Day 4 Lecture 5

Medical Imaging

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Medical Imaging

Interest in this area in Deep Learning:

MICCAI 15 MUNICH

DLMIA

1st Workshop on Deep Learning in Medical Image Analysis

MICCAI 2016 Athens GREECE

19TH INTERNATIONAL CONFERENCE ON MEDICAL IMAGE COMPUTING & COMPUTER ASSISTED INTERVENTION
October 17-21 2016
INTERCONTINENTAL ATHENAEUM
ATHENS / GREECE

DLMIA

2nd Workshop on Deep Learning in Medical Image Analysis

DeepDeep Deep LearningDeep Learning Deep Learning ApplicationsDeep Learning Applications Deep Learning Applications toDeep Learning Applications to Medical Deep Learning Applications to Medical ImageDeep Learning Applications to Medical Image Deep Learning Applications to Medical Image Analysis, Prof. Dinggang Shen, Univ. of North Carolina, USA

From DBNs to Deep ConvNets: Pushing the State of the Art in Medical Image Analysis, Prof. Gustavo Carneiro, University Adelaide, Australia

Deep Learning

Medical Imaging

Interest in this area in Deep Learning (MICCAI):

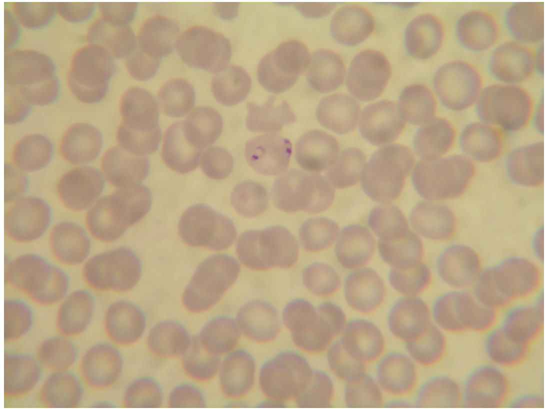
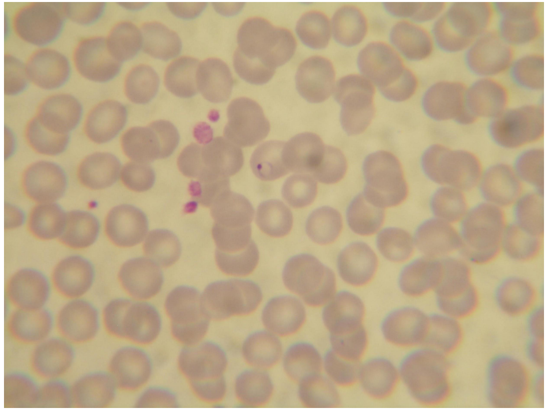
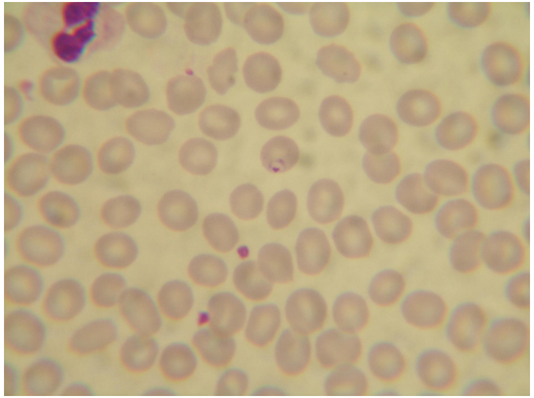
- Image description by means of deep learning techniques;
- Medical imaging-based diagnosis using deep learning;
- Medical signal-based diagnosis using deep learning;
- Medical image reconstruction using deep learning;
- Deep learning model selection;
- Meta-heuristic techniques for fine-tuning parameter in deep learning-based architectures;
- Deep learning-oriented applications.

Applications:

Breast cancer detection; skin lesion detection; organs recognition; image-based disease identification; Chest Radiograph Categorization with Deep Feature Selection; Cell Detection and recognition; Brain segmentation of tumor, stroke lesions and injuries

Detection of Malaria parasites in blood samples (Project done at UPC)

Prof. Margarita Cabrera; Josep Vidal; Daniel López Codina (Physics department)
Students: Jaume Fernández (Ms in Telecom),…
Collaboration with Drassanes Tropical Medicine and International Health Unit

All the images used correspond to positive P. Falciparum smears. Thin blood smear

Detection of Malaria parasites in blood samples (Project done at UPC)

Image acquisition → Pre-processing → [Feature extraction] → Classification

2 different techniques

- Hue binarization
- Cell segmentation

2 different methods

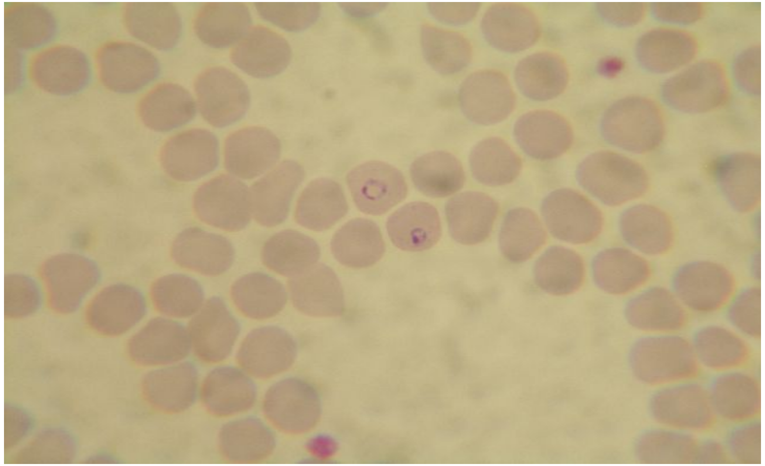
- SVM
- CNN

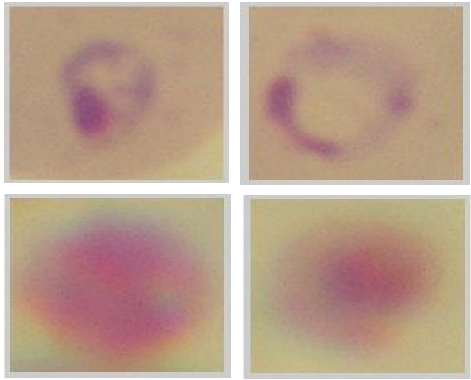
Yuanpu Xie, Fuyong Xing, Xiangfei Kong, Hai Su, Lin Yang, "*Beyond Classification: Structured Regression For Robust Cell Detection Using Beyond Classification: Structured Regression For Robust Cell Detection Using ConvolutionalBeyond Classification: Structured Regression For Robust Cell Detection Using Convolutional Neural Network*", MICCAI 2015.

Pre-processing – Hue binarization

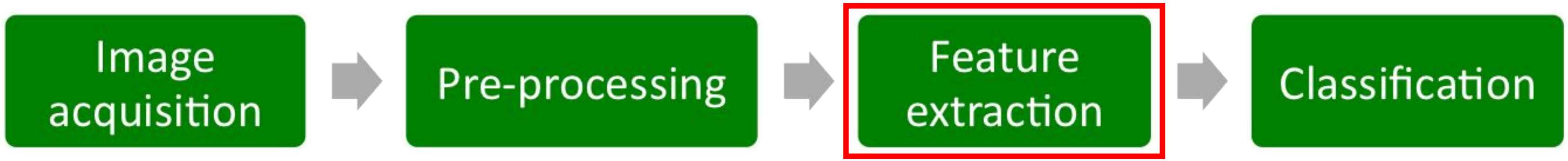
- Filter image
- Hue binarization
- Find regions and centroids
- Merge centroids
- Extract sub-image

- Create sub-images around the centroids taking the surrounding pixels





Feature Extraction for SVM Classification



Goal: Extract useful data that feeds the classification block and allows for a correct classification

- The set of chosen features is based on colour and statistical concepts
- Geometrical features have been considered but did not improve the results
- Feature extraction is only applied when the classification block is SVM

Features which give predominant differences between parasite and non-parasite sub-images must be identified

Feature Extraction for SVM Classification

Features

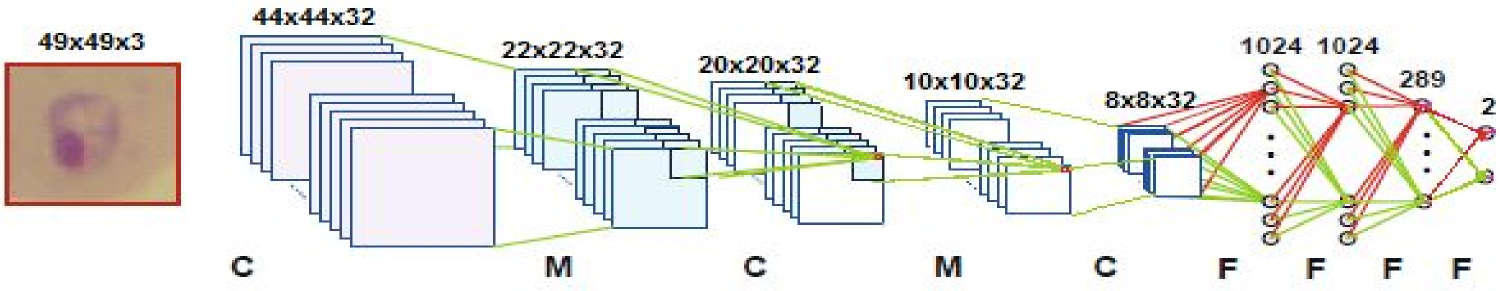
- Skewness
- Kurtosis
- Mean
- Standard deviation
- Contrast
- Correlation
- Energy
- Homogeneity

Channels

- Red
- Green
- Blue
- Gray
- Hue
- Saturation
- Value

ConvNet Proposal

- The CNN inputs are the raw sub-images (no feature extraction is done)
- Input sub-images are resized to 49x49x3
- Other CNN architectures have been tried but with worse results
- Softmax classifier at the end of the network



C: Convolutional M: Max pooling F: fully connected

Results: Data Available (extracted from 38 images)

- **Hue binarization (sub-images)**
  - 487
    - Parasite: 105
    - No-parasite: 382
- **Data augmentation**
  - 1948
    - Parasite: 420
    - No-parasite: 1528
- **Balanced dataset**
  - 840
    - Parasite: 420
    - No-parasite: 420

- **Cell segmentation (sub-images)**
  - 5659
    - Parasite: 75
    - No-parasite: 5584
- **Data augmentation**
  - 22636
    - Parasite: 300
    - No-parasite: 22336
- **Balanced dataset**
  - 600
    - Parasite: 300
    - No-parasite: 300

Results: SVM

Results for the sub-images	Hue binarization	Cell segmentation	Combination
Percentage of parasite candidates detected – **Sensitivity**	60.87% [45.37% - 74.91%]	63.64% [47.77% - 77.59%]	79.55% [64.70% - 90.20%]
Percentage of no-parasites well classified - **Specificity**	99.25% [95.91% - 99.98%]	99.88% [99.64% - 99.97%]	99.84% [99.58% - 99.96%]
Percentage of no-parasite candidates wrongly classified - **False positives rate**	0.75% [0,02% - 4.09%]	0.12% [0.03% - 0.36%]	0.16% [0.04% - 0.42%]
Num. of no-parasite candidates wrongly classified – **Num. false positives**	1	3	4

- Low cell segmentation sensitivity due to the discard of cells in the pre-processing
- The specificity and false positive rate depend on the amount of negative sub-images

Results: ConvNet

Results for the sub-images	Hue binarization	Cell segmentation
Sensitivity	99.76% [95.23% - 100%]	~~100%~~ **72%** ~~[94.04% - 100%]~~
Specificity	99.88% [95.47% - 100%]	99.78% [99.71% - 99.89%]
False positives rate	0.12% [0% - 4,43%]	0.22% [0,11% - 0,29%]

- Decrease of the cell segmentation sensitivity due to the discard of cells

The final choice is to use hue binarization sub-images

Brain Tumor Segmentation (Starting Project at UPC)

Prof. Verónica Vilaplana
Students: Adrià Casamitjana, Santi Puch, Asier Aduriz, Marcel Catà

Interest to participate in a Brain Lesion Challenge
Satellite event of MICCAI 2016

Int. Conf. on Medical Image Computing & Computer Assisted Intervention

BRAINLES: Brain Lesion Workshop and Challenges on Brain Tumor and Stroke Lesion Analysis, Traumatic Brain Injury.

Three challenges:

- BRATS: brain tumor analysis   DUE 31st of July 2016!!!!
- ISLES: stroke lesion analysis
- mTOP: traumatic brain injury

Brats: multimodal brain tumor segmentation Challenge

Preprocessing: All data sets have been aligned to the same anatomical template and interpolated to $1mm^3$ voxel resolution.

Data: The data set contains about 300 high- and low- grade glioma cases. Each data set has T1 MRI, T1 contrast-enhanced MRI, T2 MRI, and T2 FLAIR MRI volumes.

Annotations comprise the whole tumor, the tumor core (including cystic areas), and the Gd-enhanced tumor core

Brats: multimodal brain tumor segmentation Challenge

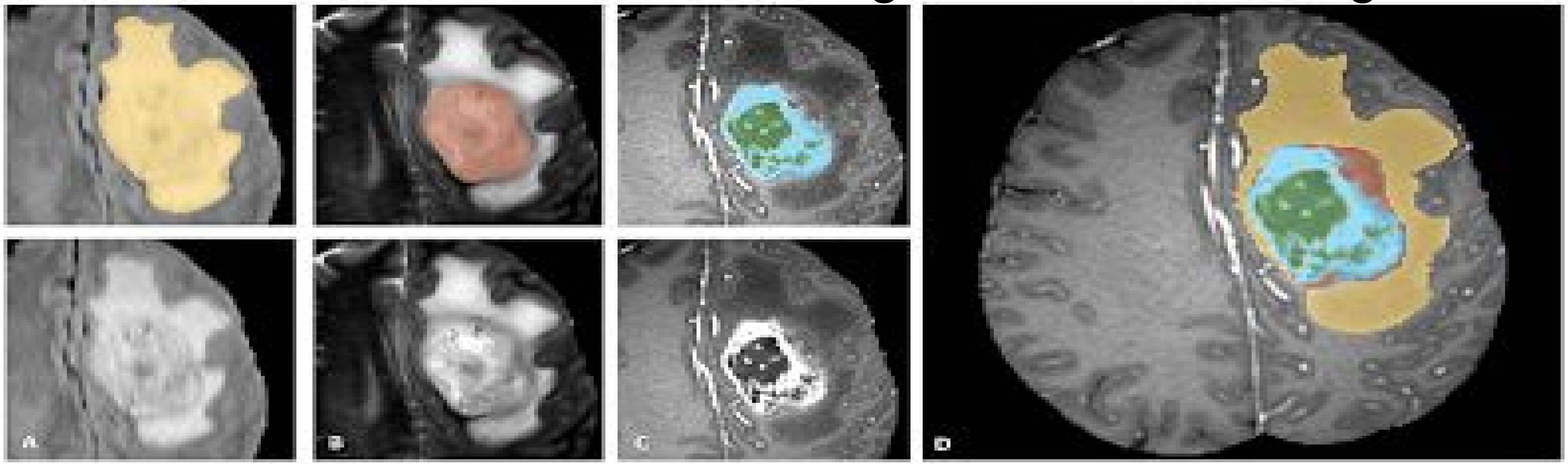


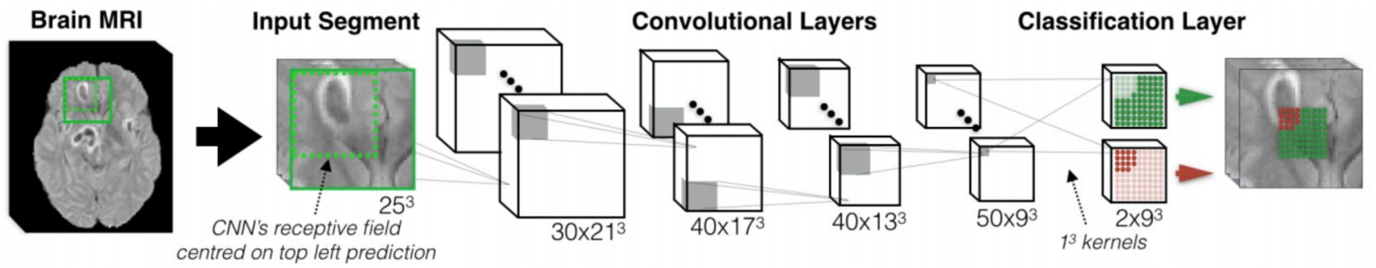
FIGURE: Manual annotation through expert raters. Shown are image patches with the tumor structures that are annotated in the different modalities (top left) and the final labels for the whole dataset (right). The image patches show from left to right: the whole tumor visible in FLAIR (Fig. A), the tumor core visible in T2 (Fig. B), the enhancing tumor structures visible in T1c (blue), surrounding the cystic/necrotic components of the core (green) (Fig. C). The segmentations are combined to generate the final labels of the tumor structures (Fig. D): edema (yellow), non-enhancing solid core (red), necrotic/cystic core (green), enhancing core (blue). (Figure from the BRATS TMI reference paper.)

Example: “DeepMedic”

Efficient Multi-Scale 3D CNN with fully connected CRF for Accurate Brain Lesion Segmentation, Konstantinos Kamnitsas, et al. 2016

- Efficient hybrid training shceme
- Use of 3D deeper networks
- Parallel convolutional pathways for multi-scale processing
- Results on BRATS 2015

Baseline CNN: Shallow



Deeper Networks

Advantatges:

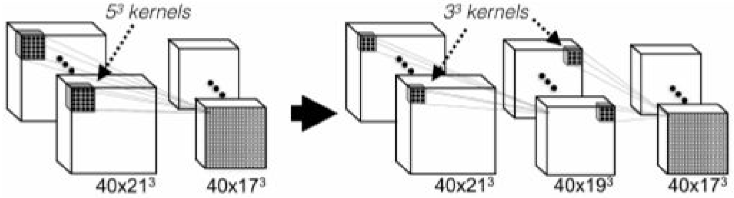
More discriminative power

Disadvantatges:

Computationally expensive

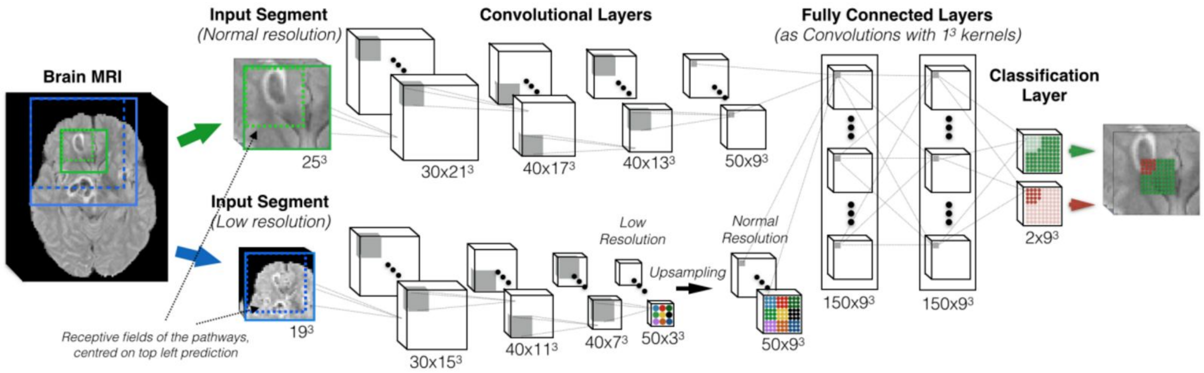
Additional trainable parameters

Solution: smaller kernels will both reduce the number of operations and the number of parameters (by $5^3 / 3^3 \simeq 4.6$)



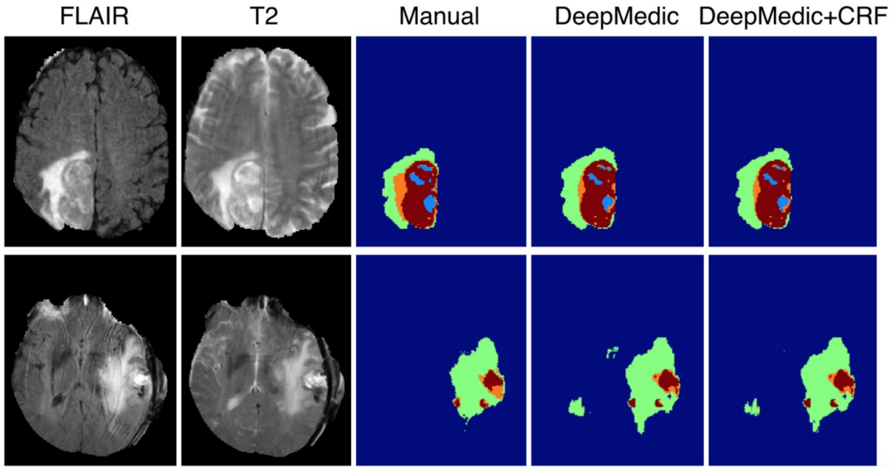
Build the deeper network on the baseline CNN by inserting extra layers in between

Multi-scale processing



Results

DeepMedic shows improvements due to its **additional information** and no to its increasing **capacity**



	DSC			Precision			Sensitivity			
	Whole	Core	Enh.	Whole	Core	Enh.	Whole	Core	Enh.	Cases
Ensemble+CRF	**90.1***	75.4	**72.8***	91.9	85.7	75.5	89.1	71.7	74.4	274
Ensemble	90.0	75.5	72.8	90.3	85.5	75.4	90.4	71.9	74.3	274
DeepMedic+CRF	**89.8****	75.0	**72.1***	91.5	84.4	75.9	89.1	72.1	72 .5	274
DeepMedic	89.7	75.0	72.0	89.7	84.2	75.6	90.5	72.3	72.5	274
bakas1	88	77	68	90	84	68	89	76	75	186
peres1	87	73	68	89	74	72	86	77	70	274
anon1	84	67	55	90	76	59	82	68	61	274
thirs1	80	66	58	84	71	53	79	66	74	267
peyrj	80	60	57	87	79	59	77	53	60	274

Ensemble: combination of 3 networks (due to randomness, same architecture) to clear unbiased errors of the network

Medical Imaging Summary

- Interest in the Area of Medical Imaging in Deep Learning:
    - ISBI 2016. MICCAI Tutorials 2015:
      Deep Learning Applications to Medical Image Analysis, Prof. Dinggang Shen, Univ. of North Carolina, USA
      From DBNs to Deep ConvNets: Pushing the State of the Art in Medical Image Analysis, Prof. Gustavo Carneiro, University Adelaide, Australia
- Example 1:
    - Malaria Parasite Detection in Blood Samples using ConvNets (UPC)
    - Yuanpu Xie, Fuyong Xing, Xiangfei Kong, Hai Su, Lin Yang, "*Beyond Classification: Structured Regression For Robust Cell Detection Using Convolutional Neural Network*", MICCAI 2015

- Example 2:
    - Brats: Challenge in brain tumor analysis
    - Efficient Multi-Scale 3D CNN with fully connected CRF for Accurate Brain Lesion Segmentation, Konstantinos Kamnitsas, et al. 2016