AUTOMATIC NUMBER PLATE RECOGNITION OF VEHICLE IMAGES BASED ON CANNY EDGE DETECTION WITH MORPHOLOGICAL OPERATIONS AND CONNECTED COMPONENT ANALYSIS

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ABSTRACT

The algorithm applied in this project includes two phases. The first phase in the algorithm is image pre-preprocessing, which includes grayscale conversion, histogram equalization and Canny edge detection. The next phase includes the method to extract the number plate which are morphological operations and Connected Component Analysis (CCA).The proposed algorithm should be able to implement suitable parameters for canny edge detection and useful CCA to increase the accuracy of no plate localization.Besides, the algorithm should able to implement a condition to detect number plates among rectangular-shaped regions using the CCA method. Furthermore, the algorithm should be able to develop an adaptive pre-processing technique to increase algorithm performance in the face of changing lighting circumstances and complex backgrounds. After we propose the algorithm, we tune the algorithm for Canny edge detection and set geometrical constraints for selecting the number plate. After that, we apply GUI to validate the number plate localization accuracy.As result, the optimal accuracy that we have obtained is 73.1% out of 97 images by using r = 3.0,T_{low} = 5.0 and T_{high} =10.0.

1.0 INTRODUCTION

With the increasing number of vehicles, the evolution of the automotive industry has significantly contributed to the need for effective licence plate recognition systems. As the number of vehicles on the road grows, Automatic Number Plate Recognition (ANPR) becomes more important for traffic management, security, and facilitating various applications. ANPR, also known as Vehicle Plate Recognition (LPR), is a critical component of automated vehicle identification. The primary goal of ANPR is to locate and decipher licence plates on automobiles and use the alphanumeric characters extracted to identify and track them. This technology has grown in importance due to its numerous applications in a variety of fields, including access control, traffic management, and law enforcement.

There are two main tasks in an ANPR system, which are vehicle number plate localization and optical character recognition (OCR). In the vehicle number plate localization, the main feature, which is the number plate will be extracted from the image. For the OCR, the algorithm will recognise the characters, which are the alphabets and numbers on the vehicle number plate. For this project, we will only focus on vehicle number plate localization by using different image processing techniques.

The field of vehicle number plate recognition faces severe hurdles due to inherent complications in ambient settings, potential confusion with vehicle headlights, and the critical requirement for thorough parameter tuning. One key challenge in vehicle number plate recognition problems is ambiguous environments. The camera may have taken an image in a variety of lighting scenarios, including daylight, dusk, night, shadow, glare, and cloudy circumstances [5]. The lighting of the image can also be affected by the reflected light of the headlights of your own or other vehicles. Besides, the surroundings of the vehicle might contain other objects with patterns which are similar to the licence plate. It might distract the algorithm and cause false localization.

The next problem in vehicle number plate recognition is confusion with similar shapes. One of the biggest obstacles to licence plate recognition is the possibility of confusion with shapes that are similar to one another, especially rectangles. The suggested approach includes steps to identify and reduce confusion caused by things that have similar shapes to licence plates. The system seeks to apply discriminative criteria in situations where the surroundings include items or car headlights that have a rectangular pattern. In order to accurately identify licence plates within the image, this discrimination focuses on separating genuine licence plate geometries from false positives. The method aims to improve the accuracy of licence plate localization when shapes that resemble the characteristic rectangle associated with licence plates are present. This is achieved by optimizing the recognition criteria and implementing custom algorithms.

The last problem is the optimized parameter tuning. A careful analysis of parameter tuning at every stage of the image processing workflow is necessary to achieve the best possible results in licence plate recognition. There are difficulties in figuring out the best values for parameters related to linked component analysis, morphological procedures, and edge detection. The system's capacity to adjust to various situations depends on a thorough parameter tuning process that takes careful account of changes in image properties and surrounding circumstances. In order to strike a delicate balance between sensitivity and specificity, a comprehensive investigation of parameter spaces is necessary in the pursuit of an efficient licence plate recognition system.There are three objectives that need to be achieved to tackle these problems:

- Able to implement suitable parameters for canny edge detection and useful Connected Component Analysis (CCA) to increase the accuracy of no plate localization.
- Able to implement a condition to detect number plates among rectangular-shaped regions using the CCA method.
- Able to develop an adaptive preprocessing technique to increase algorithm performance in the face of changing lighting and complex backgrounds.

1.1 LITERATURE REVIEW

In the literature review, various licence plate algorithms have been proposed. Detecting and recognising licence plate numbers remains a difficult task, even after years of research on the subject. This review will discuss several related works, look at what influences system performance effectiveness, and determine which well-known method is appropriate to utilise.

The review covers a wide range of algorithms and their recognition rates for different countries' licence plates. For example, algorithms based on edge detection, morphological operations, the Haar Discrete Wavelet Transform, neural networks, support vector machines, and template matching have been studied, with recognition rates ranging from 67% to 98% for various licence plates. The document also discusses the advantages and limitations of each algorithm, such as fast execution speed, adaptability to changes in licence plates, and susceptibility to environmental factors [1].

The document describes the development and implementation of a real-time licence plate detection system for parking access, utilizing Fourier Transformation and the Hidden Markov Model for character segmentation and recognition. The system successfully recognised various types of Indonesian licence plates in different light conditions and camera positions, achieving a plate recognition percentage of 84.38% with an average execution time of 5.834 seconds for all recognition processes [2].

The existing methodologies for ANPR systems involve a series of image-processing techniques and algorithms. Additionally, the paper discusses the use of the Soble filter technique, Contourlet Transform, Support Vector Machine, and Maximum Average Correlation Height filter for vehicle type recognition.

The results of the ANPR system are presented in the form of accuracy comparisons between clustering and character segmentation techniques, demonstrating the effectiveness of character segmentation in achieving commendable recognition outputs. The research also highlights the challenges faced in the segmentation process, particularly in cases of motion blur and overlapping by different vehicle bodies. Furthermore, the paper discusses the limitations of the segmentation method in producing desired results for plates at an angle and at the edge of the image, which impacted the overall accuracy of the algorithm [3].

The proposed algorithm consists of ten major steps, including image acquisition, preprocessing, contrast enhancement, edge detection, and region of interest (ROI) localization. The algorithm's effectiveness was evaluated using over 350 images of light and heavy traffic vehicles from different countries, resulting in a detection efficiency of 93.43%. The results demonstrate the algorithm's versatility in detecting various types of licence plates, regardless of colour, style of font, or material, making it suitable for real-world implementation in traffic monitoring systems and border surveillance [4].

In their study, the authors conducted a comprehensive literature review of Automatic Licence Plate Recognition (ALPR) systems, specifically focusing on the challenges encountered in the Indian context. They analyzed various research articles, conference papers, and relevant publications to identify key limitations and constraints faced by ALPR systems in India, covering factors such as plate variation, environmental variation, camera mounting variation, hardware specifications, and algorithmic techniques.

As a result, the authors identified critical challenges in the implementation of ALPR systems in India. These challenges included unstandardized licence plates with different fonts, plate occlusions due to dust and obstructions, variations in lighting conditions, and camera mounting issues. Furthermore, the authors emphasized the significance of hardware specifications, such as system internal RAM and processor, in influencing the performance of ALPR systems. They also highlighted the need for robust algorithmic techniques to address the diverse and complex conditions encountered in the Indian environment [5].

1.2 METHODOLOGY

There are two main parts in this vehicle number plate localization project, which are image preprocessing and vehicle number plate extraction. The techniques used in image preprocessing are colour conversion, image enhancement, and noise reduction. Preprocessing enables us to enhance certain features in the image that are crucial for the dataset we are working on and remove undesired distortions. After image preprocessing, feature extraction needs to be carried out to extract the number plate. We will use edge detection to extract all edges contained in the image. Next, we will apply Morphological Operations, a set of image-processing techniques that modify the structure of an object in an image. Finally, we will apply the Connected Component Analysis (CCA) which is crucial for isolating potential licence plate regions and plays a key role in the subsequent steps of your method, such as the voting process and the final decision-making criteria based on width and height. The details of the algorithm applied will be further explained in the proposed solution.

1.3 OVERVIEW OF RESULTS

After all these steps, we need to perform the vehicle number plate localization for each image in the dataset using the Java Graphical User Interface (GUI). The GUI should be able to show the bounding box of the number plate for each image. Lastly, we need to evaluate the performance of the proposed solution. We need to calculate the accuracy of localization by dividing the number of images with the correct localization by the total number of images.

2.0 METHODS

2.1 IMAGE ACQUISITION

The dataset used in this project consists of 97 images of the vehicles provided by Ondrej Martinsky. The images are in Joint Photographic Experts Group (jpg) format. The image in the dataset contains the front and rear view of the vehicle. The licence plates in the images have different sizes and orientations due to the capturing angle and distance from the vehicles.

2.2 IMAGE PRE-PROCESSING

Image preprocessing is very beneficial for improving image quality and thus preparing them for analysis and further processing. A robust preprocessing method is important for licence plate region extraction.

2.2.1 GRAYSCALE CONVERSION

First, the images will be first converted from colored RGB images to the weighted grayscale. Using the grayscale, it helps us to reduce the complexity of algorithms and computational requirements. To compute the grayscale value, we need to retrieve the RGB value of each pixel of the image. Given the formula of weighted grayscale:

$$Grayscale = 0.299 * R + 0.587 * G + 0.114 * B \quad — (1)$$

The formula placed for weight on the green (G) channel. We decided to place more weight on the G channel based on the analysis done by using ImageJ. Based on our observation, the G channel has less noise than the red (R) or blue (B) channel and it contains more information.

Figure 1: R channel from sample image

Figure 2: G channel from sample image

Figure 3: B channel from sample image

After applying the formula, we can get the new pixel value for each pixel.

Figure 4: Output of Weighted Grayscale Conversion

2.2.2 IMAGE ENHANCEMENT

Next, the image will be processed by image enhancement so that it will be more suitable for display or further image analysis. The method that we will use in this step is histogram equalization. It is used to adjust the contrast of the image when a limited range of intensity values is used to depict the image. Thus, the intensities can be more evenly dispersed on the histogram by utilizing the entire range of intensities uniformly. This enables areas with poor local contrast to gain higher contrast. It can be done by finding point operations to shift the line in the cumulative histogram to construct a uniform histogram with linear approximation.

$$F_{eq}(a) = H(a) * ((K-1)/MN) \text{ —-(2)}$$

Given that: a = Position in histogram, K= Number of intensity values, M = Width and N = height

Figure 5: Output of Histogram Equalization

2.2.3 CANNY EDGE DETECTION

Edge detection is a useful image processing technique to counter the ambiguous environment while extracting the feature of the image. It is because the edge information is stable and invariant to illumination. In this project, Canny edge detection will be applied. It is a multi-stage edge detection algorithm.

A.Gaussian Smoothing

First, the Gaussian smoothing will be applied for noise reduction. This technique works on blurring an image by a Gaussian filter to reduce the Gaussian noise in the image. The primary causes of Gaussian noise in digital images are sensor noise resulting from transmission, overheating, or insufficient lighting during capture. This process is important before applying edge detection because the edge detection algorithm is sensitive to the noisy environment. By smoothing the image, it will improve the result of the edge detection algorithm. Given that the Gaussian function in 2-D:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{r^2}{2\sigma^2}} \text{ ---(3)}$$

σ = Standard deviation of Gaussian Distribution and
r = Radius/distance from center

This process is a must and the filter has to be tuned properly otherwise it might remove the important details.

B. Finding Gradient and orientation

Next, the image will be processed using the Sobel filter to compute the gradient of the image in both the horizontal (G_x) and vertical (G_y)

directions through convolution. The edge gradient value (G) and orientation (Θ) can be calculated by using G_x and G_y. Given that the Sobel filters:

$$\begin{matrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{matrix} \qquad \begin{matrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{matrix}$$

Sobel Filter for G_x Sobel Filter for G_y

Figure 6:Sobel Filters

$$G = \sqrt{{G_x}^2 + {G_y}^2} \text{ --- } (4)$$

$$\theta = \tan^{-1}\frac{G_y}{G_x} \text{ ---}(5)$$

C. Non-maximum Suppression

The next step in Canny edge detection is non-maximum suppression. This process is to eliminate the pixel which might not be a part of the edge. The algorithm will compare the gradient value of each pixel to its neighbor in gradient directions. If the pixel is not a part of local maxima, it will be suppressed to zero. The edge direction angle is rounded to one of four angles representing vertical, horizontal and the two diagonals (0, 45, 90 and 135 degrees for example) using colors.

D. Hysteresis Thresholding

Lastly, the hysteresis thresholding will be applied. There are two threshold values that would be set, which are T_{high} and T_{low}, where T_{high} is greater than T_{low}. If the pixels with gradient magnitudes more than T_{high}, it will be considered strong edges. If the gradient magnitudes below T_{low}, it will be considered as non-edges. When the gradient magnitudes between T_{low} and T_{high}, it will be considered as weak edges. As a result, the image will be transformed to a binary image containing the edges.

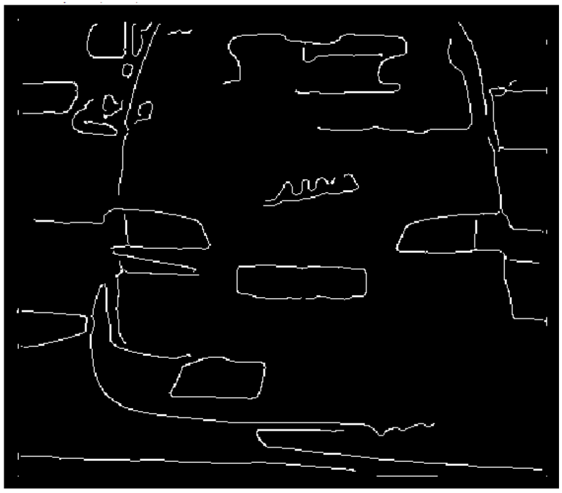

Figure 7: Output of Canny Edge Detection (r = 3.0)

2.3 NUMBER PLATE LOCALIZATION METHODS

The image processing techniques used in this step are aimed to extract the candidate number plate regions. After that, the location of the number plate will be extracted among the candidate regions.

2.3.1 MORPHOLOGICAL OPERATIONS

Morphological operations will be applied to process the geometrical structure to extract the rectangular shape of the number plate. Each pixel in the image is adjusted based on the structuring element and value of other pixels in its neighborhood. We have proposed a set of morphological operations that will be used to extract the number plate region.

First, the closing operation will be applied to filling small holes in an image so that the shape of the licence plate can be connected. Next, use the dilation to thicken the edges in the image. After that, the closing operation will be applied again to ensure that the licence plate is enclosed by the edge. Next, the fill hole operation based on the dilation will be applied to fill the background region which is surrounded by a connected border of foreground pixels.

$$X_k = \left(X_{k-1} \oplus B\right) \cap A^c \qquad k = 1,2,3,\ldots$$

Figure 8: Fill Hole Operation

After the candidate region is filled, we need to remove the thin region. First, erosion will be applied to remove floating pixels and thin lines so that only substantive objects remain. Next, the opening will be applied to remove small objects and thin lines from an image while preserving the shape and size of the licence plate.

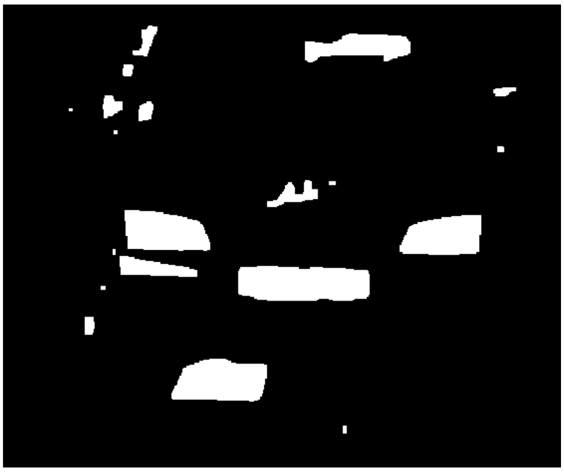

Figure 9: Output of Morphological Operation

2.3.2 Connected Component Analysis (CCA)

Lastly, Connected Component Analysis (CCA) will be applied to extract the licence plate among the labeled regions. CCA is used to group the pixels into components based on pixel connectivity in binary images. The pixels will be labeled with either different connected components or backgrounds. There are two types of connectivity, which are four-neighborhood and eight-neighborhood connectivity. There are two ways that 4-neighborhood connectivity can be defined, which are either left,right,top and bottom direction or diagonal direction. For the 8-neighborhood connectivity, it involves the connectivity of all directions. We will apply the 8-neighborhood connectivity so that we can extract the licence plate region completely.

1	2	3
4	*	5
6	7	8

Figure 10: 8-neighborhood connectivity

Figure 11: Connected Component Labeling

After the labeling process, the bounding box coordinate will be recorded as x_{min}, y_{min} ,x_{max}, y_{max} for each component. Through this value, some geometrical results can be evaluated for further analysis. Two important criterias which are width and height can be calculated through:

$$width = x_{max} - x_{min} \quad —(6)$$

$$height = y_{max} - y_{min} \quad —(7)$$

By using the width and height, the geometrical results such as area,aspect ratio and other results can be evaluated. An analysis based on the geometrical results of each component should be carried out to distinguish the licence plate from the other connected components. The geometrical constraints will be set to filter out the other components. First, the licence plate should be in rectangular or near rectangular shape. We can measure it by using circularity.

$$Circularity = 4A/P \quad —(8)$$

Where A = Area , P = Perimeter

Next, the criteria to be selected as licence plate is aspect ratio.

$$Aspect\ Ratio = width/height \quad —(9)$$

Furthermore, the total number of pixels of the connected component in the bounding box also needs to be considered. If the connected component has a complete rectangular shape, so the total number of pixels is equal to the area of the bounding box. For a perfect rectangular number plate:

Number of pixels/Area = 1

The connected component that satisfies the most criteria will be selected as licence plate. If there is more than one connected component that satisfies the most criteria, the connected component with the highest number of pixels/area will be selected as licence plate. The parameter for each criteria will be mentioned in the tuning process.

2.4 OPTIMIZED PARAMETER TUNING

After we propose the method to extract licence plates from images, we need to visualize the steps and find out the optimal parameter for some image processing techniques. There are two main steps that require parameter tuning, which are Canny edge detection and CCA. We start the experiment using 20 images from the dataset and analyze it using ImageJ.

For the Canny edge detection,we start with radius to 2.0,T_{low} to 2.5 and to T_{high} 5.0. We then use morphological operation to fill the number plate region. If the number plate region can be seen clearly, it means that the parameter is suitable. We repeat the process with slightly increasing the radius until 3.0. Although it will remove the characters from the number plate, the edge of the number plate is able to be preserved. For radius = 3.0, there are three images out of 20 that cannot extract the number plate region after using morphological operation. So, we set the radius to 3.0 and start to tune the threshold value. We try to increase the T_{high} to 10.0 to find out the stronger edges and T_{low} to 2.5 so that more edge information could be reserved.

From the 20 images, I also find out the characteristics such as width, height, aspect ratio, circularity and number of pixels per area of each number plate and conclude a suitable condition to choose the number plate among the connected components.

Table 1: Characteristics of number plate and their range

Characteristics	Range
Width	82 - 177
Height	17 - 48
Circularity	0.481- 0.627
Aspect Ratio	3.313 - 4.58
Number of pixels/Area	0.842 - 0.929

Based on this table, we came out with some geometrical constraint for a licence plate. For a rectangular licence plate, the range of circularity is in between 0.4 to 0.7. For the licence plate, the aspect ratio is in the range of 3 to 5, if the aspect ratio is smaller than 1, the connected component will be filtered out. Besides, we set a condition where the number of pixels per area should be higher than 0.8 to indicate its near rectangular shape. The width of the licence plate should be in the range of 80 to 160 and the height of the licence plate should be in the range of 15 to 50.

3.0 FINDINGS AND ARGUMENT

After we implement the methodology in the Java Program, we apply and modify the GUI from the original ANPR project by Ondrej to make the validation process faster. We found that the parameter needs to be tuned again to further improve the accuracy of licence plate localization.

We have tuned the radius of the Gaussian filter from 2.7 to 3.0 and changed T_{low} from 2.5 to 5.0 and T_{high} remained unchanged. Before that,we add some additional conditions for number plate selection. If the width of the connected component is less than 50 or height less than 15, it will be filtered out. Also, the connected component with width more than 200 will be filtered out because it might be a car front glass. For some, the number plate might be too small, so if the width is from 60 to 80 and the number of pixels per area more than 0.9, it will satisfy extra criteria.

The accuracy of licence plate localization can be calculated using:

Accuracy = (Correct localization/97)*100% ---(10)

We will calculate the accuracy for each radius of Gaussian Filter and find out the best performing parameter.

Table 2: Accuracy for each parameter set

Parameters	Accuracy
r = 2.7	70.1%
r = 2.8	73.2%
r = 2.9	70.1%
r = 3.0	69.1%

Based on the table, we can conclude that the optimal parameter is r =2.8,T_{low} = 5.0 and T_{high} = 10.0 . There are 26 images that failed to localize the number plate. We observed that the localization of the number plate really depends on the amount of edge information retained after using Canny edge detection. As example, the algorithm might fail to outline the number plate edges due to the loss of edge information.

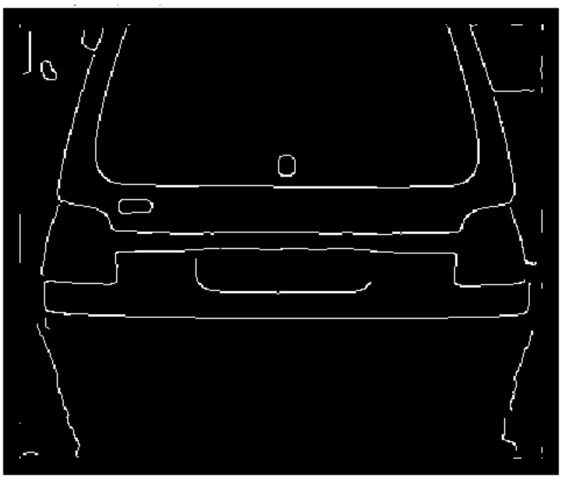

Figure 12: Example of fail extraction of edge of the number plate

After that, the morphological operation will be applied. The operation such as dilation and closing will cause the edge of the number plate to connect with another edge to form a new connected component. After the fill hole process, the region of the number plate failed to be extracted.

Figure 13: Example of fail extraction of number plate region by morphological operation

As a result, the CCA will filter out the combined region that contains the number plate because the width is out of the range.

4.0 CONCLUSIONS

In conclusion, the algorithm applied in this project includes two phases. The first phase is image pre-preprocessing,which includes grayscale conversion, histogram equalization and Canny edge detection. The next phase includes the method to extract the number plate which are morphological operations and CCA. After we propose the method, we have tuned the parameters for Canny edge detection and set the geometrical constraint for CCA. As a result, the optimal accuracy that we have obtained is 73.1% by using r = 2.8,T_{low} = 5.0 and T_{high} =10.0. Based on the result, there are 26 images that failed to localize the number plate. We notice there are two problems causing the error. The first problem is the Canny edge detection might fail to extract the edge information of the number plate. Besides, morphological operations such as dilation and closing might cause the number plate region to connect to other regions and cause false localization. We may consider improving our algorithm in future by adding other approaches such as Harris corner detection and Hough Transform to capture the rectangular number plate. It is because the accuracy of number plate localization is important to ensure the OCR can be further carried out. A successful ANPR project helps in various fields such as traffic management, law enforcement, and access control. Hence, the research in this technology has become more and more significant.

5.0 REFERENCES

Bakhtan, M.A.H., Abdullah, M. & Rahman, A.A. 2016. A review on license Plate Recognition system algorithms. 2016 International Conference on Information and Communication Technology (ICICTM).

Hermawati, F.A. & Koesdijarto, R. 2010. A REAL-TIME LICENSE PLATE DETECTION SYSTEM FOR PARKING ACCESS. TELKOMNIKA (Telecommunication Computing Electronics and Control) 8(2): 97.

Kashyap, A., Suresh, B., Patil, A., Sharma, S. & Jaiswal, A. 2018. Automatic Number Plate Recognition. 2018 International Conference on Advances in Computing, Communication Control and Networking (ICACCCN).

Moustafa, A.A. & Mousa Jaradat, M.-I.R. 2015. A New Approach for License Plate Detection and Localization: Between Reality and Applicability. International Business Research 8(11): 13.

Mukhija, P. & Dahiya,P.K. 2021. Challenges in Automatic License Plate Recognition System: An Indian Scenario. Fourth International Conference on Computational Intelligence and Communication Technologies (CCICT)-2021.

Patel, C., Patel, A. & Shah, D. 2015. A Novel Approach for Detecting Number Plate Based on Overlapping Window and Region Clustering for Indian Conditions. International Journal of Image, Graphics and Signal Processing 7(5): 58–65.

Radha, R. 2012. A Novel Approach to Extract Text From License Plate of Vehicles. Signal & Image Processing : An International Journal 3(4): 181–192.

Saqib,R., Asad,N. & Omer,I. 2012. Automated Number Plate Recognition using hough lines and template matching. Proceedings of the World Congress on Engineering and Computer Science 2012. Vol I WCECS 2012, October 24-26, San Francisco, USA.

Siddiqui, A.J., Mammeri, A. & Boukerche, A. 2016. Real-Time Vehicle Make and Model Recognition Based on a Bag of SURF Features. IEEE Transactions on Intelligent Transportation Systems 17(11): 3205–3219.

Syed, Y.A. & Sarfraz, M. 2005. Color edge enhancement based fuzzy segmentation of license plates. Ninth International Conference on Information Visualisation (IV'05).

Tang, J., Wan, L., Schooling, J., Zhao, P., Chen, J. & Wei, S. 2022. Automatic number plate recognition (ANPR) in smart cities: A systematic review on technological advancements and application cases. Cities 129: 103833.