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Number Recognition in the Saudi License Plates using Classification and Clustering Methods

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Abstract: This study is conducted for the purpose of recognizing numbers printed on the license plates images. The size of different patterns in the Saudi license plates is 20: the Arabic and English numbers. It is hard to classify all the numbers due to the similarity between specific numbers. This paper will propose to use a clustering technique called X-Means in order to regroup the numbers that have the same characteristics. Later develop a specific classification technique for each cluster. The experimentation of the proposed approach is applied on our constructed dataset gave us some limitation in classification. The results are improved by constructing a reference image for each class selected using a specific criteria from the training dataset. Moreover, the experimental results ensure better recognition accuracy by using the proposed methods rather than classifying the same dataset using other classical classifier in the state-of-art.

Keywords: license plate recognition, reference image, data mining, feature extraction feature selection, classification rules, clustering

1 Introduction

The need to recognize vehicles has increased in direct proportion to the number of vehicles being driven. License plate recognition is now an important application in traffic law enforcement techniques. Moreover, for efficiency reasons, traffic violations caught using this system ensures that violators will be automatically identified.

Here we will introduce two methods for recognizing Saudi license plate numbers. The first method uses a preprocessing technique embedded with the classification technique by nominating a reference image for each class. This will clarify the relationship between the candidate image and the reference image in the same class. The second method uses a clustering technique by grouping the numbers into independent clusters. After categorizing a candidate image to a specific cluster, the first method is applied.

The selection of the Saudi license plates is due to the saturation of approaches for the English characters in the literature. On the other hand, the Arabic case still deserves more attention for researching.

The objective is to reach an optimal classification that will have faster response time and higher recognition accuracy. However, a problem arises when working with multiple closed-set patterns together: it is not always achievable to classify all the classes, or in other cases we could have low recognition accuracy.

Our contribution in this paper is based on the proposed techniques in data mining and not image processing. We did not find a dataset in any previous work that contains each number as a single image alone. Thus the preprocessing of license plate images is applied in order to extract exactly the numbers from all captured Saudi license plates. In the study [1] several morphological operations [2,3] are used in the preprocessing step, such as dilation and erosion for all characters. These operations are used in order to reduce any gaps, rough contour, small holes in images.

In this paper, we compare our results with some well-known data mining techniques. Notice that the

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captured images are taken by the same camera having a specific image resolution.

In literature, license plate recognition is usually divided into two major parts, localization and recognition [4]. Localization locates the part of the image which contains the license plate, while recognition identifies the individual characters. This paper will only deal with the recognition aspect of characters after they are segmented.

In section 2 a brief literature review is presented about the localization and recognition of license plates. Section 3 a detailed description about the difficulties faced during the number classification methods. Section 4 proposes a preprocessing technique that may help in increasing the recognition accuracy. Section 5 proposes the clustering method that categorizes the numbers into independent clusters and uses the methods discussed in section 4. Section 6 compares our proposed algorithm with a classical classifier in the state-of-art. Finally, in section 7 a summary and future work for this study.

2 Literature Review

Various algorithms have been suggested for character recognition in license plates. There are two major approaches in the literature, which are the analytical and the global approaches [5]. In the analytical approach, each character must be segmented in order to be recognized. On the other hand, in the global approach, the segmentation process is not necessary and the whole characters in the image can be recognized.

The license plate recognition is usually done by locating a license plate using at least one of the following techniques: edge counting [6], histogram processing [7], template matching [8,9,10], blob analysis [11,12], block-based [13,14], or line processing techniques [1,15,16,17,18].

A license plate localization technique based on edge counting is presented in study [6]. In this study, the vehicle image is scanned with N-row distance and counts the existent edges. If the number of the edges is greater than a threshold value, the presence of a plate is assumed. If the plate is not found during the first scan, the algorithm is repeated with the reduced threshold value. The method features fast execution time as it scans only some rows of the image. However, this method is not capable of locating license plates in complex scenarios. Notice that they applied there study on different types of Persian (similar to Arabic) license plates.

In study [7], histogram processing is used to process the extracted lines from the image through examining the variation of grey level in the image pixels. Then the difference between the valleys and peaks are analyzed in order to localize a license plate. Histogram processing is sensitive to orientation of the image.

Template matching methods used in study [8] calculate the Hamming distance between the unknown characters in a license plate. This method is sensitive to noise and/or blurred images. Template matching is successfully implemented in study [9], where the whole recognition process is based on the computation of the root-mean-square error. In this method, the lowest root-mean-square score gives the estimate for the best position of template within the search image. Notice that they applied there study on different types of Arabic license plates in Egypt.

In study [11], blob analysis primarily works with regions instead of individual pixels. Plates are located according to characteristics determined by the bounding box surrounding the different regions. Blob analysis requires a segmentation phase to precede it to extract the possible regions. In study [12] blob labeling and clustering are used for segmentation. The studies of Kirsch, Sobel, Laplacian, Wallis, Prewitt, Frei Chen on edge detectors are compared and contrasted, and Kirschs edge detector is regarded as the most appropriate one among others.

Block-based grey scale processing technique to locate the license plate was presented in study [13]. In this method, the input image is divided into blocks. Blocks with a high edge magnitude or high edge variance are identified as the possible license plate regions. However, all the detected blocks are not license plate regions.

In study [1] the line processing techniques were used by locating different number of lines (horizontal and vertical) inside the bounding box of the character. Three different methods for recognizing characters in Saudi license plates were introduced. All methods rely on analyzing information about pixels in six lines. The first method [17], number of peaks or transitions, was an extension of a method that was developed for the Saudi license plates. It counts the number of times there is a difference between pixels along the line from black to white. The second method [16], pixel percentage method, calculates the percentage of character pixels to total number of pixels on a line. The third method [15], peak positions method, relies on the positions of the peaks of the first method rather than their number. In [1], the authors introduced the combination of the three features declared in [15,16,17] together due to the limitations in recognizing some of the characters in the Saudi license plates.

In study [18], improvements to the line processing methods in [1] were presented throughout a generalized model for the line processing work. It applies the process of quantization for the pixel percentage method presented in [16]. The quantization process constrains a continuous set of values into a relatively small discrete set. In addition, study [18] improves the process of presenting the combination of the three methods discussed in study [1] by introducing two additional combined features.

3 Number Classification Based on Feature Selection Method

This research paper utilizes the five extracted features discussed in study [18]. These features applied for all horizontal and vertical lines crossing the segmented image.

An example for each of the five extracted features is discussed in Table 1. Then we will examine the extracted features of the 70^{th} horizontal line drawn in Figure 1. The size of the sample segmented image in Figure 1 is 100x100. The quantization value assumed in this example is Q=10. This value is used to constrain a continuous set of values into a relatively small discrete set.

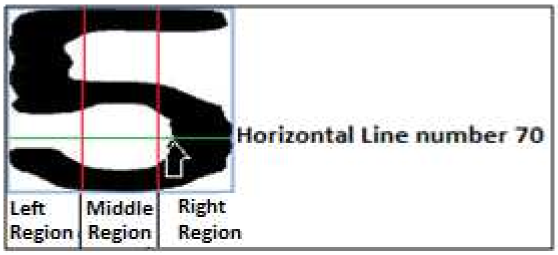

Fig. 1: Sample segmented image taken from a Saudi license plate

After the segmentation of the Arabic and English number images, we need to normalize all the segmented images to the same dimension size (h x v), where h and v represent the height and width of the extracted image respectively. Then we will extract the five features for all the horizontal and vertical lines.

For each class, there are specific values of 5 extracted features in each horizontal and vertical line. Figure 2 models a 2D plane formed by 5 features in each horizontal line. The first dimension represents the five extracted features (f_1, f_2, f_3, f_4, and f_5). The second dimension represents the line number (H_1, H_2, , H_h). Similarly, the same model can be applied for the vertical lines having v lines (V_1, V_2, , V_v).

For all classes C1 to C20, we can represent all the 5 features for horizontal lines by a cube as shown in Figure 3. Each plane in the cube represents a specific class. The total number of pillars in the horizontal cube is 5xh, and the total number of pillars in the vertical cube is 5xv. Each pillar is formed by 20 classes, since we are dealing with only the Arabic and English numbers. Notice that all the feature values are positive numbers.

After the feature extraction phase, we will be able to apply the feature selection phase. This phase selects features that are not repeated in a specific pillar of the cube. In the resulting pillar on the right of Figure 4, we keep the non-repeated feature values in the left pillar and change the other feature values to negative numbers that

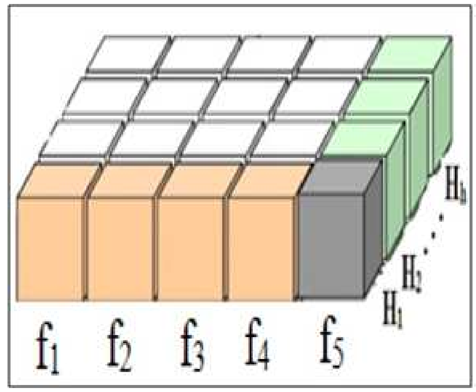

Fig. 2: A 2D plane representing the horizontal line features for a single class

Table 1: List of extracted features in an image line.

Feature 1	**Counts the number of times there is a difference between pixels along the line from black to white. We denoted the transition in Figure 1 using an arrow, thus the result of Feature 1 is 1**
Feature 2	Calculates the percentage of character pixels to total number of pixels on a line, and then multiplies the result by the quantization value. Finally, the result of this multiplication is ceiled. In Figure 1, we denoted the density as 27% of the line and the quantization value is assumed to be Q=10, thus $\lceil(0.27x10) = \lceil(2.70) = 3$
Feature 3	The occurrence of a transition in each of the three equally divided regions of the line. In Figure 1, the horizontal line can be divided into left, middle, and right regions. The result of this feature is derived to one value as 0.001 since only the right region contains a transition.
Feature 4	Is a derived feature that combines Features 2 and 1 into a single value. Therefore, the result of this feature is 3.1
Feature 5	Is a derived feature that combines Features 2, 1 and 3 into a single value. Therefore, the result of this feature is 3.1001

will be ignored in the classification phase. Thus the resulting pillar in Figure 4 can produce two classification rules:

IF Feature Value is 3 THEN it is Class 11
IF Feature Value is 2 THEN it is Class 15

Notice that the process in the feature selection phase results in the classification rules that are done automatically starting with the pillars retrieving the higher number of classes.

Section 3.1 discusses the classification rules after merging both the Arabic and English numbers into one closed-set pattern. Then we will list all the cases for

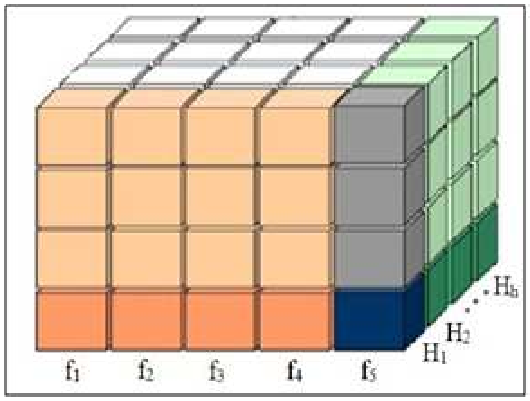

Fig. 3: A cube representing the horizontal line features for multiple classes

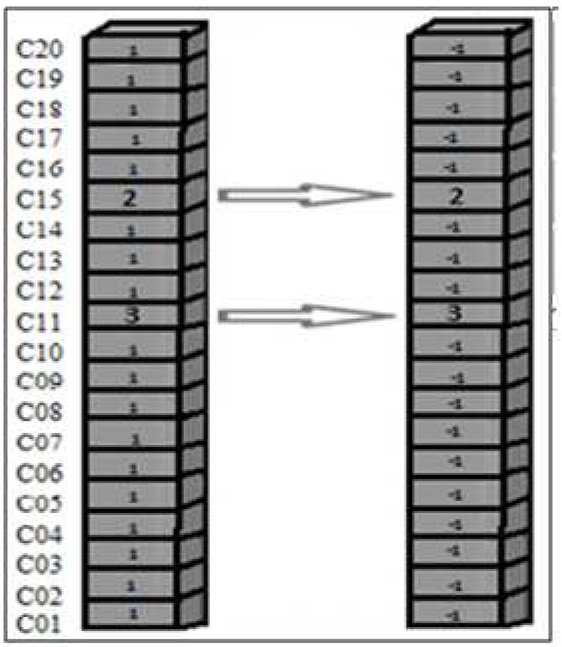

Fig. 4: A sample pillar (left) that applies the feature selection phase

unrecognized numbers using the Feature Selection technique in section 3.2

3. 1 Classification Rules for Merged Closed-Sets

The image dataset consists of 369 images that were already segmented from real Saudi license plates. 200 images are used in the training phase (10 images for each class), and the remaining 169 images are used later for the testing phase. Notice that the experimental results showed stability of classification rules when training 8, 9, and 10 datasets. A dataset is formed by 20 different images, 1 image for each class.

Upon applying the training phase discussed in study [18], the system implemented using MATLAB is able to classify the Arabic and English numbers represented in the Saudi license plates. The implemented system automatically applies the feature extraction phase using the five features in Table 1, for all horizontal and vertical lines crossing the image. The quantization value is Q = [2,100]. After the feature extraction phase, the system automatically continues by applying the feature selection phase. Finally, the system will display the classification rules that are able to classify all the 20 classes with their quantization value and the normalized image dimensions h and v.

The implemented system is able to achieve classifications to Saudi license plate numbers. Only one quantization value was displayed Q=12. The normalized image size used is h=100 and v=100. The classification rules are listed in Table 2. The Line Number column can be either a horizontal line or a vertical line, where the horizontal line is a row line starting from the top of the image, and the vertical line is a column line starting from the left side of the image. The experimental result shows that at Q=12 we are able to classify a number in the Saudi plate by checking at most 13 different pillars.

Table 2: The classification rules for the numbers in the Saudi license plates (Q=12, h=100, v=100)

Pillar Number	Feature Number	Line Number	Feature Value	Number	Class
6	1	Horizontal 6	3 2	٣ ٧	C3 C7
154	2	Horizontal 54	10	9	C19
257	3	Horizontal 57	0.001	3	C13
670	2	Horizontal 70	2	٤	C4
711	3	Vertical 11	0.001 0.11	٨ 8	C8 C18
816	4	Vertical 16	9.2	5	C15
919	5	Vertical 19	4.11 3.11 2.11 6.2101	١ ٦ 1 2	C1 C6 C11 C12
928	5	Vertical 28	5.21	٩	C9
946	5	Vertical 46	12.11 8.2101 6.211	٠ ٥ 7	C10 C5 C17
966	5	Vertical 66	4.2101	0	C20
985	5	Vertical 85	8.211	6	C16
987	5	Vertical 87	2.11	٢	C2
992	5	Vertical 92	2.1001	4	C14

The advantage of Feature Selection technique is that we are able to classify more than one class using the same pillar number. For example, the classes (١,٦, 1, 2) can be classified by applying Feature 5 on the 19th vertical line. These classes differ in their feature values, which are 4.11, 3.11, 2.11, and 6.2101 respectively.

In Figure 5, we introduce five classes (٣, 9, 3, 5,٢), where each class is classified by applying a certain feature.

In Figure 5(a), the class ٣ is classified by applying Feature 1. The system counts the number of transitions crossing the 6^{th} horizontal line, which are 3. The transition is the change in color from white to black pixel in the crossing line.

In Figure 5(b), the class 9 is classified by applying Feature 2. The system multiplies the density of black pixels (79%) crossing the 54^{th} horizontal line by the quantization value 12 and then applies the ceiling method to the value. The result is $\lceil(0.79x12) = \lceil(9.48) = 10$. The method of ceiling the result is applied in order to constrain a continuous set of values into a relatively small discrete set.

In Figure 5(c), class 3 is classified by applying Feature 3. The system will recognize the existence of at least one transition in each region of the 57^{th} horizontal line which is divided into three equal regions (Left, Middle, and Right). Thus the feature value for class 3 is 0.001

In Figure 5(d), the class 5 is classified by applying Feature 4 which is a combination of Features 2 and 1. By checking the 16^{th} vertical line, the system will show the density of black pixels as 70% with two transitions. The result of the quantized part is $\lceil(0.7x12) = \lceil(8.4) = 9$, thus the feature value for class 5 is 9.2

In Figure 5(e), the class ٢ is classified by applying Feature 5 which is the combination of Features 2, 1 and 3. The system checks the 87^{th} vertical line and will show the density of black pixels as 13% with an occurrence of a transition in the top region only. The result of the quantized part is $\lceil(0.13x12) = \lceil(1.56) = 2$, thus the feature value for class ٢ is 2.1100

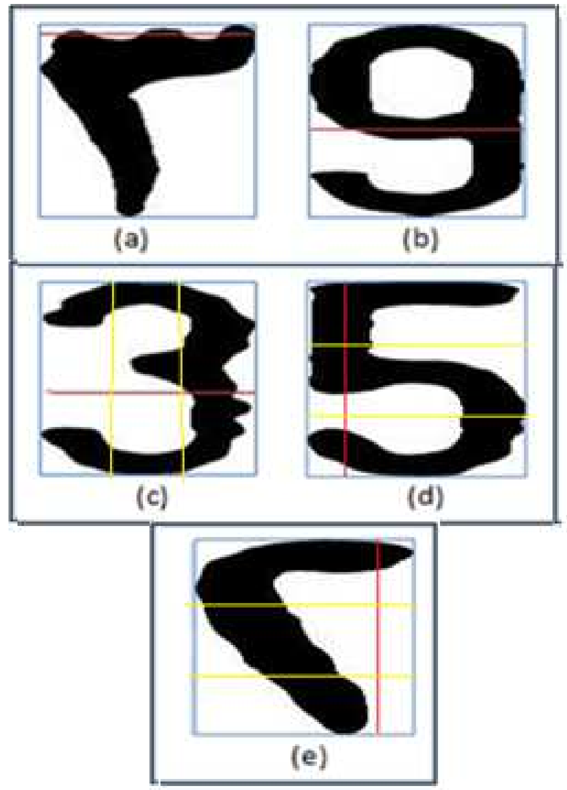

Fig. 5: Sample classes with their classification lines in the red line

3 .2 Cases of Unrecognized Numbers

During the testing phase, the system is implemented to start with the classification rules retrieving the highest number of classes in order to minimize the number of pillars checked. The result will show that 35 images out of 169 are wrongly classified in the testing phase. The misclassification happens due to one of possible three cases:

Case 1: The candidate image is classified to more than one class. For example, the Arabic number 5 was wrongly classified by another class 13, due to the erosion of the number (see Figure 6). We already discussed the feature value of the class 13 in Figure 5(c), which is true for the candidate image shown in Figure 6. In this case, the image noise affects the classification of the candidate image. The output displayed for the candidate image in Figure 6 using the Feature Selection technique is:

Image 26 belongs to Class 5
Image 26 belongs to Class 13

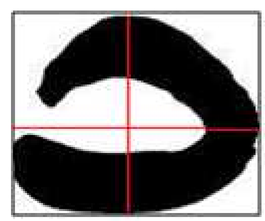

Fig. 6: Sample classes with their classification lines in the red line

Case 2: The candidate image is classified to a wrong class. For example, the number in Figure 7 was wrongly classified as 6, due to two reasons: the first reason is because both classes are classified by applying the same pillar (919). The second reason is that the feature values of classes 1 and 6 are very close depending on the quantization value. The feature values of class 1 and 6 are 4.11 and 3.11 respectively. In Figure 7 we have the density of black is equal to 25% with one transition in the top region, thus the feature value becomes 3.11 and not 4.11. However, in the training set the density of black for all images for class 1 ranges between 27% and 31% hence the feature value becomes 4.11. This classification phase did not take into consideration the image dimension before being normalized into the size 100x100. The output displayed for the candidate image in Figure 7 using the Feature Selection technique is:

Image 1 belongs to Class 6

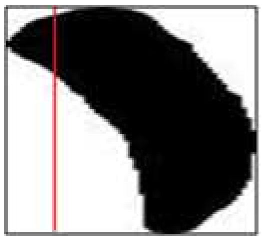

Fig. 7: Class 1 classified as 6

Case 3: The candidate image could not be classified to any class. For example, the number in Figure 8 belongs to class 19, but it was not classified correctly, since the feature value of the 54^{th} horizontal line is 11. However, in the training set the density of black for all class 19 ranges between 76% and 83%, and thus the feature value becomes 10. In this case the image noise affects the classification of the candidate image. The output for this image (Figure 8) is displayed using the Feature Selection technique will be:

Image 140 is unrecognized to any class

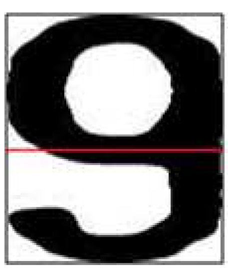

Fig. 8: Unrecognized class

4 A New Classification Method Based on Reference Image Technique

The system will nominate a reference image for each class from the training dataset. It will do so by selecting the image with the minimum cumulative image difference with all other images in the same class. In this Reference Image technique, the system will compare the candidate image with a reference image related to the same class.

In photography a grayscale digital image is an image in which the value of each pixel is a single sample and it carries only the intensity information. The gray level varies from black at the weakest intensity to white at the strongest. We calculate the average absolute difference of any two images I_1 and I_2 belong to the same class by applying the mathematical equation:

$$\mathrm{Diff}(\mathrm{I}_1,\mathrm{I}_2) = \sum_{i=1,\ j=1}^{i=h,\ j=v} (\,|\,I_1(i,j) - I_2(i,j)\,|\,)\ /\ (hxv)$$

We can calculate the percentage of the average absolute difference by dividing the result of the above equation by 255, since grayscale values vary between 0 and 255. The maximum percentage between the images in each class is presented in Table 3. These values will be considered later in the study as the maximum class threshold to be compared with the candidate images in the testing phase.

Table 3: The maximum image difference in each class.

Class	Number	Maximum Class Threshold (%)
1	١	14.8
2	٢	9.12
3	٣	11.9
4	٤	8.94
5	٥	11.4
6	٦	7.13
7	٧	12.98
8	٨	13.71
9	٩	8.69
10	٠	10.04
11	1	9.23
12	2	10.47
13	3	12.56
14	4	11.96
15	5	13.63
16	6	15.39
17	7	12.72
18	8	13.92
19	9	12.98
20	0	13.59

The Reference Image technique applies an additional image comparison with the reference image in the same class in case the classification rule is true. However, if the difference between the candidate image and the reference image in the same class is less than or equal to the maximum class threshold, then the system can display the recognized class and the process is ended.

In case all the classification rules are false, then we apply another set of processes that compare the candidate image with all the reference images in the closed-set pattern. Thus the system displays only the class that has the minimum difference between the candidate image and reference image provided that it is less than or equal to the maximum class threshold. However, in case none of the differences is below the maximum class threshold, then the system displays the failure in recognition of the candidate image.

In section 4.1 we will discuss the experimental results based on the Reference Image technique and its recovery of the unrecognised cases discussed in section 3.2. We will also compare the time performance and the recognition accuracy between different techniques in section 4.2

4. 1 Experimental Results Based on Reference Image Technique

Listed below are the recovery processes for the three unrecognized cases using the Reference Image technique:

Case 1: The candidate image is classified into two different classes simultaneously using the Feature Selection technique. However, by applying the Reference Image technique, the candidate image in Figure 6 is compared with the reference image in Class 5. The percentage of the average absolute difference evaluated is 6.26%. It is less than the 11.4% of the maximum class threshold that belongs to Class 5. Thus the recognition process for the candidate image is ended after displaying the following result:

Image 26 belongs to Class 5 with a difference with the reference image by 6.26%

Case 2: The candidate image is classified to a wrong Class 6 using the Feature Selection technique. However, the image difference between the candidate image and the reference image related to Class 6 is above the maximum class threshold. Therefore, we compare the image difference with all 20 reference images and then the class with the minimum class threshold is chosen. The output for the candidate image in Figure 7 using the Reference Image technique is:

(After checking all Reference Images) Image 1 belongs to Class 1 with a difference with the reference image by 8.23%

Case 3: The candidate image in Figure 8 was not recognized to any class using the Feature Selection technique. By applying the Reference Image technique the candidate image is classified to Class 19 after comparing the image difference to all 20 reference images. The output for the candidate image using the Reference Image technique is:

(After checking all Reference Images) Image 140 belongs to Class 19 with a difference with the reference image by 5.34%

4. 2 Testing Phase Performance Comparison

Table 4 shows a comparison between three techniques: the Feature Selection, the Reference Image and the Image Difference techniques (the Image Difference technique does not apply the Feature Selection technique).

The same testing dataset will be used for all three techniques. However, the number and type of operations differ between one technique and another. In the Feature Selection technique the imaging comparison operation is never applied, and the maximum number of feature selection operations is 169x13=2197 where 169 are the candidate images and 13 are the maximum classification rules.

In the Reference Image technique it is necessary to compare the candidate image with at least one reference image. In case the candidate image is not classified in the Feature Selection technique, then it will be compared to all reference images. In the Image Difference technique we have exactly 169x20=3380 image difference operations, since we are comparing each image in the testing dataset with all the reference images.

Table 4: A comparison between the classification techniques

Technique Name	Recognition Accuracy (%)	Total time (s)	Average time per image (ms)
Feature Selection	79.29%	1.4	8.28
Reference Image	98.22%	4.53	26.8
Image Difference	98.22%	19.61	116.04

The Feature Selection technique is a fast processing technique. It does not apply any post processing operation. The average time it takes to classify an image is 8.28ms. According to our testing dataset, the recognition accuracy of the Feature Selection technique is 79.29% (134 recognized images / 169 total images).

Although the speed of the Image Difference technique is slower than the Feature Selection technique, it provides higher recognition accuracy 98.22% (166 recognized images / 169 total images). The average time it takes to classify an image is 116.04ms.

Our proposed technique, the Reference Image technique, has a processing time 4.33 times faster than the Image Difference technique (Table 4). The Reference Image technique provides higher recognition accuracy than the Feature Selection technique 98.22% (166 recognized images / 169 total images). The average time to classify an image using the Reference Image technique is 26.8ms.

5 Enhancing the Recognition Accuracy using Clustering Method

In Table 2 it is shown that by using the Feature Selection technique, the maximum number of operations to recognize a number belongs to a Saudi license plate is 13 operations.

Another techniques will be introduced that can decrease the number of feature selection operations. In this technique we will divide the numbers into independent clusters using the X-Means algorithm [19], which is an extended version of K-Means algorithm and it selects the number of clusters itself.

In section 5.1 we will apply feature representation to select features that are able to categorize the Saudi numbers into clusters. Section 5.2 will list the classification rules for each cluster. Section 5.3 will propose a new clustering technique in the testing phase as well as it will present the time performance for different clustering techniques.

5. 1 Clustering Feature Representation

Clustering is the task of grouping a set of objects in order to make them more similar in some features to those on other groups. In this research we apply five different features. Feature 1 counts the number of transitions in each horizontal or vertical line crossing the image. In this study, the system is able to calculate the total number of horizontal and vertical transitions for the reference images having the image dimension size (100x100). The results are listed in Table 5.

Table 5: The transition characteristics for each reference image.

Class	Number	Number of Horizontal Transitions	Number of Vertical Transitions
C1	١	100	102
C2	٢	101	145
C3	٣	109	116
C4	٤	106	192
C5	٥	140	175
C6	٦	100	101
C7	٧	139	105
C8	٨	140	102
C9	٩	108	131
C10	٠	100	101
C11	1	109	109
C12	2	111	241
C13	3	126	224
C14	4	120	141
C15	5	119	254
C16	6	149	231
C17	7	102	161
C18	8	164	255
C19	9	151	226
C20	0	175	148

Table 6: The cluster centroids and there corresponding classes.

Centroid Number	Horizontal Transitions	Vertical Transitions	Classes in the Cluster
Centroid 1	116.63	121.83	١ ـ ٢ ـ ٣ ـ ٦ ـ ٧ ـ ٨ ـ ٩ - ٠ - 1 - 4 - 7 - 0
Centriod 2	133.25	224.75	٤ ـ ٥ – 2 - 3 - 5 – 6 - 8 - 9

Figure 9 represents a graph of the total number of horizontal transitions (x-axis), versus the total number of vertical transitions (y-axis) for each class. It will also classify the classes into two clusters upon using the X-Means algorithm [19]. The centroids of the clusters are denoted with a square labeled Centroid. The classes belong to Clusters 1 and 2 are denoted with a triangle and a circle respectively.

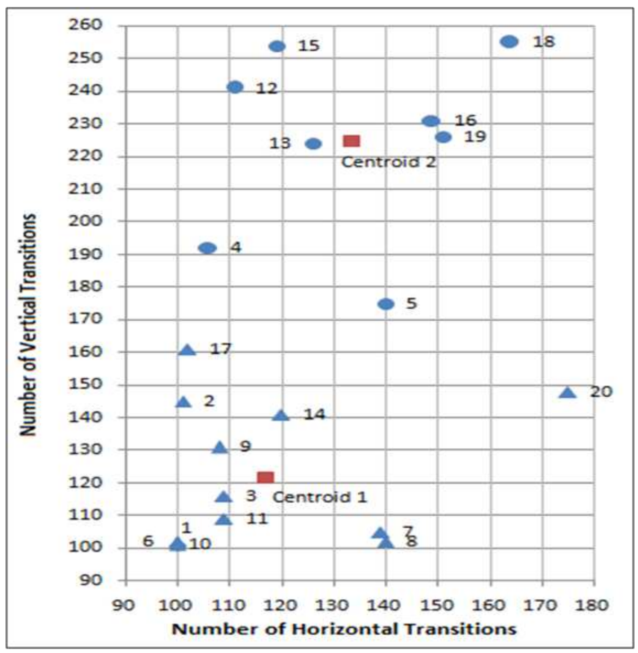

Fig. 9: 2D plotting for the transition features as labeled for each class

5. 2 Classification Rules for the Clusters

By applying the Feature Selection technique, the system will be able to classify both clusters 1 and 2. It is also able to classify an image belong to cluster 1 by checking at most 7 classification rules (Table 7). The quantization value found in the classification of cluster 1 is Q=7, and the normalized image size used is h=100, and v=100.

The system is able to classify an image belongs to cluster 2 by checking at most 3 classification rules. The quantization value found in the classification of cluster 2 is Q=3, and the normalized image size used is h=100, and v=100. The classification rules for cluster 2 are listed in Table 8.

Table 7: The classification rules for cluster 1 (Q=7, h=100, v=100)

Pillar Number	Feature Number	Line Number	Feature Value	Number
6	1	Horizontal 6	3 2	٣ ٧
279	3	Horizontal 79	0.11	٨
405	5	Horizontal 5	6.11 5.11 7.11	٢ ٦ 7
459	5	Horizontal 59	4.101 7.11 4.2101	١ ٠ 0
944	5	Vertical 44	3.21	٩
988	5	Vertical 88	7.11	1
991	5	Vertical 91	1.1001	4

Table 8: The classification rules for cluster 2 (Q=3, h=100, v=100)

Pillar Number	Feature Number	Line Number	Feature Value	Number
441	5	Horizontal 41	2.101	3
913	5	Vertical 13	3.2101 3.11 3.211	5 6 8
988	5	Vertical 88	1.1001 2.11 2.2101 3.11	٤ ٥ 2 9

5. 3 The Categorization Process and Results

The categorization of a candidate image into a cluster requires three processes:
1. Retrieve the 2-dimension coordinates in 100x100 candidate image formed by the total number of horizontal and vertical transitions 2. Calculate the Euclidean distance from the 2-dimension coordinates to the centroids 3. Assign the candidate image to the closest cluster

Thus a candidate image will first be checked to which cluster it belongs, then it is classified by checking the classification rules of that cluster. For example:

Image 164 belongs to Class 8 in Cluster 2 with a difference with the reference image by 4.42%

In this example, the candidate image is checked by at most 3 classification rules as shown in Table 8. On the other hand, it is checked on an average by 7 classification rules in the Feature Selection technique.

In the testing phase, we have only three candidate images that are categorized to a wrong cluster due to their equidistance between Centroid 1 and Centroid 2. These three images belong to Class 2 in Cluster 2 and labeled as number 5 in Figure 9. In case the candidate image is not classified in the categorized cluster, we repeat the classification procedure with other clusters. In the worst case scenario, the candidate image is checked by all 10 classification rules (Tables 7, 8) belong to both Clusters 1 and 2. A sample output will be displayed for a candidate image that is categorized to a wrong cluster:

Image 112 is not recognized to any class in Cluster 1 (After checking other clusters) Image 112 belongs to Class 2 in Cluster 2 with a difference with the reference image by 5.27%

After categorizing the candidate image to either Cluster 1 or Cluster 2, Table 9 shows the comparison between the Feature Selection and Reference Image techniques. Notice that we are using the same testing phase images in all techniques.

Table 9: A comparison between the clustering techniques

Technique Name after Clustering	Recognition Accuracy (%)	Total time (s)	Average time per image (ms)
Feature Selection	94.08%	1.04	6.15
Reference Image	98.22%	2.82	16.69

The results show an improvement in the performance speed for both Clustering techniques, due to fewer checking operations in either Clusters 1 or 2. After clustering, the recognition speed of the Feature Selection and Reference Image techniques are improved by 34% and 65% respectively when compared without applying the Clustering processes. Also after clustering, the recognition accuracy is increased by 14.79% by applying the Feature Selection technique.

If the candidate image fails to be classified by the Reference Image technique it will be checked by all reference images belong to the merged closed-set pattern. On the other hand, in the clustering techniques the candidate image will be compared with only reference images belong to the categorized cluster.

Clustering techniques need more training phase time in preparing the classification rules for each cluster, rather than to apply one training dataset for the merged closed-set pattern.

6 System Comparison

The experimentation of the proposed approach is applied on our constructed dataset. Here in this section we compare our results with a classical classifier in the state-of-art, which is the J48 pruned tree. Our dataset is divided into 2 parts:
1- The training set formed by 200 records, since we have 200 images in the training phase.
2- The testing set formed by 169 records, since we have 169 images in the testing phase Each record is formed by 1000 input attributes and exactly one output attribute. The input attributes for our constructed dataset are constructed as in the following pattern:

F1H1, F1H2, . , F1H100, F2H1, F2H2, . , F2H100, F3H1, F3H2, . , F3H100, F4H1, F4H2, . , F4H100, F5H1, F5H2, . , F5H100, F1V1, F1V2, . , F1V100, F2V1, F2V2, . , F2V100, F3V1, F3V2, . , F3V100, F4V1, F4V2, . , F4V100, F5V1, F5V2, . , F5V100

For example, F3H56 represents the value of extracted Feature 3 taken from the Horizontal line 56. Another example, F5V78 represents the value of extracted Feature 5 taken from the Vertical line 78. Each image belongs to exactly one class. Our dataset contains 20 different classes. The name of classes in the output attribute is composed by 2 parts: the literal number (One, Two, .) and then its language (En for English numbers and Ar for Arabic numbers). For example, Seven_En represents the English number 7.

The data mining tool used for training and testing our data is WEKA, and the result of the J48 pruned tree classifier shows that 145 images are classified correctly, while 24 images are incorrectly classified. The recognition accuracy of the J48 model is 85.8% (145/169). The tree model resulted from our constructed training dataset is shown in Figure 10.

Concerning the tree model in Figure 10, the process starts by checking the root node of the tree. The root node is F1H15, that checks the number of transitions in the 15^{th} horizontal line. In case the number of transitions is greater than 1, then F1H27 is processed. F1H27 checks the number of transitions in the 27^{th} horizontal line. In case the number of transitions is greater than 1, then F1H6 is processed. F1H6 checks the number of transitions in the 6^{th} horizontal line. In case the number of transitions is greater than 1, then number is recognized as the Arabic number ٧.

The tree model in Figure 10 is able to trace the recognition of all the 20 classes. The minimum and maximum number of lines to be checked in order to recognize a class are 3 and 8 respectively. For example, the numbers ٥, ٧, and 6 require 3 lines to be processed in order to be recognized, while the Arabic numbers ٠ and ٢ require 8 lines as shown in Figure 10.

7 Conclusion

In this paper, several techniques were discussed for the recognition enhancement of merged closed-set patterns. The two techniques were experimentally applied to images of numbers extracted from Saudi license plates.

The first technique proposed in this research is a classification method based on the Reference Image technique. It uses at first the Feature Selection technique, and then applies an additional image comparison with the reference image in the same class. The advantage of the Reference Image technique is that it will apply a post processing check for the accuracy of the Feature Selection technique. If the Feature Selection technique is unable to classify the candidate image, the system will apply a complete Image Difference technique with all 20 reference images.

The second technique proposed in this research is a clustering method based on the categorization of reference images. The categorization process extracts two different features from the reference images in order to categorize the 20 classes into clusters using the X-Means algorithm. For each one of these clusters a set of classification rules are developed. In the clustering method, the candidate image is categorized to a cluster before being classified. If the candidate image is categorized to a wrong cluster, then the process is continued to other clusters.

The clustering methods showed an improvement in the recognition accuracy and speed performance when compared with the classification methods. This is due to a fewer number of operations for the classification rules in the clustering methods. Each cluster contains a lower number of reference images than the whole closed-set pattern.

The constructed dataset was also trained and tested using the WEKA tool, and the results showed that our proposed system improved in the recognition accuracy by 12.42% (98.22% - 85.8%). Moreover, our proposed system was able to recognize 8 different classes out of 20 by applying at most 3 operations, while the pruned tree model requires at least 3 operations in order to recognize a class.

Future researches should focus on:

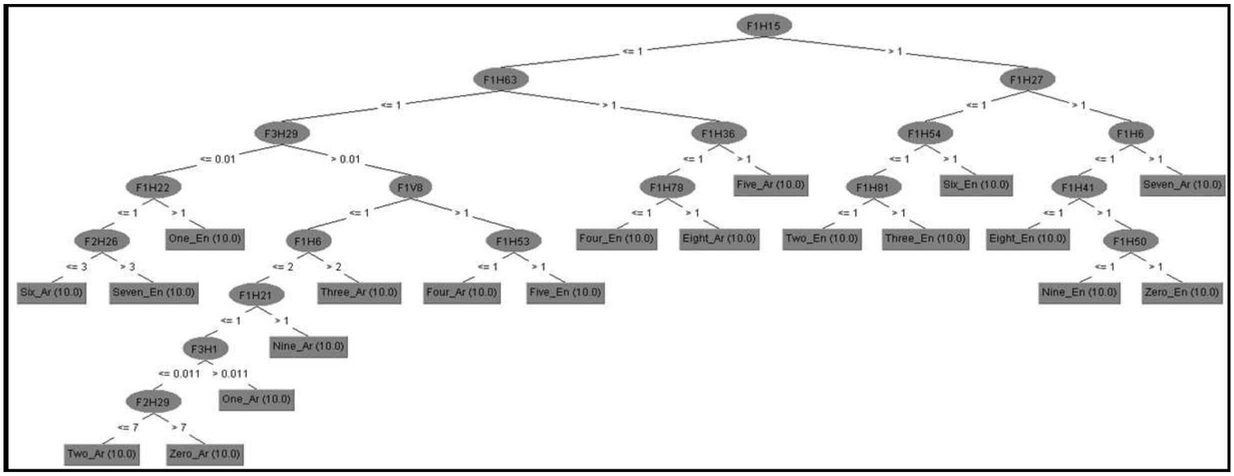

Fig. 10: J48 pruned tree model using WEKA

1- The development of a better method that estimates the maximum image difference to each class.
2- A study that can better categorize a candidate image to the correct cluster.
3- Applying parallel processing methods to check all the clusters simultaneously.
4- Both numbers and letters of license plates as one merged closed-set pattern.

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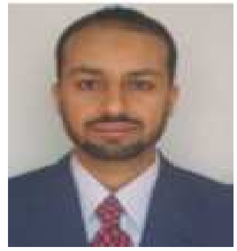

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