Deep Neural Network Training and Testing Datasets for License Plate Recognition

Ishtiaq Rasool Khan[1], Saleh M. Alshomrani[2], Muhammad Murtaza Khan[3], Susanto Rahardja[4]
University of Jeddah, College of Computer Science and Engineering, Jeddah, Saudi Arabia[1, 2, 3]
Northwestern Polytechnical University, School of Marine Science and Technology, Xi'an, China[4]

***Abstract*—Modern society has made tremendous progress towards automation to increase the quality of life and reduce the margin of human error. Intelligent transportation systems are a critical aspect of this evolution. The core technology of these systems is the automatic identification of vehicles' license plates to monitor safety and control violations of traffic rules and other crimes. The research on license plate detection and recognition has gone a long way, from traditional computer vision techniques to features (color, shape, text, etc.) based classification and finally to modern deep learning structures. The deep networks comprising hundreds of layers require enormous amounts of training data. The training dataset should contain plates from different countries; otherwise, the system will be specific to only certain types of plates (from a country or province). There are several datasets collected by researchers containing large numbers of license plates from different countries. This paper provides a detailed survey of such datasets available in the public domain. Sample images from each dataset are shown, and details such as the dataset size, size of images, download link, and country of origin are provided. This survey will be a helpful reference for new researchers in the field for the tasks of training new networks and benchmarking their performances.**

Keywords—License plate recognition; deep neural networks; public datasets

I. INTRODUCTION

License plate (LP) recognition has been a well-researched problem in the literature. The earlier works used certain features of the plates, such as height-to-width ratio, color of plate and text, font and color of text, and number and relative locations of alphanumerics, etc. [1-2]. These handcrafted features were generally specific to certain types of plates, and detection accuracy was low. The conventional object detection and recognition methods have recently been replaced by neural networks based deep learning techniques in the computer vision domain. This has resulted in improved accuracy and the ability to recognize license plates in more challenging environments [3-4].

One main issue associated with deep learning techniques is the requirement for large amounts of data for training and testing. Since these techniques are data-dependent, the data's variability and quantity make a difference in the results. Therefore, the dataset used for training a deep neural network (DNN) is important, and a DNN trained on a dataset cannot be fairly compared with another DNN trained on a different dataset. Moreover, the results reported in published literature cannot be reproduced or verified if the dataset is unavailable. Researchers working in this domain realize this issue, and many have started sharing their datasets and algorithms in the public domain. This healthy trend increases confidence in the results presented in the literature, creates benchmarks for comparing new research, and serves as a starting point for new researchers entering the field.

Several surveys have been presented in the existing literature on the techniques used for license plate detection and recognition [5-6]. However, to our knowledge, no comprehensive survey has been carried out of datasets that can be used for training and testing the DNNs for LP detection and recognition. In this paper, we review these datasets and describe their characteristics, such as the sizes of datasets and dimensions of images. We also show some sample images from each dataset.

Most of the existing datasets contain English alphanumeric plates; hence, the networks trained on them cannot perform well on plates with text in other languages. Therefore, this paper also presents a new dataset comprising 2108 license plates from Saudi Arabia. These plates contain bilingual text in Arabic and English, which poses additional challenges to the research community. First, the DNN will need to be trained to ignore Arabic characters, some of which can be easily confused with certain English characters. For example, the English "l" and the first Arabic alphabet "alif" are written similarly; there are many other similarities. Secondly, to write two strings of text on the plate, the size of the characters is generally reduced to smaller than the characters on the license plates with only English characters, which makes them hard to be detected. For the presented bilingual dataset, we provide the ground truth, i.e., the text on the LP and the coordinates of its four corners, along with the images in the dataset, to make it more useful for the research community.

The next section briefly describes several datasets comprising images of vehicles and LPs. The criterion for including a dataset in this survey is that it was published in a journal or a conference paper or used in some scientific work to test or train a DNN. Section III briefly discusses some key observations that can be made from this survey. Finally, the paper is concluded in Section IV.

II. DATASETS IN PUBLIC DOMAIN

A. Application Oriented License Plate (AOLP) dataset

One of the earliest available and widely used datasets is the Application Oriented License Plate (AOLP) dataset containing Taiwanese license plates. Collected by Hsu et al., it comprises three categories named Access Control (AC), Law

Enforcement (LE), and Road Patrol (RP), containing 681, 757, and 611 images, respectively [7]. Sample images from each subgroup are shown in Fig. 1.

At access control locations, such as toll points or entrance and exit of an area under surveillance, the vehicles must stop at a fixed passage or move slowly. The AC subset of the AOLP dataset captures these scenarios. The camera is approximately 5 meters or less away from the car in these images. The camera pan is in the [-30, 30] degrees range, and the tilt is between 0 and 60 degrees, where 0 degrees is assumed parallel to the ground. The ratio of the plate width to image width is between 0.2 and 0.25, and the plates are generally straight with an orientation of fewer than 10 degrees. Images are captured at different illuminations, including outdoor, indoor, day and night times, and various weather conditions. The size of the images is 352 x 240 pixels.

LE images have panning from -40 to 40 degrees, tilting from 20 to 70 degrees, and capturing distances less than 15m. The width of the license plate is 0.1 to 0.2 times that of the image and contains images captured by a roadside camera when the vehicle violated a traffic rule. LE images have a higher resolution of 640 x 480 pixels than AC and RP images in the dataset.

Finally, the RP images have panning from -60 to 60 degrees, tilting from 0 to 50 degrees, and capturing distances less than 15m. The width of the license plate is 0.1 to 0.4 times the image width, and the images were captured either with a handheld or a mounted camera. Road patrol purposes include searching for lost vehicles, scanning for parking violations, and security checking in a restricted area. The image resolution in this dataset is 320 x 240.

B. Caltech Cars

Caltech Cars1999 dataset [8] consists of 126 car images having a resolution of 896 x 592 pixels. The images of parked cars during the daytime are included in this dataset. Another dataset Caltech Cars2001 [9], comprising 526 images at 360 x 240 pixels resolution, has also been made available by the researchers at the same link. The images in the Cars2001 dataset were captured on a highway; therefore, there is more variation in plate sizes and capturing distances and angles in this dataset. Sample images of both datasets are displayed in Fig. 2.

C. Peking University Dataset (PKU)

The Peking University dataset (PKU) is created by the National Engineering Laboratory for Video Technology (NELVT), a research group at Peking University China. The data set was captured by surveillance cameras, in China, during both day and nighttime [10]. Images in the data set are divided into five categories: G1 (810 images, 1082x727 pixels each), G2 (700 images, 1082x727 pixels each), G3 (743 images, 1082x727 pixels each), G4 (572 images, 1600 x 1236 pixels each), and G5 (1152 images, 1600 x 1200 pixels each). All images contain front number plates. The images have good quality, and the plates are easily readable. Some images in the G5 category have multiple cars. In Fig. 3, we have shown some images from G1 and G4 categories.

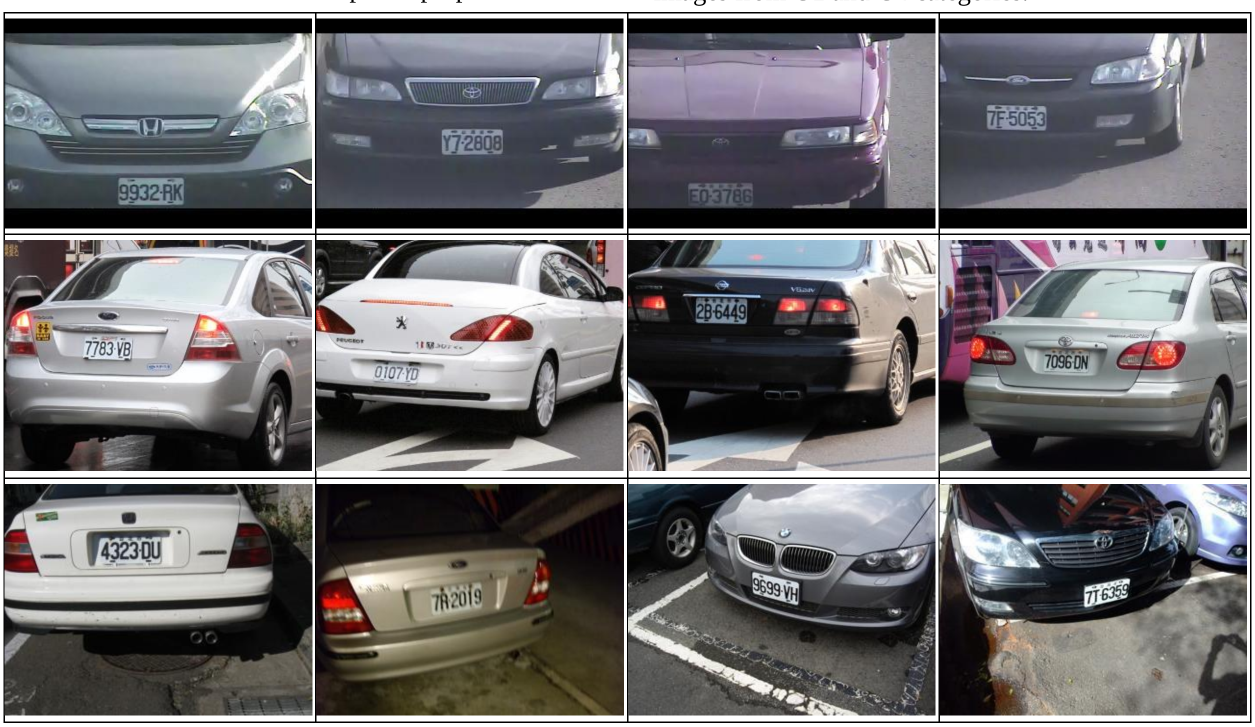

Fig. 1. Sample images from AOLP AC (top row), LE (middle row), and RP (bottom row) datasets Download link: https://github.com/AvLab-CV/AOLP.

Fig. 2. Sample images from Caltech Cars1999 (top row) and Cars2001 (bottom row) datasets Download Link: https://www.vision.caltech.edu/datasets.

Fig. 3. Sample images from PKU dataset category G1 (top row) and category G5 (bottom row) Download link: https://github.com/ofeeler/LPR/tree/master/pku_vehicle_dataset/images.

D. Synthetic Dataset

Bjorklund et al. [11] released a dataset of synthetic images for training CNNs. The synthetic plates were generated considering a wide range of conditions affecting the aspect of real plates. The synthetically generated text was projected on unconstrained backgrounds instead of cars. The authors argue that using license plates on unnatural backgrounds enhances the learning process's ability to account for large text and background variability. The major advantage of generating synthetic plates is that the laborious task of capturing and annotating thousands of plates is avoided. Plated can be generated in any pose, and the template can be changed to different fonts, shapes, and countries. The authors released a training dataset of 20,000 images containing plates and 20,000 images without plates, and a validation dataset of 2500 images with plates and 2500 images without plates. The images represent Taiwanese plates and have a resolution of 768 x 384 pixels. In Fig. 4, we have shown a few sample images containing plates.

E. University of Zagreb Dataset

Researchers at the University of Zagreb produced a database containing 500 images of Croatian license plates. The images contain rear views of cars, trucks, and buses under varying lighting conditions from various angles using a handheld digital camera. The typical sizes of the images are 1024 x 768 and 640 x 480. Some samples of these images are shown in Fig. 5.

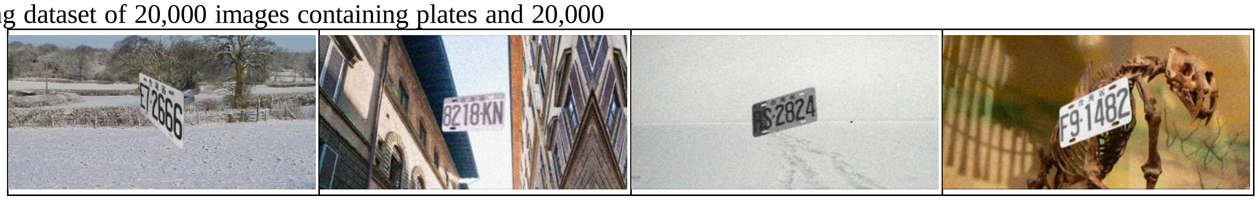

Fig. 4. Sample images from the synthetic dataset by Bjorklund et al. Download link: https://www.kaggle.com/datasets/tbjorklund/annotated-synthetic-license-plates.

Fig. 5. Sample images from the University of Zagreb dataset of car. Download link: http://www.zemris.fer.hr/projects/LicensePlates/english/results.shtml.

F. Chinese Car Parking Data Set (CCPD)

The Chinese Car Parking Data set (CCPD) [12] is a comprehensive data set, 12 GB in size, containing over 300,000 images of Chinese license plates captured with a handheld camera by license plate inspectors across China. The images were acquired between 0730 and 2200 hrs. Each image has only one plate, and the typical resolution of the images is 720 x 1160 pixels. Detailed annotations of the images are provided, with the following information: area ratio of LP to entire image, horizontal tilt, vertical tilt, bounding box's top-left and bottom-right coordinates, exact coordinates of four vertices of LP, 7-letters LP number, brightness of LP region, and blurriness of LP region. The database provides splitting for training and testing subsets. Classification based on other features, such as blur, rotation, tilt, etc., is also available. A subset with challenging images is also part of the classification. The authors updated the dataset in 2020 with new number plates containing eight digits, which are assigned to energy-efficient "green" vehicles. Sample images from CCPD are shown in Fig. 6.

G. National Technical University of Athens Dataset (NTUA)

The National Technical University of Athens released a dataset of the images of Greek license plates and categorized the content as still images and video. At this point, only one video is available, but there are a large number of images in the dataset, and they are divided into several categories based on certain characteristics (color, grayscale, and blurry images) and capture time (day or night). The images with shadows, dirt, and more than one vehicle and those taken from a close distance are stored separately. The images have different resolutions, and we found 1792 x 1312, 800 x 600, and 640 x 480 pixels images in the dataset. There are 716 images in total at this point, but the authors plan to keep adding more. Sample images of this dataset are shown in Fig. 7.

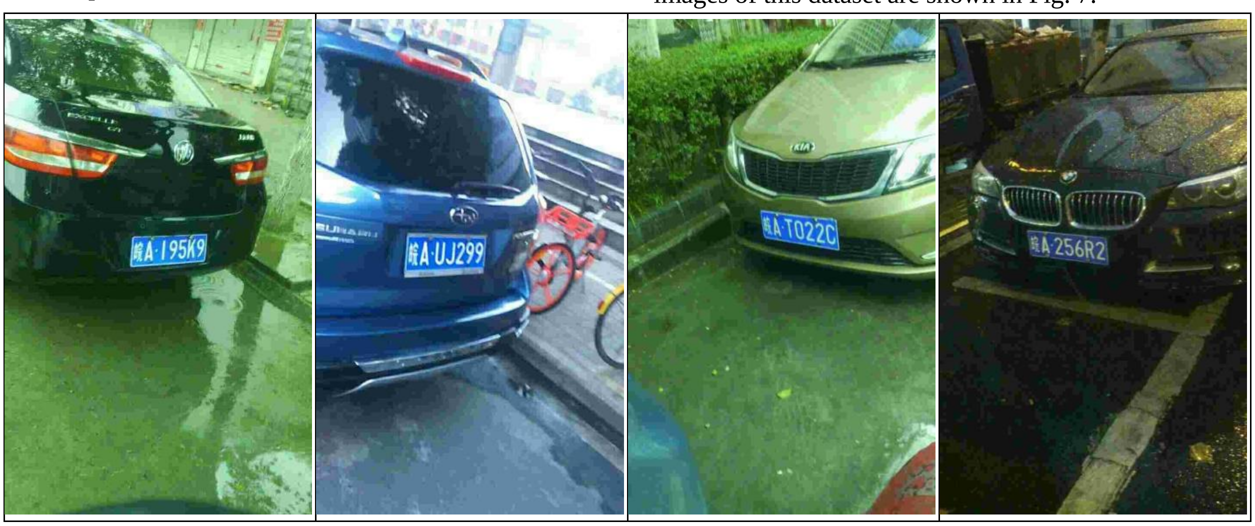

Fig. 6. Sample images from CCPD dataset Download link: https://sites.google.com/site/avlabaolp/download.

Fig. 7. Sample images from National Technical University of Athens' database of Greek plates. Download link: http://www.medialab.ntua.gr/research/LPRdatabase.html.

H. Federal University of Parana Dataset (UFPR-ALPR)

A Brazilian car dataset was released by the Federal University of Parana researchers. The dataset was referred to as UFPR-ALPR by the researchers, and it contains 4500 fully annotated images from 150 vehicles captured in real-world situations [13]. The camera and the vehicle were both moving, so several challenging scenarios were captured. Multiple images of a car taken from different angles are included in the dataset. Images are stored losslessly in PNG format and have a resolution of 1920 x 1080 pixels. Three cameras – GoPro Hero4, Huawei P9 Lite, and iPhone 7 Plus – were used to capture these images, 1500 with each camera, including 900 images of cars with gray LP, 300 images of cars with red LP, and 300 images of motorcycles with gray LP. The images are split into training, validation, and testing sets in a 40:20:40 ratio. Images are annotated with the following information: camera name, type of vehicle (car or motorcycle), manufacturer, model, and manufacturing year of car, position and text of the LP, and position of characters. Some representative images of the UFPR-ALPR dataset are shown in Fig. 8.

I. Kurpiel Dataset

A Brazilian video dataset released by Kurpiel et al. [14] comprises five videos. Under different weather conditions, the authors extracted 4070 plates in 1829 images taken at a resolution of 1920 x 1080 pixels. The plates are quite noisy, and the text is unreadable in many cases. Therefore, this dataset can be used for training and testing LP detection algorithms; however, recognizing text can sometimes be challenging or even impossible. Some samples of the LPs in this dataset are provided in Fig. 9. These are taken from the original paper. The download link is not working now, but we have included this dataset in our review, as interested readers might approach the authors directly and request access.

J. Goncalves Dataset

Another Brazilian database comprising 6,660 images with 8,683 license plate images from 815 different vehicles was accumulated by Goncalves et al. [15]. Images are divided into training (3595 images), testing (2360 images), and validation (705 images) subsets. These images have 1920 x 1080 pixels per image, and the license plate size varies from 5 x 12 pixels to 86 x 196 pixels, with an average of 22 x 57 pixels. These full HD images are stored in PNG format losslessly, one image taking 2.4 MB on average, which makes the total data size quite large. This database can be accessed by submitting a form to the authors and requesting access for non-commercial purposes. Extracted characters from license plates were shared in [16]. There are 101 on-track vehicles captured during the day with a digital camera in Full-HD resolution (1920×1080 pixels). Multiple frames are captured for each vehicle, 19.8 on average, each stored in PNG format (4.08 MB on average), making the total size of the database more than 8.5 GB. This dataset can be used in the license plate character segmentation problems. Some sample images of characters are shown in Fig. 10. The download links of both datasets are provided in the figure caption.

Fig. 8. Sample images from UFPR-ALPR dataset of Brazilian plates. Download link: https://web.inf.ufpr.br/vri/databases/ufpr-alpr/.

Fig. 9. Sample images from the dataset of Kuprial (copied from the original paper) Download link: https://pessoal.dainf.ct.utfpr.edu.br/rminetto/projects/license-plate (not accessible).

Fig. 10. Sample images of characters extracted in the Goncalves dataset. Download link: http://smartsenselab.dcc.ufmg.br/en/dataset/banco-de-dados-sense-alpr/ (vehicles) http://smartsenselab.dcc.ufmg.br/en/dataset/sense-segplate/ (characters).

K. University of California, San Diago Dataset (UCSD-Calit2)

The database shared by the University of California, San Diago (UCSD-Calit2) comprises around 10 hours of video of cars entering and leaving the campus during various hours of the day. The still frames extracted from these videos were hand labeled; thus, the data for 878 cars was annotated. The dataset also comprises 291 car images taken in the car park using a handheld digital camera. The dataset was available at the following link, which is inaccessible now: http://vision.ucsd.edu/belongie-grp/research/carRec. We have provided this link, assuming that the website might be restored in the future or interested readers may want to approach the authors.

L. Spanhel Dataset

Spanhel et al. [17] shared a database comprising relatively low-quality images for the recognition of license plates. The authors captured 9.5 hours long from 8 different bridges on highways under different conditions. They used a boosted soft cascade classifier to detect LPs and tracked them across frames with a Kalman filter. Human observers recognized the plates across a sequence of frames and annotated the whole sequence with the text of the plate. This was an efficient approach to label multiple frames at once instead of doing them one by one. There are 76,412 color images of cropped license plates in this dataset, named ReId dataset. The authors also provided a high dynamic range (HDR) dataset, which is relatively smaller in size and contains 652 images taken at different exposure times. Images were cropped manually to obtain LP images. A few samples of plates taken from the ReId and HDR datasets are shown in Fig. 11. Since the images of cars were captured from different distances and angles, the cropped images of plates have different dimensions.

M. AI Tunisia Hack 2019 Challenge Dataset

A license plate data set was made available in AI Tunisia Hack 2019 challenge. The data comprised 900 images of vehicles taken from the Internet and annotated manually for the coordinates of the bounding box containing the LP. A separate set of 900 images of extracted LPs was also provided in which the annotations mark the text of the LP. Thus, the first dataset can be used to train a network for the detection of LP, whereas the second dataset is specific to the recognition task. Sample images from both datasets are provided in Fig. 12. The images are truncated to show the cars and plates in both datasets; therefore, they have different sizes.

N. Platesmania

License plates from different countries can be downloaded from the Platesmania website, which contains license plates from more than 70 Asian, European, American, and African countries. The data set includes thousands of images. For example, there are 314830, 305643, and 190448 images of vehicles from Germany, France, and the US, respectively. Images are not annotated; hence, the researchers need to mark the bounding boxes and the plate text themselves before they can use them for training a network. A clear picture of the LP is provided with each vehicle image, but it is in image format and not the text, thus not of much use in the training task. However, the picture of the LP is quite clear, and OCR algorithms should be able to extract the text accurately. Some images of cars and their number plates from four different countries are shown in Fig. 13.

Fig. 11. Sample images from the ReId (top row) and HDR datasets (bottom row) of Czech Republic plates by Spanhel et al. Download link: https://medusa.fit.vutbr.cz/traffic/ (not accessible now).

Fig. 12. Sample images from AI Tunisia Hack 2019 challenge. Download link: https://zindi.africa/competitions/ai-hack-tunisia-2-computer-vision-challenge-2

Fig. 13. Sample images of vehicles from Japan, Kyrgyzstan, Mexico, and Russia, from Platesmania. Download link: https://platesmania.com/

O. Stanford Dataset

The cars dataset developed by Stanford University researchers contains approximately 16,185 images of 196 cars, split into 8144 training and 8041 test images [18]. The number plates are not necessarily visible, and the dataset is meant to be used for identification of the car type and not the license plate. However, we have mentioned it here for interested readers, as these details can be important in an intelligent transport system. Images have different resolutions, typically 584 x 328, 634 x 357, or similar. Classes are made at the car make, model, and year level, e.g., the 2012 Tesla Model S or 2012 BMW M3 Coupe. Annotations are provided, including class labels and bounding boxes for all images. Initially, an evaluation server was set up for automatic evaluation and comparison with the provided results. However, it has been decommissioned now, but the manual evaluation can still be done by using the test dataset's ground truth. We have provided some sample images of this dataset in Fig. 14.

P. University of Jeddah License Plate Dataset (UJLP)

The license plates in Saudi Arabia have bilingual text, i.e., the digits and characters are written on top in Arabic and at the bottom in English, and this comes with its unique challenges. First, the recognition systems trained on English characters must discard the Arabic text. Secondly, to fit both texts, the size of the characters is kept small. However, bilingual text offers a unique advantage: separate NNs can be trained on Arabic and English characters, and their results can be combined for higher accuracy. To the best of our knowledge, there has been no notable dataset of Saudi Arabian plates in the public domain. We have developed one consisting of 2108 license plates [19]. To make this dataset, we captured a large number of videos of parked and moving cars from a moving car using our mobile phones. We developed a customized software tool to extract the frames of interest from the captured videos. We also developed a tool for annotation which displays a frame and allows the user to mark the corners of the plate with mouse clicks. The coordinates of these corners are stored in a text file. The extracted images, the tools for extraction and annotation, and the annotation files are shared in the public domain and can be used for free for academic research.

The dataset captured from the traffic moving on the roads offers several challenges, such as variable size and orientation of the plates. Some samples are shown in Fig. 15. There are some very challenging images in the dataset, such as images of the plates partially covered with mud or with poor visibility due to low or bright light. This dataset can be very helpful in developing an LPR system for deployment in police cars.

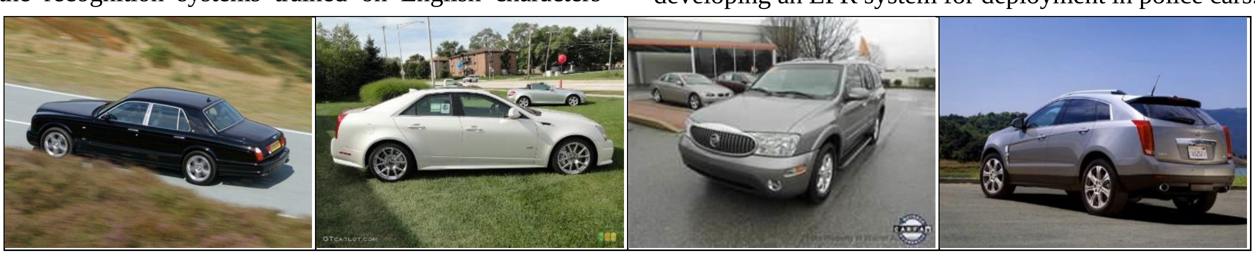

Fig. 14. Sample images of vehicles from Stanford dataset. https://ai.stanford.edu/~jkrause/cars/car_dataset.html.

Fig. 15. Sample images from the UJLP dataset. Download link: https://github.com/ishtiaqrasool/2022-Electronics-Automatic-License-Plate-Recognition-in-Real-World-Traffic-Videos.

III. Discussion

A summary of the different characteristics of the datasets discussed above is presented in Table I. The second column in the table shows the size of the dataset, i.e., the number of images and plates (if available). The largest dataset is provided on the Platesmania website, which provides plates from many countries. However, this dataset was not particularly designed for LP detection and recognition research; hence, the images are not labeled. Among the labeled datasets, CCPD is the largest, with 300,000 images of Chinese plates. The dataset of Czech Republic plates with 76,412 images is the next largest.

While comparing the detection and recognition results reported in different papers, the size of the dataset used for training must be considered; larger datasets would generally lead to better training and accuracy of the DNN. The quality of training images and the difficulty level of testing images are also important factors, and therefore the results reported using different datasets should be compared with caution.

TABLE I. Summary of the Reviewed Datasets

Dataset	# of Images	Image Size	Country
AOLP	AC: 681 LE: 757 RP: 611	AC: 352 x 240 LE: 640 x 480 RP: 320 x 240	Taiwan
Caltech Cars 1999	126	896 x 592	USA
Caltech Cars 2001	526	360 x 240	USA
PKU	G1: 810 G2: 700 G3: 743 G4: 572 G5: 1152	1082 x 727 1082 x 727 1082 x 727 1600 x 1236 1600 x 1200	China
Synthetic	Plates: 20,000 (training) + 2500 (validation) Non-Plates: 20,000 (training) + 2500 (validation)	768 x 384	Taiwan
University of Zagreb	500	1024 x 768, 640 x 480	Croatia
CCPD	300,000	720 x 1160	China
NTU Athens	716	1792 x 1312 800 x 600 640 x 480	Greece
UFPR-ALPR	4500	1920 x 1080	Brazil
Kurpiel et al. [8]	4070 LPs in 1829 images	1920 x 1080	Brazil
Goncalves et al. [9]	8683 LPs in 6600 images	1920 x 1080	Brazil
UCSD-Calit2	878	N/A	N/A
Spanhel et al. [11]	76,412 (ReID) 652 (HDR)	Not fixed	Czech Republic
AI Tunisia Hack 2019	900	Not fixed	Tunisia
Platesmania	Millions of images	Not fixed	Different countries
Stanford [12]	16,185	584 x 328 634 x 357 or close	USA
UJLP	2108	1920 x 1080 720 x 1280	Saudi Arabia

The third column in Table I compares the resolution of images in different datasets. Training a DNN with a large number of layers is a slow process; therefore, the training datasets generally comprise images of small sizes. However, with enhancements in the computational capabilities of GPUs, training images of Full High Definition (FHD) resolution, i.e., 1920 x 1080 pixels are not uncommon, as can be seen in the table. The execution time of a trained DNN to process a test image depends on the hardware platform as well as the image size. These factors should be given due consideration when comparing the efficiency of different methods reported by their respective authors.

IV. Conclusion

A detailed survey of different datasets used for training and testing of deep neural networks for license plate detection and recognition was presented. Different characteristics of these datasets were discussed. The information compiled in this paper can serve as a valuable reference for advancing research in this domain and benchmarking.

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