manufacturing process [14].

Numerous methods for extracting highly associated changes in image intensity for defects classification, the most notable of which are morphological operations and edge detection were presented. Advanced image analysis algorithms, like Local Binary Pattern, wavelet, and Gabor filter, are deployed in complex scenarios and produce improved results for classifying and identifying cracks defect [15-17] The advent of Deep Learning such as Convolutional Neural Networks (CNN) has also led to enormous ground-breaking results in object classification, detection, and recognition [18].

A work by Lian *et al.,* [19] proposed a Deep Learning-based approach for defect detection and classification in industrial images. They employed a Generative Adversarial Network (GAN) to extract features from images, achieving high accuracy in defect detection and classification tasks. A study by Chen [20] conducted research on defect detection in manufacturing processes using support vector machines. They utilized support vector machines (SVM) to detect defects, employing various features such as texture, shape, and color. Their study demonstrated the effectiveness of SVM in defect detection. Yasar *et al.,* [21] focused on the defect classification in fabric images using wavelet transform method. They utilized wavelet transform using four different feature sets (wavelet-based Principal Component Analysis, wavelet-based Gray Level Co-occurrence Matrix, Principal Component Analysis and Gray Level Co-occurrence Matrix) to extract texture features and trained a neural network classifier. The authors achieved high accuracy in classifying fabric defects. Lu *et al.,* [22] explored the defect detection and classification in ceramics manufacturing using an improved You Only Look Once Version 5 (YOLOv5) algorithm. They focused on applying Deep Learning algorithms to detect defects in ceramics manufacturing, and presented results showcasing the effectiveness of their approach.

The adoption of Deep learning-based defect detection offers flexibility in terms of the network's ability to discover various defects based on the dataset [23]. The parameters of the network learned for one network can also be applied to similar networks to produce high success rates for surface defect detection. However, the CNN training method requires enormous amounts of labelled data; and thus, huge image datasets [24] need to be collected and made available by researchers for this purpose. Therefore, this study proposed a study on automated inspection of defective ceramic tiles classification using traditional image processing techniques. The outcome of the proposed study is expected to offer high classification accuracy in a limited data in a short period, and to be beneficial to the ceramic tile industry for high volumes of ceramic tiles production. The rest of this paper is structured as follows: The image datasets and our study methodology are all described in Section 2. Section 3 presents the results and discussion. Finally, we describe our conclusions in Section 4.

## 2. Methodology

This study aims to evaluate the performance of defective ceramic tiles classification using image processing techniques. The process flowchart for defective ceramic tiles classification begins with input which is the ceramic tiles image. The image will then go through image enhancement, image segmentation, and feature extraction. Finally, the classification process is then carried out. Figure 1 portrays the flowchart of this research.

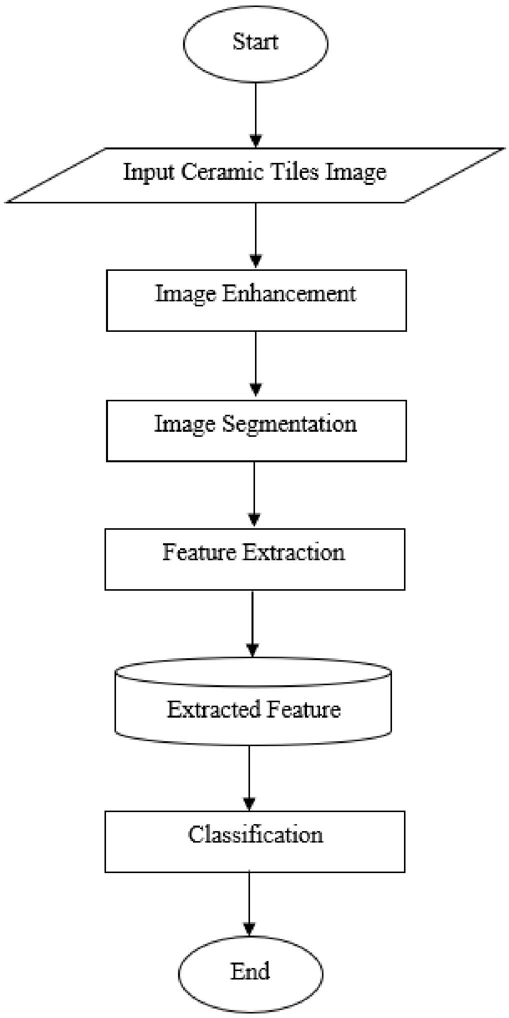



**Fig. 1.** Proposed flowchart of defective ceramic tiles classification

The image enhancement, image segmentation, feature extraction, and classification represent a few of the phases that comprise up the process flowchart. The histogram equalization technique was used to improve the ceramic tile input image. Prior to the feature extraction process being carried out, the segmentation was performed using the Sobel and global thresholding techniques. The characteristics of each type of crack, corner, and edge defect were analyzed using three shape features—mean intensity, area, and perimeter. The k-Nearest Neighbour (k-NN) classification method was then used to classify the image.

### *2.1 Defective Ceramic Tiles Images*

Hundred and fifty defective ceramic tiles images which are crack, corner, and edge were acquired. The images were then divided into a 70:30 ratio for the training and testing processes. Table 1 depicts the sample of the input image for each type of defect.

**Table 1**
Sample images of defective ceramic tiles

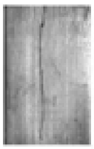
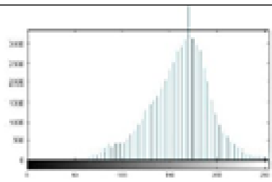
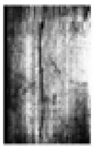
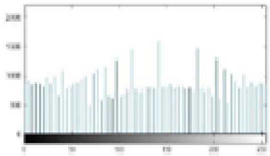
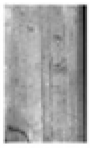
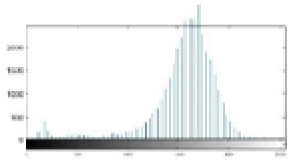
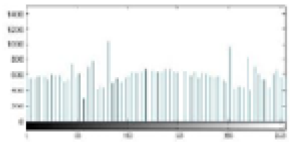
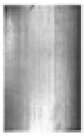
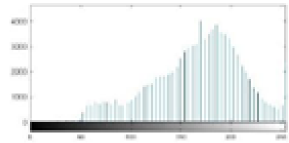
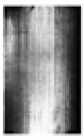
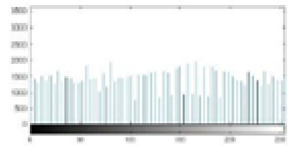
| Image | Type | Number of images |
|---|---|---|
|  | Crack | 50 |
|  | Corner | 50 |
|  | Edge | 50 |

### *2.2 Image Enhancement*

Image enhancement is generally the process to refine the look of an image. Shukla *et al.,* [25] stated that the image enhancement process involves improving the representation of the image or transforming it into a format that is the best fit for human or machine study. It is the process of adding transformations to input images to generate a more pleasing and informative image [26]. Moreover, it could also be used to recover lost information or to draw attention to specific features of interest points of an image [27].

The histogram equalization technique alters the range and intensity of an input image to obtain a histogram of the desired form. It is a histogram specification approach that equalizes the histogram in such a manner as to improve image contrast [28]. The image then becomes clearer and the process produces the image with evenly dispersed brightness levels over the histogram's entire brightness scale. The steps involved in histogram equalization are adjusting the histogram equalization using the histeq function and matching a flat histogram with 64 bins. Table 2 tabulates the sample of Histogram Equalization enhancement.

**Table 2**
The sample of Histogram Equalization enhancement

| Image | Image Condition | Histogram | |
|---|---|---|---|
| 1 | Before |  |  |
| | After |  |  |
| 2 | Before |  |  |
| | After |  |  |
| 3 | Before |  |  |
| | After |  |  |

### *2.3 Image Segmentation*

The next process is image segmentation where the input image is segmented and the techniques that have been deployed are edge-based and thresholding. It is done to simplify the transformation of an image's interpretation into something more meaningful and simpler to understand. Two sub-processes of edge-based segmentation and binarization were involved. For edge-based segmentation, the gradient-based technique is chosen to be applied, and the gradient-based operator used was the Sobel edge detector. The Sobel operator is a gradient-based technique and one of the most widely used edge detection methods as it only considers the information in both vertical and horizontal directions [29]. The Sobel edge detector employs a set of 3x3 convolution masks, one for estimating the x-direction gradient and another for calculating the y-direction gradient. Three steps were involved by using Eq. (1) where $g$ is the gradient magnitude, $g_x$ is the vertical edges, and $g_y$ is the horizontal edges:

$$|g| = |g_x| + |g_y| \tag{1}$$

i. Sobel operator mask definition for *x* and *y* direction.
ii. Gradient approximation.
iii. Magnitude of the vector computation.

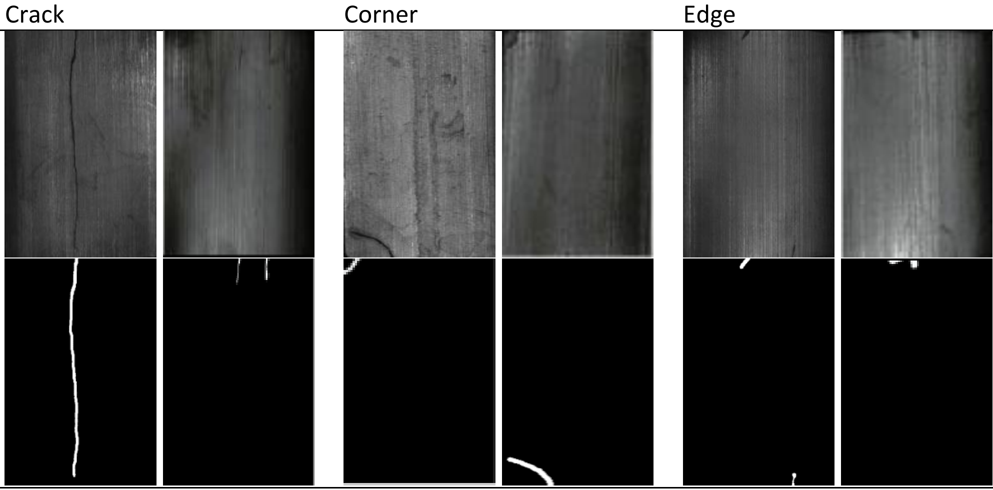
Next, in the binarization process which implemented the global thresholding, a single threshold value is used for the entire image [30]. The operation or steps for global thresholding consists of a few main steps:

i. Threshold value, *T* identification.
ii. Image histogram partitioning using the calculated threshold value, *T*.
iii. Pixels' scanning and labeling using Eq. (2), where $(x, y)$ is the current pixel value of coordinate $x$ and $y$.

$$(x, y) = \begin{cases} 1, if\ (x, y) > T \\ 0, if\ (x, y) \leq T \end{cases} \tag{2}$$

Table 3 tabulates the sample images of ceramic tiles before and after the segmentation process.

**Table 3**
The segmentation results

| Defect Type | Crack | Corner | Edge |
|---|---|---|---|
| Before Segmentation |  | | |
| After Segmentation | | | |

*2.4 Feature Extraction*

After the segmentation process, only the defective area will be left out. The features of the image were then extracted. In the feature extraction process, the most used low-level features are considered which include color, shape, and texture [31]. For this defective ceramic tiles' classification, the most suitable features are the shape features where the features of the defective areas from the tiles were extracted. Three features of mean intensity, area, and perimeter were extracted using the regionprops function and tabulated. Table 4 presents the summary of the extracted values of the ceramic tiles images which include mean intensity, area, and perimeter. The values of the extracted features are then utilized as a basis in the classification afterward.

**Table 4**
The summary of extracted features

| Defect type | Feature | Mean | Range Values |
|---|---|---|---|
| Crack | Mean Intensity | 80.83 | 56.8 - 98.0 |
| | Area | 14.29 | 1.0 - 22.0 |
| | Perimeter | 9.62 | 2.0 - 35.7 |
| Corner | Mean Intensity | 75.56 | 47.6 - 99 |
| | Area | 5.26 | 1.0 – 34.0 |
| | Perimeter | 8.20 | 2.0 – 27.3 |
| Edge | Mean Intensity | 64.88 | 36.3 – 98.0 |
| | Area | 7.14 | 1.0 – 21.0 |
| | Perimeter | 8.10 | 2.0 – 21.7 |

### *2.5 Classification*

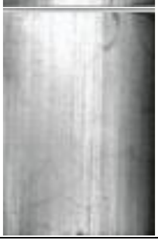
The last process is the classification process. The k-Nearest Neighbor (k-NN) was employed due to its simplicity, logic, and adaptability in classification [32]. The k-NN is a supervised machine learning method that trains from a labeled training set by pulling in training data *x* and labels *y* and learning to map the input *x* to the expected outcome *y* [33]. In the procedure of the technique, the images are grouped based on the number of votes they get from their neighbors [34].

This model utilizes the nearest attribute subsets and produces results for automated defect detection. The classes of the unknown data need to be obtained to search the k-NN. The proposed study utilized five nearest points of indexes, using the regular Pythagorean distance calculation. The classes were then extracted. Finally, the test coordinates into arrays based on the number of classes were extracted.

## 3. Results and Discussion

A confusion matrix is utilized to assess the classification of defective ceramic tiles' performance. It is conducted by comparing the results of the k-NN classification with the actual particular type of ceramic tile defects. Table 5 tabulates the samples of classification accuracy results.

**Table 5**
The sample of classification accuracy results

| Image No | Image | Actual Defect | k-NN Defect Classification | Accuracy |
|---|---|---|---|---|
| 1 |  | Crack | Crack | TRUE |
| 2 |  | Crack | Corner | FALSE |
| 3 |  | Corner | Corner | TRUE |
| 4 |  | Corner | Crack | FALSE |
| 5 |  | Edge | Edge | TRUE |
| 6 |  | Edge | Edge | TRUE |

A total of 150 images of defective ceramic tiles were assessed, with 50 images for each defect type. Table 6 summarizes the number of TRUE and FALSE classification accuracy results in the form of a confusion matrix.

The values shown in Table 6's diagonal pattern corresponded to the correct classification of defective ceramic tiles. It can be observed that 46 crack images were correctly detected as crack, whereas three images were incorrectly classified as corner, and one image as edge. Next, 44 corner images were accurately identified as corner, while four and two images were wrongly classified as crack and edge respectively. The edge images were detected 45 times correctly and a total of five times incorrectly classified into the different defective types.

Next, the performance of k-NN defective ceramic tiles classification in the comparative experiment was evaluated using three metrics which are accuracy, sensitivity, and specificity as tabulated in Table 7.

From Table 6, it is noticeable that the defective ceramic tiles classification produced a great classification for the edge, which stipulates 94.67% of accuracy. The classification of crack and corner suggested good and similar classification performance at 92.67%. On the other hand, the true positive rate (TPR) of sensitivity returned the highest percentage for crack at 92%, followed by the edge at 89.8%, and corner at 88%. Additionally, the edge produced the highest true negative rate (TPN) of specificity at 97%, 95% for the corner, and 93% for the crack. The comparable representations between these crack and corner defective tile types could reasonably lower down the percentage of accuracy. However, the overall mean accuracy of 93.34% denotes a successful classification of the defective ceramic tiles in general.

**Table 6**
The confusion matrix

| | k-NN Defect Classification | | |
|---|---|---|---|
| Actual Defect | Crack | Corner | Edge |
| Crack | 46 | 3 | 1 |
| Corner | 4 | 44 | 2 |
| Edge | 3 | 2 | 45 |

**Table 7**
The defective ceramic tiles classification performance

| | Accuracy | Sensitivity | Specificity |
|---|---|---|---|
| Crack | 92.67 | 92 | 93 |
| Corner | 92.67 | 88 | 95 |
| Edge | 94.67 | 89.8 | 97 |
| MEAN | 93.34 | 89.93 | 95 |

## 4. Conclusions

This paper presented a study on automated defective ceramic tiles classification using image processing techniques. The study is concentrating on the three different types of defective ceramic tiles which are crack, corner, and edge. The three shape features of mean intensity, area, and perimeter were extracted in analyzing the characteristics of each defect type. On another note, a k-Nearest Neighbor (k-NN) technique is used to classify the defective ceramic tiles. The application has been successful for 150 testing images. The performance of defective ceramic tiles classification is assessed using a confusion matrix. The overall mean percentage of accuracy, sensitivity, and specificity exhibited strong achievements which are 93.34%, 89.93%, and 95% respectively. It can be inferred that the proposed automated defective ceramic tiles classification using image processing is found to be successful. In the future, the most recent feature extraction and recognition methods, like deep convolutional neural networks could be utilized.

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