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EFFICIENT SURFACE CRACK DETECTION IN CERAMIC TILES USING MATLAB IMAGE PROCESSING

Merve OZKAN-OKAY[1] and Ömer AHAT[1]

[1]Department of Computer Engineering, Ankara University, Ankara, TÜRKİYE

Abstract. The significance of quality control in the ceramic tile industry cannot be overstated. Traditional approaches to quality control in this sector have relied heavily on labor-intensive manual inspection methods, which are not only costly but also less efficient. Moreover, these methods often fall short in terms of accuracy, primarily due to the challenging industrial environment and the potential for human error. To address these shortcomings, this research proposed an innovative automated inspection system utilizing advanced image processing techniques specifically designed for the ceramic tile industry. This system detects defects such as corner damage, edge damage and center cracks on tile surfaces and provides information for quality assurance processes by classifying tile quality through rigorous analysis and comparison of various quality parameters. The performance of the system is tested with a total of 120 synthetic data, including those with cracks, damaged corners and discoloration. As a result of the testing process, a 97.5% accuracy rate is obtained. Furthermore, the system operates with a processing time of approximately 0.8 seconds per piece. This study, which offers both high accuracy and efficiency, promises significant improvements in quality control processes by offering an alternative to manual inspection methods.

Keywords. Ceramic tile defect, image processing, machine learning, grid search algorithm.

1. Introduction

The ceramic tile industry relies significantly on the meticulous adherence to quality standards to ensure the production of high-grade products [1]. Despite the high level of automation in many stages of the process, detecting and classifying tile defects continues to rely mainly on expert human operators. These operators visually

merveozkan@ankara.edu.tr-Corresponding author; 0000-0002-1071-2541; ror.org/01wntqw50
ahatomer45@gmail.com; 0009-0002-8739-4729; ror.org/01wntqw50

examine each tile and categorize them into three or more categories. This task, however, is both arduous and demanding, often leading to issues such as eye fatigue and lapses in attention, which can result in **incorrect** tile classifications [2]. To sum up, traditional quality control methods are often time-consuming and costly, and sometimes lack sufficient sensitivity. In this context, the integration of image processing techniques is utilized to optimize production processes and enhance quality. Image processing techniques play a significant role in various industries. Particularly in the ceramic industry, the use of these techniques offers the potential to optimize production processes, enhance quality control, and increase efficiency. In this context, to overcome these mentioned deficiencies, this research proposed a novel system that uses image processing techniques.

There are many studies showings that the ability of software developed with the use of artificial intelligence and image processing techniques to detect defects on ceramic surfaces has increased. However, there are still some significant shortcomings in detecting defects on ceramic surfaces. While image processing systems can be effective in detecting specific flaws such as cracks, roughness, or color variations, they may fall short in capturing more complex structural defects or microscopic-level details. Additionally, the limited datasets often used to train machine learning algorithms can pose challenges for generalization. Therefore, the development of more reliable and precise methods for defect detection in the ceramic industry is crucial for increasing production process efficiency and enhancing quality standards.

The proposed automated detection system seeks to contribute the quality control process by focusing on addressing specific defects like center cracks, corner and edge damages on the tile surface. Additionally, this system aims to enhance the precision of defect identification and improve the overall efficiency of the inspection process. By conducting a thorough comparison, the quality of tiles can be effectively classified. In this context, the study initially identifies the optimal boundary values for the resize ratio and Canny edge ratio, which yield the highest accuracy rate. This determination is achieved through an algorithmic approach incorporating the grid search algorithm along with annotated data. Subsequently, morphological operations are applied to the ceramic tiles based on these values. Following the operations, cracks within the tile are detected and the results are generated.

To ascertain the effectiveness of the suggested system, a thorough evaluation was conducted utilizing a dataset comprising 120 synthetic ceramic tiles, encompassing defective tiles with cracks, corner damage, and discoloration. The results of this evaluation demonstrated a detection accuracy of 97.5%. Furthermore, the processing time for inspecting a single tile is efficient, averaging approximately 0.8 seconds. These findings highlight the potential of the proposed system to address the shortcomings of manual ceramic tile detection, presenting a high accuracy and efficiency alternative.

The remaining part of the study is structured in the following manner: a literature review on the importance of defects on ceramic surfaces and existing detection methods is presented in the second section. The methodology of the proposed method is detailed in the third section. Subsequently, applications and results of the proposed method on detecting defects on ceramic surfaces are extensively discussed in the fourth section. Lastly, the conclusion section summarizes the study's findings, alongside suggestions for prospective investigations.

2. Background Study

Over the past few years, there has been a notable surge in research on the use of machine learning and image processing techniques for detecting defects on ceramic surfaces. These techniques aim to automate the process of detecting errors in industrial production processes, thereby improving production quality. Upon examining these studies, significant results achieved thus far become evident. A summary of the relevant studies can be found in Table 1.

Mansoory et al. [3] proposed an automatic image processing system for defect detection and classification in ceramic tile surfaces during firing. The system utilizes the RIMLV operator identify defect edges and employs a Close morphological operator to refine and smoothen detected areas. Identified defects are labeled, and corresponding geometric characteristics are extracted. A multi-class SVM classifier is then applied, grounded in statistical pattern recognition theories, to discern the type of defect. The proposed system aims to eliminate defected tiles in the early stages, reducing production costs by preventing defects from reaching the coloring and packaging stages. Another algorithm presented in the article uses Radon transform, spatial domain enhancement, and morphological operands (Top-Hat, Bot-Hat) to separate perfect tiles from defective ones. The algorithm can detect the number of defects and display them, with program performance speed depending on Radon transform and its scales in the Matlab environment.

Younas et al. [4] suggested an automated defect detection method using image processing and morphological operations. The method involves resizing and converting the RGB image to grayscale, eliminating noisy artifacts, and applying an edge detection algorithm to enhance crack representation. Morphological erosion and dilation operations are sequentially applied to obtain intermediate images, and the final edges are identified through the subtraction of the eroded image from the dilated one. The suggested algorithm doesn't necessitate a distinct reference image for detection. The effectiveness of algorithm is demonstrated through testing on a set of sixty disparate images of defective tiles, achieving an average detection accuracy of 92%. This work can be improved to increase the accuracy rate.

TABLE 1. Summary of related studies.

Paper	Proposed Method	Goal/Success	Year
Mansoory et al. [3]	an automatic image processing system	proposed algorithm can detect the number of defects and display them	2008
Najafabadi et al. [11]	proposed a corner defect detection method relying on dot product analysis	revealing a 12.5% error rate for both normal and defective tiles	2011
Martinez et al. [8]	image processing system utilizing both 2D cameras and 3D laser scanners	the error rate in automated classification was lower compared to manual classification	2013
Hocanski et al. [2]	an image processing system utilizing C++ and various libraries	maximum execution time below 900 milliseconds and detection accuracy of 98%	2016
Samarawickrama et al. [5]	MATLAB-based automated surface defect detection system	proposed system achieved 96.36% accuracy rate, with each tile processed in approximately 2 seconds	2017
Hanzai et al. [6]	detecting and classifying system based on image processing	proposed work provides high accuracy and time efficiency	2017
Iglesias et al. [7]	image processing system utilizing machine learning algorithms	this study identifies traits and characterize the slabs	2018
Stephen et al. [10]	presents an approach using Convolutional Neural Networks	proposed approach enhances efficiency, relying on high-quality feature representations	2021
Younas et al. [4]	automated defect detection method based on image processing and morphological operations	achieving 92% average detection accuracy	2022
Wan et al. [9]	image processing framework based on deep learning	proposed model can address issues stemming from small defects and inadequate feature information	2022

Samarawickrama et al. [5] a surface defect detection system for ceramic tiles, utilizing MATLAB and employing image processing techniques. Their project outlines an automated inspection system for the ceramic tile industry, leveraging image processing methodologies. This system identifies color variations and various defects, including corner damages. The methodology involves comparing tiles with a reference by using image processing concepts implemented in MATLAB. This comparison enables the classification of tile quality. The system's efficacy was validated using 110 real ceramic tiles, including those with cracks, corner damages, and color variations. The system achieved a detection accuracy rate of 96.36%, with each tile processed in approximately 2 seconds. This study can be further developed in terms of processing time.

Hanzai et al. [6] introduced an image processing system aimed at detecting and classifying defects on ceramic tile surfaces within firing units. Their work outlines an automated image processing system for its exceptional precision and efficient time utilization. In the initial phase of defect detection, they utilize the RIMLV operator to detect defect edges. Moreover, they employ a Close morphological operator to collaboratively fill and refine the identified regions. Following this, all identified defects on a single ceramic tile undergo labeling, and pertinent geometric features are extracted. To classify the defect type, they utilize a multiclass SVM classifier, implementing a winner-takes-all approach grounded in statistical pattern recognition principles.

Hocanski et al. [2] introduced an image processing system utilizing C++ and various libraries to detect and classify defects on ceramic tile surfaces. Their work presents a prototype computer vision station (CVS) designed for instant identification of biscuit tile defects. The graphical user interface (GUI) application is developed with Microsoft Foundation Class (MFC), utilizing C++, and incorporates OpenCV and Nvidia CUDA libraries for algorithmic processing. The proposed system has a fast execution time of under 900 milliseconds and achieved a detection accuracy of 98%.

Iglesias et al. [7] introduced an image processing system utilizing machine learning techniques for detecting and classifying defects in slate slabs. Their study presents an automated inspection system designed to analyze slate slab attributes. This system utilizes a 3D color camera to gather data and employs tailored computer vision algorithms for analysis. The approach underwent evaluation using a dataset consisting of 70 slate slabs sourced from a Spanish mine. These slabs had been formerly assessed by a specialist. According to results, this study identifies attributes and define the slabs with inspection algorithms. The investigation focused particularly on detecting sulfides, utilizing calibration slabs that housed artificial sulfides of diverse shapes, sizes, and colors.

Martinez et al. [8] proposed an image processing system utilizing both 2D cameras and 3D laser scanners with machine learning algorithms to identify and categorize defects in slate materials. The research employed machine learning methods, utilizing numerical variables extracted from both 2D and 3D images obtained from the respective devices, offering crucial slate information. To construct an effective classification model, they employed supervised machine learning methods such as SVM and MLP neural networks, alongside non-supervised techniques like SOM and cluster analysis. Their research suggests that the automated classification exhibited a lower error rate compared to manual classification, thus reducing the inherent subjectivity associated with manual inspection in the slate classification. This work can be further improved directly with an acyclic graph methodology.

Wan et al. [9] introduced an image processing framework equipped with libraries tailored for detecting and categorizing defects in ceramic tiles using deep learning techniques. Their approach presents a detection methodology built upon an enhanced version of YOLOv5s. Initially, they deepened the network layer within the backbone network and integrated the attention mechanism CBAM module. Subsequently, they introduced a smaller-scale detection layer, transitioning the model from a three-output to a four-output prediction layer. They augmented network feature fusion within the neck network. Finally, they substituted the initial convolutions with depth wise separable convolutions, leading to the creation of a lightweight system for detecting ceramic tiles. According to empirical findings, proposed model can address issues stemming from small defects and inadequate feature information. The model can be optimized by techniques such as reducing the quantity of model parameters and model pruning.

Stephen et al. [10] presents a machine learning approach to detect ceramic surface defects through CNNs. Their method employs a CNN architecture to extract features and classify raw pixel images, leveraging the initiation of convolutional kernels based on the learned filter kernels within the network. Unlike traditional methods, which separate feature extraction and classification tasks, their approach simultaneously learns sigmoid binary-class classification alongside discriminative feature vectors. This unified approach enhances efficiency, relying on high-quality feature representations acquired through network training. In this study, enhancing the classifier's robustness can be achieved by broadening the collection of tile surface defects it can recognize.

Najafabadi et al. [11] proposed a corner defect detection method relying on dot product analysis in ceramic tile images. This research introduces a technique for visually inspecting corners of ceramic tiles using image processing methods and dot product vectors, particularly focusing on angles exceeding 92 degrees or falling below 89 degrees. Detection of such angles indicates a defective tile in our ceramic analysis. The algorithm's performance is assessed using a dataset comprising images captured from a Flaw Master system in a tile manufacturing facility, revealing a 12.5% error rate for both normal and defective tiles. Considering the results, the proposed approach is effective in corner defect identification. This study can be improved by testing it from different degrees.

Examined researches in the literature demonstrate the significant potential of using machine learning and image processing techniques in the ceramic industry for detecting and classifying defects on ceramic surfaces. These techniques have been applied with various algorithms and modeling approaches to detect, classify, and analyze surface tiles. Research indicates that these technologies can detect defects and enhance quality control in production processes. However, some researches in the literature have highlighted challenges such as scalability, real-time processing, and industrial applicability. In this context, according to the studies examined, there is a need for the development and optimization of error detection systems.

3. Methodology

A methodology has been proposed to contribute to the detection of defects in ceramics.

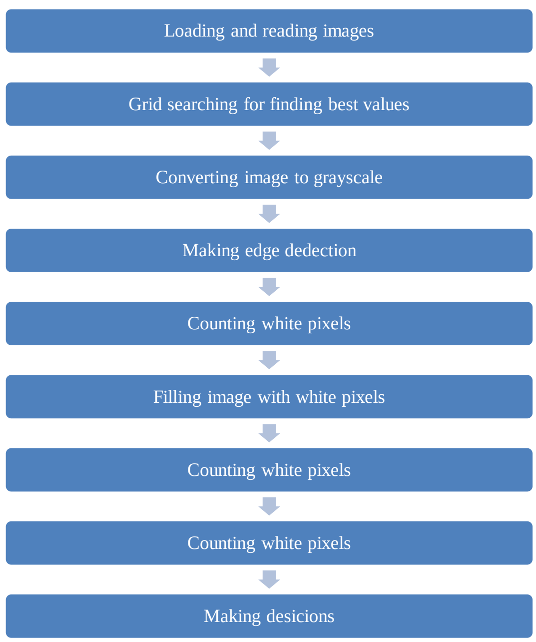

Figure 1. Workflow of methodology.

In the context of the proposed methodology, firstly, the dataset is synthetically generated with reference to existing ceramic data. After that, optimal values have been determined for the detection of defects using the Grid Search algorithm. Subsequently, the obtained values are used to process reference and test images. Finally, ceramic tiles are classified based on surface defects considered in the test image. The detailed workflow of the proposed methodology is given in Figure 1.

3.1. **Grid Search Algorithm.** The Grid Search algorithm serves as a key component of our methodology by providing a systematic framework for fine-tuning the parameters of proposed machine learning model. By exhaustively exploring a grid of potential parameter combinations, Grid Search facilitates the identification of the optimal parameter configuration that enhances performance for our target.

In the context of proposed methodology, Grid Search is used to identify optimal values for two critical parameters: the canny edge ratio and the resizing ratio. These parameters play a crucial role in the preprocessing stage of defect detection algorithm and affect the quality and accuracy of the subsequent analysis. Through iterative evaluation of various parameter combinations, Grid Search allows to identify the configuration that provides the high accuracy rate on our labeled dataset [12-13].

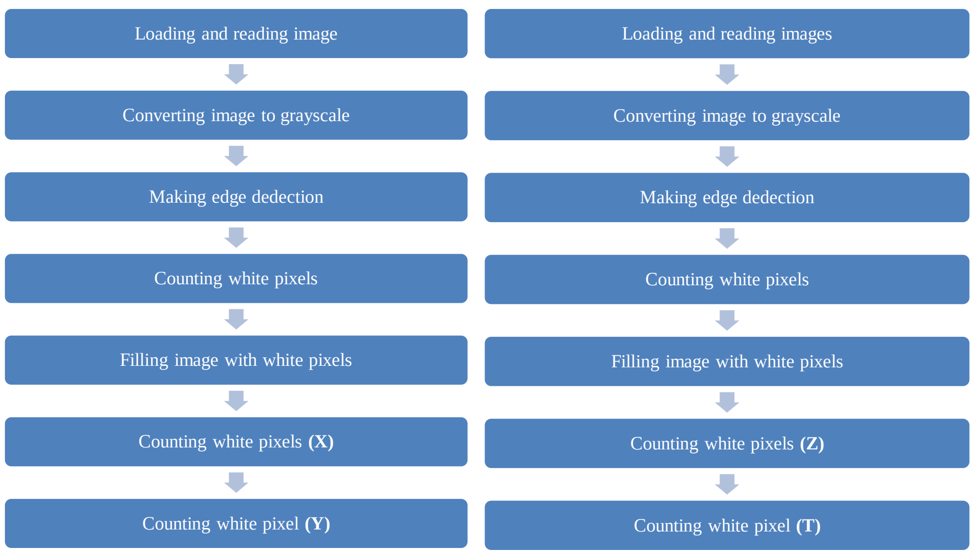

FIGURE 2. (a) Processing of the reference image; (b) Processing of the test image.

After detailed experimentation, it is observed that optimal results are obtained with a canny edge ratio of 0.13 and a resize ratio of 0.90, achieving an accuracy of 97.5%. This optimization process ensures that proposed defect detection algorithm is fine-tuned for optimal performance on a variety of ceramic tile images. Integrating Grid Search into the proposed methodology not only enhances the accuracy and reliability of the defect detection system but also streamlines the parameter optimization process, facilitating efficient model development and deployment.

3.2. **Processing the reference and test images with the obtained values.** A tile image without surface defects is taken as a reference and processed as shown in Figure 2 (a).

As in Figure 2, after reading the reference image, the image is resized to reduce its dimensions. In this way, the processing time is significantly reduced, and efficiency is increased. In this stage, a rapid resizing with bilinear interpolation, a method commonly used in image processing to estimate the values of pixels in non-integer coordinates within an image is applied.

In RGB images, edge detection is not possible, therefore the RGB image is converted to grayscale. Edge detection is the most important step of the defect detection algorithm. Except for color change detection, other defects are detected based on edge detection. In this study, edge detection is performed with a canny edge detection algorithm. The success and quality of edge detection depends on the threshold value. As a result of the grid search algorithm, the determined threshold values for this dataset are Resizing Ratio: 0.90 and Canny Ratio: 0.13.

For the next step of performing morphological operations, a binary image is required and the output of the canny edge detection algorithm is a binary image. Accordingly, there is no need to convert the reference image into any binary image. In this step, morphological filling is done to fill the edge detected image. The main reason for filling the image with holes is to treat the holes as white pixels. They are then counted for the purpose of defect detection. The next steps are basically counting the white pixels of a given image. According to Figure 2, first the white pixels of the edge detected image, denoted by X, are counted and then the white pixels of the filled image, denoted by Y, are counted. For each new series, this process must be done for a new reference tile.

After applying the Canny edge detection algorithm, the obtained binary image is used for morphological operations. In this step, morphological filling is performed to fill the detected edges in the image. The main reason for filling the image with holes is to treat the holes as white pixels, which will be counted for defect detection purposes. Subsequent steps primarily involve counting the white pixels in a specific image. According to Figure 2, first, the white pixels of the edge-detected image, indicated by X, are counted, and then the white pixels of the filled image, indicated by Y, are counted. To provide a new reference guide, this process needs to be repeated for each new ceramic series.

When the reference image has been successfully processed, the test tiles are analyzed. The processing of the test tiles is done in the same way as the processing of the reference tile as shown in Figure 2(b). In the processing of test tiles, white pixels in the edge detected image are indicated as Z and white pixels in the filled image as T.

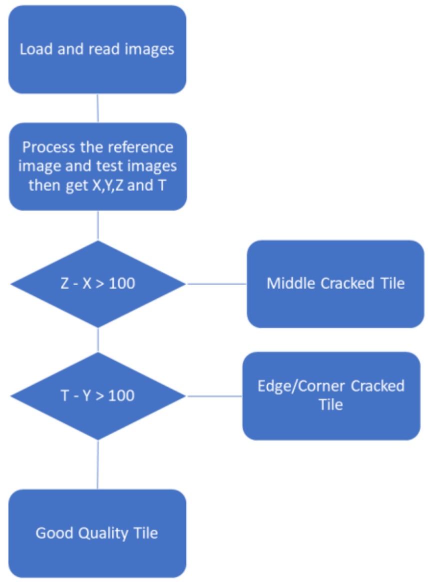

FIGURE 3. Classification of the defects.

3.3. **Classification of the Defects.** The classification of surface defects is carried out on the basis of the values obtained for variables X, Y, Z and T as illustrated in Figure 3.

3.3.1. *Checking for Cracks in the Middle of the Tile*. At this stage, tiles with cracks in the middle are detected as defective tiles. This involves assessing the variance in the count of white pixels within the edge-detected images of both the reference and test tiles. The difference is calculated as follows.

$$Z - X > 100$$

A tile with cracks in the middle has more white pixels in the edge detection image of the test tile than in the edge detection image of the reference tile (Z>X). However, when considering the number of white pixels in the morphologically filled images of the reference and test tiles, both have almost the same number of white pixels (Y=T).

3.3.2. *Checking for Cracks in a corner or edge of a tile*. Defective tiles are identified by the existence of a crack in the center. This identification process involves comparing the difference in the number of white pixels between the edge detection images of the reference and test tiles. The difference is calculated as follows.

$$Y - T > 100$$

When evaluating a tile with a crack in a corner or edge, the filled image of the test tile typically contains fewer white pixels than the filled image of the reference tile. Therefore, the "Y" value should be larger than the "T" value (Y>T). However, when comparing the white pixels in the edge detection images of the reference tile and the test tiles, it is generally observed that the number of white pixels in the edge detection image of the defective test tile is lower or almost equal to that of the reference tile (Z < X or Z = X).

4. Testing and Results

The system was tested using a variety of tiles, each containing different types of defects, as well as a normal tile without any defects. An example of the tiles used for testing purposes is shown in Figure 4.

4.1. **Edge Detection and Morphological Filling Results.** Following the completion of edge detection and morphological filling processes, the tested tiles were examined. These images were scrutinized to accurately identify the existing defects. Figure 5 depicts the edge-detected images for the test tiles.

Additionally, Figure 6 (a) and (b) presents the morphologically filled images for the test tiles.

The system was subjected to practical tests using a dataset of 120 tiles. Details for calculating accuracy are shown in Table 2.

The system has demonstrated successful performance by achieving a high accuracy rate of 97.50% on the test set.

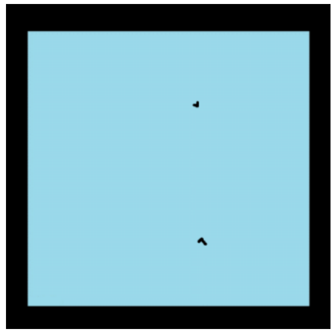

FIGURE 4. Tile example for testing.

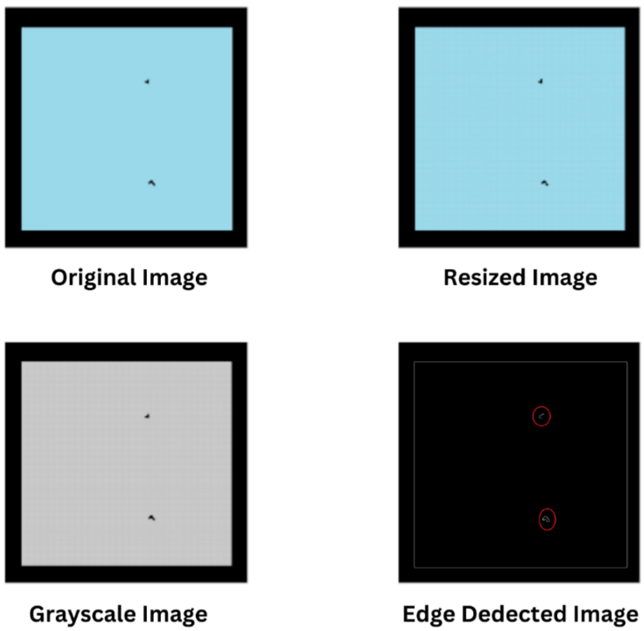

FIGURE 5. Test tile variations.

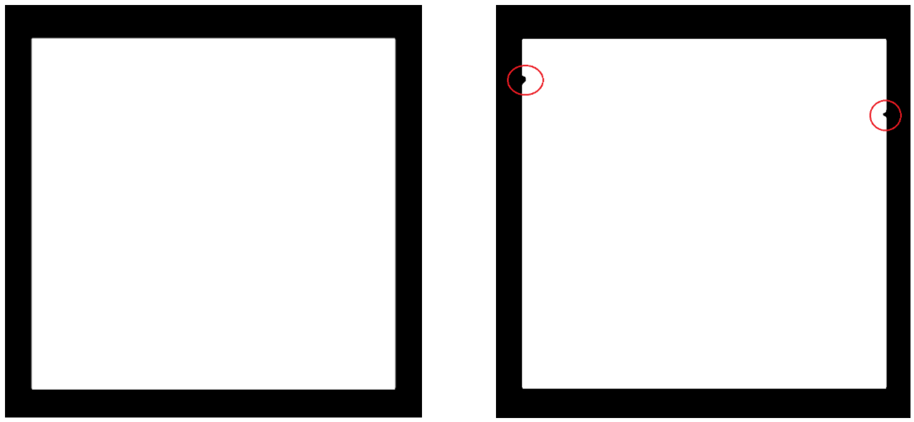

FIGURE 6. (a) Filled version of Figure 5 tile; (b) Filled version of another tile with defected edges.

TABLE 2. Precision in defect detection process.

Total number of tested tiles	120
Real number of defected tiles	100
Obtained number of defected tiles	97
Number of correct detections	20
Number of good tiles defected as a defected	0
Number of defected tiles detected as a good tile	3
Accuracy rate	97.5%
Total number of tested tiles	120

5. CONCLUSION

Detection of defects on ceramic surfaces is an important step in industrial production processes. Traditionally, such detection has been carried out manually by human inspection or simple mechanical methods, while attempts have been made to automate these processes using machine learning and image processing techniques. However, current technologies have shortcomings and limitations in detecting defects on ceramic surfaces. In this study, a method is proposed to address the deficiencies of existing methods.

The proposed method relies on Matlab's image processing techniques, following a series of key steps. Image acquisition plays an important role as the entire system depends on captured images. Maintaining consistent lighting conditions during image capture is crucial. Subsequently, the image is subjected to scaling and morphological processing. After thati edge detection using the Canny edge detector, followed by morphological filling, and counting of white pixels in both the edge-detected and morphologically filled images. The decision-making process occurs through comparing the inconsistencies in the quantity of white pixels between the reference and test tiles.

As a result of the conducted test procedures, a 97.50% accuracy rate has been achieved. The primary factors contributing to this accuracy include the careful selection of algorithms, rigorous organization of the algorithm with optimized procedures for image acquisition, and the determination of sizing and edge detection values that yielded the highest accuracy. The application of image processing techniques and presentation of results for a single tile typically take approximately 0.8 seconds, demonstrates a rapid detection rate. Proper image scaling significantly contributes to this high detection rate. Moreover, the system demonstrates effective identification of cracks in both the corners and center of ceramic tiles. The ability to keep statistical records of defected tiles and accurately determine the types of defects holds promise in terms of functionality and performance. This study will be further developed by testing not only on synthetic data but also on a real dataset to be created in the future.

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Declaration of Competing Interests The authors declare no conflict of interest.

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