RESEARCH ARTICLE OPEN ACCESS

Comparison of Algorithms in License Plate Recognition Using Convolutional Neural Network

Isa Javadov*, Ahmet Gurhanli**
**(Department of Computer Engineering, Istanbul Aydin University, Turkey*
***(Department of Computer Engineering, Istanbul Aydin University, Turkey*

ABSTRACT
With the development of technology and increasing smart cities, the number of vehicles in the countries has also incremented. With the increasing number of vehicles, the needs such as traffic controls and security controls have enlarged, and it has been difficult to follow each vehicle. Therefore, there was a need to improve the License Plate Recognition area. In this study, plate recognition has three stages. These stages are finding the plate region, character decomposition and character recognition methods. Before these stages, the image should be made clearer with some operations. Capturing and perceiving the image in flowing traffic is very difficult due to factors such as light and speed. This article first detects tools for License Plate Recognition, then applies a Convolutional Neural Network for character recognition on uncertain images and compares seven optimization algorithms. The results have been shown that accuracy and training time are superior compared to old plate recognition methods.
Keywords – Character Recognition, Convolutional Neural Network, Flowing Traffic, License Plate Recognition

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Date of Submission: 05-10-2020 Date of Acceptance: 19-10-2020

I. INTRODUCTION

With the increase in population and people living in more crowded cities, the number of vehicles has also increased. The increase in the number of vehicles made it difficult to track the vehicles.

License Plate Recognition is widely used by law enforcement agencies to track moving or stationary vehicles and provide security controls of these vehicles. License Plate Recognition is used to identify vehicle owners who do not comply with traffic rules. In addition, it is easily used in many places in life such as vehicle tool collection system.

In older methods, image processing was frequently used to perform license plate recognition. However, features such as dirty image and low contrast have made this method very difficult to use and therefore, a lot of pre-processing is required.

Convolutional Neural Network includes algorithms such as computing and image processing. So, Convolutional Neural Network accepts pre-processed input images and trains these preprocessed images with supervised learning

The main contribution of this study is that it does not require much preprocessing to determine the best model according to the results of the seven algorithms in terms of training time and accuracy. This study was trained on 29260 samples and confirmed on 7316 samples.

II. METHODOLOGY

There are many methods recommended and used for License Plate Recognition. While starting this study, considering the advantages and disadvantages of many studies, the best method was tried to be applied. Initially, some operations should be done to find the license plate region in the captured car images. Second, the characters in the license plate area must be extracted. Finally, the characters are given to the Convolutional Neural Network algorithms determined for recognition and plate recognition is completed. Convolutional Neural Network was used to recognize the characters extracted in the last stage. and this process was completed using seven optimization algorithms.

In this section, seven algorithms for License Plate Recognition are reviewed. It is necessary to some process before each algorithm applying Convolutional Neural Network. These seven algorithms were compared the accuracy value given in the test data set and how long it trained the algorithms.

2.1. Finding the Plate Region

A series of procedures must be performed to find the plate region with Convolutional Neural Network. Snapshots captured in License Plate Recognition system are in RGB format. The images in this format are converted to a gray format because the computer cannot calculate RGB format images. After that, the image converted to gray format is processed with Sobel Edge Detection algorithm. Histogram of the edge detection process is manufactured. The threshold value is determined to determine the regions that are not likely to be plates. And the horizontal and vertical columns of the histogram chart are examined, and the plate region is found by means of the average edge detection method. Then image binarization process is done and the plate is seen more clearly. Image binarization is the process of taking a grayscale image and converting it to black-and-white. Finding the plate region in the captured images is shown in Fig.1.

Fig.1 Finding the Plate Region

2.2. Character Extraction

With the last step, only the plate region remains in the image. After this step, the Connected Component Analysis is used to parse the characters on the plate region. Thus, each character is output as a separate image for character recognition.

2.3. Character Recognition

Characters extracted from the source image, where plate characters were introduced before, are searched as templates. This method is called Template Matching method. The training set of the Convolutional Neural Network was created with the visuals containing images the plate characters. The extracted characters are given to the Convolutional Neural Network as test data and the previously prepared sample template characters and the decomposed characters are compared. In this way, character recognition is made.

After most recent stage, the image is an input for optimization algorithms to be tested. The images where the above processes are applied are tried in all seven Gradient Descent optimization algorithms and the results are compared in terms of training time and accuracy.

III. COMPARISION OF ALGORITHMS LICENSE PLATE RECOGNITION

This section is the main part where the license plate recognition process takes place. In this section, seven optimization algorithms are compared in terms of training time and accuracy and Python language and Keras library are used. These algorithms are Stochastic Gradient Descent (SGD), RMSProp, Adagrad, AdaDelta, Adam, Adamax and Nadam optimization algorithms.

Brief explanation of the compared algorithms is given below.

SGD with Momentum: This method suppresses the oscillations in the SGD algorithm and speeds up the learning time [24].

RMSprop: This algorithm proposes an adaptive learning rate, it is not published, but introduced in Geoff Hinton’s course. [25]

AdaGrad: AdaGrad provides big updates for sparse parameters, while smaller updates for frequent parameters. It performs best at default values like RMSprop. The algorithm has a separate learning rate that is specific to each parameter. [26]

AdaDelta: AdaDelta is the developed version of AdaGrad. There is no need to determine the initial learning rate. It performs best at default values. [27]

Adam: Adam is an algorithm like AdaDelta. Unlike AdaDelta, it stores the Momentum changes in the cache as well as the learning rates of each parameter [28].

Adamax: It is like the Adam algorithm, but it shows the best performance at default values [28].

Nadam: It is a combination of Adam algorithm and Nesterov Momentum. It performs best at default values [29].

These seven optimization algorithms were used for this study and their comparative results were obtained. This study showed that using Convolutional Neural Network compared to the old methods has enabled plate recognition to be done faster.

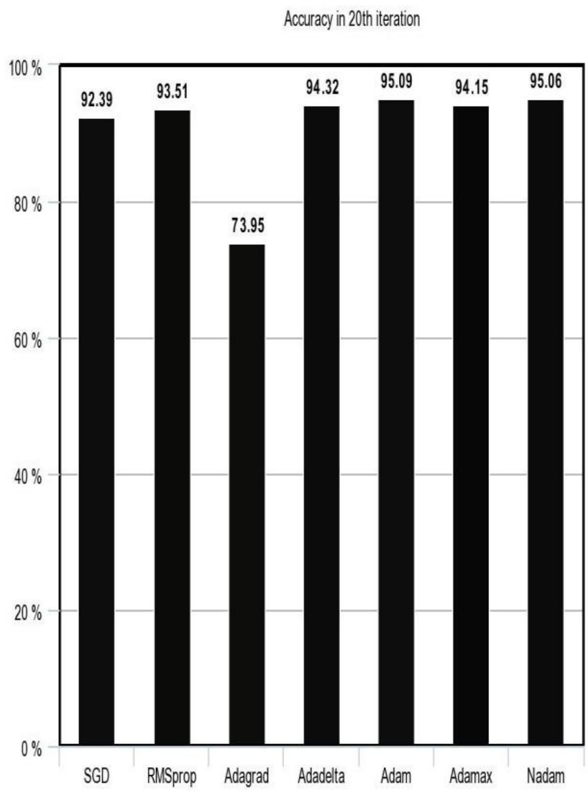
In this study, 29260 images were taken at different times of the day and distances and confirmed on 7316 samples. The License Plate Recognition system tries these images one by one in the specified algorithms and evaluates the results in terms of accuracy and training time.

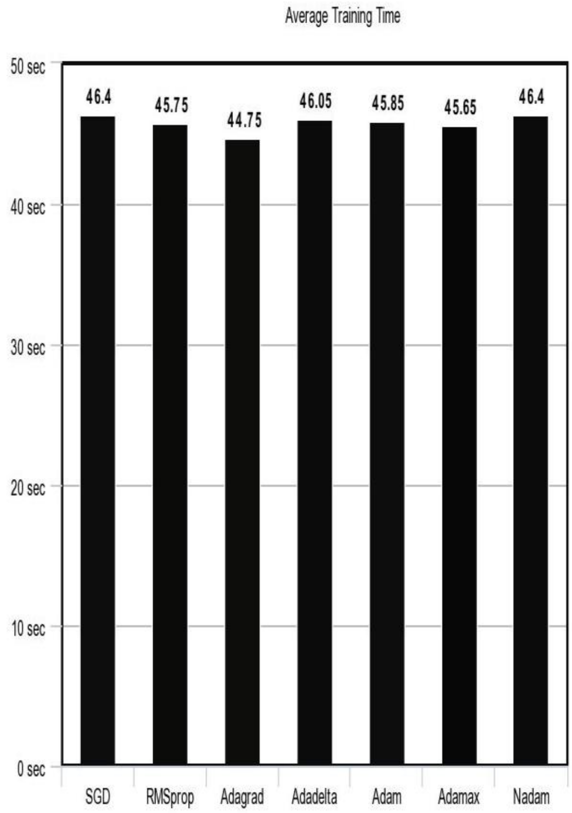
The computer, where the algorithms are trained, has Intel® Core ™ i7, Turbo Boost up to 4.5 GHz and 12 MB shared L3 cache, and AMD Radeon Pro 5300M with 4GB of GDDR6 memory and automatic graphics switching. It also has 16 GB of storage space.

The comparative result of these seven optimization algorithms are shown in Table-1. The training time and accuracy values can be increased by feeding the system with more data sets and adjusting the images given as input more cleanly.

Table 1 Comparison of Algorithms

Optimization Algorithm	Average training time (sec)	Accuracy in 1st iteration (%)	Accuracy in 20th iteration (%)
SGD	46.40 sec	% 6.68	% 92.39
RMSprop	45.75 sec	% 52.61	% 93.51
AdaGrad	44.75 sec	% 5.21	% 73.95
AdaDelta	46.05 sec	% 23.76	% 94.32
Adam	45.85 sec	% 44.40	% 95.09
Adamax	45.65 sec	% 12.53	% 94.15
Nadam	46.40 sec	% 47.84	% 95.06





IV. CONCLUSION

In this Plate Recognition System, in which random plate images are trained, Artificial Neural Networks were compared with 7 Optimization algorithms without preprocessing and the results were measured. With the applied methods, recognition was made with the characters removed from the plate region, which was detected quickly. This study, tested in seven algorithms and validated on 7316 different samples, showed that the Adam algorithm has the highest accuracy. The fastest algorithm has been proved to be the AdaGrad algorithm but since its accuracy is very low, it may not be a good choice.

REFERENCES

[1]. Atali G, Özkan S, Karayel D. “Morfolojik Görüntü İşleme Tekniği ile Yapay Sinir Ağlarında Görüntü Tahribat Analizi” APJES IV-I 2016.
[2]. Çevik K.K., Çakır A., “Görüntü İşleme Yöntemleriyle araç plakalarının tanınarak kapı kontrolünün gerçekleştirilmesi”, AKÜ, Fen bilimleri dergisi 2010.
[3]. Çelik U., Oral M., “Motorlu araçlar için plaka tanıma sistemi”. Elektrik-Elektronik-Bilgisayar Mühendisliği 10. Ulusal kongresi 2003.

[4]. Göçerler B “Yapay zekâ tabanlı plaka tanıma ile bariyer kontrolü”. Yüksek Lisans Tezi, Trakya Üniversitesi Fen Bilimleri Enstitüsü, Edirne 2005.

[5]. Başkurt M, Durmuş M, C Gümüşay M.Ü. “Yapay sinir ağları yardımıyla plaka tanıma sisteminin oluşturulması ve CBS ile bütünleştirilmesi” 13. Türkiye Harita Bilimsel ve Teknik Kurultayı, 2011.

[6]. Bakkaloğlu, “Araç Plaka Tanıma Sistemi”, Yüksek Lisans Tezi, Selçuk Üniversitesi Fen Bilimleri Enstitüsü, Konya, 2011.

[7]. D. Zheng, Y. Zhao, and J. Wang, “An efficient method of license plate location,” Pattern Recognition Letters, vol. 26, no. 15, pp. 2431–2438, 2005.

[8]. T. Avery and G. Berlin Fundamentals of Remote Sensing and Airphoto Interpretation, Maxwell Macmillan International, 1985, Chap. 15.

[9]. D. Ballard and C. Brown Computer Vision, Prentice-Hall, 1982, Chap. 2.

[10]. E. Davies Machine Vision: Theory, Algorithms and Practicalities, Academic Press, 1990, Chap. 6.

[11]. R. Gonzalez and R. Woods Digital Image Processing, Addison-Wesley Publishing Company, 1992, Chap. 2.

[12]. B. Horn Robot Vision, MIT Press, 1986, Chap. 4.

[13]. D. Vernon Machine Vision, Prentice-Hall, 1991, pp 34- 36.

[14]. Shapiro, Vladimir, Gluhchev, Georgi, Dimov, Dimo, “Towards a Multinational Car License Plate Recognition System” MVA (17), No. 3, pp. 173-183, 2006.

[15]. L. Dlagnekov “License Plate Detection Using AdaBoost”. La Jolla: Comput. Sci. Eng. Dept., Univ. California San Diego, Mar. 2004.

[16]. H. Chidiac, D. Ziou, “Classification of Image Edges”,Vision Interface’99, Troise-Rivieres, Canada, pp. 17-24, 1999.

[17]. Muhammad Sarfraz, Mohammed Jameel Ahmed, Syed A. Ghazi, "Saudi Arabian License Plate Recognition System," gmag, pp.36, 2003 International Conference on Geometric Modeling and Graphics (GMAG'03), 2003.

[18]. C.-T. Hsieh, Y.-S. Juan, and K.-M. Hung, “Multiple license plate detection for complex background” in Proc. Int Conf. AINA, 2005, vol. 2, pp. 389–392.

[19]. S. Du, M. Ibrahim, M. Shehata, and W. Badawy. “Automatic license plate recognition (ALPR): A state-of-the-art review”. Circuits and Systems for Video Technology, IEEE Trans. on, 23(2):311-325, 2013.

[20]. J. Redmon. Darknet: Open source neural networks in c. http://pjreddie.com/darknet/, 2013-2016.

[21]. Herbert Robbins and Sutton Monro A Stochastic Approximation Method The Annals of Mathematical Statistics, Vol. 22, No. 3. (Sep. 1951), pp. 400-407.

[22]. J. Kiefer and J. Wolfowitz Stochastic Estimation of the Maximum of a Regression Function Ann. Math. Statist. Volume 23, Number 3 (1952), 462-466

[23]. Leon Bottou and Frank E. Curtis and Jorge Nocedal Optimization Methods for Large-Scale Machine Learning, Technical Report, arXiv:1606.04838

[24]. Ning Qian. On the momentum term in gradient descent learning algorithms. Neural networks : the official journal of the International Neural Network Society, 12(1):145–151, 1999.

[25]. http://www.cs.toronto.edu/~tijmen/csc321/slides/lecture_slides_lec6.pdf

[26]. John Duchi, Elad Hazan, and Yoram Singer. Adaptive Subgradient Methods for Online Learning and Stochastic Optimization. Journal of Machine Learning Research, 12:2121–2159, 2011.

[27]. Matthew D. Zeiler. ADADELTA: An Adaptive Learning Rate Method. arXiv preprint arXiv:1212.5701, 2012.

[28]. Diederik P. Kingma and Jimmy Lei Ba. Adam: a Method for Stochastic Optimization. International Conference on Learning Representations, pages 1–13, 2015.

[29]. Timothy Dozat. Incorporating Nesterov Momentum into Adam. ICLR Workshop, (1):2013–2016, 2016.