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Automatic road crack detection and classification using image processing techniques, machine learning and integrated models in urban areas: A novel image binarization technique

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Abstract

The quality of the road pavement has always been one of the major concerns for governments around the world. Cracks in the asphalt are one of the most common road tensions that generally threaten the safety of roads and highways. In recent years, automated inspection methods such as image and video processing have been considered due to the high cost and error of manual methods. For this purpose, different image processing techniques and classification methods have been developed by many researchers. In this study, we propose an integrated model includes a heuristic image segmentation technique for crack detection. Furthermore, the accuracy of various classification models such as KNN, decision tree and SVM will be compared. Finally, 5-fold cross validation shows that Subspace KNN method will be more accurate than other classification models which are used in this study. On the other hand, we also simulate the depth and density of different segment of crack by utilizing density matrix values.

Keywords: Crack detection, classification, machine learning, integrated model, segmentation

1-Introduction

The quality of the road pavement has always been one of the major concerns for governments around the world. The condition of roads has constantly deteriorated due to factors such as high traffic loads, various temperature and climatic conditions. This leads to the formation of defects such as cracks and pothole on pavement roads (Cord and Chambon, 2012).

Furthermore, roads are considered as one of the strategic infrastructures of cities which are due to its high cost, maintenance plans have always been one of the key issues.

Initially, collecting the necessary information for determining the road pavement quality and preventive or corrective action was traditionally carried out by human inspections.

In the traditional approach, collecting data for pavement quality is usually done through periodic inspections.

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This method requires mental work and its results are highly dependent on the level of knowledge, skill and analyses of observers from the data of existing conditions (Oliveira and Correia, 2009) and (Mohan and Poobal, 2017).

Cracks in the asphalt are one of the most common road tensions that generally threaten the safety of roads and highways. Improvement and repair of cracks in road surfaces before deterioration can lead to a reduction in the cost of road maintenance. Due to the fact that image-based technologies provide an economical, effective and safe way of detecting deficiencies such as road crack, various image processing approaches have been presented in this area over the past two decades (Zou et al., 2012).

Since manual inspection are very costly and usually have a high error rate, using automated inspection methods such as image and video processing will be very useful. Among the techniques of image processing, fuzzy set theory, neural networks and Markov methods can be mentioned (Ayenu-Prah and Attoh-Okine, 2008).

Cracks at Continuous surface are one of the first signs of quality depreciation of roads that are heavily exposed to sustained loads and are critical and crucial for maintaining activities. Several studies have proposed different strategies for automatically detecting cracks and depths using image processing techniques.

In addition to image processing techniques, other techniques such as ۳D laser technology are also used in this area.In this method, due to the use of ۳D data as input, it is expected that the ability to detect asphalt crack and its separation from its surrounding surface will be more accurate and, naturally, using this type of data can lead to a more efficient model.

Generally, data mining techniques such as clustering and classification are also used to identify the location of distress on collected images. Therefore, different like k-means method, heuristic and meta-heuristic algorithms, separator and probabilistic models (such as Bayesian network) can also be considered for analysing and identifying the distresses of the asphalt pavement.

Intensity analysis in images of cracks, deep learning and the neural network are considered to classify the pavements cracks. But it's important to note that the advancement of technology in the field of imaging, artificial intelligence and its tools has an undeniable impact on the creation of new models, or even the use of previous models with high quality, accuracy and efficiency.

But perhaps it can be said that pixel-based image processing despite the development of newer approaches in this area, is still a popular method (Some, 2016). In using these techniques, one of the most important steps is the collection of test, training and validation dataset for the implementation of the machine learning process.

Because these data are naturally image-based, deciding whether to use two-dimensional (2D) gray scale images or three-dimensional (3D) laser scanning data set as input of model will be very influential.

Obviously, the use of 3D data due to the very high ability in separation of the cracks from the surrounding surfaces compared to the two-dimensional can have a significant impact on increasing the accuracy and performance of the model (Oliveira and Correia, 2009).

After the data collection step, the pre-processing of images, processing and, finally, their classification are the next steps in these analyses. But in automated inspection, especially by image processing techniques, the quality of images in the first phase of analysis is a challenging and important point.

In these types of images, the presence of noise data, falling shadow in the image, direction and intensity of light irradiation at the time of imaging, can often have a direct impact on determining the boundaries of the failure in the images, or Makes the system go wrong.

Among the various failures that may affect the quality of road surfaces are cracks, potholes, rutting and other deformation (Mohan and Poobal, 2017). Cracks at continuous surfaces are one of the first signs of quality deterioration of roads, which are critical for maintenance activities of roads that are extremely under continuous loads (Mohan and Poobal, 2017).

Typically, crack detection can be done in both destructive and non-destructive testing methods, which manual surfaces evaluating and analysing is considered as one of the most common non-destructive methods (Dhital and Lee, 2012).

2-Literature review

Road quality evaluation in many countries is a very important task for estimating road maintenance requirements, which, of course, requires road surface conditions to be inspected. Before the 1980s, all these inspections were carried out traditionally and manually (Cheng and Miyojim, 1998).

But then, such activities were automated with a variety of techniques that made it easier, more efficient and more secure and less costly. In recent years, in addition to image processing approaches, techniques such as laser technology have also been introduced (Chambon and Moliard, 2011).

Due to the advances made in recent years, expert systems based on different computer vision techniques have been considered. For example, Moghadas Nejad and Zakeri (2011), proposed an effective expert system based on wavelet transform and radon neural network (WRNN) to classify pavement distress and demonstrated the robustness of their methods against noise.

In detection and classification of pavement cracks, image segmentation methods are considered as a basic step. In recent research, image segmentation techniques such as thresholding, clustering methods, histogram-based methods, edge detection, and markov random fields have been considered by many researchers. Oliveira and Correia (2013), proposed a dynamic thresholding method in their preprocessing phase. Also they utilized the histogram of crack pixels to show that threshold could be used for separation of crack pixels and non-crack pixels. Then, authors presented a modified Otsu method for computing threshold value.

Clustering methods also are used in pre-processing step for distinguishing between crack points (or distress pixels) and others (non-distress pixels) (Oliveira and Correia , 2013). Furthermore, clustering can be utilized for identifying the cracks' location So that a cluster represents a crack (Ho et al., 2009). Tong, Gao, Han, and Wang (2017), used k-means process to pre-extract cracks' features and calculate their threshold. Researchers in this study also considered the length of the cracks by using deep convolutional neural networks.

Ayenu-Prah and Attoh-Okine (2008), proposed a bi-dimensional empirical mode decomposition for removing noise in digital images and then utilized Sobel edge detector to detect pavement cracks. They also compared this method with canny edge detector and investigated the ability of BEMD method to smooth an image for achieving more effective edge detection.

Tedeschi and Benedetto (2017), provided a real-time automatic recognition system based on the OpenCV library for Android-based devices which able to detect pavement distresses such as pothole, Longitudinal-Transversal, and Fatigue cracks.

In automatic recognition of pavement crack, after detection of crack in pre-processing phase, we will need to detect and classify the type of cracks in processing phase. Therefore, choosing the appropriate classification model will be very important to achieve the desired output.

Different types of cracks are classified into the following seven categories (Moghadas Nejad and Zakeri, 2011):

a. Alligator cracking
b. Block cracking
c. Longitudinal cracking
d. Hair cracking
e. Diagonal cracking
f. Multi cracking
g. Transverse cracking.

Support vector machine and neural networks are the most well-known machine learning algorithms which have been used by many researchers to classify different types of asphalt crack (Zhang et al., 2017). For example, Authors in (Gavilán et al., 2011), proposed a fully automatic approach by utilizing a linear SVM-based classifier for distinguishing 10 different types of Spanish roads' cracks.

Moghadas Nejad and Zakeri (2011), using the dynamic neural network technique for pavement crack classification and also compared their system with static neural network (SNN). Due to the ability of self-organization of the neural network and having simple structure, their system is suitable for on-line real time application. They also demonstrated that the accuracy of their model will be over 99%.

3-Data acquisition

In this study, we use a road crack image database provided by Shi et al. (see (Shi et al., 2016) and (Cui et al., 2015)) which to is called CFD. This dataset is composed of 118 urban road crack images in Beijing, China. All the images in CFD are taken by an iPhone5 with focus of 4mm, aperture of f/2.4 and exposure time of 1/134s. The width of the images ranges from 1 to 3 mm (Shi et al., 2016).

3-1-Pre-processing and crack detection

A novel image segmentation algorithm is proposed in pre-processing phase of our crack detection system. In first step of this heuristic algorithm, different initial thresholds are used. In this way, we first select a starting threshold between 0 and 1 and then convert image to binary form. Then, we start from one of the corners of the image and move horizontally to reach the first black pixel. If there isn't any other black pixel in the neighborhood of the previous point, we will remove that black pixel as a noise point. So we will continue this process and neighborhood search, to achieve initial segmented image. After that we will increase the selected initial threshold and repeat the process above while this value be lower than 1. Therefore, we should increase initial threshold value and repeat the whole of algorithm while the initial value turns to be equal to 1. Then, the corresponding variation index for each image will be calculated as follows.

Horizontal Average = mean of horizontal coordinates of black pixels in binary image (1)

Vertical Average = mean of vertical coordinates of black pixels in binary image (2)

Horizontal STD = Standard deviation of horizontal coordinates of black pixels in binary image (3)

Vertical STD = Standard deviation of vertical coordinates of black pixels in binary image (4)

$$\text{Horizontal CV} = \frac{\text{Horizontal STD}}{\text{Horizontal Average}} \tag{5}$$

$$\text{Vertical CV} = \frac{\text{Vertical STD}}{\text{Vertical Average}} \tag{6}$$

$$\text{Variation index} = \frac{\frac{\text{Vertical CV}}{\text{Horizontal CV}}}{\frac{\text{Vertical Average}}{\text{Horizontal Average}}} \tag{7}$$

Step 1 :	*Set initial threshold between 0 and 1*
Step 2 :	***For*** *threshold=initial threshold :1*
Step 3 :	*Convert image to binary image*
Step 4 :	*start from one of the corners of the image and move horizontally to reach the first black pixel*
Step 5 :	***If*** *there isn't any other black pixel in the neighbourhood*
Step 6 :	*remove that black pixel as a noise point*
Step 7 :	***End if***
Step 8 :	***End for***
Step 9 :	*Initial threshold = initial threshold + ε*
Step 10 :	***If*** *Initial threshold <1*
Step 11:	*Go to Step I*
Step 12 :	***End if***
Step 13 :	*Calculate the variation index of all images*
Step 14 :	*Index of Optimal segmented image = maximum variation index*

Fig 1. The general idea of heuristic algorithm for image binarization

Then, the maximum of calculated variation index for all binary images will be considered as best segmented image which will be utilized in the second step of heuristic algorithm as input data.

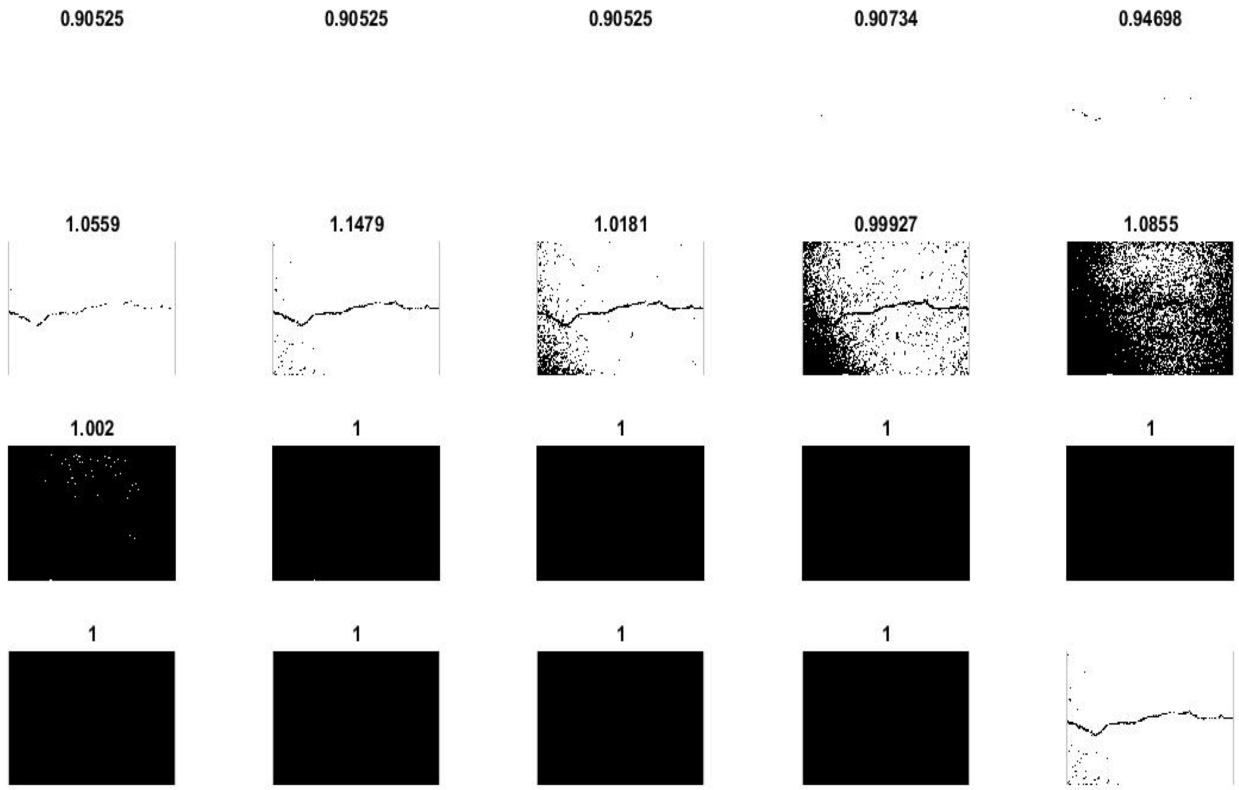

Fig 2. Image pre-processing phase to calculate the variation index of best segmented image

In second step of algorithm, the binary image corresponding to the best variation index is selected and repeats it in three dimensions to recreate a new matrix of image which is called MASK matrix. Then we multiply original image of crack and MASK image to achieve a new matrix of original image. After that we set non-zero values of the new matrix equal to 1 to transform new matrix to a 3d matrix with binary values. Now, in this step, Simple Linear Iterative Clustering Super Pixels (SLIC) method is used to eliminate the remaining noise in the image. For this purpose, first, the RGB image is converted to CIE 1976 L*a*b* values and divided into super pixels. Then, the super pixels which have non-zero values for mean of L*, a* and b* components will be removed as noise data.

Finally, by applying two above steps in pre-processing phase of integrated model, final binary image of crack will be ready to use by different classification models.

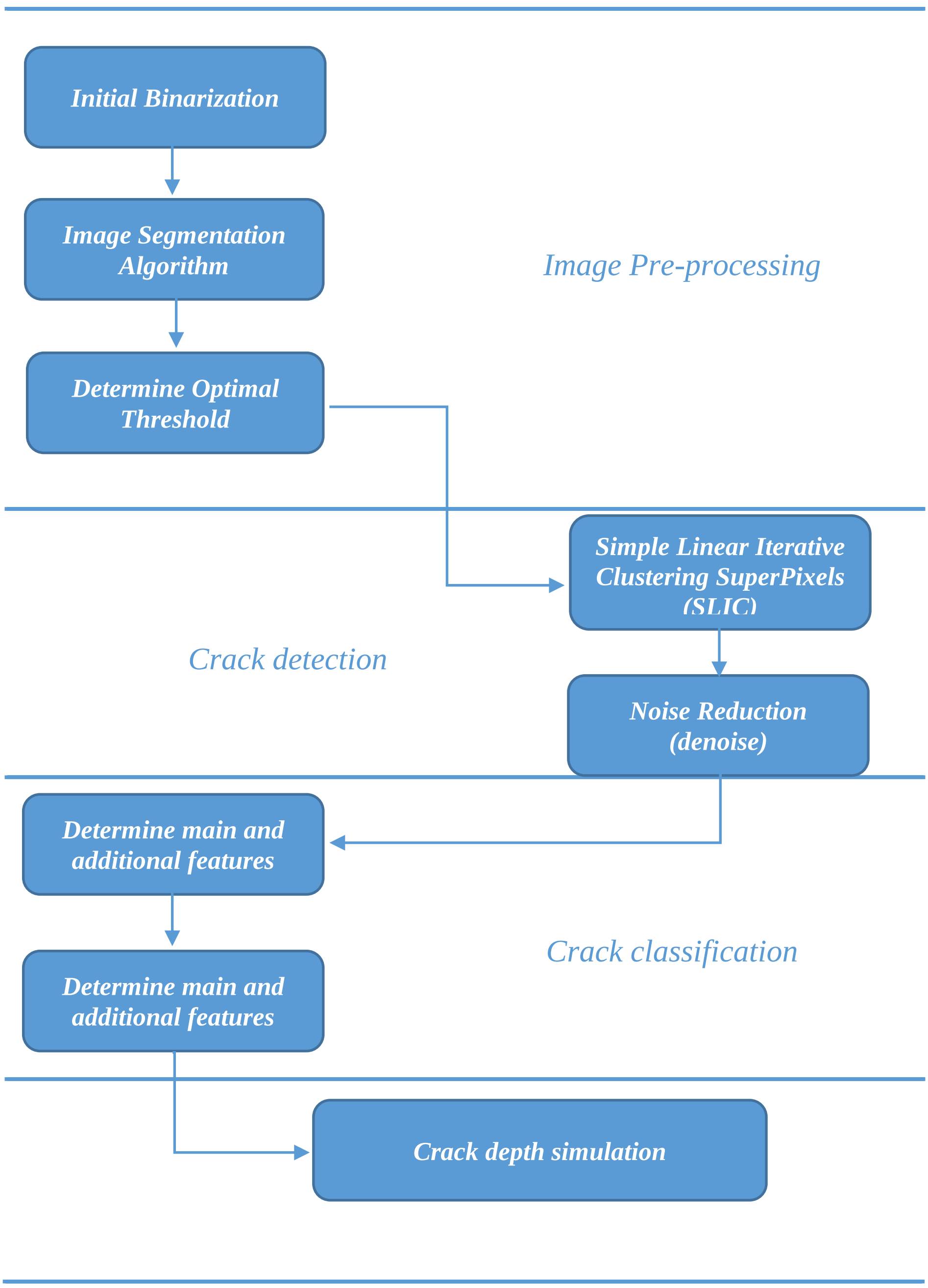

Fig 3. The diagram of integrated model

3-2-Crack Type Classification

In this section, transverse and block cracks as two common types of cracks are considered and analyzed by some classification models such as decision trees, support vector machines (SVM), nearest neighbors and etc.

For this purpose, first, it's required to determine model's predictor features and classes which include some main features and a numbers of additional features. Before describing these features, we will need to define density matrix. For computing density matrix, first, final binary image of cracks is segmented to some 10×10 segment. Then, density of each segment is calculated (equation 8).

$$\text{Density of each segment} = \frac{\text{Number of crack pixels in each segment}}{10 \times 10} \tag{8}$$

The features which are used in classification model are defined as follows.

Main features:

$$F1 = \frac{\sum_{i=1}^{M}(\sum_{j=1}^{N} DensityMatrix_{i,j})}{M} \tag{9}$$

$$F2 = \frac{\sum_{j=1}^{N}(\sum_{i=1}^{M} DensityMatrix_{i,j})}{N} \tag{10}$$

$$F3 = \frac{1}{M-1}\sum_{i=1}^{M}(DensityMatrix_{i,j} - F1)^2 \tag{11}$$

$$F4 = \frac{1}{N-1}\sum_{j=1}^{N}(DensityMatrix_{i,j} - F2)^2 \tag{12}$$

S1= Set of row index which includes crack pixels (13)

S1= Set of column index which includes crack pixels (14)

$$\mathrm{F5} = \frac{\mathrm{Max(S1)} - \mathrm{Min(S1)}}{\text{Total number of rows}} \tag{15}$$

$$\mathrm{F6} = \frac{\text{Number of rows which includes crack pixels}}{\text{Total number of rows}} \tag{16}$$

$$\mathrm{F7} = \frac{\mathrm{Max(S2)} - \mathrm{Min(S2)}}{\text{Total number of columns}} \tag{17}$$

$$\mathrm{F8} = \frac{\text{Number of columns which includes crack pixels}}{\text{Total number of columns}} \tag{18}$$

Additional features:

$$\mathrm{F9} = \frac{\text{Horizontal Average (Final binary image)}}{\text{Vertical Average (Final binary image)}} \tag{19}$$

$$\mathrm{F10} = \frac{\text{Horizontal STD (Final binary image)}}{\text{Vertical STD (Final binary image)}} \tag{20}$$

$$\mathrm{F11} = \frac{\text{Horizontal CV (Final binary image)}}{\text{Vertical CV (Final binary image)}} \tag{21}$$

$$\mathrm{F12} = \frac{\text{Horizontal Average (Density matrix)}}{\text{Vertical Average (Density matrix)}} \tag{22}$$

$$\mathrm{F13} = \frac{\mathrm{F1}}{\mathrm{F2}}, \mathrm{F14} = \frac{\mathrm{F1}}{\mathrm{F3}}, \mathrm{F15} = \frac{\mathrm{F2}}{\mathrm{F4}}, \mathrm{F16} = \frac{\mathrm{F3}}{\mathrm{F4}} \tag{23}$$

$$\mathrm{F17} = \frac{\mathrm{F5}}{\mathrm{F6}}, \mathrm{F18} = \frac{\mathrm{F5}}{\mathrm{F7}}, \mathrm{F19} = \frac{\mathrm{F7}}{\mathrm{F8}}, \mathrm{F20} = \frac{\mathrm{F6}}{\mathrm{F8}} \tag{24}$$

$$F21 = F5 \times F6, F22 = F7 \times F8 \tag{25}$$

In this research, different classification models are applied on our data set which includes 22 predictor features and a label (class) variable and are evaluated by 5-fold cross validation method. The summary of the results is detailed in the table below.

Table 1.The accuracy of different classification models based on 5-fold cross-validation

Classifier	***With all features (F1-F22)***		***With main features (F1-F8)***	
	Without PCA	***With PCA***	***Without PCA***	***With PCA***
	Accuracy		***Accuracy***	
Subspace KNN	*94.3%*	*77.4%*	*88.6%*	*80%*
RUSBoosted Trees	*91.4%*	*77.1%*	*85.7%*	*74.3%*
Weighted KNN	*85.7%*	*77.1%*	*82.9%*	*80%*
Fine KNN	*88.6%*	*80%*	*80%*	*74.3%*
Linear SVM	*85.7%*	*80%*	*80%*	*80%*
Complex Tree	*88.6%*	*71.4%*	*85.7%*	*77.1%*

As shown in table ۱, Subspace KNN has best classification accuracyamong others. The confusion matrix and ROC curve of this classifier when all features are applied, is shown below.

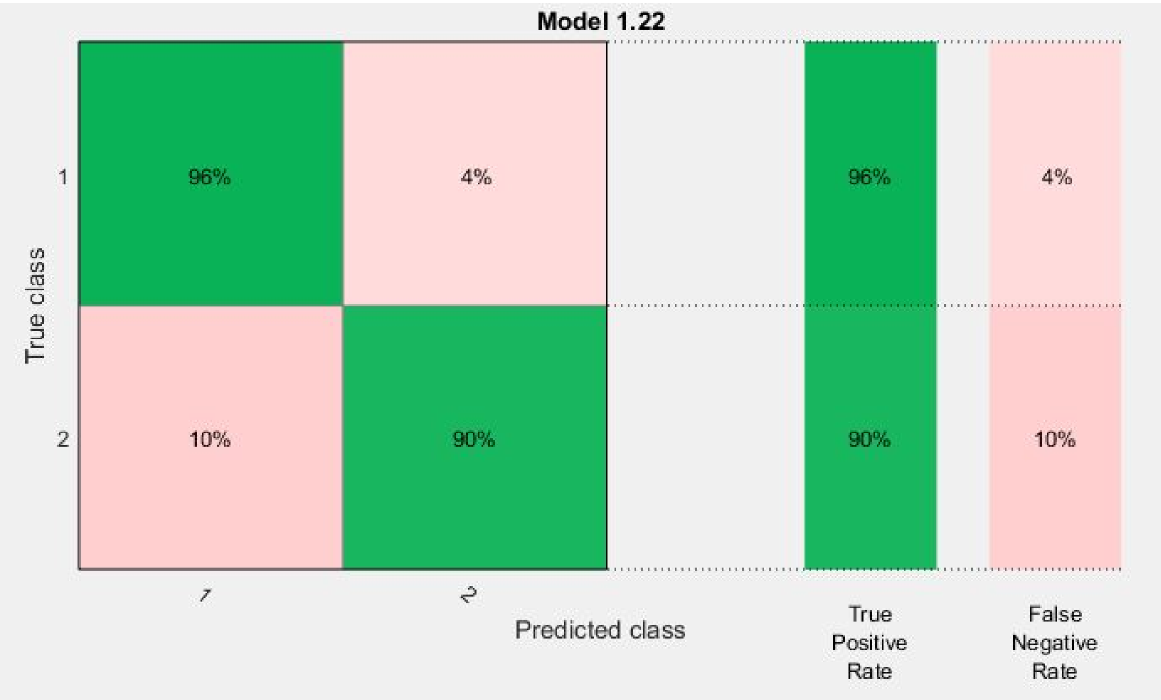

Fig 4. Confusion matrix of subspace KNN method by applying all features

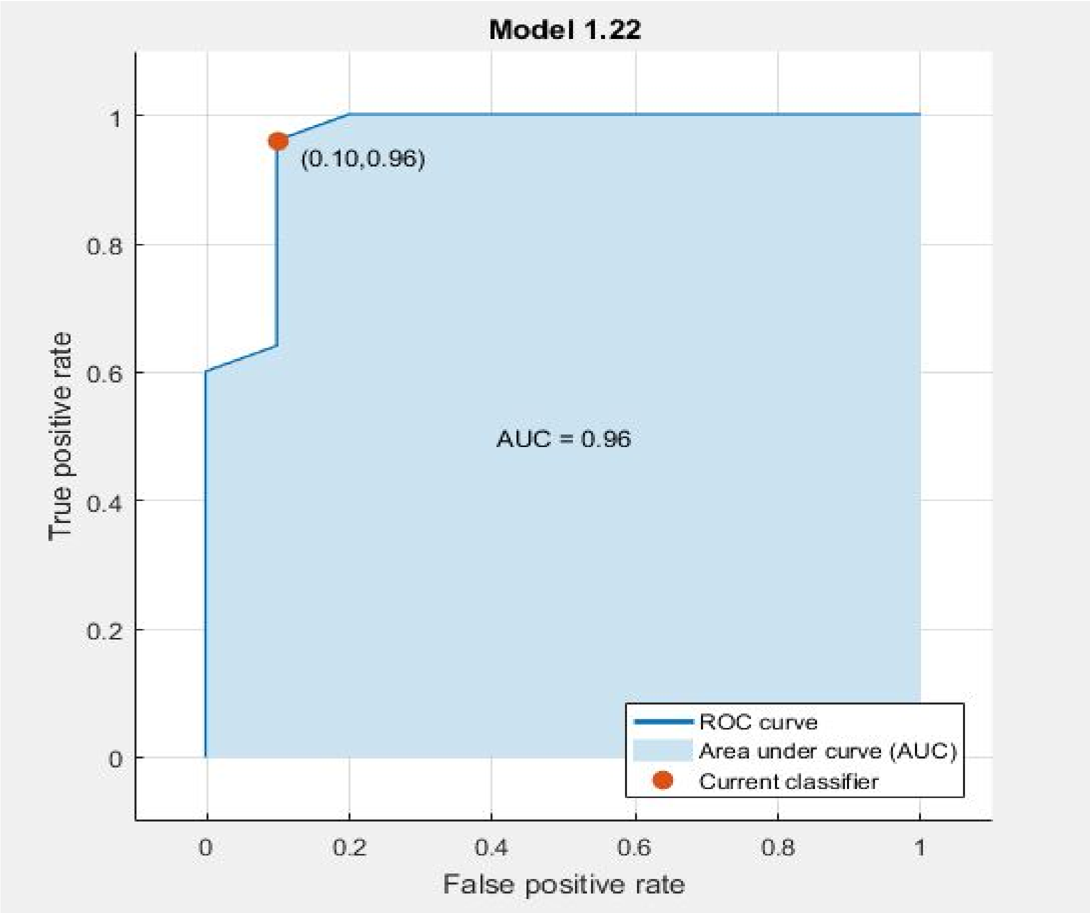

Fig 5.ROC curve of subspace KNN method by applying all features

On the other hand, it is obvious that by decreasing predictor features, the accuracy of the classification model will also decrease. In this experiment, by ignoring additional features and merely considering main features, the accuracy will decrease to 88.6% for Subspace KNN method. Its parallel coordinate plot is shown in figure 4.

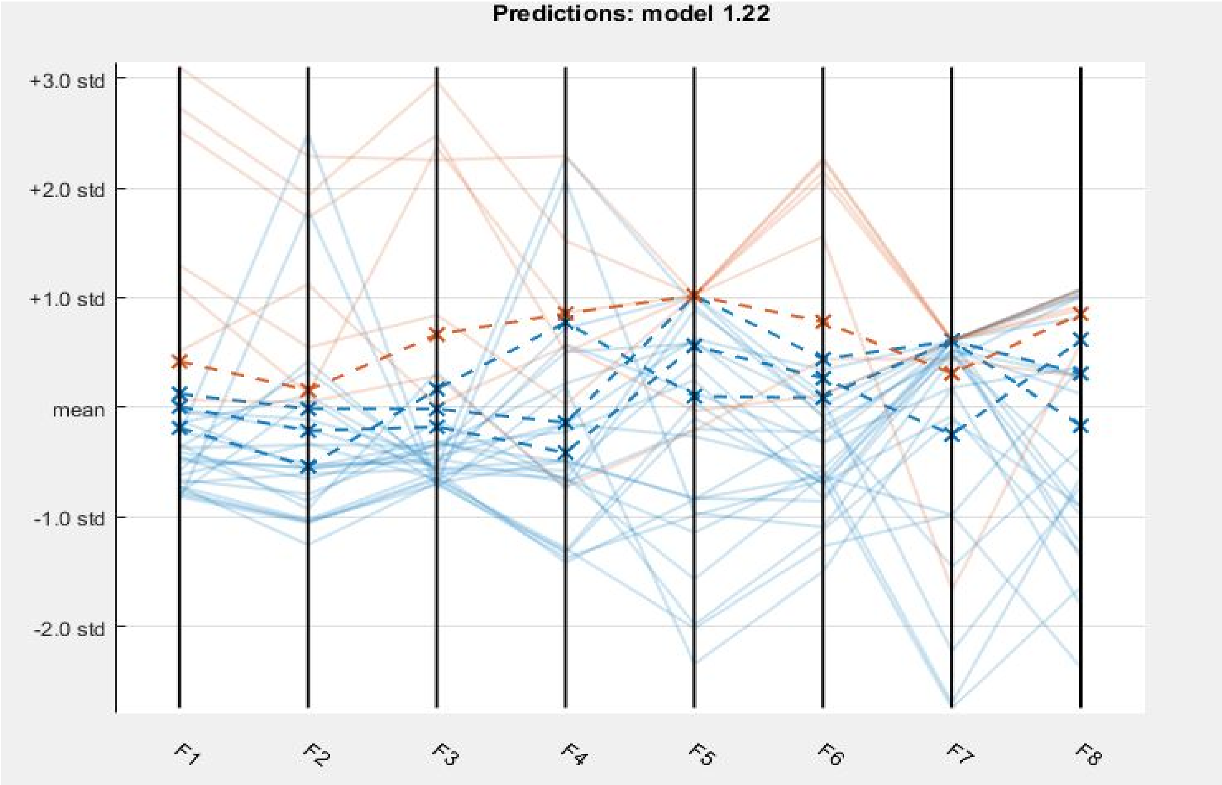

Fig 6.Parallel coordinate plot of subspace KNN with main features

4-Crack depth simulation

In this section, the depth and density of different segment of crack will be simulated by utilizing density matrix values. Therefore the density values of crack's super pixels as explained above are considered as intensity of that region of crack. So, greater density value indicates greater intensity and also deeper area. For this purpose, a sample image of existing data set is selected and simulated which is shown in figures 5-6.

Fig 7.The sample crack image

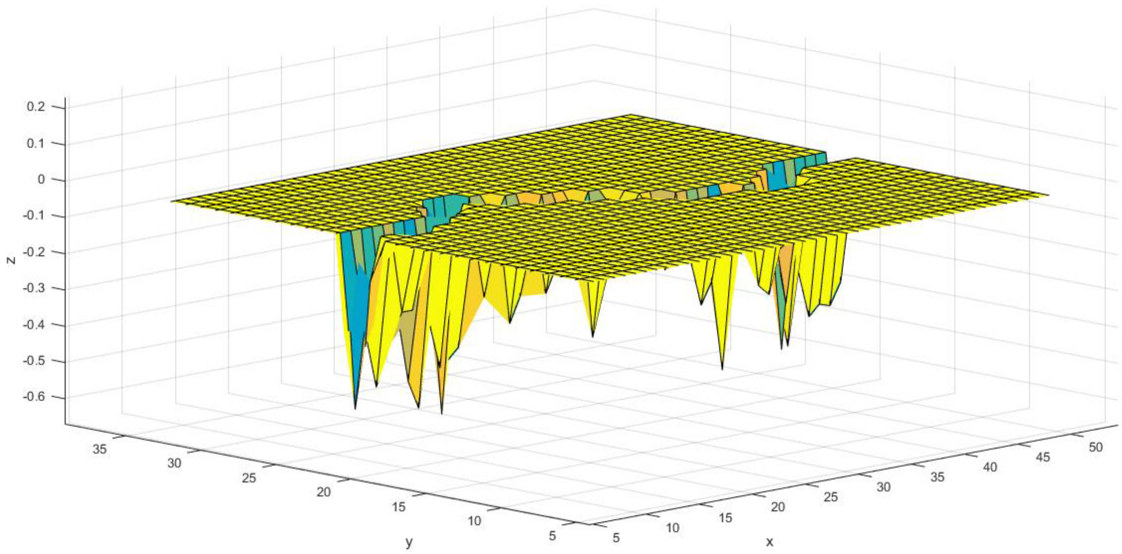

Fig 8.Simulated image of crack intensity in different regions of surface

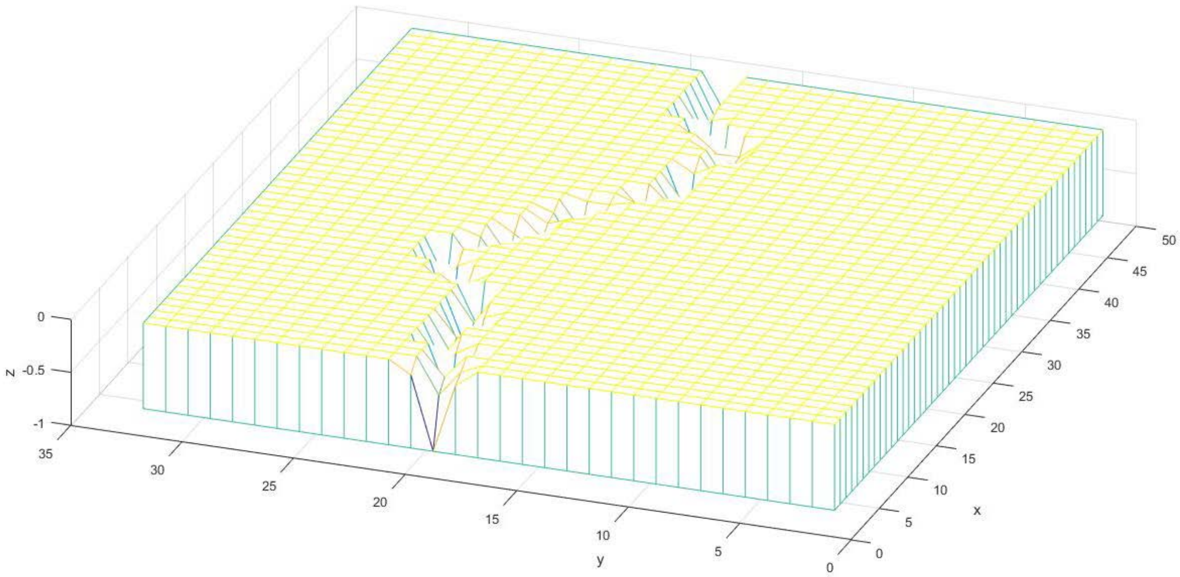

Fig 9. Simulation of original crack depth

5-Conclusion

The quality of the road pavement has always been one of the major concerns for governments around the world. Different detection and classification methods have been used by many researchers in recent years. But one of the most important issues in this field will be the accuracy of classifiers. In this study, a novel binarization technique is proposed for pre-processing crack image and also detection phase. The output quality of this stage will have a direct impact on the accuracy of classification model. Results obtained in this research show the ability of subspace KNN method Compared to others in classifying images in two transverse and block cracks. Furthermore, the simulation of crack depth will be very important to illustrate the intensity of the crack's surface. in the last section of this study, the simulation of crack image has been done by calculating density matrix values based on existing crack pixels in each super pixel. Totally, our proposed integrated model includes five main stages: pre-processing, segmentation (binarization), crack detection, crack classification and depth simulation.

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