Design and Evaluation of an XOR Auto-Associative Memory-Based Framework for Robust Iraqi License Plate Recognition

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Abstract

This project presents an enhanced Iraqi vehicle plate identification system, incorporating digital processing technologies and the XOR Auto-Associative Memory advanced associative memory algorithm, towards a fast and efficient performance under diverse conditions of imagery. The system consists of three major stages: identification of the panel area, or localization, using edge transformations and morphological operations; symbol segmentation, or segmentation, based on horizontal and vertical projections for the exact extraction of numbers and letters; and finally, recognition use of XOR operations and a binary distance criterion known as Hamming Distance.

The model was tested on 420 images of panels in different scenarios of lighting: day, night, shadows, fog, and low light. It produced an accuracy of 98.10% in identifying the panel area and 98.14% in segmenting symbols, while the XOR algorithm gave the best result in recognizing 2,958 symbols with an accuracy of 99.93% in 2.4 ms per symbol. Another contribution of this system is that it has proven to be able to work in real time, processing 15–18 panels per second.

These results confirm the efficiency of the proposed algorithm in dealing with distorted or low-quality images and stand out as a simplified and effective alternative to the traditional methods and old associative memory algorithms. Therefore, this research provides a practical and reliable framework for identifying Iraqi vehicle plates in security and traffic applications with high time requirements.

Keyword: *Iraqi License Plate Recognition (ILPR); XOR Auto-Associative Memory; Image Processing; Real-Time Recognition; Intelligent Transportation Systems (ITS)*

Introduction

During the last decades, computer vision and digital image processing technologies have undergone extensive development; this has contributed to enhancing the capability of ITS based on automation and visual information analysis. An ALPR system represents one of the most important pillars in this field, as it offers a very essential function related to the basics of traffic security applications, such as parking management, access control to sensitive areas, and monitoring vehicles required by security agencies. Efficiency in ALPR systems depends basically on their ability to cope with real challenges, such as variations in lighting conditions and shooting angles, noise, low image resolution, and panel design differences among countries. [1-2]

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Consequently, in local relevance, there is a need to develop a system for identifying Iraqi paintings characterized by different visual compositions concerning symbols and the relative height of numbers, with dissimilarities in the distribution of painted areas. [3-4]

Despite some achievements in previous studies with traditional neural networks and manual feature extraction algorithms, many systems still suffer from slow processing speeds or have little resistance to interference and noise; thus, their effectiveness in practical environments is yet to be ensured.[5-7]. Figure 1 shows the design of ancient Iraqi paintings [8, 20].

- Country: This section includes the word IQR.
- Governorate code: The following part shows the code of the governorate in question.
- Literal symbol: This letter represents the vehicle's serial number class.
- Vehicle number: The last part contains the vehicle identification number..

Figure 1. Iraqi License Plates.

This is an XOR-based strategy for developing self-associative memory architecture (Auto-Associative Memory) with the aim of improving the performance of dual-representation pattern recognition systems. The proposed method is characterized by simple computational design and the absence of the need for complex weights or training rules, as patterns are stored directly within a multidimensional matrix, which makes the size of memory proportional to the size of the pattern only, regardless of the number of patterns stored. The architecture enables access to a wide storage capacity, with a great ability to resist noise, without suffering from common problems present in associative memories, such as pattern inversion or falling into local minimum values. The recognition phase follows the application of an XOR operation between the input pattern and the stored patterns, calculating the Hamming distance for the nearest matching pattern. This makes it fast and efficient; thus, the strategy is suitable for use in real-time applications such as image processing, symbol recognition, and bi-representational data analysis. [20]

Therefore, Associative Memory Networks algorithms could achieve success in rapid pattern recognition tasks, primarily because they have been designed to work in environments where an immediate response should be given and with as few calculations as possible. Therefore, this research is going to present an enhanced algorithm for the identification of Iraqi vehicle plates based on the XOR Auto-Associative Memory strategy. The main features of the new method are its easiness of implementation and fast convergence and its high capability to deal with distorted or low-quality patterns without the need to use complex weights or complicated mathematical operations.

It is based on three major steps for operation: localization, segmentation, and recognition, and the XOR algorithm. The model is evaluated with an extended dataset containing images captured in various lighting conditions..

Literature Review

Latif O. H. Wabah H. H. A suggested machine learning-based method for identifying Arabic paintings. The process involves capturing images, detecting characters through image processing, and then segmenting them to extract Arabic numerals. The algorithm was tested on 90 images and achieved an accuracy of 97.78% in plate positioning, 45.56% in OCR, and 92.22% using KNN [12].

Abbas used G. and mortgaged A. The SSD algorithm identified the Iraqi plates, then segmented those using vertical and horizontal projections, and later relied on the KNN algorithm to determine the vehicle type. The method was tested on 500 Iraqi vehicles and achieved 98% accuracy in plate detection and 96% accuracy in segmentation [14].

Hussein B. A. developed an argument of M. S. A system for identifying license plates for security purposes. The board is detected using connected component analysis, while Kani's algorithm is used for character segmentation. In the final stage, characters are recognized using a multi-layer neural network (MLPANN), and the results are displayed via the GUI interface. The system achieved accuracy rates of 96% in panel identification and 97.872% in character recognition under various conditions [15].

Abdul Hamza D. A. Al-Aithawi A. D. The proposed recognition system consists of three main stages: initial processing, segmentation, and character recognition. After taking a photo of the vehicle, preliminary processing is done and then the panel area is precisely identified and cropped. The numbers are then segmented, and in the final stage the closest neighbor algorithm (KNN) is used to identify them. The system built using Python 3.5 and OpenCV achieved 90% accuracy on a set of 50 images [16].

Kamal N. presented. N. And George L. E. A technique for identifying Iraqi paintings based on local horizontal and vertical projections. The results showed great effectiveness, as the method recorded an accuracy of 99.16%, with an average processing time of 0.012 seconds per character [18].

Rusul Hussein, et al,. proposed a model based on modified bidirectional associative memory (MBAM), a homogeneous uncorrelated memory technique. The model works in two stages —learning stage and convergence stage— to identify traffic signs. Thanks to its high ability to withstand noise and distinguish distorted images, in addition to the small network size and speed of calculations, the model overcomes many common challenges. The system achieved 99.6% accuracy in panel positioning, 98% accuracy in character segmentation, and 100% accuracy in character recognition under various conditions [19].

Abbas, M., This article discusses the development of a method for identifying Iraqi paintings to detect violators in queue management systems. Many parties around the world have adopted traffic sign recognition technologies to enhance their capabilities in investigative and security aspects, as these technologies allow vehicle information to be extracted quickly without the need for long manual procedures. In this work, cognitive transfer was used to train two YOLOv8 models to improve the Automatic Panel Recognition System (ANPR).[21]

Methodology

The proposed method begins with the localization phase, which relies on several image processing algorithms to optimize inputs and accurately detect the vehicle plate area. This is followed by the segmentation phase, where letters and numbers are extracted from the selected board using a horizontal and vertical projection algorithm. Finally, the XOR process-based autocorrelation memory (XOR-AM) is applied to recognize all numbers and letters through the learning and convergence phases. Figure 2 shows the general sequence of operation of the proposed system.

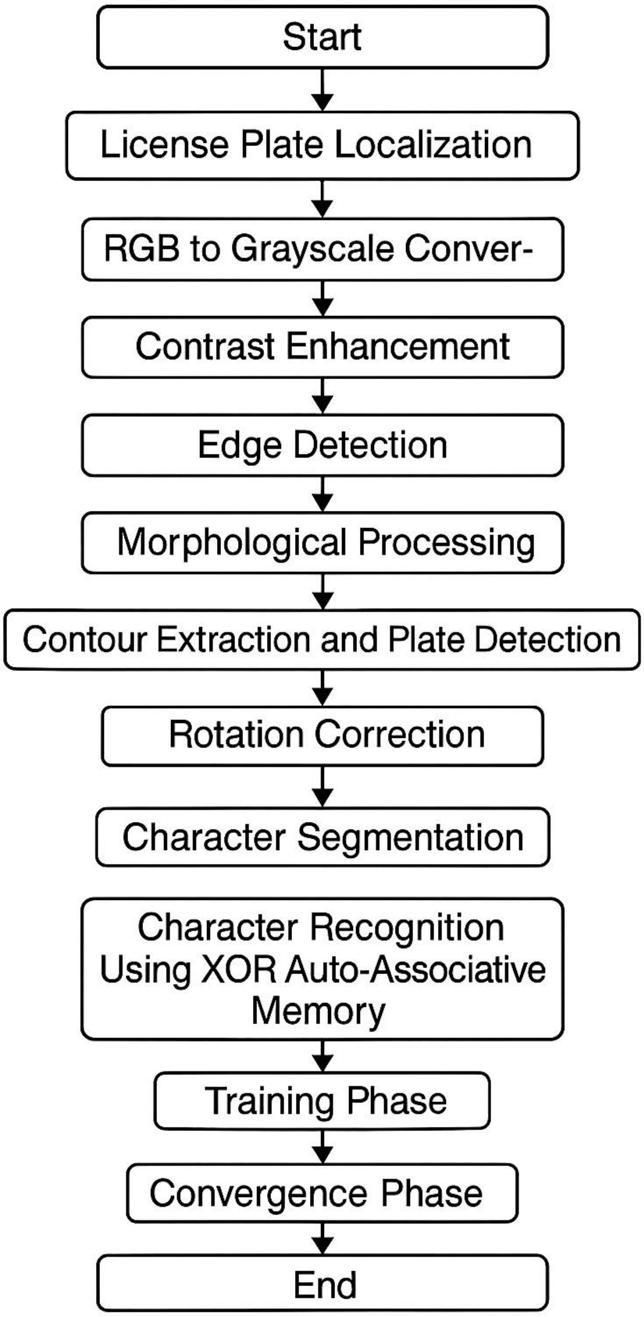

Figure 2. Proposed Methodology

License Plate Localization

The localization phase is the first step in the proposed Iraqi car plate recognition model, where the plate is extracted from the vehicle image through a set of image processing operations. The following subsection explains the detailed steps of the location phase.

RGB to Grayscale Conversion

Image Acquisition:

A digital camera was used to capture images of Iraqi vehicle license plates from the front and rear. The images were collected from different environments including streets, residential camps and public parking lots.

Pre-processing:

Pre-processing is an essential step in improving the quality of paintings, especially since the capture process took place at different times of the day and under different climatic conditions. The captured images are initially colored, where the RGB image consists of three channels: red, green, and blue, and the value range of each channel is between (0–255). To simplify the subsequent processing stages, the RGB image is converted to a gray image with only one channel, by using Equation (1).

$$I\_G(x,y) \;=\; 0.2989\, R(x,y) \;+\; 0.5870\, G(x,y) \;+\; 0.1140\, B(x,y) \; (1)$$

Contrast Enhancement

Images of vehicles are often captured under diverse lighting conditions (strong sunlight, shadows, low light), which can cause low contrast between the license plate and its background. To improve the visibility of plate edges and characters, a contrast stretching operation is applied to the grayscale image.

This operation linearly maps the original gray levels into the full dynamic range [0,255], based on the minimum and maximum intensity values in the image, so that darker regions become darker and brighter regions become brighter in a controlled manner, by using Equation (2).

$$I\_C(x,y) \;=\; ((I\_G(x,y) \;-\; I\_min) \,/\, (I\_max \;-\; I\_min)) \;\times\; 255 \; (2)$$

Where: Imin, Imax are the minimum and maximum gray values.

Edge Detection

To enhance the panel area detection process, first, the contrast of the image is enhanced. Then, a canny edge detector is applied to extract the important edges. The detector relies on a smoothing process involving a Gaussian and then calculation of the image gradient in order to determine the edge strength after noise reduction. The operator makes use of 3×3 windows across the image in order to define the edge boundaries precisely through Equations Gaussian smoothing and gradient magnitude (3, 4, 5). [9]

$$I\_S \;=\; G\_\sigma \;*\; I\_C \; (3)$$

where σG is a Gaussian kernel with standard deviation σ, and ∗*∗ denotes convolution.

$$\nabla I \;=\; (\,(\partial I\_S/\partial x)\text{^}2 \;+\; (\partial I\_S/\partial y)\text{^}2\,) \; (4)$$

Based on the gradient magnitude and two thresholds (high $_{H}$Tand low $_{L}$T), an edge map E(x,y) is generated to differentiate edge pixels from non-edge pixels:

$$E(x,y) \;=\; 1\; if\; \nabla I \;\geq\; T\_H\,;\; 0\; if\; \nabla I \;<\; T\_L \; (5)$$

Morphological Processing

After determining the gradient, the edge strength is calculated. For isolating the painting from the background, morphological processes such as expansion (Dilation) and erosion (Erosion) are done; expansion expands areas of objects and increases the thickness of the boundary, which helps to deal with the problem of discontinuous edges. Then all the internal gaps in the image are filled. The resulting edge chart is used for analyzing transition zones between dark and light colors.

Finally, the plate is exposed by identifying the most suitable contour. Then, the smallest rectangle surrounding each contour is calculated, and its side ratios and area are evaluated. Threshold values are used to determine the minimum and maximum panel area. The contour that meets these geometric conditions is then selected, and its respective area extracted from the original image. By using Equation (6,7,8,9).

$$I\_D \;=\; I\_E \;\oplus\; B \; (6)$$
$$I\_E \;=\; I\_D \;\ominus\; B \; (7)$$
$$A \;=\; \Sigma\, I\_D(x,y) \; (8)$$
$$AR\_min \;\leq\; W/H \;\leq\; AR\_max \; (9)$$

Rotation Correction

After the vehicle plate area is extracted from the original image, it is rotated at different angles in order to return it to its usual position. The angle of correct rotation is computed by the Hough Transform while the geometric correction is made very precisely using the bilinear interpolation method. Using the Equation (10, 11)

$\theta = argmax\ H(\rho, \theta)$ (10)

$I\_R = R\_\theta(I\_P)$ (11)

Character Segmentation

After the vehicle plate area is extracted from the original image and its orientation is rectified, a segmentation stage is applied to segment each number or letter independently. Modern Iraqi painting is divided into four regions, as explained in the Iraqi painting design section. Horizontal projection and vertical projection algorithms, as shown in Figure 8, are used for the precise localization of letters and numbers.

These algorithms work by calculating the sum of the pixel values at the row and column levels. The horizontal projection is calculated by summing the pixel values in each individual row, and the vertical projection is calculated by summing the pixel values in each individual column, as explained in Equations (12,13):

$$P\_hor(i) = \Sigma\ I\_R(i,j)\ (12)$$
$$P\_ver(j) = \Sigma\ I\_R(i,j)\ (13)$$

Character boundaries are estimated by locating intervals using Equation 14:

$$P\_ver(j) > T\_char\ (14)$$

Before moving to the recognition stage, each truncated symbol must be converted to a binary image, wherein all pixels turn into 0 or 1. This is accomplished via Equation 15:

$$B(x,y) = 1\ if\ I\_R(x,y) \geq T\_b\ ;\ 0\ otherwise\ (15$$

This representation is necessary because the XOR algorithm only works on binary matrices.)

Character Recognition Using XOR Auto-Associative Memory

After segmentation of the symbols and conversion to binary images comes the recognition stage, which is the stage where the system identifies the letter or number corresponding to each symbol. The proposed methodology is based on XOR Auto-Associative Memory, a simple and fast algorithm based on the principle of Hamming Similarity rather than heavy weights or multi-layer networks.

The algorithm consists of two phases:

- Training Phase
- recognition phase

Training Phase

In this phase, each character (i.e., a digit or a letter) is stored as a binary pattern inside the memory matrix.

Each pattern P_k is represented as a set of binary values as Equation 16:

$$P\_k = \{p\_\{k,1\}, p\_\{k,2\}, \dots, p\_\{k,m\}\}, p\_\{k,i\} \in \{0,1\}\ (16)$$

where: m is the number of pixels of the character.

All patterns are stored in a multi-dimensional memory matrix using Equation 17:

$$MD = [P\_1, P\_2, \dots, P\_N]\ (17)$$

The patterns are stored directly where no weights or learning rules are used, which makes the algorithm extremely fast.

Convergence Phase

In this phase, an unknown character pattern U is fed into the memory to compare it with all stored patterns and determine the closest match.

The algorithm relies on the XOR operation between the input pattern and each stored pattern. The step one computes XOR Operation using Equation 18

$$SV\_k = U \oplus P\_k\ (18)$$

Where:

$$u\_i \oplus p\_\{k,i\} = 0\ if\ equal\ ;\ 1\ if\ not\ equal\ (19)$$

While resulting vector SV_k represents the binary difference between the input pattern and the stored pattern. The step two Compute XOR Distance using Equation 20, the similarity between the two patterns is measured by counting the number of mismatched pixels:

$$D\_k = \Sigma\, SV\_k(i) \quad (20)$$

The Step three Determine Closest Match with the minimum XOR distance is selected by using Equation 21:

$$k* = argmin(D\_k) \quad (21)$$

The Final step is Recognition Result by using Equation 22, thus, the algorithm guarantees selecting the closest stored pattern to the input pattern based on the binary XOR distance.

$$Recognized\ Character = P\_\{k*\} \quad (22)$$

Results and Discussion

In comparison with its previous version, a larger and more diverse dataset was used for the evaluation of the developed Iraqi License Plate Recognition system. The dataset consists of 420 license plate images, captured under several environmental and lighting conditions, such as:

- Direct daylight
- nighttime illumination,
- Partial shadows,
- fog and low-light scenes,
- strong artificial lighting,
- Camera tilts angles ranging between 15° and 30°.

Image resolutions ranged from 720×1280 up to 1080×1920 pixels to ensure a proper review at all the various quality levels.

All experiments were conducted on the following hardware and software configuration:

- Processor: Intel Core i7
- 16 GB RAM, Memory
- Operating System: Windows 10, 64 bit
- Software Environment: MATLAB R2023a

The XOR Auto-Associative Memory algorithm has been adopted for the recognition stage, in order to evaluate its capability for fast and accurate binary pattern classification.

The Result of each stage shows in Figure 3.

License Plate Localization Results

The system demonstrated a very high ability to accurately localize license plates in the tested images.

Out of 420 images, the system correctly localized the plate region in 412 images.

Accuracy Localization=412420×100=98.10%

Factors contributing to localization failures:

1. Light reflections on the plate in nighttime images.
2. Highly tilted plates exceeding the optimal angle range.
3. Plates covered with dirt or dust, partially obscuring the boundaries.

Character Segmentation Results

After successfully localizing 412 plates, character regions were extracted using horizontal and vertical projection methods.

Extracted character counts:

- Digits: 2,134
- Letters: 824
- Total Characters: 2,958

The system correctly segmented 2,903 characters out of 2,958:

Accuracy Segmentation=29032958×100=98.14%

Common causes of segmentation errors:

- Adjacent characters merging due to strong illumination.
- Motion blur in some images.
- Slight misalignment of characters within the plate.

Recognition Results Using XOR Auto-Associative Memory

The XOR Auto-Associative Memory model was trained on **34 classes**, representing:

- 10 digits (0–9)
- 24 letters used in Iraqi license plates

Test data distribution:

- Digits: 2,134
- Letters: 824
- Total: 2,958 characters

Correctly recognized characters:

- Digits: 2,134 out of 2,134
- Letters: 822 out of 824

Accuracy Recognition=29562958×100=99.93%

Analysis:

- The highest accuracy was achieved for high-contrast character images.
- Only two characters were misclassified, due to:
  - severe noise that flipped some binary pixels,
  - slight blurring that distorted the character shape.

These results demonstrate the strong discriminatory power and robustness of the XOR Memory in binary-based recognition tasks.

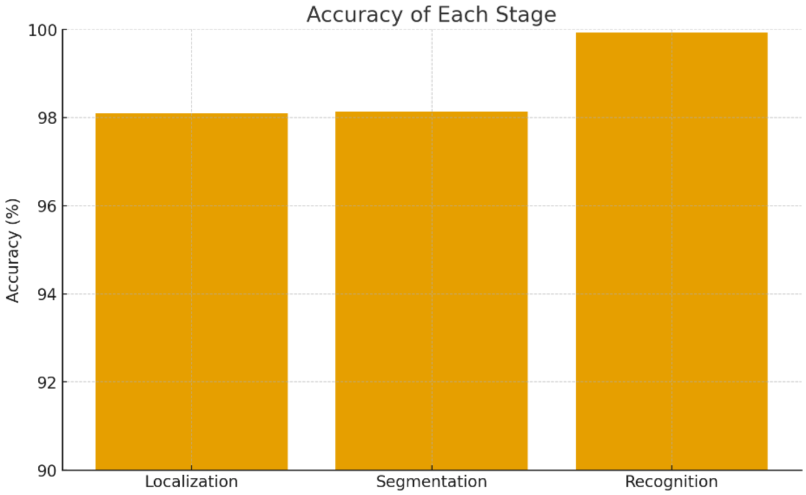

Figure 3: Result of each stage.

Processing Time Analysis

Average processing time was measured over a sample of 100 images as shown in Table 1 and Figure 4:

Table 1: Processing Time

Stage	Time (ms)
Plate Localization	42.7 ms
Character Segmentation	18.9 ms
Recognition (XOR Memory)	2.4 ms
Total per image	64.0 ms (≈ 0.064 s)

Practical throughput:

The system can process approximately 15–18 license plates per second, making it suitable for real-time applications such as:

- checkpoint systems,
- gate access control,
- Intelligent traffic monitoring.

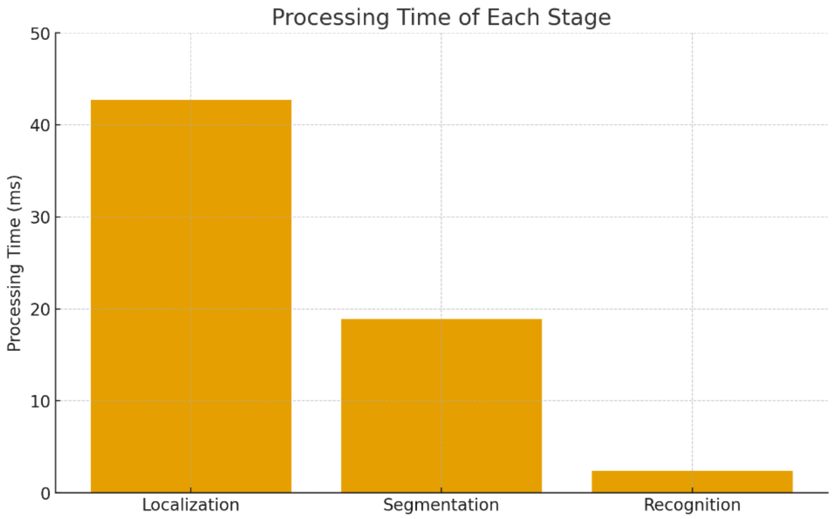

Figure 4: Processing Time

These results of the developed system for Iraqi plate recognition based on the XOR Auto-Associative Memory algorithm prove the strong and sensible performance of the system model along the different stages, starting from plate area identification and symbol segmentation to recognition. The panel identification stage had high ability with several imaging conditions, as it achieved an accuracy rate of 98.10%, which indicates the efficiency of the first image processing operations in isolating the panel area despite the variation in lighting and angle of capture. However, a few cases of reflections or extreme tilt resulted in disturbances in detecting the exact outlines of the plate. In the segmentation phase proved to be the most sensitive to external factors despite achieving an accuracy of 98.14%. The existence of strong shadows, non-uniform light, or slight vibration in the image could make the symbols stick or their edges deviate, and any change in these will directly influence the quality of the symbols passed through the recognition phase. In additional, an excellent performance is provided by the XOR algorithm in the recognition phase with an accuracy rate of 99.93%, confirming its high capability of handling binary patterns in case some pixels are distorted or affected by noise.

This superiority reflects the flexibility and computational simplicity of this algorithm compared to traditional methods dependent on complex weights or distances. In terms of processing time, it has been demonstrated that the system works efficiently within real time: the total time to process a single image reached about 0.064 seconds, which is low enough for it to be used in practical applications such as traffic inspection. Thus, these results clearly demonstrate that the developed model achieves a distinct balance between accuracy, speed, and stability, although optimizing the segmentation phase is still an important goal for further work in order to reduce errors and increase reliability in more complex environmental conditions..

Conclusion

The present research put forward a more effective and superior system of recognition of Iraqi vehicle plates, based on a set of digital image processing techniques and the XOR Auto-Associative Memory algorithm, which proved highly efficient in binary pattern recognition processes. It was found that the proposed methodology presents a marked balance between high accuracy and speed of implementation since, notwithstanding large shooting conditions, lighting, and image quality changes, the system yielded excellent performance rates at the panel identification, symbol segmentation, and recognition steps. An accuracy of 99.93% at the identification stage and a low processing time for each image confirm that the suggested algorithm can work in real time and meet the needs of practical applications in traffic flow systems, security, and access control.

Results also portrayed the XOR algorithm to be a simplified and efficient alternative to the classic associative memory algorithms because it is binary, fast in computation, and relies on a binary distance principle when making a decision. However, it was clear that the most sensitive stage to external factors such as noise, shadows, and vibration remains the segmentation phase; future research will therefore focus on increasing the accuracy and stability of the system in more challenging situations. In general, the framework provided here is practical and directly applicable. It defines steps for future development by embedding techniques of deep learning in order to enhance panel identification, improving the segmentation phase with advanced transformations, or developing hybrid versions that couple XOR with deep recognition models in order to scale up accuracy in complex environments.

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Ethics Declaration

The author confirms that this manuscript is an original work and has not been published previously, nor is it under consideration for publication elsewhere in any form or language. The research presented has been conducted with integrity and in accordance with accepted standards of scientific practice.

The author declares that all data, results, and analyses reported in this study are accurate and have not been fabricated, falsified, or inappropriately manipulated. Proper acknowledgment has been given to all sources of data, text, and ideas, and all relevant references have been cited appropriately to avoid plagiarism.

This study does not involve human participants, animals, or sensitive personal data; therefore, ethical approval was not required.

The author has ensured that no conflicts of interest exist and that the work does not contain any defamatory or unlawful statements. All applicable copyright laws and permissions have been respected.

The author agrees to provide the data supporting the findings of this study upon reasonable request and to cooperate fully with the journal in case of any ethical inquiries.

Ethics declaration: Not applicable.