DSC 43C8 – Final Project

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Agenda

Evaluating Reproducibility of Deep Learning Models

Model Comparisons and Results

PHATE, t-SNE, PCA + t-SNE Visualizations for Credit Analytics

Applying CNN, LSTM, and GRU Classification to Credit Analytics

Model Comparisons and Results

Part A: Evaluate the Reproducibility of deep learning

Investigating mnist, emodb, and kolod datasets

Datasets & CLR

CORRECT LEARNING REPRODUCIBILITY (CLR)

- The ratio that a model correctly does classification after n runs. Here we can define each run has 100 epochs. CLR can be represented as the average classification ratios of n runs

EMODB

- A well-known dataset in the field of speech emotion recognition, consisting of 535 short phrases with 7 different emotional tones (N,A,B,D,An, H, S).

KOLOD

- A publicly available dataset of single-cell RNA sequencing (scRNA-seq) data. It has 704 samples across 3 classes: embryonic stem cells, neural progenitor cells, and neural crest cells. (0,1,2)

MNIST

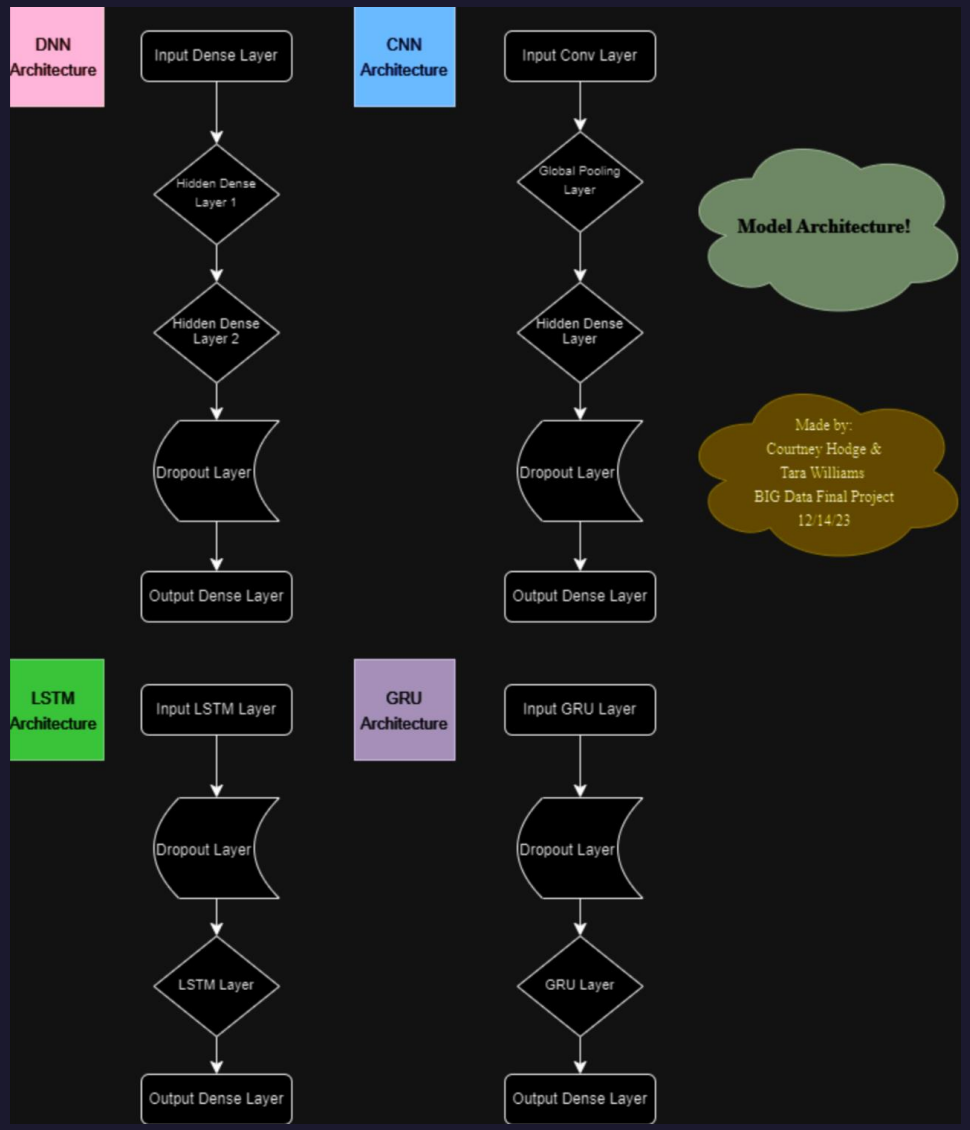
- As seen in project 2, it is a dataset comprised of images of handwritten digits (0-9) that is commonly used for machine learning models.

Initial Steps

```
########################
#####Load the Data#####
########################
emodb = pd.read_csv('/content/drive/MyDrive/Baylor F23 - S24/1-Fall/BIG data/EMODB.csv')

#mnist
from keras.datasets import mnist

#kolod
kolod = pd.read_csv('/content/drive/MyDrive/Baylor F23 - S24/1-Fall/BIG data/Kolod.csv')
```

A) Use DNN, CNN, LSTM, GRU models

Model's Architecture



B) Run each model - EMODB

EMODB

> Everything should work

```
[59] ############
     ####emodb###
     ############
     n = 5
     emodb_DNN_accuracy = 0
     for i in range(5):
       emodb_DNN_accuracy += classification_measures(emodb_DNN_model, emodb_x_train, emodb_x_test, emodb_y_train, emodb_y_test)
     emodb_DNN_CLR = emodb_DNN_accuracy/n

     emodb_CNN_accuracy = 0
     for i in range(5):
       emodb_CNN_accuracy += classification_measures(emodb_CNN_model, emodb_x_train, emodb_x_test, emodb_y_train, emodb_y_test)
     emodb_CNN_CLR = emodb_CNN_accuracy/n

     emodb_LSTM_accuracy = 0
     for i in range(5):
       emodb_LSTM_accuracy += classification_measures(emodb_LSTM_model, emodb_x_train, emodb_x_test, emodb_y_train, emodb_y_test)
     emodb_LSTM_CLR = emodb_LSTM_accuracy/n

     emodb_GRU_accuracy = 0
     for i in range(5):
       emodb_GRU_accuracy += classification_measures(emodb_GRU_model, emodb_x_train, emodb_x_test, emodb_y_train, emodb_y_test)
     emodb_GRU_CLR = emodb_GRU_accuracy/n

     print("Emodb DNN CLR: ", emodb_DNN_CLR)
     print("Emodb CNN CLR: ",emodb_CNN_CLR)
     print("Emodb LSTM CLR: ",emodb_LSTM_CLR)
     print("Emodb GRU CLR: ",emodb_GRU_CLR)
```

B) Run each model - MNIST

Mnist

Everything should work

```
]  ############
   #--mnist---#
   ############

   mnist_DNN_model = DNN("mnist", x_train)
   mnist_CNN_model = CNN("mnist",x_train)
   mnist_LSTM_model = LSTM("mnist",x_train)
   mnist_GRU_model = GRU("mnist",x_train)

   mnist_DNN_accuracy = 0
   for i in range(5):
     mnist_DNN_accuracy += mnist_class_measures(mnist_DNN_model, x_train, x_test, y_train, y_test, y_train_label)
   mnist_DNN_CLR = mnist_DNN_accuracy/n

   mnist_CNN_accuracy = 0
   for i in range(5):
     mnist_CNN_accuracy += mnist_class_measures(mnist_CNN_model, x_train, x_test, y_train, y_test, y_train_label)
   mnist_CNN_CLR = mnist_CNN_accuracy/n

   mnist_LSTM_accuracy = 0
   for i in range(5):
     mnist_LSTM_accuracy += mnist_class_measures(mnist_LSTM_model, x_train, x_test, y_train, y_test, y_train_label)
   mnist_LSTM_CLR = mnist_LSTM_accuracy/n

   mnist_GRU_accuracy = 0
   for i in range(5):
     mnist_GRU_accuracy += mnist_class_measures(mnist_GRU_model, x_train, x_test, y_train, y_test, y_train_label)
   mnist_GRU_CLR = mnist_GRU_accuracy/n

   print("mnist DNN CLR: ",mnist_DNN_CLR)
   print("mnist DNN CLR: ",mnist_CNN_CLR)
   print("mnist DNN CLR: ",mnist_LSTM_CLR)
   print("mnist DNN CLR: ",mnist_GRU_CLR)
```

B) Run each model – KOLOD

KOLOD

DNN and CNN used to work, now nothing does

LSTM

GRU

DNN

CNN

```
5] ############
   #--kolod---#
   # ############
   # n= 5

   # kolod_DNN_model = DNN("kolod", x_train)
   # kolod_CNN_model = CNN("kolod",x_train)
   # kolod_LSTM_model = LSTM("kolod",x_train)
   # kolod_GRU_model = GRU("kolod",x_train)

   # kolod_DNN_accuracy = 0
   # for i in range(5):
   #   kolod_DNN_accuracy += classification_measures(kolod_DNN_model, kolod_x_train, kolod_x_test, kolod_y_train, kolod_y_test)
   # kolod_DNN_CLR = kolod_DNN_accuracy/n


   # kolod_CNN_accuracy = 0
   # for i in range(5):
   #   kolod_CNN_accuracy += classification_measures(kolod_CNN_model, kolod_x_train, kolod_x_test, kolod_y_train, kolod_y_test)
   # kolod_CNN_CLR = kolod_CNN_accuracy/n


   # # #got stuck on lstm
   # # kolod_LSTM_accuracy = 0
   # # for i in range(5):
   # #  kolod_LSTM_accuracy += classification_measures(kolod_LSTM_model, kolod_x_train, kolod_x_test, kolod_y_train, kolod_y_test)
   # # kolod_LSTM_CLR = kolod_LSTM_accuracy/n


   # # kolod_GRU_accuracy = 0
   # # for i in range(5):
   # #  kolod_GRU_accuracy += classification_measures(kolod_GRU_model, kolod_x_train, kolod_x_test, kolod_y_train, kolod_y_test)
   # # kolod_GRU_CLR = kolod_GRU_accuracy/n

   # print("Kolod DNN CLR: ", kolod_DNN_CLR)
   # print("Kolod CNN CLR: ", kolod_CNN_CLR)
   # print("Kolod LSTM CLR: ", kolod_LSTM_CLR)
   # print("Kolod GRU CLR: ", kolod_GRU_CLR)
```

Results

EMODB

```
#----------#
#D-index: 0.0199
#----------#

Emodb DNN CLR:  0.07476635514018691
Emodb CNN CLR:  0.07476635514018691
Emodb LSTM CLR:  0.07476635514018691
Emodb GRU CLR:  0.07476635514018691
```

MNIST

```
#----------#
#D-index: 0.0151
#----------#

mnist DNN CLR:  0.37383177570093457
mnist DNN CLR:  0.37383177570093457
mnist DNN CLR:  0.37383177570093457
mnist DNN CLR:  0.37383177570093457
```

KOLOD

```
# print("Kolod DNN CLR: ", kolod_DNN_CLR)
# print("Kolod CNN CLR: ", kolod_CNN_CLR)
# print("Kolod LSTM CLR: ", kolod_LSTM_CLR)
# print("Kolod GRU CLR: ", kolod_GRU_CLR)
```

1C) Do PCA for each dataset - EMODB

Emodb PCA

Everything should work

```
#apply pca
pca = PCA(n_components = 10)
emodb_x_train_pca = pca.fit_transform(emodb_x_train)
emodb_x_test_pca = pca.transform(emodb_x_test)

#get models
emodb_DNN_PCA_model = DNN("emodb", emodb_x_test_pca)
emodb_CNN_PCA_model = CNN("emodb", emodb_x_test_pca)
emodb_LSTM_PCA_model = LSTM("emodb", emodb_x_test_pca)
emodb_GRU_PCA_model = GRU("emodb", emodb_x_test_pca)

#get CLRs
emodb_DNN_PCA_accuracy = 0
for i in range(5):
  emodb_DNN_PCA_accuracy += classification_measures(emodb_DNN_PCA_model, emodb_x_train_pca,
                                                    emodb_x_test_pca, emodb_y_train, emodb_y_test)
emodb_DNN_PCA_CLR = emodb_DNN_PCA_accuracy/n

emodb_CNN_PCA_accuracy = 0
for i in range(5):
  emodb_CNN_PCA_accuracy += classification_measures(emodb_CNN_PCA_model, emodb_x_train_pca,
                                                    emodb_x_test_pca, emodb_y_train, emodb_y_test)
emodb_CNN_PCA_CLR = emodb_CNN_PCA_accuracy/n

emodb_LSTM_PCA_accuracy = 0
for i in range(5):
  emodb_LSTM_PCA_accuracy += classification_measures(emodb_LSTM_PCA_model, emodb_x_train_pca,
                                                     emodb_x_test_pca, emodb_y_train, emodb_y_test)
emodb_LSTM_PCA_CLR = emodb_LSTM_PCA_accuracy/n

emodb_GRU_PCA_accuracy = 0
for i in range(5):
  emodb_GRU_PCA_accuracy += classification_measures(emodb_GRU_PCA_model, emodb_x_train_pca,
                                                    emodb_x_test_pca, emodb_y_train, emodb_y_test)
emodb_GRU_PCA_CLR = emodb_GRU_PCA_accuracy/n

print("Emodb DNN CLR: ", emodb_DNN_PCA_CLR)
print("Emodb CNN CLR: ", emodb_CNN_PCA_CLR)
print("Emodb LSTM CLR: ", emodb_LSTM_PCA_CLR)
print("Emodb GRU CLR: ", emodb_GRU_PCA_CLR)
```

1C) Do PCA for each dataset - MNIST

Mnist PCA

Everything should work

```
] #dnn
  def DNN_with_PCA():
    my_epochs = 10
    # Load MNIST data
    (x_train, y_train), (x_test, y_test) = mnist.load_data()

    # Flatten the images
    x_train = x_train.reshape(x_train.shape[0], -1)
    x_test = x_test.reshape(x_test.shape[0], -1)
    y_train = to_categorical(y_train)
    y_test = to_categorical(y_test)

    # Apply PCA for dimensionality reduction
    pca = PCA(n_components=100)  # Adjust number of components as needed
    x_train_pca = pca.fit_transform(x_train)
    x_test_pca = pca.transform(x_test)

    # Create a simple DNN model
    model = Sequential()
    model.add(Dense(128, input_dim=x_train_pca.shape[1], activation='relu'))
    model.add(Dense(64, activation='relu'))
    model.add(Dense(10, activation='softmax'))  # Output layer, 10 classes

    # Compile the model
    model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

    # Train the model
    model.fit(x_train_pca, y_train, epochs=my_epochs, batch_size=128, validation_data=(x_test_pca, y_test))

    # Evaluate the model
    y_pred_prob = model.predict(x_test_pca)
    y_pred = y_pred_prob.argmax(axis=1)

    # Calculate accuracy
    accuracy = accuracy_score(y_test.argmax(axis=1), y_pred)

    # Calculate D-index
    d_index = 1 - accuracy
    print("#---------#")
    print("d_index:", d_index)
    print("#---------#")


    return accuracy

  # Call the function
  accuracy = DNN_with_PCA()
  print(f"Accuracy with PCA and DNN: {accuracy}")
```

1C) Do PCA for each dataset – MNIST cont.

```python
def CNN_with_PCA():
    # Load MNIST data
    (x_train, y_train), (x_test, y_test) = mnist.load_data()

    # Reshape and normalize the data
    x_train = x_train.reshape(x_train.shape[0], -1)
    x_test = x_test.reshape(x_test.shape[0], -1)
    y_train = to_categorical(y_train)
    y_test = to_categorical(y_test)

    # Apply PCA for dimensionality reduction on flattened images
    pca = PCA(n_components=100)
    x_train_flatten = x_train.reshape(x_train.shape[0], -1)
    x_test_flatten = x_test.reshape(x_test.shape[0], -1)
    x_train_pca = pca.fit_transform(x_train_flatten)
    x_test_pca = pca.transform(x_test_flatten)

    # Reshape PCA-transformed data back to images
    x_train_pca = x_train_pca.reshape(-1, 10, 10, 1)
    x_test_pca = x_test_pca.reshape(-1, 10, 10, 1)

    # Create a CNN model
    model = Sequential()
    model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(10, 10, 1)))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Flatten())
    model.add(Dense(128, activation='relu'))
    model.add(Dense(10, activation='softmax'))  # Output layer, 10 classes

    # Compile the model
    model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

    # Train the model
    model.fit(x_train_pca, y_train, epochs=5, batch_size=128, validation_data=(x_test_pca, y_test))

    # Evaluate the model
    y_pred_prob = model.predict(x_test_pca)
    y_pred = np.argmax(y_pred_prob, axis=1)

    # Calculate accuracy
    accuracy = accuracy_score(np.argmax(y_test, axis=1), y_pred)

    # Calculate D-index
    d_index = 1 - accuracy

    return accuracy, d_index

# Call the function
accuracy, d_index = CNN_with_PCA()
print(f"Accuracy with PCA and CNN: {accuracy}")
print(f"D-index with PCA and CNN: {d_index}")
```

Results - PCA

EMODB

```
#----------#
#D-index: 0.0199
#----------#

Emodb DNN CLR:  0.07476635514018691
Emodb CNN CLR:  0.07476635514018691
Emodb LSTM CLR:  0.07476635514018691
Emodb GRU CLR:  0.07476635514018691
```

MNIST

What did not work:

- CNN
- LSTM
- GRU

```
#---------#
d_index: 0.050699999999999997
#---------#
Accuracy with PCA and DNN: 0.9493
```

```
Accuracy with PCA and CNN: 0.922
D-index with PCA and CNN: 0.07799999999999996
```

KOLOD

Total Issues with:

- DNN
- CNN
- LSTM
- GRU

2C) Do TSNE for each dataset - EMODB

Emodb tSNE

CNN

LSTM

GRU

Everything else should work

```
#do TSNE
tsne = TSNE()  # Adjust n_components as needed
emodb_tsne  = tsne.fit_transform(emodb_data)

#split data again
x_train, x_test, y_train, y_test = train_test_split(emodb_tsne, emodb_label, test_size=0.2, random_state=42)

#get model
emodb_DNN_TSNE_model = DNN_TSNE(emodb_tsne)

#get CLRs
accuracy = 0
for i in range(5):
  accuracy = classification_measures(emodb_DNN_TSNE_model, x_train, x_test, y_train, y_test)
emodb_DNN_TSNE_CLR = accuracy/n


print("Emodb DNN CLR: ", emodb_DNN_TSNE_CLR)
```

2C) Do TSNE for each dataset - MNIST

```
[75] (x_train_data, y_train_label), (x_test_data, y_test_label) = mnist.load_data()

    x_train = x_train_data.reshape(y_train_label.shape[0], x_train_data.shape[1], x_train_data.shape[2], 1)
    x_test = x_test_data.reshape(y_test_label.shape[0], x_test_data.shape[1], x_test_data.shape[2], 1)

    y_train = to_categorical(y_train_label)
    y_test = to_categorical(y_test_label)

    x_train_flat = x_train.reshape(-1, 28 * 28)
    x_test_flat = x_test.reshape(-1, 28 * 28)

    #perform tsne on mnist
    tsne = TSNE()
    train_tsne = tsne.fit_transform(x_train_flat)
    test_tsne = tsne.fit_transform(x_test_flat)
```

```
#TSNE
model = Sequential()

layer_1_node_number, layer_2_node_number, layer_3_node_number = 200, 100, 50

model.add(Dense(layer_1_node_number,activation = 'relu', input_shape = (train_tsne.shape[1],)))

model.add(Dense(layer_2_node_number, activation = 'relu'))

model.add(Dense(layer_3_node_number, activation = 'relu'))

dense_node_number = 10

model.add(Dense(dense_node_number, activation = 'softmax'))

my_epochs = 10

model.compile(optimizer = 'adam', loss = 'categorical_crossentropy', metrics= ['accuracy'])

history = model.fit(train_tsne, y_train, epochs = my_epochs, batch_size = 500, validation_data= (test_tsne, y_test))

#calculate the classificaiton measures
#in order to find these, I have to fit a classifier on PCA,
#so I will be using Support Vector Machines, svm
from sklearn.svm import SVC
#from sklearn.ensemble import GradientBoostingClassifier
import numpy as np
from sklearn.metrics import confusion_matrix, precision_score, recall_score, f1_score, accuracy_score
```

2C) Do TSNE for each dataset - MNIST cont

```
#SVM
svm = SVC()

svm.fit(train_tsne, y_train_label)

pred_labels = svm.predict(test_tsne)


#clf = GradientBoostingClassifier()
#clf.fit(train_tsne, y_train_label)
#pred_labels = clf.predict(test_tsne)


#calculating metrics for multiclass classification via 'macro'
conf_matrix = confusion_matrix(y_test_label, pred_labels)

precision = precision_score(y_test_label, pred_labels, average = 'macro')

f1 = f1_score(y_test_label, pred_labels, average = 'macro')

accuracy = accuracy_score(y_test_label, pred_labels)

recall = recall_score(y_test_label, pred_labels, average = 'macro')

d_index = 2 * (precision * recall)/(precision + recall)

#calculate specificity
TN = conf_matrix[0][0]
FP = conf_matrix[0][1:].sum()
FN = conf_matrix[1:, 0].sum()
TP = conf_matrix[1:, 1:].sum()

specificity = TN / (TN + FP)

#displaying the metrics
print("Confusion Matrix: \n", conf_matrix)
print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1 Score: {f1:.4f}")
print(f"D-index: {d_index:.4f}")
print(f"Specificity: {specificity:.4f}")
```

Results - TSNE

EMODB

What did not work:

- CNN
- LSTM
- GRU

```
#----------#
#D-index: 0.0199
#----------#

Emodb DNN CLR:  0.0149532710280373 82
```

MNIST

What did not work:

- CNN
- LSTM
- GRU

```
Accuracy: 0.1580
Precision: 0.1491
Recall: 0.1629
F1 Score: 0.1483
D-index: 0.1557
Specificity: 0.0316
```

KOLOD

Total Issues with:

- DNN
- CNN
- LSTM
- GRU

D) Increase models to 7 layers - EMODB

EMODB 7 Layers

GRU

Everything else should work

```
#get models
emodb_DNN_7_model = DNN_7_layers("emodb", emodb_x_train)
emodb_CNN_7_model = CNN_7_layers("emodb", emodb_x_train)
emodb_LSTM_7_model = LSTM_7_layers("emodb", emodb_x_train)
emodb_GRU_7_model = GRU_7_layers("emodb", emodb_x_train)

n = 5
accuracy = 0
for i in range(5):
  accuracy += classification_measures(emodb_DNN_7_model, emodb_x_train,
                                      emodb_x_test, emodb_y_train, emodb_y_test)
emodb_DNN_7_CLR = accuracy/n

accuracy = 0
for i in range(5):
  accuracy += classification_measures(emodb_CNN_7_model, emodb_x_train,
                                      emodb_x_test, emodb_y_train, emodb_y_test)
emodb_CNN_7_CLR = accuracy/n

accuracy = 0
for i in range(5):
  accuracy += classification_measures(emodb_LSTM_7_model, emodb_x_train, e
                                      modb_x_test, emodb_y_train, emodb_y_test)
emodb_LSTM_7_CLR = accuracy/n

accuracy = 0
for i in range(5):
  accuracy += classification_measures(emodb_GRU_7_model, emodb_x_train,
                                      emodb_x_test, emodb_y_train, emodb_y_test)
emodb_GRU_7_CLR = accuracy/n

print("DNN CLR: ", emodb_DNN_7_CLR)
print("CNN CLR: ", emodb_CNN_7_CLR)
print("LSTM CLR: ", emodb_LSTM_7_CLR)
print("GRU CLR: ", emodb_GRU_7_model)
```

D) Increase models to 7 layers - MNIST

MNIST 7 Layers

Everything should work

```
#reload data
(x_train, y_train_label), (x_test, y_test_label) = mnist.load_data()

x_train_data = x_train.reshape(y_train_label.shape[0], x_train.shape[1], x_train.shape[2], 1)
x_test_data = x_test.reshape(y_test_label.shape[0], x_test.shape[1], x_test.shape[2], 1)

y_train = to_categorical(y_train_label)
y_test = to_categorical(y_test_label)

#get models
mnist_DNN_7_model = DNN_7_layers("mnist", x_train_data)
mnist_CNN_7_model = CNN_7_layers("mnist", x_train_data)
mnist_LSTM_7_model = LSTM_7_layers("mnist", x_train_data)
mnist_GRU_7_model = GRU_7_layers("mnist", x_train_data)

#get CLRs
n = 5
accuracy = 0
for i in range(5):
  accuracy += mnist_classification_measures(mnist_DNN_7_model, x_train_data,
                                            x_test_data, y_train, y_test, y_test_label)
mnist_DNN_7_model = accuracy/n

accuracy = 0
for i in range(5):
  accuracy += mnist_classification_measures(mnist_CNN_7_model, x_train_data,
                                            x_test_data, y_train, y_test, y_test_label)
mnist_CNN_7_model = accuracy/n

accuracy = 0
for i in range(5):
  accuracy += mnist_classification_measures(mnist_LSTM_7_model, x_train_data,
                                            x_test_data, y_train, y_test, y_test_label)
mnist_LSTM_7_model = accuracy/n

accuracy = 0
for i in range(5):
  accuracy += GRU_7_layers_classification(mnist_GRU_7_model, x_train_data,
                                          y_train, x_test_data, y_test)
mnist_GRU_7_model = accuracy/n
```

D) Increase models to 7 layers - KOLOD

KOLOD 7 Layers

GRU

LSTM

CNN

DNN

```
#get models
kolod_DNN_7_model = DNN_7_layers("kolod", kolod_x_train)
kolod_CNN_7_model = CNN_7_layers("kolod", kolod_x_train)
# kolod_LSTM_7_model = LSTM_7_layers("kolod", kolod_x_train)
# kolod_GRU_7_model = GRU_7_layers("kolod", kolod_x_train)

n = 5
accuracy = 0
for i in range(5):
  accuracy += classification_measures(kolod_DNN_7_model, kolod_x_train,
                                      kolod_x_test, kolod_y_train, kolod_y_test)
kolod_DNN_7_CLR = accuracy/n

# accuracy = 0
# for i in range(5):
#   accuracy += classification_measures(kolod_CNN_7_model, emodb_x_train,
#                                       emodb_x_test, emodb_y_train, emodb_y_test)
# kolod_CNN_7_CLR = accuracy/n

# accuracy = 0
# for i in range(5):
#   accuracy += classification_measures(kolod_LSTM_7_model, emodb_x_train,
#                                       emodb_x_test, emodb_y_train, emodb_y_test)
# kolod_LSTM_7_CLR = accuracy/n

# accuracy = 0
# for i in range(5):
#   accuracy += classification_measures(kolod_GRU_7_model, emodb_x_train,
#                                       emodb_x_test, emodb_y_train, emodb_y_test)
# kolod_GRU_7_CLR = accuracy/n

print("DNN CLR: ", kolod_DNN_7_CLR)
#print("CNN CLR: ", kolod_CNN_7_CLR)
# print("LSTM CLR: ", kolod_LSTM_7_CLR)
# print("GRU CLR: ", kolod_GRU_7_CLR)
```

Results

EMODB

What did not work:

- GRU

```
#----------#
#D-index: 0.0199
#----------#

DNN CLR:  0.07476635514018691
CNN CLR:  0.07476635514018691
LSTM CLR:  0.07476635514018691
GRU CLR:  <keras.src.engine.sequential.Sequential object at 0x7b28ece1fcd0>
```

MNIST

```
Accuracy: 0.9853
D-index: 0.014700000000000046
DNN:  0.1135
CNN:  0.9836199999999999
LSTM:  0.8827999999999999
GRU:  0.9846199999999999
```

KOLOD

```
#----------#
#D-index: nan
#----------#

DNN CLR:  0.0
```

D) Do PCA before DNN, CNN, and LSTM

This is just the same thing as Part C!

This concludes the first half

Part B: Deep Learning with Credit Risk Analytics

Visualizing PHATE, t-SNE, and PCA + t-SNE Embedded data for Credit Risk data

Applying CNN, LSTM, and GRU Classification

Introduction to Deep Learning Models

CONVOLUTIONAL NEURAL NETWORKS (CNN)

- A feed-forward neural network, ideal for image, audio, and speech data classification; the issue of vanishing and exploding gradients are prevented through weights present in the model's algorithm

LONG SHORT-TERM MEMORY (LSTM)

- A recurrent neural network (RNN) designed to deal with the issue of vanishing gradients in traditional RNNs, capable of long-term dependencies

GATED RECURRENT UNIT (GRU)

- A RNN similar to LSTM due to its use of gates to control the flow of information; its gating mechanisms are used to selectively update the hidden state of the network at each time step

Overview of Resampling Methods

RANDOMOVERSAMPLER()

- The most naïve strategy to generate new samples, generates new samples by randomly sampling with replacement the currently available samples

SYNTHETIC MINORITY OVERSAMPLING TECHNIQUE

- One of the most commonly used oversampling methods, aims to balance class distribution by randomly increasing minority class examples by replicating them

ADAPTIVE SYNTHETIC (ADASYN)

- Similar to SMOTE but generates a different number of samples depending on an estimate of the local distribution of the class to be oversampled

SMOTEENN()

- Oversampling using SMOTE, cleaning using Edited Nearest Neighbors (ENN)

Overview of Resampling Methods

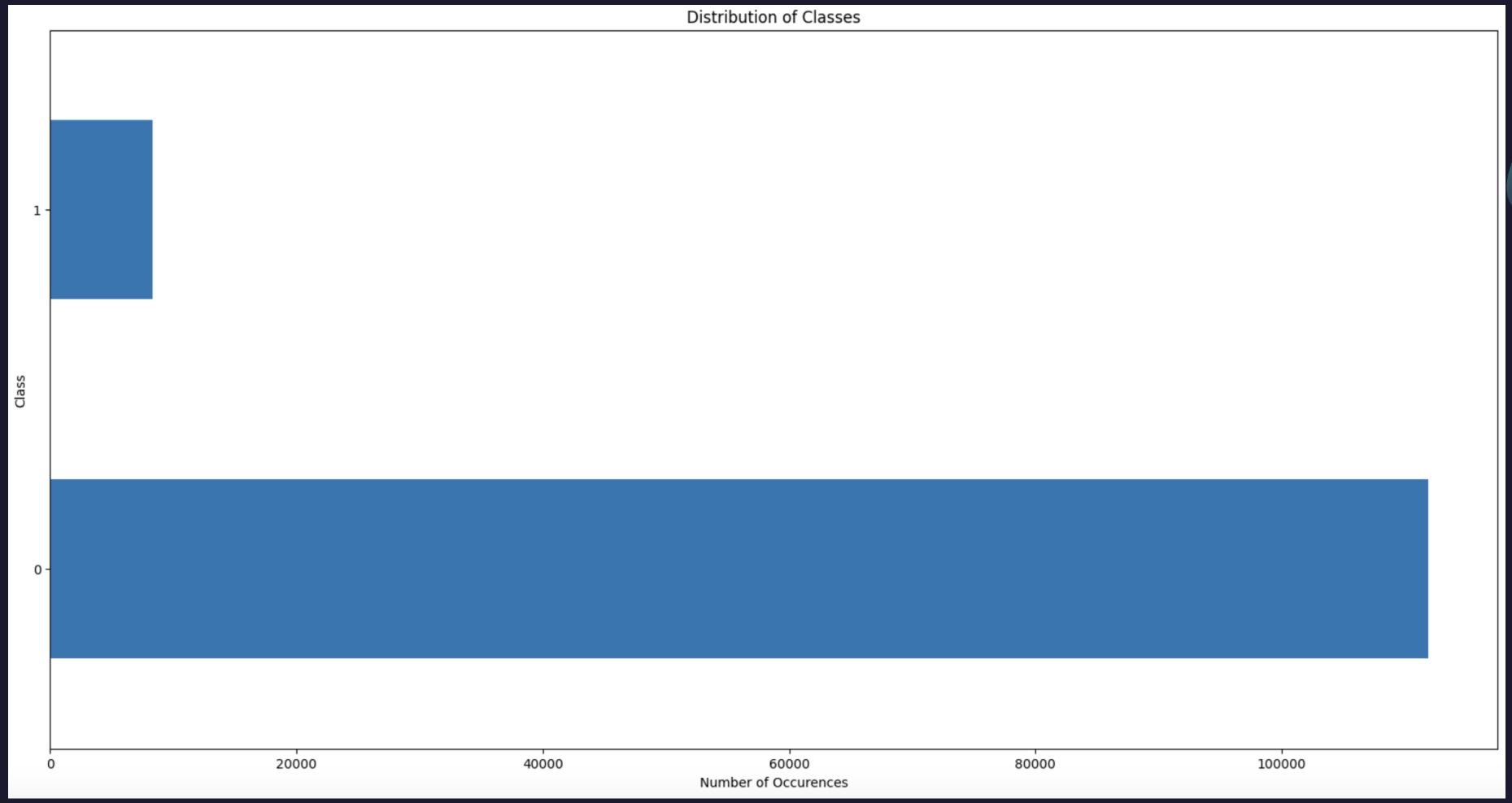
TOMEKLINKS()

- An under-sampling technique developed by Ivan Tomek, used to find samples from the majority class having the lowest Euclidean distance with the minority class data and then removing it

SMOTETOMEK()

- Oversampling using SMOTE and cleaning using the aforementioned TomekLinks technique

Overview of Credit Risk Data



LSTM & GRU Helper Functions

```python
def apply_lstm(training_data, training_labels, testing_data, testing_labels):

  # Reshaping data for LSTM
  num_features = training_data.shape[1]

  model = Sequential()
  model.add(LSTM(100, activation = "relu", input_shape = (num_features, 1)))

  # Output layer = 1, for two classes represented in data (classes 0 and 1)
  model.add(Dense(1, activation = "sigmoid"))

  # Compile model
  model.compile(optimizer = "adam", loss = "binary_crossentropy")

  # Train Model
  history = model.fit(training_data, training_labels, epochs = 50, validation_split = 0.2)

  # Collect training and testing loss history for model
  lstm_training_losses = history.history["loss"]
  lstm_testing_losses = history.history["val_loss"]

  # Make predictions for classification metrics
  predicted_labels = model.predict(testing_data)

  return lstm_training_losses, lstm_testing_losses, predicted_labels
```

```python
def apply_gru(training_data, training_labels, testing_data, testing_labels):

  num_features = training_data.shape[1]

  model = Sequential()

  model.add(GRU(32, activation = "relu", input_shape = (num_features, 1)))

  # Output layer - 1 for two classes represented in the data
  model.add(Dense(1, activation = "sigmoid"))

  # Compile model
  model.compile(optimizer = "adam", loss = "binary_crossentropy")

  # Train model
  history = model.fit(training_data, training_labels, epochs = 50, validation_split = 0.2)

  # Collect training and testing loss history for model
  gru_training_losses = history.history["loss"]
  gru_testing_losses = history.history["val_loss"]


  # Make predictions for classification metrics
  predicted_labels = model.predict(testing_data)

  return gru_training_losses, gru_testing_losses, predicted_labels
```

CNN Helper Function

```python
def apply_cnn(training_data, training_labels, testing_data, testing_labels):

  # to_categorical
  training_labels = to_categorical(training_labels)
  testing_labels = to_categorical(testing_labels)

  # Assuming your data has 10 features
  input_shape = (10, 1)

  # Build model
  model = Sequential()

  # Add first convolutional layer
  model.add(Conv1D(32, kernel_size = 3, activation = 'relu', input_shape = input_shape))
  model.add(MaxPooling1D(pool_size = 2))

  # Flatten layer
  model.add(Flatten())

  model.add(Dense(64, activation='relu'))

  # Output layer - for binary classification use 2 and sigmoid activation
  model.add(Dense(2, activation='sigmoid'))

  # Compile the model - binary_crossentropy for binary data
  model.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])

  history = model.fit(training_data, training_labels, epochs = 50, batch_size = 32, validation_split = 0.2)

  # Obtain Training and Validation Losses from model history
  cnn_training_losses = history.history["loss"]
  cnn_testing_losses = history.history["val_loss"]

  # Make predictions for classification metrics
  predicted_labels = model.predict(testing_data)

  return cnn_training_losses, cnn_testing_losses, predicted_labels
```

Classification Measures Helper Function

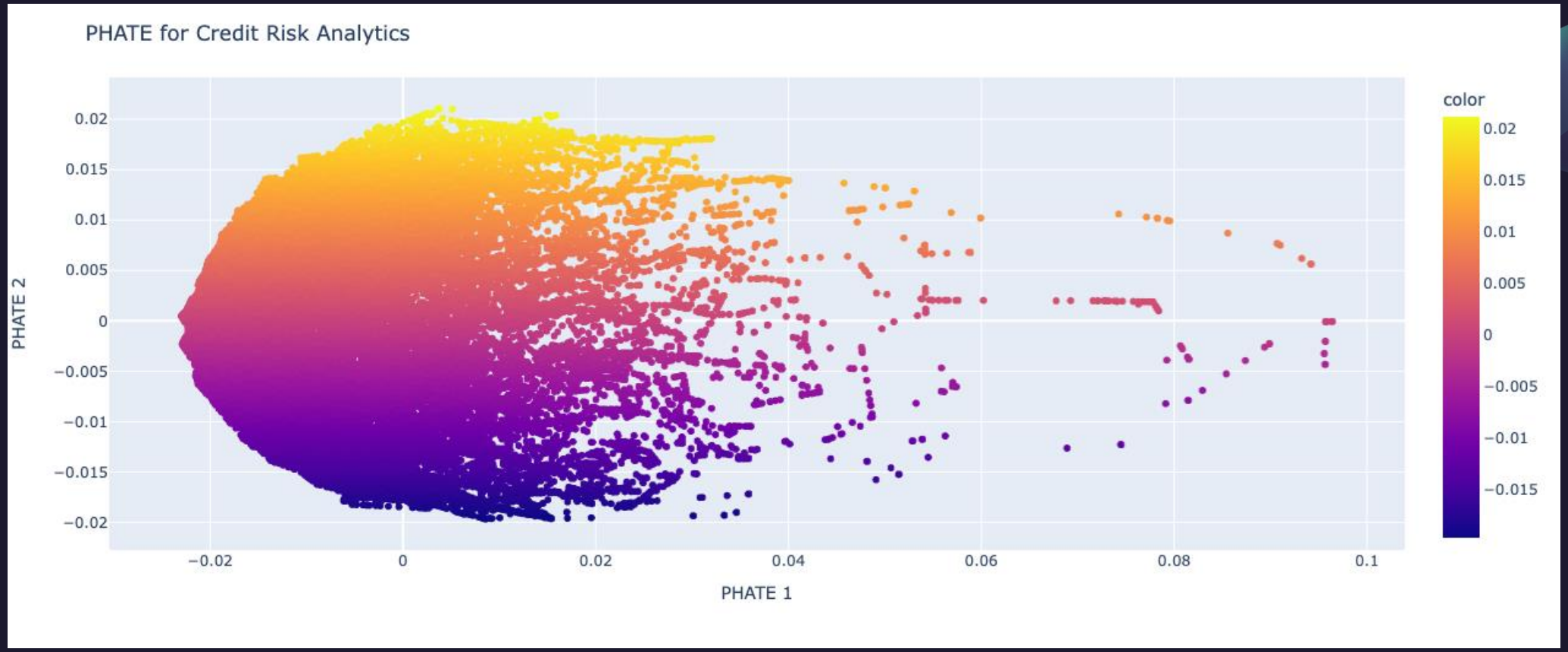
```python
# Helper Function for Calculating Classification Measures

def compute_measure(true_label, predicted_label):
  t_idx = (true_label == predicted_label) # correctly predicted
  f_idx = np.logical_not(t_idx) # incorrectly predicted
  p_idx = (true_label>0) # positive
  n_idx = np.logical_not(p_idx) # negative
  tp = np.sum(np.logical_and(t_idx, p_idx)) # TP
  tn = np.sum(np.logical_and(t_idx, n_idx)) # TN
  fp = np.sum(n_idx) - tn
  fn = np.sum(p_idx) - tp
  tp_fp_tn_fn_list = []
  tp_fp_tn_fn_list.append(tp)
  tp_fp_tn_fn_list.append(fp)
  tp_fp_tn_fn_list.append(tn)
  tp_fp_tn_fn_list.append(fn)
  tp_fp_tn_fn_list = np.array(tp_fp_tn_fn_list)
  tp = tp_fp_tn_fn_list[0]
  fp = tp_fp_tn_fn_list[1]
  tn = tp_fp_tn_fn_list[2]
  fn = tp_fp_tn_fn_list[3]

  with np.errstate(divide= 'ignore'):
    sen = (1.0 * tp)/(tp + fn)
  with np.errstate(divide= 'ignore'):
    spec = (1.0 * tn)/(tn + fp)
  with np.errstate(divide= 'ignore'):
    ppr = (1.0*tp)/(tp+fp)
  with np.errstate(divide= 'ignore'):
    npr = (1.0*tn)/(tn+fn)
  with np.errstate(divide= 'ignore'):
    f1=tp/(tp+0.5*(fp+fn))

  acc = (tp+tn)*1.0/(tp+fp+tn+fn)
  d = np.log2(1 + acc) + np.log2(1 + (sen+spec)/2)
  ans = []
  ans.append(acc)
  ans.append(sen)
  ans.append(spec)
  ans.append(ppr)
  ans.append(npr)
  ans.append(f1)
  ans.append(d)

  return ans
```

```python
# Printing Classification Report

def model_metrics(true,pred):
  ans = compute_measure(testing_labels, np.argmax(predicted_labels, axis = 1))
  print("Accuracy is {0:4f}".format(ans[0]))
  print("Sensitivity is {0:4f}".format(ans[1]))
  print("Specificity is {0:4f}".format(ans[2]))
  print("Precision is {0:4f}".format(ans[3]))
  print("Negative Prediction ratio is {0:3f}".format(ans[4]))
  print("F1-score is {0:3f}".format(ans[5]))
  print("Diagnostic index is {0:4f}".format(ans[6]))
  print("\n")
```

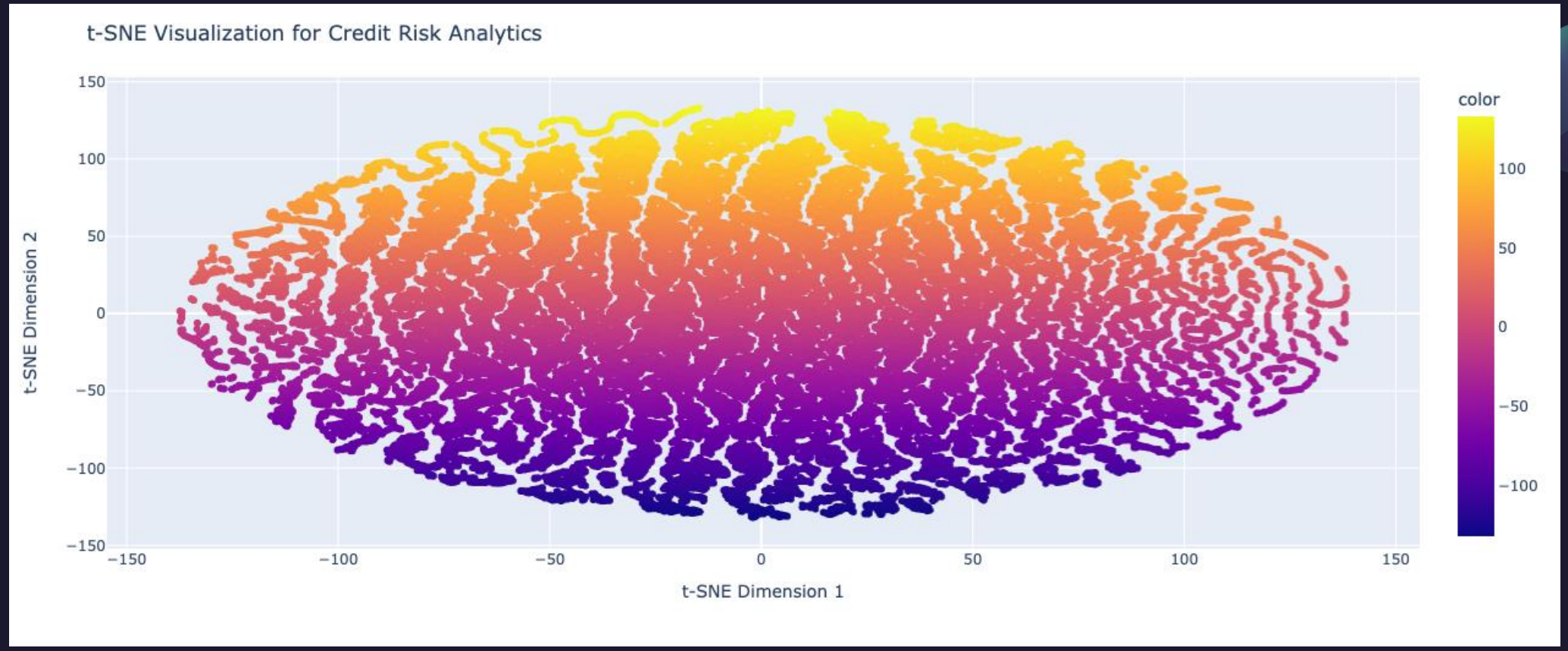
Training and Testing Loss Visualization Helper Function

```
[ ]  # Helper Function to display Training and Validation Losses
     def visualize_losses(model_type, train_losses, test_losses):

       fig = plt.figure(figsize = (20,10))
       plt.plot(train_losses, color = "#253C78", label = 'Training Loss')
       plt.plot(test_losses, color = "#D36582", linestyle = "dashed", linewidth = 2, label = 'Test Loss')
       plt.title("Training and Testing Loss Curves under Adam Solver: " + model_type)
       plt.xlabel('Epochs')
       plt.ylabel('Loss')
       plt.legend()
       plt.grid('on')
       plt.show()
```

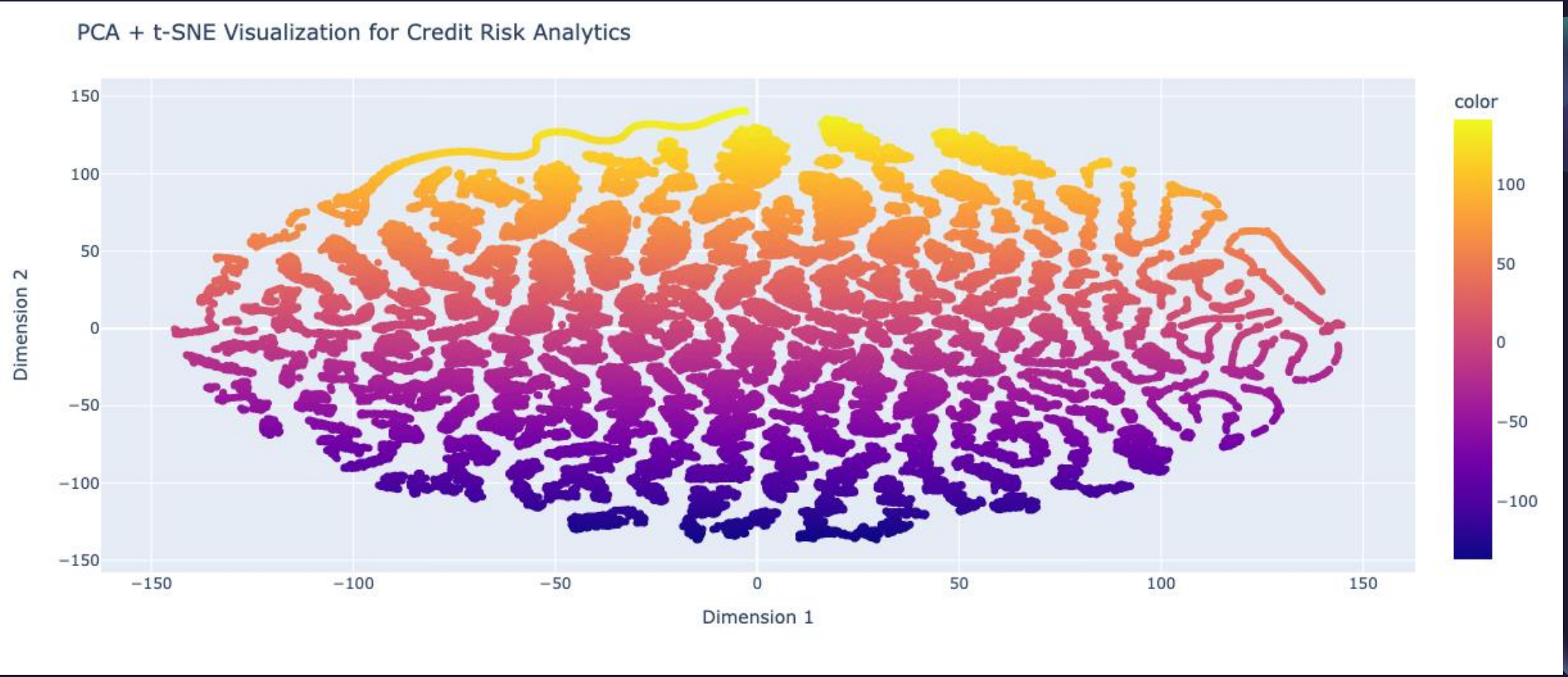
PHATE Visualization



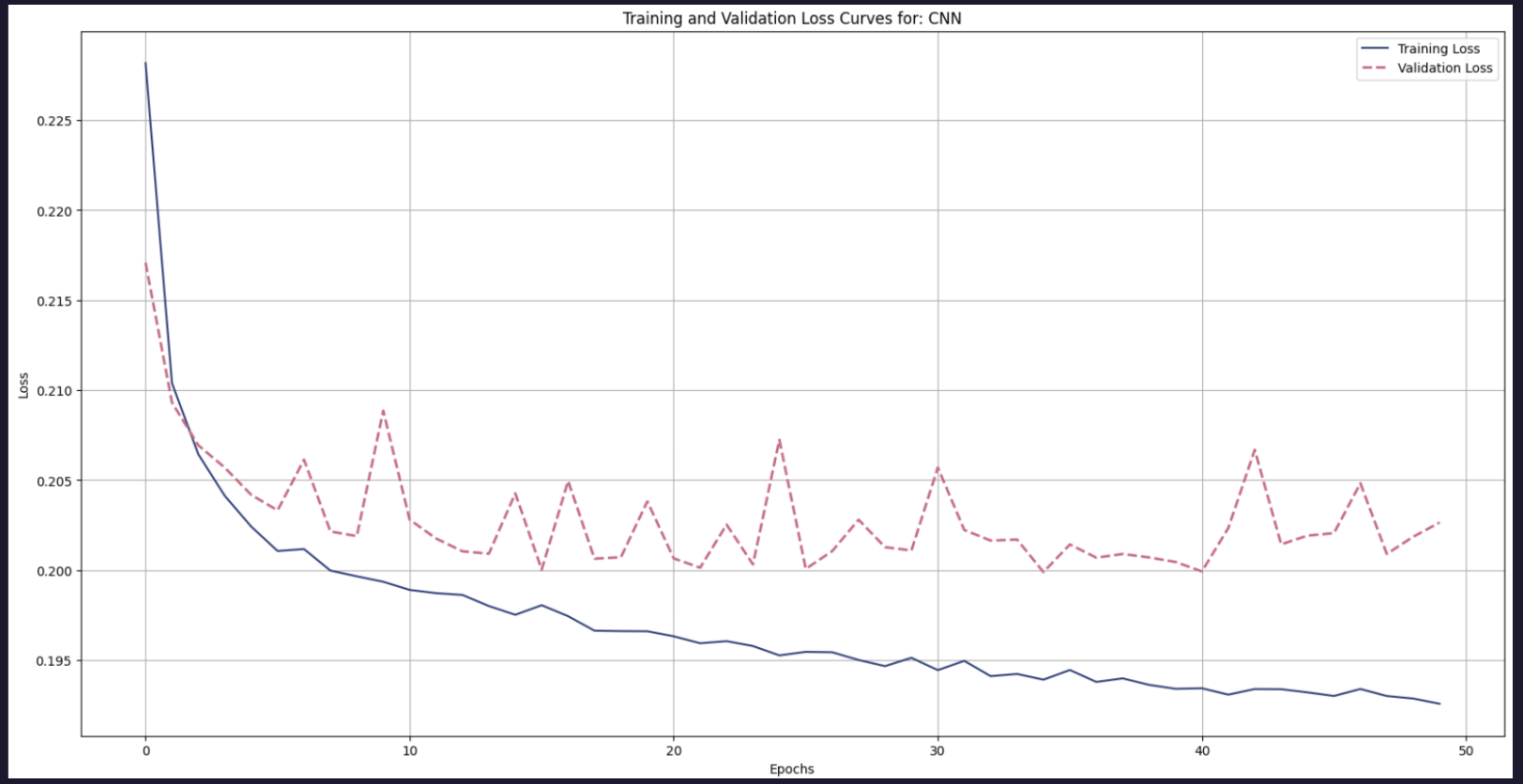
t-SNE Visualization



PCA + t-SNE Visualization

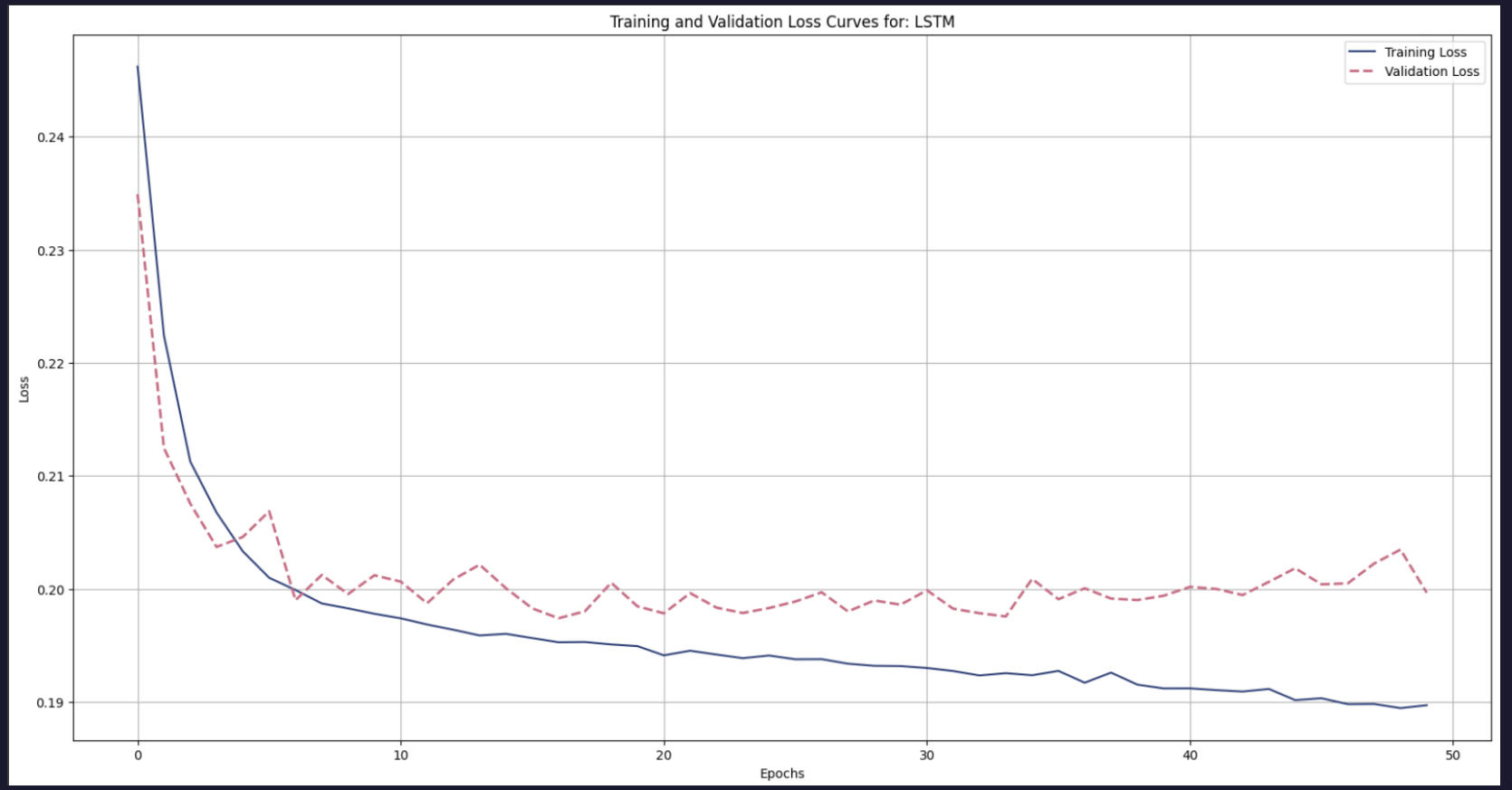


Loss History and Performance - CNN



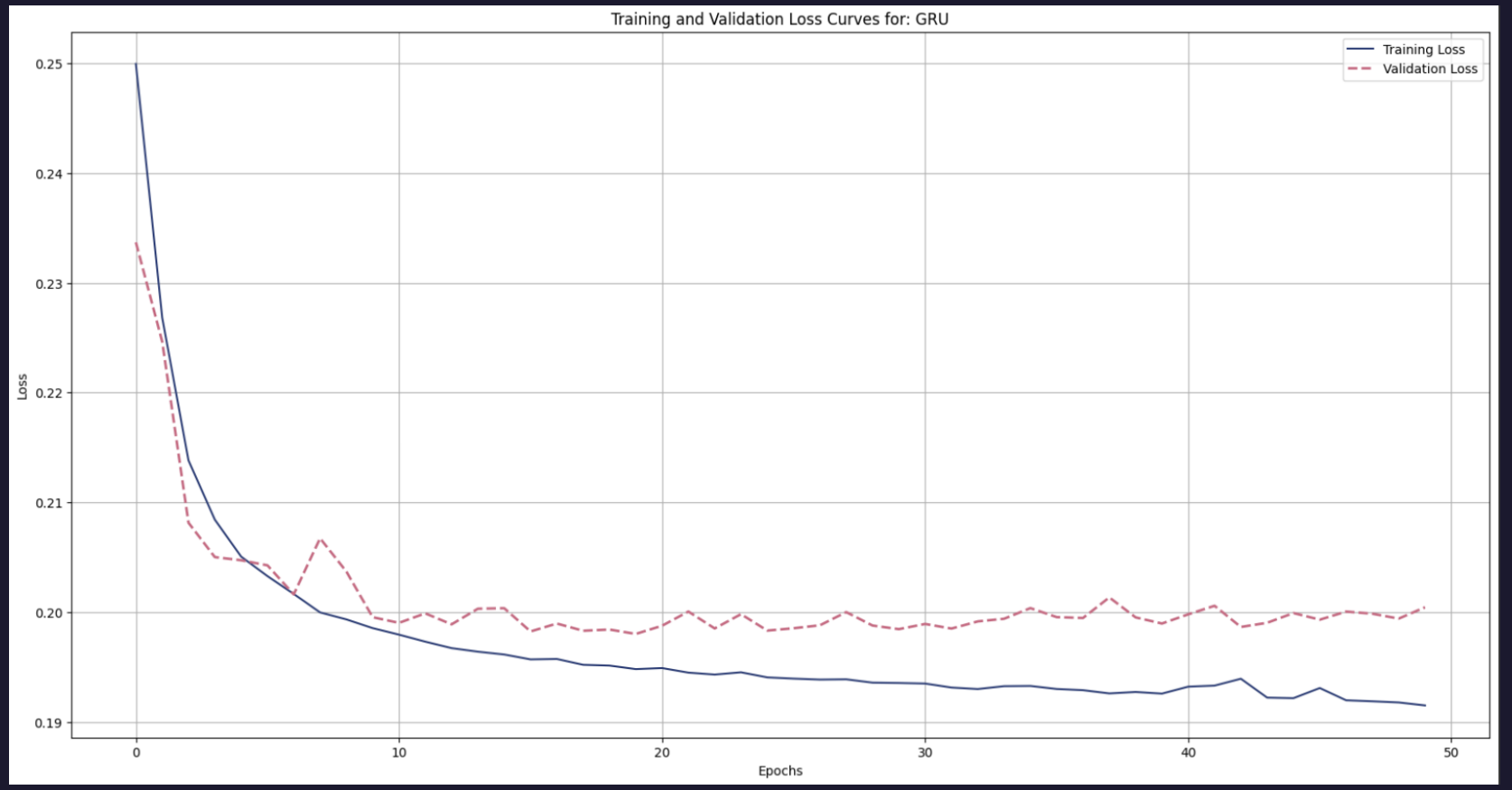

```
Accuracy is 0.931529
Sensitivity is 0.164311
Specificity is 0.989801
Precision is 0.550296
Negative Prediction ratio is 0.939738
F1-score is 0.253061
Diagnostic index is 1.606977
```

Loss History and Performance - LSTM



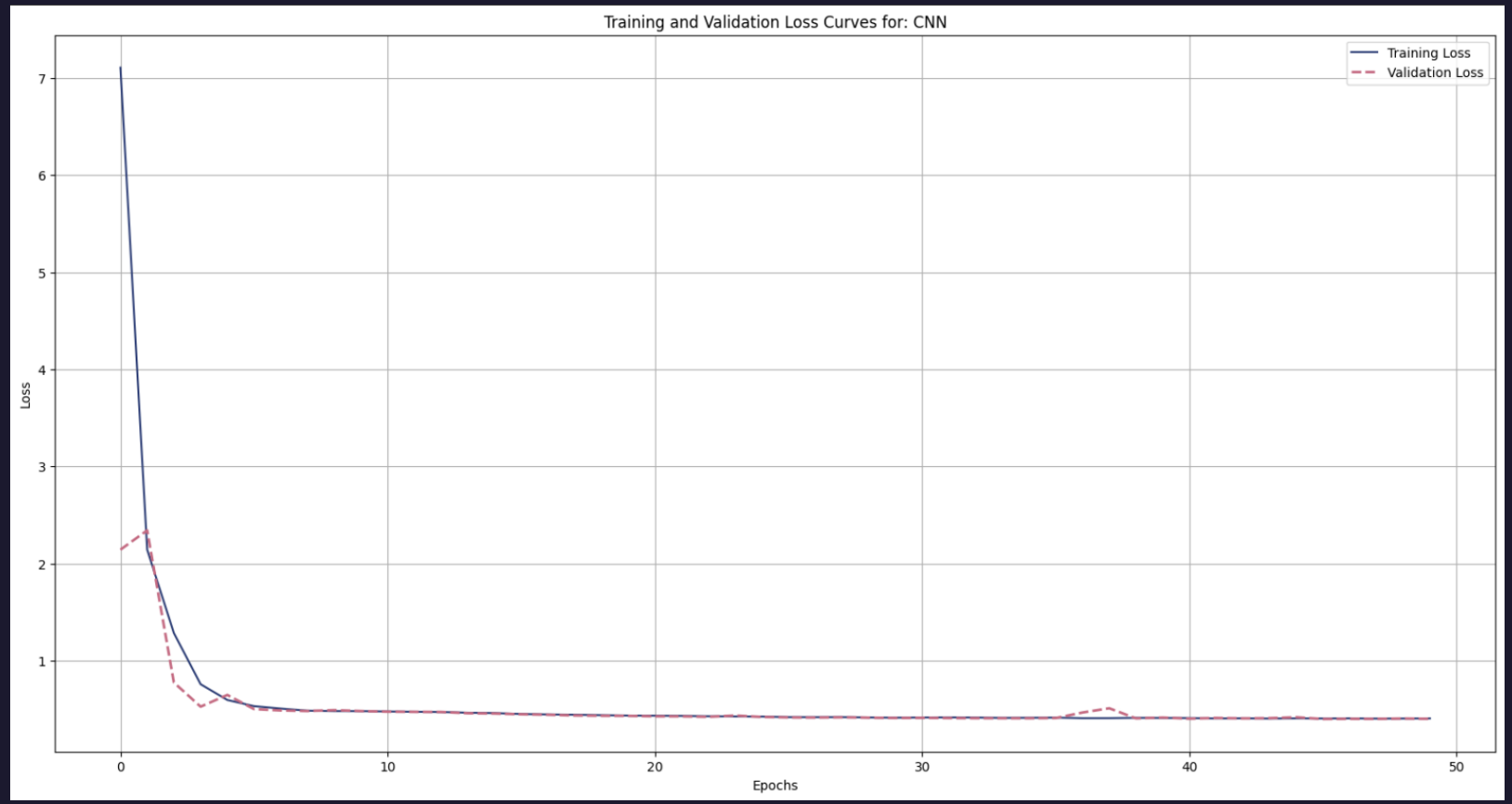

```
Accuracy is 0.929409
Sensitivity is 0.000000
Specificity is 1.000000
Precision is  nan
Negative Prediction ratio is 0.929409
F1-score is 0.000000
Diagnostic index is 1.533121
```

Loss History and Performance - GRU



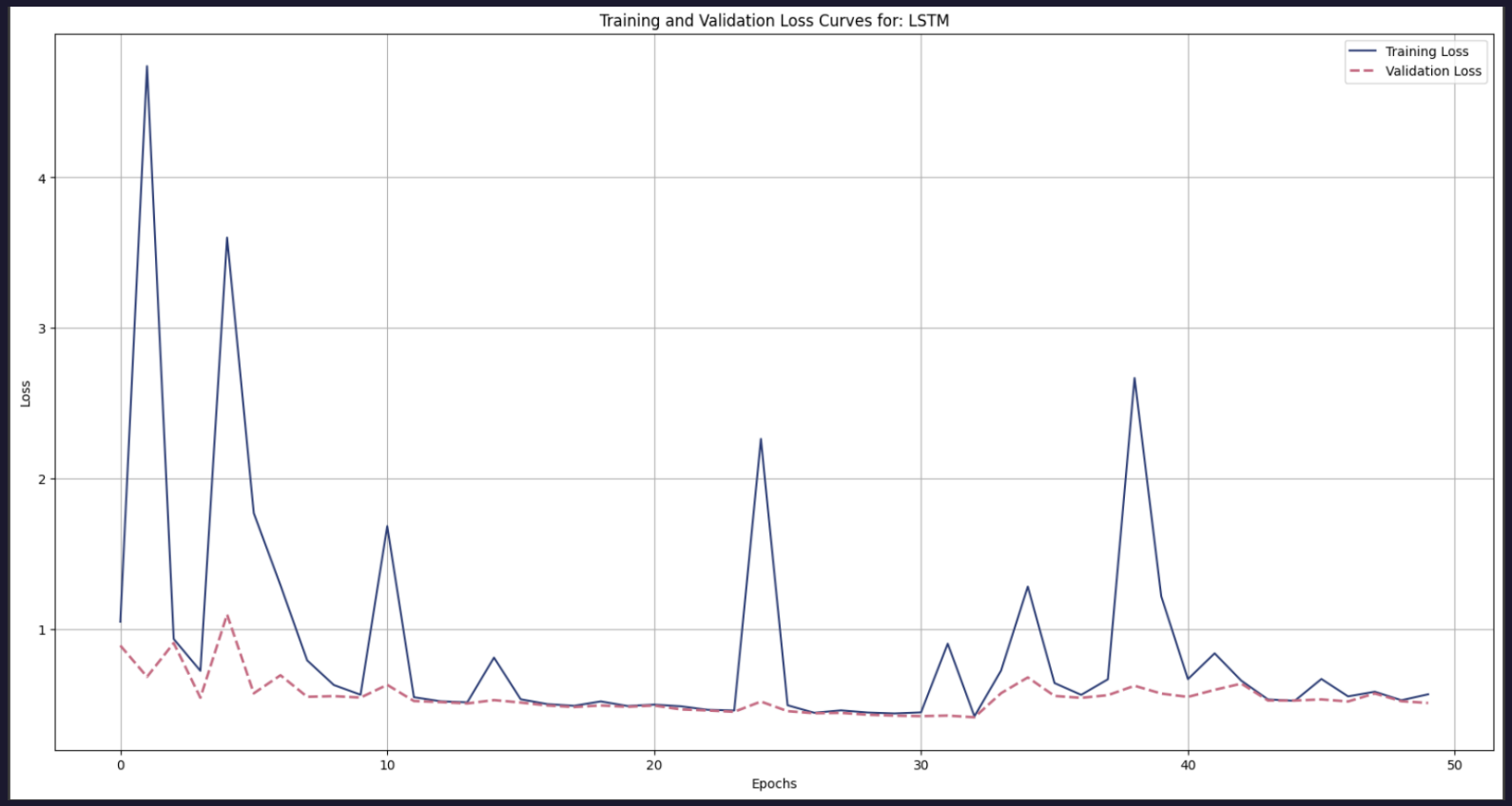

```
Accuracy is 0.929409
Sensitivity is 0.000000
Specificity is 1.000000
Precision is  nan
Negative Prediction ratio is 0.929409
F1-score is 0.000000
Diagnostic index is 1.533121
```

Loss History and Performance – CNN (with SMOTE)



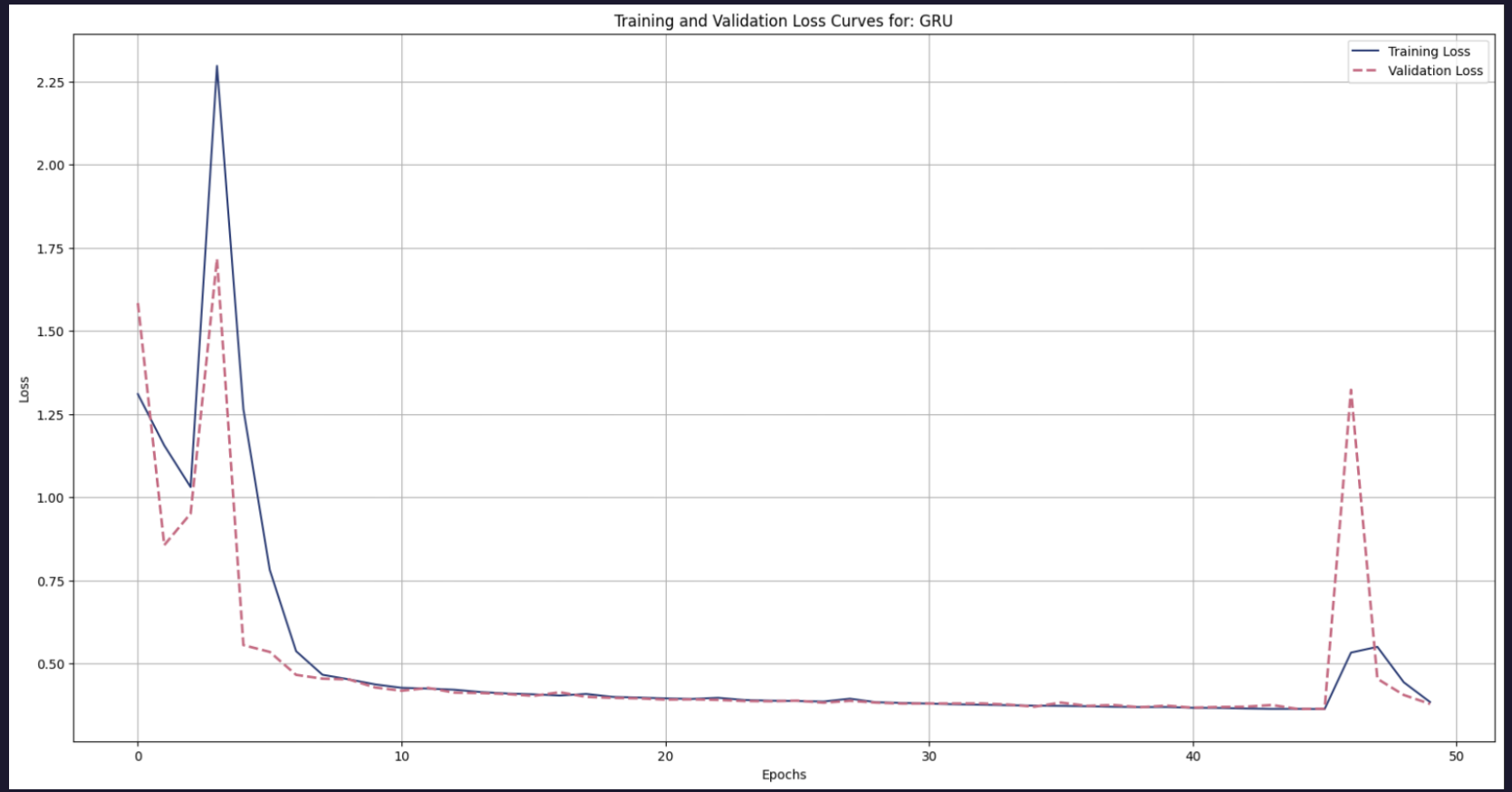

```
Accuracy is 0.809226
Sensitivity is 0.824925
Specificity is 0.793532
Precision is 0.799766
Negative Prediction ratio is 0.819297
F1-score is 0.812151
Diagnostic index is 1.710747
```

Loss History and Performance – LSTM (with SMOTE)



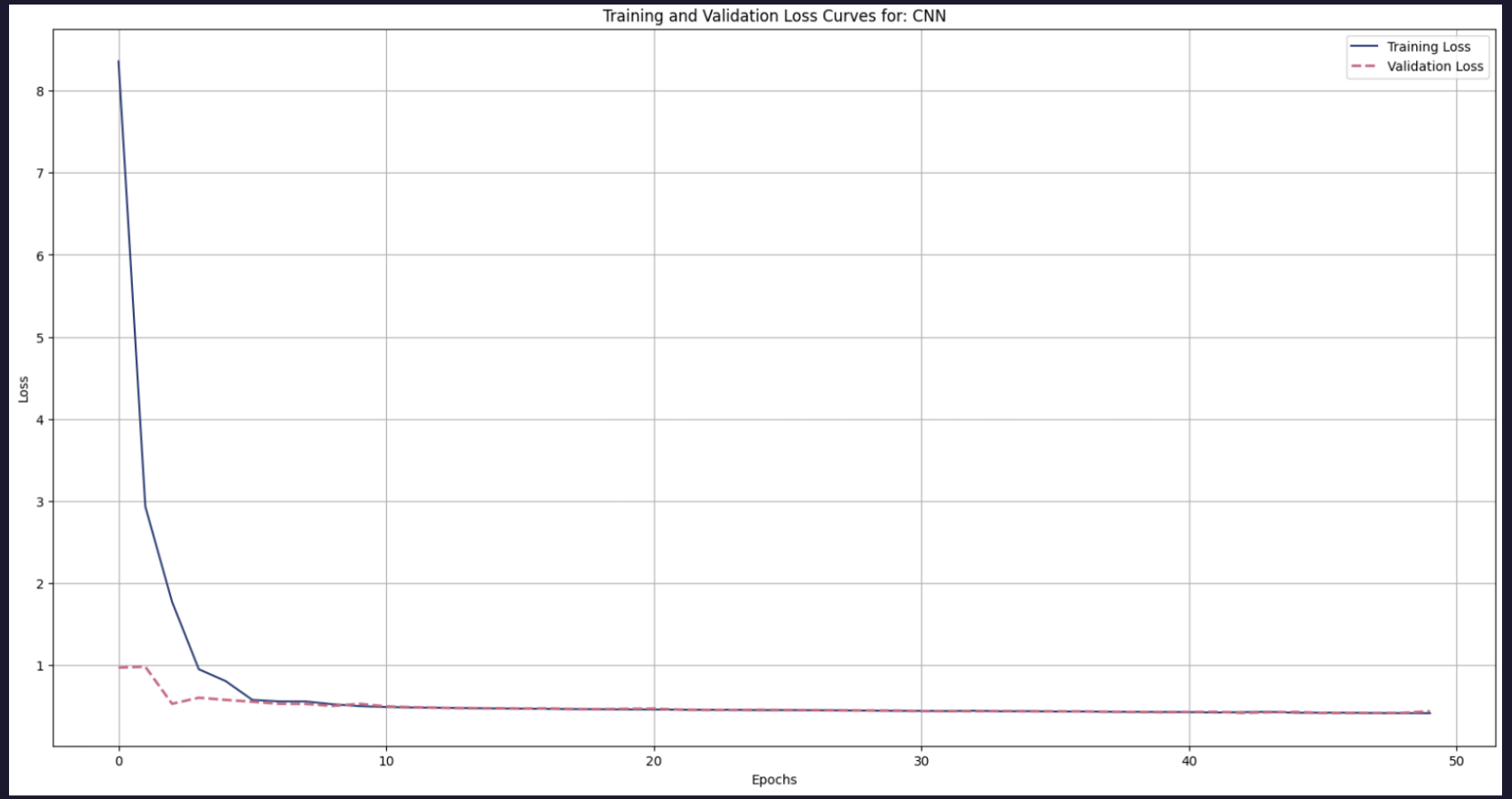

```
Accuracy is 0.500078
Sensitivity is 0.000000
Specificity is 1.000000
Precision is  nan
Negative Prediction ratio is 0.500078
F1-score is 0.000000
Diagnostic index is 1.170000
```

Loss History and Performance – GRU (with SMOTE)



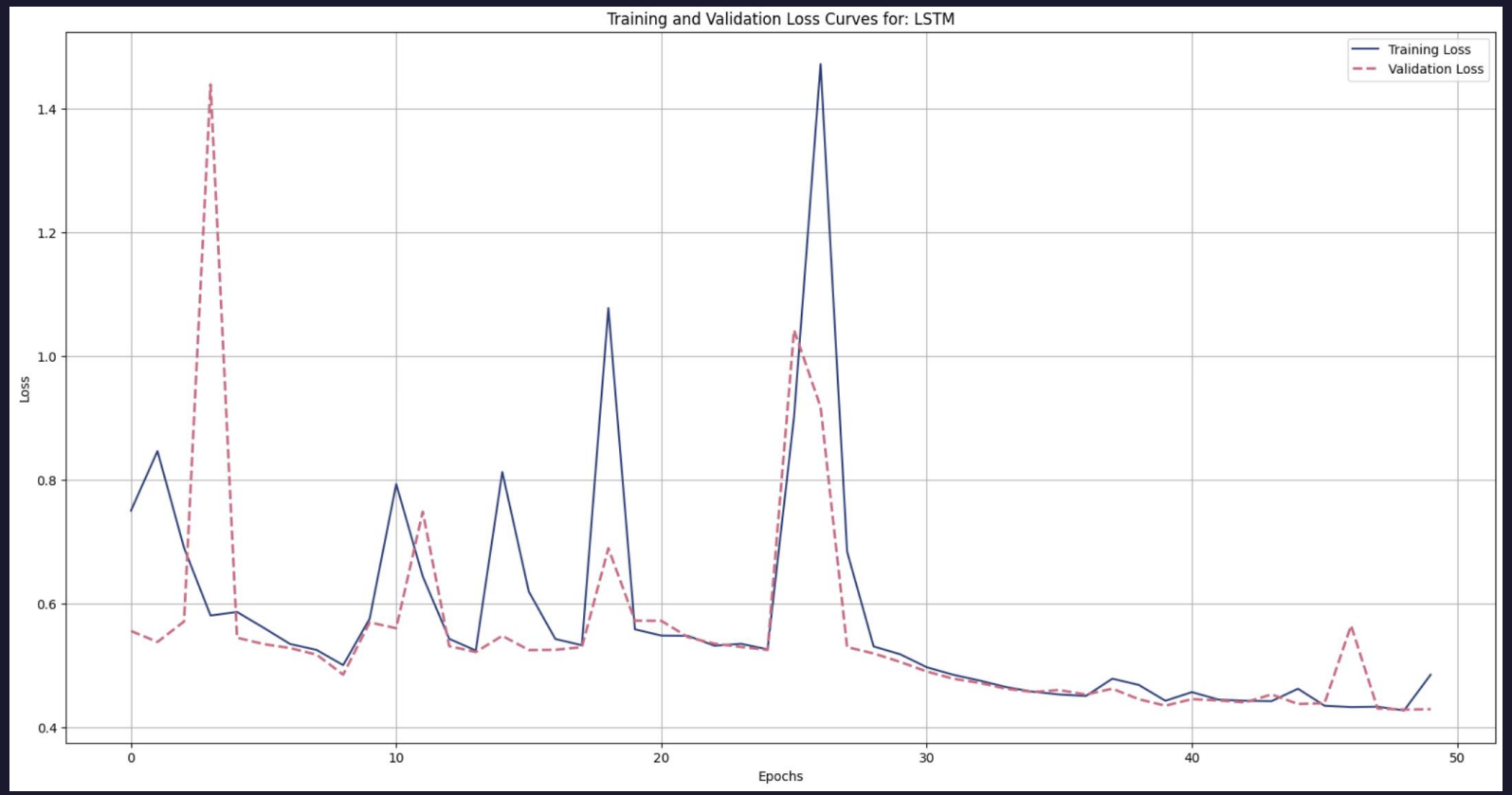

```
Accuracy is 0.500078
Sensitivity is 0.000000
Specificity is 1.000000
Precision is  nan
Negative Prediction ratio is 0.500078
F1-score is 0.000000
Diagnostic index is 1.170000
```

Loss History and Performance – CNN (with ADASYN)



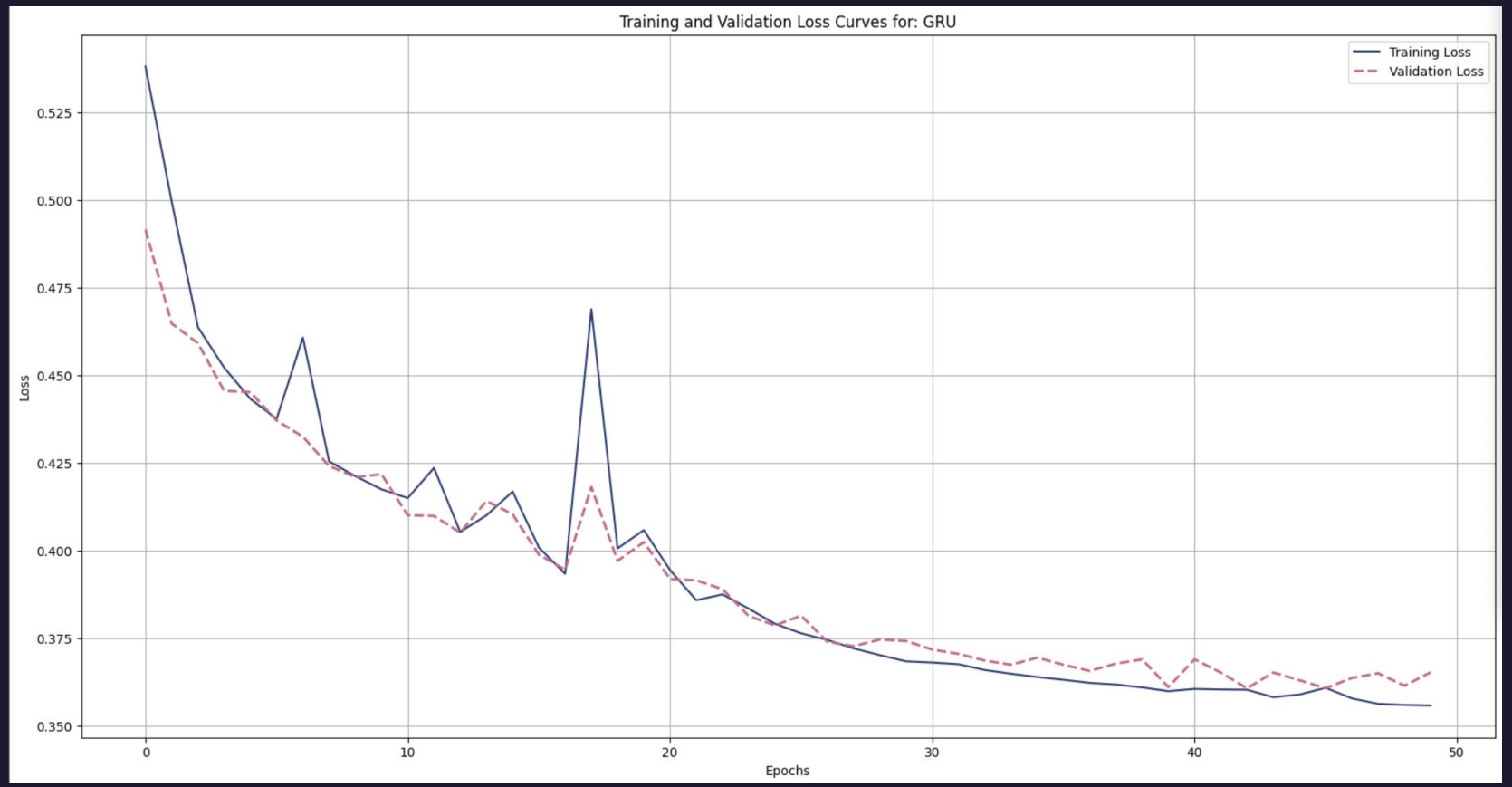

```
Accuracy is 0.794415
Sensitivity is 0.813020
Specificity is 0.775368
Precision is 0.787474
Negative Prediction ratio is 0.802003
F1-score is 0.800043
Diagnostic index is 1.686849
```

Loss History and Performance – LSTM (with ADASYN)




```
Accuracy is 0.494131
Sensitivity is 0.000000
Specificity is 1.000000
Precision is  nan
Negative Prediction ratio is 0.494131
F1-score is 0.000000
Diagnostic index is 1.164269
```

Loss History and Performance – GRU (with ADASYN)




```
Accuracy is 0.494131
Sensitivity is 0.000000
Specificity is 1.000000
Precision is  nan
Negative Prediction ratio is 0.494131
F1-score is 0.000000
Diagnostic index is 1.164269
```

Results & Conclusions

PART B

- Metrics were generally lower across all classification measures for LSTM and GRU models. This result is also shared with the models in combination with resampling methods.
- CNN, with and without resampling methods, had higher accuracy scores and higher metrics across our measured classification metrics.
- Our LSTM and GRU models had sensitivity and specificity values of 0 and 1, respectively.
- If sensitivity is 0, there are no true positives, but instead false negatives. If specificity is 1, there were no false positive predictions. Our predictions were 0 because the majority of the observations were of class 0. Therefore, our score is 1.
- The imbalance of the classes are a huge issue in making accurate predictions. Increased observations of the minority class, would be beneficial in future research as we may gain more accurate conclusions.

Thank You

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