

Deep Learning Applications in Medicine: Present and Future Perspectives Based on Experience

2017.10.31 NVIDIA Deep Learning Day

지능정보기술연구원 김휘영 PhD
astaria82@gmail.com



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- MR Image based Gleason Score Classification for Prostate Cancer Patients
- Deep Learning in Medicine

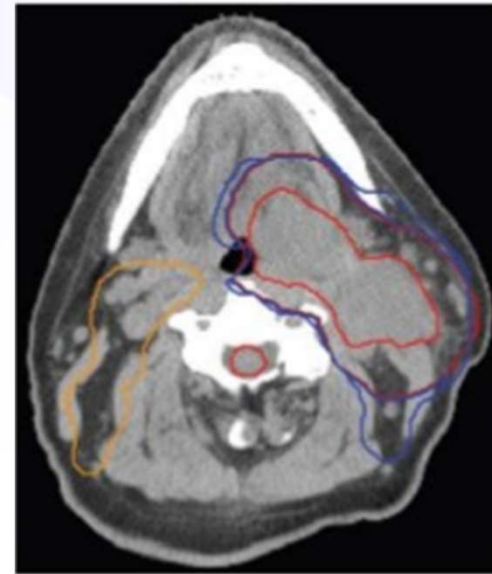
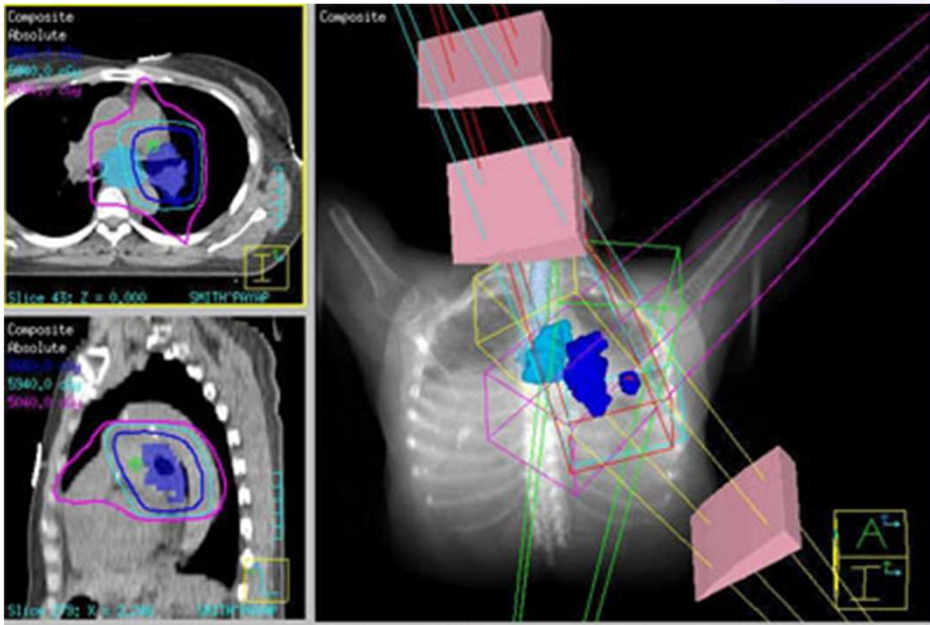
MR Image based Pseudo-CT Image Synthesis using Conditional Generative Adversarial Network

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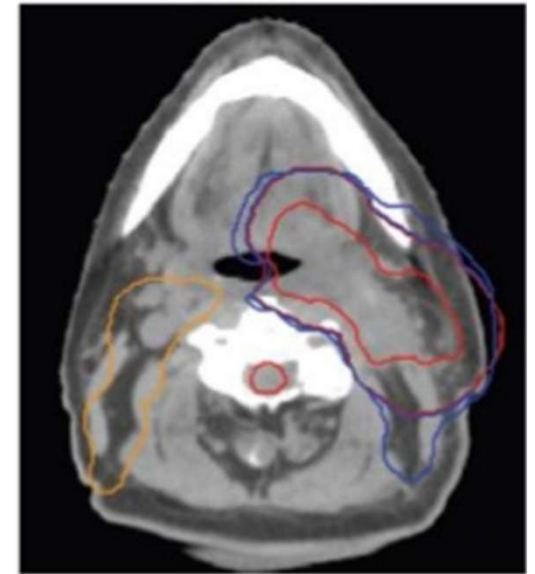
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astaria82@gmail.com



Image-guided RT Planning



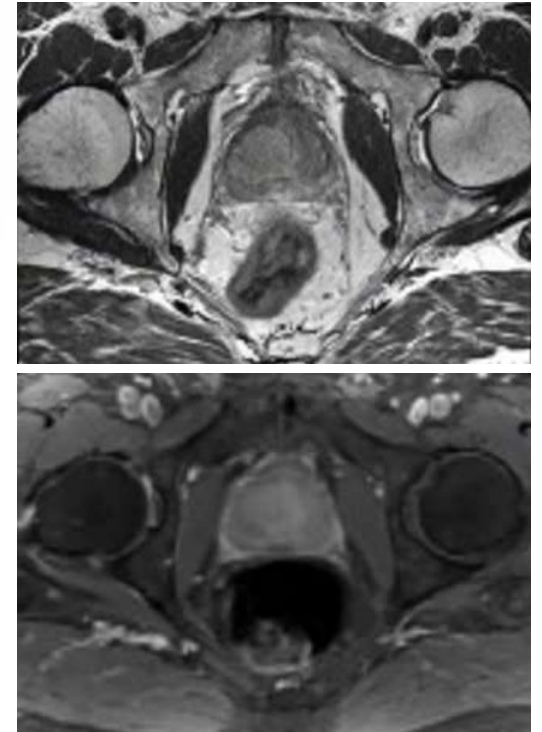
Planning CT



During Treatment

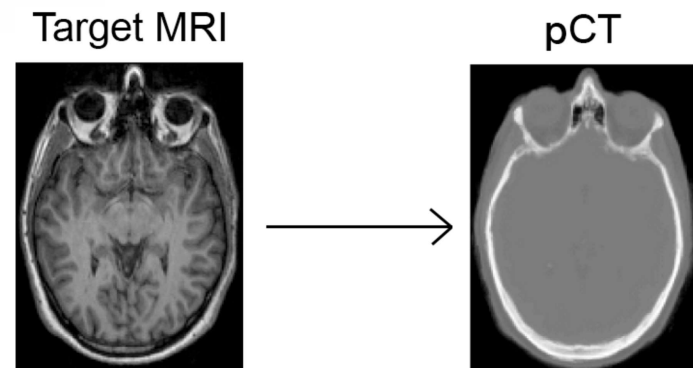
MR Image-based RT Planning

- Patients are exposed to radiation during CT imaging
 - 0.4 % of cancers were due to CT scanning (Hall *et al.* 2007)
- **not** suitable for **real-time/daily adaptive RT**
- MR-based RT benefits:
 - **Non-exposure** of X-ray radiation
 - Superior and multiple **tissue contrast** compared w/ CT
 - Reduced examination time and cost
 - Benefits to **MR-LINAC**

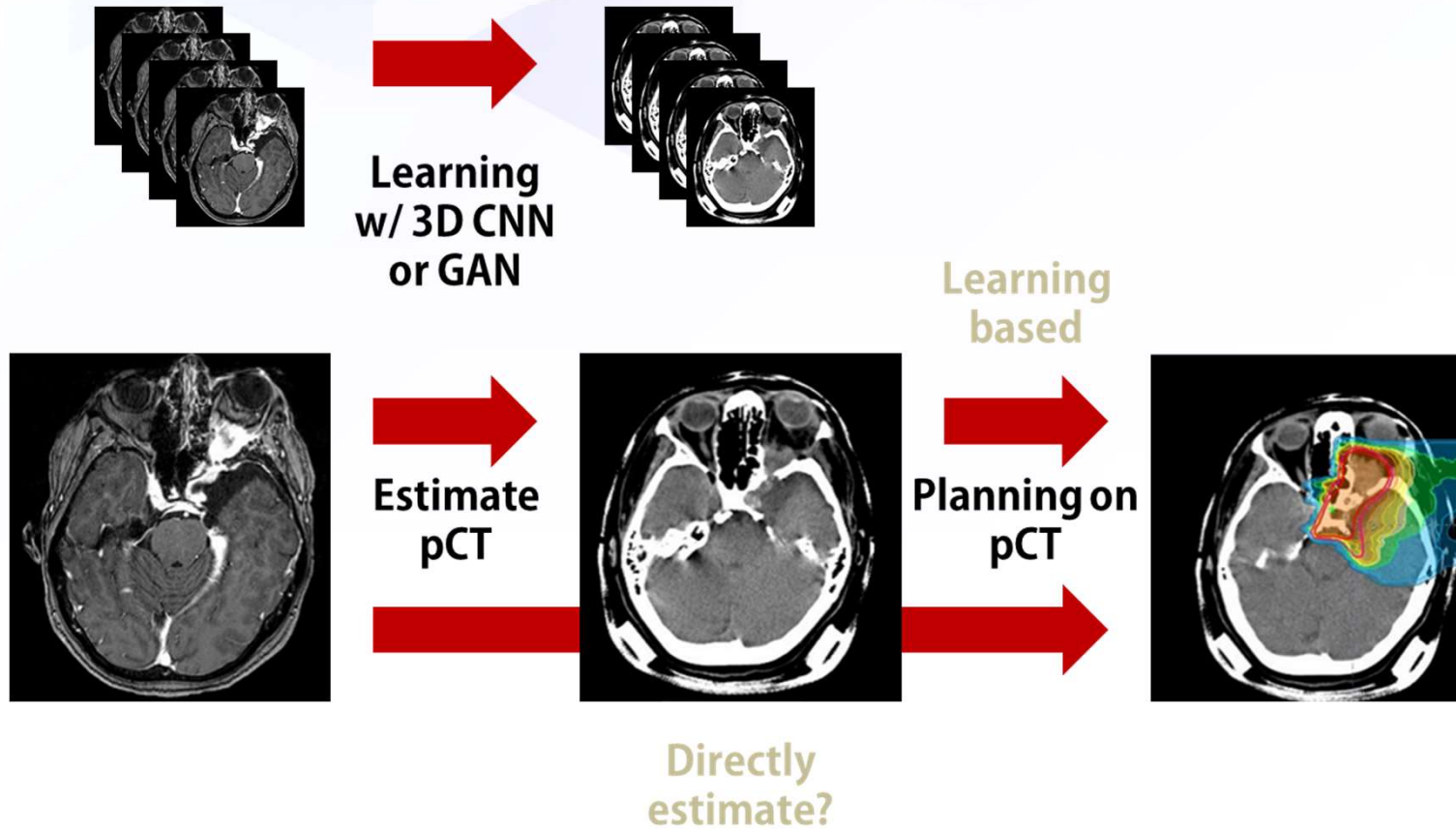


Need to estimate CT Image

- CT scan provides Hounsfield units (HU)
 - A normalized value of the **linear attenuation coefficient**
 - **Essential for dose calculation** in radiation treatment planning system (RTPS)
 - To consider tissue inhomogeneity
- MRI itself is **cannot** be directly used for treatment planning
- **Estimate CT image (pseudo CT, pCT) from MR image**
- Intensity-based & Atlas-based



Objective



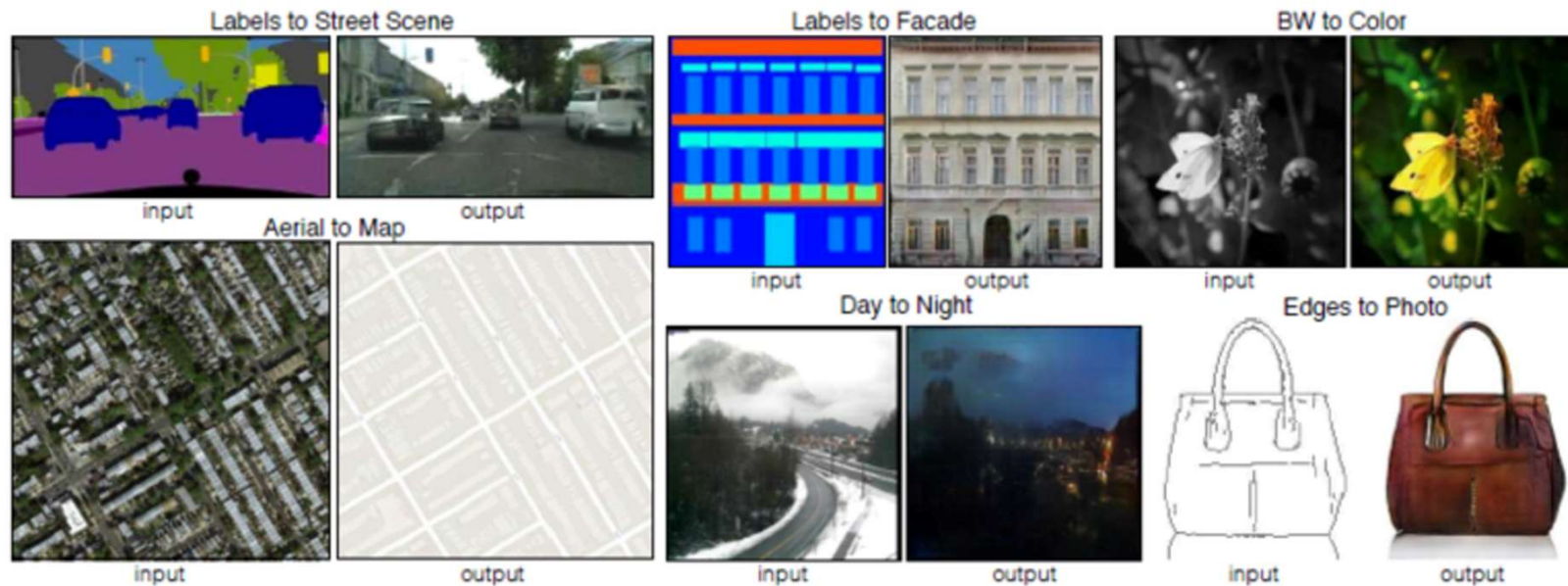
Dataset

- CT-MR image pairs of 19 glioblastoma patients
 - From TCIA (the Cancer Imaging Archive) open medical database
 - <http://www.cancerimagingarchive.net/>
- TCGA-GBM (The Cancer Genome Atlas Glioblastoma Multiforme)
 - Multi-institutional data (Henry Ford, UCSF, MDACC, Emory, Duke, ...)
 - CT, MR, Pathologic slides, Dx (with genomic data)
 - 262 patients, 575 studies w/ 481,158 images (73.5 GB)
- Candidate selection criteria
 - Has CT and MR image pairs (interval within 1 month)
 - No significant noise/motion artifact

Scarpace, L., Mikkelsen, T., Cha, soonmee, Rao, S., Tekchandani, S., Gutman, D., ... Pierce, L. J. (2016). Radiology Data from The Cancer Genome Atlas Glioblastoma Multiforme [TCGA-GBM] collection. The Cancer Imaging Archive

pix2pix

- P. Isola *et al.*, Image-to-Image Translation with Conditional Adversarial Networks, arXiv: 1611.07004v1



Conditional Generative Adversarial Network

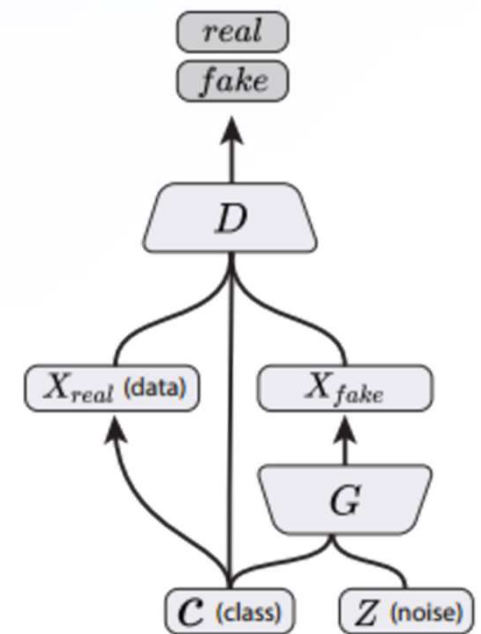
- **G (generator)** is a fully connected network
 - to generate pseudo CT images $G(C, z)$
 - from a random noise vector z
 - under the condition C (corresponding MR image)
- **D (discriminator)** is a convolutional neural network
 - discriminate btw/ an real CT image (ground truth) and an estimated pseudo-CT image.
- The G tries to minimize objective function against the D which tries to maximize it (min-max problem)

$$\mathcal{L}_{cGAN}(G, D) = \mathbb{E}_{x, y \sim p_{data}(x, y)} [\log D(x, y)] + \mathbb{E}_{x \sim p_{data}(x), z \sim p_z(z)} [\log(1 - D(x, G(x, z)))] \quad (1)$$

$$\mathcal{L}_{L1}(G) = \mathbb{E}_{x, y \sim p_{data}(x, y), z \sim p_z(z)} [\|y - G(x, z)\|_1].$$

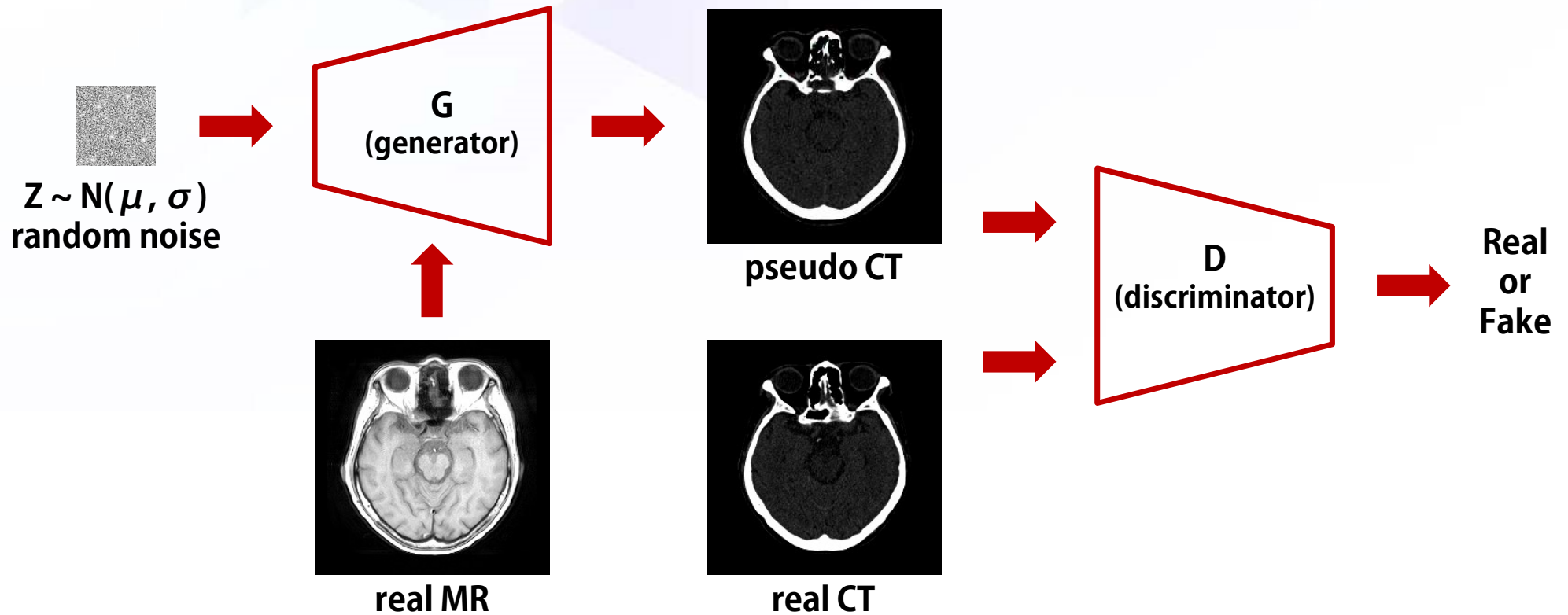
Our final objective is

$$G^* = \arg \min_G \max_D \mathcal{L}_{cGAN}(G, D) + \lambda \mathcal{L}_{L1}(G).$$

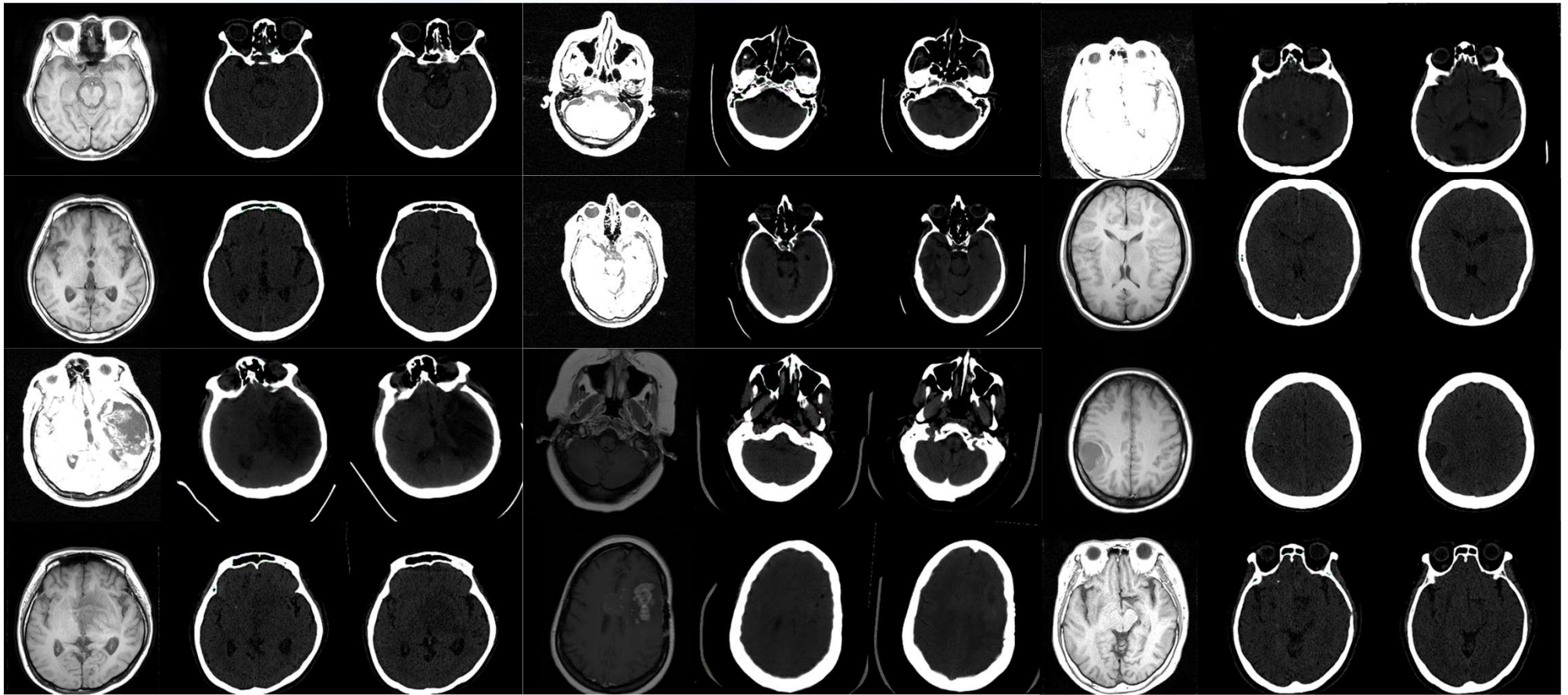


Conditional GAN
(Mirza & Osindero, 2014)

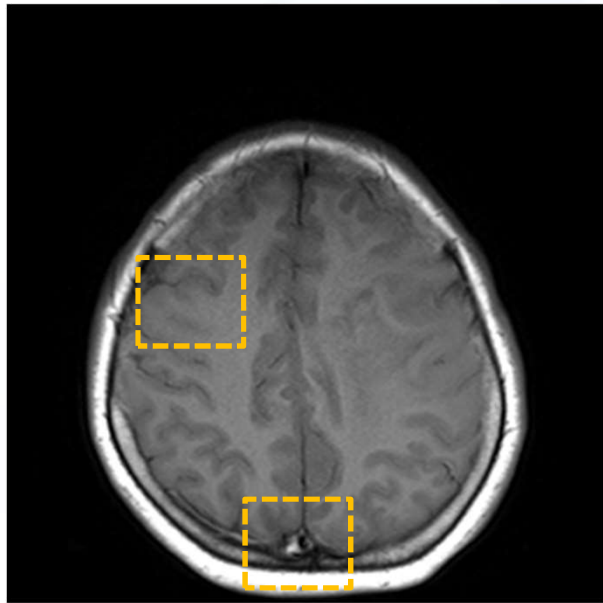
Conditional Generative Adversarial Network



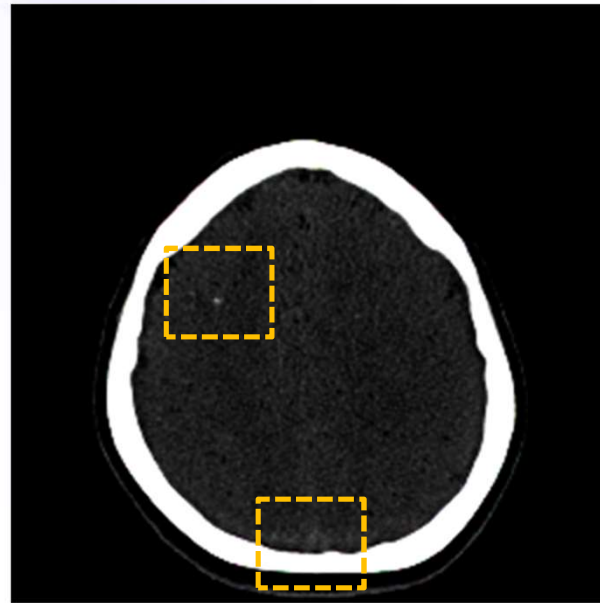
Examples



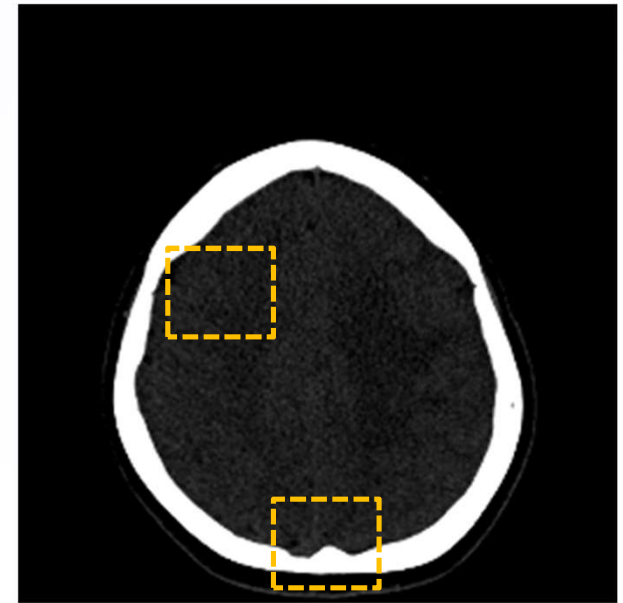
Best case (DSC = 0.986)



MR

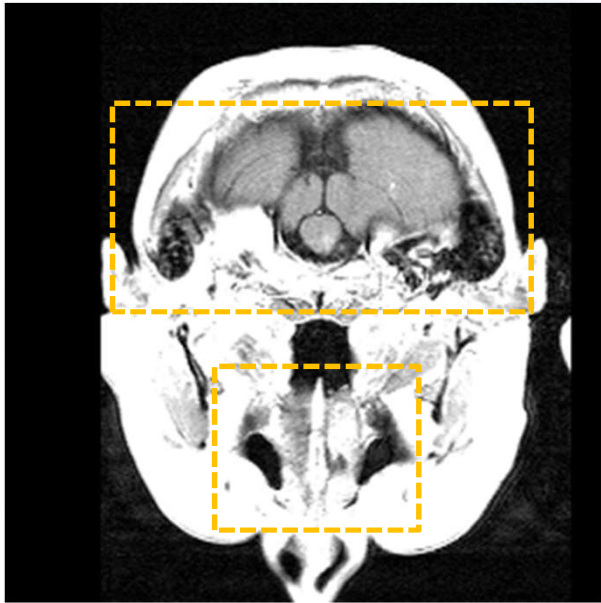


pseudo CT

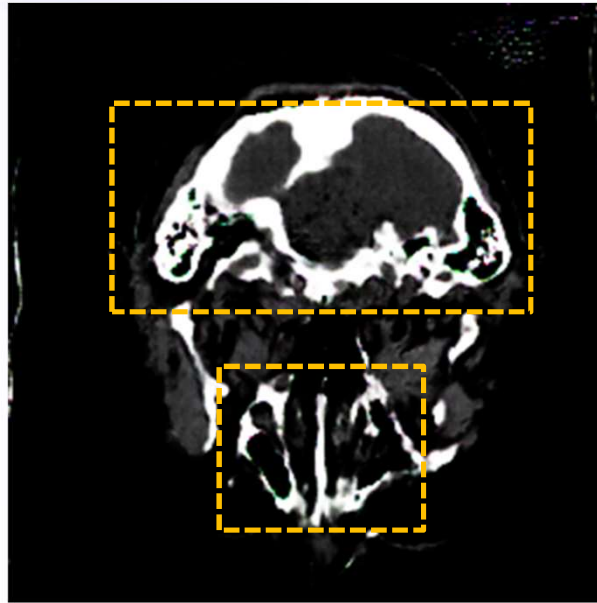


real CT
(ground truth)

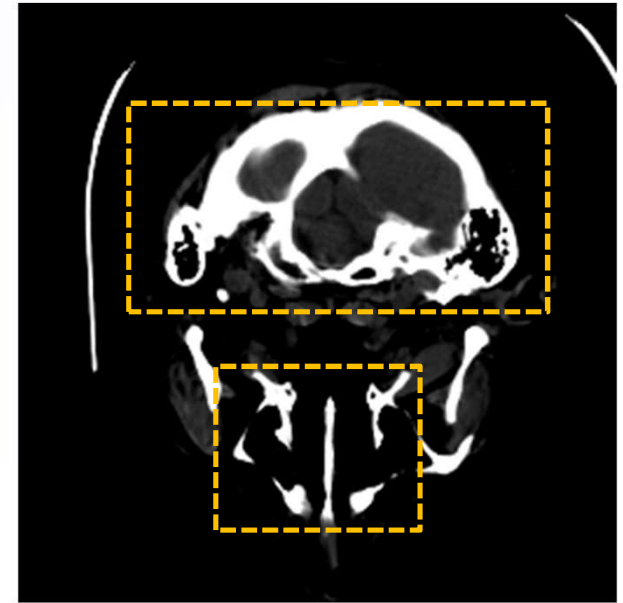
Worst case (DSC = 0.766)



MR



pseudo CT



real CT
(ground truth)

Discussion and Conclusions

- Generated pseudo-CT images well reconstructed anatomical boundaries but there were discrepancies in **cavities** and **eye ball**
- Training with more dataset will overcome overfitting and thus enhance the quality of pseudo-CT synthesis
- This results showed that our proposed method is feasible for **predicting pseudo-CT images** from their corresponding MR images.
- This technique has a potential to enable us to establish **MR-based adaptive RT** in clinic

Acknowledgement

- 서울대학교 융합과학기술대학원 예성준 교수님
- 분당서울대병원 영상의학과 이경준 교수님
- 지능정보기술연구원 이광희, 박대영 연구원

- The results shown here are in whole or part based upon data generated by the TCGA Research Network:
<http://cancergenome.nih.gov/>

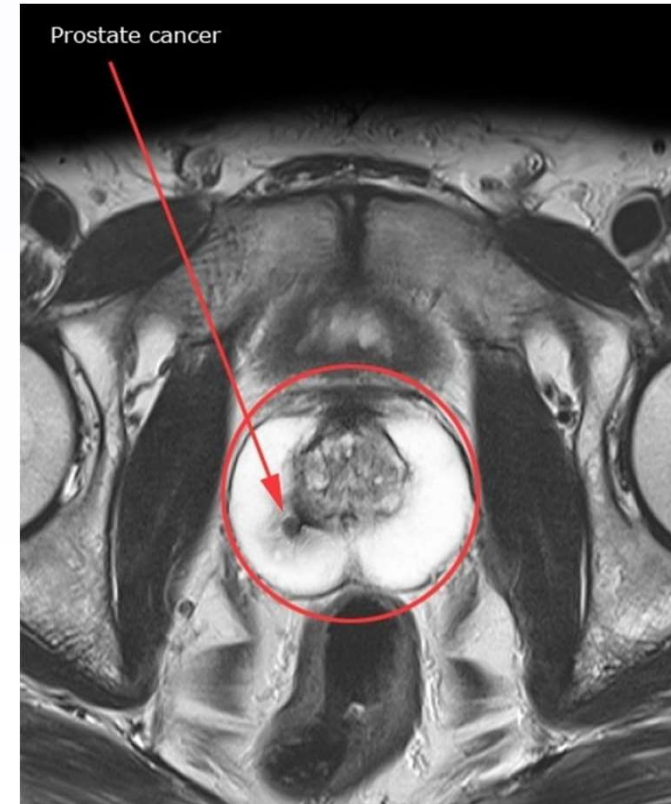
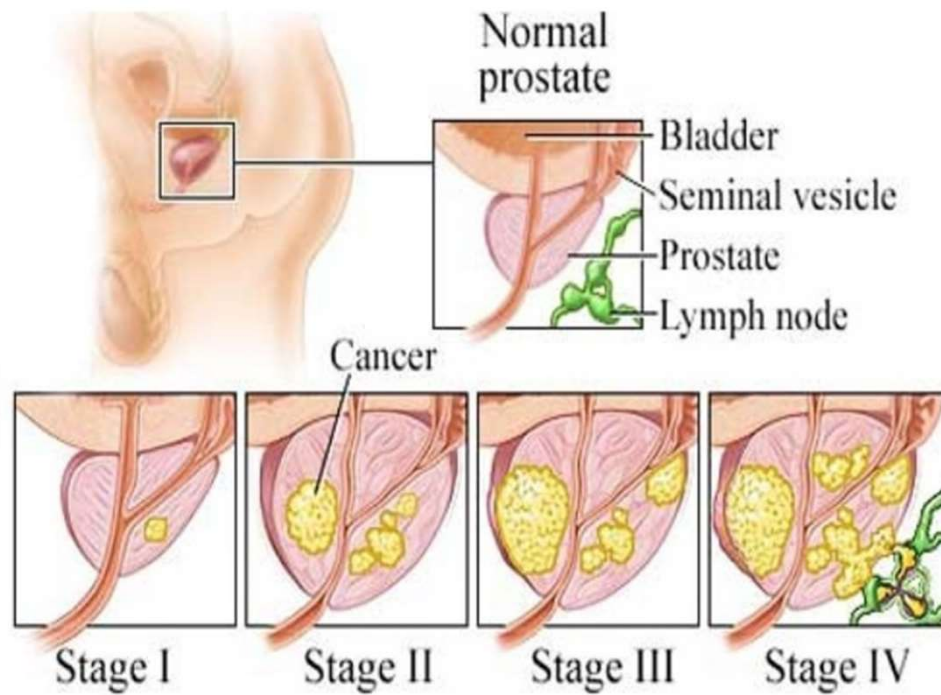
MR Image based Gleason Score Classification for Prostate Cancer Patients

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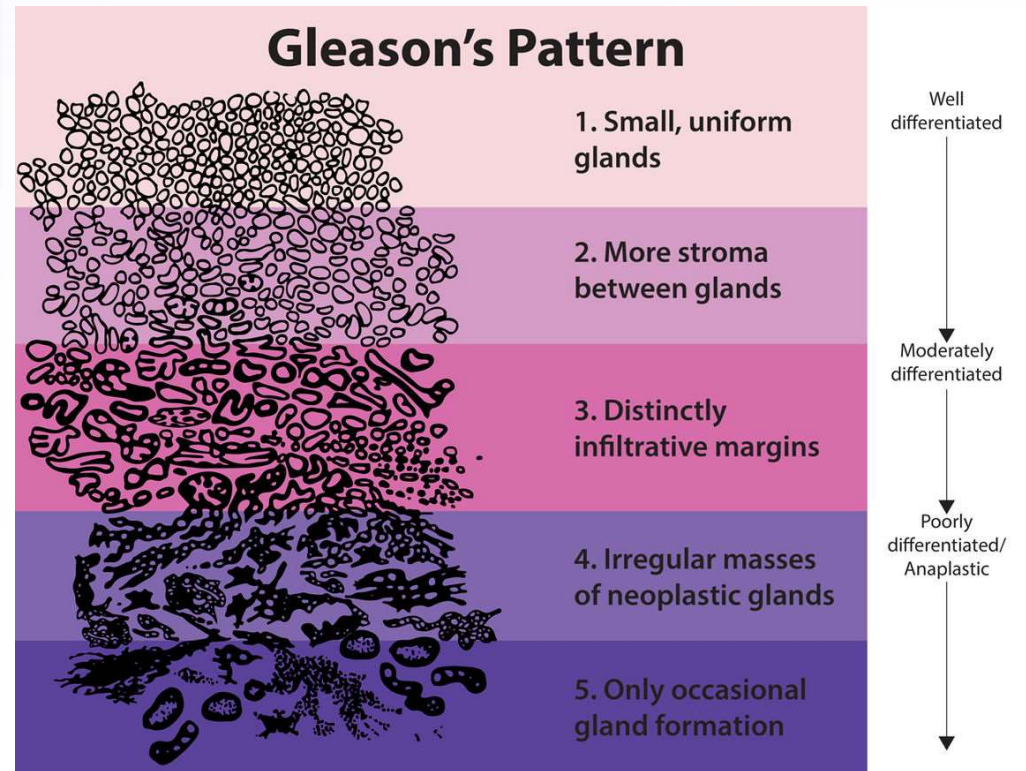


Prostate Cancer Diagnosis



Gleason Score

- A system of grading prostate cancer tissue based on how it looks under a microscope (**pathologic image**)
- Range: 2~10
- Indicates **how likely** it is that a tumor will spread



Gleason Grade Group

Grade Group 1 (Gleason score ≤ 6): Only individual discrete well-formed glands

Grade Group 2 (Gleason score $3+4 = 7$): Predominantly well-formed glands with lesser component of poorly-formed/fused/cribriform glands

Grade Group 3 (Gleason score $4+3 = 7$): Predominantly poorly formed/fused/cribriform glands with lesser component of well-formed glands

Grade Group 4 (Gleason score $4+4 = 8$; $3+5 = 8$; $5+3 = 8$) (1) Only poorly-formed/fused/cribriform glands or (2) predominantly well-formed glands and lesser component lacking glands or (3) predominantly lacking glands and lesser component of well-formed glands

Grade Group 5 (Gleason scores 9-10): Lacks gland formation (or with necrosis) with or without poorly formed/fused/cribriform glands

Epstein JI, Egevad L, Amin MB, Delahunt B, Srigley JR, Humphrey PA, the Grading Committee. The 2014 International Society of Urologic Pathology (ISUP) Consensus Conference on Gleason Grading of Prostatic Carcinoma: Definition of grading patterns and proposal for a new grading system. Am J Surg Pathol, (40)244-252, 2016

Objective

- Find quantitative **multi-parametric MRI biomarkers** for determination of Gleason Grade Group in prostate cancer



Advancing the Science,
Education & Professional
Practice of Medical Physics

My AAPM

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Public & Media

International

Medical Physicist

Members

Students

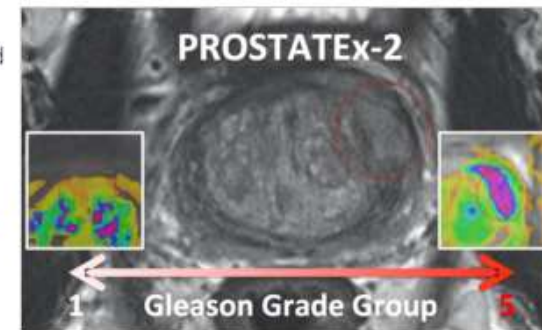
Meetings

PROSTATEx-2 CHALLENGE

SPIE-AAPM-NCI Prostate MR Gleason Grade Group Challenge

The American Association of Physicists in Medicine (AAPM), along with the SPIE (the international society for optics and photonics) and the National Cancer Institute (NCI), will conduct a part 2 "Grand Challenge" on the development of quantitative multi-parametric magnetic resonance imaging (MRI) biomarkers for the determination of Gleason Grade Group in prostate cancer. As part of the 2017 AAPM Annual Meeting, the PROSTATEx-2 Challenge will provide a unique opportunity for participants to compare their algorithms with those of others from academia, industry, and government in a structured, direct way using the same data sets.

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Data

- Total 182 findings (lesions) from 162 cases
 - 112 for training set
 - 70 for test set (release date w/o truth: Jun 5, 2017)

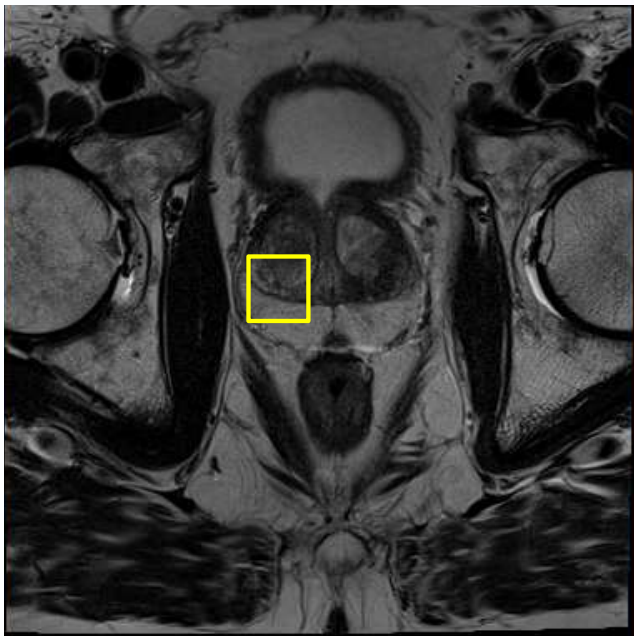
- 4 sets of MRI scan data
 - T2-weighted (axial and sagittal)
 - Dynamic contrast-enhanced (DCE)
 - Apparent diffusion coefficient (ADC)
 - Diffusion weighted imaging (DWI)

Group	1	2	3	4	5
N	36	41	20	8	7

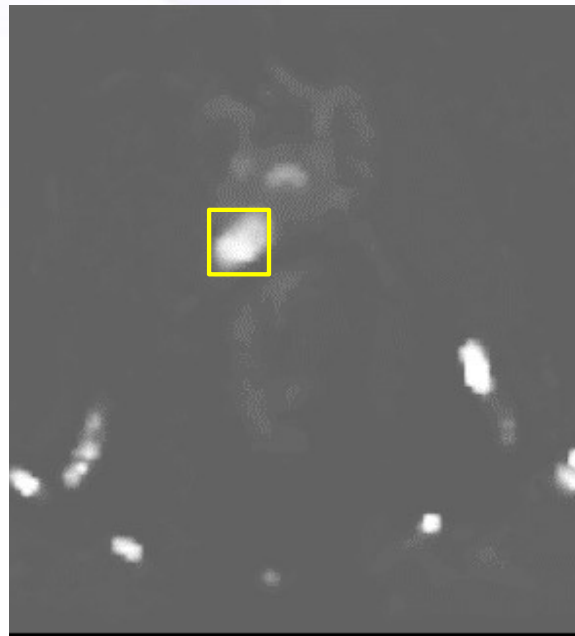
Data imbalance

- w/ Lesion location (not a mask) and known GGG

MRI Sequences



T2-weighted (axial)



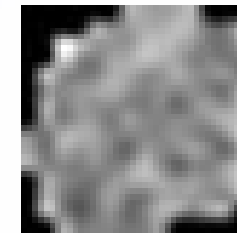
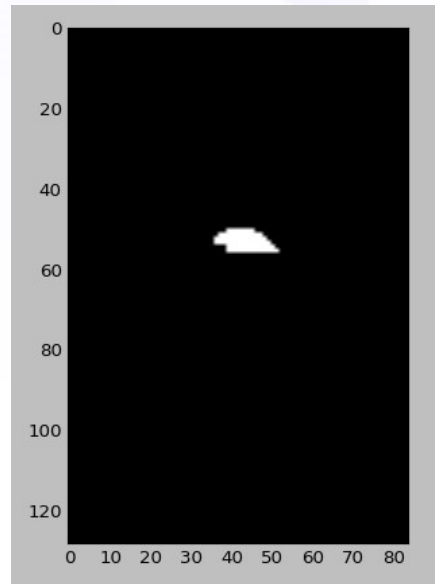
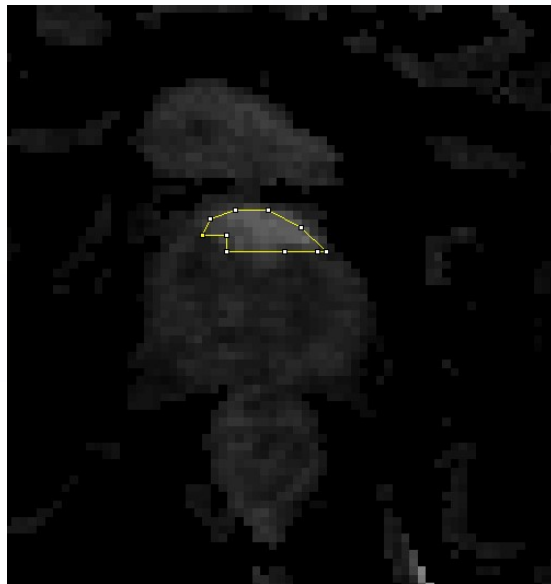
DCE



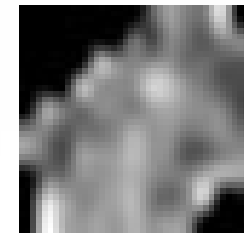
ADC

Masking

- Manual contouring (Courtesy of Dr. Woo)



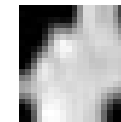
T2axial



T2sagittal



DCE



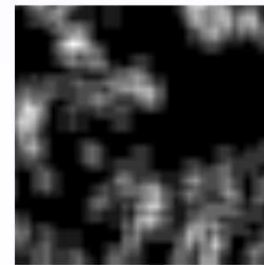
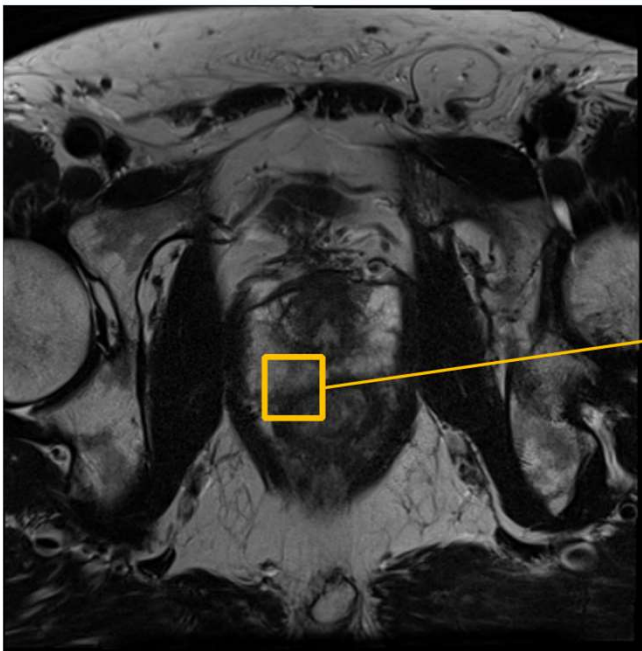
DWI



ADC

Textural Feature Map

- Calculated textural features of 5x5 image patches for each voxel



contrast



correlation



homogeneity



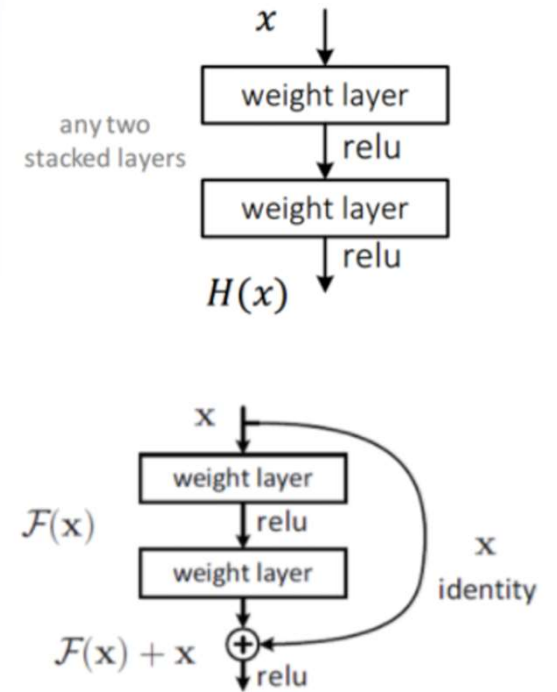
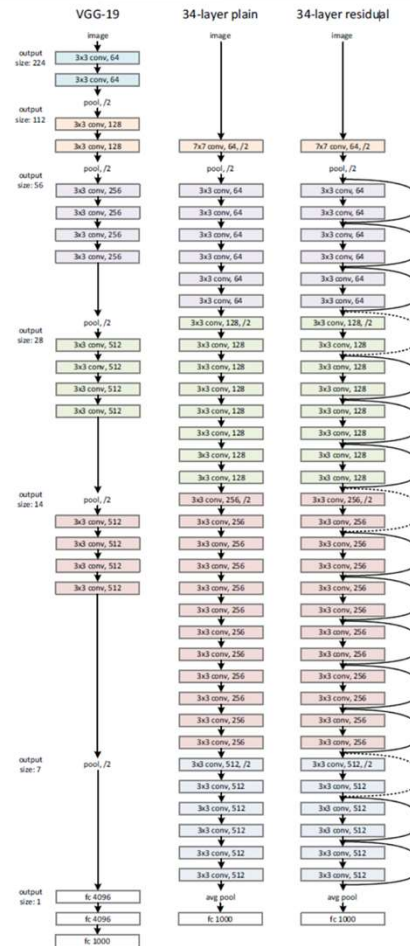
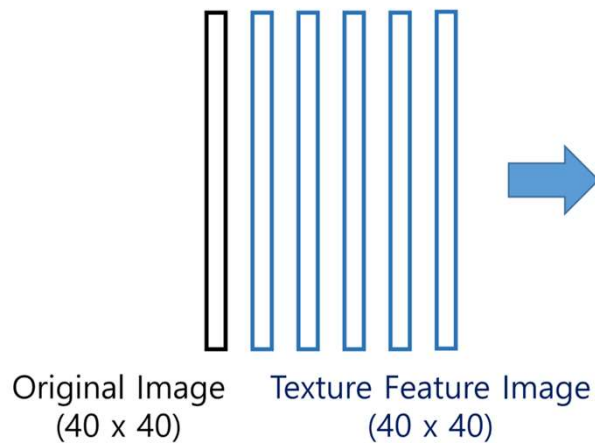
energy



entropy

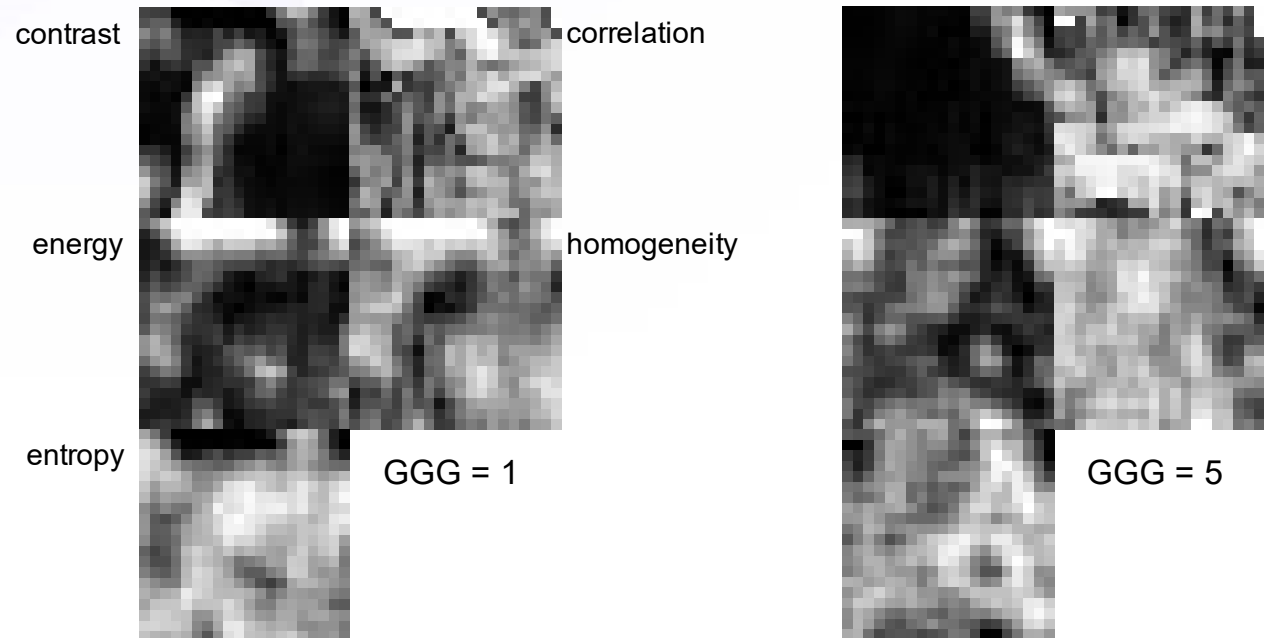
Experiment #1 (ResNet50)

- Trained w/ 7 GTX 1080



Result #1

- Validation set test accuracy = $\sim 25\%$
- Lack of training data
- Data imbalance



Experiment #2 (XGboost)

- Tree-ensemble method
 - w/ gradient boosting

Training loss

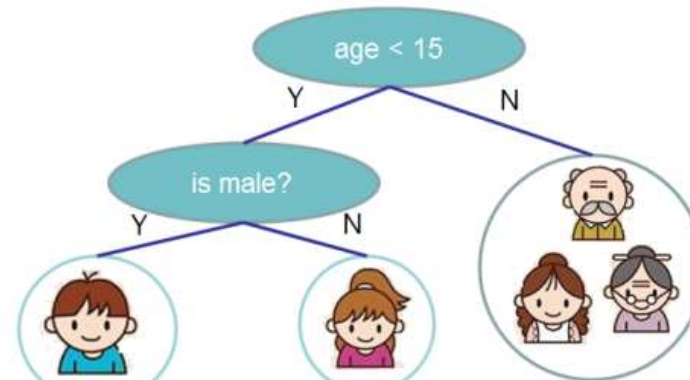
$$\sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_k \Omega(f_k), f_k \in \mathcal{F}$$

Complexity of the tree
of nodes, depth, L2 norm of leaf weights

Input: age, gender, occupation, ...



Does the person like computer games



prediction score in each leaf → +2

+0.1

-1

1st Order Features

- w/ original images of each MRI sequences
- Derived w/ Intensity volume histogram

$$P(I) = \frac{\text{number of pixels with gray level } I}{\text{total number of pixels in the region of interest}}$$

- Mean $mean = E[I] = \sum_{I=0}^{N_g-1} I P(I)$, where N_g is the number of exist gray levels

- SD $SD = \frac{1}{N_g} \sqrt{(I - mean)^2}$

- Mean skewness $Skewness = \frac{1}{SD^3} \sum_{I=0}^{N_g-1} (I - mean)^3 P(I)$

- Mean kurtosis $Kurtosis = \frac{1}{SD^4} \sum_{I=0}^{N_g-1} (I - mean)^4 P(I)$

Result #2

- Validation set test accuracy: Around **80%**
 - (Validation set = 33 % of whole training set)

- w/ all sequences: 31.65 %
- T2ax: 79.35 %
- T2sag: 82.76 %
- ADC: 73.40 %
- DWI: 80.67 %
- DCE: 85.71 %

```
XGBClassifier(base_score=0.5, colsample_bylevel=1, colsample_bytree=1,
gamma=0, learning_rate=0.3, max_delta_step=0, max_depth=10,
min_child_weight=1, missing=None, n_estimators=1000, nthread=4,
objective='binary:logistic', reg_alpha=0, reg_lambda=1,
scale_pos_weight=1, seed=0, silent=True, subsample=0.8)
[ 1.  4.  1.  3.  2.  1.  2.  3.  3.  1.  1.  5.  2.  3.  1.  1.  5.  1.
  5.  3.  1.  3.  2.  2.  3.  4.  5.  2.  2.  2.  5.  3.  1.  2.  1.  3.
  1.  3.  3.  2.  1.  3.  5.  1.  1.  4.  3.  3.  3.  2.  3.  3.  1.  1.
  3.  5.  1.  2.  1.  5.  1.  2.  2.  3.  3.  1.  5.  1.  3.  2.  4.  4.
  5.  2.  2.  1.  2.  2.  1.  2.  2.  1.  1.  3.  1.  1.  2.  3.  3.  4.
  2.  3.  2.  1.  2.  2.  2.  2.  1.  1.  3.  2.  1.  2.  2.  1.  1.  3.
  1.  5.  5.  1.  2.  4.  2.  2.  2.  1.  1.  2.  2.  3.  2.  4.  2.  5.
  1.  5.  2.  3.  2.  3.  2.  1.  1.  3.  4.  2.  2.  2.]
[1.0, 2.0, 1.0, 3.0, 2.0, 1.0, 2.0, 3.0, 3.0, 1.0, 1.0, 1.0, 2.0, 3.0, 3.0
0, 2.0, 3.0, 3.0, 2.0, 2.0, 2.0, 2.0, 5.0, 3.0, 1.0, 2.0, 1.0, 3.0, 1.0, 3
4.0, 3.0, 3.0, 3.0, 2.0, 3.0, 3.0, 1.0, 1.0, 3.0, 5.0, 1.0, 2.0, 1.0, 5.0,
, 2.0, 2.0, 4.0, 2.0, 5.0, 2.0, 2.0, 1.0, 1.0, 2.0, 1.0, 2.0, 2.0, 1.0, 3.
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4.0, 2.0, 2.0, 2.0, 3.0, 1.0, 2.0, 2.0, 3.0, 2.0, 4.0, 2.0, 1.0, 1.0, 5.0
0, 4.0, 1.0, 2.0, 2.0]
Accuracy all: 31.65%
Accuracy T2ax: 79.35%
Accuracy T2sag: 82.76%
Accuracy ADC: 73.40%
Accuracy DWI: 80.67%
Accuracy DCE: 85.71%
user@10d:~/github_21/data/whobats6_nuthan_test1.py
```

- Final test result: **0.1022** (quadratic weighted kappa, 0.2772 for 1st place team)
- Achieved **8th** highest score (out of 143 participants)

Discussion and Conclusions

- Data preprocessing was done successfully.
- Data augmentation was needed because of lack of data and imbalance among groups.
- In case of ResNet50 model, prediction accuracy was quite low.
 - Lack of data and time
- Using XGboost method, we got **meaningful prediction accuracy around 80 %** but not for test data (top 8th)
- For further research, various data augmentation methods and other deep learning models can be applied in this problem.

Acknowledgement

- 서울대학교 융합과학기술대학원 예성준 교수님
- 서울대병원 영상의학과 조정연 교수님
- 국군대전병원 영상의학과 우성민 선생님
- 서울대학교 융합과학기술대학원 이지민 연구원
- 조형주 연구원

Deep Learning in Medicine

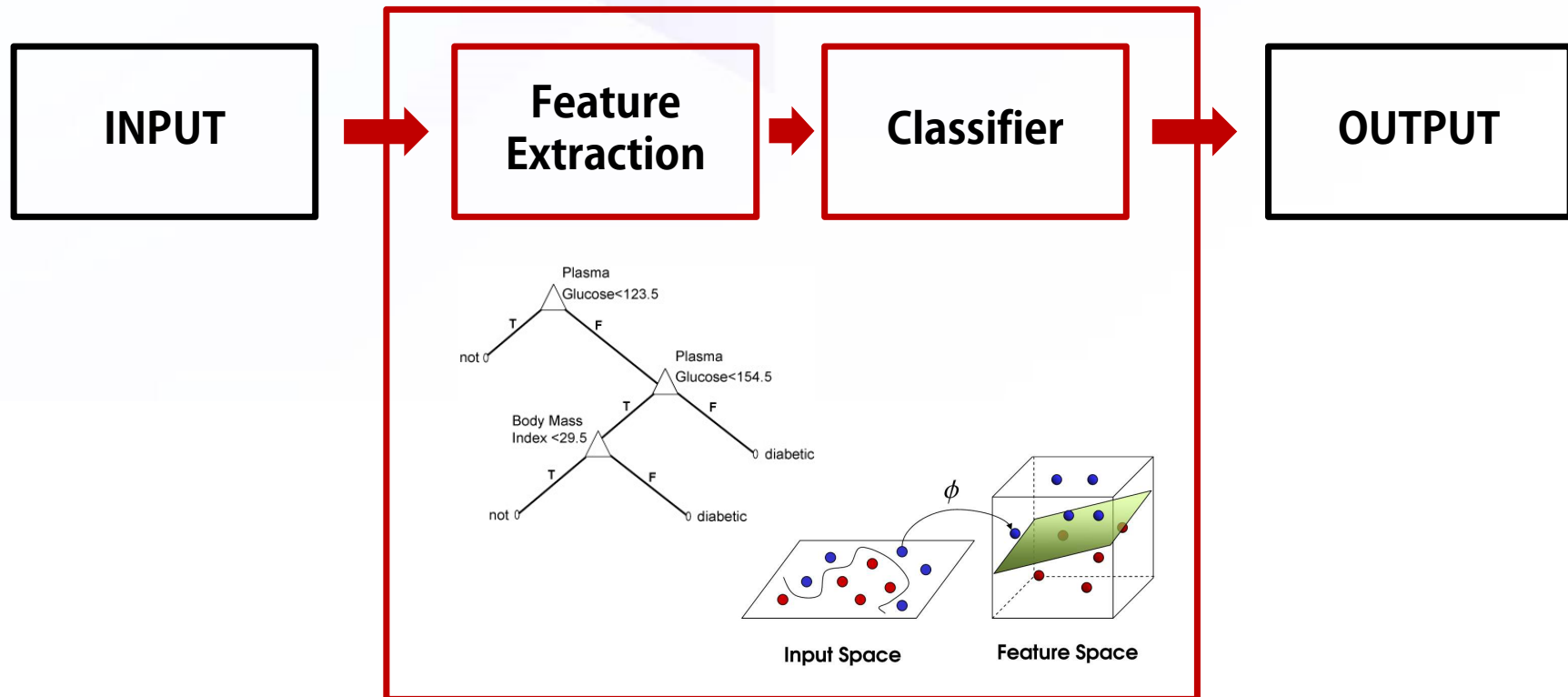
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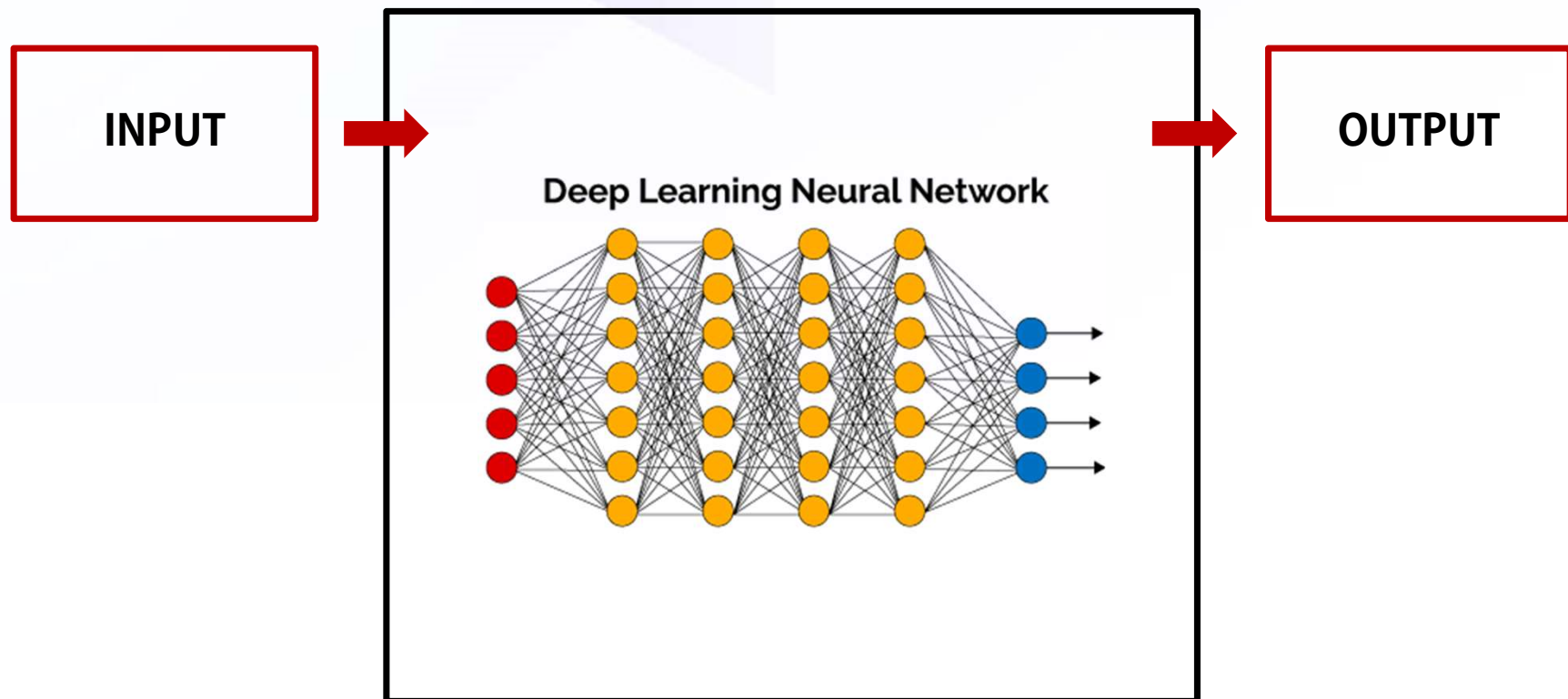
Traditional Machine Learning

Make a Program to get desired output from corresponding input data



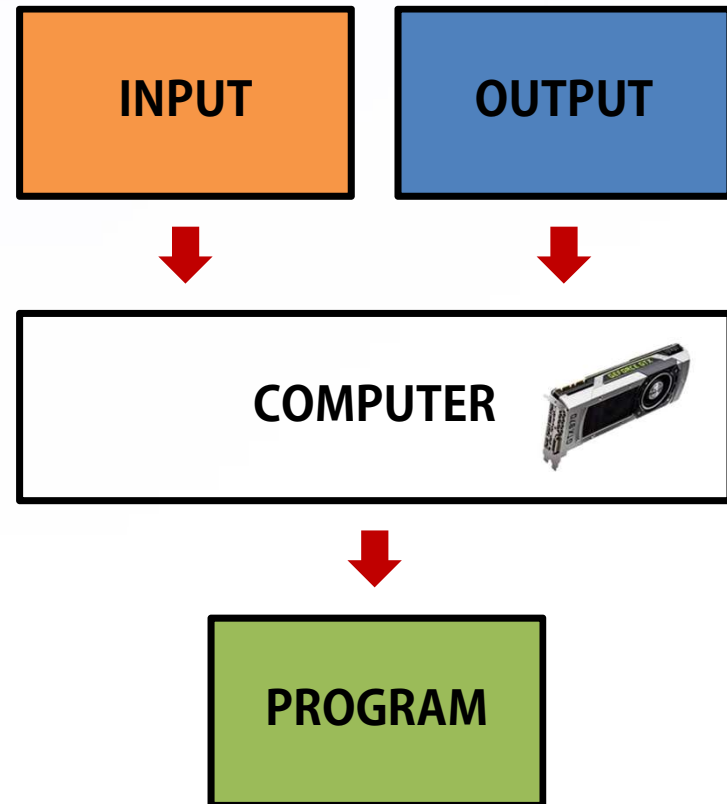
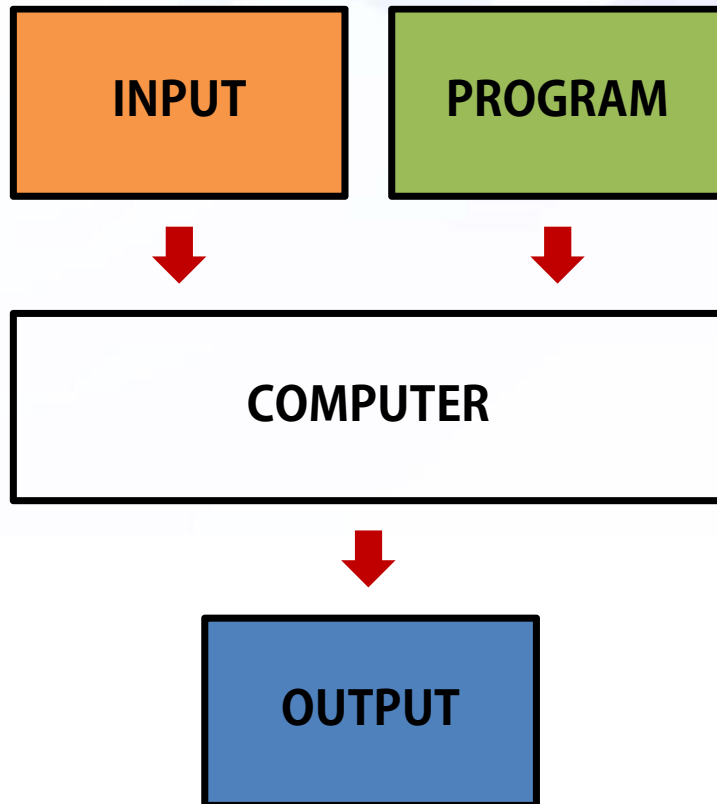
Paradigm shift

Simply **GET a Program (automatically!)** with your data



Data is ALL we need

Google YouTube Picasa





Google DeepMind

Challenge Match

8 - 15 March 2016



ALPHAGO
01:40:56

LEE SEDOL
01:35:33



AlphaGo Lee Sedol

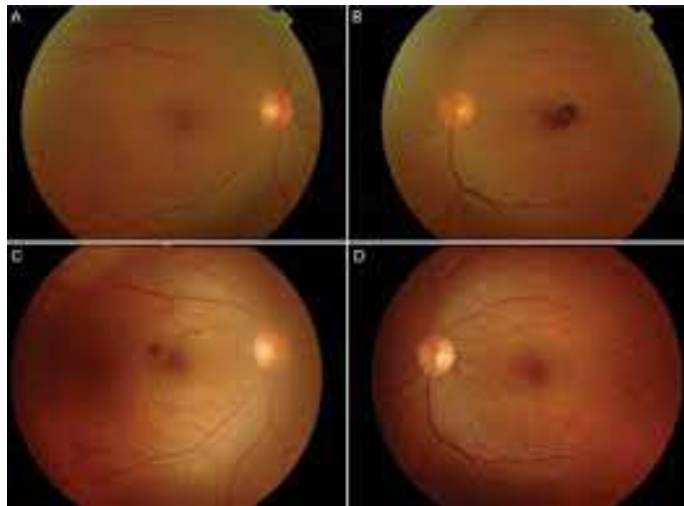
 

AI beats medical doctors

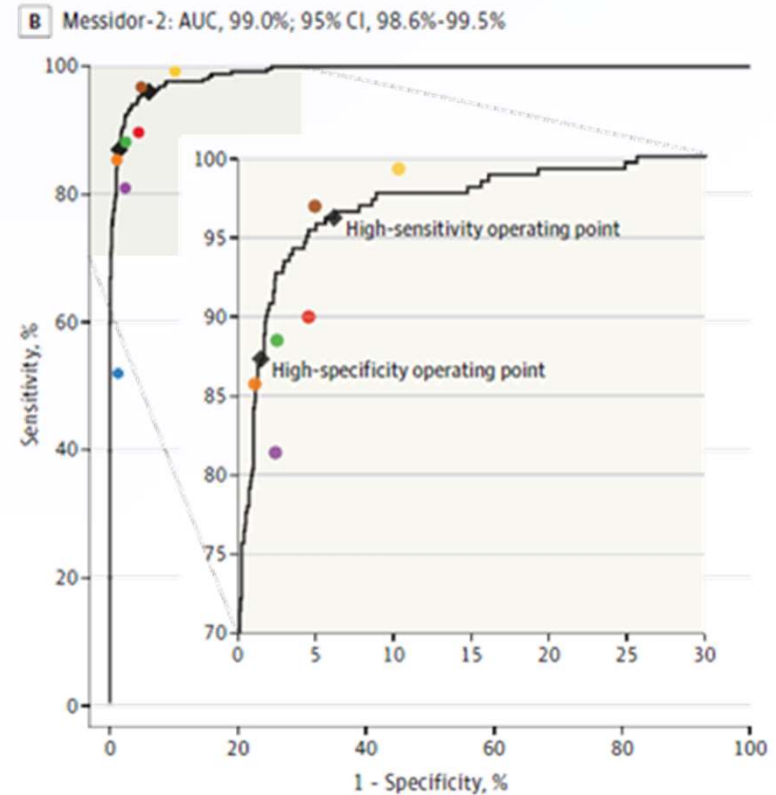
JAMA | Original Investigation | INNOVATIONS IN HEALTH CARE DELIVERY

Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs

Varun Gulshan, PhD; Lily Peng, MD, PhD; Marc Coram, PhD; Martin C. Stumpe, PhD; Derek Wu, BS; Arunachalam Narayanaswamy, PhD; Subhashini Venugopalan, MS; Kasumi Widner, MS; Tom Madams, MEng; Jorge Cuadros, OD, PhD; Ramasamy Kim, OD, DNB; Rajiv Raman, MS, DNB; Phillip C. Nelson, BS; Jessica L. Mega, MD, MPH; Dale R. Webster, PhD



Seo *et al.*, Kor J Ophthalmol (2009)



Gulshan *et al.*, JAMA (2016)

Will AI replace doctors?



중앙일보

경제

경제일반 재테크 증권 부동산 IT/과학 경제칼럼

[단독] 의사가 하는 일 70% ... 2030년엔 시도 한다

[중앙일보] 입력 2017.08.29 02:30 수정 2017.08.29 03:15 | 종합 1면 지면보기

임미진 기자 최현주 기자 정선언



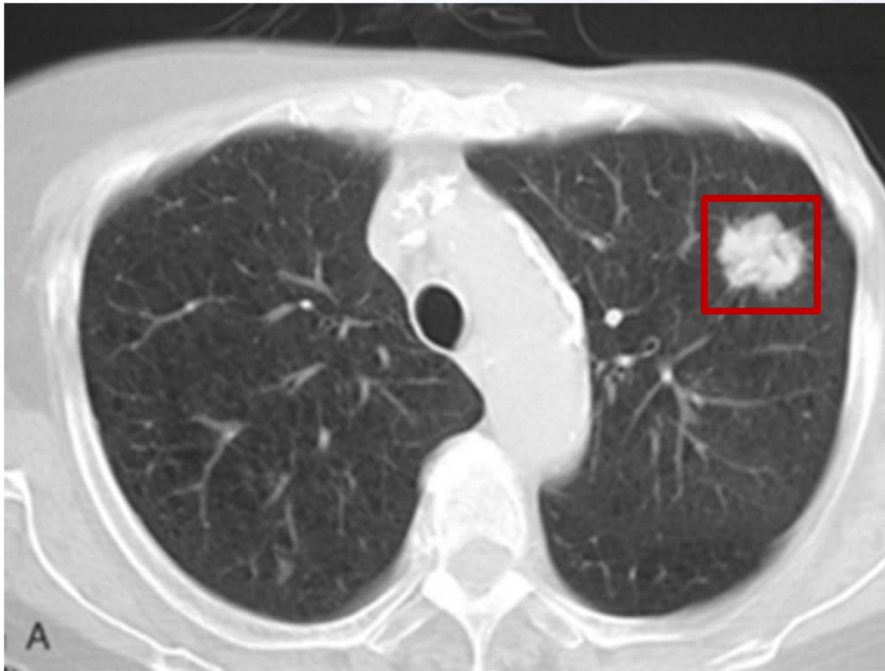
MASSACHUSETTS
GENERAL HOSPITAL



NVIDIA, Massachusetts
General Hospital Use
Artificial Intelligence to
Advance Radiology,
Pathology, Genomics

Posted on December 25, 2016 by Aaron

What we expected



Malignancy: high
Spiculation: yes
Calcification: none
...

**Probability of being diagnosed with cancer
within a 12 month time frame is 85%**

Deep Learning can do this !!

Data Science Bowl 2017

- Kaggle grand challenge
 - Make better lung cancer detection model
 - 2017.01.12 ~2017.04.12
 - Total **100,000 \$** prizes



- Ranked in the top of **2.5 %**
 - out of 1972 teams
 - Accuracy: around 77 %

Breathe in the Future

The 3rd annual Data Science Bowl aligns with Vice President Joe Biden's Cancer Moonshot™ to achieve one of the key strategic goals: unleashing the power of data against lung cancer. Together, we can pit machine learning and artificial intelligence against cancer, advancing the state of the art in future screening, care, and prevention. Let's **breathe out the past** and end the disease as we know it.

Vital Energy
Lungs fuel us with the oxygen we need in our bloodstream to provide our cells with energy, while removing the lethal waste of carbon dioxide.

Lung Cancer is the most common type of cancer with...
225,000
new cases in the U.S. in 2018¹
\$12 billion
were accounted for in healthcare costs in the U.S. every year²


Malignant Tumors
Tumors form when gene changes in the DNA of the cells mutate and promote unnatural growth. Uncontrolled growth can spread to surrounding areas or metastasize to other organs if not treated early.

Low-Dose CT scans help assess if a person is at risk of lung cancer or other pulmonary disease. Scientific research reports...
20%
of lung cancer deaths can be reduced with early detection³

However, the image assessments in use today are identifying lung lesions as potentially cancerous that later turn out to not be cancer.
High false positive rates
lead to unnecessary patient anxiety, additional follow-up imaging and interventional treatments⁴

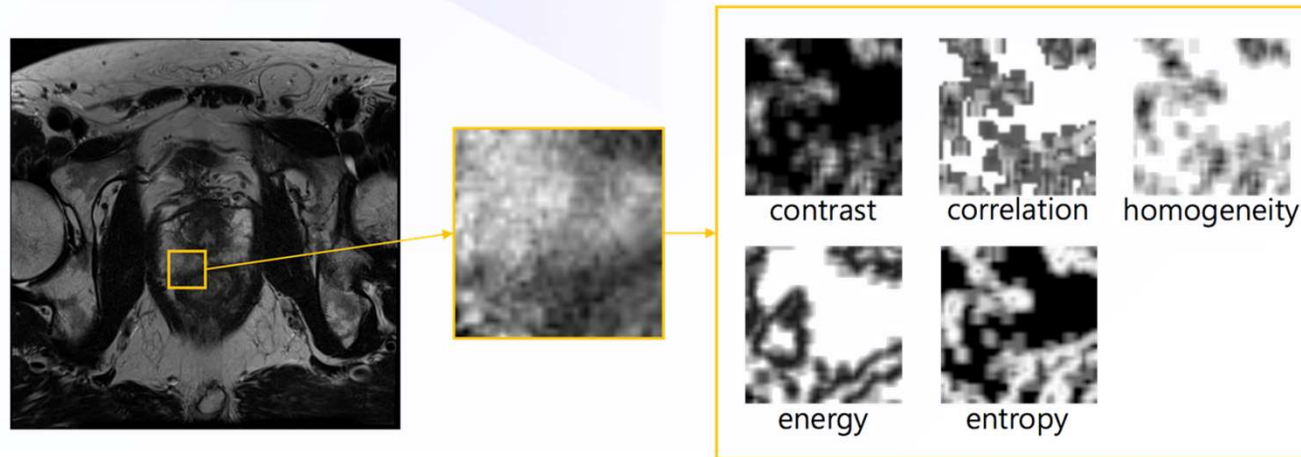
SOURCES:
¹Siegel RL, Miller KD, Jemal A. "Cancer Statistics," 2016, CA: A Cancer Journal for Clinicians, 2016, 66:7-30.
²National Institutes of Health. "Cancer costs projected to reach at least \$148 billion in 2020." <https://www.nih.gov/news-events/news-releases/cancer-costs-projected-reach-at-least-148-billion-2020>, (January 12, 2013).
³Aberle DR, Adams AM, Berg CD, et al. "Reduced lung cancer mortality with low-dose computed tomographic screening." *N Engl J Med*. 2011;363:995-409.
⁴Low-Dose CT has historically resulted in high false positive rates of around 25% (Aberle, et al., New England J Med, 2011, 363:995-409).

Breathe in the future. Breathe out the past.


#DATASCI BOWL

ProstatEX2

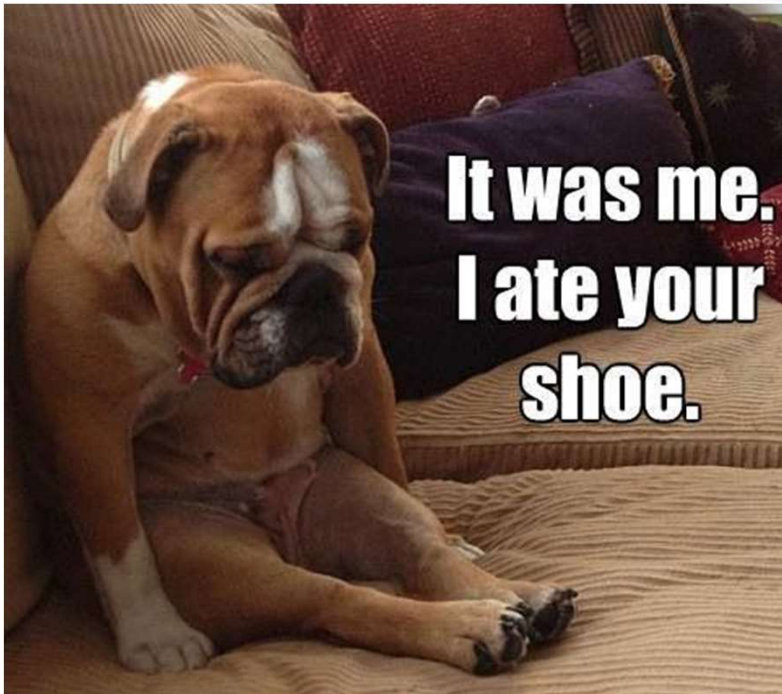
- Find quantitative **multi-parametric MRI biomarkers** for determination of **Gleason Grade Group** in prostate cancer



- Validation set test accuracy: Around **80%** (w/ DCE sequence)
- Final test result: **0.1022** (quadratic weighted kappa, 0.2772 for 1st place team)
- Achieved **8th** highest score (out of 143 participants)

Being a detective

- Prediction of being diagnosed w/ cancer within a year
 - ONLY with **imaging diagnosis**



It is a dog

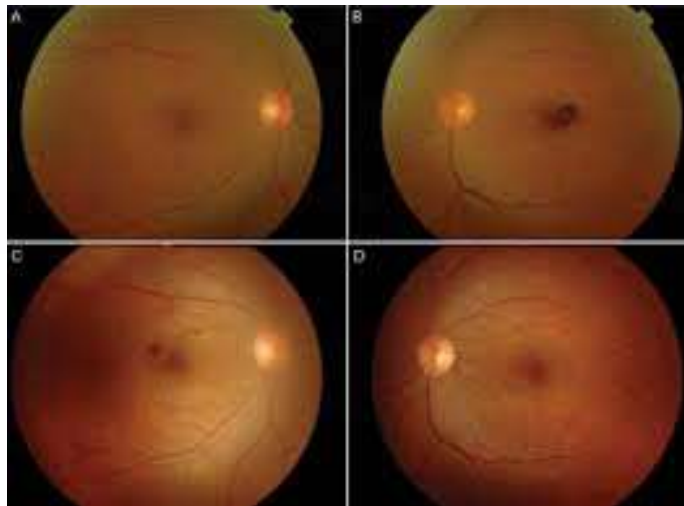
It is a dog, a bulldog. I can see dirt on the dog. (S)he will probably get sick if the dog mistakenly swallows something while (s)he rolled in a dirty spot.

AI can do what humans do

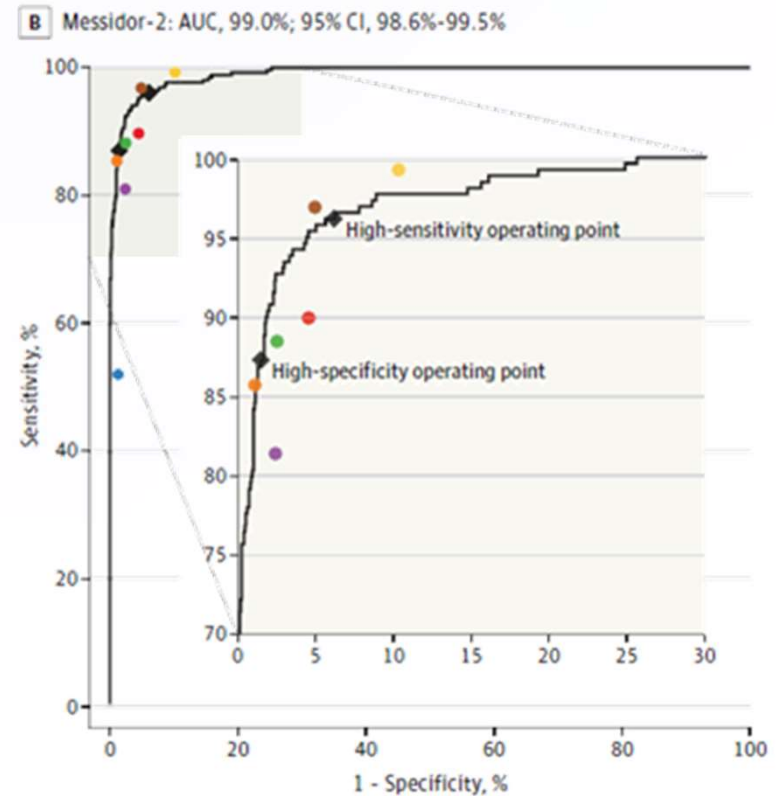
JAMA | Original Investigation | INNOVATIONS IN HEALTH CARE DELIVERY

Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs

Varun Gulshan, PhD; Lily Peng, MD, PhD; Marc Coram, PhD; Martin C. Stumpe, PhD; Derek Wu, BS; Arunachalam Narayanaswamy, PhD; Subhashini Venugopalan, MS; Kasumi Widner, MS; Tom Madams, MEng; Jorge Cuadros, OD, PhD; Ramasamy Kim, OD, DNB; Rajiv Raman, MS, DNB; Phillip C. Nelson, BS; Jessica L. Mega, MD, MPH; Dale R. Webster, PhD



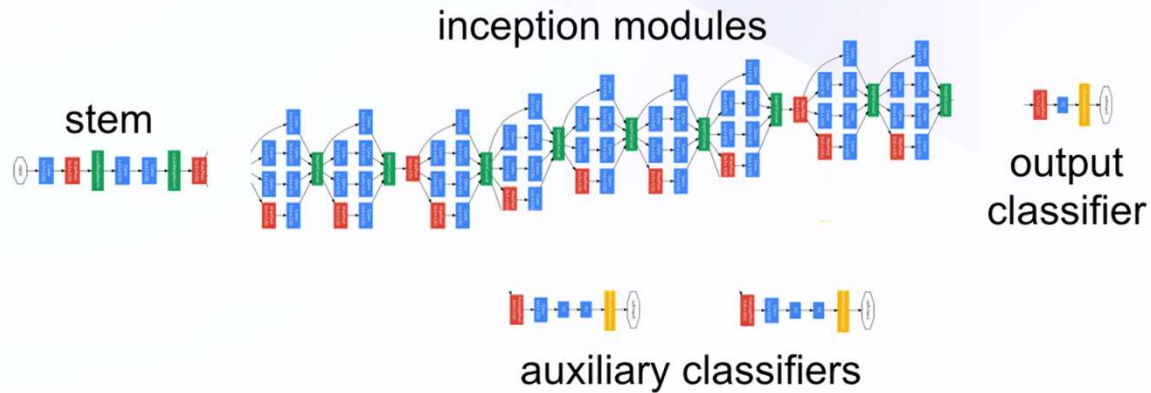
Seo *et al.*, Kor J Ophthalmol (2009)



Gulshan *et al.*, JAMA (2016)

Can we beat Google?

Technique?



DATA!!!

Characteristics	Development Data Set	EyePACS-1 Validation Data Set
No. of images	128 175	9963
No. of ophthalmologists	54	8
No. of grades per image	3-7	8
Grades per ophthalmologist, median (interquartile range)	2021 (304-8366)	8906 (8744-9360)



Dr. Hyunseok Min's PPT

Can we make Watson for oncology?



50억원 / year

News room > News releases >

IBM Closes Deal to Acquire Merge Healthcare

0.7 billion \$ (약 8천억)

Open Innovation

Arxiv Sanity Preserver
Built by @karpathy to accelerate research.
Serving last 26950 papers from cs.CV|CL|LG|AI|NE|stat.ML

User: Pass: [Login or Create](#)

most recent | **top recent** | top hype | recommended | library

Only show v1 | Last day | **Last 3 days** | Last week | Last month | Last year | All time

Top papers based on people's libraries:

OptNet: Differentiable Optimization as a Layer in Neural Networks
Brandon Amos, J. Zico Kolter
3/1/2017 cs.LG | cs.AI | math.OC | stat.ML
Submitted to ICML 2017

This paper presents OptNet, a network architecture that integrates optimization problems (here, specific individual layers in larger end-to-end trainable deep networks). These layers allow complex dependencies between traditional convolutional and fully-connected layers are not able to capture. In this paper, we develop the framework to derive the equations to perform exact differentiation through these layers and with respect to layer parameters. These layers that exploits fast GPU-based batch solves within a primal-dual interior point method, and which virtually no additional cost on top of the solve, and we highlight the application of these approaches in several examples. For example, we show that the method is capable of learning to play Sudoku given just input and output games, whereas this task is virtually impossible for other neural network architectures that we have experimented with.

Learning to Optimize Neural Nets
Ke Li, Jitendra Malik
3/1/2017 cs.LG | cs.AI | math.OC | stat.ML
10 pages, 15 figures

Features Explore Pricing

OpenAI openai

Repositories People 0

Pinned repositories

gym A toolkit for developing and comparing reinforcement learning algorithms. Python ★ 5k ↓ 1k	universe Universe is a software platform for measuring and training AI's general intelligence across the world's supply of games, websites and other applications. Python ★ 4.8k ↓ 452	rllib rllib is a framework for developing and evaluating reinforcement learning algorithms, fully compatible with OpenAI Gym. Python ★ 718 ↓ 218
improved-gan code for the paper "Improved Techniques for Training GANs" Python ★ 624 ↓ 153	kubernetes-e2e-autoscaler A batch-optimized scaling manager for Kubernetes Python ★ 351 ↓ 41	universe-starter-agent A starter agent that can solve a number of universe environments. Python ★ 495 ↓ 130

BVLC / caffe Watch 1,839 Star 16,327

Code Issues 740 Pull requests 271 Projects 0 Wiki Pulse Graphs

Model Zoo

Kevin Ke-Yun Lin edited this page 17 days ago - 104 revisions

Check out the [model zoo](#) documentation for details.

To acquire a model:

- download the model gist by `./scripts/download_model_from_gist.sh <gist_id> <dirname>` to load the model metadata, architecture, solver configuration, and so on. (`<dirname>` is optional and defaults to `caffe/models`).
- download the model weights by `./scripts/download_model_binary.py <model_dir>` where `<model_dir>` is the gist directory from the first step.

or visit the [model zoo](#) documentation for complete instructions.

Berkeley-trained models

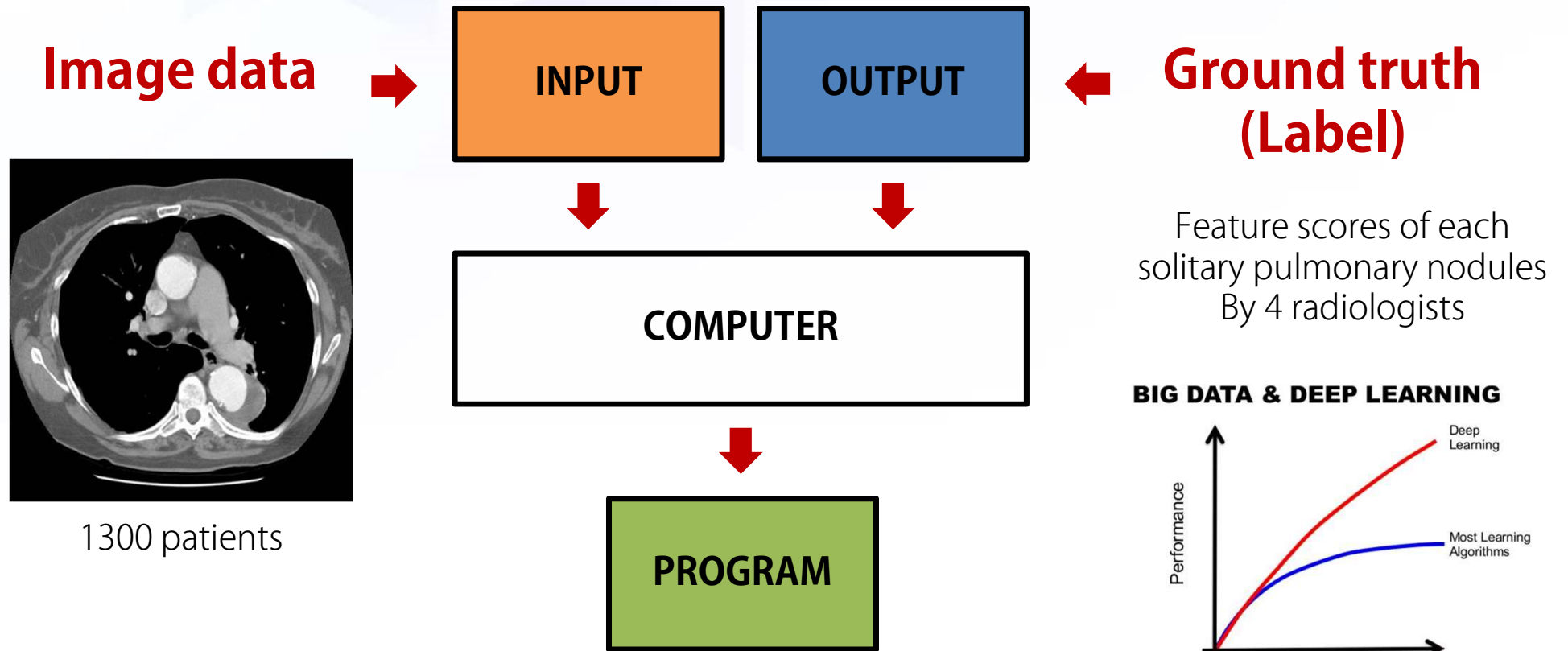
- Finetuning on Flickr Style: same as provided in `models/`, but listed here as a Gist for an example.
- BVLC GoogleNet: `models/bvlc_googlenet`

Network in Network model

The Network in Network model is described in the following ICLR-2014 paper:

Network In Network
M. Lin, Q. Chen, S. Yan
International Conference on Learning Representations, 2014 (arXiv:1409.1556)

Again, DATA is all we need



Lack of training data

Medical data



Labeled data

Cleaned data

Abnormal

Normal



Will AI replace doctors?

- I will say **NO**

- The value of **high-quality data** will rapidly increase
 - Only physicians can make high-quality (reliable) medical data
- AI extends the extent of expertise and gives new perspectives
 - w/ **commoditization** of deep learning tools (like MS words and excel)

Structural Image → Functional Image ?!?

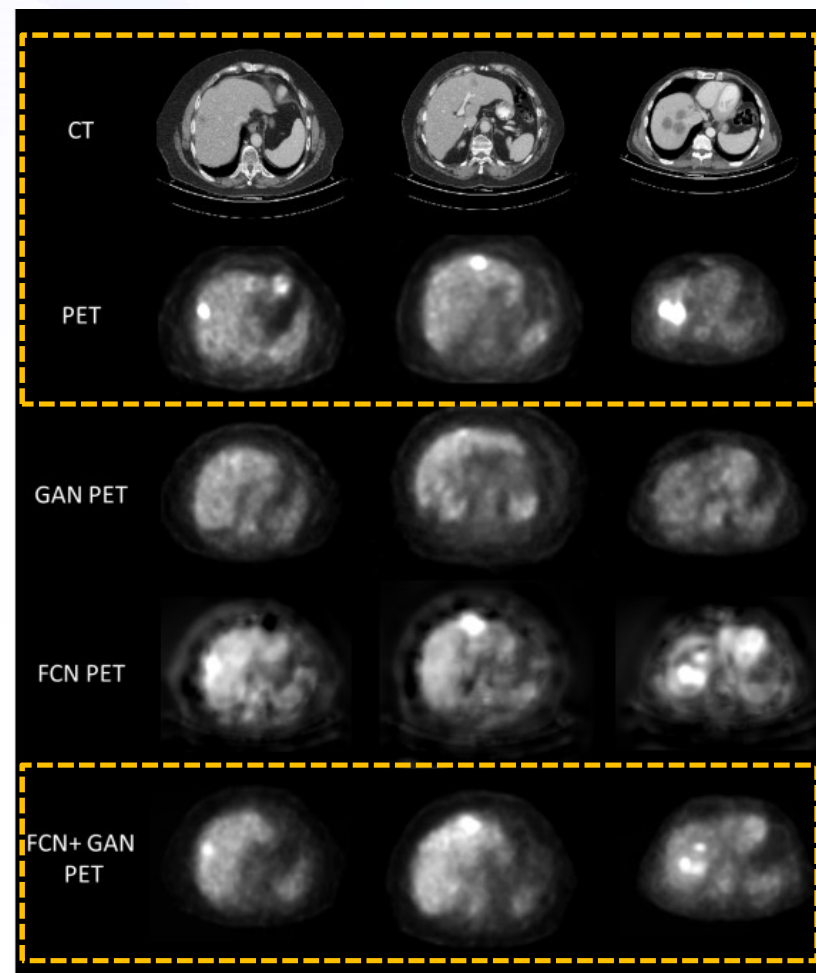
Virtual PET Images from CT Data Using Deep Convolutional Networks: Initial Results

Avi Ben-Cohen¹, Eyal Klang², Stephen P. Raskin², Michal Marianne Amitai²,
and
Hayit Greenspan¹

¹Tel Aviv University, Faculty of Engineering, Department of Biomedical Engineering,
Medical Image Processing Laboratory, Tel Aviv 69978, Israel

²Sheba Medical Center, Diagnostic Imaging Department, Abdominal Imaging Unit,
affiliated to Sackler school of medicine Tel Aviv University, Tel Hashomer 52621,
Israel

Paper accepted
@ SASHIMI2017 workshop, MICCAI 2017



AI has no responsibility

음악을 들으면 그에 해당하는 개인의 추억을 되새겨주는(영상이나 글로) 인공지능을 만들어봐도 재밌겠네요.

좋아요 · 답글 달기 · 1 · 7월 10일 오전 9:23 · 수정됨

만약 아내와 음악을 듣는데 옛노래에 연관된 이미지로 전여친 사진이 뜬다면??

좋아요 · 답글 달기 · 3 · 7월 10일 오전 9:47

인공지능은 책임을 지지 않습니다 ㅎㅎ

좋아요 · 답글 달기 · 7월 10일 오후 12:41



Thank you for your attention

2017.10.31 NVIDIA Deep Learning Day

지능정보기술연구원 김휘영 PhD
astaria82@gmail.com

