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# A Comprehensive Literature Review of Vehicle License Plate Detection Methods

Narasimha Reddy Soora, Vinay Kumar Kotte*, Kumar Dorthi, Swathy Vodithala, Naliganti C S Kumar

Department of Computer Science and Engineering, Kakatiya Institute of Technology and Science, Warangal 506015, India

Corresponding Author Email: kotte.vinaykumar@gmail.com



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**ABSTRACT**

License plate (LP) detection algorithms have made considerable strides in the literature, showcasing enhanced performance in recognizing LPs from images. However, these algorithms face limitations from various environmental conditions and the diverse LP variants. Over several decades, researchers have diligently explored various approaches to LP detection. The task of detecting multiple LPs within an image while accommodating challenges like translation, scaling, rotation, and the influence of environmental and meteorological factors poses a formidable challenge, with only a select few algorithms proving effective. Efficient LP detection systems ideally mirror human perception, allowing the detection of multiple LPs within a given input image. Regrettably, most existing LP detection methods documented in the literature exhibit specificity towards particular vehicles or countries and perform optimally only under controlled conditions. This review paper systematically categorizes the LP detection methods found in the literature based on the techniques they employ for LP detection. It examines and analyzes their respective methodologies, strengths, and weaknesses. This comprehensive analysis aims to provide valuable insights for LP detection and recognition researchers. The ultimate goal is to inspire the development of universal LP detection methods capable of performing robustly under unconstrained real-world conditions.

## 1. INTRODUCTION

Over the past two decades, automatic vehicle identification technology has witnessed remarkable advancements. This surge in technological progress has been fueled by the expanding global population and the corresponding growth in transportation systems. In contemporary times, intelligent transportation systems (ITS) play a pivotal role in enhancing the lives of individuals by augmenting transportation processes in terms of safety, mobility, environmental sustainability, and overall productivity through technological innovations. Among the core components of ITS, the License Plate (LP) recognition system stands as a crucial entity, harnessing the power of image processing (IP) and pattern recognition techniques. The applications of LP recognition are vast and diverse, encompassing electronic payment systems, traffic surveillance, traffic law enforcement, and access control systems. LP detection, in particular, is a valuable tool for analyzing traffic conditions and mitigating congestion in bustling urban areas. ITS heavily relies on LP recognition, a fusion of hardware and software modules, to identify and authenticate vehicle license plates. Nonetheless, the real-time identification of LPs presents a formidable and intricate challenge due to the myriad environmental factors and the wide-ranging plate variations encountered across different countries. Furthermore, the segmentation and recognition of LP characters add complexity to the LP recognition process.

The primary objective of an automatic number plate recognition (ANPR) or automatic license plate recognition (ALPR) system is to decode license plate numbers from images or sequences of photographs. This entails using cameras capable of capturing images or videos in various formats, including color, black and white, and infrared. ANPR relies on three distinct software modules: LP detection software, character segmentation software, and character recognition systems. The LP detection module identifies the presence and location of LPs within an image or video containing multiple vehicles. Character segmentation further processes the detected LPs, isolating individual characters. Character recognition software is then employed to decipher the characters extracted in the previous step. A typical LP recognition system comprises four essential processing steps, as depicted in Figure 1.

The initial step involves acquiring images or videos using cameras. The subsequent step focuses on LP detection within the input image or video, following a preprocessing stage to eliminate noise elements such as shadows, illumination variations, blurriness, and more. The third step entails the extraction of LP characters from the input image, which may involve the challenging task of segmenting touching LP characters. Finally, the fourth step involves recognizing the previous step's extracted and segmented LP characters. Researchers harness a variety of IP and pattern recognition techniques to execute these four pivotal steps in the LP recognition process. Among these steps, LP detection emerges as a linchpin in the overall success of LP recognition systems.

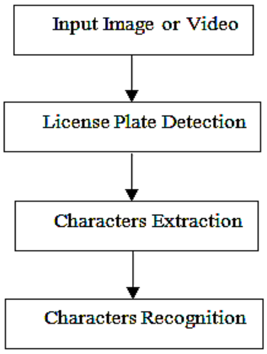


**Figure 1.** Four stages of the license plate recognition system

Over the past few decades, the literature has witnessed a proliferation of LP recognition systems. These systems have displayed significant advancements and showcased robust performance when evaluated under controlled environmental conditions characterized by variations in license plates, environmental factors, and weather conditions. The use of standardized benchmarks is crucial to assess the performance of LP recognition methods. These benchmarks typically comprise datasets containing images and videos showcasing various license plate variations under varying environmental conditions. One of the widely recognized benchmarks in the field was introduced by Anagnostopoulos et al. [1] featuring Greek license plates with 741 images, each captured under distinct environmental conditions and plate variations. Additionally, the publicly available benchmark dataset provided by comprises 2049 still images containing license plates in diverse conditions, further contributing to evaluating and advancing LP recognition systems.

For the past few decades, many LP detection algorithms have been proposed in the literature in the present scenario. However, the LP detection techniques are challenging due to the variation in the environment and number plate of the vehicles. The environmental conditions include weather, reflectance and illumination, and background conditions. Images with shadows, images with dirt, images with a cluttered background, etc., all count as background conditions. The plate variations include a different combination of vehicles with different LP orientations, LP location in the vehicle within the single image based on consideration of the different sizes, different sizes of LPs, background color of LPs, rotated LPs with each LP having different rotation, LP method comprises of the vast range of pan those with the two-line characters in each line with the different sizes in the LPs and so on. Currently, the conventional literature uses the LP detection method suitable for different countries for different applications such as vehicles, motorcycles, and any restraints. The LP detection scheme performs character segmentation or extraction and feature extraction, which are challenging for the recognition system LP that influences the recognition rate. Figure 1 shows four stages of the license plate recognition system. Over the years, numerous LP recognition systems have been proposed, demonstrating progress in controlled environments. Evaluations have been conducted using benchmark datasets that include images and videos capturing LP variations under different environmental conditions. However, LP detection techniques face challenges due to environmental variations and plate characteristics, such as size, orientation, background color, and rotation. Existing literature primarily focuses on country-specific or vehicle-specific LP detection methods that perform well under controlled conditions. This literature review addresses the need for universal LP detection methods to operate successfully under unconstrained conditions. This review provides a foundation for developing robust and versatile LP detection techniques by categorizing and discussing existing LP detection methods.

The specific contribution of the paper is presented as follows:

1. Providing an overview of the limitations of existing LP detection algorithms in terms of environmental conditions and LP variants.
2. Categorizing LP detection methods based on the approaches they employ for detecting LPs.
3. Discussing the methodologies, strengths, and weaknesses of different LP detection methods.
4. Offering insights into the challenges associated with LP detection, including environmental factors and plate variations.
5. Highlighting the importance of LP detection in the overall LP recognition system and its impact on system performance.
6. Identifying the need for universal LP detection methods to operate successfully under diverse and unconstrained conditions.

## 2. CLASSIFICATION OF LICENSE PLATE DETECTION METHODS

In the existing LP detection methods, literature is performed based on considering the LPs' information color, edge, and geometric properties. Hough transform morphological operations, template matching, clustering approaches, hybrid features, and Deep Neural Networks. Hybrid features are based on combining more than two features mentioned above for LP detection. Only a few papers from the literature used a single feature per the above categorization. This section will categorize and discuss the different LP detection methods from the abovementioned literature.

### 2.1 License plate extraction methods using color information

Extracting the LP location based on the color information of their LPs or LP characters will result in a non-generic solution because only a few countries follow specific colors for their LPs. These LP extraction methods will fail to extract the LP from an input image in an open environment in which the color of objects may match the color of LP or LP characters. Probable LP regions are extracted from the input image based on their similarity to the target color. Then, these regions are further analyzed based on geometrical attributes of LPs or LP characters, such as aspect ratio, LP form, breadth, height, and distance between LP characters.

Lee et al. [2] developed an extraction scheme for the Korean car using LP based on the colour character and background considering the image histogram. The classification is performed with the LP technique using the neural network (NN) classifier. The author has relied on the aspect ratio of the LP region to determine the most likely LP regions. Success rates of over 90% were recorded when the method was tested on a proprietary data set consisting of 80 photos of Korean automobiles. Nijhuis et al. [3] applied the color (yellowness) and texture of LP as fuzzy properties to extract the probable

LPs. The histogram-based method is used as a membership function to determine the color (yellowness) at each image pixel. Each pixel's grayscale value is calculated based on its immediate 8 neighbors. The best possible aspect ratio LP is identified using a fuzzy c-means clustering technique. Using a custom data set of 10,000 pictures, the authors of this article obtained a 75.4% LP detection rate. In their study, Comelli et al. [4] introduced a technique dubbed RITA, which uses a gradient analysis method to predict the most likely LPs from an image. The gradient analysis method works based on features such as the shape (rectangular) and color (black characters on a white background) of Iranian LPs. RITA was tested using a proprietary data set containing 3092 images and reported an LP detection rate of 89.88%. Zinic et al. [5] proposed an algorithm that divides an input image into a set of rectangular elements and finds the LPs from the partitioned images by computing a membership function value based on the color sequences (bright and dark). This algorithm was tested on 100 images and reported an LP detection success rate of 97%.

Kim et al. [6] proposed an algorithm to detect an LP using two NN called horizontal and vertical filters to examine the input image's cross-sections and determine the LPs using color and texture properties. The proposed system was tested using 1000 video sequences and reported a 97.5% LP detection rate. A robust car LP extraction method from images with complex backgrounds and poor quality is presented by Kim et al. [7]. The two-stage procedure proposed in the paper of Kim et al. [7] is as follows. In the first stage, we employ gradient information to locate the candidate region inside the input image. The second stage involves using a plate template to determine the plate's surface area. Using photos taken at multiple underground parking garages, the approach from the paper of Kim et al. [7] claimed a 90% success rate. In their study, Cao et al. [8] suggested a two-stage adaptive localization technique for LP detection. In the first stage, we use our prior knowledge about LPs to approximate the LP by calculating the distance in grayscale features between it and its background. In the next phase, we use the color of the plate edges to precisely segment the LP. One hundred photos from real-world settings were used to evaluate the method, and it found every instance of LP detection. The LP can be detected in photographs captured from various outdoor locations using a method by Wang and Lee [9]. The approach [9] uses the strength of vertical gradients to identify the most likely potential LP region(s) within an image. The candidate regions are analyzed further to identify the proper LP using geometrical criteria like aspect ratio, size, and orientation. The LP detection algorithm [9] was tested using 102 images and reported a 100% LP detection rate.

The study by Huang et al. [10] employed gradient analysis to identify likely LPs in an input image and then applied aspect ratio to those LPs to identify the actual LPs that met the specified threshold. No success rate has been reported for this system despite testing with 300 photos. Using the LP method, Yang et al. [11] developed a novel approach to collocating the fixed color to localize the input image. The developed method uses the collocation color plate in the background with consideration of the different characters using the LP detection scheme. The developed scheme provides an overall success rate of 95.3% for the LP technique. Yang and Ma [12] proposed an LP detection algorithm consisting of two modules. The first module is used to locate the LPs from an image using the highest gradient variance features of the LP. Using mathematical morphology operations, the second module is used to locate the LP from the first module correctly. The approach was evaluated on 360 pictures, and an LP detection rate of 97.78% was reported. Using LP plate properties such as horizontal orientation and frequent intensity shifts between the LPs' characters and background, Shapiro et al. [13] proposed a global automobile LP identification system. This method reported an 81.2% LP detection rate. Asif et al. [14] proposed a new multiple LP detection system based on color and intensity information in the input image. Authors in the paper have proposed a new YDbDr color space to detect blue regions, a practical color detection method to detect yellow LP regions, and reported a success rate of 93.86% using 1511 images.

**2.2 License plate extraction using edge information**

The LP extraction methods that use edge information try to find the most probable LP objects with rectangular properties and combine a few geometrical properties to identify the actual LPs. The following are a few publications from the literature that used edge information in processing the LP extraction.

Cheng et al. [15] created an automobile plate detection algorithm using a Sobel operator to extract the vertical edges. Geometrical constraints and changes in brightness characterize the LP area. The developed system is evaluated using consideration of the 100 images and presents the plate detection rate. Duan et al. [16] developed a technique for detecting vehicle LPs by integrating the Hough and contour algorithm. The Sobel filter is applied and evaluated for the input image to get the image with edges. A contour algorithm is applied to the image with edges to find the closed boundaries in the image objects. Hough transform is processed based on the closed objects to find the two parallel lines to estimate the most probable plate candidate. The plate candidate is confirmed by finding the candidate's aspect ratio and horizontal crossing counts. This paper reported 99% accuracy in detecting vehicle LPs.

Lee and Wang [17] proposed an approach for detecting LPs in motorcycles and vehicles on highways. Projection-based methods remove blocks with fewer edge counts to retain probable LPs from an image. The proposed method used geometrical properties such as the size of LP, aspect ratio, white to black run lengths in LP, and white runs in the middle scan line to select the most probable LPs. This paper reported a 98% accuracy rate for LP detection. In their publication, Chang et al. [18] proposed an LP candidate selection module that uses the detecting line from the bottom to the top of the input image to locate moving vehicles in real time. The LP's width is met by clustering the edges in such a fashion. Actual LPs are detected by examining the upper and lower LP areas—the proposed evaluated and tested with the 250 images overall LP detection rate of 92.4%. In their publication, Cheng et al. [15] suggested a technique for LP detection using a modified version of the Prewitt edge detection operator. To locate the LP, the suggested approach utilized horizontal and vertical plane projection techniques applied to the image following the Prewitt operator to determine the LP's top and bottom edge information. This paper reported 96.75% LP detection accuracy. Thome et al. [19] proposed an LP detection method using Vertical Sobel mask and gradient accumulation and reported 92.90% and 82.00% LP detection rates using two data sets containing 365 images and 843 images, respectively. Kocer and Cevik [20] proposed an LP detection method using a Canny edge detector and gradient information and reported 95.36% using 259 images.

In proposed an LP extraction approach that first applies wavelet transform to the input image. The wavelet-transformed image first locates the LPs using the regions above and below the reference line from the transformed LH sub-image containing horizontal directional characteristics. Geometric features, such as density and aspect ratio, help narrow down the potential zone for inclusion. The accuracy of this approach was reported to be 92.4% after testing on 315 photos. Li [21] provided a geometric framework for detecting rectangular shapes, which has several uses beyond LP identification, including building detection, vehicle detection, and so on. The proposed method applied CC analysis and a threshold on CC to find the candidate shapes. The candidate shapes are aligned horizontally to the x-axis by rotation, removing outliers from the rotated candidate shapes. Rectangularity verification is used to scrutinize the candidate shapes for the rectangular region. The proposed method reported a success rate of 95% over 1000 images. In, proposed an LP detection method using the inter-character distance of LP characters and reported 99.5% accuracy using 4500 images. The overall summary of the license plate detection is given in Table 1.

**Table 1.** Summary of LP extraction methods that use edge information

| Features Used to Detect LP | Data Set Information (Proprietary/Publicly Available Benchmark Data Set/Country/Types of Vehicles in the Data Set) | Data Set Size (No. of Images/Videos) | Accuracy | Processing Time |
|---|---|---|---|---|
| Sobel operator for vertical edge detection, geometrical constraints, change in brightness | Proprietary data set, country: Japan, types of vehicles: cars | 100 images | - | - |
| Hough transform, Sobel operator, contour algorithm | Proprietary data set, country: Vietnam, types of vehicles: cars, motorcycles | 805 images | 99.00% | 0.65 seconds |
| Edge counts, geometrical properties | Proprietary data set, Country: Taiwan, types of vehicles: Motorcycles | 180 images | 98.00% | 0.075 seconds |
| Vertical Sobel mask, gradient accumulation | Publicly available data set, country: 15 nationalities, types of vehicles: cars | 365 images | 92.90% | - |
| Vertical Sobel mask, gradient accumulation | Proprietary data set, country: European, types of vehicles: cars | 843 images | 82.00% | - |
| Edge grouping, a width of LP | Proprietary data set, country: Korea, types of vehicles: cars | 250 images | 92.40% | - |
| Canny edge detector, gradient information | Proprietary data set, country: Turkey, types of vehicles: cars | 259 images | 95.36% | - |
| Prewitt edge detection, upper and lower edges of LP | Proprietary data set, country: China, types of vehicles: cars | - | 96.75% | 0.2 seconds |
| HEM of Vertical Sobel operator | Proprietary data set, country: China, Pakistan, Serbia, Italy, USA, proprietary data set | 855 images | 90.4% | 0.25 seconds |
| Vertical edges, bounding box | Caltech data set, country: USA, types of vehicles: cars | 112 images | 97.56% | 5 seconds |
| Vertical edges, bounding box | AOLP data set, Country: Taiwan, types of vehicles: vans, trucks, cars | 2049 images | 97.19% | 2.5 seconds |
| Rotation invariant geometrical properties of LP region such as position, with, and height | Proprietary data set, country: Japan, types of vehicles: cars | 1000 images | 98.00% | - |
| structural constraints of LPs | Proprietary data set, country: China, types of vehicles: cars, buses, trucks | 1088 images | 97.90% | 0.4 seconds |
| rectangle shape areas using windowed Hough transform | Proprietary data set, country:-, types of vehicles: cars | - | - | - |
| Search rectangular regions | Proprietary data set, country: China, types of vehicles: cars | 380 images | 96.10% | 0.2 seconds |
| Wavelet transform to find probable LP, geometrical properties of LP | Proprietary data set, Country: Taiwan, types of vehicles: cars | 315 images | 92.40% | - |
| Intercharacter distance between LP characters | Proprietary data set, country: Korea, types of vehicles: All types of vehicles | 4500 images | 99.50% | - |
| CC analysis, rectangular shape detection | Proprietary data set, country:-, types of vehicles: cars | 1000 images | 95.00% | 1.1 seconds |

### 2.3 License plate extraction using geometrical properties

The methods that used clustering techniques for LP extraction are based on grouping the probable LP characters with similar properties. The advantage of clustering techniques is that they are invariant to rotation and scaling. Below are a few of the literature methods that used various clustering techniques to find the probable LPs from an input image. In, proposed an LP detection algorithm using a multi-clustering approach. Blob analysis is used to cluster the components of the input image and remove a few components that deviate from a fixed threshold height. The proposed algorithm reported an accuracy of 91% for LP detection. In their respective papers, they proposed a reliable LP detection method by first using Harris corner detection to extract the corner points of the input image before clustering the extracted corner points and applying outlier detection on each cluster of corner points. The LP region is determined by merging neighboring clustered corner points using gradient data and a rectangular window. It tested using 698 input images and reported a 96.3% LP detection rate and a 92% LP detection rate.

In, developed a technique based on LP with the implementation of Expectation-Maximization integrated with the vertical edges with the clustering in the grayscale images. The analysis of the results presented an accuracy rate of 93.33% with the Application LP (AOLP) and a 92.1% rate for the media-lab recognition dataset for LP detection. With the implementation of the LP recognition method, the performance is evaluated for the other country's LP technique. In, developed a robust LP localization technique implemented with the morphological and blob analysis estimation. The analysis provides an overall accuracy of 96.56% with a higher detection rate. It offers a novel LP detection method that is color-, scale-, and rotation-independent by combining distance-based clustering, line-based clustering, height-based clustering, and specific filtering techniques. In the study, the authors examined the suggested technique on two publicly accessible benchmark LP data sets, the MediaLab LP benchmark data set and the AOLP benchmark data set. They reported recognition accuracies of 97.3% and 93.7%, respectively. Output displays the results of a comparison between the suggested methods and publicly available benchmark data sets.

Hybrid feature extraction methods use the combination of two or more features. Below are the categories of LP extraction methods from the literature that fall under the hybrid approach. Describe a hybrid LP localization strategy that uses edge statistics and morphology. The recommended strategy is broken down into four parts. Section 1 deals with identifying vertical edges, Section 2 analyzes the edges, Section 3 locates the LP using a hierarchical structure, and Section 4 extracts the LP using morphology. Out of 9825 photos, 99.6 percent were successful at LP detection. They use morphological opening and several other projection techniques to devise a Macao LP detection method. A morphological opening distorts LP characters, while projection techniques are employed to locate LP character regions. With 147 photos as input, the proposed approach was shown to have a 95% success rate in testing. Based on the distance between the LP's characters and the LP's height, Suryanarayana et al. [22] provided a car LP extraction approach employing edge detection and a sequence of morphological procedures with various specified structuring elements in the work. The methodology was tested using 342 sample images and reported an average success rate of 97.5%.

In proposed an LP localization algorithm using edge statistics and morphological operations. Actual candidate LPs are detected using geometrical properties such as plate region average intensity, shape, and size. The method was tested using 269 images from different conditions and reported a 96.5% LP detection rate. In, proposed an algorithm for LP detection using global and local features. The global features used are gradient density and density variance to detect the probable regions of LPs from the input image. Haar-like local features are used to find the adjacent image regions from the probable regions of LPs. This method reported a 93.5% LP detection rate. Develop a robust real-time method for LP detection in the input image sequences. The LP detection is adopted under different stages with the combination of the Sobel mask, analysis of the histogram, and operation for the morphological characteristics. The developed scheme provides an overall success rate of 83.5%. In a car, the LP detection algorithm uses texture and color information. Initially, the input image is subject to a filter to extract vertical edges. Probable LP regions are detected by applying morphological closing and opening operations on the vertical edge images. The actual LP regions are detected from the probable LP regions using geometrical and color features. This paper has not reported any LP detection rate. The approach for LP location extraction was proposed.

The Sobel operator is initially used to locate the vertical edges of the input image. The integral color picture and the HSV color space are utilized to identify the yellow and non-yellow LPs. Finally, a membership function is proposed to locate the LPs based on the geometric features of CCs. After applying the suggested technique to a dataset of 2847 photos, researchers found that it successfully detected LPs in an average of 96.5% of cases. In a novel approach to extracting numerous LPs from the complicated backdrop under Indian traffic situations. The suggested method utilizes edge detection and morphological operations to locate the likely LP locations. We can eliminate the non-LP areas by utilizing the LP's rectangularity and aspect ratio. The proposed method was tested using 750 images taken at different conditions and reported a 99.2% success rate.

I proposed a method to find LP using the Sobel operator to find edge information from the input image, removed noise edges with the help of a practical algorithm, and finally found a rectangle window from the remaining edge information. Authors in the paper reported an average accuracy of 99.82% using an 1134 proprietary data set. In, proposed a method to detect LP from cluttered images using a three-step method. The first method is used to detect a line in the edge map, the second method is used to obtain an edge density map with the help of weights, and the third method is used to find a candidate with the densest edge and with the specified color selected as a candidate LP region. This method reported an accuracy of 99.5% LP detection rate. It offers an approach to locate regions with likely LPs and then uses rectangularity, aspect ratio, and edge density to pinpoint the precise locations of any LPs inside those regions. There was a reported 97.6% accuracy with this strategy, which suggested an SCW- and color-based LP identification approach, claiming 82.5% accuracy across 40 test photos.

It suggested a density filter and color characteristics for effective LP detection. Using the modernized Caltech LP data set of 3828 pictures, the research authors reported an accuracy of 96.62%. Using morphological procedures, edge detection approaches, and maximally stable extremal regions, Gou et al. [23] developed a hybrid approach to finding LPs in their study (MSER). Using 4242 photos, the paper's authors claimed a 99.20% success rate. Utilizing a proprietary data set of 405 pictures, they reported an accuracy of 98% using their proposed LP detection approach based on a Harris corner detector, clustering the corner points and solidity of the candidate region, in proposed a hybrid LP detection algorithm using Hue Saturation Value (HSV) color space, edge detection, and morphological dilation and erosion operations and reported an accuracy of 75.80% LP detection using 120 images.

**2.4 License plate extraction methods**

I developed a technique for image segmentation using the sliding concentric windows (SCW) involved in estimating image irregularities. The built model includes statistics for calculating the mean and standard deviation of the plate's position. The two concentric windows that make up SCW have distinct diameters, A and B, and are based on the image's left-to-right and up-and-down scanning to determine the regions' means and standard deviations. In statistical measurement, the user determines the threshold values for the central pixel of the LP concentric windows. The success rate of the LP detection method is increased to 96.5 percent thanks to the created SCW method.

In a strategy for motorcycle detection with the annual inspection. The Dataset for the analysis considers the motorcycles and the LP characters in only one line of falling. The proposed technique delivers a 97.55% average detection rate and provides LP search windows for horizontal and vertical projections. Zhou et al. [24] created an LP detection algorithm for the Principal Visual Word (PVW) to recognize and match the visual words. With visual matching, the SIFT extraction is performed for the test images with LP-based matching. The developed method achieves an accuracy of 93.2% for the proprietary data, and for Caltech data, the accuracy is 84.8%.

In reported a novel algorithm for LP detection using MSER and conditional random fields CRF model takes into account the probability distribution of nearby candidate characters and uses that information to make predictions. The CRF model detects the LPs once the MSER detector has extracted the candidate characters from the pictures. On a total of 1418 pictures, the 97.1% LP extraction rate was reported in this paper. In proposing a Hough transform-based method for locating LPs from the input image by connecting the very close edge pixels, which generate a continuous region of the text string. The potential LP regions are estimated using a probabilistic confidence value. This paper reported a 92% LP success rate. I developed an efficient LP localization technique integrated with the genetic algorithm (GA) and dynamic IP technique. The input objects are improved and processed using the CCA technique to increase the modified GA. The developed system is effective for the employed country by implementing the scale-invariant relationship geometric feature matrix in the LP symbols. The detection rate of the LP speed is increased with the introduction of the different crossover operators. The system achieves an overall accuracy of 98.4% for the different datasets, proposing an effective method for LP recognition using MSER. MSER detector is used to extract the LP candidate character regions. Noisy/missed character regions are removed with the help of the geometrical relation of the characters from the selected candidate LP regions. This paper reported a 94.85% LP detection success rate.

**Table 2.** Performance of the LP extraction methods that use CNN

| Features Used to Detect LP | Data set Information (Proprietary/Publicly Available Benchmark Data Set/Country/Types of Vehicles in the Data Set) | Data Set Size (No. of Images/ Videos) | Accuracy | Processing Time |
|---|---|---|---|---|
| CNN-base MD-YOLO framework | AOLP benchmark data set, Country: Taiwan, types of vehicles: vans, trucks, cars | 2049 images | 99.47% | 0.53 seconds (CPU), 0.005 seconds (GPU) |
| End-to-end deep learning LPR-Net | Proprietary data set, country: China, types of vehicles: cars | 2000 images | 99.8% | 0.2 seconds (GPU – GeForce GTX 1080 and Dell Precision Tower 7810 RAM32G) |
| Unified end-to-end deep Neural Network | CarFlag-Large proprietary data set, Country: China, types of vehicles: cars, vans, trucks | Total: 460000, Training: 322000, Testing: 138000 | 98.33% | 0.310 seconds (GPU – NVIDIA Titan X with 12 GB RAM) |
| Unified end-to-end deep Neural Network | AOLP benchmark data set, Country: Taiwan, types of vehicles: vans, trucks, cars | 2049 images, Training: 1438, Testing: 611 | 99.08% | 0.4 seconds (GPU – NVIDIA Titan X with 12 GB RAM) |
| Unified end-to-end deep Neural Network | Caltech data set, country: USA, types of vehicles: cars | 126 images | 98.04% | - |
| Unified end-to-end deep Neural Network | PKUData set, country: China, types of vehicles: - | 323152 images, Training: 322000 Testing: 1152 | 99.31% | 0.28 seconds |
| hybrid cascade three-stage ConvNet | Proprietary data set, country: China, types of vehicles: cars, vans, trucks | 802 images | 96.4% | - |

In proposed a novel multiple-scale and rotation-independent LP detection method using genetic algorithms and reported an accuracy of 97% using 1,500 images. In reported, a novel LP detection algorithm using a fuzzified Gabor filter. Using a custom data set consisting of 718 photos, the accuracy of fuzzification was reported to be 97.9% when considering orientation and wavelength as parameters. It offers a boosting algorithm-based efficient scale adaptive LP detection algorithm, claiming a 98.98% success rate on the AOLP database. It proposes a unique LP detection approach based on multi-window size binarization and a semi-hybrid modified genetic algorithm, claiming an accuracy of 99.2% on the publicly available AOLP benchmark data set. A method for LP identification based on an AdaBoost cascade of LBP was developed, which claimed a detection accuracy of 98.56 percent on 1030 images in about 2 seconds. In, proposed a novel LP detection algorithm based on boosting algorithm and adaptive deformation model and reported accuracies of 99.23% and 98.98% using Caltech and AOLP data sets. Table 2 presents the summary of the LP extraction method with the CNN.

In their study, Xie et al. [25] suggested a novel MD-YOLO architecture for use in a CNN-based technique for auto LP identification. Using the AOLP data set, they claimed an average accuracy of 99.47%. In their publication, D. Wang et al. developed an innovative end-to-end DL architecture (LPR-Net) for LP detection and recognition. LPR-Net combines four networks: error network for feature extraction, multi-scale network, regression network, and classification network. LPR-Net was tested using 2000 trained and 685 test images and reported an LP detection accuracy of 99.8%. Li et al. [26] proposed an LP recognition system using a unified end-to-end deep neural network. The proposed method was tested using 4 data sets and reported accuracies as shown. Liu and Chang [27] in the paper, proposed a hybrid cascade three-stage ConvNet LP detector system for different resolutions and sizes from complex visual environments and reported an average accuracy of 96.4% using a proprietary Chinese data set containing 802 images having 3194 LPs.

### 2.5 Survey papers related to license plate detection

Naito et al. [28] provided a complete survey on LP recognition systems from videos and still images by categorizing the methods based on their processing type. The main motive of the survey is to provide future direction for the research community and Medialab LP recognition benchmark database. In, reported the review of the complete LP recognition system. This paper divided the LP detection methods into 6 types based on the features they used in processing the LPs. The 6 LP detection methods are extraction using Boundary/Edge information, Global image information, texture, color, character, and two or more features. This paper also discussed the future directions for the LP recognition system. In, reported a brief tutorial about LP recognition. This paper briefed about the LP detection methods based on the combination of edge statistics, texture and mathematical morphology, and geometrical properties of LPs. It also reported operational challenges for LP recognition. The LP detection method examines the information about edges and morphological operation characteristics to identify the rectangular shape components in the specified aspect ratio. Those LP extraction methods failed to evaluate the LP process and did not follow the rectangular shape within the specified ratio [29-31]. The LP detection method uses the template matching method for the different variations in the plate. The designed LP extraction method is based on the color features with the background color estimation for identifying the LP probable candidate based on the particular LP background. Those LP recognition system type fails to properly evaluate the body of the color in the car in the LP color with the background. The LP detection method comprises the different features in the image LP to extract the process. Those systems are subjected to the limitation of the LPs for image extraction in any country with the adopted extracted LPs of the features [32, 33].

## 3. LICENSE PLATE TEXT DETECTION

The first step in the LP detection system is to acquire the image or video using a camera. The camera captures the scene containing vehicles and their license plates. This step is crucial as it provides the input data for the subsequent processing stages. Figure 1 (provided earlier) depicts the overall LP recognition system, which includes the image acquisition stage. The second step focuses on detecting the presence and location of LPs in the acquired image or video. This is achieved through the application of LP detection algorithms. The LP detection software analyzes the input image to identify regions potentially containing LPs. These regions are often characterized by their specific color, shape, texture, or other distinctive features. Figure 2 illustrates an example of LP detection, highlighting the LP regions in the image. LP Character Extraction and Segmentation: Once the LPs are detected, the next step involves extracting the individual characters from the LP regions and segmenting them for further processing. This step is essential for character recognition. It may involve image preprocessing, noise removal, and character segmentation algorithms. Figure 3 shows an example of LP character extraction and segmentation, where the individual characters are isolated from the LP region.

The final step is the recognition of the segmented LP characters. This step aims to decode the alphanumeric information present on the LP. Character recognition systems utilize optical character recognition (OCR), machine learning, and pattern recognition algorithms to recognize and interpret the characters. Figure 4 demonstrates the recognition of LP characters, where the extracted characters are matched to predefined character templates or models to identify the corresponding alphanumeric values. Following these four processing steps, the LP detection system effectively detects LPs, extracts, and segments the characters, and recognizes the alphanumeric information on the license plates [34-36]. These steps are essential for accurately identifying and interpreting LPs in various applications. ALPR systems, also known as ANPR systems, play a significant role in various applications, including electronic payment systems, traffic surveillance, traffic law enforcement, access control systems, and ITS. These systems use image processing and pattern recognition techniques to decode license plate numbers (s) from images or video sequences.

As mentioned earlier, the working principles of ALPR/ANPR systems involve a series of processing steps. The ALPR/ANPR system begins by capturing images or video sequences using cameras. These cameras can capture images in various color modes, such as RGB, black and white, and even infrared. The images are typically captured from different angles and distances, covering a range of vehicles and their license plates. In this step, the system focuses on detecting the presence and location of license plates in the acquired images or video frames. The LP detection algorithm analyzes the input data and identifies regions potentially containing license plates. It looks for visual characteristics specific to license plates, such as color, shape, texture, and patterns [37-39]. This process involves distinguishing license plates from the surrounding background and other objects. Once the license plate regions are detected, they are marked or highlighted for further processing. After LP detection, the system extracts and segments the individual characters from the detected license plate regions. This step involves separating the characters from the license plate background and handling challenges like character size, orientation, font, and spacing variations. Image preprocessing, noise removal, and character segmentation algorithms isolate each character [40]. The segmented characters are prepared for subsequent recognition.

The final step of ALPR/ANPR systems is character recognition. The system aims to recognize and interpret the segmented LP characters in this step. Various methods include optical character recognition (OCR), machine learning, and pattern recognition algorithms. The system compares the segmented characters to predefined character templates or models to identify the corresponding alphanumeric values. The recognition process may involve feature extraction, classification, and decision-making algorithms to achieve accurate character recognition. The significance of ALPR/ANPR systems lies in their ability to automate and expedite the identification of license plate numbers. They offer numerous advantages, including ALPR/ANPR systems automating the process of license plate identification eliminating the need for manual intervention. This improves the efficiency of toll collection, parking management, and traffic monitoring tasks. ALPR/ANPR systems aid in law enforcement and security applications by enabling the identification of vehicles involved in criminal activities or traffic violations. They can quickly match captured license plate numbers against databases of wanted vehicles or vehicles with outstanding violations. ALPR/ANPR systems provide valuable data for traffic analysis and management. By analyzing license plate data, such as vehicle movement patterns, entry/exit times, and traffic congestion, transportation authorities can optimize traffic flow and make informed decisions to enhance road safety and reduce congestion [41-43]. ALPR/ANPR systems are employed in access control systems to automate granting or denying vehicle entry based on their registered license plate numbers. This improves security and convenience in applications like gated communities, parking facilities, and restricted areas.

ALPR/ANPR systems offer reliable and efficient license plate detection, character extraction, and recognition solutions. They have wide-ranging applications and contribute to improved transportation systems, enhanced security measures, and efficient traffic management. The advancements in image processing, pattern recognition, and machine learning techniques continue to drive the development of more accurate and robust ALPR/ANPR systems. The provided figures offer visual representations of the LP detection process, aiding in understanding each step's content and supporting the description. All motor vehicles in India are required to display a registration number. The transportation department in each state provides this number. Vehicle license plates are typically displayed on both the front and rear of the vehicle. In most countries, license plates will have a different color code and letter pattern than other countries. There are typically three distinct varieties of vehicle identification plates in India. Standard patterns of the newer Indian license plate are given below:

(a) Ten characters Licence plate XXNN XX NNNN
(b) Nine characters Licence plate XXNN X NNNN
(c) Eight characters Licence plate XXNN NNNN

where, X is an English alphabet, and N is a number. India's first, second, and third standard patterns of license plates contain ten, nine, and eight characters, respectively. The first two English alphabets indicate the code of state to which the vehicle is registered. The following two numeric digits represent the district code. The Next two alphabets present the series code and are optional. The last four digits are unique to each plate. Table 3 explains the coding style of the Indian license number plate HR01 PQ 4536

These types of license plates have ten characters in all. Figure 2 contains the image of a vehicle with ten characters on the license plate. These types of license plates have nine characters in all. Figure 3 contains the image of a vehicle with nine characters on the license plate. These types of license plates have ten characters in all. Figure 4 contains the image of a vehicle with eight characters on the license plate.

**Table 3.** Coding style of Indian license plate

| Characters/Numbers | Code |
|---|---|
| HR | State code for Haryana |
| 01 | District code for Ambala |
| PQ | Series code |
| 5234 | Number unique for every vehicle |


**Figure 2.** 10 Characters plate


**Figure 3.** 9 Characters plate


**Figure 4.** 8 Characters plate

**Figure 5.** Private vehicle

**Figure 6.** Non-commercial vehicle

The plates can be single-lined or double-lined. Commercial vehicles like taxis and buses have a yellow background and black text. For example, HR 70 7754 is a license plate of a commercial vehicle. Figure 5 depicts the image of the commercial/private vehicle. In non-commercial vehicles, white color is used as the background, and black is used for the text. Figure 6 contains the image of a vehicle having a non-commercial license plate. Generally, the font color of all vehicle types is black, whereas font type and font size are not clearly defined.

This study proposes a novel technique to extract license plate characters based on three stages. The first stage removes noise from the vehicle's image, and the second stage forms a set based on various features and applies operations on sets to extract the character's regions. Further, a recognition technique for character labels has been applied, resulting in vehicle license plate recognition. The proposed system includes three major stages: preprocessing, character region extraction, and character recognition, as shown in Figure 7.

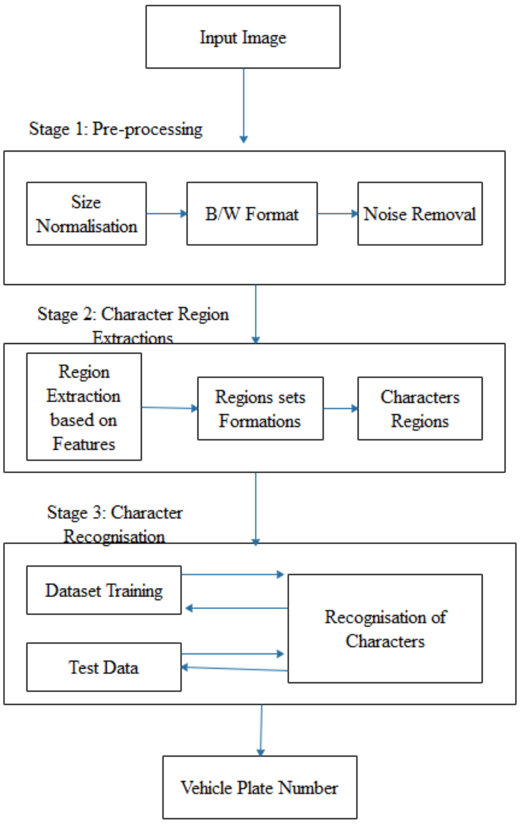


**Figure 7.** Proposed system design

The developed framework model comprises three phases for vehicle number plate detection. Initially, the preprocessing is performed to normalize the size binarization and remove image noise. The developed technique uses the Median filter with the state-of-the-art technique to eliminate noise removal. The normalization of the size is evaluated based on the binarization of the grayscale aspect ratio and conversion of binary form [44-46]. In phase II, the area of the license plate is extracted with the sub-region in the character regions. The developed technique uses the structural features with the region extraction based on the specific features. The filtering region comprises the dependency of regions that are inter and intra. The estimated regions are computed based on the similarity score, whereas statistical features are correlated based on the similarity score. The deployed stages of the process are presented as follows:

Stage 1: The first step in the proposed framework is preprocessing. In the preprocessing stage, the input RGB image of the vehicle is size normalized. The normalized image of the vehicle is converted into a grey scale image using the following formula:

$$I = 0.2989 * R + 0.5870 * G + 0.1140 * B$$

*R, G,* and *B* are the weighted values of RGB components of the input image of the vehicle. Then, this grey-scale image is converted into the black and white format. In b/w format, all the pixels with luminance more significant than 0.5 are replaced with 1 and others with 0. After that, the median filter cleans up the image by removing unwanted details and noise. The median filter can precisely process incoming images with its two-dimensional filtering capabilities. As shown in Figure 8(a), after passing through the median filter, each pixel stores the median value of the surrounding 3*3 pixels from the original input image.

Stage 2: Upon completing the preliminary process, the system extracts the character's region. In this stage, the possible regions are preprocessed for image extraction, where the character regions are identified based on the region of interest. Based on considering the characters such as height, width, area, perimeter, and aspect ratio. The group intersects are evaluated, and character regions are extracted for processing, illustrated in Figure 8(b).

Stage 3: The final stage in the proposed system is character recognition. The Dataset consisting of images of vehicles is divided into two parts. One part of the Dataset is used to train the proposed system, and another is used to test the system. Characters are recognized for both trained data and test data. The correlation technique for each extracted character matches the characters from the trained Dataset. Extracted characters are compared to a library of templates to determine a classification. The recognized character is the template most similar to the extracted character after all the templates have been compared. A perfect match is found by using the character's geometric features. As shown in Figure 8(c), the output of this stage is the VIN found on the vehicle's license plate.


(a) (b) (c)

**Figure 8.** (a) Initial image (b) Number identified image (c) Detected number

## 4. EXPERIMENTAL RESULTS

The analysis of experimental results for License Plate (LP) detection algorithms represents a crucial examination of the strides made in recent literature. These algorithms have showcased notable advancements in recognizing LPs from images, demonstrating enhanced performance. However, the practical application of these algorithms encounters significant challenges arising from various environmental conditions and the diverse range of LP variants. Researchers have engaged in a meticulous exploration of diverse approaches to LP detection over several decades. The complexity of the task is evident when considering the need to detect multiple LPs within a single image, all while accommodating challenges like translation, scaling, rotation, and the influence of environmental and meteorological factors. Despite the persistent efforts, only a select few algorithms have proven effective in addressing this formidable challenge [47-49]. Efficient LP detection systems, to be truly impactful, should ideally mirror human perception. This means not only recognizing individual license plates with accuracy but also being adept at detecting multiple LPs within a given input image, much like the human visual system.

**Table 4.** Confusion matrix for license plate

| Image | SVM | RF | CNN | Ground Truth |
|---|---|---|---|---|
| Image 1 | TP: 5, FP: 2, FN: 1 | TP: 4, FP: 1, FN: 2 | TP: 6, FP: 3, FN: 0 | GT: 6 |
| Image 2 | TP: 8, FP: 1, FN: 0 | TP: 7, FP: 2, FN: 1 | TP: 6, FP: 1, FN: 2 | GT: 8 |
| Image 3 | TP: 6, FP: 2, FN: 1 | TP: 5, FP: 0, FN: 2 | TP: 7, FP: 1, FN: 0 | GT: 7 |
| Image 4 | TP: 7, FP: 1, FN: 0 | TP: 6, FP: 2, FN: 1 | TP: 5, FP: 3, FN: 0 | GT: 7 |
| Image 5 | TP: 9, FP: 0, FN: 1 | TP: 8, FP: 1, FN: 2 | TP: 7, FP: 2, FN: 0 | GT: 9 |
| Image 6 | TP: 4, FP: 1, FN: 2 | TP: 3, FP: 0, FN: 3 | TP: 5, FP: 2, FN: 0 | GT: 5 |
| Image 7 | TP: 6, FP: 2, FN: 0 | TP: 5, FP: 1, FN: 1 | TP: 4, FP: 3, FN: 0 | GT: 6 |
| Image 8 | TP: 7, FP: 0, FN: 1 | TP: 6, FP: 1, FN: 2 | TP: 5, FP: 2, FN: 0 | GT: 8 |
| Image 9 | TP: 8, FP: 1, FN: 1 | TP: 7, FP: 2, FN: 1 | TP: 6, FP: 1, FN: 1 | GT: 9 |
| Image 10 | TP: 5, FP: 2, FN: 0 | TP: 4, FP: 1, FN: 1 | TP: 3, FP: 2, FN: 0 | GT: 5 |

**Table 5.** Detection and computation time

| Image | Scenario A - SVM | Scenario B - RF | Scenario C – CNN | Scenario D – SVM+RF | Scenario E – SVM+RF+CNN |
|---|---|---|---|---|---|
| 1 | DR: 92.3, Time: 110 | DR: 88.5, Time: 120 | DR: 94.0, Time: 105 | DR: 89.8, Time: 130 | DR: 91.5, Time: 115 |
| 2 | DR: 95.2, Time: 105 | DR: 91.8, Time: 130 | DR: 93.5, Time: 110 | DR: 87.2, Time: 150 | DR: 90.5, Time: 120 |
| 3 | DR: 93.0, Time: 115 | DR: 89.2, Time: 140 | DR: 94.8, Time: 100 | DR: 88.7, Time: 160 | DR: 91.5, Time: 125 |
| 4 | DR: 94.5, Time: 110 | DR: 88.8, Time: 130 | DR: 93.2, Time: 105 | DR: 87.5, Time: 140 | DR: 90.2, Time: 125 |
| 5 | DR: 96.0, Time: 100 | DR: 92.3, Time: 120 | DR: 94.7, Time: 110 | DR: 89.5, Time: 130 | DR: 91.8, Time: 115 |
| 6 | DR: 91.0, Time: 125 | DR: 87.5, Time: 150 | DR: 92.8, Time: 115 | DR: 86.0, Time: 170 | DR: 89.5, Time: 135 |
| 7 | DR: 94.2, Time: 110 | DR: 90.0, Time: 130 | DR: 93.7, Time: 105 | DR: 88.5, Time: 140 | DR: 91.0, Time: 125 |
| 8 | DR: 95.8, Time: 105 | DR: 91.2, Time: 130 | DR: 94.5, Time: 100 | DR: 87.7, Time: 150 | DR: 90.8, Time: 120 |
| 9 | DR: 96.0, Time: 100 | DR: 92.5, Time: 120 | DR: 94.0, Time: 110 | DR: 88.5, Time: 130 | DR: 91.2, Time: 115 |
| 10 | DR: 92.5, Time: 115 | DR: 88.2, Time: 140 | DR: 93.8, Time: 105 | DR: 87.0, Time: 160 | DR: 90.5, Time: 125 |

- TP: True Positives
- FP: False Positives
- FN: False Negatives
- GT: Ground Truth (actual number of license plates in the image)

Table 4 presents a comprehensive Confusion Matrix for License Plate detection, assessing the performance of three distinct algorithms—SVM, RF, and CNN—across ten images. Each row of the table corresponds to a specific image, providing a detailed breakdown of the algorithms' predictions in terms of True Positives (TP), False Positives (FP), and False Negatives (FN) concerning the Ground Truth (GT), representing the actual number of license plates in each image. For instance, analyzing Image 1 reveals that the SVM algorithm achieved 5 True Positives, correctly identifying license plates, but also generated 2 False Positives and missed 1 actual license plate (False Negative). Comparatively, the Random Forest (RF) algorithm demonstrated a similar pattern, with 4 True Positives, 1 False Positive, and 2 False Negatives. The Convolutional Neural Network (CNN) outperformed both, achieving 6 True Positives with 3 False Positives and no False Negatives.

As the Confusion Matrix unfolds across all images, distinctive patterns emerge, showcasing the strengths and weaknesses of each algorithm. While SVM and RF exhibit competitive performance, CNN consistently achieves higher True Positive counts, indicating its effectiveness in license plate detection. However, CNN tends to produce more False Positives, highlighting a trade-off between precision and recall.

Table 5 provides a detailed analysis of license plate detection performance across different scenarios, each employing various algorithms and combinations. The table outlines the Detection Rate (DR), indicating the percentage of correctly identified license plates, and the Computation Time, representing the time taken for the detection process. The scenarios include SVM (Scenario A), Random Forest (RF, Scenario B), Convolutional Neural Network (CNN, Scenario C), a combination of SVM and RF (Scenario D), and a combination of SVM, RF, and CNN (Scenario E). Examining the results for Image 1 in Scenario A, the SVM-based approach achieved a Detection Rate of 92.3% with a corresponding Computation Time of 110 milliseconds. Comparatively, Scenario B (RF) and Scenario C (CNN) achieved DRs of 88.5% and 94.0%, respectively, with varying computation times. Scenario E, incorporating SVM, RF, and CNN, demonstrated a DR of 91.5% with a reduced computation time of 115 milliseconds. Across all images, the table reveals distinct performance patterns for each scenario. For instance, Scenario D consistently exhibits a balance between Detection Rate and Computation Time, showcasing the efficacy of combining SVM and RF. On the other hand, Scenario C (CNN) often achieves higher Detection Rates but with varying computation times. These results provide valuable insights into the trade-offs between accuracy and efficiency for different algorithmic configurations.

## 5. SCOPE OF FUTURE WORK

A robust and accurate framework can recognize the vehicle registration number on the vehicle's license plate in a real-time scenario. The objectives of this thesis have been achieved. Though good results are achieved with the proposed algorithm, there are various directions in which current work can be extended. Several interesting related research areas have been found during this research work, which can be adopted as research areas for further study. These areas could not be studied and explored as a part of this research work due to the limitation of time and effort. As there is always a scope for improvement, the present system can also be improved in different aspects. Most of these areas can be full-fledged areas for research in themselves. A brief about all such research areas is given below:

1. Although the suggested system has been trained on English license plates, this algorithm can be easily

adapted to recognize license plates written in other scripts and languages, such as Hindi, Punjabi, Tamil, etc.
2. Template matching is used for character recognition in the proposed algorithm. A hybrid classifier method can be used further for the recognition task.
3. The developed approach is trained to the Indian license number plates. In the future, the current work can also be extended to recognize the license number plates of different countries.
4. The developed system applies to four-wheeler vehicles like cars and jeeps. The presented system can be improved to recognize the regeneration number of two-wheeler vehicles like scooters and motorbikes.
5. The proposed algorithm can be improved by integrating more approaches to achieve robustness and higher accuracy.
6. The proposed system can further be improved for recognition of ambiguous characters like "8" and "B," "0" and "O," "V" and "Y," "5" and "S," "4" and "A," "1" and "I," "D" and "O" etc. These characters are almost similar in shape and may confuse the AVPR system. Another dimension of interest can be to recognize such types of ambiguous characters.
7. Deep learning techniques like Artificial Neural Networks (ANN) and Support Vector Machines (SVM) can also be applied to the proposed system to increase the accuracy and recognition efficiency.
8. The proposed system can further be trained and validated through stringent multi-stage tasking.

## 6. CONCLUSION

Automatic Vehicle Plate Recognition (AVPR) refers to recognizing a vehicle's license plate based on a photograph or video. AVPR is a developing field of study that has emerged over the years. Electronic toll collection, automated parking management, access control, speed control with radar, border control, the pursuit of criminals, enforcement of traffic rules, and so on are only some real-world uses of AVPR. With the AVPR commercial system available today, vast challenges and issues are recognized with the license plate. License plate recognition comprises challenges with the text's presence, font, type size, blur, environmental factor, skew, and so on. The license plate variation must be evaluated based on the environment and type challenges in recognizing the number plate. This paper reviewed existing LP detection methods, classifying them into six groups according to the techniques used to identify LPs and discussing their methodologies, benefits, and drawbacks. This should help researchers in LP detection and recognition gain a better grasp on state of the art to design better robust, generalized detection techniques that can perform well even in noisy environments. Future research in ALPR or ANPR can focus on addressing several challenges and exploring new possibilities. Explore techniques for vehicle-specific LP detection that can accurately identify license plates of different vehicle types, such as cars, motorcycles, trucks, and bicycles. Develop algorithms that can handle variations in license plate size, shape, orientation, and location based on the specific vehicle type. Improve the speed and efficiency of ALPR/ANPR systems to enable real-time processing and recognition of license plates. Investigate hardware optimizations, parallel processing techniques, and algorithmic advancements to achieve faster processing times, making the systems more suitable for applications that require quick response times.

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