Parking Lot Vacancy Detection Using Deep Learning for Low-end Hardware

A paper reproduction by H. Liu, Y. Wu and S. Totland

Introduction

Parking lot vacancy detection is a use case where deep learning based computer vision techniques can play a huge role. Traditional solutions for vacancy detection are typically costly as a single sensor is needed for every parking space. Computer vision techniques however can accomplish the same task at a much lower cost as only a handful of cameras are needed.

In this project we have reproduced parts of the paper by Amato et. al. (2016) [1]. In particular, the paper introduces a lighter version of AlexNet [3], capable of running on low-end devices like a Raspberry Pi. They also introduce a new dataset CNRPark and perform experiments between this and a baseline dataset PKLot [2].

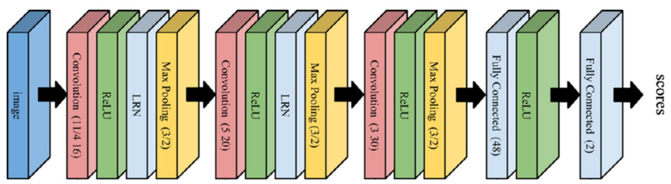
We have rewritten the code from scratch and used it to reproduce table 2 and figure 5 from the paper.

Paper Contribution

The CNRPark dataset developed by the authors has the parking lot images cropped into patches, each corresponding to a parking space in the parking lot. Each patch is then labeled as either free or taken. The dataset is further divided into sunny, rainy or overcast splits.

Parking space patches

These patches are scaled to 244x244 and fed through a binary image classifier classifying the patch as either free or taken. The network is named mAlexNet as it is a smaller version of the classic AlexNet that is able to run on lower-end hardware.



mAlexNet architecture

Our Contribution

To further verify the generalization capabilities of this method, we developed an open source image segmentation and labeling tool [4] and used this to label a second validation set, NORPark, with around 3000 patches taken from a parking lot in Trondheim, Norway.

Reproduction Results

We reproduce the experiments from the paper with our rewritten code (Python3 + PyTorch). Several of the experiments in the paper address how well training on one distribution generalizes to another. We choose the following to reproduce:

- Figure 5 : weather conditions
- Table 2 : PKLot and CNRPark.
  Results of running author's code (Python2 + Caffe) and paper accuracy are also reported.

Figure 5 reproduction

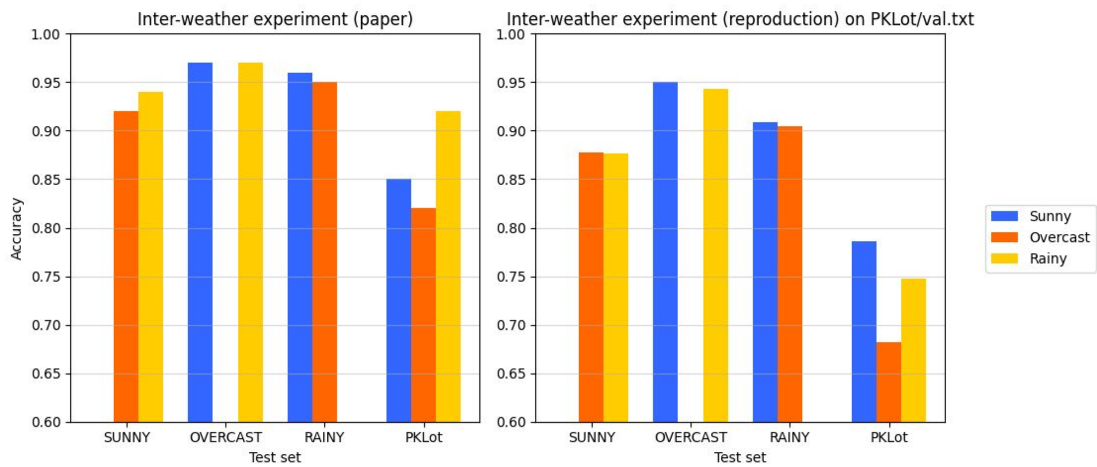


Table 2 reproduction

Method	Test set	Paper Accuracy	Caffe	Pytorch
Train on UFPR04				
mAlexNet	UFPR04	0.9954	0.9980	0.9500
mAlexNet	UFPR05	0.9329	0.6509	0.8000
mAlexNet	PUC	0.9827	0.9668	0.9200
Train on UFPR05				
mAlexNet	UFPR04	0.9369	0.8456	0.7400
mAlexNet	UFPR05	0.9949	0.9987	0.9700
mAlexNet	PUC	0.9272	0.8842	0.8900
Train on PUC				
mAlexNet	UFPR04	0.9803	0.9792	0.9400
mAlexNet	UFPR05	0.9600	0.9126	0.9300
mAlexNet	PUC	0.9990	0.9983	0.9800
Train on CNRParkOdd				
mAlexNet	CNRParkEven	0.9013	0.9347	0.8500
Train on CNRParkEven				
mAlexNet	CNRParkOdd	0.9071	0.8558	0.8500

Results on NORPark

To perform this additional test, we train the mAlexNet on both the CNRPark dataset (all splits separately) and on the PKLot dataset and then **test** on NORPark. These results are shown in the figure to the right.

Our test set results

Training set	Accuracy
SUNNY	0.8240
OVERCAST	0.7880
RAINY	0.8240
UFPR04	0.8590
UFPR05	0.8320
PUC	0.8950

Discussion

There are clear discrepancies between our reproduced results and paper results. Below are some thoughts why this might occur:

- **Figure 5** shows poor performance on PKLot.
  -> unclear instructions on the number of epochs, which might have yielded different training times than the authors.
- **Table 2** shows high variance among the results from the *Caffe* code by authors.
  -> The authors have not averaged the results over several runs, meaning that such discrepancies could be likely. The number of epochs are also not mentioned.
- **NORPark** dataset gives better results when tested on PKLot than on CNRPark.
  -> PKLot has a more similar distribution, something we have verified qualitatively.

Sources

[1] Giuseppe Amato, Fabio Carrara, Fabrizio Falchi, Claudio Gennaro, Carlo Meghini, and Claudio Vairo, Deep learning for decentralized parking lot occupancy detection, Expert Systems with Applications 72 (2017), 327–334.
[2] Almeida, P., Oliveira, L. S., Silva Jr, E., Britto Jr, A., Koerich, A., PKLot – A robust dataset for parking lot classification, Expert Systems with Applications, 42(11):4937-4949, 2015.
[3] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton, Imagenet classification with deep convolutional neural networks, Advances in Neural Information Processing Systems 25 (F. Pereira, C. J. C. Burges, L. Bottou, and K. Q. Weinberger, eds.), Curran Associates, Inc., 2012, pp. 1097–1105.
[4] https://github.com/wuyenlin/image_segmentation

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