Day 4 Lecture 5

Medical Imaging

Elisa Sayrol
Medical Imaging

Interest in this area in Deep Learning:

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
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)

2 different techniques
- Hue binarization
- Cell segmentation

2 different methods
- SVM
- CNN

Pre-processing – Hue binarization

- Create sub-images around the centroids taking the surrounding pixels
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)
### Results: SVM

<table>
<thead>
<tr>
<th>Results for the sub-images</th>
<th>Hue binarization</th>
<th>Cell segmentation</th>
<th>Combination</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage of parasite candidates detected – <strong>Sensitivity</strong></td>
<td>60.87% [45.37% - 74.91%]</td>
<td>63.64% [47.77% - 77.59%]</td>
<td>79.55% [64.70% - 90.20%]</td>
</tr>
<tr>
<td>Percentage of no-parasites well classified - <strong>Specificity</strong></td>
<td>99.25% [95.91% - 99.98%]</td>
<td>99.88% [99.64% - 99.97%]</td>
<td>99.84% [99.58% - 99.96%]</td>
</tr>
<tr>
<td>Percentage of no-parasite candidates wrongly classified - <strong>False positives rate</strong></td>
<td>0.75% [0.02% - 4.09%]</td>
<td>0.12% [0.03% - 0.36%]</td>
<td>0.16% [0.04% - 0.42%]</td>
</tr>
<tr>
<td>Num. of no-parasite candidates wrongly classified – <strong>Num. false positives</strong></td>
<td>1</td>
<td>3</td>
<td>4</td>
</tr>
</tbody>
</table>

- 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

<table>
<thead>
<tr>
<th>Results for the sub-images</th>
<th>Hue binarization</th>
<th>Cell segmentation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensitivity</td>
<td>99.76% [95.23% - 100%]</td>
<td>100% [94.04% - 100%]</td>
</tr>
<tr>
<td>Specificity</td>
<td>99.88% [95.47% - 100%]</td>
<td>99.78% [99.71% - 99.89%]</td>
</tr>
<tr>
<td>False positives rate</td>
<td>0.12% [0% - 4.43%]</td>
<td>0.22% [0.11% - 0.29%]</td>
</tr>
</tbody>
</table>

- 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
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.
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 hybrid training scheme
- Use of 3D deeper networks
- Parallel convolutional pathways for multi-scale processing
- Results on BRATS 2015
Baseline CNN: Shallow
Deeper Networks

Advantages:
  - More discriminative power
Disadvantages:
  - Computationally expensive
  - Additional trainable parameters
Solution: smaller kernels will both reduce the number of operations and the number of parameters
(by $5^3 / 3^3 \approx 4.6$)

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.
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