Lab Seminar

Intelligent Information Processing Lab

2023. 07. 12

이 새 봄

Contents

01 Previous Work

- Citrus/Kiwi Disease Classification Service System
- Efficient Data Augmentation Method for Crop Disease

Citrus/Kiwi Disease Classification Service System

- 고품질 과수작물 통합 데이터를 바탕으로 Pre-trained 5개의 딥러닝 모델을 통해 병해충 분류 연구를 수행

- 고품질 과수작물 통합 데이터

  ① 감귤, 키위 병해충을 인식하여 방제 계획을 수립할 수 있는 학습용 데이터 및 모델 구축

  ② Pre-trained model : VGGNet, ResNet, DenseNet, EfficientNet, ViT

  ③ AI-hub에서 데이터를 다운받을 수 있으며, 실제 연구 모델은 Docker 제공 + TTA 검증 완

Dataset (1/3)

- 고품질 과수작물 데이터 : 제주지역을 대상으로 감귤과 키위에 대해 고품질 과수작물 AI 학습용 데이터를 구축
- 감귤 : 20,000장, 6개의 클래스로 구성,

Citrus Fruit Normal

Citrus Fruit XCC

Citrus Leaf Red Mite

Citrus Leaf Normal

Citrus Leaf XCC

Citrus Leaf Aphid

Dataset (2/3)

- 고품질 과수작물 데이터 : 제주지역을 대상으로 감귤과 키위에 대해 고품질 과수작물 AI 학습용 데이터를 구축
- 키위 : 20,000장, 5개의 클래스로 구성,

Kiwi fruit bacterial soft rot

Kiwi fruit normal

Kiwi leaf thysanoptera

Kiwi leaf normal

Kiwi leaf spot

Dataset (3/3)

1. Kiwi / Citrus : AI Hub, 국립원예특작과학원 → Dataset : Training : Test = 7: 3 / Training : Validation : Test = 7 : 2: 1

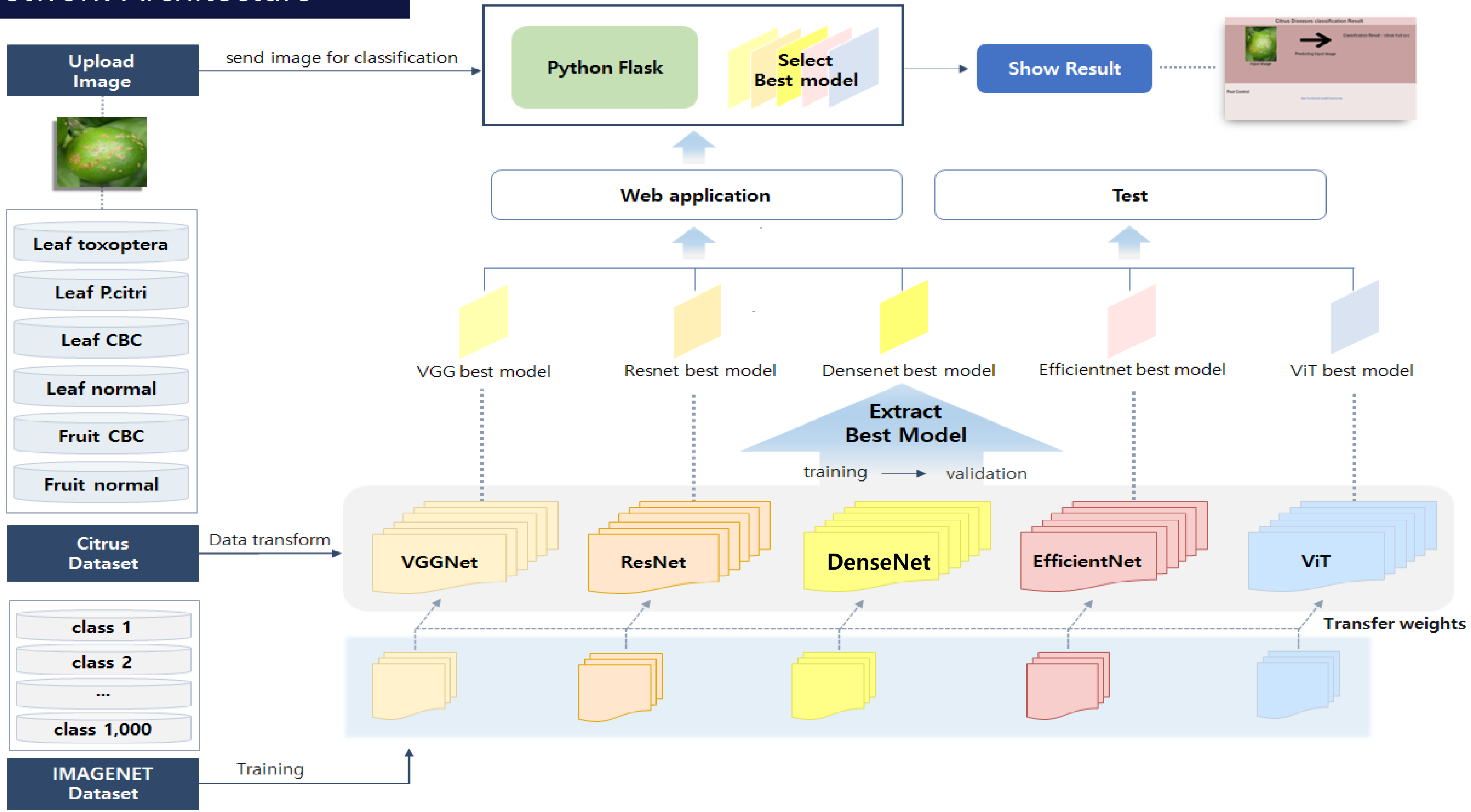
Kiwi disease dataset

Disease Type		Total
1	Kiwi fruit healthy	2,124
2	Kiwi fruit bacterial soft rot	1,737
3	Kiwi leaf healthy	2,876
4	Kiwi leaf thysanoptera	5,585
5	Kiwi leaf spot	7,678
Total		20,000

Citrus disease dataset

Disease Type		Total
1	Citrus fruit healthy	2,545
2	Citrus fruit CBC	1,716
3	Citrus leaf healthy	2,455
4	Citrus leaf CBC	9,552
5	Citrus leaf panonychus. citir	1,814
6	Citrus leaf toxoptera. citricida	1,918
Total		20,000

Network Architecture



Experiment Result

- 딥러닝 기반 과수작물 분류 모델 Validation 실험 결과 (Stratified K-fold cross-validation / k=5)

Disease	Citrus		Kiwi	
Model	F1 score	Accuracy	F1 score	Accuracy
VGGNet16	96.7	97.7	97.1 ± 0.6442	97.7 ± 0.1581
ResNet50	97.6	98.3	96.46 ± 0.497	97.56 ± 0.2074
DenseNet161	97.7	98.4	97.18 ± 0.5263	97.72 ± 0.3271
EfficientNet	98.2	98.8	90.46 ± 0.7162	91.88 ± 0.8556
ViT	98.2	98.8	97.34 ± 0.2881	98.18 ± 0.1924

Experiment Result

- 딥러닝 기반 과수작물 분류 모델 Test 실험 결과

Disease	Citrus		Kiwi	
Model	F1 score	Accuracy	F1 score	Accuracy
VGGNet16	97	97.9	98.7 ± 0.2074	99.06 ± 0.1161
ResNet50	98	98.6	98.6 ± 0.1517	98.28 ± 0.1215
DenseNet161	98.4	98.8	98.9 ± 0.0837	99.39 ± 0.0673
EfficientNet	98.6	99	98.7 ± 0.1789	99.16 ± 0.0811
ViT	97.5	98.1	98.7 ± 0.0837	99.17 ± 0.0778

Conclusion

sensors MDPI

Article

Automatic Classification Service System for Citrus Pest Recognition Based on Deep Learning

Saebom Lee [1], Gyuho Choi [1], Hyun-Cheol Park [2] and Chang Choi [1,*]

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Abstract: Plant diseases are a major cause of reduction in agricultural output, which leads to severe economic losses and unstable food supply. The citrus plant is an economically important fruit crop grown and produced worldwide. However, citrus plants are easily affected by various factors, such as climate change, pests, and diseases, resulting in reduced yield and quality. Advances in computer vision in recent years have been widely used for plant disease detection and classification, providing opportunities for early disease detection, and resulting in improvements in agriculture. Particularly, the early and accurate detection of citrus diseases, which are vulnerable to pests, is very important to prevent the spread of pests and reduce crop damage. Research on citrus pest disease is ongoing, but it is difficult to apply research results to cultivation owing to a lack of datasets for research and limited types of pests. In this study, we built a dataset by self-collecting a total of 20,000 citrus pest images, including fruits and leaves, from actual cultivation sites. The constructed dataset was trained, verified, and tested using a model that had undergone five transfer learning steps. All models used in the experiment had an average accuracy of 97% or more and an average f1 score of 96% or more. We built a web application server using the EfficientNet-b0 model, which exhibited the best performance among the five learning models. The built web application tested citrus pest disease using image samples collected from websites other than the self-collected image samples and prepared data, and both samples correctly classified the disease. The citrus pest automatic diagnosis web system using the model proposed in this study plays a useful auxiliary role in recognizing and classifying citrus diseases. This can, in turn, help improve the overall quality of citrus fruits.

Keywords: agriculture; citrus disease classification; deep learning; web application

Citation: Lee, S.; Choi, G.; Park, H.-C.; Choi, C. Automatic Classification Service System for Citrus Pest Recognition Based on Deep Learning. *Sensors* **2022**, 22, 8911. https://doi.org/10.3390/s22228911

Academic Editor: Yongwha Chung

- Journal : MDPI Sensors
- IF : 3.9
- Average JIF : Top 32.1%
- Status : Published 2022-11-18
- Kiwi : 임유리와 함께 작업 후 공동 1저자로 넣을 예정

01 Previous Work

- Citrus/Kiwi Disease Classification Service System
- Efficient Data Augmentation Method for Crop Disease

Efficient Data Augmentation Method for Crop Disease

- 컴퓨터 시스템의 발전으로 딥러닝을 적용한 다양한 농작물 병해충 인식 연구가 이루어지고 있음

- 현재 수행된 농작물 병해충 인식 연구는 다음과 같은 한계가 존재함

① 데이터셋의 크기가 작고, 병해충의 감염된 농작물의 종류가 한정적임

② 데이터 전처리 단계에서 grayscale과 수평・수직 뒤집기 등의 간단한 기하학적 데이터 증강 방법을 사용하여, 다양한 패턴을 갖고 있는 병해의 특징을 효율적으로 추출하지 못함

다양한 종류의 병해충 패턴들


① 갈변


② 점무늬


③ 가는 실을 꼰 형태


④ 해충

연구 목적

농작물 병해충을 분류를 위해 병해충에 발생한 패턴을 효과적으로 추출할 수 있는 데이터 증강 방법이 필요함

Related Work (1)

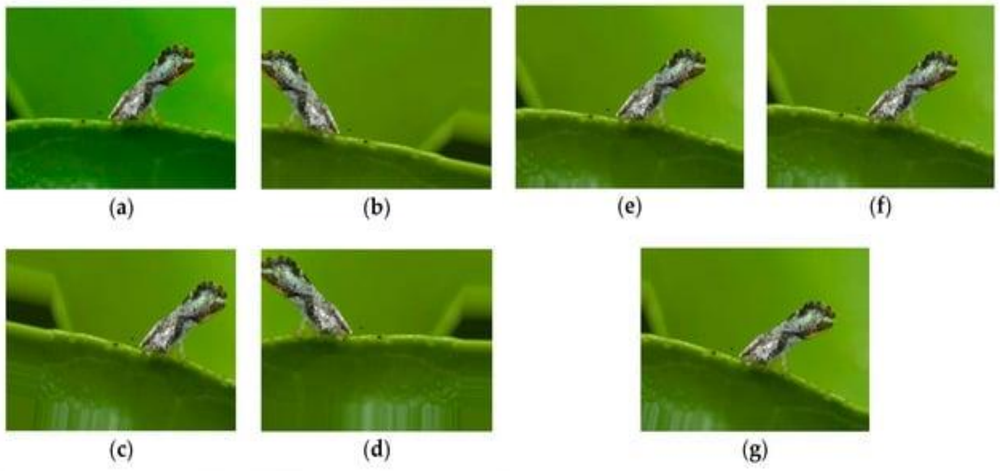
1. **(2019) Citrus pests and diseases recognition model using weakly dense connected convolution network**

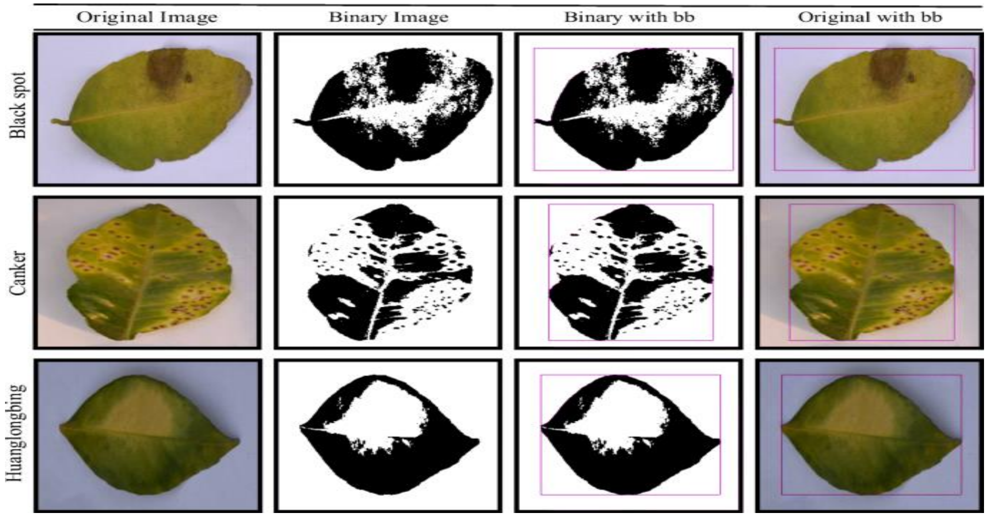
→ Random rotation, reflection, shift, and flip

Related Work (2)

2. **(2022) Citrus disease detection and classification using end-to-end anchor-based deep learning model**

→ 모든 이미지를 grayscale로 변경





1) Xing, Shuli, Marely Lee, and Keun-kwang Lee. "Citrus pests and diseases recognition model using weakly dense connected convolution network." *Sensors* 19.14 (2019): 3195.
2) Syed-Ab-Rahman, Sharifah Farhana, Mohammad Hesam Hesamian, and Mukesh Prasad. "Citrus disease detection and classification using end-to-end anchor-based deep learning model." *Applied Intelligence* 52.1 (2022)

Dataset

1. Kiwi / Citrus : AI Hub, 국립원예특작과학원

Kiwi disease dataset

Disease Type		Total
1	Kiwi fruit healthy	2,124
2	Kiwi fruit bacterial soft rot	1,737
3	Kiwi leaf healthy	2,876
4	Kiwi leaf thysanoptera	5,585
5	Kiwi leaf spot	7,678
Total		20,000

Citrus disease dataset

Disease Type		Total
1	Citrus fruit healthy	2,545
2	Citrus fruit CBC	1,716
3	Citrus leaf healthy	2,455
4	Citrus leaf CBC	9,552
5	Citrus leaf panonychus. citir	1,814
6	Citrus leaf toxoptera. citricida	1,918
Total		20,000

Dataset

2. Pepper bell / Potato / Tomato : PlantVillage

PlantVillage dataset

	Disease Type	Total
1	Pepper bell leaf bacteria spot	997
2	Pepper bell leaf healthy	1,478
3	Potato leaf early blight	1,000
4	Potato leaf late blight	1,000
5	Potato leaf healthy	152
6	Tomato leaf target spot	1,404
7	Tomato leaf early blight	1,000
8	Tomato leaf late blight	1,909

	Disease Type	Total
9	Tomato leaf mold	952
10	Tomato leaf Septoria spot	1,771
11	Tomato leaf spider mites	1,676
12	Tomato leaf mosaic virus	373
13	Tomato leaf yellow virus	3,209
14	Tomato leaf healthy	1,591
15	Tomato leaf bacteria spot	2,127
Total		20,639

Imbalanced Data Problem

Dataset : Training : Test = 7: 3 (Stratified K-fold cross-validation / k=5)

Kiwi disease dataset used in the experiment

	Disease Type	Training	Test	Total
1	Kiwi fruit healthy	1,698	426	2,124
2	Kiwi fruit bacterial soft rot	1,389	348	1,737
3	Kiwi leaf healthy	2,300	576	2,876
4	Kiwi leaf thysanoptera	4,467	1,118	5,585
5	Kiwi leaf thysanoptera	6,142	1,536	5,585

Citrus disease dataset used in the experiment

	Disease Type	Training	Test	Total
1	Citrus fruit healthy	2,035	510	2,545
2	Citrus fruit CBC	1,372	344	1,716
3	Citrus leaf healthy	1,965	490	2,455
4	Citrus leaf CBC	7,642	1,910	9,552
5	Citrus leaf panonychus. citir	1,452	362	1,814
6	Citrus leaf toxoptera. citricida	1,534	384	1,918

Imbalanced Data Problem

Dataset : Training dataset : Test dataset = 7: 3

Class : 24 / Total images : 60,165

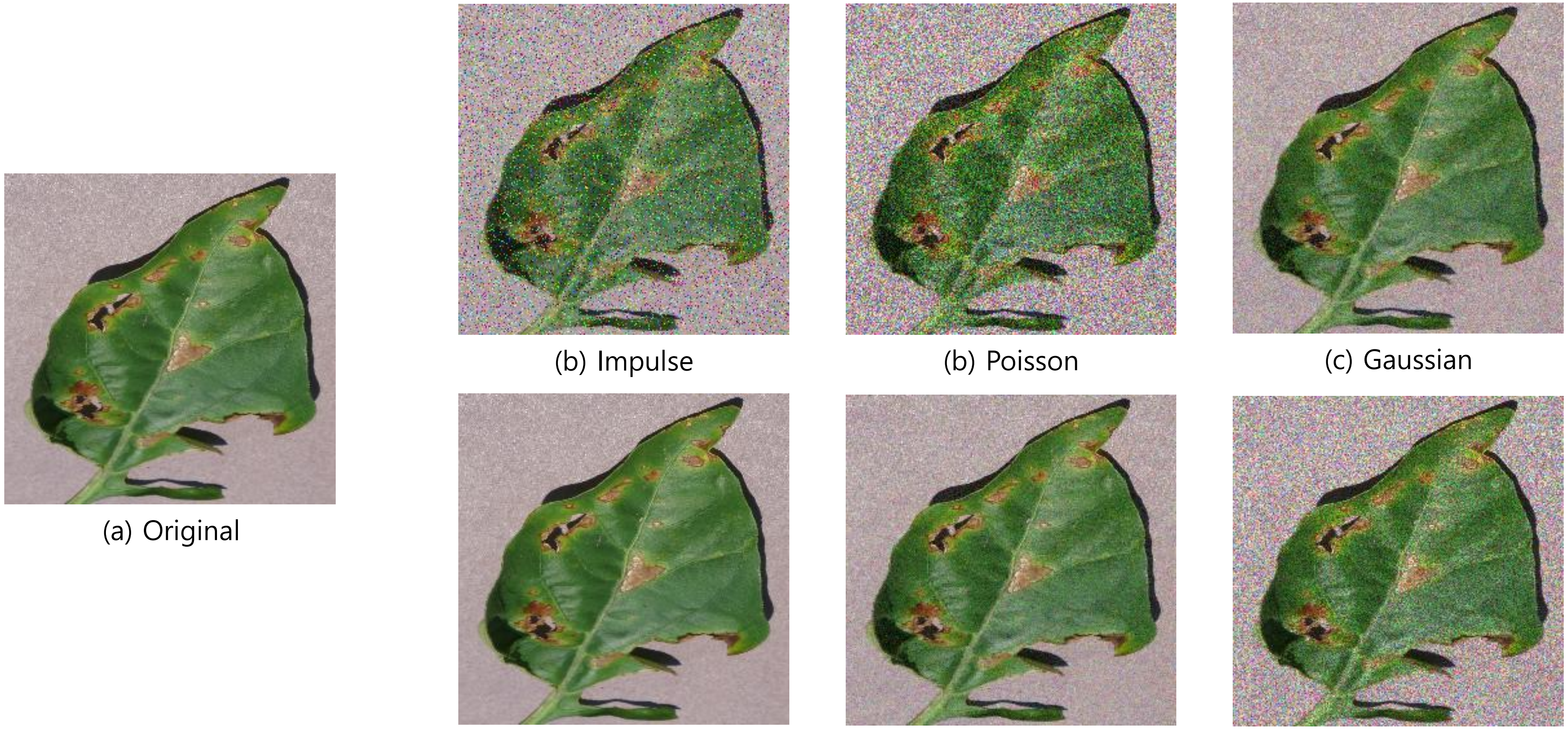
PlantVillage dataset in the experiment

	Disease Type	Training	Test	Total
1	Pepper bell bacteria spot	779 → 800	200	1,000
2	Pepper bell healthy	1,182	296	1,478
3	Potato early blight	800	200	1,000
4	Potato late blight	800	200	1,000
5	Potato healthy		X	
6	Tomato target spot	1,095	309	1,404
7	Tomato early blight	800	200	1,000
8	Tomato late blight	1,555	354	1,909

	Disease Type	Training	Test	Total
9	Tomato leaf mold	752 → 800	200	1,000
10	Tomato Septoria spot	1,432	339	1,771
11	Tomato leaf spider mites	1,319	357	1,676
12	Tomato leaf mosaic virus		X	
13	Tomato leaf yellow virus	2,578	631	3,209
14	Tomato leaf healthy	1,269	322	1,591
15	Tomato bacteria spot	1,687	440	2,127
Total				20,615

Noise Types

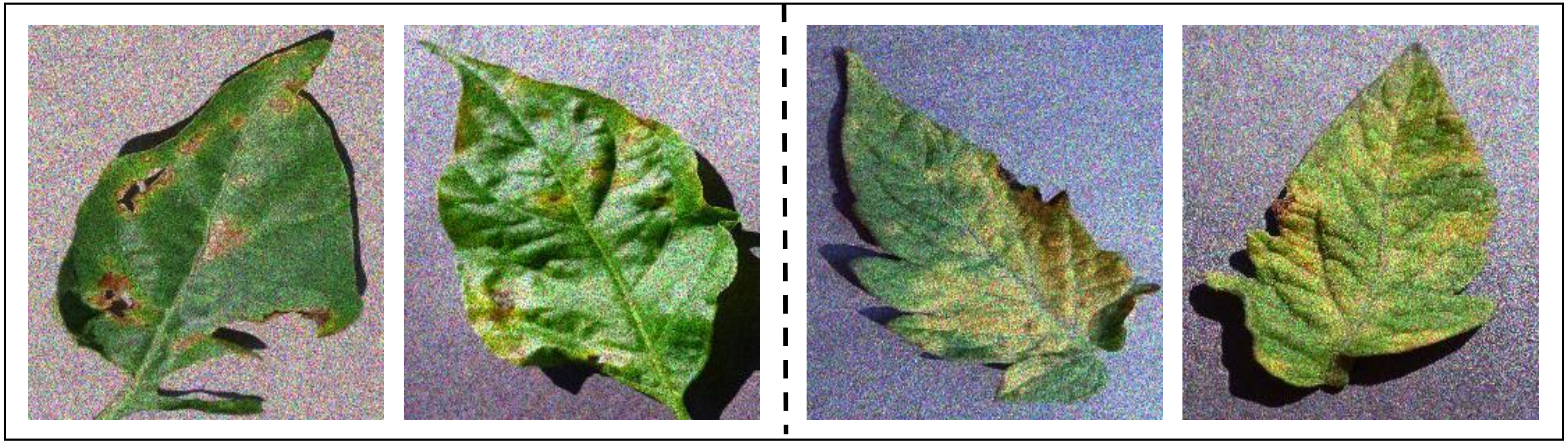
- Noise type : Impulse , Poisson , Gaussian , Uniform , Laplacian , Multiplicative Gaussian



(a) Original (b) Impulse (b) Poisson (c) Gaussian (d) Uniform (e) Laplacian (f) Multiplicative Gaussian

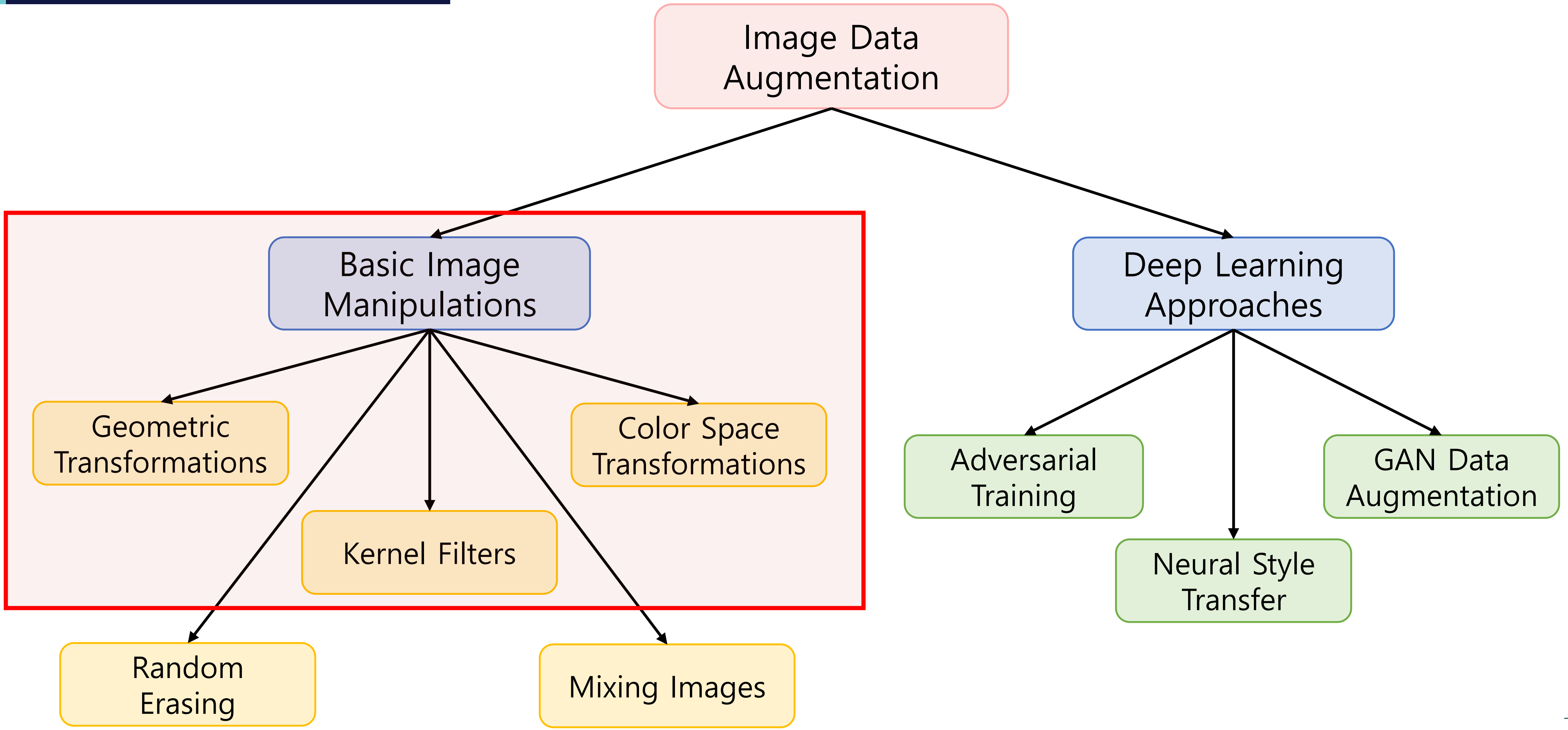
Image with added noise

- Image with multiplicative Gaussian noise



(a) Pepper bell bacterial spot (b) Tomato leaf mold

Data Augmentation Types



Sample image of crop disease (1)


(a) Kiwi fruit bacterial soft rot


(b) Kiwi fruit normal


(c) Kiwi leaf spot


(d) Pepper bell bacterial spot

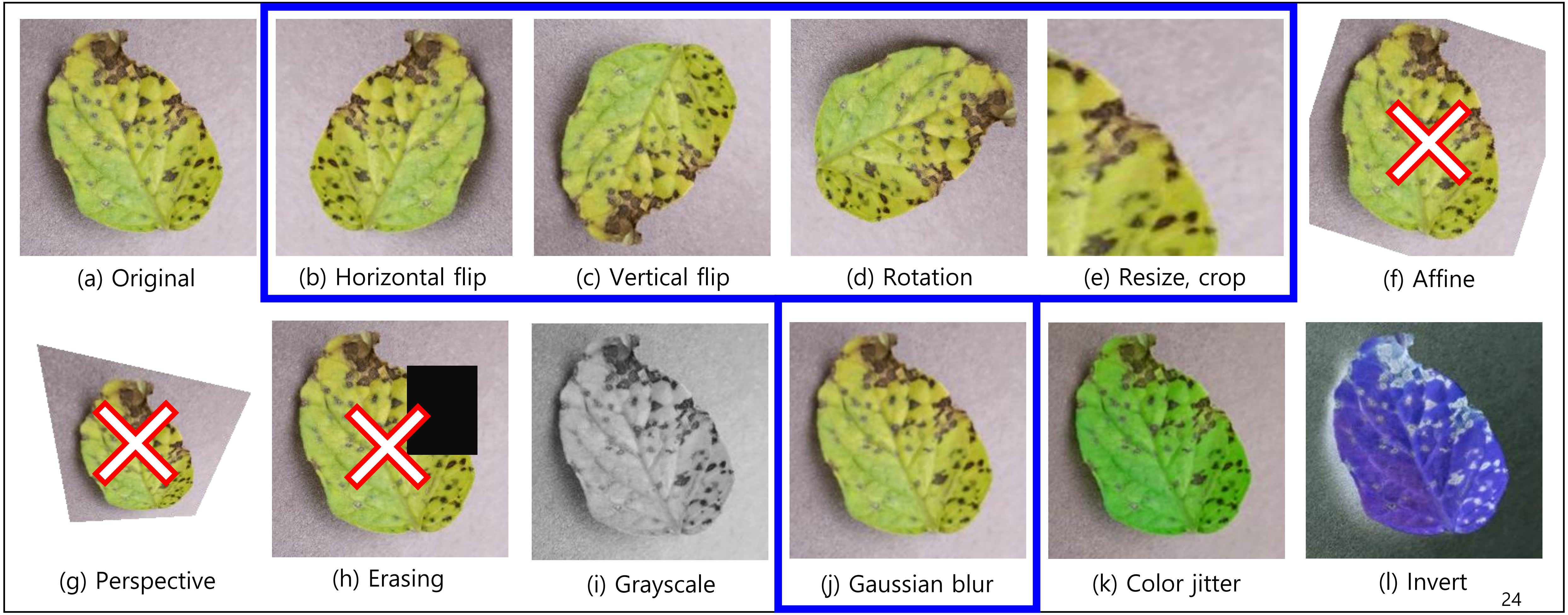

(e) Pepper bell healthy


(f) Potato early blight


(g) Potato late blight


(h) Tomato target spot

Data augmentation methods applicable for experiments (1)



(a) Original (b) Horizontal flip (c) Vertical flip (d) Rotation (e) Resize, crop (f) Affine
(g) Perspective (h) Erasing (i) Grayscale (j) Gaussian blur (k) Color jitter (l) Invert

Sample image of crop disease (2)

(a) Kiwi fruit bacterial soft rot

(b) Kiwi fruit normal

(c) Kiwi leaf spot

(d) Pepper bell bacterial spot

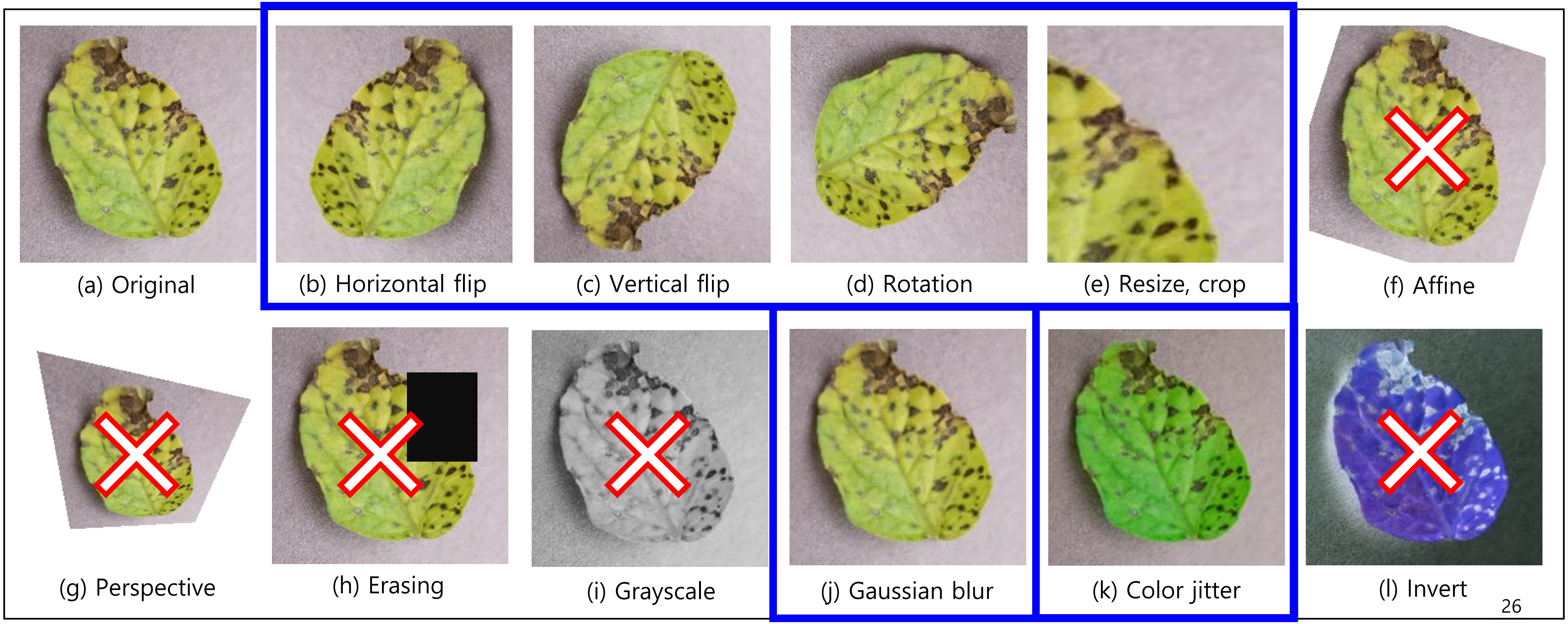
(e) Pepper bell healthy

(f) Potato early blight

(g) Potato late blight

(h) Tomato target spot

Data augmentation methods applicable for experiments (1)



Color Jitter

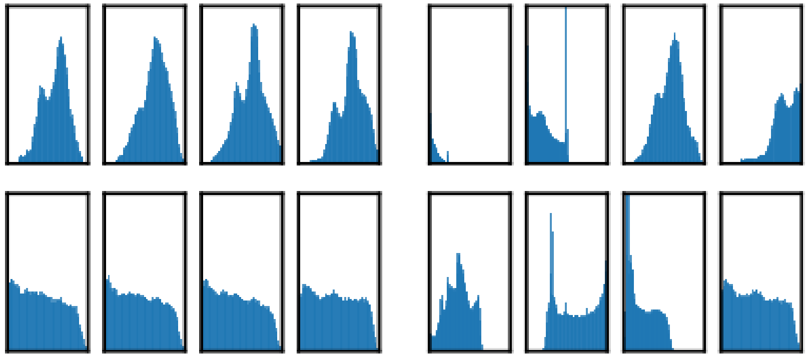
- 40% 이내에서 밝기, 대조, 채도 및 10% 이내에서 색조 적용 랜덤 적용

Original image

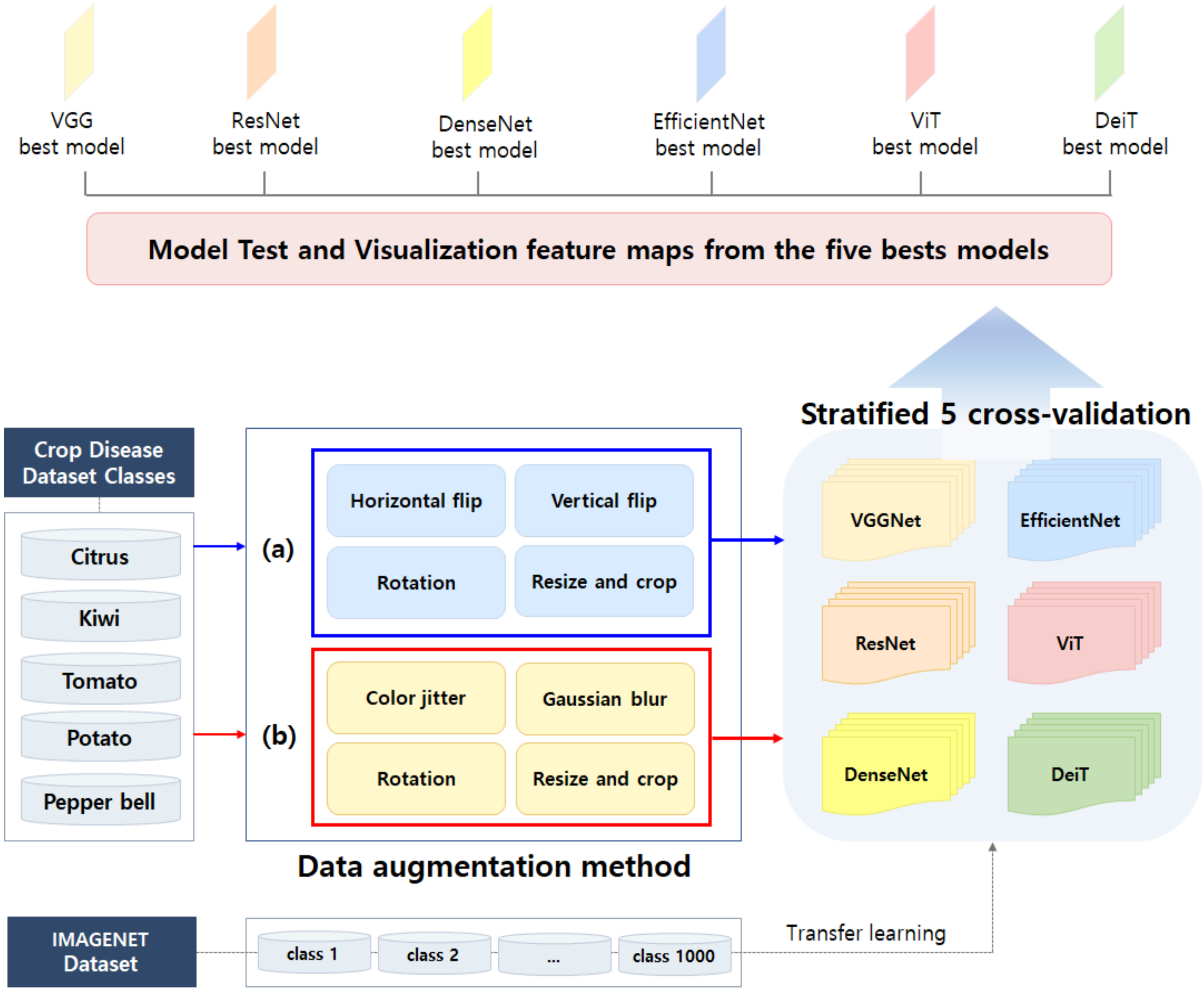
Color jitter 데이터 증강이 적용된 병해 이미지

Network Architecture

- The overall workflow of the proposed network architecture

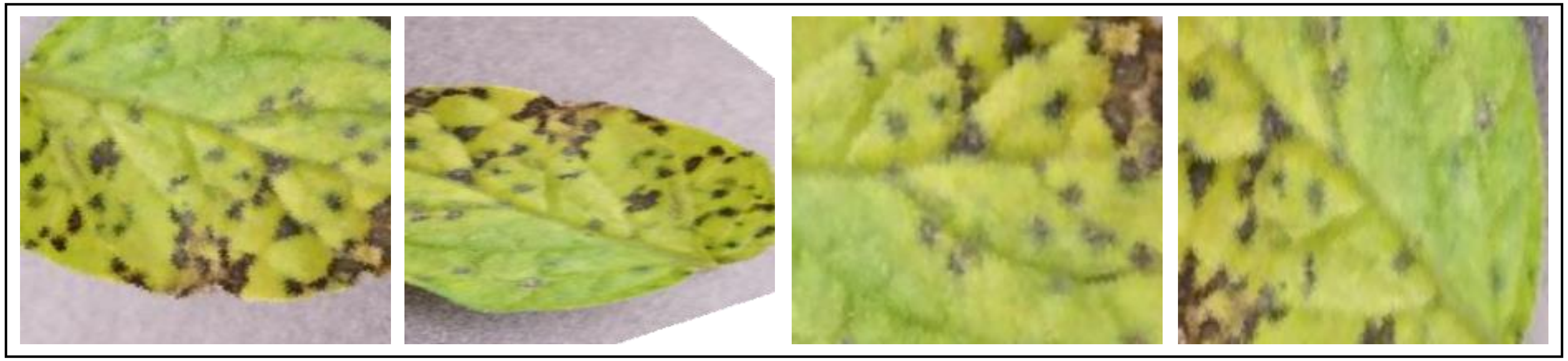


(a) Without color distortion. (b) With color distortion.



Sample image combined with data augmentation methods

a



horizontal flip + vertical flip + rotation + resize and crop

b

color jitter + vertical flip + rotation + resize and crop

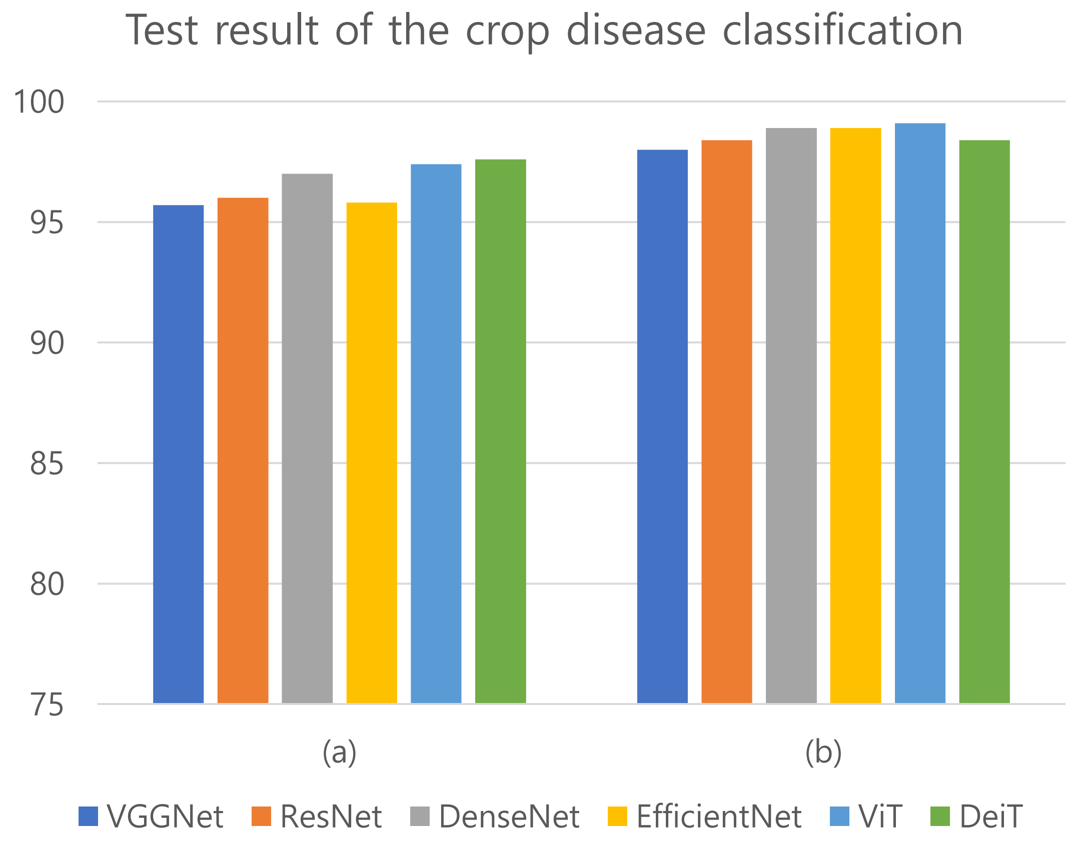
Experiment Result

- 딥러닝 기반 농작물 분류 모델 Validation 실험 결과 (Stratified K-fold cross-validation / k=5)

Method	(a)			(b)		
Model	F1 score	Accuracy	Training time	F1 score	Accuracy	Training time
VGGNet16	95.8 ± 1.3024	97.47 ± 0.0841	29 : 56 : 06	97.8 ± 0.2074	99.06 ± 0.1161	52 : 36 : 54
ResNet50	96.2 ± 0.3536	97.71 ± 0.0727	23 : 05 : 57	98.6 ± 0.1517	98.28 ± 0.1215	57 : 14 : 01
DenseNet161	97.5 ± 0.2121	98.14 ± 0.0857	50 : 28 : 07	98.9 ± 0.0837	99.39 ± 0.0673	59 : 11 : 22
EfficientNet	97.0 ± 0.2345	97.4 ± 0.1389	22 : 02 : 21	98.7 ± 0.1789	99.16 ± 0.0811	57 : 03 : 28
ViT	97.6 ± 0.1095	98.16 ± 0.0661	63 : 08: 50	98.7 ± 0.0837	99.17 ± 0.0778	64 : 21: 39
DeiT	95.5 ± 0.0234	95.35 ± 0.0287	75 : 38 : 36	95.9 ± 0.024	95.64 ± 0.029	75 : 47 : 28

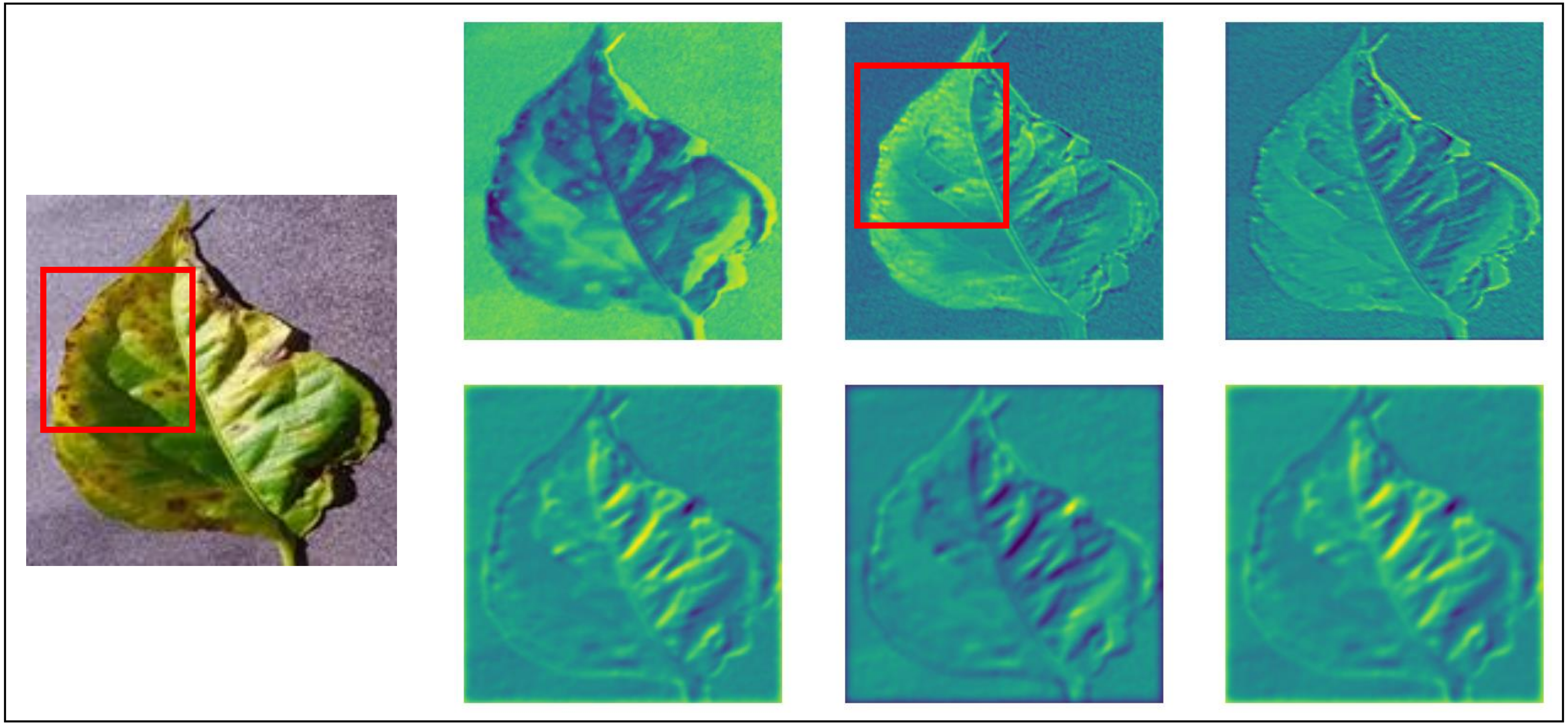
Experiment Result

- 딥러닝 기반 농작물 분류 모델 Test 실험 결과

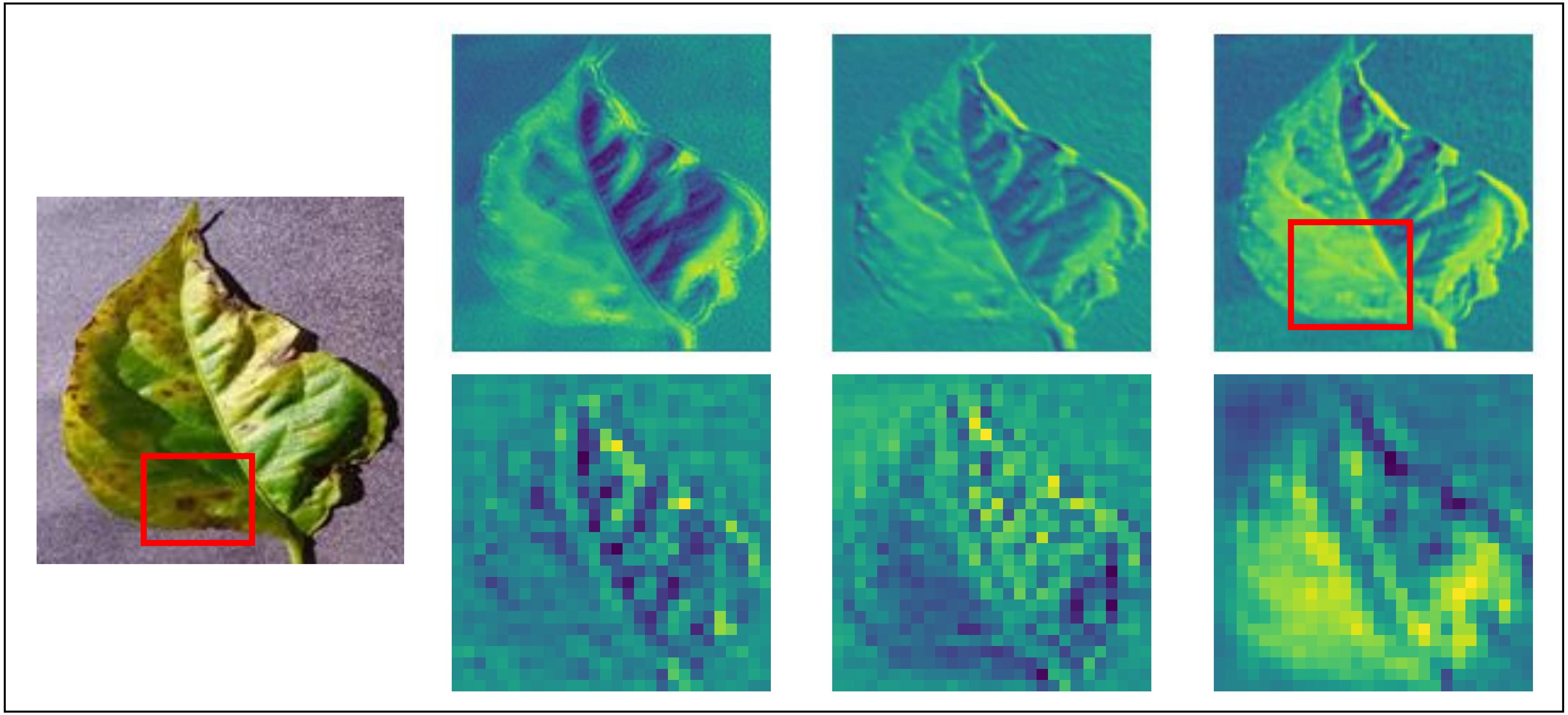


Model	F1 score	Accuracy	Recall	Precision
VGGNet16	95.7	97.3	96.59	95.86
	98	97.9	98.06	97.87
ResNet50	96	96.9	96.9	96.07
	98.4	98.3	98.4	98.46
DenseNet161	97	98	97.85	97.16
	98.9	98.8	97.85	97.16
EfficientNet	95.8	96.9	95.7	96.96
	98.9	98.7	98.8	98.92
ViT	97.4	98.2	97.42	98.45
	99.1	98.9	98.96	99.13
DeiT	97.6	98.37	97.61	98.52
	98.4	98.19	98.31	98.38

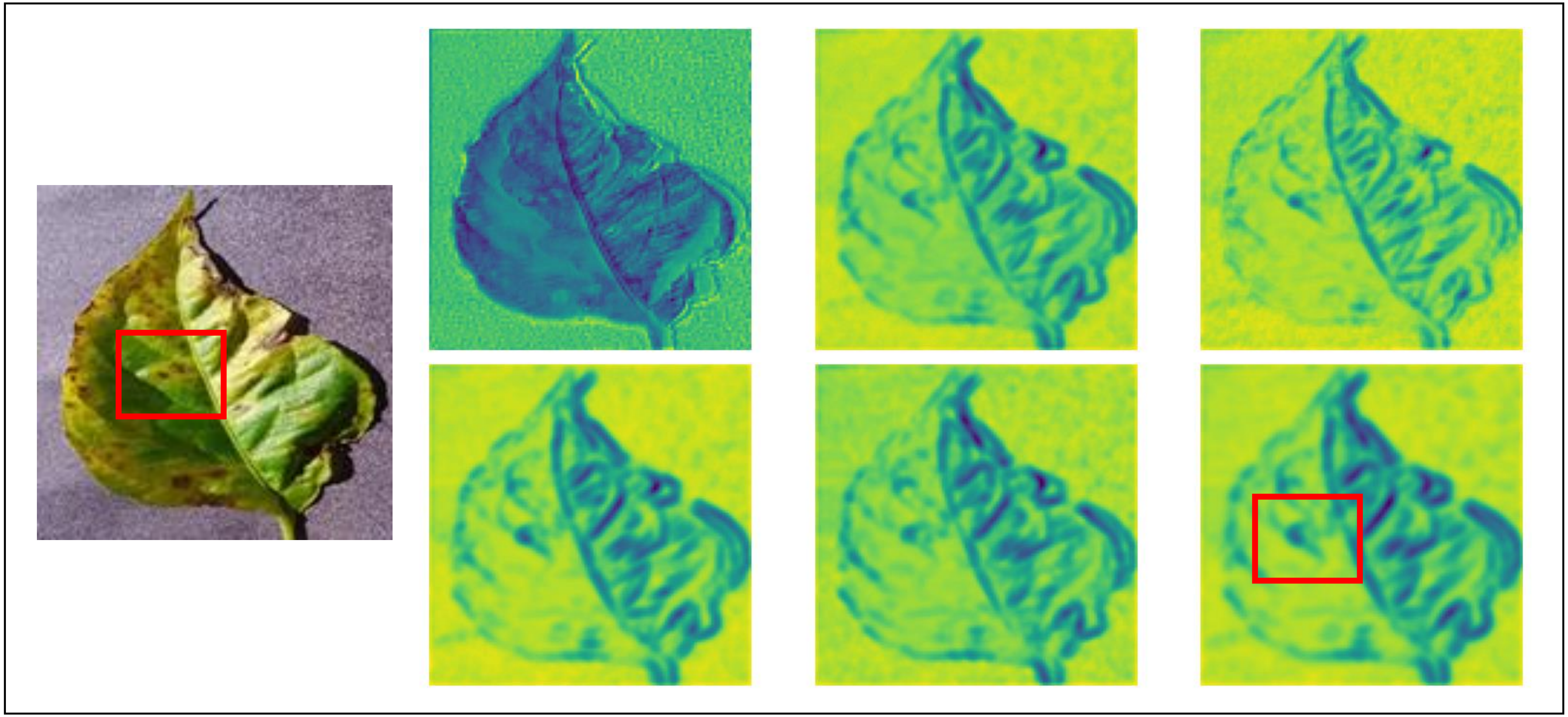
Feature map (VGGNet)



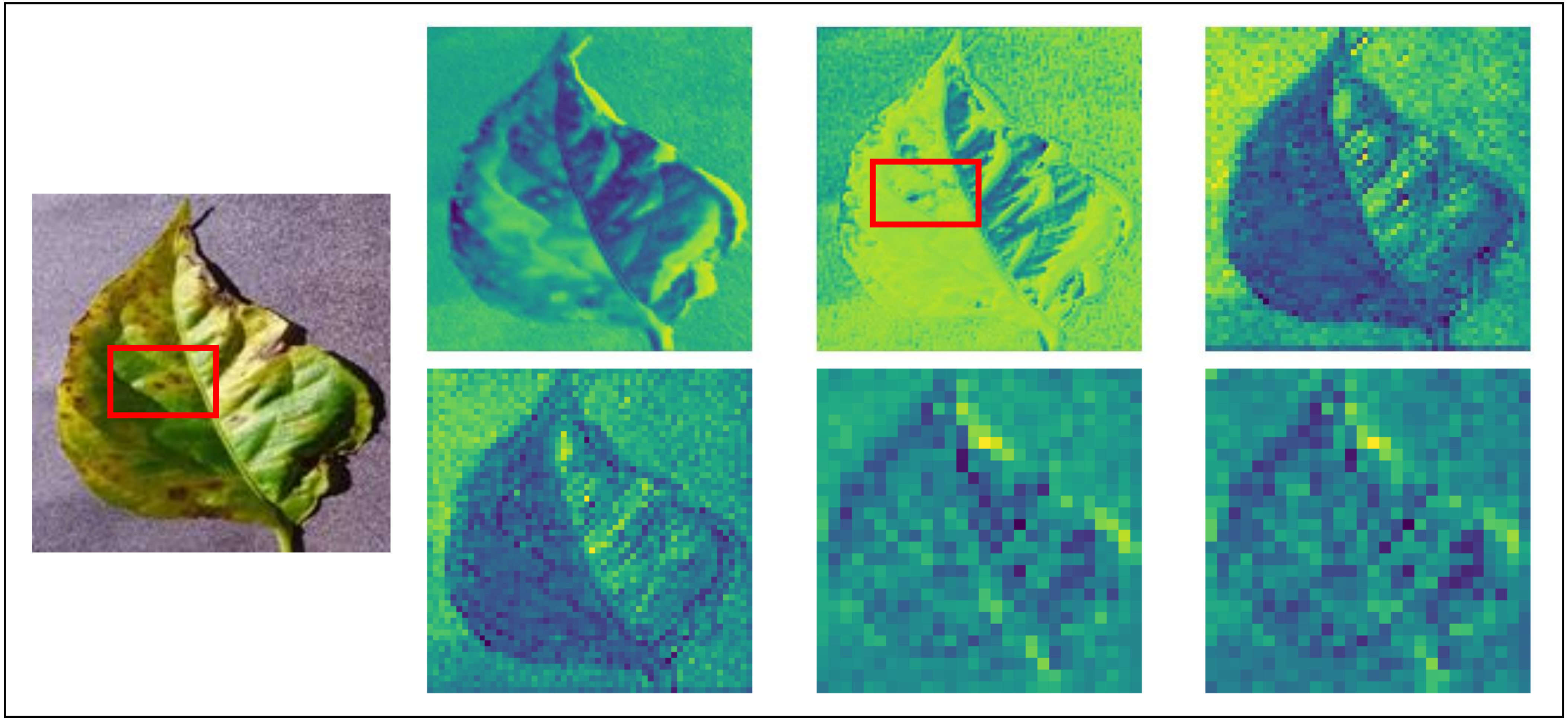
Feature map (ResNet)



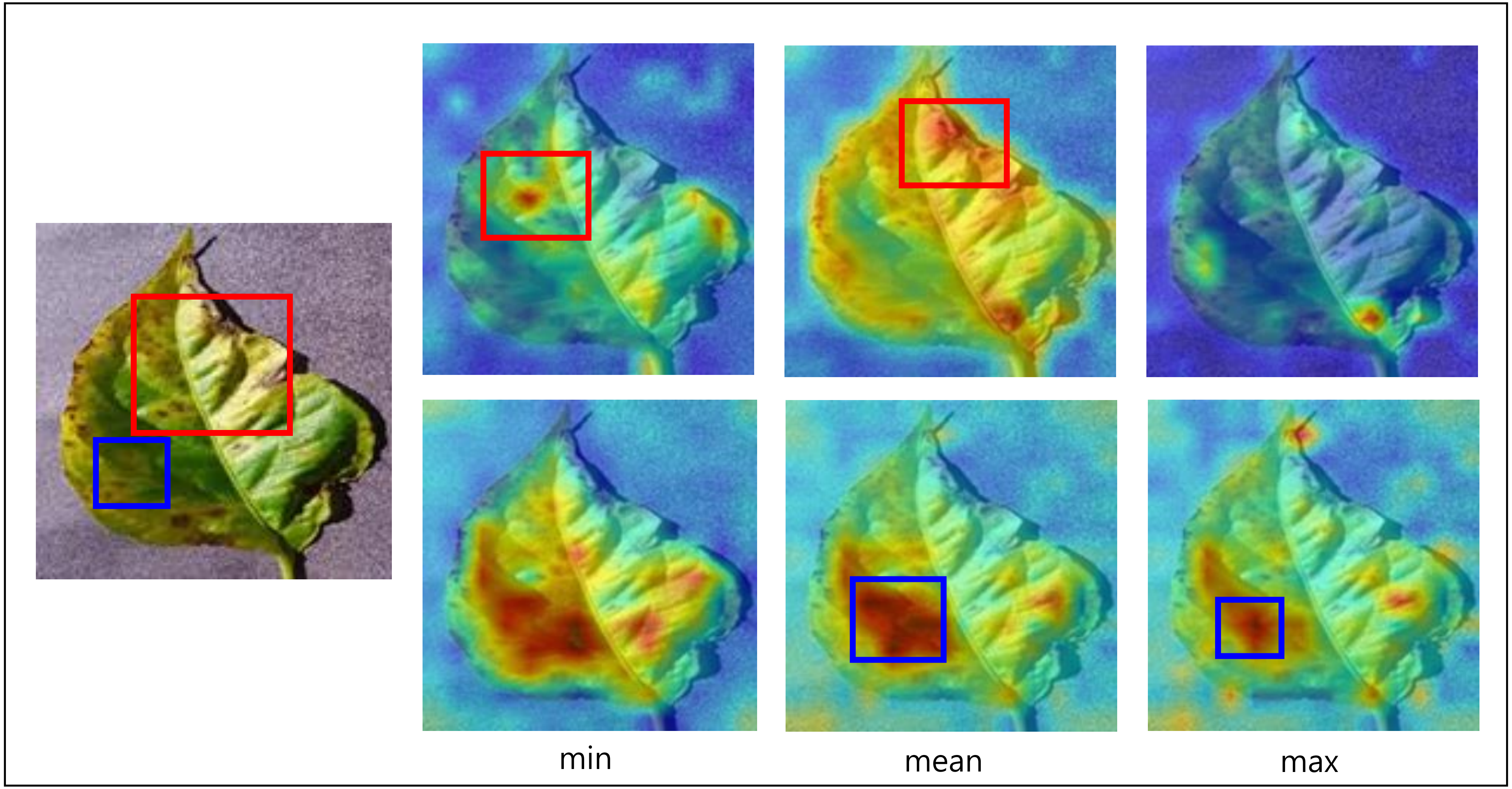
Feature map (DesnetNet)



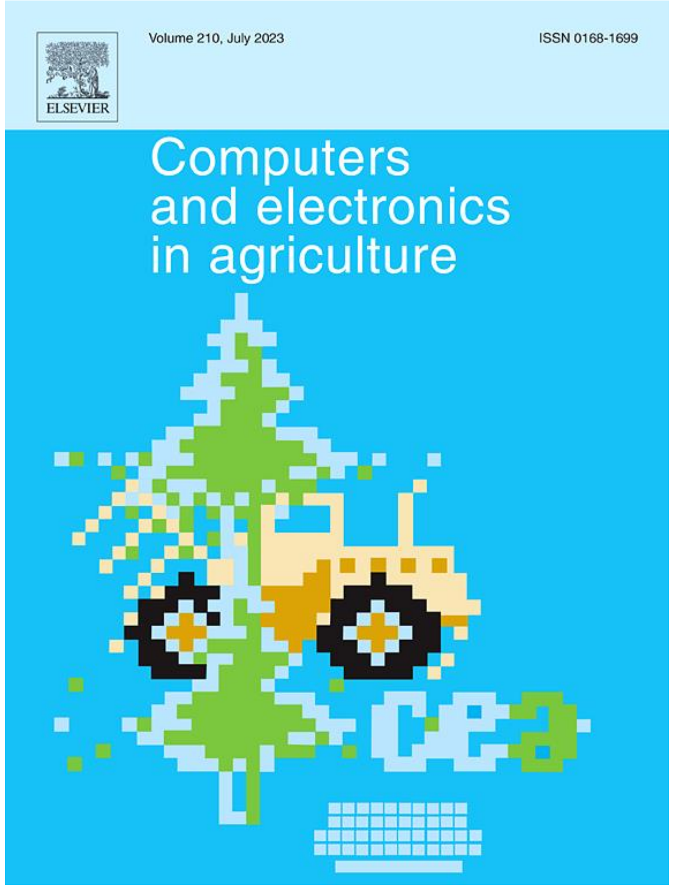
Feature map (EfficientNet)



Feature map (ViT, DeiT)



Conclusion



- Computers and Electronics in Agriculture 투고 예정

  : 농경학, 원예, 임업, 양식업을 포함하여 농업 문제를 해결하기 위한

  컴퓨터 하드웨어, 소프트웨어, 전자 계측, 시스템의 개발 및 응용 분야

- Cite Score : 13.6 (Q1)
- IF : 8.3
- Average JIF : Top 7.5

02 Work In Progress

- Adversarial Attack for ECG user authentication

Adversarial Attack for ECG user Authentication

- 주제 : **적대적 공격을 통한 심전도 사용자인증 보안기술 취약점 분석**
- 2023년 「여대학원생 공학연구팀제 지원사업」
- 연구책임자 : 이새봄
- 참여연구원 : 이명회(3학년), 나경민(3학년), 장예정(4학년)
- 연구기간 : 2023. 04. 01 ~ 2023. 10. 31 (8,000,000원)

Introduction

- 목표 : 적대적 공격을 통한 딥러닝 기반 심전도 사용자인증 기술의 안전성 분석 및 보안 취약성 검증

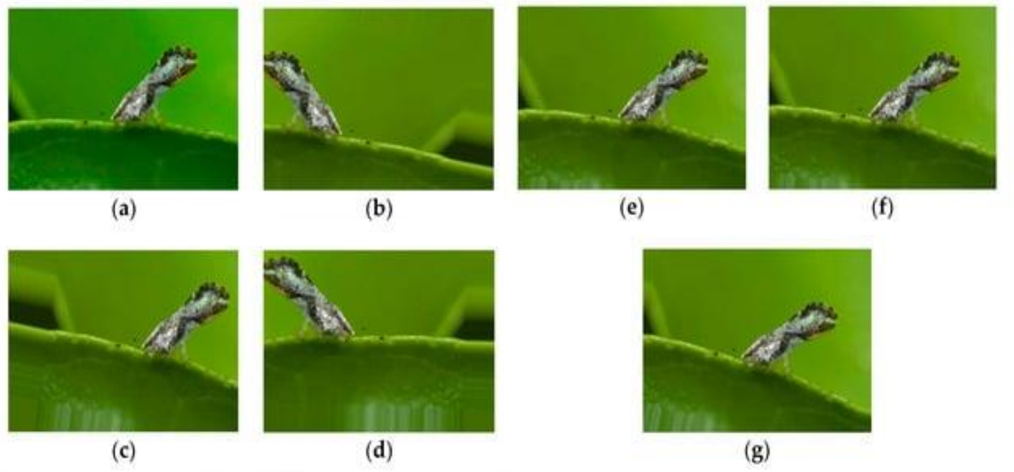
- Dataset : 김예진 연구원으로부터 심전도 전처리 데이터셋을 제공받음 → Training : Validation : Test = 7 : 2 : 1

측정기간	2016.08.23 ~ 2016.12.27	측정담당자	최규호
측정 인원	100명 : 조선대학교 IT융합 대학 대학원생 및 학부생	피험자 상태 및 조건	의자에 앉은 편안한 상태
측정 시간	1회 측정 시간 : 10초 총 60회 측정	데이터 sampling rate	50만 Hz
심전도 유형	심전도 Lead-I	전극 유형	습식 전극

Related Work (1)

1. **(2019) Citrus pests and diseases recognition model using weakly dense connected convolution network**

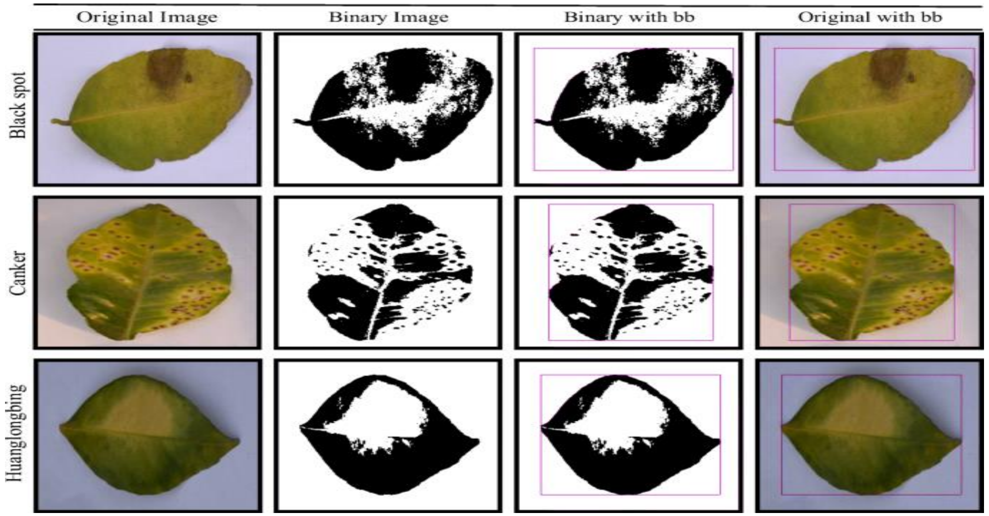
→ Random rotation, reflection, shift, and flip



Related Work (2)

2. **(2022) Citrus disease detection and classification using end-to-end anchor-based deep learning model**

→ 모든 이미지를 grayscale로 변경



3) Xing, Shuli, Marely Lee, and Keun-kwang Lee. "Citrus pests and diseases recognition model using weakly dense connected convolution network." *Sensors* 19.14 (2019): 3195.
4) Syed-Ab-Rahman, Sharifah Farhana, Mohammad Hesam Hesamian, and Mukesh Prasad. "Citrus disease detection and classification using end-to-end anchor-based deep learning model." *Applied Intelligence* 52.1 (2022)

Related Work (1)

1. (2023) Adversarial examples: attacks and defences on medical deep learning systems

- Dataset : MNIST(Medical and Non-Medical)
  - CXR : 흉부 X선 이미지
  - BS : 혈액 도말 이미지
  - DR : 당뇨병성 망박명증
- Evasion Attack : **FGSM**
- 실험 모델 : VGGNet 19
- 공격 성공률 (epsilon = 0.0003)
  - CXR : 51.84%, BS : 48.1%, DR : 47.8%

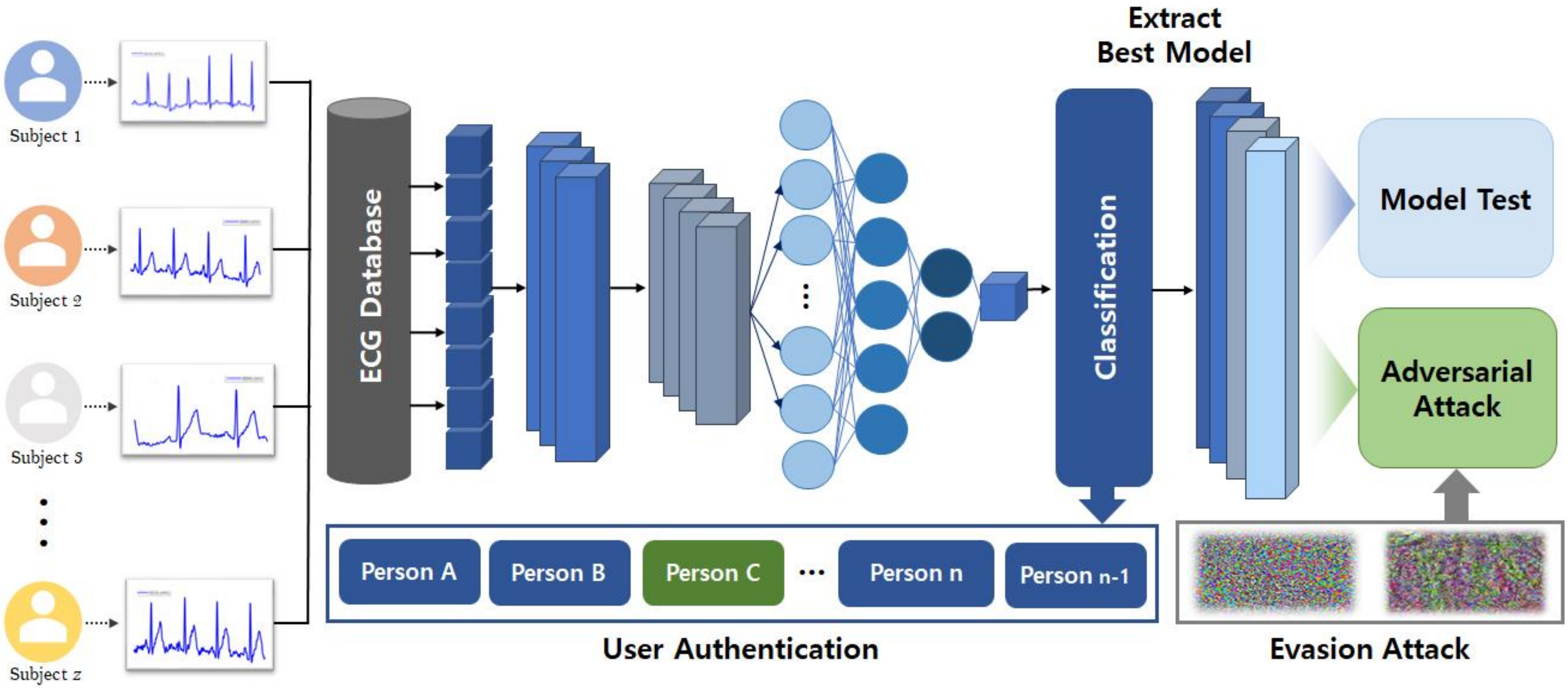
Related Work (2)

2. (2020) Deep learning models for electrocardiograms are susceptible to adversarial attack

- Dataset : 2017 PhysioNet/CinC Challenge
  - Training set : Test set = 9 : 1
- Evasion Attack : **FGSM , PGD**
- 실험 모델 : 2017 PhysioNet/CinC Challenge 에서 우승한 13계층 convolution network
- 공격 성공률
  - 50% 이상

1) Puttagunta, Murali Krishna, S. Ravi, and C. Nelson Kennedy Babu. "Adversarial examples: attacks and defences on medical deep learning systems." *Multimedia Tools and Applications* (2023): 1-37.
2) Han, Xintian, et al. "Deep learning models for electrocardiograms are susceptible to adversarial attack." *Nature medicine* 26.3 (2020): 360-363.
3) Goodfellow, S. D. et al. Towards understanding ECG rhythm classification using convolutional neural networks and attention mappings. In *Proceedings of the 3rd Machine Learning for Healthcare Conference* 83–101 (PMLR, 2018)

Method


Subject 1
Subject 2
Subject 3
Subject z
ECG Database
Extract
Best Model
Classification
Model Test
Adversarial
Attack
Person A
Person B
Person C
Person n
Person n-1
User Authentication
Evasion Attack

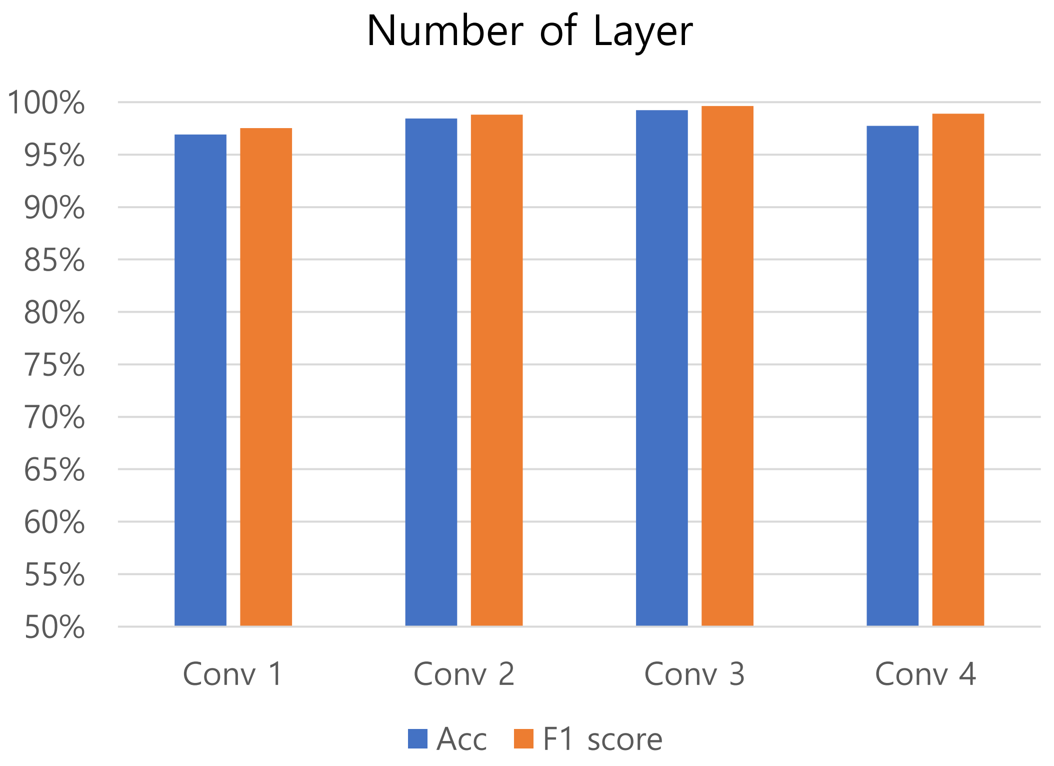
Experiment Result (1/5)

- 1D CNN Layer depth 에 따른 성능 비교 실험

Number of Layer	Accuracy	F1 score
Conv 1	96.92%	97.53%
Conv 2	98.44%	98.83%
Conv 3	99.25%	99.65%
Conv 4	97.75%	98.91%

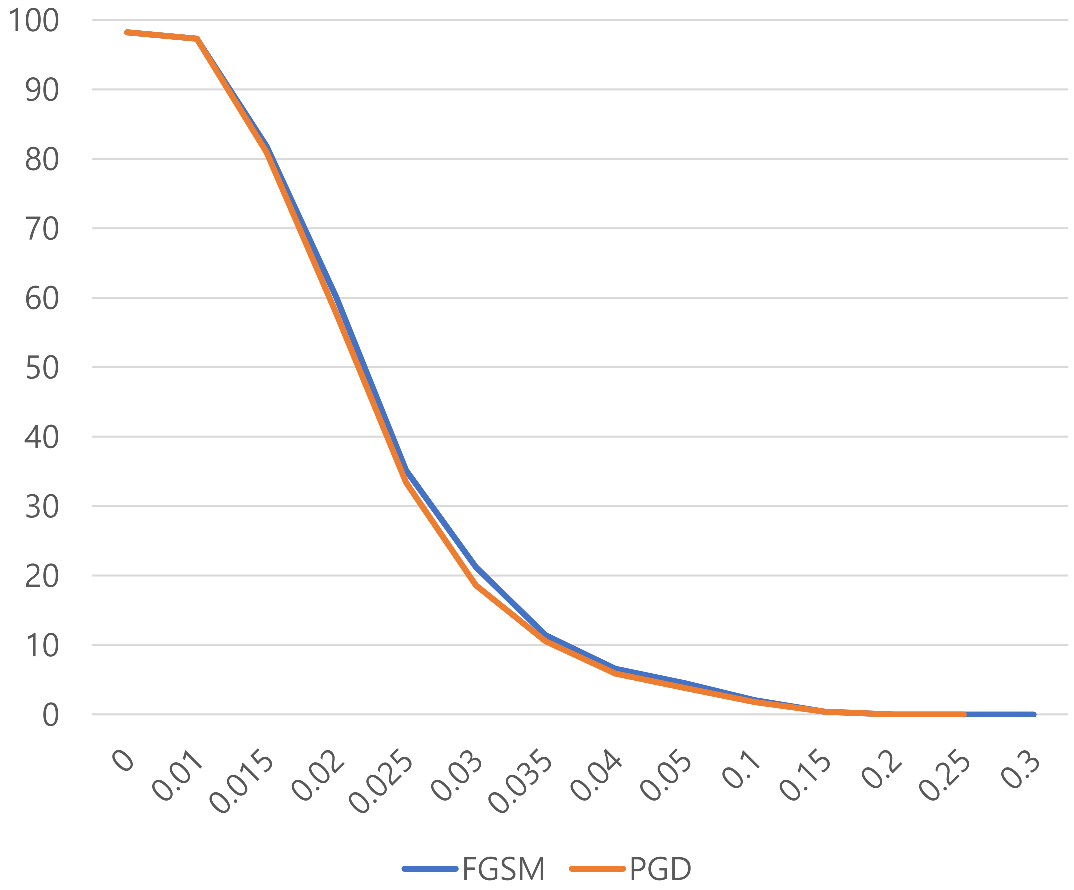
Test Dataset	Accuracy	F1 score
Conv 3	98.22%	98.21%

Conv 3에서 가장 높은 성능을 도출한 가중치 선택

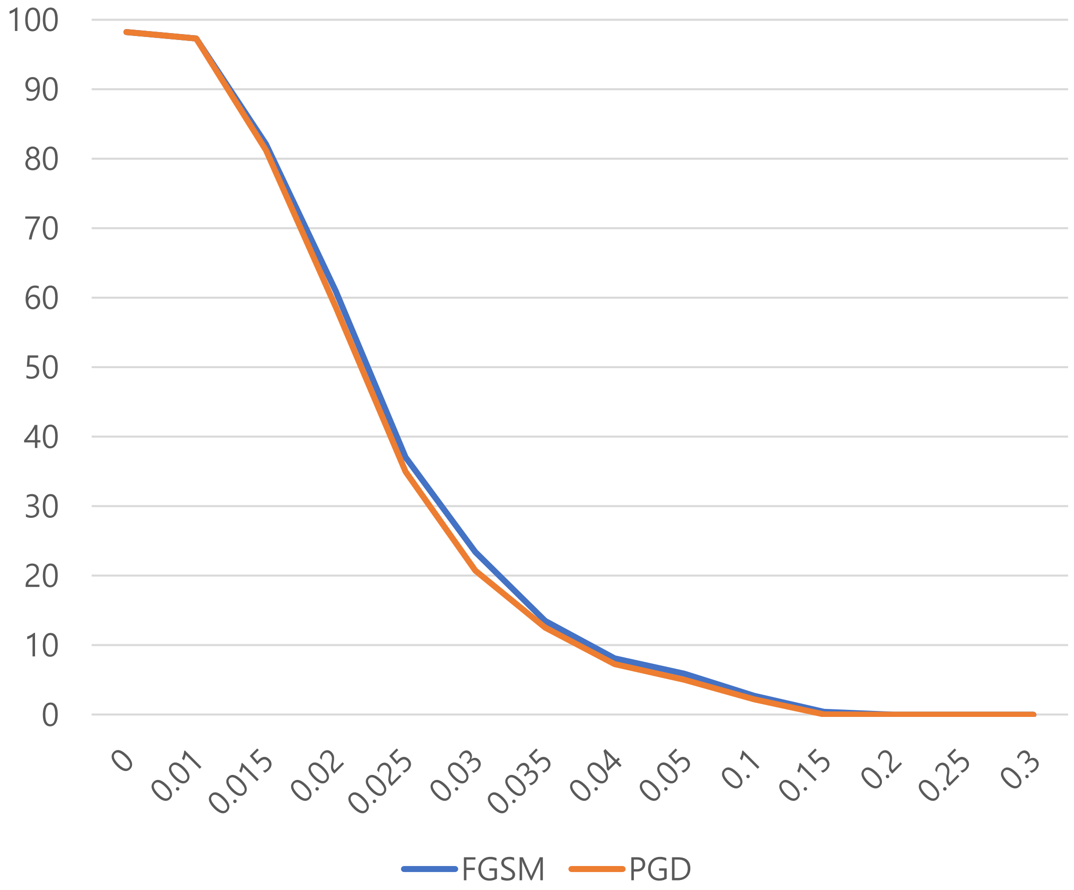


Experiment Result (2/5)

- Evasion Attack Accuracy 하락률

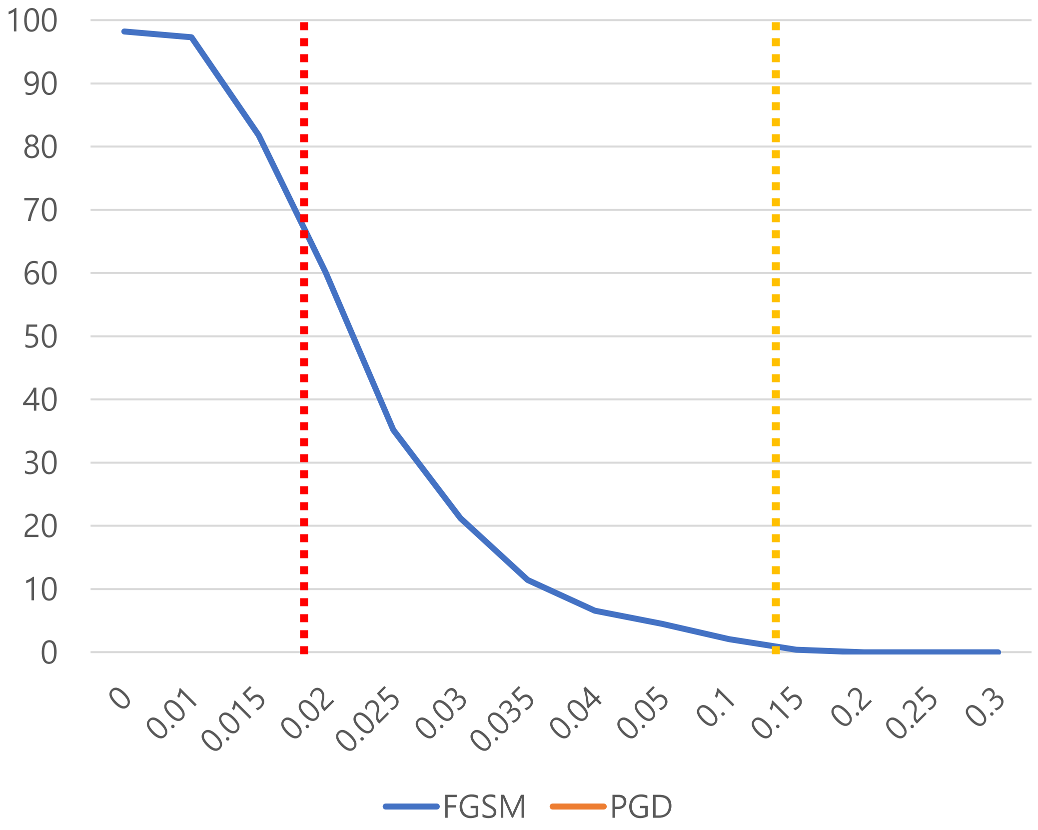


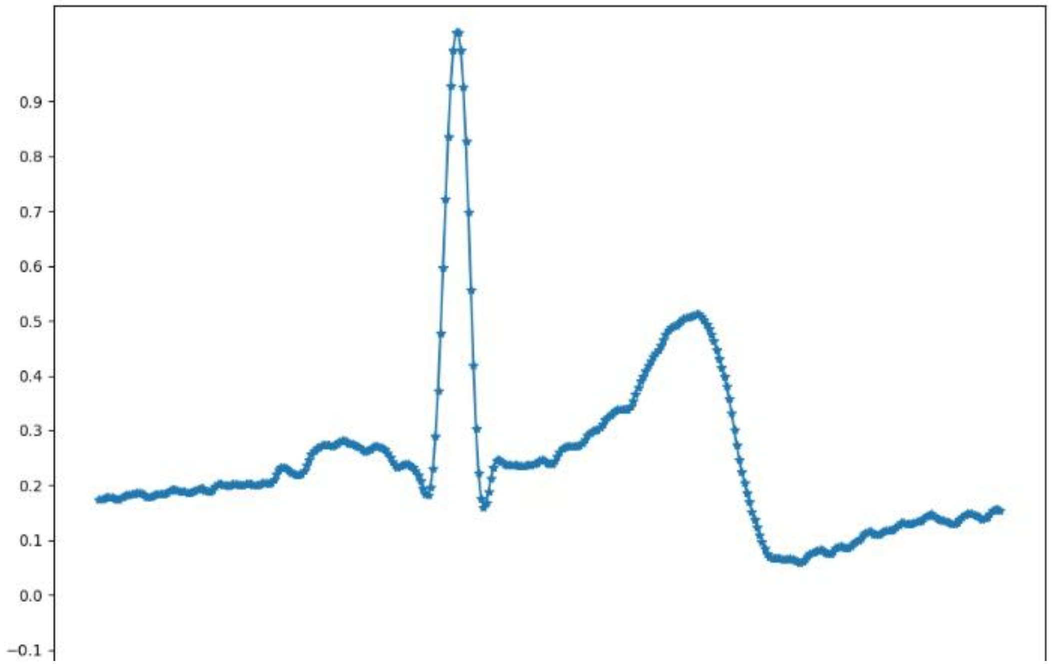
- Evasion Attack F1 score 하락률



Experiment Result (3/5)

- FGSM (Fast Gradient Sign Method) vs PGD (Projected Gradient Descent) ECG Signal

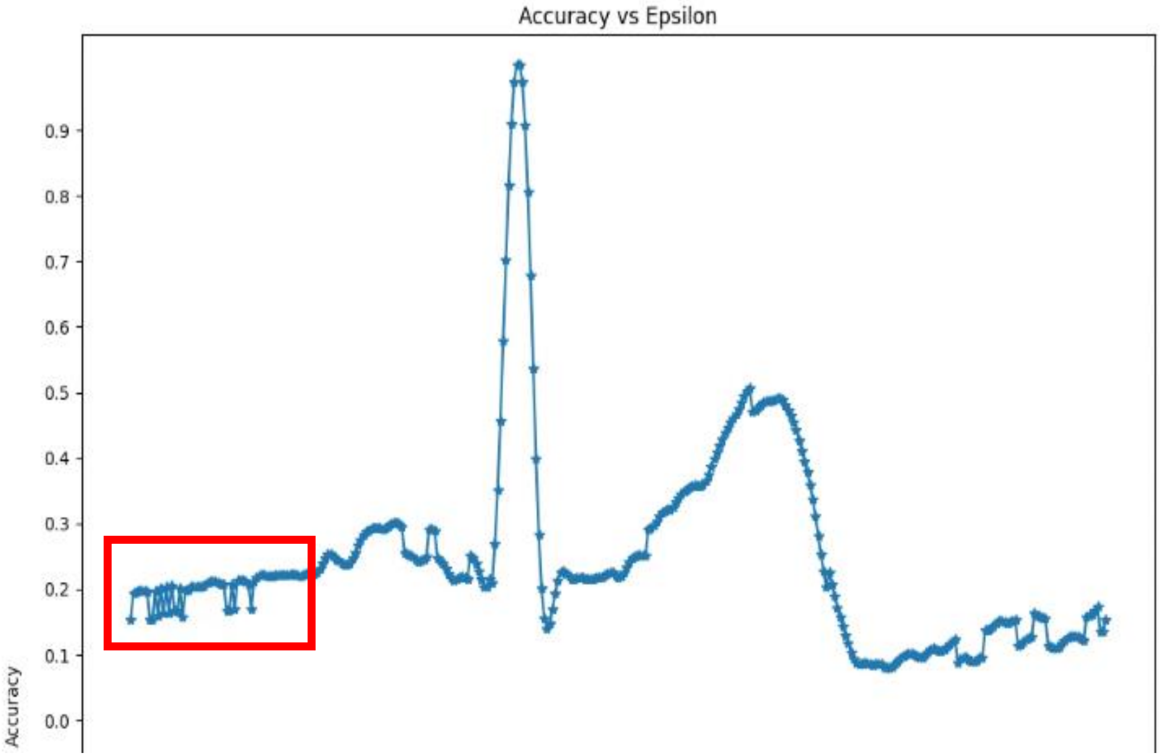




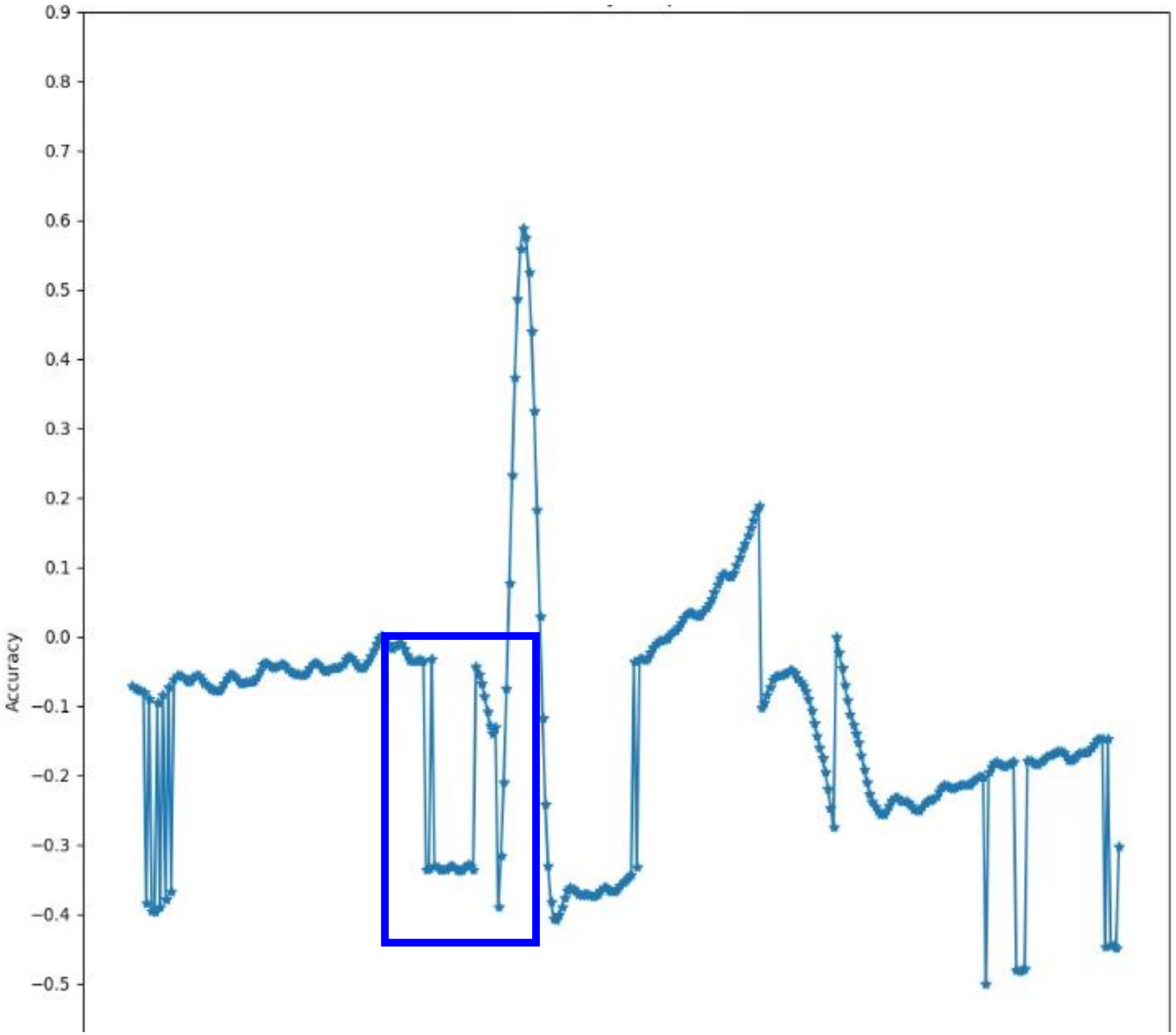
원본 ECG

Experiment Result (4/5)

- FGSM (Fast Gradient Sign Method) ECG Signal



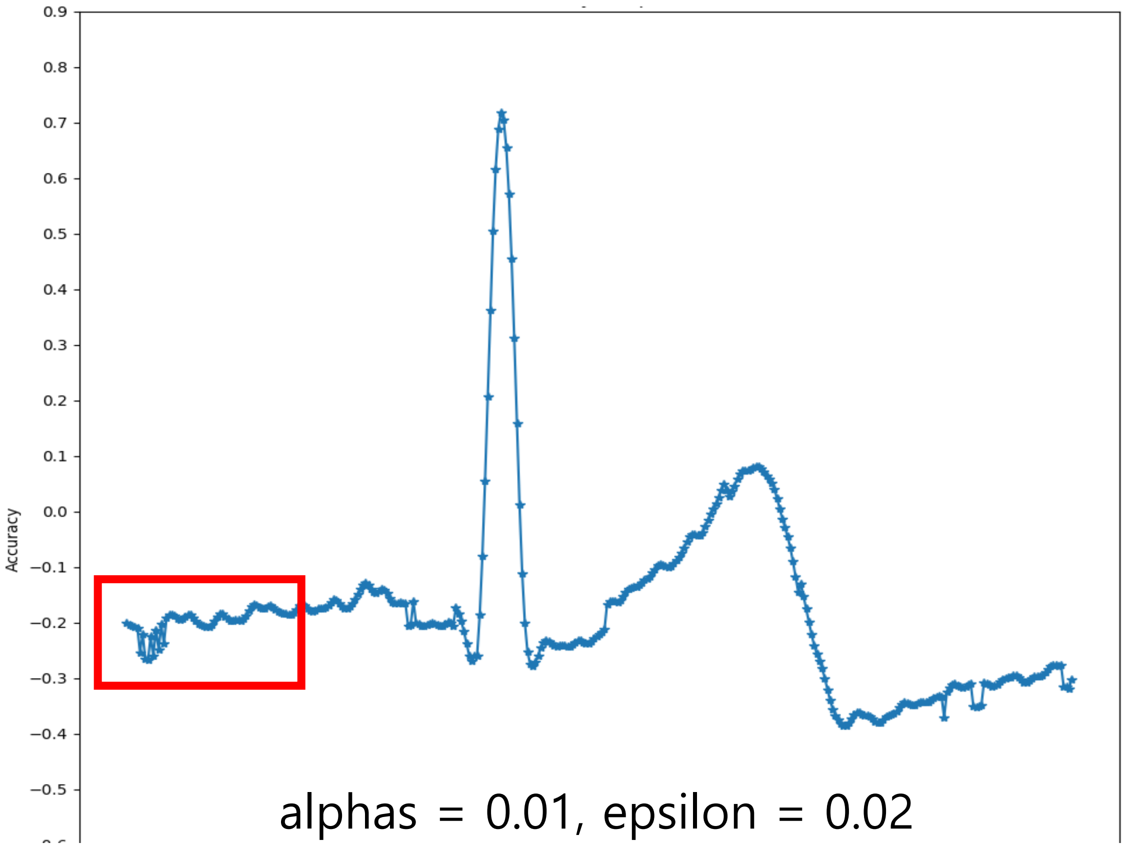
epsilon = 0.02



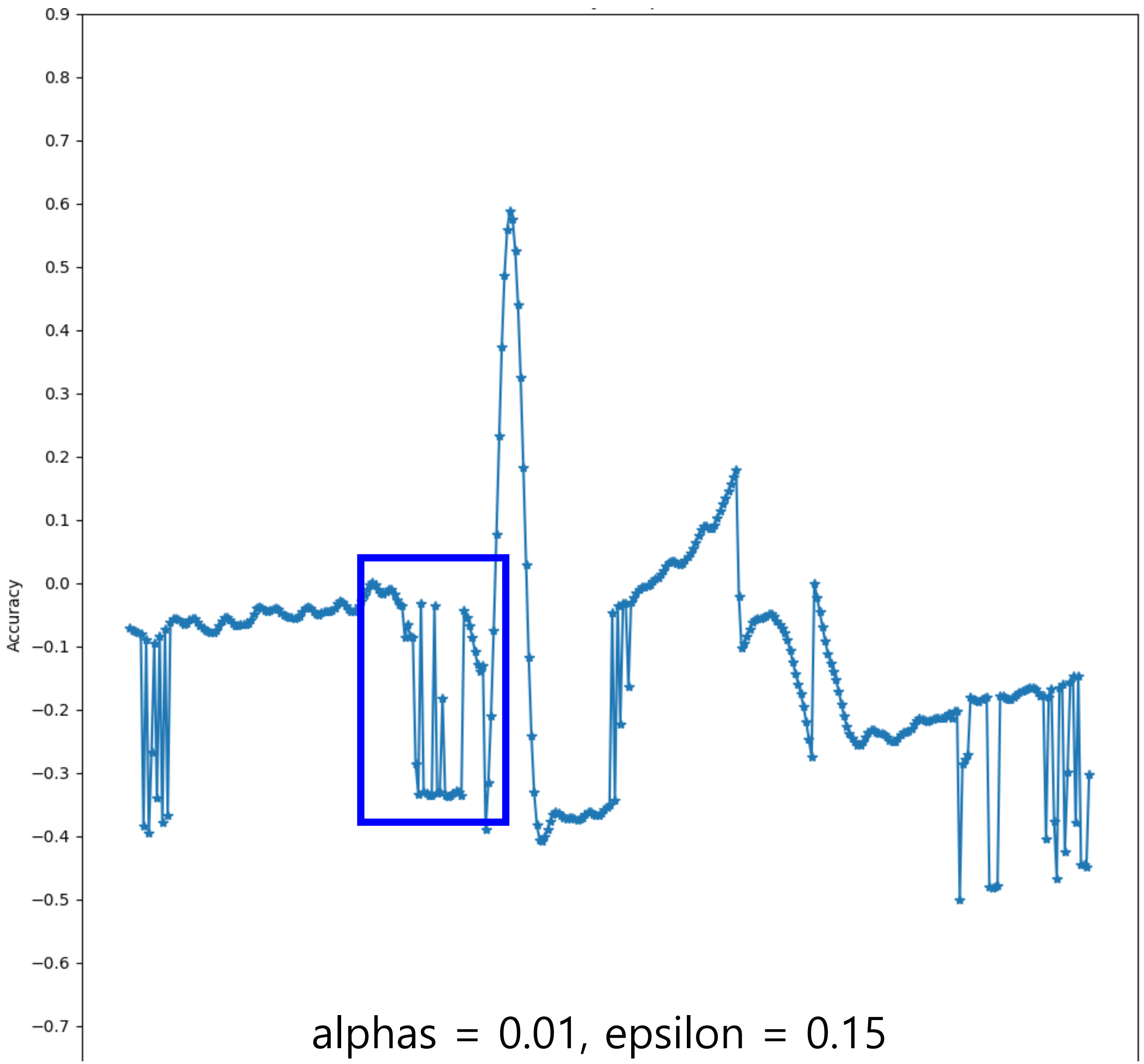
epsilon = 0.15

Experiment Result (5/5)

- PGD (Projected Gradient Descent) ECG Signal



alphas = 0.01, epsilon = 0.02



alphas = 0.01, epsilon = 0.15

Conclusion

- 적대적 공격은 딥러닝 모델의 취약점을 공격하는 기술로, 심전도 사용자인증에 매우 취약함을 알 수 있음
- FGSM, PGD 모두 성공적인 성능 하락도를 확인할 수 있음
- 이를 통해, 적대적 공격을 방어할 수 있는 방법을 연구할 필요가 존재함
- 1D CNN외 다른 모델들(LSTM, BiLSTM)을 사용하여, FGSM과 PGD의 공격 성공률을 연구할 예정

03 Work In Future

- Generating Kiwi Data through Data Diffusion Model
- Follow-up research : Adversarial Defense for ECG user authentication

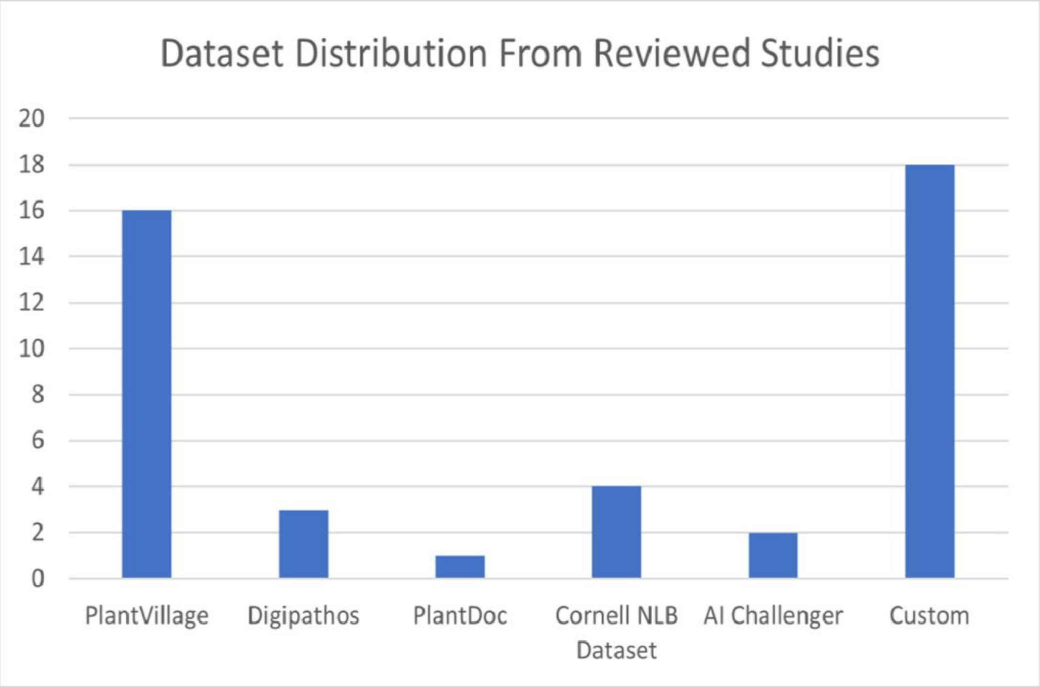
Generating Kiwi Data through Data Diffusion Model

- 주제 : **Generating Kiwi Data through Data Diffusion Model**

- 농업 데이터셋은 Open dataset이 매우 희귀함

- 현재 농작물 질병 인식 연구는 PlantVillage Dataset을 사용한 연구와 Custom Dataset을 사용한 연구가 주를 이룸

  → Diffusion Model을 통해 농작물 데이터 합성 연구가 필요



농작물 질병 연구에 수행된 Dataset (2022)

Ahmad, Aanis, Dharmendra Saraswat, and Aly El Gamal. "A survey on using deep learning techniques for plant disease diagnosis and recommendations for development of appropriate tools. " *Smart Agricultural Technology* (2022): 100083

Generating Kiwi Data through Data Diffusion Model

- 목표 : Stable Diffusion model을 통해 kiwi dataset을 합성하는 연구를 수행하고자 함

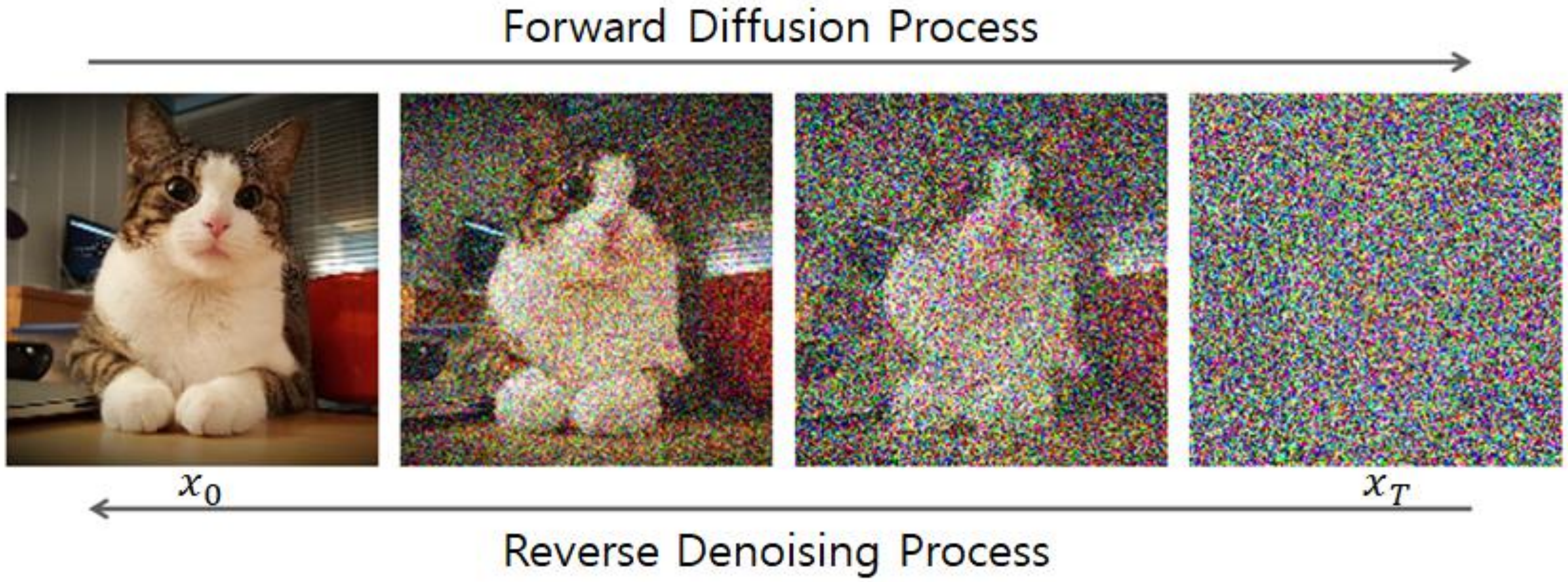
- Generator Model / GAN(Generative Adversarial Networks) : 생성자(Generative)와 판별자(Discriminator) 2개의 신경망을 경쟁시키며 학습하며, 생성자가 실제 데이터와 유사한 가짜 데이터를 생성하도록 함
  → 새로운 데이터를 처음부터 만들어내는 생성

- Diffusion Model : 이미지나 데이터의 특징을 유지하면서 노이즈를 추가/ 세부 사항을 흐리게 만들어 데이터를 변형함
  → 기존 데이터를 가공하거나 조합하여 새로운 데이터를 생성함

Generating Kiwi Data through Data Diffusion Model

- Diffusion Model

  : Input image에 Noise를 여러 단계에 걸쳐 추가하고, 정규 분포를 가진 노이즈를 제거함으로써, input image와 유사한 확률 분포를 가진 이미지를 생성하는 모델



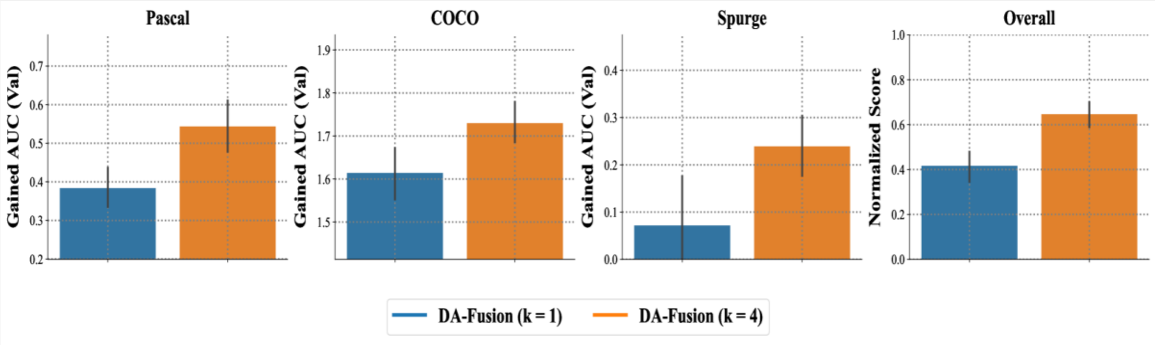
Generating Kiwi Data through Data Diffusion Model

- Diffusion Model을 통한 농작물 데이터 합성 연구가 매우 적음

관련 연구

(arXiv 2023) Effective Data Augmentation With Diffusion Models

- Dataset : Pascal, COCO, Leafy Spurge
- Model : DA-Fusion (Image-to – Image Diffusion Model에서 착안)
- Performance :



Trabucco, Brandon, et al. "Effective data augmentation with diffusion models." *arXiv preprint arXiv:2302.07944* (2023).

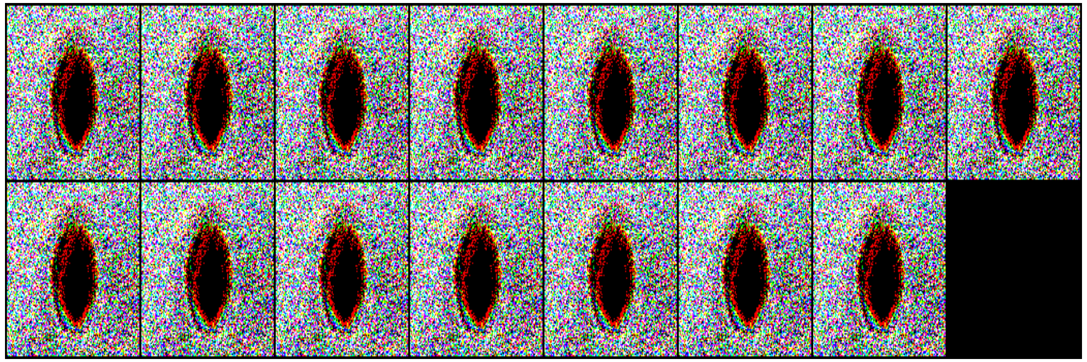
Generating Kiwi Data through Data Diffusion Model

- 현재 GAN 기반 Kiwi Data Generating 연구를 수행 중, 아직 유의미한 성능을 도출하지는 못함

[Generator Model]

① 4개의 Convolution layer

② Input – Dense – Embedding – Leaky ReLU - Conv



[Discriminator model]

① 4개의 Convolution layer

② Input – Embedding – Dense – Leaky ReLU – Conv – Flatten - Dropout

→ Diffusion Model을 사용하여 데이터 합성을 연구 수행 (Stable Diffusion Model 사용 예정)

Generating Kiwi Data through Data Diffusion Model

- 해당 연구를 수행하여, 2024년 박사과정생 연구장려금 사업에 지원할 예정

- 2023년 기준 : 연구비 20,000,000원 / 연구기간 : 1~2년

- 최종 목표는 농업 데이터셋을 합성을 통해 데이터를 생성하고, 데이터 생성 모델과 데이터 합성 모델을 비교해 보고자 함

03 Work In Future

- Generating Kiwi Data through Data Diffusion Model
- Follow-up research : Adversarial Defense for ECG user authentication

Adversarial Defense for ECG user authentication

- 주제 : **적대적 공격에 강인한 심전도 사용자인증 보안기술 연구 (후속연구)**
- 2024년 「여대학원생 공학연구팀제 지원사업」
- 연구책임자 : 이새봄
- 참여연구원 : 미정
- 연구기간 : 2024. 04. 01 ~ 2024. 10. 31 (8,000,000원)

감사합니다

발표 경청해 주셔서 감사합니다

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