A Systematic Literature Review: The Effectiveness of ANPR for Electronic Law Traffic Enforcement

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***Abstract*—Automatic number-plate recognition (ANPR) is a system that reads vehicle registration plates and generates vehicle location data using optical character recognition. The implementation of Automated Number Plate Recognition for Electronic Law Traffic Enforcement has been a common thing lately. The government is urged to use this system for its efficiency in Traffic Enforcement. This Automatic Number Plate Recognition system mainly uses similar algorithms Plate acquisition, Plate Detection/Localization, Character segmentation, and Character Recognition. There are various techniques for each Detection, Segmentation, and Recognition. The authors of this study intend to undertake a Systematic Literature Review (SLR) of previously conducted research on the subject. Therefore, this paper discusses the method/techniques in Automated Number Plate Recognition, the reason they are being used, the accuracy of each method, and the devices that can process each system. Towards the end of this study, Edge information is the most effective and accurate based on localization, for segmentation is character feature, and Support Vector Machine (SVM) for character recognition.**

Keywords*—*ANPR, automated plate number, accuracy, ETLE

I. Introduction

These days, using surveillance cameras for security purposes is a common practice. Starting from the private to commercial sectors have used this security technology to avoid criminal acts that can occur at any time. Not only can it avoid criminality in the private sector, but these surveillance cameras can be effective methods for vehicle surveillance. It can be used at many public locations to meet objectives like automatic toll text collecting, car parking, and vehicle parking systems. In addition, these surveillance cameras can also minimize police illegal levies with excessive fines. Therefore, it takes technology to monitor the vehicle that violates the rules. [1] In 2017, ETLE, or Electronic Traffic Law Enforcement, began to be implemented in Indonesia. The implementation of ETLE also requires a capable device for detecting violated vehicles. These devices must capture the plate number of the vehicles while the vehicles are moving fast.

These systems are called Automated License Plate Recognition (ALPR) in the United States.[2] ANPR or Automated Number Plate Recognition can be called ALPR or Automated License Plate Recognition. This system used OCR or Optical Character Reader as the system's primary process. This system can be divided into several main steps: number plate capturing / plate acquisition, plate detection/ localization, character segmentation, and character recognition. Most of the systems used this process as their primary process. Video cameras are placed in several places, such as red light stops. Then, the camera captures the vehicle plate number, which will be transmitted to a system that will process the image. The video camera should have a fast shutter speed to handle fast-moving cars.[3] The Police Scientific Development Branch (PSDB), Home Office, United Kingdom, developed this technology in 1976. These systems could take 1800 vehicles' number plates per minute at 120-160 miles per hour. This system costs about $10.000 to $22.000. Many methods have been developed to support this system. The methods that are being utilized, the justification for their usage, the accuracy of each method, and the equipment that can process each system will all be covered in this paper.

II. Methodology

To find relevant articles, employed a variety of criteria, such as whether they were published in English when they were written and whether they connected to the problems and purposes of this work. The PRISMA flow diagram is shown in Fig.1.

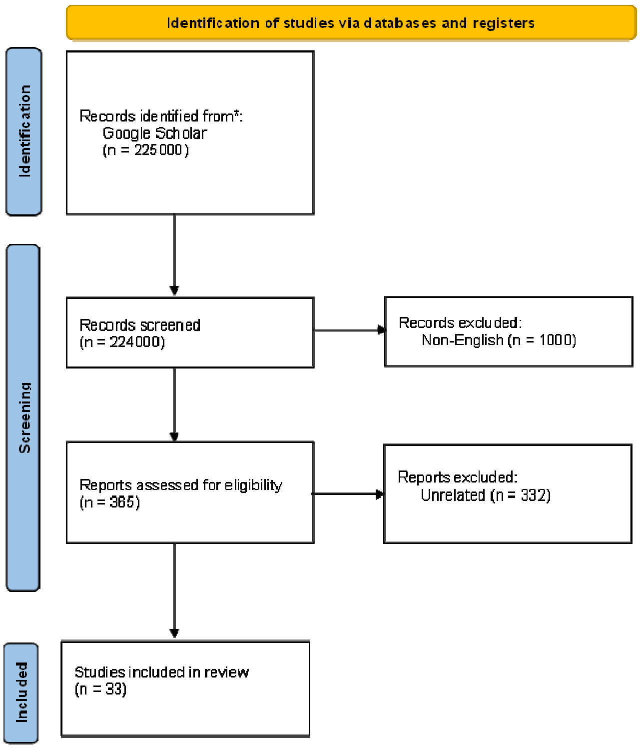

Fig. 1. PRISMA Flow Diagram.

We can see from Fig. 1 that there are a considerable number of records (n = 225,000). Following the first identification, a screening procedure was carried out, culminating in the assessment of 224,000 records. Exclusion

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2023 3rd International Conference on Electronic and Electrical Engineering and Intelligent System (ICE3IS) | 979-8-3503-2776-2/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICE3IS59323.2023.10335292

criteria such as non-English articles (n = 1,000) were used, resulting in a reduction in the number of records. The remaining 365 reports were then evaluated for eligibility, with 332 being ruled out as unconnected. Finally, the review identified 33 papers that matched the inclusion criteria.

A. Research Questions

This paper is a systematic literature review of The Effectiveness of ANPR for Electronic Law Traffic Enforcement. The research question for this systematic literature review is:

- RQ1. What kind of each technique in Automated Number Plate Recognition is used? Why are they being used?
- RQ2. How does the accuracy differ for each technique of Automated Number Plate Recognition?
- RQ3. What kind of device that able to process the system?

B. Search Strategy

This study also employs the PRISMA methodology to gather studies for this paper and to locate relevant publications using Google Scholar as a an intermediary to search for relevant papers. We gathered research papers and studies, proceeding from Google Scholar that included the key phrase " Accuracy AND Automated License Plate Recognition", "Accuracy of Automated License Plate Recognition OR Localization OR Smearing", "Accuracy of Automated License Plate Recognition OR Localization OR Edge", "Accuracy of Automated License Plate Recognition OR Localization OR Component Connected Analysis OR CCA", "Accuracy of Automated License Plate Recognition OR Segmentation OR Character Feature", "Accuracy of Automated License Plate Recognition OR Segmentation OR Vertical or Horizontal Projection", "Accuracy of Automated License Plate Recognition OR Recognition OR Deep Learning OR Convolutional Neural Network OR CNN", "Accuracy of Automated License Plate Recognition OR Recognition OR Deep Learning OR YOLOv4", "Accuracy of Automated License Plate Recognition OR Recognition OR Optical Character Recognition OR OCR", "Accuracy of Automated License Plate Recognition OR Recognition OR Support Vector Machine OR SVM". These keywords originated from our topic and research question.

III. Result and Discussion

RQ1. What kind of each technique in Automated Number Plate Recognition is used? Why are they being used?

Various strategies can be used in the context of Electronic Traffic Law Enforcement (ETLE) to process Automatic Number Plate Recognition (ANPR) systems. This research focuses on three important steps: detection/localization, segmentation, and recognition (Fig.2). The first phase, Plate Detection/Localization, is identifying the vehicle's license plate inside the collected image. The main goal is to find and isolate the number plate region from the rest of the image. This step is critical for the succeeding phases of processing. Plate Segmentation is the second stage, in which the previously recognized number plate is further processed to segment each individual character or letter on the plate. The goal is to obtain independent representations of each character by separating the number plate into discrete components. The third and last step is Plate Recognition, which involves recognizing and interpreting the segmented characters on the number plate. This process focuses on decoding the individual letters or characters one by one, allowing significant information to be extracted from the plate. These steps are carried out utilizing a number of methodologies and procedures, as detailed in Tables 1, 2, and 3. The methodologies described in these tables are based on relevant experiments and papers connected to our topic. Please refer to the cited sources for more complete explanations for a more comprehensive understanding. This new paragraph focuses on providing a clearer description of the three main phases involved in ANPR: detection/localization, segmentation, and recognition.

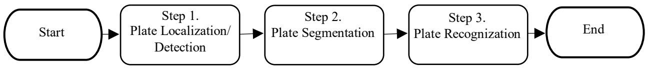

Fig. 2. SLR Flow Diagram.

Step 1. Plate Localization / Detection

TABLE I. LOCALIZATION / DETECTION CLASSIFICATION

Classification Techniques	***Number of Papers***	***Study Identifiers***
Smearing Algorithm	4	[4]–[7]
Edge Information	9	[8]–[15]
Connected Component Analysis	1	[16]

a) Smearing Algorithm

The smearing algorithm discovers and recognizes a car's features, such as its license plate. This algorithm required two threshold values for horizontal can be set as 10 & 100 and 20 & 100 for the vertical scan.[5] The Authors of [4], [6], [7] employed this smearing algorithm to detect vehicle license plates. The Authors' primary procedures in [4] are Image Capture, Preprocessing, Plate Localization, Character Segmentation, and Character Recognition. In the initial round of picture capture, 150 Malaysian license plates were photographed under varying lighting conditions and angles. Then, these images must be prepared with proper RGB colors and pixels. These images were converted to binary in the following step. The horizontal and vertical thresholds were then utilized to execute a smearing algorithm. The subsequent procedure, character segmentation, was acquired after The Region of Interest (ROI), which comprises entirely vehicle license plates, was determined by the smearing method. Authors [6] followed the same procedure as Authors [4]. The difference between the two methods is that MSER analysis is performed when the smearing step is completed. This MSER study will predict the size of a vehicle's license plate.

b) Edge Information

Various number plate identification techniques are grouped into distinct categories based on plate size, plate placement, backdrop, lighting, and pixels. Authors [8] employed Hough transform for line detection, detecting horizontal and vertical lines from a rectangular car number plate before applying hue-intensity-saturation processing (HIS). Authors [9], [15] use a morphological operator to the image to designate the plate location for focusing on the rectangular shape of the plates. Authors [10] employed a unique operator to locate the image's edge. The Canny operator measures the image's spatial gradient in two dimensions. A high threshold for low edge sensitivity and a low threshold for high edge sensitivity is applied to the gradient. After the preprocessing phases, The Authors [11] used the canny edge technique to detect the plate edges and employed several threshold strategies to limit image noise. The Authors [12] employed a Sobel edge detector to identify plate vehicle rectangles. Authors [13], [14], [16] used a similar edge detection by using vertical / projection edge detection.

c) Connected Component Analysis

The image is scanned, and its pixels are classified into components based on the connectedness of the pixels in binary image processing using the technique of Connected Component Analysis (CCA). [17], [18] This CCA is known as "connected-component labeling" (CCL), "connected-component analysis" (CCA), "blob extraction," or "region extraction," which labels a subset of connected components in a particular manner. The Authors of [16] used two phases for number plate extraction: Otsu's Threshold Method in the first step and The Connected Component Analysis in the second. Then, the Connected Component Analysis (CCAT) technique is used to recognize the rectangles that are the created license plate candidates. Detection was done while verifying the hypothesis, searching for vertical and horizontal edges. In this experiment, around 533 images were collected utilizing three video sequences.

Step 2. Character Segmentation

TABLE II. SEGMENTATION CLASSIFICATION

Classification Techniques	*Number of Papers*	*Study Identifiers*
Character Feature	4	[7], [8], [10], [19]
Vertical or Horizontal Projection	3	[11], [13], [15]

a) Character Feature

In the segmentation of plate characters, the license plate is broken down into component sections to acquire each character separately. First, the image is filtered to enhance and remove undesired noises and spots. If the characters are close together, the dilation operation is then applied to the image to separate them.[7] Character segmentation for license plate Authors [10], [19] should divide each digit, letter, and word into sub-images. The implicit segmentation program is written to divide words into segments that correspond to characters and then pass each segment to a classifier. If the categorization results are insufficient, re-invoke segmentation with a message indicating that the previous sequence was rejected. The implicit segmentation program is written to divide words into segments that correspond to characters and then pass each segment to a classifier. If the categorization results are insufficient, re-invoke segmentation with a message indicating that the previous sequence was rejected.[8]

b) Vertical and Horizontal Projection

Different hues are used for the characters and backdrop of a license plate. The generated binary image has distinct values for the number's character and backdrop.[17] The Authors utilized Vertical and Horizontal Projection [13] to remove the fake piece from the plate and determine the number of rows and symbols. Unlike Authors [11] who used Horizontal Projection, Authors [15] used Vertical Projection during segmentation processing.

Step 3. Character Recognition

TABLE III. RECOGNITION CLASSIFICATION

Classification Techniques	*Number of Papers*	*Study Identifiers*
Template Matching	5	[7], [9], [10], [12], [16]
Deep Learning	6	[20]–[25]
Tesseract OCR	7	[11], [12], [14], [26]–[29]
Support Vector Machines (SVM)	4	[15], [30]–[32]

a) Template Matching

Template matching is an efficient technique for character recognition. The best resemblance between the character's image and those in the database is considered. A statistical method based on correlation is used to measure similarity and determine the best match. Correlation is a practical image recognition approach. This method measures the correlation coefficient between a set of known images and a set of unknown images or fragments of an image of the same size, with the highest correlation coefficient yielding the best match. The Author [9] proposes a recognition solution based on morphology and template matching by examining 150 Iranian license plate numbers. In this technique, the primary step is isolating the license plate from the digital vehicle image captured by a digital camera under varying lighting, slope, distance, and angle conditions. The procedure begins with signal pre-processing and conditioning. The following license plate is localized via morphological operators. Then, a template-matching algorithm will be employed to identify the numerals and characters on the plate. Author [12] uses a similar system as Authors [7], [10] and tests 100 patterns on the system with different scenarios. Authors [16] perform a template-matching approach for character recognition employing the cross-correlation method between detected characters and templates.

b) Deep Learning

Artificial neural networks with a typical feedforward design are an approach to convolutional neural networks. In contrast to conventional vision approaches, artificial features are employed to determine the connection pattern between neurons. For specific jobs, CNN has been applied to many tasks, including image classification, face detection, facial point detection, and hand tracking.[20] CNN has the advantage of processing distorted, skewed, and illuminated datasets. Authors' [20] research on a number plate reading technique using 256 characters in 32 plate images has been successfully tested with CNN. The Authors [21] gathered approximately 2000 images obtained from various street locations under diverse environmental circumstances. By using 1917 Train Dataset and 367 Validation Dataset, The Authors employed a multiclass CNN model consisting of four layers to accurately identify and classify individual digit and character segments.

Authors [22] employ a cascade structure consisting of a fast region proposal network and an R-CNN network. In addition to eliminating false alarms, the R-CNN network regresses each detected plate's corner coordinates. This enables the estimation of an affine transformation matrix for rectifying the extracted plates. Parallel spatial transform networks and shared-weight recognizers are proposed as a new structure for the recognition stage. The system is trained and validated using approximately 18K photos of Chinese license plates. According to the results, the Authors' detector outperforms the quicker R-CNN (VGG), which is 1.5x slower in testing and 57x greater in model size. In addition to being vastly superior to previous solutions, the recognizer reduces by 57.5% the errors of a state-of-the-art character sequence encoding technique.

YOLOv4 can be described as a one-stage item identification model that extends YOLOv3 with several newly published modules and trick packs. The concept behind the YOLOv4 is You Only Look Once. Vehicle Classification, YOLOv4 VLP Detection, VLP Processing, Character Recognition, and GUI are some steps.[23] The Authors trained their proprietary model for YOLOv4 VLP Detection and implemented VLP Processing and Character Recognition. In this step, the Authors themselves performed picture preprocessing and OCR. The algorithm employed by the Authors is Otsu's Binarization. Then, both the image passing through Tesseract and each character will be identified. In the final step, the Authors created a graphical user interface for user interaction.

Authors [24] employed the same image processing algorithm as Authors [23] obtaining the OCR, the dataset trained using YOLOv4 and Convolutional Neural Network detects them. The Authors [25] present a computationally lighter real-time Automatic License Plate Recognition system that omits the ROI setting step without degrading performance. Conventional license plate recognition systems have two significant areas for improvement. First, license plate visibility must be clear. The processing of actual field data is computationally intensive, and the ROI must be determined. To circumvent these issues, we performed plate localization directly on the entire image and conducted research that accounted for low-quality license plate detection.

Artificial Neural Network was one method for recognizing license plates because separating the training and classification processes will reduce the device processing load.[33] The Authors [33] utilized a Backpropagation Neural Network, a subset of an Artificial Neural Network, whereas the Authors [8] utilized the k-Nearest Neighbor Algorithm. The Authors [19] resized sixty Iraqi license plates for binarization purposes. During Preprocessing, the pixel that was smaller than 70 pixels was eliminated. There are three ways to alter the input/output of a picture using Neural Network Learning: Supervised Learning, Unsupervised Learning, and Reinforcement Learning. Three layers comprise the Backpropagation Neural Network: Input Layer, Hidden Layer, and Output Layer. The input photos were subjected to regression, and the best character segmentation performance was determined. Authors [8] utilized the k-Nearest Neighbor Algorithm, which was trained to find the sample's nearest neighbor. Authors using around 177 license plate numbers under various conditions, 1254 characters can be recognized. The system utilized by the Authors [19] was MATLAB R2014a. The Authors [8] did not specify the system they used to conduct this experiment, but the overall system performance under various conditions achieved an accuracy of up to 73.02 percent.

c) Tesseract Optical Character Recognition (OCR)

Character recognition methods are divided into two categories: online and offline character recognition methods. OCR is one method to recognize the segmented image in online character recognition. Offline character recognition systems recognize machine-printed and handwritten texts.[14] Authors [26] utilize a range of image processing principles and MATLAB techniques to identify and capture the license plate of a vehicle using a high-resolution camera. Their system combines a video surveillance setup for speed detection with an automatic number plate recognition system, enhancing law enforcement capabilities. Authors [14] used the ANPR system in their research and produced a high percentage of age readings, particularly throughout the day. The percentage reading during the nighttime test is lower than during the daytime. Authors [11] utilized 50 Saudi license plate photos in the experiment examined in the existing stud. A masking approach was used to identify and isolate the region of interest in the picture following horizontal projection. OCR was used to read the Arabic and English letters and numerals apart from each other on the processed pictures. After mixing Arabic and English letters, text was rendered on pictures in the lower plate areas. The Author [27] employs image processing methods such as erosion, thinning, convolution, and OCR (Optical Character Recognition). The plate recognition and extracted license plate number can be utilized to search for the vehicle's owner in the current database of visitors. Like the Authors [27] employs image processing methods such as erosion, thinning, convolution, and OCR (Optical Character Recognition). The plate recognition and extracted license plate number can be utilized to search for the vehicle's owner in the current database of visitors. Like Authors [11], Authors [28], [29] used the same algorithm and achieved 95.16% and 90% accuracy.

d) Support Vector Machine (SVM)

Support Vector Machine methodology for license plate detection typically employs neural network algorithms. The most fundamental SVM is typically employed for one-on recognition, whereas multi-class SVM classification employs the concept of classifiers to achieve its objective of multi-class classification.[31] As a comparison, The Authors [15] employed SVM for character recognition to solve a binary classification problem. Image Processing by Plate Location and Character Segmentation, Feature Extraction, and passing the output (Feature Vector) to KKN for Character Recognition was The Author's [30] basic concept for this project. This Author wants to apply both KNN and SVM to increase character identification accuracy during the Character Recognition stage. The Authors [31] employ Otsu segmentation for picture segmentation, HOG for feature extraction, PCA for feature selection and integration, and SVM for classification.

RQ2. How does the accuracy differ for each technique of Automated Number Plate Recognition?

Step 1. Plate Localization / Detection

a) Smearing Algorithm

Authors [4] Experiment with 150 sample photos of Malaysian plates yielded an overall plate localization rate of 97.4 percent. Authors [7] use MATLAB 6.5 to experiment with recognizing Turkish license plates. The input photos for the system are colorful, 1200 × 1600 pixel photographs captured under various lighting situations. It has been demonstrated that the detection of plate regions is 97.6% accurate.

b) Edge Information

Authors [9] Experiment input images are 640x480 color images, and test images were captured at various lighting conditions and distances. The results of plate region localization are 97.3%. Authors [13] use vertical edge detection, and the process result is 98% with a 2% error. Authors [14] localization process success rate is 96%.

c) Connected Component Analysis

Authors [16] obtained up to 96.06 percent plate localization by integrating three distinct localization techniques, including Connected Component Analysis, Otsu Threshold, and Canny Edge Detection.

Step 2. Character Segmentation

a) Character Feature

During segmentation, the majority did not share information regarding accuracy. However, Authors [7] showed that character segmentation accuracy was 96 percent which is relatively high.

b) Vertical and Horizontal Projection

Authors [13] have evaluated using a vast number of 368 x 254-pixel photos to determine its performance. It segmented characters with 95% accuracy. It is supported by IDL 7.0. The Authors did not specify the accuracy [15], but segmentation is performed by counting the number of non-zero pixels on each column. The total number of pixels has a trough between the two characters. Character segmentation is achieved concurrently based on the actual character width, the ratio of the license plate, and other prior factors.

Step 3. Character Recognition

a) Template Matching

The Author's results indicate that the identification unit's accuracy is 92% based on 150 colorful, 640x480 pixel images. The results of Author [9] indicate that the identification unit's accuracy is 92% based on 150 colorful, 640x480 pixel images. Authors [7] employ the same methodology, resulting in overall system recognition rates of 92.57%. Authors [10] used Template Matching based approach and achieved up to 93% accuracy for 900 images used for the experiment. The Authors [12] observed that the characters and numbers on new license plates were readable and in acceptable condition for identification. At last, the recognition process achieves up to 91% accuracy. By utilizing three distinct datasets, including the Moroccan, Caltech, and AOLP, The Authors [16] outperformed the prior experiment by achieving 96.37 percent, 93.07 percent, and 92.52 percent from these three datasets, respectively.

b) Deep Learning

Research [20] of license plate character recognition techniques CNN has completed 32 plates using the results of testing on 256 characters in the image. The test results are highly satisfactory since 94% of the characters are appropriate, and only 6% are inappropriate. Authors [22] achieve 0.9755 or 97.55% for character recognition with a 0.0314-character error rate. Authors [21] obtained 97.5% accuracy on a heterogeneous dataset of 2000 photos in which environmental aspects were attempted to be captured. Authors [23] successfully tested nine vehicle images in one video and got an average accuracy of 52.8%. Authors [24] tested the vehicle image using two different sizes and found that the smaller size is more accurate and can achieve up to 90s%-character recognition. Authors [25] could test an image with high accuracy on character recognition.

c) Tesseract Optical Character Recognition (OCR)

The effectiveness and precision of the character recognition performed by Authors [12] was 91%. Authors [14] experiment overall character recognition accuracy is 83.33%. Authors [27] mentioned that the experiment was conducted on 100 license plates, and 93 were successfully identified. Therefore, the accuracy is 93%. The recognition accuracy of the suggested vehicle detection system, as determined by the Authors [29] is 95.16%.

d) Support Vector Machine (SVM)

Support Vector Machine (SVM) evaluated by the Authors [30] uses a hybrid KNN-SVM model to dramatically increase the character recognition rate from 94% to 97.03%. Authors [31] and his experiment yielded up to 99.3 percent overall performance.

RQ3. What kind of device that able to process the system?

The experiment [23] was conducted with a smartphone capable of capturing 1080p video at 30 fps and the Google Collab TESLA T4 GPU, which can run video at approximately 14 fps. In their experiment, The Authors [25] utilized an NVIDIA Jetson TX2 board with GeForce RTX 2080 Ti as their primary system. In addition, The Authors [25] compared the effect of using a different system component on the system's operation. It was determined that utilizing a different GPU altered the video FPS reading. The experiment [16] was carried out using MATLAB and an Intel Core i5 processor for the Connected Component Analysis Technique. In the Smearing method, all Authors did not specify the system they used for the experiment. However, Each Author utilized a smartphone to photograph several vehicle license plates. Author [32] uses the Support Vector Machine method, which uses Pentium IV at 3.0 GHz with 512 MB of RAM for segmenting a license plate and takes 111 milliseconds of processing time. Authors [11], [12] use MATLAB to run their software, where MATLAB does not require high-end computer specifications to run the program. The author [21] uses an Intel i7 7th-generation processor, 8 GB DDR4 2400 MHz RAM, and an NVIDIA GTX GeForce 1070 GPU computer to analyze 2000 training photos and 400 recognizing images. The system utilized by the authors [19] was MATLAB R2014a.

IV. Conclusion

Based on our research, we compare the result based on the Author's experiments in each segment method with the highest accuracy. In Localization, the Authors [4] use the Smearing algorithm to produce up to 97,6% plate localization accuracy. The Connected Component Analysis Technique (CCAT) method that was experimented with by the Authors [9] has the accuracy of plate localization at 96.06 % accurate. Authors [13] with the vertical edge detection method gain a result of 98%. Edge information is the most effective and accurate based on localization. In Segmentation, Authors [7] used character features for character segmentation, and the accuracy was 96%. Authors [13] with vertical and horizontal projection segmented characters with 95% accuracy. The effective method for segmentation is the character feature.

In the recognition process, The YOLOv4, part of deep learning conducted by the Author [24], detected characters on the license plate with an accuracy of 81% and license plate detection with a precision of 92%. Authors [29] achieved 95.16% accuracy utilizing the digital image processing method for ANPR by using OCR to detect the number of images. And the last method with the most accuracy is the Support Vector Machine (SVM) that was tested by the Authors [31], and his experiment achieved up to 99.3% overall performance. Almost all Authors of the 33 papers reviewed used computers with low specifications and the latest technology. However, an experiment conducted by one of the Authors [25] mentioned that the better the GPU of the computer, the faster it is to read high FPS videos. The researchers working on these advances can benefit from this paper's thorough analysis of current trends and potential developments in ANPR and choose suitable algorithms for their ANPR. In the future, The Authors of this paper hope that the implementation of ANPR around the world can be more evenly distributed with adequate systems in each region because it is evident from this literature review that it does not require a computer that has high specifications to be able to process video surveillance. We aim for ETLE to fulfill its goals and secure surveillance camera data from malicious hackers.

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