1장 관련연구 - GAN

- 어떤 network를 사용했고, 어떤 실험을 진행해서 어떤 결과를 얻었는지 알 수 있도록 정리
- ~는 ~를 ~에 적용하여 ~~ 형식 (음율 맞추기)
- 저자가 여러명인 경우 “Menon 외” 와 같은 방식으로 표기
- 어떤 GAN을 사용했는지
- 마지막 - GAN 기반 기법의 장단점 언급
- 순서 고려 (출판년도)

▼ 10.18 - 논문 문장 기술방식 참고

> https://s3-us-west-2.amazonaws.com/secure.notion-static.com/2539d30d-abd3-4a60-85de-7104cc70f077/1_Kim-2020-KJR-Data_Augmentation_Techniques_for_Deep_Learning-based_Medical_Image_Analyses.pdf

- 데이터증강의 배경 및 필요성: 1291쪽
- 영상변환 기반의 데이터 증강 방법의 한계점 보완
- GAN 데이터 증강 기법 개요: 1293쪽
- 의료영상에 적용사례: 현재처럼 기재되는 것은 너무 간략화되어 어떤 연구인지 알 수 없음
    - 18번(DCGAN)[2], MP출판논문(DCGAN,Pix2Pix)[3],
    - 21번(DCGAN),
    - 22번(PGGAN),
    - 26번 + StyleGAN (https://ieeexplore.ieee.org/document/9316160)

  정도로 notion 정리한 후 논문수정 반영

GENERALIZATION OF DEEP NEURAL NETWORKS FOR CHEST PATHOLOGY CLASSIFICATION IN X-RAYS USING GENERATIVE ADVERSARIAL NETWORKS

- **12 Feb 2018**
- *Hojjat Salehinejad⋆†, Shahrokh Valaee⋆, Tim Dowdell†, Errol Colak†, and Joseph Barfett†*

> https://s3-us-west-2.amazonaws.com/secure.notion-static.com/be87e9ff-c34a-4fc9-a016-6897a7610ad5/5_Salehinejad-2018-Generalization_of_deep_neural_networks_for_chest_pathology_classification_in_X-rays_using_GANs.pdf

▼ Salehinejad외 연구에서는 데이터의 불균형 극복과 분류 성능 향상을 위해 흉부 X선 데이터에 DCGAN을 적용하여 심층 합성곱 신경망(DCNN) 을 훈련시켰다.

목적

GAN 생성 이미지로 불균형 데이터 보강, 심층 합성곱 신경망(DCNN)을 사용하여 흉부 병리 분류 성능 향상

GAN

DCGAN

GeneratingChestX-Rays

- **DCGAN 훈련 Architecture**

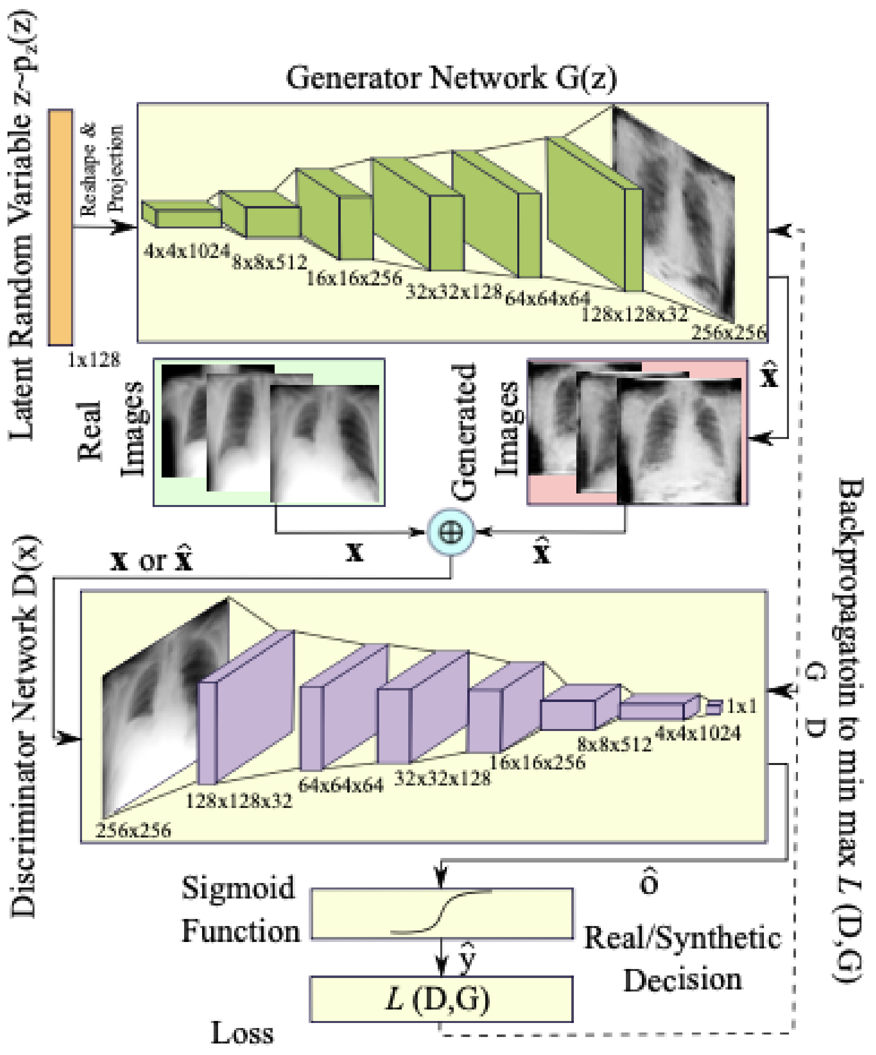


Fig. 1: Architecture of the DCGAN and training it with real chest X-rays.

(DCGAN generates chest X-rays using DCNNs for both the G and D components of the model)

Classification of Chest X-Rays

- **분류 Architecture**

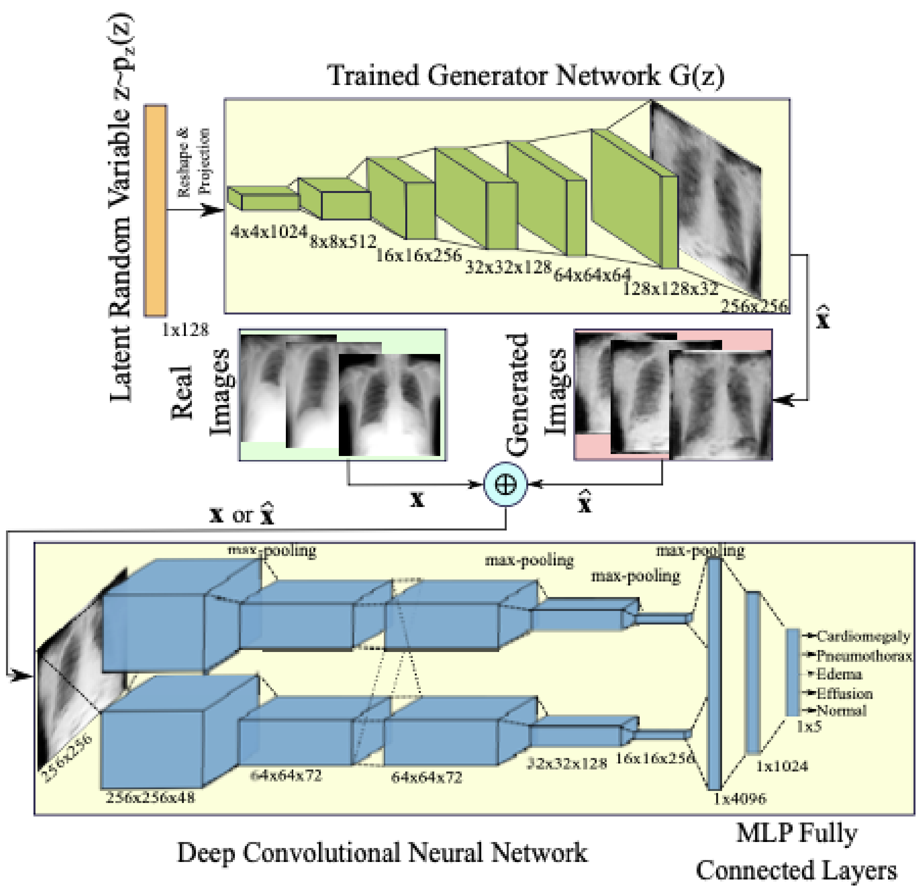


Fig. 2: Architecture of the DCNN and its training with real and generated chest X-rays from DCGAN to classify abnormalities.

- **Network**

- **AlexNet과 유사**

  (AlexNet is a successful DCNN architecture that is com- posed of five convolutional layers for feature extraction fol- lowed by three fully-connected layers for classification)

- **서로 다른 kernel 크기, feature map 크기, convolution layer 사용**

  (The proposed DCNN for chest pathology classification in this paper is fundamentally similar to AlexNet, however, uses dif- ferent kernel sizes, feature map sizes, and convolution layers as illustrated in Figure 2.)

- **tanh, sigmoid 대신 ReLU 사용**

  (The ReLU is defined as f (x) = max(0, x), which takes advantage of its non-saturating and non-linear properties as well as the ten- dency to enable more efficient learning than *tanh* or *sigmoid* activation functions [15].)

- **convolution layer 이후의 max-pooling layer은 은닉층(latent representation)을 겹치지 않는 하위 영역에서의 최대값으로 다운샘플링**

  $$O_{i,j} = max\{h_{q,r}^{(m)}\},$$

  $$q, r \in \{(2i, 2j), (2i+1, 2j), (2i, 2j+1), (2i+1, 2j+1)\},$$

  - max-pooling kernel은 변 길이가 L = 2인 정사각형

  (A max-pooling layer after the con- volution layer down-samples the latent representation by a constant factor, usually taking the maximum value over non- overlapping sub-regions such as)

- multiple convolutional, max-pooling layers 후에 max-pooled feature가 **벡터 f로 재형성** → 하나의 hidden layer**가 있는 MLP(다층 퍼셉트론) 네트워크에 공급**

  (The max-pooled features, after the multiple convolutional and max-pooling layers, are reshaped as a vec- tor, f, and are fed to a multi-layer perceptron (MLP) network with one hidden layer as illustrated in Figure 2.)

- **MLP 계층**

  $$y_c = \phi(\sum_{j=0}^{|\mathbf{f}|-1} f_j \cdot w_{j,c} + b_c)$$

  |f| = 4,096 : 벡터 f의 길이

  w : 가중치

  소프트맥스 함수 φ(·)는 각 출력 단위에 확률을 할당하는데, class c(기흉, 폐부종, 흉막융합, 정상, 심장비대) 에 해당

  $$\phi(h_c) = \frac{e^{h_c}}{\sum_{j=1}^{P} e^{h_j}}$$

  hc : 출력 단위에 대한 입력

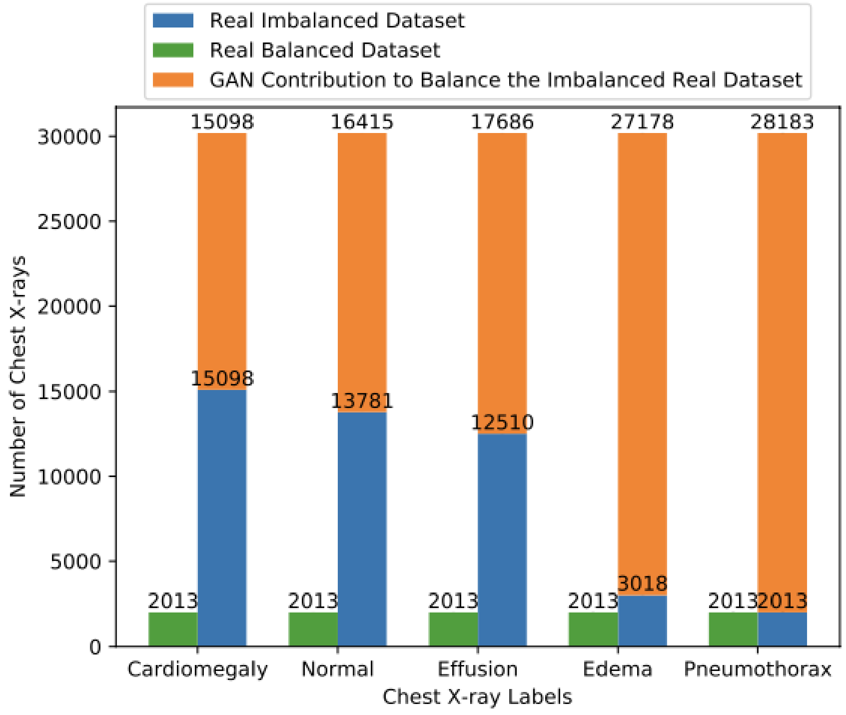
  C = 5 : 흉부 X선 class 수

EXPERIMENTS

- **Data**

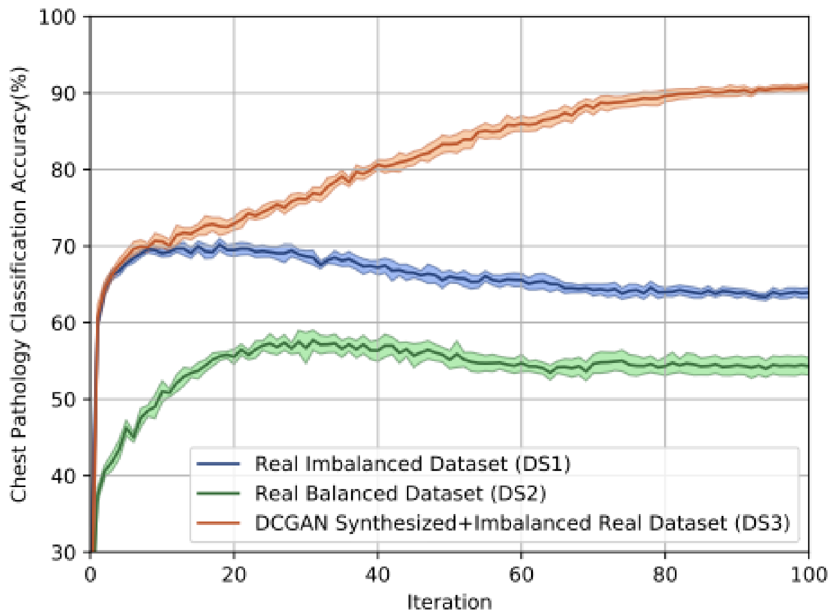
  흉부 X선 데이터

  5개 class(기흉, 폐부종, 흉막융합, 정상, 심장비대)



- **Performance Evaluation**

Accuracy (%)	DS1	DS2	DS3
Cardiomegaly	79.15	71.73	95.31
Normal	77.75	72.53	95.02
Pleural Effusion	73.64	51.23	91.19
Pulmonary Edema	65.86	50.12	89.68
Pneumothorax	57.99	48.92	88.84
Total	70.87±0.47	58.90±0.48	**92.10±0.41**



→ DCGAN에 의해 생성된 데이터가 실제 데이터를 보강하여 대규모 신경망 훈련을 위해 더 많은 양의 데이터를 제공할 수 있고, 데이터의 균형을 맞추어 분류 성능을 향상시킨다.

GAN-based synthetic medical image augmentation for increased CNN performance in liver lesion classification

- **13 Sep 2018**
- *Maayan Frid-Adar, Idit Diamant, Eyal Klang, Michal Amitai, Jacob Goldberger, Hayit Greenspan*

https://s3-us-west-2.amazonaws.com/secure.notion-static.com/7856595e-c2dd-4288-aa16-889e7e56bbbc/2_Frid-Adar-2018-Neurocomputing-GAN-based_synthetic_medical_image_augmentation_for_increased_CNN_performance_in_liver_lesion_classification.pdf

▼ Frid-Adar외 연구에서는 데이터 증강과 분류 성능 향상을 위해 간 병변 CT 영상에 어파인 기반 증강 방법을 적용하고, 생성된 영상에 DCGAN을 적용하여 합성곱 신경망(Convolutional Neural Network)을 훈련시켰다.

목적

GAN을 이용하여 수집이 어려운 의료 이미지(간 병변 CT영상) 증강

합성 데이터 증강 및 의료 이미지 분류를 위한 CNN 성능 개선

1. Synthesis of high quality focal liver lesions from CT images using generative adversarial networks (GANs).
2. Design of a CNN-based solution for the liver lesion classification task, with comparable results to state-of-the-art methods.
3. Augmentation of the CNN training set, using the generated synthetic data for improved classification results.

증강방법

고전적 데이터 증강 방법 (회전, 뒤집기, 크기조정), GAN (비교)

데이터

간 병변 CT 영상

53 cysts, 64 metastases, 65 hemangiomas

CNN architecture

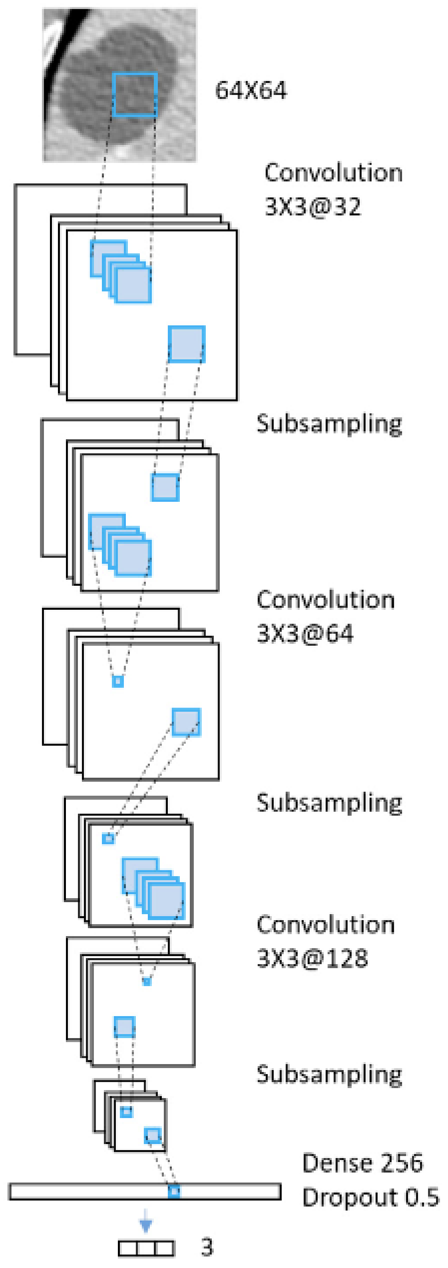


Fig. 2. The architecture of the liver lesion classification CNN.

- 작은 데이터셋으로 더 적은 수의 convolution layer 포함. 더 작은 input size 사용

  (usually contain fewer convolutional layers because of the small datasets and smaller input size.)
- 64x64 크기 input
- 3개의 convolution layer
- convolution layer 다음 max-pooling layer

- 3 class로 분류하기 위해 soft-max layer로 끝나는 두 fully-connected dense layer
- 활성화함수 ReLU
- dropout 0.5

Generating synthetic liver lesions

- **Classic data augmentation**

  transformations such as translation, rotation, scaling, flipping and shearing

- **GAN**

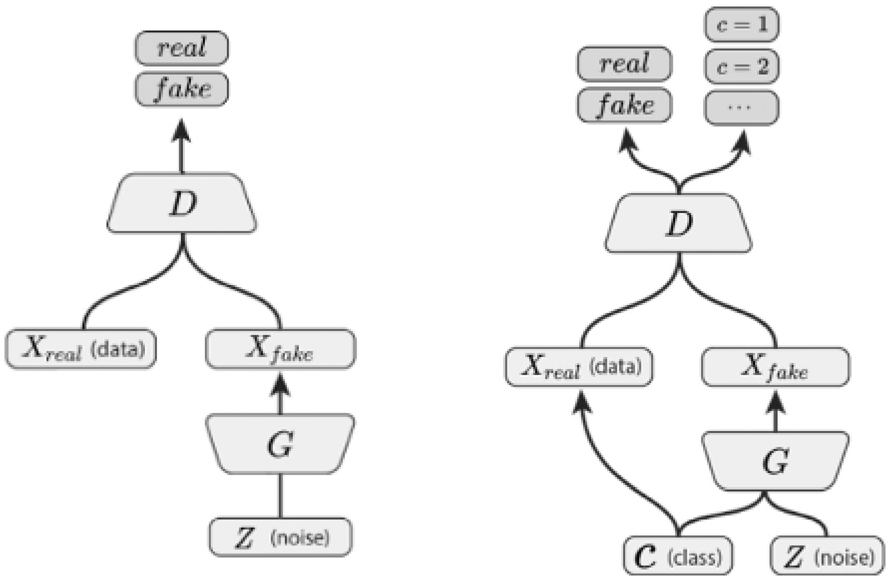


Fig. 4. (a) DCGAN architecture. (b) ACGAN architecture (Figure is taken from [11]).

DCGAN, ACGAN 비교 → DCGAN이 더 잘 수행되어 DCGAN 선택

In our experiments we found that the Deep Convolutional GAN (DCGAN) method performed better. We there-fore focus on that method in the results presented below.

Experiments & results

- **Data**

  each contained a balanced number of cyst, metastasis and hemangioma lesion ROIs

- **Experiment**

  1) CNN-AUG

  Classical data augmentation을 이용하여 병변 ROI당 480개 이미지 생성 후 무작위로 샘플링하여 선택

  2) CNN-AUG-GAN

  classical data augmentation을 통해 생성된 영상을 사용하여 DCGAN 훈련

- **Results**
  - confution matrix

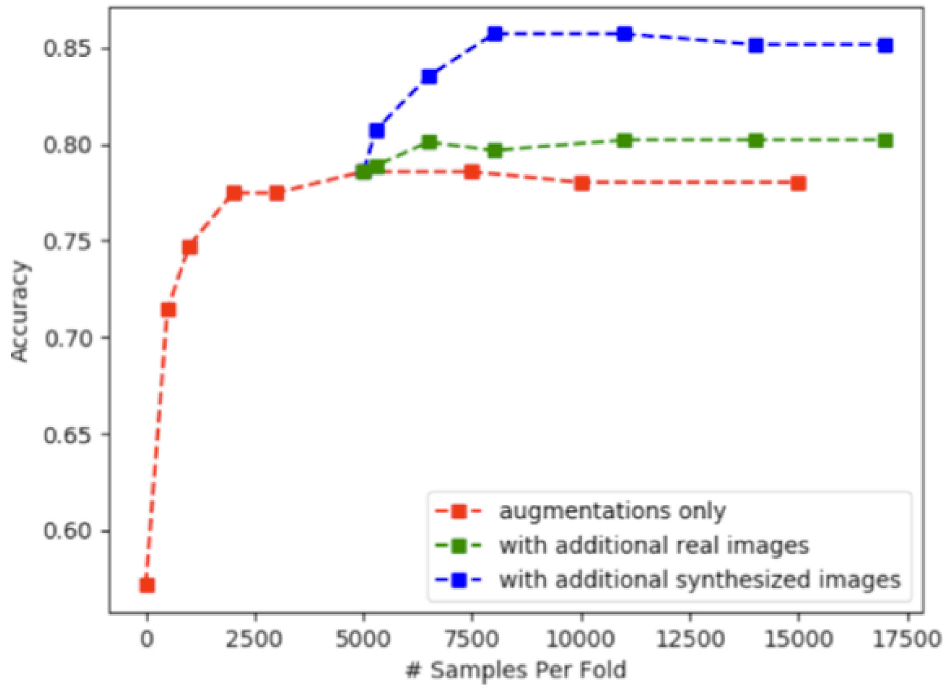
Table 2
Confusion matrix for the optimal classical data augmentation group (CNN-AUG).

True\Auto	Cyst	Met	Hem	Sensitivity (%)
Cyst	52	1	0	98.1
Met	2	44	18	68.7
Hem	0	18	47	72.3
Specificity	98.4%	83.9%	84.6%	

Table 3
Confusion matrix for the optimal synthetic data augmentation group (CNN-AUG-GAN).

True\Auto	Cyst	Met	Hem	Sensitivity (%)
Cyst	53	0	0	100
Met	2	52	10	81.2
Hem	1	13	51	78.5
Specificity	97.7%	89%	91.4%	

- training



→ 기존 영상 , 실제 영상 추가한 것보다 GAN을 적용했을 때 성능 향상

- t-SNE

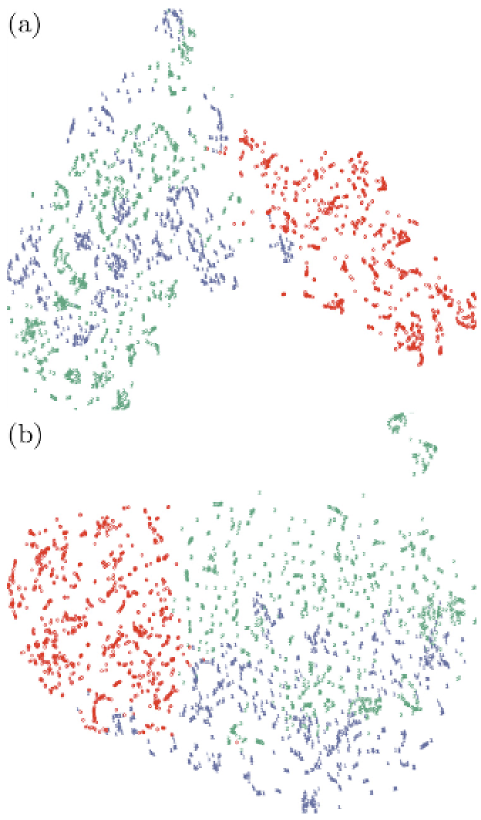


Fig. 9. T-SNE embedding of Cysts (red), Metastases (blue) and Hemangiomas (green) real lesion ROIs. (a) Features extracted from CNN-AUG (b) Features extracted from CNN-AUG-GAN. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

(a) : CNN-AUG / (b) : CNN-AUG-GAN

→ GAN을 적용했을 때 더 잘 분리됨

(When using the synthetic data augmenta- tion, in general the t-SNE visualization exhibited better separating power. This can provide intuitions for the increase in classification performance.)

- experts' results

Table 4
Summary of experts radiologists' Assessment of Lesion ROIs.

	Classification accuracy			Is ROI Real?
	Real (%)	Synthetic (%)	Total score (%)	Total score (%)
Expert 1	78	77.5	235\302=77.8	189\302=62.5
Expert 2	69.2	69.2	209\302=69.2	177\302=58.6

- Comparison with other classification methods

Table 5
Performance comparison for liver lesion classification between generative models.

Method	Sensitivity (%)	Specificity (%)
CNN-AUG-GAN (DCGAN)	**85.7**	**92.4**
CNN-AUG-GAN (ACGAN)	81.3	90.0
ACGAN discriminator	79.1	88.8

→ ACGAN 사용 시 성능 2% 감소

Table 6
Performance comparison to previous methods of liver lesion classification.

Method	Sensitivity (%)	Specificity (%)
CNN-AUG-GAN	**85.7**	**92.4**
CNN-AUG	78.6	88.4
BOVW-MI-multi representation	82.9	90.8
BOVW-MI-single representation	78.0	88.3
Gabor + SVM	74.2	86.5
GLCM + SVM	71.4	84.9

Synthetic medical images using F&BGAN for improved lung nodules classification by multi-scale VGG16

- **16 Oct 2018**
- *Defang Zhao, Dandan Zhu, Jianwei Lu, Ye Luo and Guokai Zhang*

https://s3-us-west-2.amazonaws.com/secure.notion-static.com/f8d87be1-cfe1-49ae-9487-ea0df4497a0b/6_Zhao-2018-Symmetry-Synthetic_medical_images_using_FBGAN_for_improved_lung_nodules_classification_by_multi-scale_VGG16.pdf

▼ Zhao외 연구에서는 폐암 영상 데이터를 분류하기 위해 F&BGAN(Forward and Backward GAN)을 제안하고 VGG16(M-VGG16) 네트워크를 훈련시켰다.

목적

폐결절(pulmonary nodules) 데이터셋 확대, 분류 성능 향상

F&BGAN(Forward and Backward GAN) 제안

GAN

F&BGAN : Forward GAN, Backward GAN을 포함하는 DCGAN 기반 새로운 데이터 증강 방법

ㅇㅇㅇ

Classification of focal liver lesions in CT images using convolutional neural networks with lesion information augmented patches and synthetic data augmentation

- **21 July 2021**

https://s3-us-west-2.amazonaws.com/secure.notion-static.com/8786f77b-3a4c-419c-a3ed-c2118fb2eeac/3_Lee-2021-MP-Classification_of_focal_liver_lesions_in_CT_images.pdf

▼ 국소 간 병변(FLL) 영상에 DCGAN[4]과 pix2pix[5]기법을 적용하여 CNN의 성능을 향상시킨 연구가 있다.

목적

GAN

6

CCS-GAN:COVID-19CT-scan classification with very few positive training images

- **1 Oct 2021**

https://s3-us-west-2.amazonaws.com/secure.notion-static.com/379af2f2-94f8-4bd9-ad69-3d1b071fb096/4_Menon-2021-IEEETMI-CCS-GAN_COVID-19_CT-scan_classification_with_very_few_positive_training_images.pdf

▼ Sumeet Menon은 COVID-19 양성 CT 영상을 분류하는 문제에 style transfer[7]과 자동화된 폐 분할 기법을 결합하여 CCS-GAN을 제시하였고,

목적

GAN

8