International Journal of Computer Science
Scholarly Peer Reviewed Research Journal - PRESS - OPEN ACCESS
ISSN: 2348-6600
http://www.ijcsjournal.com Volume 11, Issue 1, No 1, 2023. ISSN: 2348-6600
Reference ID: IJCS-458 PAGE NO: 3114-3121

Comparative Study on License Plate Recognition using Deep Learning

S. Sowmyayani
Department of Computer Science (SF),
St. Mary's College (Autonomous),
Thoothukudi, Tamil Nadu, India
sowmyayani@gmail.com

Abstract:

Automatic License Plate Recognition (ALPR) plays a crucial role in criminal cases, traffic accident cases and many other cases. A generalized algorithm cannot be designed since each country has different style of license plates. ALPR suffers from illumination problem, unconstrained scenario problem etc. This paper compares three recent deep learning models that are designed for ALPR. All the three models are tested on Chinese City Parking Dataset (CCPD). Experimental results are compared in terms of accuracy. It is also analysed by dividing the dataset into set of images. It is observed that VSNet achieves higher accuracy of 99.5% than other two models.

Index Terms: Convolutional Neural Network, Character Recognition, Segmentation

I. Introduction

With the global economy expanding quickly, several cities in various nations may have traffic congestion, frequent accidents, a worsening traffic environment, or other urban traffic issues. The following issues with the usage of cars are also steadily becoming more prevalent [1] along with the rise in automobile use, including cases of car theft, traffic accidents, and gridlock on the roads, severe environmental pollution, and more. Each nation is currently researching better ways to regulate and monitor automobiles in order to address these issues. If you exclusively rely on human resources, like traffic cops, you'll run into a lot of issues, such excessive costs and ineffectiveness. Therefore, it would surely offer considerable ease and benefits if intelligent traffic equipment can be adopted. This environment gave rise to research on Intelligent Transportation Systems (ITS) [2].

In order to achieve intelligent administration of cities, "intelligent video surveillance" and "intelligent transportation" are gradually added to the research agenda. The term "smart city" emerges as the need for it increases. In real life, LPR systems play a significant role in vehicle supervision, expressway toll management, intelligent parking, electronic police, and other areas. These systems may also achieve the surveillance of urban traffic in order to reduce traffic bottlenecks. Currently, there are numerous ALPR systems, but their licence plate recognition rates will be significantly decreased in the complicated environment (such as lighting circumstances, distorted licence plates, dirt licence plates, etc.) [3]. Therefore, it is very important for study to determine how to increase the rate and

International Journal of Computer Science
Scholarly Peer Reviewed Research Journal - PRESS - OPEN ACCESS
ISSN: 2348-6600
http://www.ijcsjournal.com Volume 11, Issue 1, No 1, 2023. ISSN: 2348-6600
Reference ID: IJCS-458 PAGE NO: 3114-3121

accuracy of detecting licence plates in a complicated environment.

Deep learning allows computational models of multiple processing layers to learn and represent data with multiple levels of abstraction mimicking how the brain perceives and understands the image [4]. Deep learning techniques and conventional techniques are both used to detect licence plates. Traditional techniques primarily extract features from objects based on the target's background colour, edge and shape. In order to dramatically reduce the number of candidate images recovered from crowded photographs, Hsieh et al. [5] used morphological approaches. This speeds up the licence plate detection method.

The ANPR system has following steps:

- Image Acquisition: Images of vehicle are captured.
- Pre-processing: Obtaining an estimated image and eliminate the distortions.
- Extraction of number plate: Remove irrelevant part and extract the number plate.
- Character segmentation: Segmentation or isolation of characters from the extracted license plate.
- Character recognition: Recognize letters and display the output result

The rest of the paper is organized as follows: Section II describes some related works that are made in recent years. Section III elaborates three recent methods on deep learning. Section IV analyzes those three methods with some experiments followed by conclusion in Section V.

II. Literature Survey

This section briefly discusses some innovative ALPR method. Most methods of recognition utilize methodologies of deep learning [6-7]. Upon studying these methods, it is easy to build our own ALPR architecture.

For the purpose of the security system, an LPR system is created in [8]. This system aids in tasks like detecting car licence plates, analysing those plates, and utilising the processed data for further tasks like storing, approving or rejecting vehicles. The system is put in place at the entry to regulate security in highly restricted areas like military zones or the vicinity of important government buildings like the Supreme Court, Parliament and so on.

Based on the information collected by ALPR cameras, an Origin Destination (OD) prediction technique [9] has been created. In order to minimise the original OD matrices' size and distinguish the primary structural patterns from the noisier components, the Principal Component Analysis (PCA) is used. To create the predictions, a state-space model is built for the primary structural patterns and structural deviations and integrated into the Kalman filter architecture. Three long-term pattern recognition techniques based on K-Nearest Neighbor (KNN) have also been applied.

The front or back image of the vehicle is processed in another ALPR system [10]. For character recognition, this technique makes use of the random forest classification algorithm. Based on machine learning strategies and data visualisation approaches, a Cognitive Number Plate Recognition (CNPR) system [11] has been designed. This system uses a data clustering approach to conduct knowledge production. Additionally, the database of identified number plates' hidden information patterns is employed to offer insight into the vehicle data for decision-making and analysis.

In [12], the issue of sparse trajectory reconstruction using ALPR data was covered. First, an appropriate journey time criterion is used

International Journal of Computer Science
Scholarly Peer Reviewed Research Journal - PRESS - OPEN ACCESS
ISSN: 2348-6600
Since 2012
http://www.ijcsjournal.com Volume 11, Issue 1, No 1, 2023. ISSN: 2348-6600
Reference ID: IJCS-458 PAGE NO: 3114-3121

to segment the vehicle's various travel operations, and an incomplete vehicle trajectory is then established. Then, a better K-Shortest-Path (KSP) method based on space-time prism theory generates candidate trajectories. In order to rebuild the vehicle trajectory, the auto-encoder model is used to choose the candidate trajectory with the best decision indications. In Ningbo, China, this approach has been used on a practical urban traffic network.

Zhang et al. [13] introduces a concept based on neural network recognition and computer visual processing. Convolutional Neural Network (CNN) and colour space detection make up the majority of it. The ALPR method may extract deeper features as deep learning technology progresses [14], dramatically enhancing the detection and identification accuracy. It has been explored how deep learning can be used in LPR. In order to address the three primary technical issues of licence plate skew, image noise and blur, the most sophisticated algorithms are introduced. The benefits and drawbacks of the existing LP detection algorithms and character recognition algorithms are examined and the deep learning techniques are divided into direct and indirect detection algorithms. Different LPR systems' variations in data sets, workstations, accuracy and timing are contrasted.

The OKM-CNN model, which combines segmentation based on Optimal K-means clustering and recognition based on CNN, is an efficient deep learning-based LPR model [15]. This model runs through three primary stages: detecting licence plates, segmenting using the OKM clustering approach and recognising licence plate numbers using the CNN model. The Improved Bernsen Algorithm (IBA) and Connected Component Analysis (CCA) models are used for LP identification and localisation.

A deep ALPR system [16] suitable to multinational LPs has been created to overcome this problem. The three primary components of this system are transnational LP layout detection, unified character recognition, and LP detection. The You Only Look Once (YOLO) networks form the foundation of the system. ABCNet has been used as the foundation for an LPR algorithm [17]. In order to extract image convolution characteristics of a series, CNN is employed after the source pictures with ABCNet are used to create an LP plate detection network. This approach is used to address the issue of poorly aligned training characters.

A comprehensive ALPR system [18] has been created with an emphasis on unrestricted settings in which the LP may be significantly distorted as a result of oblique views. In order to warp an LP to a fronto-parallel view and eliminate perspective-related distortions, an Improved Warped Planar Object Detection Network (IWPOD-NET) has been developed. This network is capable of detecting the four corners of an LP under a number of different scenarios.

III. RECENT METHODS ON LPR

Because of tremendous success of deep learning in computer vision problems, there was a lot of interest in applying features learned by CNN on general image recognition to other tasks such as segmentation, face recognition, and object detection. In this section three methodologies of LPR based on deep learning are discussed.

- Decoupled Attention Network (DAN) – This method has extracted deep features on LPR [19]. It uses DAN for recognition.
- Asymmetric Cycle Generative Adversarial Networks (AsymCycleGAN) – This method uses asymmetric cycle-consistency loss in CycleGAN [20].

International Journal of Computer Science
Scholarly Peer Reviewed Research Journal - PRESS - OPEN ACCESS
ISSN: 2348-6600
http://www.ijcsjournal.com Volume 11, Issue 1, No 1, 2023. ISSN: 2348-6600
Reference ID: IJCS-458 PAGE NO: 3114-3121

- VSNet – The third method uses VertexNet for LP detection and Squeeze Character Recognition Network (SCR-Net) for LP recognition, [21].

A. Decoupled Attention Network (DAN) for Text Recognition

Three parts make up DAN: a feature encoder that extracts visual features from the input image, a convolutional alignment module that performs the alignment operation based on those visual features, and a decoupled text decoder that uses both the feature map and the attention map to make the final prediction.

In conventional attention decoders, the recurrency alignment module is swapped out for a Convolutional Alignment Module (CAM). The CAM performs alignment operations from a visual standpoint rather than using previous decoding data, eradicating misalignment brought on by decoding mistakes. Through decoupling the alignment operation from relying on prior decoding outcomes, the DAN seeks to address the misalignment problem of classical attention mechanisms.

B. Asymmetric Cycle Generative Adversarial Networks (AsymCycleGAN)

For the purpose of recognising licence plates in the outdoors, a reliable framework has been created. It is made up of an elaborately built image-to-sequence network for plate identification and a customised CycleGAN model for creating licence plate images. On the one hand, the laborious human annotation task is reduced by the CycleGAN-based plate creation engine. With a more balanced character distribution and different shooting scenarios, a significant amount of training data can be gathered, which significantly improves the recognition accuracy. On the other hand, a 2D attentional-based licence plate recognizer using an Xception-based CNN encoder can reliably and effectively identify licence plates with a variety of patterns in a variety of situations.

A customised Xception network for feature extraction and a 2D-attention based Recurrent Neural Network (RNN) model for character decoding make up the two primary components of the whole LP recognition model.

C. VSNet

The outstanding design of ALPR is comprised of four key insights:

- The resampling-based cascaded framework is advantageous to both speed and accuracy.
- The highly efficient LPR should abundant additional character segmentation and RNN, but adopt a plain CNN.
- In the case of CNN, utilising vertex information on licence plates improves the recognition performance.
- The weight-shuffling approach is effective in both speed and accuracy.

VSNet is created using these findings. It consists of two CNNs that are combined in a cascaded, resampling-based fashion, namely VertexNet for licence plate detection and SCR-Net for licence plate identification. To extract the spatial properties of licence plates from VertexNet, a powerful integration block is employed. VertexNet uses a vertex-estimation branch with vertex supervisory information so that licence plate photos may be corrected as the input images for SCR-Net. Left to right feature extraction in SCR-Net is accomplished using a horizontal encoding approach, while character recognition is accomplished using a weight-sharing classifier.

International Journal of Computer Science
Scholarly Peer Reviewed Research Journal - PRESS - OPEN ACCESS
ISSN: 2348-6600
http://www.ijcsjournal.com Volume 11, Issue 1, No 1, 2023. ISSN: 2348-6600
Reference ID: IJCS-458 PAGE NO: 3114-3121

D. Pros and Cons of the Three Compared Models

All the three models have their own pros and cons. It is summarized in Table I.

TABLE I
COMPARISON OF THREE MODELS

Model	Strengths	Weakness
DAN	Effective, flexible and robust	It struggles to align the text when it encounters sounds that resemble text.
Asym CycleGAN	Different types of LP images may be produced, including those with shadows or in dim or harsh lighting, simulating real-world situations.	It is challenging to tell certain identical characters apart. Images with severe blur or occlusion cannot be detected.
VSNet	It eliminates unnecessary character elements. It prevents incorrect character segmentation from occurring during recognition.	It could work on Chinese number plates only.

IV. RESULTS ANALYSIS

A. Dataset and Metrics

All the three models are tested on publicly available dataset: CCPD [21]. This is a benchmark dataset to assess ALPR techniques. It contains 280k vehicle images, that were taken under uncontrolled circumstances, such as diverse weathers, illuminations, rotation, and vagueness. The resolution of each image is 720 x 1160. The dataset has enough annotations, including the LP character, bounding boxes, four vertices, degree of tilt in both the horizontal and vertical axes, and brightness and vagueness levels. Figure 1 shows some sample images from CCPD dataset.

The detection and recognition metrics defined in [22] are utilised for the CCPD dataset and as each image only yields a single licence plate, the detection precision is determined without taking recall into account. For each image, the detector is permitted to predict one bounding box. The precision over the testing set (overall precision) and each subset are examined. The predicted box is considered true positive if its IoU with the ground truth is more than 0.7. When the projected LP's IoU is greater than 0.6 and every character on the LP is right, the predicted LP is considered correct in the LP recognition task. The accurate LP predictions over all LPs are used to compute the recognition accuracy.

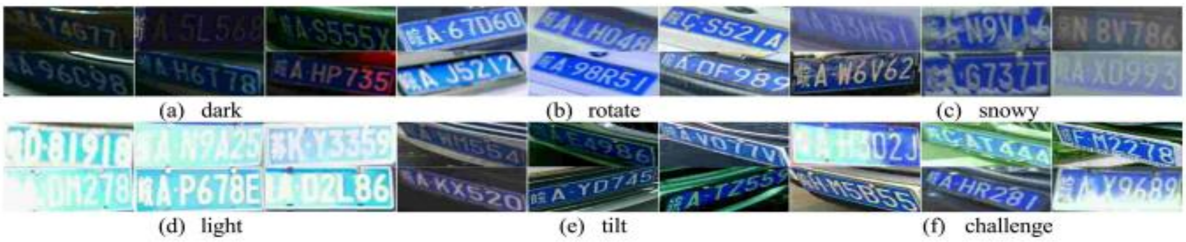

Fig. 1 Sample Images from CCPD Dataset

International Journal of Computer Science
Scholarly Peer Reviewed Research Journal - PRESS - OPEN ACCESS
ISSN: 2348-6600
http://www.ijcsjournal.com Volume 11, Issue 1, No 1, 2023. ISSN: 2348-6600
Reference ID: IJCS-458 PAGE NO: 3114-3121

B. Implementation Details

Table II displays the hyperparameters of each model. The detailed implementation setting is given below.

1) DAN

The height of the input image is set to 32 and the width is calculated with the original aspect ratio (up to 128). The learning rate is reduced to 0.1 after the third epoch.

2) AsymCycleGAN

The learning rate is multiplied by 0.9 at every 12, 000 iterations until it reaches to 0.00001. The size of input images is adjusted like DAN model. This model is tested on NVIDIA GTX1080Ti GPU with 11GB memory.

3) VSNet

License Plate Detection: In the first stage, the learning rate is multiplied by 0.1 every 3 epochs without reducing the loss. In the second stage, the initial learning rate is set to 0.0001 and the batch size is set to 4.

License plate recognition: The input image is resized to 152 × 56. When the loss is not decreased, the learning rate is multiplied by 0.5 every 3 epochs.

TABLE II
HYPERPARAMETERS OF ALL THE COMPARED MODELS

Model	Hyperparameter Setting	
DAN	Optimizer: ADADELTA Learning rate: 1 to 0.1	
AsymCycleGAN	Optimizer: ADAM Batch size: 24 Learning rate: 0.001	
VSNet	**Detection**	**Recognition**
	Optimizer: Adam Epochs: 128 Batch size:16 Learning rate: 0.001	Epochs: 200 Optimizer: Adam Batch size: 32 Learning rate: 0.0001

C. Results Analysis

Experiments are conducted on different subsets with each subset having different number of images. Table III compares the results obtained by all the three models. The number of images in each subset is given in parenthesis in the Table III.

TABLE IIII
COMPARISON OF THREE MODELS

Method/ #Images	Overall Accuracy (%)	Base (100k)	DB (20k)	FN (20k)	Rotate (10k)	Tilt (10k)	Weather (10k)	Challenge (10k)	Test Time (ms)
DAN	96.6	98.9	96.1	96.4	91.9	93.7	95.4	83.1	19.3
AsymCycleGAN	98.9	99.8	99.2	99.1	98.1	98.8	98.6	89.7	-
VSNet	99.5	99.9	99.7	99.4	99.9	99.9	99.4	94.8	11.4

http://www.ijcsjournal.com Volume 11, Issue 1, No 1, 2023. ISSN: 2348-6600
Reference ID: IJCS-458 PAGE NO: 3114-3121

From Table III, it is observed that the VSNet model achieves higher accuracy of 99.5% than other models. When individual subsets are also considered, the VSNet performs well. Although all the models use deep learning techniques, the computation time of testing is very less (approx. below 20ms). When computation time is compared, the VSNet model tests the images in only 11.4ms which is lesser than DAN model. Figure 2 shows the bar chart comparison of the three models based on accuracy.

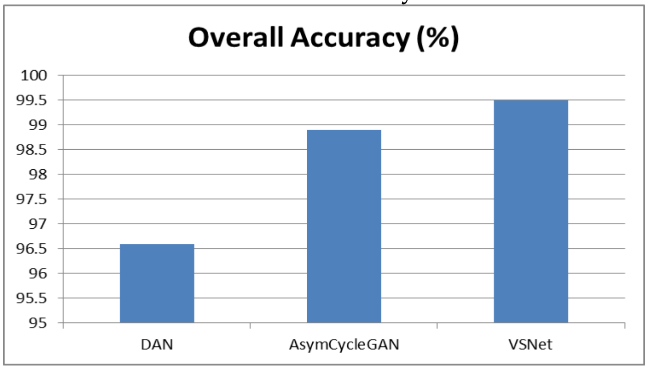

Fig. 2 Overall Accuracy of Compared Methods

V. CONCLUSION

The ALPR system consists of license plate detection, character segmentation and character recognition. Different processing techniques are examined in order to deal with uncontrolled scenarios including uneven lighting, an unfixed shooting angle, varying weather, and motion blur in real-world images. Three deep learning models such as DAN, AsymCycleGAN and VSNet are compared. The results substantially proved that the VSNet achieves overall higher accuracy of 99.5% in 11.4ms than other two models. This model can be further generalized to segment and recognize number plates of different countries.

REFERENCES

[1] Lum, Cynthia, et al, "License plate reader (LPR) police patrols in crime hot spots: an experimental evaluation in two adjacent jurisdictions," Journal of Experimental Criminology, vol. 7, no. 4, pp. 321-345, 2011.

[2] Anagnostopoulos, Christosnikolaos, et al, "A License Plate Recognition Algorithm for Intelligent Transportation System Applications," IEEE Transactions on Intelligent Transportation Systems, vol. 7, no. 3, pp. 377-392, 2006.

[3] Sanyuan, Zhang, Zhang Mingli, and Ye Xiuzi, "Car plate character extraction under complicated environment," systems, man and cybernetics, pp. 4722-4726, 2004.

[4] P.Praveena, "A Deep Learning Perspective of Computer Vision Algorithms", International Journal of Computer Science, Volume 10, Issue 1, No 1, 2022, pp. 2657-2667.

[5] J. Hsieh, S. Yu, and Y. Chen, ''Morphology-based license plate detection from complex scenes,'' presented at the Int. Conf. Pattern Recognit., 2002, doi: 10.1109/ICPR.2002.1047823.

[6] Rakhshani, S., Rashedi, E. and Nezamabadi-pour, H., 2019. License plate recognition using deep learning. Journal of Machine Vision and Image Processing, 6(1), pp.31-46.

[7] Sowmyayani, S. and Rani, P., 2022. Salient object based visual sentiment analysis by combining deep features and handcrafted features. Multimedia Tools and Applications, 81(6), pp.7941-7955.

[8] Sutar, G.T., Lohar, A.M. and Jadhav, P.M., 2019. Number plate recognition using an improved segmentation. LAP LAMBERT Academic Publishing.

International Journal of Computer Science
Scholarly Peer Reviewed Research Journal - PRESS - OPEN ACCESS
ISSN: 2348-6600
http://www.ijcsjournal.com Volume 11, Issue 1, No 1, 2023. ISSN: 2348-6600
Reference ID: IJCS-458 PAGE NO: 3114-3121

[9] Liu, J., Zheng, F., van Zuylen, H.J. and Li, J., 2020. A dynamic OD prediction approach for urban networks based on automatic number plate recognition data. Transportation Research Procedia, 47, pp.601-608.

[10] Akhtar, Z. and Ali, R., 2020. Automatic number plate recognition using random forest classifier. SN Computer Science, 1(3), pp.1-9.

[11] Agrawal, R., Agarwal, M. and Krishnamurthi, R., 2020, March. Cognitive number plate recognition using machine learning and data visualization techniques. In 2020 6th international conference on signal processing and communication (ICSC) (pp. 101-107). IEEE.

[12] Qi, X., Ji, Y., Li, W. and Zhang, S., 2021. Vehicle trajectory reconstruction on urban traffic network using automatic license plate recognition data. IEEE Access, 9, pp.49110-49120.

[13] Zhang, Y., Qiu, M., Ni, Y. and Wang, Q., 2020, October. A Novel Deep Learning Based Number Plate Detect Algorithm under Dark Lighting Conditions. In 2020 IEEE 20th International Conference on Communication Technology (ICCT) (pp. 1412-1417). IEEE.

[14] Weihong, W. and Jiaoyang, T., 2020. Research on license plate recognition algorithms based on deep learning in complex environment. IEEE Access, 8, pp.91661-91675.

[15] Pustokhina, I.V., Pustokhin, D.A., Rodrigues, J.J., Gupta, D., Khanna, A., Shankar, K., Seo, C. and Joshi, G.P., 2020. Automatic vehicle license plate recognition using optimal K-means with convolutional neural network for intelligent transportation systems. Ieee Access, 8, pp.92907-92917.

[16] Henry, C., Ahn, S.Y. and Lee, S.W., 2020. Multinational license plate recognition using generalized character sequence detection. IEEE Access, 8, pp.35185-35199.

[17] Liu, Y., Yan, J. and Xiang, Y., 2020, September. Research on license plate recognition algorithm based on ABCNet. In 2020 IEEE 3rd International Conference on Information Systems and Computer Aided Education (ICISCAE) (pp. 465-469). IEEE.

[18] Silva, S.M. and Jung, C.R., 2021. A flexible approach for automatic license plate recognition in unconstrained scenarios. IEEE Transactions on Intelligent Transportation Systems.

[19] Wang, T., Zhu, Y., Jin, L., Luo, C., Chen, X., Wu, Y., Wang, Q. and Cai, M., 2020, April. Decoupled attention network for text recognition. In Proceedings of the AAAI conference on artificial intelligence (Vol. 34, No. 07, pp. 12216-12224).

[20] Zhang, L., Wang, P., Li, H., Li, Z., Shen, C. and Zhang, Y., 2020. A robust attentional framework for license plate recognition in the wild. IEEE Transactions on Intelligent Transportation Systems, 22(11), pp.6967-6976.

[21] Wang, Y., Bian, Z.P., Zhou, Y. and Chau, L.P., 2021. Rethinking and designing a high-performing automatic license plate recognition approach. IEEE Transactions on Intelligent Transportation Systems.

[22] Zhenbo Xu, Wei Yang, Ajin Meng, Nanxue Lu, Huan Huang, Changchun Ying, and Liusheng Huang, “Towards end-to-end license plate detection and recognition: A large dataset and baseline,” in Proceedings of the European Conference on Computer Vision, 2018, pp. 255–271.