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Development of a Platform Based on Artificial Vision With SVM and KNN Algorithms for the Identification and Classification of Ceramic Tiles

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ABSTRACT

In the ceramic tile manufacturing industry, the quality of production achieved depends to a large extent on the quality of the tile, which is very important for its classification and price. Currently, this process is performed by human operators, but many industries aim to improve performance and production through automation of this process. In this work we present the development of a platform based on artificial vision that allows the identification of defects in ceramic tiles, so that we can classify them according to their quality. The algorithms chosen to develop the platform are Support Vector Machine (SVM) and K-Nearest Neighbor (KNN). In order to implement these algorithms, the images are preprocessed, the descriptors for defect detection are obtained, then the algorithms are used and the results obtained.

Keywords: Machine vision, Support vector machine, K-Nearest neighbor, Ceramic tile sortingimage processing

INTRODUCTION

The quality of the final product determines the future of the industry, and only an objective and strict inspection can guarantee the best product quality (Oh et al. 2020). The combination of automatic inspection systems in industry (machine vision) (Onita et al. 2018; Feng et al. 2019)aims to use the knowledge base to collect the information needed to determine if the product is within the correct range of parameters. These robust systems, can operate in real time on the production line, provide deterministic results and can be used in environments that are harmful to humans (radiation, temperature, toxic substances (Jiang, Wang & Zhao 2019).

The successful implementation of the automated visual inspection system is based on: application rationality, system efficiency and system performance considerations (considering integration capabilities, robustness, ease of use and capabilities including intelligence), adaptation to existing environmental conditions, image acquisition dependence on quality and resolution, production line performance, image preprocessing technology and image analysis related options (Aslam et al. 2019).

The quality control of ceramic tile manufacturing is accomplished in an environment that is not suitable for the operators, as they will be affected by high levels of noise, dust, extreme temperatures (Hocenski, Matić & Vidović 2016). Generally speaking, the production lines in these industries have a high degree of automation (Shire, Khanapurkar & Mundewadikar 2011; Hanzaei, Afshar & Barazandeh 2017), but quality control is still executed by the operators. In this sense, a person's ability to perform this process depends on his or her training, knowledge and experience, and can also lead to misclassification of products affected by fatigue and subjectivity (Najafabadi & Pourghassem 2011; Singh & Kaur 2012).

In previous work, there are methods for detecting image defects, but with some limitations (Shire et al. 2011), for edge detection as in Najabadi's work, the angle method is used by comparing them to know which ceramic is defective in edges and dimensions (Najafabadi & Pourghassem 2011) An investigation of the existing methods for the detection of defects by means of artificial vision was carried out, which can be seen in the work of Pugo-Mendez E (Pugo-Mendez & Serpa-Andrade 2021).

The article is organized as follows: in section 2 related works, in section 3 the methodology, in section 4 results and discussion, in section 5 the conclusions and in section 6 the references.

RELATED WORKS

The production of ceramic tiles is a complex process in stages: preparation of the material, followed by milling with the mixing of the material, continuing this process by pressing to obtain a tile for subsequent decoration, then firing it in a kiln at high temperatures to obtain the final product, to finish the manufacturing process the last stage is the classification and packaging of the ceramic tiles (Pugo-Mendez & Serpa-Andrade 2021). Most of the tile manufacturing process is automated except for the final stage of classification, in which a worker is in charge of detecting tile defects and classifying them by class: first, second, third and discarded (Pugo-Mendez & Serpa-Andrade 2021). Workers who perform tile classification tend to make errors in the process either due to fatigue or inattention, as well as they may not match the criteria for classification resulting in misclassification (Pugo-Mendez & Serpa-Andrade 2021).

As can be seen in Fig. 1, there is the platform developed by means of artificial vision, the operation of which will be described in the methodology section below.

METHODOLOGY

The present work proposes to develop a platform to detect ceramic defects and their respective classifications. Defects in tiles can occur in any of the production phases, from the beginning to the final phase of the process. In

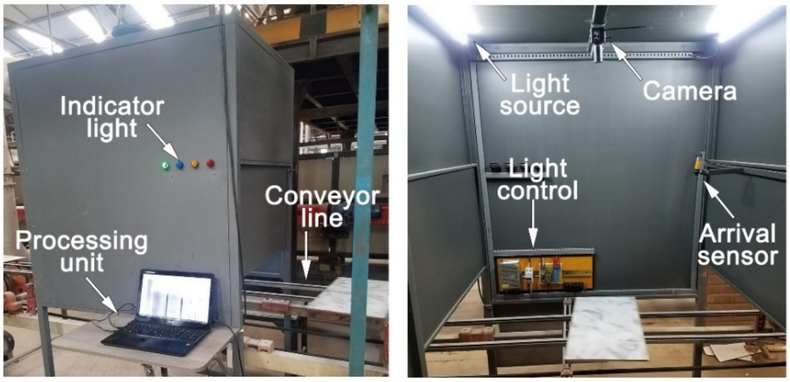

Figure 1: Artificial vision based platform model.

this work we intend to detect 6 types of defects that may be present in the manufacture of the tiles (Pugo-Mendez & Serpa-Andrade 2021):

- Scratch: tile breakage
- Pinhole: scattered isolated black-white spot
- Blob: drop on the tile surface
- Corner: corner break
- Border: edge breakage
- Glaze: blurred surface on tile

The platform was developed with the implementation of artificial vision through Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) algorithms for the detection of the ceramic defects mentioned above and their respective classifications, which will be done through a camera for the acquisition of images, for these to be optimal, it will be necessary to perform a protocol of data acquisition, frame adjustment, lighting, image preprocessing to obtain the defects of the ceramics and thus be able to do the training using the SVM and KNN algorithms, for which the analysis of the behavior of the platform in the detection and classification of ceramics will be performed (Pugo-Mendez & Serpa-Andrade 2021). The algorithms to be used are Support Vector Machine (SVM) and K-Nearest Neighbor (KNN).

Support Vector Machine (SVM)

The support vector machine classifier is a method used in the development of a hyperplane or set of hyperplanes in high quarter or unlimited dimension, which can be used for classification, or other work. Intuitively, good separation can be achieved by using the hyperplane that has the largest distance to the nearest training data point of each class (called the functional margin), because generally the larger the margin, the smaller the overall error of the classifier. However, the best separation area not only separates the data, but also has the largest margin (Nirsal et al. 2021; IEEE Centro Occidente Section & Institute of Electrical and Electronics Engineers no date).

The data in this margin area is called the support vector. Two classes can be separated by a pair of margin areas that are parallel. The first margin area bounds the first class while the second margin area bounds the second class, thus obtaining:

$$x_i.W + b \geq +1 \; f \; or \; y_i = +1 \tag{1}$$

$$x_i.W + b \geq -1 \; f \; or \; y_i = -1 \tag{2}$$

$$x_i.W + b \geq +1 \; f \; or \; y_i = 0 \tag{3}$$

K-Nearest Neighbor (KNN)

The KNN algorithm is one of the most famous classification algorithms used to predict the class of a record or (sample) with unspecified class based on the class of its neighboring records. The algorithm consists of three steps, as follows (Kuhkan 2016; IEEE Centro Occidente Section & Institute of Electrical and Electronics Engineers no date):

Calculate the distance of the input record with respect to all training records. Sorting of training records based on distance and selection of the nearest neighbor. Using the class that has the most among the k nearest-nearest neighbors (this method considers the class as the class of the input record that is observed more than all other classes among the K nearest neighbors) (Kuhkan 2016; IEEE Centro Occidente Section & Institute of Electrical and Electronics Engineers no date). In general, to predict the class of a new record, the algorithm searches for similar records among the training dataset, so if the records have n attributes, then it will consider them as a vector in an n-dimensional space and predict the class label of the new record based on a distance criterion in this space, such as the Euclidean distance, as well as the class label of the neighboring records (Kuhkan 2016; IEEE Centro Occidente Section & Institute of Electrical and Electronics Engineers no date). The classifier assumes the distance of the records from each other as a criterion of their proximity and selects the most similar records. There are numerous methods for calculating the distance, such as the Euclidean distance function, Manhattan, etc., among which the Euclidean distance function is one of the most common, defined as Equation (4) (Kuhkan 2016; IEEE Centro Occidente Section & Institute of Electrical and Electronics Engineers no date).

$$x_1 = (x_{11}, x_{12}, \ldots, x_{1n})$$

$$x_2 = (x_{21}, x_{22}, \ldots, x_{2n})$$

$$\text{dis}\,(x_1, x_2) = \sqrt{\sum_{i=1}^{n} (x_{1i} - x_{2i})^2} \tag{4}$$

One of the most important parameters in the KNN algorithm is the value of K; in fact, there is no exact value for k and its appropriate amount depends on the distribution of the data and the problem space (Kuhkan 2016; IEEE Centro Occidente Section & Institute of Electrical and Electronics Engineers no date).

Table 1. Accuracy rate with evaluation data.

Criterion/defect	Scratch	Pinhole	Blob	Corner	Border	Glaze	No defects
SVM	69,23%	72,31%	80,31%	76,21%	86,45%	51,21%	82,32%
KNN	77,27%	79,66%	83,68%	80,36%	82,78%	42,31%	89,21%

Acquisition Preprocessing and Segmentation of Imagines

The first stage in the detection of defects and the classification of ceramics is through the acquisition of images the same that is obtained from the platform this was implemented in the Rialto ceramics in a production line. For the development of the preprocessing was performed by samples of defects and also with the knowledge of experts in the classification of ceramics according to their criteria, to all images should be applied the color change to grayscale for better segmentation of defects in ceramics, so also for better performance of the algorithm the images are sized to 200 by 200 pixels. For segmentation is performed using the U-Net algorithm (Ronneberger, Fischer & Brox no date), it obtains the area of interest through the knowledge that the experts have for each of the defects presented by the ceramics, being able to represent and describe each of them, thus also a knowledge base of the defects is created with a class of each of them to be able to perform the training of the algorithms.

Recognition and Classification

Once obtained the recognition of each of the defects of the ceramics, we proceed to perform the training of the SVM and KNN algorithms taking into account that for each of the defects we have a class and also a class with which the ceramics do not have defects, the universe of data for the adjustment of the algorithms is 1800 images, The training was developed using the Tenserflow tool, Scikit Learn and keras, with which the training of the algorithms is performed with 70% of data for training and 30% for validation. For SVM classification was used with the sigmoid kernerl, in the KNN method the number of nearest neighbors was $k = 7$ with the calculation of the Euclidean distance.

In the classification is done with the criteria that the company handles that are for the first class are those ceramics that do not exceed 9% of defects, for the second class are those that do not exceed 21% of defects, for the third class are those that do not exceed 52% of defects and for the discard ceramics are those that have greater defects to the percentage of 52%, it should be noted that when the defect is rupture this ceramic will be classified as discard. Our algorithm can be seen in simplified form in the flowchart in Fig. 2.

RESULTS AND DISCUSSION

We proceed to train the algorithms with the database obtained for each of the defects that the ceramics have in order to obtain the results of each of these as shown in Table 1.

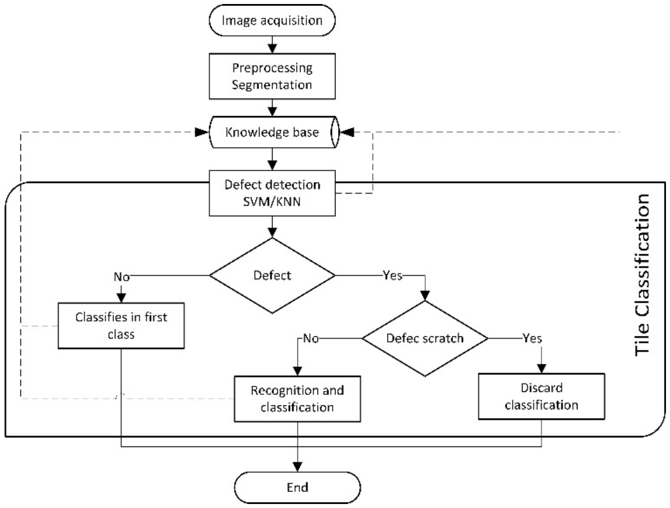

Figure 2: Ceramic detection and classification stages.

Table 2. Confusion matrix data.

Real Case	**Pronostical**		**Total**
	Defect	**Normal**	
Defect	True Positive VP	False Positives FN	Total Actual Positives TPR
Normal	False Negatives FP	True Negative VN	Total Actual Denials TNR
TOTAL	Total Positives Forecast TPP	Total Negatives Forecast TNP	Grand Total

In order to evaluate the performance of the classifier used, the confusion matrix, which is a standard statistical model evaluation tool, is employed. Also, the predictions of the defects in the columns and the normal data in the rows are presented, it can then be seen if the data of the classes generated in this case are confounded by the defects of the normal cases of the ceramics.

Table 2 shows the nomenclature of the data to be entered in the confusion matrix, these data will be used for the evaluation of the classifier from the calculation of precision, sensitivity, specificity and accuracy (Cruz & González 2008).

Precision-. It is the total number of correct positive predictions

$$P = \frac{\mathrm{VP}}{\mathrm{TPP}} * 100\% \tag{5}$$

Sensitivity-. Percentage of positive labels that were placed as positive.

$$S_e = \frac{\mathrm{VP}}{\mathrm{TPR}} * 100\% \tag{6}$$

Table 3. Confusion matrix data using SVM.

Real	Pronostical		
	Defect	Normal	
Defect	96	29	125
Normal	27	103	130
	123	132	255

Table 4. Confusion matrix data using KNN.

Real	Pronostical		
	Defect	Normal	
Defect	101	24	125
Normal	23	107	130
	124	131	255

Table 5. Confusion matrix result using SVM and KNN.

Algorithm	Precision	Sensitivity	Specificity	Accuracy
SVM	78,55%	76,85%	79,23%	78,03%
KNN	81,45%	80,80%	82,30%	81,56%

Specificity-. Percentage of negative labels that were predicted negative cases.

$$S_p = \frac{\mathrm{VN}}{\mathrm{TNR}} * 100\% \tag{7}$$

Accuracy-. Percentage predictions that were correct

$$A = \frac{\mathrm{vp} + \mathrm{vn}}{\text{Total General}} * 100\% \tag{8}$$

Equations (5)-(8) provide statistical data which are analyzed to verify the correct operation of the ceramic classifier (Cruz & González 2008).

We proceed to evaluate the performance of the classifier with the trained defects and also with ceramics that do not present defects. In the evaluation part, we proceed to verify the performance with 255 images of which 125 of these have some defect and 130 do not present defects, obtaining the following results:

As can be seen in Table 3, the results of the confusion matrix by applying SVM to 255 images we obtain the results that can be seen in Table 5.

As can be seen in Table 4, the results of the confusion matrix by applying SVM to 255 images we obtain the results that can be seen in Table 5.

Fig. 4 shows the results of the tests performed to find the effective method for defect detection. As can be seen, a comparison between SVM and KNN is established. The final result indicates that the blue color space gives better results with respect to SVM.

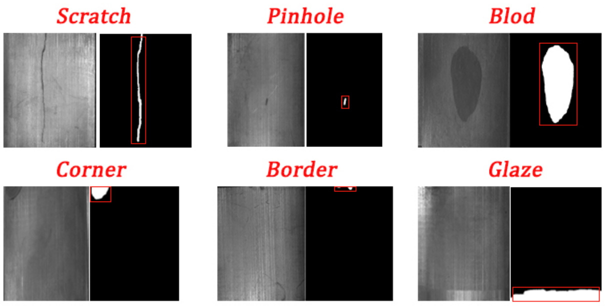

Figure 3: Segmentation of area of interest.

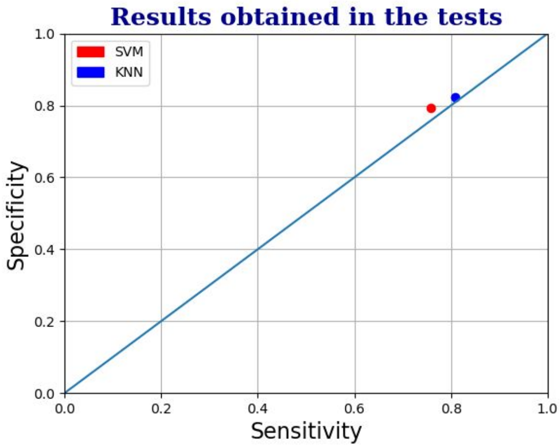

Figure 4: Results obtained represented in a ROC curve.

CONCLUSION

In this paper, we explore the potential of image analysis in the industrial application, the detection of defects in ceramics. Holes and breaks are the ones that draw special attention due to their crucial impact on the manufacturing of ceramics. Comparing with other analyzed works such as the work done by Honcenski in which detects the contour and surface of the ceramic with which detects defects in the contour and if the surface defect is big, it detects it, in the proposed method improves the detention of defects by algorithms SVM and KNN, in addition, the classification is of four classes in the proposed method, since in Honcenski's work it is classified into two classes, without defects and with defects.

We propose a ceramic tile detection and classification platform, the results obtained show that the best performing algorithm is the KNN with an accuracy of 81.45% with respect to the SVM algorithm which has an accuracy of 78.55%.

There are still some defects that are difficult to detect, such as Glaze, which is highly dependent on illumination and contrast, as well as contamination of the ceramic surface by dust, which can lead to incorrect classification. In the future, we will focus on improving the algorithms to further satisfy the comprehensive defect detection by Deep Learning and also with hardware for the cleaning of the ceramics before entering the platform.

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