LICENSE PLATE RECOGNITION TECHNIQUES: COMPARATIVE STUDY

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ABSTRACT

Vehicle License Plate Recognition (LPR) has become a crucial system for various applications such as security monitoring, parking access, law enforcement and so on. LPR is employed for the identification of vehicles using their license plate. Recently, LPR technology has evolved progressively where vast improvement had been made towards the development of the image recognition's quality and speed, as well as its state of the art methods. Although several research studies managed to resolve most of the issues that arise in LPR systems, more studies need to be conducted to improve the performance of LPR. This paper aims to provide a comprehensive analysis and comparison of different methods used in LPR. It summarizes each of the methods in terms of their accuracy, performance, strengths and weaknesses. Based on the recognition techniques used, LPR is then characterized into two categories, namely Traditional Computer Vision and Deep Learning Techniques.

Keywords: License plate recognition, LPR, deep learning, computer vision

1.0 INTRODUCTION

With the increase of vehicles on the roads, there is a need for an Intelligent Traffic Management System (ITMS) that can automatically detect, track, and perform real-time recognition. Vehicle License Plate Recognition (LPR) is the primary component in most of the traffic-related applications in ITMS. Recently, LPR has become a significant research topic for various fields such as law enforcement, Automated Gated Parking, Access Control, Toll gates, and marketing and advertisement industry. LPR is defined as the process of computer vision application and image processing technology that include the process of taking videos of vehicles, extracting the images into frames to locate the number plate and automatic identify the license plate number for vehicle identification.

The implementation of LPR was initiated in 1972 in the United Kingdom (UK) [1]. Throughout the years, LPR systems have progressively enhanced where different approaches had been developed to encounter various issues such as low image quality[2][3], distance from the camera, tilt angle, raining or foggy weather effects, or illumination [4][5][6]. Furthermore, in some countries like Malaysia, license plates have unique characteristics[4] that introduce many challenges.

The most common issues of license plate are plate numbers that are non-standard[7] or specialized-design plate[8], the different materials of the plates which may introduce lighting effect or reflection when capturing the image[9] or the problem of damaged or modification of the plate numbers. Figure 1 shows the characteristics of vehicle plate numbers that may cause difficulties for LPR systems to recognize the license plates. This paper aims to discuss and compare the most common techniques found in the literature to solve such challenges.

Figure 1: Some challenges in recognizing Malaysian License Plates

2.0 LPR TECHNIQUES

For the last two decades, a considerable amount of research has been conducted in LPR systems and various algorithms have been proposed to be used in LPR systems. Based on the data processing techniques used, the LPR systems can be characterized into two categories. These categories are traditional computer vision and deep learning techniques.

2.1 Traditional Computer Vision Techniques

In this category, image processing techniques are used to extract the feature or region of interest (ROI) and pre-define them to perform localization or recognization of the license plate (LP). The most popular traditional computer vision techniques employed in the LPR systems are Morphological Processes, Edge detection, Smearing, Histogram of oriented gradients (HOG) feature descriptor, and Support Vector Machine (SVM).

2.2 Deep Learning Techniques

Deep learning is a subfield of machine learning where the algorithms are inspired by the brain's structure and the function called Artificial Neural Networks (ANN) [10]. Studies that use ANN to detect or recognize LP are included in this category. Other techniques are Single Shot MultiBox Detector (SSD), Convolutional Neural Network (CNN or ConvNet), and Convolutional Recurrent Neural Network (CRNN). Figure 2 depicts the comparison between traditional computer vision and deep learning techniques. The main difference between these two techniques is the deep learning technique does not require the features engineering and classification phases in its pipeline. In addition to that, most traditional computer vision techniques add a pre-processing phase directly after acquiring the image and before localization process [11][16][17].

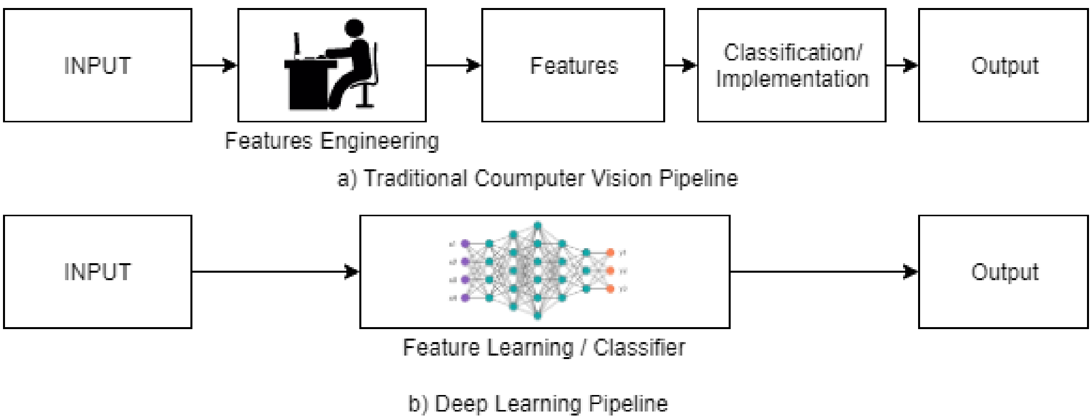

Fig. 2: Traditional Computer Vision Vs. Deep learning pipelines

However, both techniques have three similar main phases, which include the following [11]–[15];

1. Plate Localization: locating the plate position on an image.
2. Character Segmentation: segmenting the plate into regions containing characters/numbers.
3. Character Recognition: converting segments of the plate into digital form (character or number).

3.0 LPR TECHNIQUES AND ALGORITHMS

Several techniques have been employed in previous studies to provide an end-to-end solution for the LPR systems [18]. In some studies, multiple techniques are integrated to improve the LPR's accuracy and efficiency.

3.1 Traditional Computer Vision Techniques

Most traditional computer vision techniques proposed a pre-processing phase directly after acquiring the image[11][16][17]. The goal of this phase is to resize and enhance the input image to make it more suitable for computational processing[16]. One or more of the following processes is used to prepare the input for the next stage:

1. **Size normalization:** Resizing input to desirable dimensions that keep its quality and help to reduce computing time. In addition, normalization converts a random-sized image into a standard size to bring all image characters into the same size to extract features on the same footing. Researchers in [16] managed to reduce computing time from 6.07 seconds to 1.24 seconds by resizing the input image from 3264 × 2448 to 1000 × 750 pixels.
2. **Convert to grayscale:** Grayscale images are easier to segment[18] and can reduce the luminance effects[19]. A clearer input with enhanced features is the result of this process. However, some techniques, especially deep learning techniques may use coloured images as a feature to detect or recognize objects[20].
3. **Binarization:** After converting the input to grayscale, the image is converted to a binary form to facilitate segmentation and enhance edges. Binarization was implemented in [16] and [18].

The traditional computer vision techniques are also used in localization, segmentation, and recognition steps.

3.1.1 Morphological Processes

Morphological processes aim to describe the shape and structure of the object in an image. They depend on the relative ordering of the pixel in an image, not on their numerical value, making them useful for image processing[21]. In LPR systems, morphology isolates the unwanted parts from the image to extract the plate. Generally, license plates have a high variation of contrast which makes the use of morphological processes in locating the plate impacted by the changes of lighting conditions and view orientations. The open and close morphological processes are used to extract the contrast features within the plate which is a relatively stable method for images taken in a more controlled environment in terms of lighting and orientation.

Morphology is used to localize Standard Private Malaysian Plates in [22] and achieved 85.18% detection accuracy. In [23], the morphological process with convolution scores 93% in localizing and recognizing Indian plate samples. Top-hat Transform is a morphological process proposed for LP localization [24], [25], which achieved an accuracy of 96%. However, this technique has some limitations. [24] study is limited to one-row Indian license plates, while [25] study could only achieve this accuracy on standard Chinese license plates. Morphological processes have low computational complexity and achieved an outstanding accuracy and detection rate according to [25] and [26].

3.1.2 Edge detection

Edge detection is the process where the discontinuity on an image is defined in grayscale to extract an object from its background. In LPR systems, it is used to identify the regions of interest in plates (plate boundaries and characters) to extract them from an image.

In the localization phase of LP, edge detection is critical to image preprocessing. Edge is the main attribute of an object that defines its boundaries. A sudden change of some pixels with gray value is observed of a figure of straight or bowed lines in an image[27]. The plate image might be obtained in various environments, so that it may contain unwanted information or objects, However, it is more accurate to locate a standard size plate that has a fixed height-width ratio.

[28] localized 84.28% of the samples of the Iranian plates successfully using edge detection. However, implementing this technique on a non-standard plate is challenging since some of the plates have no clear boundaries or edge, especially for some private black cars.

3.1.3 Smearing

In smearing, the whole image will be scanned in horizontal and vertical lines to localize region-of-Interest (ROI). The main idea of this algorithm is to read the pixels and count the white pixels. If the number of white pixels in the scanned lines is less than the desired threshold or greater than any other desired threshold, white pixels are converted into black.

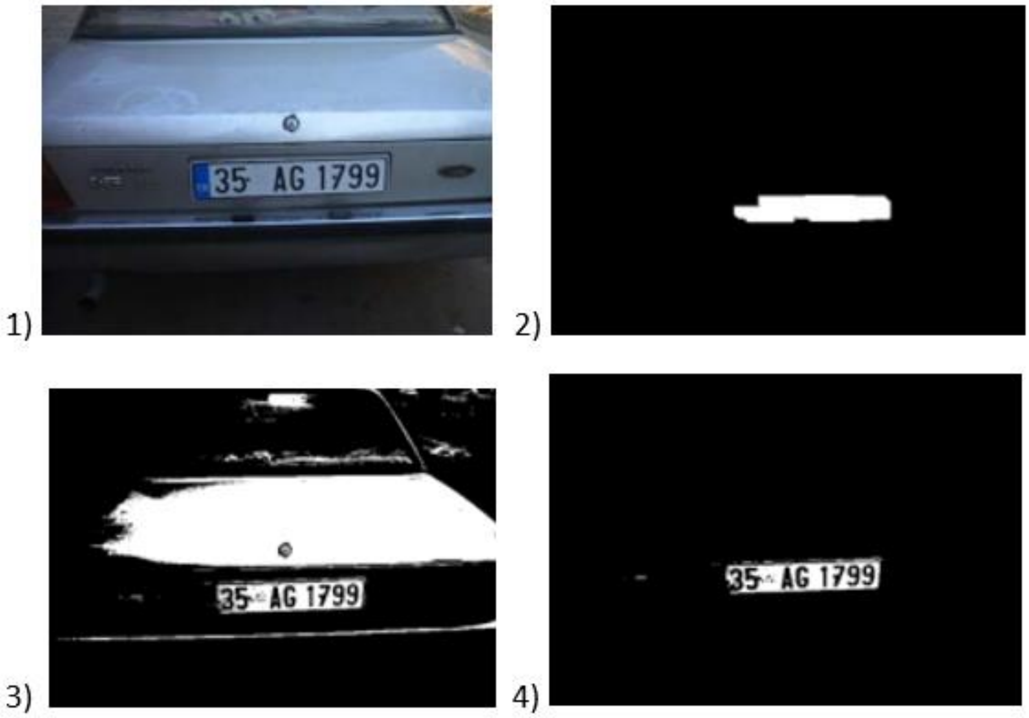

Fig. 3: Plate Region Extraction

In Figure 3, after the plate is extracted from the captured image, a smearing algorithm will be used to localize the plate characters - segmentation as shown in Figure 4 [29].

Fig. 4: Segmentation of Plate Characters

In [11], smearing algorithm is used and localized 97.4% of 150 testing Malaysian plates samples. [30] used the same technique but in combination with Line Separation & Row segmentation.

3.1.4 Histogram of Oriented Gradients (HOG)

A feature descriptor is a way to count occurrences of gradient orientation in part of the image to detect an object's patterns. HOG is a descriptor that has these steps[31]:

- The image is divided into cells - small, connected regions, then the histogram of gradient directions is calculated for the pixels of each cell.
- These cells are segmented into angular bins according to their gradient orientation.
- Each cell's pixel contributes a weighted gradient to its corresponding angular bin.
- Histograms are normalized. The grouping of cells into a block by their adjacent is the basis for grouping and normalizing histograms.
- A normalized group of histograms represents a block histogram.
- The set of these block histograms represents the descriptor.

HOG is used as a descriptor for the Support Vector Machine (SVM) classifier in [14][17]. [21] achieved 99.8% detection accuracy of 100 testing images of standard Indian plates. A similar result was achieved in [14] while considering capturing images in different angles and different illumination conditions. Furthermore, in [25], HOG descriptor is used with Hybrid Discriminative Restricted Boltzmann Machines in the character recognition phase and successfully recognized 98.2% of the characters.

3.1.5 Support Vector Machine (SVM)

SVM is a non-probabilistic binary linear supervised machine learning classifier [32]. It is based on providing a clear definition of learning. Many possible hyperplanes could be chosen when isolating two classes of data points. This technique aims to find a plane that has the maximum margin. Maximizing the margin distance provides some reinforcement so that a more accurate future data points can be classified.

Many hyperplanes are fitted to separate the classes, but there is only one optimal separating hyperplane. It has outstanding performance and takes less time to train and test. As mentioned before in [14] and [17], SVM with HOG is used for localization and performed well based on those studies. For a character recognition, HOG and SVM are used in [14] and recognized 99% of the sample's characters.

3.2 Deep Learning Localization Techniques

Deep learning LPR techniques could provide an end-to-end solution like in [33], [34] , [35], and [36]. Either one neural network or a combination of different ANNs is used for all stages. There are two types of LPR deep learning solutions[33]:

- With Segmentation: using the standard three phases pipeline of traditional computer vision techniques.
- Segmentation-free approach: the pipeline consists of plate localization and character recognition without segmentation process.

Recently, there has been a growing interest in utilizing deep learning techniques for LPR. Single Shot MultiBox Detector (SSD), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN) are the most used deep learning techniques due to their capabilities in detecting objects with high accuracy [37].

3.2.1 Single Shot MultiBox Detector (SSD)

SSD is a single deep neural network that discretizes bounding boxes' output space into a set of default boxes over different aspect ratios and scales per feature map location. The network generates scores for each object category's presence in each default box and produces adjustments to the box to better match the object shape at prediction time [38]. [39] used SSD to detect three-line Thai motorbike license plates and achieved 96.94% accuracy in recognizing the lines and 91.76% in recognizing the Thai characters.

3.2.2 Convolutional neural network (CNN or ConvNet)

A CNN is a deep learning algorithm that can take an input image and then assign weights and biases to different parts of the image to differentiate one part from the other. Unlike Fully Connected Neural Networks, CNN neurons in each layer are connected only to a portion of the previous layer activated neuron. This structure was inspired by the Visual Cortex in the human brain where individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field.

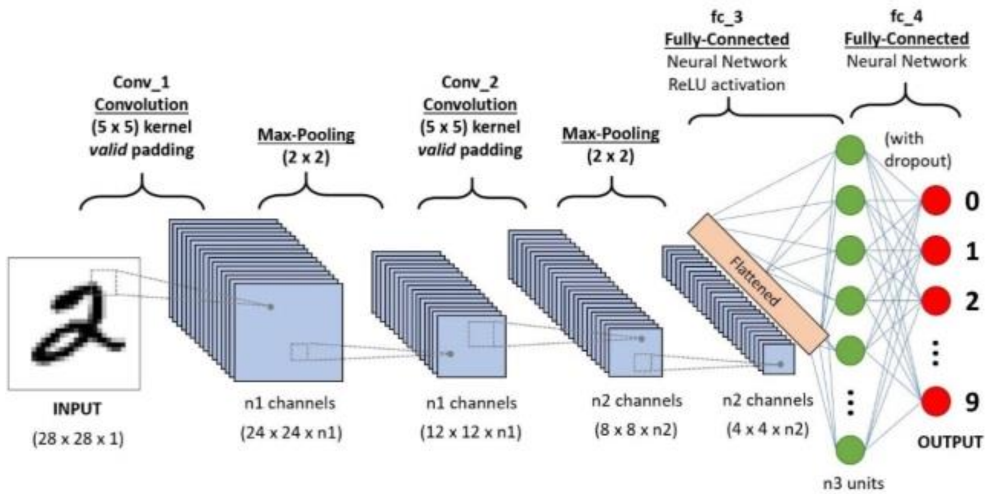

Fig. 5: A CNN classifier of handwritten digits

Authors in [35] proposed using Deep CNN, and they managed to detect 99.09% of USA plates and 99.64 of European plates. This study aimed to improve commercial software (Sighthound). However, researchers in [34] performed better than Sighthound in recognizing Brazilian plates using You-Only-Look-Once (YOLOv2), a state-of-the-art CNN algorithm.

3.2.3 Convolutional Recurrent Neural Network (CRNN)

The CRNN is the combination of two neural networks, the CNN and RNN. This combination aims to improve the CNN prediction by taking into information from the past (RNN). In [33], researchers compared two pipelines, a segmentation-free approach using CRNN. The processing speed of the recognition phase was improved from 0.012 using YOLO to 0.0076s using CRNN. However, in terms of accuracy, YOLO performs better.

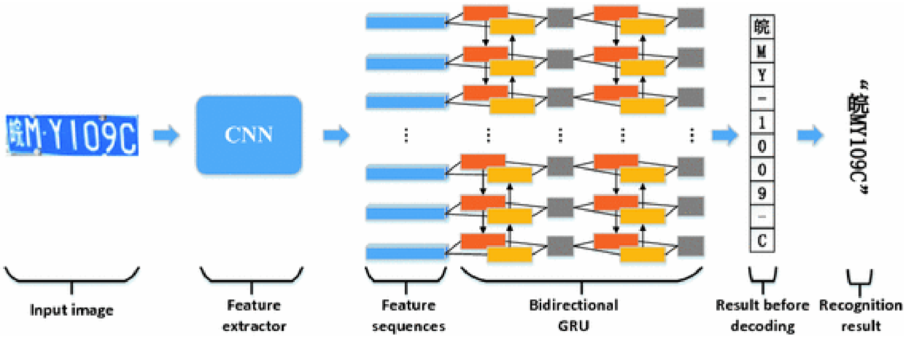

Fig. 6: CRNN Flow in LPR System [40]

4.0 FINDINGS

Traditional computer techniques have performed well in solving some specific issues faced by the LPR systems. However, providing an end-to-end solution requires the use of multiple techniques in each phase, which may affect the overall performance of the system in terms of its processing speed. It may also require different approaches to tackle different challenges or scenarios.

On the other hand, based on the results of previous studies, deep learning techniques can handle different scenarios and cases better than traditional techniques as a unified end-to-end solution. In Table 1, studies are compared based on the challenges that they are trying to solve or deal with. Furthermore, some of these challenges are introduced in some countries only, for instance, issues related to the design and layout of plates. Table 2 summarizes the success rate of each technique compared to the number of samples used in the experiment. The overall success rate is the compound result of the three stages (Localization, Segmentation, and Recognition).

5.0 CONCLUSION

The license plate detection and recognition processes are the essential elements in most of the ITMSs. Despite many techniques that have been proposed to be used in LPR systems in the literature, there are still issues that need to be addressed, which include the recognition of license plate in certain conditions, such as the non-standard design of the license plate, different environments, lighting, and weather conditions. However, deep learning techniques have shown a promising result to achieve a more efficient and optimal performance in LPR where the training of neural network with a suitable amount of data in the training dataset was used.

Table 1: Challenges discussed in previous studies

Country	Study	Challenges and Cases									
		Standard	Non-Standard	Special	Double Row	Broken	Bad Weather	Distance	Lighting	Skewed / Tilted	Real-time
Brazil	[34]	✓	✓	-	✓	-	✓	-	✓	✓	✓
China	[25]	✓	-	-	-	✓	✓	✓	✓	✓	✓
	[41]	✓	-	-	-	-	-	-	✓	-	✓
	[42]	✓	✓	-	✓	-	-	✓	✓	✓	✓
India	[30]	✓	-	-	-	-	-	-	-	-	-
	[17]	✓	-	-	-	-	-	-	-	-	-
	[23]	✓	-	-	-	-	-	-	-	-	-
	[14]	✓	-	-	-	-	-	-	✓	✓	-
	[15]	✓	-	-	-	-	✓	-	-	-	-
	[24]	✓	-	-	-	-	-	-	-	-	-
Iran	[28]	✓	-	-	-	-	✓	-	✓	✓	✓ -
Iraq	[43]	✓	-	-	-	-	-	-	✓	-	-
Malaysia	[44]	✓	-	-	-	-	✓	-	✓	✓	-
	[11]	✓	✓	-	✓	✓	✓	✓	✓	✓	-
	[16]	✓	-	-	-	-	✓	✓	✓	✓	-
	[8]	✓	✓	✓	✓	-	-	✓	✓	✓	-
	[7]	✓	-	-	✓	-	-	-	-	✓	-
	[6]	✓	-	-	✓	-	✓	-	✓	-	-
	[22]	✓	-	-	✓	-	-	-	-	✓	✓
Tunisia	[33]	✓	✓	-	✓	✓	✓	✓	✓	✓	✓
USA	[5]	✓	-	-	-	✓	✓	✓	✓	✓	-
USA & Europe	[35]	✓	✓	-	-	-	✓	-	✓	✓	✓

Table 2: Accuracy achieved by previous studies proposed techniques

Main Technique	Study	# Samples	Success Rate			
			L%	S%	R %	Overall%
CNN	[44]	20105	-	-	-	71.23
	[33]	3602	~ 98.91		~ 99.49	~ 97.67
	[34]	1800	93.5	-	78.33	~ 93.53
	[35]	328	99	-	94	93.44
		550				94.55
Template Matching	[41]	357		-		95.16
	[43]	40	87.5		85.7	-
OCR	[23]	100				93
	[6]	55	50		42	20 ~ 100
	[7]	500				~ 64
Smearing algorithm	[11]	150	97.4	96	76	~ 90.3
External Regions & Restricted Boltzmann Machines	[25]	4242	95.9	-	98.2	~ 94.1
Pearson correlation	[16]	270	100	99.6	91.1	~ 92.2
SIFT Features	[8]	150	-			81.33
Cascade classifier and core patterns	[42]	20000	99	-	-	99
Morphological processing	[22]	32 (in video)	85.18		-	85.18
HOG features, SVM	[17]	100	99.8	-	99	99
	[14]	100	99.8	-	99	99
Edge Detection	[15]	95	97.89	98.95	96.84	~93
	[24]	-	96	95	-	95
	[28]	70	84.28	77.14	71.43	84.28

L: Localization. S: Segmentation. R: Recognition.

~: Study has many accuracy values based on testing different environments (max value presented)

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