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AUTOMATIC LICENSE PLATE RECOGNITION SYSTEM: A SYSTEMATIC SURVEY

Vishakha H. Jagtap[1], Rohit V. Dhotre[2], Utkarsh R. Khandare[3], Harshada N. Khuspe[4], Rohini B. Kokare[5]

[1,2,3,4] Student, Department of Artificial Intelligence and Data Science, VPKBIET, Baramati, 413133, India
[5]Assistant Professor, Department of Artificial Intelligence and Data Science, VPKBIET, Baramati, 413133, India

[1]http://orcid.org/0009-0008-0590-2499 , [2]http://orcid.org/0009-0001-0584-2245 , [3]http://orcid.org/0009-0006-2494-071 , [4]http://orcid.org/0009-0000-6527-692X , [5] http://orcid.org/0009-0002-1633-131

Email: vishakhajagtap007@gmail.com, rohitdhotre29112001@gmail.com, utkarshkhandare2@gmail.com, harshadankhuspe0603@gmail.com, rohinikokare@gmail.com

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ABSTRACT

The capacity to naturally distinguish and extract License plate data from pictures or video streams has gathered noteworthy consideration in later a long time, owing to its potential to upgrade security, streamline activity operations, and encourage effective information collection. The Vehicle Number Plate Recognition (VNPR) system has a broader variety of applications. A sophisticated License Plate Recognition (LPR) system can be smoothly incorporated into existing processes including law enforcement, monitoring, and toll station services. Existing approaches for License Plate Recognition are limited to datasets like CCPD, AOLP, etc., and operation specific, so many of them require a constrained environment to meet the needs of the intended application. Even if there are many Vehicle Number Plate Recognition systems available today, the task is still difficult because of several aspects such as the fast-moving vehicles, inconsistent vehicle number plates, contrast problems, language of the vehicle number, processing and memory limitations, camera mount position, motion-blur, reflections, tolerance to distortion, and varying lighting conditions. The methodologies and procedures employed for ALPR in Deep Learning, Computer Vision, and Machine Learning domains in contemporary literature are investigated in this study. This paper gives a comparative study of the techniques and algorithms used for various tasks included in Vehicle Number Plate Recognition (VNPR) systems such as License Plate Detection, License Plate Recognition, Character Segmentation, etc. We outline a critical and constructive analysis of relevant studies in the ALPR, and it will also give directions for future research, and optimization of the current approaches.

I. INTRODUCTION

I.1 OVERVIEW

Currently, the automatic number plate recognition system is very useful in many fields to identify cars or vehicles, which can be classified by the number plate with any background color, which helps to identify the type of vehicle. It helps a lot. to many people who work in RTO or identify the vehicle and which car is illegal or legal This system has been used in many countries to control traffic laws and to control urban traffic. Many techniques are used for an automatic license plate recognition system. The techniques are as follows: [1] Many techniques are used for license plate recognition, but mostly CNN technology is the most accurate technique for license plate recognition of a vehicle using a camera placed on the road or public places. In [2] paper the technique used to detect license plate number is faster RCNN. This technique is more accurate than CNN. Using this faster RCNN model, we can detect any tile with any background color or number of font styles. For [3] Next technique is the OpenCV technique. This technique is based on Computer Vision. The next techniques are Vsnet [4], Support Vector Machine, RCNN and Cascade Color Space Transformation of Pixel Features, Cascaded Contrast-Color Haar-like Features, Cascaded Convolution Network. The Multi-Level Extended Local Binary Patterns and Extreme Learning Machine are also used to detect the number plate from vehicles.

I.2 SURVEY MOTIVATION

Although automatic number plate recognition systems are intended for outdoor usage, they struggle to find and identify license plates in constantly changing weather and environmental circumstances. The application of most current systems is constrained by elements like shifting lighting conditions, snow or fog, day and night, camera shaking, rotations, and occlusions. Automatic Number Plate Recognition systems, which are sensitive to changes in light and typically work in daylight, must deal with cars traveling at varied speeds in the real world. Many methods, which primarily function in daylight, are sensitive to variations in light. Production Systems for automatic number plate recognition must also satisfy non-functional criteria including acquisition and operation costs, physical specifications, power needs, and connection restrictions.

I.3 ARTICLE STRUCTURE

A comprehensive overview of license plate recognition systems is provided in Section 1. The two basic strategies are covered in Section 2. Multi-stage and single-stage ALPR for license plate recognition. Principal components of a multi-stage license plate identification, such as license plate detection and license plate recognition are discussed in Sections 3 and 4. These sections each provide the relevant advantages, difficulties, restrictions, and suggested solutions. In Section 5 different datasets used for the study are discussed with their respective parameters, advantages, and disadvantages. In Section 6, we quickly go over several evaluation parameters for the ALPR system. Section 7 addresses the challenges that need to be addressed for optimal performance of the ALPR system. Finally, Section 8 concludes the study.

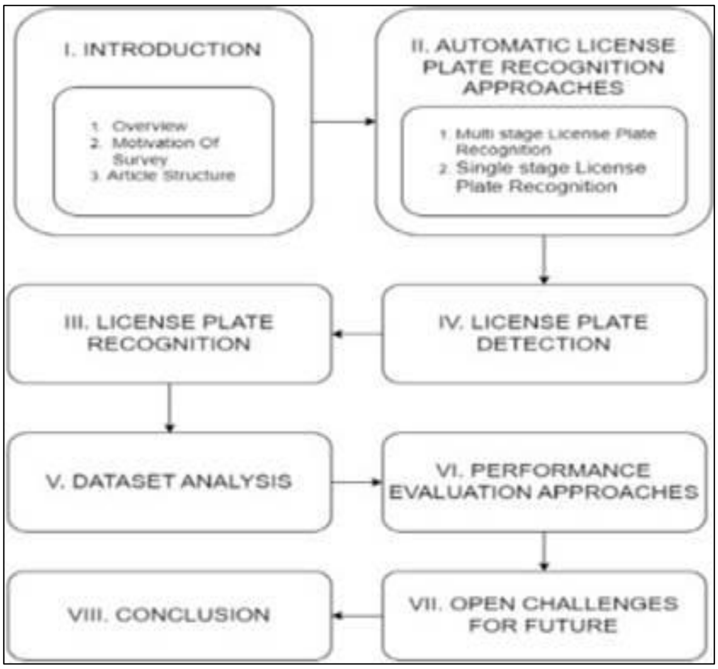

Figure 1: Structure of Paper.
Source: Authors, (2024).

II. AUTOMATED LICENSE PLATE RECOGNITION APPROACHES

II.1 MULTI-STAGE LICENSE PLATE RECOGNITION SYSTEMS

License plate recognition approaches can be broadly classified as multi-stage and single stage approaches. In multistage approaches mainly three classes are there. These include License plate detection or extraction [1], License Plate segmentation (extracting separate characters), and character recognition.

In the first stage, License plate is detected by using an attention mechanism. Region proposal network (RPN) generates the rectangular object proposals for the subsequent processing that helps to detect the number plate efficiently [1],[2],[5]. The cascaded CC-Haar-like detector, the cascaded CST-pixel detector, and the cascaded ConvNet detector make up a hybrid cascade for the detection of license plates with various resolutions [3]. A vertexNET architecture, composed of two cascaded CNNs, is used for license plate recognition [6]. The license plate detection stage is classified into two stages namely feature extraction stage and ELM classification stage [7].

In the second stage, some common techniques for the segmentation and individual character extraction are used such as vertical or horizontal projection [1]. There are some algorithms in the ALPR system that don't make use of segmentation techniques. So, this is not a mandatory stage in the ALPR system.

In the last stage, the character recognition algorithms are used such as OCR or neural networks for character recognition. Every stage in the multi-stage approach is equally important for the overall performance of the ALPR system.

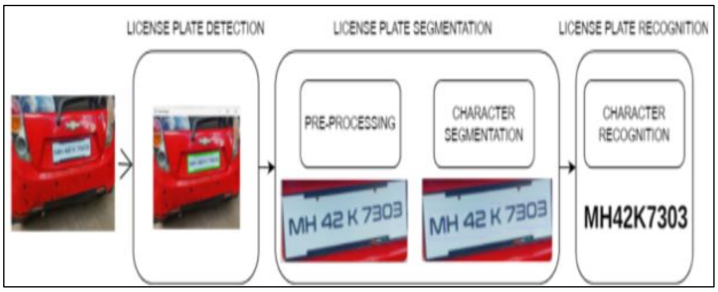

Figure 2: Stages in multi-stage ALPR system.
Source: Authors, (2024).

II.2 SINGLE-STAGE LICENSE PLATE RECOGNITION SYSTEMS

In the single stage approach, all the processes that are separated in the multi-stage approach are addressed at a single stage. Most of the advances are made in multi-stage approaches but some do use single stage approaches. These all use a single deep neural network that has been trained to detect, locate, and identify the license plate from beginning to end in a single forward pass. Such an attempt was made in the paper by Chen et al. The popular VGG-16 [4] was utilized as the basis for the backbone network he employed, which kept the convolutional layers from conv1_1 to conv5_3. For a fair comparison, the final two fully connected layers (fc6, fc7) are turned into convolutional layers and additional layers from conv6_2 to conv9_2 are also included for semantically stronger feature extraction. According to [4] proposed a 30 convolutional layers architecture structured into 9 modules, where all of them have linear residual connections except for the first and the last one. Using interleaved separable convolutions and max pooling, the entry flow raises the feature channel from 3 to 256 while down sampling the spatial dimension from 160 48 to 40 6. They use repeated ResSeparableConv blocks in the middle flow, keeping the spatial size and channel number constant, to extract deep features that contain higher level representations. We extract a middle-level feature map M of size 406512 as the attention network's context from the exit flow, along with a final feature vector F of 512 dimensions. In the sequence decoder, LSTMs with two layers and 512 hidden states each are used [8]. A 2-layer attention mechanism is used which reduces the need for segmenting each character in the license plate separately. A similar kind of single stage approach is used in which use of inception v3 with three layers of CNN and six layers of SSD 300 are used [9].

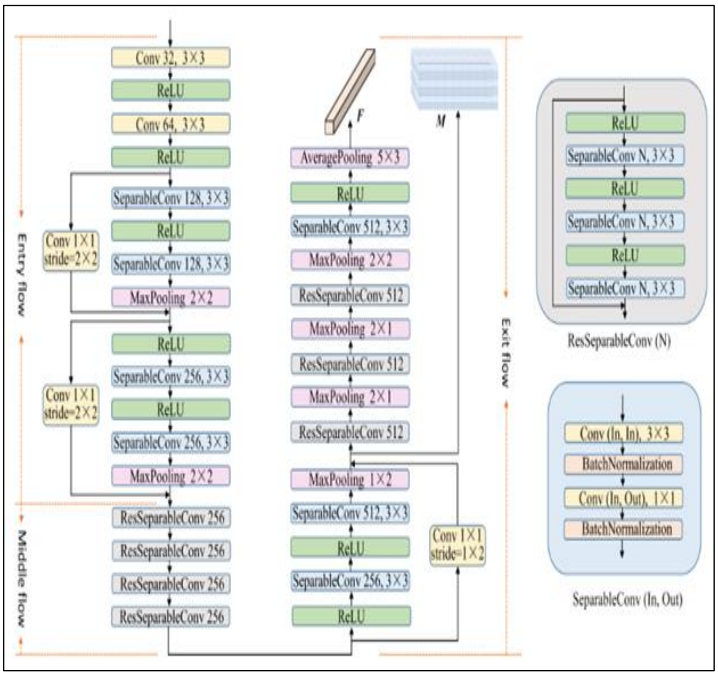

Figure 3: End-to-end CNN architecture for LP detection.
Source: [8].

III. LICENSE PLATE DETECTION

A crucial part of contemporary transportation and security systems is license plate detection. It involves locating and identifying license plates on automobiles for a variety of purposes. Detection techniques have evolved from conventional computer vision methods to more recent advances in deep learning. Finding the location of the vehicle license plate from the ingested vehicle picture and accurately segmenting the license plate from the area for character segmentation constitute the primary tasks of the license plate location. As a result, one of the crucial elements that affects how well the system works is the choice of the license plate area. Mentioned below are license plate detection approaches.

III.1 HYBRID CASCADE

A specific design is utilized to increase the precision and effectiveness of license plate detecting systems called a hybrid cascade structure. To accomplish robust and accurate license plate localisation, it integrates components of both a cascade classifier and deep learning methods. The detection of license plates with various resolutions is done using a hybrid cascade [3]. The cascaded CST-pixel detector, cascaded ConvNet detector, and cascaded CC-Haar-like detector make up this hybrid cascade structure's three components [3].

III.2 YOLO-v2

The deep learning model YOLOv2 (You Only Look Once version 2) is frequently used for tasks involving the identification of license plates. YOLOv2, which has been trained on datasets with annotated license plate areas, is excellent at real-time object identification. When used on license plates, it successfully recognizes and localizes them inside picture or video frames. It is a useful tool for many applications since the model forecasts bounding boxes that include the precise placements of the license plates. A YOLOv2 [8] detector is utilized to obtain the bounding boxes of license plates.

III.3 VERTEXNET

VertexNet [6] is a good performing one-stage detector with a limited input size, a narrow channel of high-level layers, and vertex estimation. Three components, the head, fusion, and backbone networks, make up the proposed VertexNet [6]. VertexNet is built using small-resolution input, even with character information lost, to achieve fast inference speed and reduce memory use [6].

III.4 DEPTH WISE SEPARABLE CONVOLUTIONAL BLOCK (DSCB)

A Depth Wise Separable Convolution block (DSCB) is a frequent building element in convolutional neural networks (CNNs), particularly in topologies built for efficient and lightweight model architectures such as MobileNet and Xception. Depth wise convolution and pointwise convolution are the two primary parts of the DSCB. [5] The Depth Wise Separable Convolution block (DSCB) is used to reduce the number of parameters to a minimum, allowing the model to be deployed on mobile devices.

III.5 EDGE DETECTION

In computer vision and image processing, edge detection is a key idea. It describes the method of locating the areas of a picture where substantial changes in intensity or color take place. Usually, these transitions depict the edges of features or objects in the picture. Most of the research has relied on edge-based techniques for license plate identification since every license plate is rectangular and has a defined aspect ratio. A segmentation technique built on edge detection was utilized in [10]. To find the license plate, it primarily employs the horizontal projection approach and the vertical projection method. The license plates approximate contour is found using Sobel edge detection [10].

IV. LICENSE PLATE DETECTION

License plate recognition in ALPR systems can be broadly classified into three classes, pre-processing, character segmentation, and character recognition.

IV.1 PRE-PROCESSING

The main purpose of pre-processing is to enhance the image quality to correctly enable the character recognition and henceforth enhance the recognition process. Pre-processing helps to neglect the noise, prevent the image blur, etc. The effectiveness of recognition will be impacted by the color information in color images. The license plate information is retained when the color image is converted to a grayscale image, and processing speed is also considerably increased [11].

The License Plate is resampled and rectified to a higher resolution (64 * 256) according to the vertices. This resampling step normalizes the location of characters in the LP. Another process performed is the rectification, which is achieved using perspective transformation. This generates the bird's eye view of the detected license plate [6]. Multi-level pre-processing approaches are used to pass the detected license plate through multiple stages of pre-processing. A Gaussian filter and the CLAHE method are used for multi-level pre-processing in [7],[9]. In this paper, G (σ) is the Gaussian filter with the standard deviation σ = 0.25. CLAHE (σ) is defined as a contrast-limited adaptive histogram equalization method with a standard deviation σ = 0.01[7]. A new image is produced at each stage of multi-level pre-processing which eventually expands the training image size. Based on the results of the LP detection, the License Plate images are cropped depending on the required ROI. These cropped images can be tilted vertically and horizontally. In [5] the focus is on the vertical tilt only. The image is binarized after correction of horizontal tilt. Selecting the specific pixels, starting from the first pixel value to judge the tilt level [8].

IV.2 CHARACTER SEGMENTATION

The Mask branch is used for instantly segmenting the LP characters provided input of Region Proposals which is output from the Faster R-CNN [1]. The recognition of the rivet position and white dots on the license plate to perform character segmentation [10].

IV.3 CHARACTER RECOGNITION

Character recognition is the last and hence the very important step, as the evaluation of performance is based on this step. Most of the character recognition techniques use variants of CNN [3]. Some use a single stage License Plate Recognition approach that uses end-to-end CNN architecture while some multi-stage approaches use a CNN architecture in their License Plate recognition stage [1],[4],[11],[12]. In the papers [1-4], a variant of CNN, VGG & VGG-16 are used. In the paper [1], a multi-stage license plate recognition is used which uses VGG to recognize the license plate. VGG-16 is the modified version of VGG that is used in [4] with some modification in the architecture to acquire better results.

A 2-layer LSTMs is used for recognition of license plates [8], which eliminates the need for individual character segmentation and hence gives better performance without character segmentation. Resampling and rectification of LP is done according to the vertices obtained from VertexNet. The corrected LP picture is then sent to SCR-Net. Through a forward pass, SCR-Net guesses the characters [6]. The number-plate's alphanumeric characters are recognized using the Tesseract OCR engine. Prior training is done to increase the Tesseract OCR engine's accuracy [9].

V. DATASET ANALYSIS

V.1 HZM MULTI-STYLE DATASET

The "HZM multi-style dataset" in [1] is a collection of automobile pictures taken from the Hong Kong-Zhuhai-Macao Bridge and is referred to as such because it contains several forms of license plates.176 photos are utilized for testing, and 1200 images are used to train the model in this proprietary dataset, which has a total of 1376 photographs taken from the Hong Kong-Zhuhai-Macao Bridge's entrance control system. The toll gate is where the test photographs are taken. There are 280 LPs photos altogether with a resolution of 1024 × 800 in the testing subset. Vehicles from Hong Kong, Mainland China, and Macao with a maximum of three license plates are included in the dataset.

V.2 ALOP DATASET

The 2049 license plate images in the ALOP [1],[6] collection are broken up into three categories: road patrol (RP), traffic law enforcement (LE), and access control (AC). The photos of the RP subgroup are taken at different distances and perspectives. The AOLP dataset is split into two subsets: training pictures are utilized for the remaining photos, and files with filenames that begin with "1" are used as testing images (111 images). The ratio between the groups for training and testing is around 4.5:1. LPs and characters are made and annotated using the AOLP dataset's ground truth data.

V.3 PKU DATASET

The PKU collection contains 3977 photos with Mainland China LPs. Because it solely provides the ground-truth file of LPs, this dataset is used to assess the efficacy of LP detection. Five groups (G1–G5) make up the PKU dataset [1], with G1 being the simplest and G5 being the most challenging. The [1] utilizes the other 4 groups as the testing datasets and 810 photos from G1 as the training dataset. PKU Data [6] is an LP detection dataset in which the characters in 2253 images are labelled. Three subsets are used to choose those images: G1 (daytime under normal conditions), G2 (daytime with sun glare), and G3 (nighttime).

V.4 FIELD TESTING DATASET

The field-testing dataset included 12000 photos from the Transport Bureau of the Macao S.A.R. (DSAT) [1]. There are three main types of vehicles in the dataset: automobiles, trucks, and buses. The resolution of these images is 1024 x 800. Between the training and validation sets, these photos are split in a 4:1 ratio.

V.5 LPST-110K

The LPST-110K [2] Dataset consists of pictures shot in open spaces. It is the first dataset to simultaneously handle LP and scene text for LP detection. The LPST-110K is the first dataset that provides text annotations in addition to a significant number of examples (LP and non-LP) in a picture, even when those instances are taken from scenes without any limitations. The LPST-110K dataset compiles images from hundreds of dash cameras and security cameras installed in moving cars and structures, encompassing locations in East Asia and Europe. Along with the LP Road signs, wallpaper text, banners, and commercial adverts are also included in the collection in [2] as non-LP scene texts. There are 9,795 photos and 110,000 scene text pieces in the LPST-110K collection.

The scene texts contain 51,031 LP instances and 58,969 non-LP instances. The resolution of each image in the collection is 1280 (Width) x 720 (Height) x 3 (Channels). The photos in LPST-110K are compressed using the h264 codec setting in contrast to most other LP detection datasets.

V.6 VALID

The two auto-mobile data recorders are used to record videos in 720 x 1280 resolution on the streets of a Chinese city1. The collected dataset is known as the "Vehicle and License Plate Dataset" (VALID [4]). A dataset includes a total 887 well annotated images. The test set consists of 78 photos from a single recorder. 809 additional photos from another recorder are divided randomly in the ratio 7:3 into the training set and the validation set.

V.7 DETROIT

The "Car" and "Vehicle registration plate" are part of the re-annotated DETROIT Dataset, which is a subset of the Open Image Dataset (OID).in a simple way DETROIT is called as (Dataset from Open Image Dataset). DETROIT Dataset is a re-annotated subset of the Open Image Dataset (OID), which contains "Car" and "Vehicle registration plate". For simplicity, DETROIT is called as (Dataset from Open Image Dataset) [4]. The size and aspect ratio of the DETROIT photos, which are downloaded from the Internet, can vary greatly. The test set consists of 386 images taken from the OID validation set. 1113 OID test photos are randomly split into a training set and a validation set in the ratio of 7:3.

V.8 DOC

To obtain DOC (Dataset from Cars), the location of the vehicle and the location of the license plate are combined. There are overall 105 photos in the dataset. Out of which 70% chosen at random as the training-validation set while the remaining 30% are used as the test set. The size and aspect ratio of the DOC images, which are downloaded from the Internet, vary widely.

V.9 CLPD

There are a total of 1200 images in the CLPD [8] (China License Plate Dataset) dataset, which comes from all 31 provinces on the mainland. It covers a wide range of photographic situations, vehicle types and regional codes, allowing for an in-depth analysis of current license plate recognition techniques while promoting the development of a more useful model. Licence plate images in the CLPD dataset are gathered from various kinds of real-scene image sources, such as web searches, images taken from smartphones, and driving recorder recordings of automobiles. The photography angles, shooting times, resolutions, and background are also taken into consideration when capturing LP images to account for the various conditions. Various vehicle types, including cars, trucks, police cars and new energy vehicles, are included in the CLPD dataset. The real-world dataset CLPD [6] contains a wide range of vehicle types, environment, and area codes.

V.10 CCPD

The Chinese City Parking Dataset (CCPD) [6] provides a large-scale and comprehensive Licence Plate benchmark to evaluate Automated License Plate Recognition techniques under uncontrolled conditions. CCPD contains 280k vehicle images, which is two orders of magnitude greater than other LP datasets, that were taken under uncontrolled conditions, such as diverse weathers, lighting, rotation, and vagueness. Each image has a 720 x 1160 resolution. The dataset provides sufficient annotations, including the LP character, bounding box, four vertices, degree of tilt in both the horizontal and vertical axes, brightness, and vagueness levels. The model is trained by using 100k examples of CCPD-Base, and it is tested on the remaining 100k examples of CCPD-Base and the 80k examples of sub-datasets such as CCPD-DB, CCPD-FN, CCPD-Rotate, CCPD-Tilt, CCPD-Weather, and CCPD-Challenge.

VI. PERFORMANCE EVALUATION APPROACHES

Most of the ALPR system uses loss function as the evaluation method [1],[2]. This loss function is calculated at each stage in the single stage [4],[8],[9] as well as the multi-stage approach [1-3], [5],[6]. Finally, the results are aggregated to get the right accuracy of overall ALPR systems. The accuracy is calculated as per loss value at each stage [12].

In the [2] paper the evaluation techniques used are Precision, Recall, F-measure and IoU.

VI.1 PRECISION

The ratio of the number of successfully identified bounding boxes to all acquired bounding box candidates is known as precision. [2],[5-7].

$$Precision = \frac{Tp}{Tp+Fp} \quad (1)$$

Where, Tp = correctly estimated bounding box
Fp = incorrectly estimated bounding box

VI.2 RECALL

The recall is the ratio of the correctly estimated bounding boxes among all the ground truths [2],[5],[7].

$$Recall = \frac{Tp}{Tp+Fn} \quad (2)$$

Where, Fn = the quantity of the undetected ground truth

VI.3 F-MEASURE

Benchmark for LP detection evaluation used in PKU dataset [2],[7].

$$F-measure = 2 * \frac{(Precision*Recall)}{(Precision+Recall)} \quad (3)$$

VI.4 IoU

When the detected bounding box's IoU overlaps the ground truth region by more than 50% (IoU > 0.5), it is deemed to be accurate [2],[3].

$$IoU = \frac{area(Rdet \cup Rgt)}{area(Rdet \cap Rgt)} \quad (4)$$

Where, Rdet = area of the detected bounding box
Rgt = ground truth

AP (Average Precision) is another method used for the evaluation of ALPR systems [2],[4]. AP is calculated over IoU (Intersection over Union) [2].

The performance evaluation measure Success Ratio is used in [13]. Success Ratio is the ratio of the number of success samples to the total number of samples.

$$SR = \frac{NSs}{TNs} * 100 \quad (5)$$

Where, SR = Success Ratio
NSs = Number of success samples
TNs = Total number of samples

The evaluation of classification accuracy in [9] is done using the formula below.

$$Classification\ accuracy = \frac{number\ of\ correctly\ predicted\ characters}{total\ number\ character\ predictions} \quad (6)$$

As seen in most references the performance measures are accuracy, precision, recall, F-measure, AP/IoU. In most multi-stage approaches the loss function is the best estimation of accuracy.

VII. OPEN CHALLENGES FOR FUTURE

VII.1 VARIATIONS IN BACKGROUND COLOR

License plates do have different background colors and each different color signifies different types of the vehicle. White background is for personal vehicles while the yellow one is for transport vehicles and so on. These different colors can add complexity in terms of pre-processing [3]. This is a prominent future scope to work upon.

VII.2 SPEED OF TRAINING

Image processing requires a significant amount of time. To fasten the time decoders are used. Some decoders perform sequentially and not parallelly. LSTM is such a decoder that is incapable of parallel training [8]. We can try out using a transformer like decoder to make training faster.

VII.3 CHALLENGING WEATHER CONDITIONS

Changing weather conditions affect the lumination and hence the performance of ALPR systems [7]. To adapt with the weather conditions is a major future issue. More challenging is to detect LPs at nighttime, as the luminance is lowest at that time.

VIII. CONCLUSIONS

In account for various operational and hardware constraints, a careful selection of standards and techniques is required for the design and development of an automatic license plate recognition system (ALPR). This research article has investigated and examined the currently employed ways and strategies in the most recent literature on ALPR solutions. The deep single-stage Learning-based systems have demonstrated strong results with various datasets. Although learning systems can be pre-trained on huge datasets, single-stage approaches have demonstrated greater computing efficiency and accuracy. This survey did a job of thorough analysis of linked studies and identified the specifications for actual benchmark datasets. We have outlined the current issues and made future directions for ALPR study.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Vishakha H. Jagtap, Rohit V. Dhotre, Utkarsh R. Khandare, Harshada N. Khuspe, Rohini B. Kokare.
Methodology: Vishakha H. Jagtap, Rohit V. Dhotre.
Investigation: Vishakha H. Jagtap, Rohit V. Dhotre, Utkarsh R. Khandare, Harshada N. Khuspe.
Discussion of results: Vishakha H. Jagtap, Rohit V. Dhotre, Utkarsh R. Khandare, Harshada N. Khuspe, Rohini B. Kokare.
Writing – Original Draft: Vishakha H. Jagtap, Rohit V. Dhotre, Utkarsh R. Khandare, Harshada N. Khuspe.
Writing – Review and Editing: Vishakha H. Jagtap.
Resources: Rohit V. Dhotre, Utkarsh R. Khandare, Harshada N. Khuspe.
Supervision: Rohini B. Kokare.
Approval of the final text: Rohini B. Kokare.

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