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A Systematic Review Of Current Methods And Challenges In Automatic Number Plate Recognition

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ABSTRACT

Recent years have witnessed an unprecedented increase in the number of automobiles that have been put to use thereby leading to the design and development of a monitoring system like Automated Number Plate Recognition (ANPR) to deal with several tasks like law and order, supervision, and highway kiosk related operations. The functioning pattern as well as the requirement specification of these structures is varied due to multiple disparities encountered in the proposed systems. To substantiate the case in point, the majority of these applications are executed on smartphones or any other handheld gadgets on cloud servers, maneuvered in poorly illuminated, unfavourable weather situations. There have been numerous approaches that have been designed to implement ANPR that can efficiently suit the aforementioned real-time requirements. Generally, these systems have a pre-defined framework whose major tasks include the detection of license plates, character segmentation, and recognition of individual characters. Owing to the diversity of license plate formats and constraints with respect to environmental conditions, efficiency and preciseness of recognition highly rely on an accurate detection process. This research investigates several methods and techniques utilized in ANPR systems and presents a detailed review of them as a literature survey. Our objective is thus to facilitate towards beneficial analysis, and categorization of associated studies in the domain of ANPR and recognize the critical challenges encountered by scholars and application developers. Moreover, we also intend to present relevant research directions and a comprehensive analysis of modern real-time systems that can be employed in future ventures along with commendations to optimize the existing solutions to enable them to work under intense situations.

Keywords: *Automatic Number plate recognition, Character segmentation, recognition, machine learning, computer vision, deep learning*

1. AN OVERVIEW OF ANPR TECHNOLOGY

Every single facet of our daily lives in recent years has been revolutionized by various technological advancements in the automobile sector where right from designing smart vehicles to management of traffic congestion has given rise to a novel concept known as Intelligent Transportation Systems (ITS) which has rendered a new meaning to effective transportation through increased speed, efficiency, and expediency. Automatic Number Plate Recognition (ANPR) systems [1] continue to draw ever-increasing attention owing to their applicability in ITS and have been implemented in numerous countries to enforce law and order, traffic monitoring, identifying vehicles involved in crimes, accident management, parking facilities, toll payments, locating missing vehicles, security control assessments in prohibited areas like armed forces camps, and wildlife sanctuaries. Time and again, these ANPR systems are mostly utilized with the intention of preventing fraudulent activities and strengthening security in particular regions which can considerably reduce the effort, time, and usage of limited resources. Moreover, human interference can often result in flawed understandings, as it is practically unfeasible for humans to memorize and interpret the license plates of moving vehicles in an efficient manner. A basic ANPR system (Fig 1) acquires images or video from a live camera which acts as input to the system and analyses frames for identifying vehicles and outputs the license plate in the form of text. Captured images can be black and white, infrared, or colored depending upon the requirements of the system. Multiple techniques like object detection, image processing, pattern recognition, etc., are applied to detect the license plates which is handled by a dedicated main processing module followed by alerting the authorities through a communication module that sends SMS notifications to the concerned stakeholders. This study presents a comprehensive survey of existing techniques and advancements in ANPR systems, with a complete performance evaluation of various real-time, experimented as well and simulated algorithms. This technology has the capability of detecting and recognizing vehicles by their number plates by application of recognition algorithms along with adequate hardware to enhance its precision. Several challenges as to the condition of number plates, absence of standardized formats, distortions, intricate scenes, camera clarity and its position, motion-blur, contrast-related issues, reflections, processing abilities, memory constraints, weather conditions, timing, software, hardware-based limitations, etc., may affect its overall performance.

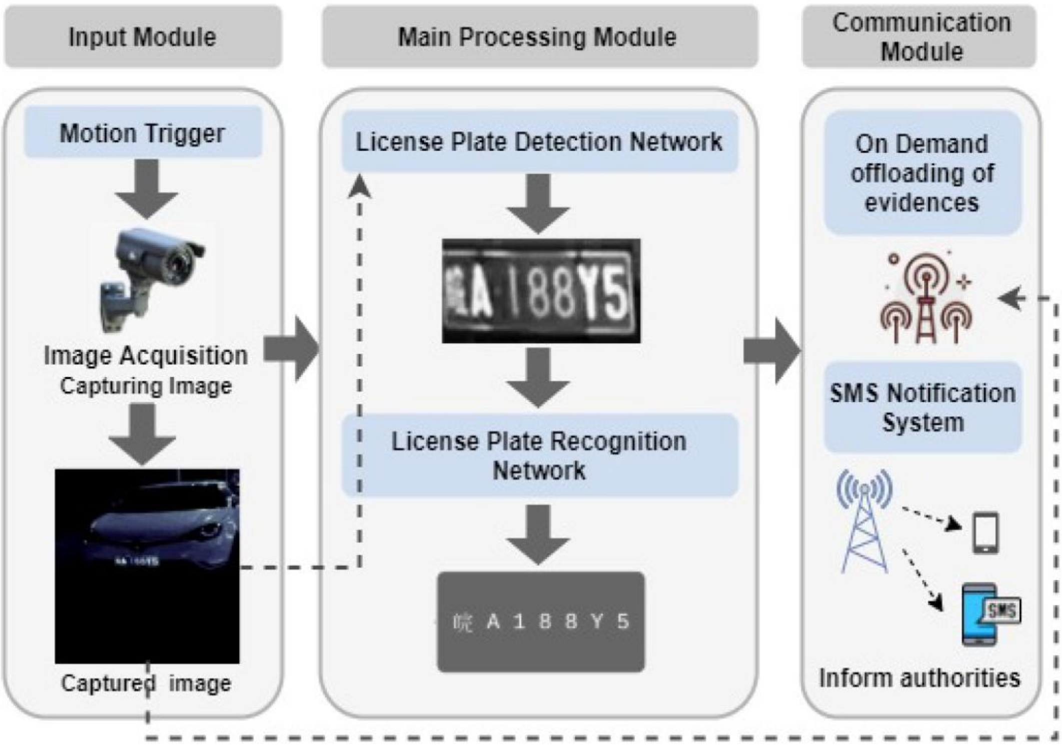


Fig 1: ANPR system (Source: Padmasiri et al, 2022)

The existence of these discrepancies, demanding environments, and other complications make ANPR an appealing ground of study for researchers. Since IoT has completely transformed the shape and future of numerous businesses, intelligent transportation systems too have begun to get revolutionized. By integrating ANPR with RFID systems, GPS, Android, etc., its complete potential can be utilized. DL techniques are widely utilized in computer vision to accomplish accuracy and better detection of results. Through appropriate citing of applicable research studies accompanied by thorough analysis and demonstration of prominent detection, segmentation, and recognition techniques that have been proposed so far, our survey attempts to offer a complete guideline on prospective trends in this area of technology.

2. SURVEY MOTIVATION AND CONTRIBUTIONS AND RESEARCH GAPS

ANPR systems are generally designed to be implemented in outdoor environments; nevertheless, it is quite challenging to identify and distinguish license plates under non-uniform/varied environmental conditions. These variations in license plates are due to several factors like size, color, font, standards, etc., thereby arriving at a single global optimized solution to detect license plates anywhere in the world is an open issue that requires attention. Moreover, tilts and occlusions of license plates too limit the applicability of the majority of the systems in real-world scenarios. Consequently, available techniques to solve ANPR deal with the aforementioned complex constraints which require complex computations. In spite of promising research contributions in this specific area, most of the studies are dedicated to providing solutions in interior and immobile environments. Nonetheless, ALPR systems are necessitated to deal with real-world settings where vehicles are moving with varying speeds, changing visions, motion blur, and differing lighting conditions. As many techniques are perceptive to illumination constraints, they still operate in daylight, hence only a few studies [2], [3], [4], have focused on designing systems that can operate both in day as well as night. Moreover, their effectiveness at night time is distinctly inferior compared to daylight performance. In addition to these constraints regarding environmental situations, constructing ANPR systems must also ensure that other requirements like acquisition cost, operational expenditures, dimensions, power utilization, connectivity issues, etc., should also be taken into account. For example, a uni-level DL solution can provide significant performance in terms of accuracy, but it could be exorbitantly priced in terms of computational complexity and resources that need to be deployed on cloud/edge devices. Whereas a multi-stage method adopting computer vision approaches can provide satisfactory outputs at a fraction of its computational expenditure. Thus, keeping all these demands in focus, our survey focuses on cost-benefit investigations among existing approaches and techniques in addition to their practical real-world applicability.

Most of the existing surveys on ANPR techniques [5], [6] concentrate on computer vision techniques which do not profoundly investigate adverse environmental circumstances. As a result, the core contribution of this study is to shift the focus from conventional ALPR models and their performance to harsh environmental variations and other demanding situations. We have surveyed more than 150 associated research articles and other online resource materials in an effort to explore and gain knowledgeable insight on concerned topic, which were published over the past decade. With the perspective of assisting both beginners as well as skilled scholars towards enabling them to construct an effective ALPR system by offering an overview of existing techniques, especially in the domains of CV and DL, extensively covering widely used methods and recognition models without getting deeper into technical knowledge of image processing and ML. Our literature review thus focuses on the subsequent contributions.

- Exploring several merits and demerits of existing ANPR systems in both an independent and integrated manner, thus helping the developers to arrive at appropriate decisions regarding particular techniques based on that.
- A detailed performance evaluation of these approaches has been presented based on several metrics like accuracy, cost, computational complexity, and reliability in accordance with variations in environmental circumstances. Furthermore, the effect of these methods on the entire ANPR system in terms of these measures has also been offered.
- Multiple benchmark requirements for ANPR systems are detailed benchmarks by a complete analysis of publicly available datasets along with their characteristic features and available solutions have also been discussed.

2.1 Identification of Research gaps and recommendations

There are multiple ANPR systems developed in recent times that are based on diverse technologies but still, there are several challenges regarding speed and the non-uniform nature of a vehicle's number plate, language heterogeneous lighting conditions, etc., which can have an impact on overall recognition rate. In this paper, almost every single ANPR approach has been discussed meticulously by considering several parameters like image size, success rate, and processing time along with suggestions to enhance the ability to detect and recognize vehicles through the utilization of DL algorithms, and successful deployment of additional hardware to maximize its accuracy has been suggested. The number plate condition, non-standardized formats, complex backgrounds, camera quality, camera position, distortion, motion blur, contrast issues, reflections, processing, memory constraints, environmental conditions, indoor/outdoor or day/night shots, software tools, and other limitations and its impact on the performance have been elaborately discussed. In order to deal with these inconsistencies with respect to challenging environments and other complexities, utilization of modern technologies like AI, Internet, and Deep learning-based integration with existing RFID systems, GPS, Android platforms and other technologies has been recommended. Moreover, Deep-Learning techniques are widely utilized in ANPR for better detection rates, thereby relevant to prior works, and analysis of multiple extraction, segmentation, and recognition techniques presents sufficient guidelines to understand and explore future trends in this area.

This literature survey is structured as follows: Section 1 provides a general overview of ANPR systems followed by survey motivation and contributions in Section 2. Different approaches of ANPR to enable detection and recognition of license plates are addressed in Section 3 and Section 4 presents the classification of LP detection methods with their respective advantages, challenges, and restraints. Section 5 reviews various learning models and their implementation structures to accomplish ANPR tasks. Section 6, discusses evaluation metrics utilized to evaluate ALPR systems. Section 7 discusses the publicly available ALPR datasets and their features. Section 8 compares the existing ANPR methods and analyses their effectiveness in real-world implementation. Finally, Section 9 concludes the survey by summarizing the relevant details followed by stating noteworthy future directions of this progressive technology.

3. AUTOMATIC NUMBER PLATE DETECTION APPROACHES

Generally, all the recent ANPR systems can be categorised into single and multi-level approaches. Li et al (2019) presented a single-stage approach using a CNN model as a feature extractor comprising of two pooling since a smaller region of the input image is only considered for license plate recognition. Feature extractor's outputs are fed into RPN [Ren et al, 2015]. After extracting local features using 3 x 3 filters they are concatenated to retain regional and interconnected data which can help in classification. Xu et al (2018) utilized VGG16 to perform feature extraction with ten CNN layers with varying receptive field dimensions. Acquiring outputs from several layers enabled the detection of license plates with varying distances from the camera. Wang et al (2019) used Bidirectional RNN to recognize number plates using classifiers to carry out feature extractions. The designed model carries out ANPR operation relatively faster in comparison with multi-stage approaches which is currently to be the most precise model for LP recognition.

As current solutions mostly take into account multi-level methodologies where 3 chief operations are utilized to carry out the ANPR task namely detection, segmentation, and recognition. Extraction of license plate characters is done in the detection stage by employing conventional CV and DL methods [24]. These algorithms apply an object detection approach to position the number plate in the input image based on specific features like shape [7,8,9,10], color [14], symmetry [15,16], texture [19], etc. During segmentation, license plates are fragmented, and individual characters are acquired using any of these operations namely morphology [20,21], connected components, labeling, and projection analysis [22]. The ultimate phase is where recognition is carried out by adopting either pattern-matching procedures or classifiers based on NNs and FL. If detection is alienated from recognition, it may have an impact on the overall accuracy and effectiveness of the ANPR process due to incorrect detection decisions like bounding boxes challenges in which missing a fraction of the license plate can affect the accuracy of the entire process. Thus, it is imperative each stage must offer satisfactory results to attain the desired performance of the entire system.

4. CLASSIFICATION OF LP DETECTION TECHNIQUES

LP localization methods can be classified into

- Conventional computer vision-based methods
- Machine learning and Deep learning-based Classifiers

The traditional CV-based LP detection can be further classified into edge, color, character, and texture-based detections.

Edge-based methods

These approaches take into consideration of the shape and aspect ratio of number plates. Since LP's are in contrast to the vehicle's color whose boundaries represent edges in the image, the horizontal and vertical edge detection process is performed. Sobel filter [7-10] with 3 × 3 convolutional matrices performs vertical and horizontal edge detection tasks. This filter is convenient to use, yet is highly susceptible to noise distortions. A novel vertical edge detection algorithm (Al-Ghaili et al [29]) was presented which was relatively faster than the Sobel filter. Heo et al [30] came forward with an integrated method that combined line grouping with the mapping of edge densities. After extracting a line segment, they are grouped in the boundary of LPs after which the mapping is done using densities of edges, and the candidate region with the highest density is obtained. Lee et al [31] employ a block-based approach where regions of LPs are arrived at by calculating the magnitude and variance of edges which is well suited for mobile vehicles and blurred plate images. Duan et al (2005) applied a contour-based algorithm and Hough Transformation to recognize line segments in input images based on which edges are detected. Edge-based approaches are used for LP detection mainly due to their speed and convenience, nevertheless, owing to their extreme sensitivity to redundant edges they are not suitable in real-time applications where images are often unclear and intricate.

Colour based Methods

These schemes depend upon the color combination, shade, contrast, and saturation of LPs to categorize pixels in input images alongside diverse lighting. Instead of the conventional RGB model, the Hue Lighting and Saturation (HLS) model is used in these approaches. Genetic Algorithm [11,12] is used to detect LPs which makes use of meta-heuristic search strategy to arrive at optimal solutions. Zhang et al [41] contributed a novel Gaussian Weight-based Histogram Intersection method where colors are matched using their histograms. To overcome sensitivity, the Gaussian function is used to carry out the intersection of histograms. The same author presented another method using mean shift-based segmentation where images are fragmented into ROI on the basis of colors and then classified using a classifier to detect LPs. Li et al [23] (2008) proposed a fuzzy-based algorithm to recognize and extract color features from the input image. Based on values from hues and saturation, fuzzy sets are formed using diverse membership operations. These color-based methods can detect distorted slant license plates but are sensitive to lighting variations. Moreover, they rely on camera specifications and can cause flawed results if the image is comprised of regions whose color is identical to LPs. Consequently, these methods should be embedded with other techniques to realize precise outcomes.

Texture based Methods

These approaches make use of characters present on the license plate to carry out recognition. The contrasting difference in color between the plate and its texts generates a transitional effect which can be seen in greyscale images too. Because of this reason distinct distribution of pixels can be observed across the around the LP section. Furthermore, this results in an increased density of edges. Xu et al [24] (2005) utilized the scan line method where the complexity of the LP region in a grey-scale area cannot be found elsewhere in the input image. As a result, this approach is independent of boundary elements. Vector quantization [17], Segmentation [18] based called Sliding Concentric Windows, histogram method, Wavelet transforms [19], and Gabor filter [18] are some of the methods proposed to analyze textures based on unlimited directions and dimensions. As texture-based techniques can be considered to be reliable owing to their ability to be applied for deformed plate detection, they also involve complex calculations and moreover, performance is not adequate in poorly lit conditions with complex settings.

Character based Methods

Detecting the LPs based on the examination of an image to look for the existence of any characters constitutes a character-based method that considers the area with characters as candidate LP region. Zimmermann et al [32] proposed a method that takes out prospective regions resembling characters from the input image. An NN classifier classifies these regions to arrive at a linear spatial composition which is then regarded as LP. Another approach (Draghici [33]) in which horizontal scanning of an image detects replicated changes in contrast and takes camera specifications into account while considering minimum vertical size limits. Cho et al [34] insisted on recognizing character regions through their width and inter-character difference to enable LP detection. These methods hold promise owing to their reliability in identifying LPs even when tilted/ rotated. The limitation is that these methods are mostly sluggish and prone to flaws especially in the presence of other texts in the input image.

Deep learning and Machine learning Classifiers

A cascading classifier mechanism where statistical features are extracted through utilizing different classifiers like Adaboost, decision tree, etc to train them to learn object detection and perform license plate localization is the most widely used methodology in statistical classifier-based LP detection. SVM [35], Mirmehdi et al [41]is used to carry out classification where a region is identified as LP or non-LP based on color and texture aspects which can be considered to be robust and efficient in comparison to the preceding texture classification schemes [36-38]. Ultimately this method employs a ranking mechanism where each pixel is presented with a score if it is a part of the plate region and these scores predict the coordinates of bounding boxes [24,40].

Several research studies have been dedicated to DL-based LP detection since the majority of the existing CV methods that employ statistical methods have been replaced by AI-based neural networks [25,26,27] owing to their high precision and entity recognition characteristics. Selmi et al [39] came forward with CNN-based localization that consisted of the pre-processing stage in which the input image is processed to eliminate noise and extract relevant elements followed by a recognition phase in which bounding boxes are extracted through a CNN classifier. Zou et al [28] have used two different CNNs for LP detection. Shallow CNN is trained to reduce computational cost through the elimination of irrelevant settings from the background followed by the detection of LPs using deep CNN that can identify the LP from residual areas. Ultimately through utilization of non-maximum suppression, accurate LP region can be detected. You-only-look-once (YOLO) (Redmon et al [42]) detector-based LP detection is the most widely used methodology in recent ANPR studies (Larocca et al [56], Hau et al, (2018), Xie et al, (2018), Montazzoli et al[50]) where direct as well as customized YOLO detectors have been employed through modification of their grid sizes and bounding box attributes can cater to the varying environmental conditions as well as multi-directions[43]. The actual YOLO framework can offer information only with respect to the concerned entity's core points like its center, length, and breadth. Nevertheless, customized models can facilitate information regarding rotational angles that can effectively be applied even under poor illumination settings and obstructions.

5. NUMBER PLATE RECOGNITION TECHNIQUES

After the successful completion of localization, the second stage of the automated multi-level LP recognition scheme is responsible for reading the images with LPs through Optical Character Recognition (OCR) that concentrates only on specific attributes within LPs.

The LP recognition methodology involves the following phases

- Image Pre-processing
- LP Character segmentation
- LP Character Recognition

Pre-processing Methods

Several algorithms employing computer vision, machine learning, deep learning, etc., have been developed to meet the multiple requirements of ANPR that arise during practical implementation. In spite of accomplishing noteworthy enhancements in the recent ANPR methods, there is a growing demand for robust techniques to adapt themselves to complex environmental constraints. As existing approaches are mostly susceptible to variations in lighting and function mostly in daylight settings., stringent regulations with respect to fonts and shade of LPs in several countries there are multiple challenges in association with outdoor images like differing ambiance, weather variations, lighting and irregular intensities, broken, tilted, etc., In order to effectively address these challenges, multiple pre-processing operations are carried out before the segmentation and recognition of characters in LPs. Bilinear rotation techniques [47], least-square approaches [48], and line-fitting schemes [49] have been widely used. Most of the conventional CV-based techniques perform binarization before segmentation to split the pixels related to characters in the input image in comparison to grey-scaled / colored images. Nonetheless, an appropriate threshold value must be determined as there are probabilities of characters getting merged with LP frames in binary images thereby posing difficulty during segmentation. To ensure accurate segmentation, this value can be characterized through various image augmentation procedures like noise elimination, equalizing histograms, enhancing resolution/contrast features, image conversion, etc., In spite of performing these pre-processing functions, it can be tough to obtain a distinct threshold value, adaptive techniques like local thresholding and Niblack's binarization have also been utilized.

LP Character Segmentation techniques

Several OCR techniques perform character segmentation prior to classification. The basic principle involved in LP character segmentation is considering the aspect of possessing a contrasting background with respect to LP characters. Since binarization can aid in the separation of foreground LP characters from background pixels, various techniques like pixel connectivity [50,51], projection profiles [9], prior knowledge [5], DL based methods [52] can be employed to accomplish effective segmentation of LP characters. In Pixel connectivity, connected pixels are labeled and those pixels with identical labels for particular objects of predefined size or aspect ratio are extracted. The constraint with respect to pixel connectivity-based methods is that they fall short in their performance if they encounter broken characters or when characters are connected during binarization, yet they are robust against angular LPs and are mostly simpler to put into practice.

In Projection profile-based methods possessing contrast colors for LP characters and background helps in detecting the initial and final coordinates of characters and then extracting the horizontal and vertical projections (Du et al, 2013). On the other hand, these techniques are sensitive to image quality and noise. Thereby, including a de-noising phase can guarantee robustness. In the Prior knowledge-based technique, various aspects like aspect ratio, and colored pixels accumulation in the image are utilized for character segmentation. Approaches like scanning the binary image vertically and horizontally are used to locate the position [9,10], in which the pixel ratio of contrast between background and characters is computed to arrive at the starting and ending coordinates of LP characters. Another technique [52], where the position of characters can be determined by resizing the segmented LP characters to a predefined dimension is also being employed. In prior knowledge-based approaches, processes are designed on a specific set of instances and may not be utilized in generalized scenarios in spite of their simplicity in implementation. Segmentation of characters using neural networks is widely used in recent approaches to replace traditional CV-based scenarios where CNN carries out the determination of bounding boxes when fed with localized LP as input. Since several aspects like datasets determining the actual performance of the ANPR system, CNN execution time, and consumption of limited resources have been stated, optimization through deep learning-based LP recognition pipelines has been proposed [61]. These techniques exclude explicit character segmentation thereby reducing the count of attributes and hence minimizing the computational complexity and cost (Montazolli et al [50], Laroca et al [51]).

LP Character Recognition Approaches

Pre-defined size-based inputs need to be fed to the ML model as outputs from segmentation normally generate segments of varying sizes, re-scaling is required before classification. As a number of characters and their relative positions and values are identified in the majority of the cases, every segment requires classification which can be done by methods like template matching, employing ML and DL techniques to extract and classify the features before segmentation. In Template matching (Sarfaraz et al [7][8], Rahman et al [52],2003) for a potential character, a pre-specified template is generated and matching is performed for every template to locate the most identical template using metrics such as Mahalobian distance, Jaccard value and normalization being performed on cross-correlations. These methods are easier to implement but do not generalize when applied to various license plates as it is difficult to handle angular rotations which require storing supplementary templates thereby maximizing computational time and storage [12,13].

Generally, the majority of the pixels do not recognize the intended LP characters, thus extraction of features is needed to distinguish uncomplicated features from input images by minimizing computational costs. Pan et al [44,45] proposed robust ML-based feature vector techniques that can extract features and effectively deal with angular rotations and noise distortions. Different approaches like eigenvector (Heigt et al [54]), Gabor filter (Hu et al [55]), Kirsh edge detection (Abdullah et al [56]), SVM (Kim et al [29]), and Hidden Markov Models (Llorens et al [53]) are employed by various researchers to classify extracted features. The main objective of using neural networks like simple multi-layer to probabilistic NN in ANPR system is its ability to process raw pixels directly and perform feature extraction as well as classification [17]. CNN and YOLO provide better accuracy in general in comparison to template matching and statistical extraction techniques. In constraint-based LP recognition systems [22] multi-stage pipeline consists of two components to perform localization and LP detection thereby traffic law enforcement-based applications can make use of this system. Fuzzy logic-based techniques (Wang et al, 2008) create maps using input images' edges, hues, saturation, and intensities to carry out pre-processing and recognition operations [46,47].

6. EVALUATION OF THE ANPR SYSTEM THROUGH PERFORMANCE METRICS

Benchmark metrics for evaluating ANPR system performance are carried out either individually for each level or for sub-components of each process. Most of the research studies are dedicated to LP detection and recognition stages as interpretation is possible only during these stages. Moreover, since ML and DL [57] are trained under losses [58] these can be applicable to single-stage models. Intersection over union(IoU) (Fig 2) is the most widely used evaluation criteria for images where evaluation matrices are used.

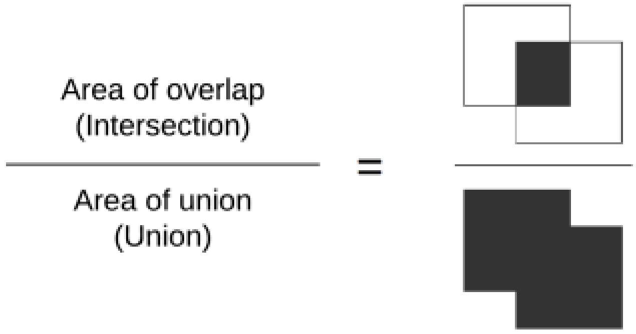


Fig 2: Intersection over union (Source: Shashirangana et al,2021)

If the prediction is right, then the Jaccard index or IoU is more than the particular threshold thereby filtering out flawed bounding boxes. On the other hand, high IoU can result in discarding many predictions during the preliminary phase itself thereby only less data is needed to train the model. Accuracy measure where the exact correlation between the bounding box and LP characters must be ensured as the most popular metric to evaluate the system performance [59,60]. Other measures like precision, speed, and recall are also calculated.

7. ANPR DATASETS

The majority of the public ANPR datasets are applicable to specific countries or regions as they have been created by assimilating data from vehicle traffic monitoring organizations, parking spaces, toll collection centers, and CCTV cameras. Commonly, these datasets collected are from Europe, Arabic countries, China, and the USA like CCPD, AOLP, UCSD, OpenALPR, etc, Most of these images are clear, center-placed, single vehicle /frame images that are captured using handheld cameras and do not contain complicated settings in opposition to real-world situations. Certain datasets like ChineseLP, UFPR-ALPR, and PKU have taken into account composite features like blurs, angles, degraded conditions of plates, obstacles, irregular lighting, varying weather conditions, various plates/frames, etc., Some datasets even contain high-resolution images as well as several frames, a few of them has been discussed in the following section.

DS Name: Ahmedov Dataset

Source: **https://www.kaggle.com/datasets/aslanahmedov/number-plate-detection**

Description: This is one of the widely used datasets for vehicle number plate detection ML models. This dataset has a variety of images in JPEG format. There are more than four hundred and fifty images in the zip. Each image has a bounding box annotation to represent the number plate, the sample data file is shown in Fig 3 and was developed for use in a ML model using the Yolo algorithm.

Figure 3 Sample Image from Aslan Ahmedov Dataset

This has a usability score of 10 which means the dataset is complete, credible, and reliable to be used in ML models. The graph mentioned in Fig 4 shows the usage and it's observed that on average at-least it's used by 25 unique scholars month on month across the globe and its updated on a daily basis.

Usage Stats:

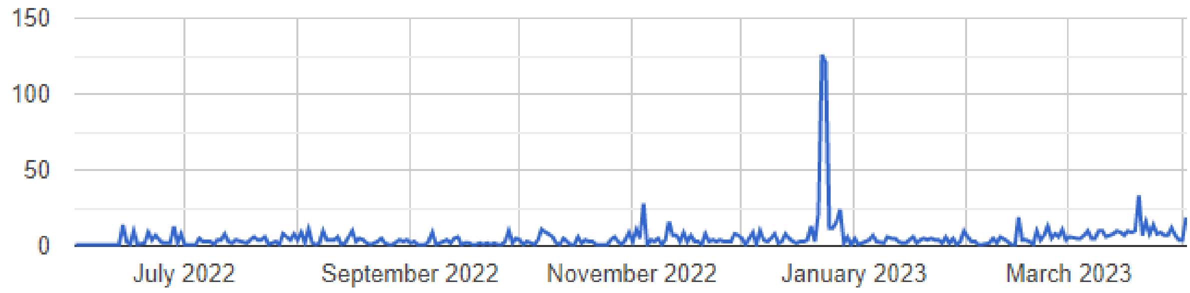


Figure 4 Ahmedov Dataset usage statistics

DS Name: Car License Plate Detection

URL: https://makeml.app/datasets/cars-license-plates

This dataset was created in 2020 as a public dataset having a usability ratio of 8.75. This has more or less the same number of images as in the Ahmedov dataset. Since the licence plate numbers are one of the PII information there are not many datasets available in public with many images. However, these two datasets have a considerable number of samples available for open access.

Figure 5 Sample Image from CLP Dataset

Annotations and the corresponding figures are available in two different folders. Annotations are given in PASCAL-VOC format (Fig 7).

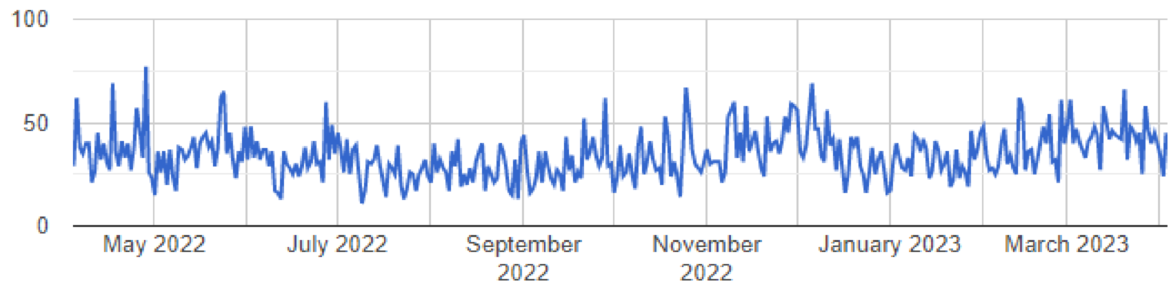
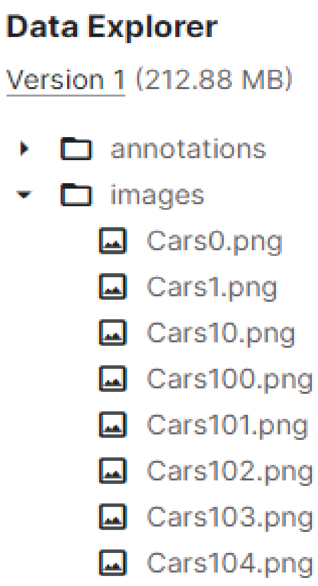


Figure 6 CLP Usage Statistics



The Average download statistics of this dataset exceeds 50 per month. Fig 6 shows the usage statistics for the period of May 2022 to March 2023. It has so far been downloaded by 25,000 plus scholars.

DS Name: Indian Number Plates Dataset

Source: https://paperswithcode.com/dataset/indian-number-plates-dataset-vehicle-number

This is one of the datasets specifically designed for Vehicles with Indian number plates. It has over 21000 images captured by 4000 odd contributors.


```
<annotation>
    <folder>images</folder>
    <filename>Cars0.png</filename>
    <size>
        <width>500</width>
        <height>268</height>
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    </size>
    <segmented>0</segmented>
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        <name>licence</name>
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        <difficult>0</difficult>
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            <ymin>125</ymin>
            <xmax>419</xmax>
            <ymax>173</ymax>
        </bndbox>
    </object>
</annotation>
```


Figure 7 CLP Dataset Annotations

Images in this dataset are diversified and it covers more than 700 rural areas across India.

Key features of this dataset are:

- Having more than 21000 images
- Images with a variety of lighting conditions
- Resolution – HD image with 1920 X 1080 clarity
- Diversified across different cities and different types of Vehicles

All samples in this database were collected in the last three years. Images were taken through mobile phones. Images in this db are suitable for ML models created for number plate recognition, vehicle detection, and automatic detection of violations in traffic. Annotations are available in multiple formats which include Tf rec, CO-CO, PASCAL-VOC, and YOLO. This is not available for free access.

Figure 8 Indian Number Plates Dataset Sample

DS Name : Dataset for License Plate Recognition

Author: Roboflow Universe Projects

Source: Roboflow https://universe.roboflow.com/roboflow-universe-projects/license-plate-recognition-rxg4e

There are more than 24,000 images in this database and it is split into three datasets. The training set contains 88% of the images captured in an HD camera. The validation set covers 8% of images and the testing set contains 1% of the total samples. Captured images can fit into multiple use cases like:

- Security and enforcement of regional laws department to detect vehicle numbers involved in traffic infringement, unlawful actions
- Automatic parking management systems
- Vehicle tracking systems especially in toll plazas to detect vehicle numbers automatically

Figure 9 Roboflow Dataset Sample

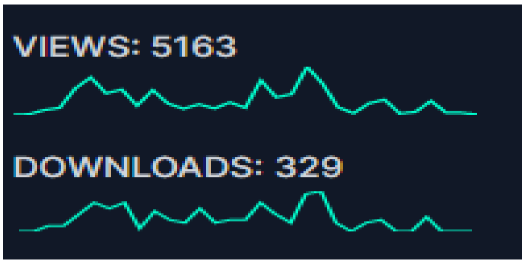

Figure 10 Roboflow DS Statistics

Fig 8 and Fig 9 shows the sample data used for training ML models and the average download count of this dataset. ML models were developed by research scholars using these training samples and the accuracy of the model was closer to 97%. Issues with these samples are confined to one region and can only be used for use cases in that region. The presence of noise in the image reduces the accuracy of the ML model. Samples are not very diversified to cover seasonal and environmental changes. Snow-covered number plates are very difficult to detect due to this reason.

Publicly available datasets are generally utilized to carry out training and evaluation of the ALPR systems, they have certain constraints like inadequate availability, non-applicability to specific requirements, more consumption of time, exertion, and expenditure to gather actual LP images to generate a devoted ANPR dataset. Another crucial issue is that these public datasets are not sufficient enough to train deep learning-based neural networks. Due to these challenges, multiple studies have been proposed to create real LP images based on translation techniques. Han et al [49] contributed an innovative model based on Generative Adversarial Network (GAN) to produce realistic LP images by employing a minimal set of authentic LPs. They had made use of around 200 accessible LP images through online web-scraping to generate over 10000 LP images by making use of generator and discriminator modules of GAN.

8. COMPARISON OF VARIOUS ANPR TECHNIQUES

Performance assessment of recent works using various techniques for each stage of the ANPR system has been provided in Table 1 in terms of accuracy rates, techniques used for segmentation, extraction, and recognition along with database and inferences has been provided. From the information, it can be inferred that the efficiency of the ANPR system is not steady as performance varies due to noise distortions, environmental conditions, techniques, and models used for training purposes.

Table 1: Performance summary of existing ANPR Techniques

Author	Extraction	Segmentation	Recognition	Database	Image condition	Accuracy rate	Inferences
Kashyap et al,[62]	Edge statistics ,morphology	Bounding box	Template Matching	9000 images	-	97%	Different types of Orientation are not taken into account
Vaishnav et al,[63]	Morphology	Region props bounding box	Template Matching	300 images	Less brightness, contrast	98%	Multiple fonts and localization-related issues need to be addressed.

Sferle et al[64]	HOG	Vertical and horizontal Histogram analysis	OCR	100 images	Multiple Conditions	88.9%	The inability to detect beyond a particular distance, and issues like image blur and contrast need to be addressed
Laroca et al[51]	YOLO Detector	CNNs, Bounding box	Data augmentation	SSIG(1000images) and UFPR-ALPR(2000 images)	1900 × 1000 pixels	97%	Only pre-defined pixel formats are used as input as they are dependent on LP layout.
Desai et al[65]	Cascade classifier	Local Binary pattern	OCR	1500 images	600 × 500 pixels with 40 × 10pixels aspect ratio	98%	Takes more time for processing, accurate detection only for the front side at a fixed angle
Sasi et al[66]	SVM and Preprocessing techniques	Contours, Threshold and Morphological operations	ANN	2000	Varying conditions	88%	Complex features result in increased computation, inability to deal with large datasets, noise issues

Singh et al[67]	ROI based filtering	Vertical Edge Detection	-	2000 videos	Several orientation and lighting conditions	87%	Format dependent
Ahmad et al[68]	Sobel filter,CCA	Vertical and horizontal pixel projections	Template matching	1000 X 800 pixels	Varying conditions	77%	Accuracy issues in variable datasets
Mutholib et al[69]	Filtering and pre-processing techniques using contrast enhancement	Vertical Projection method	ANN	500 images	Images taken in mobile Camera in 1800 X 1000 pixels format	83%	Resolution and memory constraints, mobility, and blur issues
Ashtari et al[70]	Hue and shape with vertical sweep	Histogram, CCA, Laplacian, Morphology	DT and SVM	Two sets with 1100 and 600 Images	Different lighting conditions	86%	Accurate for targeted lane and daylight settings but testing is done only on limited data sets.

9. CONCLUSION

ANPR plays a significant role in effective vehicle surveillance, smart transportation, and monitoring operations. Automobiles equipped with robust ANPR techniques can effortlessly detect concerned vehicles from different angles and provide information regarding their owners as output. Image processing techniques integrated with AI can enable the identification of number plates with improved accuracy and recognition. A detailed study on automated LP recognition has been presented to assist traffic surveillance. This paper has attempted to present a systematic survey on various LP recognition, detection, and character segmentation techniques. LPR algorithms are mostly country-specific thus several aspects like prediction of number plates, distance, background, lighting; and vehicle location need to be addressed. As LPR can be a measure of vehicle identification, it can be further explored for model identification and speed estimation as well. This study could be resourceful for traffic control management and planning operations. Day to day increase in mobility and internationalization has further increased the confrontations of building an effective LPR system that can handle LPs of various countries containing diverse character sets and syntactic structures and other future challenging tasks involved in the accurate detection of LPs.

List of Acronyms

AI	-	Artificial Intelligence
ALPR	-	Automatic License Plate Recognition System
ANN	-	Artificial Neural networks
ANPR	-	Automatic Number Plate Recognition system

CNN	-	Convolutional Neural Networks
CV	-	Computer Vision
DL	-	Deep Learning
FPS	-	Frames Per Second
GPS	-	Global Positioning System
ITS	-	Intelligent Transportation System
LP	-	License Plate
ML	-	Machine Learning
NN	-	Neural Networks
OCR	-	Optical Character Recognition
RFID	-	Radio Frequency IDentification
RNN	-	Recurrent Neural Networks
ROI	-	Region Of Interest
SVM	-	Support Vector Machines
YOLO	-	You Only Look Once

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