IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received February 26, 2020, accepted March 4, 2020, date of publication March 9, 2020, date of current version March 19, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2979185

Toward an Optimized Neutrosophic k-Means With Genetic Algorithm for Automatic Vehicle License Plate Recognition (ONKM-AVLPR)

BEDIR BEDIR YOUSIF[1], MOHAMED MAHER ATA[2], NEHAL FAWZY[3], AND MARWA OBAYA[3,4]

[1]Department of Electronics and Communications Engineering, Faculty of Engineering, Kafrelsheikh University, Kafrelsheikh 35514, Egypt
[2]Department of Electronics and Communications Engineering, MISR Higher Institute for Engineering and Technology, Mansoura 35516, Egypt
[3]Department of Electronics and Communications Engineering, Faculty of Engineering, Mansoura University, Mansoura 35516, Egypt
[4]Communications Program, Electrical Engineering Department, Faculty of Engineering, PNU University, Riyadh 84428, Saudi Arabia

Corresponding author: Mohamed Maher Ata (mmaher844@yahoo.com)

ABSTRACT The present paper proposes a new methodology for license plate (LP) recognition in the state of the art of image processing algorithms and an optimized neutrosophic set (NS) based on genetic algorithm (GA). First of all, we have performed some image processing techniques such as edge detection and morphological operations in order to utilize the (LP) localization. In addition, we have extracted the most salient features by implementing a new methodology using (GA) for optimizing the (NS) operations. The use of (NS) decreases the indeterminacy on the (LP) images. Moreover, k-means clustering algorithm has been applied to segment the (LP) characters. Finally, we have applied connected components labeling analysis (CCLA) algorithm for identifying the connected pixel regions and grouping the appropriate pixels into components to extract each character effectively. Several performance indices have been calculated in order to measure the system efficiency such as accuracy, sensitivity, specificity, dice, and jaccard coefficients. Moreover, we have created a database for all detected and recognized (LP) for testing purposes. Experimental results show that the proposed methodology has the ability to be suitable for both (Arabic –Egyptian) and English (LP). The proposed system achieves high degree of recognition accuracy for the whole system according to the following case studies; (i) for a high resolution Egyptian (LP), the proposed system achieves about 96.67% accuracy of correct recognition, (ii) for a low resolution-corrupted English (LP), the proposed system achieves about 94.27% accuracy. In addition, we have applied the proposed system on some sort of image disturbance i.e. (flash in image, external noise, and illumination variation), the proposed system achieves about 92.5% accuracy of correct identification. However, traditional methods achieve about 79% accuracy of correct identification in the presence of such image degradations. This reflects how the proposed system is generalized, optimized, and proposes high degree of recognition accuracy.

INDEX TERMS Connected components labeling analysis, genetic algorithm, k-means, letters and numbers segmentation, license plate localization, neutrosophic set.

I. INTRODUCTION

Automatic vehicle license plate recognition (AVLPR) has broadly increased in applications such as road traffic monitoring, vehicle tracking, parking, and intelligent transportation systems (ITS). License plate (LP) is a metal plate includes characters and words which is fixed on the vehicle outer body and used to recognize vehicles [1]. Due to the various discrimination of (LP) with respect to shape, size, language, signs, and colors from country to another. Many methods have been suggested for (AVLPR) depending on the country's (LP) characteristics and regulations. Localizing license plate on a complex background is a rough mission. Thus, some major factors should be considered to acquire a successful extraction of the (LP) such as plate size, image quality, plate styling, illumination condition, plate location, and background specifics [2], [3].

In the last decade, many research studies have been implemented in order to enhance the process of license plate recognition (LPR). Most of these studies depend on the

The associate editor coordinating the review of this manuscript and approving it for publication was Inês Domingues.

FIGURE 1. Sample of Egyptian and English license plates style.

traditional algorithms of image preprocessing such as plate localization, character extraction, and pattern recognition [4]. However, those techniques suffer from obvious lack in the degree of (LP) recognition efficiency especially under different image degradations ex. (flashing, blurring, darkening, or any external noise).

In this paper, we consider both the (Arabic-Egyptian) license plates and English license plates. We chose the Egyptian license plates as it would be considered as one of the most complicated (LP) case studies. Egyptian (LP) has many styles that written in both Arabic and English languages. In addition, we chose low resolution English license plates in order to validate the proposed methodology in different case studies. Fig.1 represents some samples of Egyptian license plates in both old and new style and English license plates. We consider recognizing the numbers and letters of (LPs) style with four main stages; (i) detection (localization), (ii) segmentation, (iii) recognition, (iv) database communication. In the first stage, we have detected the appropriate location of the (LP) by using means of edge detection and morphological operations. In the second stage, we have suggested an optimized neutrosophic set (NS) algorithm for extracting the most salient features in (LP) images. This optimization has been accomplished using genetic algorithm. The proposed strategy aims to reduce indeterminacy in (LP) images. Moreover, k-means algorithm has been utilized for clustering purposes, and the last step in previous stage, connected component labeling analysis (CCLA) has been applied in order to extracting characters individually.

In the third stage, characters would be recognized according to the measurement of characters matching with the templates that stored in the database. Finally, we store the recognized (LP) in Microsoft access database. Fig. 2 shows the block diagram of the proposed system.

II. RELATED WORK

P. Prabhakar *et al.* have presented a promising method for extracting license plate (LP) location and characters [5]. Algorithm was depending on converting vehicle image into gray-scale image. Then they have applied some traditional image processing algorithms to calculate the connected component in order to extracting characters individually. Their proposed methodology has achieved an accepted accuracy percentage by optimizing some parameters to achieve an acceptable recognition rate than the classical methods.

C.H.Lin *et al.* presented an effective license plate recognition system that first detects vehicles and then recovers license plates from vehicles for reducing false positives on

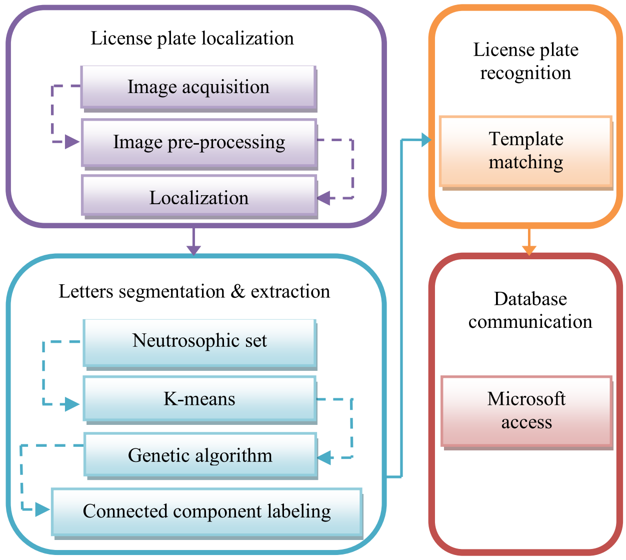


FIGURE 2. The proposed framework.

plate detection [6]. They have improved the character recognition rate of blurred and mysterious images using convolution neural networks.

A. C. Roy *et al.* have proposed a solution for Bangla license plate recognition [7]. Firstly, they have localized the license plate (LP) position of the vehicle depending on commercial license plates with unique color (green) for their country standard. They have accomplished the isolation process by using horizontal projection with threshold value. They have accomplished character segmentation criteria by using vertical projection with threshold. In addition, for recognizing characters they have used template-matching algorithm. They captured over 180 still images from roads in order to test their algorithms. They have achieved about (93%), (98.1%), and (88.8%) respectively for success rate in detection, segmentation, and recognition for Bangla license plate.

I. Ullah *et al.* this paper has focused on the detection of license plates only [8], which depend on mathematical morphological features such as (height, width, angle, and ratio) of license plate. The proposed system works for all English types of license plates which vary in shapes and size. However, their proposed system has the ability to deal with images which are complex and vary in background, size, distance, and camera angle, etc. the proposed method found the right location rate of 78% only.

S. Omran *et al.* proposed for Iraqi, an automatic license plate recognition system, by using optical character recognition (OCR) with templates matching, and correlation approach for plate recognition [9]. It is used over a 40 images, and finally it is given 87.5% for plate extraction and 85.7% for plate recognition.

B. Tiwari *et al.* introduced genetic algorithm (GA) for detecting the locations of the license plate characters [10]. This technique used to distinct the key characteristic of license plates according to symbols with robust light-on-dark edges. This technique used for overcoming the license plate (LP) detection problem depends only on the geometrical layout of the (LP) characters. The proposed technique has high impunity to changes in illumination.

K. M. Babuand *et al.* has four main steps for license plate recognition [11]. Firstly, in pre-processing, images are captured through the digital camera, adjusted the appropriate brightness, removed the noise, and converted to a gray scaled image. Secondly, they found the edges in the image inorder to extract (LP) location. Moreover, characters are segmented in (LP). Finally, they have applied template matching algorithm for recognizing each chracter in (LP)image. The whole system has achived about 91.11% accuarcy.however, they didn't deal with Some difficulties as follows (blurring image, broken (LP),and similarities between characters).

N. Rana *et al.* has discussed several detection techniques for license plate and compare their performance on similar parameters [12]. They have used signature analysis with Connected component analysis, and Euclidean distance transform). They have achieved about 92% success accuracy and failure due to the inappropriate illumination and blurring.

Vidhya. N *et al.* have presented different types of approaches as their challenges involved in detection, localization and recognition of license plate numbers [13]. This paper presents a survey of license plate recognition techniques by categorizing them based on features used in each stage and found that the highest accuracy of them was that, Edge based detection, sliding concentric window, which achieved 98.4% success accuracy.

This work introduces the following contributions: -

1- We have proposed a new methodology for license plate recognition (LPR) in the state of the art of image processing algorithms and an optimized neutrosophic set (NS) based on genetic algorithm (GA).
2- We have Extracted the most salient features by implementing a new strategy according (GA) for optimizing the (NS) operations. The use of (NS) set decreases the indeterminacy on the license plate (LP) images.
3- We have applied k-means clustering algorithm to segment the (LP) characters.
4- We have applied connected components labeling analysis (CCLA) algorithm for identifying the connected pixel regions and grouping the appropriate pixels into components to extract each character effectively.
5- The proposed system has targeted a high rate of recognition accuracy in the presence of (LP) image degradations and disruption.
6- Finally, experimental results show the following:
   i For a high resolution Egyptian (LP), the proposed system achieves about 96.67% accuracy of correct recognition.
   ii For a low resolution-corrupted English (LP), the proposed system achieves about 94.27% accuracy. Some examples of such corruptions (discontinuous or invisible letters, illumination variation, and darkening).
   iii In case of Egyptian (LP), we have applied the proposed system on some sort of image disturbance i.e. (flash in image, external noise, and illumination variation), the proposed system achieves about 92.5% accuracy of correct Binarization identification. However, traditional methods achieve about 79% accuracy of correct Binarization identification in the presence of image degradation. This reflects how the proposed system is generalized, optimized, and proposes high degree of recognition accuracy.

The remaining part of this paper is organized as follows. Section **III**, provides possibility of (LP) localization. Section **IV**, proposed a new method for segment & extract letters and numbers. Section **V**, presented how we can recognize the characters according to storing database. Section **VI**, explain experimental and results for our proposed system. Section **VII**; demonstrate storing of our result as a text in Microsoft access database. Finally, the paper is concluded in section **VIII**.

III. LICENSE PLATE LOCALIZATION

A. IMAGE ACQUISITION

The Egyptian license plate (LP) images are captured using a high resolution (Nikon) digital camera with a resolution of (5152 × 3864) pixels. Images are taken from both front and back sides of the vehicles with distance (about 2 meters and up to 3 meters far apart) at (12.00 pm). Images are collected from many places such as parks, camps, streets (https: //drive.google.com/file/d/1CUSzJgDM10zrsRo1SQj5 mibZPddFriP/view). The English (LP) images are captured by using (OLYMPUS CAMEDIA C-2040ZOOM) digital camera with a resolution of (640 × 480) pixels. The database images have included over 500 images of the rear views of several vehicles (trucks, cars, busses), taken under different lighting conditions (cloudy, sunny, rainy), as shown in Fig. 3 [14].

B. IMAGE PRE-PROCESSING

In pre-processing RGB car image as shown in Fig. 4 (a) is down scaled to 50% of its original scale in order to reduce the computational time. In addition, cutting and resizing images have been utilized in order to decrease the probability of candidate regions to be found as shown in Fig. 4(b). The RGB image contains three channels red, green and blue, each channel has value in the range (0-255), whereas gray scale image has only one channel so we convert RGB image to gray scale format as shown in Fig.4(c). In addition, we have increased the contrast of the images in order to facilitate the detection process of (LPs) [15] as shown in Fig. 4(d). Similarly, all the previously discussed steps have been applied on the English license plates as well. However, in this case, there will be no need for image cropping as the images have been captured from a very closed distance far from the vehicle itself as shown in Fig. 5.

FIGURE 3. Sample of vehicles.

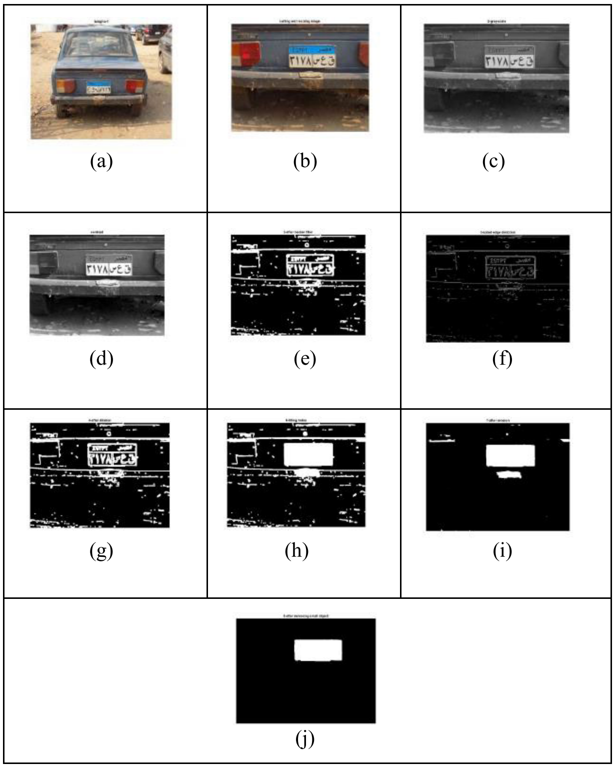


FIGURE 4. (a) RGB image, (b) Cutting and resizing image, (c) Gray scale image, (d) Contrast image, (e) Median filters, (f) Sobel edge detectors, (g) Dilation, (h) Filled image, (i) Erosion, (j) Removing unwanted objects.

C. LOCATE RECTANGLES OF PLATE VEHICLE

In the proposed system, the license plate has been extracted by applying a group of operations; (i) apply median filter with mask (3×3) for fostering image and removing noises (random appearance in black & white pixels) as shown in Fig. 4(e). (ii) apply sobel edge detector [16], [17] for detecting the appropriate edges as shown in Fig. 4(f). (iii) apply morphological operations (both image dilation and erosion) for isolating the plate from the background. Dilation used for increasing the boundary thickness to avoid broken line problem, dilation makes the objects bigger as each background pixel is transferred to an object pixel as shown in Fig. 4(g). In addition, all holes have been filled as shown in Fig. 4(h). Erosion used to allocate the candidate plate regions by using squared structuring element as shown in Fig. 4(i). Finally,

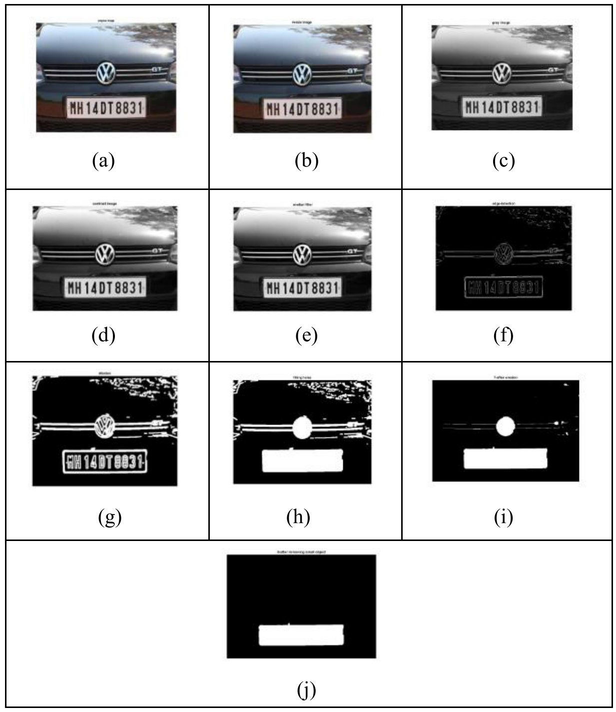


FIGURE 5. (a) RGB image, (b) Resizing image, (c) Gray scale image, (d) Contrast image, (e) Median filters, (f) Sobel edge detectors, (g) Dilation, (h) Filled image, (i) Erosion, (j) Removing unwanted objects.

(iv) there may be more than candidate area for (LP) location so removing unwanted objects have been applied as shown in Fig. 4(j), and similarity all steps for English license plates as shown in Fig. 5.

D. (LP LOCALIZATION) DETECTING CLOSED BOUNDARIES

The final step now is to localize the appropriate (LP). We have applied two basic checkers in order to guarantees getting the plate region correctly and rejecting undesirable regions. These steps are listed as follow [18]:

1) RECTANGLE SHAPE CHECKER

Check if sum of white pixels = (+5% or -5%) as a tolerance for the appropriate area of these region [19].

2) DIMENSION OF PLATE CHECKER

Check if (a < height/width of the succeed region < b).

Whereas (a, b) parameters value depend on dimensions of license plate (LP). Algorithm 1 explains briefly the (LP) detection criteria with the two checkers. Note that if the detected region has not been considered as a plate then we start the detection procedure from its first step. However, instead of using a contrasted gray-scaled image, we use green channel colored image [20]. The green channel provides enough contrast for the image, also we blur image in order to smooth (LP) edges and to

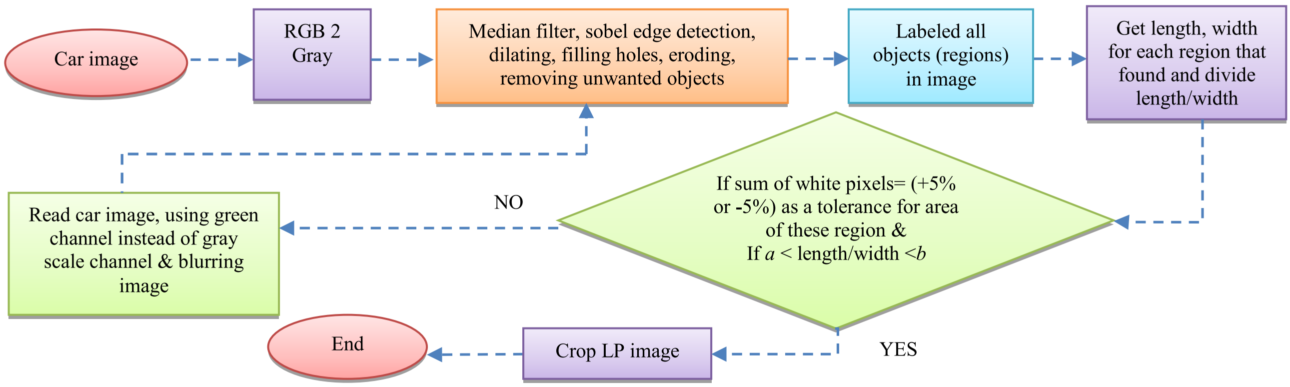


FIGURE 6. License plate localization algorithm.

Algorithm 1 Detection Stage

Input: Car image.
Output: License plate (LP) image.
Steps:
Preprocessing image (resizing, gray scale image, contrast).
Apply filtering process with some morphological operation (median filter, sobel edge detection, dilating, filling holes, eroding, removing unwanted objects) for image enhancement.
Apply bounding box around each region in image.
Label all detected objects.
Calculate length, width for each region which would be detected and calculate the ratio (length / width).
If sum of white pixels= (+5% or -5%) as a tolerance for area of these region.
Read next line.
If $a <$ (length/width) $< b$
Crop image and save it.
Else
Load path of image & crop and resize the image.
Apply green channel imaging instead of gray scale channel imaging & blur image.
Tested=true
End inner if
End outer if

reduce noise. Fig. 6 explains the whole algorithm of license plate localization.

IV. LETTERS AND NUMBERS SEGMENTATION AND EXTRACTION

The dataset of English license plates contains pictures of vehicles with domestic plates from all over Croatia [14]. The new Egyptian license plate has a standard size of (16 × 32) cm which is divided into three main regions; the upper region of the plate with 62 mm, a region from the top border of the plate contains a word of 'Egypt' in both English and Arabic languages. This region has background color that indicates the type of the car (taxi, private, etc.) as shown in Fig. 7.

The reminder region of the plate is separated vertically into two parts; right half include the plate letters, and left half include numbers. Accordingly, the Egyptian plate regions are divided into two parts with a ratio of (1:2) from the height, analyzing the first region of original image by using color filter to identify the type of the car. In addition, the second

Green	Diplomatic vehicles
Orange	Taxis
Yellow	Vehicles with unpaid customs
Gray	Buses
Dark blue	Police vehicles
Light blue	Private vehicles
Beige	Limousines and tourists buses
Red	Trucks

FIGURE 7. Database of Egyptian vehicles according to license color.

region would be analyzed in the gray scaled mode for recognizing both letters and numbers in the (LPs).

A. NEUTROSOPHIC IMAGE

Neutrosophy analysis has been utilized in order to estimate the indeterminacy (uncertainty) in the image dataset. A membership sets which contain a certain degree of falsity (F), indeterminacy (I), and truth (T). These membership functions are applied, for mapping the input image to the (NS) domain,which resulting the (NS) image (A_{NS}). So, for the image, the pixel A(x, y) is defined as A_{NS} (x, y) = A (t, i, f) = {T (x, y), I(x, y), F(x, y)} for (NS) domain giving the true, indeterminate, and false belonging to the bright pixel set. Assume A(x, y) demonstrate the intensity value of the pixel (x, y), and $\overline{A}(x, y)$ indicated to its local mean value, the membership functions can be represented as follows [21]–[24].

$$T(x, y) = \frac{\overline{A}(x, y) - \overline{A}_{\min}}{\overline{A}_{\max} - \overline{A}_{\min}}, \tag{1}$$

$$\overline{A}(x, y) = \frac{1}{b * b} \sum_{m=x-\frac{b}{2}}^{x+\frac{b}{2}} \sum_{n=j-\frac{b}{2}}^{y+\frac{b}{2}} A(m, n), \tag{2}$$

$$I(x, y) = \frac{\delta(x, y) - \delta_{\min}}{\delta_{\max} - \delta_{\min}}, \tag{3}$$

$$\delta(x, y) = abs((A(x, y) - \overline{A}(x, y))), \tag{4}$$

$$F(x, y) = 1 - T(x, y), \tag{5}$$

where the intensity value of the pixel (x, y) is A(x, y), its local mean value represented by $\overline{A}(x, y)$, and its absolute value represented by δ (x, y) where, the value of I (x, y) measuring the indeterminacy of A_{NS} (x, y). The (NS) image entropy represent as, the entropies summation of the three sets T, F, and I, which reflect the elements distribution in the (NS) domain, which would be represented as follows:

$$E_{NS} = E_T + E_I + E_F, \tag{6}$$

$$E_T = -\sum_{i=\min\{T\}}^{\max\{T\}} P_T(i)\ln(P_T(i)), \tag{7}$$

$$E_F = -\sum_{i=\min\{F\}}^{\max\{F\}} P_F(i)\ln(P_F(i)), \tag{8}$$

$$E_I = -\sum_{i=\min\{I\}}^{\max\{I\}} P_I(i)\ln(P_I(i)), \tag{9}$$

The three entropy subsets are represented by (E_T, E_I, E_F). The probabilities of the elements in the three membership functions are represented by $(P_T(i), P_I(i), P_F(i))$. In addition, the deviations in F and T create the elements distribution in the image, and the entropy of I to make F and T correlated with I.

1) α-MEAN FOR NEUTROSOPHIC IMAGE

The local mean operation for a gray level image A is [25]:

$$\overline{A}(x,y) = \frac{1}{b*b}\sum_{m=x-\frac{b}{2}}^{x+\frac{b}{2}}\sum_{n=j-\frac{b}{2}}^{y+\frac{b}{2}} A(m,n), \tag{10}$$

The (α-mean) operation for neutrosophic image A_{NS} is

$$\overline{A}_{NS}(\alpha) = A(\overline{T}(\alpha), \overline{I}(\alpha), \overline{F}(\alpha)), \tag{11}$$

where $\overline{T}(\alpha)$, $\overline{I}(\alpha)$ and $\overline{F}(\alpha)$ are expressed as follows:

$$\overline{T}(\alpha) = \begin{cases} T, & I < \alpha \\ \overline{T}_\alpha, & I \geq \alpha \end{cases} \tag{12}$$

$$\overline{F}(\alpha) = \begin{cases} F, & I < \alpha \\ \overline{F}_\alpha, & I \geq \alpha \end{cases} \tag{13}$$

$$\overline{T}_\alpha(x,y) = \frac{1}{b*b}\sum_{m=x-\frac{b}{2}}^{x+\frac{b}{2}}\sum_{n=j-\frac{b}{2}}^{y+\frac{b}{2}} T(m,n), \tag{14}$$

$$\overline{F}_\alpha(x,y) = \frac{1}{b*b}\sum_{m=x-\frac{b}{2}}^{x+\frac{b}{2}}\sum_{n=j-\frac{b}{2}}^{y+\frac{b}{2}} F(m,n), \tag{15}$$

$$\overline{I}_\alpha(x,y) = \frac{\overline{\delta}_T(x,y) - \overline{\delta}_{T_{\min}}}{\overline{\delta}_{T_{\max}} - \overline{\delta}_{T_{\min}}}, \tag{16}$$

$$\overline{\delta}_T(x,y) = abs(\overline{T}(x,y) - \overline{\overline{T}}(x,y)), \tag{17}$$

$$\overline{\overline{T}}(x,y) = \frac{1}{b*b}\sum_{m=x-\frac{b}{2}}^{x+\frac{b}{2}}\sum_{n=j-\frac{b}{2}}^{y+\frac{b}{2}} \overline{T}(m,n), \tag{18}$$

where 'b' expresses the size of the average filter, which is set as b = 3 to produce the neutrosophic set (NS) image, the absolute value of the variance between the mean intensity and its mean value of the mean intensity, are expressed by $\overline{\delta}_T(x,y)$. The entropy of I is increased by getting a uniform distribution of the elements, where the α value in the α-mean has been optimized by using Genetic algorithm (GA).

B. OPTIMIZATION IN (α–MEAN) USING GENETIC ALGORITHM

The optimal value of (α) has been adaptively estimated using the (GA) [26]–[28], as discussed in algorithm 2. The optimization fitness function is jaccard (JAC), which are statistical measurements that calculate the union '∪' and the intersection '∩' operators of any two sets. This fitness (JAC) is given by:

$$JAC(f,q) = \frac{A_{rf} \cap A_{rq}}{A_{rf} \cup A_{rq}}, \tag{19}$$

where, A_{rf} is the computerized segmented (LP) region using the proposed (ONKM) system, and A_{rq} is the ground truth (LP) region as discussed in algorithm 3. Fig. 10 illustrates the flowchart of the (ONKM) license plate character segmentation algorithm to obtain (α optimal). For achieving the maximum of (JAC) coefficient with genetic algorithm, we apply Eq. (20).

$$F(f,q) = 1 - JAC(f,q), \tag{20}$$

C. k-MEANS CLUSTERING USING OPTIMIZED (α-MEAN)

K-means is a clustering technique, which summation the objects into K groups [29]–[33]. The following mathematical expression introduces the k-means:

$$O = \sum_{j=1}^{q}\sum_{i=1}^{d_j} \left\| W_i - Z_j \right\|, \tag{21}$$

where, q is the total number of clusters, Z_j is the center of the j^{th} cluster, and d_j is the number of pixels of the j^{th} cluster. In the k-means algorithm, it is necessary to decrease O by

Algorithm 2 Genetic Algorithm

Generate random n populations.
Calculate the fitness function of these solutions.
Create new population.
Select from the population two parent chromosomes according to their fitness.
Crossover the parents for new offspring.
Mutate new offspring.
Allocate new offspring.
Use the new generated population for iteration.
  If the end restraint achieved.
  Stop, and provide the pre-eminent solution.
  End if
Repeat the preceding steps.

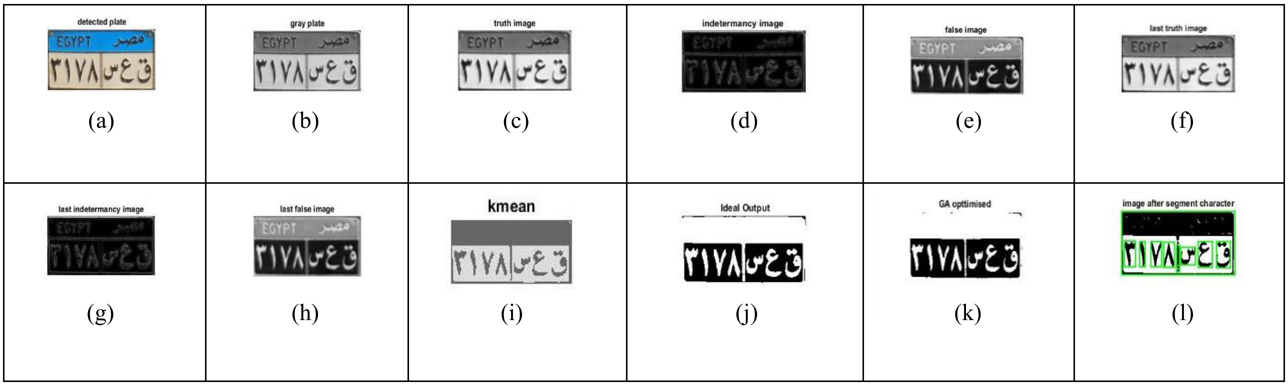


FIGURE 8. (a) Detected plate, (b) Gray plate, (c) Truth image, (d) Indeterminacy image, (e) False image, (f) Last truth image, (g) Last indeterminacy image, (h) Last false image, (i) K-mean image, (j) Ground truth image, (k) Genetic optimization output image, (l) Image after applying (CCLA).

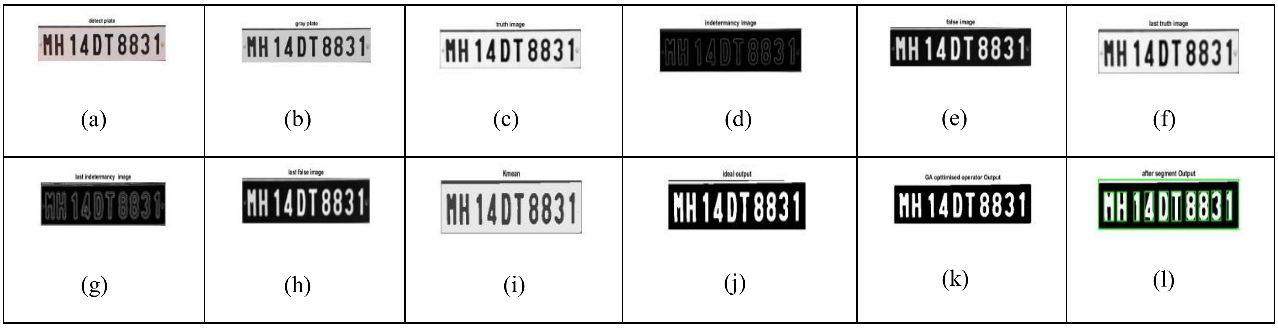


FIGURE 9. (a) Detected plate, (b) Gray plate, (c) Truth image, (d) Indeterminacy image, (e) False image, (f) Last truth image, (g) Last indeterminacy image, (h) Last false image, (i) K-mean image, (j) Ground truth image, (k) Genetic optimization output image, (l) Image after applying (CCLA).

Algorithm 3 Ground Truth Extraction

Input: license plate region image.
Output: ground truth image.
Steps:
start
Convert *Rgb2gray image.*
Binarize *gray scaled image.*
Apply *2nd order adaptive thresholding:*
  T1*: threshold value 1*
  T2*: threshold value 2*
    D: Desired
    T1 < D < T2
Dilate *D*
Fill and Extract *D*
End

applying the following condition:

$$Z_j = \frac{1}{d_j} \sum_{W_i \in C_j} W_i, \tag{22}$$

where in the dataset, W = $\{w_i, \text{i} = 1, 2, \ldots, \text{n}\}$, w_i is a sample in the d-dimensional space and $C = \{C_1, C_2, \ldots, C_q\}$ is the partition which satisfied that $W = U_{i=1}^{q} C_i$. After optimizing α, (T and I) subsets become a new value whereas the effect of the indeterminacy as follows:

$$W(x, y) = \begin{cases} T(x, y), & I(x, y) < \alpha_{optimal} \\ \overline{T}_{\alpha}(x, y), & I(x, y) \geq \alpha_{optimal} \end{cases} \tag{23}$$

Here we apply k-means clustering for the optimized (NS) to the subset (*T*).

D. CONNECTED COMPONENTS LABELING ANALYSIS (CCLA)

Connected components labeling analysis would be identified as a scanning process of image, (pixel-by-pixel) i.e. (from top to bottom, and left to right). The process aims recognize the connected pixel regions and groups into components according to the degree of pixel connectivity, whereas all the pixels in a connected component that share the same pixel intensity values, and are in some way connected with each other [34], [35]. Once all groups have been specified, each pixel is labeled with a gray level or a color according to the component, which would be assigned to each of those pixels before. Fig.8 and Fig.9 illustrate the previously discussed stages. Fig.10 introduces the whole algorithm of letters and numbers segmentation and extraction. Algorithm 4 discusses all these steps briefly.

V. CHARACTER RECOGNITION

Now, characters matching has been initialized by comparing the extracted characters with the standard letters (17 alphabets and 10 numerical) of size 42 × 24 for Egyptian license plate (LPs) [18]. Moreover, another characters matching criteria has been utilized with the standard letters (26 alphabets and 10 numerical) of size 42 × 24 for English (LPs) [36].

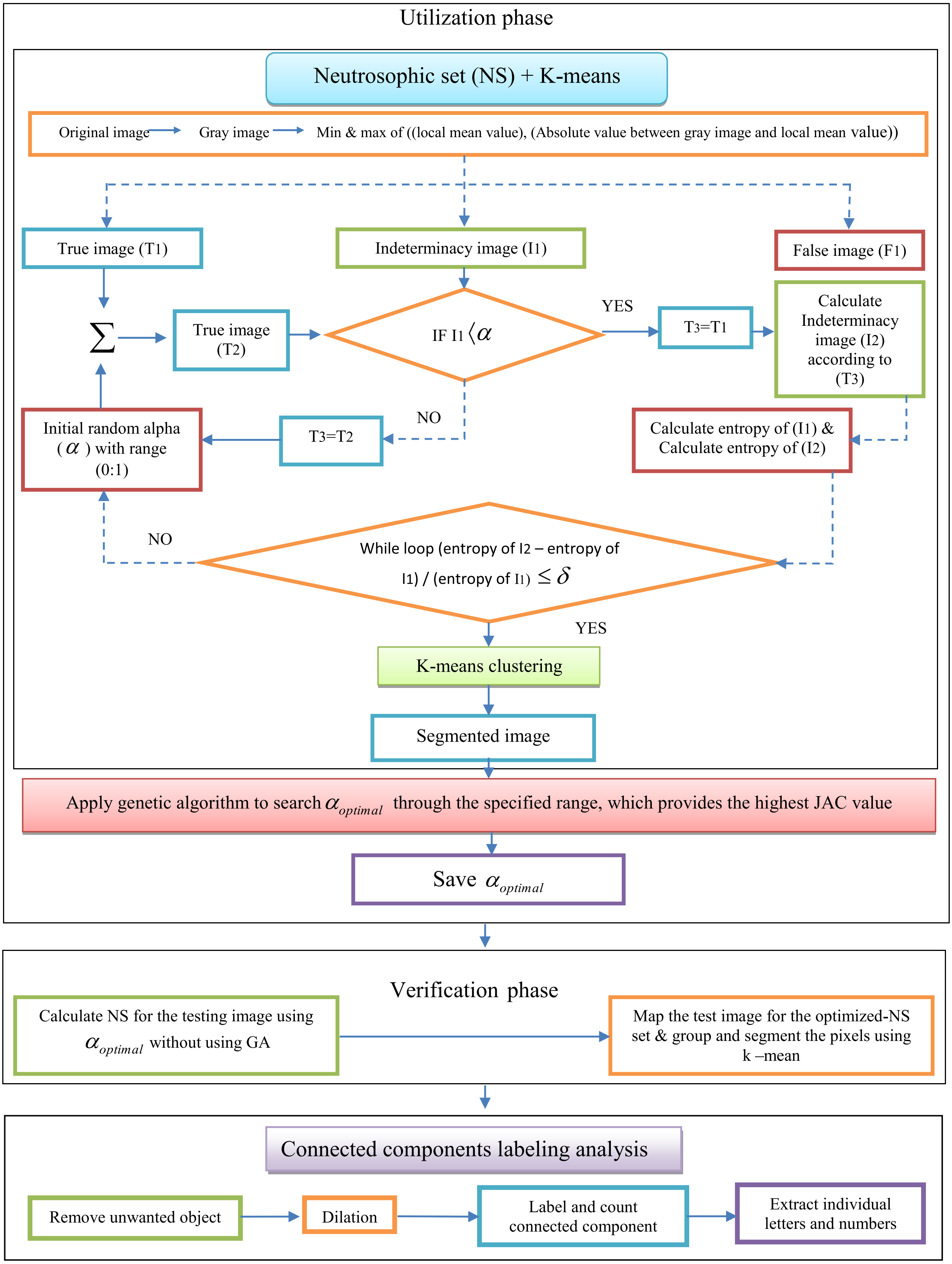


FIGURE 10. Algorithm of letters and numbers segmentation.

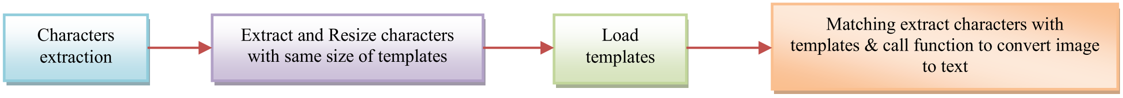


FIGURE 11. Algorithm of character recognition.

Algorithm 4 Segmentation

Input: License plate image.

Output: Letters and numbers of license plate image.

***Method*:** (NS + K-mean + Genetic algorithm + Connected component label analysis).

***Steps*:**

Utilization phase

A: NS for each image.

Read *license plate image and convert image to gray image.*
Calculate *local mean value of the gray image with averaging filter* (3×3) *according to* ***equation (2)*** *&& getting max and min of local mean value.*
Get *absolute value between gray image, and local mean value of gray image according to* ***equation (4)*** *&& getting min, max of absolute value.*
Get *truth (T) according to* ***equation (1)***.
Get *indeterminacy (I) according to* ***equation (3)***.
Get *falsity (F) according to* ***equation (5)***.

B: NS + K mean.

While loop *(abs (Entropy for new indeterminacy –Entropy for old indeterminacy) / Entropy for old indeterminacy)* $\leq \delta$.
Compute *old entropy for indeterminacy according to* ***equation (9)***.
Initialize *random alpha, set range (0 to 1).*
Compute *alpha mean of true subset according to* ***equation (12)***.
Compute *new entropy for indeterminacy according to* ***equation (9), (16)***.
    While loop=True
Apply *K-means segmentation with (K* ***=2****)clusters.*
Segment *last true image which achieve while loop condition with threshold (alpha).*
    Else
Repeat While loop
End

C: Genetic algorithm

Applying *the(GA) to search for* $\alpha_{optimal}$ *through the specified range which achieve the highest jaccard value, which the jaccard is used for measuring similarity between 2 sets, and it is the fitness function according to* ***equation (19), (20)***.

Verification phase

Calculate *(NS) for the testing image using* $\alpha_{optimal}$ *without using (GA).*
Map *the test image on the optimized - (NS) set.*
Group and Segment *the pixels by using k –means according to* ***equation (23)***.

D: Connected component Label analysis

Remove *unwanted object which less than 50 pixels.*
Dilation *for separating the characters from each other.*
Label and count *connected components& measure properties of image regions.*
Calculate *ratio between (major and minor) axis length for each object.*
Calculate *ratio between sum of black, and white pixels of each object.*
Extract *individual letters and numbers from the plates.*

In matching technique, we used the statistical cross correlation method [37].

Since there were two images (known database image and input image) in this system. Cross correlation considered as $F_1(j, k)$ for $1 \leq j \leq J$, and $F_2(j, k)$ for $1 \leq k \leq K$ expresses about two discrete images indicate to the image to be surveyed and the template, respectively. The normalized cross correlation between the images pair is expressed as Eq. (24), as shown at the bottom of the next page. Fig.11 summarizes the main steps for the recognition stage.

VI. EXPERIMENTAL RESULTS AND DISCUSSION

Experiments have been utilized using MAT LAB R2016b, processor corei5, and (4GB RAM). The proposed system has been utilized according to 250 images with size of (5152×3864) pixels for Egyptian (LPs), and 500 images with size of (640×480) pixels for English (LPs). In addition, we have recorded the results according to some image degradations such as dirty plates, non-uniform in illumination plates, noisy images, blurred images, and darkened images. Images have been taken from both directions of vehicles (forward and

TABLE 1. Experimental results.

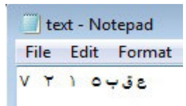
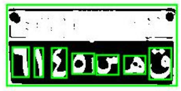
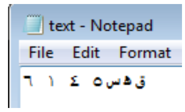
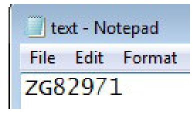
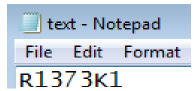
Car image	Detection stage	Segmentation stage	Recognition stage
Egyptian license plates			
			
			
English license plates			
			
			

TABLE 2. Average performance metrics using the (NS + K-means) with $\delta = 0.001$, for Egyptian license plates.

trial no	alpha-optimal	Accuracy (%)	Sensitivity (%)	Specificity (%)	Dice (%)	Jaccard (%)
1	0.1913	44.13	0	100	0	0
2	0.9229	55.87	100	0	71.69	55.87
3	0.2218	44.13	0	100	0	0
4	0.2014	44.13	0	100	0	0
5	0.3835	44.13	0	100	0	0
Average	0.3842	46.478	20	80	14.338	11.174

backward). Egyptian (LPs) images was a parted with distance, (2 up to 3m) from the vehicles. We capture Egyptian (LPs) test images with (NIKON D5200) digital camera with sensor resolution (24 MP CMOS), and they captured English (LPs) test images with (OLYMPUS CA MEDIA C-2040 ZOOM) digital camera with sensor resolution (2 MP CMOS). Images have been collected as a database from many places like parks, camps, and streets, Table 1 illustrate sample of overall system result.

A. QUANTITATIVE EVALUATION

1) CLASSICAL MEASUREMENTS

We perform classic measurements by using four variables: true positive (TP), true negative (TN), false positive (FP), and false negative (FN) [38], [39]. i) **TP**: pixels correctly segmented as the backbone in the ground truth and algorithm that we used. ii) **TN**: pixels not represented as the backbone in the ground truth and by algorithm that we used. iii) **FP**: pixels not represented as the backbone in the ground truth, but are represented as the backbone by algorithm that we used (falsely segmented). iv) **FN**: pixels represented as the backbone in the ground truth, but not represented as the backbone by the algorithm that we used.

(a) **Accuracy**: can be defined as the percentage of correctly classified instances, it can be represented as shown in Eq. (25).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \tag{25}$$

$$R(m, n) = \frac{\sum_j \sum_k F_1(j, k) F_2(j - m + (M + 1)/2, K - n + (N + 1)/2)}{\left[\sum_J \sum_K \left|F_1(j, k)^2\right|\right]^{\frac{1}{2}} \left[\sum_j \sum_k \left| F_2(j - m + (M + 1)/2, K - n + (N + 1)/2) \right|^2\right]^{\frac{1}{2}}} \tag{24}$$

TABLE 3. Average performance metrics using the (NS + K-means) with $\delta = 0.001$, for English license plates.

trial no	alpha-optimal	Accuracy (%)	Sensitivity (%)	Specificity (%)	Dice (%)	Jaccard (%)
1	0.9072	45.28	100	0	62.33	45.28
2	0.0603	54.72	0	100	0	0
3	0.6541	48.41	100	0	65.24	48.41
4	0.2707	54.71	0	100	0	0
5	0.9058	45.29	100	0	62.34	45.29
Average	0.55962	49.682	60	40	37.982	27.796

TABLE 4. Average performance metrics using the (NS + K-means + genetic algorithm) with $\delta = 0.001$, for Egyptian license plates.

trial no	alpha-optimal	Accuracy (%)	Sensitivity (%)	Specificity (%)	Dice (%)	Jaccard (%)
1	0.6001	85.73	83.66	88.36	86.76	76.62
2	0.6051	93.01	91.83	94.50	93.62	88.01
3	0.6008	90.32	89.64	91.17	91.18	83.80
4	0.6027	88.35	87.17	89.83	89.31	80.69
5	0.6053	85.99	84.29	88.15	87.05	77.08
Average	0.6028	88.68	87.318	90.402	89.584	81.24

TABLE 5. Average performance metrics using the (NS + K-means + genetic algorithm) with $\delta = 0.001$, for English license plates.

trial no	alpha-optimal	Accuracy (%)	Sensitivity (%)	Specificity (%)	Dice (%)	Jaccard (%)
1	0.6061	82.55	89.02	77.2	82.21	69.79
2	0.6017	85.98	87.18	84.99	84.92	73.8
3	0.6077	86.76	86.21	87.22	85.51	74.68
4	0.6008	86.16	86.99	85.47	85.06	74
5	0.6001	84.45	87.71	81.76	83.63	71.81
Average	0.6033	85.18	87.42	83.33	84.266	72.83

TABLE 6. Average performance metrics using the (NS + K-means) with $\delta = 0.05$, for Egyptian license plates.

trial no	alpha-optimal	Accuracy (%)	Sensitivity (%)	Specificity (%)	Dice (%)	Jaccard (%)
1	0.4222	76.82	72.06	82.57	77.28	62.97
2	0.5279	85.63	80.67	91.62	86	75.44
3	0.4167	81.46	74.92	90.57	82.47	70.18
4	0.5812	85.26	80.3	92.17	86.38	76.03
5	0.4381	84.11	83.31	91.69	87.61	77.95
Average	0.4772	83.25	78.25	89.72	83.94	72.51

(b) **Sensitivity**: determine the positive pixels in the ground truth, which specified as positive by the algorithm being estimated. Sensitivity can be determined by Eq. (26).

$$Sensitivity = \frac{TP}{TP + FN}, \tag{26}$$

(c) **Specificity**: determine the negative pixels in the ground truth, also specified as negative by the algorithm being estimated. This metric is determined by Eq. (27).

$$Specificity = \frac{TN}{TN + FP}, \tag{27}$$

TABLE 7. Average performance metrics using the (NS + K-means) with $\delta = 0.05$, for English license plates.

trial no	alpha-optimal	Accuracy (%)	Sensitivity (%)	Specificity (%)	Dice (%)	Jaccard (%)
1	0.4039	78.16	59.72	93.42	71.24	55.32
2	0.5004	78.65	60.34	93.8	71.9	56.13
3	0.4152	81.24	64.43	95.15	75.67	60.87
4	0.5049	75.05	58.29	88.91	67.9	51.4
5	0.4056	83.01	69.82	93.91	78.82	65.04
Average	0.446	79.22	62.52	93.04	73.106	57.752

TABLE 8. Average performance metrics using the (NS + K-means + genetic algorithm) with $\delta = 0.05$, for Egyptian license plates.

trial no	alpha-optimal	Accuracy (%)	Sensitivity (%)	Specificity (%)	Dice (%)	Jaccard (%)
1	0.6019	96.3	93.92	99.17	96.52	93.28
2	0.6036	96.36	94.3	98.86	96.6	93.42
3	0.6017	96.3	93.93	99.17	96.53	93.29
4	0.6044	96.62	94.70	98.81	96.46	93.16
5	0.6047	96.50	93.93	99.18	96.53	93.3
Average	0.6033	96.42	94.03	99.04	96.53	93.29

TABLE 9. Average performance metrics using the (NS + K-means + genetic algorithm) with $\delta = 0.05$, for English license plates.

trial no	alpha-optimal	Accuracy (%)	Sensitivity (%)	Specificity (%)	Dice (%)	Jaccard (%)
1	0.6051	91.91	84.49	98.05	90.44	82.55
2	0.6013	92.10	85.09	97.95	90.73	83.03
3	0.6026	92.54	87.09	97.41	91.57	84.45
4	0.6006	92.60	86.13	97.8	91.24	83.9
5	0.6035	91.85	84.33	98.07	90.35	82.4
Average	0.6026	92.2	85.43	97.86	90.866	83.266

2) SIMILARITY MATRICES

(a) **Dice coefficient (DC):** determines the range of the spatial overlap between two binary images. (DC) values range between 0 i.e. (no overlap) and 1 i.e. (Ideal compact 100%), (DC) values are calculated using Eq. (28).

$$DC(f, q) = \frac{2\left|A_{rf} \cap A_{rq}\right|}{\left|A_{rf}\right| + \left|A_{rq}\right|}, \tag{28}$$

(b) **Jaccard coefficient (JAC):** used for measuring similarity between two binary images. It can be represented as shown in Eq. (29).

$$JAC(f, q) = \frac{\left|A_{rf} \cap A_{rq}\right|}{\left|A_{rf} \cup A_{rq}\right|},$$

Or

$$JAC(f, q) = \frac{DC}{2 - DC}, \tag{29}$$

Case Study (1): Comparative study between (NS + k − means) and (NS + k-means + Genetic algorithm) for Egyptian and English license plates, by using the valuation metrics we compare performance with $\delta = 0.001$ and $\delta = 0.05$ as a threshold of (NS). Results are illustrated in Table 2, Table 3, Table 4, and Table 5, Table 6, Table 7, Table 8, and Table 9.

Note that, database of Egyptian license plates has captured with (NIKON D5200) digital camera with size of (5152 × 3864) pixels, and resolution (24 mega pixels).

However, database of English license plates was captured by using (OLYMPUS CAMEDIA C-2040ZOOM) digital camera with size of (640×480) pixels, and resolution (2 mega pixels).

TABLE 10. **Best function value with each generation of the training set for Egyptian license plate.**

Generation	f-count	Best f(x)	Mean f(x)
1	100	0.6054	**0.6603**
2	150	0.6034	**0.6561**
3	200	0.6022	**0.6611**
4	250	0.6013	**0.6594**
5	300	0.6016	**0.6562**

TABLE 11. **Best function value with each generation of the training set for English license plates.**

Generation	f-count	Best f(x)	Mean f(x)
1	100	0.6049	**0.6603**
2	150	0.6009	**0.6505**
3	200	0.6042	**0.6546**
4	250	0.6011	**0.6476**
5	300	0.6008	**0.6462**

The measured results are compared with the results of the appropriate ground truth images, which we make it. Calculations have been compromised over 250 Egyptian LP images with respect to its colors and complex background, and over 500 English (LP) images taken under various lighting conditions (cloudy, sunny, rainy), It is obvious that (NS + k-means + Genetic algorithm) at $\delta = 0.05$, achieve high rate of accuracy (about 96.4%) and high Jaccard (about 93.29%) for Egyptian license plates, and achieve accuracy (about 92.2%) and Jaccard (about 83.27%) for English license plates. However, when we apply our system in English license plates, which captured with high-resolution digital camera, we get high accuracy and high Jaccard. The average processing time for the computations of the proposed system in both databases has targeted about 0.99648525 Seconds. Experimental results have been utilized using MATLAB R2016b, processor corei5, and (4GB RAM).

The (GA) iteration results through generations are illustrated in Table 10 for Egyptian (LPs),and Table 11 for English (LPs), the generation number represented by the first column 'Generation',the accumulative number of fitness function evaluations represented by the second column 'f -count', the best fitness function value through generation represented by the third column 'Best F(x)', and the last column 'Mean f(x)' represents (best mean). The (GA) depends on the maximum (JAC) according to fivefold cross-validation.

The iteration operation of the GA in Fig.12, Fig.13 demonstrates the best and mean fitness value of the threshold of characters segmentation for the license plates.

Case study (2):

Comparative study between (traditional methods) and (NS + k-means + Genetic algorithm at $\delta = 0.05$), at critical cases [40] like:

1) **Adding salt and paper noise**: also, called binary noise, shot noise, and impulse noise. By sudden disturbances and sharp in the image signal, this degradation can be caused. It is randomly dispersed black or white or both pixels over the image.
2) **Adding Gaussian noise**: It is the best form of white noise; it is resulted by random fluctuations in the signal.
3) **Adding speckle noise**: also called a multiplicative noise and it is a main problem in some radar applications.
4) **Adding Periodic noise**: this type of degradation has a large effect, and it is difficult to remove or reduce its effect using traditional cleaning methods.
5) **Darken image**: decrease intensity of each pixel in image.
6) **Blurring image**: this is the distortion in the image because of camera motion or out of focus.

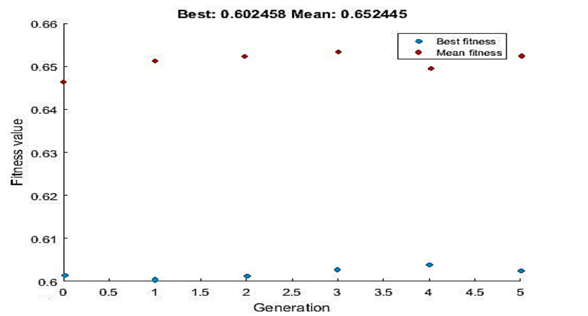


FIGURE 12. **GA iteration results over generations for Egyptian license plates.**

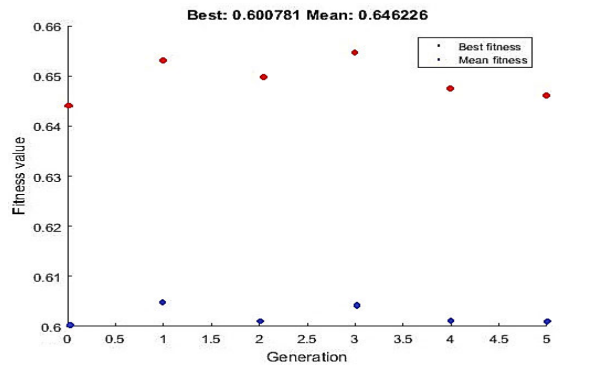


FIGURE 13. **GA iteration results over generations for English license plates.**

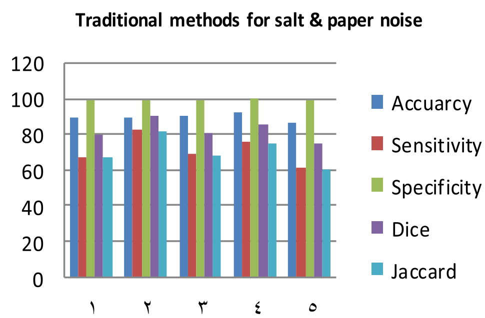


FIGURE 14. **Traditional methods for salt and paper noise.**

As we mentioned before most of researchers have presented some traditional techniques for license plates (LPs)

TABLE 12. Comparative study between (Traditional methods) and (NS + k-means + Genetic algorithm), when adding salt and paper noise.

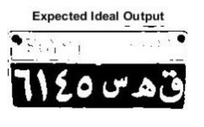
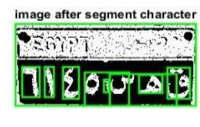
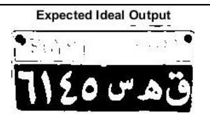
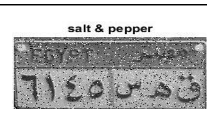
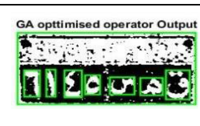
Salt and paper noise					
Type of image	**Original image**	**Gray image**	**Ground truth image**	**Image with noise**	**Segmented image**
Egyptian license plates					
Traditional methods					
(NS + k-means + Genetic algorithm)					
English license plates					
Traditional methods					
(NS + k-means + Genetic algorithm)					

TABLE 13. Comparative study between (Traditional methods) and (NS + k-means + Genetic algorithm), when adding white gaussian noise.

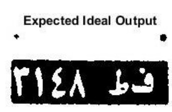
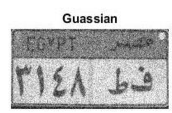
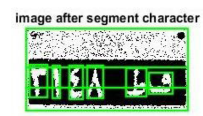
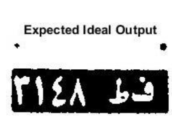
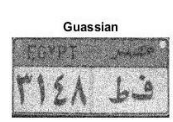
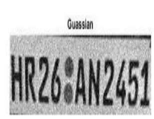
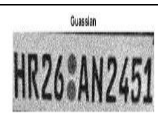
Gaussian noise					
Type of image	Original image	Gray image	Ground truth image	Image with noise	Segmented image
Egyptian license plates					
Traditional methods					
(NS + k-means + Genetic algorithm)					
English license plates					
Traditional methods					
(NS + k-means + Genetic algorithm)					

TABLE 14. Comparative study between (Traditional methods) and (NS + k-means + Genetic algorithm), when adding speckle noise.

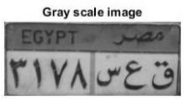
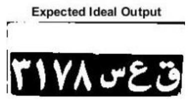
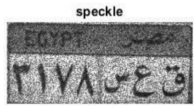
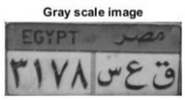
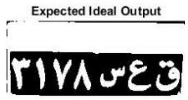
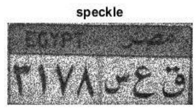
Speckle noise					
Type of image	Original image	Gray image MAGE	Ground truth image	Image with noise	Segmented image
Egyptian license plates					
Traditional methods					
(NS + k-means + Genetic algorithm)					
English license plates					
Traditional methods					
(NS + k-means + Genetic algorithm)					

TABLE 15. Comparative study between (traditional methods) and (NS + k-means + genetic algorithm), when adding periodic noise.

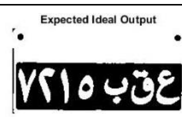
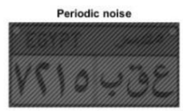
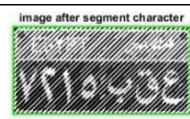
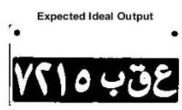
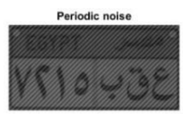
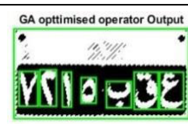
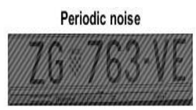
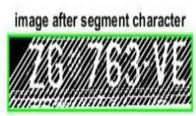
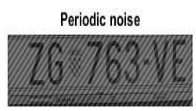
Periodic noise					
Type of image	Original image	Gray image	Ground truth image	Image with noise	Segmented image
Egyptian license plates					
Traditional methods					
(NS + k-means + Genetic algorithm)					
English license plates					
Traditional methods					
(NS + k-means + Genetic algorithm)					

TABLE 16. Comparative study between (Traditional methods) and (NS + k-means + Genetic algorithm), when reduce brightness of image.

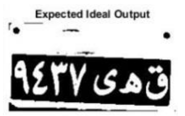
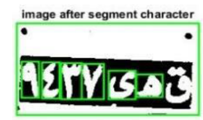
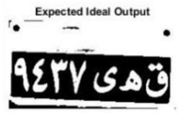
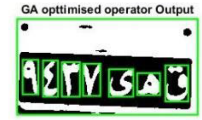
Darken image					
Type of image	Original image	Gray image	Ground truth image	Image with noise	Segmented image
Egyptian license plates					
Traditional methods					
(NS + k-means + Genetic algorithm)					
English license plates					
Traditional methods					
(NS + k-means + Genetic algorithm)					

TABLE 17. Comparative study between (traditional methods) and (NS + k-means + genetic algorithm), when blurring image.

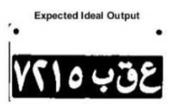
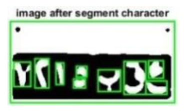
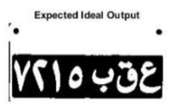
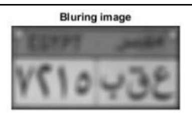
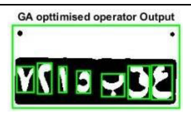
Blur image					
Type of image	Original image	Gray image	Ground truth image	Image with noise	Segmented image
Egyptian license plates					
Traditional methods					
(NS + k-means + Genetic algorithm)					
English license plates					
Traditional methods					
(NS + k-means + Genetic algorithm)					

TABLE 18. Challenges in system.

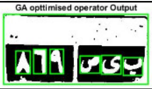
distortions image	Image after applying our proposed method	Comments
Egyptian license plates		
		Invisible letters
		Discontinuous letters
		Darkening
English license plates		
		Discontinues letters
		Illumination variation

TABLE 19. Failure in system.

Degraded accuracy		
Comments	Heavily shadow	Letters not clear

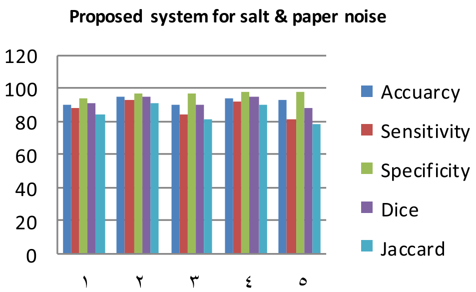


FIGURE 15. Proposed system for salt and paper noise.

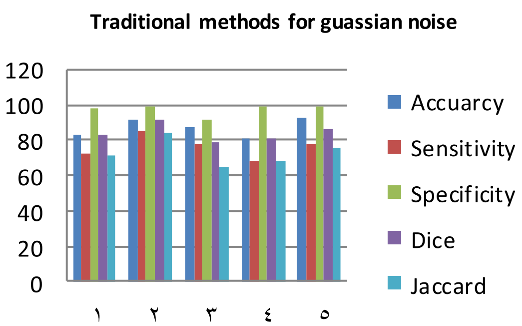


FIGURE 16. Traditional methods for Gaussian noise.

recognition [41], [4], such as converting gray scale image into binary image by using single or double thresholding techniques [42], applying filter mask such as (sobel, canny, prewitt) to find the edges. For most pattern recognition systems, some researchers have used morphological operations such as erosion and dilation, which are important processes

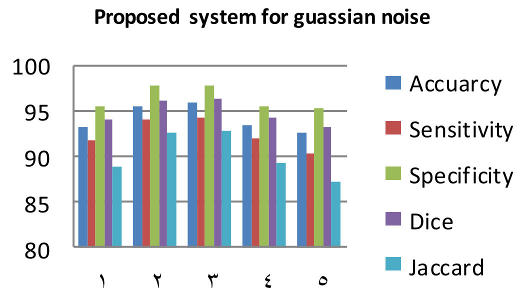


FIGURE 17. Proposed system for Gaussian noise.

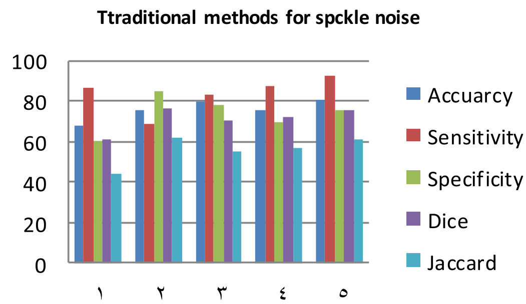


FIGURE 18. Traditional methods for speckle noise.

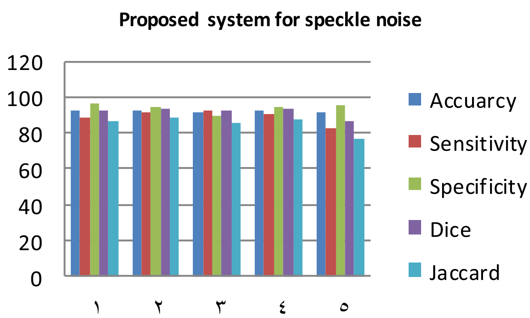


FIGURE 19. Proposed system for speckle noise.

that would be needed to eliminate noisy objects, and finally applying connected components labeling analysis (CCLA) that scans test images and groups the appropriate pixels in labeled components according to pixel connectivity.

We have illustrated a comparative study between (traditional methods) and (proposed system (NS + k-means + Genetic algorithm)) at $\delta = 0.05$, and its results related with the corresponding ground truth images.

Table (12), we have added salt & paper noise with (variance= 0.09), this affects approximately about 9% of pixels. We have noticed that the traditional method introduces obvious overlap between letters and numbers in Egyptian (LPs), and little overlap in English (LPs). However, the introduced methodology has been succeeding in detecting each letter and number.

Table (13), we have added white Gaussian noise with (mean= 0.09), and (variance = 0.01), we have noticed that traditional method introduces obvious overlap between letters and numbers and remove some pixels like dot of first letter in Egyptian (LPs), and have an error for letters detect in

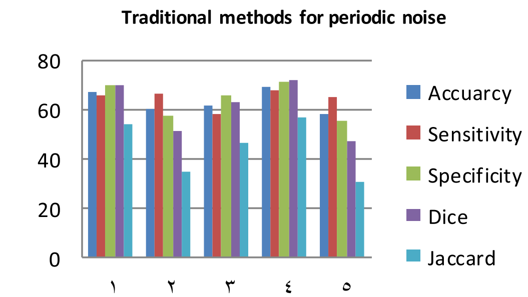


FIGURE 20. **Traditional methods for periodic noise.**

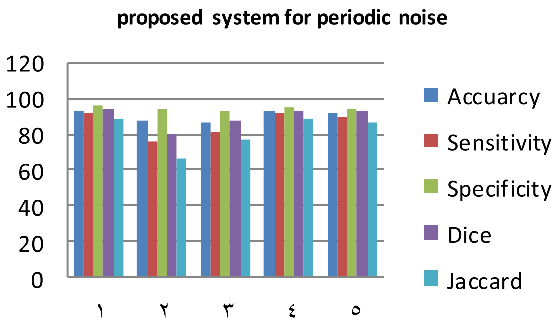


FIGURE 21. **Proposed system for periodic noise.**

English (LPs). However, the introduced methodology has been succeeding in detecting each letter and number.

Table (14), we have added speckle noise (multiplicative noise) with (variance = 0.09). We have noticed that traditional method introduces detection for some letters and overlap between other letters and numbers for Egyptian (LPs) and English (LPs). However, the introduced methodology has been succeeding in detecting each letter and number.

Table 15, we have added periodic noise, periodic function (sine function), we have noticed that traditional method could not detect any letter or number for Egyptian (LPs) and English (LPs). However, the introduced methodology has been succeeding in detecting each letter and number.

Table (16), illustrated when we reduce brightness of image (darken image), we have noticed that traditional method could not detect all of letters and numbers for Egyptian (LPs) and English (LPs). However, the introduced methodology has been succeeding in detecting each letter and number.

Table (17), illustrated when we blur image, we have noticed that the traditional method introduces obvious overlap between letters and numbers for Egyptian (LPs), and could not detect any letter for English (LPs). However, the introduced methodology has been succeeding in detecting each letter and number.

We have calculated the main performance indices over the 250 Egyptian license plate images for both traditional techniques and proposed system of interest. Similarly, the same steps can be applied over 500 English license plate images. The following case studies have been utilized and noticed:

In case of adding salt and paper noise for images, Fig.14 illustrated that average (accuracy, sensitivity, specificity,

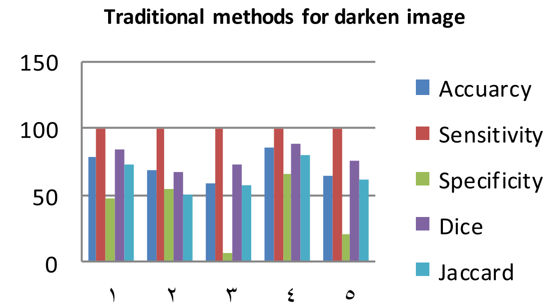


FIGURE 22. **Traditional methods for darken image.**

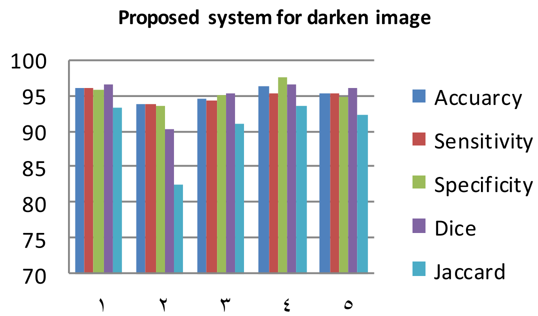


FIGURE 23. **Proposed system for darken image.**

dice, jaccard) was that (89.86%, 71.12%, 99.48%, 82.43%, 70.43%), respectively for traditional method.

Fig.15 illustrated that, average (accuracy, sensitivity, specificity, dice, jaccard) was that (92.58%, 87.80%, 96.58%, 91.87%, 84.99%), respectively for proposed system.

In case of adding Gaussian noise for images, Fig.16 illustrated that, average (accuracy, sensitivity, specificity, dice, Jaccard) was that (87.30%, 76.15%, 97.35%, 84.03%, 72.72%), respectively for traditional method.

Fig.17 illustrated that, average (accuracy, sensitivity, specificity, dice, jaccard) was that (94.18%, 92.54%, 96.43%, 94.84%, 90.21%), respectively for proposed system.

In case of adding speckle noise for images, Fig.18 illustrated that, average (accuracy, sensitivity, specificity, dice, jaccard) was that (76%, 83.67%, 73.72%, 71.20%, 55.56%), respectively for traditional method.

Fig.19 illustrated that, average (accuracy, sensitivity, specificity, dice, jaccard) was that (92.24%, 89.34%, 94.60%, 91.85%, 85.02%), respectively for proposed system.

In case of adding periodic noise for images, Fig.20 illustrates that, average (accuracy, sensitivity, specificity, dice, jaccard) was that (63.35%, 64.73%, 63.93%, 60.77%, 44.40%), respectively for traditional method.

Fig.21 illustrated that, average (accuracy, sensitivity, specificity, dice, jaccard) was that (90.43%, 86.05%, 94.20%, 89.38%, 81.4%), respectively for proposed system.

In case of reducing the brightness of images, Fig.22 illustrated that, average (accuracy, sensitivity, specificity, dice, jaccard) was that (71.05%, 99.83%, 38.58%, 77.7%, 64.21%), respectively for traditional method.

TABLE 20. Proposed method.

	Goal	methodology	success accuracy	Challenges
Our proposed methodology	The present paper proposes a new methodology for license plate (LP) recognition	We have performed some image processing techniques such as edge detection and morphological operations in order to utilize the (LP) localization. In addition, we have extracted the most salient features by implementing a new methodology using (GA) for optimizing the (NS) operations. The use of (NS) decreases the indeterminacy on the (LP) images. Moreover, k-means clustering algorithm has been applied to segment the (LP) characters. Finally, we have applied connected components labeling analysis (CCLA) algorithm for identifying the connected pixel regions and grouping the appropriate pixels into components to extract each character effectively.	For a high resolution Egyptian (LP), the proposed system achieves about 96.67% accuracy of correct recognition, (ii) for a low resolution-corrupted English (LP); the proposed system achieves about 94.27% accuracy.	The proposed system suffers from some detection and recognition problems in case of heavily image shadow and damaged plates.

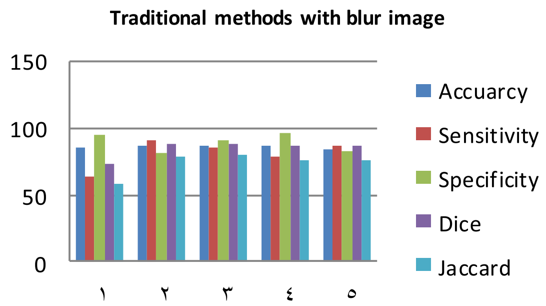


FIGURE 24. Traditional methods for blurring image.

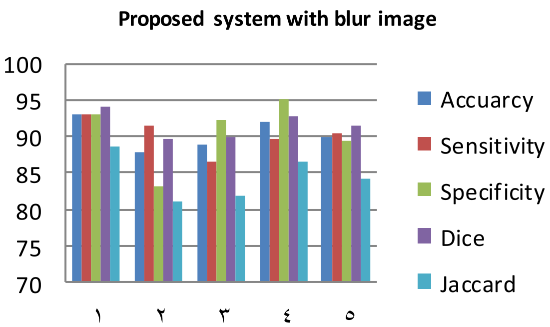


FIGURE 25. Proposed system for blurring image.

Fig.23 illustrated that, average (accuracy, sensitivity, specificity, dice, jaccard) was that (95.18%, 95.04%, 95.32%, 94.99%, 90.55%), respectively for proposed system.

In case of blurring images, Fig.24 illustrated that, average (accuracy, sensitivity, specificity, dice, jaccard) was that (86.19%, 80.81%, 89.45%, 84.74%, 73.89%), respectively for traditional method.

Fig.25 illustrated that, average (accuracy, sensitivity, specificity, dice, jaccard) was that (90.40%, 90.27%, 90.65%, 91.59%, 84.53%), respectively for proposed system.

The proposed system has targetted a high degree of recognition accuracy with the presence of some external image corruptions as shown in Table 18.

On the other hand, the proposed system suffers from some detection and recognition problems in case of heavily image shadow and damaged plates as shown in Table 19.

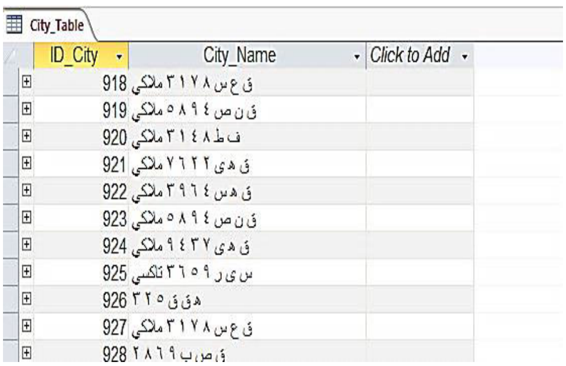


FIGURE 26. Microsoft access database.

VII. DATABASE COMMUNICATION

We build our database by using Microsoft access database connected with Mat lab 2016b as shown in Fig.26.

The graphical user interface (GUI) for character recognition with MAT LAB 2016b has been implemented and designed in order to build the appropriate (LP) recognition system as shown in Fig.27.

The following tables (20 and 21) illustrate a concluded comparison study between our proposed system and some related work of interest. We have noticed that the proposed methodology has the ability for enhancing and recognizing both (Arabic and English) (high resolution-low resolution) license plate characters and numbers successfully with a very high recognition accuracy and low computational time in comparison with the related work.

In order to evaluate the accuracy of the proposed method for different LP variations on popular and publicly available benchmark datasets [43], we have used Media Lab benchmark LP data set [44] and AOLP benchmark LP data sets [45]. We have added some important and critical case studies according to Media Lab benchmark LP data set as shown in Table 22, and also AOLP benchmark LP data sets as shown in Table 23. The two tables introduce the detection accuracy with the presence of critical LP image degradations. In addition, the average time for the computations of the

TABLE 21. Related work.

References No.	Goal	methodology	success accuracy	Challenges
P. Prabhakar et al. [5]	This paper presented a promising method for extracting license plate (LP) location and characters.	Algorithm was depending on converting vehicle image into gray-scale image and Hough lines are founded by using Hough transform .Then they have applied some traditional image processing algorithms to calculate the connected component in order to extracting characters individually.	Their proposed methodology has achieved an accepted accuracy percentage by optimizing some parameters to achieve an acceptable recognition rate than the classical methods (80-90) %.	Don't deal with complex cases, minor rotation, and skew.
C.H.Lin et al. [6]	This paper presented an effective license plate recognition system.	Detects vehicles and then recovers license plates from vehicles for reducing false positives on plate detection .They have improved the character recognition rate of blurred and mysterious images using convolution neural networks.	96.5%.	Complicated with high computationally time.
A. C. Roy et al. [7]	This paper proposed a solution for Bangla license plate recognition.	They have localized the license plate (LP) position of the vehicle depending on commercial license plates with unique color (green) for their country standard. They have accomplished the isolation process by using horizontal projection with threshold value. They have accomplished character segmentation criteria by using vertical projection with threshold. In addition, for recognizing characters they have used template-matching algorithm.	(93.3%) over a 180 sunny day, cloudy day and at night still images from roads.	Deals with unique color only (green).
I. Ullah et al. [8]	This paper Concentrated on detection of license plate.	Depend on mathematical morphology and features like (height, width, angle, and ratio) of license plate. The proposed system works for some challenging license plates which vary in shapes and size. They are used in their system images which are complex and vary in background, size, distance, and camera angle, etc.	78%.	Complicated with high computationally time.
S. Omran et al. [9]	This paper proposed an automatic license plate recognition system for Iraqi.	They have used optical character recognition (OCR) with templates matching, and correlation approach for plate recognition.	86.6% over a 40 test images.	Accuracy is very low.
B. Tiwari et al. [10]	This paper introduces genetic algorithm (GA) for detecting the locations of the license plate characters.	This technique used to distinct the key characteristic of license plates according to symbols with robust light-on-dark edges. This technique used for overcoming the license plate (LP) detection problem depends only on the geometrical layout of the (LP) characters. The proposed technique has high impunity to changes in illumination.	(80-90%).	Very complicated due to its dependency on geometrical layout.
K.M.Babuand et al.[11]	This paper deal with four steps for license plate recognition.	Firstly, in pre-processing images are captured through the digital camera, adjusted brightness of image; remove noise, then converting to gray image. Secondly finding the edges in the image for extracting (LP) location. Thirdly segmented characters in (LP) by using Bounding box method. Finally, apply template matching for recognizing each character in (LP) image.	91.11%.	They can't deal with Some difficulties as follows (blurring image, broken (LP), and similarities between characters).

TABLE 21. ***(Continued)*** **Related work.**

N. Rana et al. [12]	The paper discusses various techniques for license plate localization and compare between their technique and others according to their performance.	They have used (Signature analysis, Connected component analysis, and Euclidean distance transform).	92%.	Failure due to the improper illumination and blurring.
Vidhya. N et al. [13]	This paper studies on different types of approaches and its challenges involved in detection, localization and recognition of license plate numbers.	This paper presents a survey of license plate recognition techniques by categorizing them based on features used in each stage and found that the highest accuracy of them was that, Edge based detection, Sliding concentric window.	98.4 %.	Less immune to noise and does not work with edges which are ill defined.

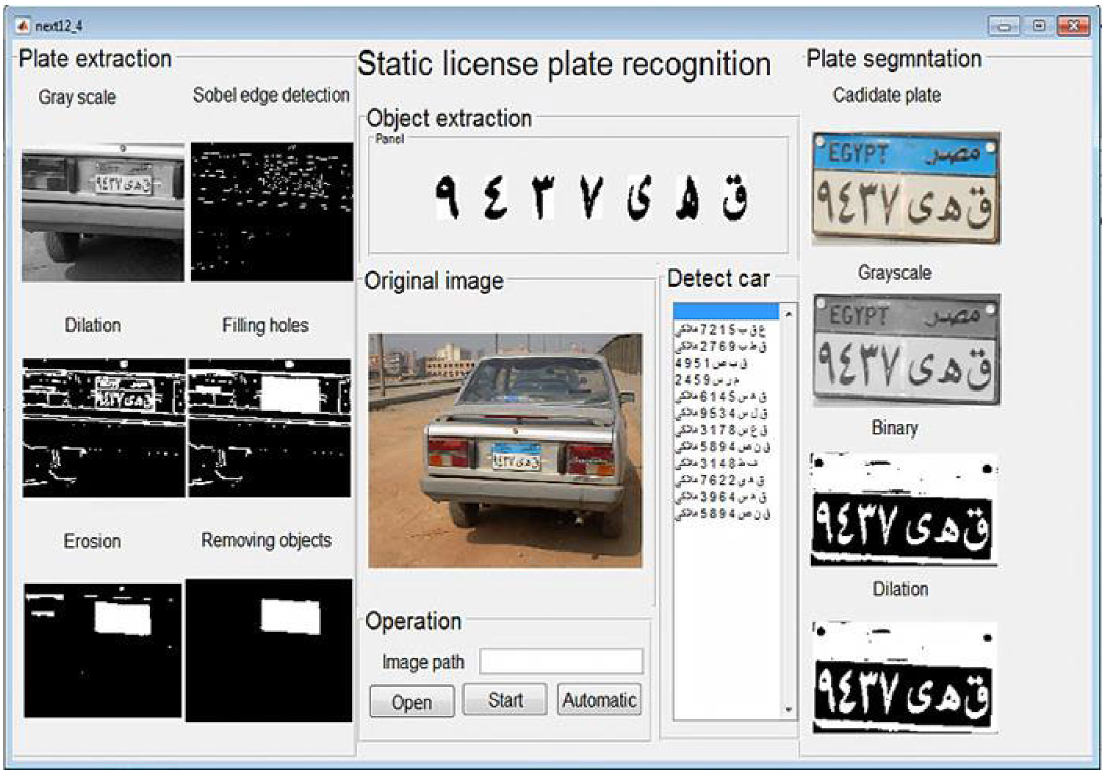


FIGURE 27. **The graphical user interface (GUI) for characters' recognition with MATLAB 2016b.**

proposed LP recognition method in both benchmarks was about 1.688535 seconds. All experiments have been utilized using MATLAB R2016b, processor corei5, and (4GB RAM).

The previously discussed Tables (22 and 23) have evaluated our proposed method for different LP variations on popular and publicly available benchmark datasets such as

TABLE 22. Media Lab benchmark LP data set.

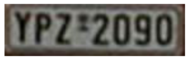
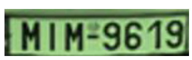
LP variations	*Original image*	*License plate image*	*Net result with proposed method*	*Accuracy*
1- Image with multiple LPs (two cars)		 	GA opttimised operator Output  GA opttimised operator Output 	95.04%
2-image with multiple vehicles with LPs and each LP is in different angle		  	GA opttimised operator Output  GA opttimised operator Output  GA opttimised operator Output 	97.07%
3-Image with blur			GA opttimised operator Output 	96.11%
4-Image with an extreme pan			GA opttimised operator Output 	90.42%
5-Image taken at night			GA opttimised operator Output 	97.18%

TABLE 22. ***(Continued)*** **Media Lab benchmark LP data set.**

6-Image with rotation				96.98%
7-Image with dirt in the LP				94.84%
8-Image with different tilt				90.72%
9-Image with distorted LP				91.11%
10-Image with a close view of small characters				97.42%

TABLE 22. ***(Continued)*** **Media Lab benchmark LP data set.**

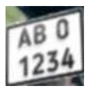
11-Image with one LP front viewed and another side viewed		 	GA opttimised operator Output  GA opttimised operator Output 	96.74%
12-Image with a rotation (an image containing motorcycle with right diagonally rotated LP)			GA opttimised operator Output 	95.80%
13- Image with a rotation (an image containing motorcycle)		 	GA opttimised operator Output  GA opttimised operator Output 	95.04%
14- Images with dirt and shadow			GA opttimised operator Output 	90.01%
			GA opttimised operator Output 	96.89%
			GA opttimised operator Output 	94.97%

TABLE 23. Aolp benchmark lp data sets.

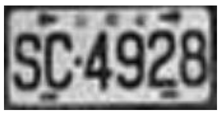
LP variations	*Original image*	*License plate image*	*Net result with proposed method*	*Accuracy*
1-Image with blur			GA opttimised operator Output 	93.52%
2-Image with an extreme pan			GA opttimised operator Output 	95.07%
3-Image taken at night			GA opttimised operator Output 	97.52%
4-Image with a rotation	 	 	GA opttimised operator Output  GA opttimised operator Output 	95.78%

TABLE 23. ***(Continued)*** **Aolp benchmark lp data sets.**

5-Image with LP fixed in a higher level			GA opttimised operator Output 	96.41%

TABLE 24. **Results of the recognition quality.**

Data set	NO. of images	Plate location	Successful Segmentation	Successful Recognition	Average Success Rate (%)	The average computational time (Seconds)	Average Mean square error (MSE)	Average Peak signal to noise ratio (PSNR) %
Proposed system for our captured Egyptian (LP) data set with high resolution	250 (100%)	248 (99.2%)	241 (96.4%)	236 (94.4%)	(96.67%)	1.128535	0.0191	17.1989 %
Proposed system for English (LPs) with low resolution	500 (100%)	495 (99%)	461 (92.2%)	458 (91.6%)	(94.27%)	0.8644355	0.0438	13.5881 %
Proposed method on Media Lab benchmark LP data set with different resolution and challenges	716 (100%)	706 (98.6%)	696 (97.21%)	685 (95.67 %)	(97.16%)	1.523185	0.0248	16.0496 %
Proposed method on AOLP benchmark LP data sets with different resolution and challenges	2049 (100%)	2010 (98.1%)	1983 (96.78%)	1967 (95.99%)	(96.96%)	1.853885	0.0282	15.4922 %

"Media Lab benchmark LP data set" and "AOLP benchmark LP data sets. We have noticed that the proposed methodology has the ability for enhancing and recognizing license plates in different variations. License plate characters and numbers have been successfully utilized with high recognition accuracy and low computational time. However, Images with heavily shadowing have been suffered from some sort of accuracy degradation (about 90.01%).

In addition, the end-to-end recognition quality, average computational time, mean square error (MSE), and peak signal to noise ratio (PSNR)) have been briefly utilized and discussed in Table 24.

PSNR has been used as a quality measurement metric for measuring the quality between original and final image. We have measured both the MSE and PSNR [46]–[49] according to Eq. (30, 31)

$$MSE = \sum_{i=1}^{M} \sum_{j=1}^{N} \left| x_{ij} - y_{ij} \right|^2, \tag{30}$$

$$PSNR = 10 * \log_{10} \left[\frac{\max^2}{MSE} \right], \tag{31}$$

where max is a maximum intensity value in an image, while M and N are height and width respectively of an image. x_{ij} is the original image and y_{ij} is final image.

Table 24 illustrates that both values of the PSNR and the MSE are good enough compared with the newly deep learning recognition techniques [50]–[54].

VIII. CONCLUSION

This paper proposes a new methodology for enhancing the recognition accuracy of license plates (Arabic-Egypt) and English. We have introduced character segmentation and extraction with (ONKM) system according to genetic algorithm. Connected components labeling analysis has been applied to guarantee a successful template matching.

The proposed system offers a successful detection with an accurate recognition in both Arabic and English license plates. A complete comparison study has been introduced between the proposed system and the traditional techniques according to standard performance indices. The proposed methodology offers a high rate of (LP) recognition accuracy in the presence of some popular image degradations. The extension of our work aims to implement the neutrosophic set according to more optimization techniques such as particle swarm, ant colony, chicken swarm, and fuzzy techniques. In addition, more image disruption and variation would be included in order to have a wide decision making criteria for the best optimizer.

COMPLIANCE WITH ETHICAL STANDARDS

Conflict of Interest: The authors declare that there is no conflict of interest regarding the manuscript.

REFERENCES

[1] H. Hu, Z. Zhang, and Y. Bai, "Car license plate location based on mathematical morphology," in *Recent Advances in Computer Science and Information Engineering*, vol. 128. Berlin, Germany: Springer, Jan. 2012, pp. 415–420.

[2] S. Du, M. Ibrahim, M. Shehata, and W. Badawy, "Automatic license plate recognition (ALPR): A state-of-the-art review," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 23, no. 2, pp. 311–325, Feb. 2013.

[3] G. L. Corneto, F. A. da Silva, D. R. Pereira, L. L. de Almeida, A. O. Artero, J. P. Papa, V. H. C. de Albuquerque, H. M. Sapia, "A new method for automatic vehicle license plate detection," *IEEE Latin Amer. Trans.*, vol. 15, no. 1, pp. 75–80, Jan. 2017.

[4] A. Conci, J. Carvalho, and T. Rauber, "A complete system for vehicle plate localization, segmentation and recognition in real life scene.," *IEEE Latin Amer. Trans.*, vol. 7, no. 5, pp. 497–506, Sep. 2009.

[5] P. Prabhakar, P. Anupama, and S. R. Resmi, "Automatic vehicle number plate detection and recognition," in *Proc. Int. Conf. Control, Instrum., Commun. Comput. Technol. (ICCICCT)*, Jul. 2014, pp. 185–190.

[6] C.-H. Lin, Y.-S. Lin, and W.-C. Liu, "An efficient license plate recognition system using convolution neural networks," in *Proc. IEEE Int. Conf. Appl. Syst. Invention (ICASI)*, Apr. 2018, pp. 224–227.

[7] A. C. Roy, M. K. Hossen, and D. Nag, "License plate detection and character recognition system for commercial vehicles based on morphological approach and template matching," in *Proc. 3rd Int. Conf. Electr. Eng. Inf. Commun. Technol. (ICEEICT)*, Sep. 2016, pp. 1–6.

[8] I. Ullah and H. J. Lee, "An approach of locating Korean vehicle license plate based on mathematical morphology and geometrical features," in *Proc. Int. Conf. Comput. Sci. Comput. Intell. (CSCI)*, Dec. 2016, pp. 836–840.

[9] S. S. Omran and J. A. Jarallah, "Iraqi car license plate recognition using OCR," in *Proc. Annu. Conf. New Trends Inf. Commun. Technol. Appl. (NTICT)*, Mar. 2017, pp. 298–303.

[10] B. Tiwari and P. Tiwari, "A result analysis of localization of license plate number using dynamic image processing techniques and genetic algorithms," *Int. Adv. Res. J. Sci. Eng. Technol.*, vol. 4, no. 1, pp. 1–4, Jan. 2017.

[11] K. M. Babu and M. V. Raghunadh, "Vehicle number plate detection and recognition using bounding box method," in *Proc. Int. Conf. Adv. Commun. Control Comput. Technol. (ICACCCT)*, May 2016, pp. 106–110.

[12] N. Rana and P. K. Dahiya, "Localization techniques in ANPR systems: A-state-of-art," *Int. J. Adv. Res. Comput. Sci. Softw. Eng.*, vol. 7, no. 5, pp. 682–686, May 2017.

[13] N. Vidhya and S. G. Sundari, "A survey on localization and recognition of license plate number," *Int. J. Advance Comput. Eng. Netw.*, vol. 3, no. 2, pp. 49–52, Feb. 2015.

[14] *License Plate Detection, Recognition and Automated Storage*. Accessed: Oct. 19, 2019. [Online]. Available: http://www.zemris.fer.hr/projects/LicensePlates/english/results.shtml

[15] H. Z. Nafchi, A. Shahkolaei, R. Hedjam, and M. Cheriet, "CorrC2G: Color to gray conversion by correlation," *IEEE Signal Process. Lett.*, vol. 24, no. 11, pp. 1651–1655, Nov. 2017.

[16] R. Hedjam, H. Z. Nafchi, M. Kalacska, and M. Cheriet, "Influence of color-to-gray conversion on the performance of document image binarization: Toward a novel optimization problem," *IEEE Trans. Image Process.*, vol. 24, no. 11, pp. 3637–3651, Nov. 2015.

[17] J. Kim and S. Lee, "Extracting major lines by recruiting zero-threshold canny edge links along Sobel highlights," *IEEE Signal Process. Lett.*, vol. 22, no. 10, pp. 1689–1692, Oct. 2015.

[18] M. A. Massoud, M. Sabee, M. Gergais, and R. Bakhit, "Automated new license plate recognition in Egypt," *Alexandria Eng. J.*, vol. 52, no. 3, pp. 319–326, Sep. 2013.

[19] B. R. Mohamed, H. M. A. El Kader, H. M. Rafaat, and M. S. Sharaf, "Automatic number plate recognition," *Int. J. Sci. Res. Publications*, vol. 3, no. 12, pp. 1–7, Dec. 2013.

[20] M. Bagabir and M. Elhafiz, "A method for sudanese vehicle license plates detection and extraction," *Int. J. Comput. Appl. Technol. Res.*, vol. 5, no. 2, pp. 110–114, 2016.

[21] S. F. Ali, H. El Ghawalby, and A. A. Salama, "From image to neutrosophic image," in *Neutrosophic Sets and Systems*. Port Fuad, Egypt: Port Said Univ., Faculty of Science, Department of Mathematics and Computer Science, Apr. 2015, pp. 1–13.

[22] D. Koundal, "Texture-based image segmentation using neutrosophic clustering," *IET Image Process.*, vol. 11, no. 8, pp. 640–645, Aug. 2017.

[23] Y. Guo and H. D. Cheng, "New neutrosophic approach to image segmentation," *Pattern Recognit.*, vol. 42, no. 5, pp. 587–595, May 2009.

[24] Y. Dong, H. Zhang, Z. Liu, C. Yang, G.-S. Xie, L. Zheng, and L. Wang, "Neutrosophic set transformation matrix factorization based active contours for color texture segmentation," *IEEE Access*, vol. 7, pp. 93887–93897, Jul. 2019.

[25] Y. Guo, H. D. Cheng, and Y. Zhang, "A new neutrosophic approach to image denoising," *New Math. Natural Comput.*, vol. 5, no. 3, pp. 653–662, Nov. 2009.

[26] G. Abo Smara and F. Khalefah, "Localization of license plate number using dynamic image processing techniques and genetic algorithms," *IEEE Trans. Evol. Comput.*, vol. 18, no. 2, pp. 244–257, Apr. 2014.

[27] G.-E. Abo-Samra, "Application independent localisation of vehicle plate number using multi-window-size binarisation and semi-hybrid genetic algorithm," *J. Eng.*, vol. 2018, no. 2, pp. 104–116, Feb. 2018.

[28] L. Liu, Z. Jia, J. Yang, and N. K. Kasabov, "SAR image change detection based on mathematical morphology and the K-means clustering algorithm," *IEEE Access*, vol. 7, pp. 43970–43978, Mar. 2019.

[29] S. Chen, X. Yang, and Y. Tian, "Discriminative hierarchical K-means tree for large-scale image classification," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 26, no. 9, pp. 2200–2205, Sep. 2015.

[30] P. Panwar, G. Gopal, and R. Kumar, "Image segmentation using K-means clustering and thresholding," *Int. Res. J. Eng. Technol. (IRJET)*, vol. 3, no. 5, pp. 1–7, May 2016.

[31] A. Bala and A. K. Sharma, "Color image segmentation using K-means clustering and morphological edge detection algorithm," *Int. J. Latest Trends Eng. Technol. (IJLTET)*, 2016, pp. 48–55.

[32] S. Kapil, M. Chawla, and M. D. Ansari, "On K-means data clustering algorithm with genetic algorithm," in *Proc. 4th Int. Conf. Parallel, Distrib. Grid Comput. (PDGC)*, 2016, pp. 202–206.

[33] A. S. Ashour, A. R. Hawas, Y. Guo, and M. A. Wahba, "A novel optimized neutrosophic K-means using genetic algorithm for skin lesion detection in dermoscopy images," *Signal, Image Video Process.*, vol. 12, no. 7, pp. 1311–1318, Oct. 2018.

[34] A. AbuBaker, R. Qahwaji, S. Ipson, and M. Saleh, "One scan connected component labeling technique," in *Proc. IEEE Int. Conf. Signal Process. Commun.*, Nov. 2007, pp. 1283–1286.

[35] L. He, X. Zhao, Y. Chao, and K. Suzuki, "Configuration-transition-based connected-component labeling," *IEEE Trans. Image Process.*, vol. 23, no. 2, pp. 943–951, Feb. 2014.

[36] D. Gilly and K. Raimond, "License plate recognition—A template matching method," *Int. J. Eng. Res. Appl.*, vol. 3, no. 2, pp. 1240–1245, Mar./Apr. 2013.
[37] B. Dhanalakshmi, G. Yogasri, and M. Mohanapriya, "Enhancing accuracy of automatic vehicle number plate recognition system using template matching algorithm," *Int. Res. J. Eng. Technol. (IRJET)*, vol. 5, no. 2, pp. 1–4, Feb. 2018.
[38] M. Vania, D. Mureja, and D. Lee, "Automatic spine segmentation from CT images using convolutional neural network via redundant generation of class labels," *J. Comput. Des. Eng.*, vol. 6, no. 2, pp. 224–232, Apr. 2019.
[39] D. S. Prabha and J. S. Kumar, "Performance evaluation of image segmentation using objective methods," *Indian J. Sci. Technol.*, vol. 9, no. 8, pp. 1–8, Feb. 2016.
[40] P. Singh and R. Shree, "A comparative study to noise models and image restoration techniques," *Int. J. Comput. Appl.*, vol. 149, no. 1, pp. 18–27, Sep. 2016.
[41] A. M. Al-Ghaili, S. Mashohor, A. R. Ramli, and A. Ismail, "Vertical-edge-based car-license-plate detection method," *IEEE Trans. Veh. Technol.*, vol. 62, no. 1, pp. 26–38, Jan. 2013.
[42] C. N. E. Anagnostopoulos, I. E. Anagnostopoulos, and I. D. Psoroulas, "License plate recognition from still images and video sequences: A survey," *IEEE Trans. Intell. Transp. Syst.*, vol. 9, no. 3, pp. 377–391, Sep. 2008.
[43] N. R. Soora and P. S. Deshpande, "Color, scale, and rotation independent multiple license plates detection in videos and still images," *Math. Problems Eng.*, vol. 2016, pp. 1–14, Jun. 2016.
[44] Accessed: Jan. 8, 2020. [Online]. Available: http://www.medialab.ntua.gr/research/LPRdatabase.html
[45] G.-S. Hsu, J.-C. Chen, and Y.-Z. Chung, "Application-oriented license plate recognition," *IEEE Trans. Veh. Technol.*, vol. 62, no. 2, pp. 552–561, Feb. 2013.
[46] B. Balamurugan and S. Dinesh, "Advanced number plate recognition using neural network," *Int. J. Adv. Res. Electron. Commun. Eng. (IJARECE)*, vol. 3, no. 12, pp. 1–4, Dec. 2014.
[47] F. PirahanSiah, S. N. H. S. Abdullah, and S. Sahran, "Adaptive image segmentation based on peak signal-to-noise ratio for a license plate recognition system," in *Proc. Int. Conf. Comput. Appl. Ind. Electron. (ICCAIE)*, Dec. 2010, pp. 468–472.
[48] S. Kaur, "An automatic number plate recognition system under image processing," *Int. J. Intell. Syst. Appl.*, vol. 8, no. 3, pp. 14–25, Mar. 2016.
[49] R. Mukherjee, A. Pundir, D. Mahato, G. Bhandari, and G. J. Saxena, "A robust algorithm for morphological, spatial image-filtering and character feature extraction and mapping employed for vehicle number plate recognition," in *Proc. Int. Conf. Wireless Commun., Signal Process. Netw. (WiSPNET)*, Mar. 2017, pp. 864–869.
[50] S.-L. Chang, L.-S. Chen, Y.-C. Chung, and S.-W. Chen, "Automatic license plate recognition," *IEEE Trans. Intell. Transp. Syst.*, vol. 5, no. 1, pp. 42–53, Mar. 2004.
[51] M. K. Hossen, A. C. Roy, S. A. Chowdhury, S. Islam, and K. Deb, "License plate detection and recognition system based on morphological approach and feed-forward neural network," *IJCSNS Int. J. Comput. Sci. Netw. Secur.*, vol. 18, no. 5, pp. 36–46, May 2018.
[52] P. Shivakumara, D. Tang, M. Asadzadehkaljahi, T. Lu, U. Pal, and M. H. Anisi, "CNN-RNN based method for license plate recognition," *CAAI Trans. Intell. Technol.*, vol. 3, no. 3, pp. 169–175, Sep. 2018.
[53] X. Zhai, F. Bensaali, and R. Sotudeh, "OCR-based neural network for ANPR," in *Proc. IEEE Int. Conf. Imag. Syst. Techn. Proc.*, Jul. 2012, pp. 393–397.
[54] H. Li, P. Wang, and C. Shen, "Toward end-to-end car license plate detection and recognition with deep neural networks," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 3, pp. 1126–1136, Mar. 2019.

BEDIR BEDIR YOUSIF received the B.Sc. degree in electronics engineering from the Faculty of Electronic Engineering, Menoufia University, Egypt, in 1999, and the M.Sc. and Ph.D. degrees from the Department of Electronics and Communications Engineering, Faculty of Engineering, Mansoura University, Mansoura, Egypt, in 2006 and 2013, respectively. He is currently an Associate Professor with the Electronics and Communications Engineering Department, Faculty of Engineering, Kafrelsheikh University, Kafrelsheikh, Egypt. He has several publications in the modeling of plasmonic devices, optical communications, optoelectronic devices, nano electronics, and antennas. His research and teaching interests include the areas of optical wireless communications, the modeling of electromagnetic devices, nano-electronics, optical devices, and optical communications.

MOHAMED MAHER ATA received the Ph.D. degree from the Electrical Communication and Electronics Department, Faculty of Engineering, Tanta University, Egypt, with the cooperation of Regina University, Canada. He is currently an Assistant Professor with the MISR Higher Institute for Engineering and Technology, Mansoura, Egypt. He has published many indexed research articles (SJR indexed-ISI indexed) in the state-of-the-art of biomedical engineering, astrophysics, electrical communication, bioinformatics, encryption, cyphering, and intelligent transportation systems (ITS). His research area of interest was utilized in the field of signal processing, image processing, multimedia, machine learning, video processing, and computer vision.

NEHAL FAWZY received the B.Sc. degree in communications and electronics engineering, in 2013. She is currently a Researcher with the Faculty of Engineering, Mansoura University. Her research interests are in the area of image and video processing.

MARWA OBAYA received the B.Sc. degree in electronics and communications engineering from the Faculty of Engineering, Mansoura University, Mansoura, Egypt, in 2001, and the M.Sc. and Ph.D. degrees from the Department of Electronics and Communications Engineering, Faculty of Engineering, Mansoura University, in 2005 and 2008, respectively. She is currently an Associate Professor with the Electronics and Communications Engineering Department, Faculty of Engineering, Mansoura University, Egypt. She is also the Director of the Communications Engineering Program, Electrical Engineering Department, Princess Nora Bint Abdurrahman University, Riyadh, Saudi Arabia. She has several publications in the biomedical engineering, optimization, and intelligent machine learning. Her research area of interest was utilized in the field of image processing, signal processing, optimization, and machine learning.