

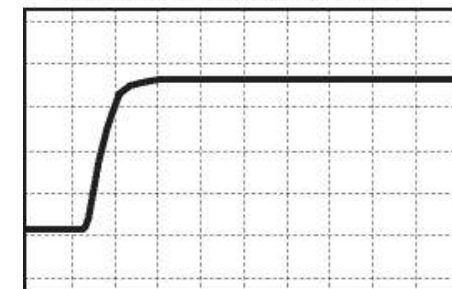
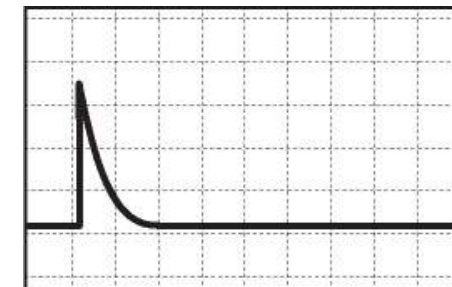
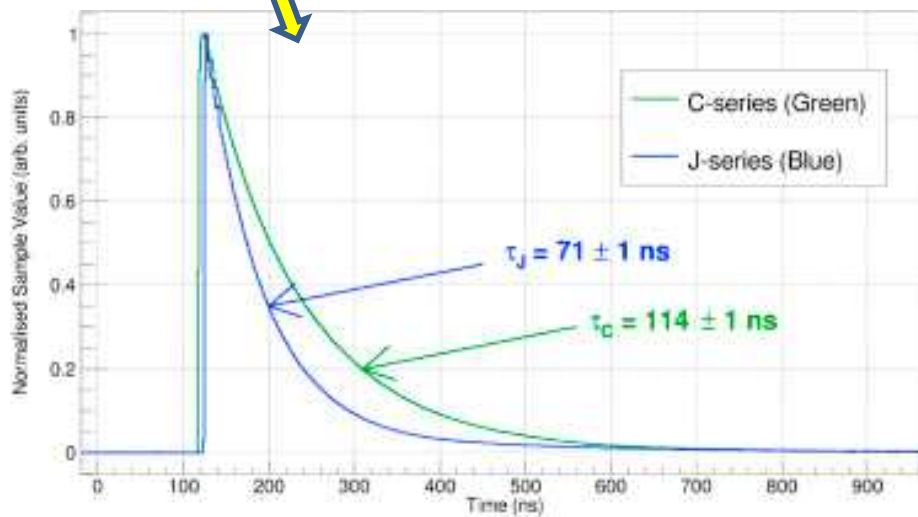
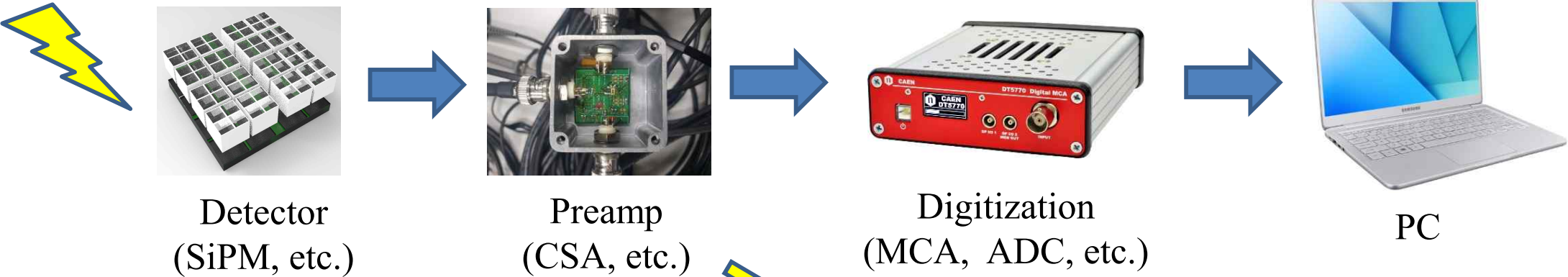
AI 기반 딥러닝 핵종 판별기술

Inyong Kwon (권인용)

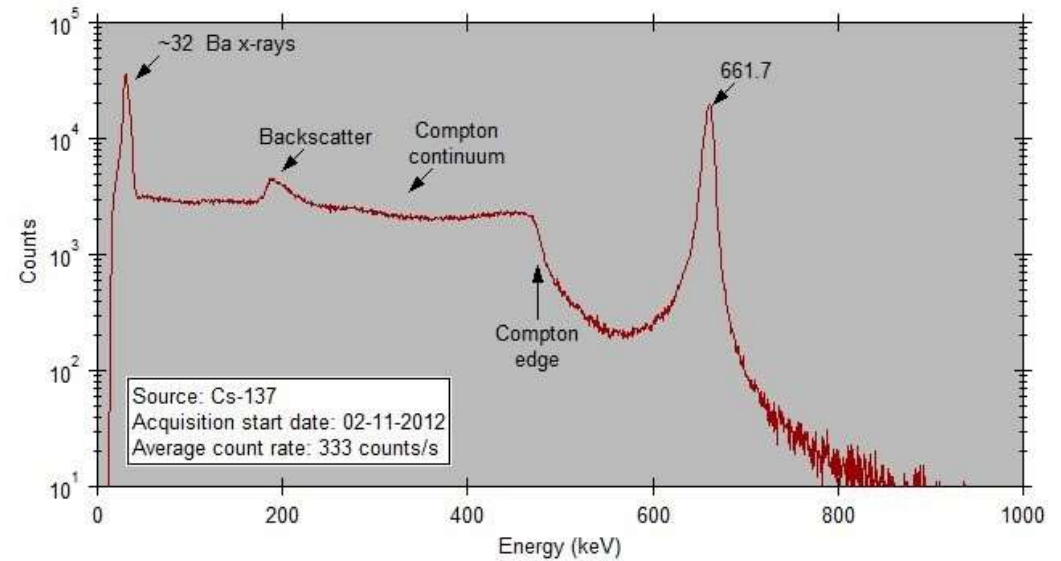
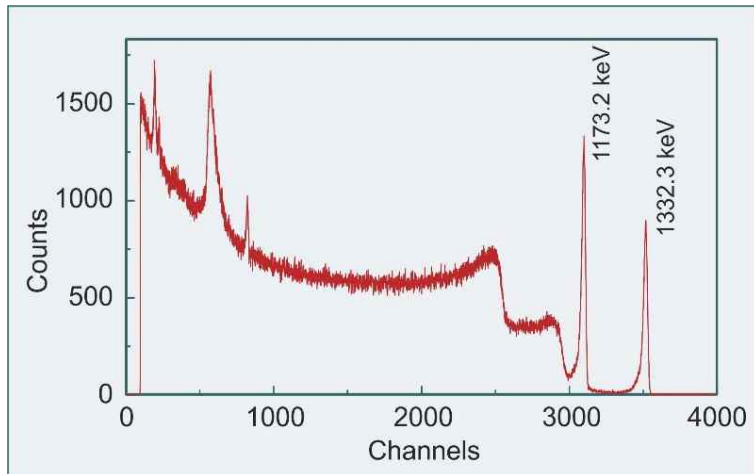
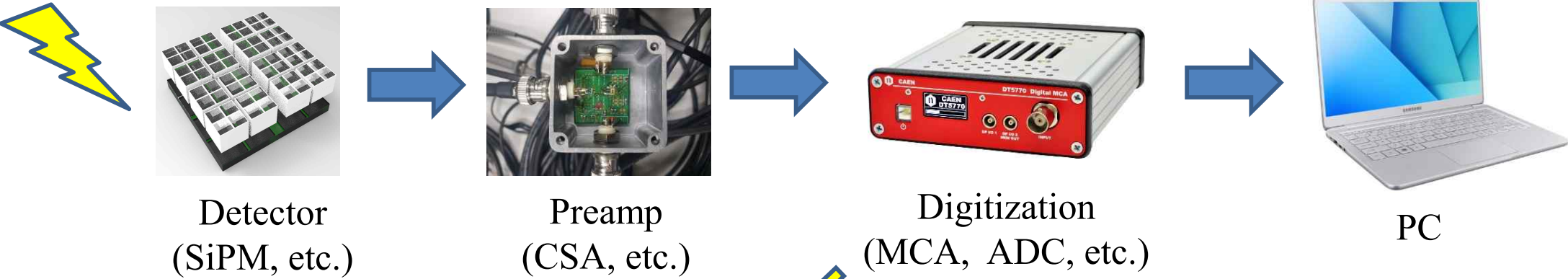


한국원자력연구원
Korea Atomic Energy Research Institute

Radiation Sensor Interface Circuit



Radiation Measurement



Radiation Measurement



[Fukushima nuclear disaster, 2011]

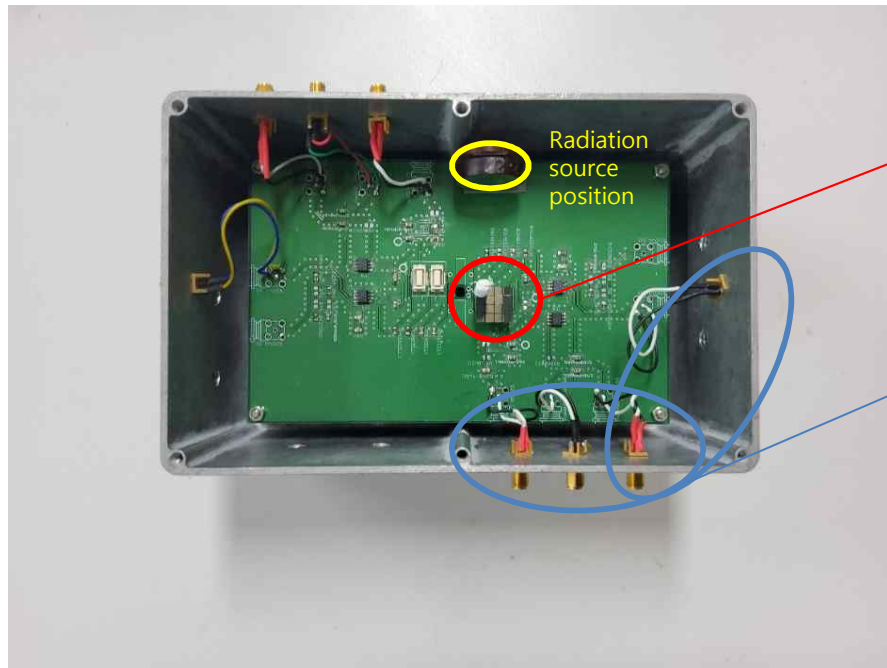


[Reactor building decommissioning, US NRC]

- Very long time (10 hours ?!)
- Radiation information required IMEEDIATELY

>> We need a real time radionuclide identification technique.

Experiment setup



Circuit for detecting radiation

► 16 cha. SiPM & plastic scintillator

- only one channel was used.
- The scintillator was bonded to SiPM with the optical glues.
- To prevent optical loss, the scintillator was enveloped with the Teflon tape.

► Input voltage

COM voltage of opAmp ; -5V, +5V

Overvoltage(sum of the breakdown voltage of SiPM and excess voltage.); 25V

► Experiment setting

- The distance was a 4cm between scintillator and radiation source.
- A radiation source with a smaller activity in complexed source was placed closer to the scintillator.

► Radiation source

- Cesium (Cs -137); activity = 5 μCi
- Cobalt (Co - 60); activity = 0.604 μCi
- Measurement target
=> Background, Cs-137, Co-60,
Cs-137 + Co-60

Experiment setup

- Experiment configuration



Fig.1. Power supply setting. – 5V(left), 25V, 5V(right).

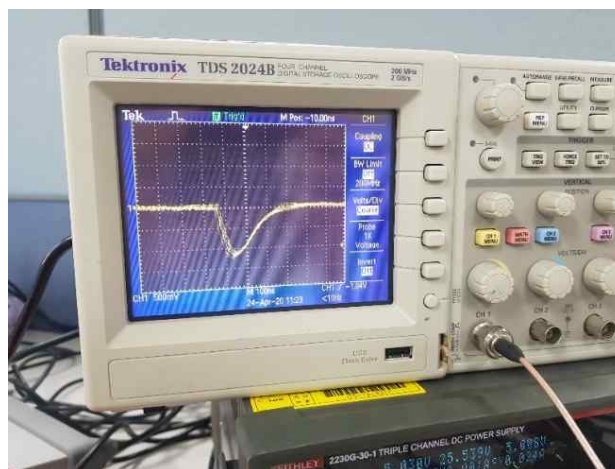


Fig.2. reverse voltage peak data.
Trigger was 120mV

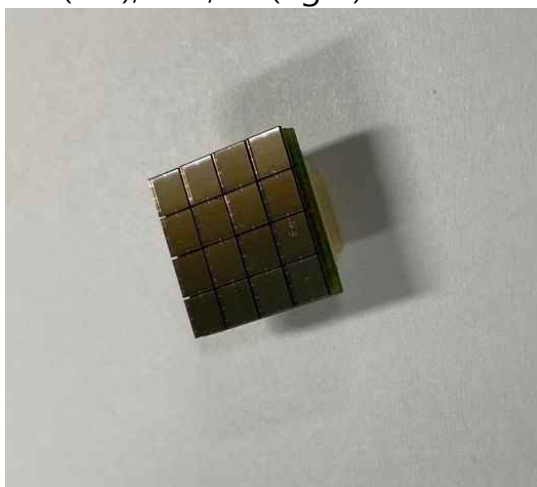


Fig. 3. 16 ch.
SiPM(SensL)

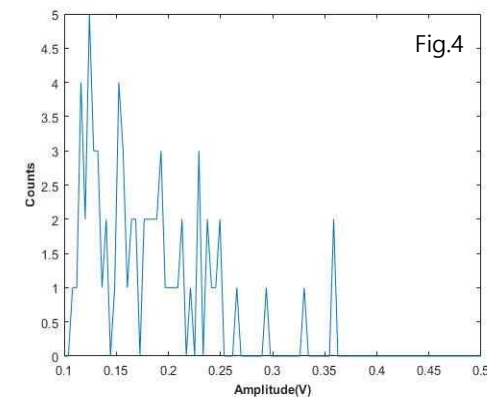
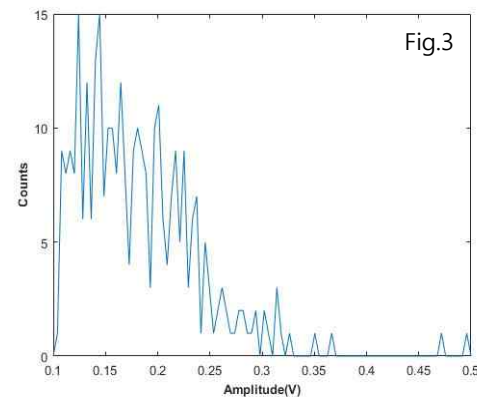
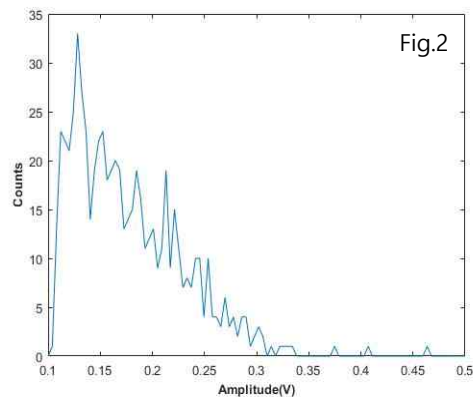
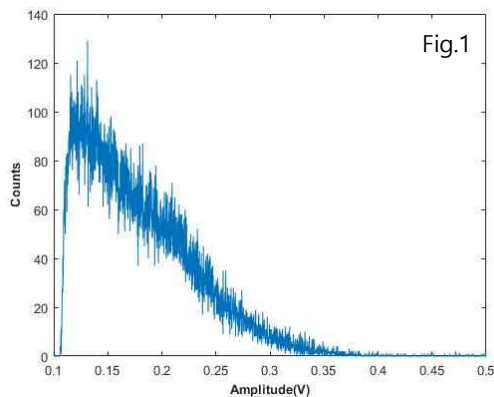
Ch.16 SiPM: Array J-30035_16P-PCB_SensL
Breakdown voltage : 24.2 V – 24.7 V
Excess voltage: 1 V – 6 V{Min - Max}
Scintillator; size: 3mm x 3mm x 20mm
Material: LySo

Experimental Data

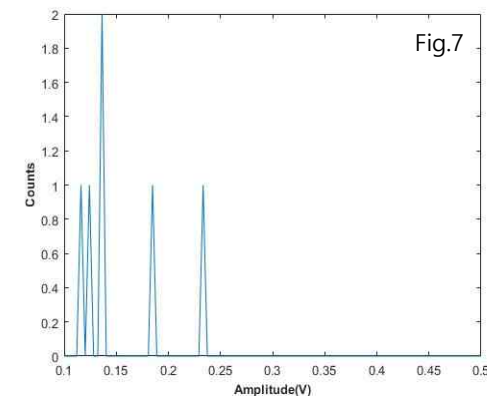
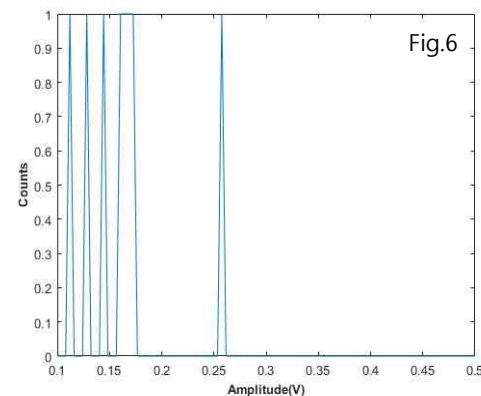
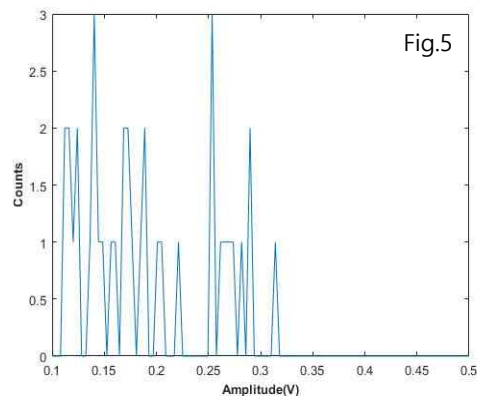
Class num.	Source	Measurement time (h:m:s)	Num. of measured data
0	Background	1:35:27	10^5 <i>counts</i>
1	Cs-137	1:05:53	10^5 <i>counts</i>
2	Co-60	1:10:14	10^5 <i>counts</i>
3	Cs-137+Co-60	1:13:29	10^5 <i>counts</i>

Experimental Data

- Background histogram (each data size)

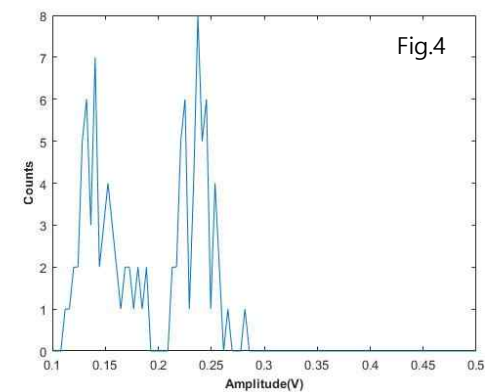
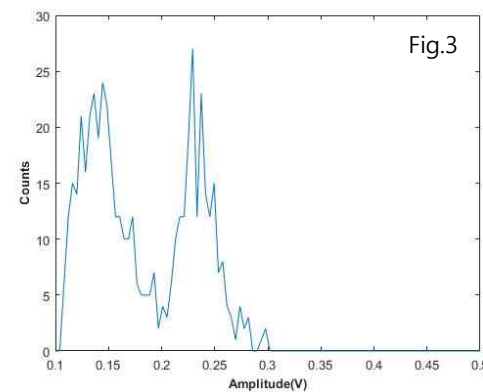
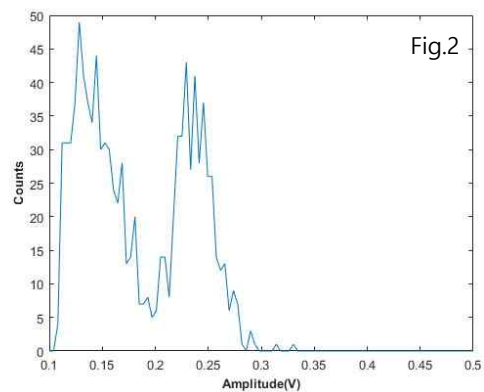
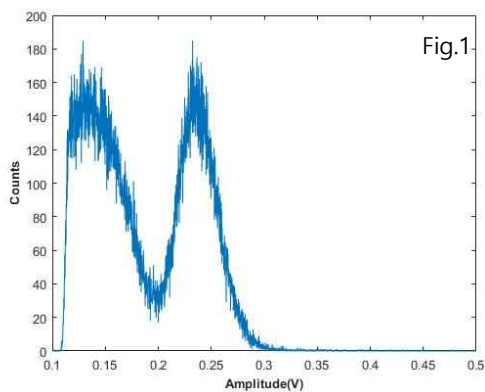


Source; background
Class number; 0
Data size; Fig.1(10 만),
Fig. 2(1000), Fig.
3(500)
Fig. 4(100), Fig. 5(50),
Fig. 5(20), Fig. 6(10).

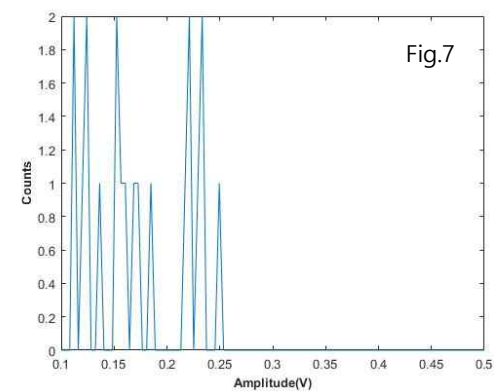
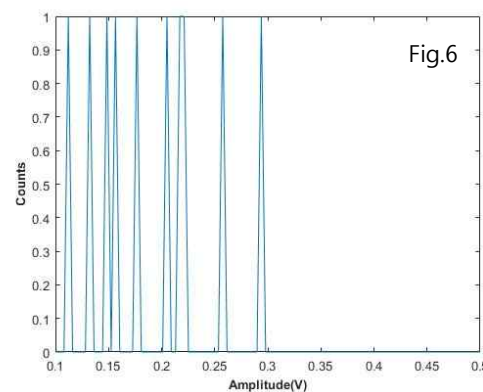
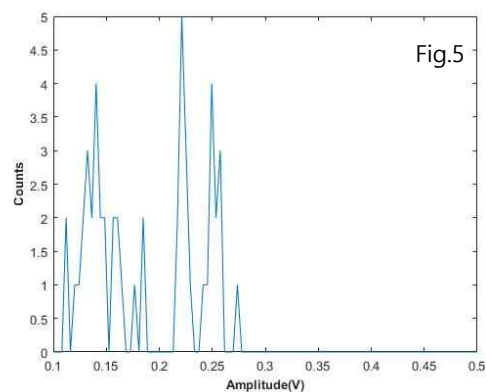


Experimental Data

- Cesium histogram (each data size)

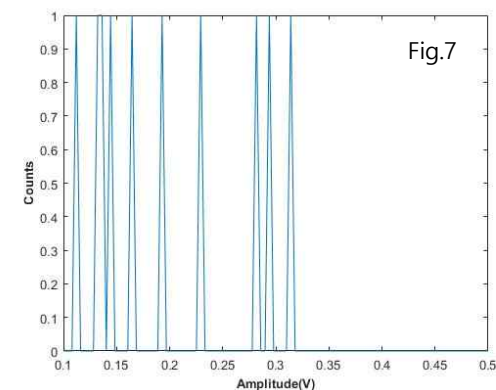
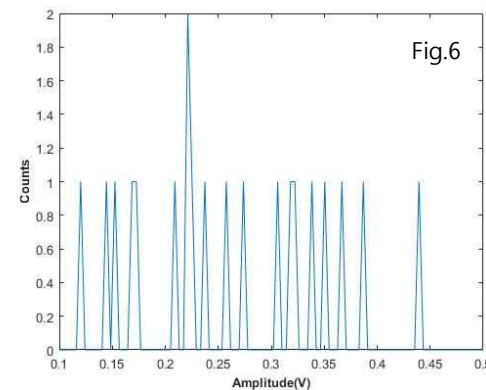
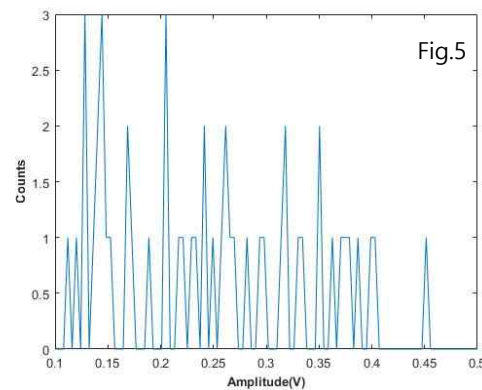
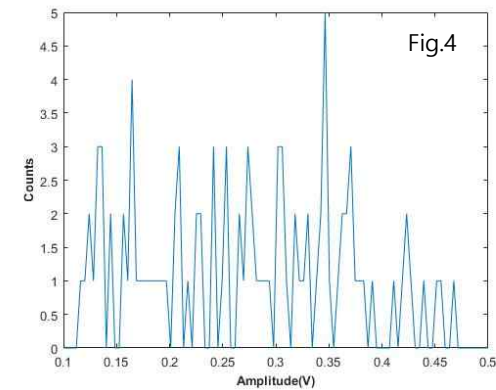
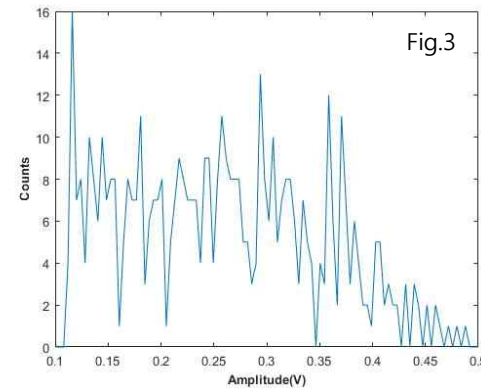
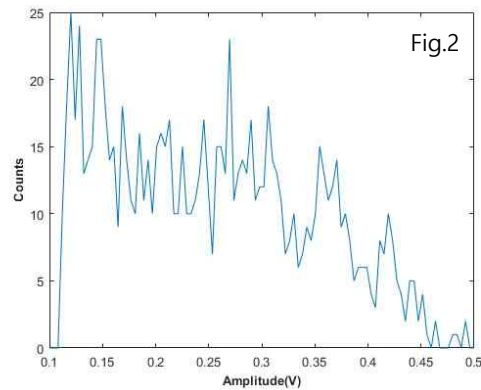
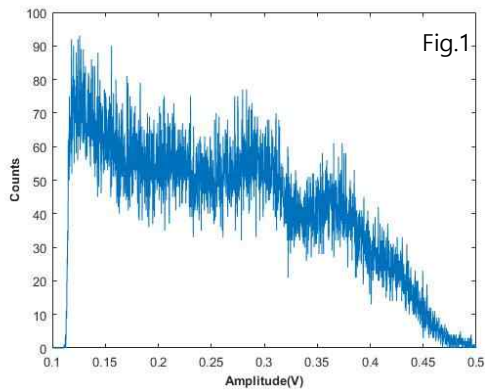


Source; Cs-137
Class number; 1
Data size; Fig.1(10 만),
Fig. 2(1000), Fig.
3(500)
Fig. 4(100), Fig. 5(50),
Fig. 5(20), Fig. 6(10).



Experimental Data

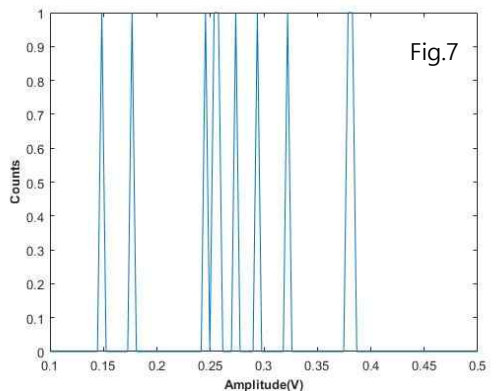
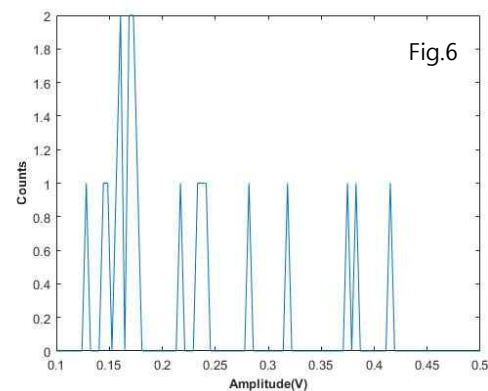
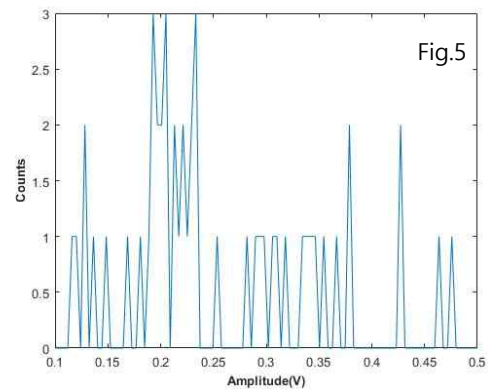
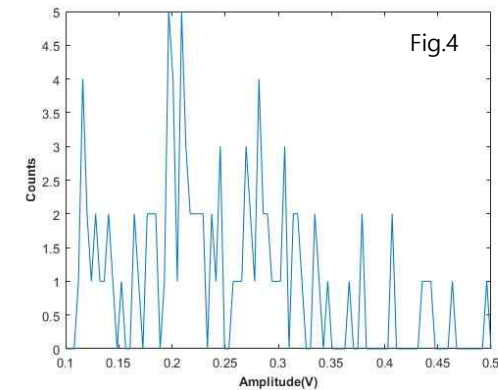
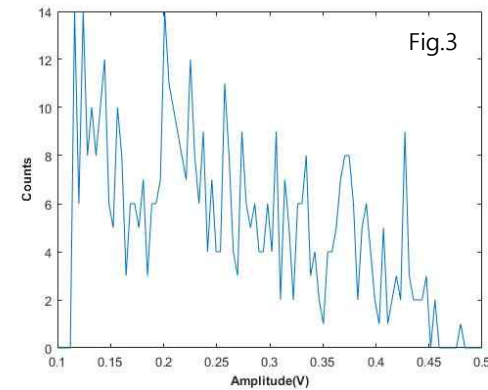
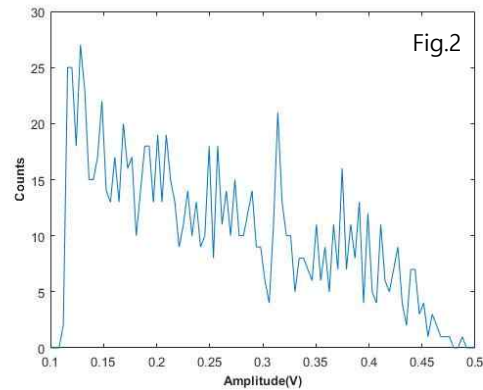
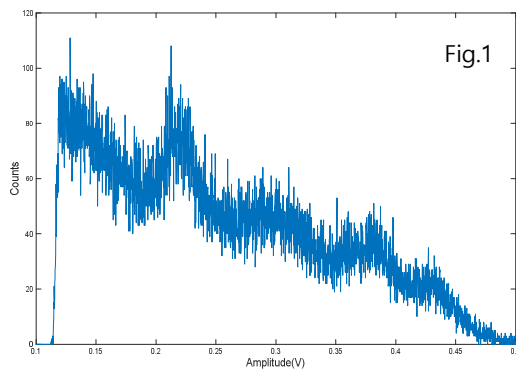
- Cobalt histogram (each data size)



Source; Co-60
Class number; 2
Data size; Fig.1(10 만),
Fig. 2(1000), Fig.
3(500)
Fig. 4(100), Fig. 5(50),
Fig. 5(20), Fig. 6(10).

Experimental Data

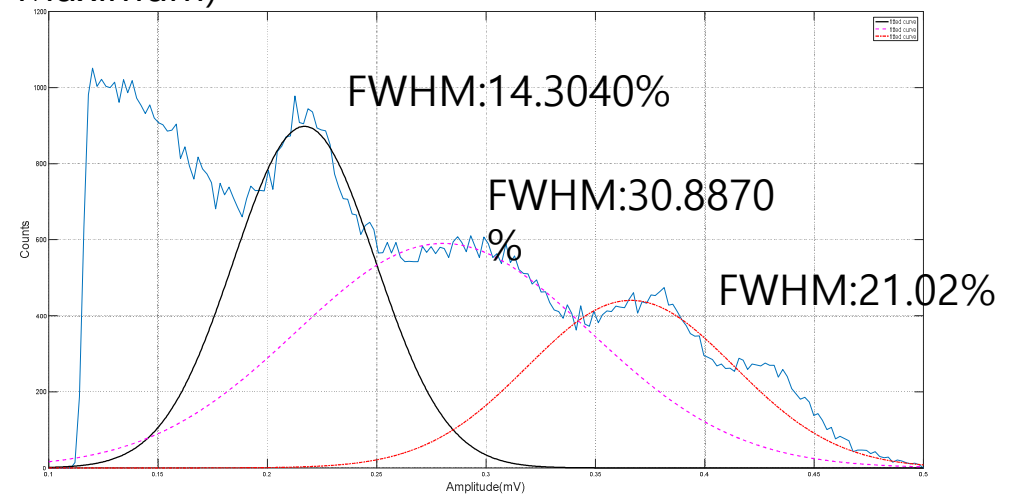
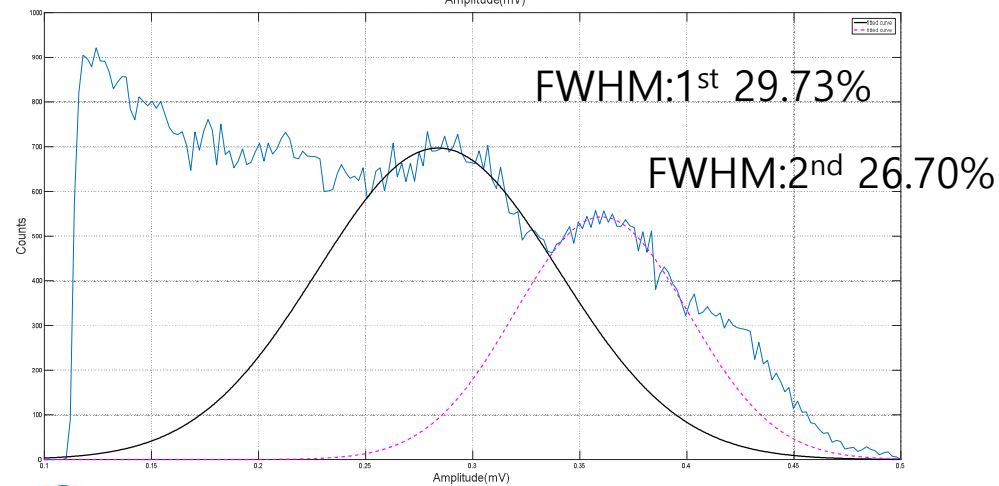
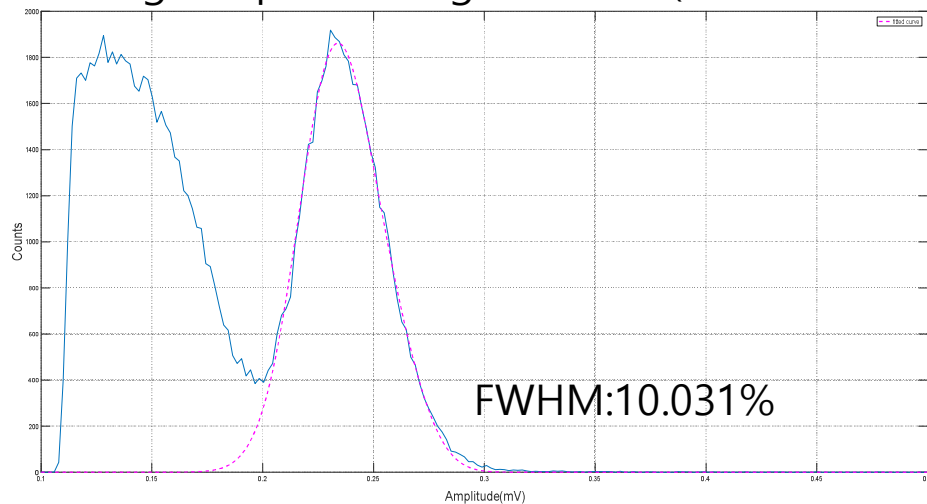
- Complexed source histogram (each data size)



Source; Cs-137+Co-60
Class number; 3
Data size; Fig.1(10 만),
Fig. 2(1000), Fig.
3(500)
Fig. 4(100), Fig. 5(50),
Fig. 5(20), Fig. 6(10).

Experimental Data

- Histogram peak fitting & FWHM(Full Width at Half Maximum)



► Source peak energy

conventional
Cs-137 : 662KeV gamma ray
Co-60 : 1st 1173 KeV, 2nd 1332KeV

► Peak Fitting

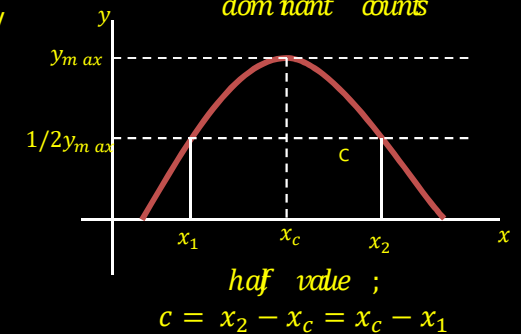
Lorentz Eq. :

$$y = (1/\delta\sqrt{2\pi}) * \exp\left(-\frac{(x-x_c)^2}{2\delta^2}\right)$$

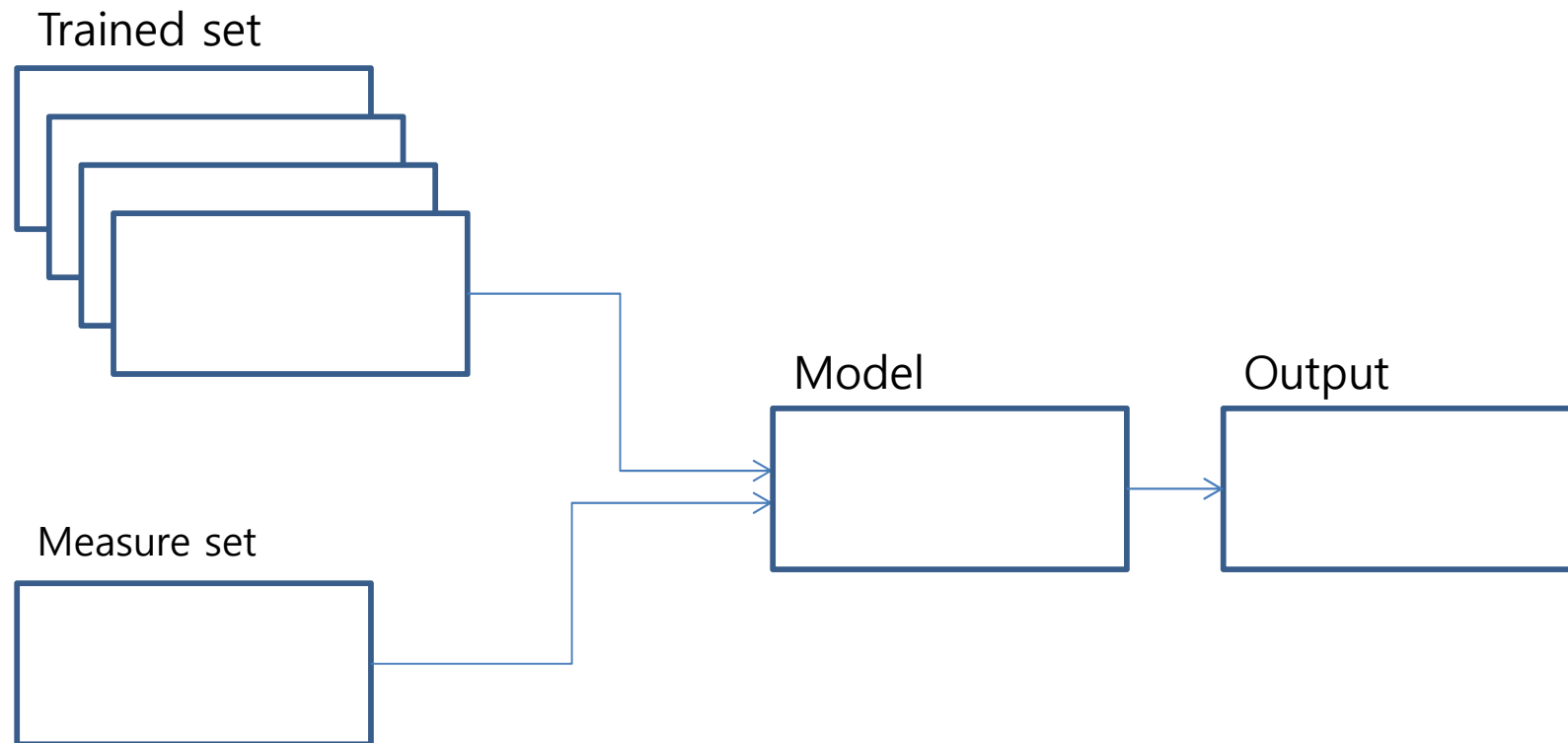
FWHM:

$$2c\sqrt{2\ln 2} = 2.35$$

$$C \propto \frac{1}{\text{dominant counts}}$$

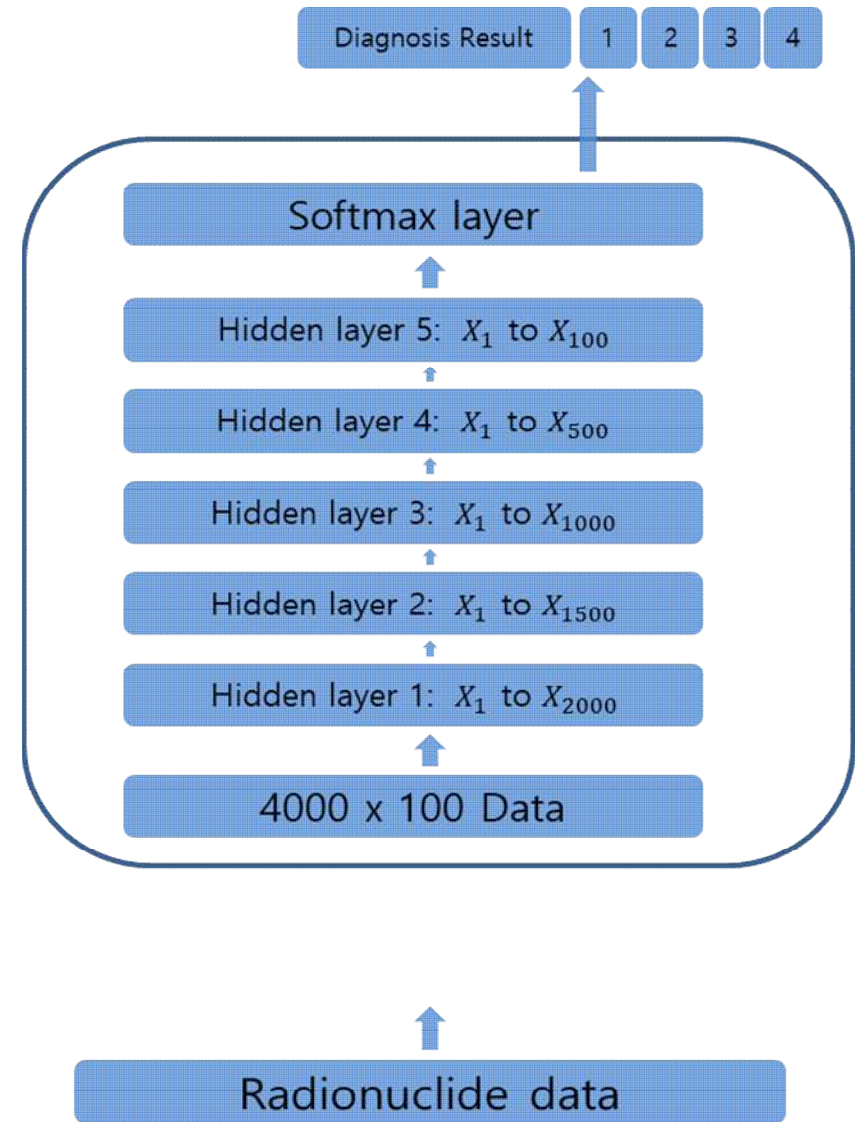


알고리즘



모델 구성

- 4 Hidden layers
- INPUT & Hidden layers >> Relu 함수
- OUTPUT layer는 Softmax 함수를 통해 4개의 결과를 확률로 출력



모델 컴파일

오차함수, 최적화함수, metrics 함수 적용

오차함수(loss)

-> class로 나누기 때문에 교차 엔트로피 계열의 범주형 교차 엔트로피 적용 (categorical_crossentropy)

최적화함수(optimizer)

-> adam

-> 현재 가장 많이 사용되는 고급 경사 하강법...

Metrics 함수

-> 정확도를 측정하기 위해 사용되는 테스트 샘플을 학습 과정에서 제외시킴으로써 과적합 문제(overfitting)을 방지하는 기능

☞ overfitting : 특정 데이터에서는 잘 작동하나 다른 데이터에서는 잘 작동하지 않는 문제

추가 적용

Early_stopping_callback 함수

-> epoch로 모델을 계속 업데이트할 때 더 이상 나아지지 않을 때 중단 기능

ModelCheckpoint 함수

-> 콜백함수로 모델이 더 이상 나아지지 않을 때의 모델을 체크포인트로 기억하여 해당 모델을 저장할 수 있음.

K 겹 교차 인증

-> 훈련데이터 셋과 계속 업데이트되는 테스트 셋을 섞어 늘려 정확도를 높일 수 있음

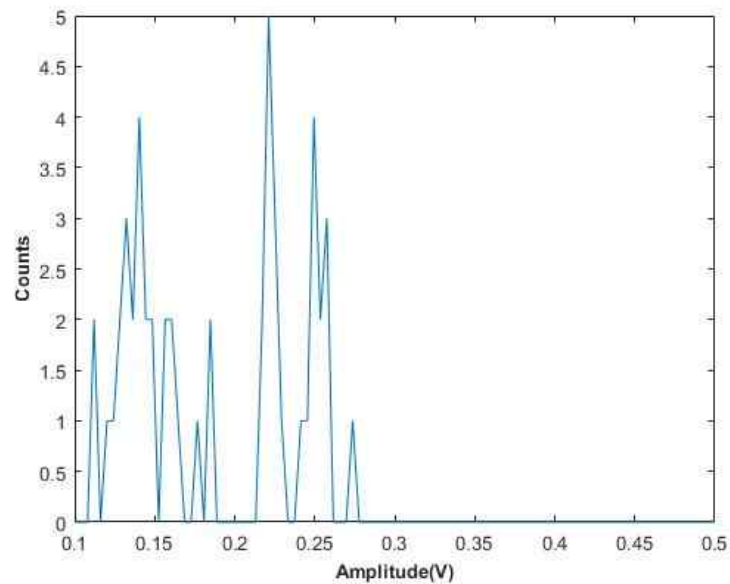
→ Voting 시스템 적용 가능

데이터 전처리 부분에서

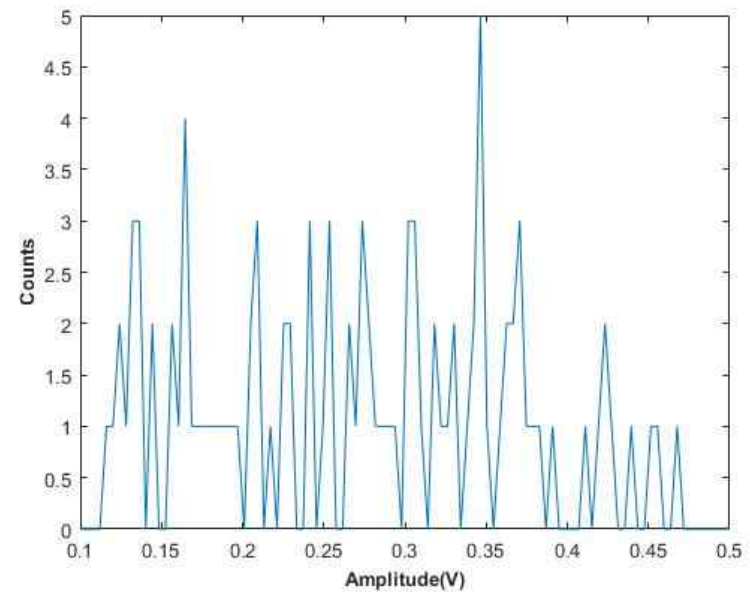
기존 알고리즘과 차별화 할 수 있는 부분 적용 고민.

Low Accuracy

Below 80%

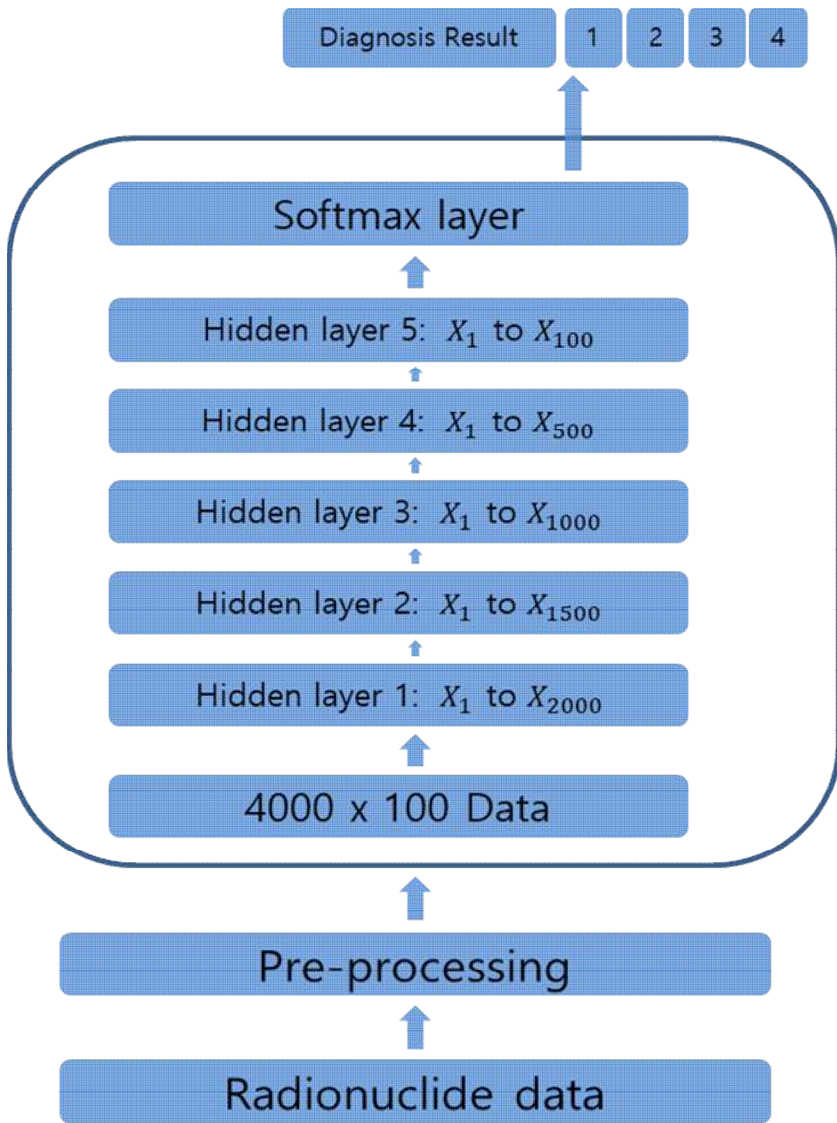


Cesium

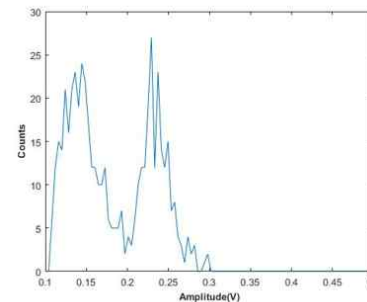


Cobalt

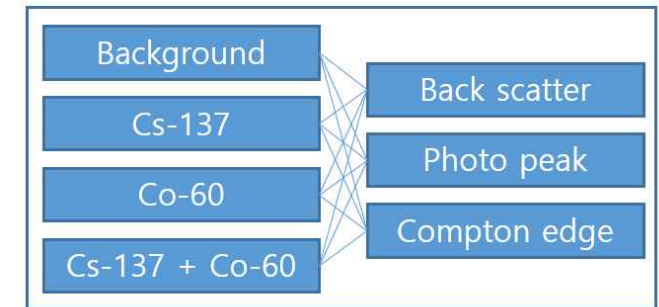
모델 구성



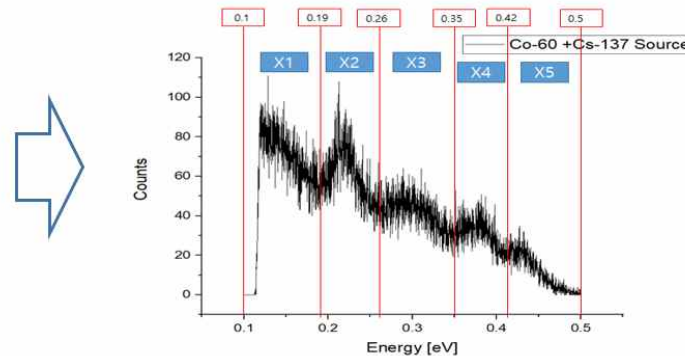
Raw data



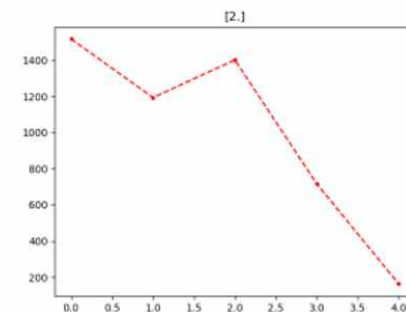
Pre-processing



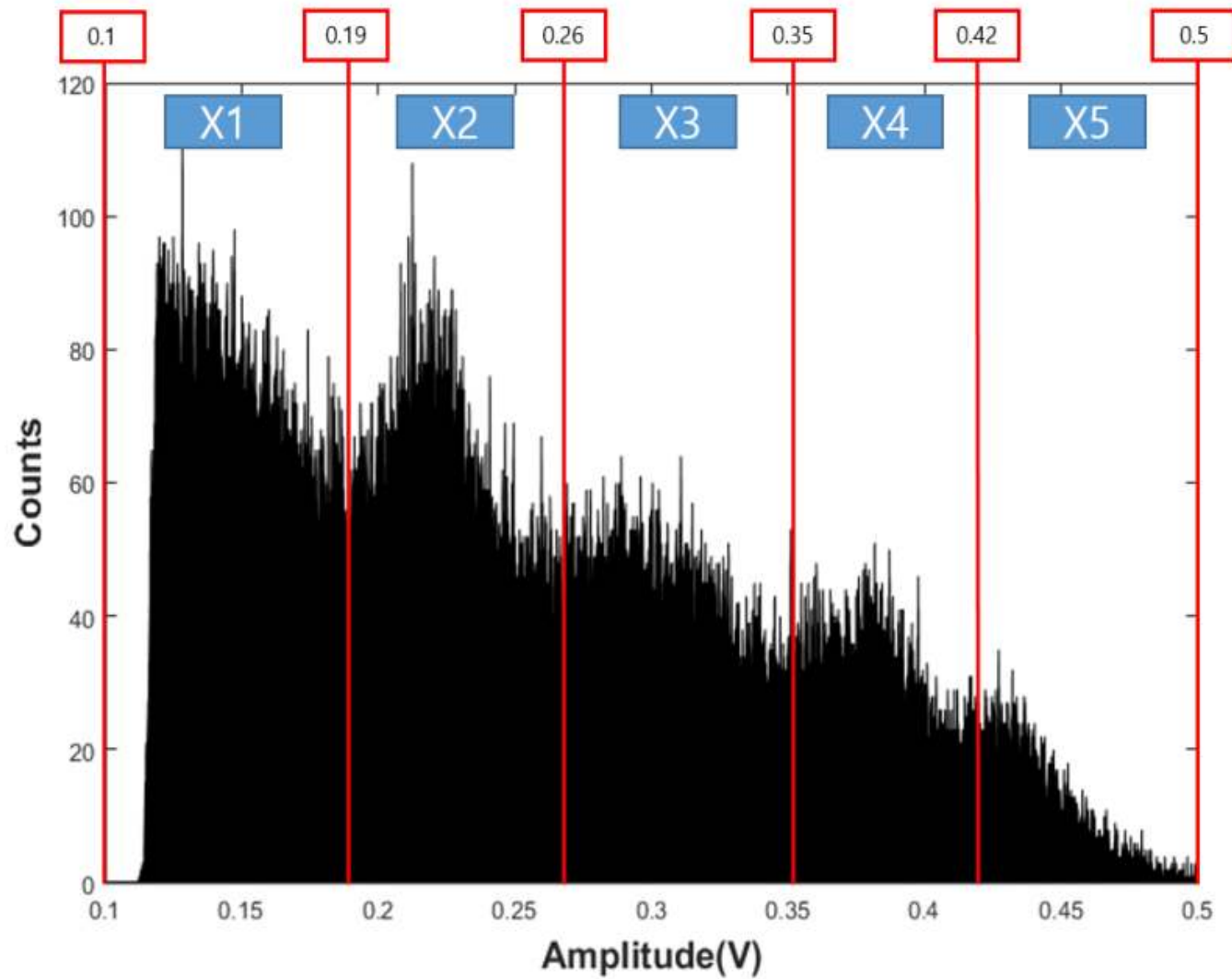
Data Integration

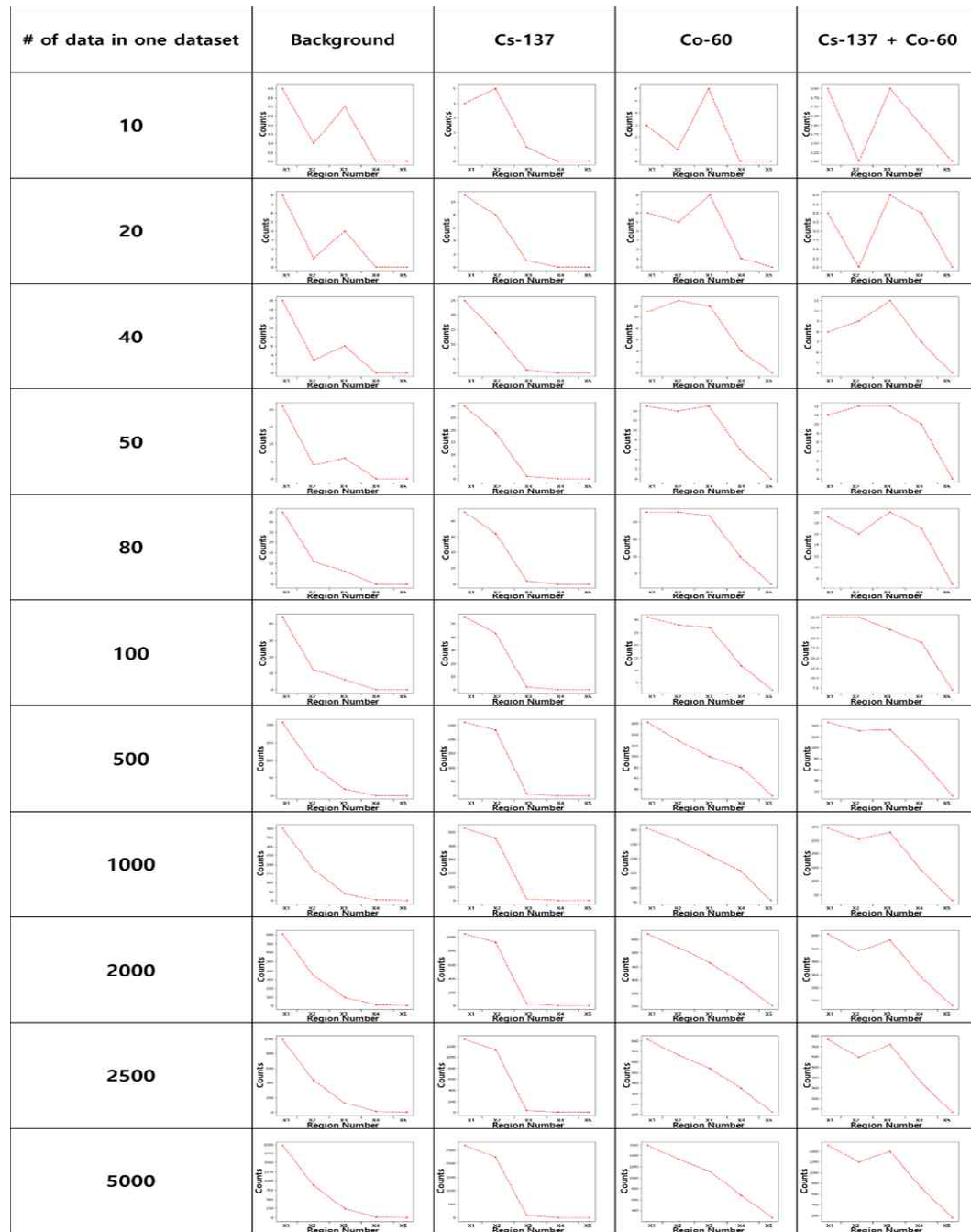
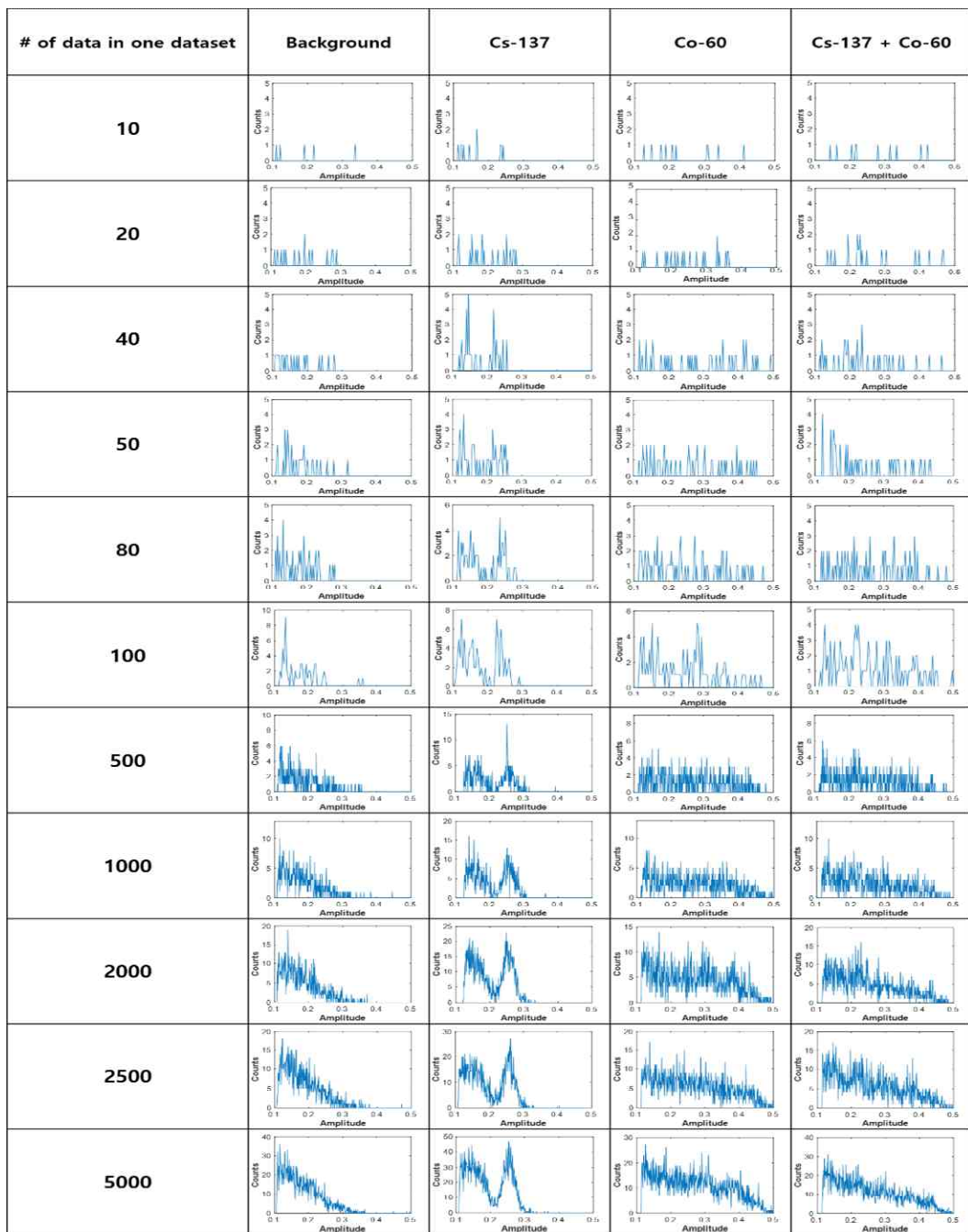


Processed data



데이터 전처리





작성 코드

```
1 from keras.models import Sequential
2 from keras.layers import Dense
3
4 import tensorflow as tf
5 import numpy as np
6 import matplotlib.pyplot as plt
7 import pandas as pd
8 import os
9
10 from sklearn.model_selection import train_test_split
11 print(tf.__version__)
12
13 #데이터셋 로드
14 df = pd.read_csv('/home/kaeri/PycharmProjects/sds/venv/bin/sds/dataset/testq_5.csv', delimiter=',')
15 dataset = df.values
16 #print(data set head())
17
18 #데이터를 X와 Y로 구분하여 저장 Attribute 0~17(X), class 18(Y)
19 X = dataset[:,0:18]
20 Y = dataset[:,18]
21
22 plt.hist(X, bins=10, density=True)
23 plt.show()
24
25 #랜덤 시드
26 seed = 0
27 np.random.seed(seed)
28 tf.set_random_seed(seed)
29
30 #합성곱과 풀링층의 구성
31 #X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.3, random_state=seed)
32
33 #모델링 구조 결정(모델 설정 and 실행)
34 model = Sequential()
35 model.add(Dense(10, input_dim=18, activation='relu')) #activation : 다음층으로 어떻게 값을 넘길지 결정(relu와 sigmoid를 가진 편이 좋음(활성화 함수))
36 model.add(Dense(1, activation='sigmoid'))
37
38 #모델 컴파일
39 model.compile(loss='mean_squared_error', optimizer='adam', metrics=['accuracy']) #loss
40 #최적화 알고리즘은 손실 값에 로그를 취해 오차가 커지면 수렴 속도가 빨라지고 오차가 작아지면 속도가 감소
41 #메트릭스 함수는 정확도를 측정하기 위해 테스트 샘플을 학습 과정에서 제외시킴으로써 과적합 문제를 방지하는 기능을 담고 있음.
42 #메트릭스 함수: 최적화 함수
43 metrics=['accuracy']
44
45 #모델 학습
46 model.fit(X, Y, epochs=30, batch_size=10)
47 #model.fit(X_train, Y_train, epochs=10, batch_size=5)
48
49 print("\n Accuracy: %.4f" % (model.evaluate(X,Y)[1]))
```

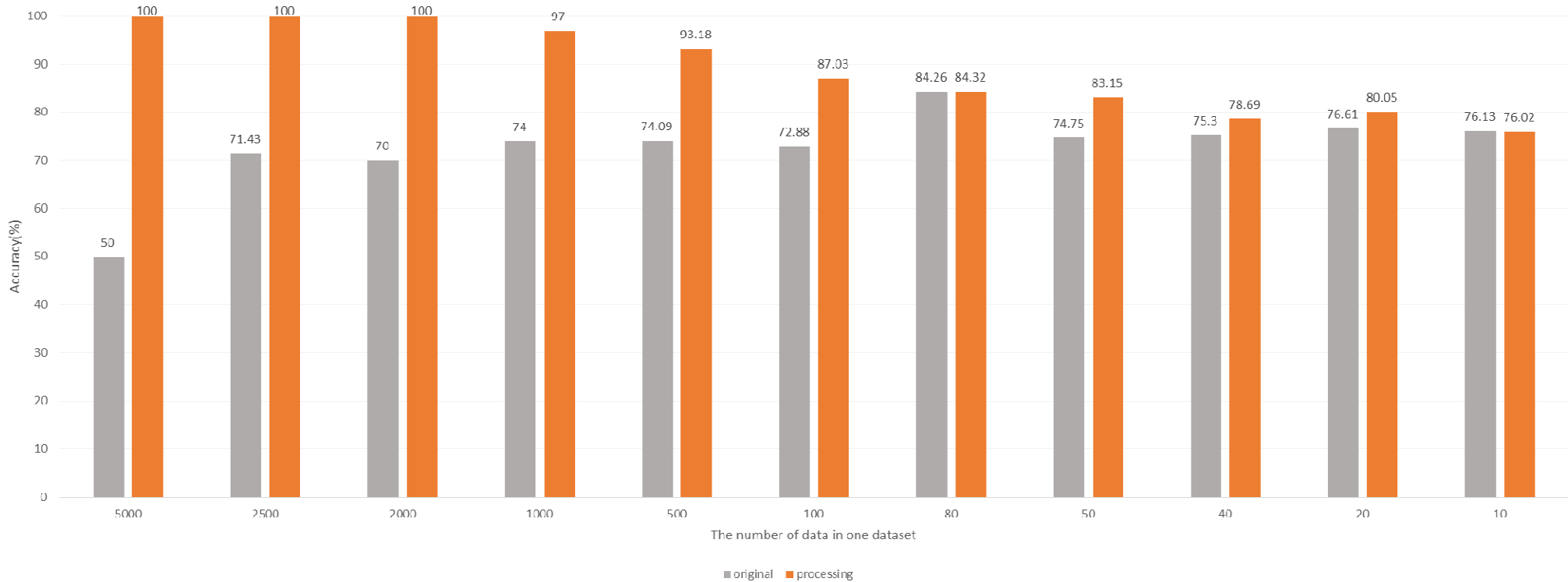
Trained dataset 구성:
Attribute(X)와 class(Y)로 분류

Measure dataset 구성:
현재 랜덤 시드로 구성

모델 구성: 1 layer는 relu, 2 layer는
softmax 활성화 함수로 구성

실행 파트: 오차 값 추적 함수, 최적화
함수, 매트릭스 함수

Result



In the international standard of ANSI N42.34, the true positive identification accuracy should be over 80% for radionuclide identification devices.

ANSI, American National Standard Performance Criteria for Hand-Held Instruments for the Detection and Identification of Radionuclides, vol. N42.34, 2006.

Conclusion & Future Work

- 핵종판별을 위한 데이터 수 (10만 >> 50) 2000배 감소
계측시간 (60분>> 1.8초 + 7초)
- 상용 계측기 및 신호처리 장비 활용
 - >> 실 계측 데이터 활용, 알고리즘 검증
 - >> 계측 후 후처리가 아닌 실시간 데이터 누적 구현
 - >> 알고리즘을 adaptive software 로 구현, 범용성 입증
 - >> 판별 가능 핵종 수 증가 가능 (단 peak energy 달라야함)

I. Kwon, D. Shin, J. Oh, C. -H. Kim and H. Kim, "Preprocessing Energy Intervals on Spectrum for Real-Time Radionuclide Identification," in *IEEE Transactions on Nuclear Science*, vol. 68, no. 8, pp. 2202-2209, Aug. 2021, doi: 10.1109/TNS.2021.3097389.



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