PhD in Information Technology and Electrical Engineering

Università degli Studi di Napoli Federico II

PhD Student: Stefano Marrone

XXXII Cycle

Training and Research Activities Report – First Year

Tutor: prof. Carlo Sansone

1. Information

I graduated cum Laude in Computer Engineering in April 2016 at University of Naples Federico II.
In February 2017 I started my first year of the PhD in Information Technology and Electrical Engineering (ITEE) XXXII Cycle at the University of Naples Federico II, under the supervision of Prof. Carlo Sansone.
Since then I hold a fellowship from the Consorzio Interuniversitario Nazionale per l'Informatica (CINI).

2. Study and Training Activities

	Credits year 1								Credits year 2								Credits year 3								Total	Check
	Estimated	1 bimonth	2 bimonth	3 bimonth	4 bimonth	5 bimonth	6 bimonth	Summary	Estimated	1 bimonth	2 bimonth	3 bimonth	4 bimonth	5 bimonth	6 bimonth	Summary	Estimated	1 bimonth	2 bimonth	3 bimonth	4 bimonth	5 bimonth	6 bimonth	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**

Ad-Hoc Modules	Lecturer	Start	End	H	CFU
Testing Automation	P. Tramontana	12/01/17	02/02/17	16	3
Ethical, legal and social aspects of ICT and Robotics	G. Tamburrini	07/03/17	04/04/17	15	3
Interoperability, Semantic Technologies and Applications	F. Amato	24/03/17	31/03/17	10	2
Games on Graphs	S. Rubin	24/04/17	27/04/17	8	1,6

Research Capacity Enhancement Modules	Lecturer	Start	End	H	CFU
Le imprese e la ricerca	M. Frizzarin	28/02/17	02/03/17	24	4
Course at Centro Linguistico di Ateneo - English C1 (CAE)	J. Parker	08/09/17	28/11/17	57	5,7

Master's Degree Modules	Lecturer	Semester	H	CFU
Advanced Computer Architecture and GPU Programming	A. Cilardo	First of a.y. 17/18	48	6
Data Mining	C. Sansone	First of a.y. 17/18	48	6

Modules from PhD Schools	Short Name	Start	End	H	CFU
3rd International Winter School on Big Data @ Department of Computer Science, University of Bari "Aldo Moro" - Bari (Italy)	BigDat 2017	13/02/17	17/02/17	53	5,3
13th TAROT Summer School on Software Testing, Verification & Validation @ Dipartimento di Ingegneria Elettrica e delle Tecnologie dell'Informazione (DIETI), Università degli Studi di Napoli Federico II - Napoli (Italy)	TAROT 2017	26/06/17	30/06/17	31,5	3,1

Seminars	Lecturer	Host	Date	H	CFU
Exploiting machine learning techniques in software development processes	D. Amalfitano	A. Picariello	18/01/17	2	0,5
Smart nanodevices for theranostics	I. Rea	C. Forestiere	24/02/17	1,5	0,3
Fuzzy Logic, Genetic Algorithms and their Application to Next Generation Networks (A)	L. Barolli	F. Amato	10/03/17	1	0,2
Fuzzy Logic, Genetic Algorithms and their Application to Next Generation Networks (B)	L. Barolli	F. Amato	14/03/17	1	0,2
From Mathematical formalization to Artificial Visual-Attention: Toward a Human-Like Robot Vision	K. Madani	A. M. Rinaldi	04/04/17	2	0,4
Living bots and alter ego	M. Gori	G. Tamburrini	04/04/17	2	0,4
Opportnunità dell'applicazione delle tecnologie Big Data nel contesto della gestione dei dati Multimediali	I. Bartoli	A. Picariello	05/05/17	2,5	0,5
Exploiting Speech Production Knowledge for Deep Learning based Automatic Speech Recognition	L. Badino	F. Cotugno	09/05/17	2	0,4
Deep Learning for Robot Navigation and Perception	W. Burgard	B. Siciliano	07/06/17	2	0,4
Wireless Opportunistic Networking	G. Karlsson	G. Ventre	28/09/17	1	0,3
LEDs in multispectral applications	U. Blaszczak	L. Bellia	29/09/17	1	0,2
Selected problems on lighting energy efficiency for indoors	P. Pracki	L. Bellia	29/09/17	1	0,2
MatLab & Simulink	MatLab srl.	G. B. Barone	27/10/17	2	0,4
Optimal Content Distribution and Multi-resource Allocation in Software Defined Virtual CDNs	C. Sterle A. M. Tulino	A. Sforza	11/12/17	2	0,4
Graph Queries: Generation, Evaluation and Learning	A. Bonifati	A. Picariello	18/12/17	2	0,5
Large Scale Integrative Bioinformatics and Systems Biology in Cancer Genomics	M. Ciccarelli	G. Ventre	18/01/18	1,5	0,3
SeeQC-eu, Hypres Quantum Engineering Company in Europe	O. Mukhanov A. Kirichenko	A.G.M. Strollo	30/01/18	1,5	0,3

Seminars from PhD Schools and Workshops	Start	End	H	CFU
Formal Methods in Artifical Intelligence (FMAI 2017) @ Dipartimento di Ingegneria Elettrica e delle Tecnologie dell'Informazione (DIETI), Università degli Studi di Napoli Federico II - Napoli (Italy)	22/02/17	23/02/17	12,5	2,5
Intelligenza Artificiale: dall'Università alle Aziende. La Rivoluzione del Deep Learning @ University of Bologna Alma Mater Studiorum - Bologna (Italy)	12/04/17		7	1,4

3. Research Activity

In the machine learning field, it is well known that what matters above classifier are the features used to describe the entities under analysis. For this reason, a lot of new features have been designed by domain experts to improve classification results in a wide spread of different fields, including computer vision task, automatic speech recognition and timeseries analysis.

This was the case until a Deep Convolution Neural Network (D-CNN or simply CNN) won the 2012 Large Scale Visual Recognition Challenge [1]. From that moment on, an increasingly interest stated to be paid by researches on the study and on the application of CNN in several contexts, giving rise to new CNN

architectures, training and optimization strategies able to compete and, in some cases, surpass humans in many tasks [2], [3].

CNN are very similar to traditional (shallow) Neural Networks since they are both made of neurons, usually organised in layers, connected to form a network in which the output of a neuron is the input of some other neurons and this elaboration chain made it possible to transform the input data in the desired output value (i.e. a class for a classification problem or a value for a regression one). However, while shallow neural networks operate on the features designed and extracted by a domain expert (figure 1), CNN use a hierarchy of convolution operations (whose kernel's weights are learned in the very same way classical neuron's weights are learned) to autonomously extract the feature that better models the problem under analysis (figure 1).

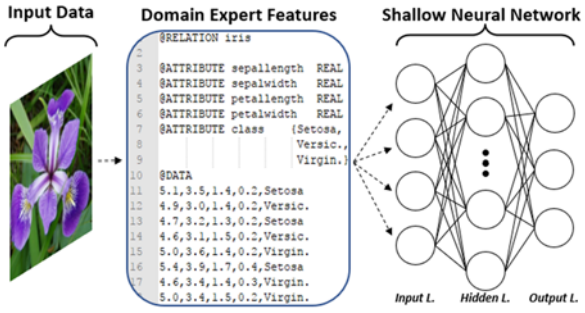

Figure 1: A representation of the classical approach in which some features (in the middle) are extracted from input data (on the left) and used to train a shallow neural network (a multilayer perceptron in the image on the right).

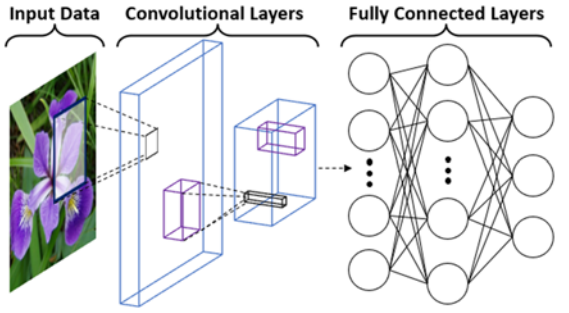

Figure 2: An exemplification of a CNN that uses a hierarchy of convolutional layer (in the middle) to autonomously learn the best representation of input data (on the left) in order to train a fully connected neurons network (on the right).

The availability of free and simple machine learning frameworks and the rise of GP-GPU computing brought Deep-Learning in many different research groups. Findings from Yoshinski et al. [4] support the use of fine-tuning and transfer learning [5] to exploit capabilities learnt in a task (usually natural image processing) for (sometimes very) different field (such as biomedical image processing). However, the other side of the coin is that, unfortunalty, many times deep-learning is applied just as a tool, without considering implications and limitations.

To verify this assumption, as case of study I analysed a recent publication by Antropova et al. [6] in which authors proposed to apply Deep Learning for the breast cancer lesion diagnosis task, by feeding a pre-trained CNN with the ROI extracted from DCE-MRI slices containing a lesion. They adopted the AlexNet architecture pre-trained on the ImageNet dataset [7] as feature extractor, by using a Support Vector Machine (SVM) for the malignant/benignant classification task (figure 3).

I compared their approach (after some consideration taken to correct some imperfection) with some state-of-the-art algorithm for the breast lesion classification task. To obtain a fair performance evaluation, k-fold cross-validation (CV) is commonly used. In this case, however, although each lesion is made of different slices, the lesion diagnosis task has to predict a single class for the whole lesion.

For this reason, it is very important to perform a Leave-One-Patient-Out Cross-Validation (LOPO-CV) instead of a slice-based k-fold CV one, in order to reliably compare different models, avoid mixing intra-patient slices in the evaluation phase.

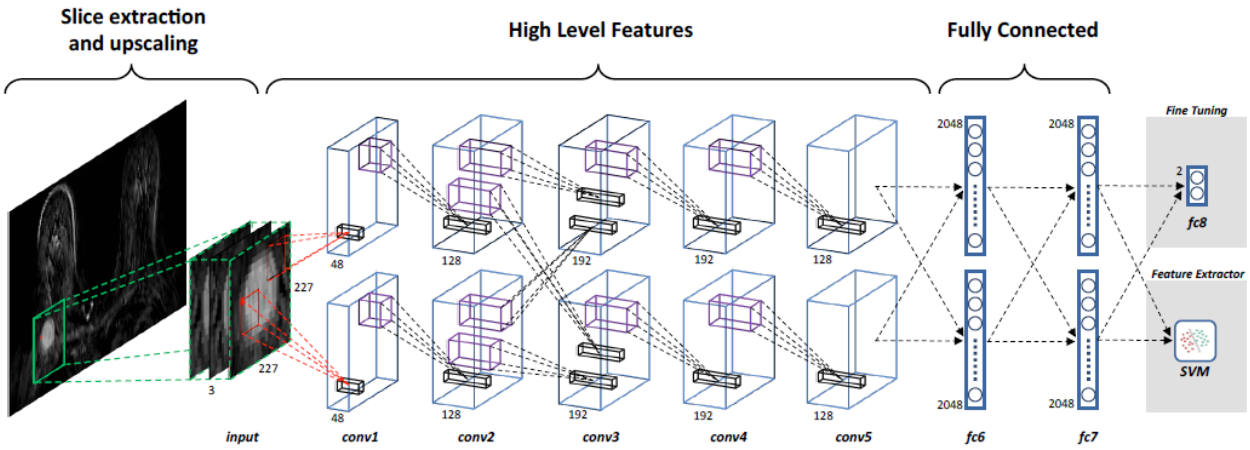

Figure 3: AlexNet architecture and its use as feature extractor or in a fine-tuning fashion.

Table 1 compares all the CNN-based approaches so far presented, while table 2 compares the best results obtained by a deep approach with those obtained by applying the methods proposed in [8, 9, 10].

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.

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 valuation (average).

These results seem to suggest that while CNNs show promising results in treating biomedical images, they must be carefully designed and tuned in order to outperform approaches specifically designed to suitably exploit data information for the specific task.

Like many ideas in AI, ANNs (both shallow and deep) are roughly inspired by biology (in this case, by the structure of the brain): an ANN is an attempt to simulate a collection of neuron-like components, connected to form a network, that send signals to each other. The inter-neurons connections are mathematically implemented by the dot product between the neurons output and some weights, whose values allow to tune the influence that each neuron has on all other neurons it is connected to.

With millions of connections in modern ANNs, decide connection weights by hand is not a viable approach. Instead, the problem of finding the right weights to perform a task is viewed as the problem of learning. However, it is worth noticing that the behaviour of the brain is not only determined by the weights of its connections, but by the overall architecture of the brain itself. Learning algorithms do not even attempt to address the neural network design process, simply doing their best with the connections that have been provided. Thus, how to determine the number of neurons, the activation function to use, what neurons connect to what, and so on?

Neuroevolution [11] (sometime also known as Evolutionary Learning) is an emerging paradigm for training neural networks through evolutionary principles that has grown up alongside more conventional deep learning. While deep learning focuses on how brain-like structures in computers can learn, neuroevolution addresses how they evolve in the first place, from their architectures to their intrinsic learning dynamics.

As in the broader field of deep learning, increases in available computation have led to a renaissance in potential applications of neuroevolution, some of which complement more conventional techniques by offering a path to novel architectures, while others reveal intriguing alternative systems of incentives for learning (even when a gradient is not available).

Prominent artificial intelligence labs and researchers are experimenting with it, a string of new successes have bolstered enthusiasm, and new opportunities for impact in deep learning are emerging.

Put simply, neuroevolution is a subfield within artificial intelligence (AI) and machine learning (ML) that consists of trying to trigger an evolutionary process similar to the one that produced our brains, except inside a computer. In other words, neuroevolution seeks to develop the means of evolving neural networks through evolutionary algorithms.

My whole research activity is mainly focused on neuroevolution techniques applied to deep neural networks for both

- Developing new techniques to improve deep learning results and understanding;
- Revisit and validate past glories approaches to the deep neural networks case.

With this aim in mind, my future research will focus on the application of neuroevolution approaches to the deep network design, tuning and training.

4. 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.

- Hesham Elhalawani, Timothy A Lin, Stefania Volpe, Abdallah S.R. Mohamed, Aubrey L. White, James Zafereo, Andrew Wong, Joel E. Berends, Shady Abohashem, Bowman Williams, Jeremy M. Aymard, Aasheesh Kanwar, Subha Perni, Crosby D. Rock, Luke Cooksey, Shauna Campbell, Pei Yang, Khanh Nguyen, Rachel Ger, Carlos Eduardo Cardenas, Xenia Fave, Carlo Sansone, Gabriele Piantadosi, **Stefano Marrone**, Rongjie Liu, Chao Huang, Kaixian Yu, Tenfei Li, Yang Yu, Youyi Zhang, Hongtu Zhu, Jeffrey S. Morris, Veerabhadran Baladandayuthapani, John W. Shumway, Alakonanda Ghosh, Andrei Pöhlmann, Hady Ahmady Phoulady, Vibhas Goyal, Guadalupe Canahuate, G. Elisabeta Marai, David Vock, Stephen Y. Lai, Dennis S. Mackin, Laurence E. Court, John Freymann, Keyvan Farahani, Jayashree Kalpathy-Cramer and Clifton D FullerIn (2018) Machine Learning Applications in Head and Neck Radiation Oncology: Lessons from Open-Source Radiomics Challenges. In: Frontiers in Radiation Oncology (submitted)

5. Conferences and Seminars

- Oral presentation of the paper “Look-Up Tables for Efficient Non-Linear Parameters Estimation” at the “International Conference on Optimization and Decision Science (ODS 2017)” – Hilton Sorrento Palace Conference Center, Sorrento (SA), Italy – from 04/09/2017 to 07/09/2017.

- Poster presentation of the paper “An Investigation of Deep Learning for Lesions Malignancy Classification in Breast DCE-MRI” at the “19th International Conference on Image Analysis and Processing (ICIAP 2017)” – Monastery of San Nicolò l’Arena, Catania (CT), Italy – from 11/09/2017 to 15/09/2017.

- Oral presentation of the paper “L Chatbots meet eHealth: automatizing healthcare” at the “Workshop on Artificial Intelligence ith Application in Health (WAIAH 2017)” – Department of Computer Science, University of Bari “Aldo Moro”, Bari (BA), Italy – 14/11/2017

6. Grant and Certification

- Winner (as member of the research group lead by prof. Carlo Sansone) of a Nvidia Titan XP GPU within the Nvidia GPU Grant program, with a project on the application of Deep Convolutional Neural Network for biomedical image processing.

7. Tutorship and Active Teaching

- From 25/10/2017 to 22/11/2017 I was a Tutor for the Analisi Matematica I module (prof. G. Moscariello), with an average of 30 students attendance.
- Since 27/10/2017 I am a Tutor for the Fondamenti di Informatica module (prof. P. Tramontana), with an average of 35 students attendance.
- Lecturer at Data Mining class exercise (prof. C. Sansone) a.y. 17/18 – “Classification approaches”, 26/10/2017 (2h)
- Lecturer at Data Mining class exercise (prof. C. Sansone) a.y. 17/18 – “Regression”, 7/11/2017 (2h)
- Lecturer at Data Mining class exercise (prof. C. Sansone) a.y. 17/18 – “Association Rules”, 9/11/2017 (2h)
- Lecturer at Data Mining class exercise (prof. C. Sansone) a.y. 17/18 – “Ensamble Learning”, 14/12/2017 (2h)
- Correlator for the Master's Degree Thesis "Pharmacokinetic-based motion correction in breast DCE-MRI" by Imma di Maro – from 01/02/17 to 10/07/2017
- Correlator for the Master's Degree Thesis "Data Mining Techniques on Massive Datasets for E-Health Applications" by Rinaldo di Marco – from 01/02/2017 to 10/07/2017
- "Correlator for the Bachelor's Degree Thesis "Document-Oriented database (MongoDB) a supporto di applicazioni di e-Health" by Valeria Borrelli – from 15/06/2017 to 10/07/2017
- Correlator for the Bachelor's Degree Thesis "Chat-bot a supporto di applicazioni e-Health" by Sarah Adamo - from 19/07/2017 to 25/09/2017
- Correlator for the Master's Degree Thesis on the evaluation of Deep Learning architecture power efficency by Alessandro Giannini – from relator 01/07/2017 (ongoing)
- Correlator for the Master's Degree Thesis on the application of Deep Convolutional Neural Network for Biomedical Image Segmentation by Alessandro Pagliaro – from 01/09/2017 (ongoing)
- Correlator for the Master's Degree Thesis on the application of Deep Convolutional Neural Network for Biomedical Image Segmentation by Paolo Ivanov – from 15/09/2017 (ongoing)
- Correlator for the Master's Degree Thesis "HOLMeS: Health OnLine Medical Suggestion. Architecture for Big Data Analytics and Machine Learning Computing" by Salvatore Buonocore – from 15/09/2017 to 04/12/2017
- Correlator for the Master's Degree Thesis "HOLMeS: Health OnLine Medical Suggestion. Machine Learning and Big Data for e-Health Applications" by Arcangelo di Palo - from 15/09/2017 to 04/12/2017
- Correlator for the Master's Degree Thesis on the application of Deep Convolutional Neural Network for Biomedical Image Segmentation by Roberta Cascella – from 01/12/17 (ongoing)
- Correlator for the Master's Degree Thesis on the analysis of software for the patient management by Luciano D'Ercole – from 07/12/17 (ongoing)

- Correlator for the Master's Degree Thesis on the application of Deep Learning by Gabriella De Cataldis – from 08/12/17 (ongoing)

8. Membership

I am a member of:

- Associazione Italiana per la ricerca in Computer Vision, Pattern recognition e machine Learning (CVPL- ex-GIRPR)
- Associazione Italiana per l'Intelligenza Artificiale (AIxIA)
- Institute of Electrical and Electronics Engineers (IEEE)
- IEEE Young Professionals
- IEEE Napoli Student Branch (lead by prof. P. Maresca). From 11/08/2017 I am the Chair of the branch.

9. Bibliography

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[3] Y. M. Assael, B. Shillingford, S. Whiteson, and N. de Freitas, “Lipnet: End-to-end sentence-level lipreading,” 2016.

[4] 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.

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[6] N. Antropova, B. Huynh, & M. Giger, “Predicting Breast Cancer Malignancy On DCE-MRI Data Using Pre-Trained Convolutional Neural Networks” in Medical physics 43 (6 Part 4), 3349-3350, 2016

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[11] D. Floreano, P. Dürr, & C. Mattiussi, “Neuroevolution: from architectures to learning,” in Evolutionary Intelligence, 1(1), 47-62, 2008.