의료 영상정보 활용 방법과 예

Oct. 30th, 2018

Young-Gon Kim

Medical Imaging & Intelligent Reality Lab (MI2RL)
Convergence Medicine/Radiology,
University of Ulsan College of Medicine
Asan Medical Center
South Korea

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    - 표준화되지 못한 어려움
  - 검체 검사 lab data
    - 장비 별 결과 수치 제각각
  - 영상 검사 medical image
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Introduction

- 익명화 관련 규제 [1]

연구·개발 보물창고 의료영상정보, 왜 쓰질 못하나?

활용 무궁무진 하지만, 법적 규제 가로막혀.."개인정보 비식별 조치 방법 모색해야"

[PDF] 의료기기 분야 규제혁신 및 산업육성 방안

policy.nl.go.kr/cmmn/FileDown.do?atchFileId=223513&fileSn=64959

2018. 7. 19. - 안전한 의료기기'포괄적 네거티브 규제'전환 ····11. III. 산업육성 중점 ....

'투찰운영 심사시스템' ... (예) AI 기반 영상진단

뉴스 관련도순 | 최신순

[이민화의 4차 산업혁명]개인데이터 익명화 개방 서둘러야

서울경제 | 39면 TOP | 2018.09.1

정보규제가 심한 국가로 분류한 이유
관의 클라우드... 의료기록과 납세기록
활용을 위해 개인정보의 익명화가...

특히 의료법 제21조에서는 진료기록인 의료영상 정보는 요건을 갖춘 가족, 국민건강보험법, 의료급여법, 형사소송법 등에 근거한 경우를 제외하고는 원칙적으로 제3자 제공이 금지돼 있다.

강 연구위원은 이처럼 보수적인 우리나라와 달리 일찍이 의료영상정보에 대한 활용 방법을 마련한 미국과 일본의 사례를 소개했다.

미국은 의료정보보호법(HIPAA; Health Insurance Portability & Accountability Act Privacy Rule)을 통해 비식별화된 개인건강정보는 별도 동의 없이도 수집 또는 이용하도록 했다.

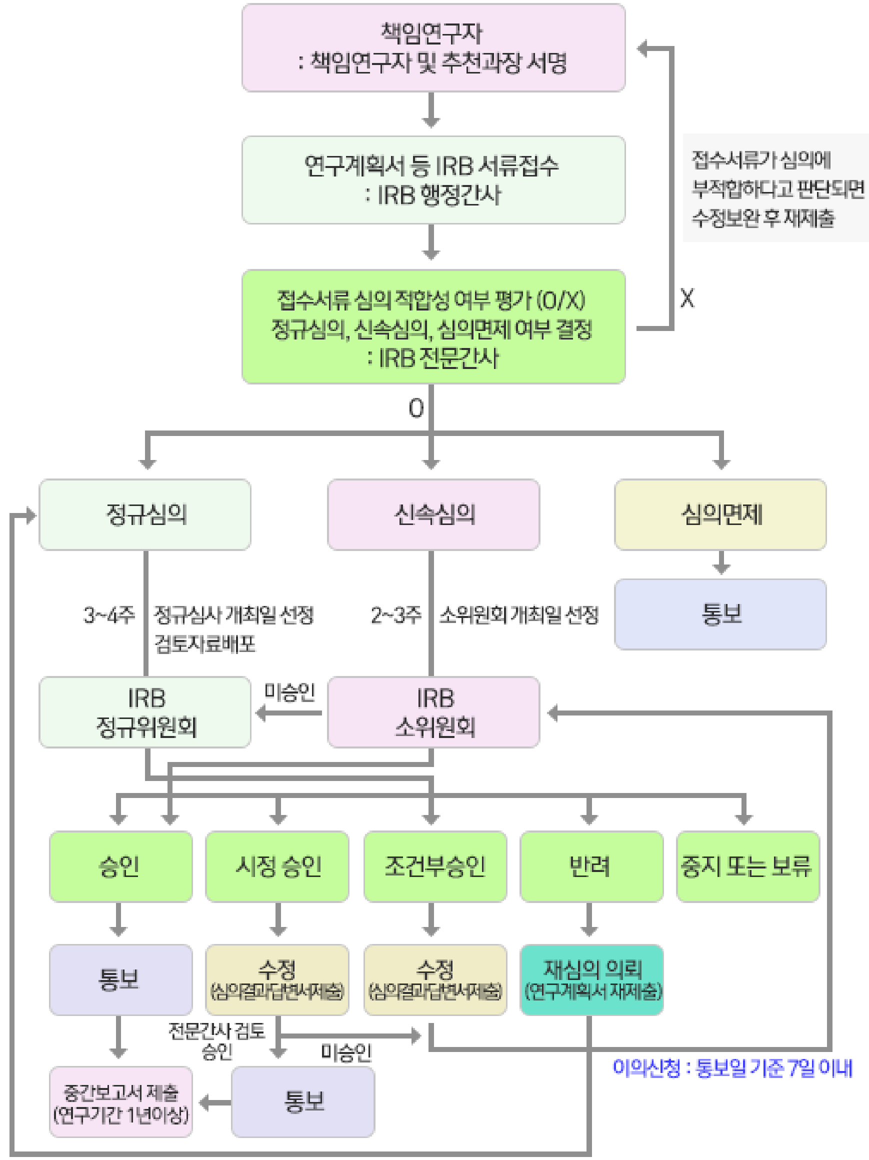
일본은 지난 5월 11일부터 건강·의료에 관한 첨단적 연구 개발 및 신산업 창출을 촉진하기 위해 '의료분야의 연구개발에 이바지하기 위한 익명가공 의료정보에 관한 법률'을 시행하고 있다.

[1] http://medipana.com/news/news_viewer.asp?NewsNum=225929&M

• 임상시험 ... nal Review B

• 임상연구 ... 안전・복지를 위하여 ... -학연구의 윤리적, 과 ... 승인할 수 있는 독립 ...

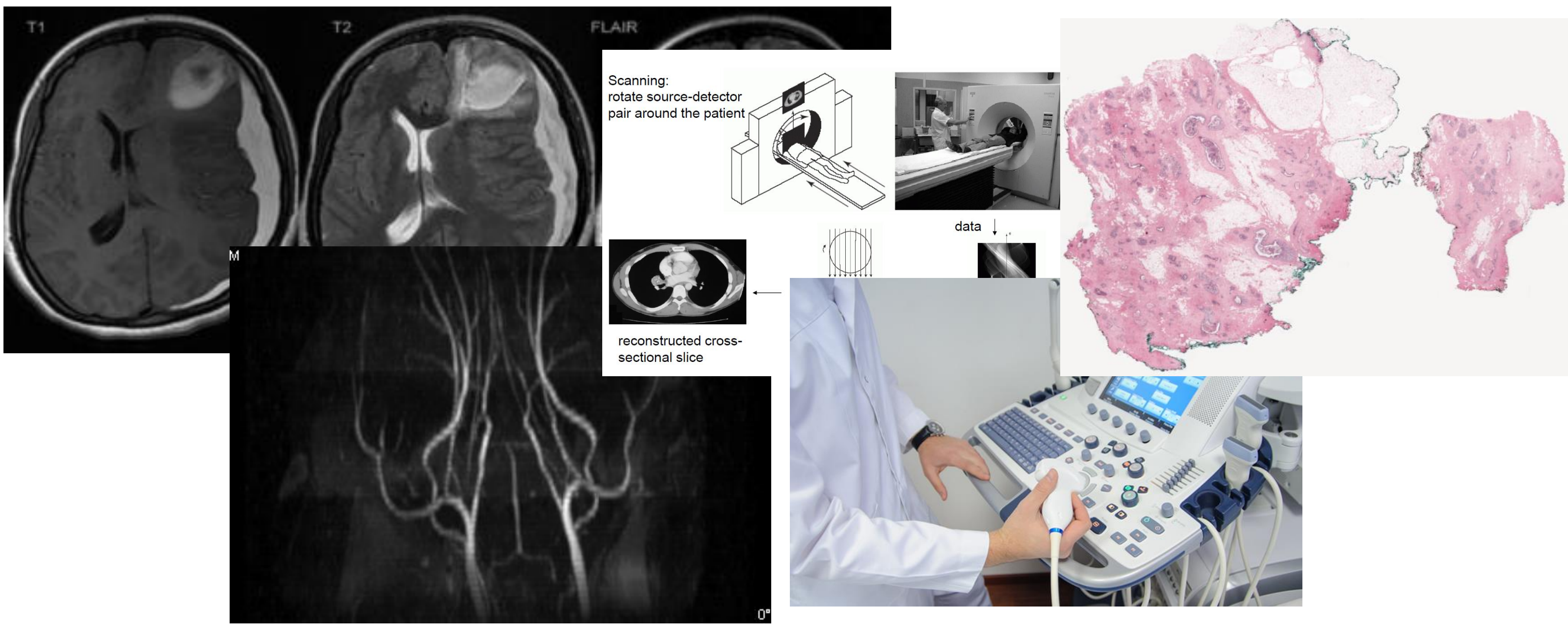
▣ 절차



- IRB승인 유효기간 : 1년
- IRB 승인 후 1년 이내 연구 시작
- 연구 기간이 1년 이상인 경우 중간보고서 IRB 제출 : 승인유효 만료 2개월 전
- 연구종료 후 종료보고서 및 결과 보고서 제출

Medical Imaging

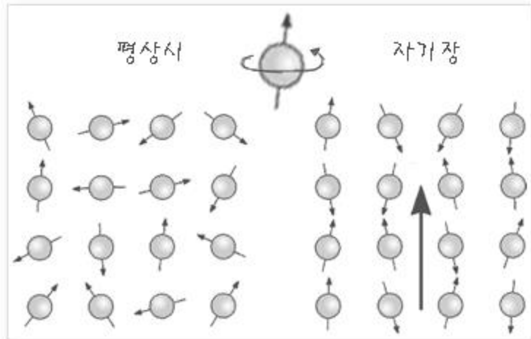
- Definition
  - Medical imaging is the technique and process of creating visual representations of the interior of a body for clinical analysis and medical intervention, as well as visual representation of the function of some organs or tissues (physiology). [3]



[3] https://en.wikipedia.org/wiki/Medical_imaging

Medical Imaging

- Image modality
  - MRI (Magnetic Resonance Imaging) [4]
    - 물질을 이루는 수소원자의 핵 안에 양성자 (proton)에 에 자기장과 고주파 신호를 주어 방출하는 에너지를 획득하여 영상화

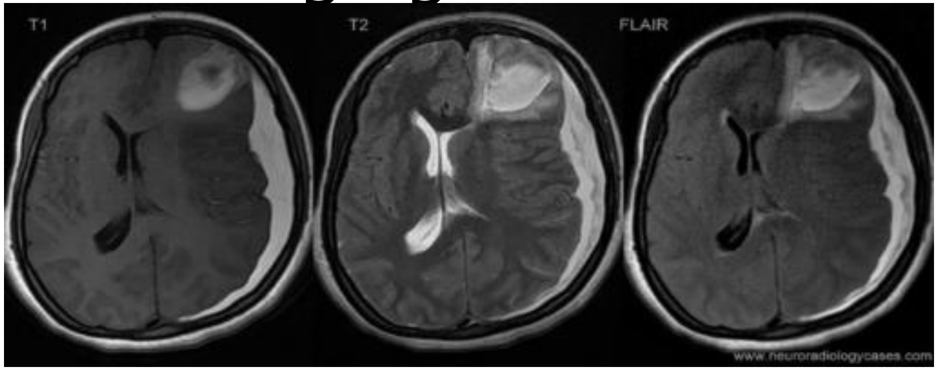


    - Sequence
      - T1, T2, DWI, angiography, GRE, etc…
    - Image pixel size
      - 256x256x20~512x512x512

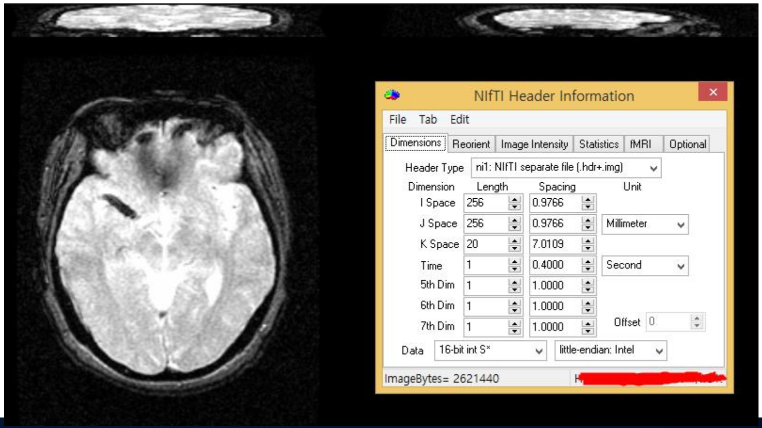
[4] https://lsy5518.wordpress.com/2014/08/22/%EC%9E%90%EA%B8%B0%EA%B3%B5%EB%AA%85%EC%98%81%EC%83%81%EB%B2%95-mri/

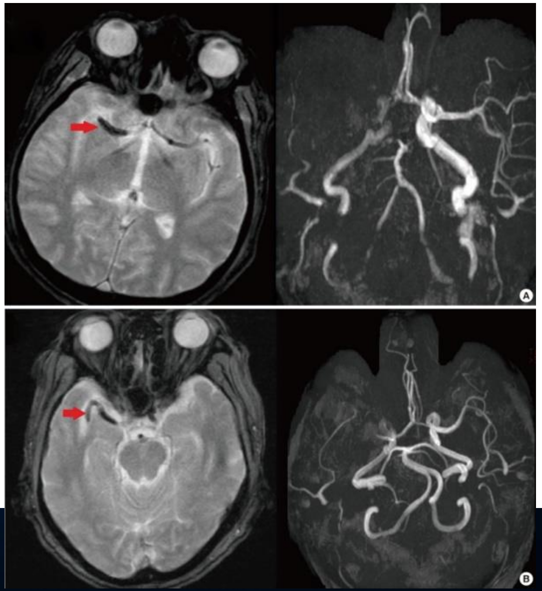
Medical Imaging

- Image modality
  - MRI (Magnetic Resonance Imging)
    - T1, T2, FLAIR



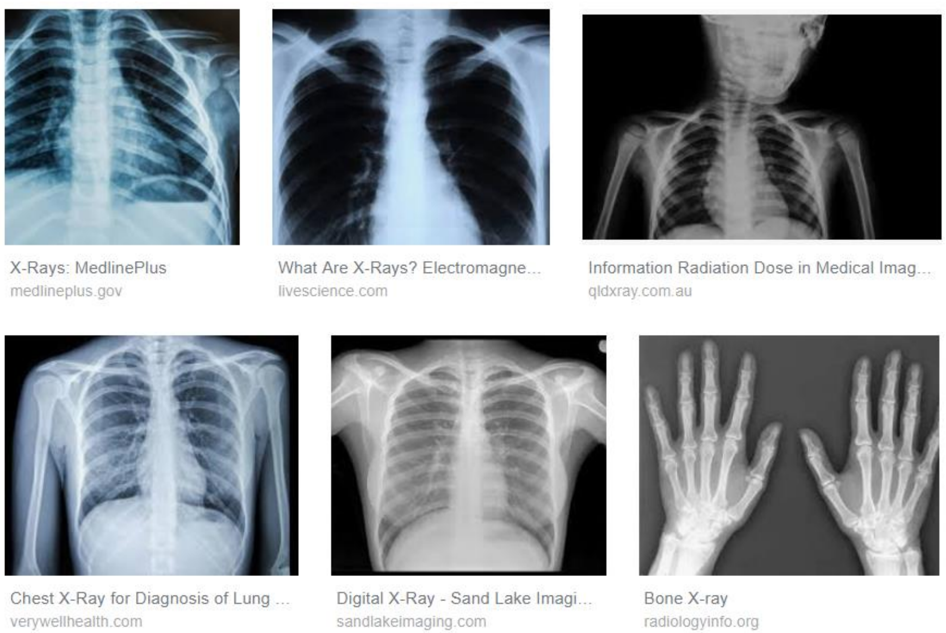
    - GRE, angiography





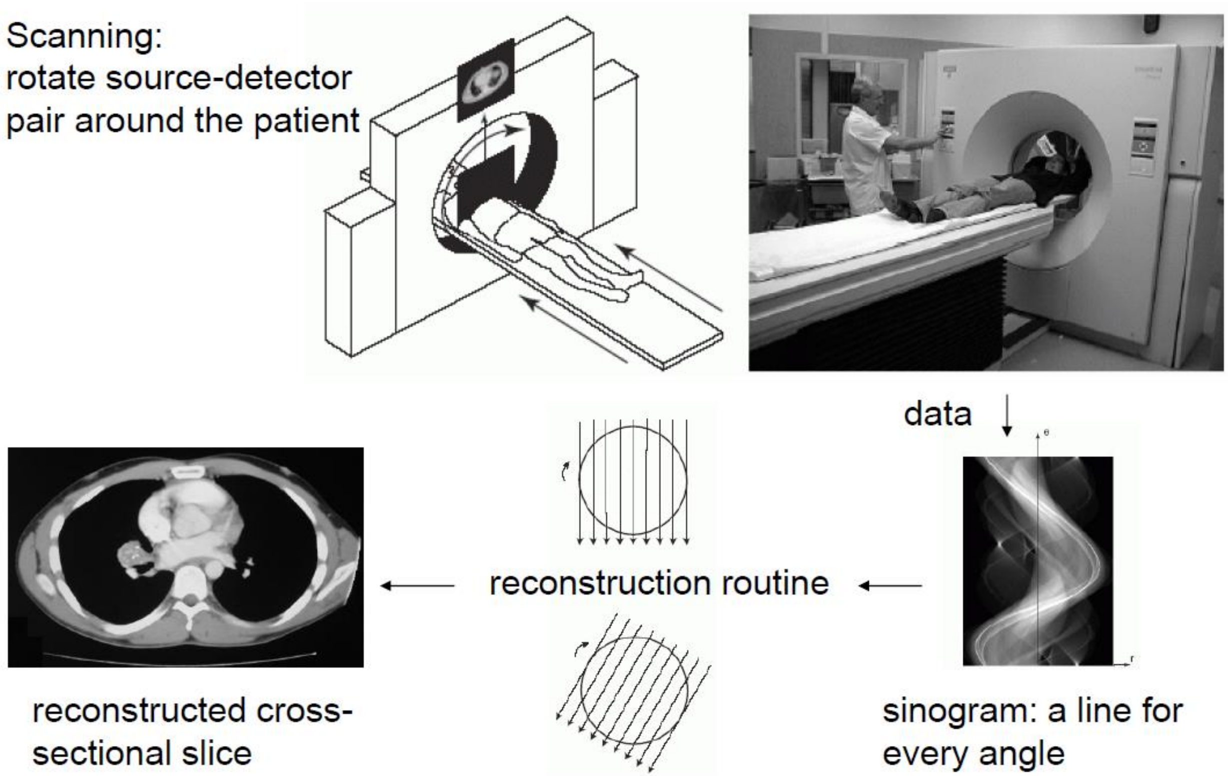
Medical Imaging

- Image modality
  - X-ray
    - 방사선의 하나로 자외선보다 파장이 짧은 전자파 투과력이 매우 크고 의료분야에서는 X선 사진, X선 CT 등으로 응용



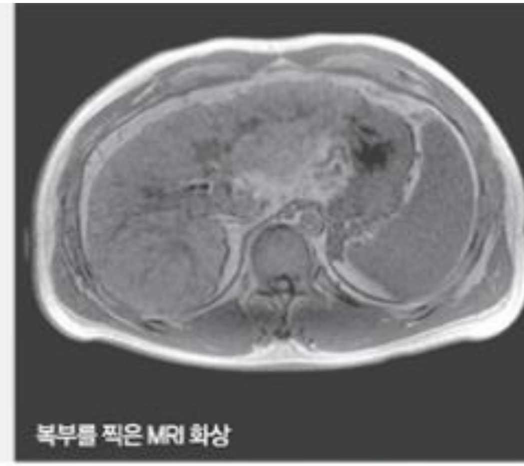
Medical Imaging

- Image modality
  - CT (Computer Tomography)



Medical Imaging

- Image modality
  - MRI vs CT [6]



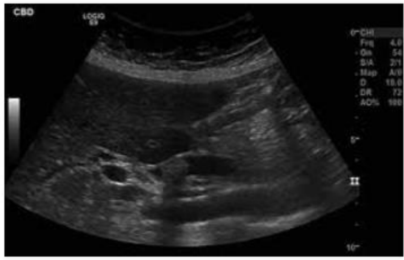
CT		MRI
X선을 이용해 컴퓨터로 재구성한 영상	검사 원리	자석과 전자기파를 이용해 컴퓨터로 재구성한 영상
검사 시간 짧음. 3차원 영상도 가능	특징	검사 시간 오래 걸림. X선을 사용하지 않아 비교적 안전
4만~20만 원	비용	-30만~40만 원(보험 적용 시) -30만~110만 원(보험 적용되지 않을 시)
평균 15~30초. 전신을 다 찍을 때는 10분	검사 시간	30~50분
각종 폐 질환, 췌장암 담도암 등 소화기관 질환, 뼈 부위	진단 부위	뇌 질환, 척추 질환, 근육 질환, 골관절 질환
조영제 부작용이 있을 수 있음. X선 노출이 많으므로 단기간 많은 검사는 인체에 해로움	주의사항	폐쇄공포증 환자는 검사에 어려움 겪음. 인공심박동기와 인공내이(內耳)를 이식받은 환자는 촬영 불가능

[6] http://news.donga.com/3/all/20071022/8502803/1

Medical Imaging

- Image modality
  - Ultrasound [7]
    - 우리가 들을 수 있는 소리보다 주파수가 큰 음파를 인체 내부로 전파시켰을 때 체내 연조직에서 반사된 음파로 얻어진 반사 영상을 이용한 검사
    - 인체에 전여 해롭지 않음

Ultrasound - Wikipedia
en.wikipedia.org

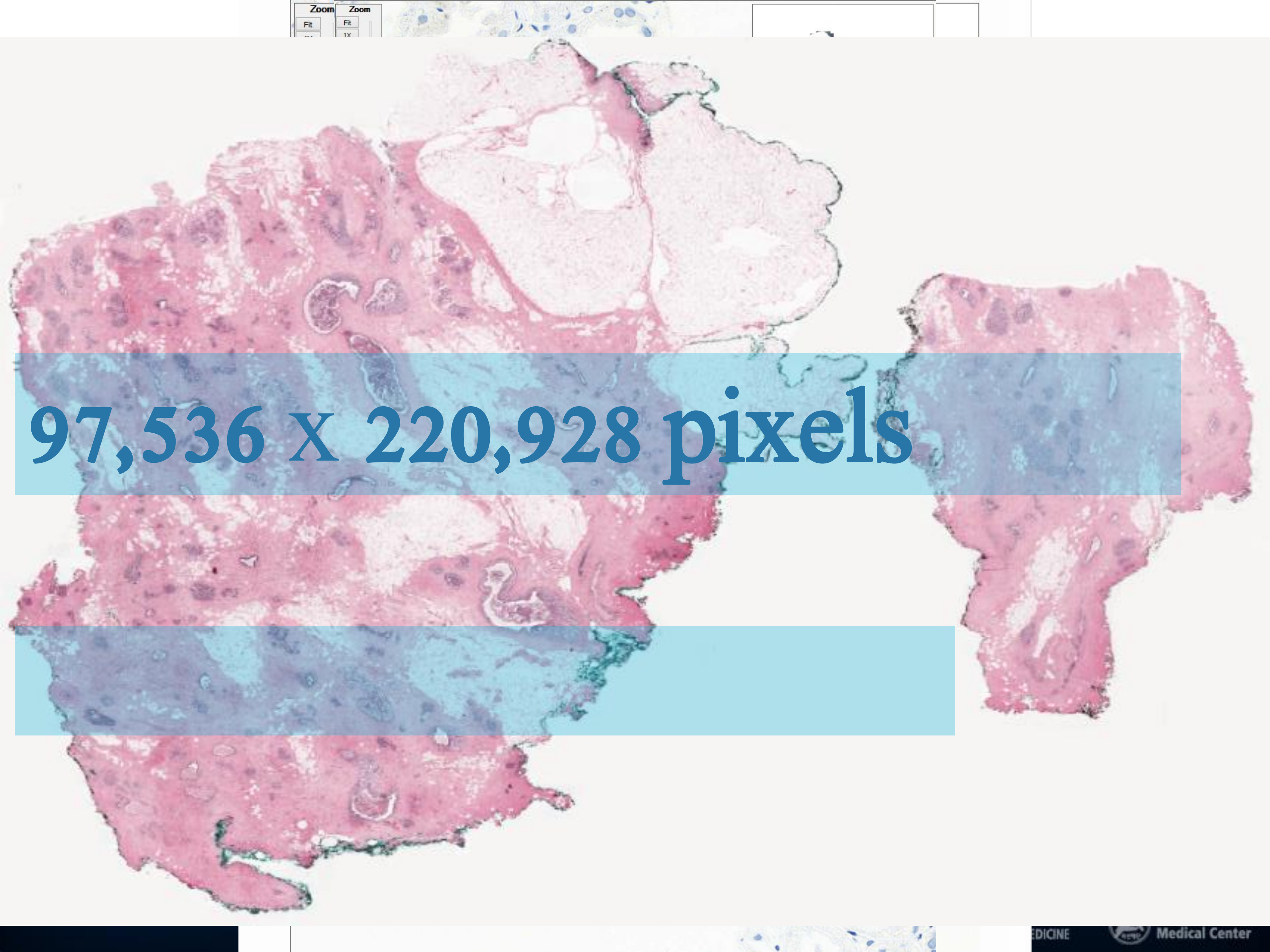


Ultrasound imaging
radiologycafe.com

Medical Imaging > Ultrasound Imaging
fda.gov

Overview of Ultrasound Imaging Syste...
maximintegrated.com

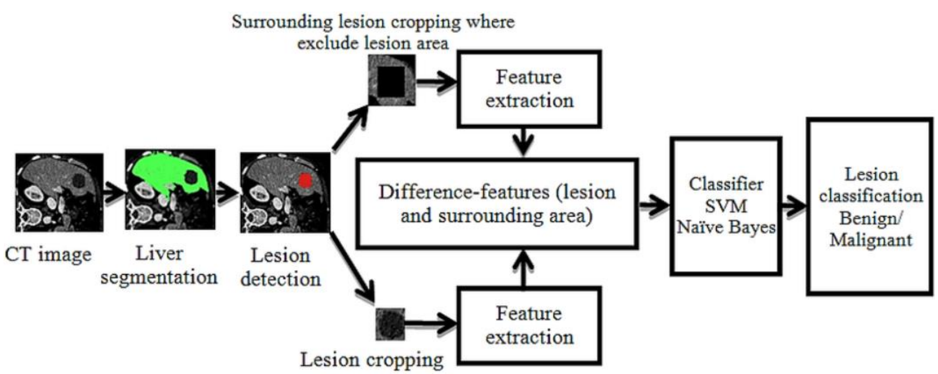
[7] https://www.ausmed.com/articles/medical-imaging-types-and-modalities/



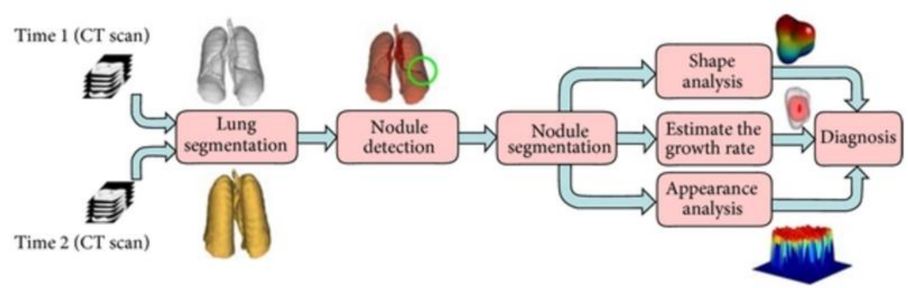
97,536 x 220,928 pixels

CAD System

- Definition [8]
  - Computer-aided detection (CADe), also called computer-aided diagnosis (CADx), are systems that assist doctors in the interpretation of medical images.
    - 영상의학과나 다른 의학자들이 분석 및 평가해야만 하는 영상정보들을 전달
    - 질병가능한 부분을 강조하게 함으로써 진단보조에 도움을 줌



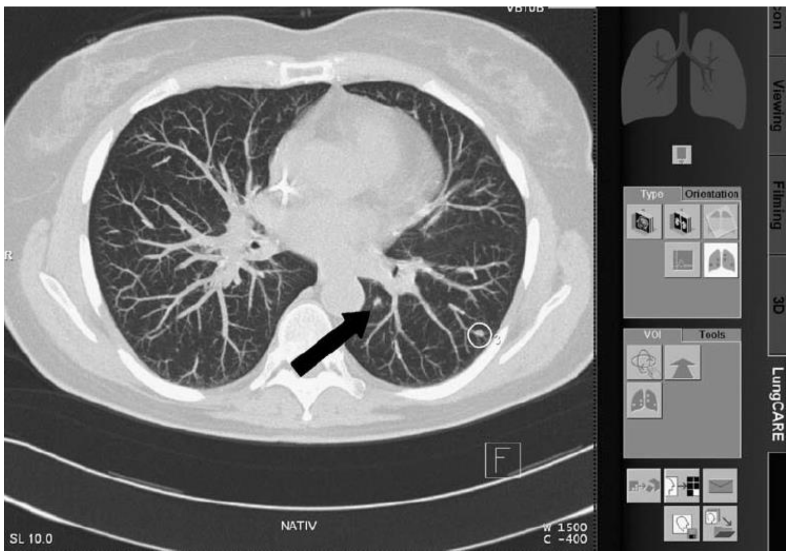
[9]



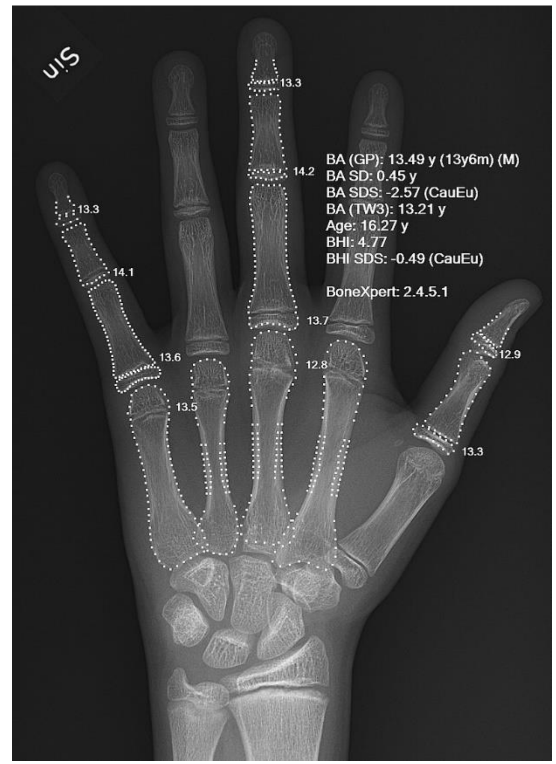
[10]

CAD System

- Application
  - 폐결절 진단용 [11]



  - 뼈나이 보조진단 [12]



[11] https://www.researchgate.net/figure/Screenshot-of-the-CAD-application-The-axial-slice-of-the-processed-case-is-displayed-in_fig3_5916250
[12] https://en.wikipedia.org/wiki/Computer-aided_diagnosis

CAD System

- Application
  - US Food and Drug Administration (FDA) approved computer-aided detection (CAD) for mammography in 1998… [13]

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Research

Original Investigation | LESS IS MORE

Diagnostic Accuracy of Digital Screening Mammography With and Without Computer-Aided Detection

Constance D. Lehman, MD, PhD; Robert D. Wellman, MS; Diana S. M. Buist, PhD; Karla Kerlikowske, MD; Anna N. A. Tosteson, ScD; Diana L. Miglioretti, PhD; for the Breast Cancer Surveillance Consortium

Invited Commentary page 1837

IMPORTANCE After the US Food and Drug Administration (FDA) approved computer-aided detection (CAD) for mammography in 1998, and the Centers for Medicare and Medicaid Services (CMS) provided increased payment in 2002, CAD technology disseminated rapidly. Despite sparse evidence that CAD improves accuracy of mammographic interpretations and costs over $400 million a year, CAD is currently used for most screening mammograms in the United States.

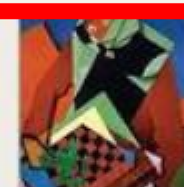
OBJECTIVE To measure performance of digital screening mammography with and without

intraradiologist performance. Sensitivity was significantly decreased for mammograms interpreted with vs without CAD in the subset of radiologists who interpreted both with and without CAD (odds ratio, 0.53; 95% CI, 0.29-0.97).

CONCLUSIONS AND RELEVANCE Computer-aided detection does not improve diagnostic accuracy of mammography. These results suggest that insurers pay more for CAD with no established benefit to women.

IMPORTANCE After the US Food and Drug Administration (FDA) approved computer-aided detection (CAD) for mammography in 1998, and the Centers for Medicare and Medicaid Services (CMS) provided increased payment in 2002, CAD technology disseminated rapidly. Despite sparse evidence that CAD improves accuracy of mammographic interpretations and costs over $400 million a year, CAD is currently used for most screening mammograms in the United States.

Author Affiliations: Department of Radiology, Massachusetts General Hospital, Boston (Lehman); Group Health Research Institute, Seattle, Washington (Wellman, Buist, Miglioretti); Departments of Medicine and Epidemiology and Biostatistics, University of California, San Francisco, San Francisco (Kerlikowske); Norris Cotton Cancer



CONCLUSIONS AND RELEVANCE Computer-aided detection does not improve diagnostic accuracy of mammography. These results suggest that insurers pay more for CAD with no established benefit to women.

UNIVERSITY OF ULSAN COLLEGE MEDICINE ASAN Medical Center

Deep Learning for Medical Image

- Journals
  - Varun Gulshan, et al., “Development an Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs”, *JAMA*, 2016 [15]
  - Babak Ehteshami Bejnordi, et al., “Diagnostic Assessment of Deep Learning Algorithms for Detection of Lymph Node Metastases in Women With Breast Cancer”, *JAMA*, 2017 [16]
  - Andre Esteva, et al., “Dermatologist-level classification of skin cancer with deep neural networks”, *Nature*, 2017 [17]

[15] https://jamanetwork.com/journals/jama/fullarticle/2588763
[16] https://jamanetwork.com/journals/jama/fullarticle/2665774
[17] https://www.nature.com/articles/nature21056

Deep Learning for Medical Image

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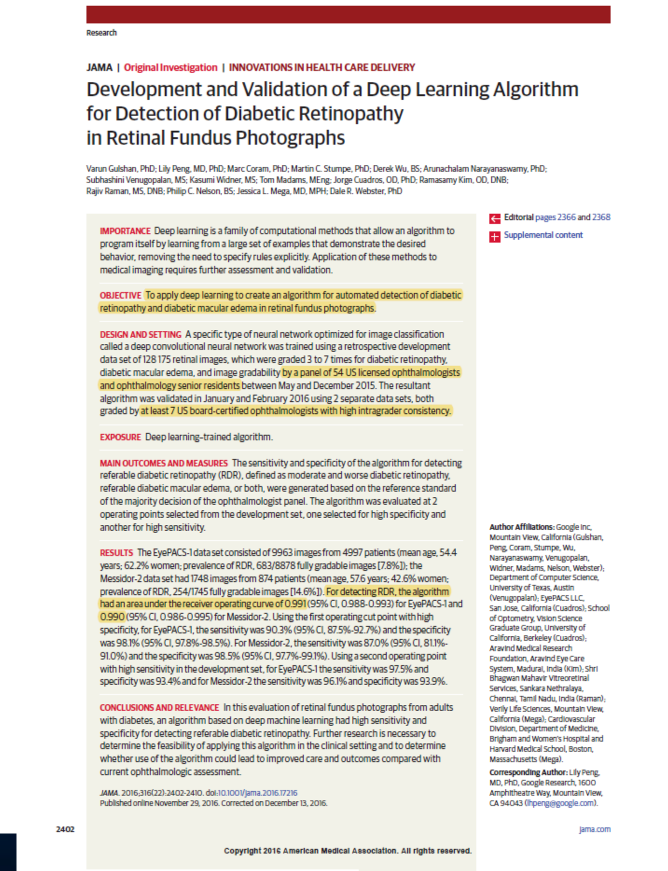


JAMA | Original Investigation | INNOVATIONS IN HEALTH CARE DELIVERY

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; Philip C. Nelson, BS; Jessica L. Mega, MD, MPH; Dale R. Webster, PhD

Editorial pages 2366 and 2368

Supplemental content

IMPORTANCE Deep learning is a family of computational methods that allow an algorithm to program itself by learning from a large set of examples that demonstrate the desired behavior, removing the need to specify rules explicitly. Application of these methods to medical imaging requires further assessment and validation.

OBJECTIVE To apply deep learning to create an algorithm for automated detection of diabetic retinopathy and diabetic macular edema in retinal fundus photographs.

DESIGN AND SETTING A specific type of neural network optimized for image classification called a deep convolutional neural network was trained using a retrospective development data set of 128 175 retinal images, which were graded 3 to 7 times for diabetic retinopathy, diabetic macular edema, and image gradability by a panel of 54 US licensed ophthalmologists and ophthalmology senior residents between May and December 2015. The resultant algorithm was validated in January and February 2016 using 2 separate data sets, both graded by at least 7 US board-certified ophthalmologists with high intragrader consistency.

EXPOSURE Deep learning–trained algorithm.

MAIN OUTCOMES AND MEASURES The sensitivity and specificity of the algorithm for detecting referable diabetic retinopathy (RDR), defined as moderate and worse diabetic retinopathy, referable diabetic macular edema, or both, were generated based on the reference standard of the majority decision of the ophthalmologist panel. The algorithm was evaluated at 2 operating points selected from the development set, one selected for high specificity and another for high sensitivity.

RESULTS The EyePACS-1 data set consisted of 9963 images from 4997 patients (mean age, 54.4 years; 62.2% women; prevalence of RDR, 683/8878 fully gradable images [7.8%]); the Messidor-2 data set had 1748 images from 874 patients (mean age, 57.6 years; 42.6% women; prevalence of RDR, 254/1745 fully gradable images [14.6%]). For detecting RDR, the algorithm had an area under the receiver operating curve of 0.991 (95% CI, 0.988-0.993) for EyePACS-1 and 0.990 (95% CI, 0.986-0.995) for Messidor-2. Using the first operating cut point with high specificity, for EyePACS-1, the sensitivity was 90.3% (95% CI, 87.5%-92.7%) and the specificity was 98.1% (95% CI, 97.8%-98.5%). For Messidor-2, the sensitivity was 87.0% (95% CI, 81.1%-91.0%) and the specificity was 98.5% (95% CI, 97.7%-99.1%). Using a second operating point with high sensitivity in the development set, for EyePACS-1 the sensitivity was 97.5% and specificity was 93.4% and for Messidor-2 the sensitivity was 96.1% and specificity was 93.9%.

CONCLUSIONS AND RELEVANCE In this evaluation of retinal fundus photographs from adults with diabetes, an algorithm based on deep machine learning had high sensitivity and specificity for detecting referable diabetic retinopathy. Further research is necessary to determine the feasibility of applying this algorithm in the clinical setting and to determine whether use of the algorithm could lead to improved care and outcomes compared with current ophthalmologic assessment.

JAMA. 2016;316(22):2402-2410. doi:10.1001/jama.2016.17216
Published online November 29, 2016. Corrected on December 13, 2016.

Author Affiliations: Google Inc, Mountain View, California (Gulshan, Peng, Coram, Stumpe, Wu, Narayanaswamy, Venugopalan, Widner, Madams, Nelson, Webster); Department of Computer Science, University of Texas, Austin (Venugopalan); EyePACS LLC, San Jose, California (Cuadros); School of Optometry, Vision Science Graduate Group, University of California, Berkeley (Cuadros); Aravind Medical Research Foundation, Aravind Eye Care System, Madurai, India (Kim); Shri Bhagwan Mahavir Vitreoretinal Services, Sankara Nethralaya, Chennai, Tamil Nadu, India (Raman); Verily Life Sciences, Mountain View, California (Mega); Cardiovascular Division, Department of Medicine, Brigham and Women's Hospital and Harvard Medical School, Boston, Massachusetts (Mega).

Corresponding Author: Lily Peng, MD, PhD, Google Research, 1600 Amphitheatre Way, Mountain View, CA 94043 (lhpeng@google.com).

Deep Learning for Medical Image

- Journals
  - Babak Ehteshami Bejnordi, et al., "Diagnostic Assessment of Deep Learning Algorithms for Detection of Lymph Node Metastases in Women With Breast Cancer", *JAMA*, 2017


Research

JAMA | Original Investigation

Diagnostic Assessment of Deep Learning Algorithms for Detection of Lymph Node Metastases in Women With Breast Cancer

Babak Ehteshami Bejnordi, MS; Mitko Veta, PhD; Paul Johannes van Diest, MD, PhD; Bram van Ginneken, PhD; Nico Karssemeijer, PhD; Geert Litjens, PhD; Jeroen A. W. M. van der Laak, PhD; and the CAMELYON16 Consortium

IMPORTANCE Application of deep learning algorithms to whole-slide pathology images can potentially improve diagnostic accuracy and efficiency.

OBJECTIVE Assess the performance of automated deep learning algorithms at detecting metastases in hematoxylin and eosin–stained tissue sections of lymph nodes of women with breast cancer and compare it with pathologists' diagnoses in a diagnostic setting.

DESIGN, SETTING, AND PARTICIPANTS Researcher challenge competition (CAMELYON16) to develop automated solutions for detecting lymph node metastases (November 2015-November 2016). A training data set of whole-slide images from 2 centers in the Netherlands with (n = 110) and without (n = 160) nodal metastases verified by immunohistochemical staining were provided to challenge participants to build algorithms. Algorithm performance was evaluated in an independent test set of 129 whole-slide images (49 with and 80 without metastases). The same test set of corresponding glass slides was also evaluated by a panel of 11 pathologists with time constraint (WTC) from the Netherlands to ascertain likelihood of nodal metastases for each slide in a flexible 2-hour session, simulating routine pathology workflow, and by 1 pathologist without time constraint (WOTC).

EXPOSURES Deep learning algorithms submitted as part of a challenge competition or pathologist interpretation.

MAIN OUTCOMES AND MEASURES The presence of specific metastatic foci and the absence vs presence of lymph node metastasis in a slide or image using receiver operating characteristic curve analysis. The 11 pathologists participating in the simulation exercise rated their diagnostic confidence as definitely normal, probably normal, equivocal, probably tumor, or definitely tumor.

RESULTS The area under the receiver operating characteristic curve (AUC) for the algorithms ranged from 0.556 to 0.994. The top-performing algorithm achieved a lesion-level, true-positive fraction comparable with that of the pathologist WOTC (72.4% [95% CI, 64.3%-80.4%]) at a mean of 0.0125 false-positives per normal whole-slide image. For the whole-slide image classification task, the best algorithm (AUC, 0.994 [95% CI, 0.983-0.999]) performed significantly better than the pathologists WTC in a diagnostic simulation (mean AUC, 0.810 [range, 0.738-0.884]; $P < .001$). The top 5 algorithms had a mean AUC that was comparable with the pathologist interpreting the slides in the absence of time constraints (mean AUC, 0.960 [range, 0.923-0.994] for the top 5 algorithms vs 0.966 [95% CI, 0.927-0.998] for the pathologist WOTC).

CONCLUSIONS AND RELEVANCE In the setting of a challenge competition, some deep learning algorithms achieved better diagnostic performance than a panel of 11 pathologists participating in a simulation exercise designed to mimic routine pathology workflow; algorithm performance was comparable with an expert pathologist interpreting whole-slide images without time constraints. Whether this approach has clinical utility will require evaluation in a clinical setting.

JAMA. 2017;318(22):2199-2210. doi:10.1001/jama.2017.14585

Editorial page 2184
Related articles page 2211 and page 2250
Supplemental content
CME Quiz at jamanetwork.com/learning and CME Questions page 2252

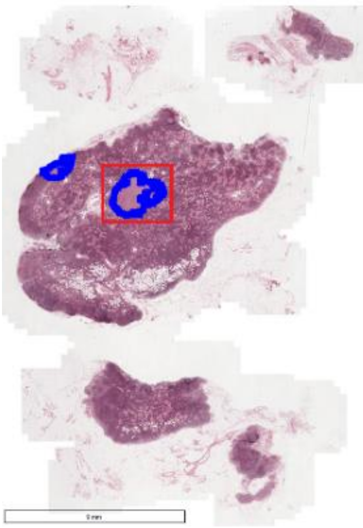
Author Affiliations: Diagnostic Image Analysis Group, Department of Radiology and Nuclear Medicine, Radboud University Medical Center, Nijmegen, the Netherlands (Ehteshami Bejnordi, van Ginneken, Karssemeijer); Medical Image Analysis Group, Eindhoven University of Technology, Eindhoven, the Netherlands (Veta); Department of Pathology, University Medical Center Utrecht, Utrecht, the Netherlands (Johannes van Diest); Department of Pathology, Radboud University Medical Center, Nijmegen, the Netherlands (Litjens, van der Laak).

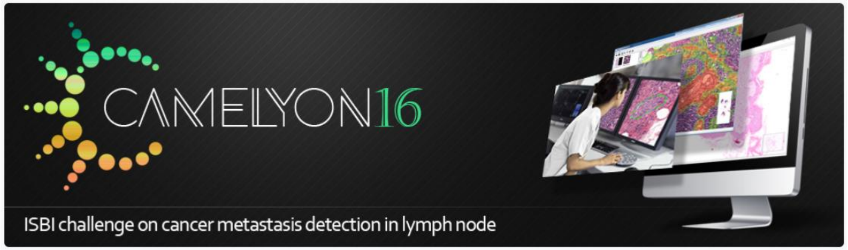
Group Information: The CAMELYON16 Consortium authors and collaborators are listed at the end of this article.

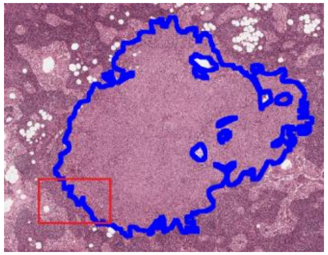
Corresponding Author: Babak Ehteshami Bejnordi, MS, Radboud University Medical Center, Postbus 9101, 6500 HB Nijmegen (ehteshami@babakint.com).

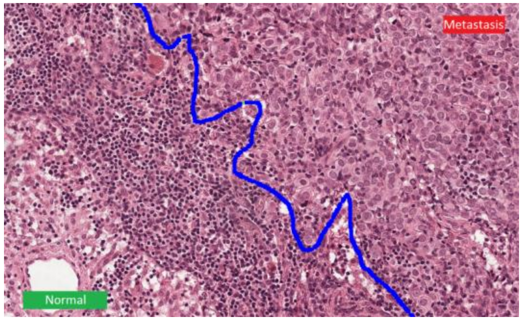
Deep Learning for Medical Image

- Journals
  - Babak Ehteshami Bejnordi, et al., "Diagnostic Assessment of Deep Learning Algorithms for Detection of Lymph Node Metastases in Women With Breast Cancer", *JAMA*, 2017
    - CAMELYON 16
      - https://camelyon16.grand-challenge.org/



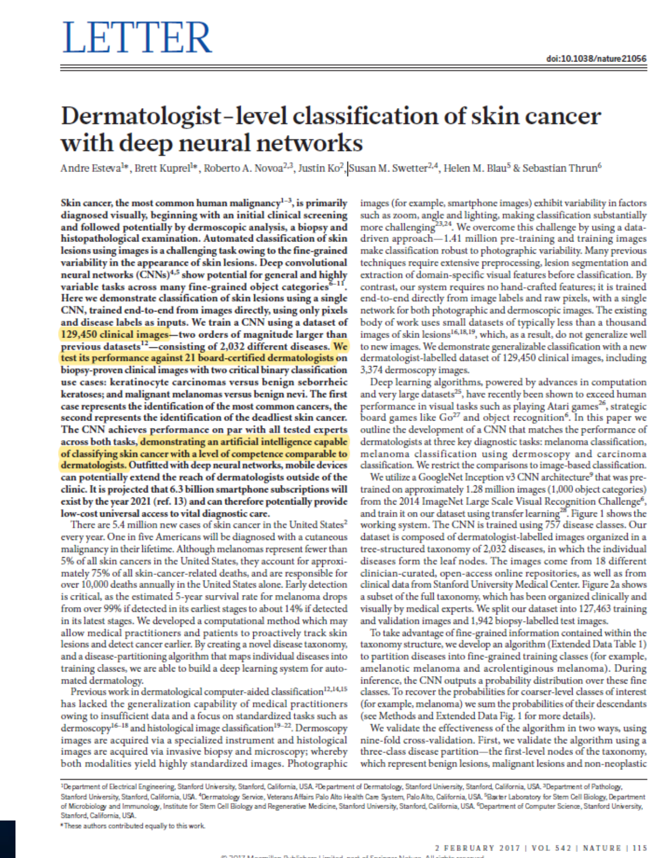






Deep Learning for Medical Image

- Journals
  - Andre Esteva, et al., "Dermatologist-level classification of skin cancer with deep neural networks", *Nature*, 2017



LETTER

doi:10.1038/nature21056

Dermatologist-level classification of skin cancer with deep neural networks

Andre Esteva[1*], Brett Kuprel[1*], Roberto A. Novoa[2,3], Justin Ko[2], Susan M. Swetter[2,4], Helen M. Blau[5] & Sebastian Thrun[6]

Skin cancer, the most common human malignancy[1–3], is primarily diagnosed visually, beginning with an initial clinical screening and followed potentially by dermoscopic analysis, a biopsy and histopathological examination. Automated classification of skin lesions using images is a challenging task owing to the fine-grained variability in the appearance of skin lesions. Deep convolutional neural networks (CNNs)[4,5] show potential for general and highly variable tasks across many fine-grained object categories[6–11]. Here we demonstrate classification of skin lesions using a single CNN, trained end-to-end from images directly, using only pixels and disease labels as inputs. We train a CNN using a dataset of 129,450 clinical images—two orders of magnitude larger than previous datasets[12]—consisting of 2,032 different diseases. We test its performance against 21 board-certified dermatologists on biopsy-proven clinical images with two critical binary classification use cases: keratinocyte carcinomas versus benign seborrheic keratoses; and malignant melanomas versus benign nevi. The first case represents the identification of the most common cancers, the second represents the identification of the deadliest skin cancer. The CNN achieves performance on par with all tested experts across both tasks, demonstrating an artificial intelligence capable of classifying skin cancer with a level of competence comparable to dermatologists. Outfitted with deep neural networks, mobile devices can potentially extend the reach of dermatologists outside of the clinic. It is projected that 6.3 billion smartphone subscriptions will exist by the year 2021 (ref. 13) and can therefore potentially provide low-cost universal access to vital diagnostic care.

There are 5.4 million new cases of skin cancer in the United States[2] every year. One in five Americans will be diagnosed with a cutaneous malignancy in their lifetime. Although melanomas represent fewer than 5% of all skin cancers in the United States, they account for approximately 75% of all skin-cancer-related deaths, and are responsible for over 10,000 deaths annually in the United States alone. Early detection is critical, as the estimated 5-year survival rate for melanoma drops from over 99% if detected in its earliest stages to about 14% if detected in its latest stages. We developed a computational method which may allow medical practitioners and patients to proactively track skin lesions and detect cancer earlier. By creating a novel disease taxonomy, and a disease-partitioning algorithm that maps individual diseases into training classes, we are able to build a deep learning system for automated dermatology.

Previous work in dermatological computer-aided classification[12,14,15] has lacked the generalization capability of medical practitioners owing to insufficient data and a focus on standardized tasks such as dermoscopy[16–18] and histological image classification[19–22]. Dermoscopy images are acquired via a specialized instrument and histological images are acquired via invasive biopsy and microscopy; whereby both modalities yield highly standardized images. Photographic images (for example, smartphone images) exhibit variability in factors such as zoom, angle and lighting, making classification substantially more challenging[23,24]. We overcome this challenge by using a data-driven approach—1.41 million pre-training and training images make classification robust to photographic variability. Many previous techniques require extensive preprocessing, lesion segmentation and extraction of domain-specific visual features before classification. By contrast, our system requires no hand-crafted features; it is trained end-to-end directly from image labels and raw pixels, with a single network for both photographic and dermoscopic images. The existing body of work uses small datasets of typically less than a thousand images of skin lesions[16,18,19], which, as a result, do not generalize well to new images. We demonstrate generalizable classification with a new dermatologist-labelled dataset of 129,450 clinical images, including 3,374 dermoscopy images.

Deep learning algorithms, powered by advances in computation and very large datasets[25], have recently been shown to exceed human performance in visual tasks such as playing Atari games[26], strategic board games like Go[27] and object recognition[6]. In this paper we outline the development of a CNN that matches the performance of dermatologists at three key diagnostic tasks: melanoma classification, melanoma classification using dermoscopy and carcinoma classification. We restrict the comparisons to image-based classification.

We utilize a GoogleNet Inception v3 CNN architecture[9] that was pre-trained on approximately 1.28 million images (1,000 object categories) from the 2014 ImageNet Large Scale Visual Recognition Challenge[6], and train it on our dataset using transfer learning[28]. Figure 1 shows the working system. The CNN is trained using 757 disease classes. Our dataset is composed of dermatologist-labelled images organized in a tree-structured taxonomy of 2,032 diseases, in which the individual diseases form the leaf nodes. The images come from 18 different clinician-curated, open-access online repositories, as well as from clinical data from Stanford University Medical Center. Figure 2a shows a subset of the full taxonomy, which has been organized clinically and visually by medical experts. We split our dataset into 127,463 training and validation images and 1,942 biopsy-labelled test images.

To take advantage of fine-grained information contained within the taxonomy structure, we develop an algorithm (Extended Data Table 1) to partition diseases into fine-grained training classes (for example, amelanotic melanoma and acrolentiginous melanoma). During inference, the CNN outputs a probability distribution over these fine classes. To recover the probabilities for coarser-level classes of interest (for example, melanoma) we sum the probabilities of their descendants (see Methods and Extended Data Fig. 1 for more details).

We validate the effectiveness of the algorithm in two ways, using nine-fold cross-validation. First, we validate the algorithm using a three-class disease partition—the first-level nodes of the taxonomy, which represent benign lesions, malignant lesions and non-neoplastic

[1]Department of Electrical Engineering, Stanford University, Stanford, California, USA. [2]Department of Dermatology, Stanford University, Stanford, California, USA. [3]Department of Pathology, Stanford University, Stanford, California, USA. [4]Dermatology Service, Veterans Affairs Palo Alto Health Care System, Palo Alto, California, USA. [5]Baxter Laboratory for Stem Cell Biology, Department of Microbiology and Immunology, Institute for Stem Cell Biology and Regenerative Medicine, Stanford University, Stanford, California, USA. [6]Department of Computer Science, Stanford University, Stanford, California, USA.
*These authors contributed equally to this work.

Deep Learning for Medical Image

- Challenges
  - MICCAI (Medical Image Computing & Computer Assisted Intervention)
  - ISBI (International Symposium and Biomedical Imaging)
  - RSNA (Radiological Society of North America)

[18] https://www.miccai2018.org/en/
[19] https://biomedicalimaging.org/2017/ https://biomedicalimaging.org/2018/
[20] https://www.nature.com/articles/nature21056

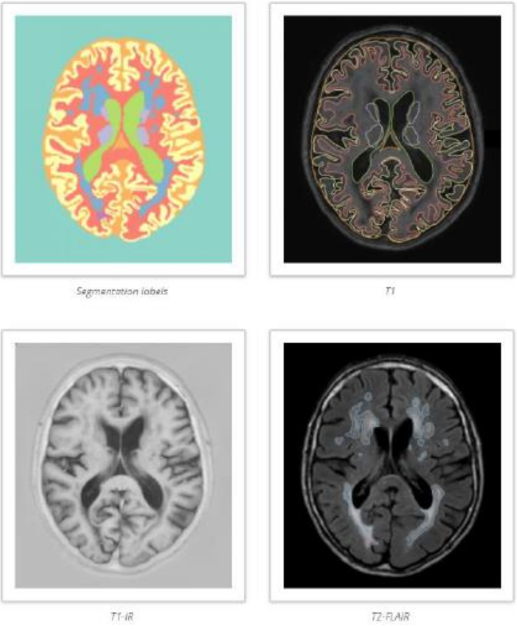
Deep Learning for Medical Image

- Challenges
  - MICCAI (Medical Image Computing & Computer Assisted Intervention)

ACRONYM	NAME	TIME	DATE	VENUE	MEETING ROOM
EndoVis18	Endoscopic Vision Challenge 2018 + CATARACTS Challenge 2018	FULL DAY	16 SEPTEMBER	Conference Center	Andalucia 2
ISLES	Ischemic Stroke Lesion Segmentation Challenge	FULL DAY	16 SEPTEMBER	Conference Center	Room D
CuRIOUS	MICCAI Challenge 2018 for Correction of Brainshift with Intra-Operative UltraSound	PM	16 SEPTEMBER	Saray Hotel	Salon Alcazaba Salon 1
CPM	Computational Precision Medicine Challenge	PM	16 SEPTEMBER	Conference Center	VIP Room
MRBrainS18	MICCAI Grand Challenge on MR Brain Image Segmentation	AM	16 SEPTEMBER	Saray Hotel	Salon Alcazaba Salon 1
BraTS	MICCAI Multimodal Brain Tumor Segmentation (BraTS) Benchmark: "Survival Prediction"	FULL DAY	16 SEPTEMBER	Conference Center	Room D
IVDM3Seg	Intervertebral Disc Segmentation Challenge 2018	AM	16 SEPTEMBER	Conference Center	Andalucia 1
ISIC	Challenge on Dermoscopic Skin Lesion Analysis Toward Melanoma Detection 2018(with workshop nr. 41)	FULL DAY	20 SEPTEMBER	Conference Center	Seminar Room 3-4-5
MSD	Medical Segmentation Decathlon	PM	20 SEPTEMBER	Conference Center	Room Albeniz
MoNuSeg	Multi-Organ Histopathology Nucleus Segmentation Challenge for H&E Stained Images 2018	FULL DAY	20 SEPTEMBER	Conference Center	Room C
MUSHAC	Multi-shell diffusion MRI harmonisation and enhancement challenge	PM	20 SEPTEMBER	Conference Center	Andalucia 2
REFUGE	Retinal Fundus Glaucoma Challenge	PM	20 SEPTEMBER	Conference Center	Room Machado

Deep Learning for Medical Image

- Challenges
  - MICCAI (Medical Image Computing & Computer Assisted Intervention)
    - MRBrainS18
      - Segmentation



LABEL	DESCRIPTION
0	Background
1	Cortical gray matter
2	Basal ganglia
3	White matter
4	White matter lesions
5	Cerebrospinal fluid in the extracerebral space
6	Ventricles
7	Cerebellum
8	Brain stem
9	Infarction
10	Other

Graymatter

Whitematter

CSF

Deep Learning for Medical Image

- Challenges
  - MICCAI (Medical Image Computing & Computer Assisted Intervention)
    - BraTS
      - Segmentation
      - Survival prediction

Multimodal Brain Tumor Segmentation Challenge 2018

• Scope • Relevance • Tasks • Data • Evaluation • Participation Summary • Data Request • Previous BraTS • People •

Scope

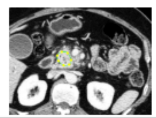
BraTS has always been focusing on the evaluation of state-of-the-art methods for the segmentation of brain tumors in multimodal magnetic resonance imaging (MRI) scans. **BraTS 2018** utilizes multi-institutional pre-operative MRI scans and **focuses on the segmentation of** intrinsically heterogeneous (in appearance, shape, and histology) **brain tumors**, namely gliomas. Furthemore, to pinpoint the clinical relevance of this segmentation task, BraTS'18 also focuses **on the prediction of patient overall survival**, via integrative analyses of radiomic features and machine learning algorithms.

IMPORTANT DATES:

30 Apr	Release of training datasets. — *Request the data here!*
1 Jul	Release of validation datasets. — *View the Leaderboard*
14 Jul	Submission of short papers, reporting proposed method & preliminary results.
30 Jul-20 Aug	Release of testing datasets for 48hr window (& performance evaluation).
30 Aug	Contacting top performing methods for preparing slides for oral presentation.
16 Sep	Challenge at MICCAI (Granada, Spain) — *View the Pre-conference Proceedings*
1 Nov	Extended LNCS paper submission deadline.

Deep Learning for Medical Image

- Challenges
  - MICCAI (Medical Image Computing & Computer Assisted Intervention)
    - CPM
      - Classification



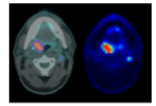
Pancreatic Cancer Survival Prediction

Organized by cpm.organizing.committee

Predict pancreatic survival from CT images and clinical data.

May 16, 2018-Aug 16, 2018

293 participants



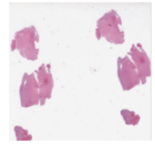
18F-FDG PET Radiomics Risk Stratifiers in Head and Neck Cancer

Organized by cpm.organizing.committee

Predict local tumor control following radiation treatment of oropharynx cancer using an ensemble of radiomics and clinical data

Jun 15, 2018-Aug 30, 2018

71 participants



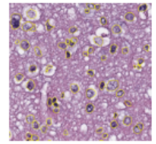
Combined Radiology and Pathology Classification

Organized by cpm.organizing.committee

The goal of this challenge is to evaluate the performance of automated classification algorithms.

Jun 29, 2018-Aug 17, 2018

241 participants



Digital Pathology: Segmentation of Nuclei in Images

Organized by cpm.organizing.committee

The goal of this challenge is to evaluate the performance of algorithms for segmentation of nuclei in tissue images.

Jun 15, 2018-Aug 17, 2018

351 participants

Deep Learning for Medical Image

- Challenges
  - MICCAI (Medical Image Computing & Computer Assisted Intervention)
    - CPM - Combined Radiology and Pathology Classification

      (2 class classification)

      – Training Phase

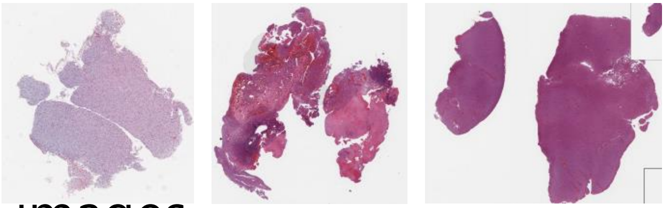
      » 32 radiology MR images

      » 32 pathology Whole slice images

      – Test Phase

      » 20 radiology MR images

      » 20 pathology Whole slice images



COMPUTATIONAL PRECISION MEDICINE

CERTIFICATE OF MERIT

AWARDED TO

YOUNGGON KIM

UNIVERSITY OF ULSAN

FOURTH PLACE

NCI-MICCAI 2018 RADIOLOGY PATHOLOGY CLASSIFICATION CHALLENGE

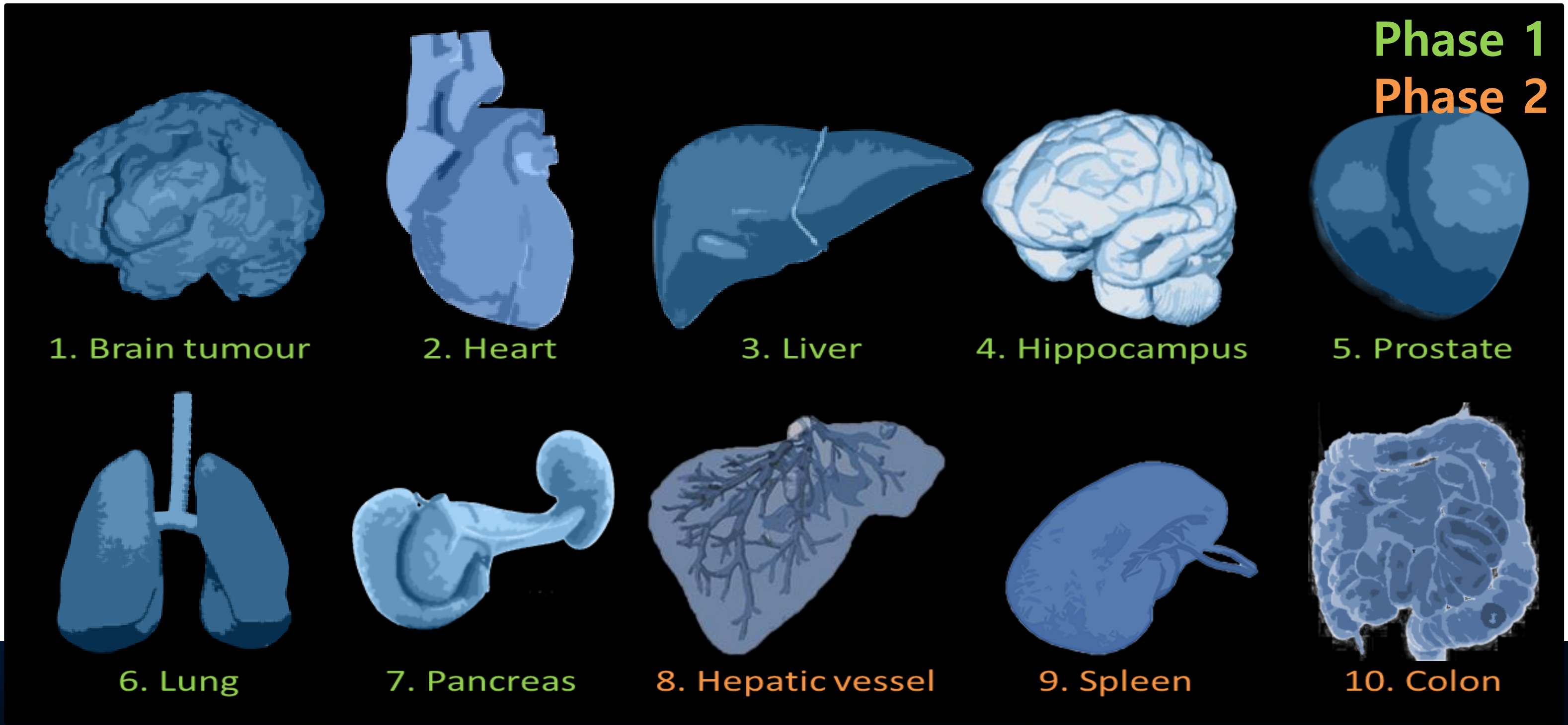
Keyvan Farahani, PhD, Program Director

CANCER IMAGING PROGRAM

NATIONAL CANCER INSTITUTE

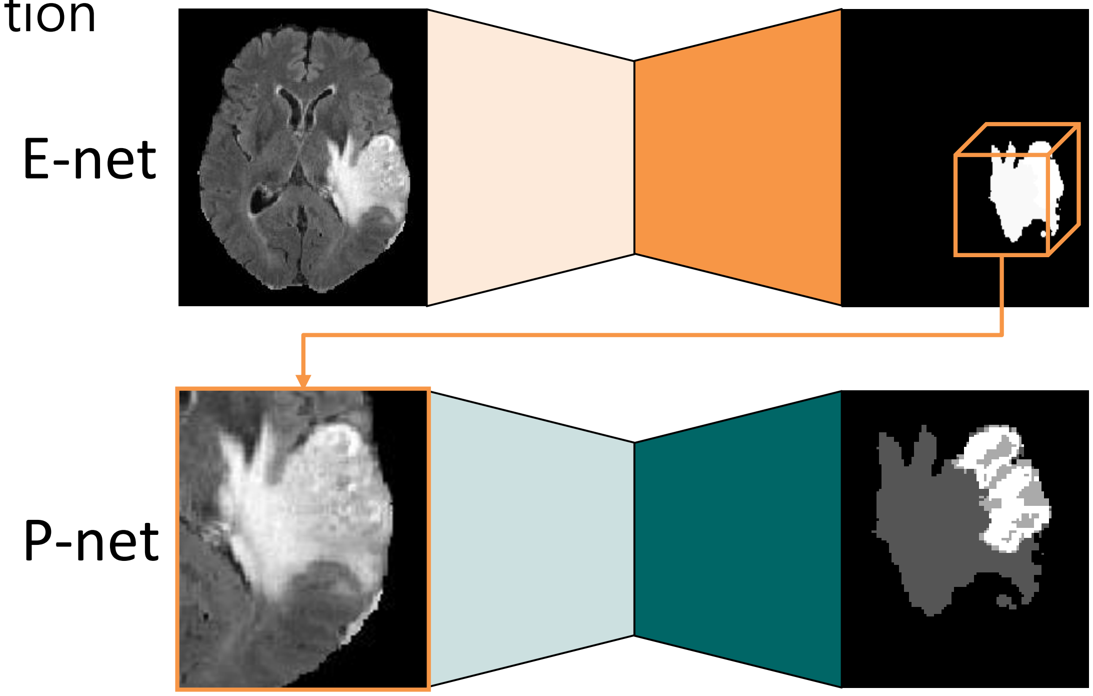
Deep Learning for Medical Image

- Challenges
  - MICCAI (Medical Image Computing & Computer Assisted Intervention)
    - MDS (Medical Segmentation Decathlon
      - Segmentation



Deep Learning for Medical Image

- Challenges
  - MICCAI (Medical Image Computing & Computer Assisted Intervention)
    - MDS (Medical Segmentation Decathlon
      - Segmentation

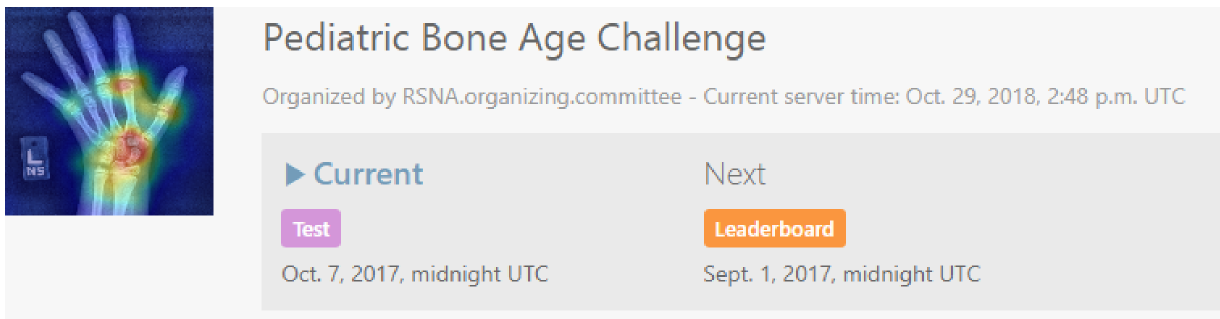


Deep Learning for Medical Image

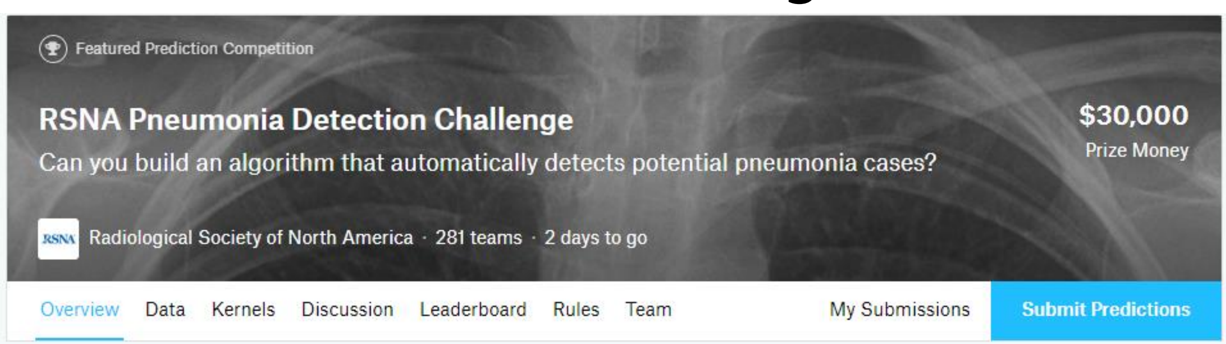
- Challenges
  - ISBI (International Symposium and Biomedical Imaging)
    - CAMELYON 16
    - CAMELYON 17
    - LiTS (Liver Tumor Segmentation Challenge)
    - Diabetic Retinopathy segmentation

Deep Learning for Medical Image

- Challenges
  - RSNA (Radiological Society of North America)
    - Pediatric Boneage Challenge



    - Pneumonia Detection Challenge



Deep Learning for Medical Image

- Deep learning based applications in Korea
  - 식약처 허가
    - 뷰노메드 본에이지 (뷰노) [14]

[14] http://www.medigatenews.com/news/1547679639

Deep Learning for Medical Image

- Deep learning based applications in Korea
  - 식약처 허가
    - 뷰노메드 본에이지 (뷰노) [14]
      - : Xray 손 영상을 통해환자의 뼈 나이를 제시하여 의사가 제시된 정보 등으로 성조숙증이나 저성장을 진단하는데 도움을 주는 의료기기
      - <u>의료 영상분석장치소프트웨어 2등급 허가</u>
      - 판매 불가능

그러나 뷰노메드 본에이지의 성공적인 개발과 식약처의 허가에도 불구하고 뷰노 측은 마음이 급하다고 말했다. 본에이지를 의료기기로 허가 받았지만 여전히 판매는 불가능한 상태이기 때문이다.

현행 국민건강보험법에 따르면 요양급여대상 또는 비급여대상으로 결정되지 않은 요양급여의 행위와 치료재료에 대해서는 요양급여대상여부의 결정을 보건복지부장관에게 신청해야 한다.

즉 의료기기로 허가를 받았으나 이것을 기존기술인지 신의료기술인지로 평가해야지 판매가 가능하다. 기존기술로 판단되면 이를 급여여부만 평가하면 되지만, 신의료기술로 분류되면 시간이 오래 걸린다. 뷰노는 이를 약 10일 전에 신청했다.

김 CSO는 "현재 걱정되는 것은 본에이지를 기존기술로 판단하지 않고, 신의료기술로 평가할 가능성이 높다는 것"이라며 "신의료기술로 평가되면 또 법적검토를 280일간 받아야 한다. 도중에 보완작업을 거치면 결국 9개월을 훌쩍 넘는데, 식약처 인허가를 받고도 1년간 더 기다려야 한다는 것"이라고 말했다.

Deep Learning for Medical Image

- Deep learning based applications in Korea
  - 식약처 허가
    - Lunit INSIGHT (루닛)
      - Xray기반 폐결절을 검출하는 검출보조소프트웨어
      - ex) https://insight.lunit.io/#examples
    - JBS-01K (제이엘케이인스펙션)
      - 뇌경색 패턴을 제시해주는 진단보조소프트웨어
    - 셀비 메디보이스 (셀바스AI) [15]
      - AI기반 음성인식 엔진
  - 식약처 임상시험 허가
    - 뷰노메드 체스트엑스레이 (뷰노)
      - Xray기반 폐암, 폐렴 등 5종의 흉부질환 검출하는 검출보조소프트웨어 (임상시험 돌입)

[15] http://m.itdaily.kr/news/articleView.html?idxno=91422