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A Literature Review On Automatic Number Plate Recognition

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Abstract: Technologies and services geared towards smart vehicles and Intelligent Transportation Systems (ITS) continue to revolutionize many aspects of human life. This paper provides a comprehensive overview of the latest techniques and progress in Automatic Number Plate Recognition (ANPR) systems, offering a comprehensive performance comparison of various real-time tested and simulated algorithms, including those involving computer vision (CV). ANPR technology can detect and recognize vehicles by their number plates using recognition techniques. Even with the best algorithms, successful ANPR system deployment may require additional hardware to maximize accuracy Performance can be undermined by various factors, including the condition of the number plate, nonstandardized formats, complex scenes, camera quality and mount position, tolerance to distortion, motion blur, contrast issues, reflections, processing and memory limitations, environmental conditions, indoor/outdoor or day/night shots, software tools, and other hardware-based constraints.

Keywords: automatic number plate recognition, image processing, computer vision, machine learning, vehicle identification, neural networks, intelligent transportation system, smart vehicle technologies, object detection and tracking, recognition

I. INTRODUCTION

Automatic Number Plate Recognition (ANPR) has become an integral integral to our lives and commitments to remain so in the future, integrating seamlessly through innovative transportation technologies. The idea of self- driving vehicles is offering many possibilities for transforming fundamental transportation systems. ANPR technology is already contributing to intelligent transportation systems by eliminating the need for human intervention. Initially, ANPR systems were limited to cameras on roadsides or at car park barriers, but over the years, they have become mobile, first deployed in vehicles, and more recently, as handheld devices due to advancements in smartphone technology.

ANPR is frequently favored in toll and parking lot industries because of its reduced provisioning costs because it recognizes registered number plates without requiring additional transponders, unlike Ultra High Frequency—Radio Frequency Identification (UHF-RFID) systems. The swift urbanization of countries represents a major development in our contemporary world, with a significant number of people moving from rural areas to cities. As traffic congestion rises, local governments often overlook the present and future mobility requirements of both residents and visitors. ANPR is increasingly employed to monitor and manage the flow of traffic, facilitating intelligent transportation.

Contemporary ANPR cameras go beyond just reading license plates; they also offer additional functionalities like vehicle counting, direction tracking, grouping, and speed measurement. This capability to accurately detect and read numerous fast- moving vehicles has driven the extensive adoption of ANPR technology across various facets of the digital landscape. Despite ANPR systems being available in various forms, they all share the core function of providing a precise, automated vehicle reading system. ANPR is employed in a wide range of applications, including access control, parking management, toll collection, user billing, delivery tracking, traffic management, law enforcement, customer service and navigation, red light and lane enforcement, queue length estimation, among others. Figure 1 illustrates the basic system diagram of both fixed and mobile ANPR technology 【2–8†source】

II. LITERATURE SURVEY

Effectively extracting number plates from images orvideos is a crucial step for ANPR systems. The extraction rate is measured by the proportion of successfully extracted plates relative to the total number of input images or detected vehicles. Generally, one camera is installed per lane, but number plates can sometimes be obscured by dirt, damaged, or positioned in a way that makes them difficult to see, as different vehicles have number plates affixed in various locations.

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Environmental factors such as lighting, motion blur, reflections, fog, and similar conditions can complicate efficient number plate extraction. Algorithms that rely on geometric features to detect rectangular-shaped license plates can struggle when multiple similar shapes appear on the vehicle. To improve accuracy, supplementary algorithms are needed to filter out undesired regions, thereby enhancing the system's ability to differentiate the number plate from other objects in the image.

Researchers have utilized a range of features for extracting number plates, and the following section provides a summary of these algorithms. High-resolution advanced cameras can often accommodate multiple lanes.; however, this requires multiple readers, leading to increased hardware costs for installation and maintenance. Real-time scenarios can face several challenges, such as cameras positioned at fixed angle capturing images of vehicles that are tilted or skewed.

III. METHODOLOGY

NP Extraction Using Edge Information Number plates usually have a specific aspect ratio and rectangular shape. In study [19], images were adjusted to a fixed aspect ratio, and the authors reviewed various algorithms from previous research [20–22], comparing them using their own dataset. One evaluated method utilized vertical edge information with the Sobel operator to detect these edges. The number plate was identified by matching preset minimum and maximum lengths with the detected edges, filtering out irrelevant ones. This approach achieved a 65.25% extraction rate across 141 images, which is notably lower than the 99.99% reported in [20]. In [23], number plate extraction was performed using both vertical and horizontal edge histogram information, reaching 90% accuracy on 50 images with different fonts and lighting conditions.

IV. NP EXTRACTION USING GLOBAL IMAGE INFORMATION

In binary image processing, the Connected Component Analysis (CCA) technique is used to label pixels into components based on connectivity. For number plate extraction, spatial attributes such as aspect ratio and area are frequently employed. Slimani et al. [39] introduced a two-step approach for this task. The first step uses Otsu's Threshold Method to handle varying lighting conditions; this adaptive thresholding technique binarizes the image effectively. The binarized image is then analyzed for rectangular shapes using the CCA technique. In the second step, edge detection is followed by a closed curve method to confirm that the detected shape is a number plate. This method achieved a 96% success rate when applied to over 2,500 Moroccan format images from video sequences.

The connected component analysis technique described in [43] achieved a successful extraction rate of 96.6% on low-quality video footage spanning over four hours. Contour detection methods are employed on binary images to identify connected objects [44]. Geometric features that resemble number plates are then selected for further analysis; however, this approach can introduce distortion errors if the image quality is poor. Additionally, cross-correlation can be used for this purpose by employing a pre- stored number plate template during 2D cross-correlation, which makes the method independent of the plate's position in the image, though it is considered time-consuming.

V. NP EXTRACTION USING COLOR TRAITS

In some regions or countries, vehicle number plates have specific color schemes. Several studies have explored color-based methods for extracting number plates in Automatic Number Plate Recognition (ANPR) systems. A common strategy involves utilizing the unique color combinations found on number plates, as these contrasts are typically specific to the plate area. Shi et al. developed a method for extracting patterns from Chinese number plates by analyzing all pixels in the image, categorized by hue, lightness, and saturation (HLS). The HLS color model, which sorts pixels into 13 color categories compared to the 6 categories in the RGB model, was chosen to match the number plate formats in mainland China. Their technique achieve correct recognition for 90% of images across different lighting conditions.
Another study [47] focused on recognizing specific colors on number plates, such as black, green, white, and red, by applying color edge detection to these colored edges.

VI. NP EXTRACTION USING TEXTURE TRAITS

Texture-based methods for number plate extraction leverage the contrast between characters and their background, which leads to notable changes in grayscale and high edge density. Techniques such as Local Binary Pattern (LBP) [55] and Histogram of Oriented Gradients (HOG) [56] were employed for this purpose in study [36]. Given the rectangular shape of number plates, LBP and HOG algorithms were utilized to analyze texture and compute histograms. This approach achieved an accuracy of 89.7% for locating number plates in 110 images. However, its effectiveness diminishes in cases of blurred images or poor lighting conditions.

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VII. NP EXTRACTION USING CHARACTER TRAITS

Character feature extraction techniques aim to locate and extract characters from the number plate. These methods involve scanning the image to detect characters and then isolating the region where these characters are found, there by identifying the number plate area. Instead of directly applying properties specific to number plates, the algorithm focuses on character-like regions within the image. These identified regions are then classified using a neural network. Subsequently, transformation techniques are employed to detect straight lines within the image.

VIII. NUMBER PLATE SEGMENTATION METHODS

The effectiveness of character segmentation is closely tied to the success of number plate extraction from an image or scene. Extracted number plates may encounter issues such as contrast variations, inconsistent lighting, or angle distortions. To overcome these problems, preprocessing techniques such as de- skewing, de-blurring, or other corrective methods may be required before segmenting the characters. These preprocessing steps can be applied either during the extraction process or after isolating the candidate area, depending on the chosen method.For images with tilted number plates, bilinear transformation is used to map the isolated number plate onto a straight rectangular form.

IX. NUMBER PLATE RECOGNITION METHODS

Template Matching is one of the most straightforward methods for character recognition. This technique involves comparing the extracted character with a set of predefined template characters through cross-correlation. The character that most closely matches one of the templates is selected. Since lighting conditions can affect gray level intensities, this method is often used with binary images to improve accuracy.

X. RESULT ANALYSIS

Some ANPR systems use basic image processing techniques, which are effective in controlled environments with predictable license plate designs. However, more advanced ANPR systems incorporate specialized object detectors such as HOG, CNN, SVM, and YOLO. Cutting-edge ANPR software with A capabilities, particularly those based on Neural Network techniques, further improves these systems. As in many other areas, computer vision and machine learning are crucial to ANPR. The variation in license plate formats across different regions and countries adds complexity to ANPR, and the requirement for real-time processing further complicates plate recognition. Integrating ML, CV, and AI techniques can greatly enhance the performance of ANPR systems.

XI. CONCLUSIONS

This paper provides an extensive review of ANPR algorithms from recent studies. We have classified these algorithms according to the features needed at various stages of the recognition process. Each stage is discussed in detail, with a summary of performance, including the issues and challenges faced. However, comparing and evaluating these algorithms consistently is challenging duOLe to the lack of a standardized dataset, as discussed further.

ANPR systems depend on intricate optical, computing, and digitizing technologies, which can lead to slow recognition speeds. Commercial ANPR solutions typically do not provide a universal system applicable to all countries.

Instead, each provider must develop a well-optimized system tailored for different regions, as a one-size-fits-all approach is inadequate. OCR engines are often fine-tuned for particular countries, so it is crucial to verify that the camera's library or engine supports the necessary countries. Each ANPR solution provided by vendors has its own advantages and limitations. The most effective system is one that meets the specific needs of the region, considering local conditions that affect performance. Future research in ANPR must address several ongoing challenges, such as developing more robust algorithms for nonstandardized formats, regardless of region. Additionally, proposed algorithms need to be tested in real-time situations rather than relying solely on pre-acquired images. Integrating high-resolution cameras can help improve algorithm performance by reducing processing times and enhancing

recognition capabilities. Another major challenge is the accurate recognition of ambiguous characters, due to similarities between certain pairs like (O, 0), (P, B), (Z, 2), (S, 5), (3, 8), (B, 8), (P, R), (D, O), (1, I),(Q, O), (C, G), (A, 4), (K, X), (F, E), (b, 6), (q,9), (p, b), (V, W), (X, Y), (V, U), (6, 8), (5, 3),(5, 8), (0, 8), (3, 9), and (4, 9). These similarities, along with image distortions such as tilting, font changes, and obstructions like snow or dirt, can easily mislead optical character recognition (OCR) systems, especially when images are captured from various angles.

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It is advisable to assess proposed algorithms for their resilience under conditions such as moving vehicles, high speeds, low contrast, inadequate or excessive lighting, and real-time scenarios. Recent progress in deep learning and computer vision has paved the way for a range of innovative applications, including safe autonomous driving, precise object recognition, and automatic image reading in diverse settings. Real-time object detectors like YOLO can be trained and tested for use in ANPR systems. The Android platform has become highly significant in the technology sector, leading to the development of numerous applications integrated with it. Several researchers have proposed ANPR systems based on Android platforms; however, these systems currently face limitations and constraints that must be addressed to enhance phone-based vehicle recognition. Future developments should focus on optimizing memory usage, incorporating GPS coordinates for geo- tagging, and integrating online databases for various applications. In addition to image processing-based ANPR systems, RFID-based vehicle verification systems are also gaining traction and being used in many countries for transportation purposes. RFID technology offers an alternative method for vehicle recognition or tracking, differing in its underlying approach from image processing-based ANPR systems. It addresses various tracking and localization challenges more effectively, which are often encountered in image processing-based solutions. Furthermore, RFID can be employed for speed detection and provides continuous tracking of vehicles, whether they are within or outside the camera's field of view. Depending on the RFID technology used, it enables ongoing monitoring of vehicles throughout their journey and can also facilitate toll payments.

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In summary, RFID operates on radio frequencies, whereas image processing- based ANPR systems rely on cameras. RFID does not require cameras and can communicate with the tag on the vehicle while in motion, eliminating many complexities associated with camera-dependent technologies.

In CS/ML-based ANPR systems, the most critical step is the extraction of the number plate from the scene, which presents significant performance challenges. RFID technology can complement ANPR systems by helping identify vehicles that might be missed by cameras.

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