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# A Survey on Deep Learning-Based Number Plate Recognition Systems in Vehicles for Real-Time Applications

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**Abstract:** *Innovation is integral to human existence, and research on modernisation aimed at enhancing daily life has proliferated in recent decades. One notable advancement is the evolution of AI, and we are in the era of machine intelligence. These developments are essential for society, as access to these amenities is not restricted to any specific group. A prevalent application of intelligent technology is traffic monitoring. A paramount application is Automatic Number Plate Recognition (ANPR) systems; various technologies are being developed to enhance performance. Research into innovative technologies, their enhancement, and the advancement of existing methods commenced several years ago and remains essential. Real-time video-based ANPR systems are complex and essential for modern intelligent transportation applications. This study presents a systematic review of real-time video-based automatic number plate recognition systems, tracing the evolution from traditional image processing to deep learning, end-to-end methods, and Transformer-based methods. We compare detection and recognition techniques and identify the limitations of current ANPR systems. The review concludes with proposed directions for developing more robust and efficient ANPR systems for real-time traffic analysis in intelligent transportation systems.*

**Keywords:** *automatic number plate recognition systems; licence plate detection; image processing; artificial intelligence; machine learning; moving vehicle detection and recognition.*

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## 1. Introduction

An image is a representation of an object or concept. Digital image processing employs algorithms to transform images into a digital format, encompassing sampling and quantisation. Image processing entails modifying an image's characteristics to improve its visual information for human comprehension or to make it more amenable to computer analysis. The procedure is termed image enhancement; the outcome is more suitable for a certain purpose than the original image (Gonzalez & Woods, 2008). Video processing is a subset of image processing in which a video is first converted into a sequence of frames, which are then analysed using image processing methods. The process is time-consuming; hence, method selection is crucial.

Automatic licence plate detection is the method of extracting a vehicle's licence plate area from an image autonomously. It represents a crucial domain within intelligent transportation systems. The initial task in the ANPR system is to identify moving vehicles, as the outcomes of this process are crucial to the entire operation. Vehicle licence plate detection precedes licence plate recognition. The datasets predominantly used by video-based ANPR systems comprise ICDAR 2015, the YVT vehicle and licence plate detection dataset, and the ALPR recognition dataset. This study begins with a concise review of traditional methodologies used in ANPR systems and subsequently analyses ANPR systems and strategies applied to video-based applications.

Our study examines several ANPR systems, the methodologies employed at each phase of the process, and systems specifically developed for video applications. We analyse each ALPR system individually, as a method used in one system for a specific function may be applied in another for a completely different objective. Initially, we delineate the diverse methodologies employed in ANPR systems, followed by a detailed discussion of video-based ANPR systems. The impetus for this study is the existence of diverse systems, each employing distinct methodologies at every phase of the process. The system's performance varies according to the number of processing stages, the methodologies employed at each stage, the characteristics of the data being processed, the video background, and other factors. Consequently, a comprehensive analysis is necessary to choose a suitable solution based on these characteristics, which is critical for enhancing real-time ANPR systems. The primary aim of the study is to analyse each element of the process comprehensively. Consequently, appropriate systems may be selected based on video quality, speed, processing time, and frame rate to enhance traffic monitoring efficiency. The workflow of the study is the evolution of automatic number plate recognition systems from traditional image processing for conventional ANPR systems to advanced deep learning methods for moving vehicles. Early systems used conventional image processing and machine learning algorithms, such as support vector machines. Later, convolutional neural networks and You Only Look Once (YOLO) models improved detection accuracy and enabled real-time performance. Most recently, Transformer-based architectures have provided greater robustness and accuracy in challenging conditions, including motion blur and adverse weather.

## 2. Traditional Methods Used for ANPR Systems

The ANPR system detects objects in images or videos, including various vehicle types, moving vehicles, and anomalies. It then classifies detected objects as licence plates or not, and uses bounding boxes to isolate licence plate regions from the background. Character recognition is performed on the isolated plate region. These processes rely on the traffic monitoring capabilities of Intelligent Transportation Systems (ITS). Real-time Automatic Number Plate Recognition systems face significant challenges from adverse environmental conditions, such as rain, fog, snow, dust, glare, and low light, which degrade image quality and reduce licence plate visibility. Motion blur caused by high vehicle speeds or camera movement further obscures character details, making plate localisation and character recognition more difficult. Changes in illumination from shadows, direct sunlight, night-time operation, or reflections create brightness and contrast fluctuations that weaken detection and recognition algorithms. Partial occlusions from vehicles, pedestrians, dirt, or physical damage can conceal characters, resulting in incomplete or incorrect recognition. These factors reduce detection accuracy, increase false positives and negatives, and compromise the reliability of ANPR systems in real-world transportation applications. Captured images are influenced by scene information (true scene, T), environmental factors (E), such as haze, rain, illumination changes, shadows, and occlusions, and device noise (N). Our goal is to enhance scene information while minimising the impact of environmental factors and device noise. By selecting a higher-performing camera, device noise can be reduced. Under varying environmental conditions, methods should be implemented to mitigate the effects of haze, rain, low illumination, and occlusion.

- The first and foremost factor is the environmental conditions, which is given in equation (1).

$$I(x, y) = f(T,\ E, N) \quad (1)$$

From equation (1), we see that the input image depends on the true data, environmental conditions, and equipment noise.

- The second factor is motion blur; increasing vehicle speed produces greater blur.

$$I(x, y) = T * k + N \qquad (2)$$

Where, k is the kernel for blur and * denotes the convolution operation.

- Another uncontrolled factor is the varying illumination. The background brightness varies according to the time of day.

$$I(x, y) = R(x, y).\, L(x, y) \qquad (3)$$

Where, $R(x, y)$ is the Reflectance of the object surface,
$L(x, y)$ is the Illumination of the scene

- Occlusion is another factor, which may result from the presence of another vehicle, a living object such as a tree, or a non-living object such as a traffic light or pole.

$$O_v = O - O_{occ} \qquad (4)$$

Where, $O_v$ is the visible object,
$O$ is the original object (True object)
$O_{occ}$ is the occluded area.

It is necessary to explicitly account for all relevant situations when designing ANPR systems. Modern ANPR systems address operational challenges by integrating advanced image enhancement techniques, deep learning models, and optimised hardware. Pre-processing methods, such as deblurring, denoising, and contrast enhancement, are used to improve image quality before plate detection. Common deblurring techniques include Wiener filtering, Blind deconvolution, and motion deblurring using convolutional neural networks (CNNs), such as DeblurGAN, MPRNet, and Restormer. Denoising approaches include Gaussian filtering, Median filtering, and deep learning-based methods, such as DnCNN and Noise2Noise. Contrast enhancement is achieved through adaptive histogram equalisation, contrast-limited adaptive histogram equalisation, Retinex-based enhancement, and deep learning-based methods, such as Zero-DCE, EnlightenGAN, and RetinexNet.

Furthermore, deep learning object detectors, such as YOLO, Transformer-based models, and attention mechanisms enhance feature extraction and system robustness under challenging conditions. Data augmentation techniques that simulate rain, fog, blur, and varying lighting during training further promote model generalisation. The use of high-resolution cameras, infrared illumination for night-time operation, multi-frame video analysis, and temporal tracking facilitates the recovery of information lost in individual frames. Collectively, these strategies enhance the robustness, accuracy, and reliability of ANPR systems across diverse environments. General methods for image recognition in traditional computer vision systems include edge detection, thresholding, morphological operations, HOG, Haar features, SIFT, SURF, and LBP. Additionally, a wide range of systems is available, spanning from conventional image processing techniques to the latest Transformer-based methods.

The PRISMA diagram shown in Figure 1 outlines the study selection process used in the present review. We established selection criteria to identify relevant, high-quality studies on real-time Automatic Number Plate Recognition systems. The literature search focused on IEEE Xplore, ScienceDirect, Springer, Sensors, Journal of Critical Reviews, arXiv, MDPI, IJRASE, and IET, which provide extensive peer-reviewed resources in computer vision, artificial intelligence, image processing, and smart transportation. Studies published from 2018 to 2026 were included to reflect recent advancements in deep learning-based ANPR systems, such as convolutional neural networks, end-to-end architectures, and Transformer-based models. Only peer-reviewed journal articles and conference papers published in English that directly address ANPR, licence plate detection, licence plate recognition, or real-time video-based vehicle identification were considered. Studies published before 2018 were excluded. Duplicate publications, non-peer-reviewed articles, review papers, book chapters, short abstracts, and studies unrelated to ANPR applications were excluded. Additionally, journal and conference papers published in languages other than English or not directly related to real-time ANPR systems were excluded. (See Figure 1)

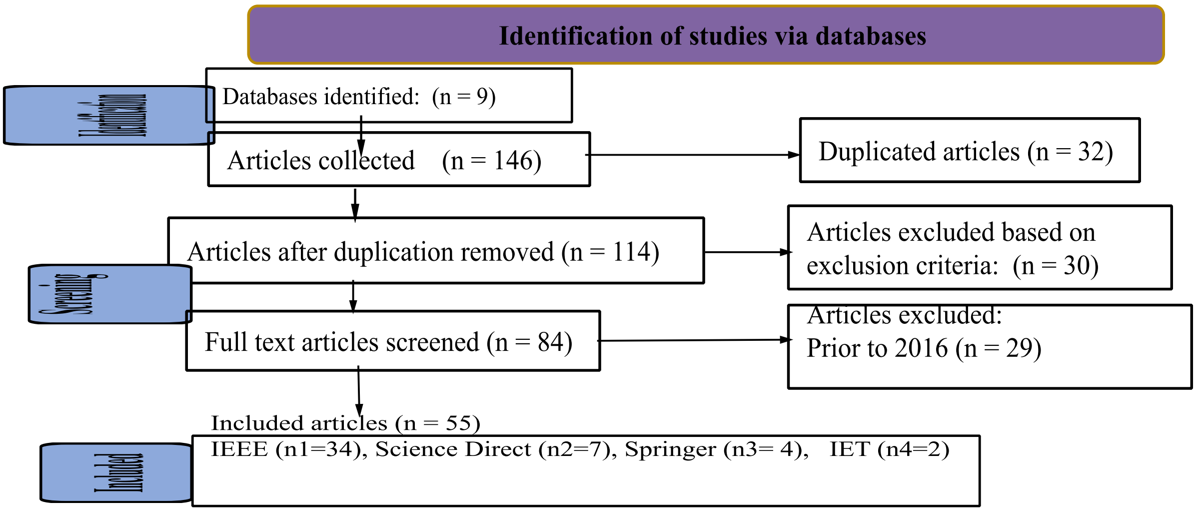


*Figure 1. PRISMA flow diagram*

A preliminary search across nine databases yielded 146 articles, of which 32 were excluded for redundancy. The subsequent phase entailed a thorough evaluation of the 114 remaining abstracts. The application of inclusion and exclusion criteria led to the elimination of 30 items. Subsequently, to evaluate the relevance of video-based ANPR systems, 84 full-text publications were examined, and 29 were excluded. As a result, 55 studies satisfied the eligibility criteria and were included in the review. IEEE Xplore was chosen for its extensive repository of technical literature and conference proceedings, which are both pertinent and authoritative in engineering and technology. ScienceDirect was selected for its comprehensive collection of credible, peer-reviewed articles relevant to the research scope. SpringerLink was selected for its extensive peer-reviewed research in computer vision, artificial intelligence, and intelligent transportation systems.

Intelligent transportation systems, particularly automatic licence plate recognition, have received extensive attention; however, certain limitations remain. This section analyses conventional methods for detecting and identifying automobile licence plates. Typically, the image is pre-processed to enhance its quality through contrast enhancement and noise reduction, as the collected images may be indistinct or noisy under both daytime and night-time conditions. The selection of pre-processing procedures depends on the image type and its background or foreground elements. Morphological processes emphasise the licence plate regions, and the resulting image is converted to a binary representation using thresholding. Ultimately, edge detection is executed on the pre-processed image, segmenting and extracting characters for identification. While these approaches are conventional in early number plate recognition systems, the methodologies employed at each stage may differ. Traditional ANPR systems primarily relied on image processing, with some employing supervised machine learning. The adoption of deep learning has grown rapidly since its introduction. Figure 2 illustrates the number of studies employing various ANPR methods included in this review.

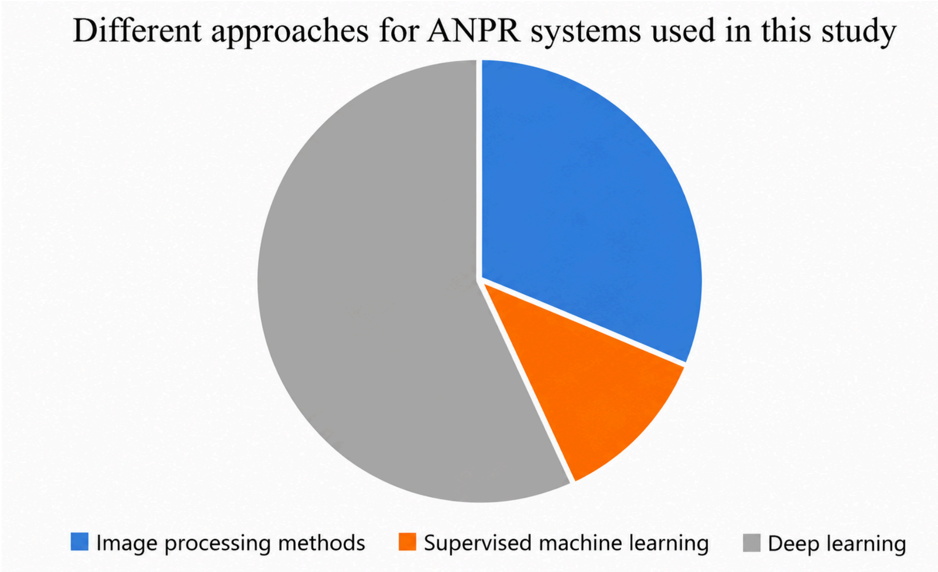


*Figure 2. Pie chart of various technologies in different stages of ANPR systems used in the proposed study*

Figure 3 outlines the predominant image processing strategies for licence plate detection, including edge detection, segmentation, and recognition.

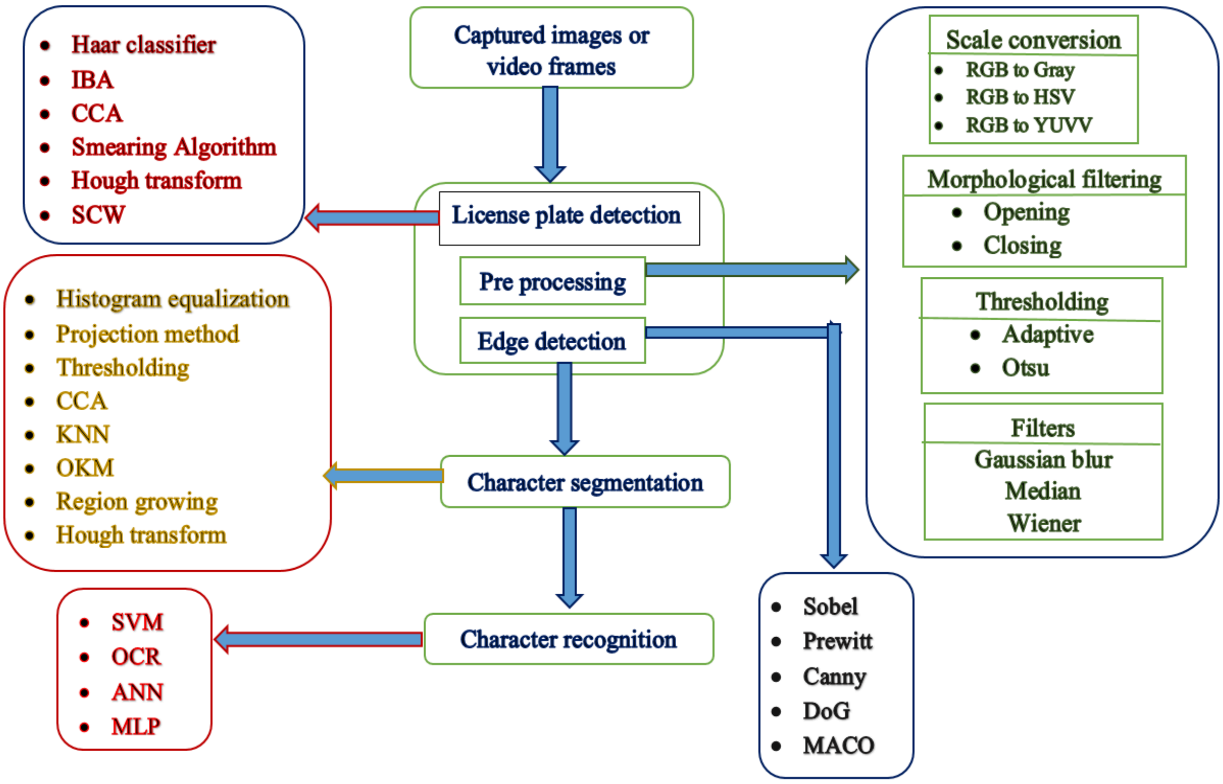


*Figure 3. Various stages and methods used in traditional ALPR systems*

In several instances, before additional processing, it is customary to resize the image and convert it to grayscale, then perform edge detection on the binarised image using thresholding. A variety of systems are detailed here. Numerous edge detection techniques are available, including the Sobel, Prewitt, and Canny methods. Sasi et al. introduced a method that employs Modified Ant Colony Optimisation (MACO) for edge detection. Then, character segmentation and extraction are performed using a hybrid approach that combines Connected Component Analysis (CCA) and a Kohonen Neural Network. Character recognition is performed using a combination of inductive learning and a Support Vector Machine (SVM). Furthermore, the method attains 94% accuracy in character extraction and segmentation (Sasi et al., 2018). Khan et al. proposed a system with four stages: (1) from the CIE-Lab colour space, they selected the luminance channel; (2) image refinement for binary segmentation of the luminance channel; (3) feature extraction using Histogram of Oriented Gradients (HOG) and geometric characteristics, followed by entropy-based feature selection; and (4) classification using SVM.

However, the feature selection strategy has limitations, leading to a high error rate and a low recognition rate (Khan et al., 2018). Yogheedha et al. proposed a system that employed image processing methods, including colour conversion, Otsu's threshold-based image segmentation, noise reduction, image subtraction, image cropping, and bounding box delineation. Then they checked the printed characters with the OCR using template matching. The system can proficiently identify licence plates even in low-light conditions.

*Table 1. Various methodologies used in traditional ANPR systems by different authors*

| Author | Pre-processing methods used | Character segmentation methods used | Character recognition methods used | Limitation |
|---|---|---|---|---|
| (Sasi et al. 2018) | Contrast enhancement: RGB-to-Gray conversion, median filtering, and adaptive histogram equalisation. LP region highlights: Morphological operation. Binarisation: Otsu's thresholding. | Hybrid CCA and KNN | Inductive learning and SVM | The method's accuracy is 94%. |
| (Khan et al. 2018) | To obtain the luminance channel : CIE-LAB transformation, split the L channel. | Binarisation: Otsu's thresholding Segmented region highlight: Morphological operation and Image subtraction. Highlight characters: 2D convolution, then the morphological operation. | SVM using (HOG, eight geometric, and entropy-based fusion features) | The recognition error rate is high. |
| (Yogheedha et al. 2018) | Resize, RGB to greyscale image | Otsu's thresholding | Template matching | Biased recognition of ambiguous and similar characters. |

The system's efficacy depends on the camera's placement and the distance between the camera and the licence plate (Yogheedha et al., 2018).

Table 1 below describes the pre-processing, edge detection, character segmentation, and recognition algorithms employed in several ANPR systems, along with their respective drawbacks.

Islam et al. used standard image processing procedures, including resizing, converting from RGB to greyscale, applying Otsu's binarisation, performing Sobel edge detection, and identifying licence plate regions using morphological operations. Region characteristics are used to extract the licence plate region from the merged greyscale image. CCA delineates the characters, followed by template matching. This approach ultimately relies on vehicle verification—template matching encounters difficulties with ambiguous or analogous characters (Islam et al., 2021). Ali et al. predominantly employed a system that captured images of the vehicle, extracted the region of the number plate, and finally used OCR for character recognition. The system, designed for Android, is efficient, accurate, and cost-effective. The LPR system is ineffective in bad weather (Ali et al., 2021). Kashyap et al. introduced a system that employed adaptive thresholding to convert the image into a binary format. Subsequently, contrast is augmented using histogram equalisation, and extraneous areas are eliminated using a median filter. The method employs the regionprops function for character segmentation, the zonal density function for feature extraction, and template matching for character recognition. The recognition method was unable to recognise the licence plate characters when the vehicle is obscured by several cars (Kashyap et al., 2018). Chowdhury et al. used a separate method in which potential vertical edge points along the text area's scan line are identified using the Sobel operator based on pixel distances. Then, scan lines are clustered by the number of vertical edge pixels per scan line or per colour chain. The text box is generated by combining two text boxes and removing those not part of the LP using area-based and edge-density-based methods. Vertical projection is applied for elimination, except for boxes containing only text, and padding reconstructs text removed by earlier steps. This method works in both indoor and outdoor settings. The method's efficiency varies depending on the blocks and text blocks detected (Chowdhury et al., 2019). In another approach, Choong et al. proposed an architecture comprising five linear stages: grayscale conversion, image binarisation, LPD, character segmentation, and recognition, with no iterations. LP detection is performed by searching the white regions of the rectangular binarised image. CCA is used for character segmentation, followed by template matching for recognition. The drawback is its lack of flexibility, making it unsuitable for adaptive outdoor environments (Choong et al., 2020).

A different approach, identified by Medvedeva et al., detects contours using their geometric properties, which are detected through a mathematical framework based on a 2D discrete-value Markov chain with two states. Here, licence plates are located by examining bit planes of the most significant bits to minimise resource use. Character recognition has an accuracy of about 92% (Medvedeva et al., 2020). ALPR systems use many sophisticated deep learning methods in the detection and recognition stages; these methods have improved significantly. In some systems, different deep learning networks are used for separate stages, such as detection or recognition. In contrast, in others, a single deep learning model handles all processes from input to output. The choice of approach depends on various parameters. We can apply deep learning techniques to specific tasks or combine them with image processing methods for certain systems. In single-model systems, the input image is fed into a deep neural network that produces the identified character as output. In both approaches, deep learning systems are trained on input and target outputs, enabling them to perform tasks such as number plate recognition after training when given a vehicle image.

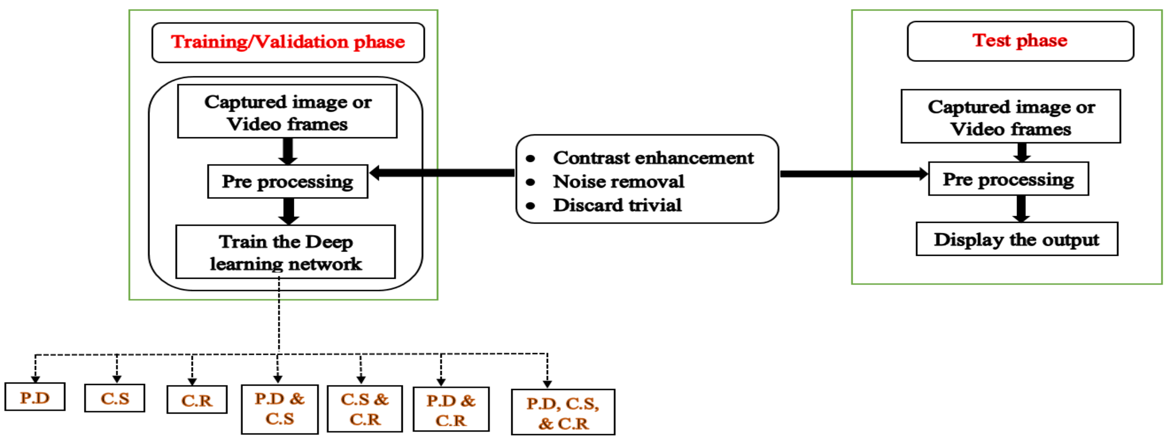


*Figure 4. Block diagram of an ALPR system using deep learning*

Plate Detection (PD); Character segmentation (CS); Character Recognition (CR)

Deep learning models can be trained separately for plate detection, character segmentation, or character recognition, or these processes can be combined using machine learning. Deep learning typically includes training, validation, and testing. During training, the network learns from the input data and the desired outputs. In testing, the system generates or predicts the outputs based on the trained network. Consistent pre-processing methods for noise removal, contrast enhancement, and detail elimination are used in both training and testing. Figure 4 presents the stages of an ANPR system using deep learning, including image pre-processing and model training.

Tarigan et al. initially employed a GA to determine optimal parameters for a BPNN in an ANPR system. The input image underwent pre-processing, after which the BPNN recognised the output; however, feed-forward processing was slower with more hidden neurons (Tarigan et al., 2017). Selmi et al. shifted their approach and used a CNN implemented in TensorFlow to detect licence plates (LP) from pre-processed images. Upon LP detection, the authors defined an LP bounding box in the image, and this identified region underwent further processing—specifically, detail enhancement using a Canny Edge detector before segmentation. For character classification, another CNN model is implemented in TensorFlow to recognise LP characters. The researchers also noted persistent flaws due to steep inclines, illegible plates, multiple LPs, and challenging meteorological conditions (Selmi et al., 2017). To address multi-directional detection issues, Xie et al. adopted MD-YOLO, an improved version of YOLO that uses directed regression to detect licence plates. Attention-Like MD-YOLO further enhances this by employing a pre-positive CNN to remove redundant information, and ALMD-YOLO integrates pre-positive elements with MD-YOLO. They trained each model with distinct loss functions and datasets. Despite these advancements, accurately identifying car licence plates from multiple angles, especially under adverse conditions such as low contrast, poor lighting, and unintentional obstructions, remains a significant challenge (Xie et al., 2018).

Laroca et al. utilise a pair of CNNs to detect vehicles and licence plates. First, one CNN detects the licence plate (LP). Next, a specialised CNN (CR-Net) handles character segmentation and recognition. Instead of a single network for both steps, the system uses separate CNNs: the first isolates and partitions LP characters, while the second recognises those characters. For the recognition task, the system employs two dedicated networks: one designed for numeric digits and another for letters. After recognising LPs, the system examines temporal redundancy by linking all vehicle frames. The new dataset's recognition rate under challenging situations is 78.33%. However, character segmentation and recognition performance declines for inclined LPs and distorted characters (Laroca et al., 2018). Rabbani et al. proposed that connected-component and aspect-ratio features help detect LPs after pre-processing. The method applies various image processing techniques, including resizing, binarisation, CCA, enhancement, and noise reduction. A threshold guides the identification and extraction of LPs, and connected components segment the characters. Subsequently, a deep CNN specialises in character recognition. Poorly connected characters may still lead to recognition errors (Rabbani et al., 2018).

Wang et al. proposed the multi-task convolutional neural network (MTLPR) detection module, which uses P-Net, R-Net, and O-Net in three phases. First, P-Net produces licence plate candidates and bounding box vectors. Second, R-Net further refines these results. Third, O-Net finds the plate's four corners and removes overlapping windows. The recognition module then applies a perspective transformation to the four corner points to reduce noise. This method increases accuracy and speed, with recognition precision up to 98% (Wang et al., 2019). To locate the licence plate, Zhang et al. first used the Sobel-Color algorithm, which combines colour features, edge detection, and the MSER algorithm. SVM assessed the suitability of the localised region. A character segmentation algorithm then splits characters and removes false edge characters. Finally, a LeNet-5 deep network recognises plate characters. However, the technique does not perform well for double-line, military, police, or other non-standard plates (Zhang et al., 2019). Table 2 presents distinct deep convolutional neural networks for automatic number plate detection and recognition systems, along with their performance drawbacks. As shown in table 2, CNNs are used for vehicle detection, number plate detection, character segmentation, plate recognition, and character recognition.

*Table 2. Various deep learning methods used traditionally, the corresponding operations, and drawbacks*

| **Author** | **Technologies applied** | **Corresponding process** | **Drawbacks** |
|---|---|---|---|
| (Rabbani et al. 2018) | CCA | Character segmentation | If the characters are not properly linked, the process's precision could be compromised. |
| | CNN | Recognition | |
| (Wang et al. 2019) | MTCNN | Licence plate detection | Not Mentioned |
| | CRNN and CTC | Character recognition | |
| (Zhang et al. 2019) | Contouring | Character segmentation | Not suitable for police, military, or double-line distribution LPs or other unusual LPs |
| | CNN with LeNet-5 | Recognition | |
| (Joshua et al. 2020) | YOLO | Detection of LP | Incorrectly categorises LPs for noise in the segmentation process or when dealing with non-standard or damaged plates and similar-looking digits. |
| | CNN with ResNet | Classification of plate numbers. | |

The system proposed by Babu et al. employed YOLO for number plate detection and recognition. To recognise all letter characters on number plates and detect the letters A-Z (excluding O) and digits 0-9, they trained a 37-class CNN specifically for character recognition. The YOLO model receives the extracted ROI to detect plates, while the CNN recognises the individual characters. The recognised outputs are then sorted from left to right to match the order on the number plate. The algorithm detected number plates with 100% accuracy and recognised characters with 91% accuracy (Babu et al., 2019). Joshua et al. introduced a separate ResNet model that classifies licence plate characters, while a YOLO model identifies Indonesian vehicle licence plates. Several pre-processing and image segmentation techniques are used for digit recognition. YOLO demonstrates higher plate detection precision than ResNet but can misclassify characters due to segmentation noise, non-standard or damaged plates, and look-alike digits (Joshua et al., 2020). Sahu et al. annotated the dataset and trained the YOLOv3 model to detect car licence plates in their study. They split the entire dataset into training and validation subsets. Subsequently, the detected licence plate is converted from BGR to greyscale, blurred, binarised, and then the characters are segmented using YOLOv3. For Indian car plates, a real-time detection and recognition system achieves 70% accuracy with a conventional method, but improves to 80% with YOLOv3 (Sahu et al., 2020).

Huang et al. introduced a single neural network, ALPRNet, to detect and recognise mixed-style licence plates. ALPRNet utilised two fully convolutional, single-stage object detection models to simultaneously identify and classify licence plates and characters, resulting in an assembly module that constructs the LP strings. By treating licence plate characters and licence plate numbers equally, ALPRNet produces bounding boxes and corresponding labels for each item. This approach eliminates the need for recurrent neural networks (RNNs), typically used in optical character recognition methods in traditional systems, making it a one-stage convolutional network. While ALPRNet performs well on multi-style licence plates, it shows the least performance for multiple vehicles in a single image (Huang et al., 2021). Building on convolutional methods, Yang et al. extracted intrinsic image characteristics of Chinese characters using a CNN without fully connected layers, which requires gradient-based training. Expanding on this foundation, the authors also proposed a deep architecture for Chinese Licence Plate Recognition (CLPR) that integrates Convolutional Neural Networks with a kernel-based Extreme Learning Machine (KELM). Although the proposed deep architecture adequately recognises most Chinese characters, it did not classify the image of ‘zang’, and the memory efficiency of KELM remains limited (Yang et al., 2018).

*Table 3. Deep learning methods used in ANPR systems by different authors*

| Author | Deep learning method used and stage | Advantage | Disadvantage |
|---|---|---|---|
| (Xie et al. 2018) | MD-YOLO is used for detection | Able to solve rotational issues in real-time scenarios. | The method is complicated. Low resolution, low illumination, occlusion etc. affect it and cause poor performance. |
| (Laroca et al. 2018) | Two CNNs for LP and vehicle identification, followed by a second CNN with CR-NET for character recognition and segmentation. | Without temporal redundancy, the full recognition rate is 85.45%, while achieving a full recognition rate of 93.53% with temporal redundancy. | The recognition rate is 81.8%, with temporal redundancy. |
| (Babu et al. 2019) | YOLO model detects and recognises | Accurate for NP detection | Recognition accuracy is 91% |
| (Atikuzzaman et al. 2019) | CNN is used for detection and recognition | Detection and recognition accuracy are high | It is limited to different weather and light conditions. |
| (Pustokhina et al. 2020) | CNN is used for character recognition | Provides 0.981 recognition accuracy | The method is limited to a multiple-lingual number plate |
| (Huang et al. 2021) | A single neural network called ALPRNet | It achieves 98.21% accuracy on multi-style datasets. | Including multiple car licence plates in a single picture is improper. |
| (Yang et al. 2018) | CNN serves as a feature extractor for the classification-using kernel-based ELM classifier. | Result in a shorter training time. | Both ELM and KELM are memory inefficient. |

The different deep learning methods used in ANPR systems at various stages, along with their advantages and disadvantages, are described in Table 3. The data in Table 3 show that all these methods have deficiencies, and elimination of these limitations are essential at the corresponding stages for better performance. The most commonly used deep learning method is CNN; the network selection varies from one to another. Seo and Kang proposed a Layout-independent Automatic Licence Plate Detection and Recognition. The LP detection network comprises a lightweight, fundamental backbone for feature extraction and a highly adaptable heat map-based detection head that estimates the LP's bounding box and corner points. Recognition networks use detection network patches to recognise text. The recognition network uses feature extraction, a Deformable Attention Stage, and attention-based recognition. The network achieved good performance, with only a few false positives, by generating a single bounding-box prediction per image. The method cannot be applied to diverse scenarios (Seo & Kang, 2021). The system introduced by Wang et al. employed a digital image correlation algorithm to detect and locate licence plates, utilising edge analysis, character segmentation, and character quantity calculation. Subsequently, a Convolutional Neural Network is applied for character recognition and classification to achieve clear, accurate plate formations. Due to its robustness and generalisability, the system is suitable for traffic monitoring. The accuracy depended on the colour of the characters and the plate (Wang et al., 2022). The work of Sarma et al. demonstrated an easy-to-use approach for automatically detecting and recognising licence plates in locked areas. They suggested an architecture that comprises three primary components: a) licence plate detection, b) licence plate segmentation, and c) character recognition using a CNN classifier to recognise segmented digits (Sarma et al., 2023).

### 3. ANPR Systems for Moving Vehicles

Numerous studies have been conducted to enhance performance across diverse environments, with ongoing research continuing to advance the field. The approaches employed differ according to the technologies implemented at each stage, ranging from image processing techniques to deep learning methods. The accompanying pie chart included the different methods used in ANPR systems in different stages of the process examined in this section of the study. Traditionally, image processing methods predominated in ANPR systems; however, deep learning approaches have become increasingly prevalent. Among deep learning techniques, YOLO was the most widely adopted, though transformer-based methods have become popular in a relatively short period of time. The pie chart included the methods used in ANPR systems in different stages in the study. These details are provided in Figure 5.

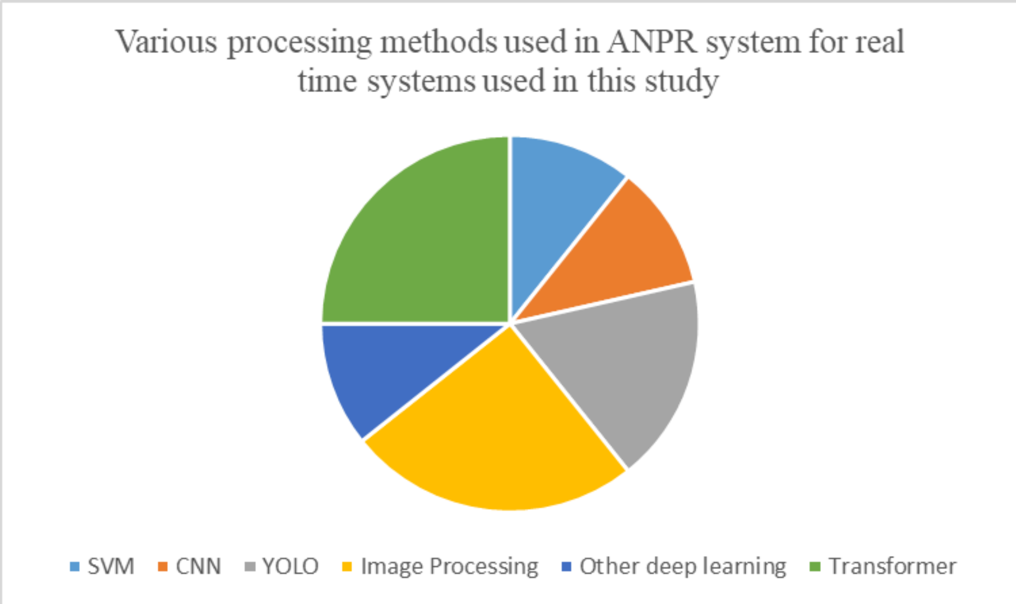


*Figure 5. Distribution of ANPR methods identified in this review*

### *3.1. Image Processing Approaches*

The various image processing techniques applicable to different stages of video-based ANPR systems, along with their drawbacks, are presented in Table 4. Most distorted video frames require image processing techniques for enhancement.

*Table 4. Various image processing methods used in video-based ANPR systems and their limitations*

| Author | Methods used | Limitation of the system |
|---|---|---|
| (Roy et al., 2016) | The fractional Poisson operator in the Laplacian enhanced low-contrast features by using edges and their neighbours. | Text identification and recognition accuracy is lower than those of scanned documents for document analysis. |
| (Soora & Deshpande, 2016) | CCA is used to label the components | The algorithm fails to distinguish LPs from missing characters due to noise, such as very dirty or fuzzy images, or when they come into contact with the LP border. |
| | Various clustering methods used to identify probable LPs | |
| | LP characters contain some non-LP clusters, but thinning and resizing can remove them. | |
| (Zhang et al. , 2018) | Creates a weighted mean for pixel values to increase the contrast gap between text and backdrop. | The approach improves text details but not text detection. |
| | For each input image, generate one enhanced image in colour space and another in the frequency domain. | |
| | A new fusion method uses text property weights to merge better photos to enhance the text. | |
| (Lin et al., 2018) | LBP algorithm for detection | The detection accuracy is lower, but the computation time is high. |
| | Wolf-Jolien and Sauovola's methods to binarise | |
| | Connected blobs to find the LP's character-sized area | |

| | | |
|---|---|---|
| | Hough lines and horizontal/vertical lines for plate edges<br>Re-map to a standard size and orientation to de-skew<br>Vertical histogram to find the gaps in the character for segmentation<br>Tesseract OCR engine for OCR phase | |
| (Varma et al., 2020) | The pre-processing methods included thresholding, Gaussian smoothing, and morphological alteration.<br>NP segmentation uses border and contour filters based on character dimension and spatial localisation.<br>After RoI filtering, de-skew and KNN character identification. | Not specified |
| (Davix et al., 2020) | The car plate's position is the binary value times the image's original value. | The system fails to move vehicles, including multiple vehicles, in a video. |
| (Karahan et al., 2022) | The Gaussian Mixture Model detects, tracks, and counts vehicles.<br>Prewitt operator and OCR to recognise the vehicle's LP. | Not specified |

### *3.2. SVM-Based Approaches*

After thresholding, Panahi and Gholampour divided the image into M × N blocks, and CCA was applied to detect the licence plate region. These features were then applied to the revised RANSAC (Random Sample Consensus) algorithm to identify vehicle plates with a high detection rate. Then, the character candidate was validated using an SVM to classify the plate as clean, medium, or dirty, and an adaptive threshold will be applied based on plate quality. They extracted features from the resulting image using CCA and recognised the characters using a 27-class SVM. This ANPR system is language-independent; they tested it using an existing English plate dataset and obtained 97% overall accuracy. The precision for the dirty plate subset of the dataset was 91.4% (Panahi & Gholampour, 2017). Raghunandan et al. presented an innovative mathematical framework that employs the Riesz fractional operator to enhance edge details in licence plate images, effectively mitigating distortions caused by various factors and improving the efficiency of text detection and recognition. The MSER approach, used to detect character candidates, functions as a character-level classifier that eliminates incorrect text candidates and then arranges characters into lines of text. They utilised a Histogram of Oriented Gradients features with varying window sizes for the recognition phase. These features were then fed into an SVM classifier using a radial basis function (RBF) kernel to achieve final recognition. This model outperforms current baseline enhancement methods across quality metrics. However, the recognition approach shows inferior performance compared with licence plate detection (Raghunandan et al., 2018). Bagi et al. introduced a method that segments a video into six frames based on duration, then analyzes them for license plate extraction and recognition. The grey-scale vehicle image is filtered in both directions to achieve a smoother, higher-quality image with reduced masking artefacts. Then, histogram leveling is applied to enhance the image. The edges are detected using the Sobel operator on thresholded, binarised images. Morphological operations are employed to isolate the plate areas. The system applies to text segmentation and spectral analysis. Connected components are extracted that contain only characters. SVM is used for recognition using HOG features (Bagi et al., 2019).

### *3.3. CNN-Based Approaches*

Zherzdev and Gruzdev proposed LPRNet, which is a comprehensive automatic LPR approach that uses a lightweight CNN to avoid character segmentation. First, the Spatial Transform layer pre-processes the input image to improve recognition performance. LocNet then estimates the best transformation parameters, and CTC loss enables segmentation-free, end-to-end training. LPRNet performs real-time inference on CPUs, GPUs, and FPGAs (Zherzdev & Gruzdev, 2018). In the proposed system, Palanivel et al. recorded video and processed it using Faster R-CNN models before passing the detected licence plates to OCR. Next, the recognised plate numbers are checked against the database to retrieve the corresponding information. The ELM classifier learns ML-ELBP features and produces robust feature vectors or trained network models to detect various LPs. System performance was assessed at 99.10% detection accuracy, 98.2% precision, and an F-measure of 98.86%, with a 5% false-positive rate. The average detection time per vehicle was approximately 0.98 seconds (Palanivel et al., 2020). Jawale et al. introduced the recognition process with four main stages: capturing the plate with a Haar Cascade, pre-processing the regions by binarisation, segmenting characters by evaluating the height-to-width ratio of each character's bounding box, and finally identifying characters using CNNs, MobileNet, Inception V3, and ResNet50. CNN-based recognition achieves 98.5% precision with a loss of 4.25%. . This technology works efficiently in conditions with poor lighting, blur, fog, or slanted plates (Jawale et al., 2023).

### *3.4. YOLO-Based Approaches*

YOLO is not a single network but a method for creating detection networks. Initially, Song et al. supplied the system with video footage of the traffic scene. Next, the road surface region was retrieved and segmented. After segmentation, the YOLOv3 approach was applied to detect vehicles in the highway environment. Finally, the system used the ORB feature to track and gather traffic data. This segmentation technique enhances detection accuracy, especially for smaller vehicle objects (Song et al., 2019). Amrouche et al. prepared a customised dataset and trained the YOLOv3 model on the original images until convergence. They collected the data, then labelled the images, which was the most complex and time-consuming process. Afterward, they split the dataset into a training set and a validation set. The system employed YOLOv3 with a Darknet variant for vehicle LPD, achieving an overall efficiency of approximately 92.83% (Amrouche et al., 2022). For Korean cars, Park et al. designed a comprehensive vehicle type and licence plate recognition system (KVT-LPR) applicable to multilane highways and urban settings, using YOLOv4. The KVT-LPR system first analyses a high-resolution input image extracted from a high-resolution video. The VT-LP detector then categorises seven classes, comprising six unique Korean automobiles and their licence plates in the supplied image. The next step involves the LPC detector, which recognises 68 numbers and characters found on Korean license plates. The entire system used 4K high-resolution images to identify small licence plates measuring just 100 pixels wide. Limitations include the absence of certain Korean LP styles and characters in the dataset (Park et al., 2022). Dhonde et al. also developed a system for detecting vehicle speed and licence plates. Using the presented approach, they first utilised the YOLOv5 algorithm to segment and extract vehicles from a video source. Then, a straightforward algorithm was used to compute the vehicle's speed; after the LP images were detected. Lastly, OCR was performed on the captured licence plate images (Dhonde et al., 2022). The method proposed by Farid et al. relies on the YOLOv5 architecture for vehicle identification and categorisation. They used transfer learning to fine-tune the pre-trained weights of the YOLOv5 model. The proposed method improves detection accuracy under demanding conditions in the DAWN dataset, such as fog, rain, snow, and sand. However, the process does not address cases involving occluded vehicles or motion blur affecting moving objects (Farid et al., 2023).

### *3.5. Other Deep Learning Approaches*

Shaharniya proposed a foreground identification system based on low-rank and structured sparsity decomposition (LSD). This method splits a video frame matrix into a low-rank background and a sparse foreground. The identified object is further binarised, followed by edge segmentation for number plate localisation. Next, horizontal and vertical projection characteristics are recovered for character segmentation and ANN recognition. It can leverage existing traffic-monitoring infrastructure without modification or setup. Nevertheless, the method encounters difficulties when detecting double-row licence plates (Shaharniya, 2020). Zhang et al. introduced an end-to-end deep learning framework to automate licence plate identification, tracking, and recognition for real-world traffic recordings. In complicated, uncontrolled situations, a flow-guided spatiotemporal attention network detects licence plates. This strategy is computationally demanding and cannot be used in real time without degrading performance (Zhang et al., 2021). Tom et al. integrated a deep neural network to localise the LP and detect characters in a single forward pass, thereby improving licence plate recognition (LPR) efficiency. Car licence plates are read and displayed after identification. The ImageAI library is used to train deep learning models (Tom et al., 2022).

*Table5. Performance evaluation of the ANPR systems reviewed in this study*

| Author | Dataset | LPD | LPR | Author | Dataset | LPD | LPR |
|---|---|---|---|---|---|---|---|
| (Khan et al. 2018) | Caltech | NA | 99.8 | (Seo & Kang, 2021) | CCPD | NA | A:88.07 |
| | Own dataset | | 99.5 | (Wang et al. 2023) | Own dataset | NA | A:93.8 |
| (Islam et al. 2021) | Own dataset | A:94 | A:96.1 | (Panahi & Gholampour, 2017) | Own dataset | 98.7 | 97.6 |
| (Ali et al. 2021) | Own dataset | NA | Pr:95 | | | | |
| (Kashyap et al. 2018) | NA | NA | 82.6 | (Raghunandan et al. 2018) | UCSD-1 | 82.03 | 76.34 |
| (Choong et al. 2020) | NA | R: 89 | | | ICDAR 2015-SR | NA | 77.38 |
| (Medvedeva et al. 2020) | NA | NA | A: 92 | (Bagi et al. 2019) | Own dataset | NA | A:85 |
| | | | | (Zherzdev & Gruzdev, 2018) | CLPD | NA | A: 95 |
| (Tarigan et al. 2017) | Own dataset | NA | Single character A:97.18 | (Palanivel et al. 2020) | Own dataset | A: 99.1 | NA |
| | | | | (Jawale et al. 2023) | Indian LP | NA | CNN: 98.5 |
| | | | Whole characters A:85.97 | | ImageNet | | |
| | | | | (Amrouche et al. 2022) | Own dataset | A: 95 | NA |
| (Selmi et al. 2017) | Caltech | P:93.8 | A:94.8 | (Park et al. 2022) | Own dataset | One lane: P:98 | NA |
| | | | | | | Two lane: P:92 | |
| | | | | | | Three lane: P:92 | |
| | AOLP-LE | P:93.5 | A:95.4 | | | Four lane: P:87 | |
| (Xie et al. 2018) | AOLP-LE | P:99.43 | NA | (Farid et al. 2023) | PKU | mAP: 99.92 | NA |
| | | | | | COCO | mAP: 52.31 | |
| (Laroca et al. 2018) | SSIG | NA | A: 93.53 | | DAWN | mAP: 34.50 | |
| | UFPR ALPR | | A: 78.33 | (Shaharniya, 2020) | Own dataset | NA | A:97 |
| (Rabbani et al. 2018) | Own dataset | 93.78 | 97.03 | (Zhang et al. 2021) | UFPR ALPR | P:99.11 | A:95.44 |
| | | | | | SSIG-SegPlate | P:99.63 | A:98.88 |
| Wang et al. 2019 | CCPD | P: 98 | | (Soora & Deshpande, 2016) | MediaLab | 97.3 | NA |
| | | | | | AOLP | 93.7 | |
| (Babu et al. 2019) | Own dataset | A:100 | A:91 | (Zhang et al. 2018) | Own dataset | NA | P:60.1 |
| (Joshua et al. 2020) | Own dataset | A:94.9 | A: 80 | (Lin et al. 2018) | Own dataset | A: 100 | A:90 |
| (Sahu et al. 2020) | Own dataset | NA | A:90 | (Varma et al. 2020) | Own dataset | A: 98.02 | A: 96.22 |
| (Yang et al. 2018) | Own dataset | NA | A:96.38 | (Davix et al. 2020) | Own dataset | NA | A: 98.1 |

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### *3.6. Transformer-Based Approaches*

Xia et al. first evaluated the performance of YOLOv7 trained on a custom dataset for licence plate detection in complex environments. Subsequently, they integrated YOLOv7 with a Transformer architecture. Their findings indicated that licence plate detection with YOLOv7 achieved higher accuracy than conventional detectors. Incorporating a Transformer model reduced the number of floating-point operations (FLOPs) while maintaining the same accuracy as YOLOv7 alone (Xia et al., 2022). Rai et al. developed a complete encoder-decoder model for Automatic Licence Plate Recognition that accurately identifies license plate numbers from vehicle images (Rai et al., 2023). Saitov and Filchenkov developed a detection model utilising YOLOv8 for object detection and the TrOCR transformer for licence plate character recognition. The model achieved a mean average precision (mAP@50) of 0.983. The character recognition rate for Nomeroffapp was lower than that of TrOCR (Saitov & Filchenkov, 2023). Xia et al. introduced the Chinese Licence Plate Transformer (CLPT) model. A Transformer encoder processes licence plate images, and the resulting tokens are classified into four categories using the Auto Token Classify (ATC) mechanism: province, main, suffix, and noise. The first three categories are used to predict the corresponding parts of the licence plate. The authors used YOLOv8-pose as the licence plate detector, which provides accurate bounding-box and key-point detection to correct perspective distortion (Xia et al., 2024).

Ramasubramanian et al. introduced an advanced automatic number plate recognition (ANPR) system utilising a deep learning-based Transformer architecture. The study emphasises the global feature-extraction capabilities of vision transformers, structuring the ANPR system into three primary components: licence plate detection using You Only Look Once V8 (YOLO), character segmentation via morphological techniques, and alphanumeric recognition via an optimised Vision Transformer (ViT) model. The system was evaluated by the authors on established datasets, including UFPR-ALPR and OpenALPR, across diverse vehicle types, illumination conditions, and viewing angles. The reported results demonstrate high performance, with a licence plate detection rate of 98.72%, a character recognition rate of 97.84%, and an end-to-end system accuracy of 96.91% (Ramasubramanian et al., 2025). Dittakan et al. studied licence plate recognition using deep learning models for vehicle and plate detection, and applied YOLO and Transformer models for character recognition. YOLOv5nu achieved a Mean Average Precision (mAP) of 0.995 for licence plate detection. The Transformer model performed well in character recognition, with an accuracy of 0.9108 and a loss of 0.0326. However, both models showed reduced accuracy in low-light conditions and with complex plate layouts, limiting their effectiveness (Dittakan et al., 2025). Lee and Park conducted a comparative analysis of a CNN–RNN–based model and a MobileNetV3–Transformer–based model for licence plate character recognition. Their system employed YOLOv12 for plate detection, followed by character recognition using either a CNN with an Attention-LSTM decoder or a MobileNetV3 with a Transformer decoder. The findings indicate that sequence decoder performance is highly dependent on the dataset and is significantly affected by feature quality and region-of-interest stability (Lee & Park, 2026).

## 4. Conclusion

Intelligent technology applications in traffic monitoring systems have become increasingly crucial. In the modern world, traffic system management and surveillance are essential. In this context, an efficient and accurate mechanism for addressing these challenges within a reasonable time frame is essential. AI has outperformed many previous technologies in terms of efficiency. One of the fascinating applications of AI in intelligent transport systems is automatic number plate detection and recognition. To date, under ANPR systems, various methods have been developed, but several factors limit their performance. Consequently, analysing the techniques employed and their limitations is essential for improving performance in real-time applications. In this study, we examined current video-based ANPR systems, identified performance gaps, and specified areas for improvement. To better understand the performance metrics of various ANPR systems in video, we specifically included the systems employed in video. To improve performance in real-time applications, methodological advances remain necessary. This review focuses exclusively on video-based ANPR systems, covering approaches ranging from image processing to transformer-based methods, and does not address other challenging operating conditions.

To conclude, traditional image processing methods had many limitations due to their reliance on pixel-wise operations. Following the introduction of deep learning methods, performance improved substantially. Furthermore, the latest transformer-based methods perform more accurately and efficiently under various severe conditions. Nevertheless, there remains scope to further improve ANPR systems through recent transformer-based methods to enhance performance across all processing stages and operating environments within Intelligent Transportation Systems (ITS).

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