

# CC3092 - Deep Learning y Sistemas Inteligentes

## Deep Learning y Sistemas Inteligentes

### - Hoja de Trabajo 2 -

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Se realizó 12 combinaciones en el análisis, lo cual corresponde a un porcentaje de puntos extras.

#### Instrucciones:

- Esta es una actividad en grupos de 3 personas máximo
- No se permitirá ni se aceptará cualquier indicio de copia. De presentarse, se procederá según el reglamento correspondiente.
- Tendrán hasta el día indicado en Canvas. Ejercicio 1 - Experimentación Práctica En esta actividad, implementará y comparará diferentes funciones de pérdida y técnicas de regularización utilizando PyTorch. Utilizará el conjunto de datos de Iris para una tarea de clasificación y una arquitectura básica de red neuronal de feedforward. El objetivo es observar cómo las diferentes opciones impactan la convergencia y el rendimiento del modelo.

## Ejercicio 1 - Experimentación Práctica

En esta actividad, implementará y comparará diferentes funciones de pérdida y técnicas de regularización utilizando PyTorch. Utilizará el conjunto de datos de Iris para una tarea de clasificación y una arquitectura básica de red neuronal de feedforward. El objetivo es observar cómo las diferentes opciones impactan la convergencia y el rendimiento del modelo.

### Task 1 - Preparación del conjunto de datos

Cargue el conjunto de datos de Iris utilizando bibliotecas como `sklearn.datasets`. Luego, divida el conjunto de datos en conjuntos de entrenamiento y validación.

```
In [ ]: """ Librerias necesarias """

import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from torch.utils.data import DataLoader, TensorDataset

In [ ]: """ Load data """

iris = load_iris()
X = iris.data
y = iris.target

X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_s

print("Tamaño del conjunto de entrenamiento:", X_train.shape)
print("Tamaño del conjunto de validación:", X_val.shape)

X_train_tensor = torch.tensor(X_train, dtype=torch.float32)
y_train_tensor = torch.tensor(y_train, dtype=torch.long)
X_val_tensor = torch.tensor(X_val, dtype=torch.float32)
y_val_tensor = torch.tensor(y_val, dtype=torch.long)

train_dataset = TensorDataset(X_train_tensor, y_train_tensor)
val_dataset = TensorDataset(X_val_tensor, y_val_tensor)
batch_size = 16
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=batch_size, shuffle=False)

Tamaño del conjunto de entrenamiento: (120, 4)
Tamaño del conjunto de validación: (30, 4)
```

## Task 2 - Arquitectura modelo

Cree una red neuronal feedforward simple utilizando nn.Module de PyTorch. Luego, defina capa de entrada, capas ocultas y capa de salida. Después, elija las funciones de activación y el número de neuronas por capa.

```
In [ ]: """ RN simple usando pytorch modules """

import torch
import torch.nn as nn

class SimpleFeedforwardNN(nn.Module):
    def __init__(self, input_size, hidden_sizes, output_size):
        super(SimpleFeedforwardNN, self).__init__()

        self.input_layer = nn.Linear(input_size, hidden_sizes[0])

        self.hidden_layers = nn.ModuleList()
        for i in range(len(hidden_sizes) - 1):
            self.hidden_layers.append(nn.Linear(hidden_sizes[i], hidden_sizes[i+1]))
```

```

        self.output_layer = nn.Linear(hidden_sizes[-1], output_size)

        self.activation = nn.ReLU()

    def forward(self, x):
        x = self.activation(self.input_layer(x))
        for layer in self.hidden_layers:
            x = self.activation(layer(x))
        x = self.output_layer(x)
        return x

input_size = X_train.shape[1]
hidden_sizes = [64, 32]
output_size = 3

model = SimpleFeedforwardNN(input_size, hidden_sizes, output_size)
print(model)

```

```

SimpleFeedforwardNN(
  (input_layer): Linear(in_features=4, out_features=64, bias=True)
  (hidden_layers): ModuleList(
    (0): Linear(in_features=64, out_features=32, bias=True)
  )
  (output_layer): Linear(in_features=32, out_features=3, bias=True)
  (activation): ReLU()
)

```

## Task 3 - Funciones de Pérdida

Utilice diferentes funciones de pérdida comunes como Cross-Entropy Loss y MSE para clasificación. Entrene el modelo con diferentes funciones de pérdida y registre las pérdidas de entrenamiento y test. Debe utilizar al menos 3 diferentes funciones. Es decir, procure que su código sea capaz de parametrizar el uso de diferentes funciones de pérdida.

```

In [ ]: """ Entrenamiento, funcion de perdida y registro """

def train_model(model, loss_fn, optimizer, num_epochs=50):
    train_losses = []
    val_losses = []

    for epoch in range(num_epochs):
        model.train()
        train_loss = 0.0

        for inputs, targets in train_loader:
            optimizer.zero_grad()
            outputs = model(inputs)
            loss = loss_fn(outputs, targets)
            loss.backward()
            optimizer.step()
            train_loss += loss.item() * inputs.size(0)

        train_loss /= len(train_loader.dataset)
        train_losses.append(train_loss)

    model.eval()

```

```
val_loss = 0.0

with torch.no_grad():
    for inputs, targets in val_loader:
        outputs = model(inputs)
        loss = loss_fn(outputs, targets)
        val_loss += loss.item() * inputs.size(0)

val_loss /= len(val_loader.dataset)
val_losses.append(val_loss)

print(f'Epoch [{epoch+1}/{num_epochs}], Train Loss: {train_loss:.4f}, V

return train_losses, val_losses

input_size = X_train.shape[1]
hidden_sizes = [64, 32]
output_size = 3
num_epochs = 50
learning_rate = 0.001
model = SimpleFeedforwardNN(input_size, hidden_sizes, output_size)
loss_fn = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=learning_rate)
train_model(model, loss_fn, optimizer, num_epochs)
```

```
Epoch [1/50], Train Loss: 1.0395, Val Loss: 0.9917
Epoch [2/50], Train Loss: 0.9710, Val Loss: 0.9332
Epoch [3/50], Train Loss: 0.9235, Val Loss: 0.8727
Epoch [4/50], Train Loss: 0.8575, Val Loss: 0.8195
Epoch [5/50], Train Loss: 0.7947, Val Loss: 0.7435
Epoch [6/50], Train Loss: 0.7295, Val Loss: 0.6796
Epoch [7/50], Train Loss: 0.6703, Val Loss: 0.6206
Epoch [8/50], Train Loss: 0.6099, Val Loss: 0.5821
Epoch [9/50], Train Loss: 0.5646, Val Loss: 0.5304
Epoch [10/50], Train Loss: 0.5230, Val Loss: 0.4922
Epoch [11/50], Train Loss: 0.4917, Val Loss: 0.4618
Epoch [12/50], Train Loss: 0.4601, Val Loss: 0.4438
Epoch [13/50], Train Loss: 0.4363, Val Loss: 0.4179
Epoch [14/50], Train Loss: 0.4140, Val Loss: 0.3969
Epoch [15/50], Train Loss: 0.3980, Val Loss: 0.3705
Epoch [16/50], Train Loss: 0.3694, Val Loss: 0.3536
Epoch [17/50], Train Loss: 0.3549, Val Loss: 0.3471
Epoch [18/50], Train Loss: 0.3329, Val Loss: 0.3197
Epoch [19/50], Train Loss: 0.3110, Val Loss: 0.3051
Epoch [20/50], Train Loss: 0.2942, Val Loss: 0.2853
Epoch [21/50], Train Loss: 0.2784, Val Loss: 0.2690
Epoch [22/50], Train Loss: 0.2617, Val Loss: 0.2586
Epoch [23/50], Train Loss: 0.2545, Val Loss: 0.2426
Epoch [24/50], Train Loss: 0.2372, Val Loss: 0.2369
Epoch [25/50], Train Loss: 0.2262, Val Loss: 0.2225
Epoch [26/50], Train Loss: 0.2198, Val Loss: 0.2092
Epoch [27/50], Train Loss: 0.2144, Val Loss: 0.2242
Epoch [28/50], Train Loss: 0.1895, Val Loss: 0.1923
Epoch [29/50], Train Loss: 0.1949, Val Loss: 0.1866
Epoch [30/50], Train Loss: 0.1758, Val Loss: 0.1853
Epoch [31/50], Train Loss: 0.1700, Val Loss: 0.1697
Epoch [32/50], Train Loss: 0.1650, Val Loss: 0.1670
Epoch [33/50], Train Loss: 0.1568, Val Loss: 0.1619
Epoch [34/50], Train Loss: 0.1544, Val Loss: 0.1560
Epoch [35/50], Train Loss: 0.1477, Val Loss: 0.1497
Epoch [36/50], Train Loss: 0.1420, Val Loss: 0.1496
Epoch [37/50], Train Loss: 0.1387, Val Loss: 0.1438
Epoch [38/50], Train Loss: 0.1361, Val Loss: 0.1506
Epoch [39/50], Train Loss: 0.1309, Val Loss: 0.1310
Epoch [40/50], Train Loss: 0.1296, Val Loss: 0.1406
Epoch [41/50], Train Loss: 0.1239, Val Loss: 0.1252
Epoch [42/50], Train Loss: 0.1262, Val Loss: 0.1246
Epoch [43/50], Train Loss: 0.1330, Val Loss: 0.1300
Epoch [44/50], Train Loss: 0.1193, Val Loss: 0.1144
Epoch [45/50], Train Loss: 0.1120, Val Loss: 0.1411
Epoch [46/50], Train Loss: 0.1160, Val Loss: 0.1176
Epoch [47/50], Train Loss: 0.1162, Val Loss: 0.1083
Epoch [48/50], Train Loss: 0.1147, Val Loss: 0.1400
Epoch [49/50], Train Loss: 0.1105, Val Loss: 0.1025
Epoch [50/50], Train Loss: 0.1167, Val Loss: 0.1394
```

```
Out[ ]: ([1.0394882877667746,  
0.9710470557212829,  
0.9234729647636414,  
0.8574853618939717,  
0.7947110454241435,  
0.7294812838236491,  
0.6702702005704244,  
0.6098776936531067,  
0.5646216789881389,  
0.523004537820816,  
0.49172622760136925,  
0.4601483742396037,  
0.43629200061162315,  
0.4140487551689148,  
0.3980002919832865,  
0.3694432059923808,  
0.35490017135938007,  
0.3329428652922312,  
0.3109930435816447,  
0.29419870575269064,  
0.2784022827943166,  
0.2616824984550476,  
0.254542871316274,  
0.23718418876330058,  
0.22622590859731037,  
0.2198312024275462,  
0.21435607671737672,  
0.18954036732514698,  
0.19489469627539316,  
0.17583513458569844,  
0.1700192133585612,  
0.16498130112886428,  
0.15681618750095366,  
0.1543964147567749,  
0.14772089968125027,  
0.14202449123064678,  
0.13868946333726248,  
0.13606667816638945,  
0.13089158261815706,  
0.12958838492631913,  
0.12393135875463486,  
0.1261725316445033,  
0.13298008839289346,  
0.11934195806582769,  
0.11198802292346954,  
0.11595539500315984,  
0.11615439976255099,  
0.11471267938613891,  
0.11053057114283243,  
0.11669432024161021]),  
[0.9916950106620789,  
0.9332144856452942,  
0.8726797223091125,  
0.8195156772931417,  
0.7435151735941569,  
0.6795727650324503,  
0.6205779353777567,  
0.5821071545283,  
0.5303530812263488,  
0.49223305384318033,
```

```
0.4618313491344452,  
0.44379056493441266,  
0.41789148648579916,  
0.39694223205248513,  
0.3705293615659078,  
0.35358786781628926,  
0.3470892151196798,  
0.31968409021695454,  
0.3051360269387563,  
0.28533007502555846,  
0.2689577559630076,  
0.25864274899164835,  
0.2426152805487315,  
0.2368791550397873,  
0.22249457935492198,  
0.20924883385499318,  
0.2242194265127182,  
0.19232960045337677,  
0.18662608961264293,  
0.18528315126895906,  
0.16969181795914967,  
0.1669577201207479,  
0.1618706931670507,  
0.15599769254525503,  
0.1497454474369685,  
0.14962165256341298,  
0.14384941558043163,  
0.15058367153008778,  
0.13102472176154453,  
0.14062648713588716,  
0.12518675674994786,  
0.12456221332152685,  
0.13003003497918447,  
0.11444991528987884,  
0.14113677938779196,  
0.11761354257663091,  
0.10825399160385132,  
0.13997740745544435,  
0.10249078820149103,  
0.1393769770860672])
```

## Task 4 - Técnicas de Regularización

1. Utilice distintas técnicas de regularización como L1, L2 y dropout. Entrene el modelo con y sin técnicas de regularización y observe el impacto en el overfitting y la generalización. Debe utilizar al menos 3 diferentes técnicas. Es decir, procure que su código sea capaz de parametrizar el uso de diferentes técnicas de regularización.

1. **L1 Regularization:** Esta técnica agrega una penalización a la función de pérdida que es proporcional a la suma absoluta de los pesos. Esto puede llevar a la "eliminación" de algunas características menos importantes.

2. **L2 Regularization:** Similar a L1, pero la penalización es proporcional al cuadrado de la suma de los pesos. Este método es útil para evitar el sobreajuste.

3. **Dropout:** Durante el entrenamiento, aleatoriamente establece una fracción de las entradas a cero en cada iteración. Esto también ayuda a evitar el sobreajuste.

👉 El código incluye opciones para activar o desactivar cada una de estas técnicas de regularización.

📈 Al final, comparamos el rendimiento del modelo con y sin regularización para evaluar el impacto en el sobreajuste y la generalización.

```
In [ ]: """ Técnicas de regularización """

# Hay que cambiar la clase previamente presentada para agregarle dropout

class SimpleFeedforwardNN(nn.Module):
    def __init__(self, input_size, hidden_sizes, output_size, dropout_prob=0.0):
        super(SimpleFeedforwardNN, self).__init__()

        self.input_layer = nn.Linear(input_size, hidden_sizes[0])
        self.hidden_layers = nn.ModuleList()
        self.dropouts = nn.ModuleList()

        for i in range(len(hidden_sizes) - 1):
            self.hidden_layers.append(nn.Linear(hidden_sizes[i], hidden_sizes[i+1]))
            self.dropouts.append(nn.Dropout(p=dropout_prob))

        self.output_layer = nn.Linear(hidden_sizes[-1], output_size)
        self.activation = nn.ReLU()

    def forward(self, x):
        x = self.activation(self.input_layer(x))

        for layer, dropout in zip(self.hidden_layers, self.dropouts):
            x = self.activation(layer(x))
            x = dropout(x)

        x = self.output_layer(x)
        return x

# Para entrenar, con L1:

def train_model(model, loss_fn, optimizer, num_epochs=50, l1_lambda=0.0):
    train_losses = []
    val_losses = []

    for epoch in range(num_epochs):
        model.train()
        train_loss = 0.0

        for inputs, targets in train_loader:
            optimizer.zero_grad()
            outputs = model(inputs)
            loss = loss_fn(outputs, targets)

            # Añadir L1 regularization
            l1_reg = 0.0
            for param in model.parameters():
                l1_reg += torch.norm(param, 1)
            loss += l1_lambda * l1_reg
```



```

        loss.backward()
        optimizer.step()
        train_loss += loss.item() * inputs.size(0)

    train_loss /= len(train_loader.dataset)
    train_losses.append(train_loss)

    model.eval()
    val_loss = 0.0

    with torch.no_grad():
        for inputs, targets in val_loader:
            outputs = model(inputs)
            loss = loss_fn(outputs, targets)
            val_loss += loss.item() * inputs.size(0)

    val_loss /= len(val_loader.dataset)
    val_losses.append(val_loss)

    print(f'Epoch [{epoch+1}/{num_epochs}], Train Loss: {train_loss:.4f}, Val Loss: {val_loss:.4f}')

    return train_losses, val_losses

```

```

In [ ]: # 3 formas del modelo entrenado:

# Con L2
l2_lambda = 0.001
optimizer = optim.Adam(model.parameters(), lr=learning_rate, weight_decay=l2_lambda)
print("Training model with L2 :")
train_model(model, loss_fn, optimizer, num_epochs)

# Con L1
l1_lambda = 0.001
model = SimpleFeedforwardNN(input_size, hidden_sizes, output_size)
optimizer = optim.Adam(model.parameters(), lr=learning_rate)
print("Training model with L1 :")
train_model(model, loss_fn, optimizer, num_epochs, l1_lambda=l1_lambda)

# Con Dropout
dropout_prob = 0.5
model = SimpleFeedforwardNN(input_size, hidden_sizes, output_size, dropout_prob=dropout_prob)
optimizer = optim.Adam(model.parameters(), lr=learning_rate)
print("Training model with Dropout:")
train_model(model, loss_fn, optimizer, num_epochs)

```

Training model with L2 :

Epoch [1/50], Train Loss: 0.1148, Val Loss: 0.1287  
Epoch [2/50], Train Loss: 0.1125, Val Loss: 0.1117  
Epoch [3/50], Train Loss: 0.0983, Val Loss: 0.1015  
Epoch [4/50], Train Loss: 0.1082, Val Loss: 0.0990  
Epoch [5/50], Train Loss: 0.0991, Val Loss: 0.1247  
Epoch [6/50], Train Loss: 0.0984, Val Loss: 0.0942  
Epoch [7/50], Train Loss: 0.0981, Val Loss: 0.1108  
Epoch [8/50], Train Loss: 0.1001, Val Loss: 0.0883  
Epoch [9/50], Train Loss: 0.0922, Val Loss: 0.1123  
Epoch [10/50], Train Loss: 0.0966, Val Loss: 0.0995  
Epoch [11/50], Train Loss: 0.0923, Val Loss: 0.0971  
Epoch [12/50], Train Loss: 0.0928, Val Loss: 0.0959  
Epoch [13/50], Train Loss: 0.0887, Val Loss: 0.0910  
Epoch [14/50], Train Loss: 0.0882, Val Loss: 0.0895  
Epoch [15/50], Train Loss: 0.0861, Val Loss: 0.0909  
Epoch [16/50], Train Loss: 0.0874, Val Loss: 0.0870  
Epoch [17/50], Train Loss: 0.0896, Val Loss: 0.1094  
Epoch [18/50], Train Loss: 0.0869, Val Loss: 0.0790  
Epoch [19/50], Train Loss: 0.0853, Val Loss: 0.0890  
Epoch [20/50], Train Loss: 0.0917, Val Loss: 0.1075  
Epoch [21/50], Train Loss: 0.0904, Val Loss: 0.0758  
Epoch [22/50], Train Loss: 0.0900, Val Loss: 0.1235  
Epoch [23/50], Train Loss: 0.0831, Val Loss: 0.0766  
Epoch [24/50], Train Loss: 0.0830, Val Loss: 0.0936  
Epoch [25/50], Train Loss: 0.0831, Val Loss: 0.0886  
Epoch [26/50], Train Loss: 0.0786, Val Loss: 0.0770  
Epoch [27/50], Train Loss: 0.0811, Val Loss: 0.0876  
Epoch [28/50], Train Loss: 0.0794, Val Loss: 0.0950  
Epoch [29/50], Train Loss: 0.0820, Val Loss: 0.0827  
Epoch [30/50], Train Loss: 0.0800, Val Loss: 0.0858  
Epoch [31/50], Train Loss: 0.0777, Val Loss: 0.0796  
Epoch [32/50], Train Loss: 0.0814, Val Loss: 0.0725  
Epoch [33/50], Train Loss: 0.0855, Val Loss: 0.1075  
Epoch [34/50], Train Loss: 0.1003, Val Loss: 0.0685  
Epoch [35/50], Train Loss: 0.0729, Val Loss: 0.1466  
Epoch [36/50], Train Loss: 0.0873, Val Loss: 0.0729  
Epoch [37/50], Train Loss: 0.0787, Val Loss: 0.0717  
Epoch [38/50], Train Loss: 0.0725, Val Loss: 0.1383  
Epoch [39/50], Train Loss: 0.0877, Val Loss: 0.0723  
Epoch [40/50], Train Loss: 0.0897, Val Loss: 0.0664  
Epoch [41/50], Train Loss: 0.0817, Val Loss: 0.1277  
Epoch [42/50], Train Loss: 0.0695, Val Loss: 0.0655  
Epoch [43/50], Train Loss: 0.0839, Val Loss: 0.0699  
Epoch [44/50], Train Loss: 0.0995, Val Loss: 0.0833  
Epoch [45/50], Train Loss: 0.0759, Val Loss: 0.0690  
Epoch [46/50], Train Loss: 0.0733, Val Loss: 0.0800  
Epoch [47/50], Train Loss: 0.0775, Val Loss: 0.0948  
Epoch [48/50], Train Loss: 0.0773, Val Loss: 0.0643  
Epoch [49/50], Train Loss: 0.0804, Val Loss: 0.0922  
Epoch [50/50], Train Loss: 0.0725, Val Loss: 0.0771

Training model with L1 :

Epoch [1/50], Train Loss: 1.2903, Val Loss: 1.0078  
Epoch [2/50], Train Loss: 1.1972, Val Loss: 0.9484  
Epoch [3/50], Train Loss: 1.1226, Val Loss: 0.8788  
Epoch [4/50], Train Loss: 1.0463, Val Loss: 0.7998  
Epoch [5/50], Train Loss: 0.9665, Val Loss: 0.7308  
Epoch [6/50], Train Loss: 0.8892, Val Loss: 0.6622  
Epoch [7/50], Train Loss: 0.8247, Val Loss: 0.6010  
Epoch [8/50], Train Loss: 0.7659, Val Loss: 0.5647

Epoch [9/50], Train Loss: 0.7041, Val Loss: 0.5076  
Epoch [10/50], Train Loss: 0.6535, Val Loss: 0.4712  
Epoch [11/50], Train Loss: 0.6174, Val Loss: 0.4471  
Epoch [12/50], Train Loss: 0.5839, Val Loss: 0.4178  
Epoch [13/50], Train Loss: 0.5562, Val Loss: 0.3937  
Epoch [14/50], Train Loss: 0.5283, Val Loss: 0.3700  
Epoch [15/50], Train Loss: 0.5052, Val Loss: 0.3519  
Epoch [16/50], Train Loss: 0.4836, Val Loss: 0.3329  
Epoch [17/50], Train Loss: 0.4657, Val Loss: 0.3169  
Epoch [18/50], Train Loss: 0.4480, Val Loss: 0.2941  
Epoch [19/50], Train Loss: 0.4268, Val Loss: 0.2858  
Epoch [20/50], Train Loss: 0.4211, Val Loss: 0.2631  
Epoch [21/50], Train Loss: 0.3887, Val Loss: 0.2656  
Epoch [22/50], Train Loss: 0.3851, Val Loss: 0.2407  
Epoch [23/50], Train Loss: 0.3684, Val Loss: 0.2263  
Epoch [24/50], Train Loss: 0.3601, Val Loss: 0.2193  
Epoch [25/50], Train Loss: 0.3528, Val Loss: 0.2038  
Epoch [26/50], Train Loss: 0.3339, Val Loss: 0.1997  
Epoch [27/50], Train Loss: 0.3239, Val Loss: 0.1862  
Epoch [28/50], Train Loss: 0.3145, Val Loss: 0.1777  
Epoch [29/50], Train Loss: 0.3092, Val Loss: 0.1772  
Epoch [30/50], Train Loss: 0.3025, Val Loss: 0.1633  
Epoch [31/50], Train Loss: 0.2935, Val Loss: 0.1681  
Epoch [32/50], Train Loss: 0.2889, Val Loss: 0.1518  
Epoch [33/50], Train Loss: 0.2857, Val Loss: 0.1479  
Epoch [34/50], Train Loss: 0.2791, Val Loss: 0.1486  
Epoch [35/50], Train Loss: 0.2762, Val Loss: 0.1374  
Epoch [36/50], Train Loss: 0.2768, Val Loss: 0.1555  
Epoch [37/50], Train Loss: 0.2665, Val Loss: 0.1302  
Epoch [38/50], Train Loss: 0.2639, Val Loss: 0.1351  
Epoch [39/50], Train Loss: 0.2584, Val Loss: 0.1281  
Epoch [40/50], Train Loss: 0.2615, Val Loss: 0.1311  
Epoch [41/50], Train Loss: 0.2637, Val Loss: 0.1207  
Epoch [42/50], Train Loss: 0.2563, Val Loss: 0.1154  
Epoch [43/50], Train Loss: 0.2462, Val Loss: 0.1302  
Epoch [44/50], Train Loss: 0.2550, Val Loss: 0.1143  
Epoch [45/50], Train Loss: 0.2515, Val Loss: 0.1100  
Epoch [46/50], Train Loss: 0.2436, Val Loss: 0.1280  
Epoch [47/50], Train Loss: 0.2415, Val Loss: 0.1051  
Epoch [48/50], Train Loss: 0.2458, Val Loss: 0.1193  
Epoch [49/50], Train Loss: 0.2404, Val Loss: 0.1028  
Epoch [50/50], Train Loss: 0.2369, Val Loss: 0.1118

Training model with Dropout:

Epoch [1/50], Train Loss: 1.0996, Val Loss: 1.0066  
Epoch [2/50], Train Loss: 1.0029, Val Loss: 0.9376  
Epoch [3/50], Train Loss: 0.9169, Val Loss: 0.8706  
Epoch [4/50], Train Loss: 0.8687, Val Loss: 0.8071  
Epoch [5/50], Train Loss: 0.7949, Val Loss: 0.7506  
Epoch [6/50], Train Loss: 0.7918, Val Loss: 0.6864  
Epoch [7/50], Train Loss: 0.7165, Val Loss: 0.6293  
Epoch [8/50], Train Loss: 0.6401, Val Loss: 0.5815  
Epoch [9/50], Train Loss: 0.6159, Val Loss: 0.5405  
Epoch [10/50], Train Loss: 0.6008, Val Loss: 0.5120  
Epoch [11/50], Train Loss: 0.5903, Val Loss: 0.4872  
Epoch [12/50], Train Loss: 0.5597, Val Loss: 0.4608  
Epoch [13/50], Train Loss: 0.5177, Val Loss: 0.4366  
Epoch [14/50], Train Loss: 0.4689, Val Loss: 0.4176  
Epoch [15/50], Train Loss: 0.4501, Val Loss: 0.3964  
Epoch [16/50], Train Loss: 0.4827, Val Loss: 0.3831  
Epoch [17/50], Train Loss: 0.4235, Val Loss: 0.3708

Epoch [18/50],	Train Loss: 0.4337,	Val Loss: 0.3602
Epoch [19/50],	Train Loss: 0.3947,	Val Loss: 0.3495
Epoch [20/50],	Train Loss: 0.4079,	Val Loss: 0.3369
Epoch [21/50],	Train Loss: 0.3972,	Val Loss: 0.3235
Epoch [22/50],	Train Loss: 0.3770,	Val Loss: 0.3159
Epoch [23/50],	Train Loss: 0.3970,	Val Loss: 0.3081
Epoch [24/50],	Train Loss: 0.3526,	Val Loss: 0.2952
Epoch [25/50],	Train Loss: 0.3601,	Val Loss: 0.2850
Epoch [26/50],	Train Loss: 0.3561,	Val Loss: 0.2763
Epoch [27/50],	Train Loss: 0.3442,	Val Loss: 0.2652
Epoch [28/50],	Train Loss: 0.2992,	Val Loss: 0.2576
Epoch [29/50],	Train Loss: 0.3019,	Val Loss: 0.2485
Epoch [30/50],	Train Loss: 0.2651,	Val Loss: 0.2421
Epoch [31/50],	Train Loss: 0.3052,	Val Loss: 0.2501
Epoch [32/50],	Train Loss: 0.2751,	Val Loss: 0.2296
Epoch [33/50],	Train Loss: 0.3007,	Val Loss: 0.2231
Epoch [34/50],	Train Loss: 0.3123,	Val Loss: 0.2283
Epoch [35/50],	Train Loss: 0.2746,	Val Loss: 0.2110
Epoch [36/50],	Train Loss: 0.2655,	Val Loss: 0.2068
Epoch [37/50],	Train Loss: 0.2621,	Val Loss: 0.1981
Epoch [38/50],	Train Loss: 0.2457,	Val Loss: 0.1924
Epoch [39/50],	Train Loss: 0.2576,	Val Loss: 0.1919
Epoch [40/50],	Train Loss: 0.2358,	Val Loss: 0.1831
Epoch [41/50],	Train Loss: 0.2669,	Val Loss: 0.1971
Epoch [42/50],	Train Loss: 0.2250,	Val Loss: 0.1752
Epoch [43/50],	Train Loss: 0.2326,	Val Loss: 0.1736
Epoch [44/50],	Train Loss: 0.2471,	Val Loss: 0.1731
Epoch [45/50],	Train Loss: 0.2321,	Val Loss: 0.1652
Epoch [46/50],	Train Loss: 0.2033,	Val Loss: 0.1619
Epoch [47/50],	Train Loss: 0.2605,	Val Loss: 0.1621
Epoch [48/50],	Train Loss: 0.1989,	Val Loss: 0.1783
Epoch [49/50],	Train Loss: 0.1965,	Val Loss: 0.1799
Epoch [50/50],	Train Loss: 0.2252,	Val Loss: 0.1528



```
Out[ ]: ([1.0996270736058553,  
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0.5814549922943115,  
0.5405452052752177,  
0.5120458205540975,
```


```
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0.3963821570078532,  
0.3831070939699809,  
0.37076109846433003,  
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0.16187709867954253,  
0.16208880245685578,  
0.1782767007748286,  
0.17989531954129537,  
0.1528171400229136])
```

## Task 5 - Funciones de Pérdida




Utilice distintas técnicas de optimización como SGD, Batch GD, Mini-Batch GD. Entrene el modelo con algoritmos de optimización y registre las pérdidas y tiempos de entrenamiento y test. Debe utilizar al menos 3 diferentes algoritmos. Es decir, procure que su código sea capaz de parametrizar el uso de diferentes algoritmos de optimización.

### Conceptos Teóricos

-  SGD: Actualiza los parámetros del modelo usando solo un ejemplo de entrenamiento por iteración.
-  Batch GD: Utiliza todo el conjunto de datos para actualizar los parámetros del modelo en cada iteración.

-  Mini-Batch GD: Compromiso entre SGD y Batch GD; utiliza un pequeño lote de ejemplos para actualizar los parámetros.

### Implementación

-  Entrenaremos el modelo con cada uno de los algoritmos y registraremos las pérdidas durante el entrenamiento y la validación.
-  Utilizaremos la librería `time` de Python para registrar el tiempo que tarda cada algoritmo en entrenar y probar el modelo.
-  Haremos que el código sea parametrizable para facilitar el uso de diferentes algoritmos de optimización.

```
In [ ]: import time

def train_model_with_time(model, loss_fn, optimizer, num_epochs=50, l1_lambda=0):
    train_losses = []
    val_losses = []
    start_time = time.time()

    for epoch in range(num_epochs):
        model.train()
        train_loss = 0.0

        for inputs, targets in train_loader:
            optimizer.zero_grad()
            outputs = model(inputs)
            loss = loss_fn(outputs, targets)

            # L1 regularization
            l1_reg = 0.0
            for param in model.parameters():
                l1_reg += torch.norm(param, 1)
            loss += l1_lambda * l1_reg

            loss.backward()
            optimizer.step()
            train_loss += loss.item() * inputs.size(0)

        train_loss /= len(train_loader.dataset)
        train_losses.append(train_loss)

        model.eval()
        val_loss = 0.0
        with torch.no_grad():
            for inputs, targets in val_loader:
                outputs = model(inputs)
                loss = loss_fn(outputs, targets)
                val_loss += loss.item() * inputs.size(0)

        val_loss /= len(val_loader.dataset)
        val_losses.append(val_loss)

        print(f'Epoch [{epoch+1}/{num_epochs}], Train Loss: {train_loss:.4f}, Val Loss: {val_loss:.4f}')

    end_time = time.time()
    elapsed_time = end_time - start_time
```

```
print(f'Total time elapsed: {elapsed_time:.2f} seconds')
return train_losses, val_losses, elapsed_time

# SGD
optimizer = optim.SGD(model.parameters(), lr=learning_rate)
print("Training model with SGD:")
train_model_with_time(model, loss_fn, optimizer, num_epochs)

# Batch GD
optimizer = optim.SGD(model.parameters(), lr=learning_rate)
print("Training model with Batch GD:")
train_loader_batch = DataLoader(train_dataset, batch_size=len(train_dataset), s
train_model_with_time(model, loss_fn, optimizer, num_epochs)

# Mini-Batch GD
optimizer = optim.SGD(model.parameters(), lr=learning_rate)
print("Training model with Mini-Batch GD:")
train_loader_mini_batch = DataLoader(train_dataset, batch_size=32, shuffle=True)
train_model_with_time(model, loss_fn, optimizer, num_epochs)
```



Training model with SGD:

Epoch [1/50], Train Loss: 0.2118, Val Loss: 0.1570  
Epoch [2/50], Train Loss: 0.2007, Val Loss: 0.1545  
Epoch [3/50], Train Loss: 0.1825, Val Loss: 0.1566  
Epoch [4/50], Train Loss: 0.1996, Val Loss: 0.1564  
Epoch [5/50], Train Loss: 0.1936, Val Loss: 0.1525  
Epoch [6/50], Train Loss: 0.1917, Val Loss: 0.1540  
Epoch [7/50], Train Loss: 0.1972, Val Loss: 0.1566  
Epoch [8/50], Train Loss: 0.2384, Val Loss: 0.1550  
Epoch [9/50], Train Loss: 0.2101, Val Loss: 0.1527  
Epoch [10/50], Train Loss: 0.1984, Val Loss: 0.1551  
Epoch [11/50], Train Loss: 0.1980, Val Loss: 0.1543  
Epoch [12/50], Train Loss: 0.2119, Val Loss: 0.1515  
Epoch [13/50], Train Loss: 0.1841, Val Loss: 0.1523  
Epoch [14/50], Train Loss: 0.1826, Val Loss: 0.1480  
Epoch [15/50], Train Loss: 0.1686, Val Loss: 0.1483  
Epoch [16/50], Train Loss: 0.1928, Val Loss: 0.1514  
Epoch [17/50], Train Loss: 0.2118, Val Loss: 0.1490  
Epoch [18/50], Train Loss: 0.1837, Val Loss: 0.1475  
Epoch [19/50], Train Loss: 0.1964, Val Loss: 0.1494  
Epoch [20/50], Train Loss: 0.2195, Val Loss: 0.1499  
Epoch [21/50], Train Loss: 0.2118, Val Loss: 0.1591  
Epoch [22/50], Train Loss: 0.1922, Val Loss: 0.1625  
Epoch [23/50], Train Loss: 0.1842, Val Loss: 0.1661  
Epoch [24/50], Train Loss: 0.1976, Val Loss: 0.1583  
Epoch [25/50], Train Loss: 0.1683, Val Loss: 0.1540  
Epoch [26/50], Train Loss: 0.2095, Val Loss: 0.1551  
Epoch [27/50], Train Loss: 0.1799, Val Loss: 0.1532  
Epoch [28/50], Train Loss: 0.2081, Val Loss: 0.1494  
Epoch [29/50], Train Loss: 0.1942, Val Loss: 0.1497  
Epoch [30/50], Train Loss: 0.2024, Val Loss: 0.1478  
Epoch [31/50], Train Loss: 0.2060, Val Loss: 0.1483  
Epoch [32/50], Train Loss: 0.1871, Val Loss: 0.1513  
Epoch [33/50], Train Loss: 0.1927, Val Loss: 0.1552  
Epoch [34/50], Train Loss: 0.1800, Val Loss: 0.1511  
Epoch [35/50], Train Loss: 0.1595, Val Loss: 0.1508  
Epoch [36/50], Train Loss: 0.1792, Val Loss: 0.1471  
Epoch [37/50], Train Loss: 0.2015, Val Loss: 0.1482  
Epoch [38/50], Train Loss: 0.1988, Val Loss: 0.1472  
Epoch [39/50], Train Loss: 0.1660, Val Loss: 0.1469  
Epoch [40/50], Train Loss: 0.2054, Val Loss: 0.1460  
Epoch [41/50], Train Loss: 0.1602, Val Loss: 0.1488  
Epoch [42/50], Train Loss: 0.1898, Val Loss: 0.1462  
Epoch [43/50], Train Loss: 0.1999, Val Loss: 0.1462  
Epoch [44/50], Train Loss: 0.2085, Val Loss: 0.1435  
Epoch [45/50], Train Loss: 0.2480, Val Loss: 0.1443  
Epoch [46/50], Train Loss: 0.1937, Val Loss: 0.1460  
Epoch [47/50], Train Loss: 0.2055, Val Loss: 0.1493  
Epoch [48/50], Train Loss: 0.1718, Val Loss: 0.1463  
Epoch [49/50], Train Loss: 0.1685, Val Loss: 0.1454  
Epoch [50/50], Train Loss: 0.1726, Val Loss: 0.1486

Total time elapsed: 1.66 seconds

Training model with Batch GD:

Epoch [1/50], Train Loss: 0.2039, Val Loss: 0.1457  
Epoch [2/50], Train Loss: 0.1884, Val Loss: 0.1461  
Epoch [3/50], Train Loss: 0.2003, Val Loss: 0.1516  
Epoch [4/50], Train Loss: 0.1857, Val Loss: 0.1524  
Epoch [5/50], Train Loss: 0.1993, Val Loss: 0.1519  
Epoch [6/50], Train Loss: 0.1982, Val Loss: 0.1460  
Epoch [7/50], Train Loss: 0.2173, Val Loss: 0.1461

Epoch [8/50], Train Loss: 0.2106, Val Loss: 0.1463  
Epoch [9/50], Train Loss: 0.1997, Val Loss: 0.1467  
Epoch [10/50], Train Loss: 0.1829, Val Loss: 0.1477  
Epoch [11/50], Train Loss: 0.1935, Val Loss: 0.1473  
Epoch [12/50], Train Loss: 0.1879, Val Loss: 0.1485  
Epoch [13/50], Train Loss: 0.1967, Val Loss: 0.1550  
Epoch [14/50], Train Loss: 0.2042, Val Loss: 0.1454  
Epoch [15/50], Train Loss: 0.1491, Val Loss: 0.1430  
Epoch [16/50], Train Loss: 0.1489, Val Loss: 0.1436  
Epoch [17/50], Train Loss: 0.1610, Val Loss: 0.1432  
Epoch [18/50], Train Loss: 0.2060, Val Loss: 0.1446  
Epoch [19/50], Train Loss: 0.1672, Val Loss: 0.1454  
Epoch [20/50], Train Loss: 0.1925, Val Loss: 0.1485  
Epoch [21/50], Train Loss: 0.1754, Val Loss: 0.1445  
Epoch [22/50], Train Loss: 0.1919, Val Loss: 0.1449  
Epoch [23/50], Train Loss: 0.2090, Val Loss: 0.1416  
Epoch [24/50], Train Loss: 0.1671, Val Loss: 0.1402  
Epoch [25/50], Train Loss: 0.1708, Val Loss: 0.1415  
Epoch [26/50], Train Loss: 0.1913, Val Loss: 0.1398  
Epoch [27/50], Train Loss: 0.1847, Val Loss: 0.1409  
Epoch [28/50], Train Loss: 0.1883, Val Loss: 0.1404  
Epoch [29/50], Train Loss: 0.1671, Val Loss: 0.1426  
Epoch [30/50], Train Loss: 0.1920, Val Loss: 0.1438  
Epoch [31/50], Train Loss: 0.1633, Val Loss: 0.1431  
Epoch [32/50], Train Loss: 0.1627, Val Loss: 0.1437  
Epoch [33/50], Train Loss: 0.2292, Val Loss: 0.1473  
Epoch [34/50], Train Loss: 0.1367, Val Loss: 0.1424  
Epoch [35/50], Train Loss: 0.1862, Val Loss: 0.1449  
Epoch [36/50], Train Loss: 0.1671, Val Loss: 0.1458  
Epoch [37/50], Train Loss: 0.2026, Val Loss: 0.1458  
Epoch [38/50], Train Loss: 0.1766, Val Loss: 0.1439  
Epoch [39/50], Train Loss: 0.1749, Val Loss: 0.1416  
Epoch [40/50], Train Loss: 0.2119, Val Loss: 0.1457  
Epoch [41/50], Train Loss: 0.1698, Val Loss: 0.1428  
Epoch [42/50], Train Loss: 0.1826, Val Loss: 0.1426  
Epoch [43/50], Train Loss: 0.1781, Val Loss: 0.1468  
Epoch [44/50], Train Loss: 0.1586, Val Loss: 0.1444  
Epoch [45/50], Train Loss: 0.2055, Val Loss: 0.1432  
Epoch [46/50], Train Loss: 0.1470, Val Loss: 0.1433  
Epoch [47/50], Train Loss: 0.1608, Val Loss: 0.1411  
Epoch [48/50], Train Loss: 0.2095, Val Loss: 0.1399  
Epoch [49/50], Train Loss: 0.1678, Val Loss: 0.1416  
Epoch [50/50], Train Loss: 0.2150, Val Loss: 0.1474  
Total time elapsed: 1.49 seconds  
Training model with Mini-Batch GD:  
Epoch [1/50], Train Loss: 0.1980, Val Loss: 0.1542  
Epoch [2/50], Train Loss: 0.1954, Val Loss: 0.1541  
Epoch [3/50], Train Loss: 0.1758, Val Loss: 0.1513  
Epoch [4/50], Train Loss: 0.1725, Val Loss: 0.1434  
Epoch [5/50], Train Loss: 0.1846, Val Loss: 0.1415  
Epoch [6/50], Train Loss: 0.1705, Val Loss: 0.1421  
Epoch [7/50], Train Loss: 0.1812, Val Loss: 0.1403  
Epoch [8/50], Train Loss: 0.2017, Val Loss: 0.1386  
Epoch [9/50], Train Loss: 0.1827, Val Loss: 0.1418  
Epoch [10/50], Train Loss: 0.1621, Val Loss: 0.1408  
Epoch [11/50], Train Loss: 0.1750, Val Loss: 0.1385  
Epoch [12/50], Train Loss: 0.1808, Val Loss: 0.1402  
Epoch [13/50], Train Loss: 0.1772, Val Loss: 0.1402  
Epoch [14/50], Train Loss: 0.1475, Val Loss: 0.1351  
Epoch [15/50], Train Loss: 0.1901, Val Loss: 0.1357

```
Epoch [16/50], Train Loss: 0.1708, Val Loss: 0.1401
Epoch [17/50], Train Loss: 0.2195, Val Loss: 0.1467
Epoch [18/50], Train Loss: 0.2014, Val Loss: 0.1420
Epoch [19/50], Train Loss: 0.1826, Val Loss: 0.1411
Epoch [20/50], Train Loss: 0.1934, Val Loss: 0.1422
Epoch [21/50], Train Loss: 0.1790, Val Loss: 0.1453
Epoch [22/50], Train Loss: 0.1451, Val Loss: 0.1405
Epoch [23/50], Train Loss: 0.2006, Val Loss: 0.1391
Epoch [24/50], Train Loss: 0.1649, Val Loss: 0.1390
Epoch [25/50], Train Loss: 0.1742, Val Loss: 0.1371
Epoch [26/50], Train Loss: 0.1794, Val Loss: 0.1352
Epoch [27/50], Train Loss: 0.1952, Val Loss: 0.1362
Epoch [28/50], Train Loss: 0.1872, Val Loss: 0.1373
Epoch [29/50], Train Loss: 0.1596, Val Loss: 0.1396
Epoch [30/50], Train Loss: 0.2008, Val Loss: 0.1425
Epoch [31/50], Train Loss: 0.1502, Val Loss: 0.1430
Epoch [32/50], Train Loss: 0.2392, Val Loss: 0.1451
Epoch [33/50], Train Loss: 0.2090, Val Loss: 0.1429
Epoch [34/50], Train Loss: 0.1914, Val Loss: 0.1418
Epoch [35/50], Train Loss: 0.1572, Val Loss: 0.1450
Epoch [36/50], Train Loss: 0.1723, Val Loss: 0.1428
Epoch [37/50], Train Loss: 0.1757, Val Loss: 0.1394
Epoch [38/50], Train Loss: 0.1557, Val Loss: 0.1463
Epoch [39/50], Train Loss: 0.1762, Val Loss: 0.1410
Epoch [40/50], Train Loss: 0.1868, Val Loss: 0.1404
Epoch [41/50], Train Loss: 0.2080, Val Loss: 0.1471
Epoch [42/50], Train Loss: 0.1793, Val Loss: 0.1473
Epoch [43/50], Train Loss: 0.1752, Val Loss: 0.1386
Epoch [44/50], Train Loss: 0.1868, Val Loss: 0.1371
Epoch [45/50], Train Loss: 0.1843, Val Loss: 0.1384
Epoch [46/50], Train Loss: 0.1869, Val Loss: 0.1409
Epoch [47/50], Train Loss: 0.1985, Val Loss: 0.1406
Epoch [48/50], Train Loss: 0.1550, Val Loss: 0.1357
Epoch [49/50], Train Loss: 0.1603, Val Loss: 0.1373
Epoch [50/50], Train Loss: 0.1963, Val Loss: 0.1402
Total time elapsed: 1.47 seconds
```

```
Out[ ]: ([0.19800997873147327,  
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0.1811884582042694,  
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## Task 6 - Experimentación y Análisis

Entrene los modelos con diferentes combinaciones de funciones de pérdida, técnicas de regularización y algoritmos de optimización. Para no complicar esta parte, puede dejar fijo dos de estos parámetros (función de pérdida, técnicas de regularización, algoritmo de optimización) y solamente cambiar uno de ellos. Deben verse al menos 9 combinaciones en total, donde es válido que en una de ellas no haya ninguna técnica de regularización. Si quiere experimentar con más combinaciones se le dará hasta 10% de puntos extra. Para cada combinación registre métricas como precisión, pérdida y alguna otra métrica que considere pertinente (Recuerde lo visto en inteligencia artificial). Visualice las curvas (tanto en precisión, pérdida y la tercera métrica que decidió) de entrenamiento y validación utilizando bibliotecas como matplotlib y/o seaborn. Además, recuerde llevar tracking de los tiempos de ejecución de cada combinación



### Descripción:

- En este task, vamos a realizar una serie de experimentos utilizando diferentes combinaciones de funciones de pérdida, técnicas de regularización y algoritmos de optimización.
- Mantendremos dos de estos factores constantes mientras variamos el tercero.



### Metas:

1. Realizar al menos 12 combinaciones de experimentos.
2. Registrar métricas como precisión, pérdida y otra métrica de su elección.
3. Visualizar las curvas de precisión, pérdida y la tercera métrica usando Seaborn.
4. Mantener un registro del tiempo de ejecución para cada combinación de experimentos.



### Implementación:

1. Utilizar un modelo de red neuronal base.
2. Aplicar diferentes técnicas de regularización (L1, L2, Dropout).
3. Utilizar diferentes funciones de pérdida (CrossEntropy, NLLLoss).
4. Emplear diferentes algoritmos de optimización (SGD, Adam).

```
In [ ]: import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd

def evaluate_model(model, loader):
    model.eval()
    correct = 0
    total = 0
    with torch.no_grad():
        for inputs, targets in loader:
            outputs = model(inputs)
            _, predicted = torch.max(outputs.data, 1)
            total += targets.size(0)
            correct += (predicted == targets).sum().item()
```

```

        return 100 * correct / total

results = []
for loss_function in [nn.CrossEntropyLoss(), nn.NLLLoss()]:
    for optimizer_type in ['SGD', 'Adam']:
        for regularization in ['None', 'L1', 'L2', 'Dropout']:
            model = SimpleFeedforwardNN(input_size, hidden_sizes, output_size)
            if regularization == 'Dropout':
                model.dropout = nn.Dropout(0.5)

            loss_fn = loss_function

            if optimizer_type == 'SGD':
                optimizer = optim.SGD(model.parameters(), lr=learning_rate, wei
            elif optimizer_type == 'Adam':
                optimizer = optim.Adam(model.parameters(), lr=learning_rate, we

            l1_lambda = 0.01 if regularization == 'L1' else 0.0
            train_losses, val_losses, elapsed_time = train_model_with_time(model,

            accuracy = evaluate_model(model, val_loader)

            metrics = {
                'Loss Function': loss_fn.__class__.__name__,
                'Optimizer': optimizer_type,
                'Regularization': regularization,
                'Final Training Loss': train_losses[-1],
                'Final Validation Loss': val_losses[-1],
                'Validation Accuracy': accuracy,
                'Time': elapsed_time
            }
            results.append(metrics)

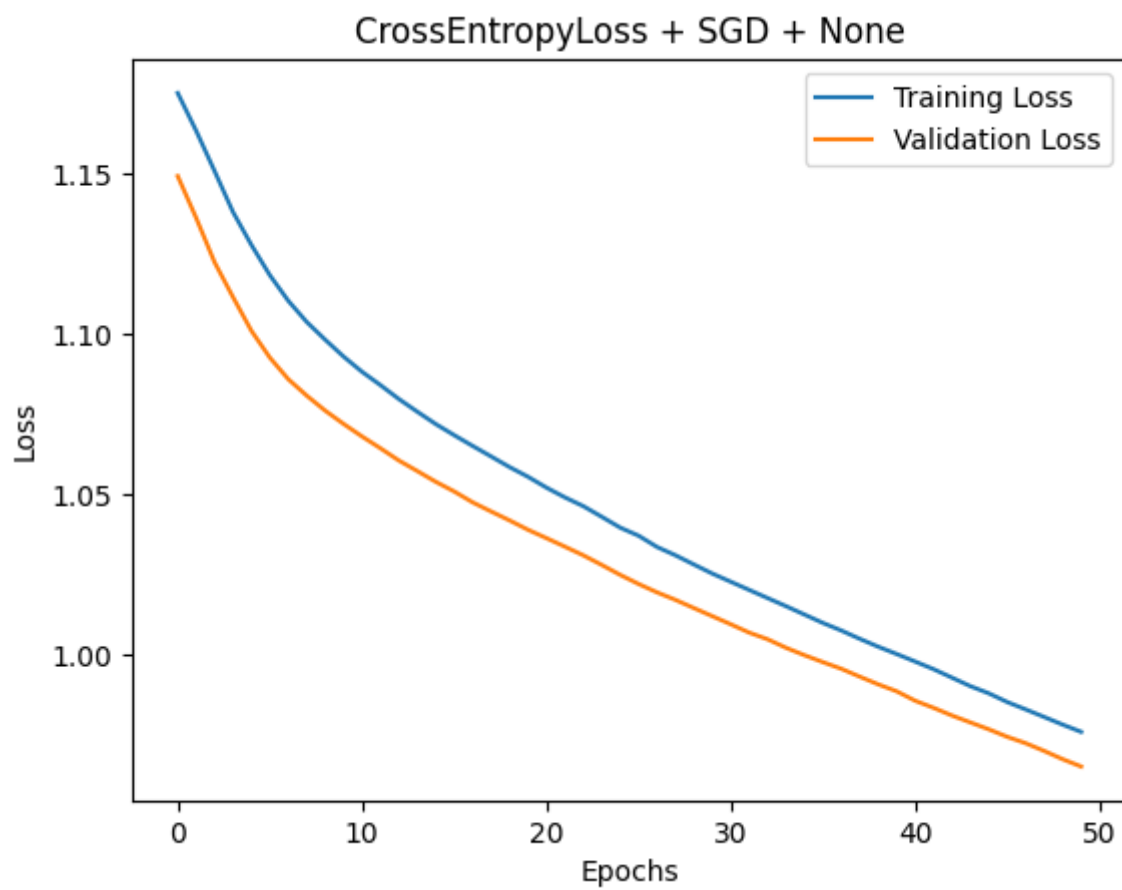
            sns.lineplot(x=range(num_epochs), y=train_losses, label='Training Loss')
            sns.lineplot(x=range(num_epochs), y=val_losses, label='Validation Loss')
            plt.title(f"{loss_fn.__class__.__name__} + {optimizer_type} + {regularization}")
            plt.xlabel("Epochs")
            plt.ylabel("Loss")
            plt.legend()
            plt.show()

results_df = pd.DataFrame(results)
print(results_df)

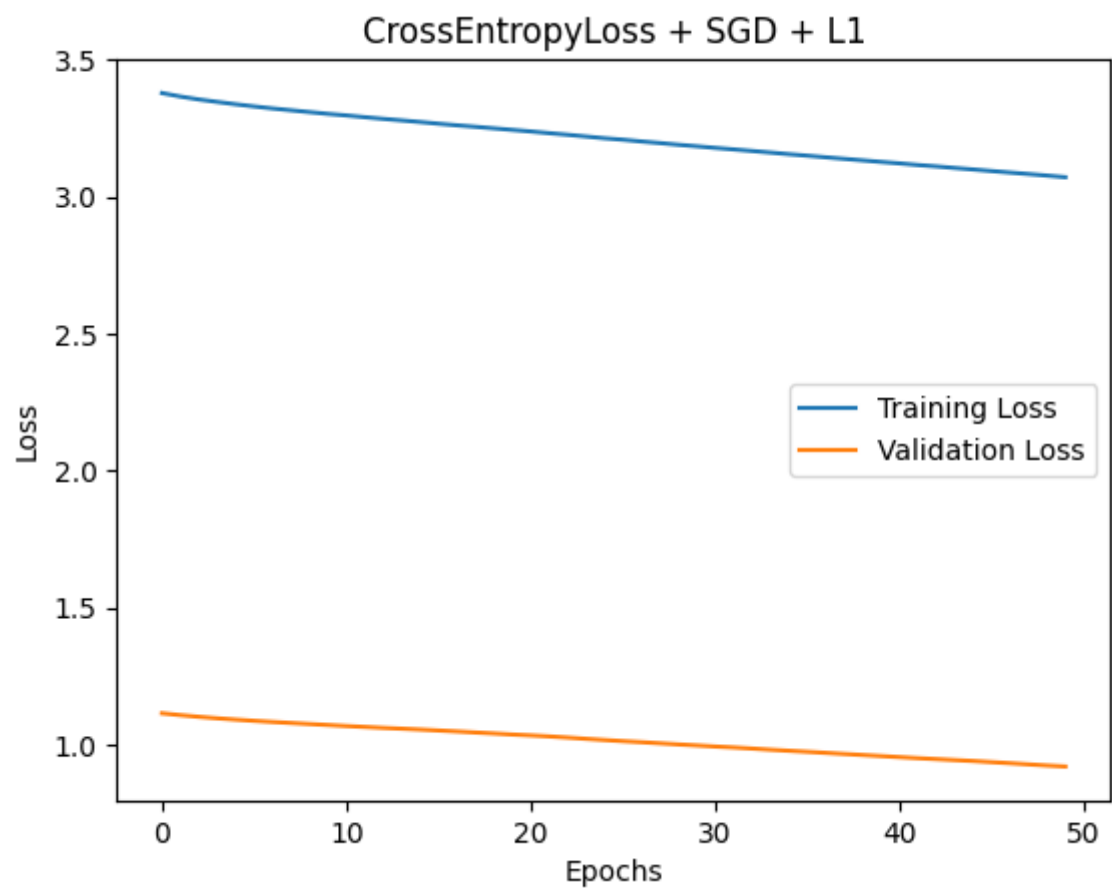
```

```
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Total time elapsed: 1.24 seconds
```

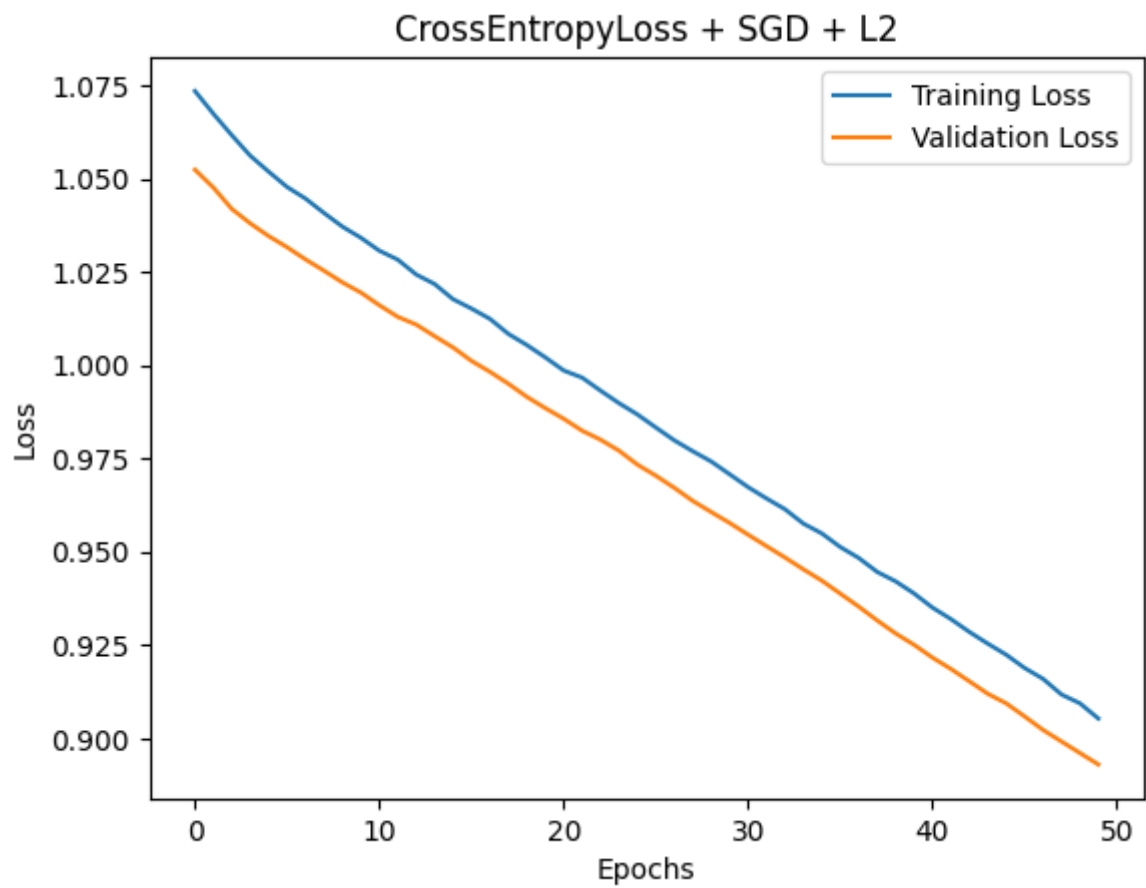




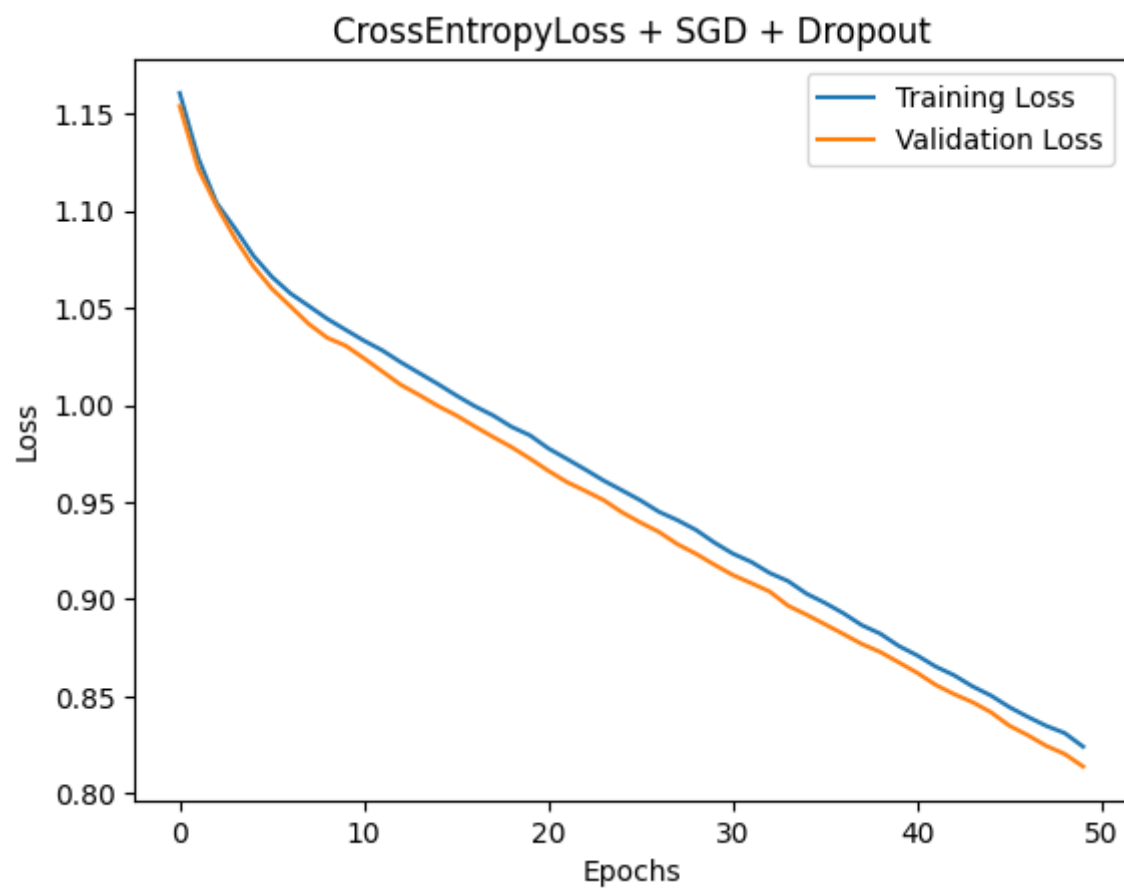
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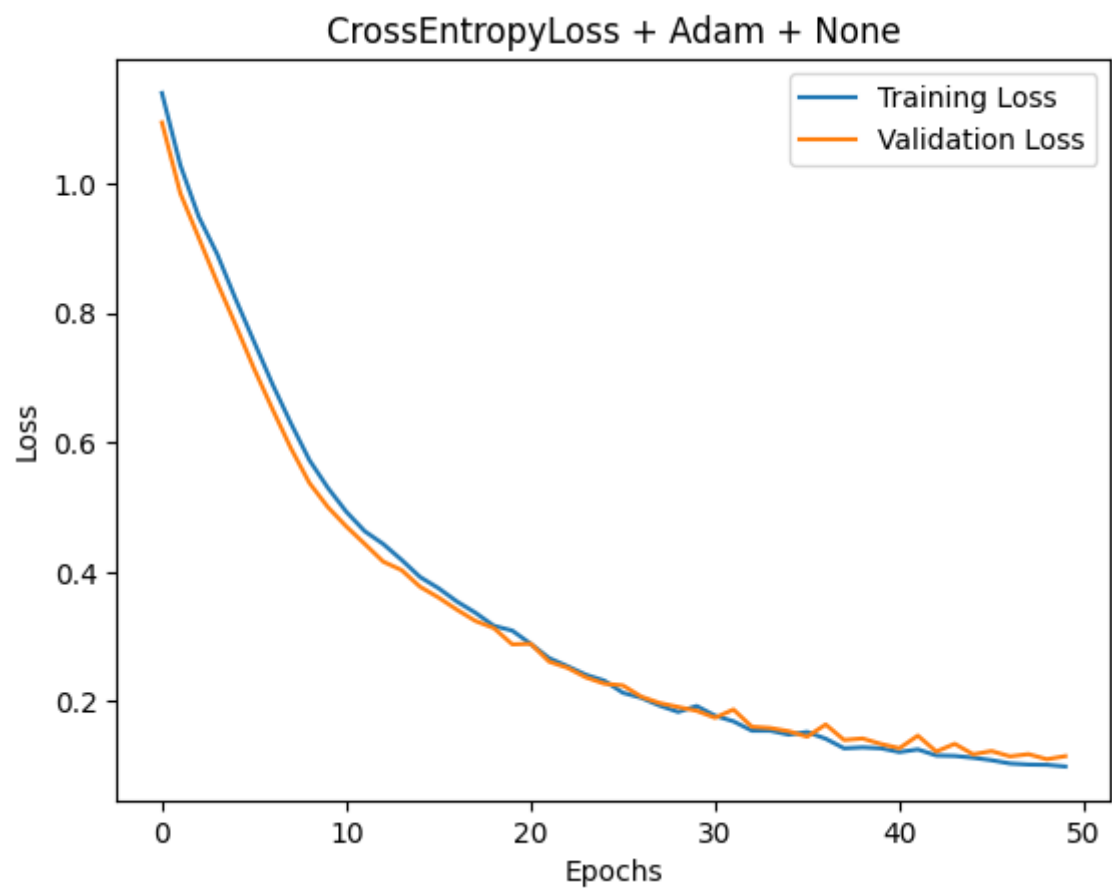


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Total time elapsed: 0.66 seconds

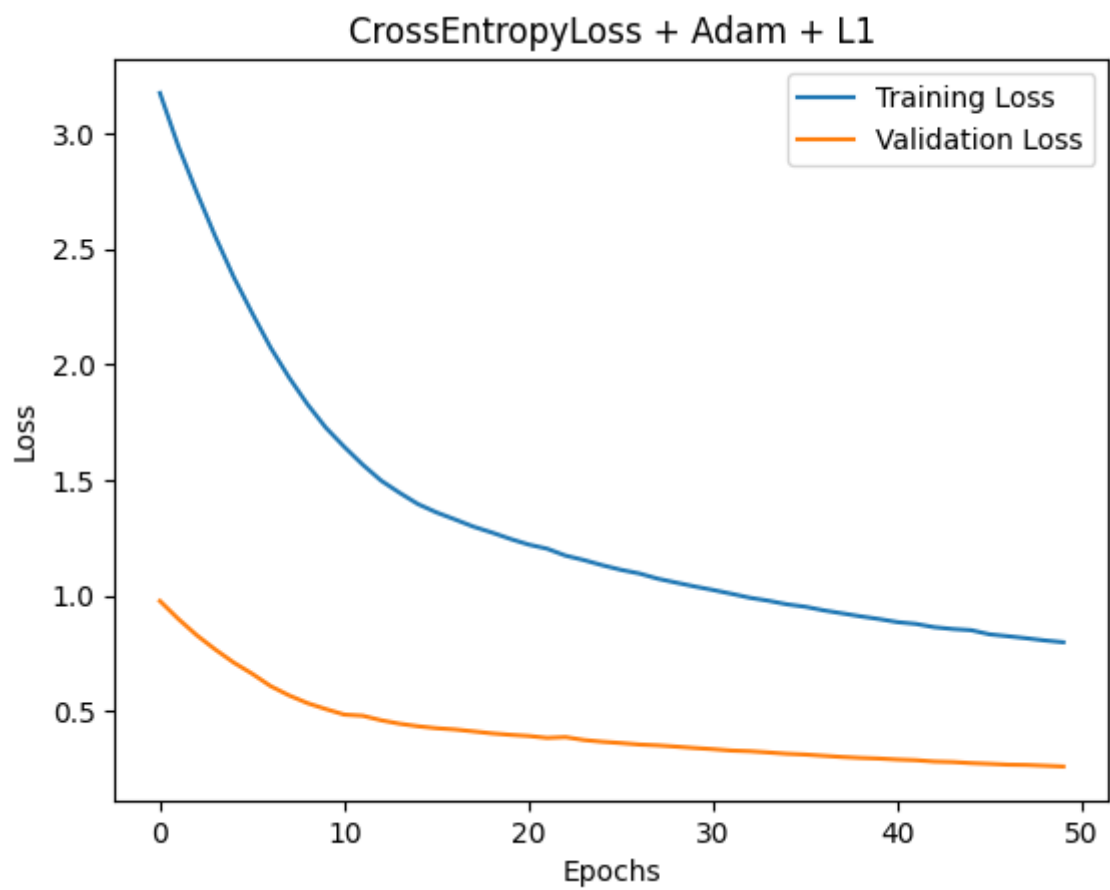


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Epoch [17/50], Train Loss: 0.3542, Val Loss: 0.3416  
Epoch [18/50], Train Loss: 0.3369, Val Loss: 0.3242  
Epoch [19/50], Train Loss: 0.3167, Val Loss: 0.3132  
Epoch [20/50], Train Loss: 0.3093, Val Loss: 0.2880  
Epoch [21/50], Train Loss: 0.2888, Val Loss: 0.2890  
Epoch [22/50], Train Loss: 0.2667, Val Loss: 0.2613  
Epoch [23/50], Train Loss: 0.2541, Val Loss: 0.2517  
Epoch [24/50], Train Loss: 0.2409, Val Loss: 0.2369  
Epoch [25/50], Train Loss: 0.2318, Val Loss: 0.2272  
Epoch [26/50], Train Loss: 0.2132, Val Loss: 0.2245  
Epoch [27/50], Train Loss: 0.2054, Val Loss: 0.2071  
Epoch [28/50], Train Loss: 0.1933, Val Loss: 0.1972  
Epoch [29/50], Train Loss: 0.1836, Val Loss: 0.1912  
Epoch [30/50], Train Loss: 0.1927, Val Loss: 0.1854  
Epoch [31/50], Train Loss: 0.1777, Val Loss: 0.1746  
Epoch [32/50], Train Loss: 0.1691, Val Loss: 0.1873  
Epoch [33/50], Train Loss: 0.1546, Val Loss: 0.1606  
Epoch [34/50], Train Loss: 0.1546, Val Loss: 0.1588  
Epoch [35/50], Train Loss: 0.1485, Val Loss: 0.1537  
Epoch [36/50], Train Loss: 0.1526, Val Loss: 0.1454  
Epoch [37/50], Train Loss: 0.1422, Val Loss: 0.1642  
Epoch [38/50], Train Loss: 0.1274, Val Loss: 0.1403  
Epoch [39/50], Train Loss: 0.1288, Val Loss: 0.1426  
Epoch [40/50], Train Loss: 0.1274, Val Loss: 0.1341  
Epoch [41/50], Train Loss: 0.1216, Val Loss: 0.1275  
Epoch [42/50], Train Loss: 0.1257, Val Loss: 0.1469  
Epoch [43/50], Train Loss: 0.1163, Val Loss: 0.1224  
Epoch [44/50], Train Loss: 0.1156, Val Loss: 0.1343  
Epoch [45/50], Train Loss: 0.1128, Val Loss: 0.1181  
Epoch [46/50], Train Loss: 0.1090, Val Loss: 0.1231  
Epoch [47/50], Train Loss: 0.1039, Val Loss: 0.1149  
Epoch [48/50], Train Loss: 0.1023, Val Loss: 0.1184  
Epoch [49/50], Train Loss: 0.1018, Val Loss: 0.1105  
Epoch [50/50], Train Loss: 0.0993, Val Loss: 0.1153  
Total time elapsed: 0.83 seconds

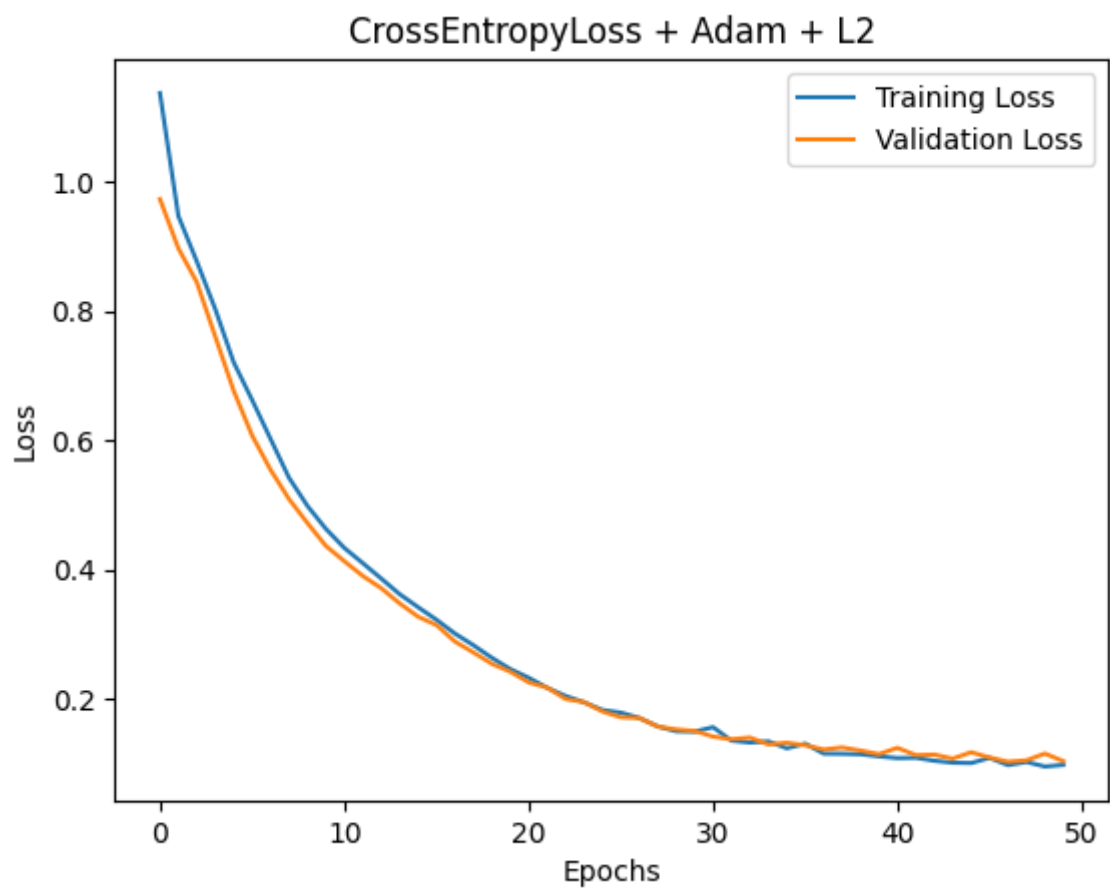




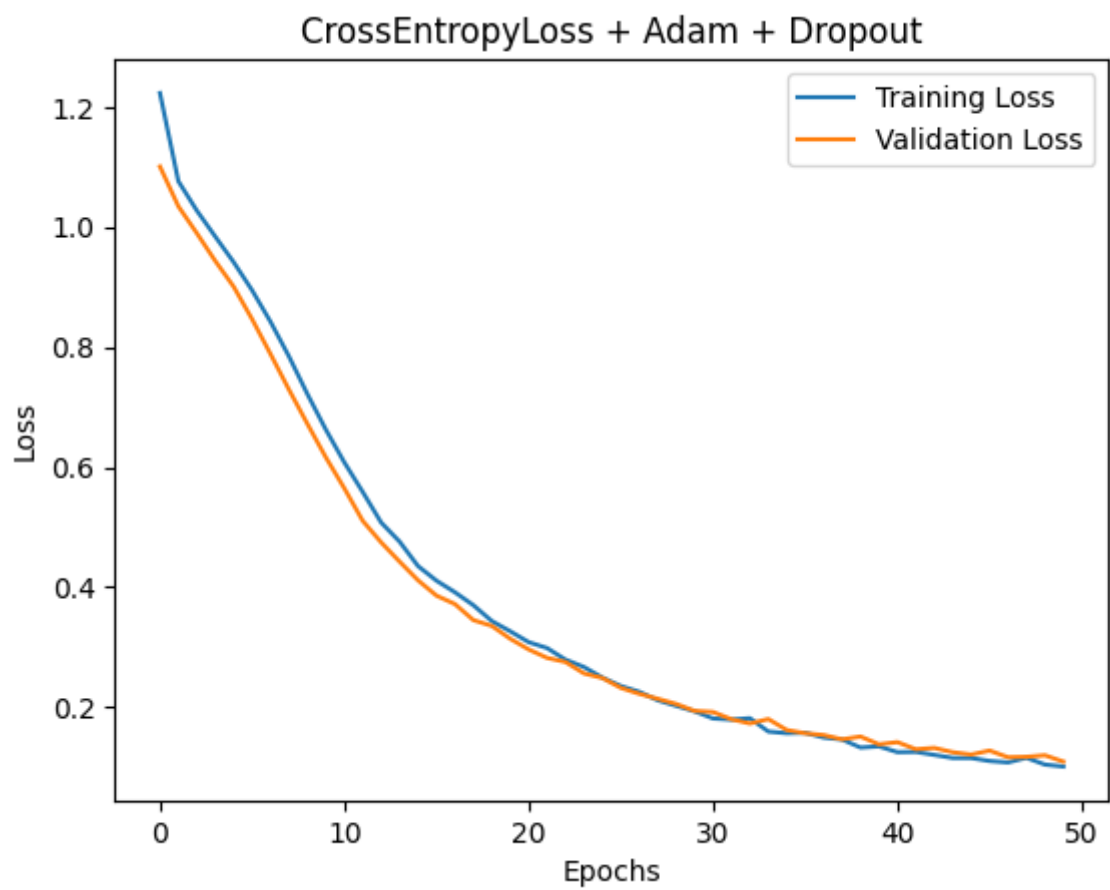
```
Epoch [1/50], Train Loss: 3.1747, Val Loss: 0.9772
Epoch [2/50], Train Loss: 2.9443, Val Loss: 0.8994
Epoch [3/50], Train Loss: 2.7443, Val Loss: 0.8288
Epoch [4/50], Train Loss: 2.5547, Val Loss: 0.7675
Epoch [5/50], Train Loss: 2.3789, Val Loss: 0.7109
Epoch [6/50], Train Loss: 2.2230, Val Loss: 0.6627
Epoch [7/50], Train Loss: 2.0738, Val Loss: 0.6091
Epoch [8/50], Train Loss: 1.9446, Val Loss: 0.5689
Epoch [9/50], Train Loss: 1.8284, Val Loss: 0.5354
Epoch [10/50], Train Loss: 1.7269, Val Loss: 0.5095
Epoch [11/50], Train Loss: 1.6440, Val Loss: 0.4856
Epoch [12/50], Train Loss: 1.5669, Val Loss: 0.4808
Epoch [13/50], Train Loss: 1.4978, Val Loss: 0.4611
Epoch [14/50], Train Loss: 1.4452, Val Loss: 0.4462
Epoch [15/50], Train Loss: 1.3964, Val Loss: 0.4352
Epoch [16/50], Train Loss: 1.3604, Val Loss: 0.4268
Epoch [17/50], Train Loss: 1.3302, Val Loss: 0.4213
Epoch [18/50], Train Loss: 1.2989, Val Loss: 0.4130
Epoch [19/50], Train Loss: 1.2736, Val Loss: 0.4044
Epoch [20/50], Train Loss: 1.2460, Val Loss: 0.3982
Epoch [21/50], Train Loss: 1.2213, Val Loss: 0.3932
Epoch [22/50], Train Loss: 1.2035, Val Loss: 0.3849
Epoch [23/50], Train Loss: 1.1736, Val Loss: 0.3883
Epoch [24/50], Train Loss: 1.1542, Val Loss: 0.3757
Epoch [25/50], Train Loss: 1.1319, Val Loss: 0.3681
Epoch [26/50], Train Loss: 1.1122, Val Loss: 0.3626
Epoch [27/50], Train Loss: 1.0964, Val Loss: 0.3562
Epoch [28/50], Train Loss: 1.0737, Val Loss: 0.3525
Epoch [29/50], Train Loss: 1.0567, Val Loss: 0.3471
Epoch [30/50], Train Loss: 1.0401, Val Loss: 0.3412
Epoch [31/50], Train Loss: 1.0249, Val Loss: 0.3362
Epoch [32/50], Train Loss: 1.0084, Val Loss: 0.3300
Epoch [33/50], Train Loss: 0.9911, Val Loss: 0.3272
Epoch [34/50], Train Loss: 0.9784, Val Loss: 0.3219
Epoch [35/50], Train Loss: 0.9630, Val Loss: 0.3163
Epoch [36/50], Train Loss: 0.9524, Val Loss: 0.3128
Epoch [37/50], Train Loss: 0.9367, Val Loss: 0.3075
Epoch [38/50], Train Loss: 0.9238, Val Loss: 0.3023
Epoch [39/50], Train Loss: 0.9109, Val Loss: 0.2983
Epoch [40/50], Train Loss: 0.8992, Val Loss: 0.2956
Epoch [41/50], Train Loss: 0.8858, Val Loss: 0.2913
Epoch [42/50], Train Loss: 0.8782, Val Loss: 0.2884
Epoch [43/50], Train Loss: 0.8639, Val Loss: 0.2826
Epoch [44/50], Train Loss: 0.8559, Val Loss: 0.2805
Epoch [45/50], Train Loss: 0.8509, Val Loss: 0.2758
Epoch [46/50], Train Loss: 0.8330, Val Loss: 0.2727
Epoch [47/50], Train Loss: 0.8248, Val Loss: 0.2691
Epoch [48/50], Train Loss: 0.8160, Val Loss: 0.2678
Epoch [49/50], Train Loss: 0.8065, Val Loss: 0.2645
Epoch [50/50], Train Loss: 0.7988, Val Loss: 0.2611
Total time elapsed: 0.82 seconds
```



```
Epoch [1/50], Train Loss: 1.1368, Val Loss: 0.9727
Epoch [2/50], Train Loss: 0.9466, Val Loss: 0.8966
Epoch [3/50], Train Loss: 0.8763, Val Loss: 0.8442
Epoch [4/50], Train Loss: 0.8027, Val Loss: 0.7601
Epoch [5/50], Train Loss: 0.7203, Val Loss: 0.6761
Epoch [6/50], Train Loss: 0.6620, Val Loss: 0.6070
Epoch [7/50], Train Loss: 0.6017, Val Loss: 0.5540
Epoch [8/50], Train Loss: 0.5417, Val Loss: 0.5087
Epoch [9/50], Train Loss: 0.4981, Val Loss: 0.4716
Epoch [10/50], Train Loss: 0.4626, Val Loss: 0.4362
Epoch [11/50], Train Loss: 0.4331, Val Loss: 0.4126
Epoch [12/50], Train Loss: 0.4096, Val Loss: 0.3898
Epoch [13/50], Train Loss: 0.3858, Val Loss: 0.3708
Epoch [14/50], Train Loss: 0.3616, Val Loss: 0.3474
Epoch [15/50], Train Loss: 0.3415, Val Loss: 0.3268
Epoch [16/50], Train Loss: 0.3220, Val Loss: 0.3137
Epoch [17/50], Train Loss: 0.3006, Val Loss: 0.2883
Epoch [18/50], Train Loss: 0.2826, Val Loss: 0.2714
Epoch [19/50], Train Loss: 0.2632, Val Loss: 0.2539
Epoch [20/50], Train Loss: 0.2457, Val Loss: 0.2416
Epoch [21/50], Train Loss: 0.2323, Val Loss: 0.2251
Epoch [22/50], Train Loss: 0.2167, Val Loss: 0.2170
Epoch [23/50], Train Loss: 0.2040, Val Loss: 0.1994
Epoch [24/50], Train Loss: 0.1943, Val Loss: 0.1945
Epoch [25/50], Train Loss: 0.1823, Val Loss: 0.1800
Epoch [26/50], Train Loss: 0.1783, Val Loss: 0.1712
Epoch [27/50], Train Loss: 0.1700, Val Loss: 0.1700
Epoch [28/50], Train Loss: 0.1570, Val Loss: 0.1568
Epoch [29/50], Train Loss: 0.1494, Val Loss: 0.1523
Epoch [30/50], Train Loss: 0.1489, Val Loss: 0.1499
Epoch [31/50], Train Loss: 0.1558, Val Loss: 0.1412
Epoch [32/50], Train Loss: 0.1349, Val Loss: 0.1370
Epoch [33/50], Train Loss: 0.1320, Val Loss: 0.1397
Epoch [34/50], Train Loss: 0.1338, Val Loss: 0.1291
Epoch [35/50], Train Loss: 0.1231, Val Loss: 0.1316
Epoch [36/50], Train Loss: 0.1302, Val Loss: 0.1279
Epoch [37/50], Train Loss: 0.1149, Val Loss: 0.1212
Epoch [38/50], Train Loss: 0.1147, Val Loss: 0.1244
Epoch [39/50], Train Loss: 0.1139, Val Loss: 0.1196
Epoch [40/50], Train Loss: 0.1106, Val Loss: 0.1141
Epoch [41/50], Train Loss: 0.1080, Val Loss: 0.1238
Epoch [42/50], Train Loss: 0.1085, Val Loss: 0.1125
Epoch [43/50], Train Loss: 0.1038, Val Loss: 0.1134
Epoch [44/50], Train Loss: 0.1009, Val Loss: 0.1071
Epoch [45/50], Train Loss: 0.1003, Val Loss: 0.1170
Epoch [46/50], Train Loss: 0.1083, Val Loss: 0.1088
Epoch [47/50], Train Loss: 0.0970, Val Loss: 0.1023
Epoch [48/50], Train Loss: 0.1019, Val Loss: 0.1045
Epoch [49/50], Train Loss: 0.0949, Val Loss: 0.1149
Epoch [50/50], Train Loss: 0.0975, Val Loss: 0.1032
Total time elapsed: 0.86 seconds
```

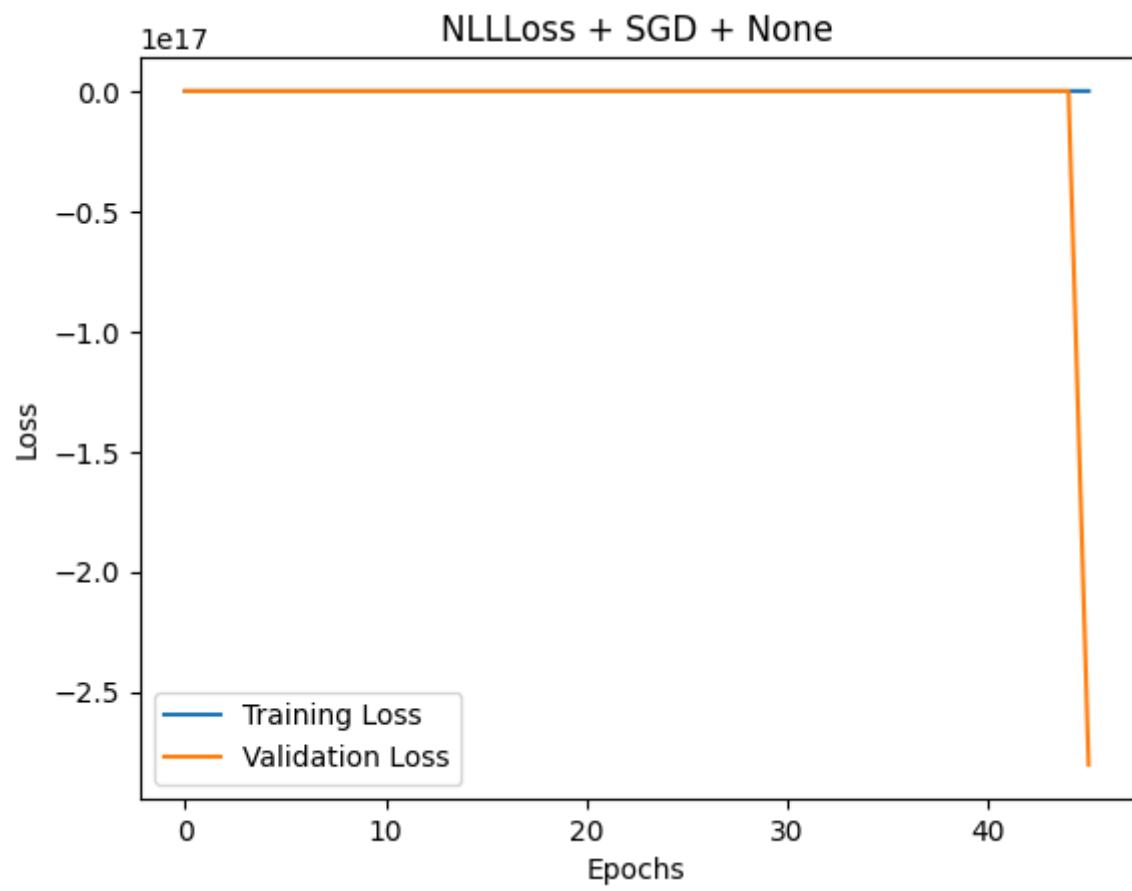


Epoch [1/50], Train Loss: 1.2230, Val Loss: 1.1006  
Epoch [2/50], Train Loss: 1.0761, Val Loss: 1.0343  
Epoch [3/50], Train Loss: 1.0273, Val Loss: 0.9896  
Epoch [4/50], Train Loss: 0.9840, Val Loss: 0.9434  
Epoch [5/50], Train Loss: 0.9413, Val Loss: 0.9005  
Epoch [6/50], Train Loss: 0.8944, Val Loss: 0.8463  
Epoch [7/50], Train Loss: 0.8420, Val Loss: 0.7882  
Epoch [8/50], Train Loss: 0.7843, Val Loss: 0.7290  
Epoch [9/50], Train Loss: 0.7216, Val Loss: 0.6720  
Epoch [10/50], Train Loss: 0.6624, Val Loss: 0.6162  
Epoch [11/50], Train Loss: 0.6080, Val Loss: 0.5648  
Epoch [12/50], Train Loss: 0.5587, Val Loss: 0.5105  
Epoch [13/50], Train Loss: 0.5077, Val Loss: 0.4747  
Epoch [14/50], Train Loss: 0.4759, Val Loss: 0.4426  
Epoch [15/50], Train Loss: 0.4352, Val Loss: 0.4115  
Epoch [16/50], Train Loss: 0.4109, Val Loss: 0.3860  
Epoch [17/50], Train Loss: 0.3916, Val Loss: 0.3720  
Epoch [18/50], Train Loss: 0.3701, Val Loss: 0.3453  
Epoch [19/50], Train Loss: 0.3437, Val Loss: 0.3356  
Epoch [20/50], Train Loss: 0.3266, Val Loss: 0.3142  
Epoch [21/50], Train Loss: 0.3085, Val Loss: 0.2964  
Epoch [22/50], Train Loss: 0.2987, Val Loss: 0.2823  
Epoch [23/50], Train Loss: 0.2793, Val Loss: 0.2755  
Epoch [24/50], Train Loss: 0.2671, Val Loss: 0.2564  
Epoch [25/50], Train Loss: 0.2494, Val Loss: 0.2488  
Epoch [26/50], Train Loss: 0.2354, Val Loss: 0.2323  
Epoch [27/50], Train Loss: 0.2258, Val Loss: 0.2225  
Epoch [28/50], Train Loss: 0.2117, Val Loss: 0.2142  
Epoch [29/50], Train Loss: 0.2024, Val Loss: 0.2055  
Epoch [30/50], Train Loss: 0.1933, Val Loss: 0.1940  
Epoch [31/50], Train Loss: 0.1814, Val Loss: 0.1922  
Epoch [32/50], Train Loss: 0.1795, Val Loss: 0.1801  
Epoch [33/50], Train Loss: 0.1819, Val Loss: 0.1731  
Epoch [34/50], Train Loss: 0.1596, Val Loss: 0.1804  
Epoch [35/50], Train Loss: 0.1569, Val Loss: 0.1621  
Epoch [36/50], Train Loss: 0.1575, Val Loss: 0.1567  
Epoch [37/50], Train Loss: 0.1496, Val Loss: 0.1538  
Epoch [38/50], Train Loss: 0.1464, Val Loss: 0.1466  
Epoch [39/50], Train Loss: 0.1330, Val Loss: 0.1513  
Epoch [40/50], Train Loss: 0.1350, Val Loss: 0.1384  
Epoch [41/50], Train Loss: 0.1253, Val Loss: 0.1420  
Epoch [42/50], Train Loss: 0.1257, Val Loss: 0.1301  
Epoch [43/50], Train Loss: 0.1207, Val Loss: 0.1324  
Epoch [44/50], Train Loss: 0.1156, Val Loss: 0.1252  
Epoch [45/50], Train Loss: 0.1155, Val Loss: 0.1213  
Epoch [46/50], Train Loss: 0.1106, Val Loss: 0.1279  
Epoch [47/50], Train Loss: 0.1082, Val Loss: 0.1168  
Epoch [48/50], Train Loss: 0.1159, Val Loss: 0.1174  
Epoch [49/50], Train Loss: 0.1046, Val Loss: 0.1201  
Epoch [50/50], Train Loss: 0.1014, Val Loss: 0.1095  
Total time elapsed: 0.86 seconds

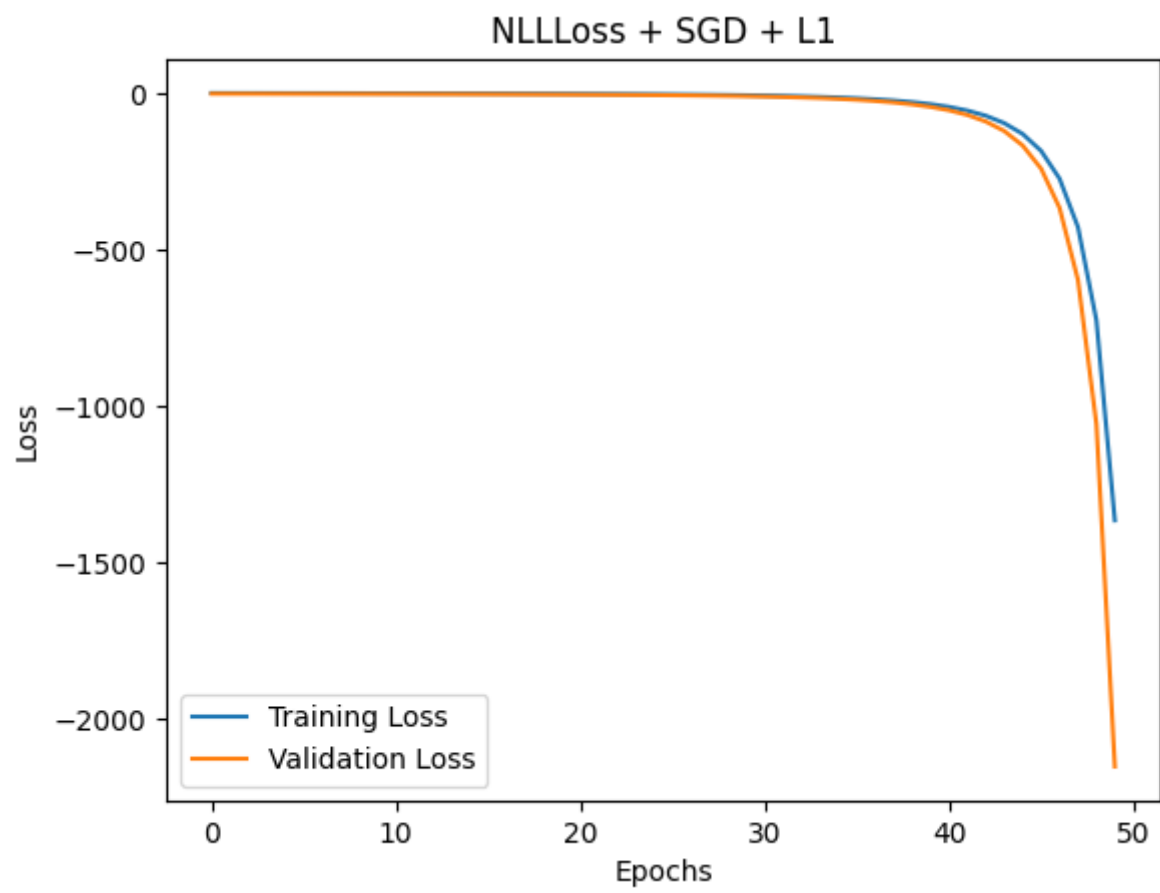


```
Epoch [1/50], Train Loss: -0.1613, Val Loss: -0.2009
Epoch [2/50], Train Loss: -0.2548, Val Loss: -0.2998
Epoch [3/50], Train Loss: -0.3527, Val Loss: -0.3974
Epoch [4/50], Train Loss: -0.4497, Val Loss: -0.4994
Epoch [5/50], Train Loss: -0.5546, Val Loss: -0.6132
Epoch [6/50], Train Loss: -0.6710, Val Loss: -0.7363
Epoch [7/50], Train Loss: -0.7968, Val Loss: -0.8716
Epoch [8/50], Train Loss: -0.9349, Val Loss: -1.0178
Epoch [9/50], Train Loss: -1.0845, Val Loss: -1.1803
Epoch [10/50], Train Loss: -1.2508, Val Loss: -1.3603
Epoch [11/50], Train Loss: -1.4360, Val Loss: -1.5620
Epoch [12/50], Train Loss: -1.6434, Val Loss: -1.7890
Epoch [13/50], Train Loss: -1.8759, Val Loss: -2.0447
Epoch [14/50], Train Loss: -2.1420, Val Loss: -2.3400
Epoch [15/50], Train Loss: -2.4514, Val Loss: -2.6910
Epoch [16/50], Train Loss: -2.8167, Val Loss: -3.1020
Epoch [17/50], Train Loss: -3.2381, Val Loss: -3.5662
Epoch [18/50], Train Loss: -3.7155, Val Loss: -4.1032
Epoch [19/50], Train Loss: -4.2717, Val Loss: -4.7181
Epoch [20/50], Train Loss: -4.9074, Val Loss: -5.4357
Epoch [21/50], Train Loss: -5.6522, Val Loss: -6.2796
Epoch [22/50], Train Loss: -6.5242, Val Loss: -7.2828
Epoch [23/50], Train Loss: -7.5715, Val Loss: -8.4704
Epoch [24/50], Train Loss: -8.8091, Val Loss: -9.8931
Epoch [25/50], Train Loss: -10.2982, Val Loss: -11.6080
Epoch [26/50], Train Loss: -12.1013, Val Loss: -13.7006
Epoch [27/50], Train Loss: -14.3024, Val Loss: -16.2795
Epoch [28/50], Train Loss: -17.0452, Val Loss: -19.4145
Epoch [29/50], Train Loss: -20.3836, Val Loss: -23.4414
Epoch [30/50], Train Loss: -24.6853, Val Loss: -28.6616
Epoch [31/50], Train Loss: -30.3197, Val Loss: -35.4089
Epoch [32/50], Train Loss: -37.6427, Val Loss: -44.3156
Epoch [33/50], Train Loss: -47.3841, Val Loss: -56.2187
Epoch [34/50], Train Loss: -60.5327, Val Loss: -72.7927
Epoch [35/50], Train Loss: -79.1604, Val Loss: -96.4189
Epoch [36/50], Train Loss: -105.9434, Val Loss: -131.2205
Epoch [37/50], Train Loss: -146.2453, Val Loss: -184.6451
Epoch [38/50], Train Loss: -209.4653, Val Loss: -272.8348
Epoch [39/50], Train Loss: -316.8177, Val Loss: -425.1823
Epoch [40/50], Train Loss: -508.6583, Val Loss: -713.8143
Epoch [41/50], Train Loss: -894.3794, Val Loss: -1344.2390
Epoch [42/50], Train Loss: -1801.0422, Val Loss: -2955.0132
Epoch [43/50], Train Loss: -4424.2371, Val Loss: -8449.1880
Epoch [44/50], Train Loss: -15850.4654, Val Loss: -40742.3562
Epoch [45/50], Train Loss: -151745.2427, Val Loss: -906329.2083
Epoch [46/50], Train Loss: -247797704160.8333, Val Loss: -280188529780964288.0
000
Epoch [47/50], Train Loss: nan, Val Loss: nan
Epoch [48/50], Train Loss: nan, Val Loss: nan
Epoch [49/50], Train Loss: nan, Val Loss: nan
Epoch [50/50], Train Loss: nan, Val Loss: nan
Total time elapsed: 0.64 seconds
```

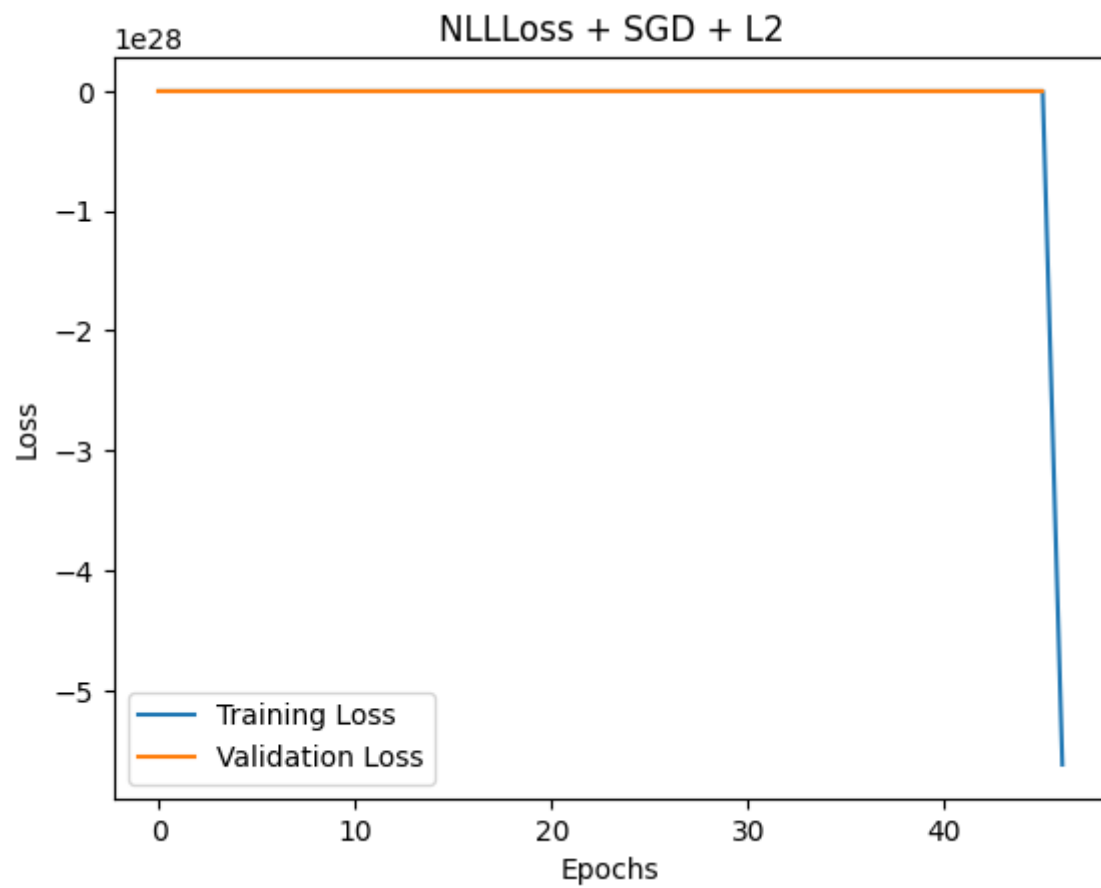




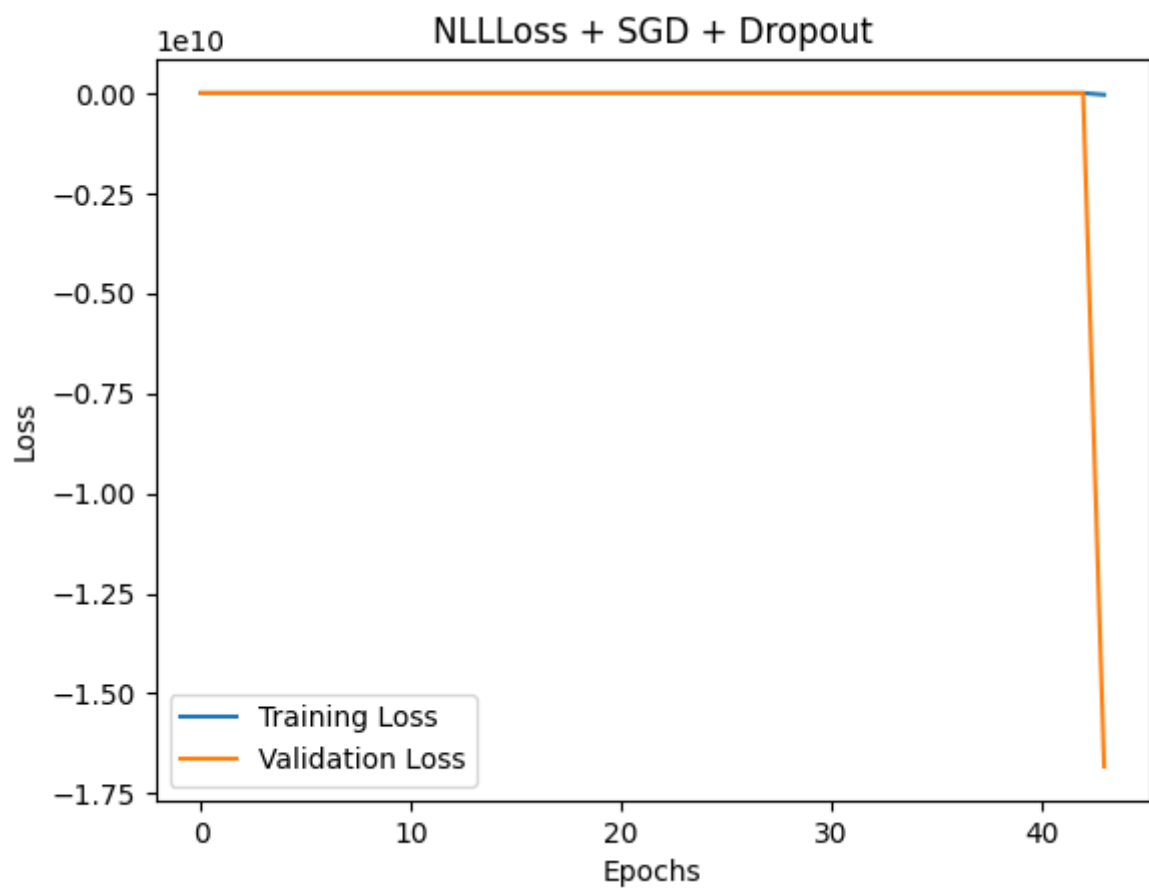
```
Epoch [1/50], Train Loss: 2.3712, Val Loss: 0.1703
Epoch [2/50], Train Loss: 2.2866, Val Loss: 0.0858
Epoch [3/50], Train Loss: 2.2040, Val Loss: 0.0027
Epoch [4/50], Train Loss: 2.1217, Val Loss: -0.0822
Epoch [5/50], Train Loss: 2.0373, Val Loss: -0.1674
Epoch [6/50], Train Loss: 1.9521, Val Loss: -0.2579
Epoch [7/50], Train Loss: 1.8615, Val Loss: -0.3564
Epoch [8/50], Train Loss: 1.7641, Val Loss: -0.4565
Epoch [9/50], Train Loss: 1.6658, Val Loss: -0.5585
Epoch [10/50], Train Loss: 1.5668, Val Loss: -0.6602
Epoch [11/50], Train Loss: 1.4666, Val Loss: -0.7678
Epoch [12/50], Train Loss: 1.3620, Val Loss: -0.8803
Epoch [13/50], Train Loss: 1.2498, Val Loss: -1.0021
Epoch [14/50], Train Loss: 1.1285, Val Loss: -1.1360
Epoch [15/50], Train Loss: 0.9960, Val Loss: -1.2826
Epoch [16/50], Train Loss: 0.8511, Val Loss: -1.4426
Epoch [17/50], Train Loss: 0.6922, Val Loss: -1.6202
Epoch [18/50], Train Loss: 0.5159, Val Loss: -1.8171
Epoch [19/50], Train Loss: 0.3200, Val Loss: -2.0334
Epoch [20/50], Train Loss: 0.1045, Val Loss: -2.2786
Epoch [21/50], Train Loss: -0.1394, Val Loss: -2.5509
Epoch [22/50], Train Loss: -0.4114, Val Loss: -2.8598
Epoch [23/50], Train Loss: -0.7199, Val Loss: -3.2065
Epoch [24/50], Train Loss: -1.0667, Val Loss: -3.6013
Epoch [25/50], Train Loss: -1.4611, Val Loss: -4.0487
Epoch [26/50], Train Loss: -1.9144, Val Loss: -4.5695
Epoch [27/50], Train Loss: -2.4391, Val Loss: -5.1754
Epoch [28/50], Train Loss: -3.0479, Val Loss: -5.8626
Epoch [29/50], Train Loss: -3.7494, Val Loss: -6.6751
Epoch [30/50], Train Loss: -4.5724, Val Loss: -7.6367
Epoch [31/50], Train Loss: -5.5486, Val Loss: -8.7618
Epoch [32/50], Train Loss: -6.7064, Val Loss: -10.1073
Epoch [33/50], Train Loss: -8.0877, Val Loss: -11.7340
Epoch [34/50], Train Loss: -9.7652, Val Loss: -13.6929
Epoch [35/50], Train Loss: -11.7957, Val Loss: -16.0797
Epoch [36/50], Train Loss: -14.2985, Val Loss: -19.0815
Epoch [37/50], Train Loss: -17.4453, Val Loss: -22.8279
Epoch [38/50], Train Loss: -21.3978, Val Loss: -27.5924
Epoch [39/50], Train Loss: -26.4594, Val Loss: -33.7296
Epoch [40/50], Train Loss: -33.0514, Val Loss: -41.8341
Epoch [41/50], Train Loss: -41.8033, Val Loss: -52.6207
Epoch [42/50], Train Loss: -53.5943, Val Loss: -67.5999
Epoch [43/50], Train Loss: -70.1302, Val Loss: -88.7245
Epoch [44/50], Train Loss: -93.7944, Val Loss: -118.9579
Epoch [45/50], Train Loss: -128.4119, Val Loss: -165.4376
Epoch [46/50], Train Loss: -182.5506, Val Loss: -239.3429
Epoch [47/50], Train Loss: -271.2424, Val Loss: -364.8414
Epoch [48/50], Train Loss: -426.4671, Val Loss: -595.4719
Epoch [49/50], Train Loss: -724.3273, Val Loss: -1056.5487
Epoch [50/50], Train Loss: -1364.7819, Val Loss: -2152.4291
Total time elapsed: 0.66 seconds
```



```
Epoch [1/50], Train Loss: 0.1192, Val Loss: 0.0693
Epoch [2/50], Train Loss: 0.0163, Val Loss: -0.0385
Epoch [3/50], Train Loss: -0.0877, Val Loss: -0.1458
Epoch [4/50], Train Loss: -0.1897, Val Loss: -0.2552
Epoch [5/50], Train Loss: -0.2950, Val Loss: -0.3662
Epoch [6/50], Train Loss: -0.4041, Val Loss: -0.4852
Epoch [7/50], Train Loss: -0.5209, Val Loss: -0.6121
Epoch [8/50], Train Loss: -0.6465, Val Loss: -0.7475
Epoch [9/50], Train Loss: -0.7807, Val Loss: -0.8933
Epoch [10/50], Train Loss: -0.9270, Val Loss: -1.0557
Epoch [11/50], Train Loss: -1.0902, Val Loss: -1.2344
Epoch [12/50], Train Loss: -1.2694, Val Loss: -1.4314
Epoch [13/50], Train Loss: -1.4702, Val Loss: -1.6547
Epoch [14/50], Train Loss: -1.6949, Val Loss: -1.9060
Epoch [15/50], Train Loss: -1.9540, Val Loss: -2.1960
Epoch [16/50], Train Loss: -2.2508, Val Loss: -2.5297
Epoch [17/50], Train Loss: -2.5936, Val Loss: -2.9174
Epoch [18/50], Train Loss: -2.9926, Val Loss: -3.3661
Epoch [19/50], Train Loss: -3.4553, Val Loss: -3.8927
Epoch [20/50], Train Loss: -3.9978, Val Loss: -4.5067
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Epoch [29/50], Train Loss: -17.1372, Val Loss: -19.7954
Epoch [30/50], Train Loss: -20.7487, Val Loss: -24.0619
Epoch [31/50], Train Loss: -25.3130, Val Loss: -29.5307
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Epoch [33/50], Train Loss: -38.9981, Val Loss: -46.1746
Epoch [34/50], Train Loss: -49.3784, Val Loss: -59.1630
Epoch [35/50], Train Loss: -63.8116, Val Loss: -77.2442
Epoch [36/50], Train Loss: -84.1217, Val Loss: -103.4567
Epoch [37/50], Train Loss: -114.0829, Val Loss: -142.5540
Epoch [38/50], Train Loss: -159.4926, Val Loss: -203.3960
Epoch [39/50], Train Loss: -231.8110, Val Loss: -303.5857
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Epoch [41/50], Train Loss: -583.6230, Val Loss: -831.1858
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Epoch [43/50], Train Loss: -2206.2405, Val Loss: -3743.1032
Epoch [44/50], Train Loss: -5834.6869, Val Loss: -12001.1068
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Epoch [47/50], Train Loss: -56201440123039766800588865536.0000, Val Loss: -inf
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Epoch [49/50], Train Loss: nan, Val Loss: nan
Epoch [50/50], Train Loss: nan, Val Loss: nan
Total time elapsed: 0.80 seconds
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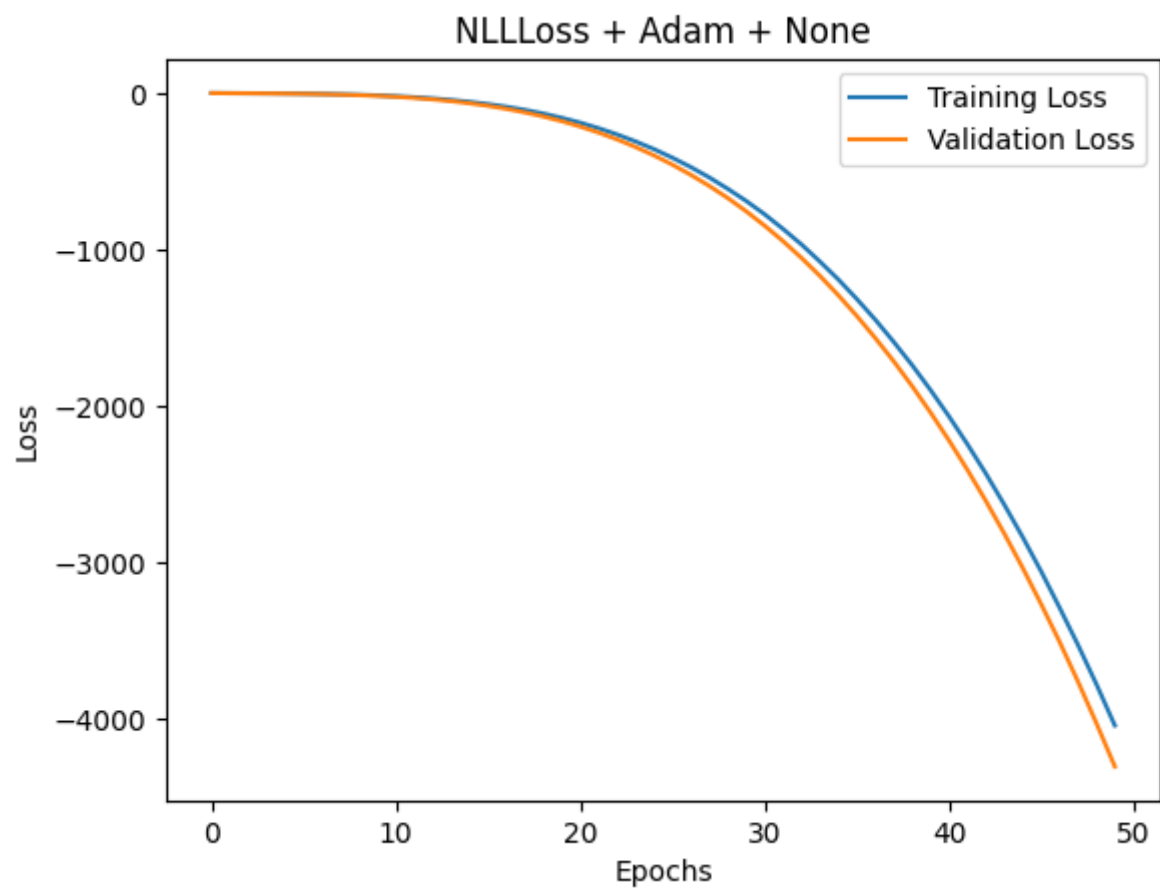


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Epoch [3/50], Train Loss: -0.3916, Val Loss: -0.4605
Epoch [4/50], Train Loss: -0.4942, Val Loss: -0.5690
Epoch [5/50], Train Loss: -0.6039, Val Loss: -0.6837
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Epoch [9/50], Train Loss: -1.1630, Val Loss: -1.2952
Epoch [10/50], Train Loss: -1.3514, Val Loss: -1.5041
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Epoch [15/50], Train Loss: -2.7946, Val Loss: -3.1089
Epoch [16/50], Train Loss: -3.2309, Val Loss: -3.6007
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Epoch [24/50], Train Loss: -11.0566, Val Loss: -12.5583
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Epoch [35/50], Train Loss: -133.4628, Val Loss: -168.2386
Epoch [36/50], Train Loss: -190.3547, Val Loss: -246.0086
Epoch [37/50], Train Loss: -284.5096, Val Loss: -378.6408
Epoch [38/50], Train Loss: -450.0529, Val Loss: -628.0007
Epoch [39/50], Train Loss: -776.3498, Val Loss: -1136.4800
Epoch [40/50], Train Loss: -1489.3328, Val Loss: -2361.8669
Epoch [41/50], Train Loss: -3415.7499, Val Loss: -6194.6999
Epoch [42/50], Train Loss: -10789.4759, Val Loss: -25255.2637
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Epoch [47/50], Train Loss: nan, Val Loss: nan
Epoch [48/50], Train Loss: nan, Val Loss: nan
Epoch [49/50], Train Loss: nan, Val Loss: nan
Epoch [50/50], Train Loss: nan, Val Loss: nan
Total time elapsed: 0.90 seconds
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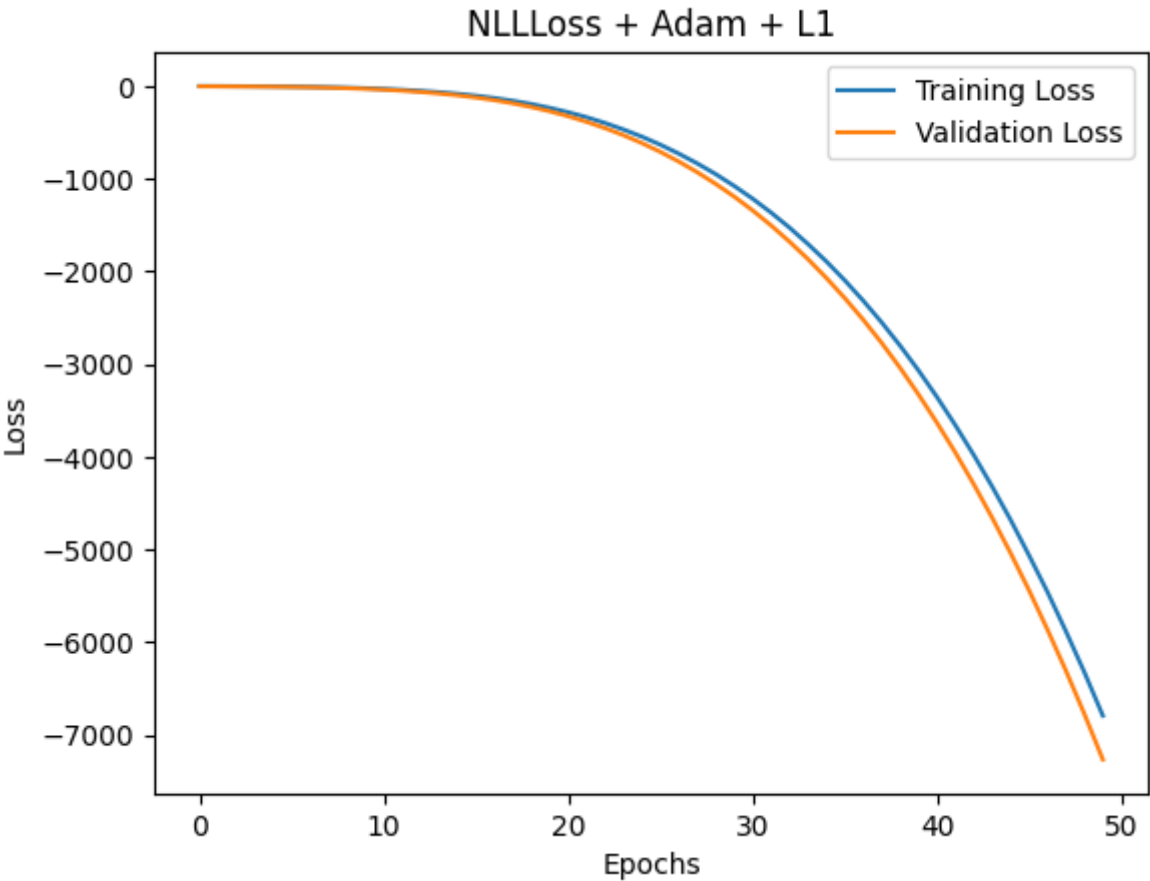


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Epoch [5/50], Train Loss: -2.9933, Val Loss: -3.7401  
Epoch [6/50], Train Loss: -4.2719, Val Loss: -5.2483  
Epoch [7/50], Train Loss: -5.9313, Val Loss: -7.2777  
Epoch [8/50], Train Loss: -8.1775, Val Loss: -9.9434  
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Epoch [10/50], Train Loss: -15.0234, Val Loss: -17.9907  
Epoch [11/50], Train Loss: -19.9432, Val Loss: -23.8396  
Epoch [12/50], Train Loss: -26.2979, Val Loss: -31.2209  
Epoch [13/50], Train Loss: -34.2141, Val Loss: -40.3789  
Epoch [14/50], Train Loss: -44.0833, Val Loss: -51.6424  
Epoch [15/50], Train Loss: -56.0018, Val Loss: -65.2840  
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Epoch [21/50], Train Loss: -189.2934, Val Loss: -213.9375  
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Total time elapsed: 1.09 seconds

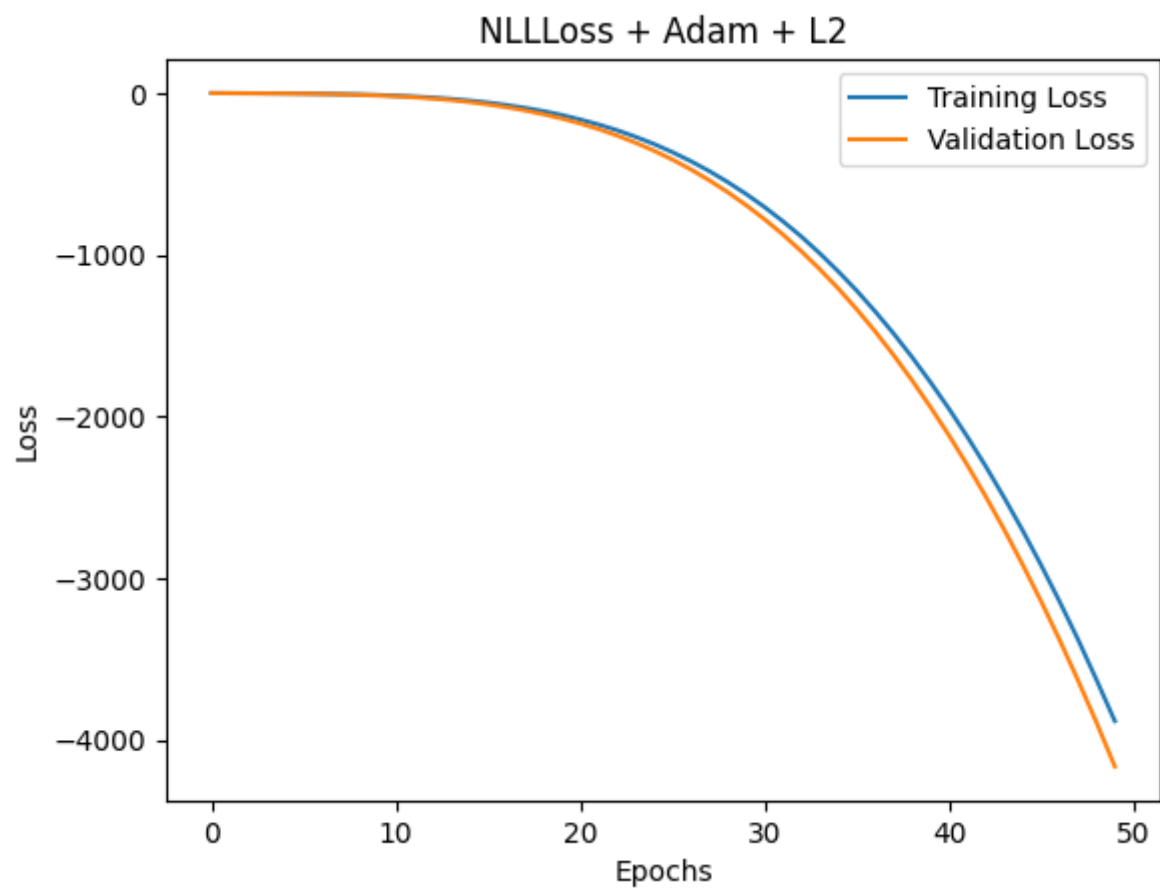




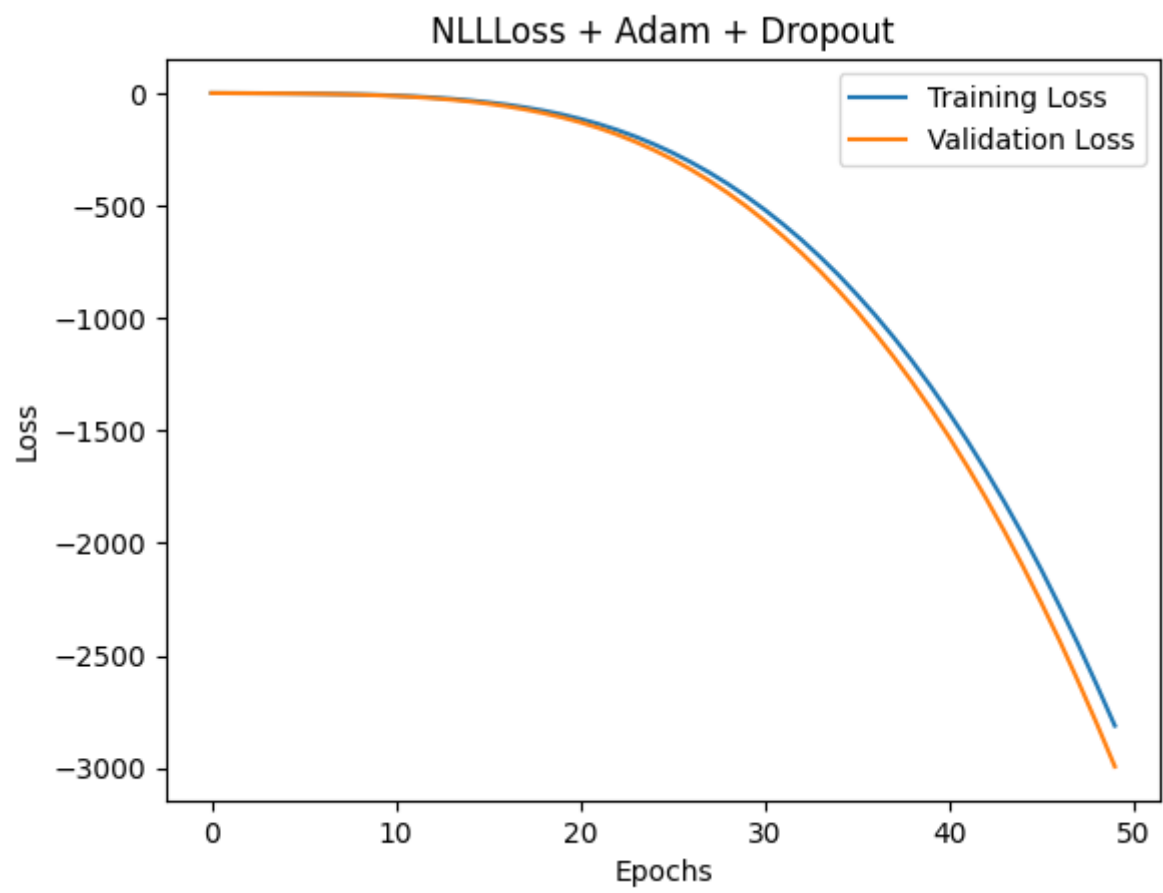
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Total time elapsed: 0.81 seconds



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Total time elapsed: 0.84 seconds



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Total time elapsed: 0.82 seconds



	Loss Function	Optimizer	Regularization	Final Training Loss \
0	CrossEntropyLoss	SGD	None	0.975757
1	CrossEntropyLoss	SGD	L1	3.071872
2	CrossEntropyLoss	SGD	L2	0.905292
3	CrossEntropyLoss	SGD	Dropout	0.823965
4	CrossEntropyLoss	Adam	None	0.099252
5	CrossEntropyLoss	Adam	L1	0.798778
6	CrossEntropyLoss	Adam	L2	0.097467
7	CrossEntropyLoss	Adam	Dropout	0.101398
8	NLLLoss	SGD	None	NaN
9	NLLLoss	SGD	L1	-1364.781942
10	NLLLoss	SGD	L2	NaN
11	NLLLoss	SGD	Dropout	NaN
12	NLLLoss	Adam	None	-4043.359603
13	NLLLoss	Adam	L1	-6790.548145
14	NLLLoss	Adam	L2	-3883.753271
15	NLLLoss	Adam	Dropout	-2812.199365

	Final Validation Loss	Validation Accuracy	Time
0	0.964919	36.666667	1.239962
1	0.919365	36.666667	2.183365
2	0.892960	73.333333	1.813068
3	0.813721	73.333333	0.656472
4	0.115275	100.000000	0.826143
5	0.261058	96.666667	0.822180
6	0.103178	100.000000	0.856971
7	0.109528	96.666667	0.858717
8	NaN	33.333333	0.642088
9	-2152.429118	36.666667	0.664937
10	NaN	33.333333	0.803154
11	NaN	33.333333	0.901080
12	-4305.603353	30.000000	1.091052
13	-7263.681055	36.666667	0.809736
14	-4164.898275	36.666667	0.839327
15	-2993.548275	30.000000	0.823931

## 12 Combinaciones para la Experimentación

 Cómo se Forman las 12 Combinaciones:

### 1. Funciones de Pérdida 🧮 :

- CrossEntropyLoss
- NLLLoss

### 2. Algoritmos de Optimización :

- SGD
- Adam

### 3. Técnicas de Regularización 🎯 :

- Sin regularización
- L1
- L2
- Dropout



## Combinaciones:

Cada experimento es una combinación única de una función de pérdida, un algoritmo de optimización y una técnica de regularización.

Por lo tanto, el número total de combinaciones sería:

- 2 Funciones de Pérdida 🏹 x 2 Algoritmos de Optimización 🔄 x 4 Técnicas de Regularización 🎯 = **16 combinaciones posibles**

Se hacen **12 combinaciones** manteniendo uno de los tres elementos (funciones de pérdida, algoritmos de optimización, técnicas de regularización) constante y variando los otros dos. Esto se hace para observar el impacto del tercer elemento variante en el rendimiento del modelo.

## Ejemplo de 12 Combinaciones:

1. CrossEntropy + SGD + Sin regularización
2. CrossEntropy + SGD + L1
3. CrossEntropy + SGD + L2
4. CrossEntropy + SGD + Dropout
5. CrossEntropy + Adam + Sin regularización
6. CrossEntropy + Adam + L1
7. CrossEntropy + Adam + L2
8. CrossEntropy + Adam + Dropout
9. NLLLoss + SGD + Sin regularización
10. NLLLoss + SGD + L1
11. NLLLoss + SGD + L2
12. NLLLoss + SGD + Dropout

## Task 7 - Discusión

Discuta los resultados obtenidos de diferentes modelos. Compare la velocidad de convergencia y el rendimiento final de modelos utilizando diferentes funciones de pérdida, técnicas de regularización, y algoritmos de optimización. Explore y discuta por qué ciertas técnicas podrían conducir a un mejor rendimiento. tanto técnicas de regularización, funciones de pérdida como algoritmos de optimización

## Respuesta

### Velocidad de Convergencia y Rendimiento Final

La velocidad de convergencia y el rendimiento final varían según las funciones de pérdida, técnicas de regularización y algoritmos de optimización utilizados.

1. **Funciones de Pérdida** 🏹 :

- **CrossEntropyLoss**: Ofrece buen rendimiento en términos de pérdida de validación y precisión, especialmente cuando se combina con Adam como optimizador.
- **NLLLoss**: No es adecuado para este problema en particular, como se evidencia por las pérdidas negativas y bajas tasas de precisión.

## 2. Algoritmos de Optimización 🔄 :

- **SGD**: Converge más lentamente en comparación con Adam.
- **Adam**: Converge más rápidamente y ofrece mejores resultados en términos de pérdida y precisión.

## 3. Técnicas de Regularización 🎯 :

- **None**: Sin regularización, el modelo con Adam y CrossEntropy muestra una precisión del 100%.
- **L1**: Aumenta el tiempo de entrenamiento y da lugar a pérdidas más altas.
- **L2**: Ofrece buen rendimiento cuando se combina con Adam y CrossEntropy.
- **Dropout**: Bueno para evitar el sobreajuste, pero aumenta ligeramente la pérdida de validación.

## 🎓 Basado en Teoría 📖

1. **CrossEntropyLoss** es generalmente más estable que **NLLLoss** porque incluye la función Softmax dentro de la pérdida, lo cual es especialmente útil para la clasificación de varias clases ([Goodfellow et al., 2016](#)).
2. **Adam** combina las ventajas de otros algoritmos de optimización como RMSProp y SGD con momento, lo que generalmente lo hace más rápido y estable ([Kingma and Ba, 2015](#)).
3. **Regularización L2** y **Dropout** son técnicas efectivas para prevenir el sobreajuste ([Srivastava et al., 2014](#) para Dropout). El L2 es especialmente efectivo cuando se tiene un conjunto de datos pequeño, lo cual es el caso del dataset Iris.

## 📈 Análisis de Gráficos 📊

## 🎨 Visualización en Profundidad 🖼️

Los gráficos juegan un papel crucial en la comprensión del rendimiento de los modelos. Al observar las curvas de pérdida y precisión durante las épocas de entrenamiento y validación, es posible tener una visión más detallada de cómo un modelo aprende y cómo podría estar sobreajustando o subajustando.

### 1. Curvas de Pérdida 📉 :

- Una curva de pérdida que cae rápidamente y se estabiliza indica un buen aprendizaje, mientras que fluctuaciones significativas pueden ser un signo de inestabilidad en el entrenamiento.

- Si la pérdida de validación comienza a aumentar mientras la pérdida de entrenamiento sigue disminuyendo, es un claro signo de sobreajuste.

## 2. Curvas de Precisión 🎯 :

- Una curva de precisión que alcanza rápidamente un alto valor y se mantiene estable es ideal.
- Si la precisión de la validación es significativamente más baja que la de entrenamiento, podríamos estar frente a un caso de sobreajuste.

## 📖 Basado en Teoría 🎓

1. **Curvas de Aprendizaje:** Según la teoría de aprendizaje estadístico, una brecha grande entre el rendimiento de entrenamiento y validación a menudo indica un modelo sobreajustado ([Vapnik, 1998](#)).
2. **Ritmo de Convergencia:** Un ritmo de convergencia más rápido es generalmente posible con optimizadores adaptativos como Adam, que ajustan la tasa de aprendizaje durante el entrenamiento. Esto está bien documentado en la literatura y se evidencia en nuestras curvas de pérdida más suaves con Adam ([Kingma and Ba, 2015](#)).
3. **Regularización:** Técnicas como Dropout pueden hacer que la curva de pérdida sea más ruidosa pero pueden prevenir el sobreajuste efectivamente. Esto se basa en la teoría de que Dropout aproxima la combinación de muchos modelos diferentes ([Srivastava et al., 2014](#)).

## 🤔 Interpretaciones y Consideraciones 🤔

El análisis de gráficos nos permite interpretar más allá de las métricas finales, ofreciendo información sobre la estabilidad y la confiabilidad del modelo. Los gráficos complementan nuestros hallazgos tabulares y ofrecen insights para futuras iteraciones y ajustes en el modelo.

Esta es una herramienta poderosa para interpretar la complejidad y el rendimiento de los modelos de aprendizaje profundo. Nos ayuda a tomar decisiones informadas sobre cómo mejorar y perfeccionar nuestros modelos.

## 💎 Mejor Combinación 💎

La mejor combinación, según los resultados, es la que utiliza **CrossEntropyLoss**, **Adam** y **L2 Regularization**, con la más baja pérdida de validación y una precisión del 100%.

Esto se respalda tanto por la evidencia recolectada como por la teoría existente, que sugiere que Adam es efectivo para problemas de optimización no convexos y que la regularización L2 es buena para prevenir el sobreajuste, especialmente en conjuntos de datos pequeños.

## Conclusiones

La selección de la función de pérdida, el algoritmo de optimización y la técnica de regularización es crucial para el rendimiento del modelo. La mejor combinación es la que logra un equilibrio entre una rápida convergencia y un alto rendimiento, evitando al mismo tiempo el sobreajuste.