Data-efficient Convolutional Neural Networks for Treatment Decision Support in Acute Ischemic Stroke

Adam Hilbert, BSc* **Bastiaan S. Veeling, MSc*** **Henk A. Marquering, PhD†**

Abstract

A data-efficient Deep Learning method is presented to explore outcome prediction in Ischemic Stroke using full-sized 2D CT images. We show promising results on 3 different prediction tasks with equal or higher performance than conventional CNNs while reducing model-parameters and overfitting on limited data sets.

1 Introduction

Stroke has remained the second leading cause of death in the last 15 years accounting for 6.24 million deaths yearly [1]. Ischemic Stroke accounts for 87% of this number. Caused by a blood clot (thrombus) that blocks an intracranial vessel, it hinders the necessary blood supply to a part of the brain. Deprived of oxygen, the brain loses as many neurons in 1 hour as it would in 3.6 years of normal aging [7], thus early recognition and treatment allocation is crucial.

Ischemic stroke diagnosis and decision making leverages multiple clinical variables and radiological characteristics primarily. These are determined on two image modalities: Non-Contrast Computed Tomography (NCCT) and Computed Tomography Angiography (CTA). In favor of standardized prognosis, CT scans are quantified by various stroke scores, relying on specific, visually observable phenomena. To date, these complex tasks are performed by physicians and are negatively influenced by subjectivity, fatigue and inter-rater variability.

Deep learning, in particular Convolutional Neural Networks (CNNs), has the potential to be a key enabler of efficient and automated stroke imaging. Therefore, we propose an advanced, highly parameter-efficient CNN-based model for outcome prediction. We evaluate it against conventional CNN-based model as a baseline and find promising performance. Our models cope typically better with small medical data sets while retaining equal or higher performance than our baseline.

Related work utilizing Deep Learning in stroke imaging has so far solely focused on predicting the presence of specific phenomena in small patches of images, without the direct association to outcome [6]. To the best of our knowledge, this is the first work employing CNNs for whole image classification in the domain of stroke, and the first Deep Learning approach, which studies predictors of outcome of Intra-Arterial Treatment using raw CT images as input.

2 Methods

2.1 DenseNet architecture

The proposed model is based on a DenseNet architecture [3], in which every layer receives the feature-maps of all preceding layers and transmits its own output to all subsequent ones. We used a 21 layer deep architecture comprised of 4 dense blocks with bottleneck layers, a growth rate of

*University of Amsterdam

†Department of Biomedical Engineering and Physics Academical Medical Center, Amsterdam

1st Conference on Medical Imaging with Deep Learning (MIDL 2018), Amsterdam, The Netherlands.

8 and 0.5 reduction in transition layers. 11×11 convolution was employed in the initial and 5×5 convolution in composite layers.

In ischemic stroke, the occlusion of a vessel affects the blood supply only on one hemisphere. To exploit this prior knowledge and the center-alignment of images, we adapt the last average pooling layer to generate one set of feature maps per hemispheres.

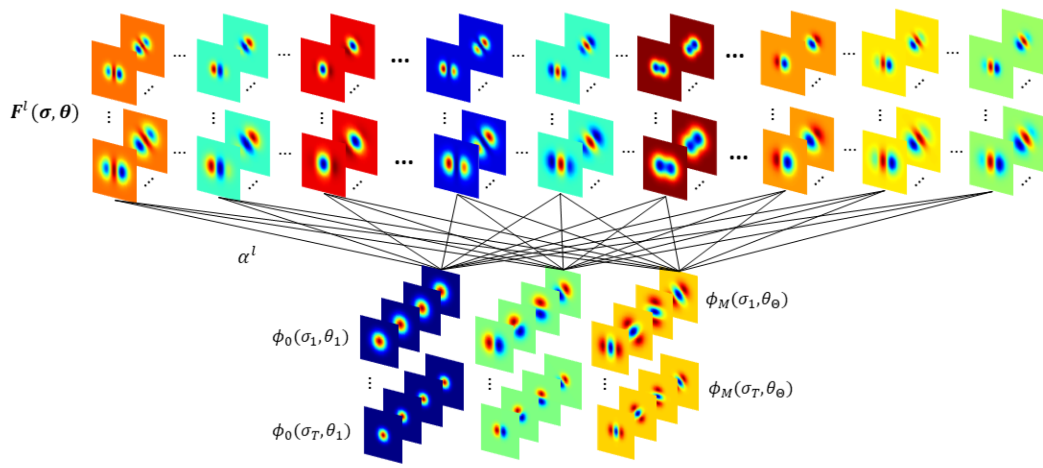


Figure 1: MSO-RFNN layer up to 2nd order of derivative. ϕ denote the fixed filters, α the trainable weights and **F** the effective filters.

2.2 Multi-Scale and -Orientation Structured Receptive Field Neural Networks

Structured Receptive Neural Networks (RFNNs) are a special type of CNN, where the effective convolutional filters are replaced by the linear combination of a fixed basis set of Gaussian derivative filters, shown in Figure 1. Only the combination weights are learned thus reducing the model parameters of the DenseNet architecture. This technique introduces prior knowledge about spatial properties of local features into the model, which has been shown to lead to superior results over conventional CNNs on small data sets.

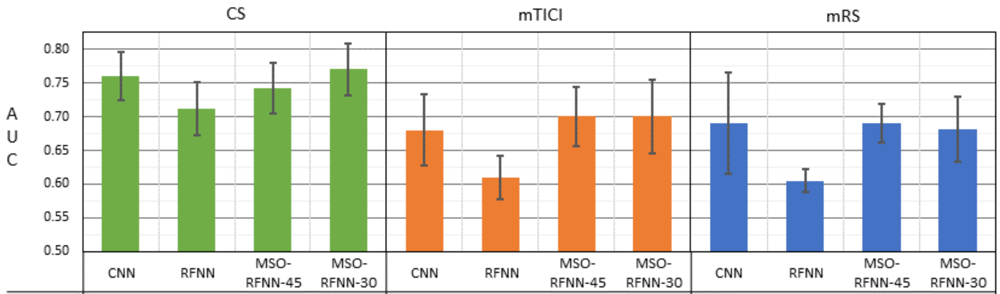
Additionally to using the multi-scale extension in [4], we introduce multiple orientations of the filters by making use of the steerability of Gaussian derivatives. We call the proposed model Multi-Scale and -Orientation Structured Receptive Neural Network (MSO-RFNN), and refer to the degree of sampling orientations by e.g. MSO-RFNN-45. To steer each effective filter we construct each basis filter from a minimal set of x-y separable Gaussians of the given order following the guidelines of [2]. The effective filters used in the proposed convolutional layer emerge as a multi-scale and -orientation filter bank, illustrated in Figure 1. Note, that the α weights are shared across scales and orientations.

Moreover, we propose an aggregation method to handle the increased number of filters in a convolutional layer described above. To this end, we feed the output of the convolutions into an additional 1×1 convolution. This enables that an effective selection or combination of scales and orientations is learned in each layer and MSO-RFNN layers can replace CNN layers in any CNN architecture.

3 Experiments

3.1 Data

We used CTA images of stroke patients registered in [5] between March 2014 and June 2016. We studied the patients only who received Intra-Arterial Treatment (IAT). 3 data sets were constructed according to 3 different output labels to predict: 1) functional outcome at 90 days defined by the modified Rankin Scale (mRS) 2) radiological outcome directly post-procedure defined by the modified Thrombolysis in Cerebral Infarction (mTICI) score and 3) collateral circulation assessed by the Collateral Score (CS) all defined by [5]. The sizes of the data sets were 772, 800 and 970 in the same order.



	CS				mTICI				mRS			
	CNN	RFNN	MSO-RFNN-45	MSO-RFNN-30	CNN	RFNN	MSO-RFNN-45	MSO-RFNN-30	CNN	RFNN	MSO-RFNN-45	MSO-RFNN-30
AUC	0.76	0.71	0.74	**0.77**	0.68	0.61	**0.70**	**0.70**	**0.69**	0.60	**0.69**	0.68
± std	**0.04**	**0.04**	**0.04**	**0.04**	0.05	**0.03**	0.04	0.05	0.08	**0.02**	0.03	0.05
# of par.	59.90K	27.40K	**21.20K**	24.30K	59.90K	27.40K	**21.20K**	24.30K	59.90K	27.40K	**21.20K**	24.30K
Train ACC	90.3%	**66.7%**	69.6%	71.1%	88.5%	**59.6%**	62.6%	66.0%	93.6%	**61.5%**	67.0%	65.3%

Figure 2: Results of predicting CS, mTICI and mRS; mean test Area Under Curve (AUC), its standard deviation (±std), number of parameters to train (# of par.), mean final training accuracy (Train ACC).

3.2 Pre-processing

The skull of the patients was removed, images were resampled to isotropic pixelspacing of 1mm×1mm×1mm and aligned to centered location and orientation. We cropped/zero-padded resulting images to have uniform dimensions and computed 2D Maximum Intensity Projections (MIPs) of size 433×433. Pixel values were thresholded between +50 and +300 Hounsfield Units and were normalized to zero mean and unit variance with training set statistics.

3.3 Results

Figure 2 shows results of 4-fold cross-validation with 10% of the training set held out for validation on the 3 mentioned benchmarks. MSO-RFNNs obtain equal or superior performance over all other models in terms of AUC score on test set and higher generalization according to the lower std of AUC than conventional CNNs. We also note the significant difference in the number of model parameters and training accuracy at the final epoch of training.

4 Conclusion

In this paper we presented MSO-RFNNs, a data-efficient deep learning approach for whole-image classification on limited data sets. Promising results were achieved in predicting the mRS, mTICI and Collateral Score that all have important prognostic value for stroke decision support. We found that MSO-RFNNs provide a structured, more transparent model than conventional CNNs, while retaining their effective performance. Our preliminary results suggest for further exploration of possible improvements.

References

[1] E.. Benjamin and Blaha. Heart disease and stroke statistics. *Circulation*, 2017.

[2] W. T. Freeman and E. H. Adelson. The design and use of steerable filters. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 13(9):891–906, Sep 1991.

[3] G. Huanget al. Densely connected convolutional networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2017.

[4] J. Jacobsen et al. Structured receptive fields in cnns. In *CVPR*, June 2016.

[5] I. G H Jansen et al. Endovascular treatment for acute ischaemic stroke in routine clinical practice: prospective, observational cohort study (mr clean registry). *BMJ*, 360, 2018.

[6] A. Lisowska et al. Context-aware convolutional neural networks for stroke sign detection in non-contrast ct scans. In *Medical Image Understanding and Analysis*, pages 494–505, Cham, 2017.

[7] Jeffrey L. Saver. Time is brain—quantified. *Stroke*, 37(1):263–266, 2006.