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Automated License Plate Recognition: A Survey on Methods and Techniques

JITHMI SHASHIRANGANA[1], HESHAN PADMASIRI[1], (Member, IEEE), DULANI MEEDENIYA[1], (Member, IEEE), AND CHARITH PERERA[2]

[1]Department of Computer Science & Engineering, University of Moratuwa, Moratuwa 10400, Sri Lanka
[2]School of Computer Science and Informatics, Cardiff University, Cardiff CF24 3AA, U.K.

Corresponding author: Dulani Meedeniya (dulanim@cse.mrt.ac.lk)

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ABSTRACT With the explosive growth in the number of vehicles in use, automated license plate recognition (ALPR) systems are required for a wide range of tasks such as law enforcement, surveillance, and toll booth operations. The operational specifications of these systems are diverse due to the differences in the intended application. For instance, they may need to run on handheld devices or cloud servers, or operate in low light and adverse weather conditions. In order to meet these requirements, a variety of techniques have been developed for license plate recognition. Even though there has been a notable improvement in the current ALPR methods, there is a requirement to be filled in ALPR techniques for a complex environment. Thus, many approaches are sensitive to the changes in illumination and operate mostly in daylight. This study explores the methods and techniques used in ALPR in recent literature. We present a critical and constructive analysis of related studies in the field of ALPR and identify the open challenge faced by researchers and developers. Further, we provide future research directions and recommendations to optimize the current solutions to work under extreme conditions.

INDEX TERMS Automatic license plate recognition (ALPR), character recognition, character segmentation, license plate detection, multi-stage plate recognition, single-stage plate recognition.

I. INTRODUCTION

Automatic License Plate Recognition (ALPR) systems are attracting an increasing interest due to their applicability in intelligent transportation systems that have been installed in many countries for tasks such as traffic law enforcement and traffic monitoring. Besides, ALPR systems are also used to manage exit and entrance in vehicle parks, collect toll payments, and to control security measures in restricted areas like military campsites, and protected sanctuaries. Often, these ALPR systems are employed to prevent fraud and to intensify security in specific areas. For instance, they can be helpful when searching for missing vehicles or vehicles related to crimes. Unless for ALPR systems, this task requires a sizable amount of labour, time, and resources. Also, manual intervention in such tasks may leads to erroneous interpretations, and in the meantime, it is practically difficult for a human to remember or to read a license plate of a moving vehicle efficiently.

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Generally, an ALPR system takes an image or a video stream as the input to the system and, if the given frame contains a vehicle it outputs the content of the license plate, usually as a text. These systems consist of a camera to capture the images of the vehicles. Those images can be either colour, black and white, or infrared depending on the requirements for the system. Techniques such as object detection [1], [2], [3], [4], image processing [5], [6], and pattern recognition [7], [8] are used to detect and read the license plate.

A. SURVEY MOTIVATION

Most of the ALPR systems are designed to deploy outdoors. However, it is challenging to detect and recognize license plates under changing environmental and weather conditions. These factors include illumination changes, snow or fog weather conditions, and day and night. Besides, there may exist issues related to the cameras and license plate variations. For instance, dust and vibrations of the camera may result in a blurry image, which makes the recognition task problematic and produce erroneous output. Similarly, it is complex to process when there are many license plates in a given image.

The variations of the license plates across different regions such as size, colour, font, and standards, have made it challenging to provide one global solution to detect and recognize a license plate anywhere in the world. Moreover, there are other factors such as rotations and occlusions of the license plates that limit the applicability of most of the existing systems to real-world applications. Thus, the techniques to solve ALPR under existing constraints are computationally demanding and complex [9], [10], [11], [12], [13], [14].

Regardless of the progress in the area of ALPR, many studies are limited to proceed in indoor conditions and stationary backgrounds. However, ALPR systems need to deal with moving vehicles with varying speeds in the real-world and it is challenging due to reasons such as changing views, motion blur effect, and lighting conditions. Accordingly, many approaches are sensitive to the changes in illumination and operate mostly in daylight. Few studies [12], [13], [14], have focused on developing systems that can operate both in the day and night time, however, their performance in the nighttime is contrastingly less compared to day time performance of the same system. In addition to these challenges concerning environmental conditions, production ALPR systems must satisfy several non-functional requirements such as cost of acquisition and operation, physical dimensions, power consumption and connectivity constraints. For instance, while a single-stage deep learning solution can give a state-of-the-art performance in terms of accuracy, it may prohibitively expensive in terms of computations and resources to be deployed at scale on edge devices. At the same time, a multi-stage approach using classical computer vision techniques may able to provide acceptable performance at a fraction of the computational cost. Thus, the ALPR pipeline assemble requires a thorough cost-benefit analysis among the applicable approaches and techniques.

B. SURVEY CONTRIBUTION

Among the existing surveys [15], [16] of ALPR context, many studies have focused on traditional computer vision techniques for license plate recognition. Moreover, none of them has profoundly investigated aspects such as single-stage license plate recognition techniques, ALPR datasets and license plate recognition techniques in adverse environmental conditions. Therefore, the main contribution of this study has focused on the state-of-the-art ALPR models and their performance in unfavourable environmental changes and other challenging conditions. We have explored the above 100 related research articles and online resources covering the entire subject area, which were published over the last two decades.

We expect the audience of this survey to be both novice and expert individuals who are interested in developing ALPR systems by providing an intuition of the available techniques, approaches and models. The survey is aimed primarily at the researchers and developers in the field of computer vision and deep learning. However, our survey is not mainly aimed at providing deeper technical knowledge of available image processing and machine learning techniques. Rather, we mainly consider the potential for provision and application of available image processing, computer vision, and deep learning techniques for the ALPR task. Our survey focuses on the following contributions.

- We explore the advantages and disadvantages of techniques and methods in both individual and holistic way, thus the ALPR system designers can make decisions on that.
- We present the performance of these selections based on accuracy, computational cost and robustness to varying environmental conditions. Further, we analyze the impact of each selection to the rest of the system in terms of accuracy and computational costs.
- We propose several requirements for an ALPR benchmark by analyzing publicly available ALPR datasets along with their current issues and available solutions.

C. ARTICLE STRUCTURE

This study is structured as shown in Figure 1. Section I describes a general overview of license plate recognition systems. Section II discusses the two main approaches in ALPR, which are multi-stage and single-stage license plate recognition. The main parts of the multi-stage license plate recognition, namely license plate detection and license plate recognition are addressed in Section III and Section IV, respectively. Each of these sections presents the respective benefits, challenges, limitations and the proposed methods. Section V reviews different learning models and implementation frameworks that made over the years to solve the ALPR task. In Section VI, we briefly discuss several evaluation matrics related to ALPR systems. Section VII presents a set of basic requirements for a real-world benchmark for ALPR. Also, we then discuss some publicly available ALPR datasets, related issues and a possible solution to those issues by introducing synthetic datasets for ALPR. Section VIII addresses the open challenges in ALPR and present our recommendations for optimizing the current solutions. After that, Section IX presents an overall discussion on the existing ALPR methods and a comparison of the related studies.Finally, Section X concludes the survey paper.

II. AUTOMATIC LICENSE PLATE RECOGNITION APPROACHES

A. MULTI-STAGE LICENSE PLATE RECOGNITION SYSTEMS

The existing ALPR systems can be broadly divided into two categories as multistage and single-stage methods. Most of the existing solutions for the ALPR task have considered the multi-stage method, which consists of three main steps. The first stage is the license plate detection or extraction. Existing algorithms use traditional computer vision techniques and deep learning methods with object detection to locate the license plate in an image. Traditional computer vision techniques are mainly based on the features of the license plate such as shape [7], [17], [6], [18], colour

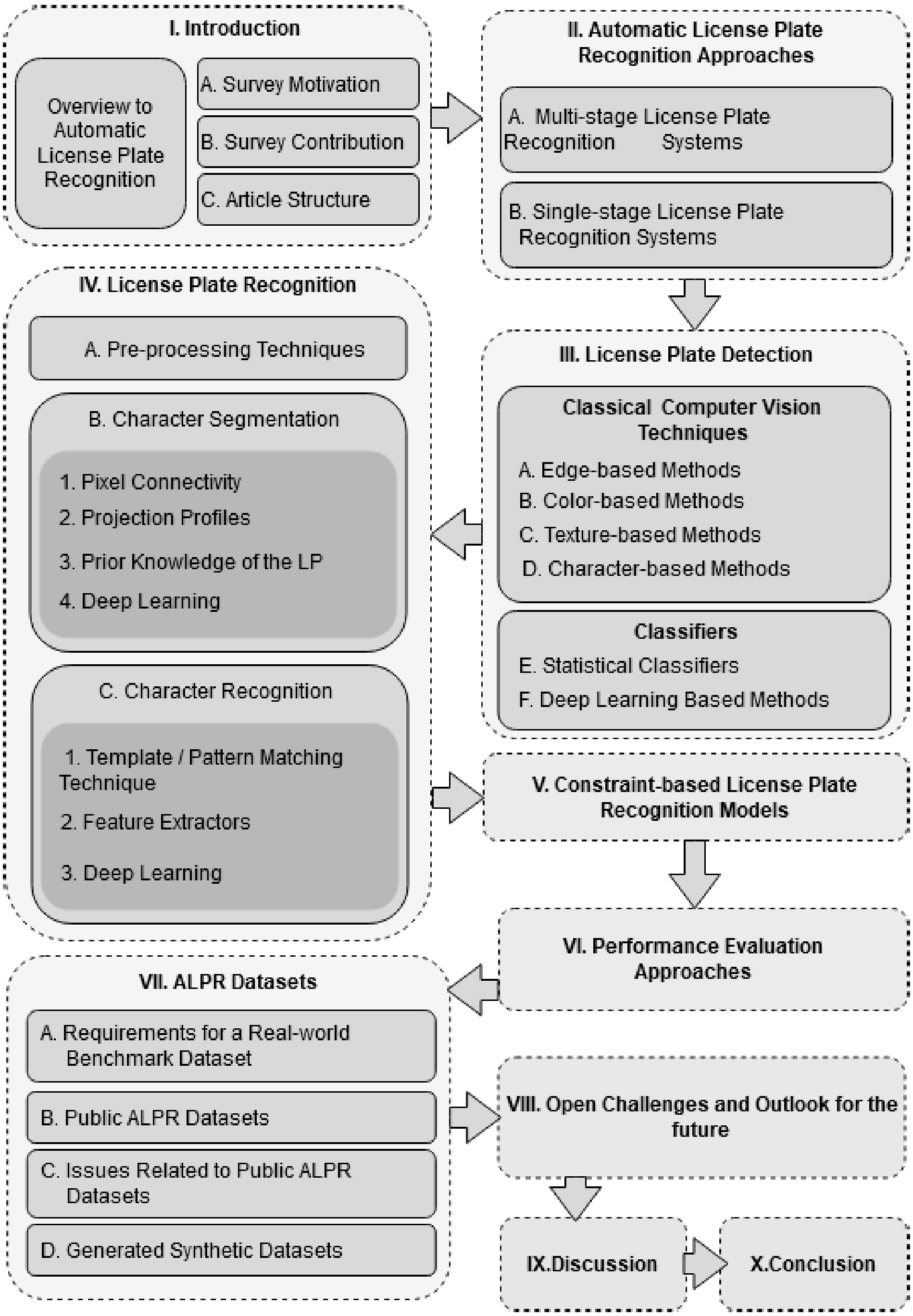

FIGURE 1. Structure of the review process.

[19], [20], [21], [22], symmetry [23], texture [24], [25], [26], [27], [28], etc. In the second stage, the license plate is segmented and the characters are extracted using some common techniques such as mathematical morphology [29], connected components, relaxation labelling, and vertical and horizontal projection [15]. However, the character segmentation stage is not necessarily performed in every multi-stage ALPR system, because there are some segmentation-free algorithms in which this stage is omitted.

The final stage is the recognition of the characters using pattern matching techniques or classifiers like neural networks and fuzzy classifiers. However, the main downside of separating detection from recognition is its impact on the accuracy and efficiency of the overall recognition process. This happens mainly due to the imperfection of the detection process such as flaws in the bounding box prediction. For instance, if the detection process misses a part of a license plate, it will affect to reduce the overall accuracy of the

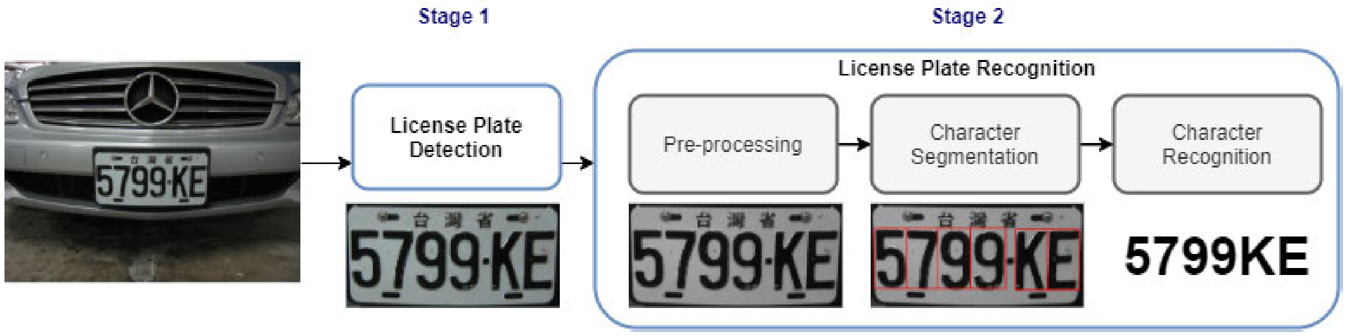

FIGURE 2. Main stages in a multi-stage license plate recognition system.

recognition process. Thus, in a multi-stage approach, it is important to achieve satisfying results in each stage. Figure 2 shows the main processing stages in a multi-stage plate recognition system and the details are discussed in Section 3 and Section 4.

B. SINGLE-STAGE LICENSE PLATE RECOGNITION SYSTEMS

While most of the existing work on license plate recognition has been focused on multi-stage processes, recently there had been several successful attempts at single-stage processes. All of these attempts to the best of our knowledge uses a single deep neural network, which is trained for end-to-end detection, localization and recognition of the license plate in a single forward pass. License plate recognition can be considered as a specific case in object detection. Similar to single-stage object detectors these models can exploit the fact license plate detection and recognition being highly correlated [30]. This allows models to share parameters and have fewer parameters than a typical two-stage model will require. As a result, they can be faster and efficient than comparable two-stage method [30], [31].

First such attempt we know was by Li *et al.* [30]. Their approach has used VGG16, which is a convolutional neural network model [32] as a feature extractor. They have modified VGG16 to use only two pooling layers instead of five, as the license plate encompasses a smaller area in a typical image. Then the output from the feature extractors is fed into a Region Proposal Network (RPN) [33]. They have done modifications such as the use of two rectangular convolution filters instead of the typical 3×3 filters. This is to better exploit the fact that license plates have a larger aspect ratio and rectangular filters perform well than square filters. Then extracted local features by these filters have been concatenated to keep local and contextual information aiding in license plate classification stage. These concatenated feature maps are then fed to separate sets of convolutional layers for classification as a license plate or not and for box regression. This RPN was then trained end-to-end. Given a large number of proposals, only the RPN generated 256 anchors were sampled randomly and calculated the losses. In test time the proposals were subject to non-maximum suppression to select only 100 proposals with higher confidence. Given that proposal, regions are of variable size and subjected to Return on Investment (RoI) pooling [34]. The outcome of RoI pooling is then passed into two separate sub-networks called license plate detection network and other license plate recognition network. License plate detection network is a fully connected network with two outputs. One for the probability that the RoI is a license plate and other for the bounding box coordinates. License plate recognition network is responsible for recognizing characters in the license plate. In order to avoid character segmentation, they have modelled this as a sequence labelling problem using Bidirectional RNNs.

A similar approach was suggested by Xu *et al.* [31]. Instead of directly using an existing network such as VGG16 [32] for feature extraction, they have used a simplified Convolutional Neural Network (CNN) with 10 layers. CNN sub-network is trained to predict bounding boxes directly. The output from layers 1, 3 and 5 of the feature extractor was then fed via RoI pooling [34] to multiple classifiers. They have used outputs from multiple layers because each layer has different receptive field sizes [35]. This has allowed detecting license plate at a different distance to the camera. Unlike in [30], which has used a single Bidirectional Recurrent Neural Networks (BRNN) to recognise the license plate, they have used simpler classifiers for each character in the license plate exploiting the fact that license plates have a fixed number of characters. Use of individual classifiers and simpler feature extractions have allowed them to create a model that is relatively shallower allowing significantly faster processing compared with other single and multi-stage approaches. Though their model is relatively simple to the best of our knowledge, their approach is currently the most accurate model for license plate detection.

III. LICENSE PLATE DETECTION

The general definition of a license plate is ‘‘a metal or plastic plate attached to a vehicle that helps to identify them uniquely’’. Yet, this definition is not comprehended by a machine. In order to detect a license plate, a definition that can be understood by a machine is required. Considering its features, the definition for a license plate can be stated as ‘‘a

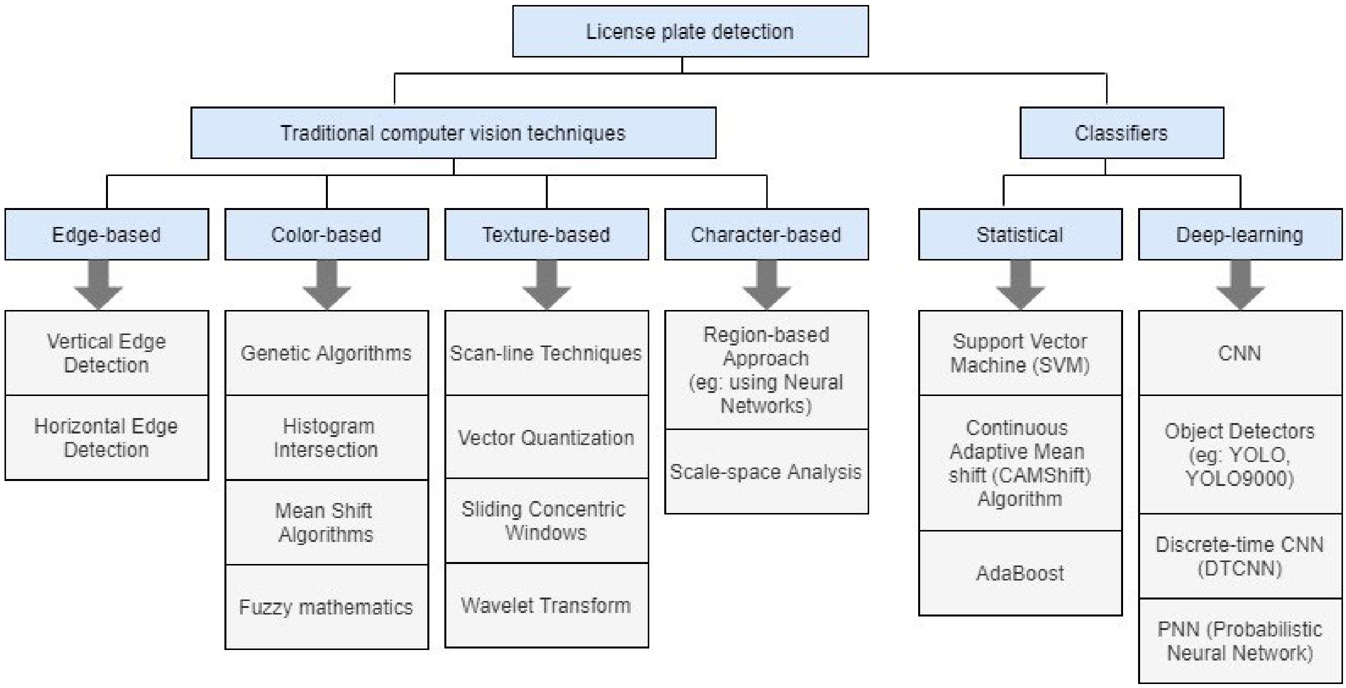

FIGURE 3. Classification of related license plate detection techniques.

rectangular area of a vehicle with a high density of horizontal and vertical edges'' [25]. Based on these features, many algorithms have been put forward to solve the license plate detection task and some of them are rooted in traditional computer vision techniques and some in deep learning. Figure 3 shows a classification of the license plate detection techniques that are used in existing methods. Table 1 compares those localization methods along with the benefits and the limitations of each method.

A. EDGE-BASED METHODS

Considering that every license plate is rectangular and has a known aspect ratio, most of the studies have relied on edge-based approaches for license plate detection. Since the license plate colour is distinct to the colour of the vehicle body, the boundary of the license plate appears as an edge in the image. There are two kinds of edges in an image as horizontal and vertical edges. When two horizontal edges are concerned it is known as horizontal edge detection and for two vertical edges, it is called vertical edge detection. Several studies have used Sobel filter for edge detection [7], [17], [6], [18]. The Sobel filter has two 3×3 convolutional matrices and one is dedicated for vertical and the other for horizontal edge detection. Ease of use is one of the key advantages of this method. One of the major drawbacks of this approach is its responsiveness to noise.

In [7], [17], Luo *et al.* and Sarfraz *et al.* have used a Sobel filter to extract only the vertical edges. However, using only the horizontal lines leads to erroneous results as the vehicle bumper can be mistaken as a horizontal edge of the license plate. Sarfraz *et al.* [7] proposed a method to generate some candidate rectangles in the image using the vertical edge detection. The candidate rectangle that has the same aspect ratio as the license plate was then detected as the plate. This method has claimed a success rate of 96.2% even under different illumination conditions. A new vertical edge detection algorithm that is faster than the Sobel filter was proposed in [5]. The authors have reported that the new algorithm is 7-9 times faster than the Sobel filter and effective in extracting the license plate details in the later stages of processing.

Heo *et al.* [36] have developed a new method for license plate extraction with the combination of a line-grouping algorithm and an edge-density mapping algorithm. The line-grouping algorithm extracts the line segments and groups the line segments at the license plate boundary, while the edge-density map detects the region that is highly dense with lines as the candidate plate. They have shown a success rate of 99.45% for the new algorithm. A block-based algorithm for license plate extraction is discussed in [37]. They have identified the license plate region by considering the regions with a high edge magnitude and a variance. Their approach is well suited for moving vehicles and images with unclear plate boundaries.

In the traditional approach, Hough Transformation is used to identify the straight lines in the images. This approach gives an advantage of detecting lines up to an inclination of 30°. Yet, the method consumes more time and memory. Also, Hough transformation is highly sensitive to boundary deformations. As a result, it is not used when there are any unclear boundaries in the license plate. Therefore, Duan *et al.* [38] have proposed a new method combining

TABLE 1. Comparison of license plate localization methods.

Technique	Advantages	Limitations	References
Edge-based methods	Simple, faster	Sensitive to unwanted edges, not suitable to be applied with blurry and complex images	[7], [17], [6], [18], [5], [36], [37], [38]
Colour-based methods	Robust against deformations and rotations	Sensitive to illumination changes	[19], [20], [21], [39], [22]
Texture-based methods	Robust against boundary deformations in the license plates	Computationally complex, work poorly with complex backgrounds and illumination changes	[24], [25], [26], [40], [27], [28], [41]
Character-based methods	Can be used for rotated plates	Time consuming and not suitable for images with any other texts	[42], [43], [44]
Using statistical classifiers	Accurate, robustness to environmental changes, efficient	Computationally complex	[45], [46], [47], [48], [49], [50], [51]
Deep learning based methods	Efficient, robustness to environmental changes	Resource consuming, computationally complex	[1], [2], [3], [4], [52], [29], [53]

Hough transformation with a contouring algorithm and achieved faster results and higher accuracy of 98.8%. Many studies have used edge-based approaches for license plate detection as they are simple and faster. However, these methods are highly sensitive to unwanted edges and not suitable to be used with blurry and complex images.

B. COLOUR-BASED METHODS

Colour-based methods rely on the fact that the colour of a license plate is different from the background colour of the vehicle. Also, the colour combination of the plate and its characters is nowhere found in the image other than the plate region. The Hue, Lightness, and Saturation (HLS) colour model can be used to classify the pixels in an input image against different illuminations. Unlike the Red, Green, and Blue (RGB) model, the HLS model has classified pixels into 13 categories and was tested on Chinese license plates. Yet, the HLS model is sensitive to the noise. Few studies have used the Genetic Algorithm as a search heuristic for identifying the license plate colour. For instance, [19] is a preliminary work that uses Genetic algorithm for license plate detection and requires deeper analysis as future extensions.

Zhang *et al.* [20] have proposed a novel algorithm called Gaussian Weighted Histogram Intersection (GWHI) for license plate classification. Histogram intersection is used to match two colours by matching their colour histograms. The sensitivity to illumination is the major problem in conventional histogram intersection methods. Therefore, they have added a Gaussian function as a modification to the conventional histogram intersection. A robust license plate localization method using mean shift segmentation is discussed in [21]. They have segmented the vehicle images into regions of interest using the Mean shift algorithm, which is based on the colours in the image. These regions were classified using a Mahalanobis classifier to detect license plates. Another study [39] followed a region-based approach to localize the license plates using a similar approach to [21].

In order to compete with the uncertainties in real-time applications such as illumination changes, Wang *et al.* [22] have proposed an algorithm to recognize the colour of the license plate using fuzzy mathematics. The Hue, Saturation, Value (HSV) model is used to extract the colour features from the image. The three components of the HSV model: hue, saturation, and value are mapped to fuzzy sets using different membership functions.

The colour-based methods can be used to detect deformed or inclined license plates. Yet, they are rarely used alone for plate detection as they are sensitive to illumination changes. Also, they depend on the specifications of the camera that is used to capture the images. Besides, they make erroneous results if the image contains other regions with the same colour as of the license plate. Therefore these methods are often combined with some other technique to achieve accurate results.

C. TEXTURE-BASED METHODS

Texture-based methods use the presence of characters on the license plate as the base for plate detection. Due to the significant colour difference between the plate and its characters, it creates a frequent colour transition on the license plate. Hence, if the image is grey-scaled there is a notable difference between the characters and the plate background. Thus, it creates a unique pixel intensity distribution around the plate region. Moreover, the colour transition makes the plate region to have a high edge density.

In [24], they have used scan-line techniques for license plate detection. These methods are based on the fact that the complexity of the plate region in a grey-scaled image is not seen anywhere in the image. Therefore, this method does not depend on the boundary details. Zunino *et al.* [25] have presented a novel method for localization using Vector Quantization (VQ). While several studies have considered features of the candidates like edges and contrast, VQ methods have considered the actual content of the license plate. The authors have reported a detection accuracy of 98% and have tested in a real-time industrial application. Often the license plate creates inconsistencies in the texture of the input image, which disclose its presence in the image. Considering this, Anagnostopoulos *et al.* [26] have presented a new segmentation technique called Sliding Concentric Windows

(SCW) for license plate detection. It was employed for the faster and more accurate detection of the plate regions by exploiting those irregularities in the image texture. They have reported accuracy of 96.5% for license plate detection. A similar approach to this is presented in [40] with the combination of Sliding Concentric Windows and the histogram method. However, this method achieved better results by increasing the overall detection accuracy.

In texture analysis, the Gabor filter is often used. A key advantage of using a Gabor filter is its ability to analyze texture in infinite directions and scales. A method for license plate localization using Gabor filter is described in [27]. However, this method is time-consuming and less efficient for images that need large analysis. Hsieh *et al.* [28] have presented a method based on the Wavelet Transform for license plate detection. As shown in Figure 4 there are four sub-bands (or sub-images) in Wavelet Transform namely LL, HL, LH, and HH where H and L stand for high and low frequencies, respectively. The LL sub-band contains the original image passed through a low-pass filter and the rest contain the missing details. HL sub-band has the characteristics in the vertical direction, while LH has the characteristics in the horizontal direction. The method described in [28] was consist of three stages. In the first stage, the Wavelet transform is performed on a binary image using a Haar-scaling function. In the next stage, a reference line with the maximum horizontal variation is found with the help of the LH sub-band. Then the reference line is used to extract the candidate regions and finally, the license plate is accurately located from the extracted candidates. The reported detection accuracy in 92.4%.

In [41], another Wavelet transform based method is described. However, they have used HL sub-band for feature extraction and then verified the features using the LH sub-band by looking for the presence of a horizontal line around the feature. They report an accuracy of 97.33% for the localization process.

All the texture-based methods are robust against license plate deformation and it is a key advantage of using these methods. Still, these methods involve complex computations and work poorly with complex backgrounds and different illumination conditions.

D. CHARACTER-BASED METHODS

Examining an image for the presence of characters and locating them is also used for license plate detection. These methods are categorized as character-based methods and consider the region with characters as the possible plate region. Matas and Zimmermann [42] have proposed a method that extracts all character-like regions in an image. A neural network classifier is then used to classify those extreme regions and if any linear spatial configuration is found, it is assumed as the possible region with the license plate. This method is claimed to be robust against different illumination conditions and viewpoints and the reported detection accuracy is 95%.

In [43], Draghici has scanned the image horizontally to detect any repeating contrast changes with a minimum of 15 pixels in length. This approach is made under three main assumptions; (1) the contrast between the background and the characters is sufficiently good, (2) the license plate contains at least 3-4 characters, (3) the minimum vertical size of a character is 15 pixels. However, the minimum vertical size measure depends on the camera specifications and has to be calibrated for any hardware change. The reported detection rate for this approach is 99% in outdoor conditions. Cho *et al.* [44] have proposed a method to recognize the character region using the character width and the difference that holds between the characters and the license plate background. They have used the inter-character distance to extract the exact plate region and reported a detection rate of 99.5%. Moreover, character-based methods are advantageous due to their robustness to licence plate rotations. However, these methods are time-consuming and often prone to errors if there are other texts in the input image.

E. STATISTICAL CLASSIFIERS

Several studies have used Haar-like features with Adaptive Boosting (AdaBoost) to train cascade classifiers for license plate detection [46], [47], [47], [48]. In [46], a decision tree based cascaded classifier with AdaBoost training is proposed. They used a combination of statistical and Haar-like features for training since statistical features simplify the process. This enhanced algorithm has achieved a detection rate of 94.5% under different illumination conditions and viewpoints. A similar approach to [46] has presented in [47] for license plate detection. They have also used statistical features for simplicity and the selected local Haar-like features to train the cascade classifier with AdaBoost learning. They have reported a detection rate of 93.5%.

Kim *et al.* [49] have proposed a new algorithm based on colour texture for object detection and demonstrated with a license plate localization system. They have extended the previous studies [50], [51] on texture classification by following a Support Vector Machine (SVM) based approach for identifying plate regions. The SVM has used to classify a region as a license plate or non-plate using its colour and texture properties. The SVM-based method was significantly robust and efficient when compared to the previous approaches for texture classification. After the classification stage, each pixel indicates a probability or a score for it being a part of the plate region and these scores are used to predict the bounding box by applying the continuously adaptive mean-shift algorithm (CAMShift). This combination of SVM and CAMShift has provided a high detection rate with efficient processing.

F. DEEP-LEARNING TECHNIQUES

According to the recent development in computer vision approaches, most of the statistical methods have been replaced by deep learning neural networks due to their high accuracy in object detection. Embracing this fact, many studies in license plate detection have used different types of

FIGURE 4. Original input image (left) and result of wavelet transform on the image (right) according to [28].

neural networks. In [52], Selmi *et al.*, have presented a localization method using a Convolutional Neural Network (CNN). In their study, they have followed two major steps in the license plate detection stage. In the first stage, pre-processing techniques were applied to the input image to remove the noise and extracted the finer elements or details from the image. In the next stage, possible bounding boxes for the plate region have extracted and distinguished as a license plate or non-plate using a CNN classifier. The experiment was tested on the Caltech data set and the recall and the f-score accuracy reported is 93.8% and 91.3%, respectively. Another study using CNNs was proposed by Zou *et al.* [29]. They have used two CNNs named shallow CNN and deep CNN, which are trained end-to-end for license plate detection. The shallow CNN was used to reduce the computational cost by removing most of the background regions from the image. Then the more powerful deep CNN was used to detect the license plate from the remaining regions. Finally, they have used non-maximum suppression (NMS) to locate the exact plate region. The experimental results have shown above average results for accuracy with a less computational cost.

The success of state-of-the-art, real-time object detectors such as You-only-look-once (YOLO) [53], have inspired the license plate detection process in many recent ALPR studies. Several studies have used the state-of-the-art YOLO object detector for license plate detection [1], [2], [3], and [4]. In [1], Laroca *et al.*, have used YOLO (version 2) [54] object detector to build an efficient and robust system for localization. They have used two separate CNNs for vehicle detection and license plate detection. This study has shown promising results over existing methods for both SegPlate (SSIG) [55] dataset and Federal University of Parana (UFPR-ALPR) dataset.

Many studies in license plate detection have given significant results under constrained environments. For instance, Gee-Sern *et al.* [2] have proposed a novel method using YOLO and YOLO-9000 (YOLO-2) for localizing license plate in the wild. Detecting a license plate is a challenging task in the wild due to the changing weather conditions and lightning. Despite their high performance in other object detection tasks such as face recognition [56], [57], the direct use of YOLO detectors exhibit comparatively low performance in license plate detection. Hence, they have customized the YOLO and YOLO-2 models by modifying their grid sizes and bounding box parameters. This method has shown encouraging results in different environmental conditions such as day-time, night-time and wet environment.

Xie *et al.* [3] have presented a similar approach to the work done in [2]. They have improved the original YOLO framework to handle multi-directions; hence named as MD-YOLO framework. The original YOLO framework gives only the information about the object's center coordinates, height and width. However, for any given license plate the MD-YOLO model also provides information about its angle of rotation. Figure 5 illustrates the redesigned CNN architecture for the MD-YOLO model. Further, the model performs well in poor illumination conditions and occlusions.

IV. LICENSE PLATE RECOGNITION

As the second stage in a multi-stage automated license plate recognition pipeline, this stage is responsible for ''reading'' the license plate ones the detection stage have localized it. This is a specific case of optical character recognition that considers certain features in the license plate. For instance, many countries have strict regulation regarding the font and colour of the license plate and usually, they are selected to be easy to read. However, there are some unique issues associated with the license plates [58]. For instance, since the image is taken outdoors, the system designers have to consider aspects such as variable ambient light, uneven brightness, effect of weather. Despite having a standard license plate, they still could be damaged or rotated. Figure 6 shows the recognition pipeline of a typical ALPR system with possible

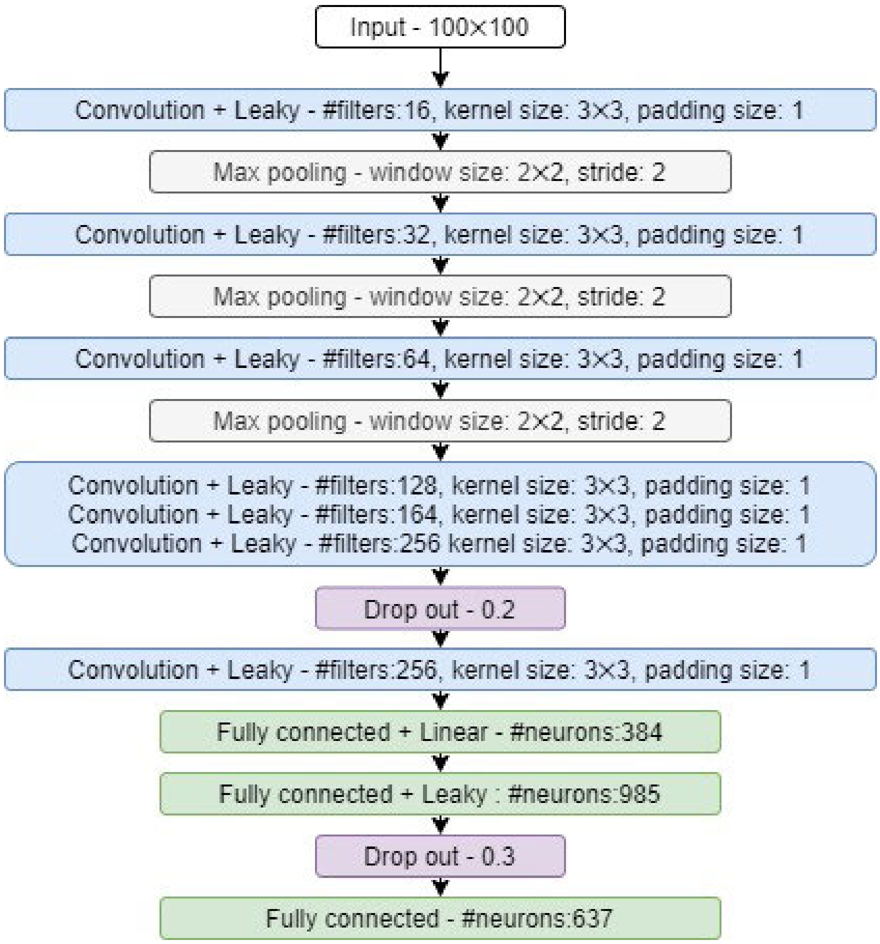

FIGURE 5. CNN architecture for the MD-YOLO model in [3].

techniques applicable for each stage. However, some of the tasks can be omitted depending on the selected techniques.

A. PRE-PROCESSING TECHNIQUES

Several pre-processing tasks performs before the character segmentation and recognition to handle unique challenges in license plate recognition. For example, rotation techniques such as bilinear transformations [59], least square-based methods [60] and line fitting methods [61] have been used in related studies. In many classical machine vision-based techniques for character recognition, the image is binarized before segmentation. The process makes it easier to separate the pixels belong to the characters in the image, compared to grey-scale or colour images. However, the threshold for this binarization must be determined correctly, to avoid the combining of the characters or merging with the license plate frame in the binary image, which makes it difficult to segment [15]. The threshold value can be defined using image enhancement techniques such as noise removal, histogram equalization, contrast enhancement and grey level transformation. However, even with these enhancements, it can be hard to get a single threshold. In such cases, adaptive binarization techniques such as local thresholding [62] and Niblack's binarization method (NBM) have used.

B. CHARACTER SEGMENTATION

In many optical character recognition techniques, the characters are first segmented before the classification. License plate character segmentation techniques consider the attribute of having contrasting colours for the background and characters. Binarization of the image makes this separation easier, as the foreground (character) and background pixels get the opposite "colours" in binarization. Table 2 compares the existing methods for segmentation by considering their advantages and limitations in use.

1) CHARACTER SEGMENTATION USING PIXEL CONNECTIVITY

Pixel connectivity is a simple methods for character segmentation [63], [64]. Here, the connected pixels are labelled and if the pixels of the same label for an object of predetermined size or aspect ration, then they are extracted as a character. One problem with pixel connectivity based methods is that they fail with broken characters or when characters are

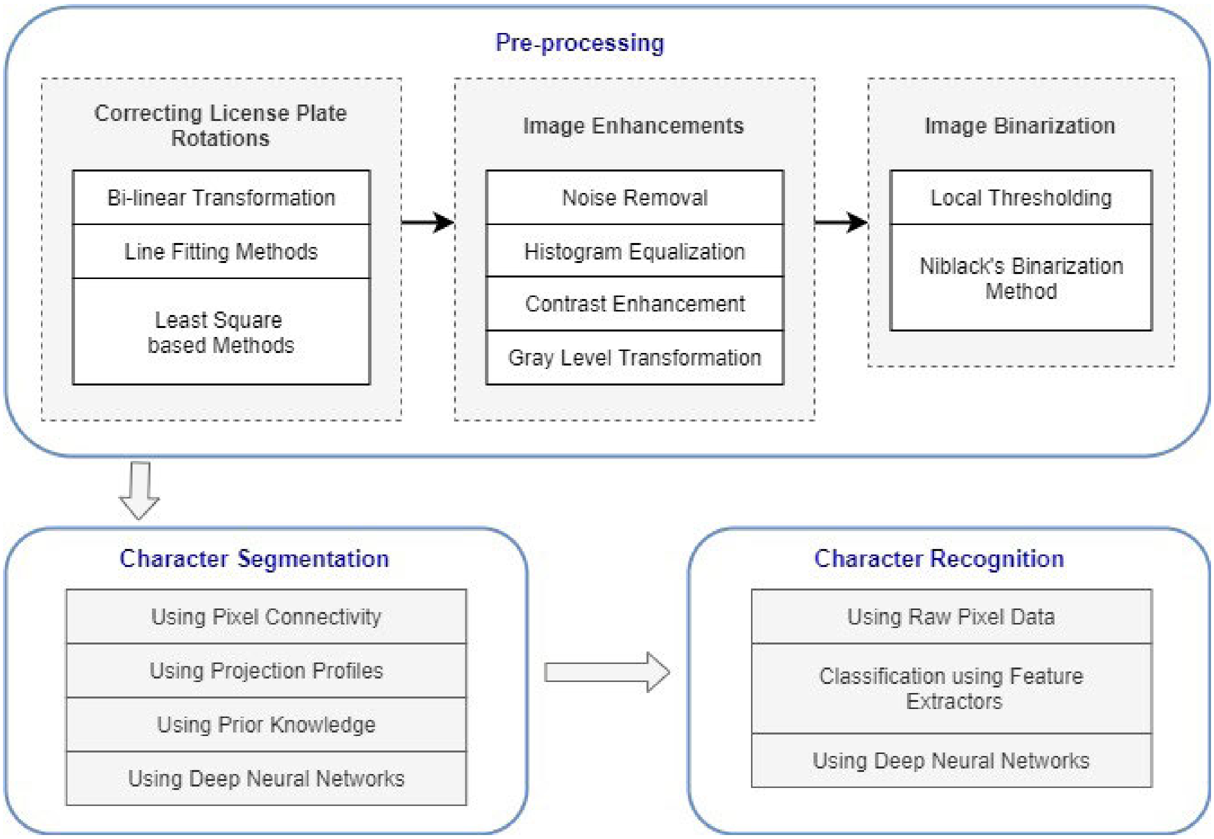

FIGURE 6. License plate recognition pipeline with associated techniques.

joined due to binarization threshold selection. However, pixel connectivity based methods are robust against rotated license plates and relatively simple to implement. Lack of need for pre-processing to compensate for license plate rotation further simplifies the license plate recognition pipeline.

2) CHARACTER SEGMENTATION USING PROJECTION PROFILES

Projection profiles methods use the fact that having opposite colours for the character and background pixels in the license plate image after image binarization. Typically vertical projections are used to detect the starting and ending positions of the character and then horizontal projects are used to extract the character [15]. However, project-based techniques are sensitive to image quality and image noise. As a result, a denoising stage has to be included in the pre-processing stage of the recognition pipeline. Although these methods give low robust values compared to pixel connectivity based methods for rotations, the projection-based methods are still robust to rotations and independent on character positions.

3) CHARACTER SEGMENTATION USING PRIOR KNOWLEDGE

Prior knowledge about the license plate such as the aspect ratio of the characters, the ratio of various coloured pixels in the image is used for character segmentation. For instance, Busch *et al.* [6] have scanned the binary image horizontally to find the location, where the pixel ratio of background pixels to character pixels increases beyond a predefined threshold, to find the starting position of the character and opposite for the ending point of the character. A simple approach was used by Paliy *et al.* [65], by resizing the extracted license plate to a fixed size, where they had predetermined the position of characters. Approaches based on prior knowledge tend to be simple to implement; however, these methods are usually specific to the regions where they were designed to operate and do not generalize in other instances.

4) CHARACTER SEGMENTATION USING DEEP LEARNING

Neural network has become a recent approach for character segmentation, which uses CNN for the task associated with computer vision [1]. A localized license plate is given as the input for the CNN and the bounding boxes of each character are produced as the output. However, depending on the dataset, the CNN execution consumes more time and resources compared to the traditional computer vision-based techniques. In addition, several deep learning-based license plate recognition pipelines have omitted explicit character segmentation in favour of implicit character segmentation in later stages, which leads to reduce the number of parameters and the computational cost [4], [66].

TABLE 2. Comparison of character segmentation methods.

Technique	Advantages	Limitations	References
Pixel connectivity	Simple, robust to rotation	Not suitable to be applied with joined or broken characters	[63], [64]
Projection profiles	Robust to rotation, independent of character positions	Sensitive to noise and font changes, number of characters in the license plate should be known	[15]
Using prior knowledge about the license plate	Simple	Specific to the regions where they were designed to operate	[6], [65]
Deep neural networks	Reduce the amount of parameters and the computational cost		[4], [66]

C. CHARACTER RECOGNITION

Many classification techniques require fixed-size inputs to the learning model. Since the output from the segmentation stage is vary in size, the input segments are re-scaled before the classification. Because the number of characters, their relative position and possible values are known in most cases, each segment is classified individually to be of one of the possible values. This can be considered in three cases, (1) Compare all the pixel values of the raw image data directly with the predefined templates, (2) Use different image processing and machine learning techniques to extract features before classifying the segments, (3) Use deep learning techniques to classify segments.

1) TEMPLATE AND PATTERN MATCHING TECHNIQUES

Given that license plate usually have a known font and character size, one popular option is to use template matching techniques to classify characters [7], [8]. Template matching is typically used with binarized images. For each possible character, a predefined template is created and each segment is matched with each template to find the most similar template. Here, the similarity is measured using metrics such as Mahalobian distance, Jaccard value, Hausdorff distance, Hamming distance and normalized cross-correlation. These methods are simple to implement but do not generalize well for different types of license plates due to their nature. Besides, this technique is difficult to use if there are several possible templates in terms of typography. In order to handle the rotations in characters, additional templates have to be stored which further increases computation time and processing memory.

2) CHARACTER RECOGNITION USING FEATURE EXTRACTORS

In general, all the pixels are not required to recognize a character. Thus, feature extractors are used to distinct simpler features from the images by reducing the computational costs [8]. Some feature extraction techniques can extract features, which are robust against rotations and image noise [60]. In these methods, a feature vector is generated using a transformation on each segment and then classifies using a machine learning model. Some of the feature extractors techniques are eigenvector transformation [67], Gabor filter [68], Kirsh edge detection [69]. Machine learning models such as SVM [70] and Hidden Markov Models (HMM) [62] are used to classify the extracted features.

3) CHARACTER RECOGNITION USING DEEP LEARNING

Advantage of using neural networks is that they can be given the raw pixel data directly and act as both feature extractors and classifiers on their own. Various forms of neural networks ranging from simple multi-layer perceptrons to Probabilistic Neural Networks (PNN) [26] and discrete-time cellular networks have been used for this task. However, many recent studies [4] have used CNN, which have shown great potential in many computer vision tasks. Another recent approach is to directly use object detection based techniques [66] such as YOLO. Although deep learning-based approaches are relatively computationally expensive than the alternative methods like template matching and statistical feature extractors, they provide better accuracy in general.

V. CONSTRAINT-BASED LICENSE PLATE RECOGNITION MODELS

A constraint-based license plate recognition system for the Taiwan license plates has proposed by Chang *et al.* [22]. As shown in Figure 7, the model is based on multi-stage plate recognition disciplines and consists of two sub-modules for license plate localization and number identification. The system is designed to combine with an event detection system for, traffic law enforcement. Since Taiwan license plates are in four colours white, black, red, and green, they have used a colour edge detector sensitive only to black-white, red-white, and green-white edges as a localization technique. The input to the plate locating module is an RGB image, and an edge map is created using colour edge detection. Then, the RGB image is transformed into HSI (Hue, Saturation, Intensity) space, as the HSI model is invariance to illumination, shading, viewing directions, and surface orientations. The license plate region has extracted using fuzzy techniques and created the corresponding edge, hue, saturation, and intensity fuzzy maps. The cell entry of a fuzzy map indicates the degree of the cell occupying the license plate. Finally, these fuzzy maps are combined using a two-stage fuzzy aggregator, and the plate region is located using the integrated map.

The next phase, which is the number identification consists of two main modules for pre-processing and recognition. They have used pre-processing techniques like binarization with a variable thresholding technique, connected

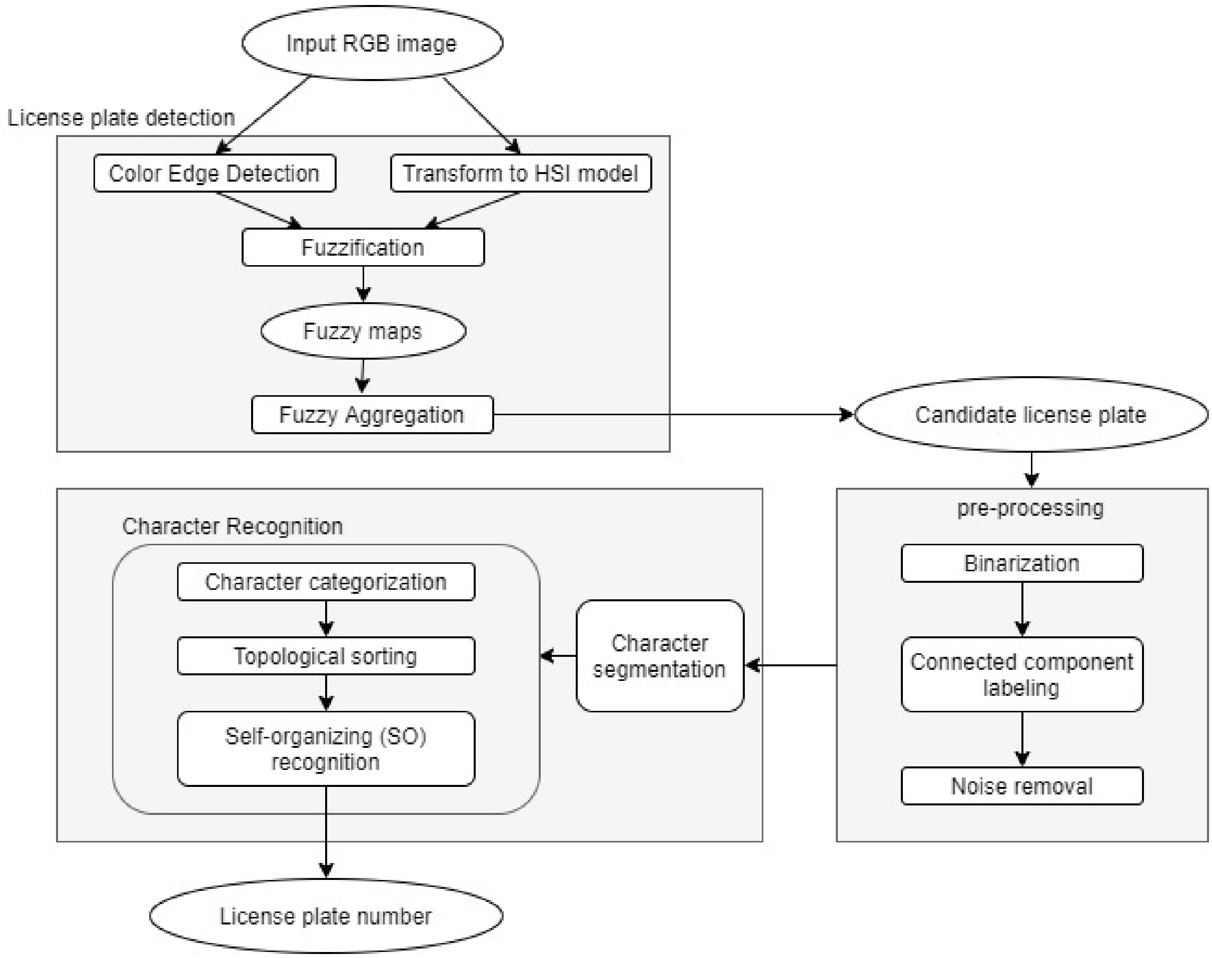

FIGURE 7. Flowchart diagram of the complete ALPR process [22].

component, and noise removal in sequential order. The optical character recognition is done in three main steps, followed by a character segmentation stage. The steps are categorizing characters as numerical or alphabetical, topological sorting, and self-organizing (SO) recognition based on Kohonen's SO network. However, they have identified some issues in distinguishing characters like 8 with B, and 0 with D. Hence, they have defined an ambiguity character set, so that, if the system finds any character belongs to that set, an additional comparison is performed. Although the proposed algorithm is limited to a specific country, there is a possibility to extend for other types as well. The system has shown a detection rate of 97.9%, and a recognition rate of 95.6%, where the overall success rate is reported as 93.7%.

Another approach to building an automatic license plate recognition system is proposed in [38], to read Vietnamese license plates at traffic tolls. The system consists of four modules for pre-processing, plate detection, character segmentation, and recognition. Since they have considered boundary features for license plate detection, the pre-processing stage has enhanced the edge features of the input image. The pre-processing stage employs algorithms such as grey-scaling, normalizing, and histogram equalization. It transforms the input image to a grey-scale and creates an edge map using the Sobel filter. Then a local adaptive thresholding algorithm is used to binarize the image and is fed to the detection module. Here, a boundary-based approach is used for license plate detection. Although Hough Transform is a common algorithm for edge detection, its long execution time and complex computation limit its applicability in real-world scenarios. Thus, they have used a combination of the Hough Transform and Contour algorithm for faster and more accurate results. However, to prevent false detection, a verification phase is used to evaluate whether the candidate is a license plate or not. The character segmentation module has used horizontal and vertical projection, and the character recognition module has used HMMs. The reported rates of success for license plate detection, segmentation, and recognition modules are 98.76%, 97.61%, and 97.52%, respectively. Thus the overall success rate is reported as 92.85%.

A preliminary study to recognize Saudi Arabian license plates is discussed in [7]. Initially, the system has transformed the input images into grey-scaled images and feeds them to the plate extraction module. The plate extraction is done in three steps: detecting vertical edges, filtering, and vertical edge matching. As most vehicles have more horizontal lines than vertical lines, they have performed vertical edge detection using Sobel and Prewitt edge detectors to avoid the unwanted complexity of the algorithm. Then they have applied the seed-filling algorithm to filter the unwanted objects. Finally, the possible plate regions are extracted by matching with the standard height to width ratio of Saudi Arabian license plates. Also, in the segmentation stage, they have removed the upper part of the license plate to avoid any distractions from logos and bolts. Then the image is binarized and segmented using vertical projection. After segmenting the characters, they have normalized images to a size of 40×40 and recognized them using template matching techniques. In this method, the detection, segmentation and recognition accuracies were given as 96.22%, 94.04% and 95.24%, respectively.

Another novel algorithm is proposed by Wen *et al.* [9], to recognize license plates by removing the shadow from the plates under uneven illumination conditions. This study has improved existing algorithms for pre-processing and character recognition. Thus, the system performs well for complex scenarios like illumination variance, plate variations and rotation. As the main contribution, they have considered the pre-processing stage a predominant stage. Instead of using global thresholding techniques for binarization, they have applied adaptive local binary methods. Thus, two local binary methods: Otsu and improved version of the local Bernsen algorithm are used for shadow removal. In the license plate detection phase, they have used a pixel-based method called Connected Component Analysis (CCA). However, prior to the segmentation the detected license plates are resized to 100×200 pixels and processed for tilt correction in both vertical and horizontal directions. Next, the segmentation is performed using projection techniques and all the characters are resized to a uniform size. Finally, for character recognition, they have used an SVM classifier with input features like contour features, and stroke direction features such as Global Direction Contributivity Density (G-DCD), and Local Direction Contributivity Density (L-DCD). Moreover, this method is less restrictive and more robust in complex environments. The reported success rates for license plate detection, character segmentation and recognition are 97.16%, 98.34%, and 97.88%, respectively. The overall success rate is stated as 93.54%.

VI. PERFORMANCE EVALUATION APPROACHES

The performance measures of ALPR systems have been evaluated separately for each stage or a subset of stages of the processes. Many studies have considered license plate detection and recognition stages to evaluate the performance, as these stages can be interpreted easily. Another reason is, most of the machine learning and deep learning approaches are trained under losses defined for each of these stages[30], [31], [71], [4]. This applies for single-stage models as well [30], [31].

Consider the performance measures of license plate detection. Since it is a simplified problem of object detection with

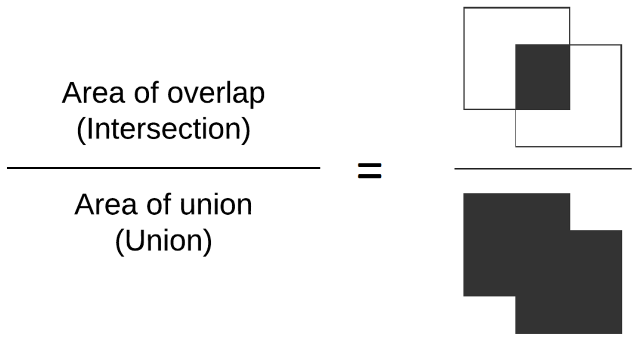

FIGURE 8. Intersection over union for images.

only one class, the same evaluation matrix is used. The perdition is considered as correct, if the Intersection over Union (IoU), also known as Jaccard index is higher than certain threshold [30], [31], [71], [4]. It is a measure of similarity between finite sample sets defined in Equation 1, where A and B are the sets and μ is a measure on the measurable space of A and B. However when considering the images, the areas covered by bounding boxes are used as the measures for ground truth and predictions, as shown in Figure 8.

$$J_{\mu}(A, B) = \frac{\mu(A \cap B)}{\mu(A \cup B} \tag{1}$$

Higher IoU threshold helps filter out imperfect bounding boxes [31]. However, a very high IoU value can result in rejecting many predictions at the early stage, so that the rest of the system will get fewer data to learn the model. Moreover, in the recognition stage, both the bounding box and the letters in the license plate must be correct, as an incorrectly recognized character leads to the incorrect identification of a vehicle. Generally, for the IoU threshold, the values less than the threshold are used for detection in the early stages, and the correctness of later stages depend on that [31], [71]. Once the final prediction is labelled as correct or not for a given set to IoU thresholds, the additional measures such as precision and recall can be calculated.

The speed metric is another evaluation method in ALPR systems. Unlike the accuracy metric, which depends only on the model and the dataset, the speed metric depends on the corresponding hardware platform as well. Since ALPR systems work with video streams, another common measure is the processing frames per second (FPS) value [31]. This is the number of frames (images) the system can process per second. Another equivalent metric is the time taken to process a single image [4], [72], [73], [74]. It is advantageous to measuring processing time for image over FPS value, as the processing time is a direct measure of the model speed and FPS value includes the time it takes to sample frames from the video stream.

VII. DATASETS FOR AUTOMATIC LICENSE PLATE RECOGNITION

Recent ALPR systems use large datasets With the advancement of deep learning techniques. However, collecting an adequate amount of license plate images is challenging and expensive. For instance, the datasets for ALPR require advanced specifications depending on the country or the region where the system is deployed. Thus, a dataset created for one study may be less useful for another. Moreover, some studies have used synthetic datasets instead of real license plate image datasets and have achieved encouraging results. However, there is a need for a benchmark dataset that signifies the common real-world conditions and challenges, so that it can be used as a systematic measure to evaluate and compare the different ALPRs. Further, many studies have used customized dataset for evaluation and comparison, and some of them do not contain images from any challenging real-world settings. This section describes requirements for a real-world benchmark dataset for ALPR to highlight the required directions in future efforts.

A. REQUIREMENTS FOR A REAL-WORLD BENCHMARK DATASET

Some of the general requirements of real-world benchmark datasets for ALPR are as follows.

- License plate variations across different regions
  - *Size*: Have license plates with different standard aspect ratios (height to width)
  - *colour*: Cover a wide range of foreground and background license plate colours by considering the impact of regional changes and capturing devices.
  - *Font and language used*: Represent license plates from different nations. Thus, there is a diversity in the languages and the fonts used.
  - *License plate location*: Cover different types of vehicles because the license plate location depends on the vehicle type.
  - *Style*: Collect license plates from different styles, as some license plates have only one row of characters displaying the number, while others have more than one row with characters. Also, there exist license plates with the country's flags on it.
- Environment variations
  - *Lighting conditions*: Images taken under different illumination conditions (bright light, dawn, dusk, night, shadows on vehicles, vehicle headlight)
  - *Weather conditions*: Collect images under different weather conditions (rainy, snowy, foggy, cloudy, windy etc.)
  - *Background*: Collect images with different background patterns and textures.
  - *Diversity of scenarios*: Cover different road scenarios where ALPR can be applied. (countryside roads, highways, parking lots, etc.)
- Different viewpoints: Have images taken from varying viewpoints, rotation, scale, camera positions to avoid any skewed results.
- Challenging conditions: Include images with challenging scenarios like occlusions, degraded plates, plate rotations, dirt on plates, multiple plates, partially hidden plates, broken license plate characters etc.
- Image quality: images should be acquired with different quality cameras (high and low resolution).
- Availability: Make it publicly available for others' use.

B. PUBLIC ALPR DATASETS

Most of the public datasets for ALPR are specific to a region or a country. Often, these public datasets are created by collecting data from traffic monitoring systems, parking lots, highway toll stations, and surveillance cameras. Generally, the datasets collected in the USA and Europe such as UCSD and OpenALPR, are relatively simple. The images are mostly captured using handheld cameras and often, there exists only one vehicle per frame. Also, they carry less complicated scenarios in the real-world, and generally, the license plates are well centered in the image.

Nevertheless, Chinese datasets such as ChineseLP, AOLP, UFPR-ALPR, CCPD, and PKU are difficult to recognize. They have considered complex scenarios like plate inclinations, degradation, occlusions, uneven illumination conditions, changing weather conditions, multiple plates per frame, etc. Also, the datasets such as SSIG-SegPlate and UFPR-ALPR, have high-resolution images and multiple frames of the same scenario. Table 3, gives a comparison of these datasets.

C. ISSUES RELATED TO PUBLIC ALPR DATASETS

Many publicly available datasets have several issues based on the volume and composition when using in real-world applications. Most of the datasets have labels for only a single-stage such as a license plate detection or does not contain annotated data. Therefore, when using these datasets in the license plate recognition process, extra effort is needed to annotate the images to use in other stages. On the other hand, these data are often collected from traffic monitoring systems, parking lot entrances, highway toll stations, and surveillance cameras. Thus, the images may under even illumination conditions or any supplementary lights at nighttime. Sometimes, they have fixed viewpoints, orientations, and meanwhile, most of the vehicle images are frontal.

Another major limitation of the existing datasets is the volume. According to Table 3, most of the datasets are limited to 2000-5000 images that are composed of still images or snapshots of video frames. Therefore, it is difficult to evaluate the performance of the images with motion blur, if the vehicle is moving. Hence, moving cameras (mounted to a vehicle) are recommended to create ALPR datasets. Further, these datasets are composed of common types of vehicles like cars, motorcycles, and trucks. Therefore, there is a requirement to extend the dataset by adding more types of vehicles and update regularly to keep track of the new models. Thus, it is important to have comprehensive ALPR datasets to fulfil the aforementioned requirements.

TABLE 3. Comparison of publicly available ALPR datasets.

Dataset	Year	Country	Images	Resolution	Recognition	Vehicles	Description
GAP-LP [75]	2019	Tunisia	9175	Various	Difficult	Cars	Uneven illumination conditions, different view angles
CCPD [31]	2018	Chinese	250K	720 × 1160	Difficult	Cars	Uneven illuminations, different view angles and positions, different weather conditions, blurred images
UFPR-ALPR [1]	2018	Chinese	4500	1920 × 1080	Difficult	Cars, motorcycles	Uneven illuminations, different view angles and distances, both vehicle and camera are moving, PNG format
PKU Dataset [74]	2017	Chinese	3828	Variance	Difficult	Cars, Trucks	Uneven illuminations (nighttime), single-plate and multi-plate images, different weather conditions (sunny, shady, rainy)
SSIG-SegPlate [55]	2016	Brazilian	2000	1920 × 1080	Difficult	Passenger vehicles, buses, trucks, police cars, service vehicles	Clear images, close vehicle distance, mostly front view images, different font, dirt on plates, challenging scenes, created specifically to evaluate character segmentation phase
OpenALPR - EU [76]	2016	Europe, Brazil, US	108	Various	Easy	Car, Truck etc.	Mostly frontal, close vehicle distance, uniform illumination
CD-HARD [77]	2016	Multiple	102	Various	Difficult	Cars	Recognize plates from multiple countries, clear images, distorted plates, mostly oblique
AOLP [75]	2013	Taiwanese	2049	Variance	Difficult	Cars, other	Uneven illuminations (indoor, outdoor, daytime, nighttime), different weather conditions, three subsets: access control, roadside images, road patrol
ChineseLP [73]	2012	Chinese	410	Variance	Difficult	Cars	Multiple plates in an image, 160 images downloaded from the internet and 250 taken, different backgrounds, rotations, different scales, uneven illumination
USCD [78]	2005	American	291	640 × 480	Easy	Cars	One vehicle per image, different illuminations, still images and video snapshots

D. GENERATED SYNTHETIC DATASETS

Generally. public datasets are mostly used for training and evaluating the ALPR systems, as it consumes time, effort and cost to collect real license plate images to create a dedicated ALPR dataset. However, public datasets may not always be applicable and sufficient for a specific task. For instance, a publicly available dataset for Chinese license plates cannot be applied to a system that recognizes European license plates as the dataset is composed of Chinese characters. Also, the majority of the datasets may not sufficient to train a deep neural network. As a result, several studies have proposed to generate realistic license plate images using image-to-image translation techniques.

A study by Han *et al.* [79] has proposed a novel approach to generate realistic Korean license plate images using a small set of real license plates. They have used 159 online available license plate images which were collected through web-scraping. However, using the state-of-the-art Generative Adversarial Network (GAN) based methods for image-to-image translation, they have generated over 9000 license plate images. In order to test the performance of the generated synthetic dataset, they have proposed an end-to-end license plate recognition module by modifying the state-of-the-art YOLOv2 model and showed a success rate of 98.72% by solely training on the synthetic data. A similar approach is addressed in [80], to recognize license plates of moving vehicles using a synthetically generated dataset. They have applied the CycleGAN model with the Wasserstein distance loss as in Wasserstein GAN (WGAN) [81] and trained using the real and synthetic images simultaneously.

One of the major limitations of the existing ALPR systems is the low performance at night-time or no performance, due to the limited night-time data. In order to create a dataset for night vision Thermal Infrared (TIR) images are more preferable. Although there is a considerable amount of labelled RGB datasets for ALPR, there is a lack of datasets with TIR images. Consequently, Zhang *et al.* [82], have proposed an approach to translate labelled RGB images to TIR. Although the study is not particularly in the ALPR context, their approach has become a new intuition for many systems that need TIR data for training. They have considered both paired and unpaired image-to-image translation models, which are namely pix2pix and CycleGAN, respectively. Thus, they have created a large set of a labelled synthetic TIR dataset to train the network model and shown that the results outperform a network trained with a small set of real TIR images. Although the application is based on object tracking, this can be used as a technique to translate RGB license plate images to TIR.

VIII. OPEN CHALLENGES AND OUTLOOK FOR THE FUTURE

ALPR is exploited in various applications that involve vehicle identification, such as controlling limited access to restricted areas, automating parking systems and payments, monitoring

TABLE 4. Multi-style ALPR systems with countries supported.

Reference	Applied Country	Techniques d: License Plate Detection r: License Plate Recognition	Performance
[26]	European	d: Connected Component Analysis, Sliding Concentric Window (SCW) method r: Neural Network (PNN)	86.0% (overall)
[83]	USA, Singapore, China, Australia, South Africa	d: Density-based region growing method r: ANN	90.1% (overall)
[90]	India	d: Feature-based method r: Statistical feature extraction	82.0% (overall)
[91]	China	d: Using salient features r: Template matching	93.1% (overall)
[92]	China	d: colour-based methods r: Template matching and neural network	96%-98% (overall)
[93]	China	d: weighted statistics r: BP neural network	91.2%-96.1% (recognition)
[22]	China	colour recognition of license plates using fuzzy maps	95.05% (Shanghai), 92.17% (Shenzhen) and 93.23% (Beijing)
[94]	China	d: Improved Prewitt arithmetic operator	96.75% (detection)
[95]	Israel, Bulgaria	d: Roberts' edge operator r: adaptive iterative thresholding and connected component analysis, template matching	81.2% (localization), 91.0% (recognition)
[96]	Korea	d: colour-based methods	96% (overall)
[97]	Korea	d: Edge-based methods r: Template matching	92.4% (overall)
[98]	Japan	d: Character-based method r: Template Matching	99% (conventional plates), 97% (highly inclined plates)
[99]	France, Spain, Netherlands, United Kingdom, Germany, Italy	d: gradient-based strategy, vertical Sobel mask filter r: statistical classifier	97.5% (detection), 98% (recognition)
[40]	Australia	r: Region-based method	97.6% (detection)
[100]	Iran	Scale invariant feature transform (SIFT)	89%
[101]	Iran	image enhancement methods (intensity variance, edge density) d: MNS (multimodal neighborhood signature)	-
[102]	USA	-	95% (detection), 60% (recognition)
[103]	China & 104 other countries	d: colour-based method	94.7%
[104]	58 different countries (including Algeria, Cyprus, Denmark, Germany, Finland, France, India, Norway, Portugal, U.S.A,)	r: MLP Neural Network	91.59% (overall)

toll fee payments, controlling state border pass and security measures in countries, traffic management and law enforcement. These applications are beneficial to the community by preventing crimes and frauds, reducing required manpower and ensuring security. Although there has been a notable improvement in ALPR methods, there is a need for a robust and efficient system to deal with different types of license plates and changing environmental conditions.

A. CHALLENGING ILLUMINATION AND WEATHER CONDITIONS

Overcoming illumination and weather changes are common challenges faced by the research community in ALPR. Although several existing solutions have shown impressive results in day-time performance, most of them operate with low performances in the nighttime. Most of the real-world applications require license plate detection at night-time. While some algorithms [9], [10] support the changing illumination conditions and issues related to low contrast, they fail to perform well at night-time with poor illumination conditions. Moreover, the related studies that have addressed night-time license plate detection do not perform efficiently and accurately [12], [13], [14], compared to the existing systems for day-time performance. Generally, specific Infra-Red (IR) cameras are used for image acquisition, as a hardware solution for license plate detection at night-time. Thus, possible optimizations to improve the performance and accuracy of the license plate detection systems at night-time is a major future research direction. Further, few studies have addressed the license plate detection challenges associated with hazardous weather conditions like rain or fog. In [11], Azam and Islam have proposed an algorithm to remove rain streams and fog from the images. However, there is a requirement for a generic solution that can detect license plates during extreme weather conditions.

B. MULTI-STYLE LICENSE PLATES

Generally, license plates from different nations or regions contain different standards in terms of the fonts, languages,

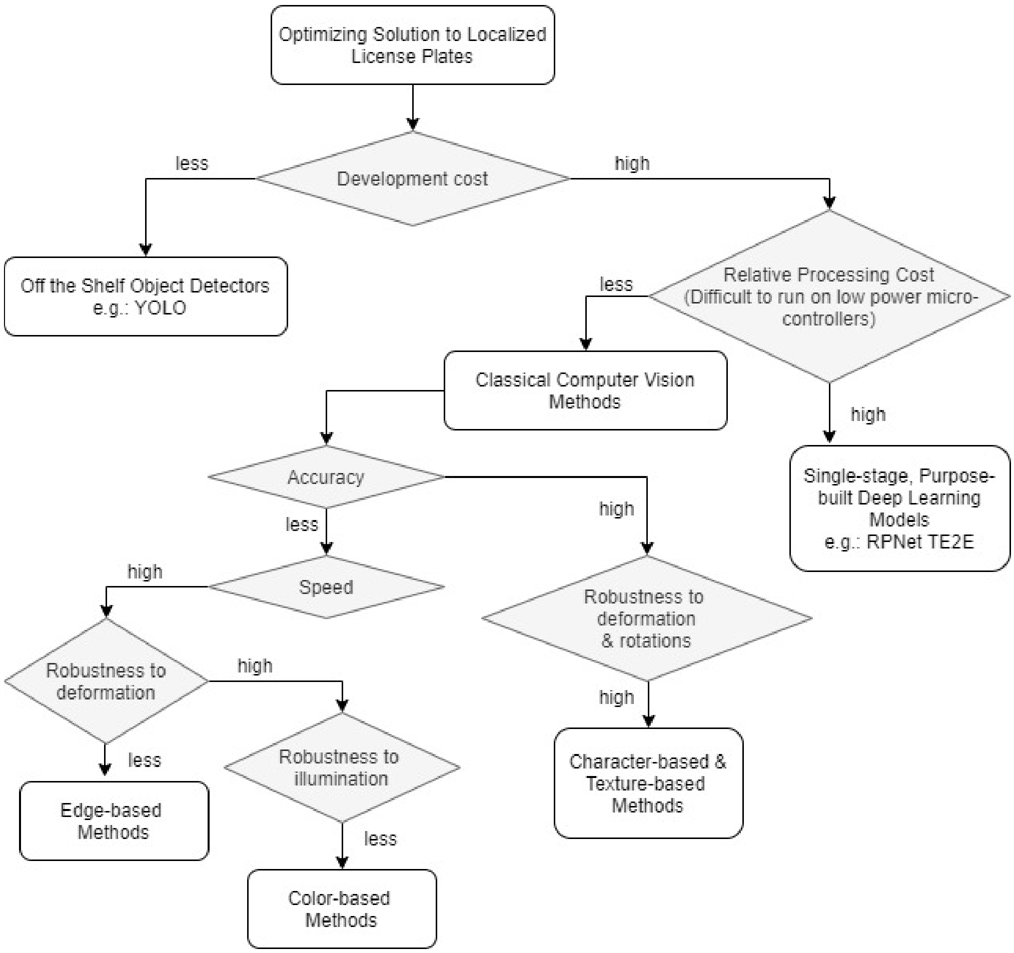

FIGURE 9. Recommended Techniques to use in constrained environments.

TABLE 5. Adverse conditions under which models have been tested.

Reference	Night time operation	Adverse weather conditions (rain, fog, etc.)	Multiple countires	Rotated/tilted
Matas et al.,2005 [42]	✓(synthetic)			✓
Wang et al.,2007 [48]				✓
Zhang et al.,2010 [45]	✓			
Selmi et al.,2017 [52]	✓	✓		
Hsu et al.,2017 [2]	✓	✓		
Xu et al.,2018 [31]	✓	✓		✓
Xie et al.,2018 [3]	✓	✓		
Laroca et al.,2018 [55]				✓
Laroca et al.,2019 [66]			✓	✓
Li et al.,2019 [30]	✓	✓	✓	

license plate number patterns, background, and foreground colours. Even within a region, these properties may differ among vehicle models such as cars, trucks and bikes. Besides, the font can vary between old and new license plate styles for the same vehicle model. According to the related literature, most of the solutions are country-specific. Thus, producing a global solution to detect any license plate has become challenging. Although few studies have addressed the multi-style license plate detection, still there are many limitations to be addressed. Consequently, Jiao *et al.* [83], have proposed a configurable method to recognize license plates from different nations. They have identified four parameters related to the license plates as plate rotation angle, character line number, types of characters, and character format. This was developed using four different algorithms and achieved a success rate of 90% for a dataset with 16800 images. However, this approach has shown low performance when applying for other license plates in specific countries and

TABLE 6. Comparison of techniques and performance of license plate detection.

Ref.	Edge based	colour based	Texture based	Character based	Statistical classifier	Deep learning	Dataset	Image Condition	Processing Time	Performance
[55]	-	-	-	-	-	✓	SSIG	1920 × 1080 pixels in PNG format, 2000 images	1.65555ms	100% (recall/ accuracy)
[66]	-	-	-	-	-	✓		8-public datasets	-	99.45% (recall)
[17]	✓	-	-	-	-	-	custom	762 × 288 pixels, low-quality	92ms	99.90%
[4]	-	-	-	-	-	✓	custom	1920 × 1080 pixels	-	99.51% (recall)
[44]	-	-	-	✓	-	-	custom	640 × 480 pixels	0.2s	99.5%
[109]	✓	-	-	-	-	-	custom	800×600 pixels, rotated, different lighting conditions	0.65s	98.8%
[38]	✓	-	-	-	-	-	custom	800×600 pixels, in different times and places, 805 images	0.65s	98.76%
[37]	✓	-	-	-	-	-	custom	-	0.075s	98%
[22]	✓	✓	-	-	-	-	custom	set1-640×480 (639 images), set2-768 × 512 (449 images)	0.4s	97.9%
[26]	-	-	✓	-	-	-	custom	minimum LP-16 × 46 pixels, different environments and illuminations	111ms	96.5%
[7]	✓	-	-	-	-	-	custom	640 × 480, grey-scale, various illumination conditions (noon, evening)	-	96.22%
[31]	-	-	-	-	-	✓	CCPD	720 × 1160 (pixels), 3 channels, tilted, various distances, illumination & weather conditions, blurry	-	94.50%
[46]	-	-	-	-	✓	-	custom	-	-	94.5%
[52]	-	-	-	-	-	✓	Caltech	896 × 592, colour and real world images	-	93.8% (recall), 93.1%(f-score)

TABLE 7. Comparison of techniques used for segmentation and recognition stages.

ref	Segmentation technique				Segmentation performance (accuracy)	Recognition technique			Recognition performance (accuracy)
	Pixel connectivity	Projections	Prior knowledge	Deep learning		Template matching	Feature extraction	Deep learning	
[55]	-	-	-	✓	99.98%(recall)	-	-	✓	85.45%
[66]	-	-	-	-	-	-	-	✓	99.92%(recall)
[4]	-	-	-	-	-	-	-	✓	99%(recall)
[38]	-	✓	-	-	97.61%	-	✓	-	97.52%
[37]	-	✓	-	-	97.61%	-	✓	-	97.52%
[22]	-	-	-	-	94.04%	-	-	✓	95.6%
[26]	✓	-	-	-	-	-	-	✓	89.1%(overall)
[7]	-	✓	-	-	94.04%	✓	-	-	95.24%
[31]	-	-	-	-	-	-	-	✓	95.5%(overall)
[63]	✓	-	-	-	93.4%	✓	-	-	87.3%
[65]	-	-	✓	-	-	-	-	✓	87%(overall)

different weather conditions. Further, several studies have considered the recognition of multi-national plates. They have used multi-style processing by replacing the detection, segmentation and recognition pipelines [84], [85]. Table 4 provides a comparison of existing multi-style ALPR systems with the applied countries.

C. EXISTENCE OF MULTIPLE LICENSE PLATES IN AN IMAGE

Most ALPR systems handle only the images with a single license plate in it. However, in real scenarios, an image contains multiple license plates and many methods were not able to read multiple license plates at a time. For instance, the algorithms presented in [37], [49], [86], [28], [87], [26], [88], [89], [46], [47] have tested for multi-plate recognition, and successful results were shown only in [37].

D. CAMERA RELATED ISSUES

The position of the camera and its hardware specifications affect the performance of the ALPR systems. Challenging variations in the license plate images are caused when the camera is not positioned well. In addition, when the distance between the vehicle and the camera is high, the license plate number becomes unclear and hard to read. Also, the plate may be tilted or rotated depending on the viewing angle of the mounted camera and only a few studies have shown good performances with tilted license plate images. While positioning a camera it is also important to center the location of the captured plates as it simplifies the license plate detection task. Moreover, the required hardware specifications need to be decided with expert knowledge to achieve good results, as the image quality depends on the properties of the camera. Thus, if the software solution highly depends on the hardware specification, then issues may arise when replacing equipment with different specifications. For instance, if the system supports cameras with low resolutions and black and white images, then the solution may not work with a high-resolution camera. Further, the selection of the appropriate hardware impacts on the efficiency of the system. For example, if the system is deployed to operate at nighttime, it is often beneficial to use an IR camera. Besides, the equipment used should withstand common environmental issues like vibrations, dust and challenging weather conditions.

E. DEMAND FOR RESOURCES AND POWER

The production ALPR systems must satisfy non-functional requirements such as cost of acquisition and operation, physical dimensions, power consumption and connectivity constraints. Thus, assembling an ALPR pipeline requires expert knowledge to select appropriate techniques and feasibility study with an analysis of the costs and benefits of each option. For instance, a single-stage deep learning solution can result in a good performance in terms of accuracy, it may be expensive in terms of computations and resources to be deployed at scale on edge devices. In contrast, a multi-stage approach using classical computer vision techniques may provide acceptable performance at a less computational cost. Generally, many ALPR solutions consume more resources and require expensive hardware and internet connectivity for the operation. Therefore, their applications are limited only to the areas with better internet connectivity and power supply. Hence, it is a vital issue for future researchers to develop systems that can operate with less power consumption and no demand for internet connection. This will be useful to implement practical solutions for the rural areas, with a high demand for ALPR systems.

F. CHALLENGES WITH MOVING VEHICLES

Most often ALPR systems are limited to proceed in indoor conditions and stationary backgrounds. However, the real applications need to deal with moving vehicles with varying speeds. This result in constraint-based environments with changing views, motion blur effect, and changing lighting conditions. On the other hand, the standard TV cameras do not support with vehicles moving at high speeds due to the motion blur effect. Video-based ALPR systems can be used to addresses this problem [105], [106], [107]. The study by Arth *et al.* [106], have used Viola-Jones classifier to detect license plates and reported encouraging results. They have proposed an efficient method to deal with moving vehicles irrespective of their moving speed. Also, their system does not depend on any additional illumination and is claimed to be fully autonomous and embedded on a smart camera.

G. DEGRADED LICENSE PLATES

Most of the existing ALPR systems fail to recognize broken or damaged license plates. The systems that detect license plates using edge-based approaches are often sensitive to the damaged and broken plates and maybe failed during the detection process. In contrast, colour-based approaches are robust against the damages in the license plate. However, systems may fail in the segmentation or the recognition stage, due to the broken or attached characters on the license number plate. A study by Chang *et al.* [108], have used a Self-Organizing (SO) neural network for character recognition and it was robust to noisy, broken, or incomplete characters. They reported an overall success of 93.7% for the license plate recognition task.

In Figure 9, we provide insight for the recommended techniques for different constraints related to non-functional requirements such as cost, accuracy, speed and other challenging environmental conditions. Table 5 compares existing approaches that operate in adverse environmental and plate conditions.

Multi-stage license plate recognition approaches have been widely used in related studies. However, the separation of the two stages: detection and recognition, affect the low performance in terms of the accuracy and the efficiency, as an error in the localization or segmentation can fail the entire recognition process. Moreover, the dependency between the stages and the less efficient CPUs used in intermediate operations result in a time-consuming and less efficient recognition process. In contrast, single-stage license plate recognition systems have shown high performance and efficiency [30], [31]. However, there is a need for future studies on the single-plate license plate recognition to develop efficient and accurate systems.

IX. DISCUSSION

Table 6 and Table 7, provide a comparison of existing ALPR models in terms of their performance and the techniques used for license plate detection, character segmentation and recognition, respectively.

The existing ALPR solutions can be broadly divided into two categories as multi-stage license plate recognition and single-stage license plate recognition. Multi-stage license plate recognition systems separate plate recognition into three stages: license plate detection, character segmentation and character recognition. For the past two decades, more than 95% of the studies in ALPR have followed multi-stage license plate recognition disciplines. In the license plate detection stage, the plate is extracted using traditional computer vision techniques considering features such as shape, colour, texture and existence of characters. Also, several studies used statistical classifiers with Haar-like features for better performance. With the recent advancements in the deep learning paradigm, object detection was also employed in the license plate detection process. However, the performance of the deep learning-based methods was outstanding and robust under constrained conditions, compared to the traditional techniques. Considering all the solutions from the early stages, the focus of related studies were based on traditional computer vision techniques and nearly 50% of the studies have used edge-based methods for license plate detection. However, more than 80% of the studies have embedded deep learning methods for license plate detection in recent years.

Accordingly, different pre-processing techniques such as binarization are applied on images, before the character segmentation, which leads to better recognition accuracy. Generally, pre-processing techniques are used to handle rotations, remove noise, enhance contrast levels. The character segmentation techniques consider aspects such as the colour contrast between the license plate background and the character foreground. In the recognition stage, the segmented characters are classified using pattern matching, statistical classifiers and deep learning methods. Moreover, the earlier pattern matching techniques are replaced by deep learning methods such as object detectors to overcome the performance and memory constraints. However, it is challenging to produce a generic and optimal solution for ALPR due to the associated constraint-based environmental and license plate variation conditions such as rotations, occlusions, illumination changes, interfering objects and shadows. Accordingly, few of the existing ALPR systems provide efficient solutions under challenging conditions.

This survey has considered above 100 related studies published in reputed venues. Among them, nearly 60 studies were journal publications and about 50 articles are conference papers that were published during the year 2000-2020. The indexing and ranking details of the respective journals are given in the appendix section. Although there are few surveys [15], [16] done in this specific field, we believe that our study describes the latest research with the state-of-the-art solutions. We provide critical and constructive analysis of existing published literature in the field of ALPR and identify some specific limitations and challenges. Moreover, we provide comparisons of existing ALPR methods with their key advantages and limitations in practical use. We also provide recommendations to optimize the ALPR algorithms in terms of latency, performance and cost, which will be beneficial for future researchers and developers.

X. CONCLUSION

The design and development of an automated license plate recognition system (ALPR) require careful selection of specifications and techniques to work with different operational and hardware constraints. This survey paper has explored and analysed the existing approaches and techniques used in ALPR solutions in recent literature. The single-stage deep learning-based solutions have shown high performances with diverse datasets. The multi-stage object detection based deep learning solutions can be pre-trained on large datasets, however, they have shown less computational efficiency and accuracy than single-stage approaches. This paper has done an extensive comparison of the related studies and identified the requirements for benchmark datasets in practice. Further, we have described the open challenges and suggested future research directions for ALPR solutions.

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JITHMI SHASHIRANGANA is currently pursuing the bachelor's degree with the Department of Computer Science & Engineering, University of Moratuwa, Sri Lanka. She has research experience in computer vision and deep learning.

HESHAN PADMASIRI (Member, IEEE) is currently pursuing the bachelor's degree with the Department of Computer Science & Engineering, University of Moratuwa, Sri Lanka. He has research experience in computer vision and deep learning.

DULANI MEEDENIYA (Member, IEEE) received the Ph.D. degree in computer science from the University of St Andrews, U.K. She is currently a Senior Lecturer with the Department of Computer Science & Engineering, University of Moratuwa, Sri Lanka. Her research interests include software modeling and design, data engineering, bio-health informatics, and computer vision. She is also a Fellow of HEA (UK), MIET, MIEEE, and a Charted Engineer registered with EC (UK).

CHARITH PERERA received the B.Sc. (Hons.) degree in computer science from Staffordshire University, U.K., the M.B.A. in business administration from the University of Wales, Cardiff, U.K., and the Ph.D. degree in computer science from The Australian National University, Canberra, Australia. He is currently a Senior Lecturer with Cardiff University, U.K. Previously, he worked at the Information Engineering Laboratory, ICT Centre, CSIRO. His research interests include the Internet of Things, sensing as a service, privacy, middleware platforms, and sensing infrastructure. He is a member of the ACM.