FinalProject_RNN

December 4, 2021

1 CS 634 Final Term Project Implentation

Option - II: Deep Learning

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Github: https://github.com/srd22-njit/CS634_Final

1.1 Import the important libraries

[15]:
```
# For the Nueral Network
import torch
import torchvision
import torch.nn as nn
import torch.optim as optim
import torch.nn.functional as F
from torch.utils.data import DataLoader, ConcatDataset
import torchvision.datasets as datasets
import torchvision.transforms as transforms

# For the operations
import pickle
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import KFold
```

1.2 Enable GPU

Enable GPU for faster training

[ ]:
```
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
device
```

[ ]:
```
device(type='cuda')
```

1.3 Hyperparameters

Define our hyperparameters for the NN

[ ]:
```
input_size = 28
sequence_length = 28
num_layers = 2
hidden_size = 256
num_classes = 2
learning_rate = 0.001
batch_size = 64
num_epochs = 1
n_folds = 10
```

1.4 Load Dataset

- We first laod the inbuild MNIST dataset, and we devide the data into train & test by specifying `train=True` & `train=False`.
- We then extract images from both train & test data with labels as 0 or 1 (binary classification.)

[16]:
```
train_dataset = datasets.MNIST(root='./dataset/', train=True,␣
 ↪transform=transforms.ToTensor(), download =True)
test_dataset = datasets.MNIST(root='./dataset/', train=False,␣
 ↪transform=transforms.ToTensor(), download =True)

idx = (train_dataset.targets==0) | (train_dataset.targets==1)
train_dataset.targets = train_dataset.targets[idx]
train_dataset.data = train_dataset.data[idx]

idx = (test_dataset.targets==0) | (test_dataset.targets==1)
test_dataset.targets = test_dataset.targets[idx]
test_dataset.data = test_dataset.data[idx]
```

1.5 Dataset

Let's look into what the dataset looks like

[32]:
```
idx = 1
plt.title(f"Label: {test_dataset[idx][1]}")
plt.imshow(test_dataset[idx][0].reshape(28,28), cmap='gray')
print(test_dataset[idx][0].reshape(28,28))
```

```
tensor([[0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
         0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
         0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
         0.0000],
        [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
         0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
         0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
```

```
 0.0000],
[0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000],
[0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
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 0.0000],
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 0.0000],
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 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000],
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 0.0000],
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 0.2431, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000],
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 0.0000],
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 0.0000],
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 0.9843, 0.9843, 0.4118, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000],
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 0.4275, 0.9843, 0.9922, 0.9843, 0.1373, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000],
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 0.1216, 0.7843, 0.9922, 0.9843, 0.1373, 0.0000, 0.0000, 0.0000, 0.0000,
```

```
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 0.4275, 0.9843, 0.9922, 0.9843, 0.1373, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000],
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 0.0000],
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 0.9843, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.5647, 0.9843,
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 0.0000],
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 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
```

```
 0.0000],
[0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000],
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 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000]])
```
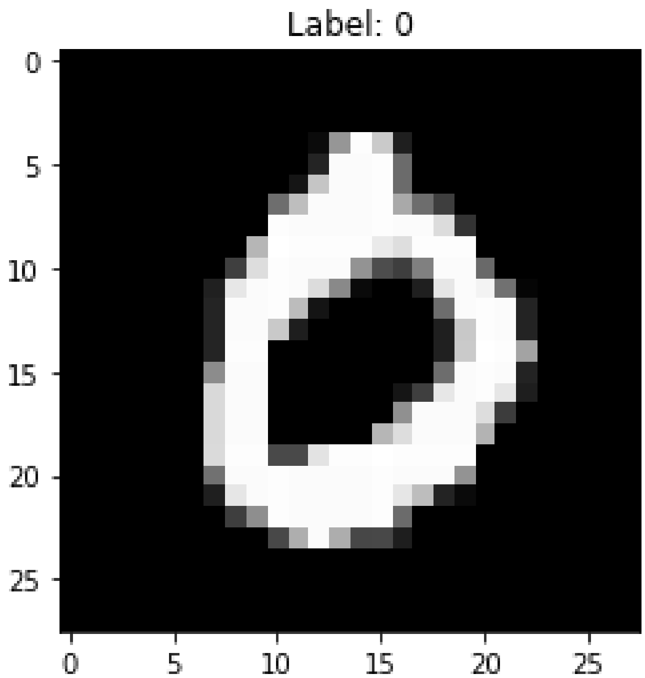



2 Concatinate Dataset

We concatinate our datasets so as to make a single dataset out of it. We'll devide them again during K-Fold section.

[ ]:
```
dataset = ConcatDataset([train_dataset, test_dataset])
```

2.1 Define the Nueral Network

Use `nn.Module` in order to use Neural Network with PyTorch. The `typeRNN` attribute will tell Neural which kind of Neural Network we want to use. Options: * RNN * GRU * LSMT

[ ]:
```
# Create an RNN
class RNN(nn.Module):
```

```
    def __init__(self, input_size, hidden_size, num_layers,␣
↪num_classes,typeRNN="RNN"):
        super(RNN, self).__init__()
        self.hidden_size = hidden_size
        self.num_layers = num_layers
        self.rnn = nn.RNN(input_size, hidden_size, num_layers, batch_first=True)
        self.gru = nn.GRU(input_size, hidden_size, num_layers, batch_first=True)
        self.lstm = nn.LSTM(
            input_size, hidden_size, num_layers, batch_first=True,␣
↪bidirectional=True
        )
        self.fc = nn.Linear(hidden_size * 2, num_classes)
        self.typeRNN = typeRNN
        print(self.typeRNN)

    def forward(self, x):
      if self.typeRNN == "BRNN":
        h0 = torch.zeros(self.num_layers * 2, x.size(0), self.hidden_size).
↪to(device)
        c0 = torch.zeros(self.num_layers * 2, x.size(0), self.hidden_size).
↪to(device)
        out, _ = self.lstm(x, (h0, c0))
        out = self.fc(out[:, -1, :])
        return out

      h0 = torch.zeros(self.num_layers, x.size(0), self.hidden_size).to(device)
      if self.typeRNN == "RNN":
        out, _ = self.rnn(x, h0)

      if self.typeRNN == "GRU":
        out, _ = self.gru(x, h0)

      out = out.reshape(out.shape[0], -1)
      out = self.fc(out)
      return out
```

[ ]:
```
typeRNN = "BRNN"
model = RNN(input_size, hidden_size, num_layers, num_classes,typeRNN).to(device)
```

```
BRNN
```

2.2 Add Loss & Optimizers

We use `CrossEntropyLoss` as our loss function. We use `Adam` as our optimizer.

[ ]:
```
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=learning_rate)
```

2.3 Train the model.

We train the model, calculate the accuracy, and design the confusion matrix for each epoch.

- We first devide the dataset back into train & test sets.
- Then we convert into DataLoader class and make batches out of it.
- We feed the data to our model and then train our model.
- We store the predictions along with actual data into `KFOLD_confusion_dict`
  - `KFOLD_confusion_dict` will hold all the data. (ie. predictions and actual results from each fold and each epoch)

[ ]:
```
KFOLD_confusion_dict = {}
kfold = KFold(n_splits=n_folds, shuffle=True)

for fold, (train_ids, test_ids) in enumerate(kfold.split(dataset)):
  train_dataset1, test_dataset1, confusion_dict = [], [], {}

  for id in train_ids:
    train_dataset1.append(dataset[id])
  for id in test_ids:
    test_dataset1.append(dataset[id])

  train_loader = DataLoader(dataset = train_dataset1, batch_size =batch_size,␣
 ↪shuffle=False)
  test_loader = DataLoader(dataset = test_dataset1, batch_size =batch_size,␣
 ↪shuffle=False)

  model = RNN(input_size, hidden_size, num_layers, num_classes,typeRNN).
 ↪to(device)
  criterion = nn.CrossEntropyLoss()
  optimizer = optim.Adam(model.parameters(), lr=learning_rate)

  print('--------------------------------')
  print(f'FOLD {fold}')
  print('--------------------------------')

  for epoch in range(num_epochs):
    all_preds = []
    all_y = []
    num_correct = 0
    num_samples = 0
    for data, targets in train_loader:
      # Get data to cuda if possible
      data = data.to(device=device).squeeze(1)
      targets = targets.to(device=device)

      # forward
      scores = model(data)
```

```
     _,predictions = scores.max(1)
     all_preds = all_preds + [item.item() for item in predictions]
     all_y = all_y + [item.item() for item in targets]

     num_correct += (predictions == targets).sum()
     num_samples += predictions.size(0)

     loss = criterion(scores, targets)

     # backward
     optimizer.zero_grad()
     loss.backward()

     # gradient descent or adam step
     optimizer.step()
   print(f"Epoch: {epoch} - Got {num_correct} / {num_samples} with accuracy {float(num_correct)/float(num_samples)*100:.2f}")
   confusion_dict[epoch] = pd.DataFrame(list(zip(all_preds,all_y)), columns=["Predicted","Actual"])
 KFOLD_confusion_dict[fold] = confusion_dict
```

```
BRNN
--------------------------------
FOLD 0
--------------------------------
Epoch: 0 - Got 13018 / 13302 with accuracy 97.86
BRNN
--------------------------------
FOLD 1
--------------------------------
Epoch: 0 - Got 12943 / 13302 with accuracy 97.30
BRNN
--------------------------------
FOLD 2
--------------------------------
Epoch: 0 - Got 13039 / 13302 with accuracy 98.02
BRNN
--------------------------------
FOLD 3
--------------------------------
Epoch: 0 - Got 12956 / 13302 with accuracy 97.40
BRNN
--------------------------------
FOLD 4
--------------------------------
Epoch: 0 - Got 12987 / 13302 with accuracy 97.63
```

```
BRNN
--------------------------------
FOLD 5
--------------------------------
Epoch: 0 - Got 12969 / 13302 with accuracy 97.50
BRNN
--------------------------------
FOLD 6
--------------------------------
Epoch: 0 - Got 13034 / 13302 with accuracy 97.99
BRNN
--------------------------------
FOLD 7
--------------------------------
Epoch: 0 - Got 13002 / 13302 with accuracy 97.74
BRNN
--------------------------------
FOLD 8
--------------------------------
Epoch: 0 - Got 13014 / 13302 with accuracy 97.83
BRNN
--------------------------------
FOLD 9
--------------------------------
Epoch: 0 - Got 13036 / 13302 with accuracy 98.00
```

2.4 Store the data

Stores/Pickles the data to file

[ ]:
```
with open('/content/drive/MyDrive/Sem 1/DM/KFOLD_confusion_dict.pickle', 'wb')␣
↪as handle:
    pickle.dump(KFOLD_confusion_dict, handle, protocol=pickle.HIGHEST_PROTOCOL)
```

[ ]:
```
with open('/content/drive/MyDrive/Sem 1/DM/KFOLD_confusion_dict.pickle', 'rb')␣
↪as handle:
    KFOLD_confusion_dict = pickle.load(handle)
```

[ ]:
```
KFOLD_confusion_dict[0][0]
```

[ ]:

	Predicted	Actual
0	0	0
1	0	1
2	0	1
3	0	1
4	0	1
…	…	…
13297	1	1

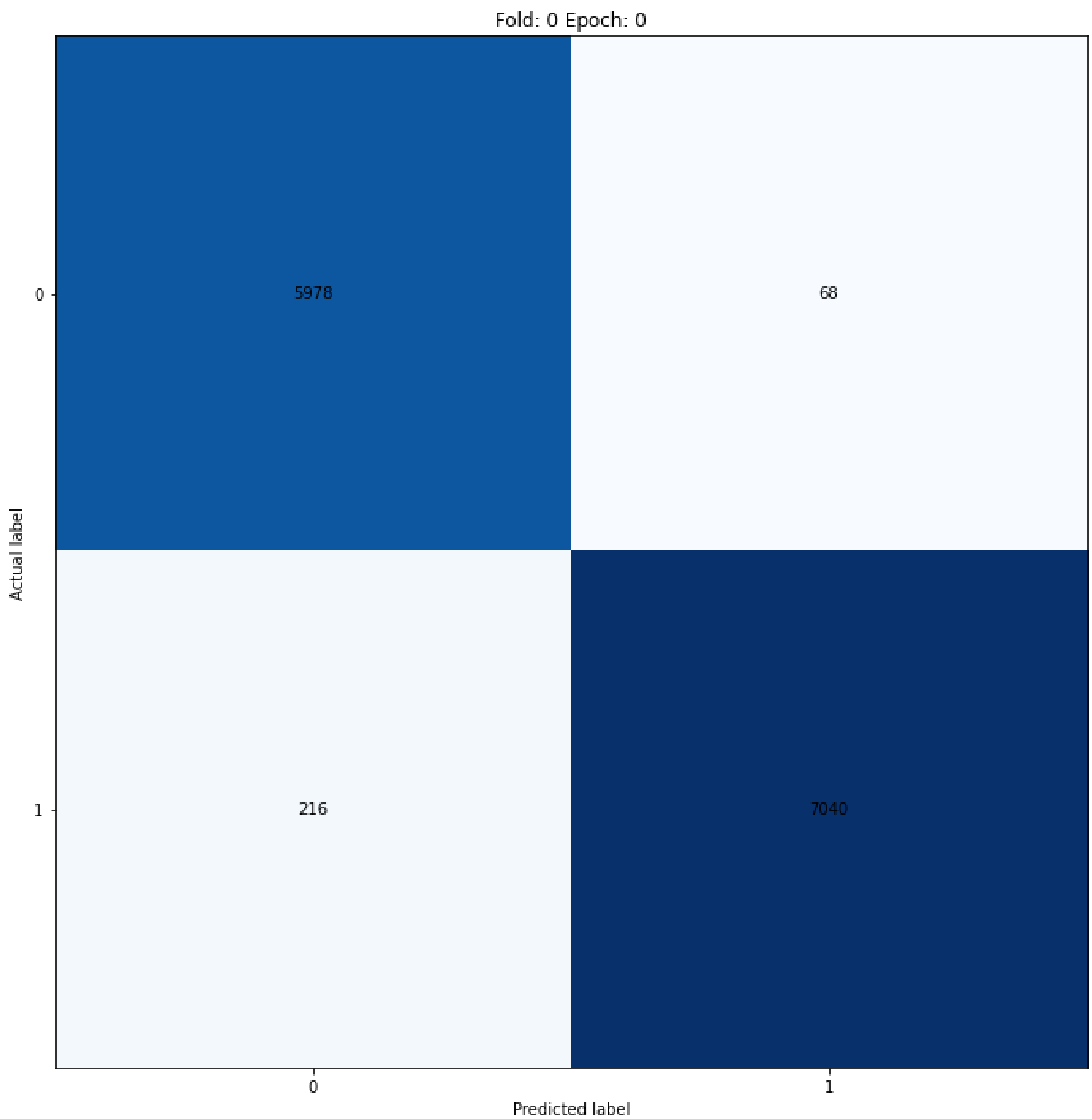
```
13298          0        0
13299          1        1
13300          0        0
13301          1        1

[13302 rows x 2 columns]
```

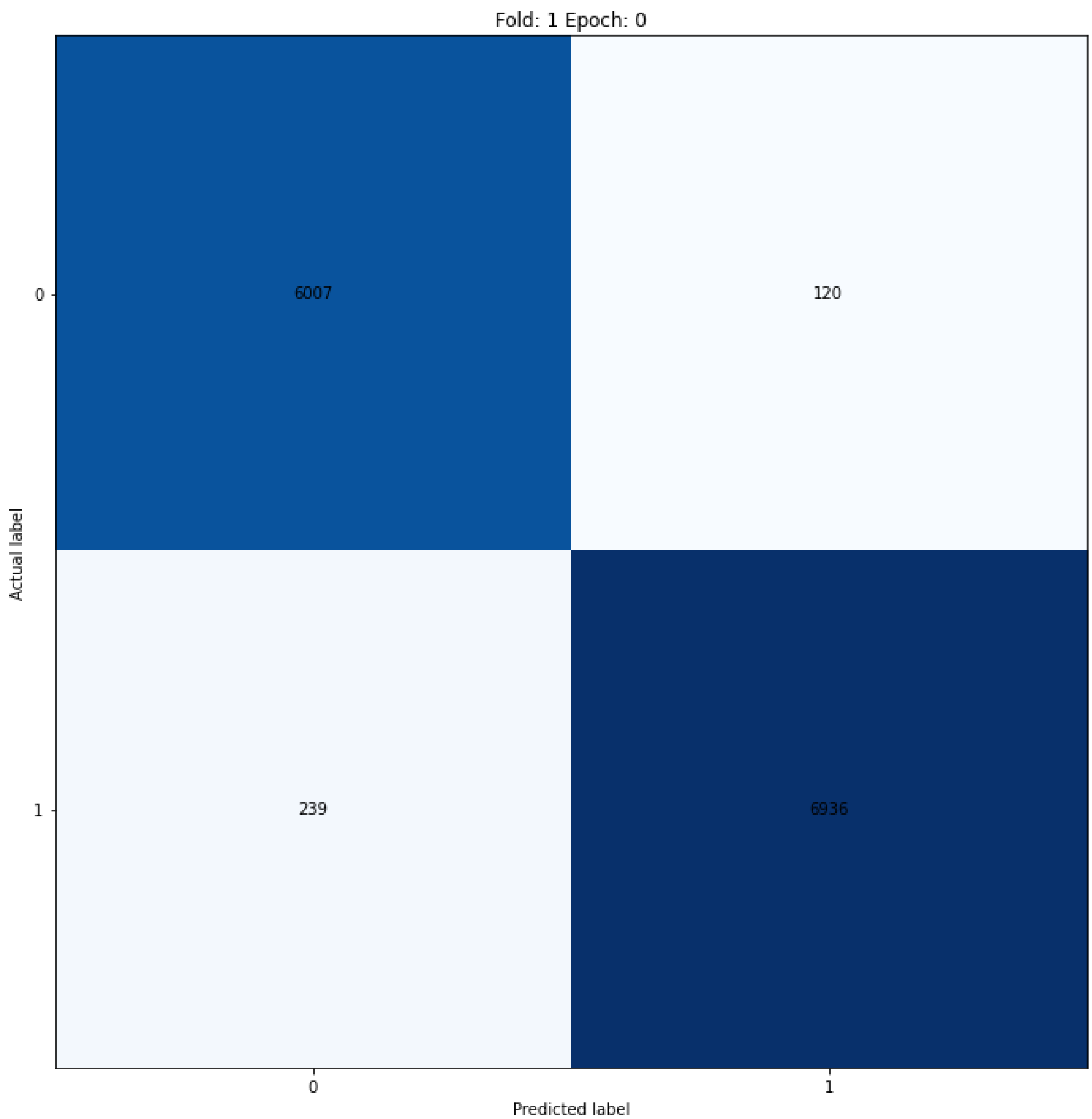
3 Confusion Matrix & Performance Evaluation

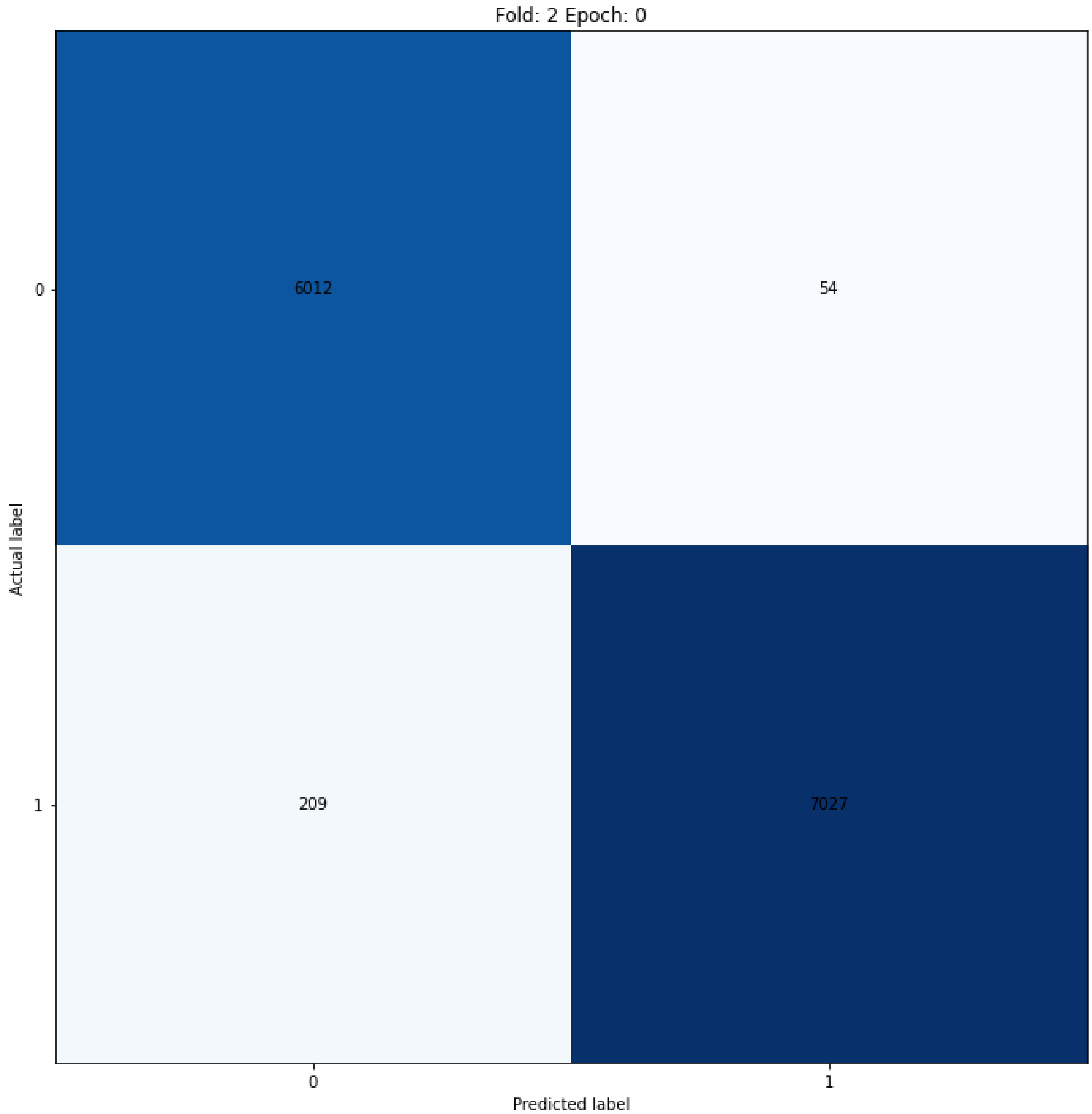
3.1 Confusion Matrix

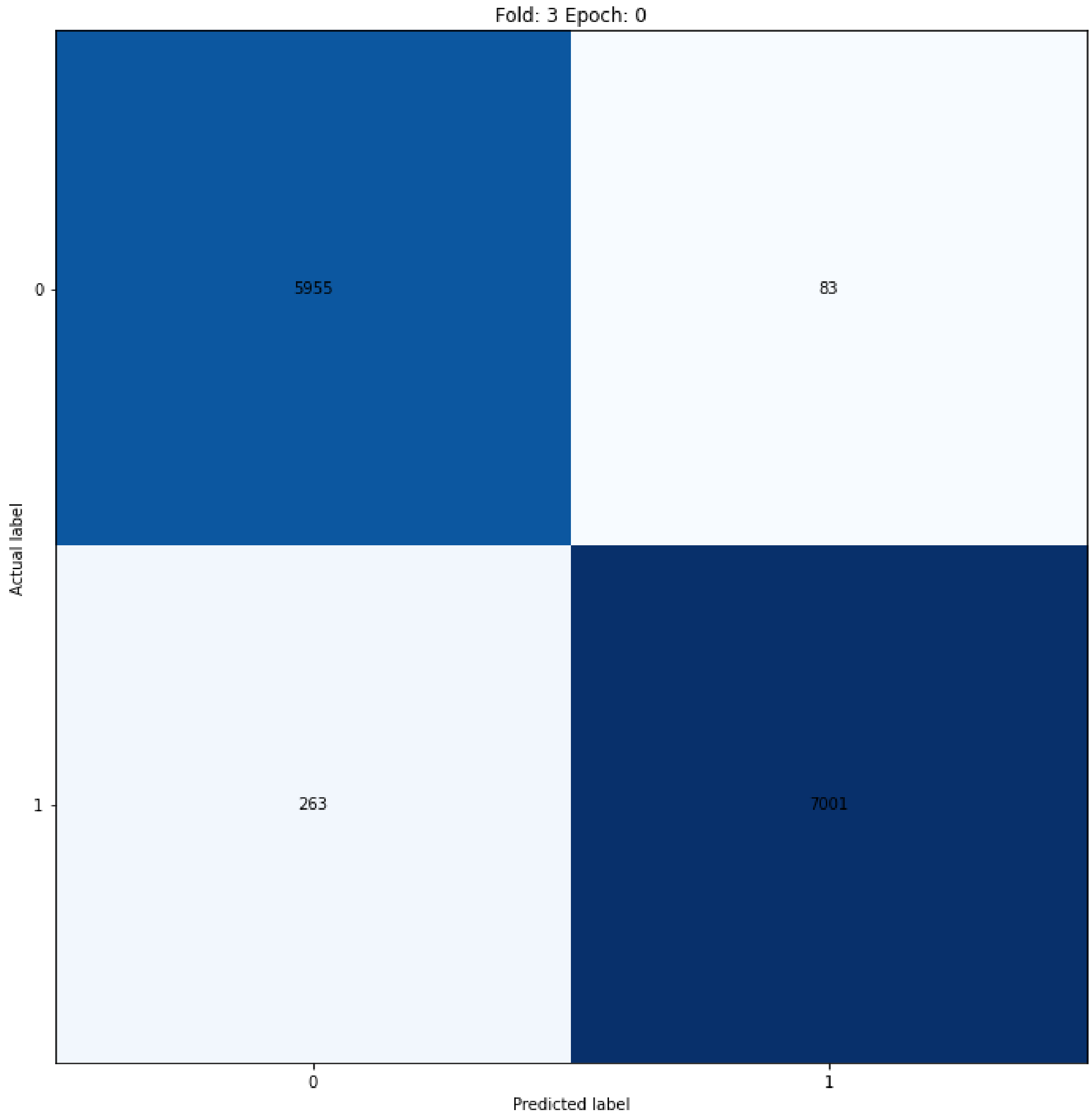
We use our predictions from each fold and plot the confusion matrix.

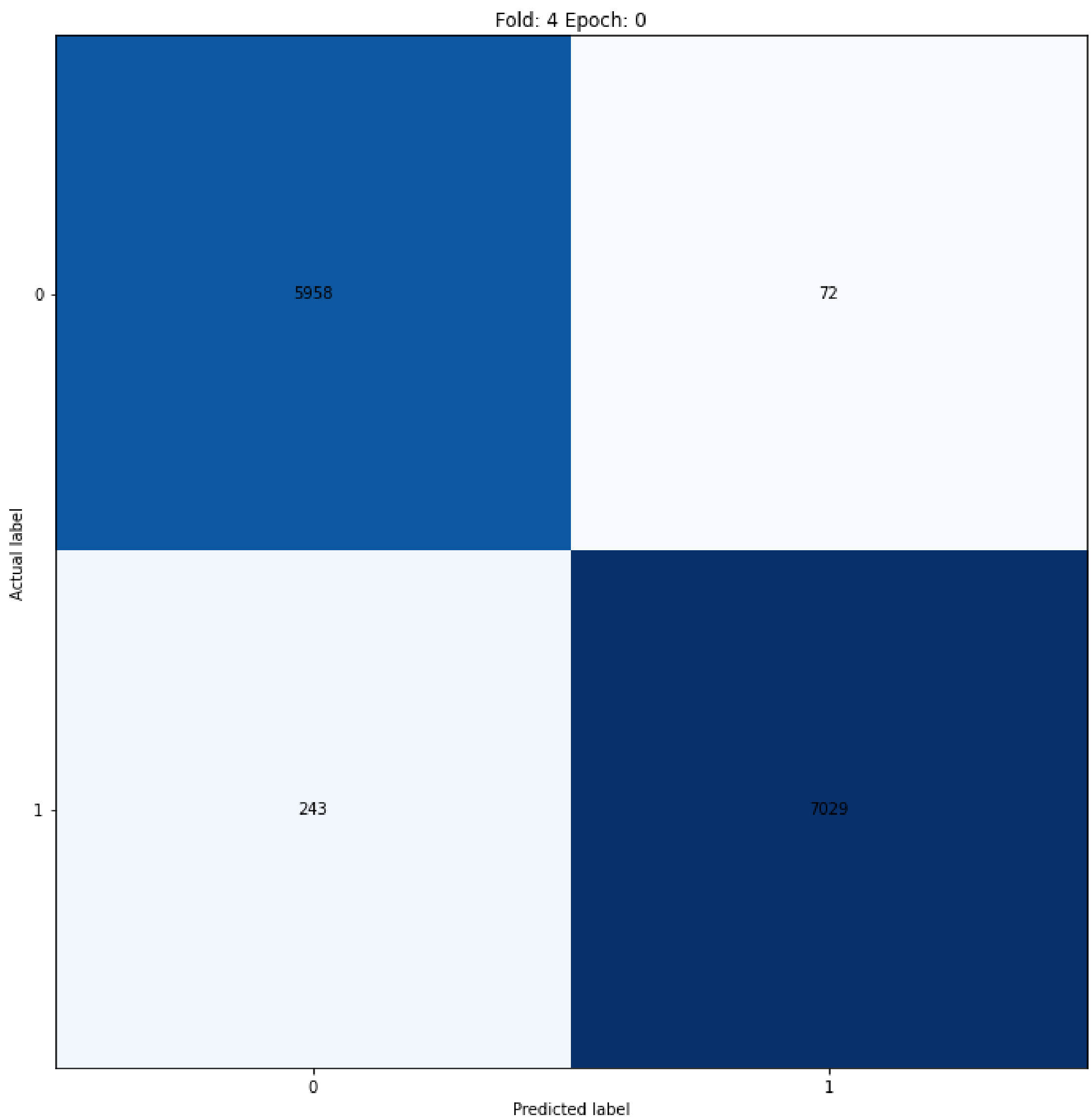
[ ]:
```
from sklearn.metrics import confusion_matrix
for fold, confusion_dict in  KFOLD_confusion_dict.items():
  for key, val in confusion_dict.items():
    cm = confusion_matrix(val['Predicted'], val["Actual"])
    fig, ax = plt.subplots(figsize=(14,12))         # Sample figsize in inches
    plt.imshow(cm,interpolation='none',cmap='Blues')
    for (i, j), z in np.ndenumerate(cm):
        plt.text(j, i, z, ha='center', va='center')
    plt.xlabel("Predicted label")
    plt.ylabel("Actual label")
    plt.xticks([0,1])
    plt.yticks([0,1])
    plt.title(f"Fold: {fold} Epoch: {key}")
plt.show()
```


Fold: 0 Epoch: 0
5978
68
216
7040
0
1
Actual label
0
1
Predicted label

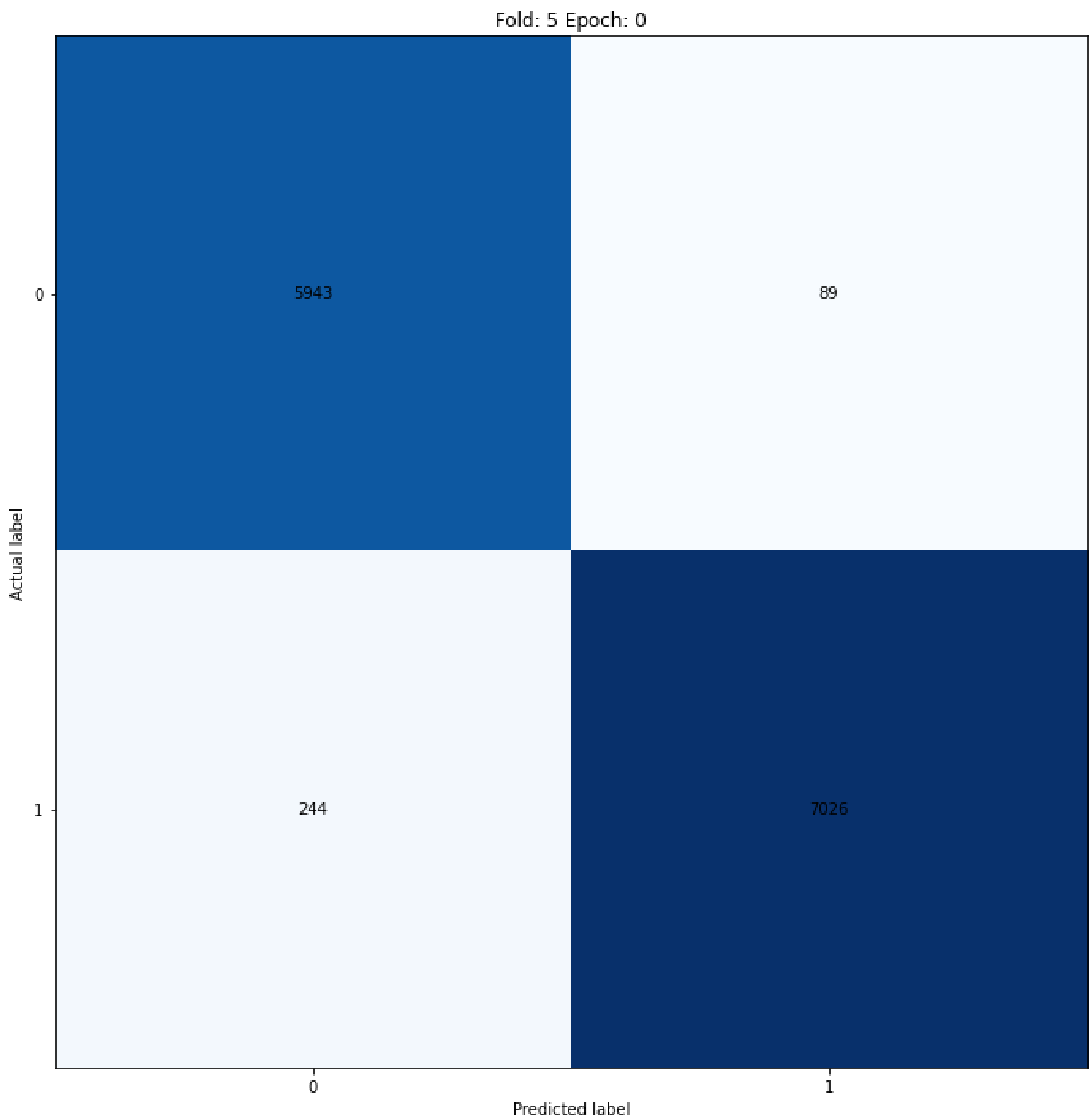

Fold: 1 Epoch: 0
6007
120
239
6936
0
1
Actual label
0
1
Predicted label

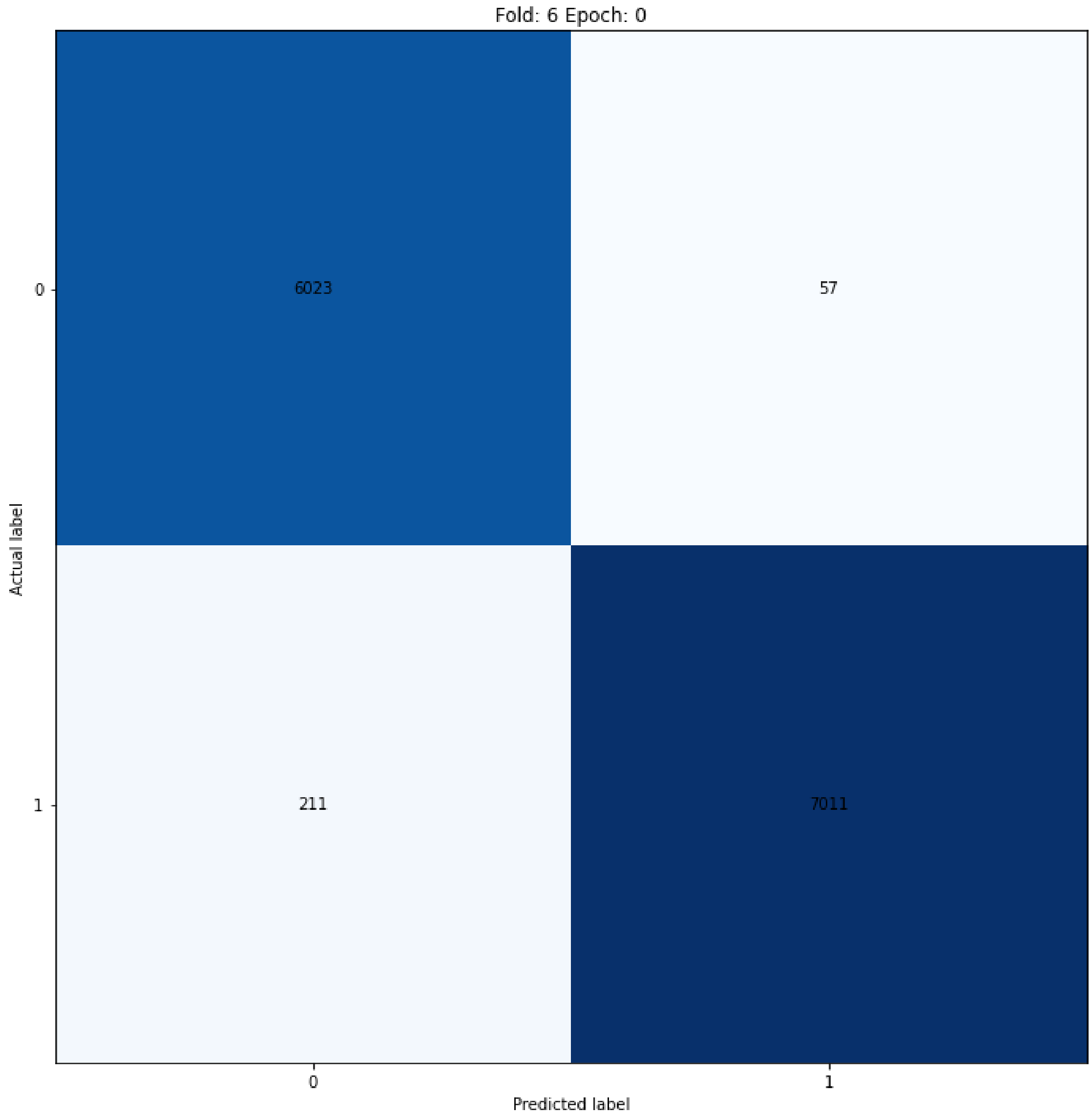

Fold: 2 Epoch: 0
6012
54
209
7027
0
1
Actual label
0
1
Predicted label

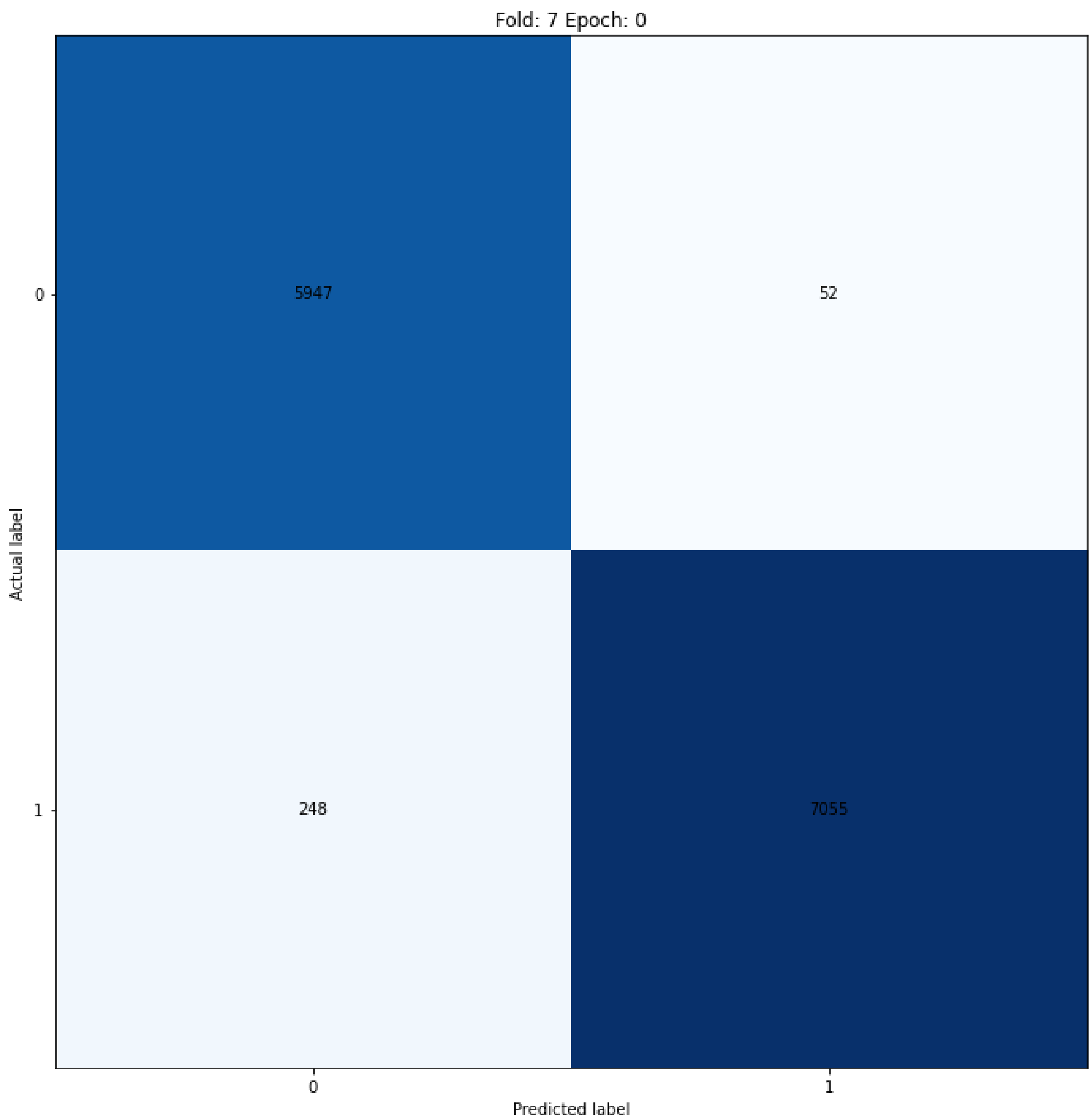

Fold: 3 Epoch: 0
5955
83
263
7001
0
1
Actual label
0
1
Predicted label

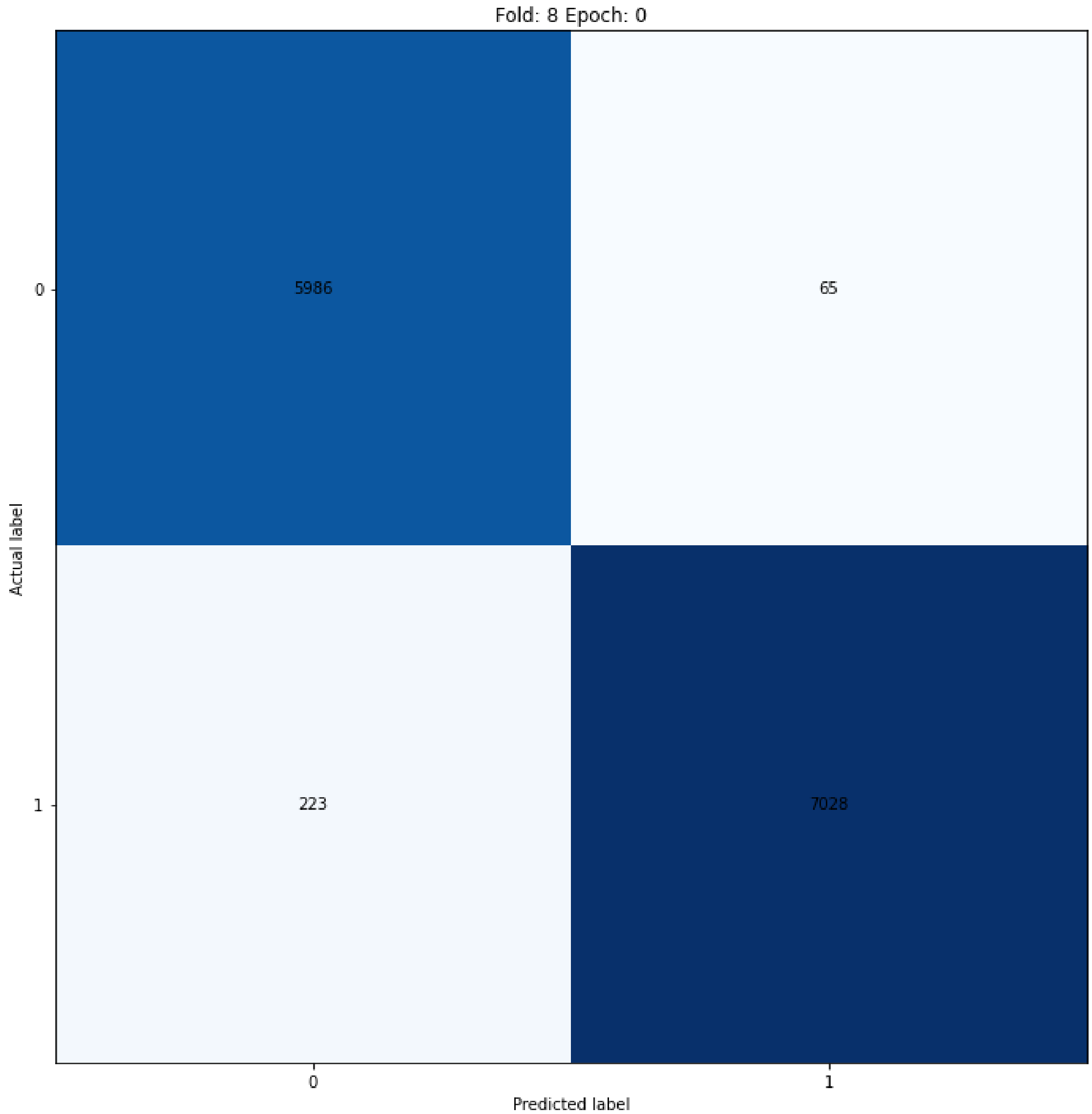


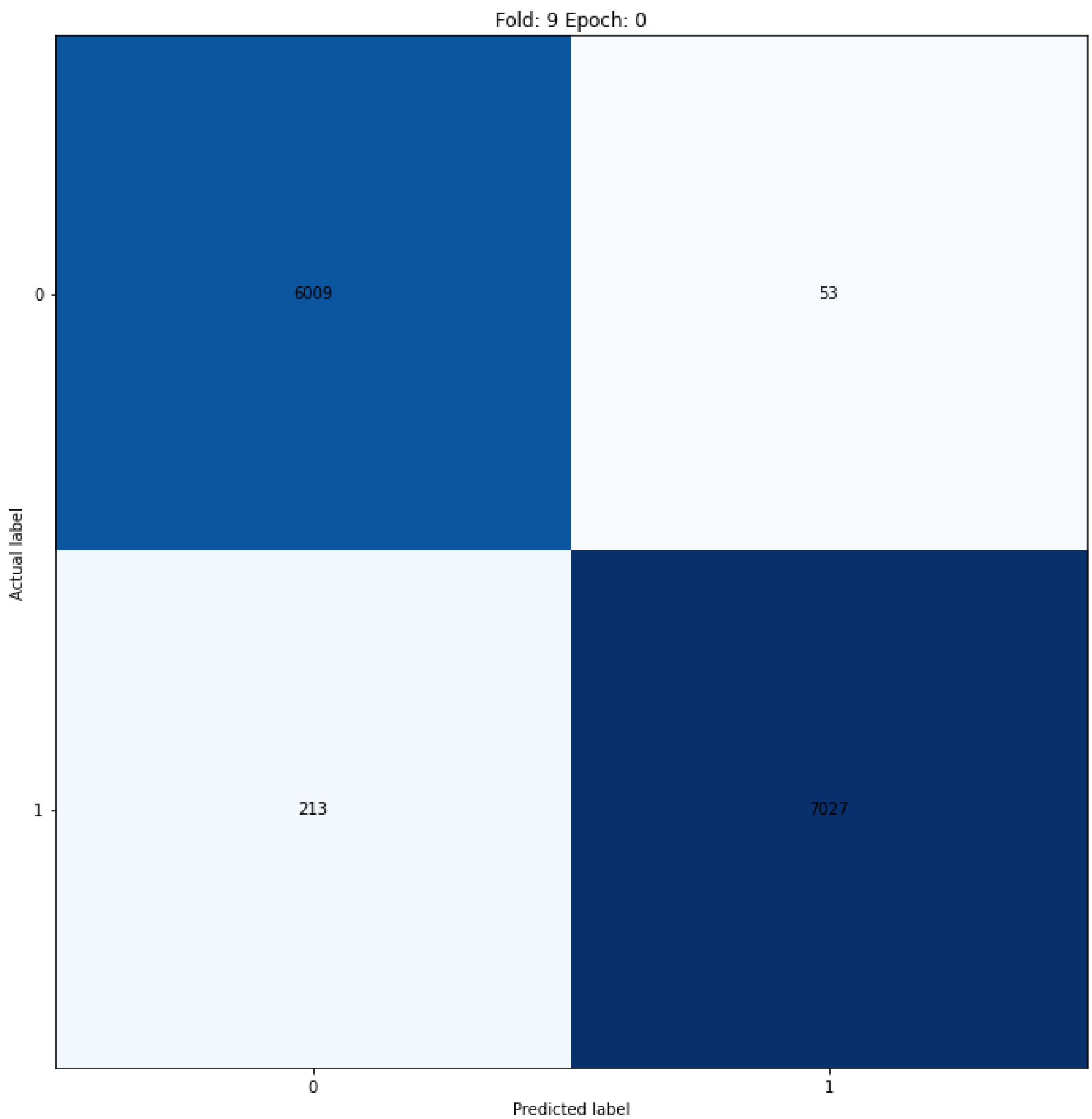
Fold: 4 Epoch: 0
5958
72
243
7029
0
1
Actual label
0
1
Predicted label


Fold: 5 Epoch: 0
5943
89
244
7026
Actual label
0
1
Predicted label
0
1


Fold: 6 Epoch: 0
Actual label
Predicted label
0
1
0
1
6023
57
211
7011


Fold: 7 Epoch: 0
5947
52
248
7055
0
1
Actual label
0
1
Predicted label


Fold: 8 Epoch: 0
Actual label
Predicted label
0
1
0
1
5986
65
223
7028


Fold: 9 Epoch: 0
Actual label
Predicted label
0
1
0
1
6009
53
213
7027

3.2 Evaluating Classifier Performance

Now we calucalte the following for each fold:

1. P: the number of positive examples P = TP + FN
2. N: the number of negative examples N = TN + FP
3. True positive (TP): the number of positive examples correctly predicted by the classification model.
4. True negative (TN): the number of negative examples correctly predicted by the classification model.
5. False positive (FP): the number of negative examples wrongly predicted as positive by the classification model.
6. False negative (FN): the number of positive examples wrongly predicted as negative by the classification model.
7. True positive rate (TPR) or sensitivity: the fraction of positive examples predicted correctly by the model: TPR = TP/(TP + FN) = TP/P
8. True negative rate (TNR) or specificity: the fraction of negative examples predicted correctly by the model: TNR = TN/(TN + FP) = TN/N
9. False positive rate (FPR): fraction of negative examples predicted as positive: FPR = FP/(TN + FP) = FP/N
10. False negative rate (FNR): fraction of positive examples predicted as negative: FNR = FN/(TP + FN) = FN/P
11. Recall (r) or sensitivity: r = TP/(TP + FN) = TP/P
12. Precision (p): p = TP/(TP + FP) F 1 measure (F 1): F 1 = (2 × TP)/(2 × TP + FP + FN) = 2 × (p × r)/(p + r)
13. Accuracy (Acc): Acc = (TP + TN)/(TP + FP + FN + TN) = (TP + TN)/(P + N)
14. Error rate (Err): Err = (FP + FN)/(TP + FP + FN + TN) = (FP + FN)/(P + N)

[ ]:
```
def all_conf_matrix():
  matrix_fold = {}
  for fold, confusion_dict in  KFOLD_confusion_dict.items():
    all_matrix = {}
    for epoch, value in confusion_dict.items():
      # print(f"\nFor fold {fold} & For epoch {epoch}")

      p = int(value[(value["Actual"] == 1)]['Actual'].count())
      n = int(value[(value["Actual"] == 0)]['Actual'].count())

      tp = int(value[(value["Predicted"] == 1) & (value["Actual"] ==␣
↪1)]['Predicted'].count())
      tn = int(value[(value["Predicted"] != 1) & (value["Actual"] !=␣
↪1)]['Predicted'].count())
      fp = int(value[(value["Predicted"] == 1) & (value["Actual"] !=␣
↪1)]['Predicted'].count())
      fn = int(value[(value["Predicted"] != 1) & (value["Actual"] ==␣
↪1)]['Predicted'].count())

      tpr = round(tp/(tp + fn), 2)
      tnr = round(tn/(tn + fp), 2)
      fpr = round(fp/(tn + fp), 2)
      fnr = round(fn/(tp + fn), 2)

      recall = round(tp/p, 2)
      precision = round(tp/(tp+fp), 2)
```

```
    f1_score = round((2 * recall * precision)/(recall + precision), 2)
    acc = round((tp + tn)/(p + n), 2)
    err_rate = round((fp + fn)/(p + n), 2)

    headings = ["Positives", "Negatives",
                "True Positives", "True Negatives", "False Positives", "False␣
↪Negatives",
                "True Positive Rate", "True Negative Rate", "False Positive␣
↪Rate", "False Negative Rate",
                "Recall or Sensitivity", "Precision", "F1 Score", "Accuracy",␣
↪"Error Rate"
                ]
    values = [p, n, tp, tn, fp, fn, tpr, tnr, fpr, fnr, recall, precision,␣
↪f1_score, acc, err_rate]
    matrix = pd.DataFrame(values, columns = [f"Fold {fold}"], index=headings)

    all_matrix[epoch] = matrix
  matrix_fold[fold] = all_matrix
return matrix_fold
```

[ ]:
```
all_matrices = all_conf_matrix()
final_matrix = pd.DataFrame()
for fold, matrix in all_matrices.items():
  for epoch, pd_matrix in matrix.items():
    # print(f"\nConfusion Matrix for fold: {fold} epoch: {epoch}\n")
    # print(f"{pd_matrix}")
    final_matrix = pd.concat([final_matrix, pd_matrix], axis = 1)

final_matrix["Average"] = final_matrix.mean(axis=1)
```

3.3 Display Evaluating Classifier Performance

[ ]:
```
final_matrix
```

[ ]:

```
                      Fold 0   Fold 1   Fold 2  …   Fold 8   Fold 9
Average
Positives            7108.00  7056.00  7081.00  …  7093.00  7080.00
7089.300
Negatives            6194.00  6246.00  6221.00  …  6209.00  6222.00
6212.700
True Positives       7040.00  6936.00  7027.00  …  7028.00  7027.00
7018.000
True Negatives       5978.00  6007.00  6012.00  …  5986.00  6009.00
5981.800
False Positives       216.00   239.00   209.00  …   223.00   213.00
230.900
```

```
False Negatives          68.00    120.00    54.00  ...    65.00    53.00
71.300
True Positive Rate        0.99      0.98     0.99  ...     0.99     0.99
0.989
True Negative Rate        0.97      0.96     0.97  ...     0.96     0.97
0.964
False Positive Rate       0.03      0.04     0.03  ...     0.04     0.03
0.036
False Negative Rate       0.01      0.02     0.01  ...     0.01     0.01
0.011
Recall or Sensitivity     0.99      0.98     0.99  ...     0.99     0.99
0.989
Precision                 0.97      0.97     0.97  ...     0.97     0.97
0.969
F1 Score                  0.98      0.97     0.98  ...     0.98     0.98
0.978
Accuracy                  0.98      0.97     0.98  ...     0.98     0.98
0.977
Error Rate                0.02      0.03     0.02  ...     0.02     0.02
0.023

[15 rows x 11 columns]
```

	Fold 0	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Fold 6	Fold 7	Fold 8	Fold 9	Average
Positives	7108.00	7056.00	7081.00	7084.00	7101.00	7115.00	7068.00	7107.00	7093.00	7080.00	7089.300
Negatives	6194.00	6246.00	6221.00	6218.00	6201.00	6187.00	6234.00	6195.00	6209.00	6222.00	6212.700
True Positives	7040.00	6936.00	7027.00	7001.00	7029.00	7026.00	7011.00	7055.00	7028.00	7027.00	7018.000
True Negatives	5978.00	6007.00	6012.00	5955.00	5958.00	5943.00	6023.00	5947.00	5986.00	6009.00	5981.800
False Positives	216.00	239.00	209.00	263.00	243.00	244.00	211.00	248.00	223.00	213.00	230.900
False Negatives	68.00	120.00	54.00	83.00	72.00	89.00	57.00	52.00	65.00	53.00	71.300
True Positive Rate	0.99	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.989
True Negative Rate	0.97	0.96	0.97	0.96	0.96	0.96	0.97	0.96	0.96	0.97	0.964
False Positive Rate	0.03	0.04	0.03	0.04	0.04	0.04	0.03	0.04	0.04	0.03	0.036
False Negative Rate	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.011
Recall or Sensitivity	0.99	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.989
Precision	0.97	0.97	0.97	0.96	0.97	0.97	0.97	0.97	0.97	0.97	0.969
F1 Score	0.98	0.97	0.98	0.97	0.98	0.98	0.98	0.98	0.98	0.98	0.978
Accuracy	0.98	0.97	0.98	0.97	0.98	0.97	0.98	0.98	0.98	0.98	0.977
Error Rate	0.02	0.03	0.02	0.03	0.02	0.03	0.02	0.02	0.02	0.02	0.023

[ ]: