LPRNET: LICENSE PLATE RECOGNITION VIA DEEP NEURAL NETWORKS

LPRNet is an end-to-end method for the Automatic License Plate Recognition without using the approach of character segmentation. LPRNet consists of a fully lightweight Convolutional Neural Network. The solution is expected to be used in embedded systems with a high level of accuracy using Chinese license plates.

Authors
Tomas Carvajal
Camila Medina
Carlos Paredes
Paola Vilaseca

Affiliations
Universidad Privada Boliviana

INTRODUCTION

Automatic License Plate Recognition is an important challenge that can be used in parking management, traffic management, digital security surveillance, and vehicle recognition. The implementation of this is a complex problem due to many factors as blurry images, poor lighting conditions, variability of license plates numbers, physical impact, and weather conditions.

The LPRNet algorithm introduces a new design without the use of the pre-segmentation and consequent recognition of characters. LPRNet is a Deep Convolutional Neural Network, that can be partially ported in an FPGA and other embedded devices.

ARCHITECTURE

The basic building block of our CNN model backbone has 4 layers of convolution and followed the best practices using the Batch Normalization and Relu activation after each convolution operation.

Layer Type	Parameters/Dimensions
Input	$C_{in} \times H \times W$ feature map
Convolution	# $C_{out}/4$ 1x1 stride 1
Convolution	# $C_{out}/4$ 3x1 strideh=1, padh=1
Convolution	# $C_{out}/4$ 1x3 stridew=1, padw=1
Convolution	# C_{out} 1x1 stride 1
Output	$C_{out} \times H \times W$ feature map

Table 1. **Small Basic Block** From [1]

The Backbone of the network architecture uses a raw RGB image for the input and calculates the spatially distributed rich features.

ARCHITECTURE

Layer Type	Parameters
Input	94x24 pixels RGB image
Convolution	#64 3x3 stride 1
MaxPooling	#64 3x3 stride 1
Small basic block	#128 3x3 stride 1
MaxPooling	#64 3x3 stride (2, 1)
Small basic block	#256 3x3 stride 1
Small basic block	#256 3x3 stride 1
MaxPooling	#64 3x3 stride (2, 1)
Dropout	0.5 ratio
Convolution	#256 4x1 stride 1
Dropout	0.5 ratio
Convolution	# class_number 1x13 stride 1

Table 2. **Back-Bone Network Architecture**
From [1]

Fuente: https://arxiv.org/pdf/1806.10447.pdf

RESULTS

This part was divided into 3 sections, which are the following:

- Chinese License Plates dataset: shows recognition accuracies achieved by differ-ent models. (Table 3)
- Ablation study: shows a sum-mary of architecture approaches and their impact on accu-racy. (Table 4)
- Performance analysis: The LPRNet reduced model was ported to various hard-ware platforms including CPU, GPU and FPGA. (Table 5)

Method	Recognition Accuracy, %	GFLOPs
LPRNet baseline	94.1	0.71
LPRNet basic	95.0	0.34
LPRNet reduced	94.0	0.163

Table 3. **Results on Chinese License Plates.**

Target platform	1 LP processing time
GPU + cuDNN	3 ms
CPU (using Caffe [22])	11-15 ms
CPU + FPGA (using DLA [23])	4 ms[1]
CPU (using IE from Intel OpenVINO [24])	1.3 ms

Table 5. **Effects of various tricks on LPRNet quality.**

Approach	LPRNet							
Global context				✓	✓	✓	✓	✓
Data augm.	✓	✓	✓		✓	✓	✓	✓
STN-alignment		✓	✓			✓	✓	✓
Beam Search			✓				✓	✓
Post-filtering			✓					✓
Accuracy, %	53.4	58.6	59.0	62.95	91.6	94.4	94.4	95.0

Table 4. **Effects of various tricks on LPRNet quality.**

Fuente: https://arxiv.org/pdf/1806.10447.pdf From [1]

CONCLUSION

In this work, we have shown that for License Plate Recognition one can utilize pretty small convolutional neu-ral networks. LPRNet model was introduced, which can be used for challenging data, achieving up to 95% recognition accuracy. Architecture details, its motivation and the abla-tion study was conducted.
We showed that LPRNet can perform inference in real-time on a variety of hardware architectures including CPU, GPU and FPGA. We have no doubt that LPRNet could at-tain real-time performance even on more specialized em-bedded low-power devices.
The LPRNet can likely be compressed using modern pruning and quantization techniques, which would poten-tially help to reduce the computational complexity even fur-ther.
As a future direction of research, LPRNet work can be extended by merging CNN-based detection part into our al-gorithm, so that both detection and recognition tasks will be evaluated as a single network in order to outperform the LBP-based cascaded detector quality.

Reference
[1] Gruzdev, A., & Zherzdev, S. (2018). LPRNet: license plate recognition via deep neural networks. arXiv preprint arXiv:1806.10447.