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융합연구과제 A팀 Machine Learning Potential

Deep Learning for Computer-aided Diagnosis & Medical Image Analysis

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Wed, May 27, 2015

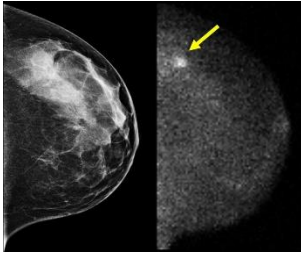
Outline

- Introduction | Joint Research
- Background | Deep Learning
- Research Proposals

Introduction

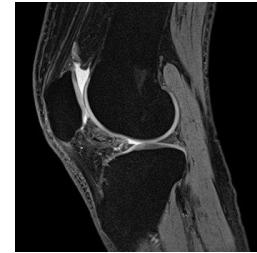
Joint Research

IVY Lab



Computer-aided breast cancer detection in X-ray

SIIT Lab

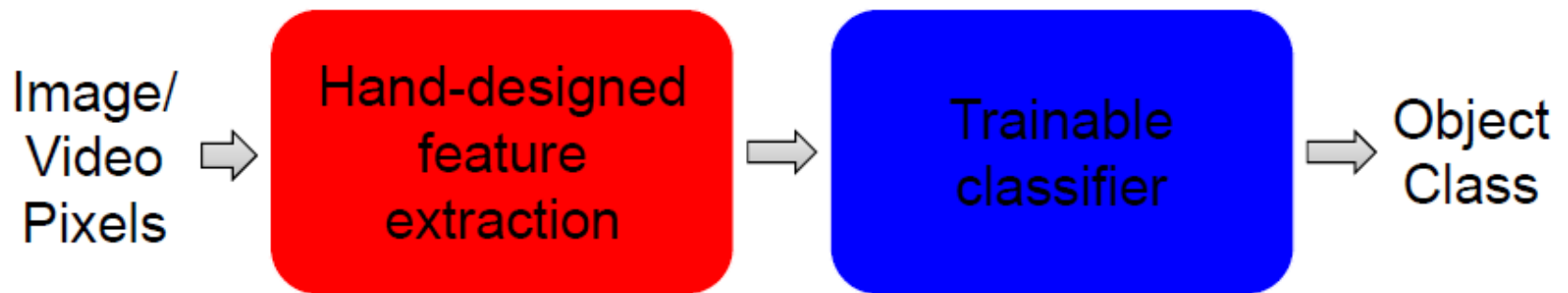


Knee MRI cartilage segmentation

Machine Learning Potential: Deep Learning

Studying & applying deep learning techniques for our CAD & MIA tasks

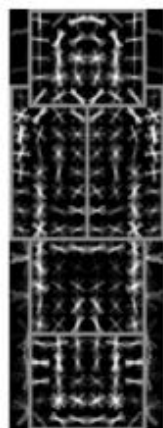
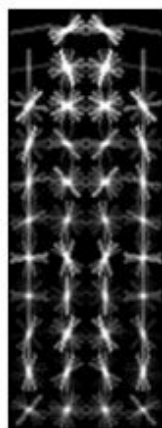
Traditional Recognition Approach



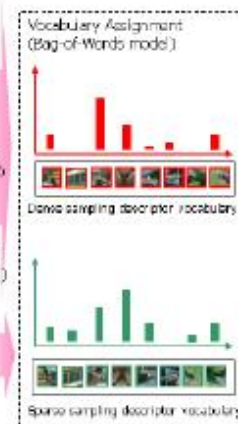
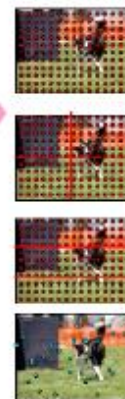
- Features are not learned
- Trainable classifier is often generic (e.g. SVM)

Traditional Recognition Approach

- Features are key to recent progress in recognition
- Multitude of hand-designed features currently in use
 - SIFT, HOG,
- Where next? Better classifiers? Or keep building more features?



Felzenszwalb, Girshick,
McAllester and Ramanan, PAMI 2007



- ▶ Low level features: SIFT and its variants, LBP, HOG.
- ▶ Dense sampling and interest point detector;
- ▶ Represented as Bags of Words;

Yan & Huang

(Winner of PASCAL 2010 classification competition)

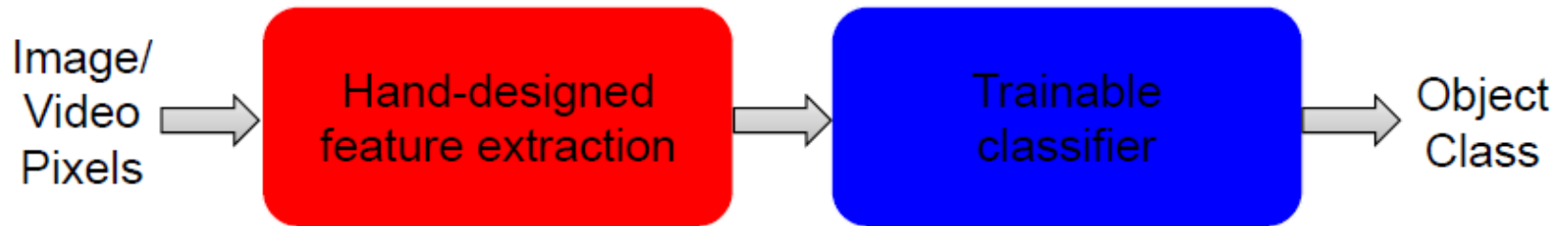
What about learning the features?

- Learn a *feature hierarchy* all the way from pixels to classifier
- Each layer extracts features from the output of previous layer
- Train all layers jointly



“Shallow” vs. “deep” architectures

Traditional recognition: “Shallow” architecture

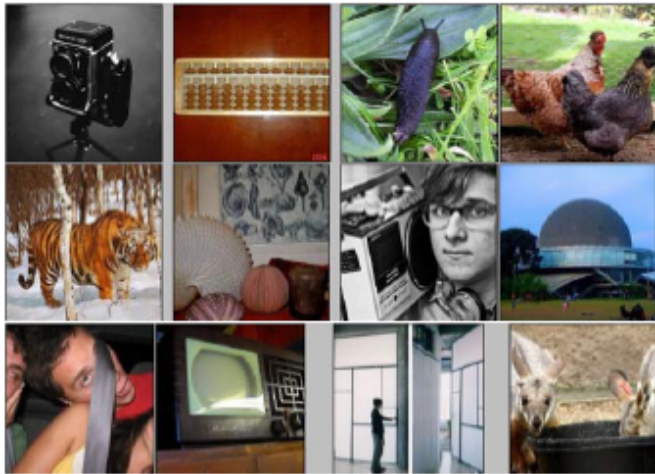


Deep learning: “Deep” architecture



ImageNet Challenge 2012

IM  GENET



[Deng et al. CVPR 2009]

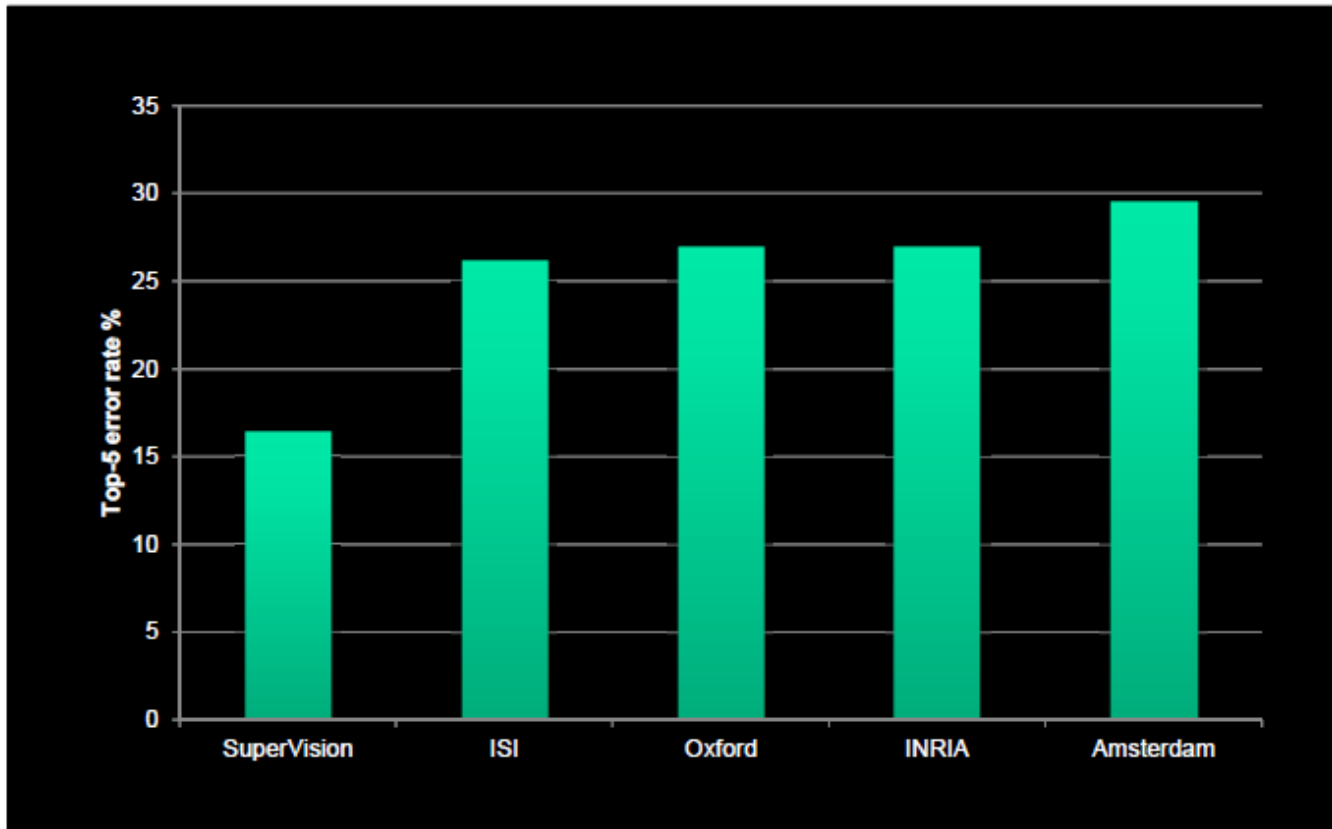
- ~14 million labeled images, 20k classes
- Images gathered from Internet
- Human labels via Amazon Turk
- Challenge: 1.2 million training images, 1000 classes

A. Krizhevsky, I. Sutskever, and G. Hinton, [ImageNet Classification with Deep Convolutional Neural Networks](#), NIPS 2012

ImageNet Challenge 2012

Krizhevsky et al. -- **16.4% error** (top-5)

Next best (non-convnet) – **26.2% error**



May 12, 2015, 12:01 AM ET

Baidu Leads in Artificial Intelligence Benchmark

By Robert McMillan



Baidu's Minwa supercomputer.

Baidu

Baidu Inc. says it has posted the world's best results on a closely watched artificial intelligence benchmark. It had a secret weapon, according to researchers at the Chinese search giant: Minwa.

The company's Minwa supercomputer scanned ImageNet, a database of just over one million pictures, and taught itself how to sort them into a predefined set of roughly 1,000 different categories. This meant learning the difference between a French loaf and a meatloaf, but also trickier challenges such as distinguishing a Lakeland terrier from a wire-haired fox terrier.

Five years ago, the better than the best

Microsoft's software had a 4.94% error rate; Google achieved 4.8%. Baidu said that it had reduced the error rate further to 4.58%.

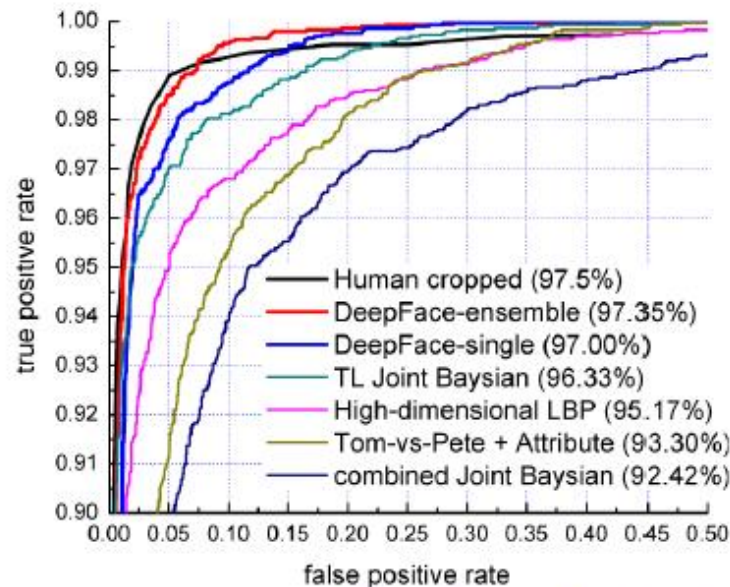
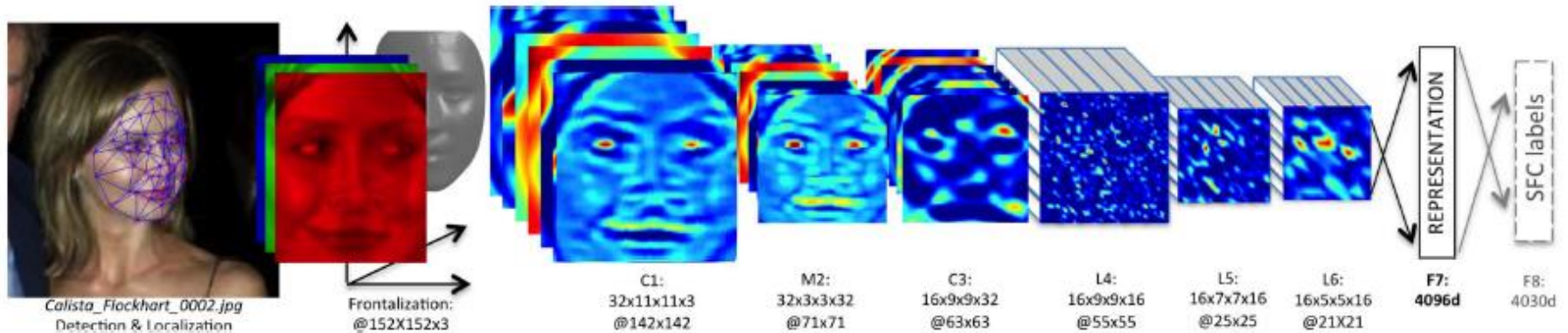
Baidu have all done

With practice, humans reduced the error rate

The so-called deep learning algorithms that Baidu and others are using to ace these tests have only recently made the leap from academia to Silicon Valley. But they're starting to have an impact in daily life.

said that it had

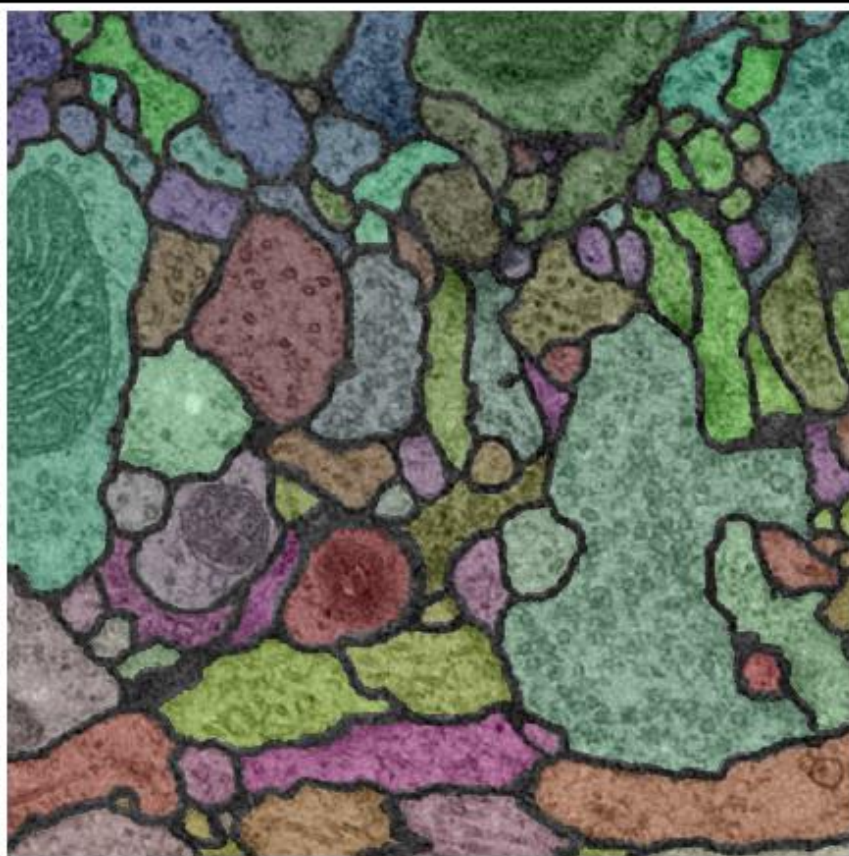
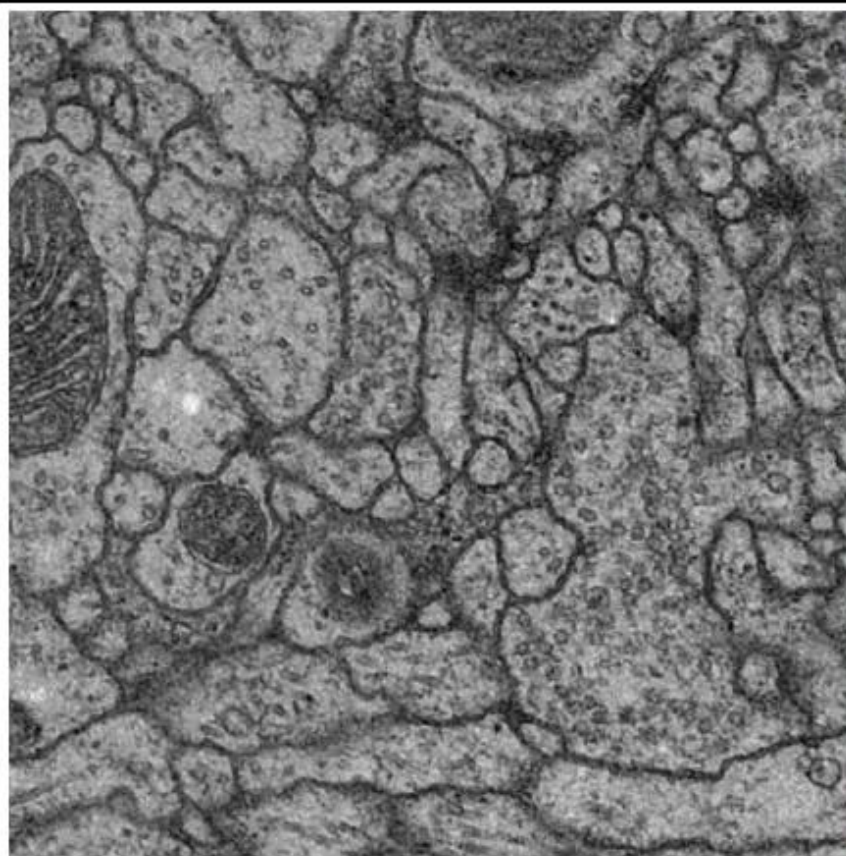
CNN features for face verification



Y. Taigman, M. Yang, M. Ranzato, L. Wolf, [DeepFace: Closing the Gap to Human-Level Performance in Face Verification](#), CVPR 2014, to appear.

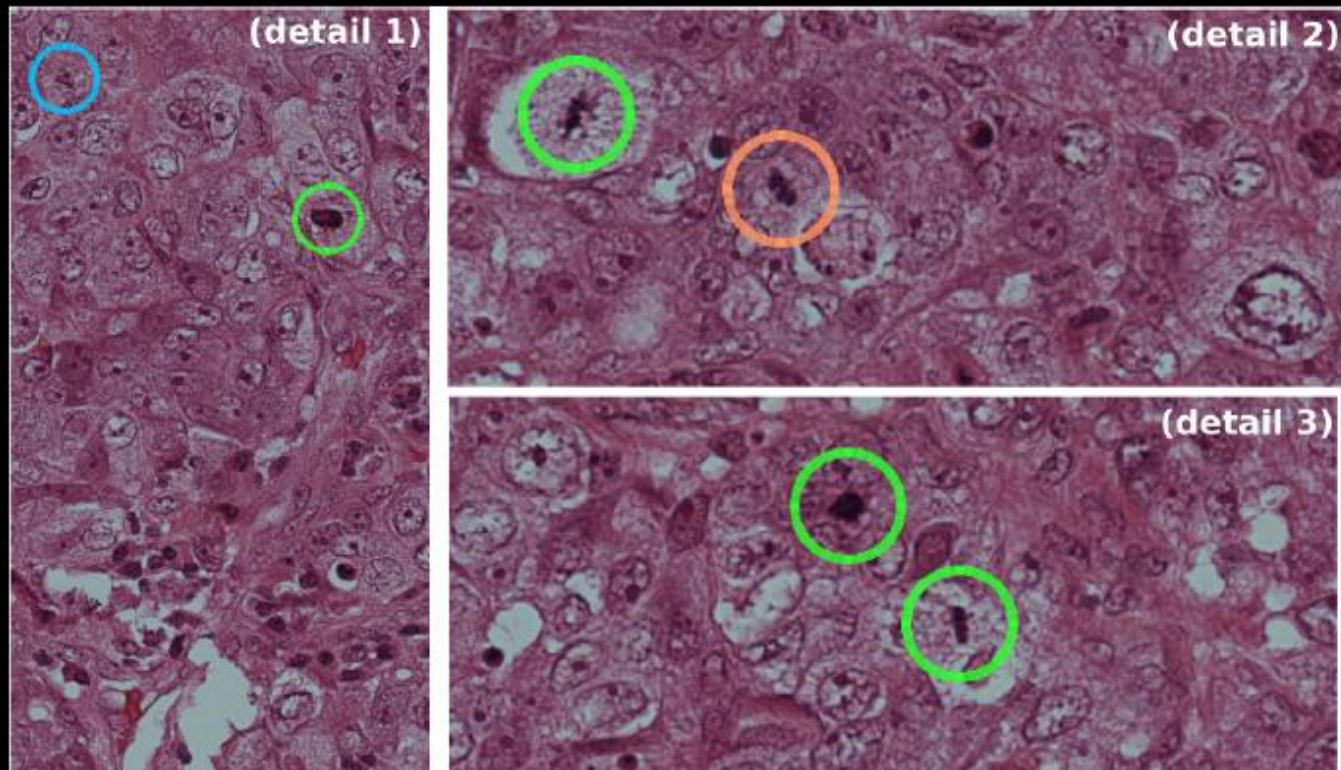
Segmentation

- Ciresan et al. “DNN segment neuronal membranes...” NIPS 2012
- Turaga et al. “Maximin learning of image segmentation” NIPS 2009



Biological Detection

- D. Ciresan, A. Giusti, L.M. Gambardella, J. Schmidhuber - Mitosis Detection in Breast Cancer Histology Images using Deep Neural Networks (MICCAI 2013)



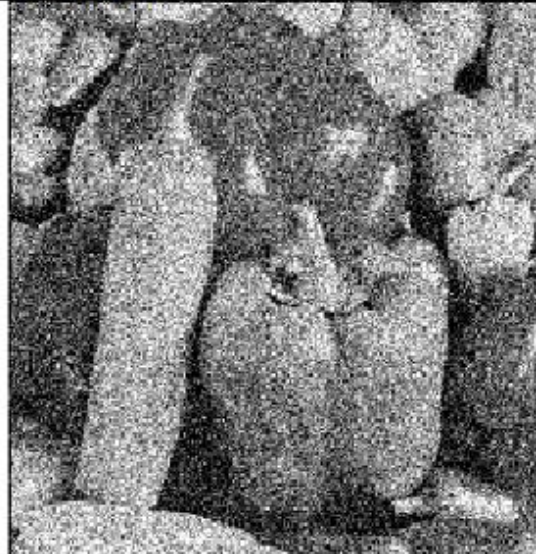
Denoising

- Burger et al. “Can plain NNs compete with BM3D?” CVPR 2012

Original



Noised



Denoised



Removing Artifacts

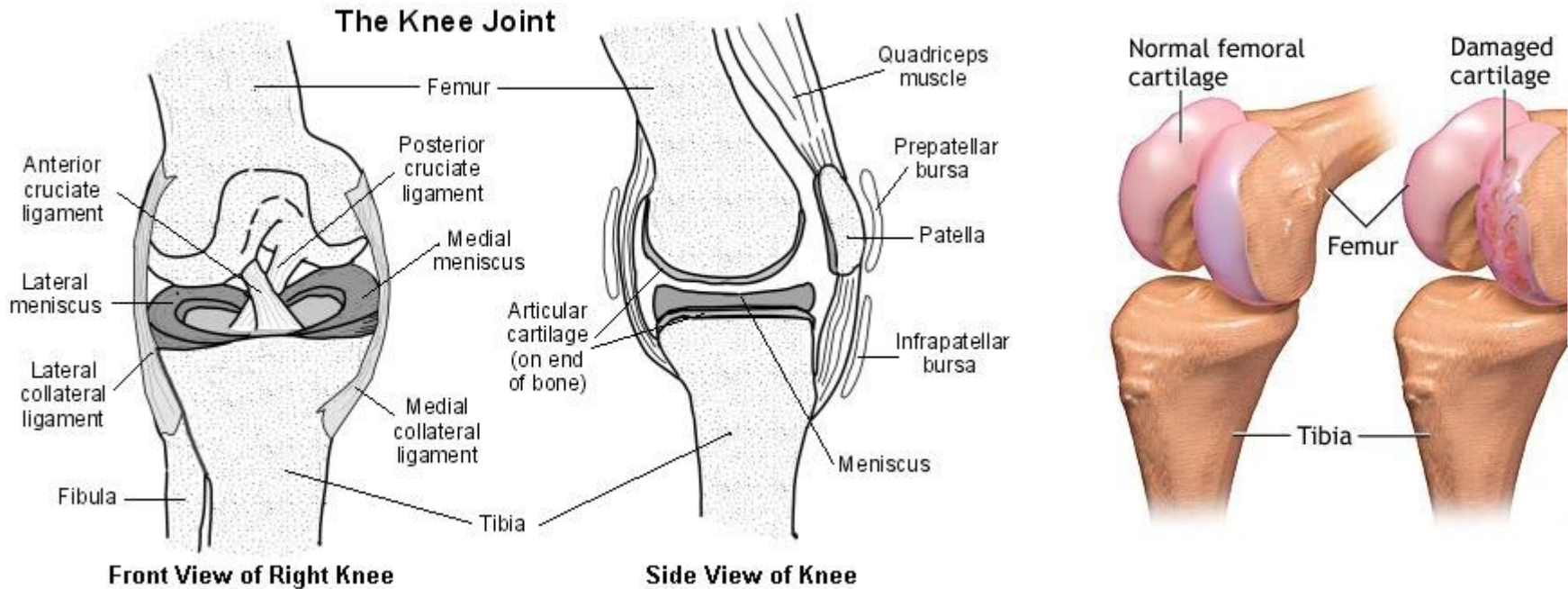
[Eigen et al. "Restoring an Image Taken Through a Window Covered with Dirt or Rain" ICCV 2013]



Research Proposals

Cartilage in Knee MRI

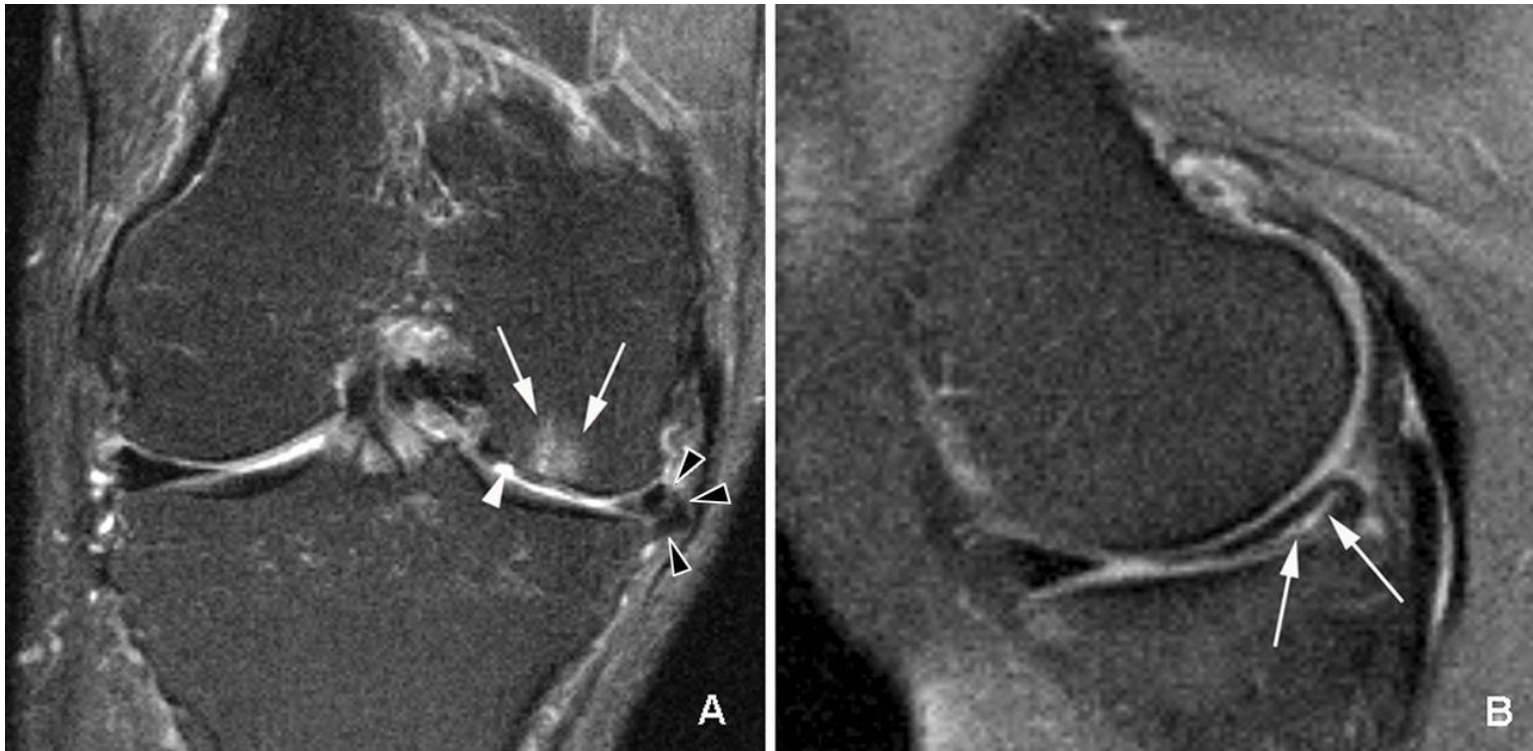
Knee Cartilage Damage & Osteoarthritis (OA)



Research Proposals

Knee Cartilage Seg.

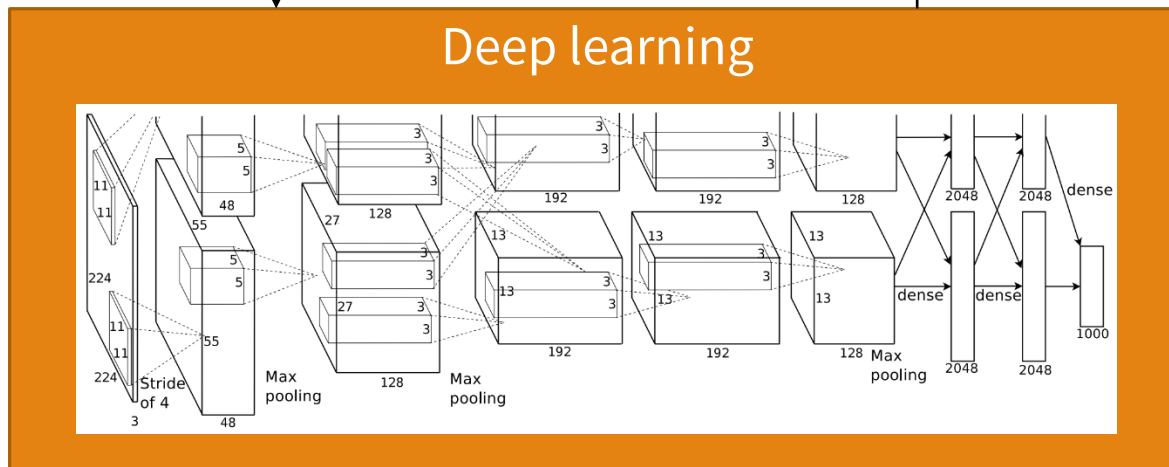
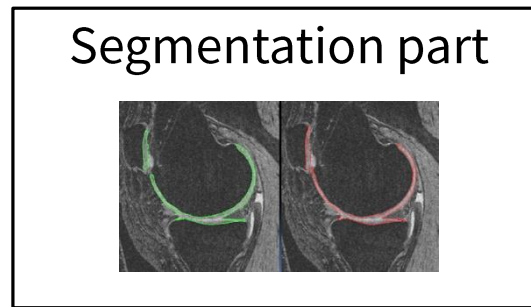
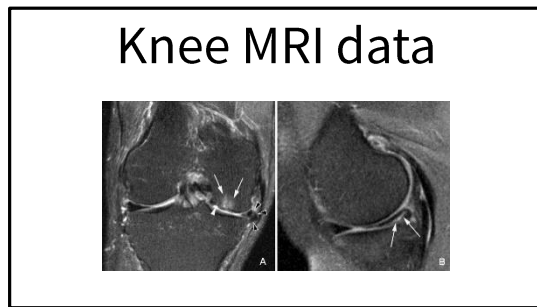
Challenges in Knee MRI Cartilage Segmentation



Research Proposals

DeepCART Deep Learning for Knee Cartilage Seg.

Deep feature learning for knee MRI cartilage segmentation



Issues

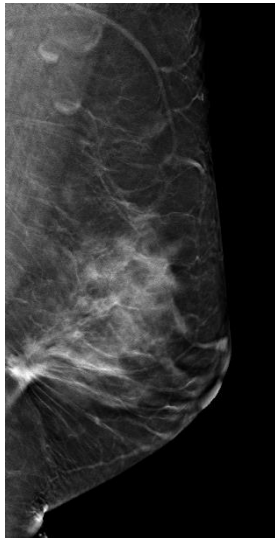
- Deep architecture
 - RBM, DBN
 - CNN
- Input format for DL
 - 2D patches
 - Tri-planar
 - 3D
- Choice of seg. Part
 - Multi-atlas
 - Voxel class.

Research Proposals

What is CAD?

Computer-aided detection (CAD) for breast cancer screening

Medical image acquisition



X-ray image
(mammography/digital
breast tomosynthesis)

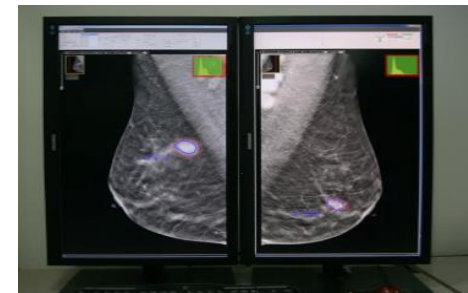


* Double reading, which is standard practice in the UK, significantly improves the sensitivity and specificity

First reading



Second reading



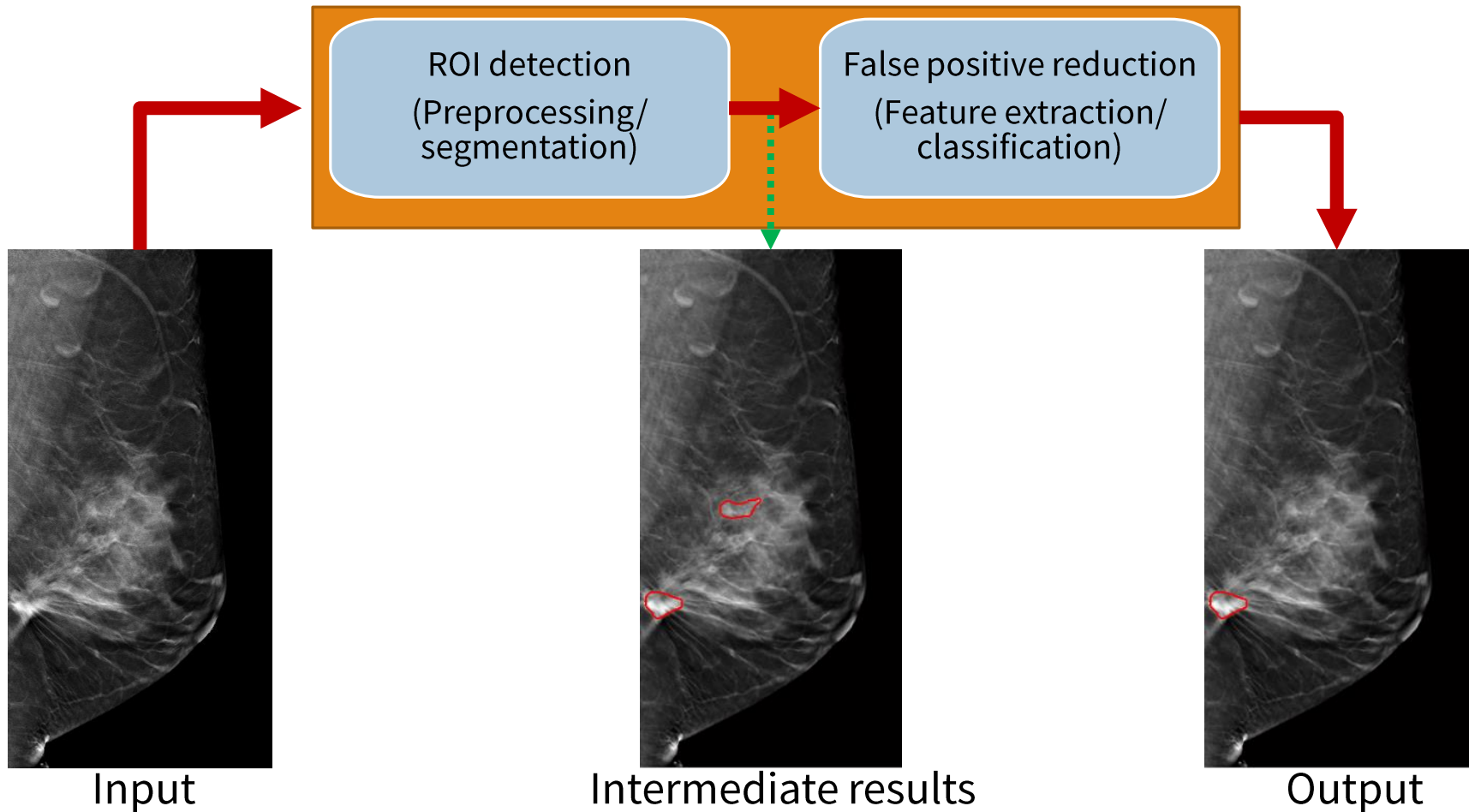
Computer aided detection
(CAD) can replace the
second reader



Increasing throughput and
effectiveness of the screening

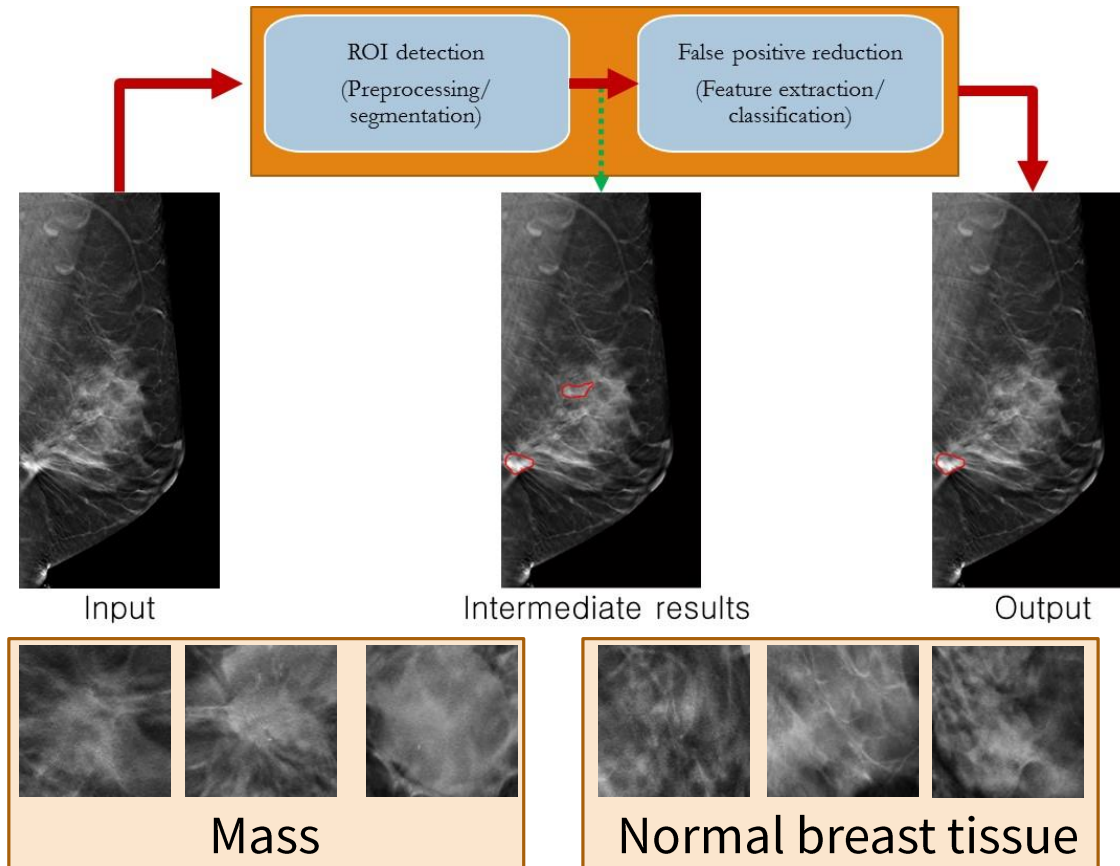
Research Proposals

General CAD System



Research Proposals

Challenges in Breast CAD

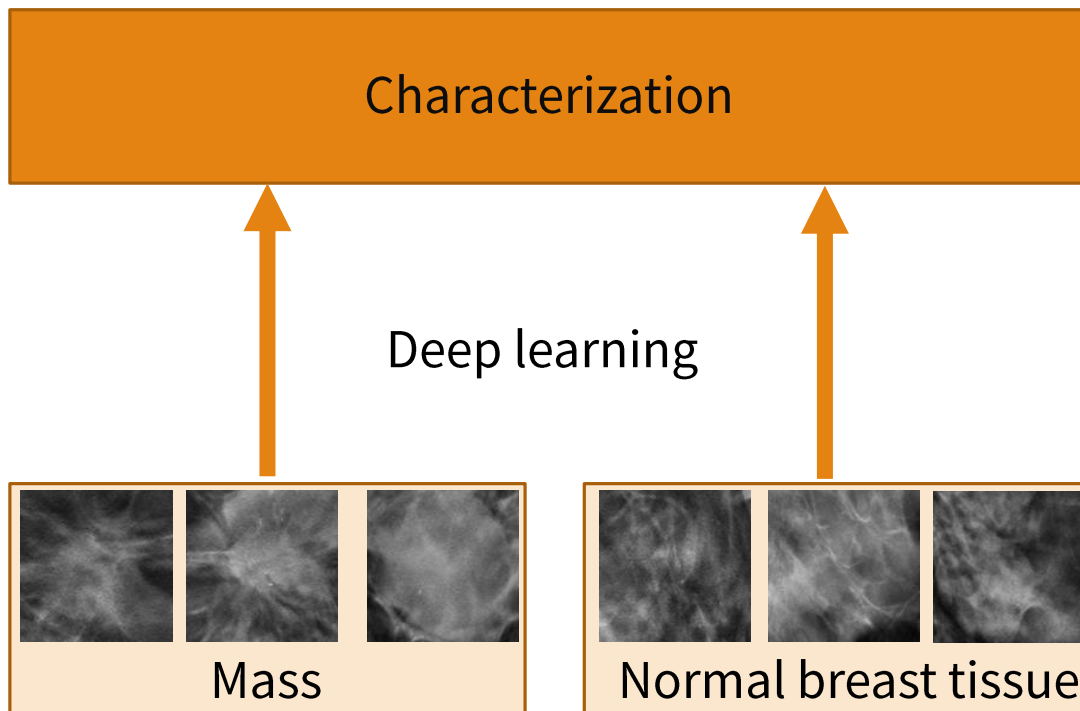


- Sensitivity of current CAD systems for masses is high, but the specificity is not due to **high false-positive (FP) detection rates**.
- In CAD systems, a FP is usually a region being normal tissue, but interpreted by the computer algorithms as a suspicious one.
- High FP rates **increase the recall rate** in clinical CAD environment, while it induces **unnecessary biopsies**.
- To reduce costs and patient discomfort, **it is important to characterize masses and normal breast tissues**.

DeepBMC: Deep learning for breast mass characterization

Research Proposals

DeepBMC Deep Learning for Breast Mass Characterization



- Motivation

- ✓ It is difficult to characterize the masses in conventional way.

- Expected results from DeepBMC:

- ✓ Learning the hidden and latent characteristics in data
- ✓ Learning the radiologist's high level concept

Research Proposals

Research Schedule

Monthly schedule	5	6	7	8	9	10
DeepBMC						
1. 관련 연구 조사	Active	Active	Completed	Completed	Completed	Completed
2. 알고리즘 및 실험 설계	Completed	Completed	Active	Active	Completed	Completed
3. 실험 결과 분석	Completed	Completed	Completed	Completed	Active	Active
DeepCART						
1. 관련 연구 조사	Active	Active	Active	Completed	Completed	Completed
2. 알고리즘 및 실험 설계	Completed	Active	Active	Active	Active	Completed
3. 실험 결과 분석	Completed	Completed	Completed	Completed	Active	Active

Q&A

Thank you.