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Car Plates Recognition System Using Deep Learning

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Abstract: *Car plate recognition (CPR) systems provide valuable benefits to both the people and governments. At the level of people, CPR systems facilitate performing tasks related to parking and reporting stealing cars, while at the governmental level they can be employed for arranging traffic flow, monitoring borders and tracking criminal traffic. Due to these advantages, CPR systems have been received significant attention from research groups. Traditional CPR systems suffer from high computational costs as well as low performance and recognition accuracy. To overcome this challenge, deep learning technique are used. However, to build a robust CPR system, two kinds of factors must be taken into consideration, which are external and internal factors. External factors related to poor quality of car plate due to some accidents, broken content, and rusty chars. External factors are related to weather conditions such as rainy, dusty, or foggy cases. The reviewed related works show low resistance against the two types of factors. In this paper, the Convolutional Neural Network (CNN) is employed to build a robust CPR system. In the first stage of this paper, the problem is stated along with the research questions, as well as the general overview of the methodology. It is expected to have a CPR system as an outcome of this paper and this system has high resistance against internal and external factors.*

Key Word: *car plate recognition (CPR); factors; deep learning; Convolutional Neural Network (CNN); Cost; performance.*

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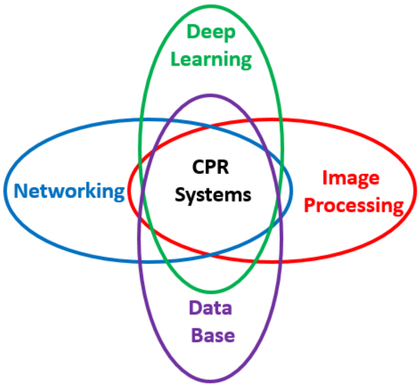
I. Introduction

In the research field of car plate recognition, researchers differentiate between two main terms, which are Car Plate Detection (CPD) and Care Plate Recognition (CPR). By definition, CPD is a term that refers to the process of localization of the car plate within a given image that includes the whole parts of the car. In other words, the CPD is the process of isolating the car plate from the other objects that can be found in the image, such as the mirrors, the wheels, and lights etc [1]. The CPR is a term that refers to the process of determining the identity of the owner's car (i.e., recognizing the content of the pate including numbers and letters) [2] Depending on the previous definition, the CPR includes the CPD.

The CPR based systems can be seen from a special point of view that for a point of intersection among various research areas. The CPR involves four main research areas, as shown in Figure no 1.

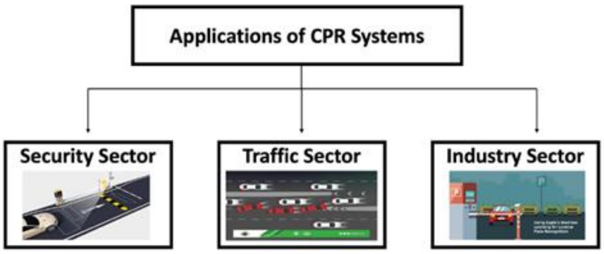
Figure no 1: The Intersection of CPR Systems and Other Research Fields.



As shown in Figure no 1, CPR systems intersect with four main research fields, where each field has its own concepts and contributes in a special part in the process of building the CPR systems.

The motivation behind this paper comes from the importance of CPR systems and their applications in our realistic life. Figure no 2. shows some important applications of CPR systems.

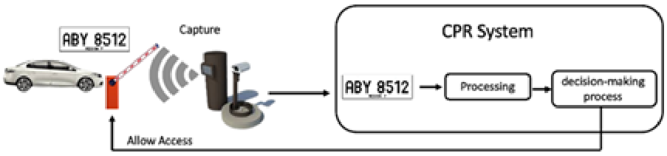
Figure no 2: Applications of CPR Systems.



As shown in Figure no 2, the CPR systems contribute in the industry sector through employing them to construct smart parking systems. Such parking systems facilitate the mobility of crowds at peak hours and also manage the traffic areas for good cities planning [3].In the traffic sector, CPR systems are used to detect the cars that exceed the dead line of the speed that is pre-determined by traffic authorities (i.e., Saher) [4]. In the security sector, governments need to have monitoring boundary systems to check and detect the cars of passengers or the intruders. CPR systems form the backbone of such security boundary systems [5].

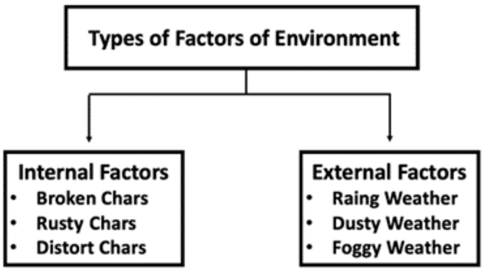
The problem is presented in a gradual manner, so that firstly the scenario of executing of the CPR system is provided without taking into account that the car plate is captured in a typical environment. Then, the scenario of executing of the CPR system is provided taking into account that the car plate is captured in real environment. Figure no 3 illustrates the first scenario.

Figure no 3: Executing of the CPR System Taking into Account a Typical Environment.



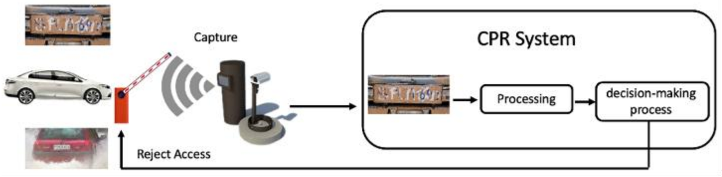
As shown in Figure no 3, the camera (linked with the border security system) takes a photo of the front of the car. Then the car plate is processed for making decision about if it is authenticated or not. After that, the border security system issues a signal to the control panel to allow access the car. The problem is arisen when the car is located in abnormal environment, where the decision is changed. In other words, there are two kind of factors that control the environment within which the car plate is captured, a shown in Figure no 4.

Figure no 4: Factors that Control the Environment.



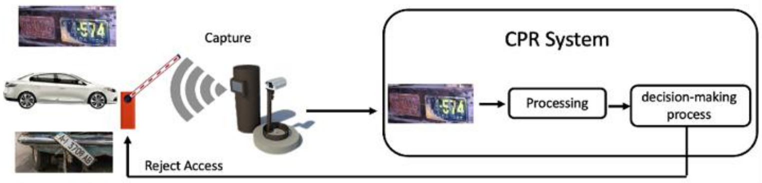
As shown in Figure no 4, weather conditions may be located during capturing the care plate, where it is happened that some drops of water bluer the car plate, and the same when the weather is dusty or foggy. The second factor is related to the content of the car plate, where the objects (chars) that form the car plate may be broken by a collision with heavy objects, rusty chars due to the long-time of parking, or distort chars due to an accident. All of these factors must be taken into consideration in the CPR systems. Otherwise, a problem will be happened, as shown in Figure no 5 and Figure no 6.

Figure no 5: Negative Impact of External Factors.



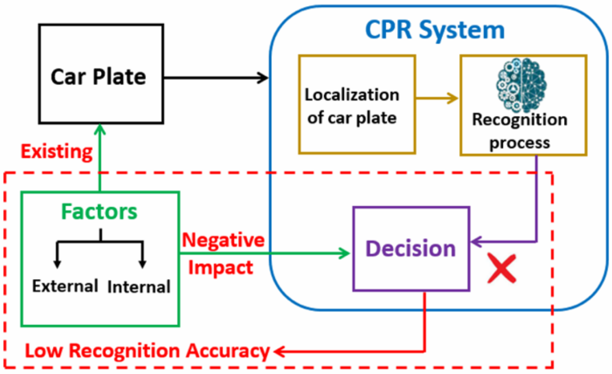
As shown in Figure no 5, the border security system rejects the access because it cannot recognize the car plate in spite of that the car is authenticated. Therefore, external factors negatively affect the accuracy of the system.

Figure no 6: Negative Impact of Internal Factors.



As shown in Figure no 6, the border security system behaves the same as in the Figure no 5, and the root reason is relating to the distortion on the content of the car plate. Therefore, internal also factors negatively affect the accuracy of the system.
From artificial intelligence point of view, the problem stated above is translated into a low accuracy of car plate recognition. Figure no 7 illustrates the idea.

Figure no 7: Problem of CPR Systems from Artificial Point of View.

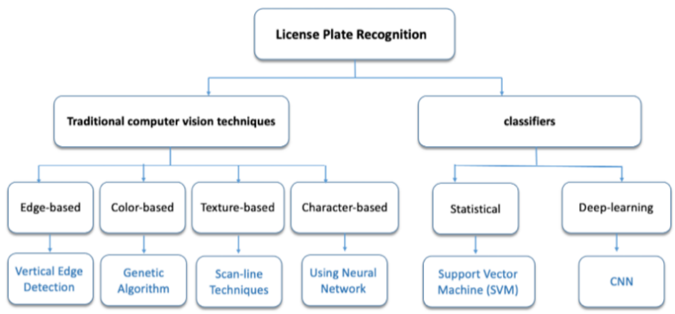


As shown in Figure no 7, existing one or two of the factors (internal and external) affects negatively on the decision-making unit in the CPR system. The result is low recognition accuracy.

II. Related work

The approaches that are proposed previously in the domain of car plate detection and recognition can be divided into two main categories, which are traditional category and advanced category. Each category has its own techniques that is used in the process of detecting and recognizing. Figure no 8 shows the categories.

Figure no 8: Categories of Car Plate Detection and Recognition.



As shown in Figure no 8, classifiers can be statistical or deep learning (i.e., can be built using statistical methods or deep learning methods). For statistical classifiers, they based on Support Vector Machine (SVM). The key idea behind the SVM based systems is to group the data (letters and numbers) into some categories based on the distance between the manipulated char and the center of the category. The SVM uses a margin to enhance the quality of the outputs of the system 6. Since this research concerns about deep learning-based systems, we focus on the CNN-based systems.

For deep learning classifiers, they use artificial intelligence with its advanced methods to train and test car plate recognition systems. The authors in the work [1]. depend on the fact that state "there is a positive relationship between the increasing number of the cars that are running on roads and the increasing number of accidents" to highlight that the problem committing traffic crimes is pressing to be solved. The presence of a system capable of detecting license plates helps the responsible authorities in the process of arresting traffic violations. In response to this need, the tuners proposed a license plate detection system for the Bangladesh Ministry of Transport. This smart system consists of two phases, which are the vehicle plate content detection phase and the character recognition phase within the plate. In the first stage, the letters are isolated from the rest of the elements in the painting that do not represent letters. Then the system improves the accuracy of the detected characters and surrounds them with a rectangle in order to start training on them. In the number recognition stage, convolutional neural networks are used to extract features and practice them.

The proposed system is trained on 700 hand-assembled images with the accuracy achieved being 98.2 %. The advantages of this paper are related to the high level of accuracy achieved, especially in light of dealing with the relatively difficult language of Bengali. But the drawbacks of this paper can be summed up by focusing on one type of language in which car license plates are written. Meaning that the proposed system may give unfortunate results if it is trained on Spanish license plates, for example.

The authors of the work [7] manipulated the problem related to detect and recognize Iranian car plates. In depth, the process of detecting car license plates, especially if there are some of characters inside, is a difficult problem. The reason behind this is related to different conditions that may be faced during the detecting and recognizing process. The authors deal with weather, lighting, and noise conditions, which negatively affect the level of detection accuracy. In responding to this issue, the authors proposed the unified License Plate Detection (LPD) and Character Recognition (CR) system. The proposed system goes through many steps, the system takes the car image as an input. Then an optimization is done on the captured image. Next, the plate of the car is isolated from the car image. Here, the process of learning the model starts, where the model is trained on three datasets for the purpose of detecting and recognizing the chars and the numbers of the plate car. Three different data sets are used to train and test the proposed system. The datasets cover a wide range of features that reflect a difficult environment that mimic the real life (i.e., the images are from various font size, have different color backgrounds, have different levels of noise and luminance). Table no 1. summarizes the most important properties of the used datasets.

Table no 1: Description of the Data Sets Used in ref [7].

Dataset NO	Dataset Name	Dataset size	Properties
1	Fashtam semi	5,219	Different wither and illumination condition
2	Roudbar toll road camera outputs	6,371	Multiple views of vehicles and license plates
3	Collected real	3,982	Color images

Conducted experimental results on the three datasets show that the accuracy of the proposed system is 95.05%. The main advantages of the LPD-CR system are (1) it has a high accuracy degree; and (2) it has the ability of detecting plats in real-time. The long processing time forms the major disadvantage of this paper.

The authors of the work [8]. stated that the works that are proposed in the field of License Plate Detection and Recognition (LPDR) are not typical. The authors justified this fact by declaring that the previous works are conducted within a frame of good conditions and they use capturing image systems of high quality. In other words, the previous works manipulate images of cars of excellent quality and no strict environmental conditions are taken into consideration, such blurring images or rainy weather referred as external factors. In addition, there are some internal factors that are included in the car plate itself and contribute to degrade the accuracy of the detection system, such as character styles, such as different sizes, fonts, and distortion.

There are car plate detection and car plate recognition. The goal of the first stage is detecting the place of the plate (i.e., isolating the plate from other objects such as wheels, and lights). The goal of the second stage is recognizing the content of the car plate (i.e., letters and numbers). In the detection stage, a CNN based system is used. It has a unique feature which is eliminating the false positives (which are the images that the system cannot detect them). Then, the detected plates are surrounded by boxes as a mark for successful process. It is worth mentioning that eliminating false positives depends on some rules and this procedure is performed by the Convolutional Neural Networks (CNN). As for the recognition stage, another deep learning technique is used, which are Recurrent Neural Networks (RNN). The RNN is effective when dealing with text data (training on text data). Since the content of the car plate is a text, the problem of recognizing the car plate can be converted into a sequence labeling problem. for the used data set for training phase, the authors relied on the International Conference on Document Analysis and Recognition (ICDAR) data set. The results show that the system achieved 97.39 % in terms of precision. The advantage of this paper is related to high level of accuracy due to high level of precision. In addition, segmentation is avoided due to using CNN for feature extracting. However, the disadvantage is related to low resistance against rotation or bilinear attacks (non-geometric attacks).

In addition to the general problem that the car plate recognition systems suffer from, which is the low accuracy due to the poor capturing devices (or cameras) and the noise caused by the environmental factors that surround the car plate, the authors of the work [9]. mentioned to another problem. The problem is related to the shape of some chars that are similar to each other's so that the recognition system fails to distinguish between them. The authors give some examples about this problem, such as the (8) number and (B) letter as well as the (T) letter and (7) number. When a recognition system fails to recognize such chars, the prediction process (or classification) will be of poor accuracy

There is a preprocessing step, followed by two main recognition methods. The goal of the preprocessing step is to enhance the quality of the car image as could as possible as well as detecting the car plate (i.e., determining the location of the plate among other objects such as lights or wheels). After that, the image is used as an input for statistical method. This statistical method consists of four sub classifiers that use the voting technique in the process of classification. voting technique means that if more than the half of the sub-classifiers determine that the car plate is recognized for a certain person, the output will be confirmed according to the popularity. The second recognition method is structural one. This method starts if the car plate has some chars that belong to similarity set. The similarity set includes the chars that are similar to each other's. if the car plate contains such similar chars, the structural method extracts the features and forms a decision tree for generating the final classification output. For the dataset that is used for training, it is collected manually, where the size of this dataset is 50 images taken from different angels during the capturing process. The test of the system shows that the recognition rate is 95.41. The advantage of this paper is related to manipulating a special problem related to the similarity of chars. This reflects PowerPoint when it comes to applying this system on Chinese cars, where there are large number of chars similar to each other's. however, the disadvantage is related to accentuated problem when dealing with area of video text analysis.

The authors in the ref [10]. handled the problem of recognizing plate cars in Arabic country which is Egypt. They justified the importance of the need for an effective car plate recognition system by (1) the increased number of cars in Egypt; and (2) huge number of families tend to have more than one car. The feature of this paper is related to recognizing the Arabic chars located in the Egyptian cars. The authors proposed a system that consists of three main stages, which are detecting the car plate, recognizing the chars located in the content of the plate, and communication with a data base.

Firstly, the car image is captured using a certain device. To identify the exact location of the plate, edge detection method is used. edge detection means that both the angels and boundaries (height and width) that form the shape of the plate are determined. Then, the plate image is passed to a filter for cleaning (smoothing) purpose. after that, the car plate is segmented, which refers to isolating the content of the plate (numbers and letters separately). In the second stage, the chars are recognized based on statistical approach (that depends on simple matching). Finally, the recognized car plate is sent to a data base to be compared with the content of it. If the content is located, then the car is considered recognized for a specific person. For results, the authors achieve 91 % accuracy. The advantage of this paper is that it is considered as a core for developing an advanced car monitoring system specialized for Arabic cars. However, the disadvantage is that it did not take into consideration the impact of the environmental factors.

The authors of the work [11]. deal with a problem of two faces. The first face is related to low accuracy of recognizing the car plates in a natural space due to the continuous changes that control it, such as rain, dust, shadows etc. The second face is related to the general scenario used in other car plate recognition approaches, which consists of two separated stages (detection stage, where exact location of the car plate is determined and recognition stage, where the content of plate is recognized). To solve the previous problems, the authors propose a deep learning car plate recognition system that uses two techniques of deep learning combined with a single stage rather than two stages.

The whole car image is used as an input. Then the CNN network starts its work by scanning the input image in a convolutional manner for the purpose of extracting features. Depending on the extracted features, the Region of Interest (RoI), which represents the location of car plate, is formed. After that, the features of the RoI are pooled for the detection by the fully connected layers of the CNN. At the same time, the features are passed to the RNN network for recognition. The RNN handles the content of the car plate as a text. Combining the two kinds of the neural networks allows to take the strong properties of each one, which are reflected as a good level of both detection and recognition in natural scenes. A Chinese data set is used for training and testing called CarFlag-Large. The system is also tested using the Application-Oriented License Plate (AOLP) database. For the results, the system outperforms the similar system in terms of speed (it achieves 300 ms), recognition rate (95 %), and detection rate (99.38 %). The advantage of this system is related to shoot wo birds in a one stone (i.e., performing detection and recognition at the same time), which leads to better processing time. the disadvantage is related to low resistance against lightening attacks.

In their work [12], Marko et al. addressed the limitation of using Optical Character Recognition (OCR) for car plate recognition. The problem with OCR is related to its high computational cost and complexity due to several steps that are required as well as handling chars (letters and numbers) on the plate individually. To overcome this problem, the authors employ deep learning to enhance the OCR system by supporting it by CNN. The key idea of enhancement is related to replace the localization step in the OCR by car plate detection based on CNN. In addition, the step of manipulating the chars individually is replaced by classifying the chars based on the features extracted by the CNN. In the OCR, localization step means the plate car location is identified depending on allaying the body of the car. This requires (1) converting the background into binary color system; (2) extracting edges of the shape of the car; and (3) comparing the objects included in the shape with a reference shape to locate the plate. Such steps lead to high mathematical operations in terms of image processing. In contrast, the CNN is trained on a data set of image cars which requires less time for detecting the plate car. Manipulating the content of the plate (chars) individually requires isolating the chars by surrounding each char using a rectangle to start the procedure of matching between each char and the content of what is stored in the data base (i.e., the shapes of numbers and letters). This also consumes the processing time, which is reflected negatively on the recognition time. Using CNN facilitate this process based on a series of convolutional and pooling layers to extract features and using the features in the process of prediction (i.e., classifying the chars of the plate for recognition purpose). The authors achieved overall accuracy is 98% for plate detection, 97% for letters recognition and 94.5% for digit recognition. The advantage of this system is related to highlight the employing of CNN to lowering the complexity and prediction time. however, the downside is that the system did not tested under threats of noise and blurring attacks.

As shown in Figure no 8 (classification figure), the traditional based CPR systems can belong to one of four categories, which are edge-based systems, color-based systems, texture-based systems, and char-based systems. The traditional based CPR systems suffers from high complicity, poor responding time, and low level of accuracy [13]. The reason is that they depend on pure image processing operations, which can be seen as manual methods (not automatic ones to give them the feature of intelligence as in deep learning based systems).

To define the research gap, we rely on a comparison way among the reviews systems depending on some criteria. The criteria that rule the comparison is (1) resistance against internal and external factors, computational cost, time performance, and accuracy. Table no 2. summarizes the comparison.

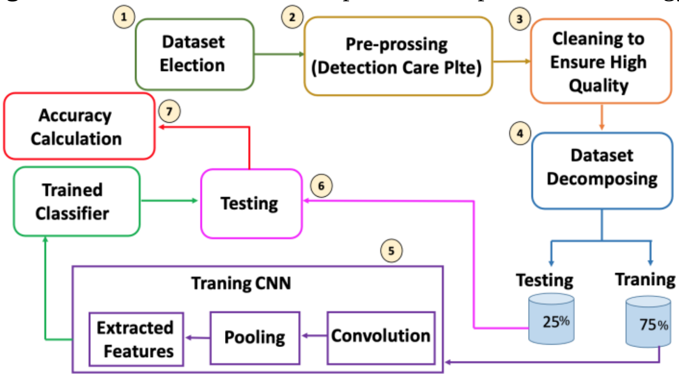
Table no 2: Comparison of Reviewed CPR Systems.

Class	Ref	Criteria (×: not achieved, √: achieved, Ɵ: unknown)							
		Resistance Against Internal Factors			Resistance Against External Factors			Cost	Accuracy
		Broken	Dusty	Distort	Rain	Dusty	Foggy		
Deep Learning Based CPR Systems	[1]	×	×	×	×	×	×	Low	High
	[7]	×	×	Ɵ	×	×	√	High	High
	[8]	×	×	×	Ɵ	Ɵ	Ɵ	Low	High
	[9]	√	×	√	Ɵ	Ɵ	Ɵ	High	High
	[10]	√	Ɵ	√	×	×	×	Low	High
	[11]	Ɵ	Ɵ	√	×	×	×	Low	High
	[12]	×	Ɵ	Ɵ	Ɵ	×	Ɵ	High	High

III. METHODOLOGY

This paper employs the CNN deep learning technique to construct a classifier that has the ability of recognizing care plates. There are seven main steps that adjust the proposed methodology. Figure no 9 gives an overview about the proposed methodology and the main steps.

Figure no 9: Overview of the Steps of the Proposed Methodology.



Data set election

In this step, the data set that is used for training the intelligent model is selected. There are many data sets for car plates available on the internet. The most common data set that is used frequently in researches is the Kaggle data set [14]. However, this data set suffers from many issues, which are:

- It does not contain Arabic Saudi plate cars, where all images are related to European or American countries. Therefore, no Arabic chars or numbers are contained within the content of the images.
- The images do not include internal and external factors. Therefore, they cannot be used for achieving the main objective of this paper.
- The images are varying in patterns. In other words, there is no standard pattern that is followed in the images. for example, some plate cars have a series of numbers or chars in consequences, while others have series of numbers and chars with vertical location. In addition, some plates consist of chars followed by a number followed by other chars. As a result, there is no clear pattern that adjusts the plate cars as the same way in the Arabic Saudi cars.

Figure no 10 shows a sample image from the Kaggel data set that supports the issues mentioned above

Figure no 10: Some Images from the Kaggle Dataset

Due to the shortage of the Kaggle data set, we moved towards collecting the plate cars manually to build the data set that will be used for training. In this context, 50 Arabic Saudi Plate Cars (ASPCs) are gathered from various resources, such as cars of family, cars of friends, cars of neighbors, and cars from laundry. Table no 3 presents a brief summarization about the ASPCs dataset.

Table no 3: Description of ASPCs dataset.

Number of images	Image type	Size of image
50	GPEG	various

Figure no 11 shows a sample from the ASPCs dataset.

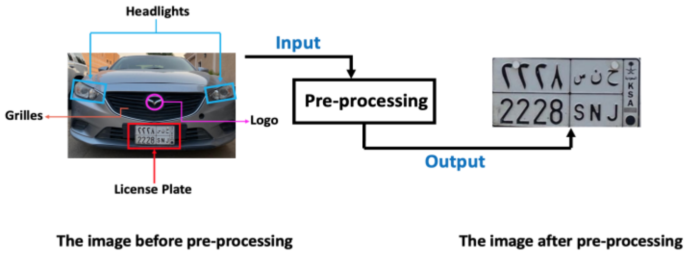
Figure no 11: Some Images from the ASPCs Dataset.

As show in Figure no 11, the car plate is captured from Infront of the car (as it is noticed in the first three cars located on the upper raw) or from the background (as it is noticed in the other three cars located in the lower raw). In addition, the number of objects that are included in the photos (besides the car plate) varies according to the angel of capturing. Moreover, the captured cars are located in natural views, parking at university, on roads of neighborhood, or car wash.

Pre-Processing Step

In this step, the plate of the car is localized. The car images included in the data set have many objects. For example, for a given car image, it may happen that the image includes front lights, wheels, cover of engine, and the plate. The plate of the care needs to be isolated from other objects, which referred as pre-processing. Figure no 12 shows a car image taken from the ASPCs dataset before and after pre-processing step.

Figure no 12: Input and Output of Pre-processing Step.

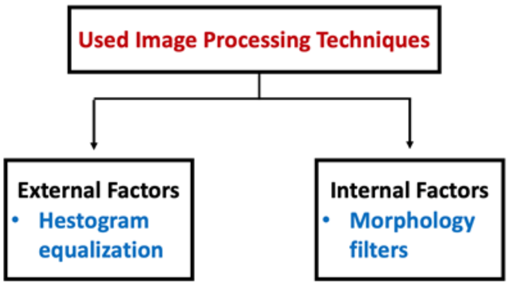


In Figure no 12, the car image is captured from the face. Therefore, there are many objects located in this image, which are logo, headlights, grilles and license plate. The input of the pre-processing step is the care image with all objects. After performing the pre-processing step, the output will be only the car plate object.

Cleaning

In this step, some image processing operations are performed for the purpose of enhancing the quality of the car plate image isolated from the previous step. This step contributes to adopt the proposed system with both internal and external factors. Two kinds of image processing techniques are employed in this paper to deal with previous factors, as shown in Figure no 13.

Figure no 13: Image Processing Techniques used for Internal and External Factors.



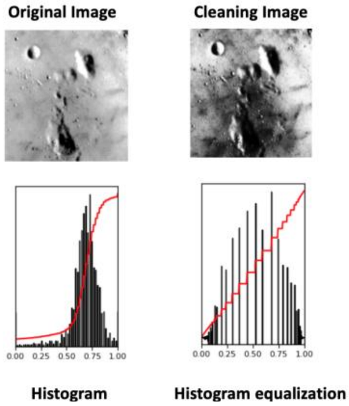
1. Histogram Equalization

In general, histogram in image processing can be defend as a graphical representation of the number of colors of pixels located in a given image (mathematically as a function of their intensity). From structure point of view, histogram consists of bins, each bin represents a certain intensity value range. The histogram can be obtained by navigating all pixels and assigning each to a bin relying on the pixel intensity. The final value of a bin is the number of pixels assigned to it according to their colors. For a given image (Img) where $Img: \lambda \longrightarrow [0, N-1]$, the binned histogram for Img is the function :

$$h(i) = number\ of\ pixels\ \{(u, v) | \psi_i \leq Img(u, v) < \psi_{i+1}\}$$

Histogram equalization is a method in image processing that targets contrast adjustment using the image's histogram [15]. One of the main purposes of histogram equalization, also known as histogram flattening, is improving contrast in images that suffer from either blurry or have a background that is unclear. In addition, histogram equalization helps sharpen an image [16]. Figure no 14 shows a visual benefit of using histogram equalization.

Figure no 14: Example of Enhancing Contrast Using Histogram Equalization [17].



It is clear that the feature provided by the histogram equalization contributes to the treatment of External Factors because it improves the differentiation of the image and thus increases its quality by clarifying the elements that make up the content of the car dashboard (to deal with them directly) and highlighting the unwanted elements in order to filter them such as: water droplets, fog, the dust.

Let f be a given image represented as a m, by m. matrix of integer pixel intensities ranging from 0 to L–1. L is the number of possible intensity values, often 256. Let p denote the normalized histogram off with a bin for each possible intensity. So

$$p_n = \frac{number\ of\ pixels\ withe\ intensity\ n}{total\ number\ of\ pixels} \qquad n = 0, 1, \ldots, L-1.$$

The histogram equalized image g will be defined by

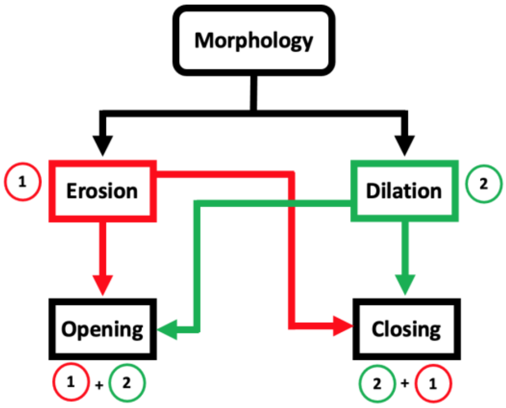
$$g_{i,j} \ = floor\left((L-1)\sum_{n=0}^{f_{i,j}} p_n\right)$$

where floor [18]. rounds down to the nearest integer

2. Morphing filters

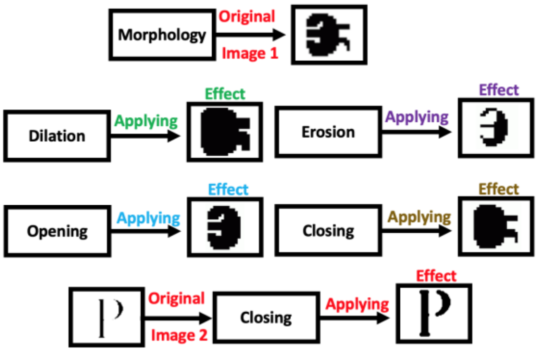
In image processing domain, morphing is a term that refers to shape-based manipulating images by applying some operations that are tightly-coupled with the values of neighboring pixels for the purpose of enhancing the objects that are included within images and form their structure [19]. In terms of operations, morphing filters refer to the actual manipulations that are applied on given images. There are two major morphing filters, which are erosion and dilation. From erosion and dilation, two another filters are derived, as shown in Figure no 15.

Figure no 15: Basic Morphing Filters and Derived Filters.



As shown in Figure no 15, the derived opening morphing filter is generated by applying erosion followed by dilation, while the derived closing morphing filter is generated by applying dilation followed by erosion [20]. To illustrate the effects of the morphing filters, figure no 18 shows some original images and the outputs of applying the different morphing filters mentioned above.

Figure no 16: Morphing Filters and their Effects.



As shown in Figure no 16, the effect of dilation is widening the edges of the object, so it benefits to fill holes if it is found. The effect of erosion is smoothing the edges of the object, so it benefits to minimize the boundaries of object. The effect of opening results in more recognizing the object, while the effect of the closing results in filling internal hols and highlighting the boundaries of the object. As a result, the morphing filters can effectively deal with internal factors. The lower part of Figure 18 shows how applying closing results in recognizing the blurred "P" letter.

Data Base Division

In this step, the car plates data set that is cleaned is divided into two data sets. One is used for training and the second is used for testing. The mechanism of dividing depends on allocating 80% of the original data set for training and the rest (20%) for testing. Since the total number of Saudi car plates is 50, this means that 40 images are used for training and 10 are used for testing

Training Phase

The training data set is used for training the Region-based Convolutional Neural Network (RCNN). The process of training incudes series of two main procedures, which are convolutional procedure and pooling one. The convolutional procedure aims at scanning the given car plate in a convolutional manner using some filters. The output of the convolutional procedure is partial features that approximately shape the car plate. The pooling procedure aims at collecting (or combination\assembling) the partial features in a one container to shape the car plate (i.e., the content, which consists of chars and numbers). The output of the pooling procedure is a vector of features that are extracted. At the end of this step, a trained classifier is ready for testing.

Testing Phase

In this step, the trained classifier along with the testing data set are involved in a testing process\phase. Testing process aims at measuring the quality of the classification (i.e., the ability of the trained classifier to predict a given car plate).

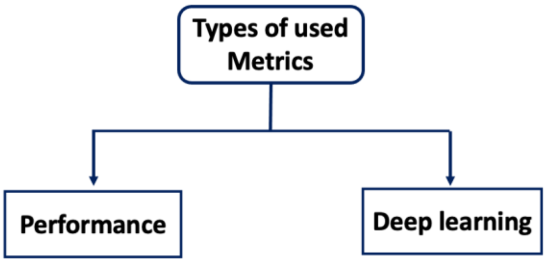
Reporting Accuracy

In this step, the accuracy that represents the benchmark of quality of the trained classifier is calculated. For example, in the testing data set has (100) car plate image, and the trained classifier classified (90) image correctly, then the accuracy will be 90%.

1. Mechanism of Evaluation

In this paper, two types of metrics are used for evaluation, as shown in Figure no 17.

Figure no 17: Metrics for Evaluation Purpose.



As shown in Figure no 17, there are two types of metrics that are used in this paper. They are explained as described below.

Deep Learning-Based Metrics

In deep learning and artificial intelligence domain, the confusion matrix is a term that refers to the different cases that may be occurred with a given classifier taking into consideration the output of the classifier and the value of classes in reality. In this context, it can be seen as an effective framework used for providing insights analyzing how well a classifier can recognize records (in this paper, cars plates) of different classes [21]. The confusion matrix is established using four terms:

- True positives (TP): positive records that are correctly labelled by the classifier. In this paper, True Positive Arabic Car Plate (TPACP) abbreviation is used to express this term.
- True negatives (TN): negative records that are correctly labelled by the classifier. In this paper, True Negative Arabic Car Plate (TNACP) abbreviation is used to express this term.
- False positives (FP): negative records that are incorrectly labelled positive. In this paper, False Positive Arabic Car Plate (FPACP) abbreviation is used to express this term.
- False negatives (FN): positive records that are mislabeled negative. In this paper, False Negative Arabic Car Plate (FNACP) abbreviation is used to express this term.

Table no 4. shows the confusion matrix in terms of the TPACP, FPACP, FNACP, and TNACP values.

Table no 4: Confusion Matrix.

Actual class (Predicted class)	Confusion matrix		
	CP	¬ CP	Total
CP	TPACP	FPACP	TPACP + FPACP = P
¬ CP	FNACP	TNACP	FNACP + TNACP= N

Relying on the confusion matrix, the accuracy, sensitivity, and error rate metrics are derived. For a given classifier, the accuracy can be calculated by:

$$\boldsymbol{Accuracy} = \frac{(\mathbf{TPACP+TNACP})}{\boldsymbol{number\ of\ all}\ \mathbf{car}\ \boldsymbol{images\ in\ the\ testing\ set}} \quad (1)$$

Mechanisms for accuracy-based evaluation. The fact states that a higher accuracy corresponds to a better classifier output.

Sensitivity refers to the true positive recognition rate. It is given by:

$$\boldsymbol{Sensitivity} = \frac{\boldsymbol{TPACP}}{\boldsymbol{P}} \quad (2)$$

Mechanisms for sensitivity-based evaluation. The fact states that a higher sensitivity corresponds to a better classifier output.

The error rate is defined as the ratio of mistakes made by the classifier during the prediction process. It is defined as:

$$eror\ rate = 1 - accuracy \quad (3)$$

Mechanisms for error rate-based evaluation. The fact states that a higher accuracy corresponds to a good classifier output.

Performance-Based Metrics

$$PT = TCPD + TEQ + TCR \quad (4)$$

Where: PT (Performance time), TCPD (Time spend on Car Plate Detection), TEQ (Time Enhancing Quality), TCR (Time spend on Car Recognition)

IV. Chapter Of Results

Introduction

This chapter presents the experimental results of the proposed intelligent. According to the metrics defined in the previous chapter, the results are documented. The system is executed many times to obtain results. To arrange things, the setup of the system is explained, followed by evaluations and discussions are presented.

Setup

The proposed intelligent system is implemented using the MATLAB programming language. After designing and implementing the proposed system, it is executed on a laptop that has the specifications summarized in Table no 5.

Table no 4: Specifications

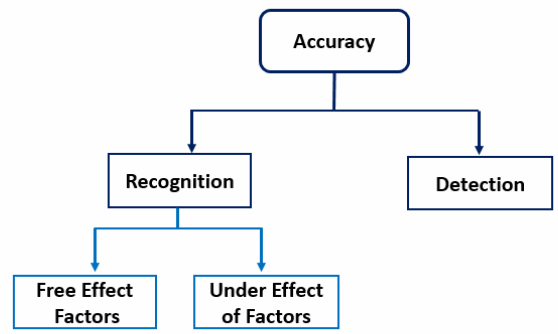
Item	Details (value)
Operating system	MacOS Big Sur
System type	Version 11.6
System model	MacBook Pro (Retina, 13-inch, Mid 2014)
Processor	2.6 GHz Dual-Core Intel Core i5
RAM	8 GB 1600 MHz DDR3
Display chip type	Intel Iris 1536 MB

Results and Dissections

Documenting the results of experimentations is conducted along with a comparison with two systems that are proposed previously and explained in the related work chapter. They are: (1) LPD-CR System, published in 2020, where it achieved 95.05 % accuracy; and (2) OCR-CNN System, published in 2017, where it achieved 98 % accuracy.

The metrics that are defined in the previous chapter are used to arrange documentation of results. For the accuracy metric, Figure no 18 shows the corresponding arrangement of using accuracy to evaluate the proposed system from different points of views.

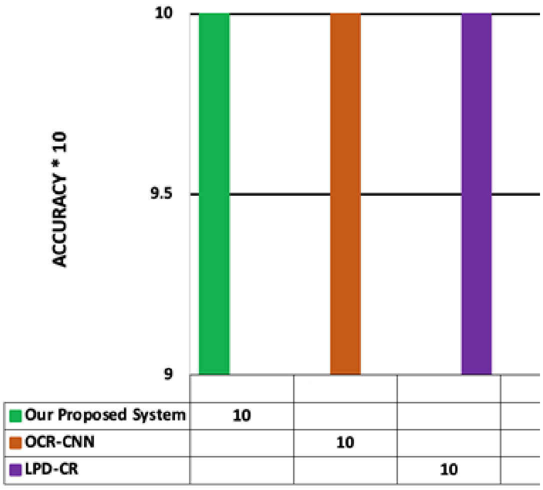
Figure no 18: Using Accuracy Metric to Evaluate the Proposed System from Different Perspectives.



As shown in Figure no 18, the proposed system is evaluated in terms of detection of car plates as well as recognition of them under two cases, which are free effect factors and under effect of factors.

For the detection of the car plates, figure no 19 illustrates the values of accuracy metric for the three systems involved in the comparison.

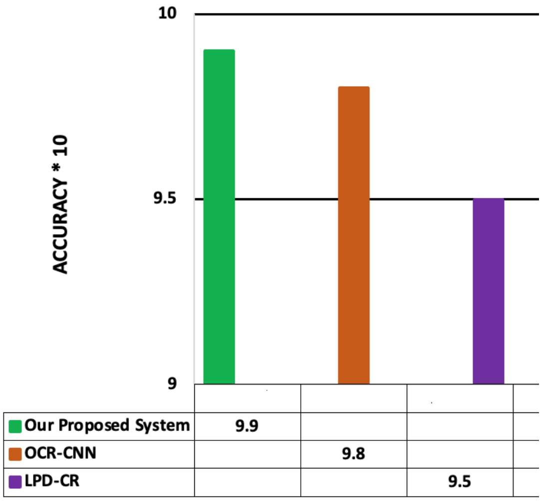
Figure no 19: Accuracy of Car Plate Detection for Three Systems.



As shown in Figure no 19, the accuracy of detection of car plate for the all systems is 100 %. That is because all the three systems have an excellent ability to locate the car plate for further manipulation (i.e., recognition, which are the most important aspect).

For the recognition according to free effect of factors, figure no 20 illustrates the values of accuracy metric for the three systems involved in the comparison.

Figure no 20: Accuracy of Recognition According Free Effect of Factors.

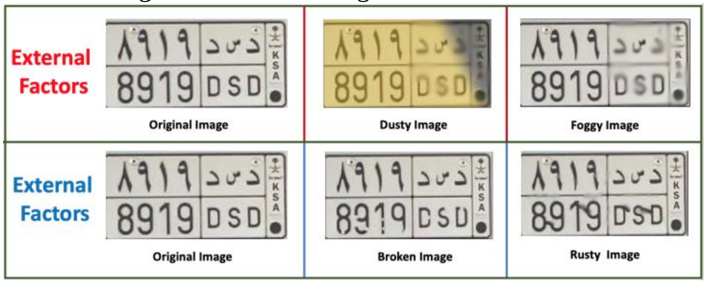


As shown in Figure no 20, the accuracies of the car plate recognition systems are ranked so that our proposed system occupies the top followed by the OCR-CNN system, and finally the LDR-CR system comes at the end. The reason why our proposed system gives better level of accuracy is related to (1) enhancing the region of interest which contains exactly the letters and numbers of the car plate; and (2) using the CNN that trained on a clear and high quality features. The OCR-CNN performed an enhancement step, but it is located before determining the region of interest, which in turn distributes the focus of extracting the features on the whole images (i.e., other objects that are not related to the care plate). In addition, the OCR concept mainly depends on a matching process between the shape of the char and what is stored in the data base to recognize chars, which is weak when compared to training on clear features. When compared to the LPD-CR system, the OCR-CNN achieves better accuracy. This is because both the LDR and the OCR-CNN systems uses CNN, but the CNN is supported by the OCR contributes to enhance the ratio of features that are extracted, and thus, leads to more extensive training, which results in higher recognition accuracy.

As for the accuracy of recognition under the effects of factors, some of the care plates included in the original data set are manipulated to shape the internal and external factors. Actually, internal and external factors are not contained in any data set that is available online. In addition, we tried to collect some damaged

Saudi car plates from the Traffic Management in Tabuk City, but unfortunately, no desired car plated are located. Therefore, we moved to construct our own data set that contains the internal and external factors. The images included in the original data set are manipulated using Photoshop. Photoshop is considered an important tool used for adding some effects to original images that can be seen as an integral part of them, where the human eyes cannot recognize the added effects. Therefore, it is an excellent choice to cover the shortage of existing car plate data base with internal and external factors. Figure no 21 shown instances about the car plates before and after adding internal and external factors using Photoshop.

Figure no 21: Original Care Plate Image with Internal and External Factors.



To explain the process of generating external factors located in the upper row of Figure 21 the following steps gives the details for dusty image:

- Load original image.
- Applying Blur tool to add blurring.
- Appling Quick mask mode for adding a kind of dusting.
- Save dusty image.

The following steps gives the details for foggy image:

- Load original image.
- Blur tool to add blurring.
- Save foggy image.

To explain the process of generating internal factors located in the lower row of Figure 21, the following steps gives the details for broken image:

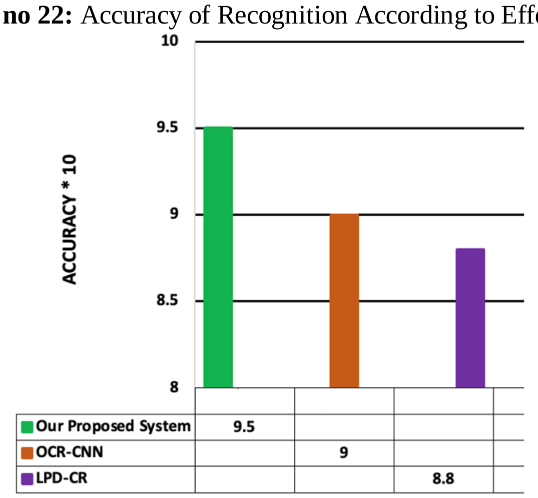
- Load original image.
- Brush tool to add blurring.
- Save broken image

The following steps gives the details for rusty image:

- Load original image.
- Brush tool
- Applying eyedropper toll (for adding lines to refer to accidents)
- Save rusty image

Figure no 22 shows the accuracy of recognition under the effects of the two factors along with the comparison with the two selected systems.

Figure no 22: Accuracy of Recognition According to Effects of Factors.



Discussion. In general, Figure no 22 shows that the accuracy of the recognition is decreased after applying the effects, which is expected due to the difficulty of extracting clear features for training procedure. In spite of this, the proposed system in this paper still occupies the top when compared to other systems. The reason behind this is related to the effective employment of the histogram equalization technique that targets the external factors (where it mitigates the negative impact represented by higher level of blurring), as well as the morphing filters techniques that target the internal factors (where they mitigate the negative effect represented by gaps or linked chars due to rusty). The amount of negative effect of the two factors can be quantified based on calculating the difference in accuracies (before and after applying the two kinds of factors). The difference is ($9.9 - 9.5 = 0.4$). However, the other systems experienced significant amount of decreasing in the degree of accuracy ($9.8 - 9 = 0.8$ and $9.5 - 8.8 = 0.7$, for the OCR-CNN and the LDR-CR systems respectively). The reason is that they are not supported by effective techniques that take into consideration such factors. It is worth mentioning that the amount of negative effect related to the OCR-CNN system is larger than the one related to the LDR-CR systems, which in turn reflects lower resistance against such factors. This can be justified by the fact that both internal and external factors target the core of the OCR-CNN system (particularly the OCR aspect) where such factors confuse the recognition system a lot.

In terms of error rate, and sensitivity, Table no 5. shows the results before and after applying internal and external factors.

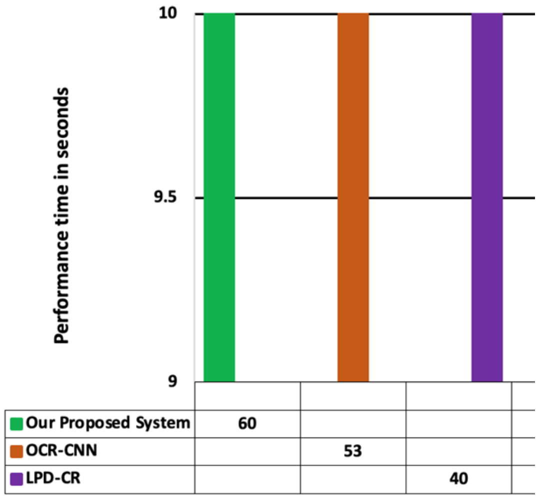
Table no 5: Values of Error Rate and Sensitivity Metrics.

Metrex			
Case	System	Error rate	Sensitivity
Before applying external and internal factors	Our proposed system	$1 - 9.9 = 0.1$	9.7
	LDP-CR System	$1 - 9.8 = 0.2$	9.5
	OCR-CNN System	$1 - 9.5 = 0.5$	9.3
After applying external and internal factors	Our proposed system	$1 - 9.5 = 0.5$	9.4
	LDP-CR System	$1 - 9 = 1$	8.7
	OCR-CNN System	$1 - 8.8 = 1.2$	8.3

Discussion. As shown in Table no 5, the sensitivity of the proposed system is the best in the two cases (i.e., before and after applying internal and external factors). This means that the ratio of recognition of the positive cases is high when compared to the other systems, which in turn reflects high degree of usability in real world (because the governmental traffic center concerns about the true recognition of the care plates). The reason why the sensitivity of the proposed system is higher than other systems is linked with the higher accuracy. In other words, there is a positive relationship between the accuracy and the sensitivity, which leads to higher degree wen compared to other systems.

For evaluation based on performance time, figure no 23 shows the comparison among the three systems that are involved, where the vertical axis refers to the performance time in seconds.

Figure no 23: Values of Performance Time Metric for the Three Systems.



Discussion. Figure no 23 shows that the worst performance is related to the proposed system introduced in this paper, followed by the OCR-CNN system, and the best system is the LDR-CR one. The reason why the proposed system comes in the last rank is related to the additional operations to deal with internal and external factors. In other words, the histogram equalization technique that is used to manipulate the external factors consumes time to execute its mission, and this time is added to the total performance time. On other had, the morphing filters techniques that are used to maintain the internal factors also require extra time to end their mission, and again this additional time is added to the performance time. The two times required for manipulating internal and external factors are not involved in the other systems, which is reflected in a manner of long performance time. The OCR-CNN requires addition time related to the OCR task, which is not involved in the LPD-CR system, which in turn justifies why the performance time of the OCR-CNN is longer than the performance time of the LDP-CR system. However, in spite of that the performance time of our proposed system is longer than other systems, the ability of recognition the car plates in hard condition (i.e., internal and external factors) is better than others which is the main objective of this paper.

V. Conclusion

Car plate recognition (CPR) systems provide valuable benefits to both the people and governments. At the level of people, CPR systems facilitate performing tasks related to parking and reporting stealing cars, while at the governmental level they can be employed for arranging traffic flow, monitoring borders and tracking criminal traffic. Due to these advantages, CPR systems have been received significant attention from research groups. Traditional CPR systems suffer from high computational costs as well as low performance and recognition accuracy. To overcome this challenge, deep learning technique are used. However, to build a robust CPR system, two kinds of factors must be taken into consideration, which are external and internal factors. External factors related to poor quality of car plate due to some accidents, broken content, and rusty chars. External factors are related to weather conditions such as rainy, dusty, or foggy cases. The reviewed related works show low resistance against the two types of factors. In this paper, the Convolutional Neural Network (CNN) is employed to build a robust CPR system. In the first stage of this paper, the problem is stated along with the research questions, as well as the general overview of the methodology. It is expected to have a CPR system as an outcome of this paper and this system has high resistance against internal and external factors.

The limitation related to this paper is for the performance aspect, where the proposed system suffers from long time pf processing when compared to the other systems. In addition, the difficulty of obtaining real car plates from the traffic governmental center of Tabuk City (due to restrict regulations of COVID-19) forms an obstacle to deal with real Saudi car plates.

In future work, we tend to enhance the performance time by dealing with novel parallel algorithms or using some platforms such as Hadoop or Spark to perform tasks in parallel. In addition, we will try to apply the proposed system on a real data set collected from the traffic center of Tabuk City.

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