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
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.

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 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 immunity to changes in illumination.

K. M. Babuand et al. have 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 character in (LP) image. The whole system has achieved about 91.11% accuracy. 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 79% 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/1CUSzJgDM10zrsRo1SdQ5mibZPdFipi/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 x 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, (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
Algorithm 1 Detection Stage

Input: Car image.
Output: License plate (LP) image.

Steps:

1. Preprocessing image (resizing, gray scale image, contrast).
2. Apply filtering process with some morphological operation (median filter, sobel edge detection, dilating, filling holes, eroding, removing unwanted objects) for image enhancement.
3. Apply bounding box around each region in image.
4. Label all detected objects.
5. Calculate length, width for each region which would be detected and calculate the ratio (length/width).
6. If sum of white pixels = \((+5\% \text{ or } -5\%)\) as a tolerance for area of these region & If \(a < \text{length/width} < b\)
7. Crop image and save it.
8. Else Load path of image & crop and resize the image. Apply green channel imaging instead of gray scale channel imaging & blur image.
9. Tested=true
10. End inner if
11. 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 \((16 \times 32)\) 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 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 \(A_{NS}(x, y) = A(t, i, f)\) 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].

\[
T(x, y) = \frac{\overline{A}(x, y) - \overline{A}_{\min}}{\overline{A}_{\max} - \overline{A}_{\min}}, \quad (1)
\]

\[
\overline{A}(x, y) = \frac{1}{b + b} \sum_{m=x-h}^{x+h} \sum_{n=y-h}^{y+h} A(m, n), \quad (2)
\]

\[
I(x, y) = \frac{\delta(x, y) - \delta_{\min}}{\delta_{\max} - \delta_{\min}}, \quad (3)
\]

\[
\delta(x, y) = abs((A(x, y) - \overline{A}(x, y))), \quad (4)
\]

\[
F(x, y) = 1 - T(x, y), \quad (5)
\]

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 \(\delta(x, y)\) 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:

$$E_{NS} = E_T + E_F,$$

$$E_T = - \sum_{i=\text{min}[T]}^{\text{max}[T]} P_T(i) \ln(P_T(i)), \quad (7)$$

$$E_F = - \sum_{i=\text{min}[F]}^{\text{max}[F]} P_F(i) \ln(P_F(i)), \quad (8)$$

$$E_I = - \sum_{i=\text{min}[I]}^{\text{max}[I]} P_I(i) \ln(P_I(i)). \quad (9)$$

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) $\alpha$-MEAN FOR NEUTROSOPHIC IMAGE

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

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

The ($\alpha$-mean) operation for neutrosophic image $A_{NS}$ is

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

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

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

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

$$\overline{T}_a(x, y) = \frac{1}{b^2} \sum_{m=x-\frac{b}{2}}^{x+\frac{b}{2}} \sum_{n=y-\frac{b}{2}}^{y+\frac{b}{2}} T(m,n), \quad (14)$$

$$\overline{F}_a(x, y) = \frac{1}{b^2} \sum_{m=x-\frac{b}{2}}^{x+\frac{b}{2}} \sum_{n=y-\frac{b}{2}}^{y+\frac{b}{2}} F(m,n), \quad (15)$$

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

$$\overline{I}_a(x, y) = \frac{\overline{T}(x, y) - \overline{T}_{\text{min}}}{\overline{T}_{\text{max}} - \overline{T}_{\text{min}}}, \quad (16)$$

$$\overline{T}(x, y) = \text{abs}(\overline{T}(x, y) - \overline{T}(x, y)), \quad (17)$$

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

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 $\overline{T}(x, y)$. The entropy of $I$ is increased by getting a uniform distribution of the elements, where the $\alpha$ value in the $\alpha$-mean has been optimized by using Genetic algorithm (GA).

B. OPTIMIZATION IN ($\alpha$-MEAN) USING GENETIC ALGORITHM

The optimal value of ($\alpha$) has been adaptively estimated using the (GA) [26]–[28], as discussed in algorithm 2. The optimization fitness function is jacard (JAC), which are statistical measurements that calculate the union ‘$\cup$‘ and the intersection ‘$\cap$‘ operators of any two sets. This fitness (JAC) is given by:

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

where, $A_{rf}$ is the computed 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 ($\alpha$ optimal). For achieving the maximum of (JAC) coefficient with genetic algorithm, we apply Eq. (20).

$$F(f, q) = 1 - JAC(f, q), \quad (20)$$

C. k-MEANS CLUSTERING USING OPTIMIZED ($\alpha$-MEAN)

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

$$O = \sum_{j=1}^{q} \sum_{i=1}^{d_j} \|W_i - Z_j\|, \quad (21)$$

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.
Algorithm 3 Ground Truth Extraction

**Input**: license plate region image.
**Output**: ground truth image.

**Steps**:

1. **start**
2. **Convert** Rgb2gray image.
3. **Binarize** gray scaled image.
4. **Apply** 2\textsuperscript{nd} order adaptive thresholding:
   - **T1**: threshold value 1
   - **T2**: threshold value 2
   - **D**: Desired
   - **T1 < D < T2**
5. **Dilate** \( D \)
6. **Fill and Extract** \( D \)
7. **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, \( W = \{w_i, i = 1, 2, \ldots, n\} \), \( w_i \) is a sample in the d-dimensional space and \( C = \{C_1, C_2, \ldots, C_q\} \) is the partition which satisfied that \( W = \bigcup_{i=1}^{q} C_i \). After optimizing \( a \), \( (T \text{ and I}) \) subsets become a new value whereas the effect of the indeterminacy as follows:

\[
W(x, y) = \begin{cases} 
T(x, y), & I(x, y) < a_{\text{optimal}} \\
I(x, y), & I(x, y) \geq a_{\text{optimal}} 
\end{cases} \tag{23}
\]

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 \( \times \{24} \) 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 \( \times \{24} \) for English (LPs) [36].
FIGURE 10. Algorithm of letters and numbers segmentation.
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 x 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) ≤ δ.
- **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 α_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 α_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 x 3864) pixels for Egyptian (LPs), and 500 images with size of (640 x 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 |
|-----------|----------------|--------------------|-------------------|
|           | Original image | ![Image](image1.png) | ![Image](image2.png) |
|           | Original image | ![Image](image3.png) | ![Image](image4.png) |
| English license plates |
| ![Image](image5.png) | ![Image](image6.png) | ![Image](image7.png) |

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).

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}.$$  

$$R(m, n) = \frac{\sum_{j} \sum_{k} F_1(j, k) F_2(j - m + (M + 1)/2, K - n + (N + 1)/2)}{\left[ \sum_{j} \sum_{k} F_1(j, k)^2 \right]^{\frac{1}{2}} \left[ \sum_{j} \sum_{k} F_2(j - m + (M + 1)/2, K - n + (N + 1)/2)^2 \right]^{\frac{1}{2}}}.$$  

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

| trial no | alpha-optim | 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-optim | Accuracy (%) | Sensitivity (%) | Specificity (%) | Dice (%) | Jaccard (%) |
|----------|-------------|--------------|-----------------|-----------------|----------|-------------|
| 1        | 0.6001      | 85.73        | 83.66           | 88.36           | 86.76    | 78.62       |
| 2        | 0.6051      | 93.01        | 91.83           | 94.30           | 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        | 0.6080        | 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).

\[
Sensitivity = \frac{TP}{TP + FN}, \quad (26)
\]

(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).

\[
Specificity = \frac{TN}{TN + FP}, \quad (27)
\]
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          | 73.04    | 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        | 96.49        | 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).

$$DC(f, q) = \frac{2 \left| A_{ij} \cap A_{jq} \right|}{\left| A_{ij} \right| + \left| A_{jq} \right|},$$

(28)

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

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

Or

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

(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 $(5152 \times 3864)$ 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 $(640 \times 480)$ pixels, and resolution (2 mega pixels).
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 \((\text{NS} + \text{k-means} + \text{Genetic algorithm}) \) 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 \((\text{NS} + \text{k-means} + \text{Genetic algorithm}) \) 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.

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.

| Type of image | Original image | Gray image | Ground truth image | Image with noise | Segmented image |
|---------------|----------------|------------|--------------------|------------------|-----------------|
| **Egyptian license plates**                      |               |            |                    |                  |                 |
| Traditional methods                  | ![Original image](image1) | ![Gray scale image](image2) | ![Expected Ideal Output](image3) | ![salt & pepper](image4) | ![Image after segment character](image5) |
| (NS + k-means + Genetic algorithm)      | ![Original image](image6) | ![Gray scale image](image7) | ![Expected Ideal Output](image8) | ![salt & pepper](image9) | ![GA optimized operator Output](image10) |
| **English license plates**             |               |            |                    |                  |                 |
| Traditional methods                  | ![Original image](image11) | ![Gray scale image](image12) | ![Expected Ideal Output](image13) | ![salt & pepper](image14) | ![Image after segment character](image15) |
| (NS + k-means + Genetic algorithm)      | ![Original image](image16) | ![Gray scale image](image17) | ![Expected Ideal Output](image18) | ![salt & pepper](image19) | ![GA optimized operator Output](image20) |

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

| Type of image | Original image | Gray image | Ground truth image | Image with noise | Segmented image |
|---------------|----------------|------------|--------------------|------------------|-----------------|
| **Egyptian license plates**                      |               |            |                    |                  |                 |
| Traditional methods                  | ![Original image](image21) | ![Gray scale image](image22) | ![Expected Ideal Output](image23) | ![Gaussian](image24) | ![Image after segment character](image25) |
| (NS + k-means + Genetic algorithm)      | ![Original image](image26) | ![Gray scale image](image27) | ![Expected Ideal Output](image28) | ![Gaussian](image29) | ![GA optimized operator Output](image30) |
| **English license plates**             |               |            |                    |                  |                 |
| Traditional methods                  | ![Original image](image31) | ![Gray scale image](image32) | ![Expected Ideal Output](image33) | ![Gaussian](image34) | ![Image after segment character](image35) |
| (NS + k-means + Genetic algorithm)      | ![Original image](image36) | ![Gray scale image](image37) | ![Expected Ideal Output](image38) | ![Gaussian](image39) | ![GA optimized operator Output](image40) |
**TABLE 14.** Comparative study between (traditional methods) and (NS + k-means + Genetic algorithm), when adding speckle noise.

| Type of image | Original image | Gray image | Ground truth image | Image with noise | Segmented image |
|---------------|----------------|------------|--------------------|------------------|-----------------|
| Egyptian license plates | ![Original image](image1) | ![Gray scale image](image2) | ![Expected Ideal Output](image3) | ![Image after segment character](image4) | ![Segmented image](image5) |
| (NS + k-means + Genetic algorithm) | ![Original image](image6) | ![Gray scale image](image7) | ![Expected Ideal Output](image8) | ![Image after segment character](image9) | ![Segmented image](image10) |

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

| Type of image | Original image | Gray image | Ground truth image | Image with noise | Segmented image |
|---------------|----------------|------------|--------------------|------------------|-----------------|
| Egyptian license plates | ![Original image](image11) | ![Gray scale image](image12) | ![Expected Ideal Output](image13) | ![Image after segment character](image14) | ![Segmented image](image15) |
| (NS + k-means + Genetic algorithm) | ![Original image](image16) | ![Gray scale image](image17) | ![Expected Ideal Output](image18) | ![Image after segment character](image19) | ![Segmented image](image20) |

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

| Type of image | Original image | Gray image | Ground truth image | Image with noise | Segmented image |
|---------------|----------------|------------|--------------------|------------------|-----------------|
| English license plates | ![Original image](image21) | ![Gray scale image](image22) | ![Expected Ideal Output](image23) | ![Image after segment character](image24) | ![Segmented image](image25) |
| (NS + k-means + Genetic algorithm) | ![Original image](image26) | ![Gray scale image](image27) | ![Expected Ideal Output](image28) | ![Image after segment character](image29) | ![Segmented image](image30) |
### 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 | ![Original image](image1) | ![Gray scale image](image2) | ![Expected ideal Output](image3) | ![Darken image](image4) | ![Image after segment character](image5) |
| Traditional methods  | ![Original image](image1) | ![Gray scale image](image2) | ![Expected ideal Output](image3) | ![Darken image](image4) | ![Image after segment character](image5) |
| (NS + k-means + Genetic algorithm) | ![Original image](image1) | ![Gray scale image](image2) | ![Expected ideal Output](image3) | ![Darken image](image4) | ![GA optimised operator Output](image5) |
| English license plates | ![Original image](image1) | ![Gray scale image](image2) | ![Expected ideal Output](image3) | ![Darken image](image4) | ![Image after segment character](image5) |
| Traditional methods  | ![Original image](image1) | ![Gray scale image](image2) | ![Expected ideal Output](image3) | ![Darken image](image4) | ![Image after segment character](image5) |
| (NS + k-means + Genetic algorithm) | ![Original image](image1) | ![Gray scale image](image2) | ![Expected ideal Output](image3) | ![Darken image](image4) | ![GA optimised operator Output](image5) |

### 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 | ![Original image](image1) | ![Gray scale image](image2) | ![Expected ideal Output](image3) | ![Blurring image](image4) | ![GA optimised operator Output](image5) |
| Traditional methods  | ![Original image](image1) | ![Gray scale image](image2) | ![Expected ideal Output](image3) | ![Blurring image](image4) | ![Image after segment character](image5) |
| (NS + k-means + Genetic algorithm) | ![Original image](image1) | ![Gray scale image](image2) | ![Expected ideal Output](image3) | ![Blurring image](image4) | ![GA optimised operator Output](image5) |
| English license plates | ![Original image](image1) | ![Gray scale image](image2) | ![Expected ideal Output](image3) | ![Blurring image](image4) | ![Image after segment character](image5) |
| Traditional methods  | ![Original image](image1) | ![Gray scale image](image2) | ![Expected ideal Output](image3) | ![Blurring image](image4) | ![Image after segment character](image5) |
| (NS + k-means + Genetic algorithm) | ![Original image](image1) | ![Gray scale image](image2) | ![Expected ideal Output](image3) | ![Blurring image](image4) | ![GA optimised operator Output](image5) |
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 δ = 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 and remove some pixels like dot of first letter in Egyptian (LPs), and have an error for letters detect in
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, 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 periodic noise for images, Fig.16 illustrated that, average (accuracy, sensitivity, specificity, dice, jaccard) was that (63.35%, 64.73%, 63.93%, 60.77%, 44.40%), respectively for traditional method.

Fig.17 illustrated that, average (accuracy, sensitivity, specificity, dice, jaccard) was that (92.24%, 89.34%, 94.60%, 91.58%, 84.40%), respectively for traditional method.

In case of adding periodic noise for images, Fig.20 illustrates that, average (accuracy, sensitivity, specificity, dice, jaccard) was that (76%, 83.67%, 73.72%, 71.20%, 55.56%), 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 adding speckle noise for images, Fig.18 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.19 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 reducing the brightness of images, Fig.22 illustrated that, average (accuracy, sensitivity, specificity, dice, jaccard) was that (76%, 83.67%, 73.72%, 71.20%, 55.56%), respectively for traditional method.

In case of blurring image, Fig.23 illustrated that, average (accuracy, sensitivity, specificity, dice, jaccard) was that (59.34%, 64.35%, 64.73%, 63.93%, 60.77%, 44.40%), 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. |

Fig. 24. Traditional methods for blurring image.

Fig. 25. Proposed system for blurring image.

Fig. 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 found 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.

| Proposed Method | Description | Result | Comments |
|-----------------|-------------|--------|---------|
| N. Rana et al. [12] | The paper discusses various techniques for license plate localization and compares between their technique and others according to their performance. | 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. |

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...
| LP variations | Original image | License plate image | Net result with proposed method | Accuracy |
|---------------|---------------|--------------------|---------------------------------|----------|
| 1- Image with multiple LPs (two cars) | ![Original Image](image1.jpg) | ![License Plate Image](image2.jpg) | GA optimised operator Output | 95.04% |
| 2-image with multiple vehicles with LPs and each LP is in different angle | ![Original Image](image3.jpg) | ![License Plate Image](image4.jpg) | GA optimised operator Output | 97.07% |
| 3-Image with blur | ![Original Image](image5.jpg) | ![License Plate Image](image6.jpg) | GA optimised operator Output | 96.11% |
| 4-Image with an extreme pan | ![Original Image](image7.jpg) | ![License Plate Image](image8.jpg) | GA optimised operator Output | 90.42% |
| 5-Image taken at night | ![Original Image](image9.jpg) | ![License Plate Image](image10.jpg) | GA optimised operator Output | 97.18% |
| 6-Image with rotation | GA optimised operator Output | 96.98% |
|-----------------------|-----------------------------|--------|
| 7-Image with dirt in the LP | GA optimised operator Output | 94.84% |
| 8-Image with different tilt | GA optimised operator Output | 90.72% |
| 9-Image with distorted LP | GA optimised operator Output | 91.11% |
| 10-Image with a close view of small characters | GA optimised operator Output | 97.42% |
| Table 22. (Continued) Media Lab benchmark LP data set. |
|------------------------------------------------------|
| **11-Image with one LP front viewed and another side viewed** | **GA optimised operator Output** | **96.74%** |
| ![Image](image1.png) | ![Image](image2.png) | ![Image](image3.png) |
| **12-Image with a rotation (an image containing motorcycle with right diagonally rotated LP)** | **GA optimised operator Output** | **95.80%** |
| ![Image](image4.png) | ![Image](image5.png) | ![Image](image6.png) |
| **13- Image with a rotation (an image containing motorcycle)** | **GA optimised operator Output** | **95.04%** |
| ![Image](image7.png) | ![Image](image8.png) | ![Image](image9.png) |
| **14- Images with dirt and shadow** | **GA optimised operator Output** | **90.01%** |
| ![Image](image10.png) | ![Image](image11.png) | ![Image](image12.png) |
| **GA optimised operator Output** | **96.89%** |
| ![Image](image13.png) | ![Image](image14.png) | ![Image](image15.png) |
| **GA optimised operator Output** | **94.97%** |
| ![Image](image16.png) | ![Image](image17.png) | ![Image](image18.png) |
### TABLE 23. Aolp benchmark lp data sets.

| LP variations | Original image | License plate image | Net result with proposed method | Accuracy |
|---------------|----------------|---------------------|---------------------------------|----------|
| 1-Image with blur | ![Image](image1.png) | ![License Plate](image2.png) | GA optimised operator Output | 93.52% |
| 2-Image with an extreme pan | ![Image](image3.png) | ![License Plate](image4.png) | GA optimised operator Output | 95.07% |
| 3-Image taken at night | ![Image](image5.png) | ![License Plate](image6.png) | GA optimised operator Output | 97.52% |
| 4-Image with a rotation | ![Image](image7.png) | ![License Plate](image8.png) | GA optimised operator Output | 95.78% |
TABLE 23. (Continued) Aolp benchmark lp data sets.

| 5-Image with LP fixed in a higher level | GA optimised 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%) | 1.522185 | 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)

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

\[
PSNR = 10 \times \log_{10} \left( \frac{\text{max}^2}{MSE} \right), \tag{31}
\]

where \( \text{max} \) 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 neurofuzzy 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.

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