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Hetero-associative Memory Based New Iraqi License Plate Recognition

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Abstract

As a result of recent developments in highway research as well as the increased use of vehicles, there has been a significant interest paid to the most current, effective, and precise Intelligent Transportation System (ITS). In the field of computer vision or digital image processing, the identification of specific objects in an image plays a crucial role in the creation of a comprehensive image. There is a challenge associated with Vehicle License Plate Recognition (VLPR) because of the variation in viewpoints, multiple formats, and non-uniform lighting conditions at the time of acquisition of the image, shape, and color, in addition, the difficulties like poor image resolution, blurry image, poor lighting, and low contrast, these must be overcome. This paper proposed a model by using Modify Bidirectional Associative Memory (MBAM), which is one type of Hetero-associative memory, MBAM works in two phases (learning and convergence phases) to recognize the number plate, and this proposed model can overcome these difficulties because MBAM's associative memory has a high ability to accept noise and distinguish distorted images, as well as the speed of the calculation process due to the small size of the network. The accuracy of plate region localization is 99.6%, the accuracy for character segmentation is 98%, and the achieved accuracy for character recognition is 100% in various circumstances

Keywords: Hetero-associative Memory, License Plate Recognition (LPR), Modify Bidirectional Associative Memory (MBAM), Neural Network, and Vehicles.

Introduction

Vehicle numbers have increased enormously in recent years. As a result, it has been difficult to detect criminal activities or traffic violations involving a vehicle or individual. Automated License Plate Recognition Systems (ALPRs) have been in use for quite some time with the advent of Artificial Intelligence. ALPRs are an identification system that detects and recognizes License Plates (LP) based on images. Law enforcement and smart city services are also served by ALPRs. It recognizes the characters on the plate to identify the vehicle[1].

LPR is a common method; consists of four blocks: the image of vehicle acquisition, localization of license plate, segmentation, classification and character standardization, and character analysis. The license plate locating procedure is very complex throughout the machinery, given that it has a direct impact on the efficiency and accuracy of the following procedures. In addition, it is of great importance to solve problems in the presence of lighting conditions and some other tedious backgrounds. Some developers have shown great methods for LP mode such as edge prediction algorithms; using line-sensitive filters to extract slab regions, window plots, and computational morphological approaches [2]. Although the preset models can handle the position of the license plate, they have many disadvantages, such as illumination sensitivity, versatility absence to be applied in different platforms, and high calculation time [2, 3].

Many methods used for LPR, but one of the important and frequently used sciences is the artificial intelligence algorithms that are used to extract the numbers and letters present in license plates. It does this by searching images or videos to identify the number plate and then convert them into digital data that can be used. It can determine the state of the license plate and can also set vehicle characteristics such as model, year, and color[4]. Then the digital data extracted from the license plate is compared with existing databases such as hot databases to automate and alert entry to secure communities or facilities. Also, some law enforcement agencies use license plate data captured by cameras against criminal activities [4,5].

The LP contains letters and numbers, it is a rectangular metal plate that is attached to the vehicle, and this plate is used to identify the vehicle. The LPR system can be defined as a method to identify a vehicle automatically using a computer device and it contains many applications such as imposing control on vehicles entering restricted areas like government buildings and airports, as well as security to track vehicles[6].

Modify Bidirectional Associative Memory (MBAM)

Associative memory is defined as stored data collectively in a weight matrix or memory form, that is used to generate outputs corresponding to certain inputs, there are two types of associative memory

- Automatic associative memory
- Heterogeneous associative memory[7]

One of the common types of hetero-associative memory is Bidirectional Associative Memory Neural Network (BAM NN), but this network has many limitations, such as local minimum, limited noise ratio, and limited stored pattern, in addition, scale and shift problems[7,8]. These limitations are resolved by using Modify Bidirectional Associative Memory (MBAM) except for the shifting and scaling problems[9].

MBAM Architecture

MBAM has a small architecture, and limited number of nodes (only two), where the possible number of vectors are (2^2) the number of weights required is only (4), this means that the size of the network will be fixed size at (4), each node in the input layer is connected to all nodes in the output layer, these connections represent the weight for all the vectors in the pattern, as shown in Fig 1. This modification will speed the computational process and increase the ability for noise tolerance. However, the vector elements will be represented by a bipolar representation that will either be 1 or -1. The data is compressed and the crucial details in the image are kept by employing the bipolar representation.[9, 10].

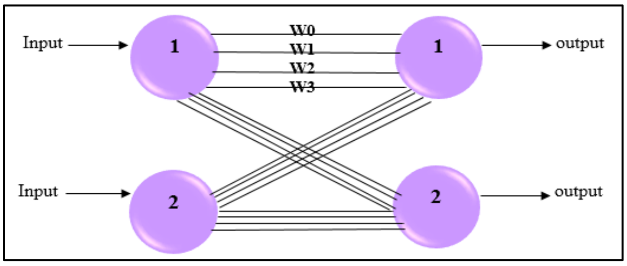

Figure 1. Modified Bidirectional Associative Memory (MBAM) Architecture[9]

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MBAM Algorithms

MBAM work with two phases: learning and convergence phases, as explain in the next subsection.

Learning Phase

Flow patterns and codes are the inputs for the learning phase, MBAM will split the pattern into many vectors each vector with a length of two, and deals with each vector individually not with the whole pattern, and this splitting will lead to benefits in the work as shown in Fig. 2 That is, there are no more than four possibilities for all vectors as shown in Table 1. To find the weight matrix for all vectors using Eq. 1, then assign save vector weight (svw) for each vector using Eq. 2[9,10].

$$w_i = v_i * c \qquad 1$$

Where: (v_i: Vector, c: Pattern Code, w_i: Weight matrix)

$$svw = f\big(Decode(v)\big)\begin{cases} 0 & \{means\ w0 \\ 1 & \{means\ w1 \\ 2 & \{means\ w2 \\ 3 & \{means\ w3 \end{cases} \qquad 2$$

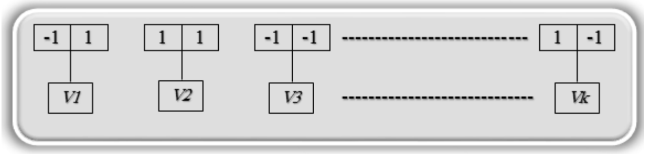

Figure 2. Splitting Trainings Patterns *n* Vectors.

Table 1. All Potential Vectors.

No	Vector with Binary Representation		Vector with Bipolar Representation	
0	0	0	-1	-1
1	0	1	-1	1
2	1	0	1	-1
3	1	1	1	1

Where the output for this phase will be stored in the lookup table as shown in Fig.3.

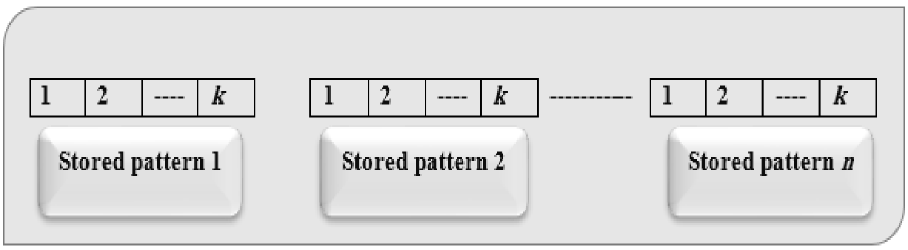

Figure 3. Lookup Table for Stored Patterns.

Convergence Phase

The unknown code or pattern is the input in the convergence phase, while the output of this phase is based on the learning phase. The first and second bi-directions in this phase are from pattern to code and from code to pattern, respectively[9,10].

In pattern to code algorithm, the pattern will also split into many vectors each vector with a length of two, when all vectors multiply with svw in unknown patterns the convergence phase will stop. Then by using Eq 3 energy function (ep) will correlate unknown patterns and codes that were stored svw in lookup the table that was built during the learning phase[9,10].

$$ep = -0.5 * \sum_{i=1}^{n} (y_i)^2 \qquad 3$$

Where, n is the number of vectors and y_i is the result multiplying vectors with *svw*.

Related work

The related works for Iraqi license plates have been modified using different methods, the details are as follows:

Hashem NM, Abbas HK., [11] the entire vehicle in the chosen location is featured in the film video for the study. The video clips in the study are 18 in total and have a camera height of 1.5 meters. The images are taken out from the video clip and used as training data for the cascade approach. After the training phase, license plate detection is done via cascading classification. Two methods of local time recording and various weather conditions were used to calculate the accuracy of all data. The initial method used for vehicle license plate recognition depends on video, the accuracy of the results for this study was 100% for XML file (training file), while the accuracy was 99.8%, for saved clipped images in the file.

Latif O H, Yaba H H., [12] the research that is being presented makes use of machine learning to identify Arabic license plates. Firstly, images of license plates are captured, and by using image processing, detection is done then character segmentation is used to find the Arabic numeric characters on the plate. The proposed algorithm has been tested on 90 image license plates downloads from the internet. Plate localization, background color detection, and Arabic number detection all have success rates of 97.78% overall, 45.56% in Optical Character Recognition (OCR), and 92.22% in K-Nearest Neighbors (KNN).

Hussein KA, Al-Ani ZTA., [13] this research used edge detection and mathematical morphology to segment and extract the license plate from the vehicle. Build the edge of the image by converting the color image to grayscale by computing the difference among pixels and neighbors. The Sobel filter is used to extract the edge of the license plate. Used images' mathematical morphology for dilation and erosion to create a smooth image, and then use images that are submitted to the license plate recognition stage to increase the effectiveness of segmentation processing. To identify the license plate using a multi-layer perceptron network. Due to the precise extraction of the plate region, characters can be precisely extracted from LP.

Abbass G, Marhoon A.,[14] this research focuses on using Single Shot Detector (SSD) deep learning algorithm to identify Iraqi license plates. Then segmenting the license plate using vertical and horizontal projections. The KNN technique was lastly used to define the type of vehicle. A set of 500 various Iraqi vehicles were used to examine the suggested method. The success results rate was 98% for plate detection and the success results rate was 96% for segmenting.

Hussain B A, Hathal MS., [15] in this research, the suggested system uses various image circumstances and performance evaluations based on various metrics, this system effectively recognized and identified multi-style Iraqi license plate, and the accuracy result for this system was 91.99%. This outcome demonstrates the proposed effectiveness technique in comparison to other methods already in use, and the processing time average for one character is 0.242s.

Hussain BA, Hathal MS., [16] this method is employed for security purposes, like tracking stolen vehicles and the restriction of entry to certain locations. The suggested recognition system uses the LPRs, which make use of a digital camera to gather vehicle plate numbers. The proposed system consists of three phases: vehicle license plate localization, vehicle license plate character segmentation, and vehicle license plate character recognition. The LP detection is presented using connects component analysis and canny edge, which has been used for character segmentation. The license plate characters are finally identified and detected using a Multi-Layer Perceptron Artificial Neural Network (MLPANN) model, and the findings are shown as text on a Graphic User Interface (GUI). Under various circumstances, the suggested system successfully rates for identifies LP and recognizes characters with rates of 96% and 97.872%.

Abd Alhamza DA, Alaythawy AD., [17], the Arabic number on the plate is identified in this study with the detection of the license plate. The main objective of the study was to recognize and comprehend car plates with numbers or characters because it was challenging to recognize the same thing in various contexts. Additionally, it provides LPR, which comprises three basic stages: segmentation and character recognition after pre-processing to detect license plates. The first step involves pre-processing of the car's image that is captured with a camera. When a license plate is detected, a matching license plate is checked to clip the right plate into the image. Separate segmentation is carried out by dividing the

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numbers. KNN one of the fundamental machine learning algorithms used to match numbers with each other, is employed in the final stage of the process to recognize numbers. The accuracy performance of the system, which was constructed using Python 3.5 and the Open CV library with 50 photos, was 90%.

Ali GK., [18] in this research, attempts to develop an image recognition-based system that can recognize characters on new vehicles license plates in Iraq, utilizing optical character recognition technology, to capture the image of a vehicle digital camera and then match the result of the image of the vehicle to all of the vehicle plate numbers that are contained in the database.

Kamal NN, George LE., [19] in this study, a new technique for identifying Iraqi license plates utilizing local horizontal projection and vertical projection was introduced, and its efficacy is evaluated. The resulting rate for this study was 99.16%, and the average speed for each character was 0.012 seconds[19].

Iraqi License Plate Layout

Fig 4 shows the old Iraqi License Plates and Fig. 5 shows the new Iraqi License Plates, they are divided into four regions: [20, 21]

- Country this region contains the word IQR kr
- The next region is the governorate code
- The letter is a code for the vehicle's serial number
- The last region is vehicle ID.

Figure 4. Old Iraqi License Plates.

Figure 5. New Iraqi License Plates.

Methodology

The first stage of the proposed method is localization, it used many algorithms to improve and detect the region of the LP in the vehicle, and then the segmentation stage to extract the letters/ numbers from the license plate using horizontal and vertical projection algorithm, Finally, apply MBAM to recognize all numbers and characters on the license plate thought learn ad convergence phases, as shown in Fig. 6.

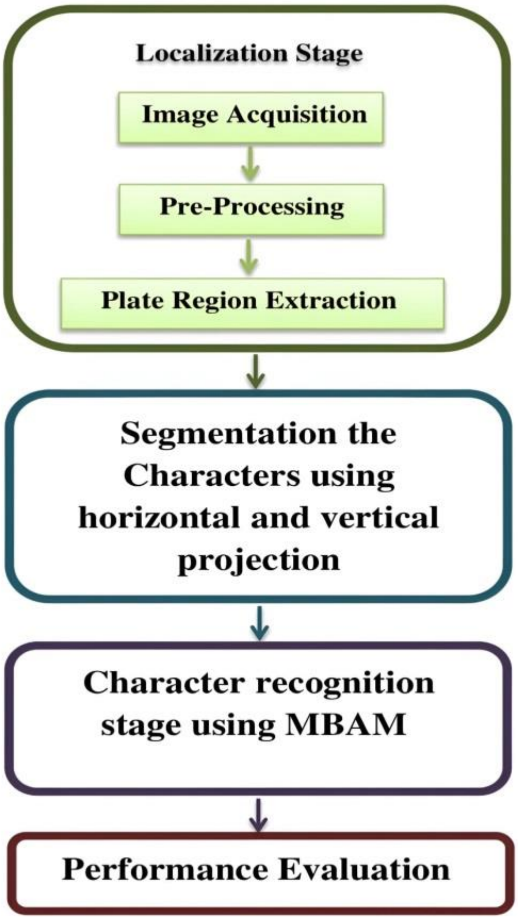

Figure 6. Proposed Methodology

Localization Stage

The first stage in the proposed Iraqi license plate model is Localization Stage, in this stage extraction of the plate from the vehicle image by applying many operations. The next subsection illustrates the steps for Localization Stage.

Image Acquisition: a digital camera was used to capture images of the Iraqi license plates from either the front or back of the vehicles. Images are

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gathered in a variety of locations, including streets, camps, and parks.

Pre-processing: Pre-processing is very important to improve license plate images because these images are captured at different times of day and in different weather conditions. The captured images are color as shown in Fig. 7 (a), where RGB image consists of three channels red, green, and blue. The values range for each channel (0-255) should be converted from RGB Image into grayscale Image because grayscale has one channel as shown in Fig. 7 (b), using Eq. 4: [22]

$$\text{Grayscale Value} = 0.2989*R+0.5870*G+0.1140*B \qquad 4$$

To facilitate the detection process of license plate images the contrast should be increased[23] as shown in Fig. 7 (c). Then apply a canny edge detector[24] to detect the appropriate edges, A Canny edge filter depends on the first derivative of Gaussian smoothing. The next step is to determine the edge strength by using the image's gradient after image smoothing and noise removal. This operator works with 3x3 window matrices in this process.

The gradient's edge strength is then determined as shown in Fig. 7 (d). To isolate the plate from the backdrop, morphological techniques such as image dilation and image erosion should be used. As shown in Fig. 7 (e), dilation enlarges objects by transferring each background pixel to an object pixel, increasing border thickness to prevent broken line problems. Then all holes in the image is filled as shown in Fig. 7 (f). This edge map was then used to identify the points where the black and white hues transitioned.

Finally, the detection of the LP from the image as shown in Fig. 7 (j) by finding a more relevant and less number of contours in the LP, then finding the smallest rectangular area enclosed by each of the contours and validating their side area and ratios, maximum and minimum areas of the plate are defined by using thresholding, to get the perfect contour in LP by finding the contours and validating the side ratios, validated region and bound rectangle area of the largest contour in that region. Finally, extracting that contour from the original image.

After extracting the LP region from the original image, the LP will be rotated with different angles, to retrieve it into a normal location using the bilinear interpolation method with the correct angle that is calculated by using the Hough transform[25].

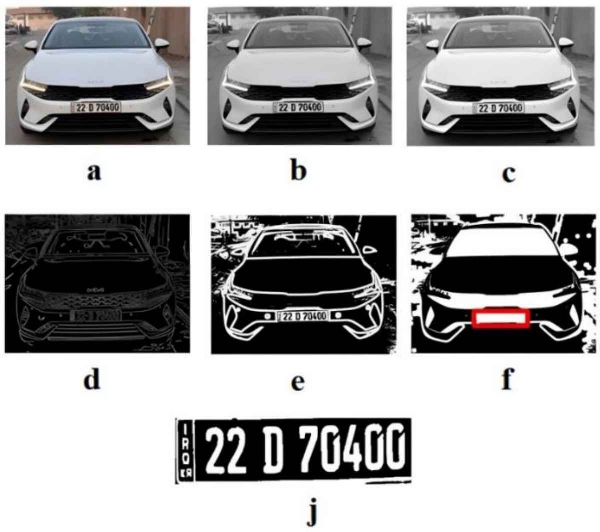

Figure 7. Pre-processing for License Plate.

Segmentation Stage

After extracting the vehicle license plate region from the original image and rotated LP to correct position, the segmentation stage is used to extract each letter/number of the LP image, the new Iraqi license plate is divided into four regions as explained in the **Section Iraqi License Plate Layout**, the horizontal and vertical projections

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algorithms are used to detect selected the actual letters/ numbers in the LP as shown in Fig. 8. This algorithm can compute horizontal, vertical and diagonal lines, by computing the total number of pixels in each row, and computing the total number of pixels in each column of the LP as shown in Eq. 5 and Eq. 6 respectively [26].

$$\text{P\_hor} = \sum_{i=0}^{C}\sum_{j=0}^{R} O(i,j) \qquad 5$$

$$P_{\_ver} = \sum_{i=0}^{R}\sum_{j=0}^{C} O(i,j) \qquad 6$$

Where:

C: Width of the LP
R: Height of the LP
P_{hor}: Projection of the Horizontal Array
P_{ver}: Projection of the Vertical Array
O(i,j): Value of the Pixels

Figure 8. Select Each Character from the License Plate

Recognition Stage

After segmenting all characters and numbers on the license plate, Character recognition is an essential part of the proposed system, by which the segmented characters are detected and recognized. The algorithm used in this stage is Modify Bidirectional Associative Memory (MBAM)[9] , this algorithm works with two phases: learning and convergence phases.

In the learning stage, where learning is limited to one sample for each letter/number With the corresponding code is represented by the ASCII code and then sorting it in a lookup table as shown in Algorithm 1.

Algorithm 1: Apply MBAM Learning Algorithm
Input: characters/ numbers with its codes.
Output: lookup table.
Step_one: Repeat step_A and step_B until end all letters/numbers with its codes: **Step_A**: Split characters/numbers to group of vectors with length two. **Step_B**: For each vector, repetition step_B1, step_B2, and step_B3: **Step_B1**: Set weight matrix for all vectors v, as following: $svwi = vi * c$ **Where**: c is ASCII code **Step_B2**: Assign Save Vector Weight (svw) as following: $svw = f(Decode(v))\begin{cases} 0 & \{means \quad w0 \\ 1 & \{means \quad w1 \\ 2 & \{means \quad w2 \\ 3 & \{means \quad w3 \end{cases}$ **Where**: convert binary to decimal by using Decode Function. **Step_B3**: store svw for all characters/numbers vectors in lookup table. **Step_two**: End

In convergence phase using the pattern to code an algorithm to recognize the unknown numbers/ letters in a plate by matching the unknown characters/ numbers with the store lookup table, which is established through the learning phase as shown in Algorithm 2. Where the minimum value in the energy function represents the number/character code that will be returned.

Algorithm 2: Apply MBAM Pattern to Code Algorithm
Input: n of unknown characters/ numbers.
Output: code for each characters/ numbers.
Step_one: Repeat step_A and step_B until the unknown letters/ numbers is ended: **Step_A**: Split characters/numbers to group of vectors with length two. **Step_B**: for all n vectors (v) in the unknown letters/ numbers should Sum the energy function with its corresponding vector that stored in lookup table: $ep = -0.5\sum vi * svwi * yi \; n \; i{=}1$ Where: yi is : $yi = vi * svwi$ **Step_two**: select minimum energy function to convergence the unknown letters/ numbers to determine stored code ($minc$) Minc=min(ep) **Where**: the min function used to select minimum ep in array of ep. **Step_three**: End

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Results and Discussion

To evaluate the performance and stability of the proposed Iraqi License Plate model, the dataset used in this work depends on several images with various resolution rates and sizes, due to the lack of a complete data set that contains Iraqi LP images, the images were captured from 1 to 5 meters distance between camera and vehicle at a 90° angle from the horizontal.

The simulation experiments were carried out in a development environment using Matlab R2022a and Operating System (OS) Windows 10 (64-bit), The hardware used to implement this study processor: Intel ® Core (TM) i7-4500U CPU @ 1.80GHz 2.40. With a Memory of 8.00 GB.

The image LP is transferred from the digital camera to the computer and stored in JPG format. The image dataset contained 255 sample images that were taken under different conditions, such as strong sunshine, shadow, and cloudy weather. The images were taken with dimensions (950 * 650 pixels).

The accuracy of the results of plate region localization is 99.6%, the accuracy for character segmentation is 98%, and the achieved accuracy for character recognition is 100% in various circumstances as illustrated in Table 2.

Table 2. License Plate Success Rate

Stage	Samples Number	Number of Correct Results	Success Rate (%)
Plate Region Localization	255	252	98.82%
Character Segmentation	252	251	99.6%
Character Recognition	252 Letter 1224 Numbers	252 Letter 1224 Numbers	100%

The related works which were presented in the previous section shows that there are nine papers with a goal similar to the present paper. These papers used different techniques to detected the characters. Therefore, it is useful to compare the proposed Hetero-associative Memory Based New Iraqi License Plate Recognition in this paper with the methods in those papers. Hence, a comparison study has been conduct by evaluating these papers.

This comparison focused on comparing the accuracy of the results for character recognition as shown in Fig 9. The results of the proposed method show that the accuracy for character recognition was higher comparing with the other works.

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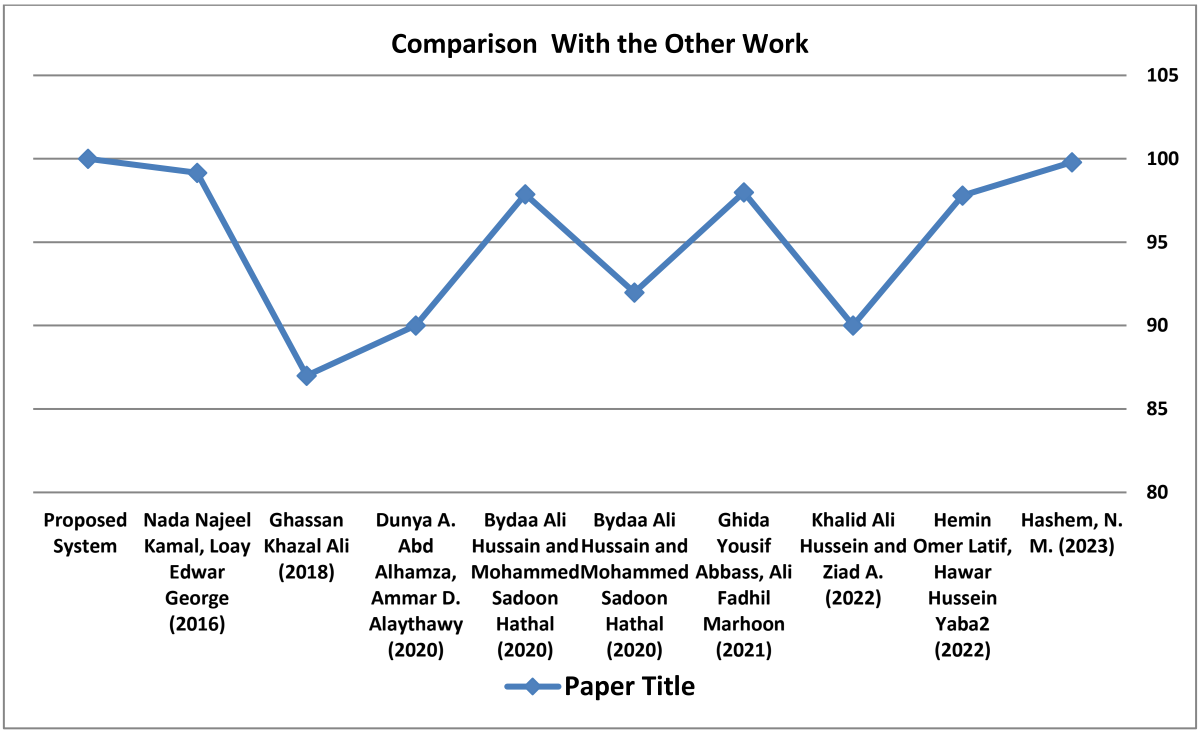

Figure 9. Shows Average Accuracy Result for Character Recognition that compares them.

Conclusion

This paper focused on developing a license plate recognition system by developing a recognition stage using Modify Bidirectional Associative Memory (MBAM), which is one type of Hetero-associative memory. The MBAM allows recognizing letters and characters on the plate through two phases: the learning phase and convergence phase, firstly the learning phases is applied to one sample for each character/number and which is then sorted it in the lookup table, and then the convergence phase is applied to the unknown license plate.

The images of the vehicles were captured from (1 to 5 m) distance at 90° angle from the horizontal. The images of the license plate is transferred from the digital camera to the computer and stored in JPG format. The image dataset contained 255 sample images that were taken under different conditions, such as strong sunshine, shadow, and cloudy weather.

This proposed model was able to overcome difficulties like poor image resolution, blurry image, poor lighting, and low contrast because MBAM's associative memory efficiency is as high as 100% even the noise rate is high, which indicates that it will distinguish numbers/letters that are distorted, poor in resolution, poor in lighting and low in contrast.

Experimentally the proposed system shows plate region localization of 99.6%, an accuracy for character segmentation is 98%, and *an* achieved accuracy for character recognition is 100% in various circumstances.

Authors' Declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images, that are not ours, have been included with the necessary permission for re-publication, which is attached to the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee at University of Baghdad.

Authors' Contribution Statement

R. H. H., I. S. A., R. M. H. and A. s. a. A. K.. Contributed to the implementation and design of the research, to the analysis of the results and to the writing of the manuscript.

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التعرف على لوحة الترخيص العراقية الجديدة القائمة على الذاكرة الترابطية المتغايرة

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الخلاصة

نتيجة للتطورات الأخيرة في أبحاث الطرق السريعة بالإضافة إلى زيادة استخدام المركبات، كان هناك اهتمام كبير بنظام النقل الذكي الأكثر حداثة وفعالية ودقة (ITS) في مجال رؤية الكمبيوتر أو معالجة الصور الرقمية، يلعب تحديد كائنات معينة في صورة دورًا مهمًا في إنشاء صورة شاملة. هناك تحدٍ مرتبط بالتعرف على لوحة ترخيص السيارة (VLPR) بسبب الاختلاف في وجهة النظر، والتنسيقات المتعددة، وظروف الإضاءة غير الموحدة في وقت الحصول على الصورة والشكل واللون، بالإضافة إلى الصعوبات مثل ضعف دقة الصورة ، الصورة الباهتة ، الإضاءة السيئة، التباين المنخفض، يجب التغلب عليها. اقترحت هذه الورقة نموذجًا باستخدام تعديل الذاكرة الترابطية ثنائية الاتجاه (MBAM)، وهي نوع واحد من الذاكرة الترابطية غير المتجانسة، وتعمل MBAM على مرحلتين)مرحلتي التعلم والتقارب) للتعرف على اللوحة، ويمكن لهذا النموذج المقترح التغلب على تلك الصعوبات بسبب قدرة الذاكرة الترابطية لـ MBAM على قبول الضوضاء وتمييز الصور المشوهة، وكذلك سرعة عملية الحساب نظرًا لصغر حجم الشبكة. نتيجة دقة تحديد منطقة اللوحة هي 99.6٪، ودقة تجزئة الأحرف 98٪، والدقة المحققة للتعرف على الأحرف هي100 ٪ في ظروف مختلفة.

الكلمات المفتاحية: الذاكرة الترابطية غير المتجانسة، تمييز لوحة الترخيص، تعديل الذاكرة الترابطية ثنائية الاتجاه (MBAM)، الشبكات العصبية والمركبات.