Benchmarking Algorithms for Automatic License Plate Recognition

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Abstract—We evaluated a lightweight Convolutional Neural Network (CNN) called LPRNet [1] for automatic License Plate Recognition (LPR). We evaluated the algorithm on two datasets, one composed of real license plate images and the other of synthetic license plate images. In addition, we compared its performance against Tesseract [2], an Optical Character Recognition engine. We measured performance based on recognition accuracy and Levenshtein Distance. LPRNet is an end-to-end framework and demonstrated robust performance on both datasets, delivering 90 and 89 percent recognition accuracy on test sets of 1000 real and synthetic license plate images, respectively. Tesseract was not trained using real license plate images and performed well only on the synthetic dataset after pre-processing steps delivering 93 percent recognition accuracy. Finally, Pareto analysis for frequency analysis of misclassified characters allowed us to find in detail which characters were the most conflicting ones according to the percentage of accumulated error. Depending on the region, license plate images possess particular characteristics. Once properly trained, LPRNet can be used to recognize characters from a specific region and dataset. Future work can focus on applying transfer learning to utilize the features learned by LPRNet and fine-tune it given a smaller, newer dataset of license plates.

Index Terms—License Plate Recognition, Computer Vision, Convolutional Neural Network, Optical Character Recognition, Pareto analysis

I. INTRODUCTION

License Plate Recognition (LPR) aims at accurately retrieving a digital string of characters given a License Plate image. The retrieved digitalized License Plate can be stored in a database to perform several tasks automatically for different applications such as Vehicle Traffic Management, Parking Tolls, Digital Surveillance Systems, and Access Control to Buildings. LPR is a solution that allows automatic vehicle control, reducing costs on human labor. Moreover, in some populated countries, the number of vehicles on the streets grows faster than the number of inhabitants. For example, between 1990 and 2015, the vehicle growth rate was 3.5 faster than the growth rate of the Mexican population [3]. In Bolivia, the number of vehicles grew by 38 percent between 2014 and 2019 [4]. Therefore, automatic LPR systems are considered to help automate transportation, its management, and security.

In this study, we evaluated the performance of a deep network called LPRNet [1]. We performed tests on two license plates datasets. In addition, we compared its performance against Tesseract [2]. While LPRNet was designed to recognize characters from license plates, Tesseract is generally used to recognize characters from documents. Since we had a synthetic dataset available for tests, we selected Tesseract as a baseline for comparison, at least on the synthetic images. We were also interested in testing if LPRNet was able to maintain its performance when trained on a different dataset, given that license plates on each country have unique characteristics. We assumed that a robust system should recognize characters independently of the dataset in use if adequately trained. Besides, we expected LPRNet to be similarly good either on a real and a synthetic dataset. We evaluated recognition accuracy using a test dataset containing 1000 real license plates images [1] and a subset from a dataset of synthetic license plates images [5], with 10000 images for training and 1000 images for testing.

The contribution of this study is the benchmarking of LPRNet [1] and Tesseract [2] for automatic license plate recognition on two different datasets and the proposal of a framework based on Pareto Analysis [6] for conflicting characters detection. The article is organized as follows, section II presents the problem statement, section III the proposed solution with both analyzed algorithms, section III-C describes the datasets, pre-processing, and evaluation metrics, section IV presents the experiments and results. Finally, we conclude in section V.

II. PROBLEM STATEMENT

License Plate Recognition is an application of computer vision for intelligent transportation. Deep learning architectures are currently used to retrieve characters from license plates. Previous models included a segmentation step before recognizing each character, combined with heuristics from the dataset in question [7]. More recently, end-to-end architectures automatically allow learning properties from raw images for their predictions. End-to-end eliminates the need for intermediate pre-processing steps such as segmentation, thresholding, or the use of heuristics. The advantage of an automatic end-to-end system over a system that relies on heuristics is that by training the model on the dataset in use, the system should be able to discover relevant features on its own.

III. THE PROPOSED SOLUTION

We selected LPRNet for our experiments because its implementation allowed us to train the network from scratch using a selected dataset. Since the alternative dataset we had
at disposal for testing was a dataset of synthetic images, we compared LPRNet’s performance against Tesseract, which is generally used for Optical Character Recognition from documents. Although Tesseract might not be a natural selection for our application, it allowed us to benchmark LPRNet on the alternative synthetic dataset. If the evaluated algorithms prove to adapt to different datasets, we could expect them to work on a newly collected dataset, given that license plates posses unique characteristics from their particular region.

A. LPRNet

Convolutional Neural Networks (CNNs) are deep learning models delivering state-of-the-art results in computer vision [8]. These models simulate neural activation and hierarchical brain processing. In perceptual tasks, CNNs demonstrate to learn relevant representations that are robust to data variability. CNNs learn suitable filters or feature maps on each processing layer, given input images for recognition.

LPRNet is a fast CNN that inputs RGB images of 94x24 pixels and outputs a sequence of characters [1]. After all convolutional layers, it follows batch normalization and ReLU activation. LPRNet’s architecture is designed to be lightweight and has two main components, a Backbone and Small Basic Blocks. LPRNet uses Connectionist Temporal Classification (CTC) to control the loss for training as end-to-end learning instead of a segmentation process. The Backbone architecture of the network can be seen in Table I, and the architecture of the Small Basic Blocks can be seen in Table II. This network was trained with Adam optimizer, batch size 32, gradient noise reduction filter [9]. In addition, PNG images were converted to JPG format.

1. Input 94x24 Pixels RGB image
2. Convolution Filters 64, 3x3, stride 1
3. Max Pooling Filters 64, 3x3, stride 1
4. Small Basic Block Filters 128, 3x3, stride 1
5. Max Pooling Filters 64, 3x3, stride (2,1)
6. Small Basic Block Filters 256, 3x3, stride 1
7. Max Pooling Filters 64, 3x3, stride 1
8. Dropvout 0.5 ratio
9. Convolution Number of class number, 1x13, stride 1

| Layer Type | Parameters |
|------------|------------|
| Input      | 94x24 Pixels RGB image |
| Convolution| Filters 64, 3x3, stride 1 |
| Max Pooling| Filters 64, 3x3, stride 1 |
| Small Basic Block| Filters 128, 3x3, stride 1 |
| Max Pooling| Filters 64, 3x3, stride (2,1) |
| Small Basic Block| Filters 256, 3x3, stride 1 |
| Max Pooling| Filters 64, 3x3, stride 1 |
| Dropout    | 0.5 ratio |
| Convolution| Number of class number, 1x13, stride 1 |

TABLE I: The LPRNet backbone structure from [1].

D. Data Pre-Processing

Turkish dataset images were rescaled to 94x24 pixels to match the dimensions of the Chinese dataset. We used an antialiasing method, which uses a high-quality resolution reduction filter [9]. In addition, PNG images were converted to JPG format.

B. Tesseract

Tesseract [2] is an open source for Optical Character Recognition that expects binary images and outputs a digital string of characters per input. First, Tesseract uses Adaptive Thresholding to binarize images, followed by Connected Component Analysis to find lines and words which are organized as units. Then, if a word is recognized, it aims at finding edges of characters that match their training set. Tesseract was originally trained using 60 160 samples of 94 characters, with 20 samples per class in 8 fonts and 4 presentations: normal, italic, bold, and bold-italic [2].

C. Data Sets

We used two datasets. The first dataset consists of Chinese license plates dataset with 1 000 RGB real images sized 94x24 pixels, JPG format [1]. The images are characterized by being taken at different angles and in real situations; see Fig. 1a. The second dataset consists of a subset from the Synthetic Turkey license plates [5]. We selected the images at random. We used 10 000 images for training and 1000 images for testing. The images are sized 1025x218 pixels in PNG format. The license plates of this dataset are synthetic images designed in a single frontal view, see Fig. 1b.

![Chinese dataset (Real License Plate)](image1)

![Turkey dataset (Synthetic License Plate)](image2)

Fig. 1: Examples of images per dataset [1], [5]. 1a, Chinese dataset (real) and 1b, Turkey dataset (synthetic).

E. Pre-Processing for Tesseract

Initially, Tesseract delivered poor results on the synthetic dataset. Therefore, we extracted the interest region as seen in Fig. 2. Once the interest region was extracted, Tesseract was able to recognize characters accurately from the synthetic Turkey dataset. However, it was not able to recognize characters from the Chinese dataset. Therefore, we applied image manipulation techniques such as thresholding and binarization before sending the images to Tesseract, but they did not yield significant changes.

![01 D 4075](image3)
F. Evaluation metrics

We used two metrics for evaluation. First, we evaluated accuracy expressed as:

\[
Accuracy = \frac{TP}{TP + TN_1 + TN_2}
\]  

(1)

where True Positive (TP) is the correct classification of the license plate, True Negative \(TN_1\) represents a misclassification when the lengths of the strings between label and prediction are different, and \(TN_2\) represents a misclassification when the string lengths are equal. This measure only considers the fraction of fully correctly classified license plates over correctly classified and misclassified license plates. However, it could be that a misclassified license plate contains more than one erroneous character.

Therefore, we also used the Levenshtein distance between the ground truth labels and the algorithms’ outputs. Levenshtein distance measures the smallest number of insertions, deletions, or substitutions needed to transform one sequence of characters to another [10]. See an example in Table III.

| License Plate | Classification | Levenshtein Distance |
|---------------|----------------|----------------------|
| 16 IJ 522    | 16WW522        | 2                    |
| 55 L 3929    | 55L3928        | 1                    |

TABLE III: Examples of Levenshtein Distance. License plates, classification and corresponding Levenshtein Distance.

IV. RESULTS

We evaluated LPRNet and Tesseract on the synthetic Turkey license plates dataset, as seen in Table IV. Only LPRNet was evaluated on the real Chinese license plates dataset because we could not train Tesseract on this dataset. We evaluated license plate recognition considering mean accuracy and mean Levenshtein distance. In all cases, we used a test set of 1000 images. We tested the pre-trained LPRNet network. This network was pre-trained on a dataset with 11,696 Chinese license plates [1]. On a test set of 1000 images, LPRNet delivered a mean accuracy of 90 percent and a low mean Levenshtein of 0.047. For the Turkey dataset, images were resized and then converted from RGB to BGR. We re-trained the network with 10,000 Turkey license plates, obtaining 88.6 percent mean accuracy and mean Levenshtein of 0.3 on a test set of 1000 images.

Tesseract was not trained. On the Chinese test set of 1000 images, Tesseract could not recognize characters. Preliminary tests on the Turkey dataset did not deliver good results either. Therefore, we performed the pre-processing tasks described in section III-E. We cropped all license plates such that images contained only characters. Then, Tesseract delivered up to 93 percent mean accuracy and a low mean Levenshtein distance.

We wondered if Tesseract could deliver similar performance for the Chinese license plates dataset if re-trained on this dataset. However, training Tesseract was out of our possibilities. LPRNet proved robust and appropriate for use on different datasets if properly trained. It is known that for deep learning networks, the more samples for training, the better the results [11]. Our training set for the synthetic dataset was smaller than the training dataset of the real images. It seems possible that with a larger dataset for training, the performance of LPRNet could improve. Given that dataset collection is a costly process, transfer learning could be applied when using LPRNet on a new and much smaller dataset.

Fig. 3, Fig. 4 and Fig. 5 show a subsample of randomly selected plates that were misclassified by each algorithm. Table V summarizes the number of misclassified license plates on each dataset. In some cases, the length of the output string is the same length as that of the target string. In other cases, the length of the output string has a different length than that of the target string. In the next section, we evaluated misclassified characters of outputs with the same length.

Tesseract analysis

We used Pareto analysis for both algorithms (Tesseract and LPRNet) to identify misclassified license plates, where the predicted output had the same length as the target string. Pareto analysis obtains a percentage of frequency of misclassified

| Algorithm | Pre-Processing | Dataset Description | Mean Accuracy | Mean Levenshtein Distance |
|-----------|----------------|---------------------|---------------|---------------------------|
| LPRNet    | -              | Chinese Real Images | 0.900         | 0.047                     |
| LPRNet    | Resize, RGB to BGR | Synthetic Turkey Images | 0.886         | 0.030                     |
| Tesseract | Resize, Crop   | Synthetic Turkey Images | 0.933         | 0.054                     |

TABLE IV: Benchmarking LPRNET and Tesseract on real Chinese and synthetic Turkey License Plates datasets. LPRNet’s mean accuracy on both datasets is 89 percent. Tesseract achieves 93 percent accuracy on the synthetic dataset.
Fig. 3: Sample of 5 plates out of 100 misclassified by LPRNet on Chinese dataset.

| Plate   | LPRNet misclassification |
|---------|--------------------------|
| 皖AC585D |                          |
| 皖AJ1542 |                          |
| 皖NX589Y |                          |
| 皖A8DC31 |                          |
| 皖RM6396 |                          |

Fig. 4: Sample of 5 plates out of 114 misclassified by LPRNet on Turkish dataset.

| Plate   | LPRNet misclassification |
|---------|--------------------------|
| 01BNU35 |                          |
| 02L4S78 |                          |
| 08RFM60 |                          |
| 38GVK61 |                          |
| 39GLF53 |                          |

Fig. 5: Sample of 5 plates out of 67 misclassified by Tesseract on Turkish plates.

| Plate   | Tesseract misclassification |
|---------|-----------------------------|
| 3107646 |                             |
| 5107011 |                             |
| 56UI992 |                             |
| 5717125 |                             |
| 70TI627 |                             |

TABLE V: Number of misclassified license plates depending on the length.

| Algorithm | Test set | Same length | Different length | Total misclassified |
|-----------|----------|-------------|------------------|---------------------|
| LPRNet    | Chinese  | 40          | 60               | 100                 |
| LPRNet    | Turkish  | 26          | 88               | 114                 |
| Tesseract | Turkish  | 49          | 18               | 67                  |

V. Conclusion

LPRNet demonstrated robustness in recognizing characters from both license plate datasets, either from real images or synthetic images, given that the network is properly trained with the corresponding dataset. Tesseract was not trained...
on real license plate images and performed well on the synthetic dataset only. We wondered if Tesseract could also perform well on the real images from the Chinese dataset, if adequately trained on it. However, training Tesseract was out of our reach. Pareto analysis helped us identify the misclassified character frequencies automatically. For both algorithms, distinguishing ‘0’ from ‘O’ proved to be difficult. Without Pareto analysis, it would be time consuming to discover which are the conflicting characters. LPRNet, a lightweight deep learning network, demonstrated to learn relevant filters for a given dataset. We observe that LPRNet’s reported performance can be achieved with at least 10,000 license plates images. Collecting this amount of sample images could be a long and costly process. Future work could investigate applying transfer learning to utilize the features learned by LPRNet, and fine-tune the network on a new and smaller dataset from a particular region. The application of smart technologies for automatic license plate recognition constitute a step towards better transportation, its management, and security.

REFERENCES

[1] S. Zherzdev and A. Gruzdev, “LPRNet: License plate recognition via deep neural networks,” arXiv preprint arXiv:1806.10447, 2018.
[2] R. Smith, “An overview of the tesseract ocr engine,” in Ninth international conference on document analysis and recognition (ICDAR 2007), vol. 2, pp. 629–633, IEEE, 2007.
[3] IMCO, “Indice de movilidad urbana 2018: Barrios Mejor Conectados para ciudades más equitativas.” https://imco.org.mx/indice-movilidad-urbana-2018-barrios-mejor-conectados-ciudades-mas-equitativas/, 2019. Accessed: 31-7-2021.
[4] Instituto Nacional de Estadística de Bolivia, “Parque Automotor.” https://www.ine.gob.bo/index.php/estadisticas-economicas/transportes/parque-automotor-cuadros-estadisticos/, 2019. Accessed: 23-7-2021.
[5] T. Üstünkök, “Synthetic turkish license plates.” https://www.kaggle.com/tustunkok/synthetic-turkish-license-plates, 2019. Accessed: 2-7-2021.
[6] H. Gutiérrez Pulido and V. Salazar, Control estadístico de calidad y seis sigma. MCGRALL-HILL, 2004.
[7] S. Montazzoli and C. Jung, “Real-time brazilian license plate detection and recognition using deep convolutional neural networks,” in 2017 30th SIBGRAPI conference on graphics, patterns and images (SIBGRAPI), pp. 55–62, IEEE, 2017.
[8] M. Z. Alom, T. M. Taha, C. Yakopcic, S. Westberg, P. Sidike, M. S. Nasrin, M. Hasan, B. C. Van Essen, A. A. Awwal, and V. K. Asari, “A state-of-the-art survey on deep learning theory and architectures,” Electronics, vol. 8, no. 3, p. 292, 2019.
[9] A. Clark, “Pillow (pill fork) documentation.” 2015.
[10] V. I. Levenshtein et al., “Binary codes capable of correcting deletions, insertions, and reversals,” in Soviet physics doklady, vol. 10, pp. 707–710, Soviet Union, 1966.
[11] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” nature, vol. 521, no. 7553, pp. 436–444, 2015.
Fig. 9: False Negative Characters. Pareto chart for LPRNet. Set: 26 of 1000 synthetic Turkey license plates misclassified (same length).

Fig. 10: False Positive Characters. Pareto chart for Tesseract. Set: 49 of 1000 synthetic Turkey license plates misclassified (same length).

Fig. 11: False Negative Characters. Pareto chart for Tesseract. Set: 49 of 1000 synthetic Turkey license plates misclassified (same length).