The International Symposium on Biomedical Imaging (ISBI) is a premier peer-reviewed scientific conference dedicated to mathematical, algorithmic, and computational aspects of biomedical imaging using innovative imaging modalities on humans and small animals.

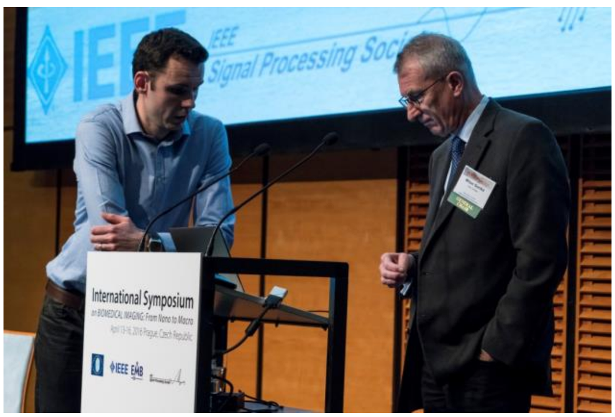
During the conference, I attended several relevant preconference tutorials on cutting edge technologies for medical imaging offered by renowned professors from the medical imaging domain. The purpose of the tutorials is to provide knowledge of the latest results, trends, activities and applications in the domain of medical image analysis, image registration, machine learning, and deep learning such as SimpleITK via Insight Segmentation and Registration Toolkit (ITK), Deep belief networks (DBN), Deep neural network (DNN), Restricted Boltzmann machine (RBM), and Convolutional neural network (CNN). Such topics are very much in line with my current needs to advance my PhD research.

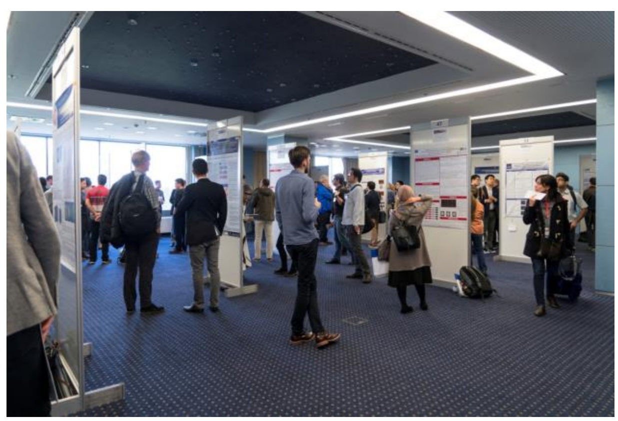
The ultimate objective of my doctoral study is to build an Unsupervised Computer-Aided Diagnosis (UCAD) system for early diagnosis of lung cancer in the computer tomography (CT) imaging. So far, I have proposed various novel methods for the early detection of lung cancer, which has been positively accepted and published in two recent peer-reviewed IEEE conferences. The recognition of my research papers gives me the clarity to further continue exploring new challenges in my research. Consequently, I have developed a method for Computer-Aided Detection (CAD) system, which incorporates the proposed methods and machine learning based technique (i.e. artificial neural network (ANN)) for the detection of cancerous nodules from the initially segmented nodule candidates.

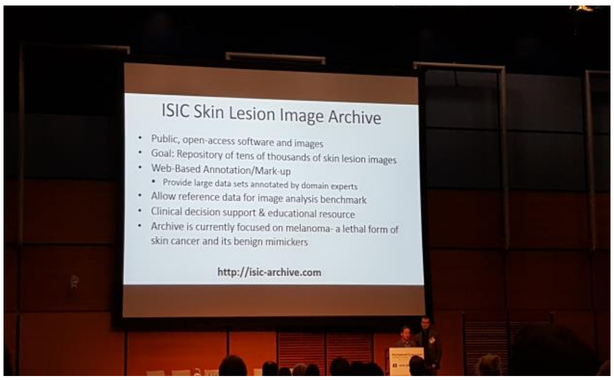
However, to achieve the ultimate objective of my research, I need to obtain advanced knowledge, skills and experience to develop some further novel image registration and deep learning approaches.

Conclusively, the five days conference provided me the rare combination of accelerated knowledge growth and the experience to get on the challenging path of developing image processing based applications. Especially there, various machine learning techniques and medical image analysis techniques taught by the pioneering tutors in an outstanding environment will definitely help me to move on with my current work.

Some pictures from the lectures of summer school

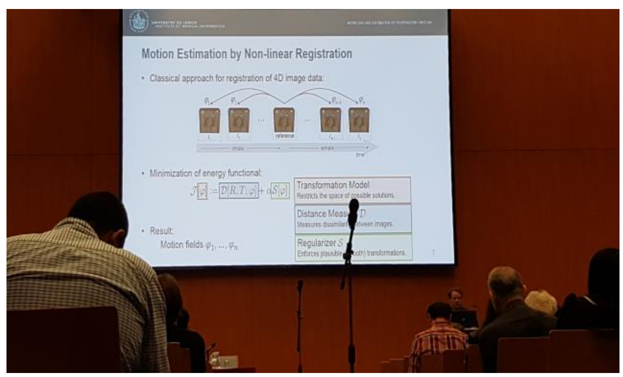


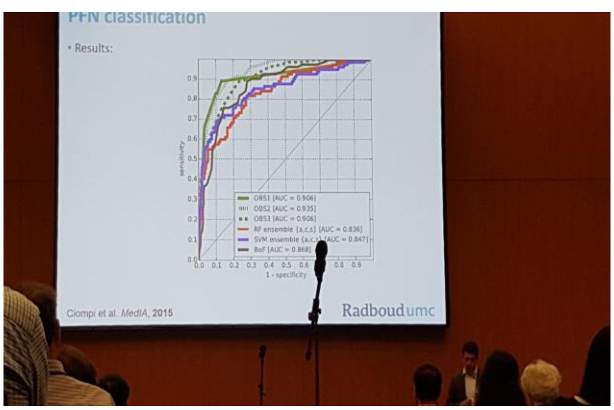


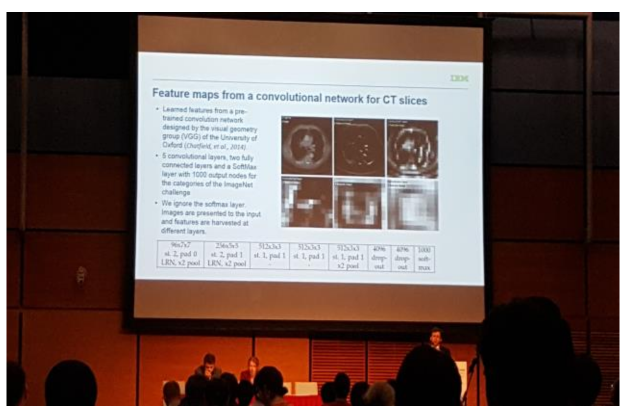

ISIC Skin Lesion Image Archive
Public, open-access software and images
Goal: Repository of tens of thousands of skin lesion images
Web-Based Annotation/Mark-up
Provide large data sets annotated by domain experts
Allow reference data for image analysis benchmark
Clinical decision support & educational resource
Archive is currently focused on melanoma- a lethal form of skin cancer and its benign mimickers
http://isic-archive.com

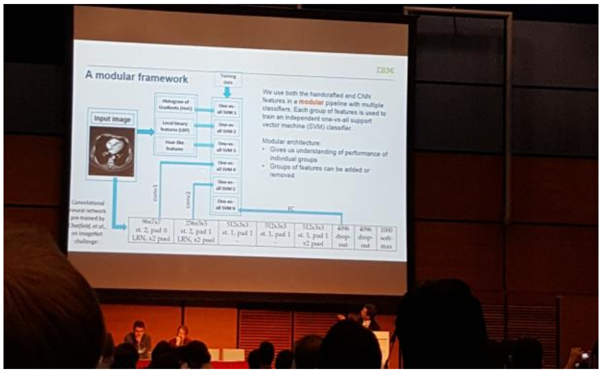

Background
Lung cancer is a major killer
NLST trial: screening with the use of low-dose CT reduces mortality from lung cancer with 20%
Lung cancer screening using low-dose CT is being implemented in the U.S. and possibly, other countries will soon follow
CAD could play an important role to make screening efficient
Radboudumc

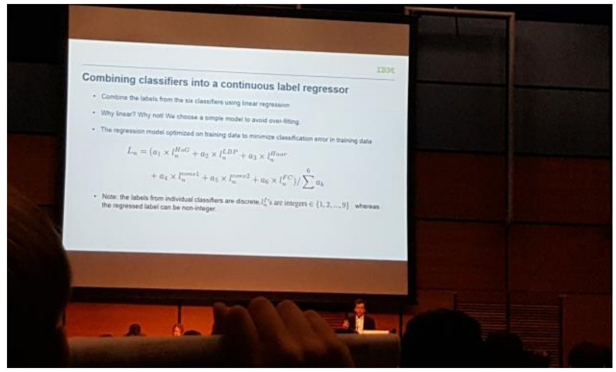

Motion Estimation by Non-linear Registration
Classical approach for registration of 4D image data:
Minimization of energy functional:
Transformation Model
Restricts the space of possible solutions.
Distance Measure
Regularizer
Motion fields $\varphi_1, \ldots, \varphi_n$

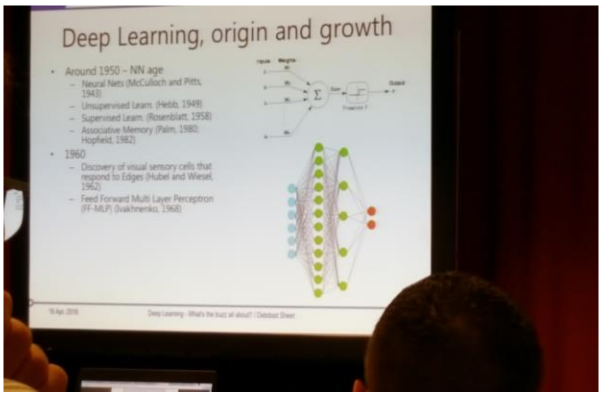

Motion Estimation by Non-linear Registration
Classical approach for registration of 4D image data:
Minimization of energy functional:
Transformation Model
Restricts the space of possible solutions.
Result:
Motion fields $\varphi_1, \ldots, \varphi_n$

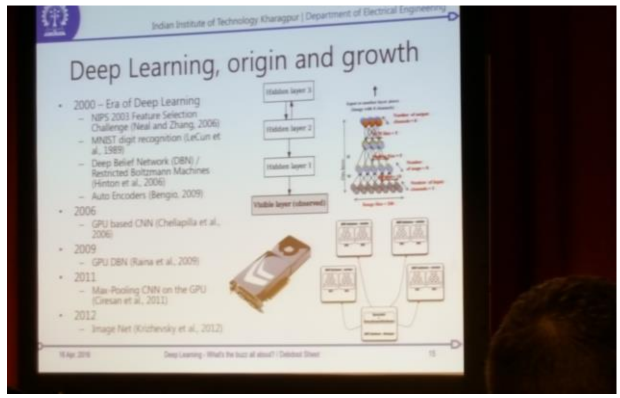

PFN classification
Results:
OBS1 [AUC = 0.906]
OBS2 [AUC = 0.935]
OBS3 [AUC = 0.906]
RF ensemble {a,c,s} [AUC = 0.836]
SVM ensemble {a,c,s} [AUC = 0.847]
BoF [AUC = 0.868]
sensitivity
1 - specificity
Ciompi et al. MedIA, 2015
Radboudumc

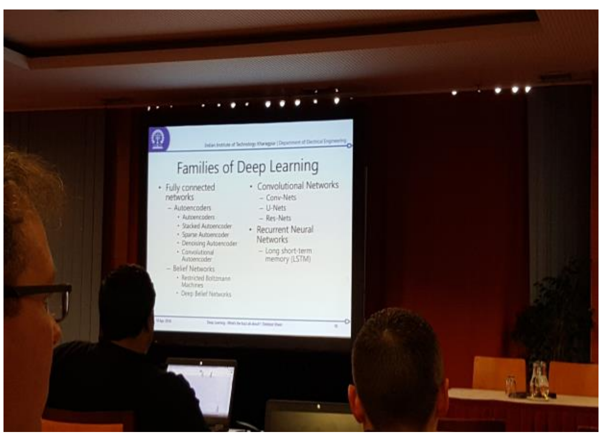

Feature maps from a convolutional network for CT slices


A modular framework
IBM
Training data
Input image
Histogram of Gradients (HoG)
Local binary features (LBP)
Haar like features
One-vs-all SVM 1
One-vs-all SVM 2
One-vs-all SVM 3
One-vs-all SVM 4
One-vs-all SVM 5
One-vs-all SVM 6
conv1
conv2
FC
Convolutional neural network pre-trained by Chatfield, et al., on ImageNet challenge
96x7x7 st. 2, pad 0 LRN, x2 pool
256x5x5 st. 2, pad 1 LRN, x2 pool
512x3x3 st. 1, pad 1
512x3x3 st. 1, pad 1
512x3x3 st. 1, pad 1 x2 pool
4096 drop-out
4096 drop-out
1000 soft-max
We use both the handcrafted and CNN features in a modular pipeline with multiple classifiers. Each group of features is used to train an independent one-vs-all support vector machine (SVM) classifier.
Modular architecture:
Gives us understanding of performance of individual groups
Groups of features can be added or removed


Combining classifiers into a continuous label regressor
IBM
Combine the labels from the six classifiers using linear regression
Why linear? Why not! We choose a simple model to avoid over-fitting
The regression model optimized on training data to minimize classification error in training data
$L_n = (a_1 \times l_n^{HoG} + a_2 \times l_n^{LBP} + a_3 \times l_n^{Haar} + a_4 \times l_n^{conv1} + a_5 \times l_n^{conv2} + a_6 \times l_n^{FC}) / \sum^{6} a_k$
Note: the labels from individual classifiers are discrete, l_n^f's are integers $\in \{1, 2, ..., 9\}$ whereas the regressed label can be non-integer.


Deep Learning, origin and growth
Around 1950 – NN age
Neural Nets (McCulloch and Pitts, 1943)
Unsupervised Learn. (Hebb, 1949)
Supervised Learn. (Rosenblatt, 1958)
Associative Memory (Palm, 1980; Hopfield, 1982)
1960
Discovery of visual sensory cells that respond to Edges (Hubel and Wiesel, 1962)
Feed Forward Multi Layer Perceptron (FF-MLP) (Ivakhnenko, 1968)
Deep Learning - What's the buzz all about? | Debdoot Sheet


Indian Institute of Technology Kharagpur | Department of Electrical Engineering
Deep Learning, origin and growth
2000 – Era of Deep Learning
NIPS 2003 Feature Selection Challenge (Neal and Zhang, 2006)
MNIST digit recognition (LeCun et al., 1989)
Deep Belief Network (DBN) / Restricted Boltzmann Machines (Hinton et al., 2006)
Auto Encoders (Bengio, 2009)
2006
GPU based CNN (Chellapilla et al., 2006)
2009
GPU DBN (Raina et al., 2009)
2011
Max-Pooling CNN on the GPU (Ciresan et al., 2011)
2012
Image Net (Krizhevsky et al., 2012)
Hidden layer 3
Hidden layer 2
Hidden layer 1
Visible layer (observed)
Deep Learning - What's the buzz all about? | Debdoot Sheet


Families of Deep Learning
Fully connected networks
Autoencoders
Autoencoders
Stacked Autoencoder
Sparse Autoencoder
Denoising Autoencoder
Convolutional Autoencoder
Belief Networks
Restricted Boltzmann Machines
Deep Belief Networks
Convolutional Networks
Conv-Nets
U-Nets
Res-Nets
Recurrent Neural Networks
Long short-term memory (LSTM)


Transfer vs. Full Deep Architecture
Multi-scale modeling of OCT speckles
Random forest learning
Stacked Auto-Encoders, Logistic Regression
Random Forest
Ground truth
Labeled tissue
ISBI 2014
http://www.facweb.iitkgp.ernet.in/~debdoot/current.html