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Tutor: Prof. Carlo Sansone

XXXII Cycle - I year presentation

Exploring Deep Learning Capabilities and Applicability

Università degli Studi di Napoli Federico II

Background

- Graduated cum Laude in Computer Engineering in April 2016 at University of Naples Federico II.

- Researcher in the Priamus Research Group, under the supervision of Prof. Carlo Sansone.

- Fellowship from the Consorzio Interuniversitario Nazionale per l'Informatica (CINI).

Problem

- The availability of free and simple machine learning frameworks and the rise of GP-GPU computing brought Deep-Learning in many different fields.
- Findings from Yoshinski et al.[1] support the use of transfer learning to exploit capabilities learnt in a task (usually natural image processing) for (sometimes very) different field (such as biomedical image processing).
- Deep-Learning can also be used as a feature extractor, relieving researcher from the duty of feature engineering.
- The other side of the coin is that, unfortunately, using deep-learning as a black-box could not always be the most effective way to use it.

[1] J. Yosinski, J. Clune, Y. Bengio, H., & Lipson, "How transferable are features in deep neural networks?" In Advances in neural information processing systems, 3320-3328, 2014.

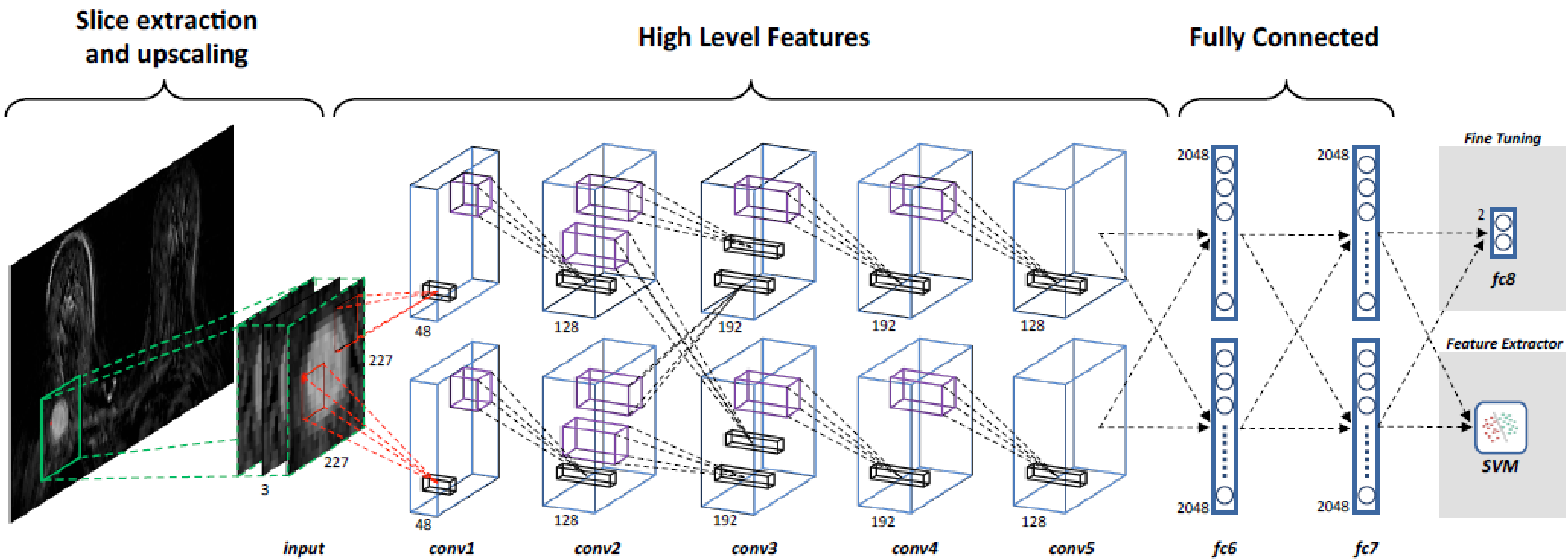
Research Activity

- To verify these assumptions, I analysed a recent publication by Antropova et al.[2] that performs breast lesion classification by Fine-Tuning a Deep Convolutional Neural Networks (AlexNet).
- I compared their approach with some state-of-the-art algorithms.
- Leave-One-Patient-Out Cross-Validation (LOPO-CV) is performed to reliably compare different models, avoid mixing intra-patient slices in the test phase.

> - I also explored i) the application of deep learning for natural language understanding within a chat-bot application, ii) correlation analysis between oropharynx cancer and human papilloma virus, iii) developed a method for fast curve fitting by using look-up tables.

[1] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in Advances in neural information processing systems, 2012, pp. 1097–1105.

Fine-Tuning vs Transfer Learning



- Fine-Tuning replace the output layer and train the net as a whole
- Transfer Learning use the CNN as a feature extractor and separately train an external classifier

Results 1/2

Training Modality	Combining Strategy	ACC [%]	SEN [%]	SPE [%]	AUC [%]
Feature Extraction	Majority Voting	76.19	78.26	73.68	76.43
	Weighted Majority Voting	73.81	78.26	68.42	75.97
	WMV by Slice Area	76.19	78.26	73.68	76.20
	Naïve Bayes	76.19	82.61	68.42	72.77
	Max Prob. Value per Slice	71.43	78.26	63.16	74.83
	Biggest Slice	76.19	73.91	78.95	76.43
Fine Tuning	Majority Voting	71.43	82.61	57.89	72.65
	Weighted Majority Voting	69.05	82.61	52.63	73.23
	WMV by Slice Area	69.05	82.61	52.63	71.40
	Naive Bayes	66.67	82.61	47.37	71.17
	Max Prob. Value per Slice	69.05	82.61	52.63	73.00
	Biggest Slice	73.81	86.96	57.89	72.43

Table 1. Comparing different AlexNet training modalities, varying the slice combining strategy. Average values obtained in Leave-One-Patient-Out CV over 42 patients are reported.

Results 2/2

Methodology	ACC [%]	SEN [%]	SPE [%]	AUC [%]	Training Time [s]	Testing Time [ms]
LBP-TOP (Piantadosi et al. [20])	83.33	95.14	66.67	88.41	1.11	8.25
Best CNN	76.19	73.91	78.95	76.43	379.30	1247.39
Dyn. & Morph. + MCS (Fusco et al. [7])	69.05	78.26	57.89	68.08	5.34	62.34
Decision Trees (Glaßer et al. [9])	64.29	95.65	26.32	60.98	-	5.41

Table 2. Comparison of the best results obtained by a CNN-based lesion diagnosis approach with those achieved by other state-of-the-art approaches. Average values obtained in Leave-One-Patient-Out CV over 42 patients are reported. Reported times are per each patient evaluation (average).

- Results show that while promising results in treating DCE-MRI can be obtained by using transfer learning, CNNs have to be carefully designed and tuned in order to outperform approaches specifically designed to exploit all the available data information.

Products

- **Marrone S.,** Piantadosi G., Sansone M., Sansone C. (2017) Look-Up Tables for Efficient Non-Linear Parameters Estimation. In: Sforza A., Sterle C. (eds) Optimization and Decision Science: Methodologies and Applications. ODS 2017. Springer Proceedings in Mathematics & Statistics, vol 217. Springer, Cham.

- **Marrone S.,** Piantadosi G., Fusco R., Petrillo A., Sansone M., Sansone C. (2017) An Investigation of Deep Learning for Lesions Malignancy Classification in Breast DCE-MRI. In: Battiato S., Gallo G., Schettini R., Stanco F. (eds) Image Analysis and Processing - ICIAP 2017. ICIAP 2017. Lecture Notes in Computer Science, vol 10485. Springer, Cham.

- Amato F., **Marrone S.,** Moscato V., Piantadosi G., Picariello A., Sansone, C. (2017) Chatbots meet eHealth: automatizing healthcare. In: D. Impedovo, G. Pirlo, Proceedings of the Workshop on Artificial Intelligence with Application in Health co-located with the 16th International Conference of the Italian Association for Artificial Intelligence - AI*IA 2017. Vol-1982.

- …, Sansone C., Piantadosi G., **Marrone S.,** … (2018) Machine Learning Applications in Head and Neck Radiation Oncology: Lessons from Open-Source Radiomics Challenges. In: Frontiers in Radiation Oncology (submitted)

I Year Report
and Next Year Estimations

	Credits year 1								Credits year 2								Credits year 3								Total	Check
	Estimated	bimonth 1	bimonth 2	bimonth 3	bimonth 4	bimonth 5	bimonth 6	Summary	Estimated	bimonth 1	bimonth 2	bimonth 3	bimonth 4	bimonth 5	bimonth 6	Summary	Estimated	bimonth 1	bimonth 2	bimonth 3	bimonth 4	bimonth 5	bimonth 6	Summary		
Modules	26	0	3	0	3	3	11	**39,7**	20							**0**	5							**0**	**39,7**	30-70
Seminars	10	3,7	3,1	0,4	0,7	0,4	1,5	**9,8**	10							**0**	5							**0**	**9,8**	10-30
Research	20	2,3	2,2	1,8	1,5	1,5	1,2	**10,5**	30							**0**	50							**0**	**10,5**	80-140
	60	18,3	8,9	8,3	2,2	1,9	20	**60,0**	60	0	0	0	0	0	0	**0**	60	0	0	0	0	0	0	**0**	**60,0**	180

- My next studies will focus on the design of new techniques for the automatic design of Deep Network architectures, neuron weights and bias allocation in transfer learning.