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A method for license plate recognition in low-resolution conditions

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Abstract. With the widespread application of license plate recognition technology, the development of license plate recognition technology is becoming increasingly advanced. However, in some low-resolution situations, the efficiency and accuracy of license plate recognition are greatly reduced. To understand the development in this area, this paper conducts research from two perspectives: traditional methods and deep learning methods. Among the traditional methods, this paper discusses methods based on ALBP, methods based on image vertical projection feature analysis and geometric features of character segmentation algorithms, and methods based on character region perception of end-to-end license plate recognition algorithms. Among the license plate recognition methods based on deep learning, this paper discusses algorithms such as AOD-Net, YOLOv5, LPRNet, CRNN+CTC, and FasterR-CNN. The purpose of this review is to help readers understand how researchers have overcome low resolution by improving the existing recognition methods in the development of license plate recognition technology, and point out the shortcomings of each improved method so that readers can understand the development and existing problems in this field.

1 Introduction

As the economy develops rapidly and urbanization intensifies, the quantity of motor vehicles in China has been growing at an exponential rate. According to statistics, at the end of 1996, the number of various types of motor vehicles in China was approximately 20 million, among which the number of automobiles was about 10 million [1]. By 2010, this figure had soared to 70 million. This increase not only enhances the complexity of traffic management but also imposes higher requirements on technology related to the recognition of road license plates. Although traditional license plate recognition techniques have yielded satisfactory outcomes, their recognition performance drops conspicuously in certain low-resolution scenarios. Low resolution exerts a considerable influence on license plate recognition technology, particularly having a major impact on the efficiency and accuracy of recognition.

In recent years, the introduction and rapid advancement of deep learning techniques have offered a superior solution for license plate recognition. Convolutional Neural Networks (CNNs) [2], Recurrent Neural Networks (RNNs) [3], Long Short-Term Memory (LSTM) [4],

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Generative Adversarial (GAN) [5], and other deep learning models automatically extract features and conduct complex pattern recognition through training on large-scale datasets, thereby significantly enhancing the recognition accuracy in various environments. In the case of low resolution, deep learning models can effectively cope with different types of blur problems by leveraging the learned local features and global information of images. The advancement of technology has not merely enhanced the degree of accuracy in license plate recognition but also strengthened the stability and robustness of the system in complex circumstances such as adverse weather conditions.

This article conducts an in-depth exploration of how license plate recognition technology copes with blurred image quality and the resulting related issues in the backdrop of deep learning models. Firstly, this paper briefly expounds on the influence of low resolution concerning license plate recognition technology and briefly presents the basic process of license plate recognition. Subsequently, for different types of blurring scenarios, this paper conducts an analysis and puts forward corresponding solutions, as well as improvements to the methods. Moreover, it elaborates on the shortcomings of the methods and the aspects that require improvement.

2 The influence of low resolution on license plate recognition

In the case of low resolution, the decline in character clarity will lead to difficulties in accurately presenting details, thus affecting the recognition accuracy. For instance, the numeral 0 and the character 'o', as well as the numeral '1' and the character 'I', might be confounded in a low-resolution setting. License plate recognition technology is highly susceptible to variations in lighting. Excessive or uneven lighting will significantly impact the recognition efficiency and accuracy.

Strong illumination will intensify image noise, making the already blurry images in low resolution even more indistinct. Particularly, some light-colored and small characters might be concealed by the noise and thus hard to discern. Strong illumination might also lead to overexposure, resulting in certain areas of the license plate becoming white and causing the loss of some character information. This further elevates the difficulty of license plate recognition in a low-resolution context.

Weak or uneven lighting can likewise have an impact on license plate recognition. Weak lighting will darken the image as a whole, diminishing the contrast existing between the features of the license plate and its background color, thereby making the contours of the characters difficult to distinguish. While uneven lighting will lead to certain parts of the license plate being brighter and some parts darker, forming shadows. The shadowed parts are hard to identify at low resolution. For instance, the left part of the letter 'k' is well illuminated, yet the right part generates a shadow due to insufficient light, which might lead the recognition system to misidentify it as the letter 'I' or the number 1.

3 The fundamental process of image recognition

3.1 Image collection

Image acquisition constitutes the first and rather crucial step in license plate recognition, with the key point residing in how to effectively capture clear and identifiable images for subsequent various treatments. Image acquisition is mainly dependent on cameras. Commonly seen cameras comprise fixed cameras, mobile cameras, high-speed cameras, etc.

Fixed cameras are typically installed at fixed positions like highway toll stations, parking lot entrances, and traffic signal lights. The working principle of them is rather straightforward.

They are capable of continuously monitoring and automatically capturing the images of passing vehicles. For instance, the fixed cameras at the entrances of highways can identify vehicle information in real time and effectuate automatic fee deductions, thereby enhancing the traffic efficiency of vehicles.

Infrared cameras are applicable in circumstances with inferior lighting conditions, as well as certain environments during nighttime or rainy weather. Infrared cameras are chiefly employed for license plate recognition at night and various monitoring works, being capable of enhancing recognition efficiency and accuracy in low-light settings.

3.2 Image processing

Image preprocessing constitutes a crucial stage in the system of license plate recognition. To conduct a series of operations on the collected raw images to enhance image quality and facilitate subsequent analysis and processing. Preprocessing generally encompasses procedures like grayscaling, noise reduction, contrast improvement, normalization, and binarization. These operations have the ability to raise the clarity and identifiability of the image, providing a better image basis for subsequent procedures like license plate localization, segmentation, and character recognition. In the stage of license plate localization, the objective is to identify the position in which the license plate is located in the preprocessed image. Commonly employed approaches comprise morphological operations, contour detection, and Hough transformation. With these techniques, the rectangular area of the license plate can be precisely ascertained. License plate segmentation means extracting the identified license plate area from the original image and creating an independent license plate image, laying a foundation for the subsequent recognition and extraction of characters.

3.3 Character handling

Character processing mainly comprises two steps: Character division and recognition of characters. Character segmentation is a main task in license plate recognition, which is to further divide the character-containing regions that have undergone pre-processing into individual and independent single characters. Character segmentation can roughly be classified into three steps: locating the character regions, conducting feature analysis, and performing segmentation operations. Character segmentation serves as a linkage in license plate recognition, splitting the characters in the cropped license plate image into separate parts, thereby facilitating precise identification of the license plate number in the subsequent procedure.

Character recognition follows closely and mainly encompasses two crucial processes. Firstly, feature extraction is carried out, extracting feature information such as strokes and contours from the segmented characters or images. Secondly, there is classification recognition. In this process, the extracted character features are compared with predefined character templates. More sophisticated recognition approaches employ machine learning and deep learning algorithms are employed to determine the specific types of characters based on the extracted character features. Common recognition tasks encompass the identification of letters, symbols, and Chinese characters on license plates.

3.4 Result output

Output the recognized crucial information such as license plate characters, and store the recognition results in the database. In real-life and practical applications, once the data is transferred to the database, it will also be transmitted to other systems through certain interfaces, to facilitate subsequent practical uses.

4 Approaches to license plate recognition

4.1 Conventional approaches

As intelligent transportation and pattern recognition technologies progress, the conventional recognition approach relying on binary images has been unable to meet the practical requirements. These approaches usually lose some essential structural information in the binarization process. However, the method for Chinese character recognition based on grayscale images can avoid this problem. In the literature [6], the Local Binary Patterns (LBP) operator was introduced for character recognition, thereby increasing the recognition rate of Chinese characters on license plates from the previous 74.25% to 98.80%. Moreover, based on the existing LBP operator, they further proposed an Advanced Local Binary Pattern (ALBP) algorithm, which conspicuously reduced the recognition time of Chinese characters. The experimental outcomes imply that this approach demonstrates considerable robustness in the identification of grayscale Chinese characters on low-quality license plates. Compared to traditional recognition approaches, both the recognition accuracy and speed have witnessed significant enhancements. Although the method based on ALBP has obtained a favorable recognition rate and a relatively fast recognition speed in the character recognition of low-resolution license plates, this method still presents certain limitations. ALBP is rather sensitive to noise, blurring, or other interfering factors (such as dirt, and reflection), and in actual applications, license plate images frequently encounter multiple interferences, which might result in a decrease in recognition accuracy. Furthermore, LBP and its modified versions mainly concentrate on the extraction of local features and are relatively weak in capturing global features. In certain circumstances, the global shape and layout of characters exert significant influences on recognition as well. Hence, there might exist deficiencies in feature extraction.

This is because traditional vertical projection segmentation algorithms are susceptible to character missegmentation issues during the license plate recognition process, particularly in the case of low resolution. Literature [7] brought forward a character segmentation algorithm based on the analysis of image vertical projection features and geometric characteristics. This algorithm constrains the process of the traditional vertical projection segmentation algorithm by considering the width of the characters and the spacing width between the characters, effectively resolving the incorrect segmentation problem of left-right structured Chinese characters. Via this improvement, the accuracy of character segmentation was remarkably enhanced, thereby exerting an important role in the correct recognition of license plates [7]. Although the character segmentation algorithms based on the analysis of image vertical projection features and geometric characteristics possess certain advantages in addressing the missegmentation issues in traditional approaches, this method still has some drawbacks and limitations. First of all, it is highly reliant on the character spacing, and the segmentation effect of the algorithm is closely associated with the width of the characters and the width of the intervals between characters, if the character spacing in the license plate image is non-uniform or subject to noise interference, the segmentation effect may be influenced. Secondly, this algorithm is rather sensitive to the quality of the image. Low-quality images (such as blurring, noise, shadows, etc.) might lead to erroneous segmentation results. Finally, regarding parameter settings, the algorithm requires adjusting parameters such as character width and spacing width by the specific application scenario. If these parameters are not set reasonably, it may also have an impact on the segmentation effect.

As the application demands for vehicle license plates in the intelligent transportation field keep upgrading continuously, license plate recognition still encounters numerous challenges in natural scenarios. To cope with the issue of unstable license plate recognition resolution resulting from variable natural illumination and diverse shooting angles, the literature [8] put forward an end-to-end license plate recognition algorithm that depends on character region perception. This algorithm, through the introduction of a character region perception network, directly positions the characters in the image and enables character recognition without going through the license plate detection step, effectively optimizing the license plate recognition process. This approach employs ResNet18 as the backbone network and integrates a low-computation segmentation head constituted by the Feature Pyramid Encoding Module (FPEM) and Feature Fusion Module (FFM), compensating for the deficiencies of lightweight networks and enhancing real-time performance while guaranteeing the algorithm's accuracy. Through constructing an artificial dataset related to license plate content for the pre-training of the character perception network, the character perception ability and algorithm accuracy were further improved. Experimental results indicate that in the experiments on the CCPD dataset, the proposed algorithm attained an average accuracy of 46% while maintaining an inference speed of 6 frames per second, which is approximately 3% higher than the existing baseline model. The end-to-end license plate recognition algorithm based on character region perception demonstrates outstanding performance in coping with the challenges of license plate recognition in natural scenarios, particularly in optimizing the recognition process and enhancing real-time performance. Nevertheless, this approach also entails certain latent shortcomings and limitations, primarily manifested in its reliance on the dataset and its susceptibility to lighting and angles. Regarding the dependence on the dataset, the pre-training of this algorithm relies on the artificially constructed dataset related to license plate content. If the diversity and representativeness of the dataset are inadequate, it might result in a deterioration of the model's generalization ability in practical applications, influencing the recognition accuracy. Concerning the sensitivity to lighting and angle, even though this method has been optimized for natural lighting and shooting angles, it might still encounter recognition challenges under extreme lighting circumstances (such as intense reflection and shadows) or extreme angles (such as inclination and blurriness).

4.2 The methodology of license plate recognition employing deep learning

When it comes to the issue of relatively low resolution caused by hazy weather, the literature [9] proposed a method for recognizing license plate numbers in hazy weather based on deep learning. This method initially employs the AOD-Net algorithm to conduct defogging preprocessing of the vehicle image. Subsequently, a license plate detection network, ACG_YOLOv5s, is designed based on the YOLOv5 network. ACG_YOLOv5s is founded upon the YOLOv5s network, incorporating the Convolutional Block Attention Module (CBAM) to enhance the model's anti-interference ability. The Adaptive Spatial Feature Fusion (ASFF) is introduced, which assigns varying weights to different feature layers of the network by the weights learned adaptively by the model, thereby highlighting crucial feature information. The Ghost Convolution Module (Ghost) is employed to replace traditional convolution, reducing the parameter quantity during the network training process while guaranteeing the model's efficacy. Ultimately, the License Plate Recognition Network (LPRNet) is utilized for the recognition of the detected license plate images. The experimental outcomes demonstrate that the improved ACG_YOLOv5s network achieves a vehicle license plate detection accuracy of 99.6%, and the LPRNet attains an identification accuracy of 96% with a relatively small memory occupancy.

This method of license plate recognition based on deep learning in hazy weather conditions has shown remarkable accuracy and performance. However, it still presents certain potential shortcomings and limitations. The AOD-Net algorithm within this approach can handle the license plate recognition issue in hazy weather rather perfectly. However, its performance in other extreme circumstances, like heavy rain or blizzard conditions, might be suboptimal. The objective of every scientific study is to be implemented in practical scenarios.

Nevertheless, in real life, there can't be only hazy weather. Hence, this method possesses certain limitations. Secondly, the ACG_YOLOv5s network, due to the incorporation of modules like CBAM, ASFF, and Ghost convolution, has witnessed a significant escalation in its model complexity and computational difficulty. Particularly in real-time application scenarios, it might fail to fulfill the requirements for real-time processing. In conclusion, although this approach has attained a relatively high accuracy in license plate recognition under hazy weather conditions, the aforementioned drawbacks and limitations still require consideration and resolution in practical applications, to boost the robustness and application scope of the system.

On highways, vehicles travel at a relatively high speed, or under certain weather conditions resulting in lower resolution, all of which give rise to extremely blurred images during vehicle recognition. To address the character recognition issue of blurred license plates in reality, the literature [10] presents a license plate character recognition algorithm without character segmentation based on an upgraded Convolutional Neural Network + Recurrent Neural Network + Connectionist Temporal Classification (CRNN + CTC). Firstly, a marginally modified form of the deep separable convolutional network replaces the standard CNN in CRNN. The RNN serves as the two-directional long short-term memory network and the CTC loss function is adopted for its training. Secondly, to prevent overfitting during the training process, an L2 regularization term is incorporated into the loss function and the training dataset is enlarged. Finally, the batch normalization algorithm was employed to speed up the learning rate during the training process. The experiments employing this method indicate that, in contrast to several other approaches in complex environments, this algorithm has made certain enhancements in the average license plate recognition accuracy and recognition precision, and speed throughout three experimental test sets.

Moreover, the robustness and generalization capacity of the network are even more remarkable. The enhanced CRNN + CTC license plate character recognition algorithm undoubtedly possesses specific advantages in the field of blurred license plate recognition. To put it briefly, CRNN combines convolutional layers and recurrent layers, having the ability to extract features effectively and deal with sequential data, and therefore is appropriate for the recognition tasks of license plate characters. The CTC loss function enables the model to handle sequences of variable lengths, being suitable for cases where the quantity of characters in the license plate is not fixed. Nevertheless, this approach concurrently presents certain deficiencies. For instance, it is relatively sensitive to extremely blurry situations. Even though the improved model performs well on blurred images, for extremely blurry or overly noisy license plate images, the recognition performance may still decline. Secondly, this approach has highly demanding requirements for training data, necessitating a substantial volume of high-quality and diverse training data. It is not accommodating to low-quality data. Finally, when it comes to computing, this method consumes a considerable amount of resources. Because the CRNN model is relatively complex compared to other models, it requires a large amount of computing resources during the training or inference process. Particularly when handling high-resolution images, the amount of computing resources it consumes is especially prominent.

In relation to the current license plate recognition methods based on the partitioning of license plate characters, the problem is that the resolution is decreased under specific natural scenarios such as strong illumination or dimness, failing to locate and inability to correctly segment license plate characters, the recognition effect of license plate characters was directly influenced, and a license plate location and recognition method based on deep learning was proposed in Reference [11]. Firstly, the FasterR-CNN [12] algorithm in deep learning is adopted for license plate localization, and the k-means++ algorithm is employed to select the optimum size of the license plate region, addressing the issue that existing license plate localization methods fail to accurately position license plates in some natural scenarios.

Subsequently, improvements and reconstructions were made based on the AlexNet network model [13], and an enhanced convolutional neural network model, AlexNet-L, was proposed. This model is an end-to-end network model specifically developed for the identification of license plate characters. It is capable of increasing the accuracy of license plate recognition and eliminating the impact of incorrect license plate character segmentation on license plate character recognition in existing license plate recognition approaches based on license plate character segmentation. The experimental outcomes demonstrate that this method can improve the accuracy and efficiency of license plate localization and character recognition more effectively. This approach, apart from presenting its outstanding performance, also has a number of disadvantages. First and foremost, it is evident that the model is overly complex. While the combination of multiple algorithms and models can enhance the performance of license plate recognition, due to the excessive complexity of the model, the degree of dependence on data and the requirements for computing resources during practical operation are significantly elevated. At the same time, the k-means++ algorithm also possesses certain limitations. Although the k-means++ algorithm has made improvements in the selection of initial cluster centers compared to the ordinary k-means algorithm, it is still likely to be constrained by the initial conditions, resulting in a local optimal solution and thereby influencing the selection of the size of the license plate area.

With the advancement and maturation of machine vision technology, Li et al. developed a set of license plate recognition algorithms relying on deep learning algorithms to address the issue of low efficiency in license plate recognition under low-resolution circumstances and applied it in the traffic monitoring scenario. This algorithm has the capability of precisely identifying the license plate details of vehicles passing through traffic intersections. The detection precision in terms of mAP can exceed 99%, and the precision of recognition can be greater than 94%. The detection algorithm employs YOLOV4 [14]. It has the ability to accurately detect the positional specifics of the license plate within the image. The recognition algorithm makes use of CRNN, and the detected ROI (Region of Interest) area is cut for text recognition and is utilized and adopted on the NVIDIA Jetson AGX Xavier embedded edge computing device. Deployment is executed with the TensorRT acceleration library for end-to-end realization. The identification of all license plate information in an image merely takes 17ms [15]. Although the license plate recognition system based on YOLOv4 and CRNN exhibits outstanding performance in terms of detection accuracy and recognition speed, certain deficiencies still exist. From the aspect of NVIDIA, although rapid processing can be realized on NVIDIA Jetson AGX Xavier, the system still encounters the issue of delayed processing in situations and scenarios with high traffic, such as during the morning and evening peak hours. Furthermore, this approach demands extensive training on datasets. If there are license plate styles and models that have never occurred in the dataset, it poses a significant challenge for this method. Ultimately, although the combination of the two algorithms, YOLOv4 and CRNN, exhibits relatively superior performance, like other complex computational models and algorithms, it demands a considerable amount of computing resources and memory. This is not favorable for those embedded systems or low-power devices with restricted resources.

Up to now, license plate recognition technology has been rather mature in some specific scenarios, for instance, recognition at the entry and exit locations of parking lots recognition at highway toll booths, along with fixed-point license plate recognition at the entrances of residential communities. These static license plate recognition and license plate recognition technologies in specific circumstances have reached a considerable level of maturity. Nevertheless, license plate recognition in natural scenes still poses a challenge, since the complex environment strongly affects image parameters, and aspects such as resolution are significantly affected during recognition. In order to enhance the performance of license plate recognition in natural scenes, the literature [16] puts forward a solution for recognizing real

Chinese license plate photos by employing a DCNN-RNN model. By applying the Deep Convolutional Neural Network (DCNN), the license plate is located, and its features are extracted following the correction process. Eventually, The RNN model is adopted to convert the deep features into characters without conducting character segmentation. This advanced system attains a 92.32% accuracy rate and the recall rate amounts to 91.89 percent respectively on the dataset of car accident scenes gathered in a natural scene. Moreover, it achieves an accuracy rate of 92.88% and a recall rate of 92.09%, respectively, on the California Institute of Technology Cars 1999 dataset [16].

This approach of employing DCNN and RNN models for license plate recognition in natural scenes has demonstrated favorable performance in terms of accuracy and recall rates; however, it concurrently presents certain deficiencies. Firstly, similar to other refined deep learning-based license plate recognition methods, the DCNN model and the RNN model are relatively susceptible to complex natural surroundings. Their performance varies under diverse lighting circumstances and specific weather conditions. For instance, in natural environments such as those with high light intensity, large shadowed areas, or rain, snow, etc. the recognition efficiency of this approach will be significantly impacted. Secondly, in terms of real-time processing capacity, the DCNN and RNN models involve complex computations. This drawback results in their inadequate capacity to handle real-time issues and their deficiency in processing speed for real-time problems. They do not hold an advantage in certain scenarios that require rapid responses, such as traffic monitoring in circulation sections and similar scenarios. Finally, in terms of the generalization ability of the models, the DCNN and RNN models have overly strict requirements for the training data. If the training data is not sufficiently rich and diverse, this would result in the method performing well in certain specific circumstances, but demonstrating relatively poor performance in untrained scenarios, thereby causing a deficiency in generalization ability.

5 Conclusion

The core content of this article focuses on the examination of license plate recognition under the condition of poor resolution. It is categorized based on traditional approaches and deep learning-based methods and summarizes and elaborates on some existing license plate recognition methods for low-resolution scenarios. However, these methods still have some shortcomings that have not been ameliorated, such as sensitivity to extreme environments, deficiency in generalization ability, and high complexity of the models. It is anticipated that these issues will be addressed in future research and work, thereby enhancing the robustness and applicability of the upgraded license plate recognition methods. This review is intended to enable readers to have a preliminary acquaintance with The domain of license plate recognition and an initial comprehension of the license plate recognition approaches in low-resolution circumstances.

References

1. T. Chao, Current Issues and Countermeasures in the Motor Vehicle Insurance Market. Guangxi Fin. Res. **3**, 40-42 (1998)
2. B. Xu, K. Cen, J. Huang, H. Shen, X. Cheng, A Survey of Graph Convolutional Networks. J. Comput. Sci. **43**(5), 755-780 (2020)
3. J. Liu, Z. Song, A Survey of Recurrent Neural Networks. Control Decis. **37**(11), (2022), 2753-2768
4. Y. Guan, G. Su, Y. Sheng, Bidirectional Long Short-Term Memory Network for Time Series Prediction. J. Xi'an Univ. Electron. Sci. Technol. **51**(3), (2024), 103-112

5. J. Liang, J. Wei, Z. Jiang, A Survey of Generative Adversarial Networks (GANs). Comput. Sci. Explor. **14**(1), 1-17 (2020)
6. Y. Wang, H. Zhang, X. Fang, J. Guo, Low-Resolution License Plate Chinese Character Recognition Based on Improved LBP. J. Chin. Inf. Process. **23**(5), 86-91 (2009)
7. W. Yao, T. Zhen, Z. Lü, Y. Zhu, Z. Li, B. Gui, P. Guo, Research on License Plate Character Segmentation and Recognition Technology. Mod. Electron. Tech. **43**(19), 65-69 (2020)
8. Y. Li, Y. Shu, X. Fan, H. Su, B. Li, End-to-End License Plate Recognition Method Based on Character Region Perception. Radio Eng. **52**(6), 940-946 (2022)
9. Y. Yang, J. Wang, J. Jiang, A Deep Learning-Based License Plate Recognition Method in Haze Weather. Liquid Cryst. Display. **39**(2), 205-216 (2024)
10. C. Zhang, Y. Li, B. Kang, Y. Chang, A Deep Learning-Based Algorithm for Fuzzy License Plate Character Recognition. Laser Optoelectron. Prog. **58**(16), 251-258 (2021)
11. X. Li, W. Min, Q. Han, R. Liu, Deep Learning-Based License Plate Localization and Recognition Method. Comput. Aided Des. Graph. **31**(6), 979-987 (2019)
12. Qin Lijuan, Zhao Yuhui. Car Plate Detection Algorithm Based on Faster RCNN [J]. Electronic World, 2019, (24): 70-71. DOI: 10.19353/j.cnki.dzsj.2019.24.034.
13. K. Krizhevsky, I. Sutskever, G. E. Hinton, Imagenet classification with deep convolutional neural networks. Advances Neural Inf. Process. Syst. **25**, (2012)
14. S. Jiang, S. Yin, T. Luo, et al., Multi-Object Vehicle Detection Algorithm Based on Improved YOLOv4, Comput. Eng. Des. **45**(04), 1181-1188 (2024)
15. X. L. Xingxing, D. Chao, Y. P. Panpan, et al., Research on the Application of Deep Learning-Based License Plate Computer Recognition System in Traffic Scenarios. J. Phys. Conf. Ser. **2033**(1), (2021)
16. J. Wang, X. Liu, A. Liu, et al., A Deep Learning-Based Method for Vehicle License Plate Recognition in Natural Scenes. APSIPA Trans. Signal Inf. Process. **8**, (2019)