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Deep Learning Based License Plate Recognition

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Abstract- **Now-a-days traffic violation is becoming a serious problem. This traffic violation may include parking problems, toll booth violations, wrong lane violations etc. Also day by day the number of vehicles is increasing. Hence the said violations are creating critical issues. In connection with this issue, the authors published their work under the heading of license plate detection and recognition (LPRS). They used different techniques for LPRS implementation. Recently a deep learning based LPRS depicted the promising results in the recognition of license plate. This paper reviews different LPRS implementation techniques and presents the deep learning based technique as in the purpose of LPRS.**

Index Terms- **Convolutional Neural Networks, Deep Learning, License Plate Recognition System.**

I. INTRODUCTION

A license plate detection and recognition (LPRS) is a part of a computer vision field. The computer vision filed is growing day by day with outputting challenging results by exploiting machine learning and deep learning techniques. A license plate is a principal identifier in vehicle transportation.

The implementation of LPRS systems mainly deals with the research areas such as Image processing, Computer Vision, Neural Networks Pattern Recognition, Artificial Intelligence etc.

The main motivation behind this work is to survey different LPRS techniques so that to develop a LPRS and such system could be used to automatically open a barrier into a secured area for only authorized persons. This may replace security guards at the barriers. Also such a LPRS could be utilized to identify a stolen vehicle. Whenever a stolen vehicle come across a LPRS enabled camera, then a guard will be alerted by LPRS system. In this application, the LPRS will play a crucial role.

The LPRS includes applications such as smart parking, Border security, toll booths, identification of stolen vehicles etc.

Basically the LPRS includes two steps as license plate detection and license plate recognition. The rest of the paper focuses on literature review of LPRS and also it considers one of the successful LPRS implementations. Later the paper describes LPRS methodology using CNN. The method is presented by Rohith Polishetty et al. in [28]. This paper considers the method of [28] as a part of LPRS methodology.

II. LITERATURE REVIEW

The authors published research work on LPRS. They worked with different methodologies and algorithms. Recently some of the authors considered cloud platform for LPRS implementation. In [28], different LPRS techniques are discussed. Here this paper includes the techniques which are discussed in [28]. This section considers the effort taken by various authors towards LPRS implementation [28].

V. Kamat and S. Ganesan [12] in 1995, to find the edges surrounded by the number plate, Hough transformation is applied

Kim K. K., Kim K. I., et al. [14] in 2000, Neural networks localize the license plate using colour features to classify the colours and regions using pixel based RBG image.

T. Naito, T. Tsukada, K [17] in 2000, the authors presented that the existing dynamic range of a conventional video camera is insufficient for license plate recognition purposes.

Y. Yanamura, M. Goto, D. Nishiyama et al. [9] in 2003, utilized techniques such as edge detection or threshold over a video sequence.

B. Hongliang and L.Changping [8] in 2004, edge detection or threshold techniques are utilized over a video sequence.

S. Yohimori, Y. Mitsukura, et al. [11] in 2004, to find the edges surrounded by the number plate, Hough transform is applied.

Abdullah, Siti Norul Huda Sheikh, et al. [2] in 2007, different feature extractors in recognition of license plate are compared.

Anagnostopoulos, Christos-Nikolaos E., et al. [10] in 2008, Connected Component Analysis (CCA) is a represented process that is effectively admissible towards low resolution videos.

Flores, Marco Javier, Jose Maria Armingol, et al. [18] in 2008, depending upon distance between the camera and vehicle, inclination of camera to the vehicle, and the lighting conditions, many difficulties are usually encountered in the experimental determination and theoretical estimation of reliable LPR properties.

T. Wang, D. Wu, A. Coates, and A. Y. Ng [21] in 2012, claimed an unsupervised learning as 3-Layer CNN for character classification with 2-way for class of text/non text and 62-way for word recognition.

Du, Shan, et al. [1] in 2013, different template matching techniques such as Mahalanobic distance, Bayes decision, Jacquards value; Hausdorff distance and the Hamming distance are claimed.

Zhang, Yi, Zhi Qiang Zha, and Lian Fa Bai [19] in 2013, template matching, and grey scale imaging to reduce brightness have been successfully performed in the past in various circumstances after resizing the characters.

Hsu, Gee-Sern, Jiun-Chang Chen, and Yu-Zu Chung [29] in 2013, AOLP database is composed and made available to the research community for the research purposes.

Anagnostopoulos, Christos-Nikolaos E. [15] in 2014, Genetic algorithm is presented to be a feasible option, however the relationship of brightness over the colour density plays a vital role in determining the aspect ratio of localization region.

M. Jaderberg, A. Vedaldi, and A. Zisserman [22] in 2014, Maxout and dropout technique claimed and the presented technique has better character classification.

B. Su and S. Lu [23] in 2014, Connectionist Temporal Classification (CTC) with RNN is presented for the application of word recognition.

P. He, W. Huang, Y. Qiao, C. C. Loy, and X. Tang [24] in 2015, extracted features from fully connected layer of CNN.

Li, Hui, and Chunhua Shen [30] in 2016, claimed that global and local features are collected by CNN.

Rohith Polishetty, Mehdi Roopaei, Paul Rad [28] in 2016, a cloud-based LPRS is addressed in the context of efficiency where accuracy and speed of processing plays a critical role towards its success. Signature-based features technique as a deep convolutional neural network in a cloud platform is proposed for plate localization, character detection and segmentation.

III. LPRS METHODOLOGY

In this work, ours proposed method is a LPDS (License Plate Detection System) which is based on a designed feature-based CNN with combination of ReLU and Conv in its layer for recognition phase. The ReLU attempts to find the character/number feature while the Conv recognizes the background with a featureweighting algorithm [28].

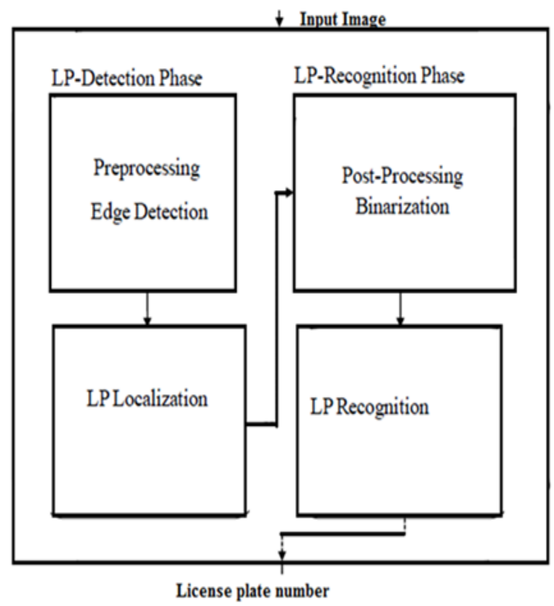

Fig. 1 LPDR System

The new structure of LP recognition extracts the character/number features and cluttered background features is also determined. This makes the algorithm more robust to many challenging conditions. The proposed LPDS algorithm speeds up the training phase using bare-metal cloud servers with cuDNN kernels optimized for K80 and M40 NVIDIA GPUs [28]. The Fig. 1 depicts the block diagram of LPDR system.

A] License Plate Pre-processing

It is the first step of car LPDS. In this process, a gray scale format of the vehicle image used as an input and then canny edge detection is applied to enhance the required sharpening of the image to make a feed for the first designed CNN as detection phase [28].

B] License Plate Detection-Localization

Firstly, feature filtering mechanism is used to detect boundary box of the LP. The detected boundary, feature window (FW) for LP is localized by a series of CNN normalization and pooling methods [28].

The License Plate Detection-Localization goes through different steps. The algorithm for this detection is shown below [28]. It comprises of image preprocessing, feature selection and feature extraction. And finally we get output as a detected license plate in which we are interested as shown in Fig. 2. The next step is license plate character recognition.

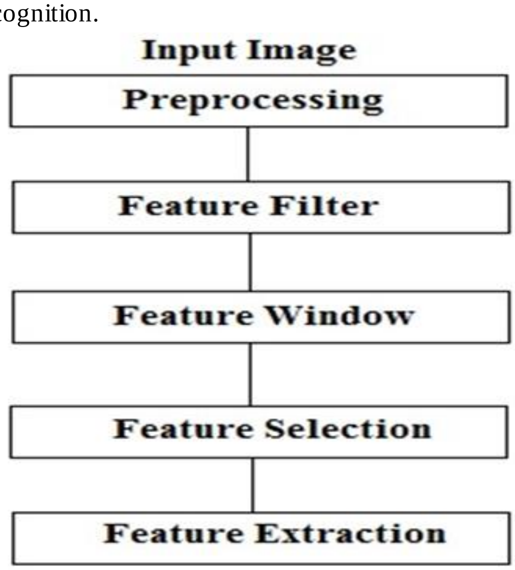

Fig. 2 Feature Localization and Feature Extraction [28]

C] License Plate Character Recognition

The last step is recognition of the license plate features convolutional neural networks. The first step in this process is license plate binarization. The extracted license plate from Phase - I is binarized for improving the image contrast that is beneficial for accuracy of number recognition [28]. The license plate recognition step receives input from license plate detection step as detected license plate. Then it goes through the step of ReLU and ConvNet. It is then forwarded through feature weighting and the last step is normalization a shown in Fig. 3.

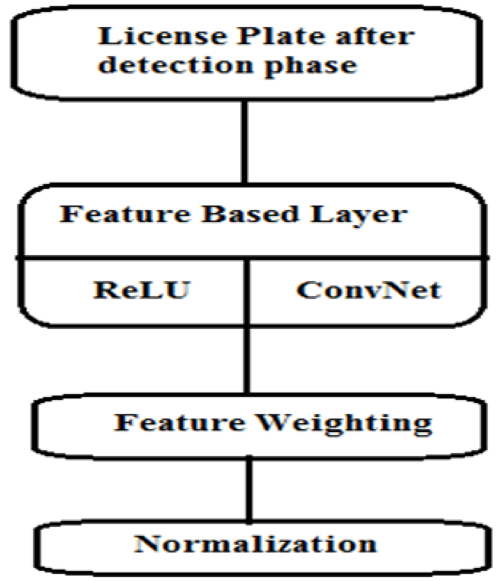

Fig. 3 Feature Extraction in CNN Recognition Architecture [28]

The authors found that global threshold and Edge based binarization are best suited for these scenarios producing better results for number recognition. These two methods for binarization use multiple threshold values to segment foreground regions to create higher contrast license plate images for number recognition [28].

D] Feature Map Selection

This Visual Saliency extracts the license plate. The main purpose of the saliency map is to represent the “conspicuity” or “saliency” at every location in the visual field by a scalar quantity and to guide the selection of attended locations. A combination of the feature maps is modeled as a dynamical NN (Neural Network). It provides bottom-up input to the saliency map [28].

IV. RESULT AND DISCUSSION

The output is in the form of detected image and the recognized image. The below Fig. 4 indicates the output of the LPRS system [20]. The red rectangle shows ground-truth while green rectangle depicts the proposed system’s detection result. The yellow tag indicates the license plate recognition result. The evaluation criterion for the LPRS system includes two terminologies as Precision and Recall [28].

Fig. 3 Image detection and recognition

The precision can be evaluated as below.

$$Precision = \frac{Number\ of\ correctly\ detected\ license\ plate}{Total\ number\ of\ detected\ regions}$$

And the Recall can be evaluated as below

$$Recall = \frac{Number\ of\ correctly\ detected\ license\ plate}{Total\ number\ of\ groundtruth}$$

The results of LPRS implementation [28] are tabulated in Table 1. It gives the accuracy of the proposed algorithm in the terms of Precision and Recall for various datasets. It gives the evaluation for both phases including LP detection and LP recognition. The proposed method gives good accuracy in both the phases. Table 2 gives the comparison of different methods with AOLP (Application Oriented License Plate) database. A compared to other methods, the proposed method gives best results in the form of Precision and Recall

Table 1 Accuracy of the proposed algorithm [28]

Dataset / Phase	Caltech Cars (%)	AC (%)	LE (%)	RP (%)	VGG Oxford (%)	Media Lab LPR (%)
LP Detection	93.67	96.73	94.56	95.34	96.45	97.34
LP Recognition	94.28	98.87	97.12	98.64	95.12	94.46

Table 2 Comparison of different methods with AOLP database

Data / Approach	AOLP_AC		AOLP_LE		AOLP_RP	
	Precision	Recall	Precision	Recall	Precision	Recall
Hsu *et al.*	91	96	91	95	91	94
Li *et al.*	98.53	98.38	97.75	97.62	95.28	95.58
Proposed Method	98.93	98.87	98.34	96.81	96.28	97.43

V. CONCLUSION

The LPRS techniques need to be implemented or checked with various techniques. The modern techniques- machine learning and deep learning should be also adopted in connection with LPRS techniques. This paper explained about the concept of LPRS. It focused on different LPRS techniques. It reviewed various papers published recently in the field of LPRS. As per the results, the LPRS using CNN gives the best result. The future scope of this work is to implement LPRS technique based on new algorithms of deep learning to get best results as a part of license plate detection and recognition.

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REFERENCES

[1] Du, Shan, et al. "Automatic license plate recognition (ALPR): A state-of-the-art review." IEEE Transactions on circuits and systems for video technology 23.2 (2013): 311-325.

[2] Abdullah, Siti Norul Huda Sheikh, et al. "Comparison of feature extractors in license plate recognition." Modeling & Simulation, 2007. AMS'07. First Asia International Conference on. IEEE, 2007.

[3] Hsieh, Ching Tang, and Yu-Shan Juan. "Wavelet transform based license plate detection for cluttered scene." WSEAS Transactions on Computers 4.1 (2005): 40-44.

[4] Sulehria, Humayun Karim, Danish Irfan Ye Zhang, and Atif Karim Sulehria. "Vehicle number plate recognition using mathematical

morphology and neural networks." WSEAS Transactions on Computers 7 (2008).

[5] Sulehria, Humayun K., Ye Zhang, and Danish Irfan. "Mathematical Morphology Methodology for Extraction of Vehicle Number Plates." International journal of computers 1.3 (2007): 69-73.

[6] Villegas, Osslan Osiris Vergara, et al. "License plate recognition using a novel fuzzy multilayer neural network." International journal of computers 3.1 (2009): 31-40.

[7] Available:http://itsdeployment2.ed.ornl.gov/technology_overview/

[8] B. Hongliang and L.Changping, "A hybrid license plate extraction method based on edge stastistics and morphology," Proc. IEEE 17th Int. Conf. Pattern Recognition., vol.2, pp.831-834.

[9] Y. Yanamura, M. Goto, D. Nishiyama, M. Soga, H. Nakatani, and H. Saji, "Extraction and tracking of the license plate using Hough transform and voted block matching," in Proc. IEEE Intell. Vehicles Symp., Piscataway, NJ, 2003, pp. 243-246.

[10] Anagnostopoulos, Christos-Nikolaos E., et al. "License plate recognition from still images and video sequences: A survey." IEEE Transactions on intelligent transportation systems 9.3 (2008): 377-391.

[11] S. Yohimori, Y. Mitsukura, M. Fukumi, N. Akamatsu, and W. Pedrycz, "License plate detection system by using threshold function and improved template matching method," in Proc. NAFIPS, 2004, pp. 357-362.

[12] V. Kamat and S. Ganesan, "An efficient implementation of the Hough transform for detecting vehicle license plates using DSP's," in Proc. Real-Time Technol. Appl. Symp., 1995, pp.58-59.

[13] F. Kahraman, B. Kurt, and M. Gokmen, "License plate character segmentation based on the Gabor transform and vector quantization," in Proc. ISCIS, 2003, pp. 381-388.

[14] Kim K. K., Kim K. I., Kim J. B. and Kim H. J., "Learning-based Approach for License Plate Recognition", Proceedings of the IEEE Signal Processing Society, vol. 2, 2000, pp.614-623.

[15] Anagnostopoulos, Christos-Nikolaos E. "License Plate Recognition: A Brief Tutorial." IEEE Intell. Transport. Syst. Mag. 6.1 (2014): 59-67.

[16] [Online].Available:http://www.ezcctv.com/license-platerecognition.htm

[17] T. Naito, T. Tsukada, K. Yamada, K. Kozuka, and S. Yamamoto, "Robust license-plate recognition method for passing vehicles under outside environment," IEEE Trans. Veh. Tech., Vol. 49, no. 6, pp.2309–2319, Nov. 2000.

[18] Flores, Marco Javier, Jose Maria Armingol, and Arturo de la Escalera. "Real-time drowsiness detection system for an intelligent vehicle" Intelligent Vehicles Symposium, IEEE, 2008.

[19] Zhang, Yi, Zhi Qiang Zha, and Lian Fa Bai. "A license plate character segmentation method based on character contour and template matching." Applied Mechanics and Materials. Vol. 333. Trans Tech Publications, 2013.

[20] Li, Hui, and Chunhua Shen. "Reading Car License Plates Using Deep Convolutional Neural Networks and LSTMs." arXiv preprint arXiv: 1601.05610 (2016).

[21] T. Wang, D. Wu, A. Coates, and A. Y. Ng, "End-to-end text recognition with convolutional neural networks," in Proc. IEEE Int. Conf. Patt. Recogn., 2012, pp. 3304–3308.

[22] M. Jaderberg, A. Vedaldi, and A. Zisserman, "Deep features for text spotting," in Proc. Eur. Conf. Comp. Vis., 2014, pp. 512–528.

[23] B. Su and S. Lu, "Accurate scene text recognition based on recurrent neural network," in Proc. Asi. Conf. Comp. Vis., 2014, pp. 35–48.

[24] P. He, W. Huang, Y. Qiao, C. C. Loy, and X. Tang, "Reading scene text in deep convolutional sequences," Technical report, 2015. [Online]. Available: http://arxiv.org/abs/1506.04395

[25] Chetlur, Sharan, et al. "cuDNN: Efficient primitives for deep learning." arXiv preprint arXiv: 1410.0759 (2014).

[26] Harris, Chris, and Mike Stephens. "A combined corner and edge detector." Alvey vision conference. Vol. 15. 1988.

[27] Buades, Antoni, Bartomeu Coll, and J-M. Morel. "A non-local algorithm for image denoising." 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05). Vol. 2. IEEE, 2005.

[28] Rohith Polishetty, Mehdi Roopaei, Paul Rad. "A Next-Generation Secure Cloud-Based Deep Learning License Plate Recognition for Smart Cities", 15th IEEE International Conference on

Machine Learning and Applications, pp. 287-294, 2016.

[29] Hsu, Gee-Sern, Jiun-Chang Chen, and Yu-Zu Chung" Application-oriented license plate recognition" IEEE transactions on vehicular technology 62.2 (2013): 552-561.

[30] Li, Hui, and Chunhua Shen. "Reading Car License Plates Using Deep Convolutional Neural Networks and LSTMs." arXiv preprint arXiv: 1601.05610, 2016.