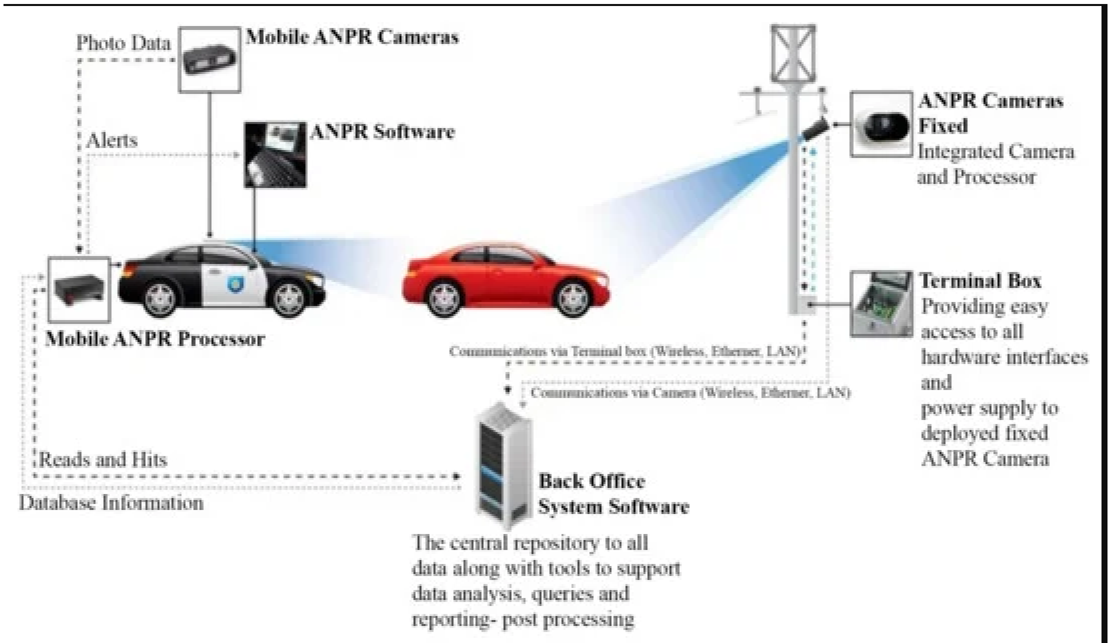


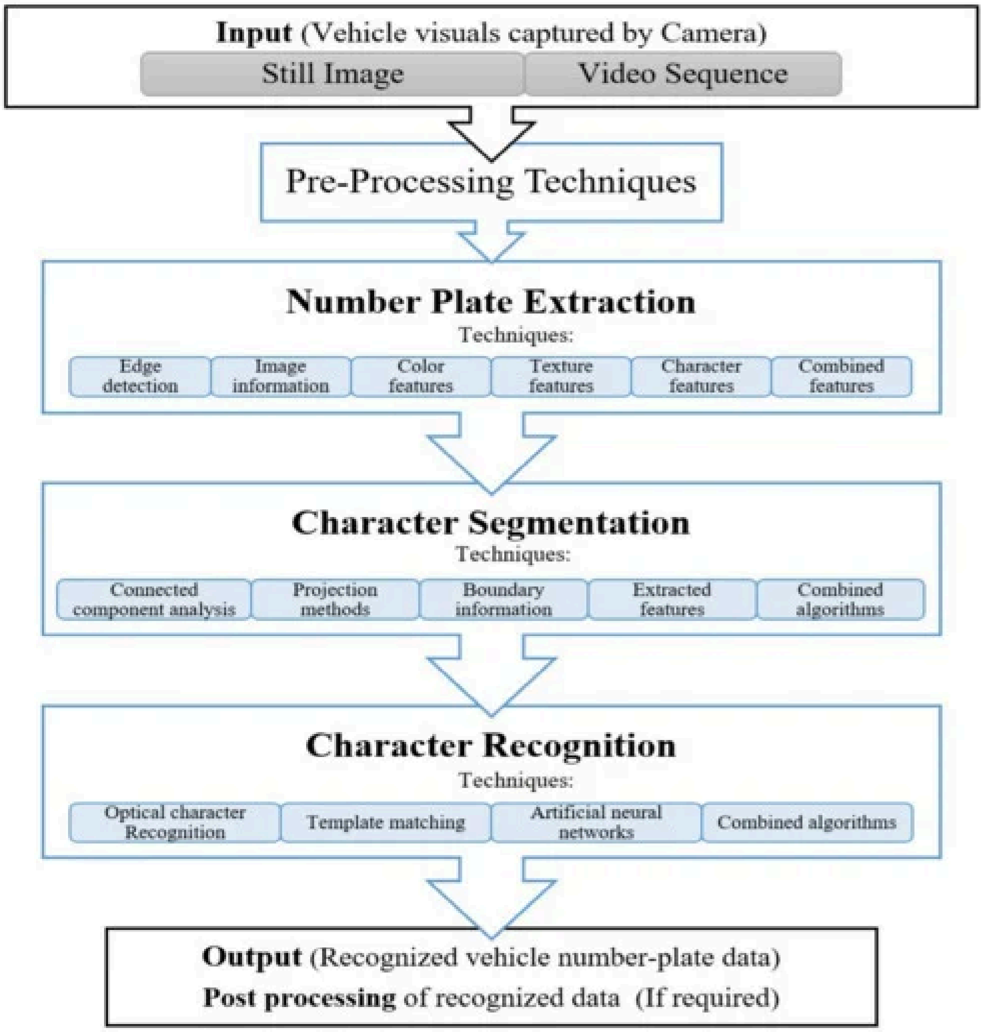
(Source: latech.us, accessed on 5 November 2020).

Number Plate Recognition involves acquisition of number plate images from the intended scene, using a camera. Either still images or a photographic video is captured and further processed by a series of image processing based recognition algorithms to attain an alpha-numeric conversion of the captured images into a text entry. After obtaining a good quality image of the scene/vehicle, then the core dependence of any ANPR system is on the robustness of its algorithms. These algorithms need a very careful consideration and require thousands of lines of software coding to get desired results and cover all system complexities. As a whole, a series of primary algorithms are necessary for smart vehicle technologies and ANPR to be effective.

A typical ANPR system goes through the general process of image acquisition (input to the system), number plate extraction (NPE), character segmentation (CS) and character recognition (CR) (as output from the system) [9]. After successful recognition of the vehicle the data can be accessed and used for post processing operations as required. The vehicles data is sent to the connected back office system software which is the central repository to all data along with tools to support data analysis, queries and reporting accordingly. This data collected can be utilized for several other intelligent transportation applications since ANPR systems not just visually capture the vehicle images but also record the metadata in their central repository. This can potentially include vehicle recognition through date and time stamping as well as exact location, whilst storing a comprehensive database of traffic movement. This data can be helpful in modelling different transport systems and their analysis.

The image taken from the scene may experience some complexities depending upon the type of camera used, its resolution, lightening/illumination aids, the mounting position, area/lanes coverage capability, complex scenes, shutter speed and other environmental and system constraints

When a vehicle is detected in the scene/image, the system uses plate localization functions to extract the license plate from the vehicle image, a process commonly termed as Number Plate Extraction. Characters on the extracted number plate are then segmented prior to recognition process. Character segmentation is an algorithm that locates the alpha numeric characters on a number plate. The segmented characters are then translated into an alpha numeric text entry using the optical character recognition (OCR) techniques. For character recognition, algorithms such as template matching or neural network classifiers are used. The performance of an ANPR system relies on the effectiveness of each individual stage. A parameter used to quantify the whole process is the performance-rate or success-rate, which is the ratio of the number of number-plates successfully recognized to the total number of input images taken. The performance rate involves all the three stages of recognition process, number plate extraction, segmentation and character recognition. The general processes involved in ANPR systems is shown in the figure below (Lubna et al., 2021).



- Number Plate Extraction

Method 1

*Sobel based Vertical Edge Detector
*Sliding window technique, it has the size similar to that of the number plate size
*Requires prior knowledge of the number plate size
*Threshold tuning required and needs to setup for each set

Method 2

*Gradient analysis
*Vertical histogram along with morphology techniques
*Connected Component Analysis

Method 3

*Geometrical shape of the number plate

- Character Segmentation Method

*Pixel projection in which both vertical and horizontal directions employed
*Fast and robust
*Dealt with tilt factor by adding additional layer of vertical projection

- Character Recognition Techniques

Method 1

*Template Matching
*Adaptive threshold
*Pixel-wise matching is performed
*The simplest method known for recognition

Method 2

*Neural Networks classifiers

Extraction Using Edge Information

Number plate extraction commonly relies on edge detection techniques, leveraging the plate's rectangular shape and aspect ratio. Vertical edge detection, often performed using the Sobel operator, identifies relevant edges by filtering out unwanted ones, achieving success rates ranging from 65.25% to 100% depending on dataset size and preprocessing. Methods combining vertical and horizontal edges or using filters like Gabor, Canny, and Sobel enhance accuracy, with Gabor filters excelling at noise reduction. Advanced approaches such as Vertical Edge Detection Algorithm (VEDA) and block-based methods improve robustness, with success rates up to 96%. Techniques like Hough Transform and Generalized Symmetry Transform are used for line and corner detection but vary in computational efficiency. Morphological enhancements and preprocessing steps, such as noise removal and contrast adjustment, further optimize results, achieving up to 98% extraction accuracy and 75–85% overall performance on large datasets.

Extraction Using Global Image Information

Number plate extraction using global image information often employs Connected Component Analysis (CCA) to label pixel components based on connectivity, leveraging spatial features like aspect ratio and area. Slimani et al. [39] proposed a two-step method combining Otsu's adaptive thresholding and CCA to detect rectangular shapes, achieving 96% success on 2500 Moroccan format images. A similar method recorded a 96.6% success rate on low-quality four-hour video footage ([43]), though low-quality images may cause distortion errors. Contour detection identifies connected objects resembling number plates, while cross-correlation with pre-stored templates allows position-independent extraction but is computationally intensive ([45]).

Extraction Using Color Features

Number plate extraction using color features leverages the unique color contrasts of plates specific to regions or countries. Techniques often utilize advanced color models like HLS, HSV, or HSI instead of grayscale, classifying pixels based on hue, saturation, and lightness. For example, Shi et al. [46] achieved 90% recognition for Chinese plates using the HLS model, while a neural network in [48] identified Korean plates with white-green-red colors. Color edge detection ([47]) and projection methods enhance localization, with rates up to 97.9%. The mean shift algorithm ([50, 51]) and its fast variant ([52]) segment candidate regions, achieving detection accuracies around 92–97.6%. Fuzzy logic ([53]) improves robustness under varying lighting, recording average recognition rates above 92%. HSI-based statistical thresholds ([54]) detect specific colors like yellow and green in plates, although issues like RGB sensitivity to illumination and false detections in color-matching areas remain challenges. Despite drawbacks, color-based methods are effective for detecting deformed or inclined plates.

Extraction Using Texture Features

Number plate extraction techniques based on character features often exploit the significant grayscale transitions and high edge density between characters and their background. Local Binary Pattern (LBP) and Histogram of Oriented Gradients (HOG) methods classify textures and calculate histograms, achieving 89.7% accuracy for 110 images but struggling with blurred or low-light conditions ([36]). Line weight density maps and scan line techniques analyze color transitions, with methods like horizontal line scanning achieving extraction rates of 99.2% and significantly reduced processing times ([57]). Combining density maps with neural networks enhances results, yielding 97.23% success at an average of 0.0093 s per image ([60]). Texture-based approaches, such as sliding concentric windows, leverage abrupt changes to locate plates, achieving up to 98% success when paired with histogram and Gabor filters, though these methods can be computationally expensive ([54], [67]). Wavelet transform techniques, analyzing horizontal reference lines, achieve up to 97.3% accuracy in 0.2 s ([68]), while Haar-like features with adaptive boosting deliver robust detection rates of 99% across varied conditions ([71]).

Extraction Using Character Features

Character feature-based number plate extraction techniques identify and extract regions containing characters on the plate. These methods rely on scanning the image for character-like features and classifying the identified regions. In [72], character areas are identified and classified using a neural network, while [73] employs Hough transformation to detect parallel lines enclosing the plate area, achieving alignment with character properties. Scale-space analysis ([74]) identifies blobs as character candidates, while inter-character spacing is analyzed in [75] to achieve an extraction accuracy of 99.5%. Two-stage classification approaches, like in [76], use AdaBoost classifiers to identify potential character regions and SVM with SIFT to refine and eliminate non-character areas. Although these methods can be accurate, they are time-intensive due to processing all binary image objects and may struggle with errors if other text exists on the image.

Extraction Using Feature Learning

Feature-learning-based number plate (NP) extraction employs hybrid methods combining multiple characteristics, leveraging advanced techniques like deep learning and neural networks. YOLO, a CNN-based detector, achieves high accuracy (93.53% for SSIG and 78.33% for UFPR-ALPR datasets) by using data augmentation and fine-tuning. Other approaches integrate texture and color features, such as fuzzy logic classifiers ([82]) and neural networks trained for edge and color detection ([83]-[86]). Time-Delay Neural Networks (TDNNs) analyze pixel similarity for extraction ([86]), while covariance matrices combine spatial and statistical data ([88]). Techniques like wavelet transforms ([87]), HLS decomposition, and discrete wavelet transform ([91]) enhance edge detection and noise reduction. Modified Census Transform (MCT) improves accuracy by refining candidate regions through post-processing ([92]). Deep learning methods like CNNs excel in character segmentation and recognition, achieving segmentation accuracy of 99% ([93]). However, ANPR systems heavily rely on large, annotated datasets for robust training and performance improvements.

Segmentation Using Connected Components

Number plate **segmentation** using connected components involves labeling pixels in a binary image based on their connectivity to identify character regions. This method evaluates labeled regions for aspect ratios and sizes corresponding to number plate characters. High accuracy rates have been achieved, such as 99.75% with 958 HD images in [26] and 99.5% in various lighting conditions in [24]. However, challenges arise when dealing with joined or broken characters, which can hinder performance. Hybrid approaches, like combining connected components with blob coloring ([47]), have shown promise in improving accuracy, achieving 93.7% in specific cases.

Segmentation Using Vertical/Horizontal Projection

The vertical and horizontal projection method uses pixel intensity profiles to isolate characters. Vertical projection identifies the boundaries of individual characters, while horizontal projection refines **segmentation**. This method is effective because it relies on the contrasting pixel values between characters and the background. It has demonstrated high accuracy, such as 99.2% for over 30,000 images with processing times of 10–20 ms ([104]). However, its reliance on character count and sensitivity to noise or image quality are limitations. Nevertheless, it remains a widely adopted and straightforward technique.

Segmentation Using Characters Features

Segmentation using character features leverages prior knowledge of character properties, such as dimensions or color distributions, for effective isolation. Techniques like RGB color extraction ([112]) and hybrid binarization for damaged plates ([115]) have achieved success, with segmentation rates reaching 98.5%. Advanced methods, such as YOLO-based models ([78]) and template-matching approaches ([113]), further enhance segmentation by incorporating neural networks and resizing extracted plates to predefined templates. While effective, these methods may struggle with plate misalignment or severe damage but offer strong results for standardized plates, as seen with Taiwanese and Chinese layouts.

Segmentation Using Boundary Information

Segmentation using boundary information focuses on detecting contours or edges within an image to isolate characters. Techniques such as vertical edge detection combined with long edge removal ([116, 117]) help to identify the contours of characters in number plates. Another approach utilizes the closed curved technique ([39]) to handle complex character boundaries. In [36], vertical histograms are employed to segment characters, while an adaptive morphology method proposed in [118] addresses the challenge of severely degraded number plates. This method merges sections determined by histogram-based algorithms, further enhancing segmentation in tough conditions. The morphological techniques are often applied to handle overlapping characters, a common issue in number plate segmentation. For instance, the morphological thickening algorithm in [119] isolates overlapping characters by enhancing reference lines, while morphological thinning ([119]) detects the baseline to separate connected characters. These approaches have been successfully applied to a set of 1189 degraded images, achieving a segmentation rate of 84.5% for 1005 correctly segmented images. These methods excel in dealing with challenging scenarios, such as closely packed or overlapping characters.

Character Recognition Using Template Matching

Template matching is a simple method for **character recognition** in number plates, where the extracted characters are compared to a set of predefined templates using cross-correlation. It works well for binary images and is effective when characters are not broken, tilted, or resized. However, variations such as orientation and lighting changes can reduce its accuracy. Several enhancements, such as using multiple templates for each character or applying techniques like normalized cross-correlation, can address these issues. Studies have shown high success rates with template matching. For instance, recognition rates of up to 98.1% were achieved for Moroccan-format number plates, and extraction rates of 100% and recognition rates of 90% were obtained in various conditions. However, the method still faces challenges with real-time variations, such as tilting and lighting changes, which may require further adjustments. Despite this, it remains an efficient and widely used approach in practical applications.

Character Recognition Using Extracted Features

Character recognition using extracted features offers an alternative to template matching by reducing processing time and focusing only on the relevant pixels. Various methods are employed for feature extraction, such as using Support Vector Machines (SVM) to classify features, and techniques like vertical and horizontal binary character projections, Hoteling transformation, and block division. These methods generate characteristic vectors that represent each character, allowing for faster and more efficient recognition compared to template matching. For example, dividing characters into pixel blocks and using predefined templates for matching can improve recognition accuracy, although it may struggle with skewed, occluded, or angled number plates. Other feature extraction methods, like using Gabor filters and Kirsch edge detection, focus on character contours or edges, which can be useful for identifying multi-font or variable-sized characters. These techniques also help address issues like character rotation and inclination, which are often problematic in traditional methods. Some approaches incorporate advanced techniques such as thinning operations, neural networks, and scene analysis to further refine character identification. Overall, feature extraction techniques improve the speed and accuracy of character recognition by concentrating on important features, reducing the impact of irrelevant pixels, and providing more robust handling of varied plate conditions. However, challenges such as occlusion, skew, and font variation may still limit the performance of some methods.