Optimizing Automation License Plate Recognition (ALPR) Performance Through Adaptive Image Processing Techniques

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Abstract

ALPR systems are implemented to traffic, toll access management and yet face challenges in diverse conditions. This study optimizes ALPR performance by using adaptive image processing techniques to address this challenge. Three techniques flow were developed, with the second technique flow method having achieved highest accuracy using AI Image Enlargement, ESPCN model, and Adaptive Thresholding Gaussian Mean. The proposed ALPR system had utilized Faster R-CNN model for detection and character recognition. Real-world datasets were utilized for training and testing. This study aims to enhance the ALPR reliability and applicability, proposing a novel image technique flow to improve accuracy in the real-world scenarios.

Keywords: ALPR (Automated License Plate Recognition), Image Processing Techniques, AI (Artificial Intelligence), Accuracy Optimization, OCR (Optical Character Recognition)

1. Introduction

Automation License Plate Recognition (ALPR) have been utilized in various sectors like toll payment, and parking management in enhancing the security and operational efficiency. The common working principle of ALPR system went through 4 main stages as depicted in Fig.1. ALPR system utilizes cameras to capture license plate numbers, then transformed into alphanumeric characters by Optical Character Recognition (OCR). The alphanumeric numbers are then compared to the license plates with the pre-existing database for authorization and access control.

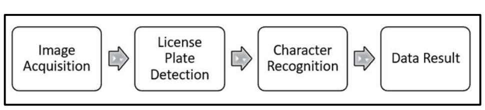


Fig. 1 The Working Principle of ALPR System

Leveraging Artificial Intelligence (AI), ALPR system has improved the performance by facilitating a seamless license plate detection and recognition process[1], elucidating how AI transform ALPR into robust technology. With Deep Learning approach in the license plate detection and recognition such as Convolutional Neural Network (CNN)[2] and YOLOv5[3], [4]. The integration of AI in image processing also significantly improves the ALPR accuracy and speed. Techniques like image enhancement, rescaling, and noise-reduction enhance clarity. AI-based methods including image enlargement and image sharpening to overcome the poor illumination.

Despite the ALPR system with AI technology, ALPR system still faces several challenges when it comes to real-world application. One notably challenge is environmental conditions. Environmental surroundings such as lightning conditions (day, night, sunny and raining), unfavorable condition, sight impedance, providing to the complexity of license plate recognition. The consequences of this challenge can impact the quality of captured images and subsequently affect the recognition accuracy. Poor quality image captured by the camera such as license plate captured unclear and noise also one of the challenges. The ALPR system faced difficulty recognizing characters which can lead to low ALPR performance.

This paper focuses on addressing the ALPR challenges in the real-world scenario. Implementing advanced image processing techniques flow, the ALPR system can enhance accuracy and reliability in license plate detection and recognition under diverse environmental conditions.

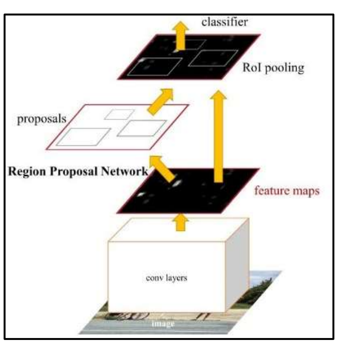
The outcomes of this research us expected to obtain significant advancement in ALPR technology, particularly in image processing capabilities. By developing and evaluating novel techniques on improving ALPR performance, this study not only seeks to provide practical solution on the challenges encountered by ALPR systems in real-world application but also assist engineers and researchers in making informed decisions when assessing the effectiveness of the proposed ALPR system.

2. Related Work

In the pursuit of advancing understanding of the ALPR system, a comprehensive review of related work lays the groundwork for the exploration. This section begins with object detection algorithms, OCR, and image processing techniques, essential components in implementing the ALPR system. By continuously trying various image processing techniques and achieving the desired accuracy outcome in proposed ALPR system. Understanding background those algorithms and image techniques is crucial for operating and evaluating their role in enhancing characters recognition accuracy.

2.1. *Object Detection Algorithms*

Localizing vehicle license plates is one of the primary functions of the ALPR system. Initially, the input vehicle license plate is received, and throughout the process of localizing the license plate, the output is solely containing of the sub-image containing license plate. Leveraging a neutral network model on performing license plate detection is beneficial due to its efficiency and accuracy. Efficiency is crucial in real-time processing of toll payment and car tracking. Additionally. Neutral networks can be trained on large datasets enabling the model able to detect objects accurately.



. Fig. 2 The Architecture of Faster R-CNN model

Faster Region-Based Convolutional Neutral Network (Faster R-CNN) is a unified, solely network architecture as depicted in Fig. 2 for object detection consisting of two modules which are Region Proposal Network (RPN) and Fast R-CNN model. The fast R-CNN model proposed by Girshick et al., processes the input image through the CNN backbone, then a region proposal is used for object region identification by implementing Region of Interest (RoI) pooling and fully connected layer [5]. In Faster R-CNN model, RPN is created for generating region proposals while Fast-R-CNN is for detecting objects in proposal regions. Then, the RPN predicts the region proposal by using sliding window method over the output convolution feature map and convert to a low-dimensional feature. It feeds this feature into two fully connected layers shown in Fig. 3 a box regression layer (reg) and a box classification layer (cls). Reg, box regression layer returns a 4-Dimensional defining the bounding box of the region while cls, a box classification layer generates the objectness score for each region proposal. The reg layer outputs 4k coordinates for k boxes, while the cls layer outputs 2k estimates the probabilities of presence object. These proposals are parameterized relative to k reference boxes called anchors, which are associated with a particular scale and aspect ratio. The output of the RPN is a set of rectangular object proposals with detection confidence.

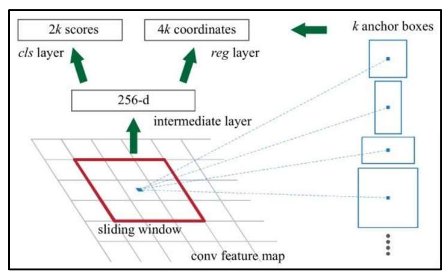


Fig. 3 Region Proposal Network

The loss function in Faster R-CNN's Region Proposal Networks (RPN) assists to train the model by comparing the predicted outputs with the correct information. It has two parts which are the classification loss (Lcls) and the regression loss (Lreg). The Lcls part determines the presence of anchor, while the Lreg regression part regresses the coordinates of the predicted bounding boxes. The loss function is normalised and weighted to minimize the difference between predictions and ground-truth data, making the model better at generating accurate region proposals.

The loss equation for an image. $\boldsymbol{i}$ is the anchor index in a mini-batch and $\boldsymbol{p_i}$ is the predicted probability of the anchor being an anchor. $\boldsymbol{p_i^*}$ is the ground-truth label which 1 is the anchor in positive while 0 is the anchor in negative. $\boldsymbol{t_i}$, a vector representing 4 parameterized coordinates of the predicted bounding box, while the $\boldsymbol{t_i^*}$ represent the ground-truth box associated with positive anchor. The classification $\boldsymbol{L_{cls}}$ is log loss over two class which determine the presence of object. $\boldsymbol{N_{cls}}$ and $\boldsymbol{N_{reg}}$ are the number of anchors.

$$L(\{p_i\},\{t_i\}) = \frac{1}{N_{cls}}\sum_i L_{cls}(p_i,p_i^*) + \lambda\frac{1}{N_{reg}}\sum_i p_i^* L_{reg}(t_i,t_i^*) \quad (1)$$

In [6] had proposed a Faster-R-CNN model in License plate detection. The model performed well at 96.63% of precision and 94.40% of recall. In [7], proposed multi-class detection system using Faster-R-CNN with Inception V2 model with the precision and recall have value of 90.00%. In [8], proposed a Faster-R-CNN model and detect with various license plates.The model scored high results,91.95% of precision and 83.97% of recall with 0.826 of mAP. In [9], had proposed a Faster R-CNN model with Inception ResNet V2 backbone network. They optimised the model using Stochastic Gradient Descent (SGD) during the training process with a momentum value set to 0.89. The learning rate metric is optimised to 0.00019 and the batch size is set to 1. In preprocessing stage, the image is undergoing resizing operation with 600 x 1024 pixels. Overall performance of the proposed model results with 99.66% of precision, 79.40% of recall and 1.39s or 1390ms of processing time.

2.2. *Optical Character Recognition (OCR)*

Deep learning-based OCR is a system that employs deep learning algorithms to recognize characters from images, letters, or scanned documents. The deep learning-based OCR works by analyzing pixel data from source to identify individual characters and transcribe them accurately. CNNs particularly commonly used in OCR because CNNs handles identifying patterns in visual data[10]. The main three components in CNNs, making it capable of recognizing features patterns and variations in text.

Faster R-CNN builds on the CNN backbone, also widely used in image recognition tasks. A study by B. Wang et al., demonstrated Faster R-CNN as scene text recognition had achieve approximately 90% of accuracy. From those studies proved the Faster R-CNN suitable performs recognition task due to the RPN network able to distinguish all the possible candidates' boxes from the extracted source[11]. Lee et al. had proposed a real-time ALPR system that implemented Faster R-CNN to perform detection and recognition task under adverse weather environments. The result had achieved accuracy of 99.94% with the average operating speed of 80ms/image [12].

2.3. *Image Processing Techniques*

Image processing plays a pivotal role in the realm of ALPR systems as it significantly enhances speed of processing time[13], [14], versality and cost-effectiveness. Through researching on image processing techniques, it came across by [15] emphasize that the image processing hinges upon positive impact on ALPR accuracy improvement.

2.3.1 Gray Scaling

A greyscale image is characterised by the absence of colours other than shades of grey, ranging from black to white. These algorithms simplify the conversion by manipulating the colour information, resulting in an image that retains only the grey intensity values. In [16], proposed a pre-processing method by converting the colour image to grayscale then Gaussian filter used to remove the noise. Converting a colour or RGB image to a greyscale image serves several purposes, including reducing file size and improving loading speed[17].

2.3.2 Bilateral Filter

Bilateral filter performs noise reduction on the image thus resulting in clearer and more reliable license plate recognition [18]. With the iterative bilateral filter, the filter can remove the noise and distortion from a grayscale image. Bilateral filter works by applying a weighted average to the pixel values of an image. These weights are determined based on the spatial distance and intensity difference from the central pixels. Equation 1 shows formula of bilateral filter with spatial distance depending on the image values. The bilateral filter starts with a Gaussian smoothing. The Gaussian function is used to calculate the weights, ensuring that pixels in close proximity with similar intensities are assigned higher weights than those with divergent intensity values.

$$BF[I]_p = \frac{1}{W_p}\sum_{q\epsilon S} G_{\sigma_s}(\|p-q\|)G_{\sigma_r}(|I_p-I_q|)I_q \quad (2)$$

A normalized weighted average is presented in equation (2), where BF is bilateral filter and $[I]_p$ is the amount of filtering of the image. The G_{σ_s} represent a spatial Gaussian weighting that reduces the influence of pixel distance, G_{σ_r} represent the range Gaussian weighting that diminishes the influence of pixels q when their intensity values differ from I_p.

2.3.3 Morphological Operators

Morphological operators are one of the image processing techniques developed to address the shape or morphology of image's features. Morphological operators are commonly employed to eliminate the imperfections during segmentation process. There are few examples of morphological operators as outlined in Fig. 4 such as dilation, erosion, opening, closing and morphological filtering. This technique can be applied to the ALPR system to improve accuracy and efficiency on license plate detection and character recognition.

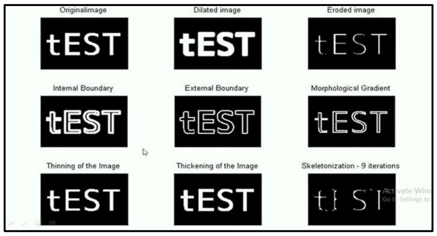


Fig. 4 The Morphological Operators

A study by Hsrshitta et al. had applied morphological operators such as dilation on the image. The dilation technique can fill the gaps and holes in the license plate region, making it easier to segment and extract the characters from the background[19]. Another study from Parsun et al. had employed morphological operations, particularly erosion and dilation, to shape and resize image features [20]. This process successfully removed connected components and tiny objects. The opening operation is performed on refined those boundaries, while dilation is performed on filling up the holes, resulting in the smooth extraction of characters.

2.3.4 Adaptive Histogram Equalisation

Adaptive Histogram Equalisation (AHE) is a technique used to adjust the contrast of an image through redistributing pixel intensities. It works by transforming the image so that the output image histogram is approximately flat, meaning that pixel intensities are spread over a wider area. This can help to enhance the information in an image and make it easier to recognise certain features such as license plate. According [21], the histogram equalization is a beneficial technique in image preprocessing for binarization threshold value selection. It effectively enhances the contrast gradient of the image by redistributing the various grey levels present in the image.

2.3.5 Fast Non-Local Mean Denoising

Fast Non-Local Means (Fast NLM) is an algorithm that is used for image denoising. Its effective address challenges encountered by traditional denoising filters such as blurring. The Fast NLM algorithm leverages weights depending on Euclidean distance to perform a comparison of the geometric structure to improve the comprehensive analysis of the image composition.

Euclidean distance is a fundamental geometry and commonly used in image processing where $\omega(m,n)$ represents the weights based on Euclidean distance.

$$NL[\mathrm{I}](\mathrm{m}) = \sum_{N\epsilon l} \omega(m,n)\mathrm{I}(n) \tag{3}$$

$$NL[\mathrm{I}](\mathrm{m}) = \sum_{N\epsilon l} \omega(m,n)\mathrm{I}(n) \tag{4}$$

$$Z(\mathrm{m}) = \sum_{n} e^{-\frac{G\sigma(\tau)||I(M+\tau)-I(n+\tau)||_2^2}{d^2}} \tag{5}$$

The Fast NLM algorithm in Equation (6) and (7) outlined improvement achieved by modifying the weight calculation, $\omega(m,n)$ from one dimension to two dimensions.

$$\omega(m,n) = \frac{1}{Z(m)} H_i\big(I(m+s) - I(m-s)\big) \tag{6}$$

$$H_i = \sum_{q=0}^{s} e^{-\frac{||I-I(q+\tau)||_2^2}{d^2}} \tag{7}$$

Fast NLM algorithm ideally improves time resolution approximately four times compared to the NLM algorithm, proving the Fast NLM algorithm reduce the processing denoising time[22].

2.3.6 Adaptive Thresholding

Adaptive Thresholding is an image processing technique that can segmentize an image into several foreground and background regions. It involves setting a threshold value that separates the foreground and background regions. A general threshold or global threshold value usually is fixed for all pixels in the image. However, the threshold value in adaptive thresholding is adjusted locally based on the pixel intensity and its surrounding neighborhood. In case, the global thresholding with the uniform threshold value and leads the image is dim as all the pixel intensity is fixed in the image. In contrast, the image after applying adaptive thresholding method is more clearer and contrast. This is because the pixel intensity on the image that applied adaptive thresholding hinges upon to the local properties of images [23].

2.3.7 Image Enlargement

Image enlargement is one of the image processing techniques that focus on transforming the low-resolution image to high-resolution image. Image resolution represents the number of details or pixels of an image, typically measured in pixels per inch

(PPI) and dots per inch (DPI). This process is crucial due to it transforming the details or pixels in a certain region of the image. A high-resolution image consists of more pixels or high pixel intensity, resulting in sharper and refined visual content.

3. Materials and Methods

Overview of ALPR system from overall input image to output character recognition result, as outlined in Fig. *5*. The proposed existing ALPR utilized Faster R-CNN on license plate detection and recognition after being trained with a bunch of datasets consisting of rear trucks captured in cargo terminals. The process began with an input image consisting of a rear truck captured at a cargo terminal, passing through the license plate detection. During this process, the license plate was detected by pretrained Faster R-CNN, and the output was a sub-image consisting of the license plate. Then, this output was the input for license plate recognition, undergoing segmentation process to segmentize each character and convert them into alphanumeric characters.

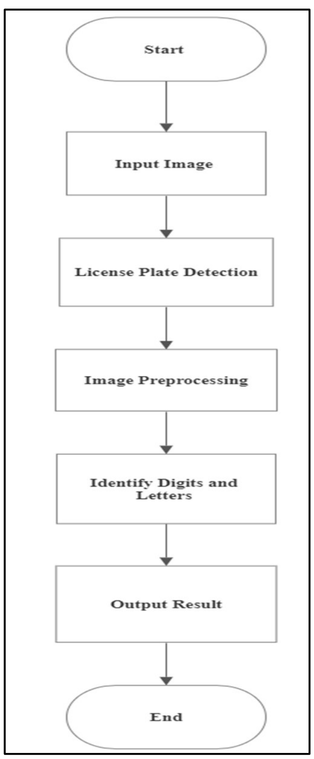


Fig. 5 Overview of ALPR system

The optimization of the ALPR system was explored through a comparative analysis of various image processing techniques. The focus was on experimenting with various image processing techniques to enhance the system's performance by designing an image processing process flow applied to the sub-image (consisting only of the license plate). The process involved trial and error, where multiple image processing flows were experimented with to improve contrast and sharpness.

3.1. *Fundamental Image Processing Steps for OCR Optimization*

The fundamental image processing flow involved several steps of image processing techniques, enabling the characters easier to be recognized under character recognition. Initially, denoising to remove the unnecessary noise, sharpen the edge of the characters, and is then converted into grayscale image. Grayscale image not only reduces the complexity on various channels, but also enhances contrast.

Despite these improvements, the grayscale images still struggle to distinguish subtle details. To address this, sharpening techniques, adaptive thresholding, and noise reduction techniques are applied to the grayscale image.

3.2. *Method 1: Image Processing Technique with Basic Thresholding, Morphological Operations*

The first method of image processing technique flow as outlined in Fig. 6 for applying to ALPR system.

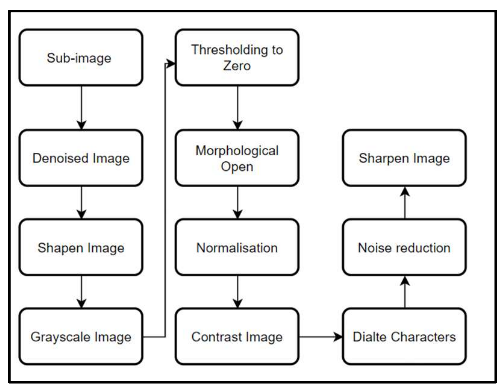


Fig. 6 The First Proposed Image Processing Technique Flow

To enable characters to stand out from the background, the grayscale image then converts into black background by applying Thresholding to Zero, as shown in Equation (8).

$$dst = \begin{cases} src(x,y) & if\ src(x,y) > threshold \\ 0 & otherwise \end{cases} \quad (8)$$

Thresholding to zero sets a threshold as a cutoff point. If the pixels are higher than the threshold value it remains while the pixels go to zero if they are lower than the threshold value.

The morphological open involves operation which are erosion then dilation approached after the thresholding for removing tiny object from the foreground while remaining the large structural characters. This operation removed unwanted noise while preserving overall details on the image. Normalization technique applied to the image for ensuring consistent pixel intensity ranges. After the pixel is consistent across the image, the contrast is applied, and noise reduction takes place for removing noise. The bilateral filter for preserving the edge details and Fast Non-Local Mean Denoising played role in noise reduction. By combining those techniques, the presence of noise can be removed well at the same time also preserve the overall characters are clear to see and recognized. The output of the image is visually improved on edge and shape of characters after applying sharpening techniques.

3.3. *Method 2: Image Processing Technique with Image Enlargement and ATGM*

The second method of image processing technique flow as outlined in Fig. 7 for applying to ALPR system.

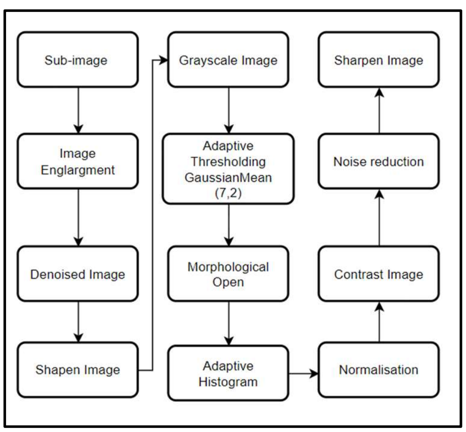


Fig. 7 The second Proposed Image Processing Technique Flow

Image enlargement was applied on the input image by using ESPCN model. ESPCN, also known as Enhanced Sub-Pixel Convolutional Network, is an AI model, designed to enlarge the image from low resolution input image to high resolution image. The process involves passing the input image through convolutional neural networks and utilizing the learn weighted to perform super resolution. Removing noise and sharpening the characters as fundamental steps before converting the sub-image into grayscale to increase contrast.

In the second method, image processing flow, the Thresholding to Zero was replaced by Adaptive Thresholding Gaussian Mean. The thresholding value is a Gaussian weighted sum of the neighborhood value, maxValue with minus the constant, C. With the block size, B, the size of the pixel neighborhood to calculate the threshold value. The second method applied block size set to 7 and constant set to 2. In this condition, each pixel's local mean is calculated based on 7 x 7 neighborhood, and this mean is subtracted by the constant value to determine the adaptive threshold.

With this adaptive approach can effectively address issues related to uneven lighting, enhance image quality, and improve the visibility of license plate characters in images. Consequently, license plates captured under nighttime conditions can be recognized well.

The morphological Open approached eliminating noise and tiny unwanted details by utilizing erosion and dilation operation. The subsequent Adaptive Histogram Equalization (AHE) was applied, dividing an image into smaller regions, and applying histogram equalization independently to each region. The subsequent steps are the same as those of the first method of image processing flow.

3.4. *Method 2: Image Processing Technique with Image Enlargement and ATGM*

The third method of image processing technique flow as outlined in Fig. 8 for applying to ALPR system.

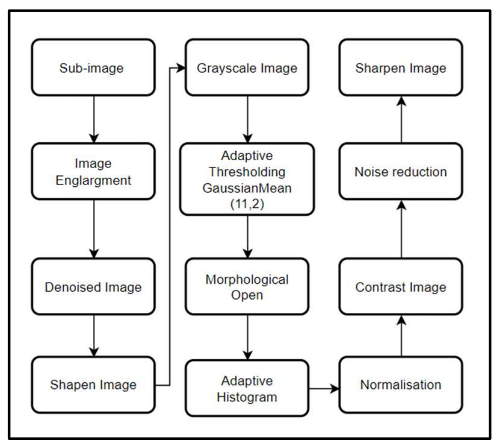


Fig. 8 The Third Proposed Image Processing Technique Flow

The method closely resembled the second method, with the only difference being the use of a block size, B, set to 11. Implementing the larger block size, each pixel's local mean is calculated based on 11 x 11 neighborhood, and this mean is subtracted by the constant value to determine the adaptive threshold. As the license plate input image contains white characters on a black background, the larger block size covers a more extensive region, potentially providing a more contrasted image compared to the second method of the image processing flow.

4. Results and Discussion

The enhancement of ALPR performance through the implementation of three various image processing technique flows were developed. The developed techniques aim to optimize the recognition accuracy and processing efficiency of the ALPR system. Each characteristic of these image processing methods and the distinct differences of each method can be seen and compared in Table 1.

The first method of image processing flow did not involve image enlargement. This leads to recognition models that recognize different characters. In Fig. 9, an image with the license number of 'BND 508', the recognition on character '8' was detected out possible character 'B' with 97.06%. In addition, in the same image, the character '1' was indeed misrecognized by the model.

Table 1 Summaries of Image Processing Techniques Flows

	Method 1	Method 2	Method 3
Image Enlargement Operation	No	Yes, ESPCN model with factor of 3	Yes, ESPCN model with factor of 3
Basic Thresholding Operation	Yes, Thresholding to zero	No	No
Adaptive Thresholding Operation	No	Yes, Adaptive Thresholding Gaussian Mean	Yes, Adaptive Thresholding Gaussian Mean
Morphological Operation	Yes, Morphological Opening and Dilation used	Yes, Morphological Open used	Yes, Morphological Open used
OCR Recognition time	Fastest	Slower than Method 1 but faster than Method 3	Slowest
Characters Recognition Performance	Generally identifiable, but with occasional multiple predictions	Accurate recognition for each character without ambiguity	Some characters exhibit difficulty in recognition, leading to decreased accuracy
Total Processing Time	3.95 seconds per image	5.06 seconds per image	4.82 seconds per image

Fig. 9 The 'test8.jpg' Image

The output image dimension after applying image enlargement is larger. By implementing ESPCN model with the enlargement factor of 3, the enlarged image dimension is 3 times larger than the original image. This process aims to enhance the details and overall quality of the visual content. The proficient recognition of characters can be attributed not only to the image enlargement but also to the implementation of various image techniques within the second method resolution images resulted in pixelated and blurry characters, which further hindered the model's ability to recognize the intricate details that differentiate characters like '1' from others. Nevertheless, the OCR recognition time was the shortest compared with the second and third method of the image processing flow.

The Adaptive Thresholding Gaussian Mean was applied to the second and third methods of the image processing flow. The threshold value in the third method was larger than in the second method flow. This was because the mean intensity calculated from a larger neighbourhood of 11 x 11 pixels was likely influenced by a broader range of pixel values, leading to a higher threshold value compared to the smaller neighbourhood of 7 x 7 pixels under the same constant adjustment. Consequently, the background of the second method in Fig. 10(a) became grey, while the background of the third method, as illustrated in Fig. 10(b) turned black.

(a)

(b)

Fig. 10 The background of Second Method(a) and Third Method(b) After Applying Adaptive Thresholding Gaussian Mean

The OCR recognition time utilized in the second and third methods was longer than the first method because both methods implemented image enlargement. However, with similar image processing steps, the second method proved to be faster than the third method. The potential reason for this was only the size of the neighborhood used in both methods consumed time.

From the Table 1, it concluded that the second method emerged as the most effective within the image processing flow among these considered methods. Each image subjected to the second method exhibited successful recognition, with characters being distinctly clear and easily identified following the application of image processing techniques. Although the processing time is relatively slower, the overarching objective of proposing a robust ALPR system is achieved, ensuring precise accuracy in character recognition.

4.1. *Real Life Verification*

The performance of the characters recognition was evaluated on four different scenarios of vehicle license plates by applying the second method of image processing technique. To ensure the proposed model's ability to handle these scenarios, 20 images were prepared for each, a total of 80 images. The results were then compared under various conditions, including daytime with clear visibility, daytime with visible characters, some background visibility, nighttime with presence of vehicle light and nighttime with presence of strong vehicle light.

Table 2 Comparison between Various Scenarios

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Environment	Daytime with clear visibility	Daytime with visible characters	Nighttime with normal light	Nighttime with strong light
Challenge Level	Low	Low	Medium	High
Is License Plate Detected?	Yes	Yes	Yes	Yes
LP Detection Result	100%	100%	100%	100%
Character Recognition Result	100%	100%	80%	100%
Each Character Recognition Result	100%	90%	70%	50%
Can the Image Technique Flow Handle These Scenarios?	Yes	Yes	Yes	Yes

Table 2 showed the analysis of ALPR system performance highlights the impact of surrounding environments on license plate recognition accuracy. The proposed image processing flow, Method 2, played a significant role in making the characters clear, standing out from the background. While the proposed system performed excellent in scenario 1. In the nighttime scenario, particularly those with strong backlights, showed the biggest challenge, with recognition accuracy dropping to 50%.

In Scenario 1, the rear license plate was detected with 100% accuracy during daytime indicating the existing model had successful learning of license plate patterns. By implementing Method 2 image processing flow, the ALPR system achieved 100% detection and recognition rate with an impressive average character accuracy of 99.96% in optimal lighting conditions.

In Scenario 2, challenges emerged as the front license plate captured in daytime exhibited background visibility issues and the presence of dirt, impacting character recognition. Despite these challenges, the Method 2 technique is able to make the characters clear and easily recognized. By applying a Gaussian mean in this scenario, the technique ensures a smooth transition between different light levels, contributing to an overall enhancement in image quality Hence, the system maintained a high accuracy level, achieving 100% detection and an average character accuracy of 99.89%.

In Scenario 3, where license plate was captured in nighttime conditions. The challenges emerged as the truck light impacted the license plate visibility. However, the APLR managed to detect and recognize the license plate with 100% accuracy in the dimmer environment by applying the Method 2 technique. The result showed a slight decline in character recognition accuracy was observed in 20% of images due to low light conditions and the impact of truck light.

In Scenario 4, where a truck was captured at nighttime with strong lights. There were several challenges in this scenario, including dark surroundings and the effect of the vehicle's lights on the license plate. These challenges made it difficult for the proposed model to distinguish the license plate, even though it could recognize the characters on the license plate. Nonetheless, the proposed model not only 100% detected the license plate successfully but also segmented and recognized the characters effectively.

These scenarios may represent an ideal situation, it serves as an important benchmark for evaluating the performance of the proposed model and can be utilized to establish a more robust standard for future comparisons in evaluations.

Overall, the implementation of Method 2 image processing technique flow had significantly enhanced the performance of ALPR system across various scenarios. The ALPR system proved its robustness in detecting license plate and character recognition in those challenges such as background visibility issues, varying light conditions, and the dirt presence. These results underscore the importance of ongoing optimization efforts to address challenges and ensure the consistency and accuracy of ALPR performance in diverse environments.

5. Conclusion

This paper successfully developed an adaptive image processing technique flow to optimize the ALPR system. This study involved a comprehensive comparison of various image processing techniques flows for license plate recognition, evaluating the ALPR performance across four diverse types of scenarios. The second method of image processing technique flow demonstrated significant improvements in character recognition accuracy. By implementing Adaptive Thresholding Gaussian Mean and AI image enlargement had provided higher resolution and enhanced details. Furthermore, the evaluation of ALPR system revealed some factors affecting its performance such as spacing between characters, background noise, vehicles' light, surrounding lightning conditions can significantly impact its performance. These findings suggest that there is room for improvement in terms of making such ALPR system more robust to these factors in the context of license plate recognition. Overall, this study provides valuable insights into license plate recognition and has important implications for future research in this field. Future research could explore other neural network architectures or investigate new image processing techniques method ways to improve the robustness of ALPR system.

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