딥러닝 스터디

과제 – 와인

20223114 서예은

CONTENTS

1. 개요
2. 신경망 구성
3. 코드 리뷰
4. 결과

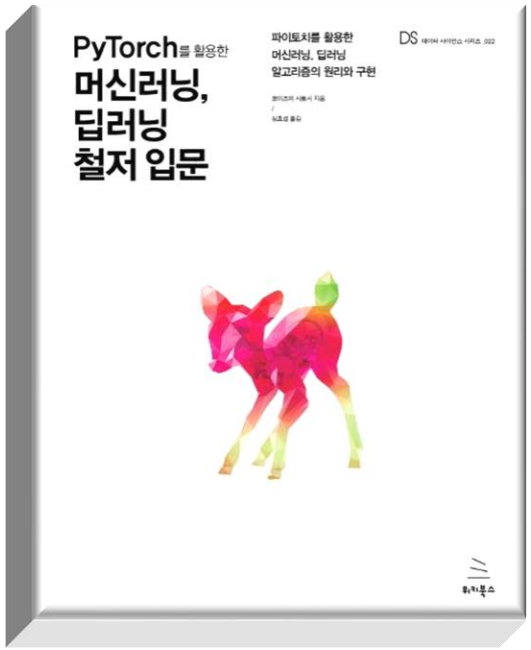
1. 개요

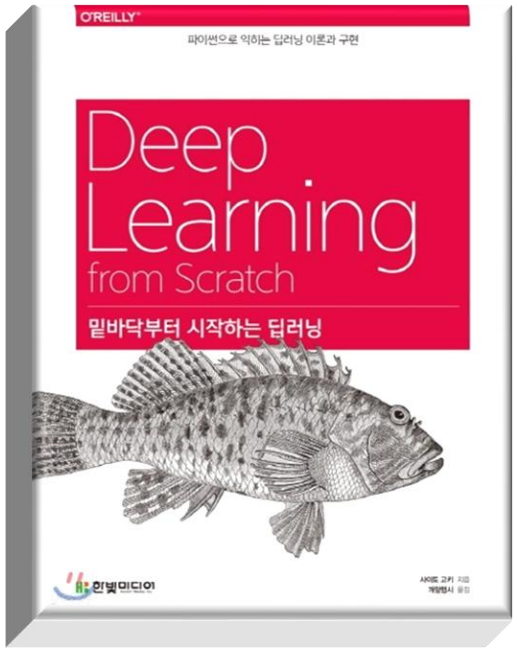
참고 문헌

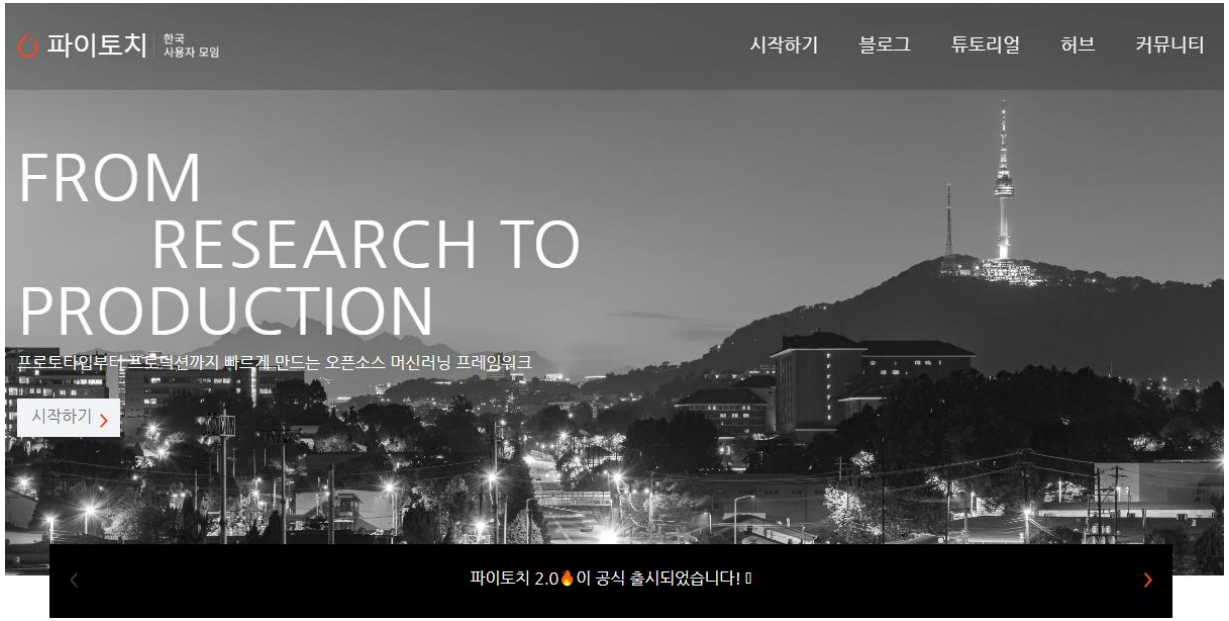
1. PyTorch를 활용한 머신러닝, 딥러닝 철저 입문
2. 밑바닥부터 시작하는 딥러닝

참고 사이트

- 파이토치 공식 사이트







1. 개요

라이브러리

1. Pytorch
   - **신경망 구축**에 사용되는 소프트웨어 기반 오픈소스 러닝 프레임워크
2. Pandas
   - **데이터 처리**와 **분석**을 위한 라이브러리
3. Numpy
   - 대규모 **다차원 배열과 행렬** 연산에 필요한 다양한 함수와 메소드를 제공하는 라이브러리
4. Mataplotlib
   - **데이터 시각화**와 2D 그래프 플롯에 사용되는 라이브러리
5. Sklearn
   - **머신러닝 분석**할 때 유용하게 사용할 수 있는 라이브러리

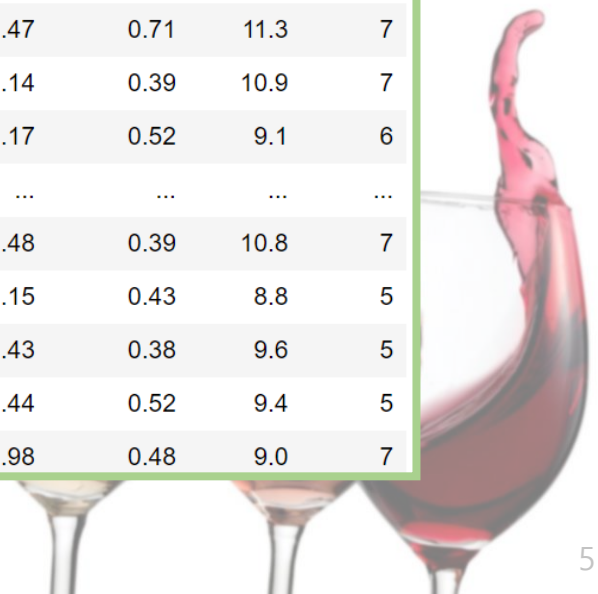
1. 개요

와인 데이터

- 설명 변수 : 레드 와인, 화이트 와인 (0,1)
- 목적 변수 : 총 12 가지의 와인 성분

	label	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	0	4.6	0.52	0.15	2.1	0.054	8.0	65.0	0.99340	3.90	0.56	13.1	4
1	1	6.2	0.25	0.25	1.4	0.030	35.0	105.0	0.99120	3.30	0.44	11.1	7
2	0	6.4	0.57	0.12	2.3	0.120	25.0	36.0	0.99519	3.47	0.71	11.3	7
3	1	7.8	0.30	0.40	1.8	0.028	23.0	122.0	0.99140	3.14	0.39	10.9	7
4	1	7.1	0.25	0.32	10.3	0.041	66.0	272.0	0.99690	3.17	0.52	9.1	6
...	...	...	...	...	...	...	...	...	...	...	...	...	...
1995	1	5.0	0.17	0.56	1.5	0.026	24.0	115.0	0.99060	3.48	0.39	10.8	7
1996	1	6.4	0.21	0.50	11.6	0.042	45.0	153.0	0.99720	3.15	0.43	8.8	5
1997	1	7.3	0.25	0.29	7.5	0.049	38.0	158.0	0.99650	3.43	0.38	9.6	5
1998	0	7.2	0.41	0.30	2.1	0.083	35.0	72.0	0.99700	3.44	0.52	9.4	5
1999	1	7.2	0.23	0.39	14.2	0.058	49.0	192.0	0.99790	2.98	0.48	9.0	7

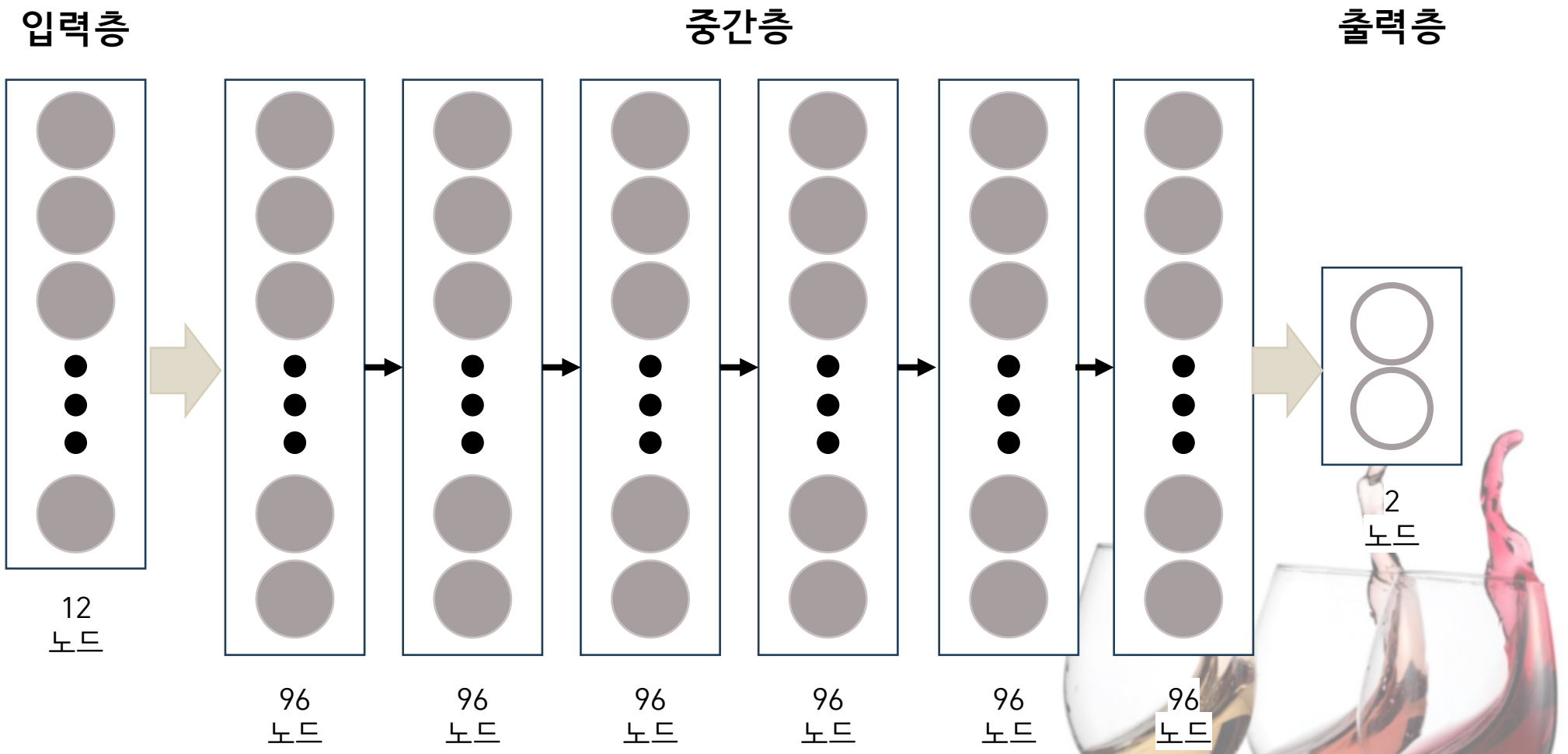
▲ Train Data



2. 신경망 구성

입력
(설명 변수)

fixed acidity
volatile acidity
citric acid
residual sugar
chlorides
free sulfur dioxide
total sulfur dioxide
density
pH
Sulphates
alcohol
quality



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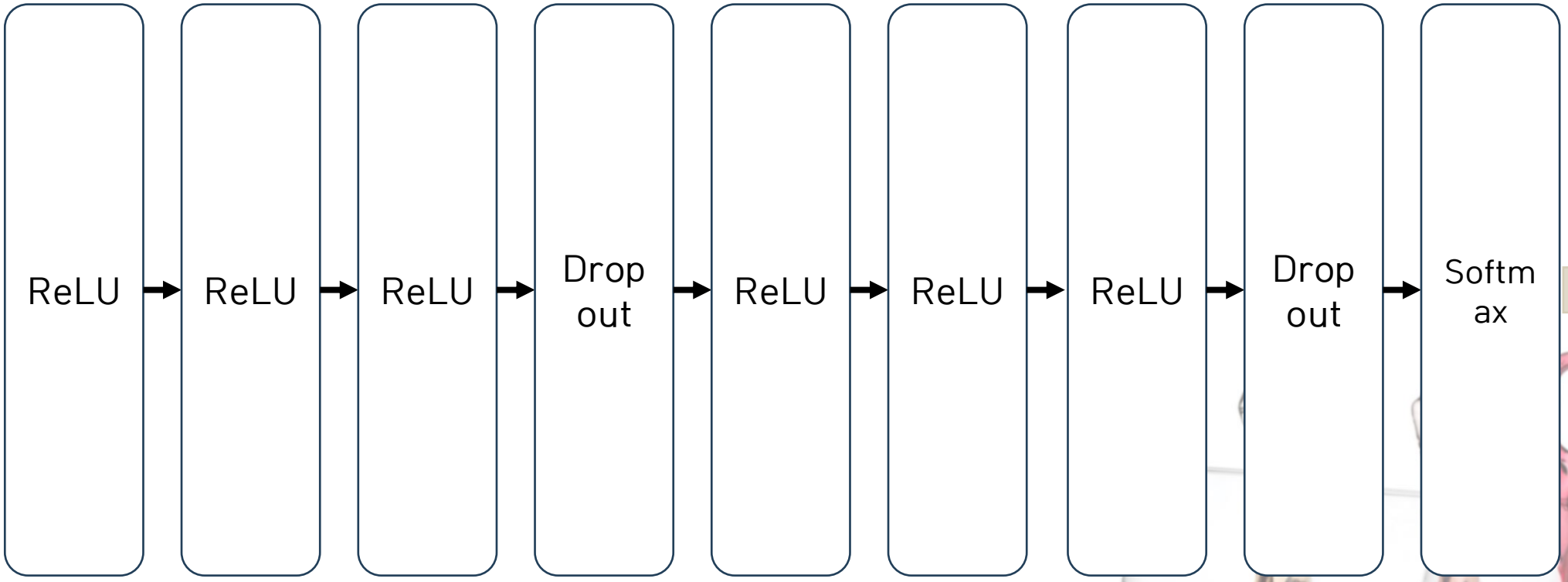


3. 코드 리뷰

```
train_df = pd.read_csv('train.csv')
train_df = pd.DataFrame(train_df)

wine_target =train_df['label']
df_attr = train_df.drop(['label'],axis=1)

wine_data = df_attr[0:2000]
wine_target = wine_target[0:2000]
#Splitting
x_train, x_test, y_train, y_test = train_test_split(wine_data, wine_target,test_size=0.2)

#Numpy
x_train = np.array(x_train).astype(np.float32)
y_train = np.array(y_train).astype(np.longlong)
x_test = np.array(x_test).astype(np.float32)
y_test = np.array(y_test).astype(np.longlong)
#Tensor
x_train = torch.from_numpy(x_train).float()
y_train = torch.from_numpy(y_train).long()
x_test = torch.from_numpy(x_test).float()
y_test = torch.from_numpy(y_test).long()

train = TensorDataset(x_train, y_train)
train_loader = DataLoader(train, batch_size = 16, shuffle=True)
```

훈련 데이터를 가져와 분류

훈련/ 테스트 데이터로 분할

파이토치로 다루기 위해
텐서로 변환(넘파이 -> 텐서)

설명 변수와 목적 변수의 텐서를 합침

3. 코드 리뷰

```python
class Net(nn.Module):

    def __init__(self):
        super(Net,self).__init__()
        self.fc1 = nn.Linear(12,96)
        self.fc2 = nn.Linear(96,96)
        self.fc3 = nn.Linear(96,96)
        self.fc4 = nn.Linear(96,96)
        self.fc5 = nn.Linear(96,96)
        self.fc6 = nn.Linear(96,96)
        self.dropout = nn.Dropout(0.25)
        self.fc10 = nn.Linear(96,2)

    def forward(self, x):
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = F.relu(self.fc3(x))
        x = (self.dropout(x))
        x = F.relu(self.fc4(x))
        x = F.relu(self.fc5(x))
        x = F.relu(self.fc6(x))
        x = (self.dropout(x))
        x = self.fc10(x)
        return F.log_softmax(x, dim=1)
```

6개의 은닉층,
2개의 출력을 가진 출력층 구성

드롭아웃 으로 과적합을 방지

파이토치 함수를 사용하여
활성화 함수로 ReLu 함수,
SoftMax 함수로
클래스 확률 출력

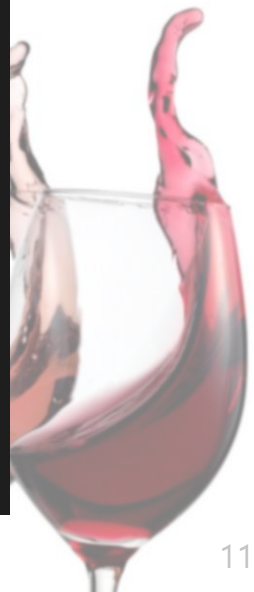
3. 코드 리뷰

```
    def predict(self, x):
        with torch.no_grad():
            x = self.forward(x)
        return x

    def accuracy(self, x, t):
        y = self.predict(x)
        y = torch.argmax(y, dim=1)
        if t.ndim ≠ 1:
            t = torch.argmax(t, dim=1)
        accuracy = torch.sum(y == t).item() / float(x.shape[0])
        return accuracy
```

정확도 측정

3. 코드 리뷰

```
model = Net()
criterion = nn.CrossEntropyLoss() CrossEntropLoss로 오차를 계산
optimizer = torch.optim.Adam(model.parameters(), lr=1e-4, weight_decay=1e-5)
                                  Adam을 적용해 가중치를 최적화

loss_list = []
train_acc_list = []
test_acc_list = []
loss_avg = []

for epoch in range(200):
    total_loss = 0
    for x_train, y_train in train_loader:

        optimizer.zero_grad()경사 초기화
        output = model(x_train)
        loss = criterion(output, y_train) 오차 계산
        loss.backward()
        optimizer.step()가중치 업데이트
        total_loss += loss.item()
```



3. 코드 리뷰

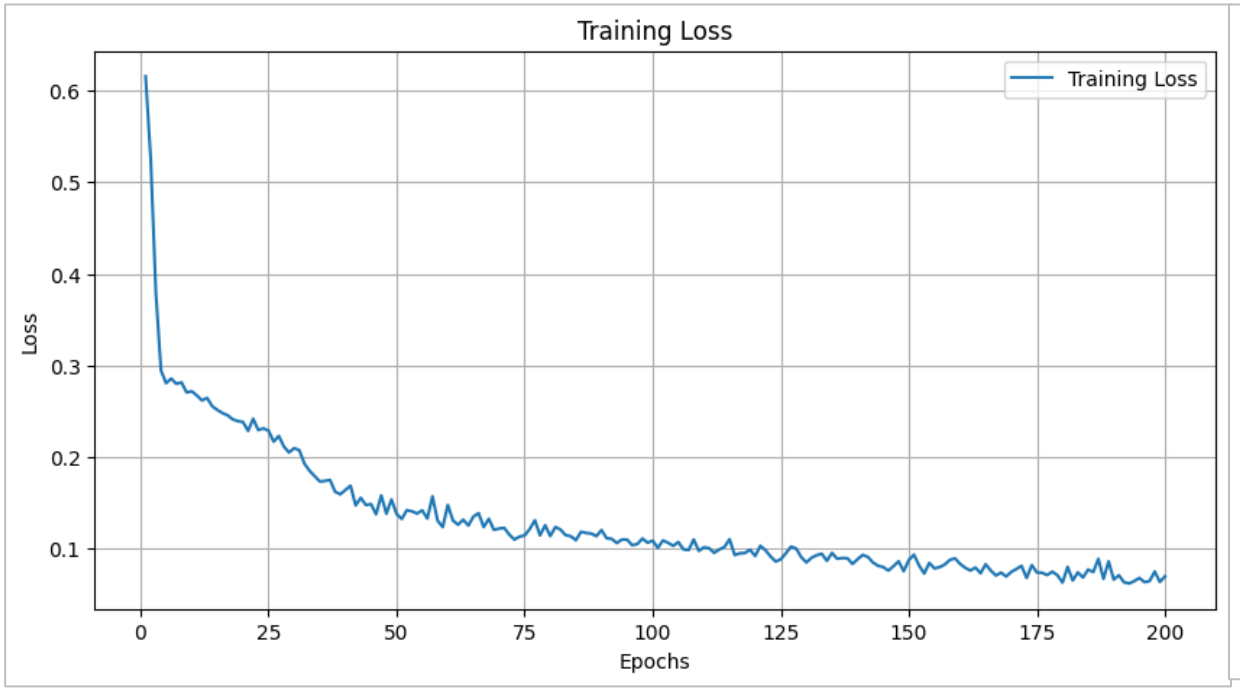
```python
for epoch in range(200):
    for x_train, y_train in train_loader:
        ...
    epoch_loss = total_loss / len(train_loader)
    loss_avg.append(epoch_loss)
    if epoch % 10 ==0:
        print("==========================================")
    print("Epoch: {}, Loss: {:.4f}".format(epoch, total_loss / len(train_loader)))

    train_acc = model.accuracy(x_train, y_train)
    test_acc = model.accuracy(x_test, y_test)
    train_acc_list.append(train_acc)
    test_acc_list.append(test_acc)
    print("train acc:" + str(train_acc) + ", test acc:" + str(test_acc))
```

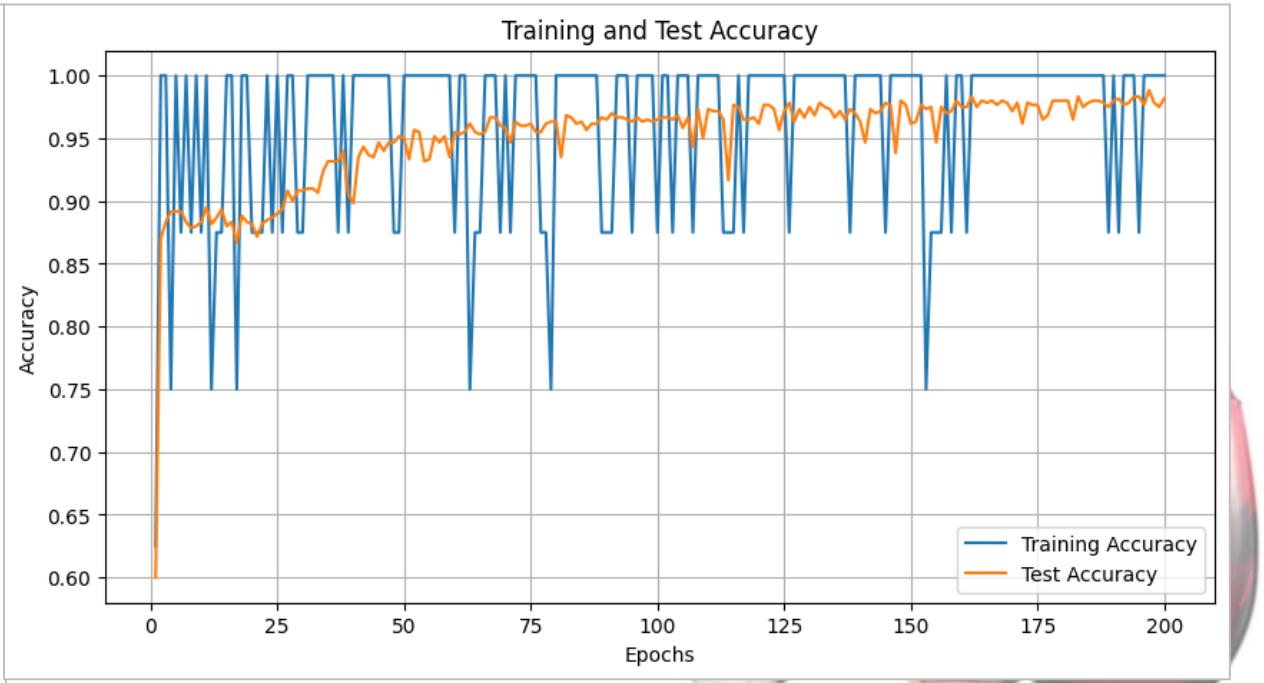
에폭별 평균 손실 계산

에폭별 정확도 계산

4. 결과

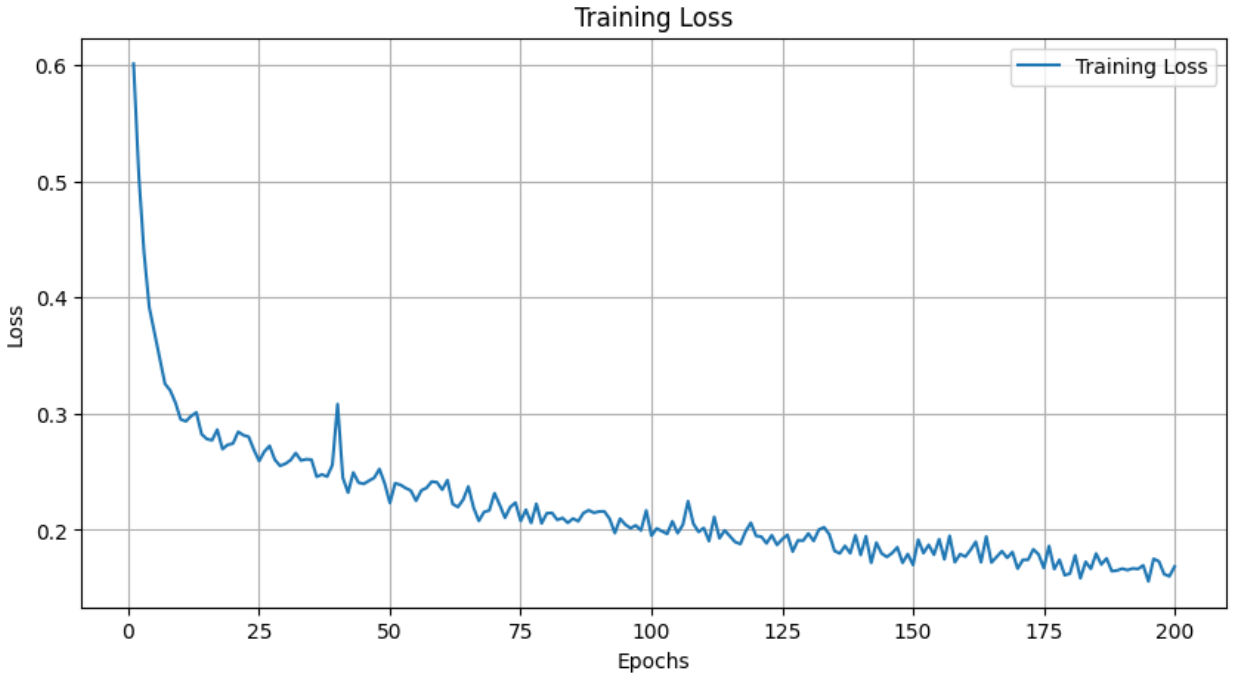
- Accuracy : 약 96.83%
- Adam
- ReLU 3 + Dropout + ReLU 3 + Dropout + Softmax

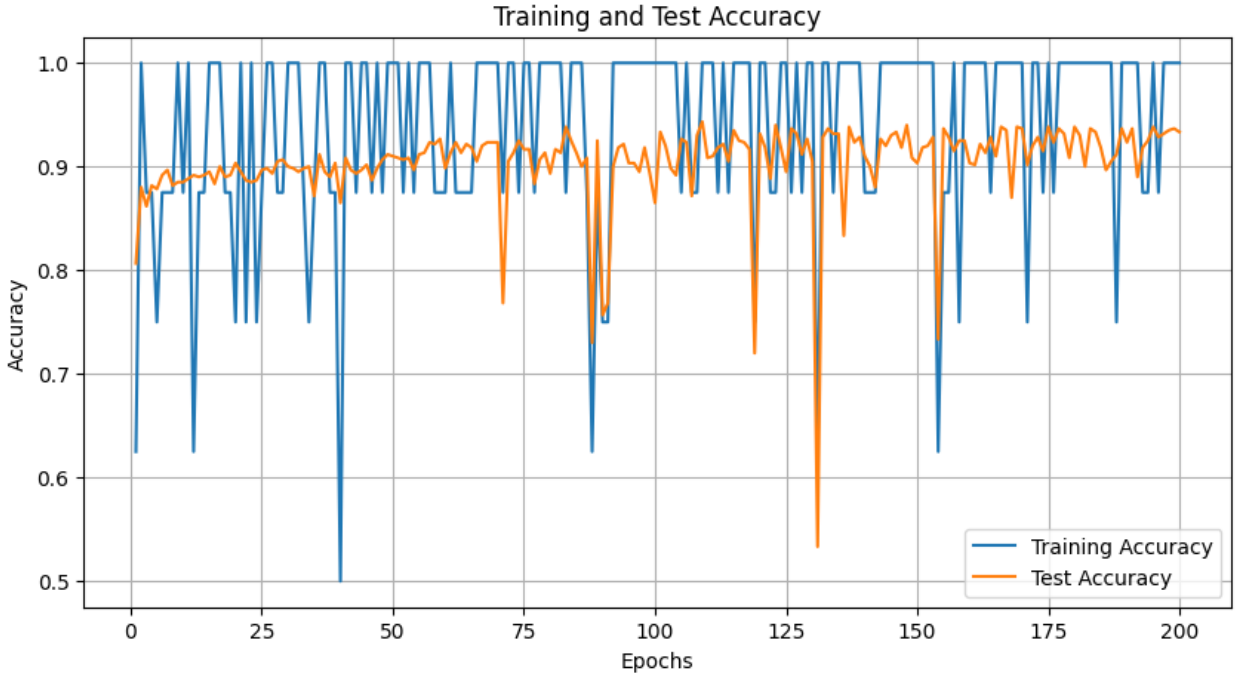




4. 결과

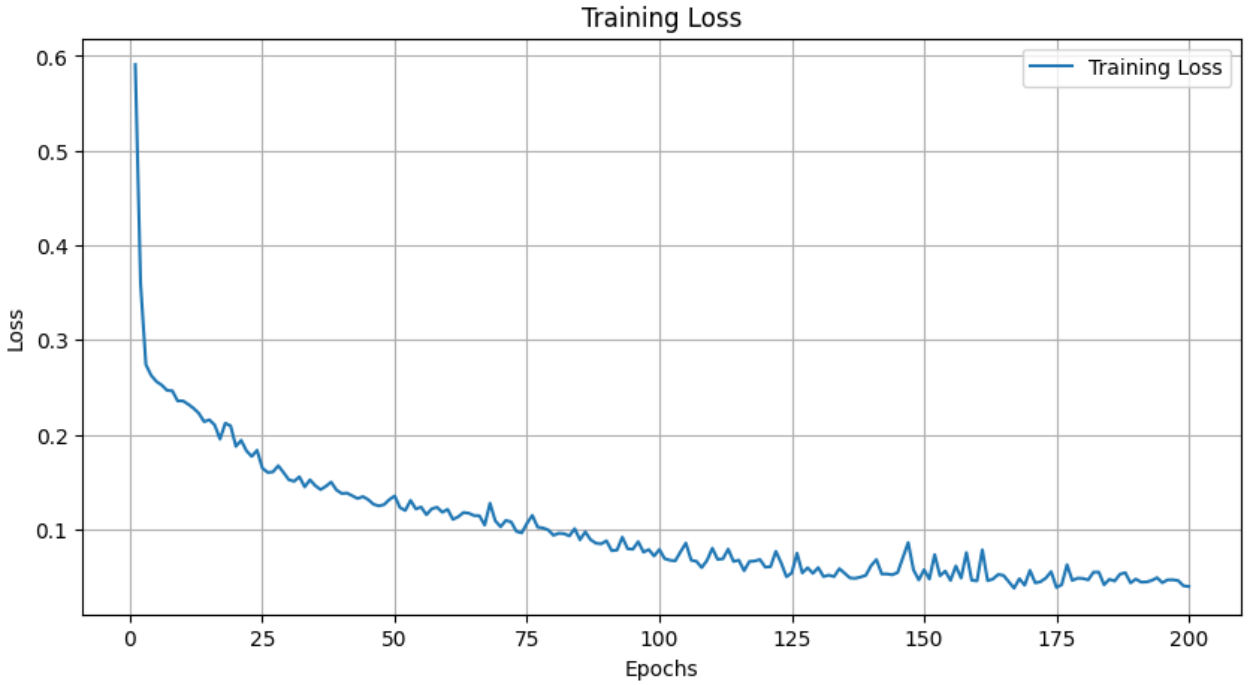
- Accuracy : 약 93.83%
- SGD
- ReLU 3 + Dropout + ReLU 3 + Dropout+ Softmax

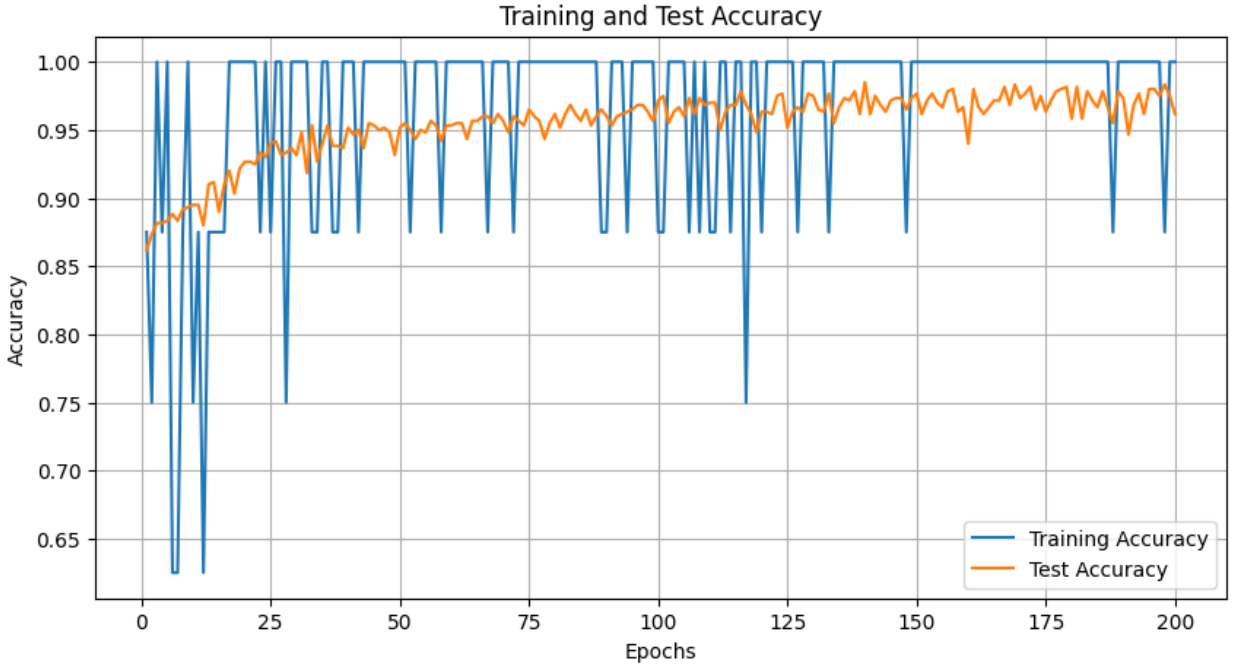




4. 결과

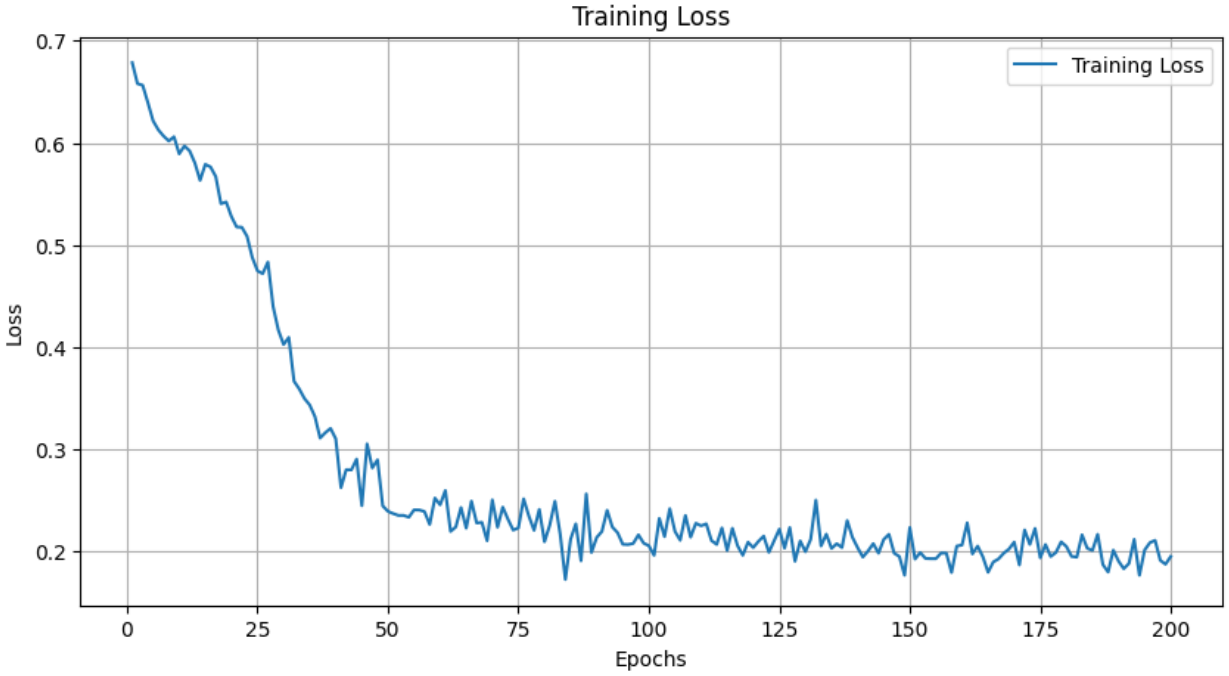
- Accuracy : 약 96.16%
- Adam
- ReLU 6 + Softmax

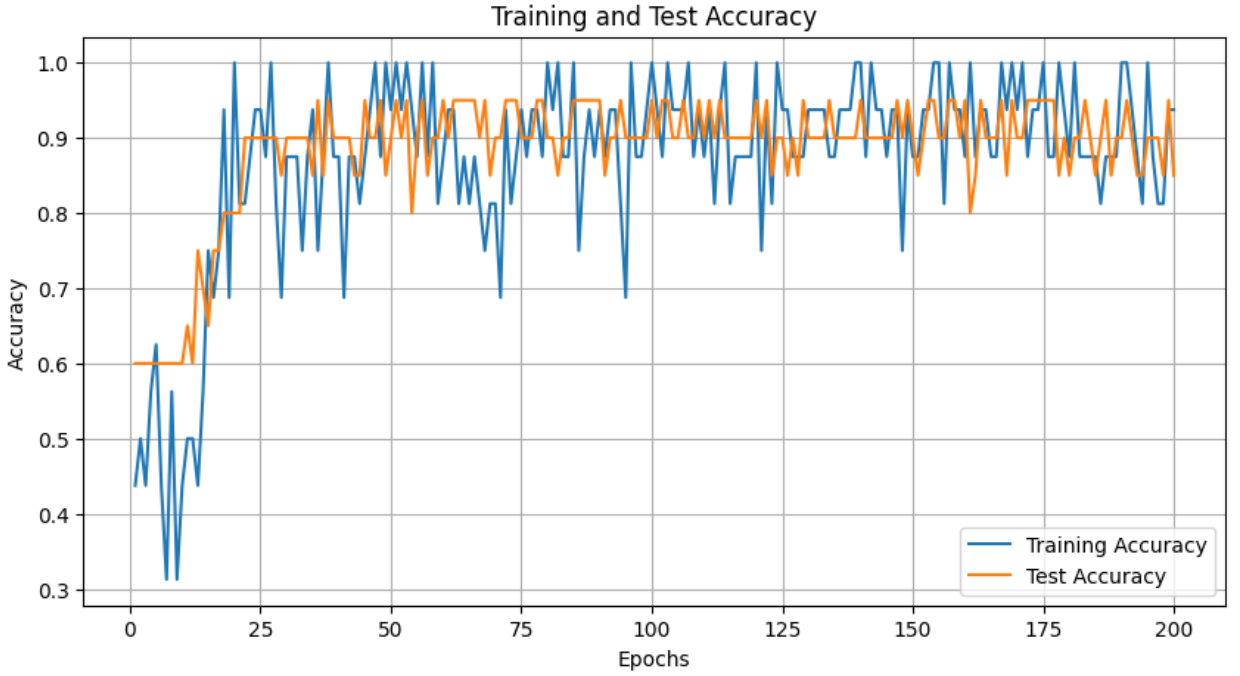




4. 결과 – 추가 데이터

- Accuracy : 약 90%
- Adam
- ReLU 3 + Dropout + ReLU 3 + Softmax





THANK YOU!