DEEP LEARNING IN BIG MEDICAL IMAGE DATA

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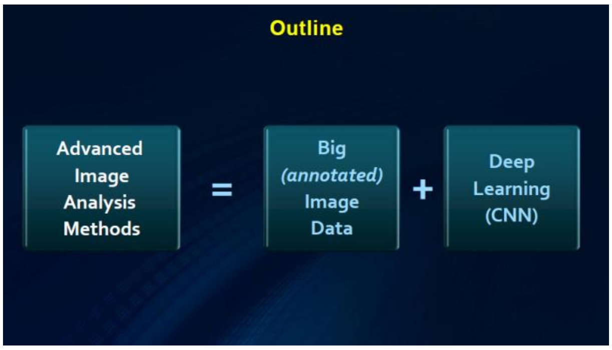
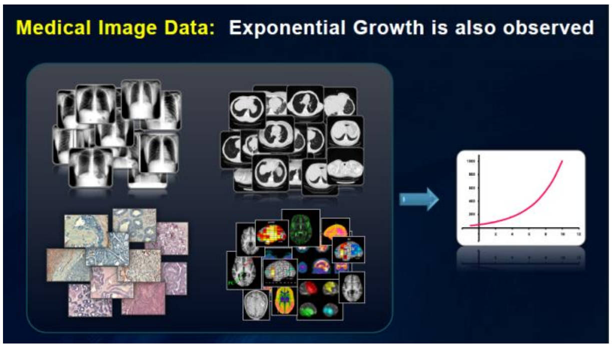
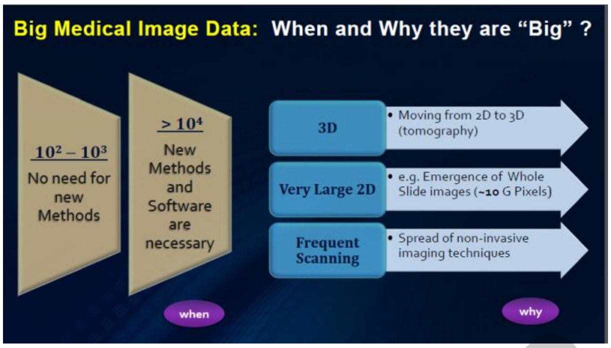
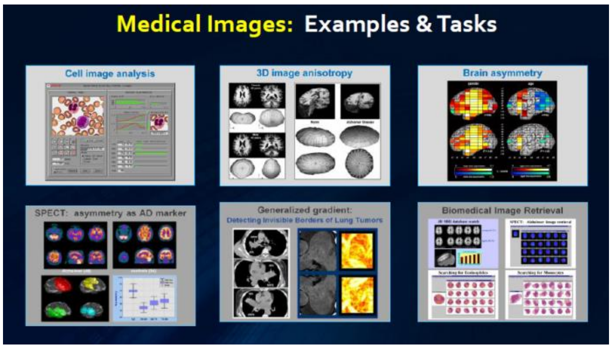
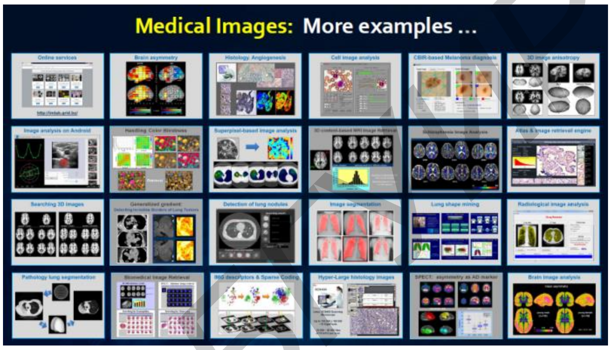
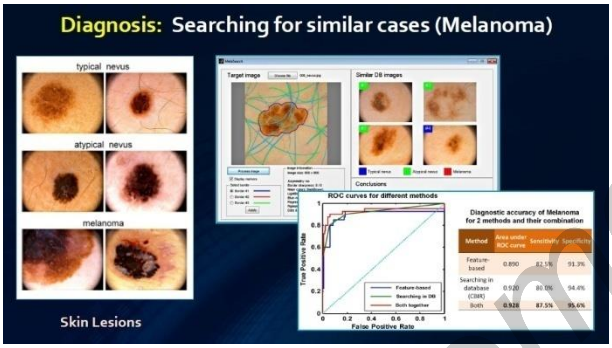


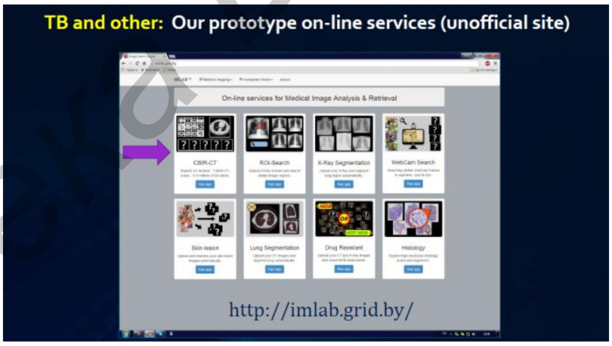

Medical Image Data: Exponential Growth is also observed

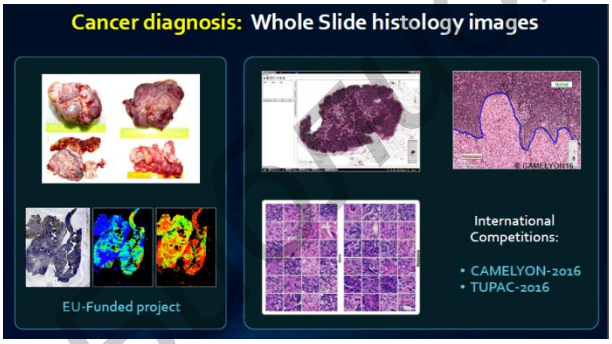

Big Medical Image Data: When and Why they are "Big" ?
10² – 10³
No need for new Methods
> 10⁴
New Methods and Software are necessary
3D
Moving from 2D to 3D (tomography)
Very Large 2D
e.g. Emergence of Whole Slide images (~10 G Pixels)
Frequent Scanning
Spread of non-invasive imaging techniques
when
why

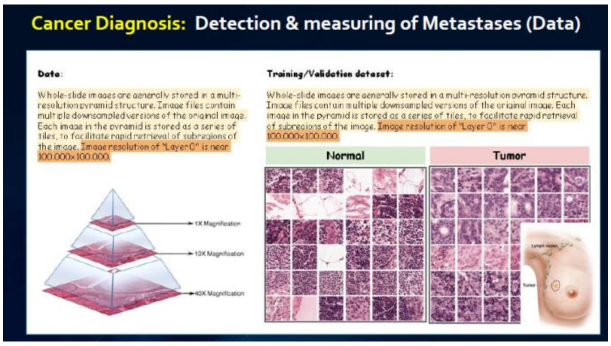

Medical Images: Examples & Tasks
Cell image analysis
3D image anisotropy
Brain asymmetry
SPECT: asymmetry as AD marker
Generalized gradient:
Detecting Invisible Borders of Lung Tumors
Biomedical Image Retrieval

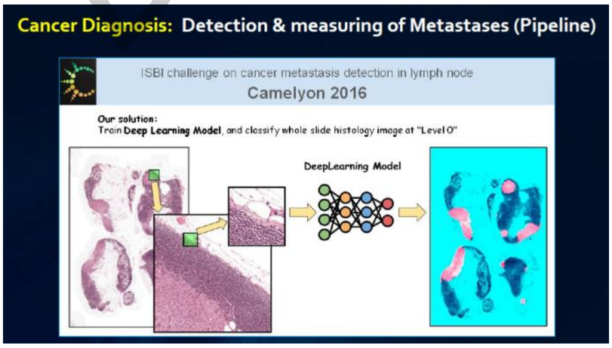

Medical Images: More examples ...

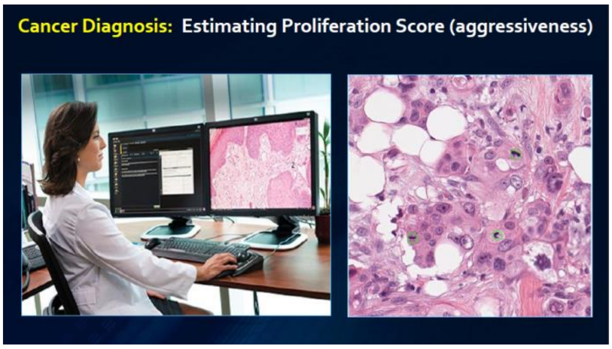

Diagnosis: Searching for similar cases (Melanoma)
typical nevus
atypical nevus
melanoma
Skin Lesions
ROC curves for different methods
Diagnostic accuracy of Melanoma for 2 methods and their combination
True Positive Rate
False Positive Rate

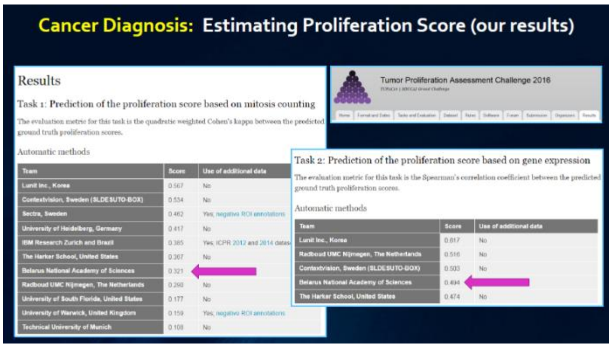

TB and other: Our prototype on-line services (unofficial site)
On-line services for Medical Image Analysis & Retrieval
http://imlab.grid.by/

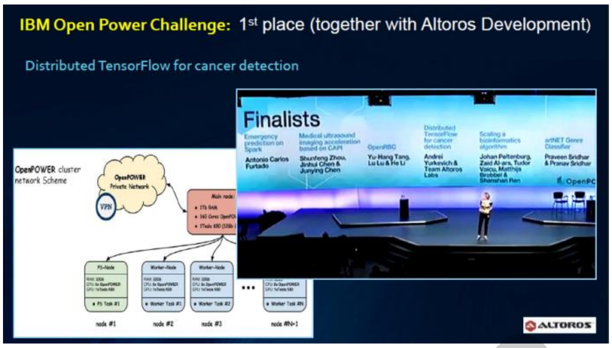

Cancer diagnosis: Whole Slide histology images
EU-Funded project
International Competitions:
• CAMELYON-2016
• TUPAC-2016

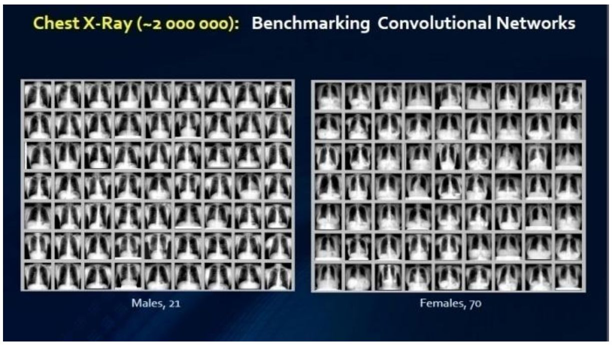

Cancer Diagnosis: Detection & measuring of Metastases (Data)
Data:
Training/Validation dataset:
Normal
Tumor

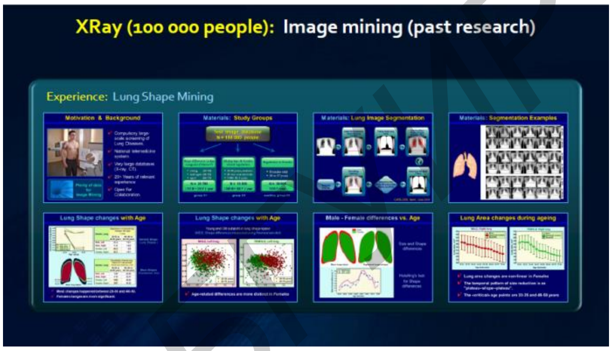

Cancer Diagnosis: Detection & measuring of Metastases (Pipeline)
ISBI challenge on cancer metastasis detection in lymph node
Camelyon 2016
Our solution:
Train Deep Learning Model, and classify whole slide histology image at "Level 0"
DeepLearning Model

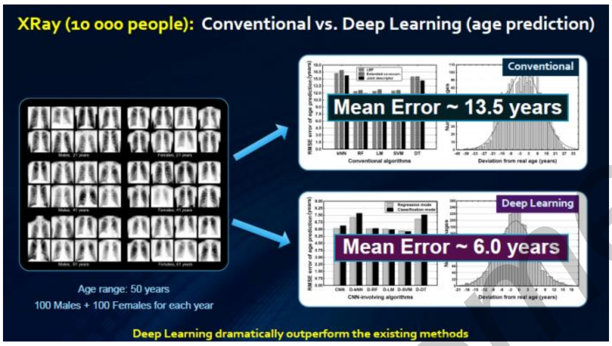

Cancer Diagnosis: Estimating Proliferation Score (aggressiveness)

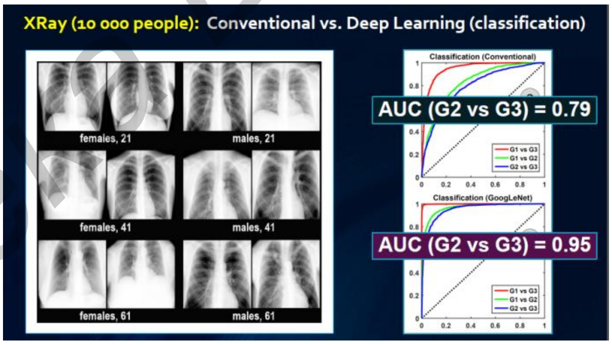

Cancer Diagnosis: Estimating Proliferation Score (our results)
Results
Task 1: Prediction of the proliferation score based on mitosis counting
Automatic methods
Tumor Proliferation Assessment Challenge 2016
Task 2: Prediction of the proliferation score based on gene expression
Automatic methods

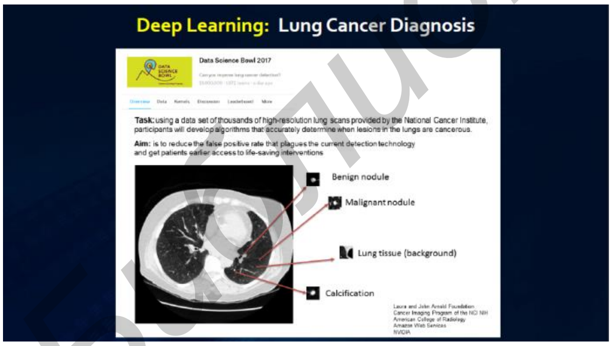

IBM Open Power Challenge: 1st place (together with Altoros Development)
Distributed TensorFlow for cancer detection
Finalists
OpenPOWER cluster network Scheme
ALTOROS

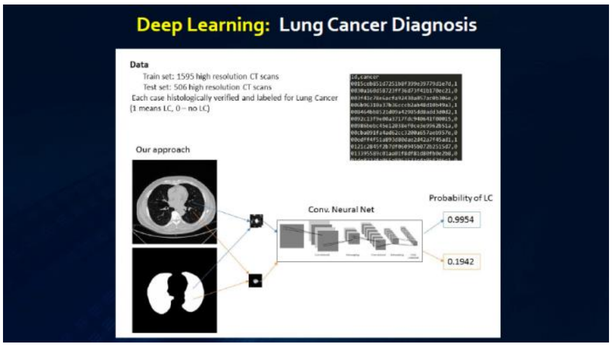

Chest X-Ray (~2 000 000): Benchmarking Convolutional Networks
Males, 21
Females, 70

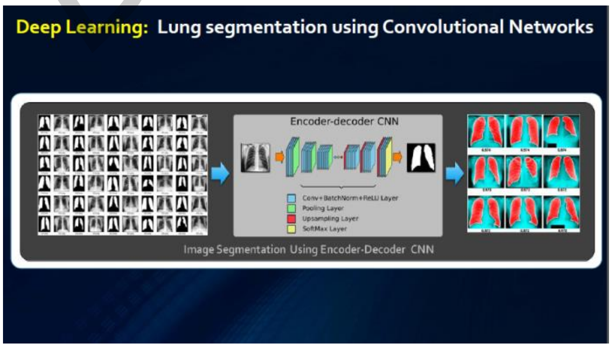

XRay (100 000 people): Image mining (past research)
Experience: Lung Shape Mining

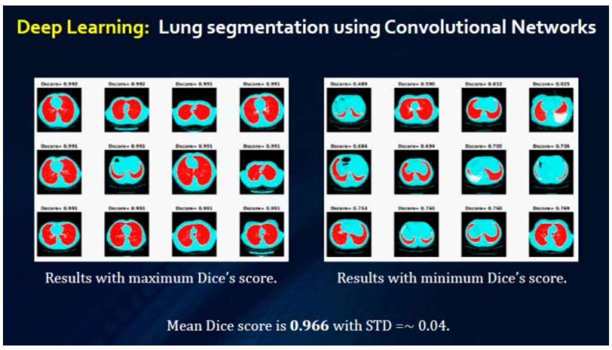

XRay (10 000 people): Conventional vs. Deep Learning (age prediction)
Conventional
Mean Error ~ 13.5 years
Deep Learning
Mean Error ~ 6.0 years
Age range: 50 years
100 Males + 100 Females for each year
Deep Learning dramatically outperform the existing methods

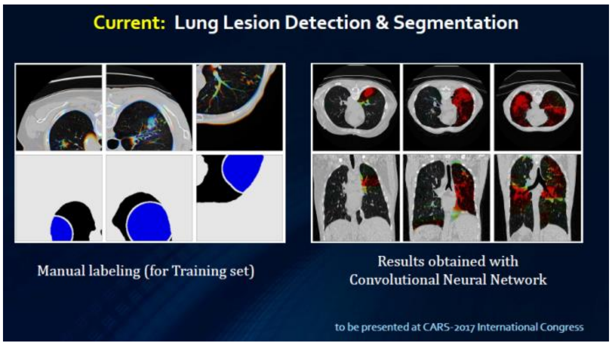

XRay (10 000 people): Conventional vs. Deep Learning (classification)
females, 21
males, 21
females, 41
males, 41
females, 61
males, 61
Classification (Conventional)
AUC (G2 vs G3) = 0.79
Classification (GoogLeNet)
AUC (G2 vs G3) = 0.95

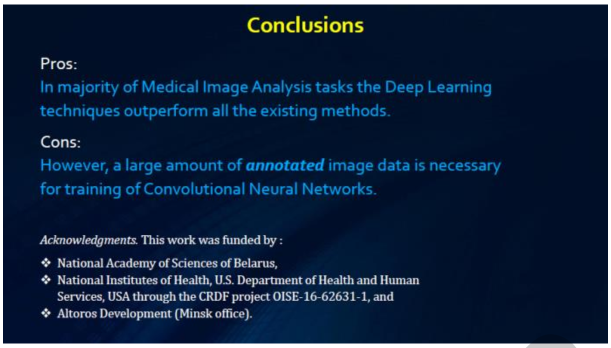

Deep Learning: Lung Cancer Diagnosis
Data Science Bowl 2017
Task: using a data set of thousands of high-resolution lung scans provided by the National Cancer Institute, participants will develop algorithms that accurately determine when lesions in the lungs are cancerous.
Aim: is to reduce the false positive rate that plagues the current detection technology and get patients earlier access to life-saving interventions
Benign nodule
Malignant nodule
Lung tissue (background)
Calcification


Deep Learning: Lung Cancer Diagnosis
Data
Train set: 1595 high resolution CT scans
Test set: 506 high resolution CT scans
Each case histologically verified and labeled for Lung Cancer (1 means LC, 0 – no LC)
Our approach
Conv. Neural Net
Probability of LC
0.9954
0.1942


Deep Learning: Lung segmentation using Convolutional Networks
Encoder-decoder CNN
Image Segmentation Using Encoder-Decoder CNN


Deep Learning: Lung segmentation using Convolutional Networks
Results with maximum Dice's score.
Results with minimum Dice's score.
Mean Dice score is 0.966 with STD =~ 0.04.


Current: Lung Lesion Detection & Segmentation
Manual labeling (for Training set)
Results obtained with Convolutional Neural Network
to be presented at CARS-2017 International Congress


Conclusions
Pros:
In majority of Medical Image Analysis tasks the Deep Learning techniques outperform all the existing methods.
Cons:
However, a large amount of annotated image data is necessary for training of Convolutional Neural Networks.
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