Implementation of Multi Layer Perceptron Algorithm from scratch

```
import torch
print(torch.__version__)
import torch.nn as nn
import numpy as np

import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset

import matplotlib.pyplot as plt
```

```
2.8.0+cu126
```

```
import torchvision
import torchvision.datasets as datasets
from torchvision import transforms

transform = transforms.Compose([
    transforms.ToTensor(),              # Converts to float tensor
[0,1] and adds channel dimension
    transforms.Lambda(lambda x: x.view(-1))  # Flatten tensor of
dimension 28x28 to vector of size 784
])

mnist_trainset = datasets.MNIST(root='./data', train=True,
download=True, transform=transform)
mnist_testset = datasets.MNIST(root='./data', train=False,
download=True, transform=transform)

print(f"The number of images in training dataset are
{len(mnist_trainset)}")
print(f"The number of images in test dataset are
{len(mnist_testset)}")

print(mnist_trainset.data.shape)
print(mnist_testset.data.shape)
```

```
The number of images in training dataset are 60000
The number of images in test dataset are 10000
torch.Size([60000, 28, 28])
torch.Size([10000, 28, 28])
```

```
print(mnist_trainset[0][0].shape)
```

```
torch.Size([784])
```

```
batch_size = 64
train_loader = DataLoader(mnist_trainset, batch_size=batch_size,
shuffle=True)
test_loader = DataLoader(mnist_testset, batch_size=batch_size,
shuffle=False)
```

#**Question 1 Part A:**

#Implementing Multi Layer Perceptron using Sigmoid Activation function

Model architecture:

- Input layer (784 neurons)
- Hidden layers with 500, 250, and 100 neurons using Sigmoid activations
- Output layer with 10 neurons (linear, raw logits)
- Use of softmax for probability assignment
- Glorot uniform weight initialization and zeros biases per assignment

```
class MLP(nn.Module):
  def __init__(self, input_dim = 784, hidden_dims = [500, 250, 100],
output_dim = 10 ):

      layer_sizes = [input_dim] + hidden_dims + [output_dim]

      # Initialize weights and biases (Glorot initialization, zero
biases)
      self.weights = []
      self.biases = []
      for i in range(len(layer_sizes) - 1):
          ip_layer_size = layer_sizes[i]
          op_layer_size = layer_sizes[i + 1]
          limit = np.sqrt(6 / (ip_layer_size + op_layer_size))
          W = np.random.uniform(-limit, limit, size=(ip_layer_size,
op_layer_size))
          b = np.zeros((1, op_layer_size))
          self.weights.append(W)
          self.biases.append(b)

  def sigmoid(self, x):
        return 1 / (1 + np.exp(-x))

  def sigmoid_derivative(self, x):
        return x * (1 - x)

  def softmax(self, x):
        exp_x = np.exp(x - np.max(x))
        return exp_x / exp_x.sum(axis=1, keepdims=True)

  def forward(self, X):
        # Storing the inputs in arrays for backpropogation
```

```
        self.inputs = []
        self.z_values = []

        # Input layer to first hidden layer
        z1 = X @ self.weights[0] + self.biases[0]
        a1 = self.sigmoid(z1)

        # First hidden layer to second hidden layer
        z2 = a1 @ self.weights[1] + self.biases[1]
        a2 = self.sigmoid(z2)

        # Second hidden layer to third one
        z3 = a2 @ self.weights[2] + self.biases[2]
        a3 = self.sigmoid(z3)

        # Third hidden layer to raw output
        z4 = a3 @ self.weights[3] + self.biases[3]

        # Outut layer
        output = self.softmax(z4)

        self.inputs = [X, a1, a2, a3]
        self.z_values = [z1, z2, z3, z4]

        return output

  def compute_loss(self, y_true, y_pred):
        m = y_true.shape[0]  #number of samples in the batch
        eps = 1e-9  #value to avoid log(0)
        log_preds = np.log(y_pred + eps)  #log of prediction
        loss = -np.sum(y_true * log_preds) / m
        return loss

  def backward(self, y_true, y_pred, learning_rate):
        m = y_true.shape[0]

        delta4 = (y_pred - y_true) / m  # output error

        dW4 = self.inputs[3].T @ delta4
        db4 = np.sum(delta4, axis=0, keepdims=True)

        delta3 = delta4 @ self.weights[3].T *
self.sigmoid_derivative(self.inputs[3])
        dW3 = self.inputs[2].T @ delta3
        db3 = np.sum(delta3, axis=0, keepdims=True)

        delta2 = delta3 @ self.weights[2].T *
self.sigmoid_derivative(self.inputs[2])
        dW2 = self.inputs[1].T @ delta2
        db2 = np.sum(delta2, axis=0, keepdims=True)
```

```python
        delta1 = delta2 @ self.weights[1].T *
self.sigmoid_derivative(self.inputs[1])
        dW1 = self.inputs[0].T @ delta1
        db1 = np.sum(delta1, axis=0, keepdims=True)

        # Update weights and biases
        self.weights[3] -= learning_rate * dW4
        self.biases[3] -= learning_rate * db4

        self.weights[2] -= learning_rate * dW3
        self.biases[2] -= learning_rate * db3

        self.weights[1] -= learning_rate * dW2
        self.biases[1] -= learning_rate * db2

        self.weights[0] -= learning_rate * dW1
        self.biases[0] -= learning_rate * db1

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(device)
```

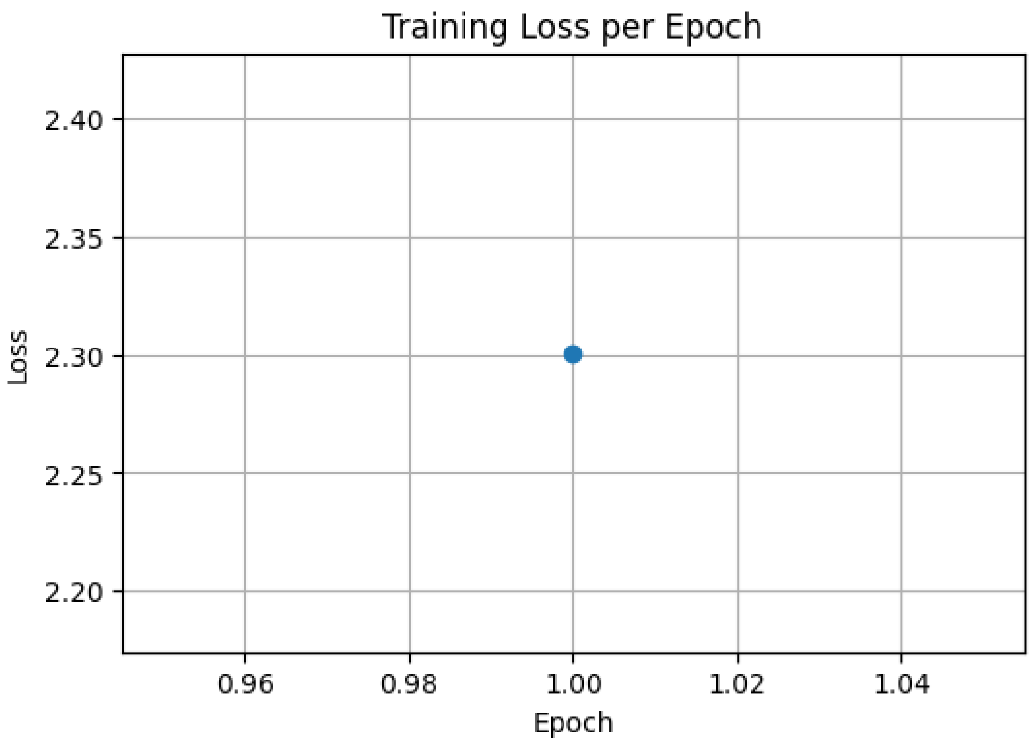
```
cpu
```

```python
def one_hot_encode(labels, num_classes=10):
    return np.eye(num_classes)[labels]

def train(model, train_loader, epochs=15, learning_rate=0.01,
log_interval=200):
    loss_history = []     # epoch losses
    iter_losses = []      # losses every 200 updates
    iters = []            # iteration numbers

    iteration = 0

    for epoch in range(epochs):
        epoch_loss = 0.0
        batch_count = 0

        for images, labels in train_loader:
            iteration += 1
            X = images.numpy()
            y_indices = labels.numpy()
            y = one_hot_encode(y_indices)

            output = model.forward(X)
            loss = model.compute_loss(y, output)

            epoch_loss += float(loss)
            batch_count += 1
            model.backward(y, output, learning_rate)
```

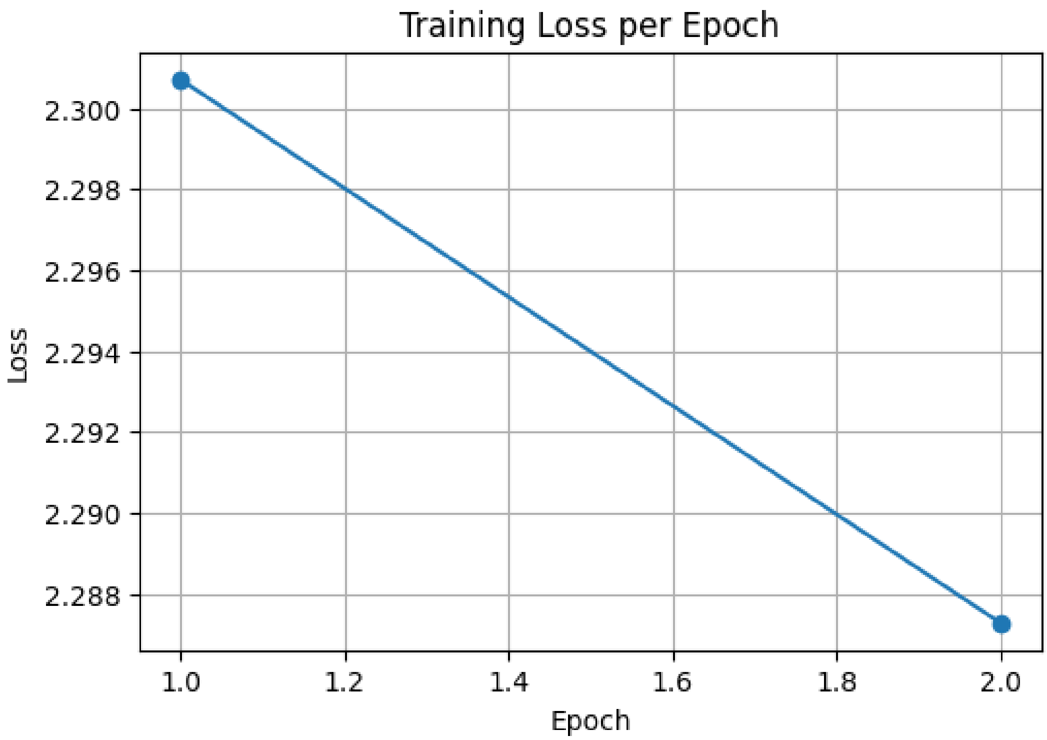
```
            # log every 200 updates
            if iteration % log_interval == 0:
                avg_loss_so_far = epoch_loss / batch_count
                iter_losses.append(avg_loss_so_far)
                iters.append(iteration)

        avg_loss = epoch_loss / batch_count
        loss_history.append(avg_loss)
        print(f"Epoch {epoch+1}/{epochs}, Loss: {avg_loss:.4f}")

        # plot epoch curve so far
        plt.figure(figsize=(6,4))
        plt.plot(range(1, len(loss_history)+1), loss_history,
marker='o')
        plt.title("Training Loss per Epoch")
        plt.xlabel("Epoch")
        plt.ylabel("Loss")
        plt.grid(True)
        plt.show()

    # plot iteration-based curve once at the end
    plt.figure(figsize=(6,4))
    plt.plot(iters, iter_losses, marker='o')
    plt.title(f"Training Loss (every {log_interval} updates)")
    plt.xlabel("Iterations (batch updates)")
    plt.ylabel("Loss")
    plt.grid(True)
    plt.show()

    return loss_history, iters, iter_losses

from sklearn.metrics import confusion_matrix, classification_report

def predict(model, X):
    probs = model.forward(X)
    preds = np.argmax(probs, axis=1)
    return preds

def evaluate(model, X, y_true):
    preds = predict(model, X)
    accuracy = np.mean(preds == y_true)
    print(f"Accuracy: {accuracy*100:.4f}%")

    print("Confusion Matrix:")
    print(confusion_matrix(y_true, preds))

    print("\nClassification Report:")
    print(classification_report(y_true, preds))

    return accuracy
```

```python
def plot_training_curves(train_losses):
    plt.figure(figsize=(8,5))
    plt.plot(range(1, len(train_losses)+1), train_losses, marker='o')
    plt.title("Training Loss over Epochs")
    plt.xlabel("Epoch")
    plt.ylabel("Loss")
    plt.grid(True)
    plt.show()

model = MLP()
loss_history, iter_num, iter_loss = train(model, train_loader, 15,
0.01)
```

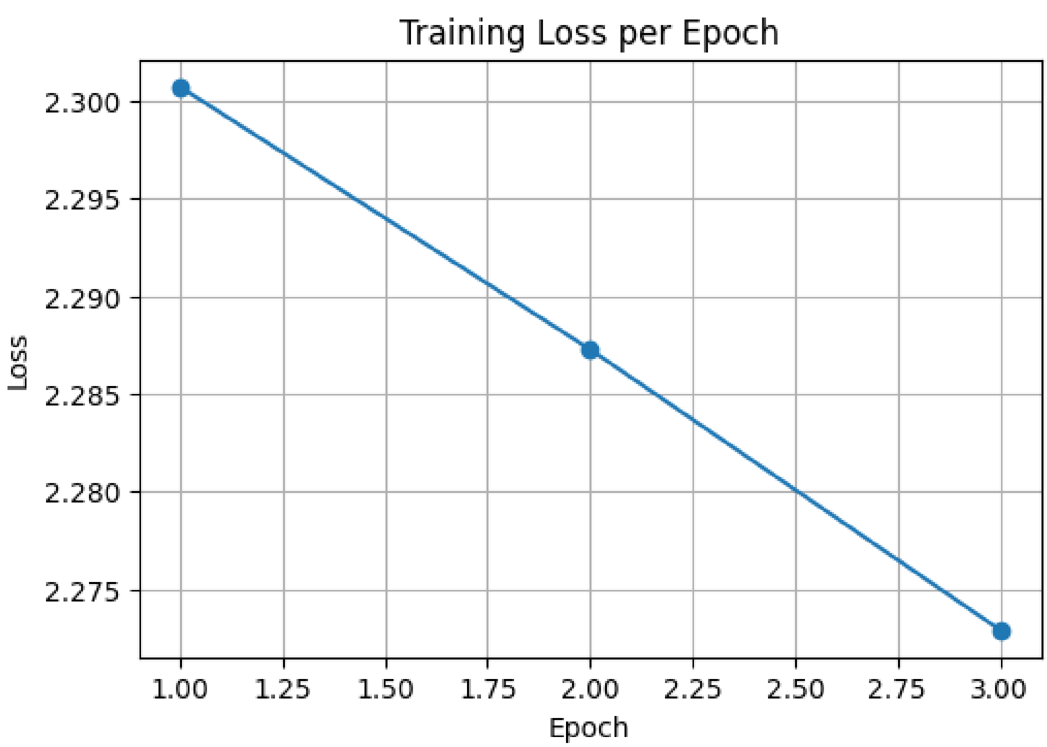
```
Epoch 1/15, Loss: 2.3007
```



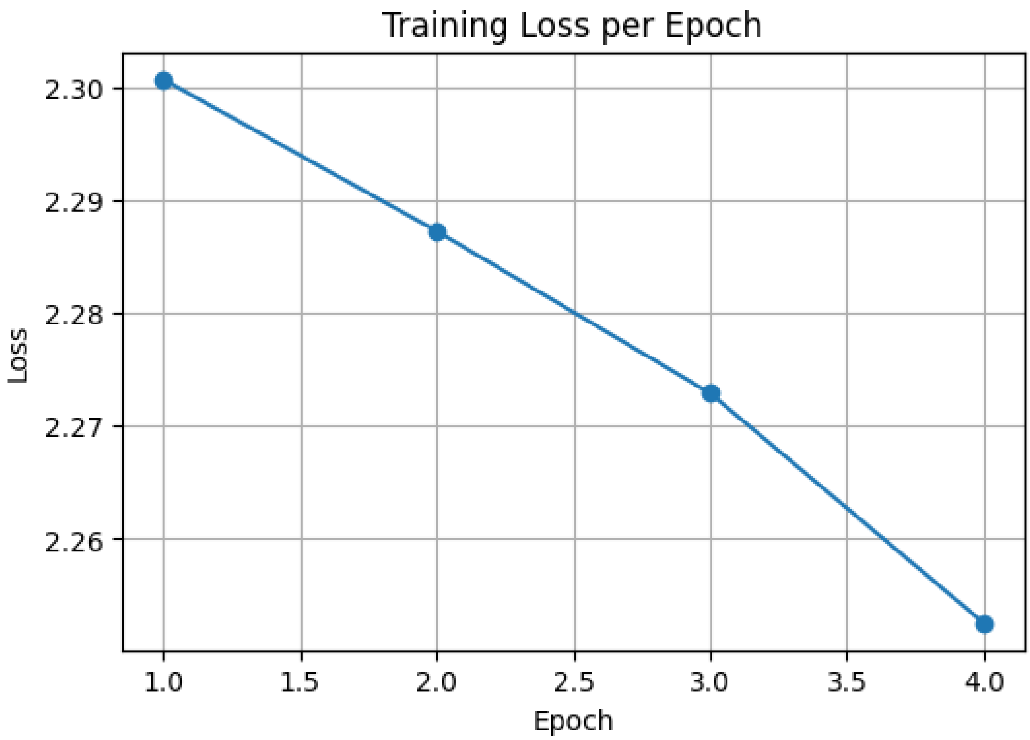

```
Epoch 2/15, Loss: 2.2873
```



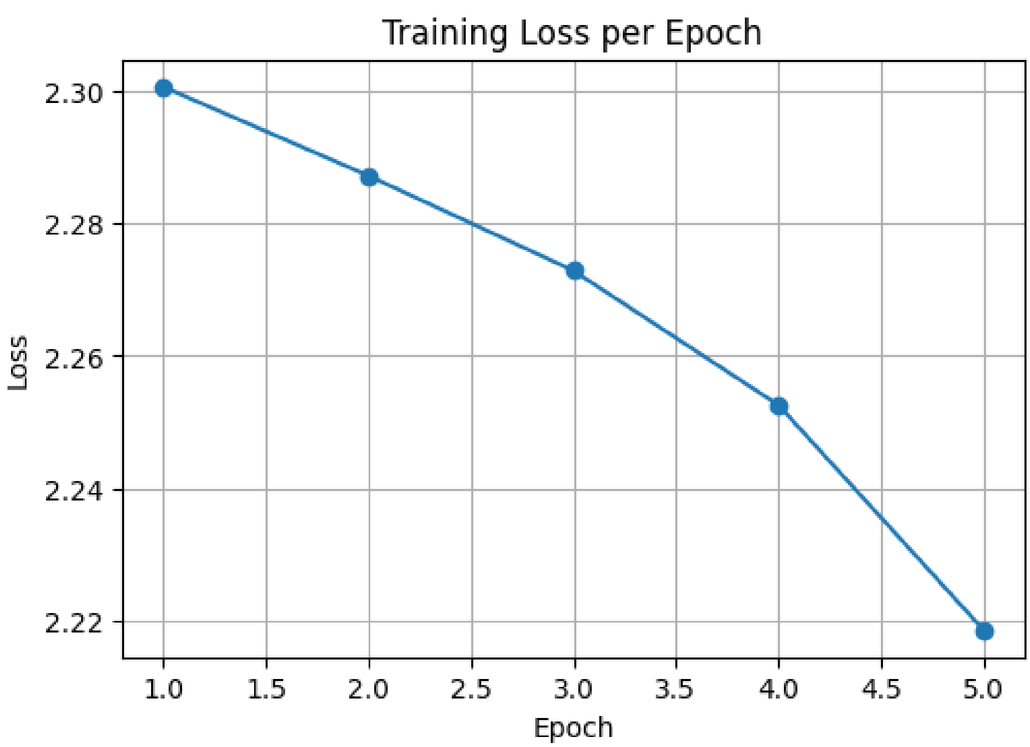

```
Epoch 3/15, Loss: 2.2729
```



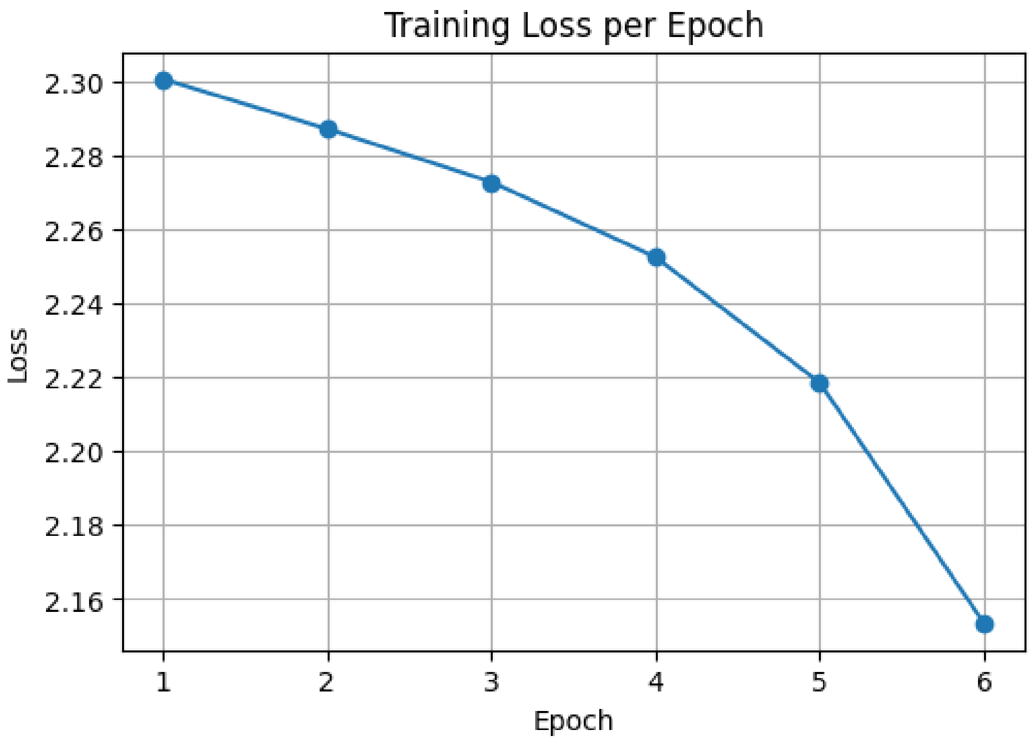

```
Epoch 4/15, Loss: 2.2526
```



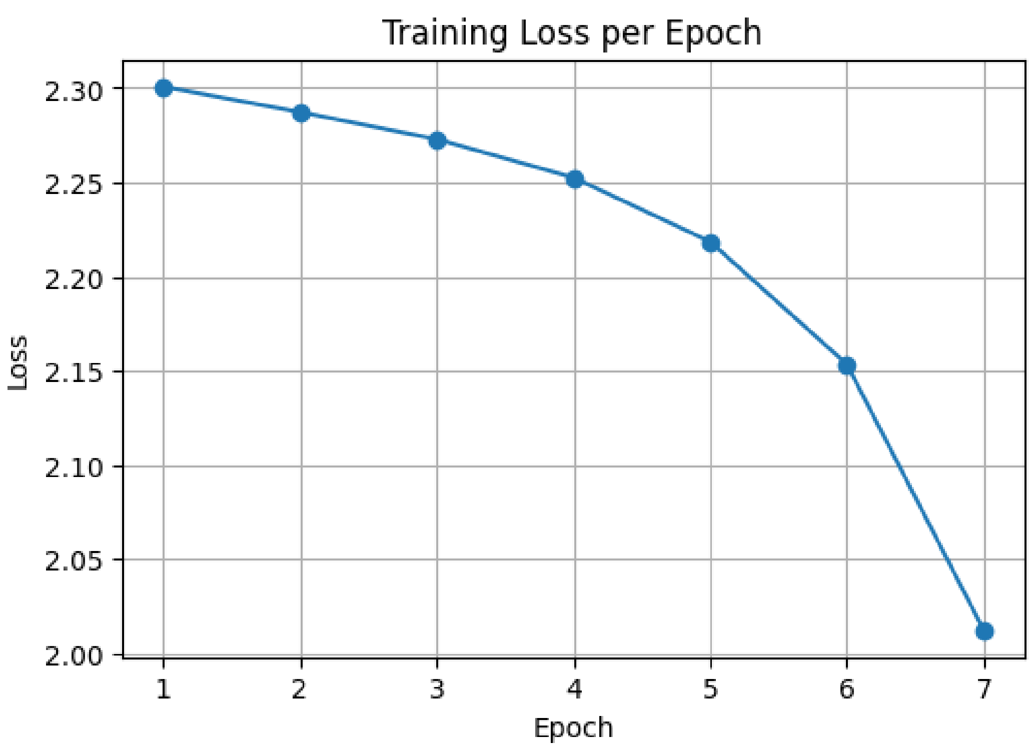

```
Epoch 5/15, Loss: 2.2186
```



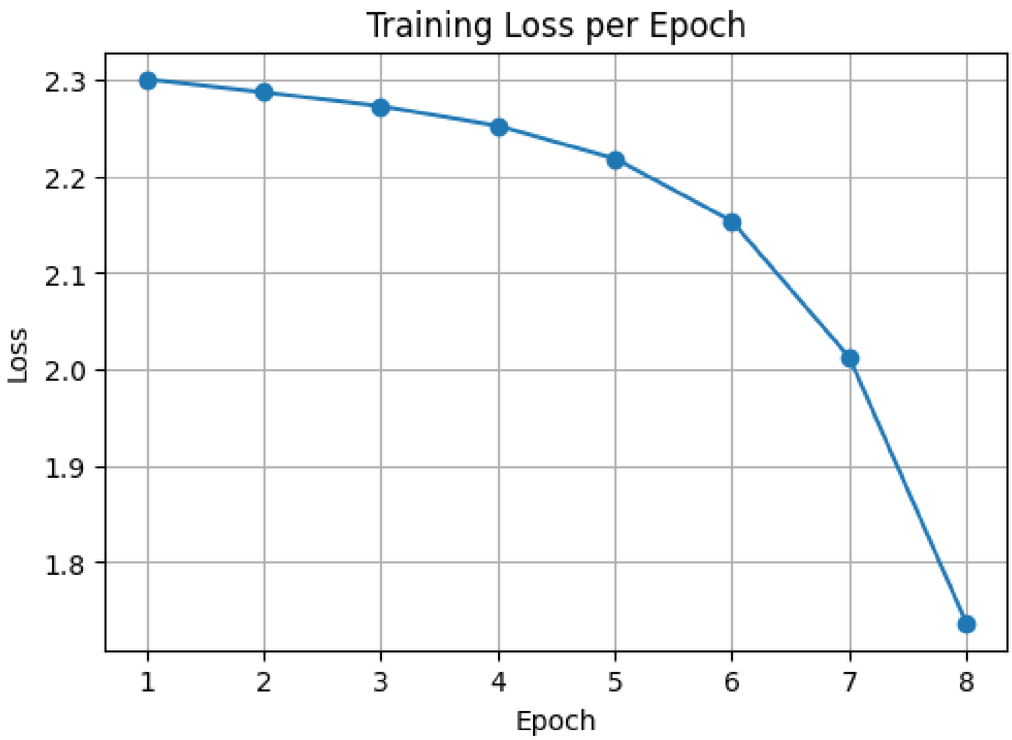

```
Epoch 6/15, Loss: 2.1535
```



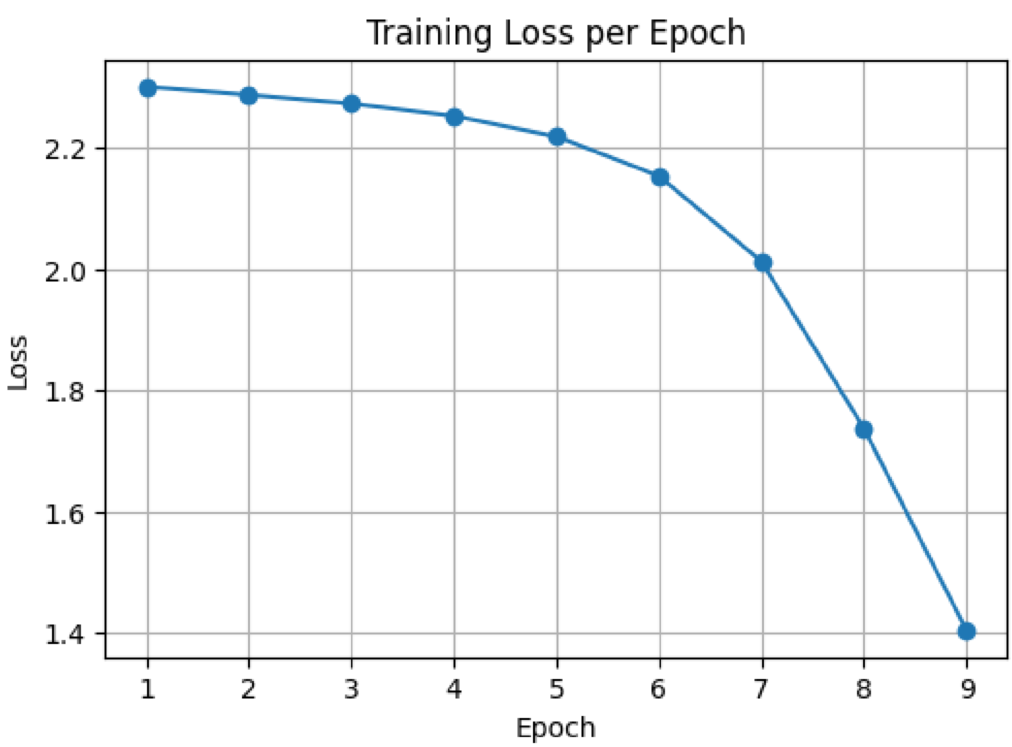

```
Epoch 7/15, Loss: 2.0126
```



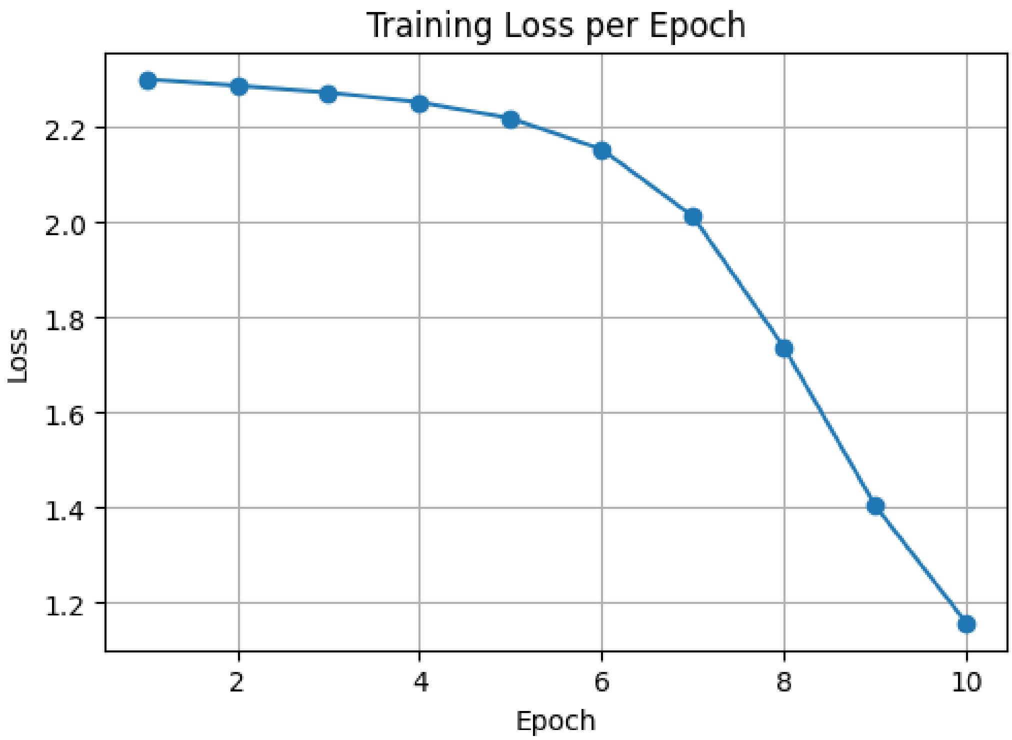

```
Epoch 8/15, Loss: 1.7371
```



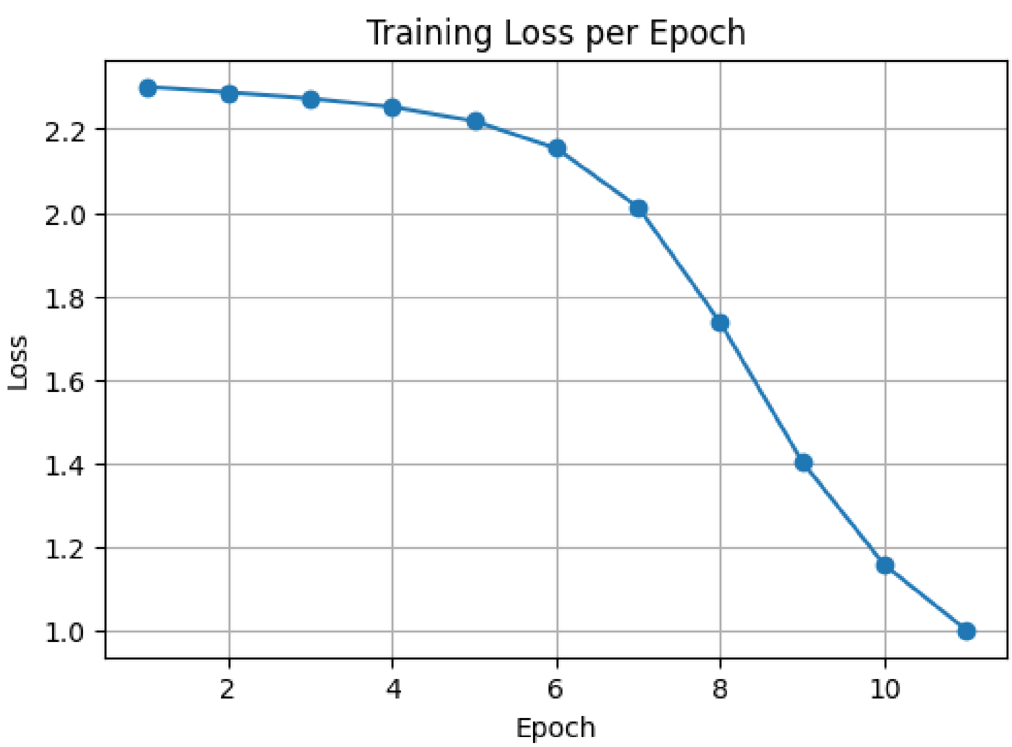

```
Epoch 9/15, Loss: 1.4044
```



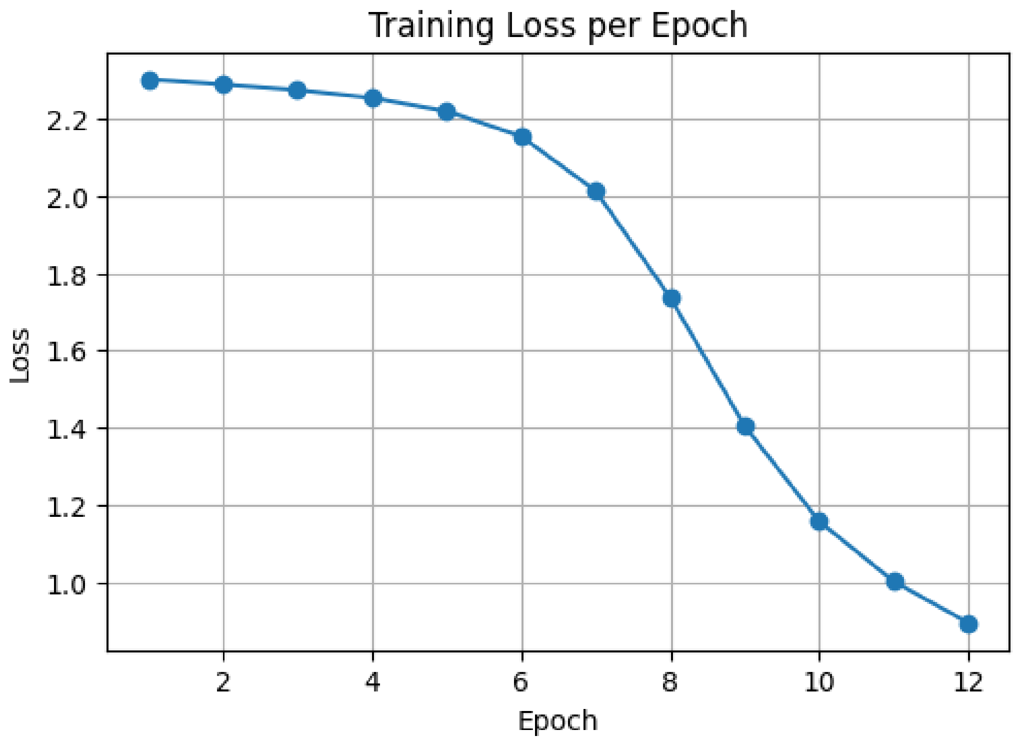

```
Epoch 10/15, Loss: 1.1582
```



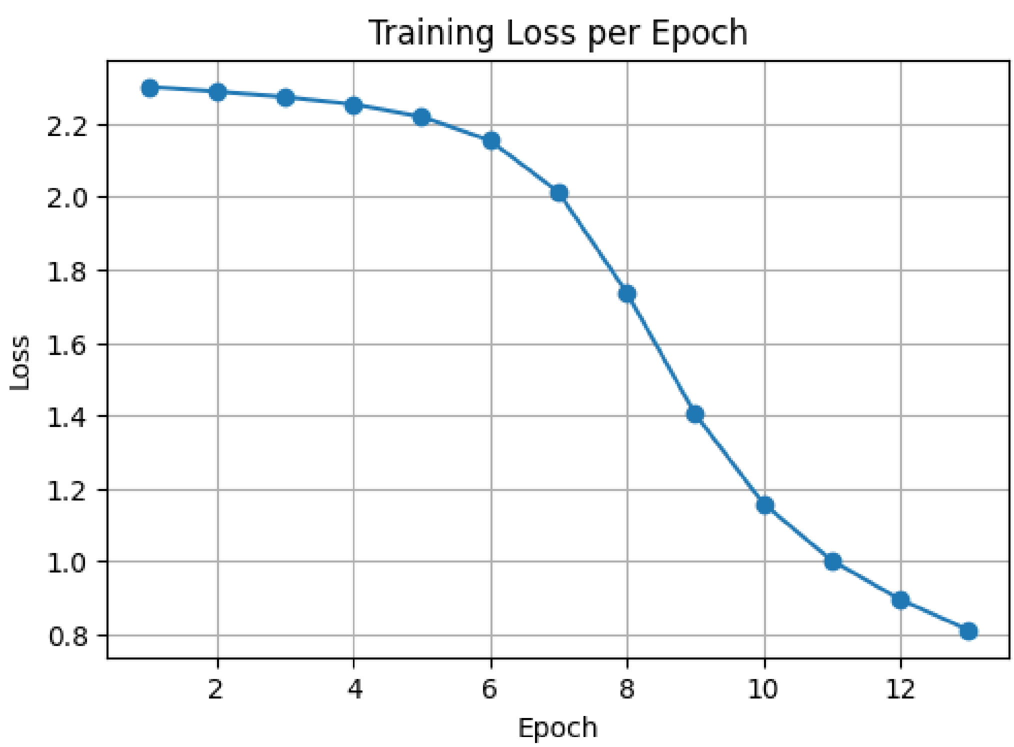

```
Epoch 11/15, Loss: 1.0025
```



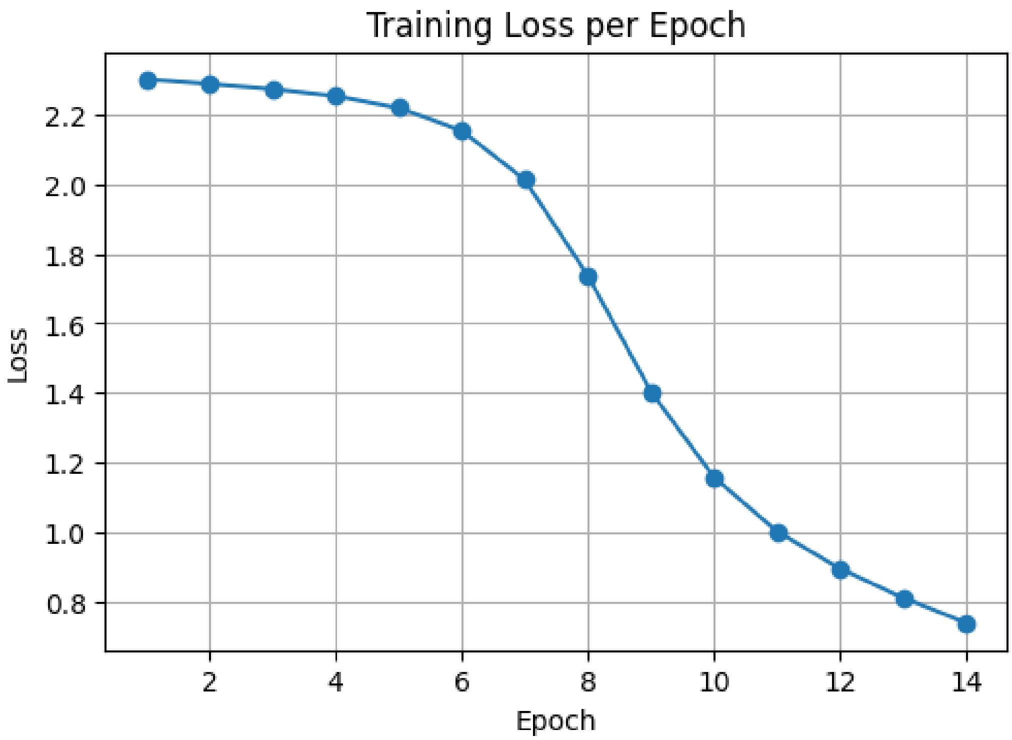

```
Epoch 12/15, Loss: 0.8956
```



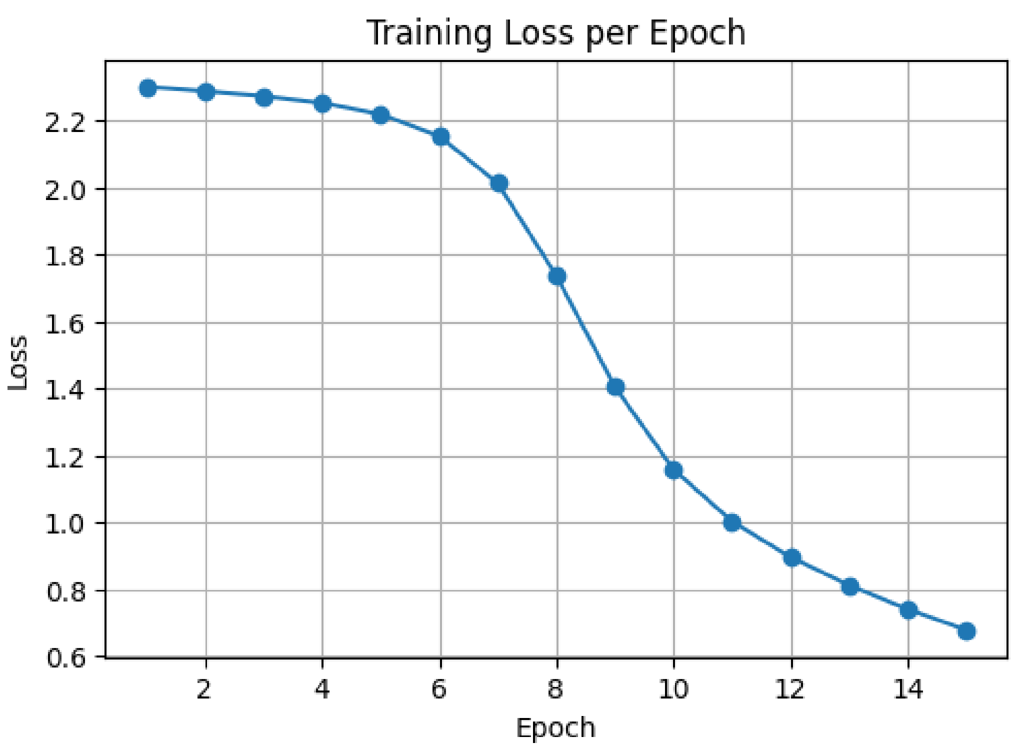

```
Epoch 13/15, Loss: 0.8119
```

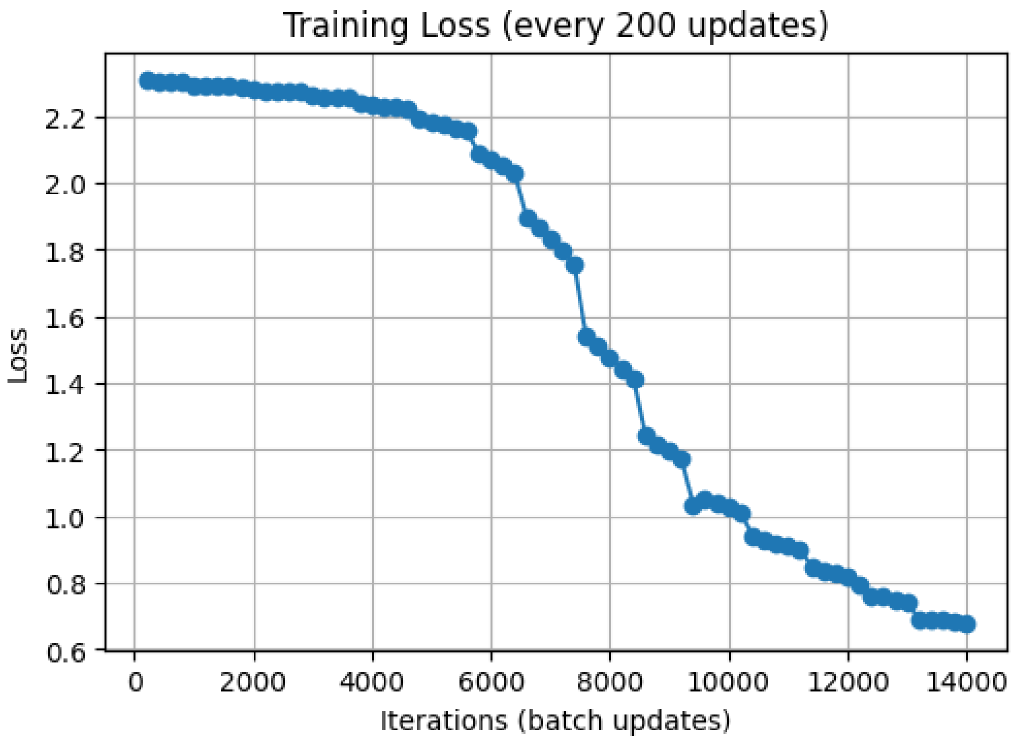



```
Epoch 14/15, Loss: 0.7401
```

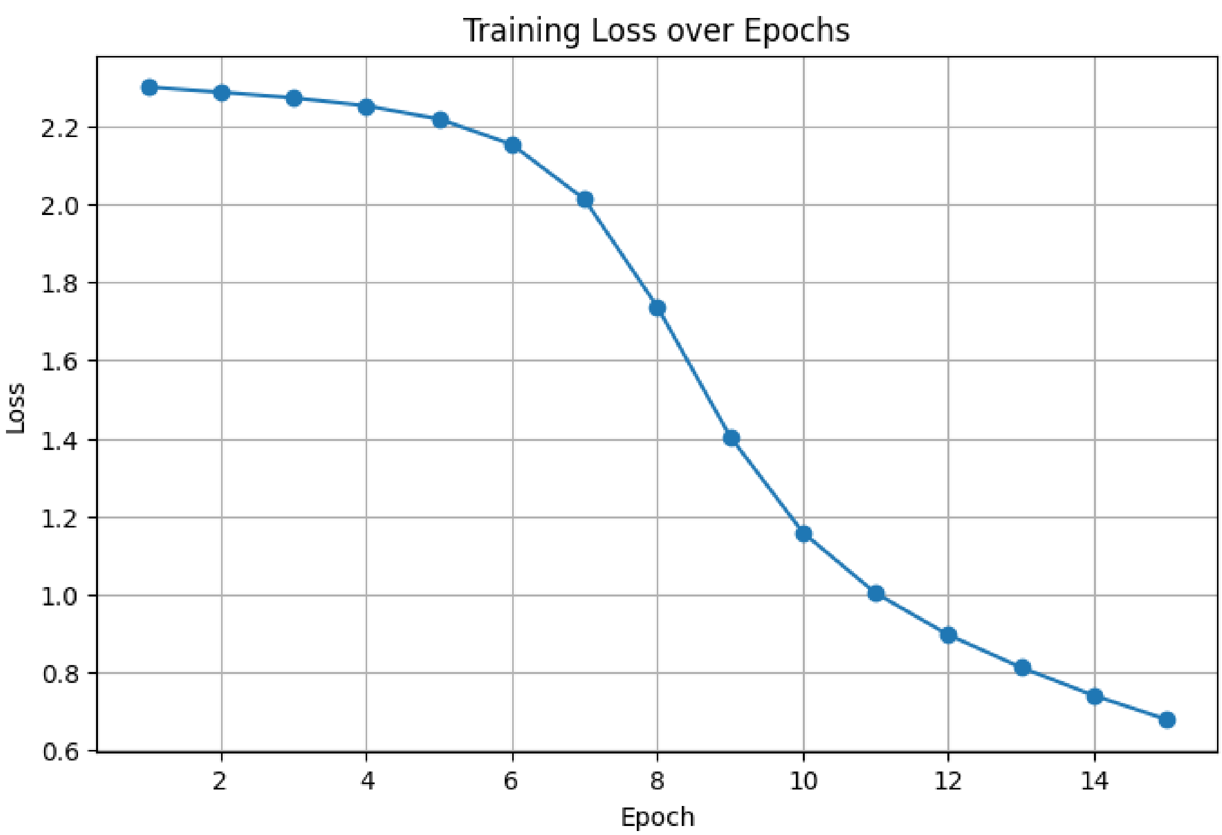



```
Epoch 15/15, Loss: 0.6783
```






```
plot_training_curves(loss_history)
```



```python
# Prepare test set in numpy format
X_test_np = mnist_testset.data.numpy().reshape(-1, 28*28) / 255.0
y_test_np = mnist_testset.targets.numpy()

print("---- Test Set Evaluation ----")
evaluate(model, X_test_np, y_test_np)
```

```
---- Test Set Evaluation ----
Accuracy: 82.3200%
Confusion Matrix:
[[ 944    0    2    1    3   19    9    1    1    0]
 [    0 1114    3    3    0    0    3    1   10    1]
 [   15   28  840   25   27    8   52   12   25    0]
 [    5    7   47  810    2   64    0   21   50    4]
 [    2   12    1    0  832    0   30    1    5   99]
 [   27    6   24   92   35  593   32   11   41   31]
 [   29    4   15    0   11   18  879    0    2    0]
 [    6   45   12    2   12    1    0  916    7   27]
 [   12   29   37   66   25   86   21   13  651   34]
 [   14    7    2    8  207   17    3   94    4  653]]

Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.96      0.93       980
           1       0.89      0.98      0.93      1135
           2       0.85      0.81      0.83      1032
           3       0.80      0.80      0.80      1010
           4       0.72      0.85      0.78       982
           5       0.74      0.66      0.70       892
           6       0.85      0.92      0.88       958
           7       0.86      0.89      0.87      1028
           8       0.82      0.67      0.74       974
           9       0.77      0.65      0.70      1009

    accuracy                           0.82     10000
   macro avg       0.82      0.82      0.82     10000
weighted avg       0.82      0.82      0.82     10000


np.float64(0.8232)
```

Results for MLP using Sigmoid activation function

- Classfication accuracy over test data = **82.30%**
- Training loss after 15 epochs = **0.6783**

#**Question 1 Part B**

#Implementing Multi Layer Perceptron Algorithm using ReLu activation function

Model architecture:

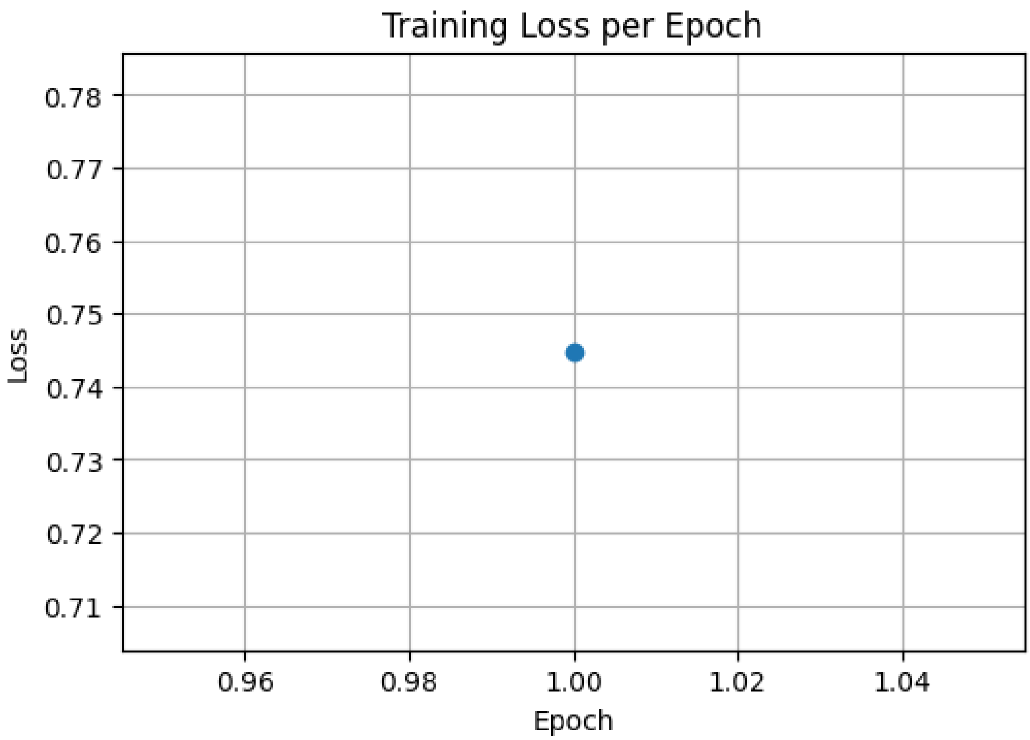
- Input layer (784 neurons)
- Hidden layers with 500, 250, and 100 neurons using ReLu as activation function
- Output layer with 10 neurons (linear, raw logits)
- Use of softmax for probability assignment
- Glorot uniform weight initialization and zeros biases per assignment

```
class MLP_ReLu(nn.Module):
    def __init__(self, input_dim=784, hidden_dims=[500, 250, 100],
output_dim=10 ):

        layer_sizes = [input_dim] + hidden_dims + [output_dim]

        # Initialize weights and biases (Glorot initialization, zero
biases)
        self.weights = []
        self.biases = []
        for i in range(len(layer_sizes) - 1):
            ip__layer_size = layer_sizes[i]
            op__layer_size = layer_sizes[i + 1]
            limit = np.sqrt(6 / (ip__layer_size + op__layer_size))
            W = np.random.uniform(-limit, limit, size=(ip__layer_size,
op__layer_size))
            b = np.zeros((1, op__layer_size))
            self.weights.append(W)
            self.biases.append(b)

    def relu(self, x):
        return np.maximum(0, x)

    def relu_derivative(self, x):
        return (x > 0).astype(float)

    def softmax(self, x):
        exp_x = np.exp(x - np.max(x))
        return exp_x / exp_x.sum(axis=1, keepdims=True)

    def forward(self, X):
        self.inputs = []
        self.z_values = []

        # Input layer to first hidden layer
        z1 = X @ self.weights[0] + self.biases[0]
        a1 = self.relu(z1)

        # First hidden layer to second hidden layer
```

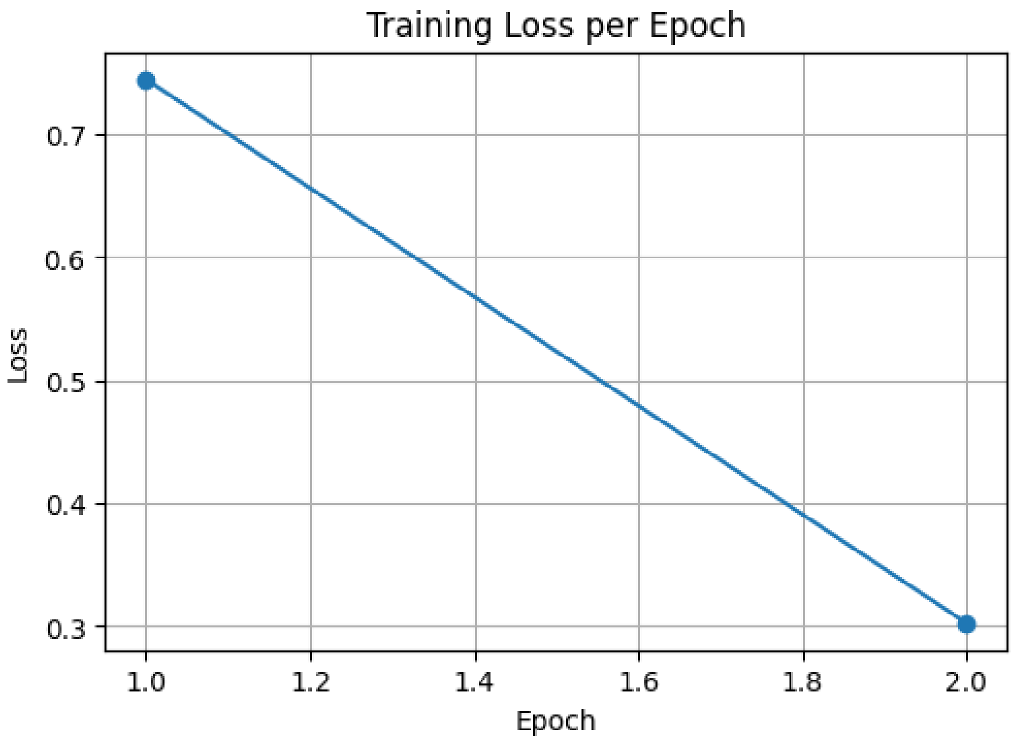
```
        z2 = a1 @ self.weights[1] + self.biases[1]
        a2 = self.relu(z2)

        # Second hidden layer to third one
        z3 = a2 @ self.weights[2] + self.biases[2]
        a3 = self.relu(z3)

        # Third hidden layer to output using Softmax
        z4 = a3 @ self.weights[3] + self.biases[3]
        output = self.softmax(z4)

        self.inputs = [X, a1, a2, a3]
        self.z_values = [z1, z2, z3, z4]
        return output

    def compute_loss(self, y_true, y_pred):
        m = y_true.shape[0]  #number of samples in the batch
        eps = 1e-9  #value to avoid log(0)
        log_preds = np.log(y_pred + eps)  #log of prediction
        loss = -np.sum(y_true * log_preds) / m
        return loss

    def backward(self, y_true, y_pred, learning_rate):
        m = y_true.shape[0]
        delta4 = (y_pred - y_true) / m

        dW4 = self.inputs[3].T @ delta4
        db4 = np.sum(delta4, axis=0, keepdims=True)

        delta3 = delta4 @ self.weights[3].T *
self.relu_derivative(self.inputs[3])
        dW3 = self.inputs[2].T @ delta3
        db3 = np.sum(delta3, axis=0, keepdims=True)

        delta2 = delta3 @ self.weights[2].T *
self.relu_derivative(self.inputs[2])
        dW2 = self.inputs[1].T @ delta2
        db2 = np.sum(delta2, axis=0, keepdims=True)

        delta1 = delta2 @ self.weights[1].T *
self.relu_derivative(self.inputs[1])
        dW1 = self.inputs[0].T @ delta1
        db1 = np.sum(delta1, axis=0, keepdims=True)

        # Update weights and biases
        self.weights[3] -= learning_rate * dW4
        self.biases[3] -= learning_rate * db4

        self.weights[2] -= learning_rate * dW3
        self.biases[2] -= learning_rate * db3
```

```
        self.weights[1] -= learning_rate * dW2
        self.biases[1] -= learning_rate * db2

        self.weights[0] -= learning_rate * dW1
        self.biases[0] -= learning_rate * db1

model = MLP_ReLu()
loss_history_ReLu, iter_ReLu, iter_loss_ReLu = train(model,
train_loader)
```

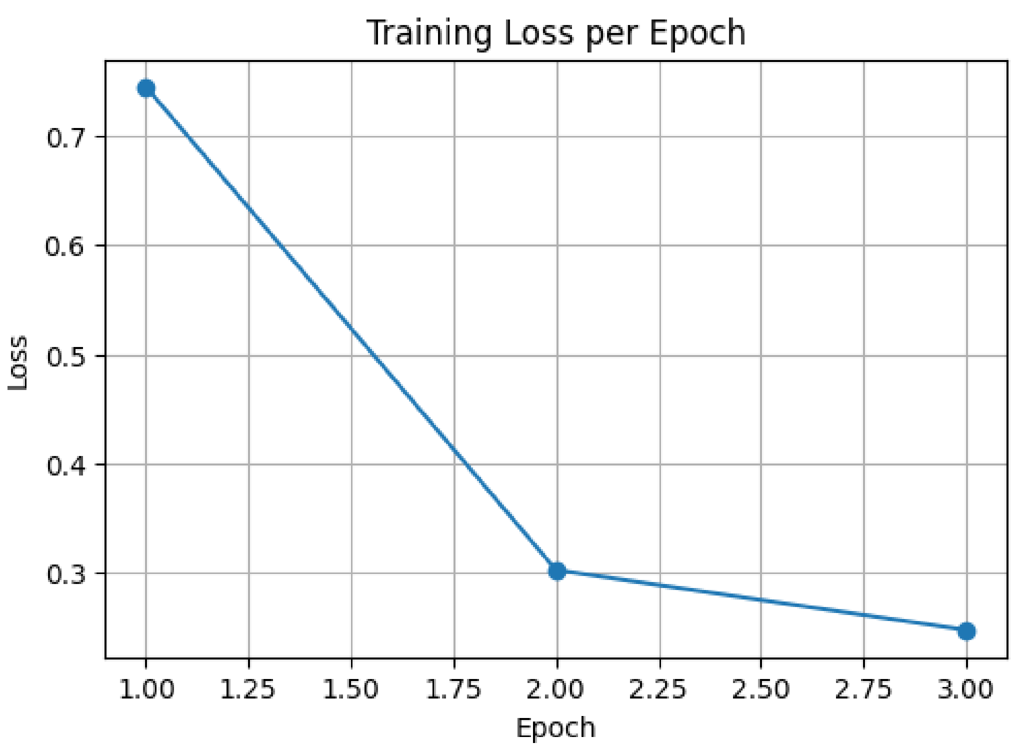
```
Epoch 1/15, Loss: 0.7448
```



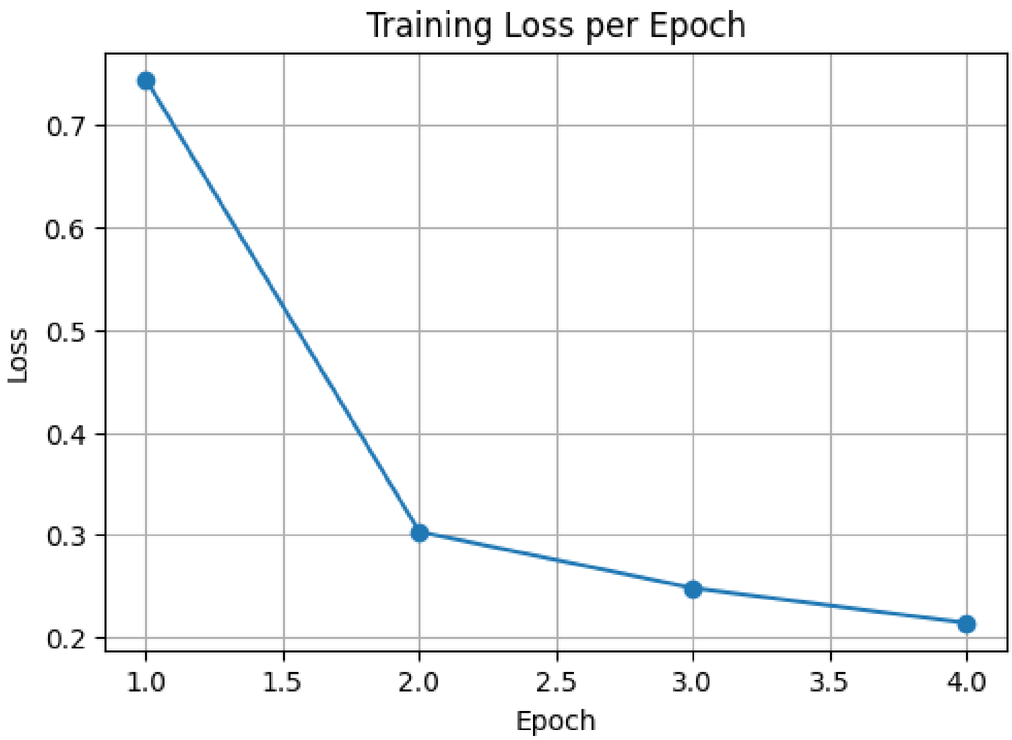

```
Epoch 2/15, Loss: 0.3028
```



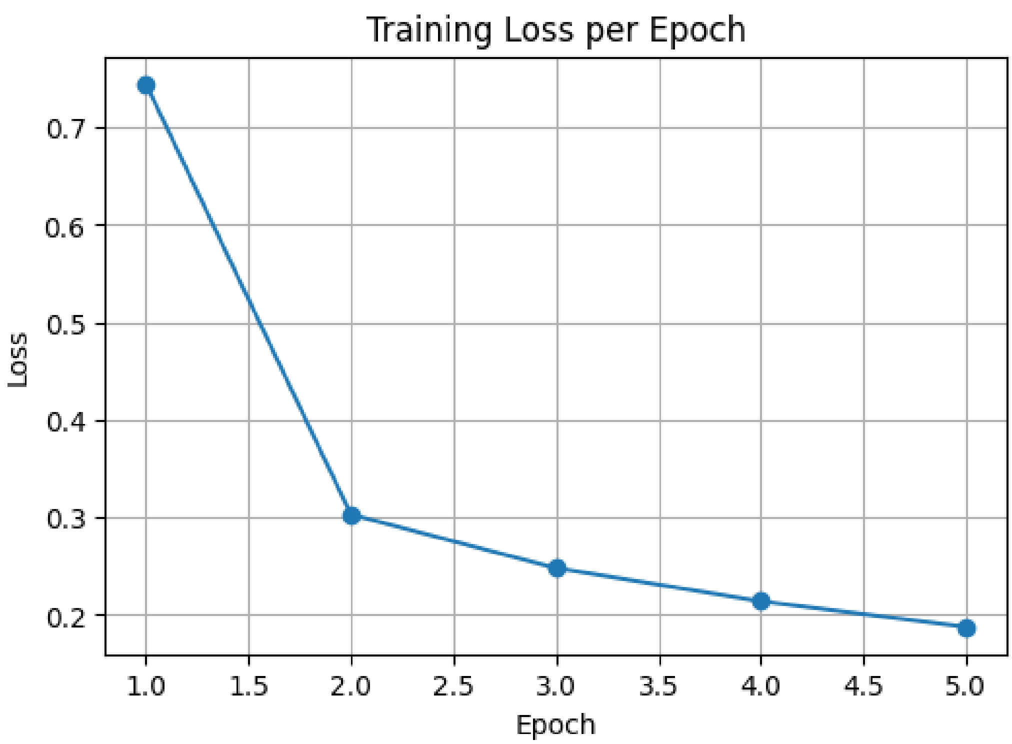

```
Epoch 3/15, Loss: 0.2479
```



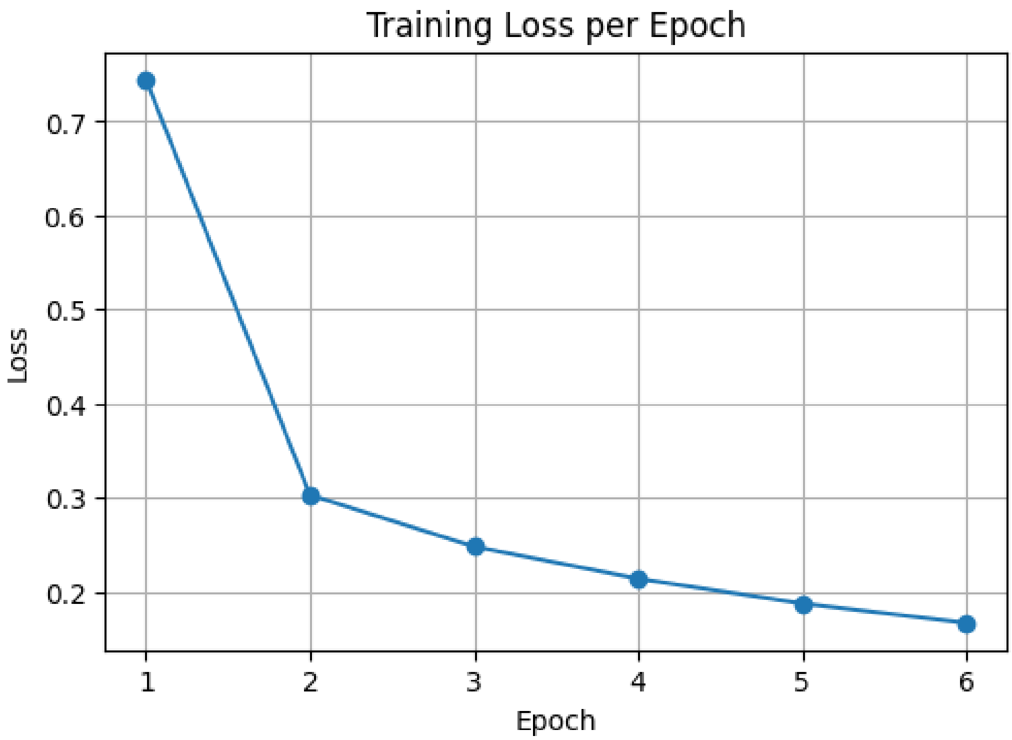

```
Epoch 4/15, Loss: 0.2138
```



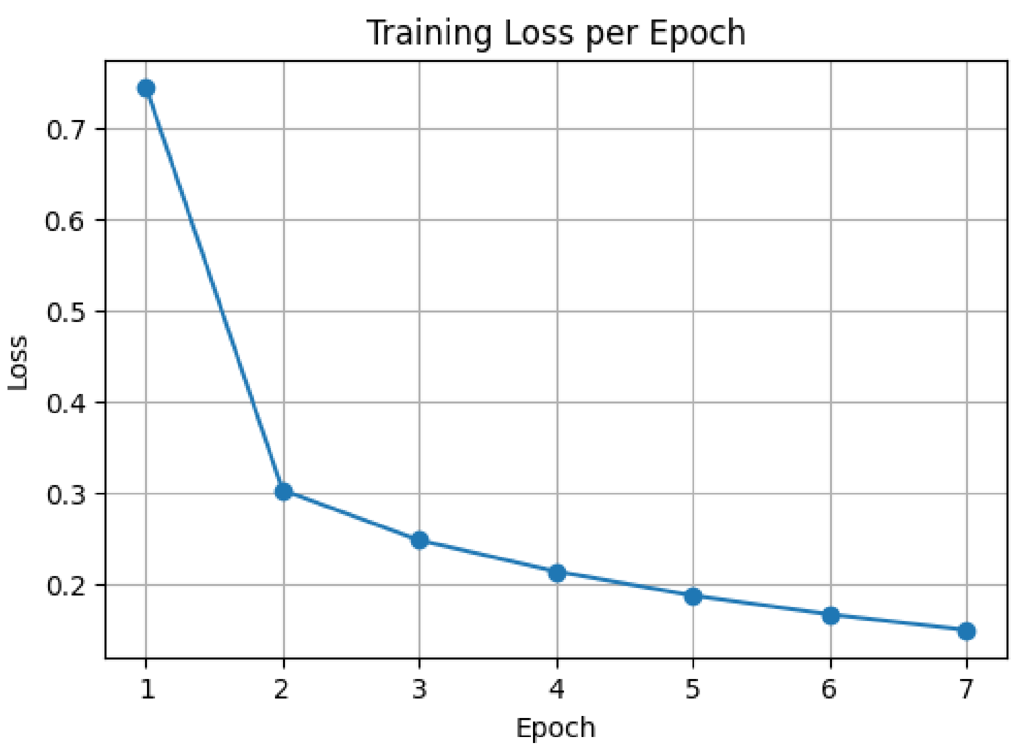

```
Epoch 5/15, Loss: 0.1874
```



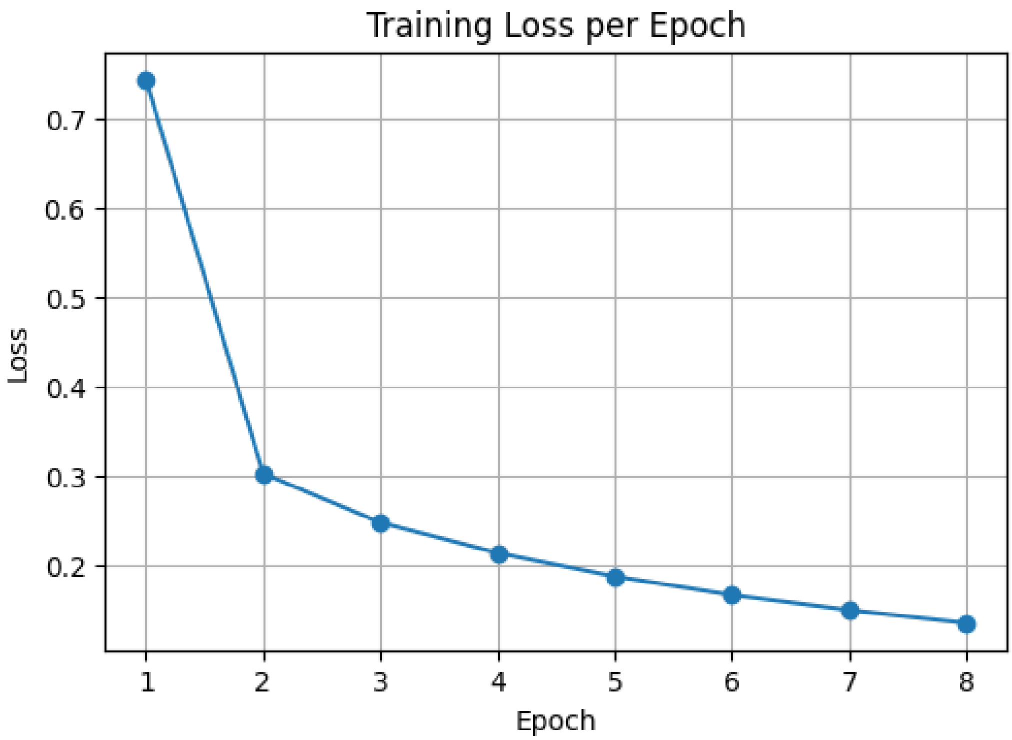

```
Epoch 6/15, Loss: 0.1668
```



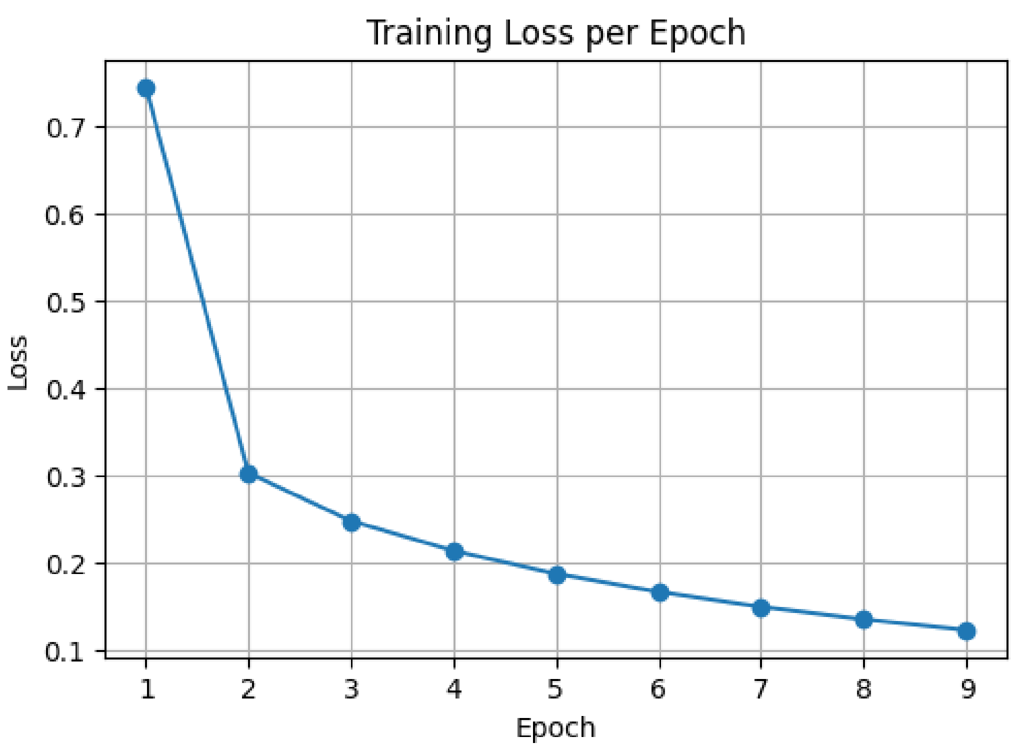

```
Epoch 7/15, Loss: 0.1496
```



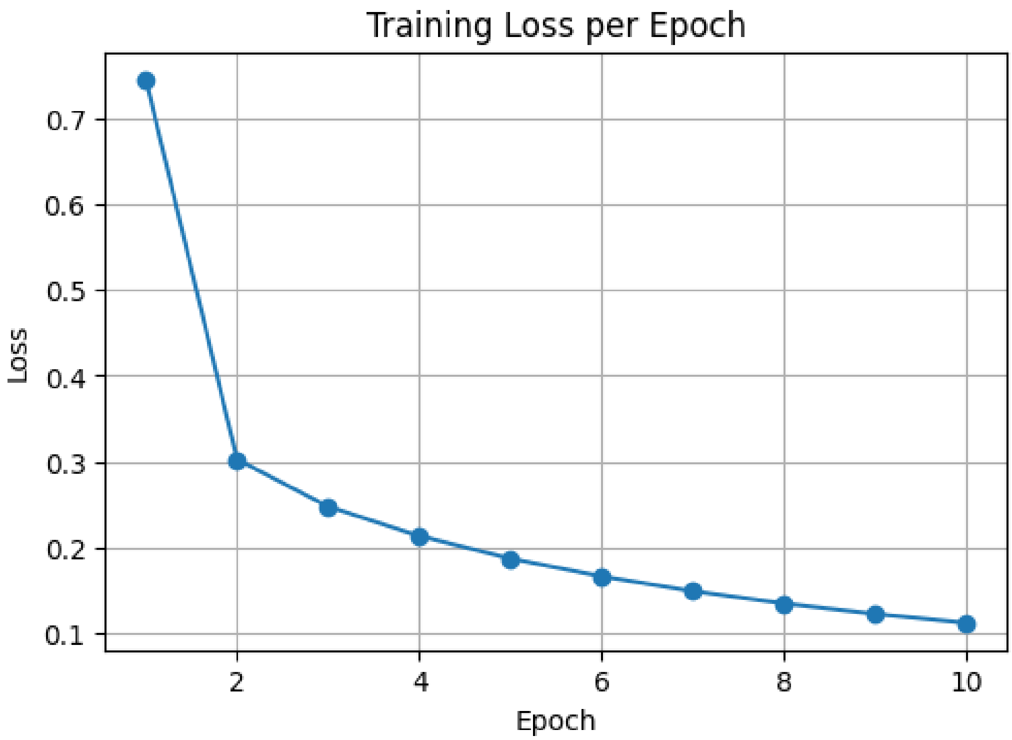

```
Epoch 8/15, Loss: 0.1353
```



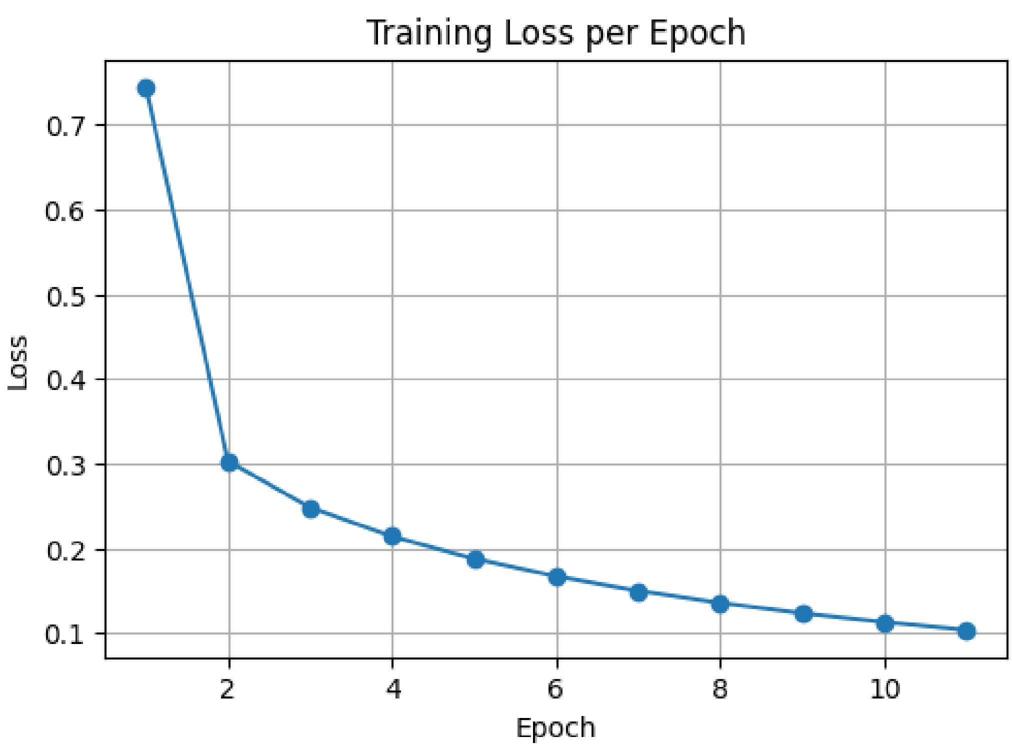

```
Epoch 9/15, Loss: 0.1231
```



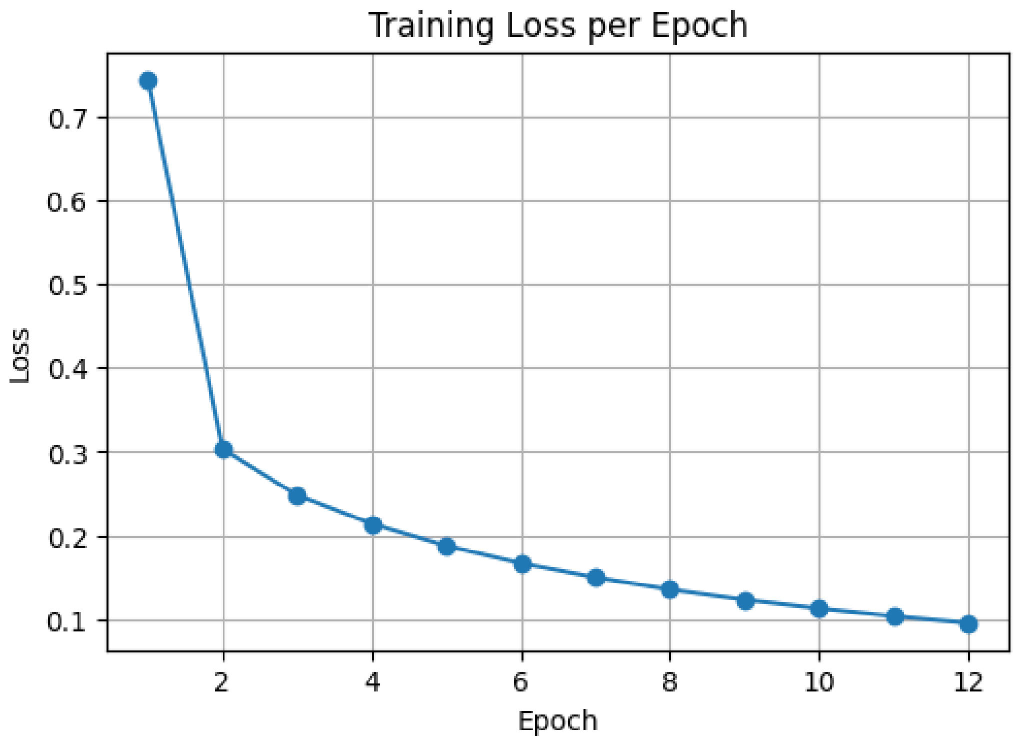

```
Epoch 10/15, Loss: 0.1127
```



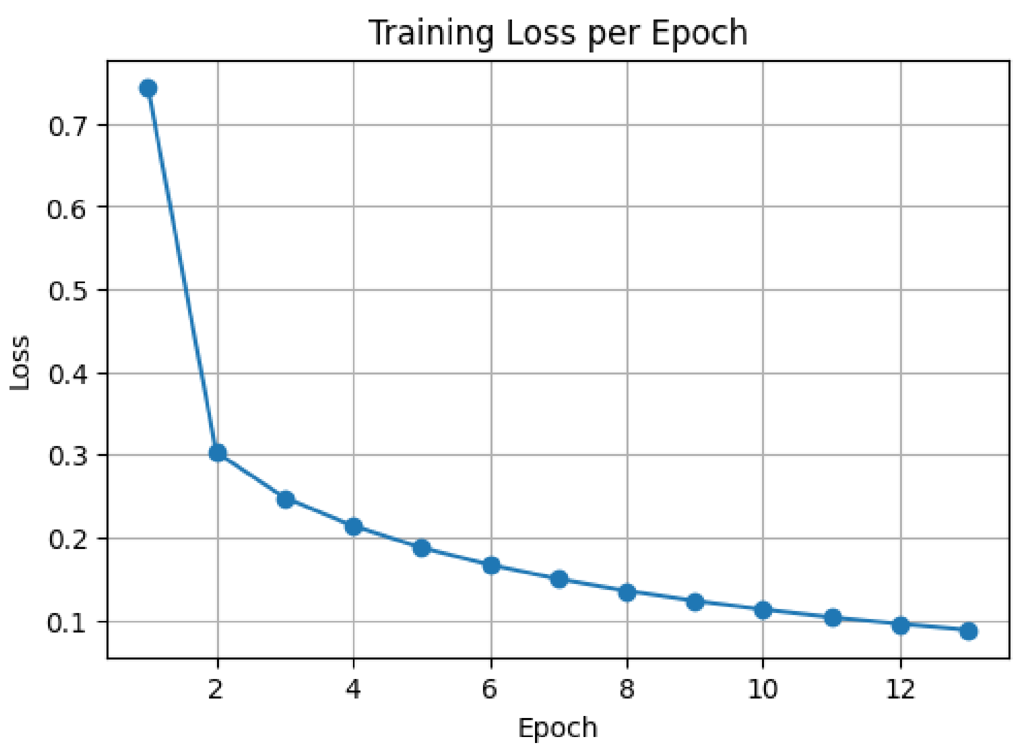

```
Epoch 11/15, Loss: 0.1033
```



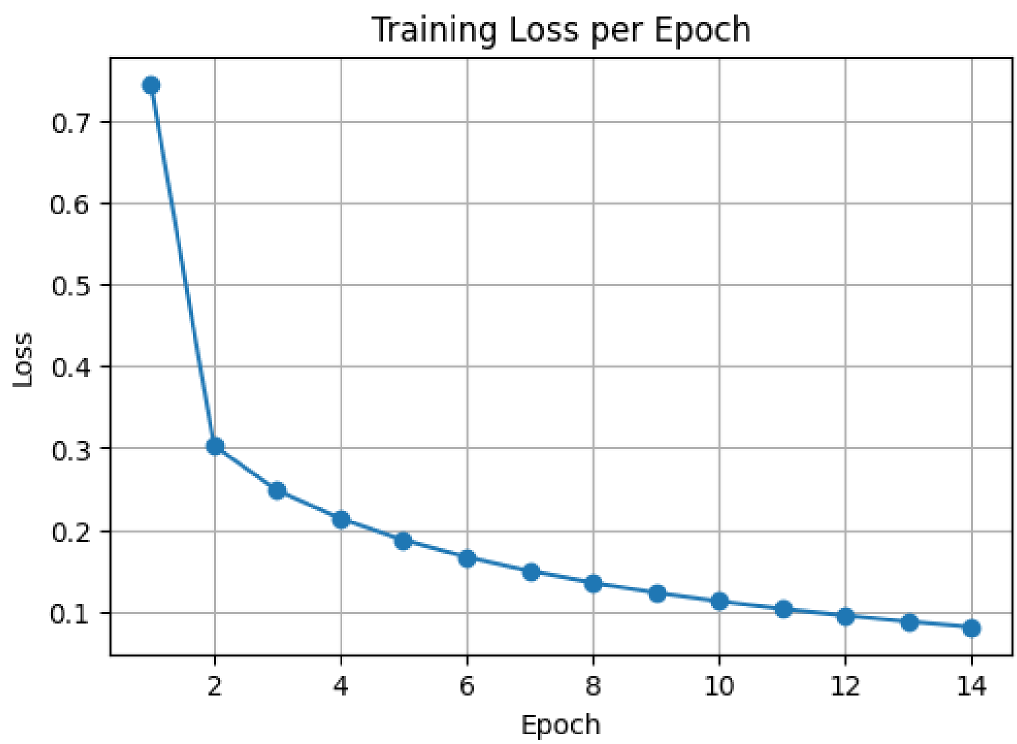

```
Epoch 12/15, Loss: 0.0952
```



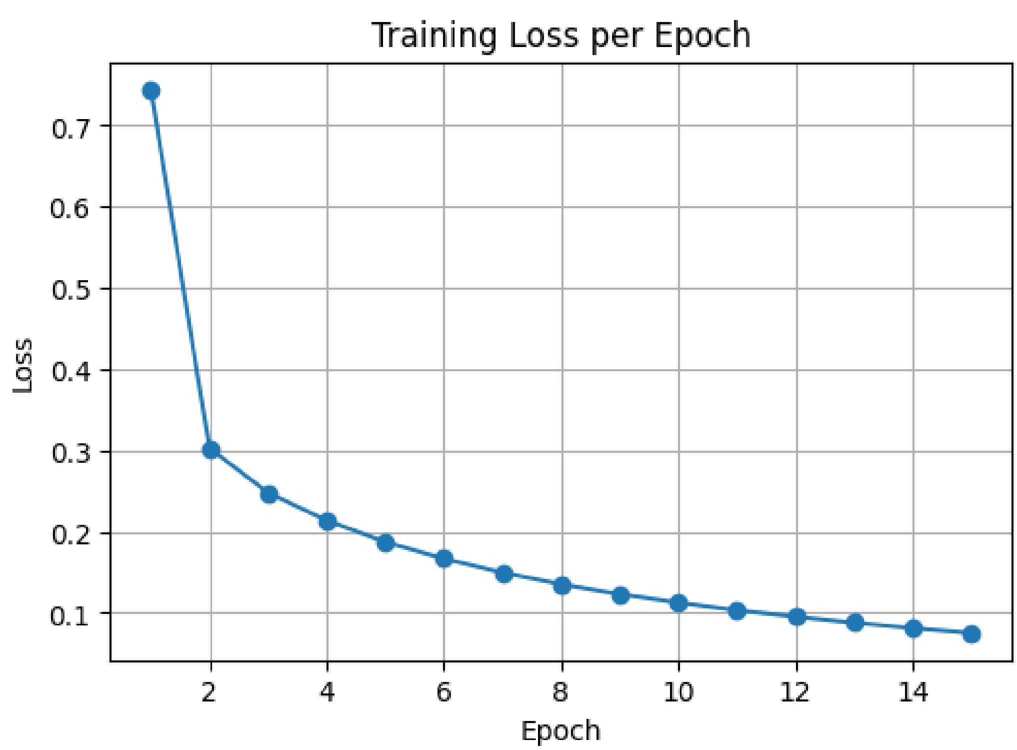

```
Epoch 13/15, Loss: 0.0878
```

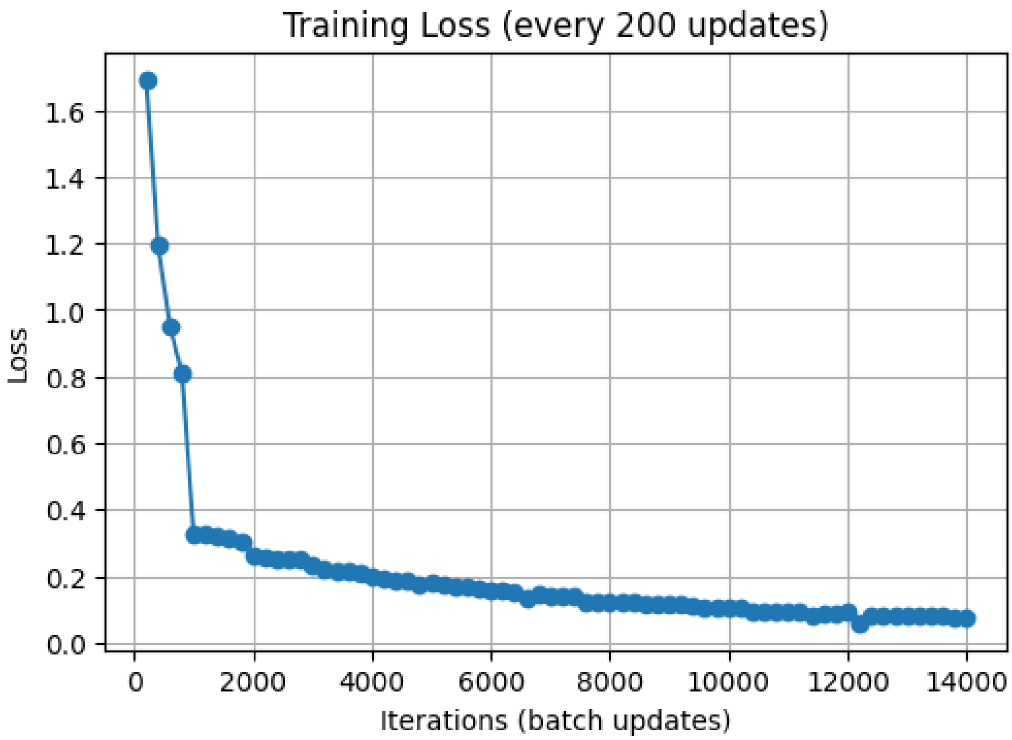



```
Epoch 14/15, Loss: 0.0812
```

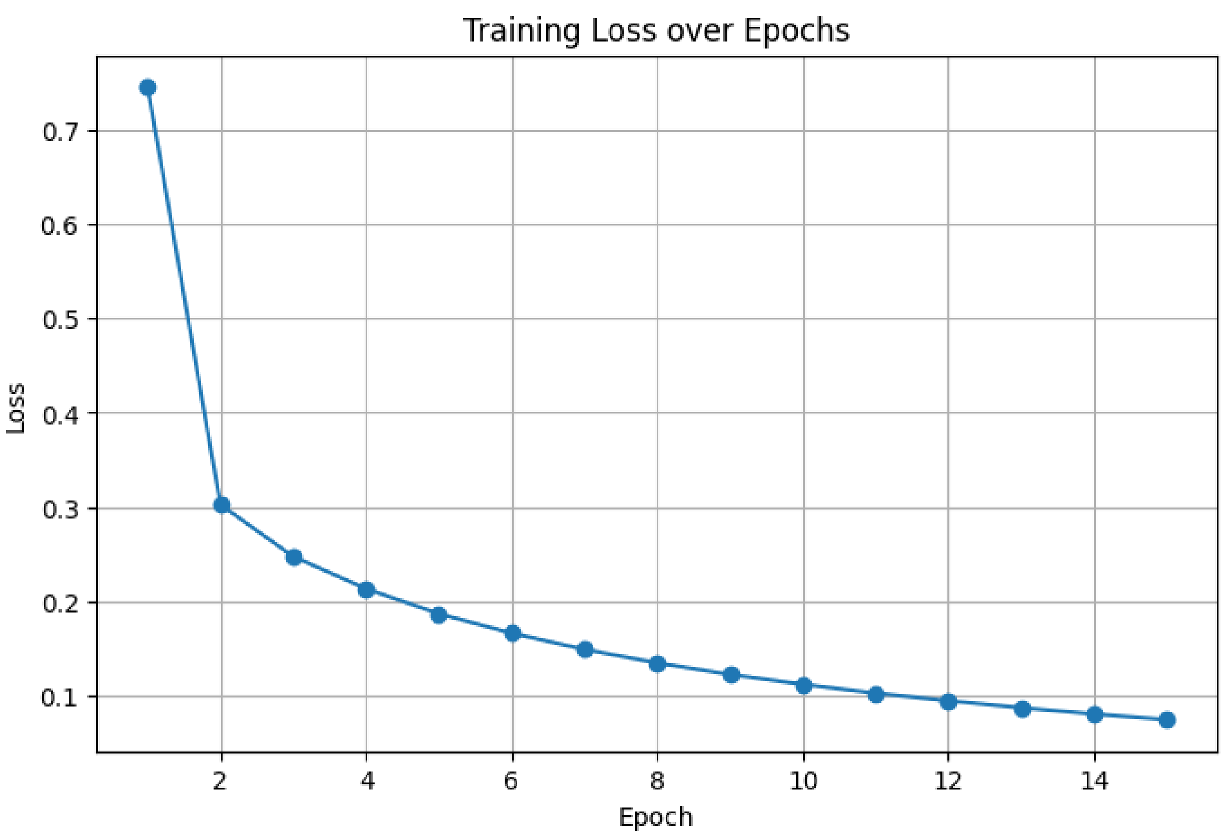



```
Epoch 15/15, Loss: 0.0753
```






```
plot_training_curves(loss_history_ReLu)
```



```python
# Prepare test set in numpy format
X_test_np = mnist_testset.data.numpy().reshape(-1, 28*28) / 255.0
y_test_np = mnist_testset.targets.numpy()

print("---- Test Set Evaluation ----")
evaluate(model, X_test_np, y_test_np)
```

```
---- Test Set Evaluation ----
Accuracy: 97.1200%
Confusion Matrix:
[[ 963    0    1    1    0    5    4    2    2    2]
 [    0 1126    4    0    0    1    4    0    0    0]
 [    4    3 1003    4    4    0    2    6    6    0]
 [    0    0    4  983    0    8    0    7    5    3]
 [    2    0    4    1  957    0    3    2    2   11]
 [    4    0    0    6    2  866    9    0    3    2]
 [    6    3    0    0    6   10  931    0    2    0]
 [    1    9   10    4    2    1    0  990    2    9]
 [    3    0    3    9    3    6    7    6  933    4]
 [    4    5    1    8   17    3    1    7    3  960]]

Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.98      0.98       980
           1       0.98      0.99      0.99      1135
           2       0.97      0.97      0.97      1032
           3       0.97      0.97      0.97      1010
           4       0.97      0.97      0.97       982
           5       0.96      0.97      0.97       892
           6       0.97      0.97      0.97       958
           7       0.97      0.96      0.97      1028
           8       0.97      0.96      0.97       974
           9       0.97      0.95      0.96      1009

    accuracy                           0.97     10000
   macro avg       0.97      0.97      0.97     10000
weighted avg       0.97      0.97      0.97     10000


np.float64(0.9712)
```

Results for MLP using ReLU activation function

- Classfication accuracy over test data = **97.12%**
- Training loss after 15 epochs = **0.0753**

#**Question 1 Part C**

#Implementing Multi Layer Perceptron Algorithm using Tan Hyperbolic activation function

Model architecture:

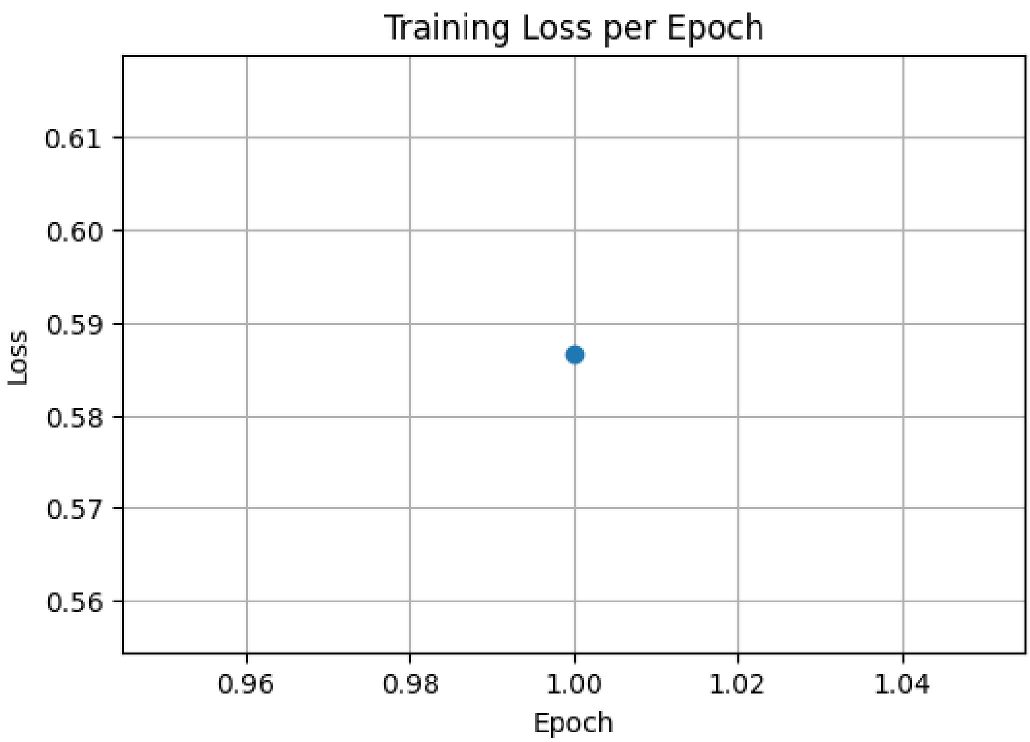
- Input layer (784 neurons)
- Hidden layers with 500, 250, and 100 neurons using Tanh as activation
- Output layer with 10 neurons (linear, raw logits)
- Use of softmax for probability assignment
- Glorot uniform weight initialization and zeros biases per assignment

```
class MLP_tanh:
    def __init__(self, input_dim = 784, hidden_dims = [500, 250, 100],
output_dim = 10 ):

      layer_sizes = [input_dim] + hidden_dims + [output_dim]

      # Initialize weights and biases (Glorot initialization, zero
biases)
      self.weights = []
      self.biases = []
      for i in range(len(layer_sizes) - 1):
          ip__layer_size = layer_sizes[i]
          op__layer_size = layer_sizes[i + 1]
          limit = np.sqrt(6 / (ip__layer_size + op__layer_size))
          W = np.random.uniform(-limit, limit, size=(ip__layer_size,
op__layer_size))
          b = np.zeros((1, op__layer_size))
          self.weights.append(W)
          self.biases.append(b)

    def tanh(self, x):
        return np.tanh(x)

    def tanh_derivative(self, x):
        return 1.0 - np.tanh(x)**2

    def softmax(self, x):
        exp_x = np.exp(x - np.max(x, axis=1, keepdims=True))
        return exp_x / exp_x.sum(axis=1, keepdims=True)

    def forward(self, X):
        self.inputs = []
        self.z_values = []

        # Input layer to first hidden layer
        z1 = X @ self.weights[0] + self.biases[0]
        a1 = self.tanh(z1)

        # First hidden layer to second hidden layer
```

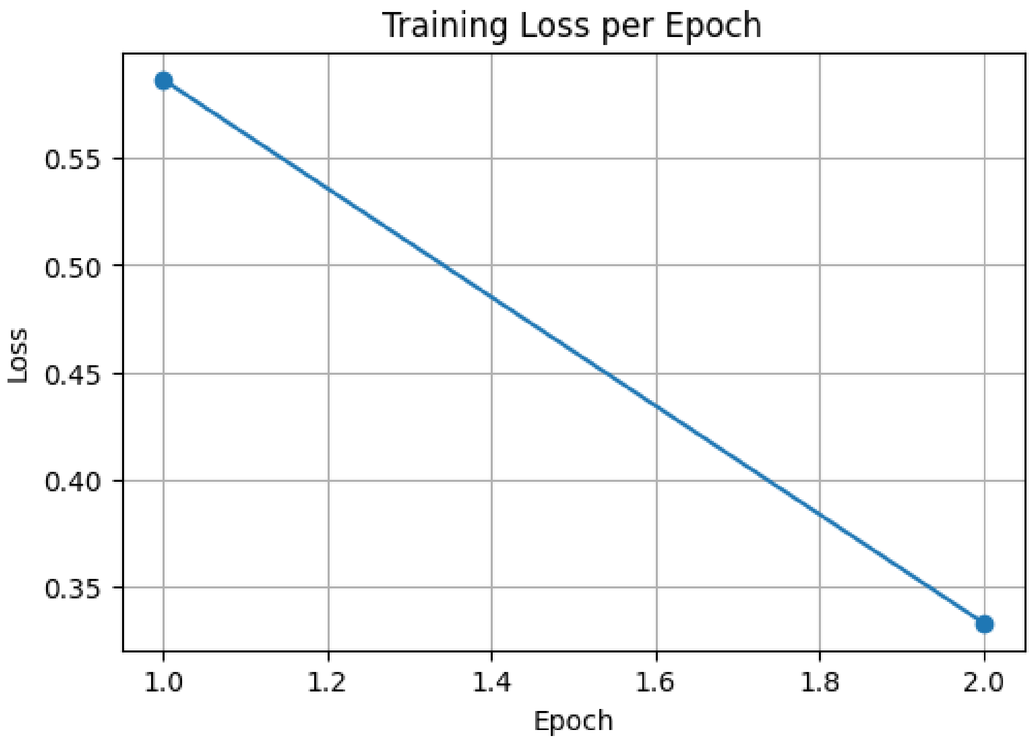
```
        z2 = a1 @ self.weights[1] + self.biases[1]
        a2 = self.tanh(z2)

        # Second hidden layer to third one
        z3 = a2 @ self.weights[2] + self.biases[2]
        a3 = self.tanh(z3)

        # Third hidden layer to output using Softmax
        z4 = a3 @ self.weights[3] + self.biases[3]
        output = self.softmax(z4)

        self.inputs = [X, a1, a2, a3]
        self.z_values = [z1, z2, z3, z4]
        return output

    def compute_loss(self, y_true, y_pred):
      m = y_true.shape[0]  #number of samples in the batch
      eps = 1e-9  #value to avoid log(0)
      log_preds = np.log(y_pred + eps)  #log of prediction
      loss = -np.sum(y_true * log_preds) / m
      return loss

    def backward(self, y_true, y_pred, learning_rate):
        m = y_true.shape[0]
        delta4 = (y_pred - y_true) / m

        dW4 = self.inputs[3].T @ delta4
        db4 = np.sum(delta4, axis=0, keepdims=True)

        delta3 = delta4 @ self.weights[3].T *
self.tanh_derivative(self.inputs[3])
        dW3 = self.inputs[2].T @ delta3
        db3 = np.sum(delta3, axis=0, keepdims=True)

        delta2 = delta3 @ self.weights[2].T *
self.tanh_derivative(self.inputs[2])
        dW2 = self.inputs[1].T @ delta2
        db2 = np.sum(delta2, axis=0, keepdims=True)

        delta1 = delta2 @ self.weights[1].T *
self.tanh_derivative(self.inputs[1])
        dW1 = self.inputs[0].T @ delta1
        db1 = np.sum(delta1, axis=0, keepdims=True)

        # Update weights and biases
        self.weights[3] -= learning_rate * dW4
        self.biases[3] -= learning_rate * db4

        self.weights[2] -= learning_rate * dW3
        self.biases[2] -= learning_rate * db3
```

```
        self.weights[1] -= learning_rate * dW2
        self.biases[1] -= learning_rate * db2

        self.weights[0] -= learning_rate * dW1
        self.biases[0] -= learning_rate * db1

model = MLP_tanh()
loss_history_tanh, iter_tanh, iter_loss_tanh = train(model,
train_loader)
```

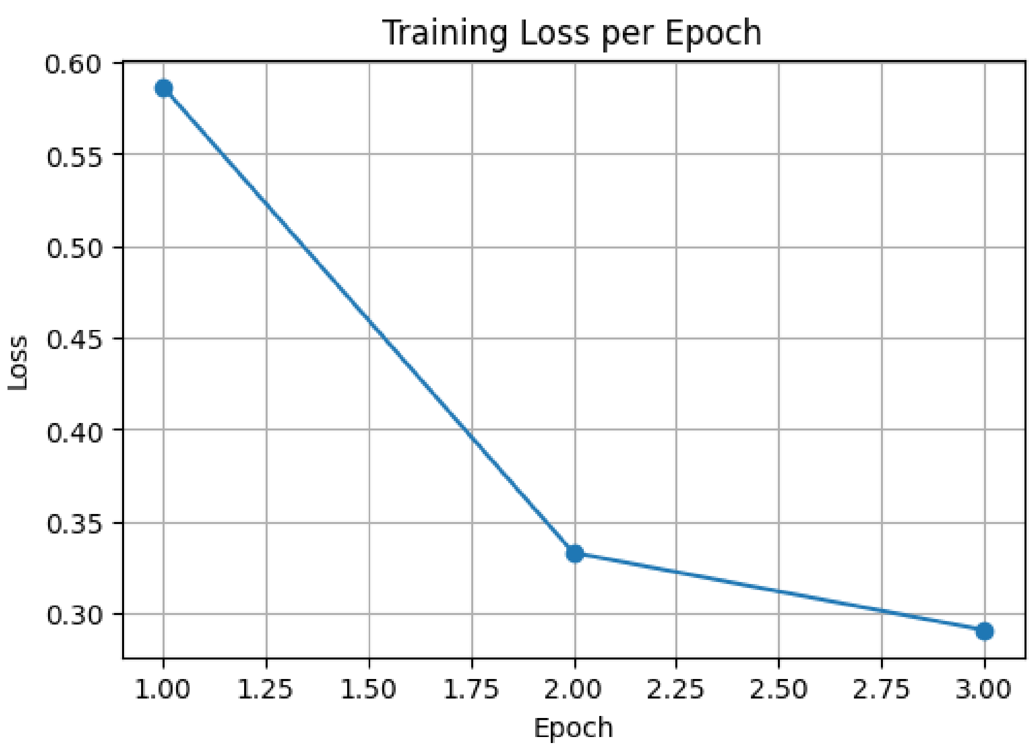
```
Epoch 1/15, Loss: 0.5867
```



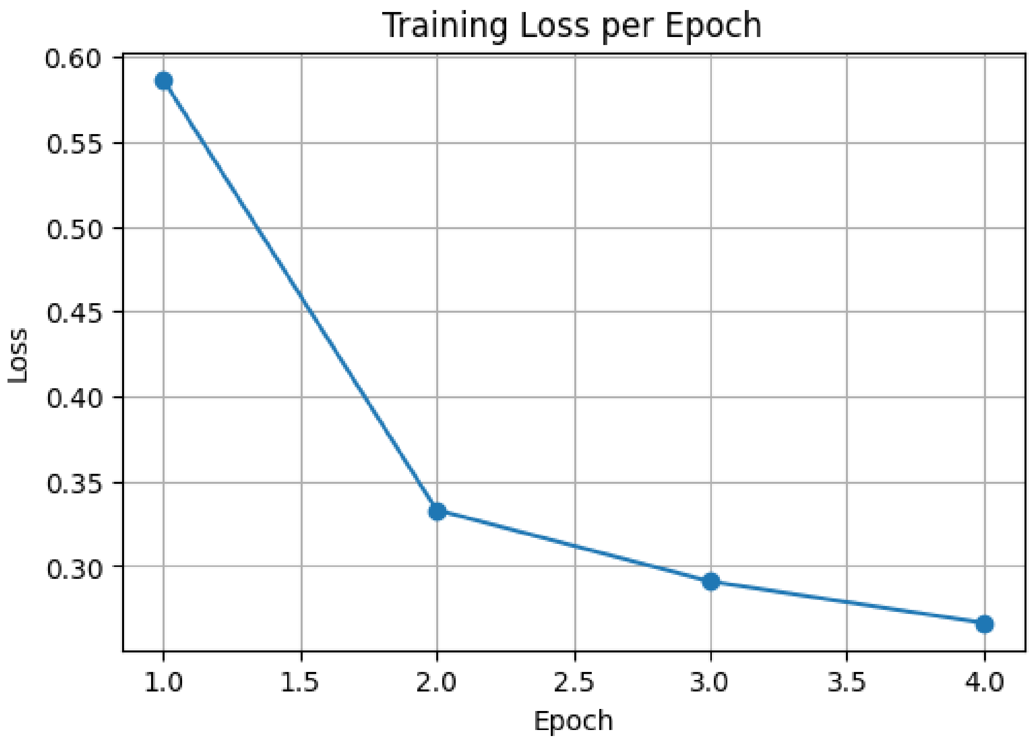

```
Epoch 2/15, Loss: 0.3330
```



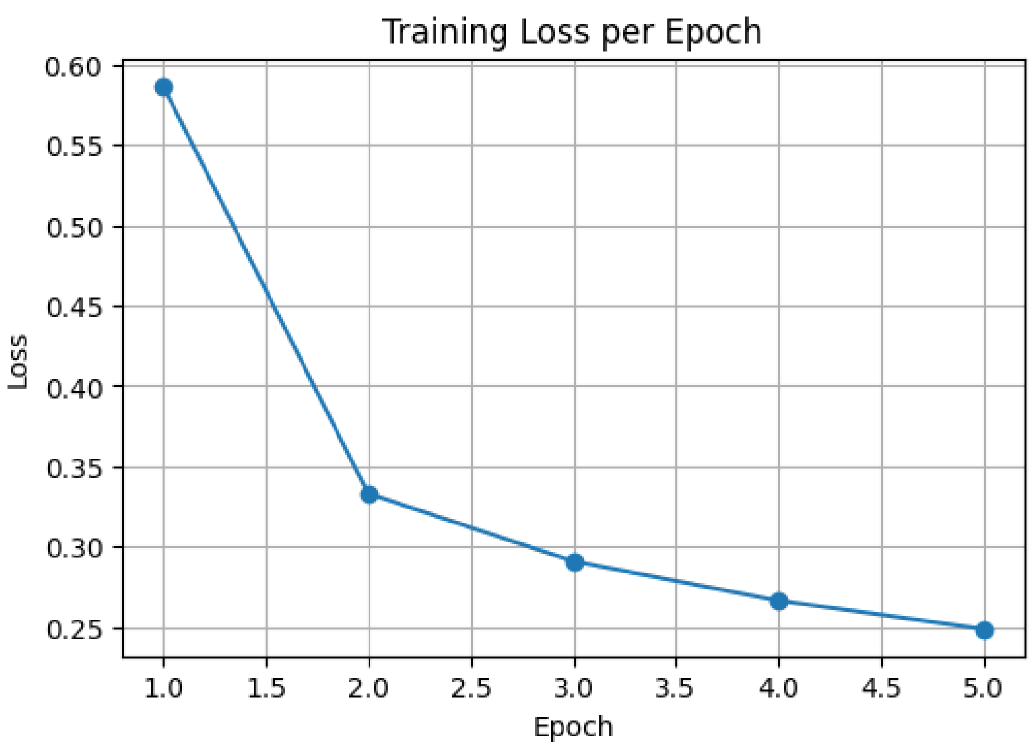

```
Epoch 3/15, Loss: 0.2909
```



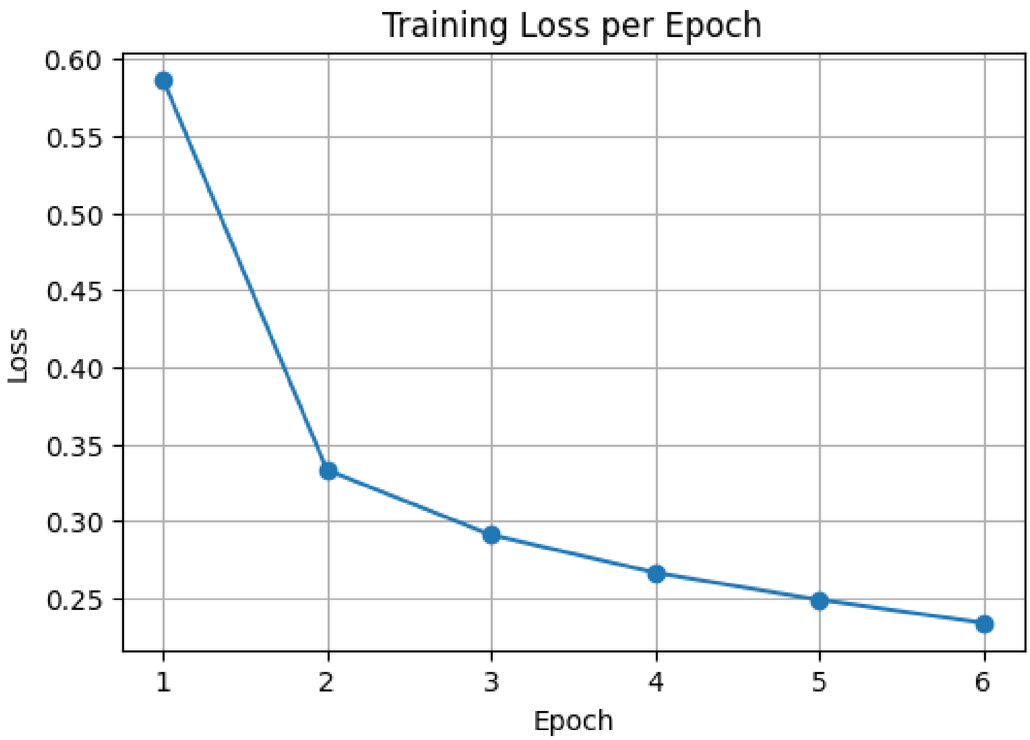

```
Epoch 4/15, Loss: 0.2665
```



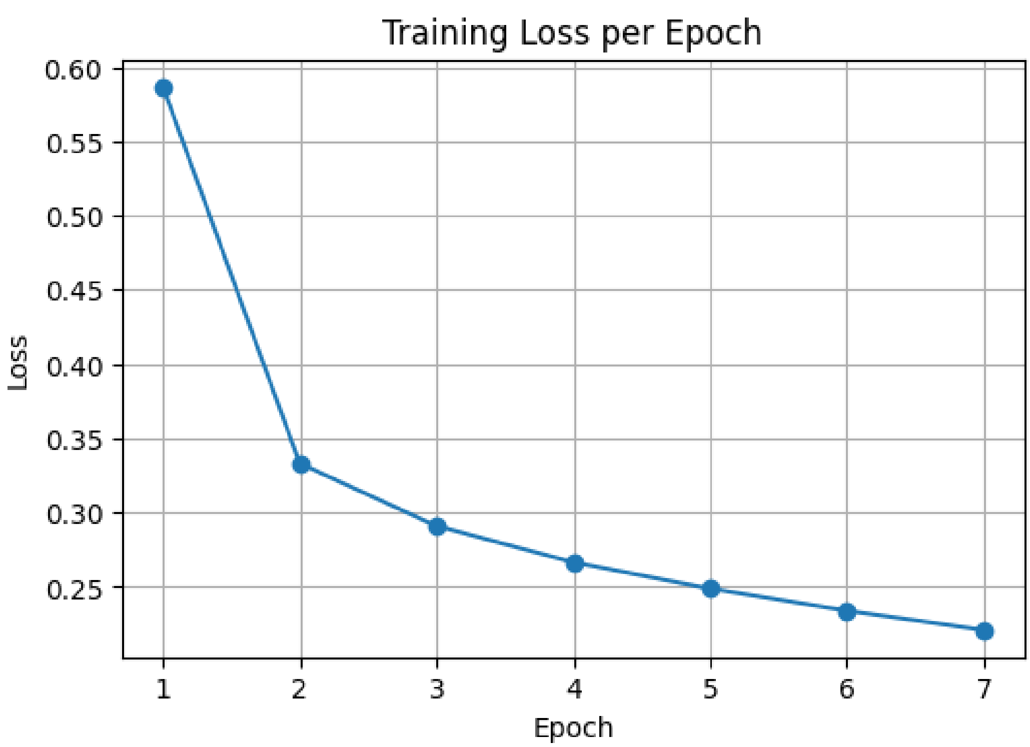

```
Epoch 5/15, Loss: 0.2488
```



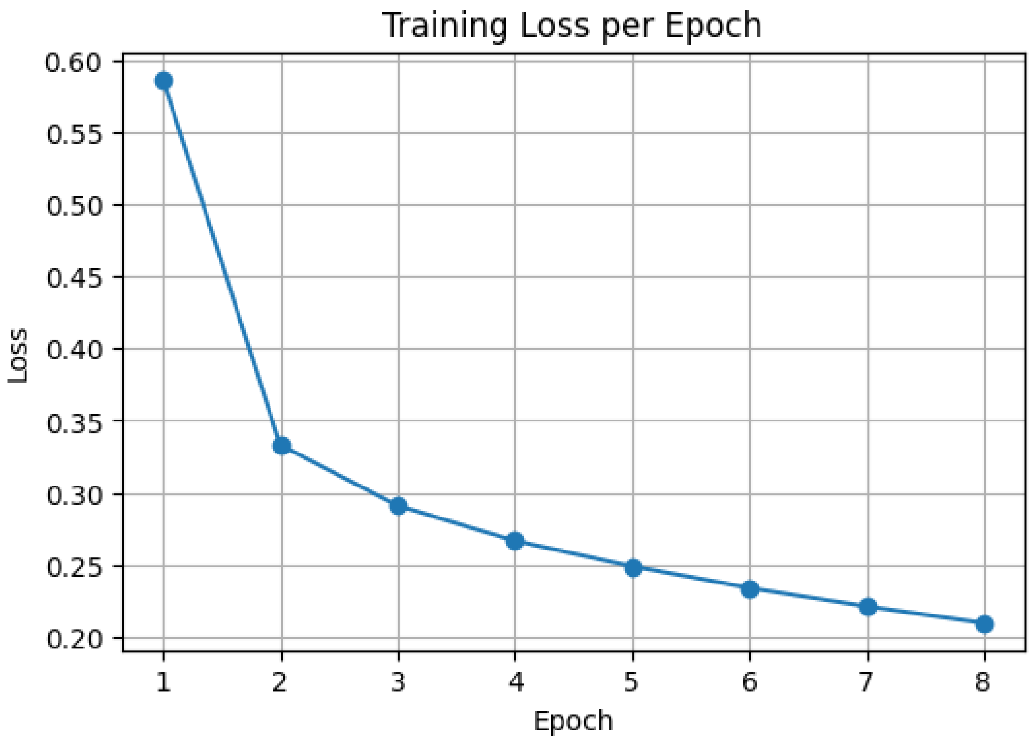

```
Epoch 6/15, Loss: 0.2339
```



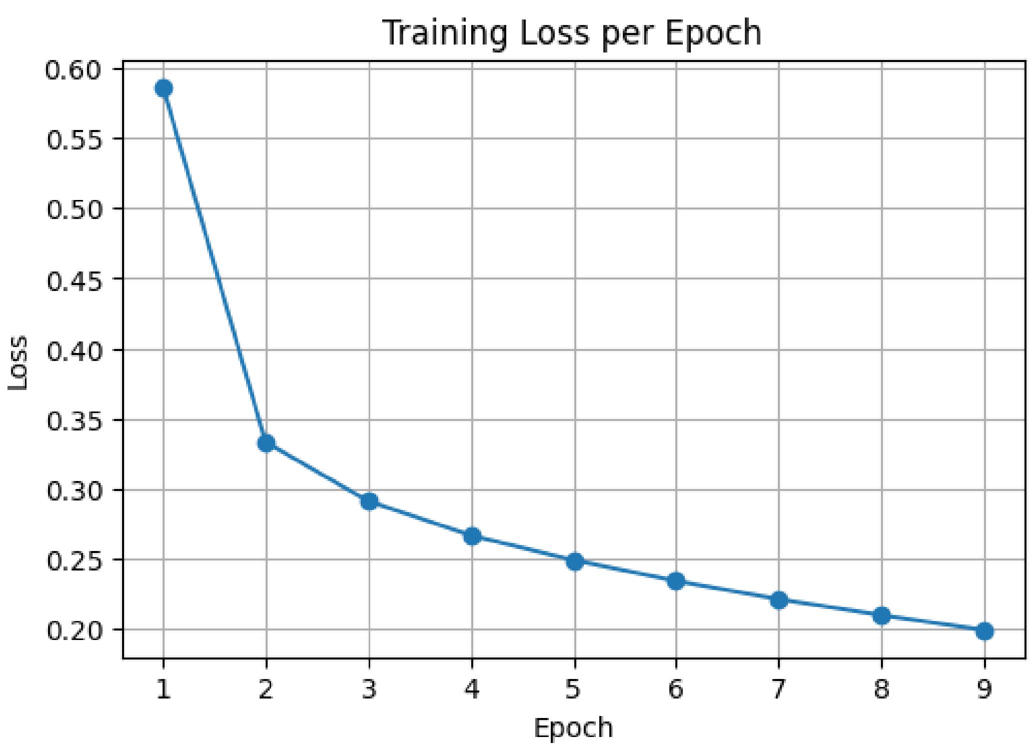

```
Epoch 7/15, Loss: 0.2209
```



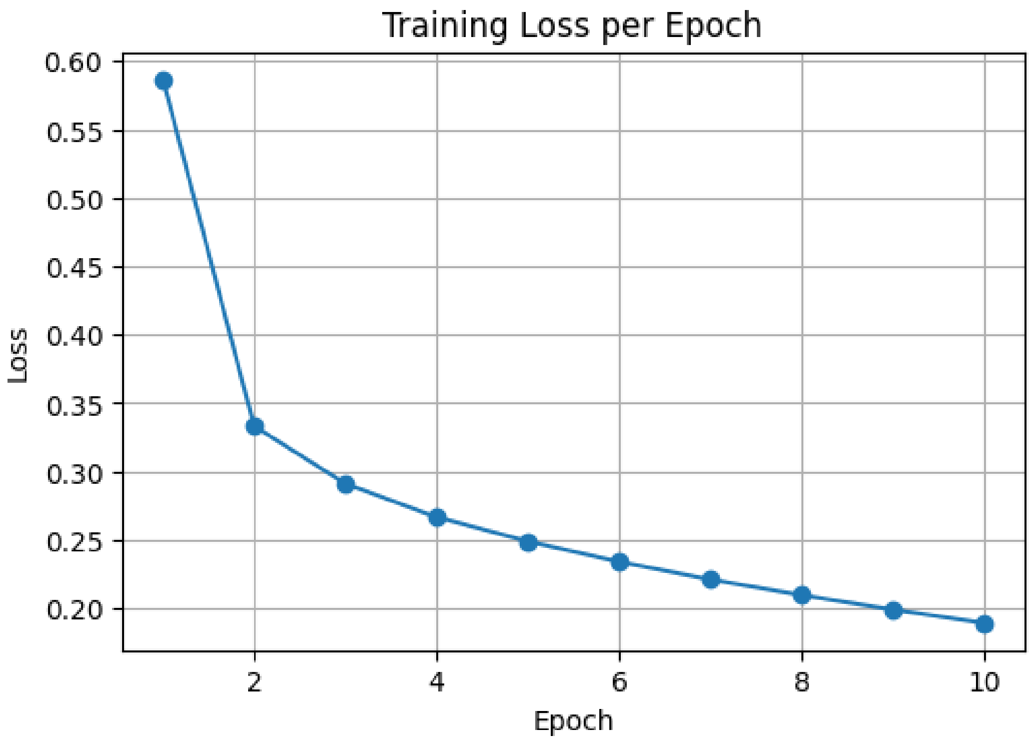

```
Epoch 8/15, Loss: 0.2095
```



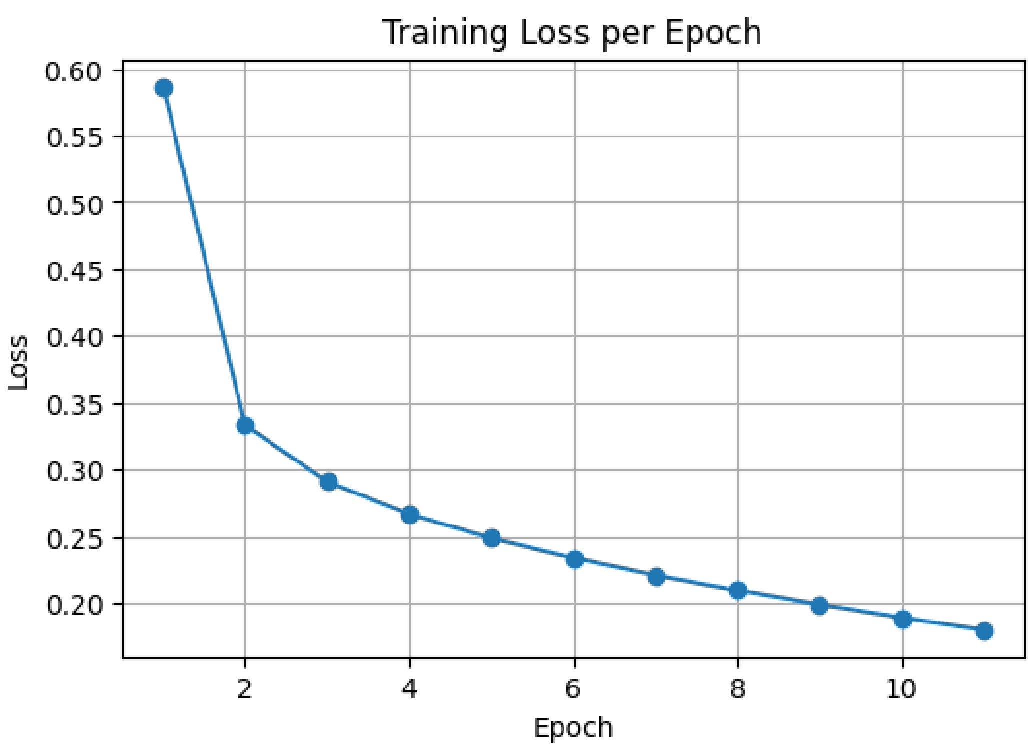

```
Epoch 9/15, Loss: 0.1989
```



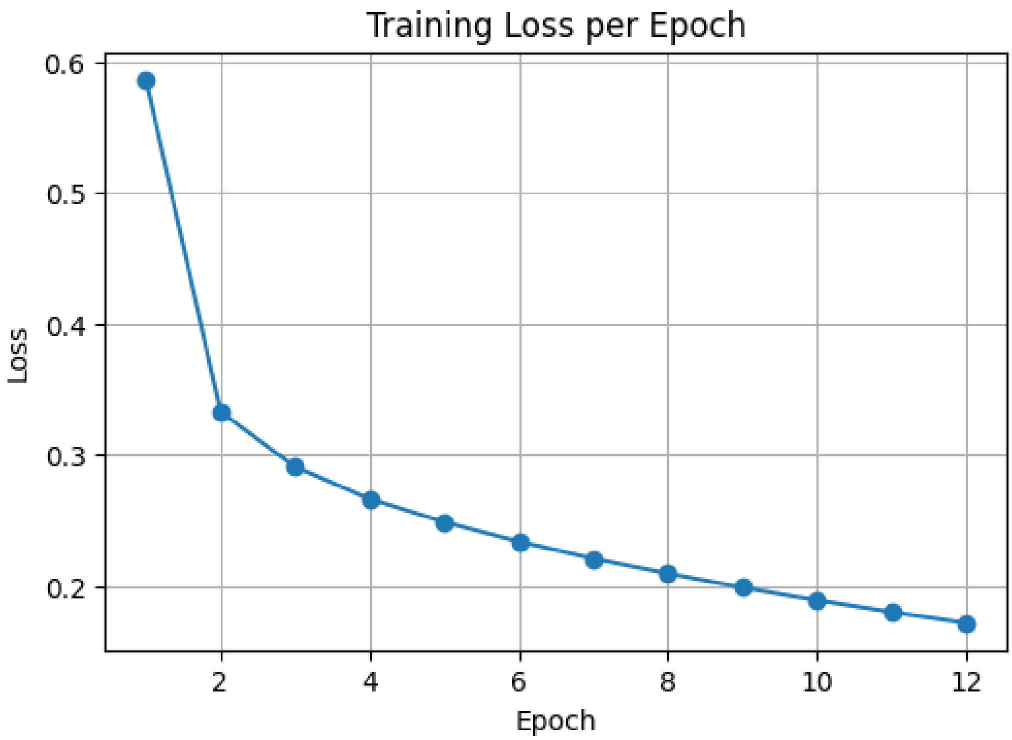

```
Epoch 10/15, Loss: 0.1891
```



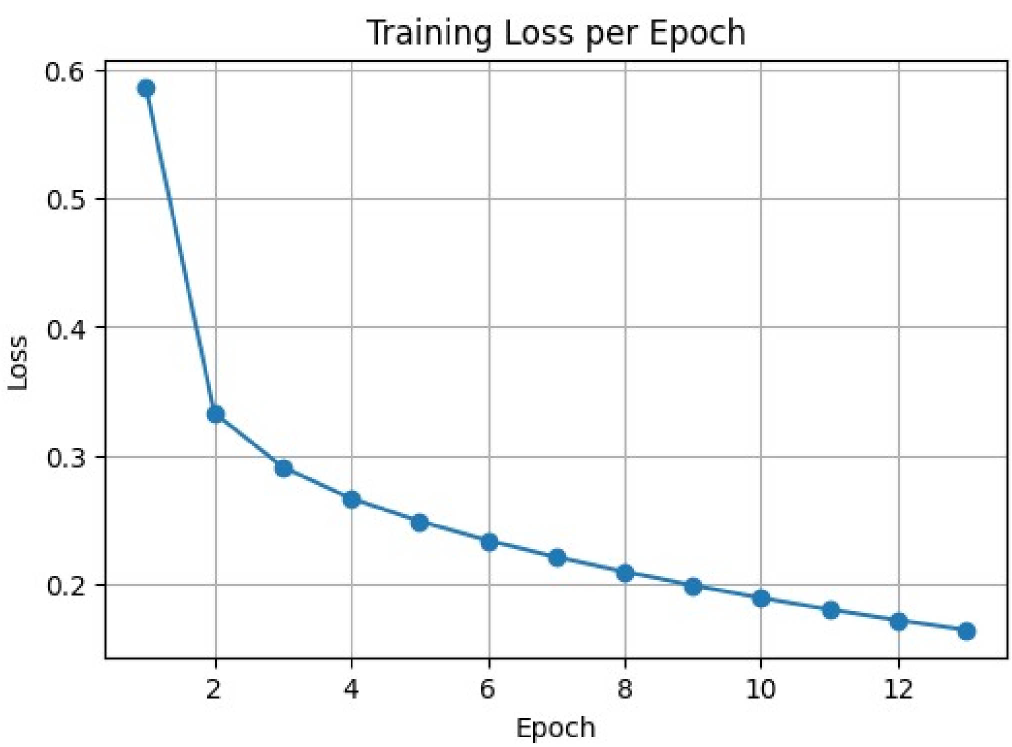

```
Epoch 11/15, Loss: 0.1801
```



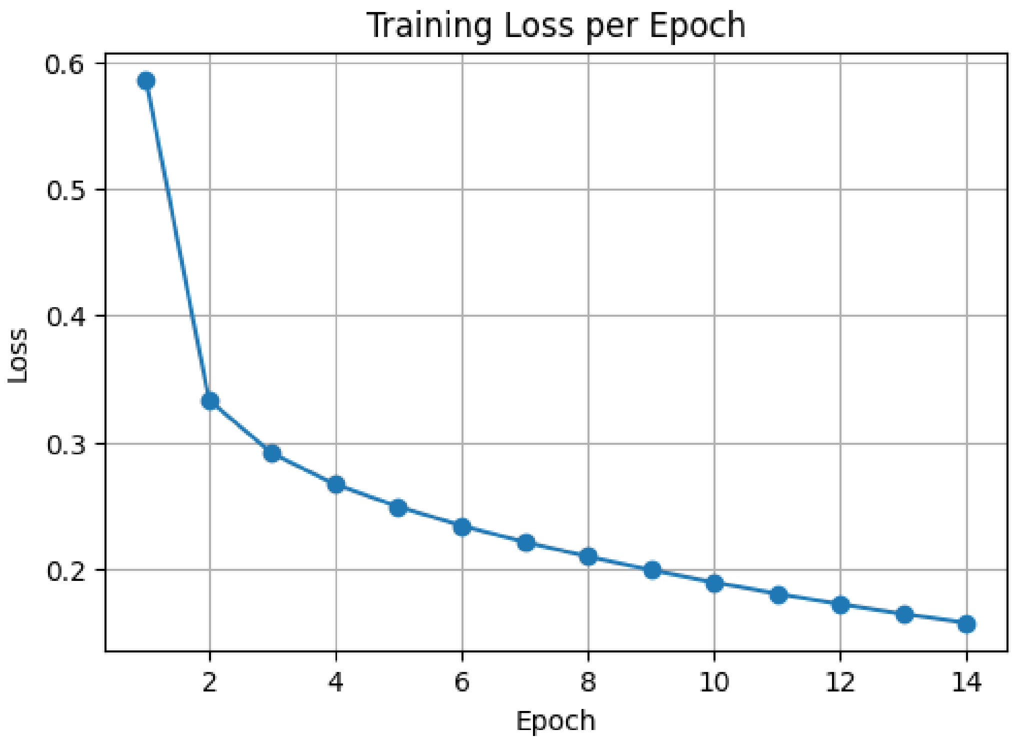

```
Epoch 12/15, Loss: 0.1718
```



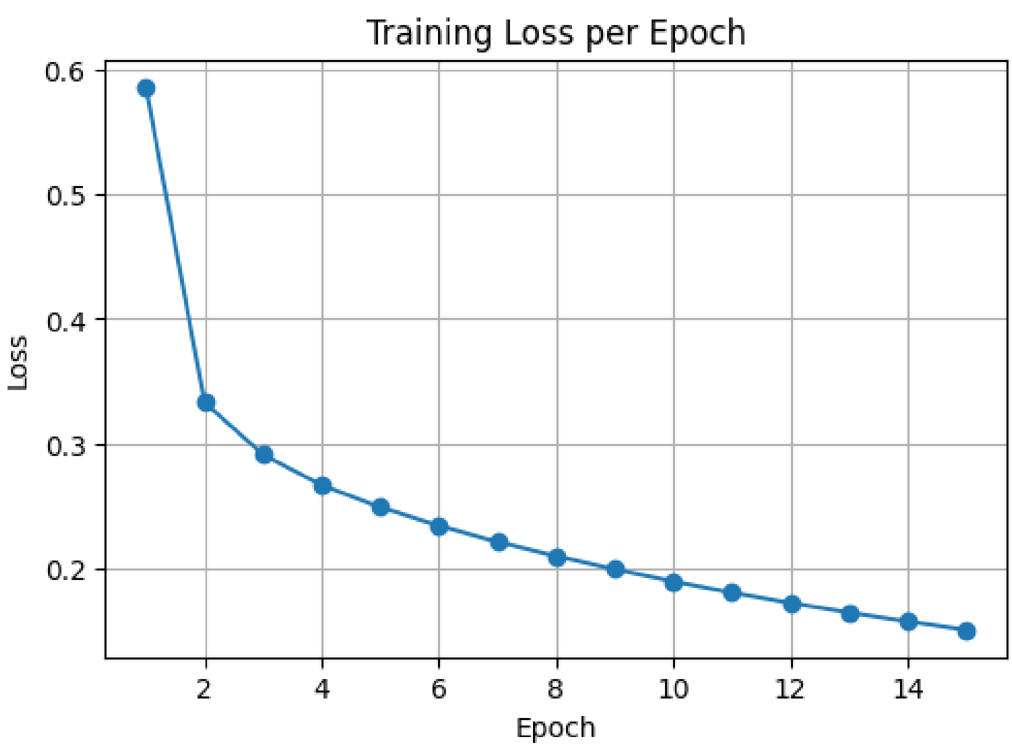

```
Epoch 13/15, Loss: 0.1642
```

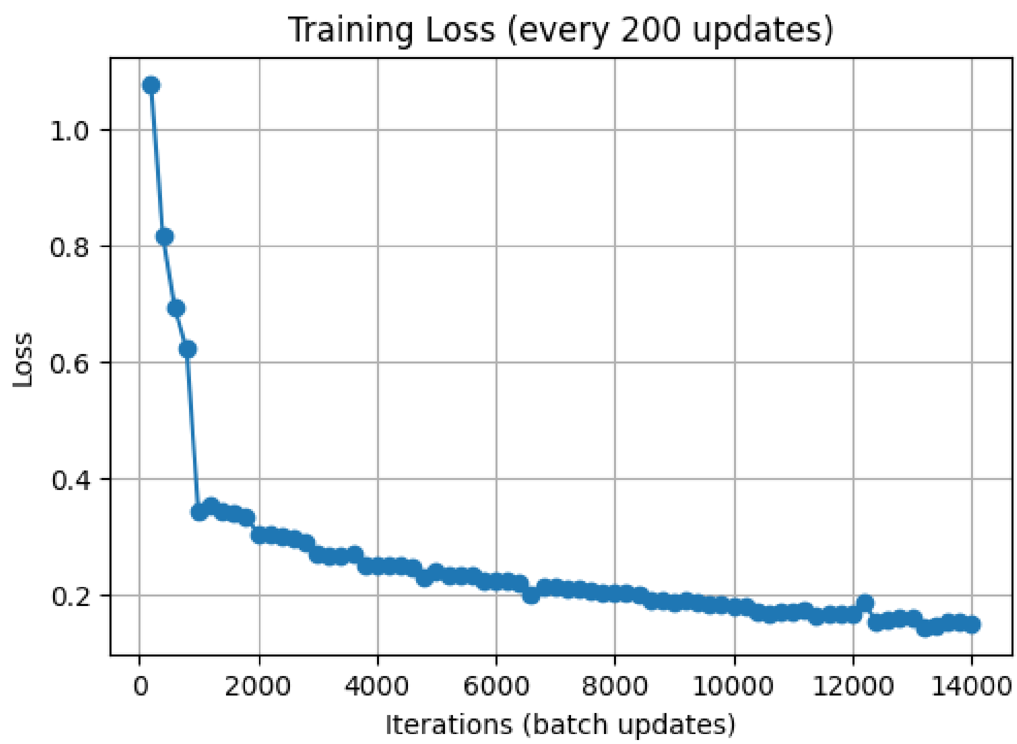



```
Epoch 14/15, Loss: 0.1570
```

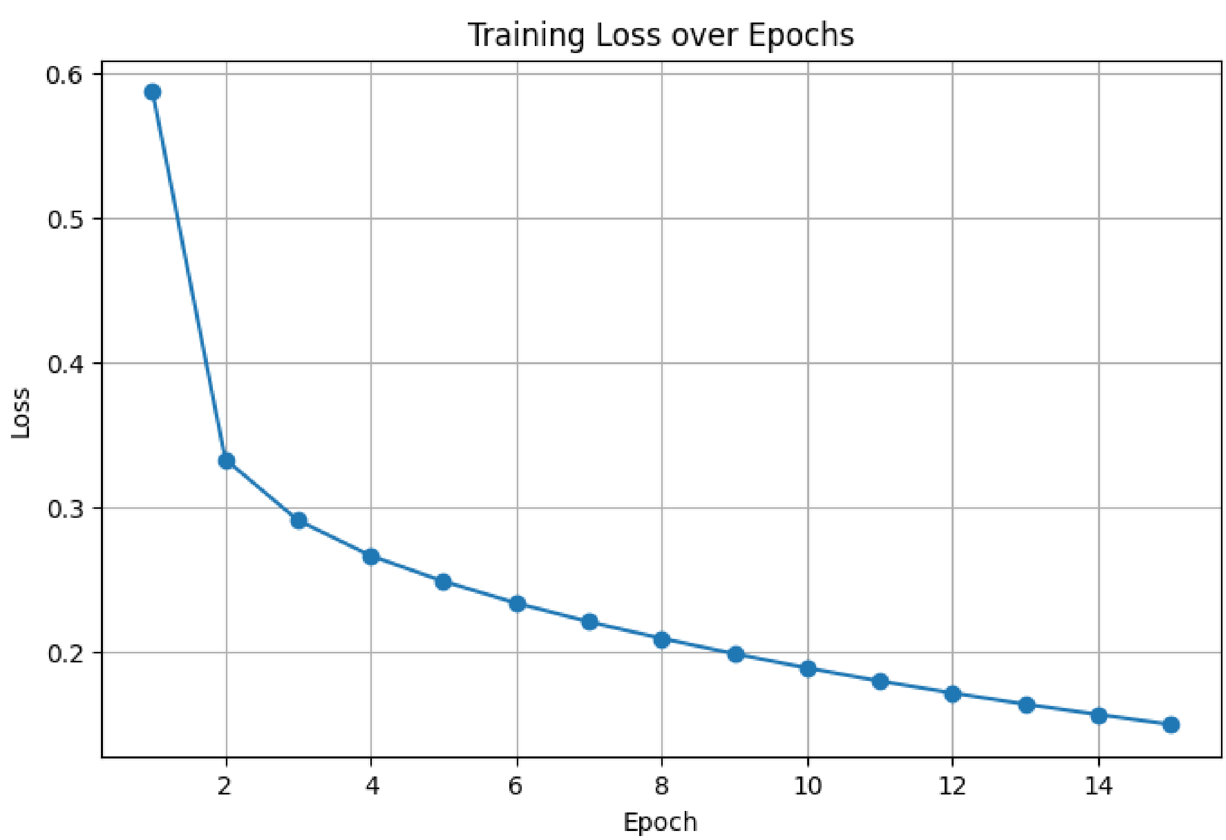



```
Epoch 15/15, Loss: 0.1501
```






```
plot_training_curves(loss_history_tanh)
```



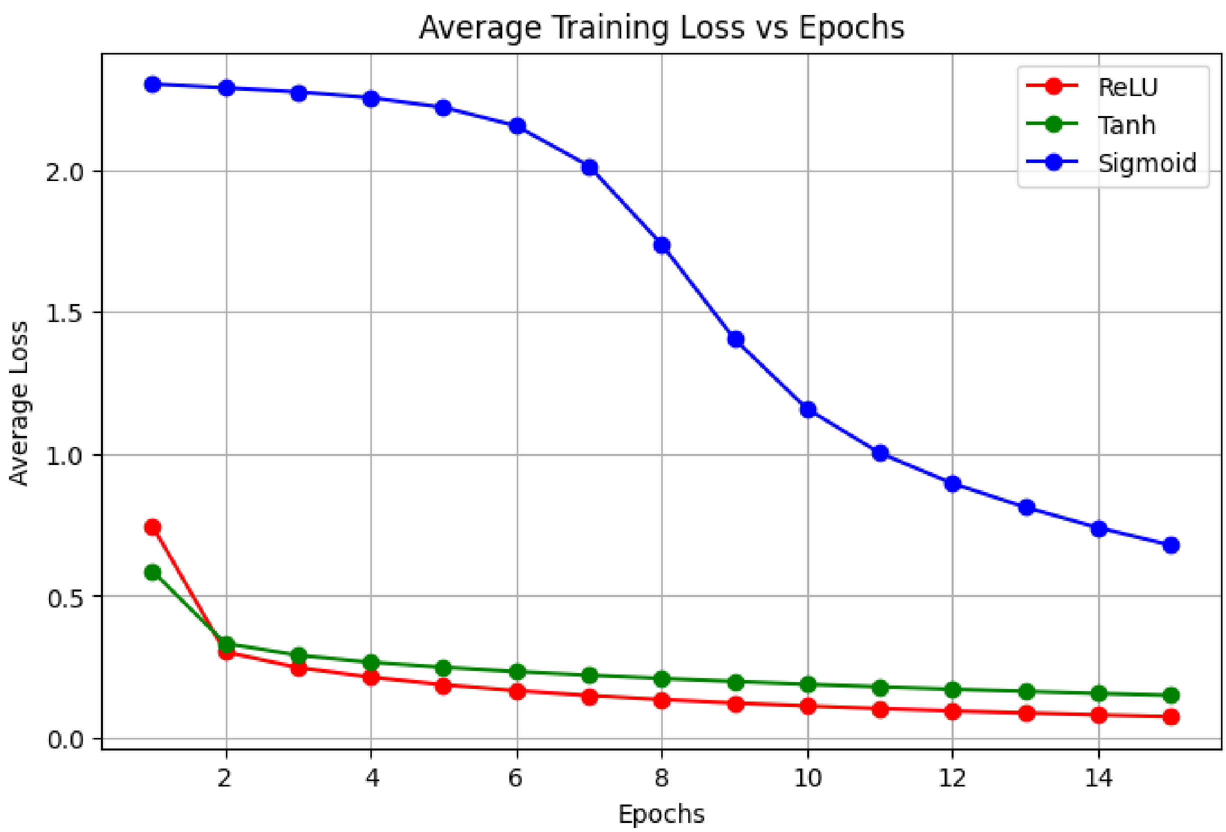
```
# Prepare test set in numpy format
X_test_np = mnist_testset.data.numpy().reshape(-1, 28*28) / 255.0
y_test_np = mnist_testset.targets.numpy()

print("---- Test Set Evaluation ----")
evaluate(model, X_test_np, y_test_np)
```

```
---- Test Set Evaluation ----
Accuracy: 95.4700%
Confusion Matrix:
[[ 968    0    1    3    0    3    3    1    1    0]
 [    0 1120    3    2    0    1    3    2    4    0]
 [    6    1  988    5    4    1    9    6   11    1]
 [    0    0   12  972    0    7    0    9    9    1]
 [    1    0    9    0  931    0    6    3    5   27]
 [    8    2    0   24    2  827   12    2   11    4]
 [    9    3    6    2    3    8  923    1    3    0]
 [    2    6   20    6    2    2    0  969    2   19]
 [    3    3    8   20    6    9    7    9  909    0]
 [    9    6    2   13   18    4    1   12    4  940]]

Classification Report:
              precision    recall  f1-score   support

           0       0.96      0.99      0.97       980
           1       0.98      0.99      0.98      1135
           2       0.94      0.96      0.95      1032
           3       0.93      0.96      0.95      1010
           4       0.96      0.95      0.96       982
           5       0.96      0.93      0.94       892
           6       0.96      0.96      0.96       958
           7       0.96      0.94      0.95      1028
           8       0.95      0.93      0.94       974
           9       0.95      0.93      0.94      1009

    accuracy                           0.95     10000
   macro avg       0.95      0.95      0.95     10000
weighted avg       0.95      0.95      0.95     10000


np.float64(0.9547)
```

Results for MLP using Tan Hyperbolic activation function

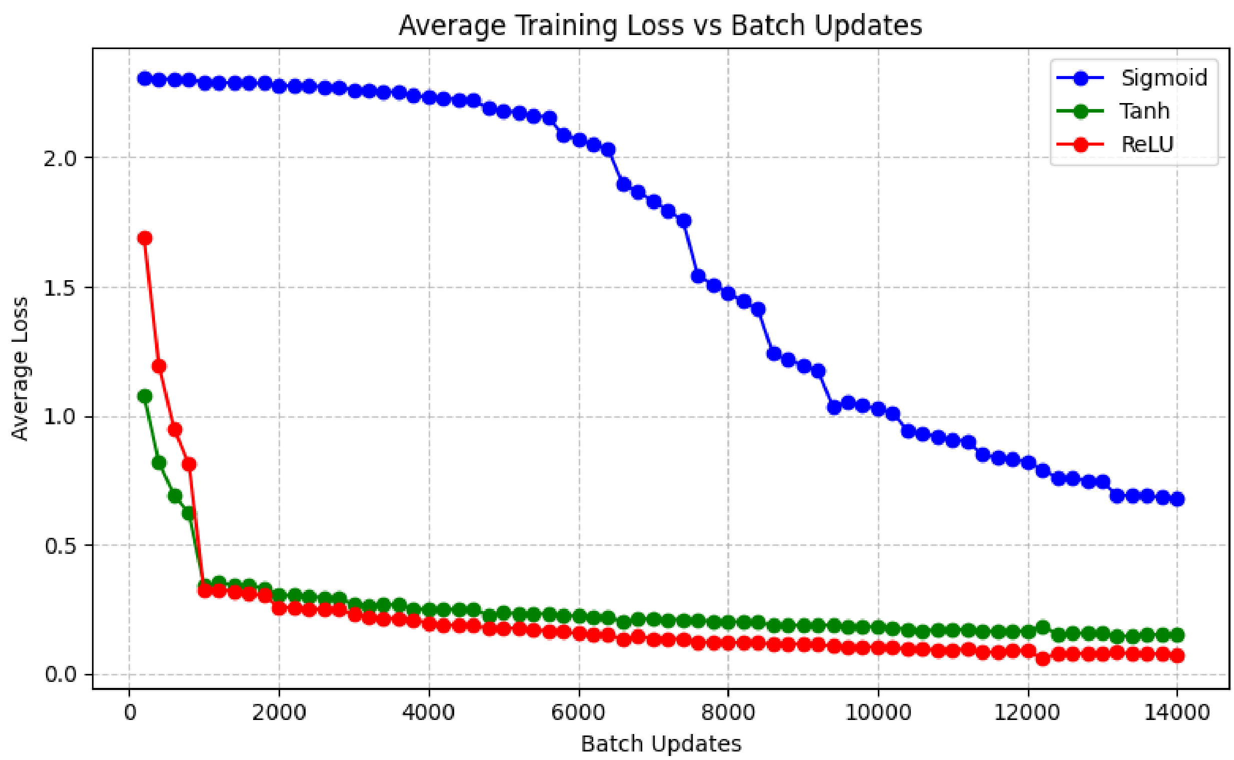
- Classfication accuracy over test data = **95.47%**
- Training loss after 15 epochs = **0.1501**

```
epochs = range(1, len(loss_history) + 1)

plt.figure(figsize=(8,5))
plt.plot(epochs, loss_history_ReLu, marker='o', label="ReLU",
color='r')
plt.plot(epochs, loss_history_tanh, marker='o', label="Tanh",
color='g')
plt.plot(epochs, loss_history, marker='o', label="Sigmoid", color='b')

plt.title("Average Training Loss vs Epochs")
plt.xlabel("Epochs")
plt.ylabel("Average Loss")
plt.legend()
plt.grid(True)
plt.show()
```




```
plt.figure(figsize=(8,5))

# Plot each activation using its own iteration indices
plt.plot(iter_tanh, iter_loss, marker='o', color='b', label="Sigmoid")
plt.plot(iter_tanh, iter_loss_tanh, marker='o', color='g',
label="Tanh")
plt.plot(iter_ReLu, iter_loss_ReLu, marker='o', color='r',
```

```
label="ReLU")

plt.title("Average Training Loss vs Batch Updates")
plt.xlabel("Batch Updates")
plt.ylabel("Average Loss")
plt.legend()
plt.grid(True, linestyle="--", alpha=0.7)
plt.tight_layout()
plt.show()
```



Comparison for the different activation functions

- Test accuracy for sigmoid activation function = 82.30%
- Test accuracy for ReLU activation function = 97.12%
- Test accuracy for Tan Hyperbolic activation function = 95.47%

Conclusions:-

- The Tanh and ReLU activation functions perform almost identical.
- The Sigmoid activation function struggles to deliver good training and testing processes.

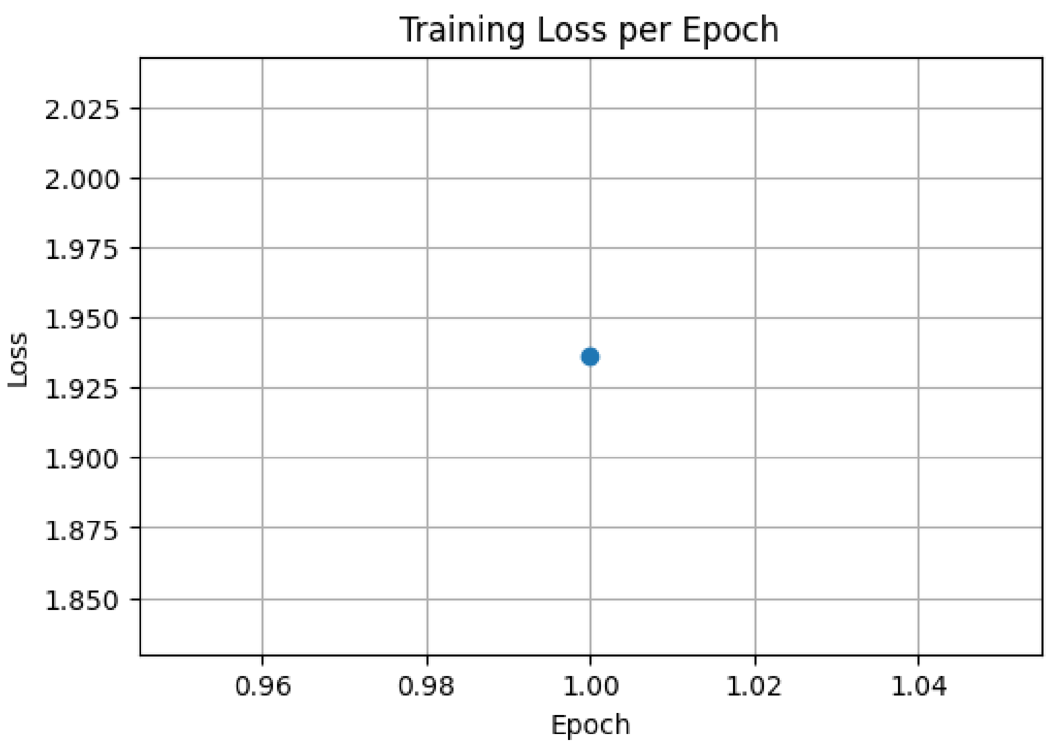
- The ReLU activation function performes relatively better.

Analyzing the MLP algorithm for different learning rates

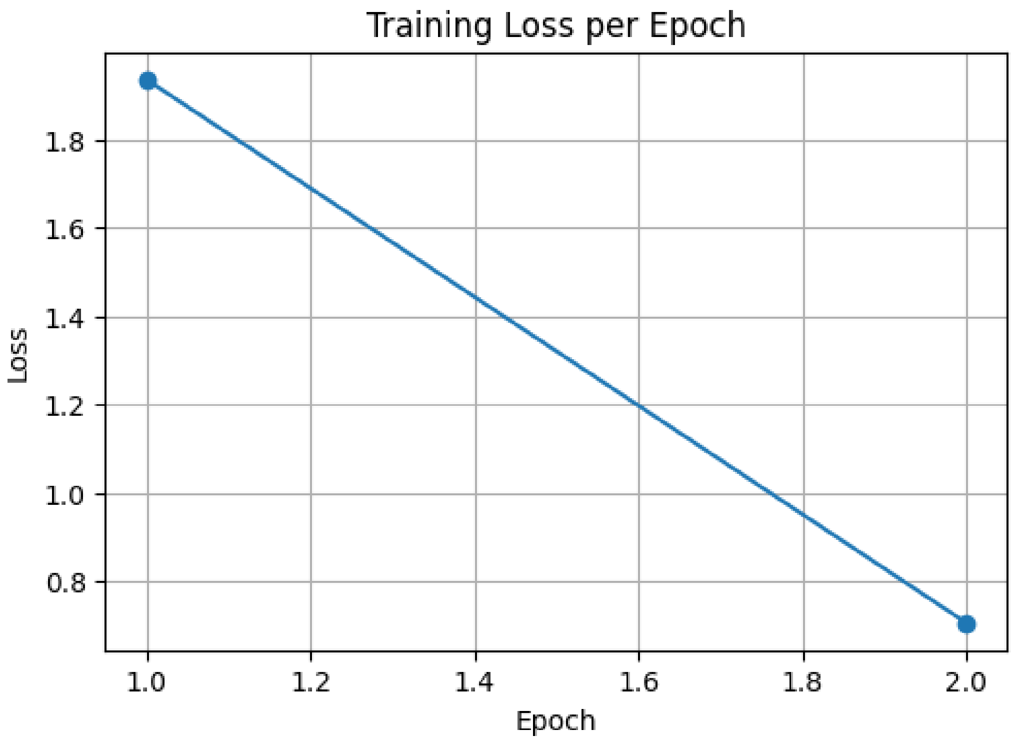
- **Learning rate = 0.1**

```
model_1 = MLP()
loss_history_sigmoid_1, iter_sigmoid_1, iter_loss_sigmoid_1 =
train(model_1, train_loader, 15, 0.1)
```

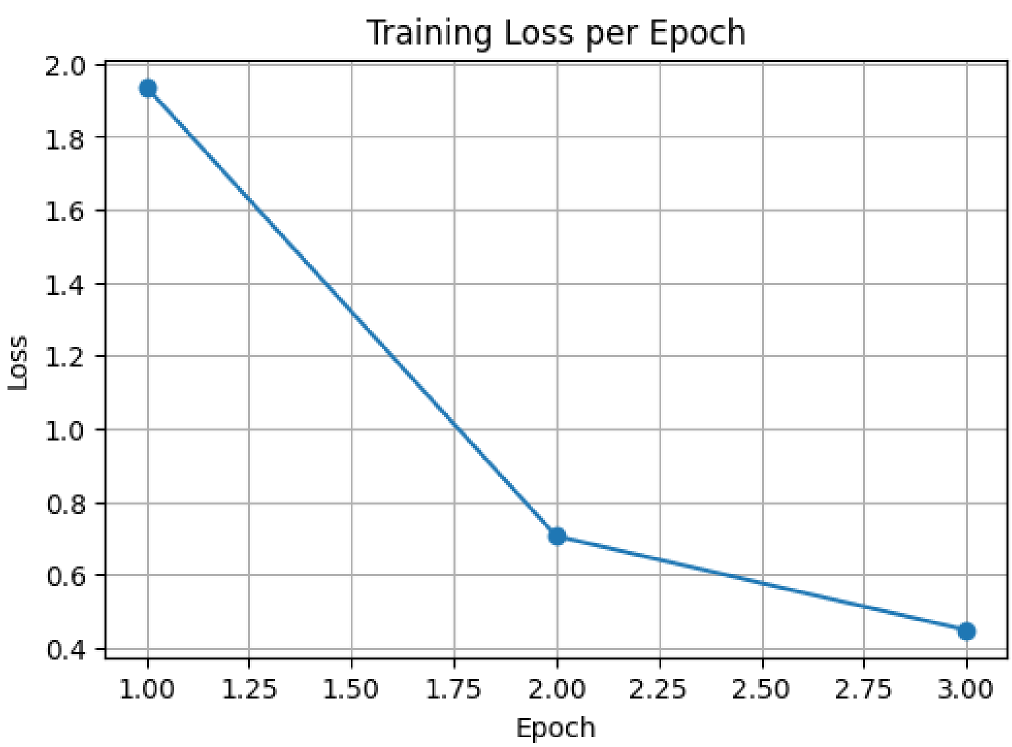
```
Epoch 1/15, Loss: 1.9364
```



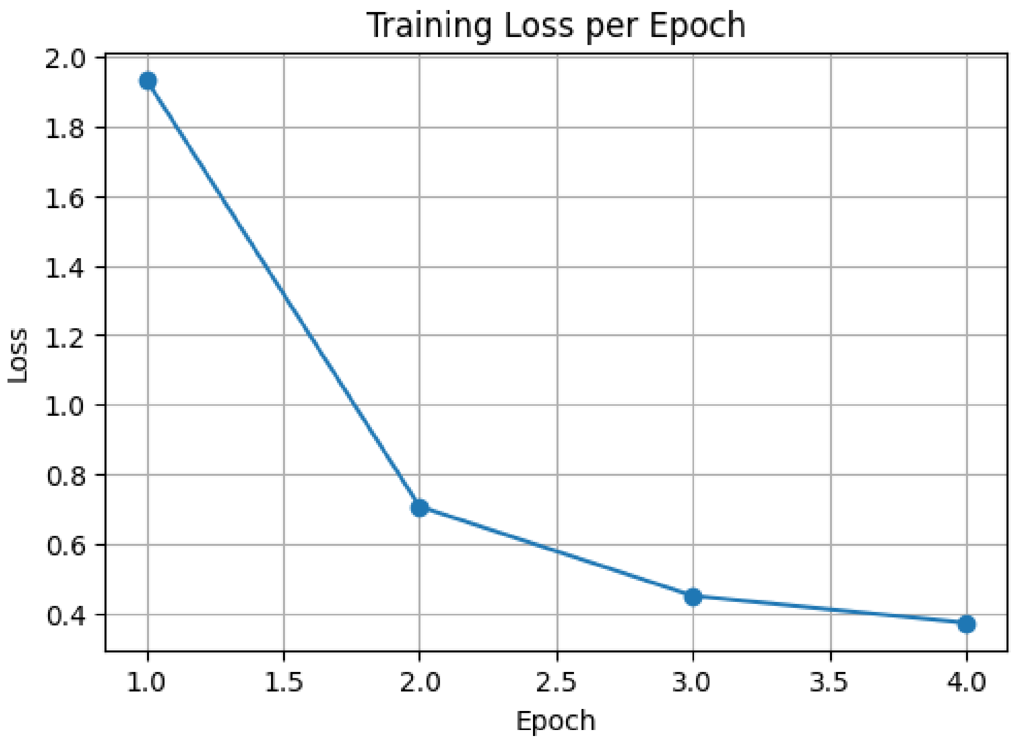

```
Epoch 2/15, Loss: 0.7062
```



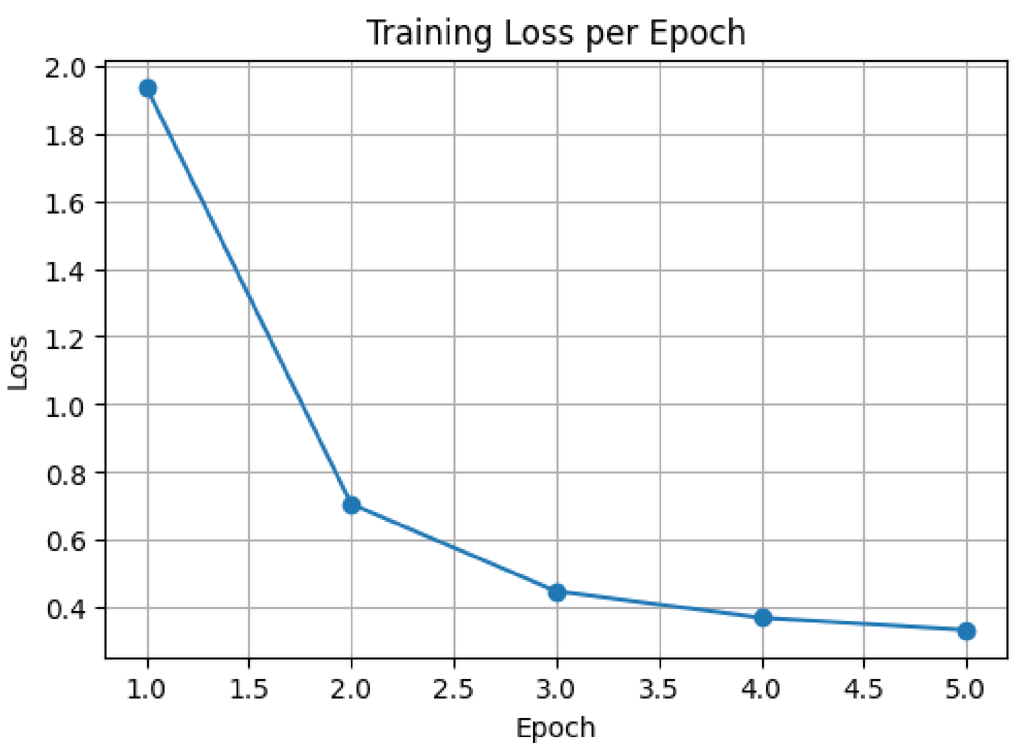

```
Epoch 3/15, Loss: 0.4492
```



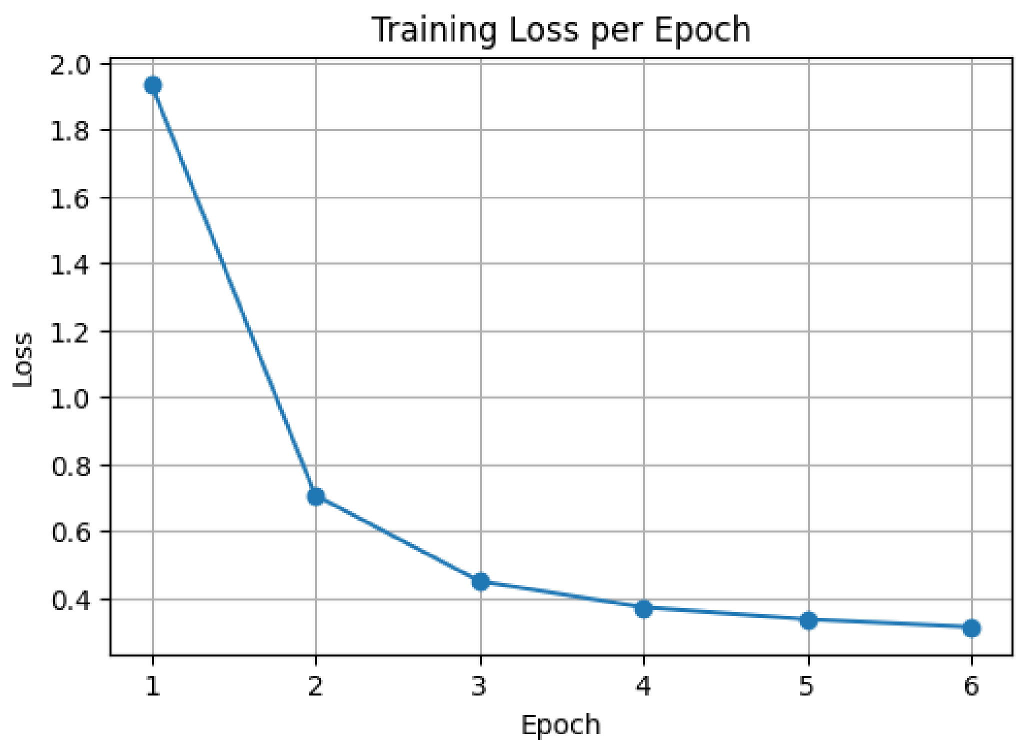

```
Epoch 4/15, Loss: 0.3712
```



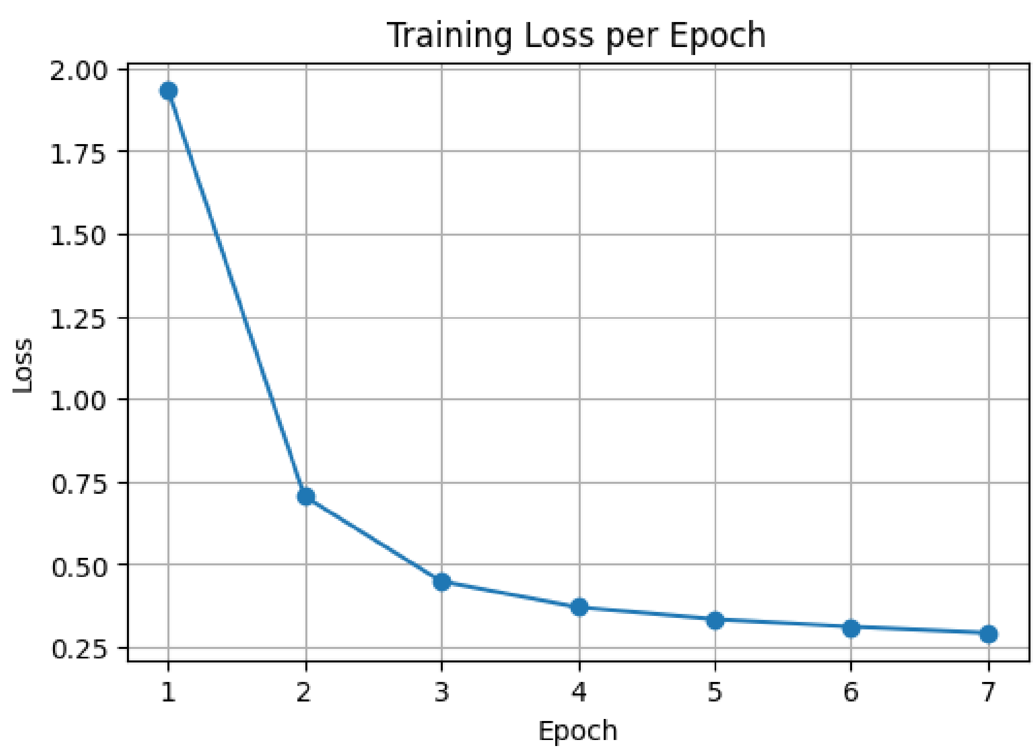

```
Epoch 5/15, Loss: 0.3349
```



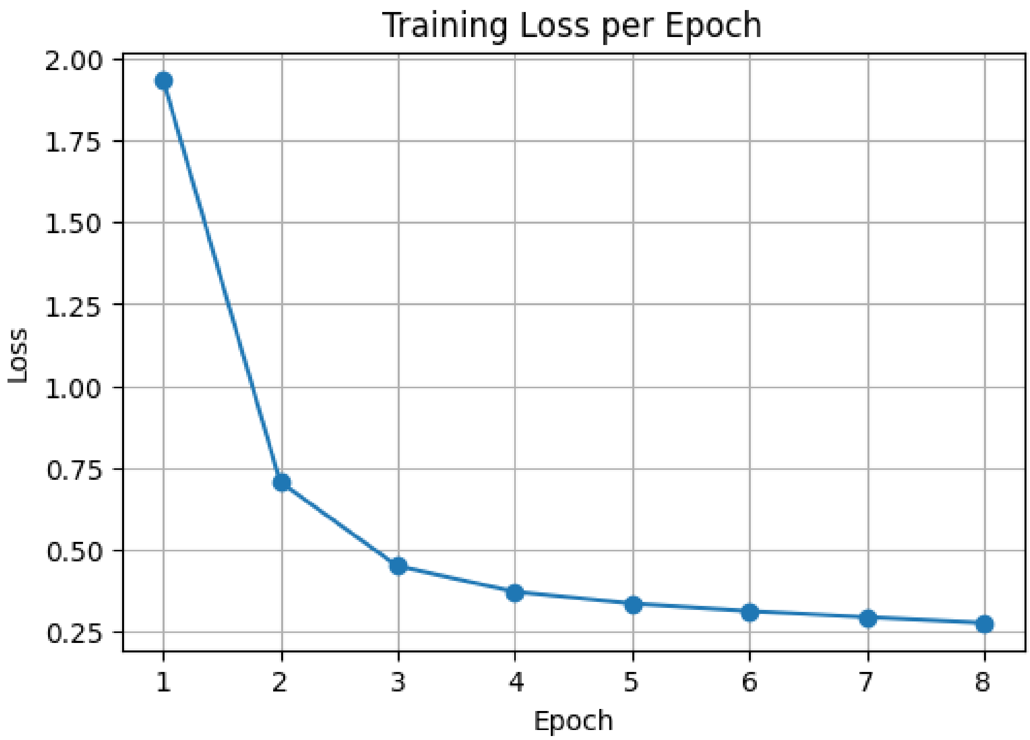

```
Epoch 6/15, Loss: 0.3120
```



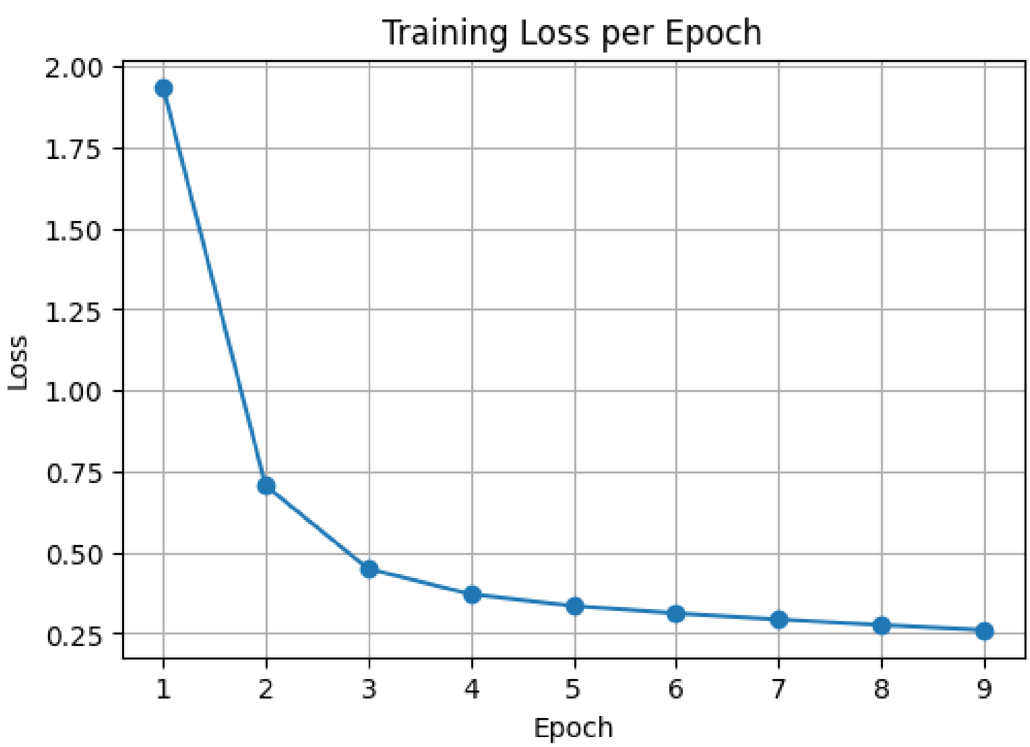

```
Epoch 7/15, Loss: 0.2933
```



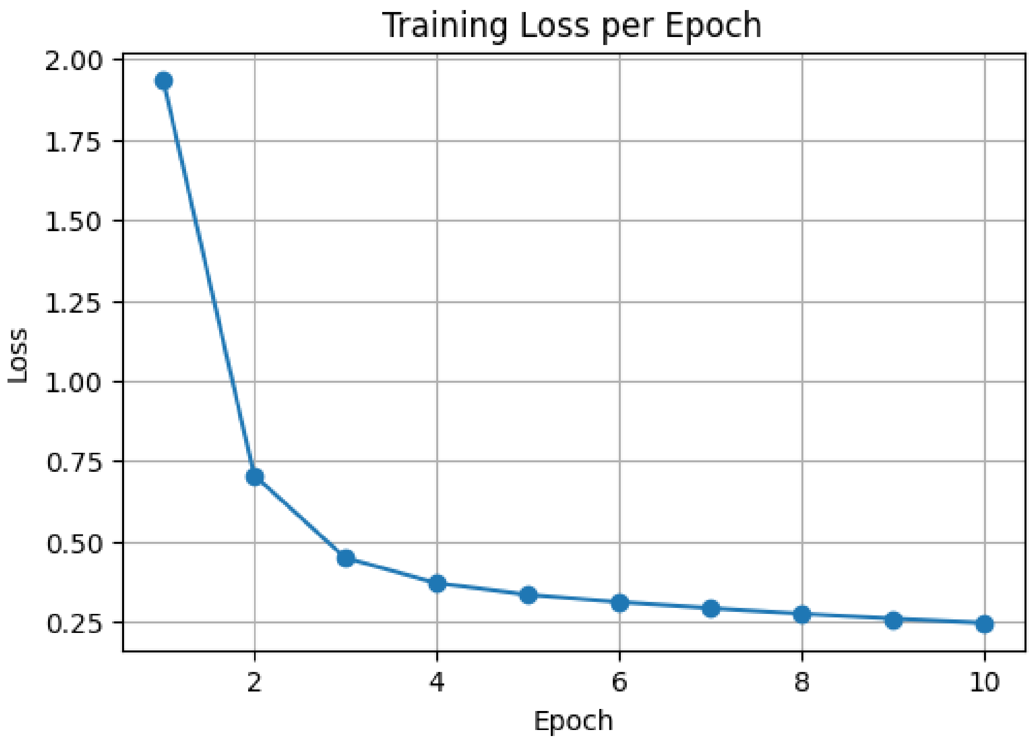

```
Epoch 8/15, Loss: 0.2757
```



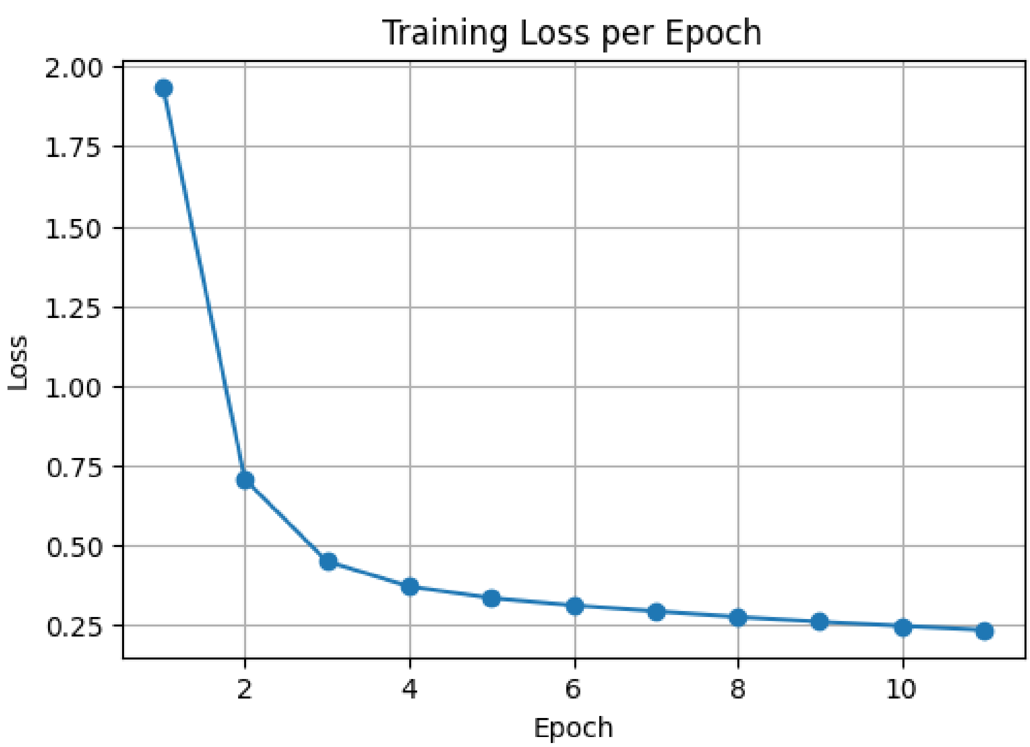

```
Epoch 9/15, Loss: 0.2606
```



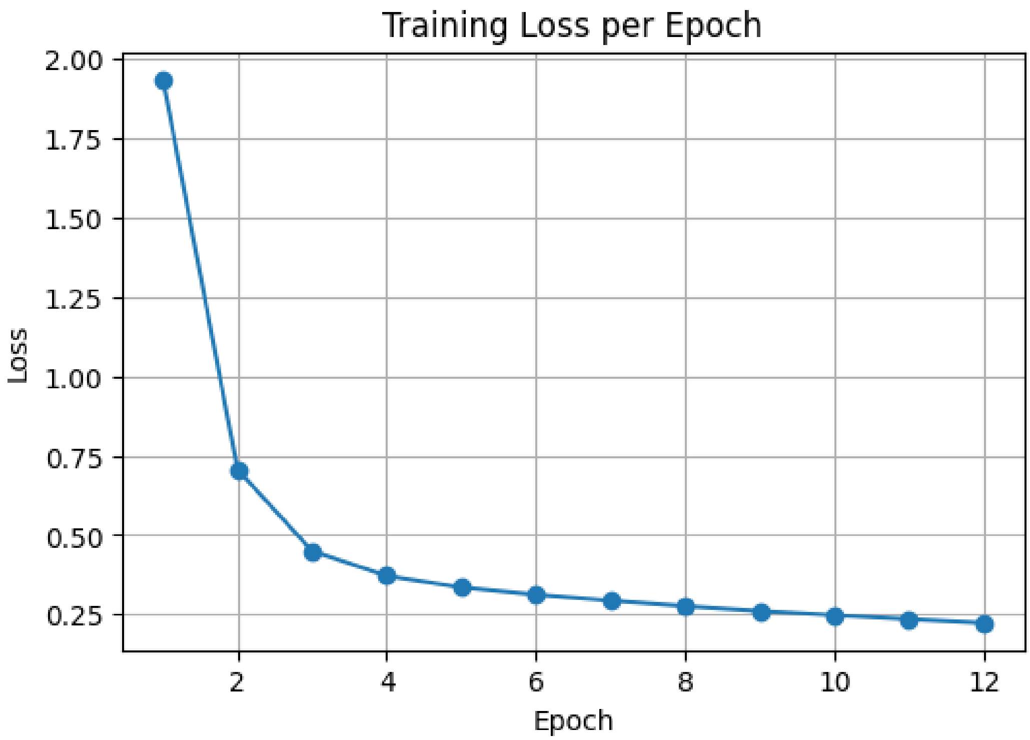

```
Epoch 10/15, Loss: 0.2473
```



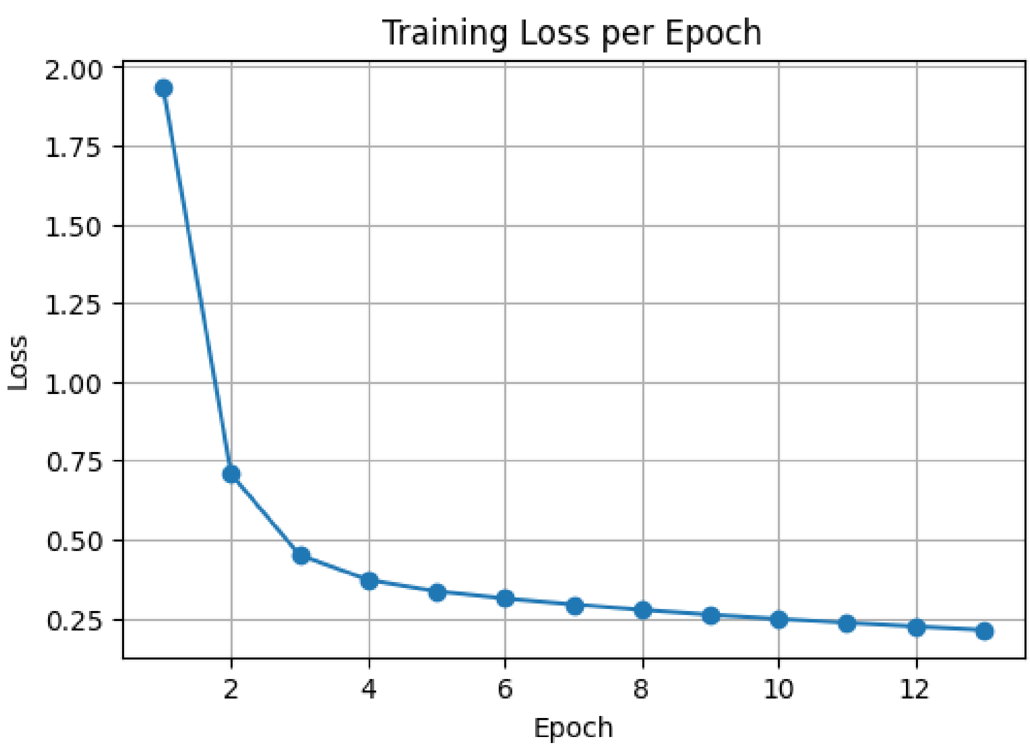

```
Epoch 11/15, Loss: 0.2347
```



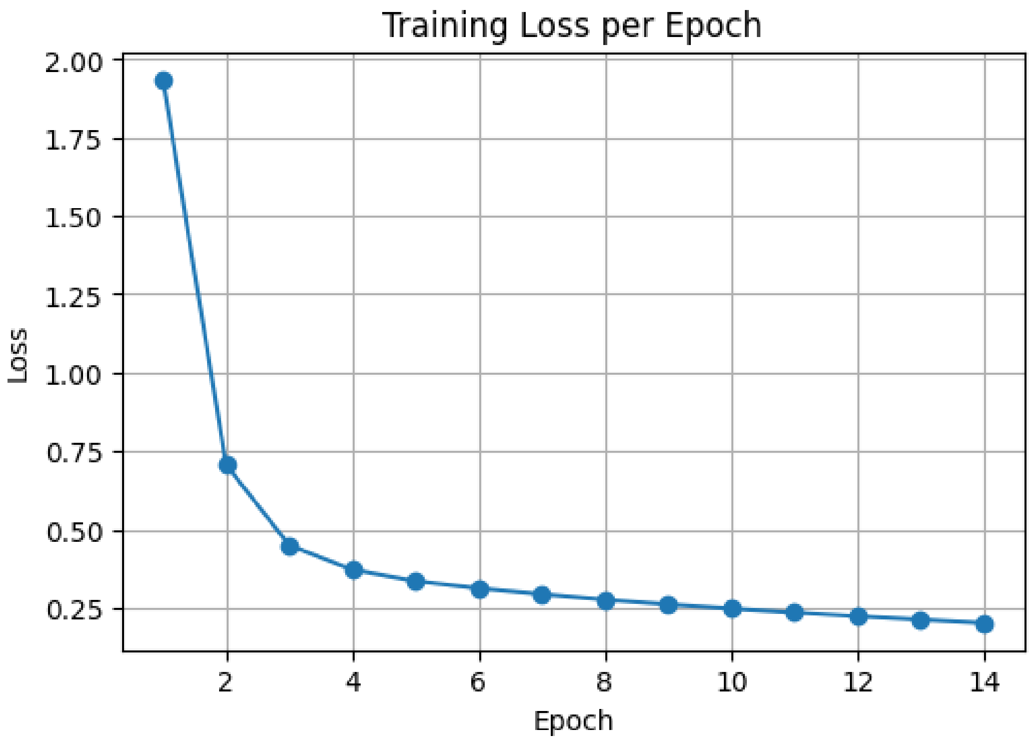

```
Epoch 12/15, Loss: 0.2229
```



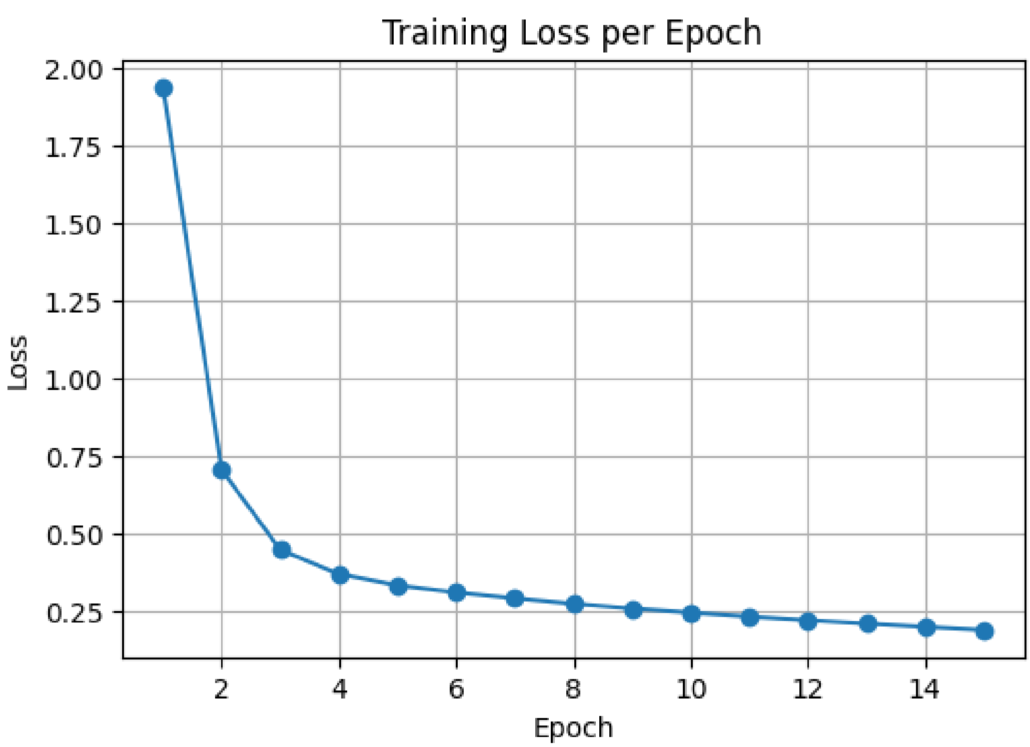

```
Epoch 13/15, Loss: 0.2119
```

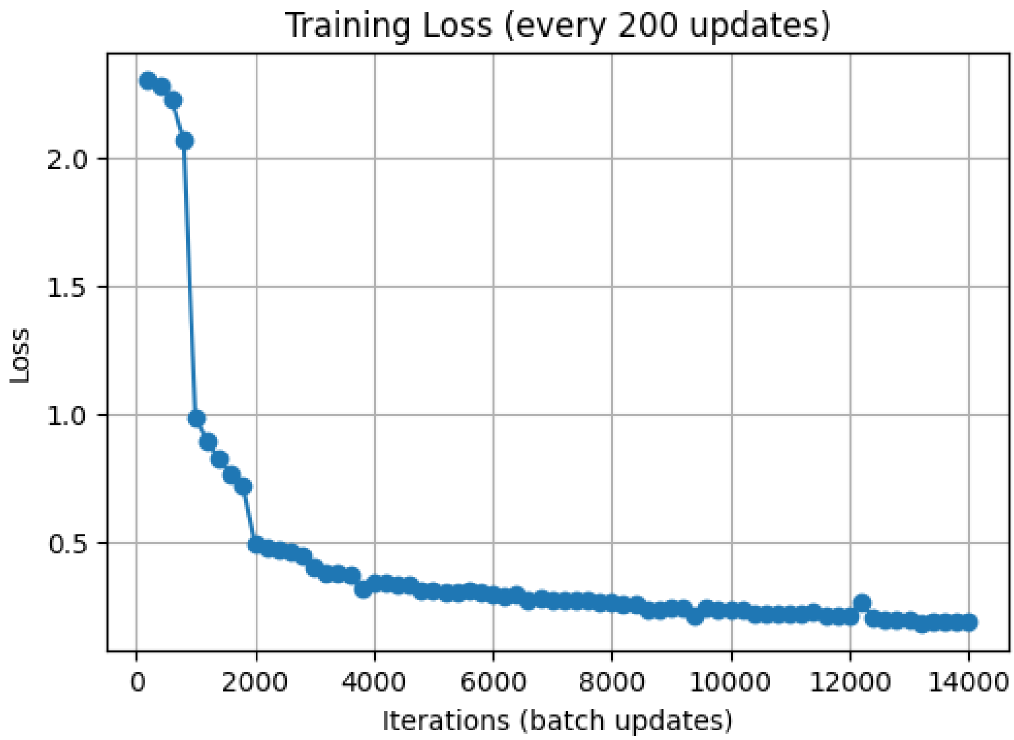



```
Epoch 14/15, Loss: 0.2014
```

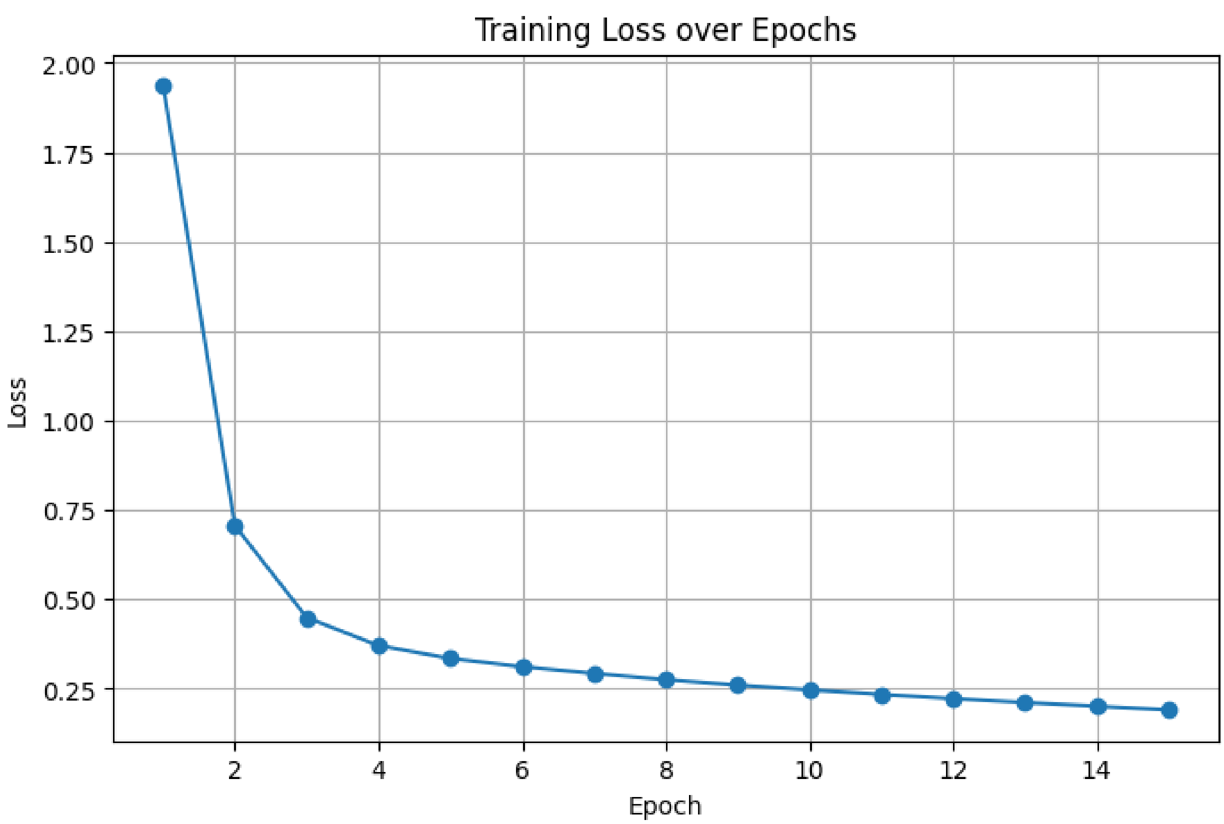



```
Epoch 15/15, Loss: 0.1915
```






```
plot_training_curves(loss_history_sigmoid_1)
```



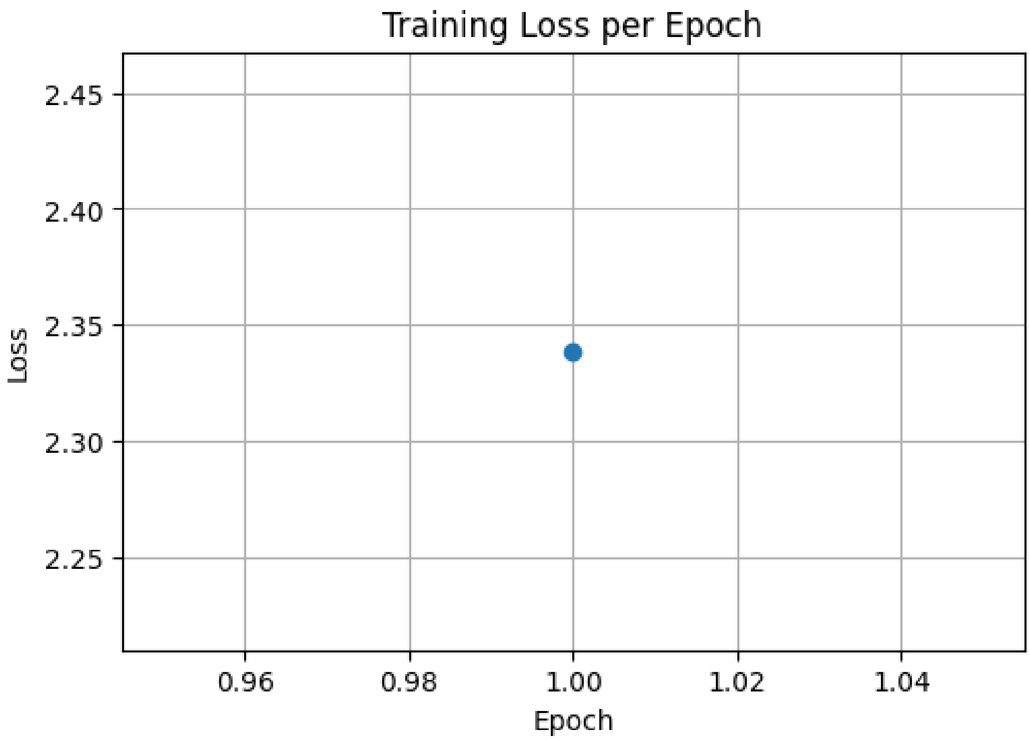
```
X_test_np = mnist_testset.data.numpy().reshape(-1, 28*28) / 255.0
y_test_np = mnist_testset.targets.numpy()

print("Test Set Evaluation for Learning rate = 0.1")
evaluate(model_1, X_test_np, y_test_np)
```

```
Test Set Evaluation for Learning rate = 0.1
Accuracy: 94.2500%
Confusion Matrix:
[[ 963    0    1    1    0    8    5    2    0    0]
 [    0 1113    2    2    0    2    4    2   10    0]
 [   12    2  965    6    4    4   13   11   13    2]
 [    0    0   15  953    0   25    1    8    6    2]
 [    3    2    4    0  906    2   12    2    4   47]
 [    7    1    0   16    2  837   11    1   13    4]
 [   12    3    2    1    7   23  907    0    3    0]
 [    3    8   18    8    1    2    0  972    0   16]
 [    6    4    4   20    5   49    8   10  865    3]
 [   10    5    1    8   15    8    1   13    4  944]]

Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.98      0.96       980
           1       0.98      0.98      0.98      1135
           2       0.95      0.94      0.94      1032
           3       0.94      0.94      0.94      1010
           4       0.96      0.92      0.94       982
           5       0.87      0.94      0.90       892
           6       0.94      0.95      0.94       958
           7       0.95      0.95      0.95      1028
           8       0.94      0.89      0.91       974
           9       0.93      0.94      0.93      1009

    accuracy                           0.94     10000
   macro avg       0.94      0.94      0.94     10000
weighted avg       0.94      0.94      0.94     10000


np.float64(0.9425)
```

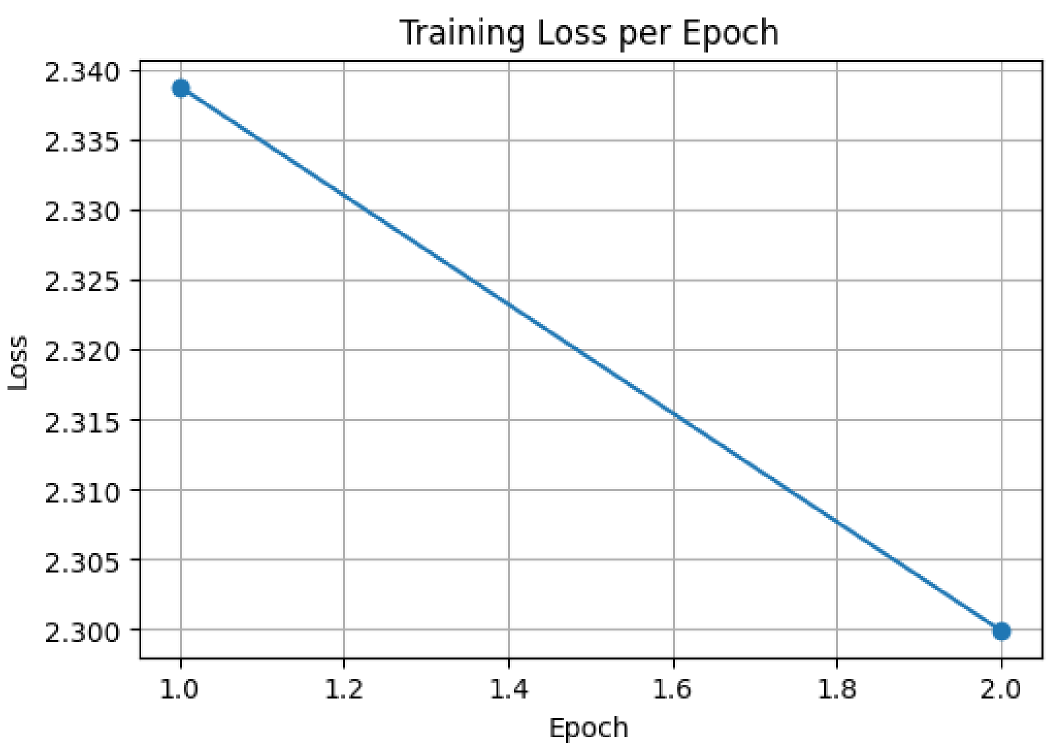
- **Learning rate = 0.001**

```
model_2 = MLP()
loss_history_sigmoid_2, iter_sigmoid_2, iter_loss_sigmoid_2 =
train(model_2, train_loader, 15, 0.001)
```

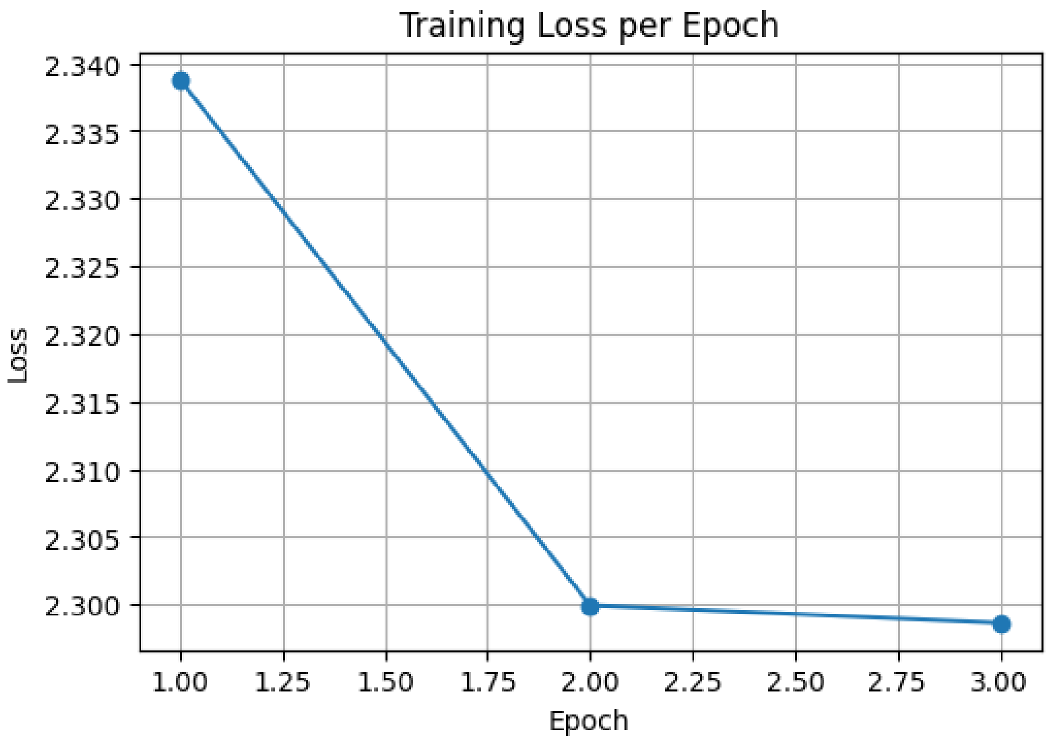
```
Epoch 1/15, Loss: 2.3388
```



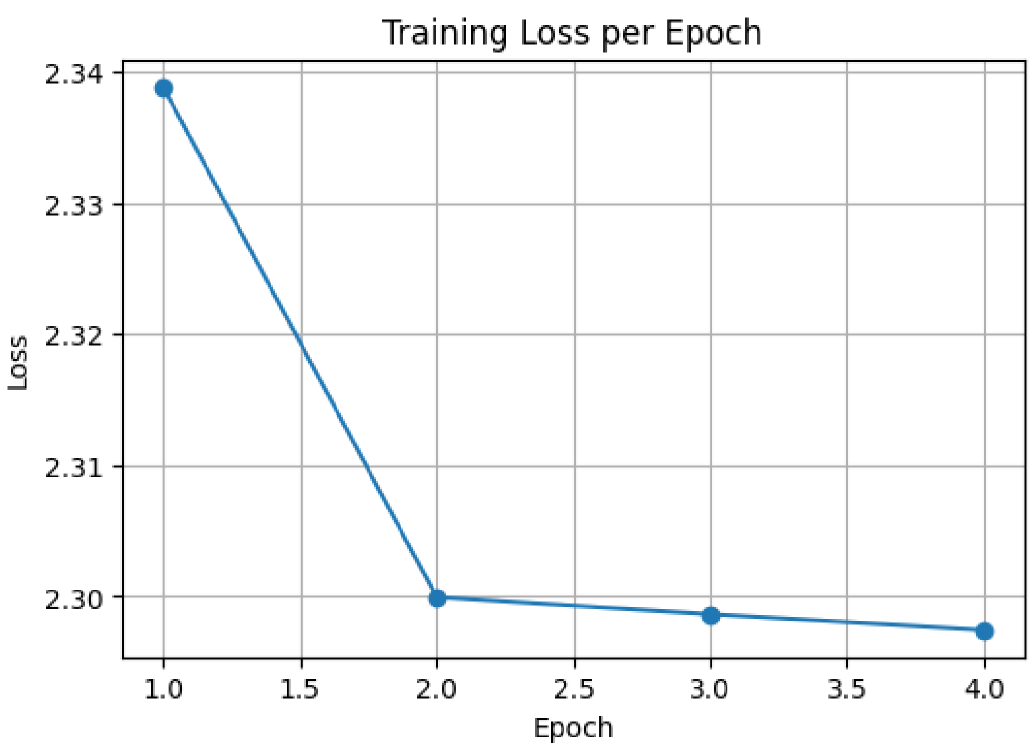

```
Epoch 2/15, Loss: 2.3000
```



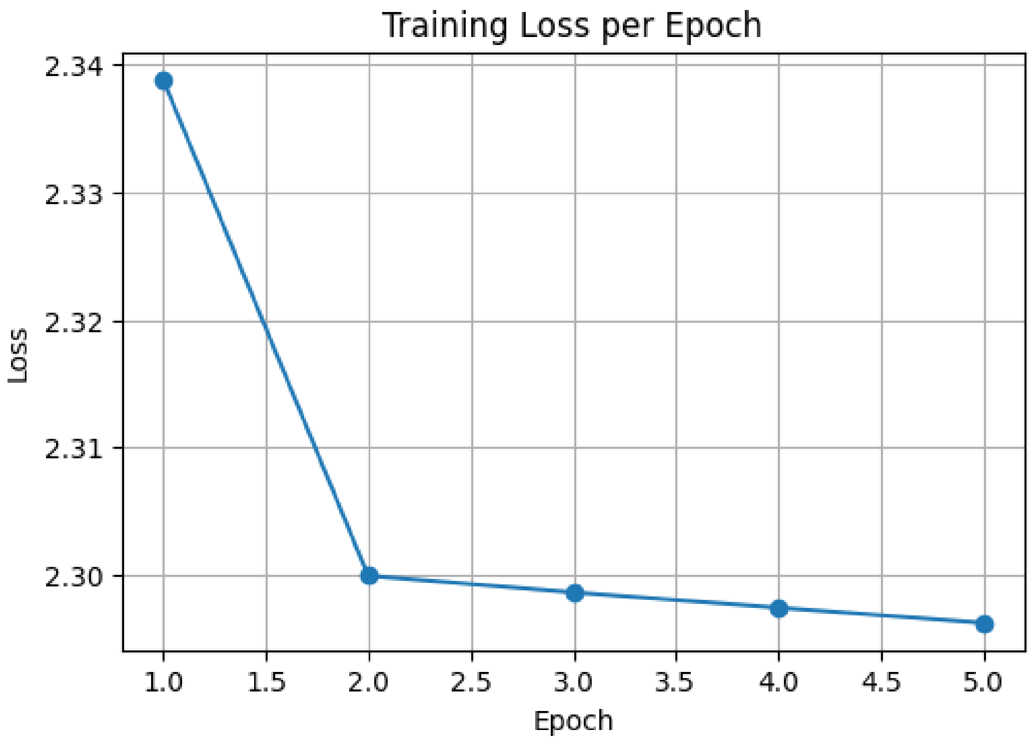

```
Epoch 3/15, Loss: 2.2987
```



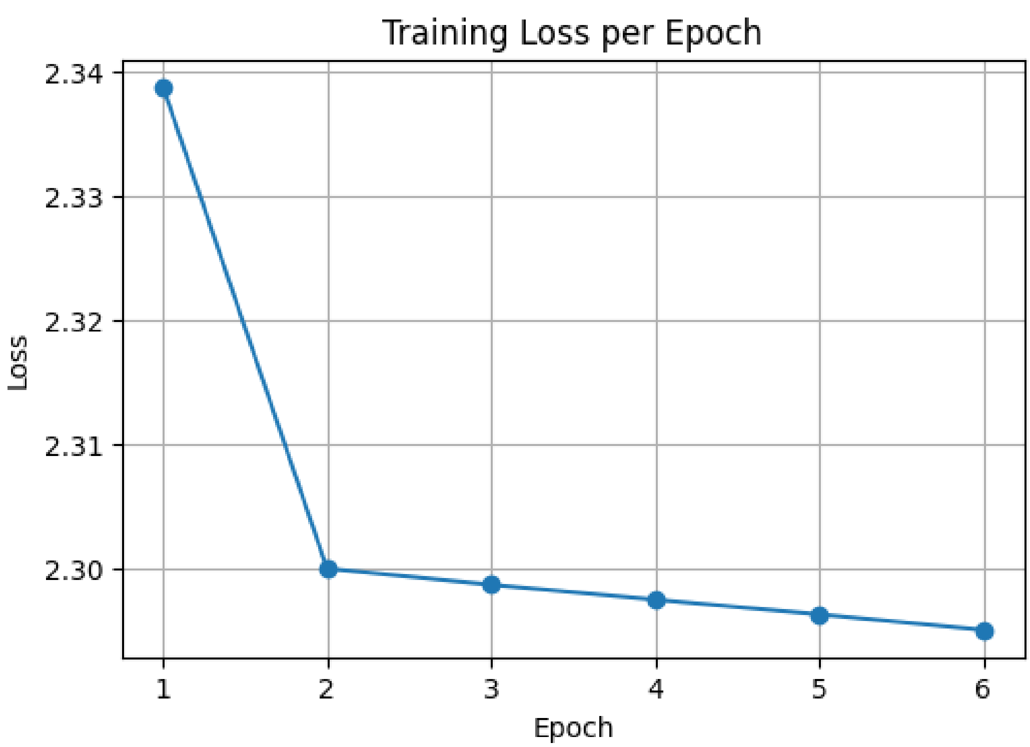

```
Epoch 4/15, Loss: 2.2975
```



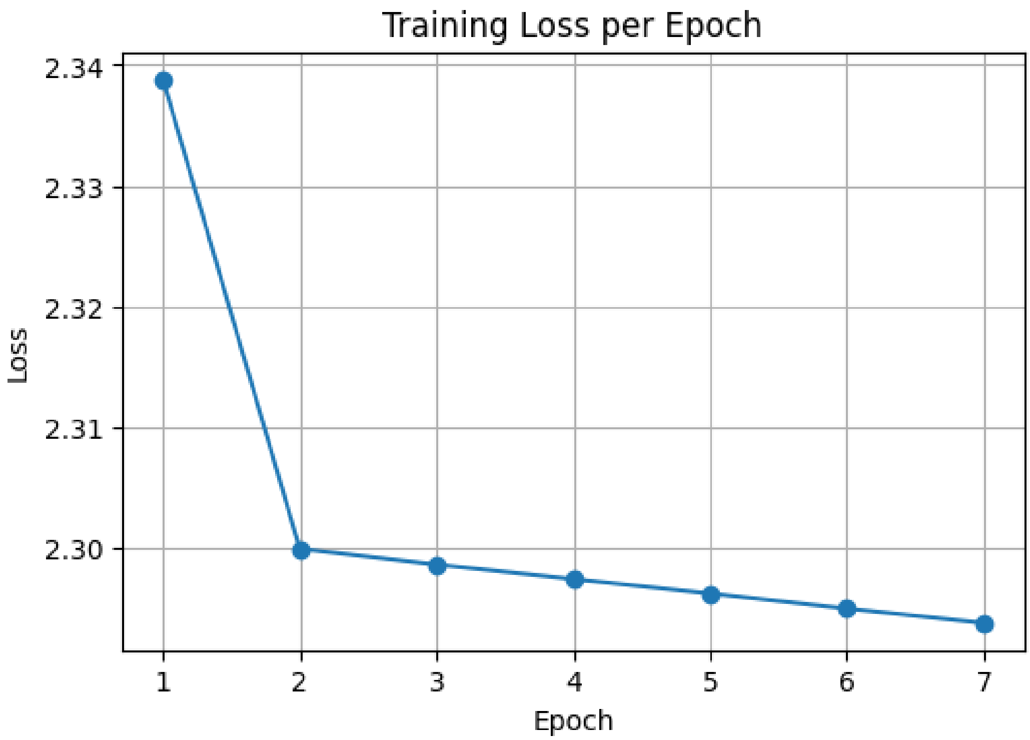

```
Epoch 5/15, Loss: 2.2963
```



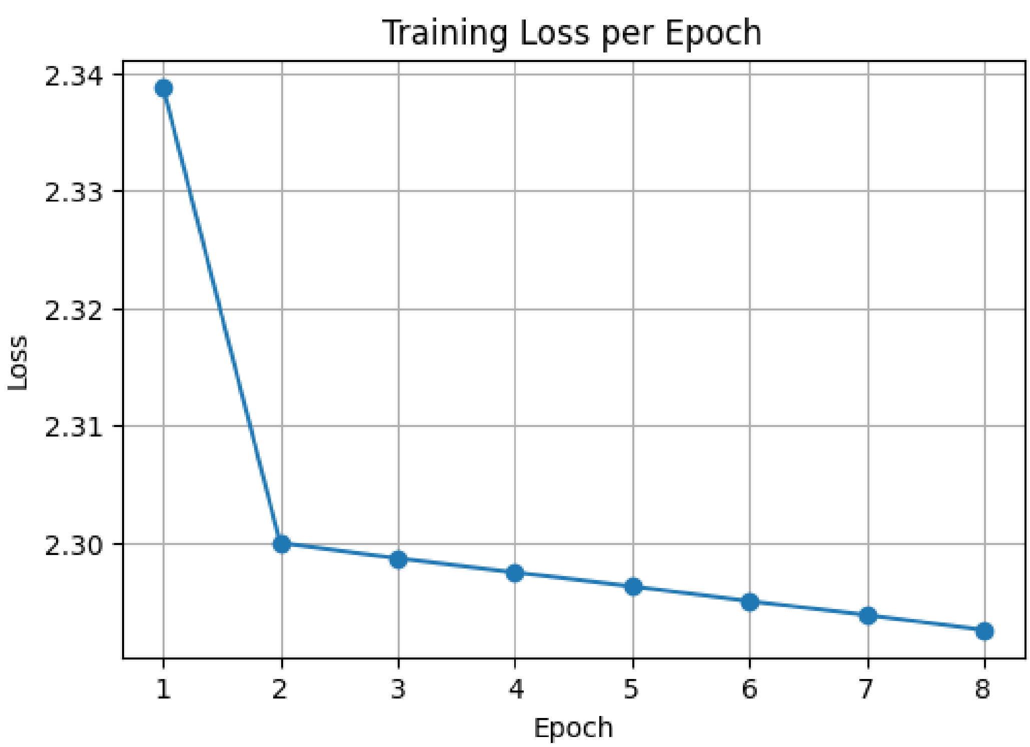

```
Epoch 6/15, Loss: 2.2950
```



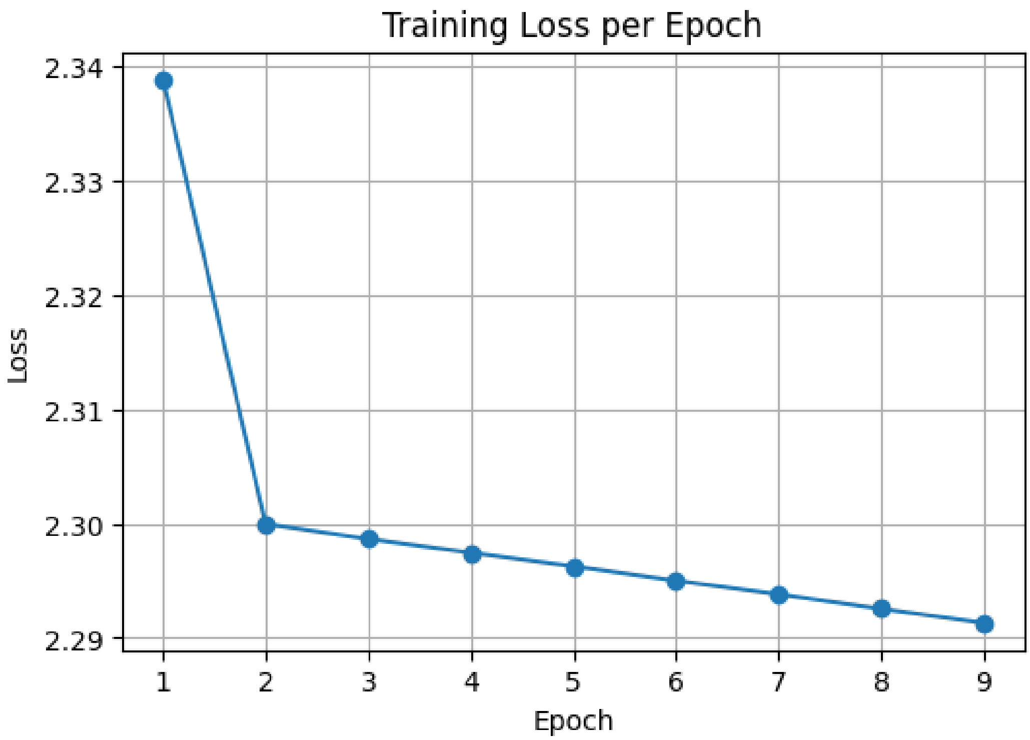

```
Epoch 7/15, Loss: 2.2938
```



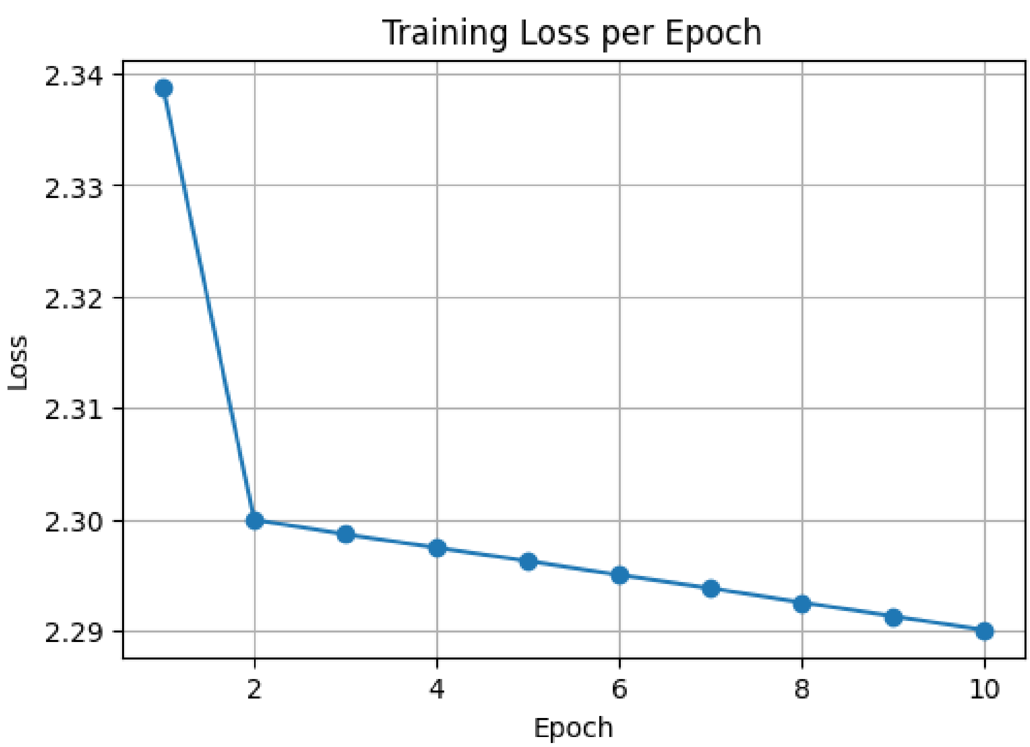

```
Epoch 8/15, Loss: 2.2925
```



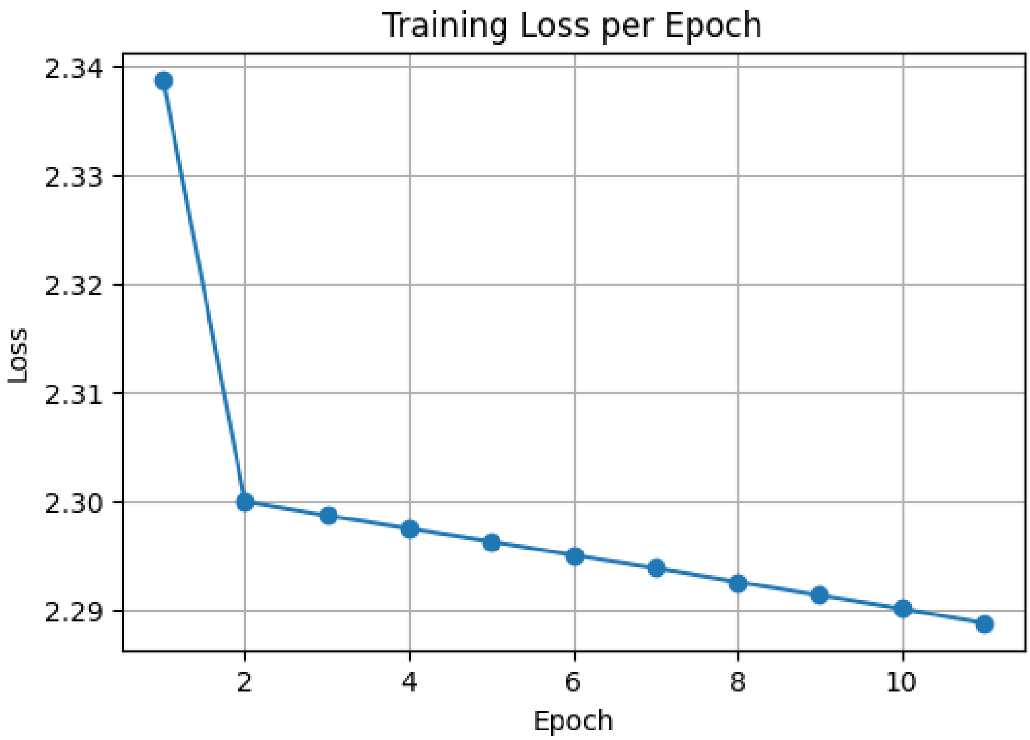

```
Epoch 9/15, Loss: 2.2913
```



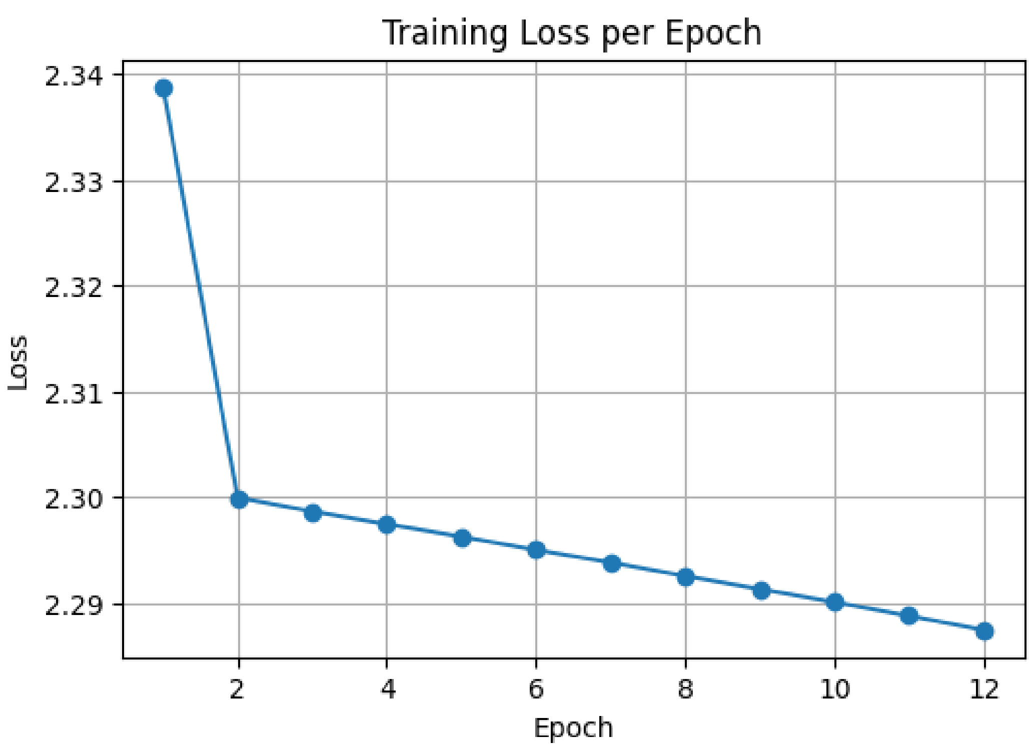

```
Epoch 10/15, Loss: 2.2901
```



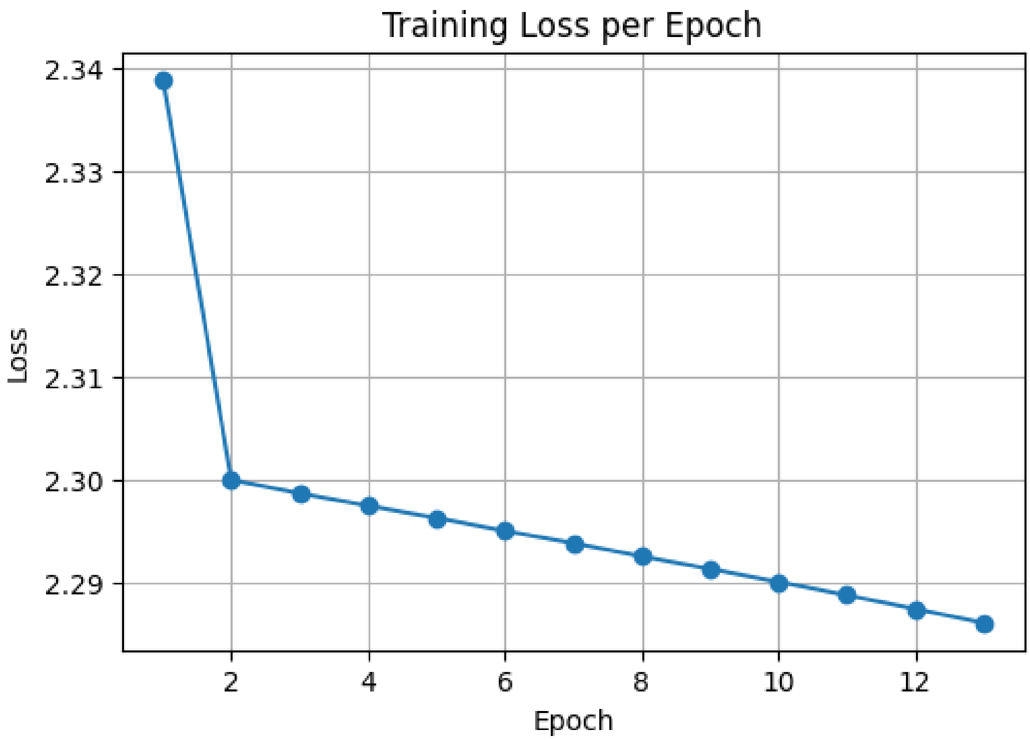

```
Epoch 11/15, Loss: 2.2888
```



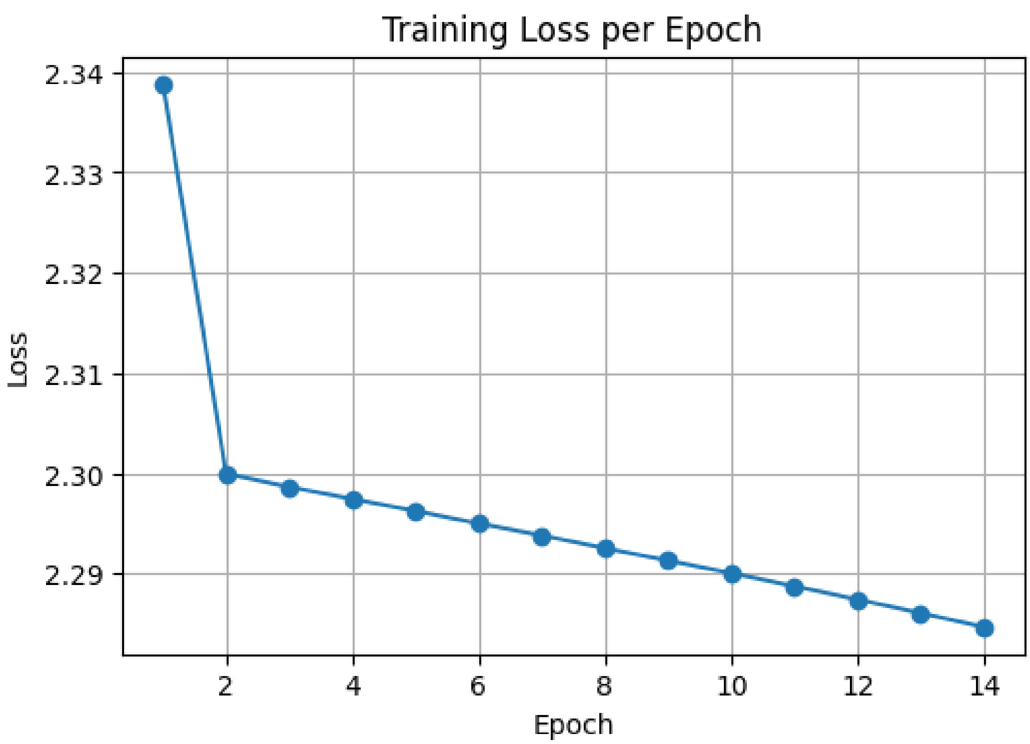

```
Epoch 12/15, Loss: 2.2874
```



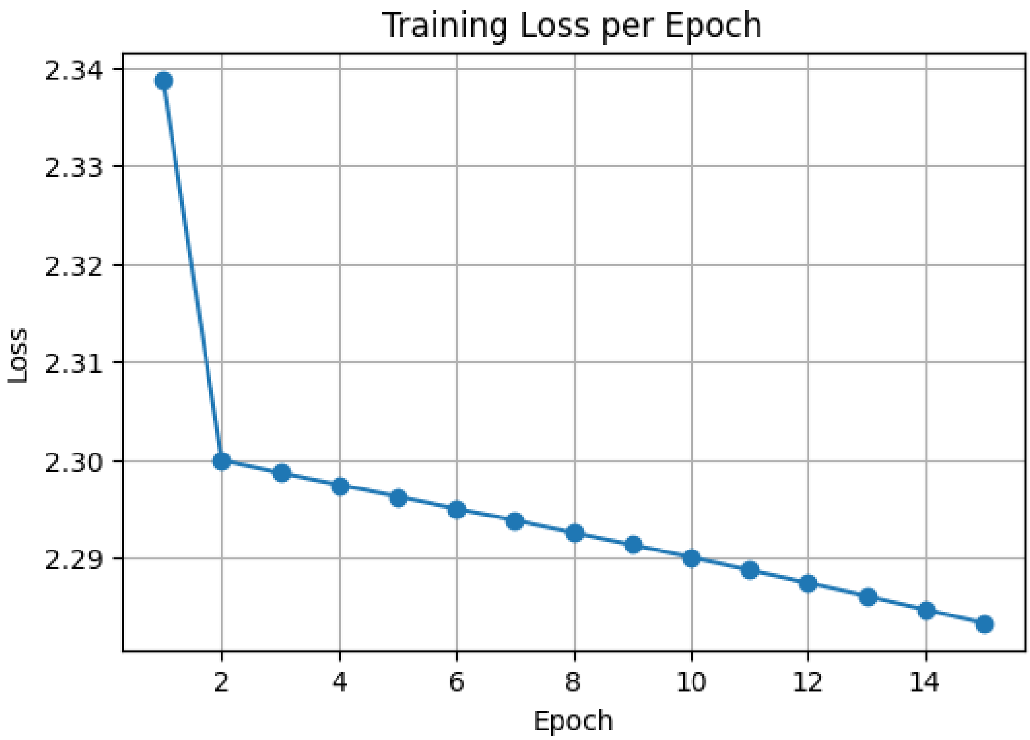

```
Epoch 13/15, Loss: 2.2861
```

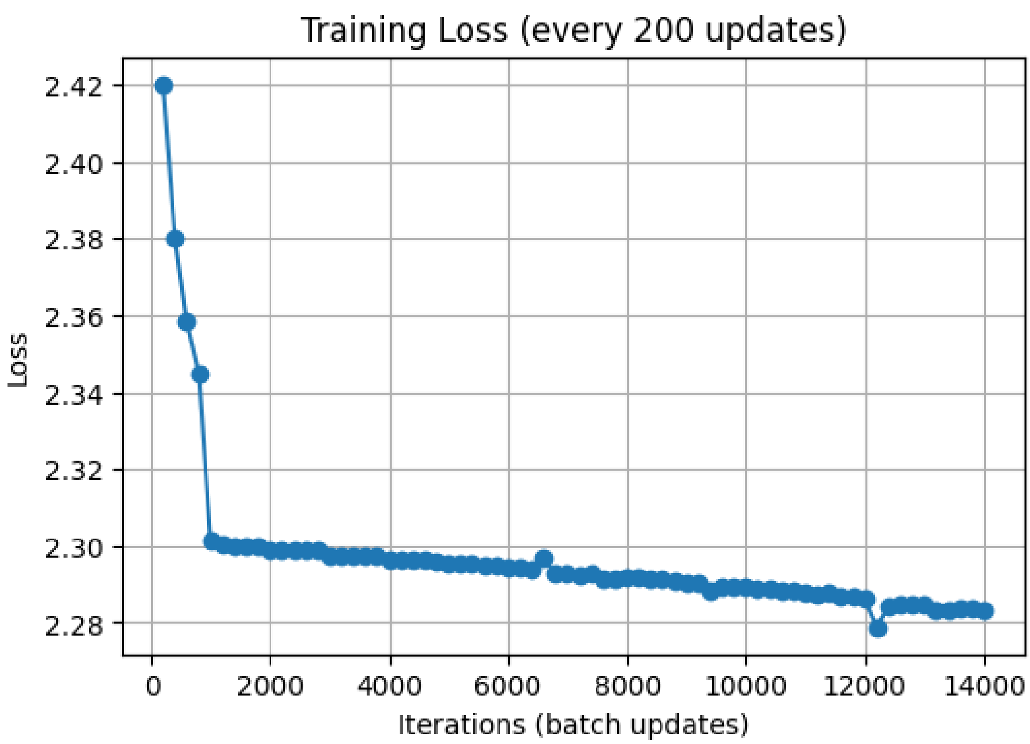



```
Epoch 14/15, Loss: 2.2847
```

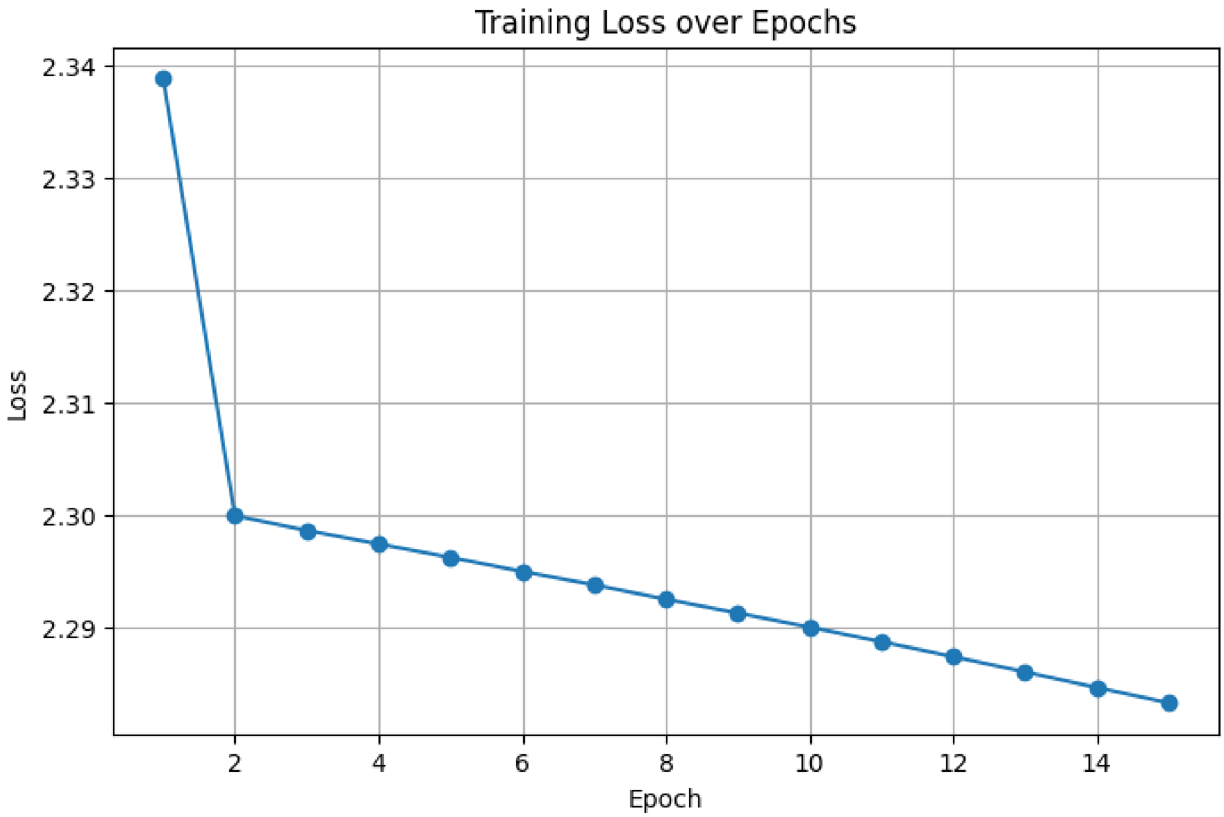



```
Epoch 15/15, Loss: 2.2833
```






```
plot_training_curves(loss_history_sigmoid_2)
```




```
X_test_np = mnist_testset.data.numpy().reshape(-1, 28*28) / 255.0
y_test_np = mnist_testset.targets.numpy()

print("Test Set Evaluation for Learning rate = 0.001")
evaluate(model_2, X_test_np, y_test_np)
```

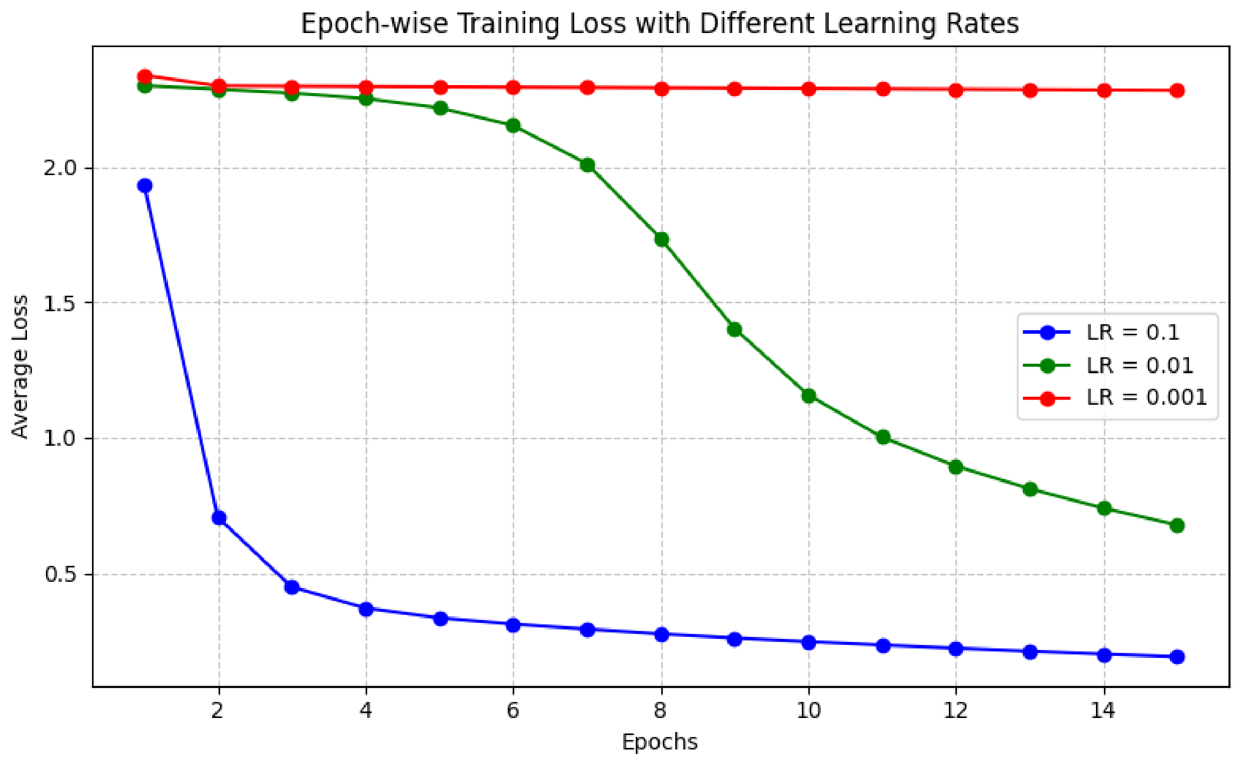
```
Test Set Evaluation for Learning rate = 0.001
Accuracy: 11.5600%
Confusion Matrix:
[[  19  961    0    0    0    0    0    0    0    0]
 [   0 1135    0    0    0    0    0    0    0    0]
 [   0 1032    0    0    0    0    0    0    0    0]
 [   0 1008    0    2    0    0    0    0    0    0]
 [   0  982    0    0    0    0    0    0    0    0]
 [   0  892    0    0    0    0    0    0    0    0]
 [   0  958    0    0    0    0    0    0    0    0]
 [   0 1028    0    0    0    0    0    0    0    0]
 [   0  974    0    0    0    0    0    0    0    0]
 [   0 1009    0    0    0    0    0    0    0    0]]

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.02      0.04       980
           1       0.11      1.00      0.20      1135
```

```
           2       0.00      0.00      0.00      1032
           3       1.00      0.00      0.00      1010
           4       0.00      0.00      0.00       982
           5       0.00      0.00      0.00       892
           6       0.00      0.00      0.00       958
           7       0.00      0.00      0.00      1028
           8       0.00      0.00      0.00       974
           9       0.00      0.00      0.00      1009

    accuracy                           0.12     10000
   macro avg       0.21      0.10      0.02     10000
weighted avg       0.21      0.12      0.03     10000
```

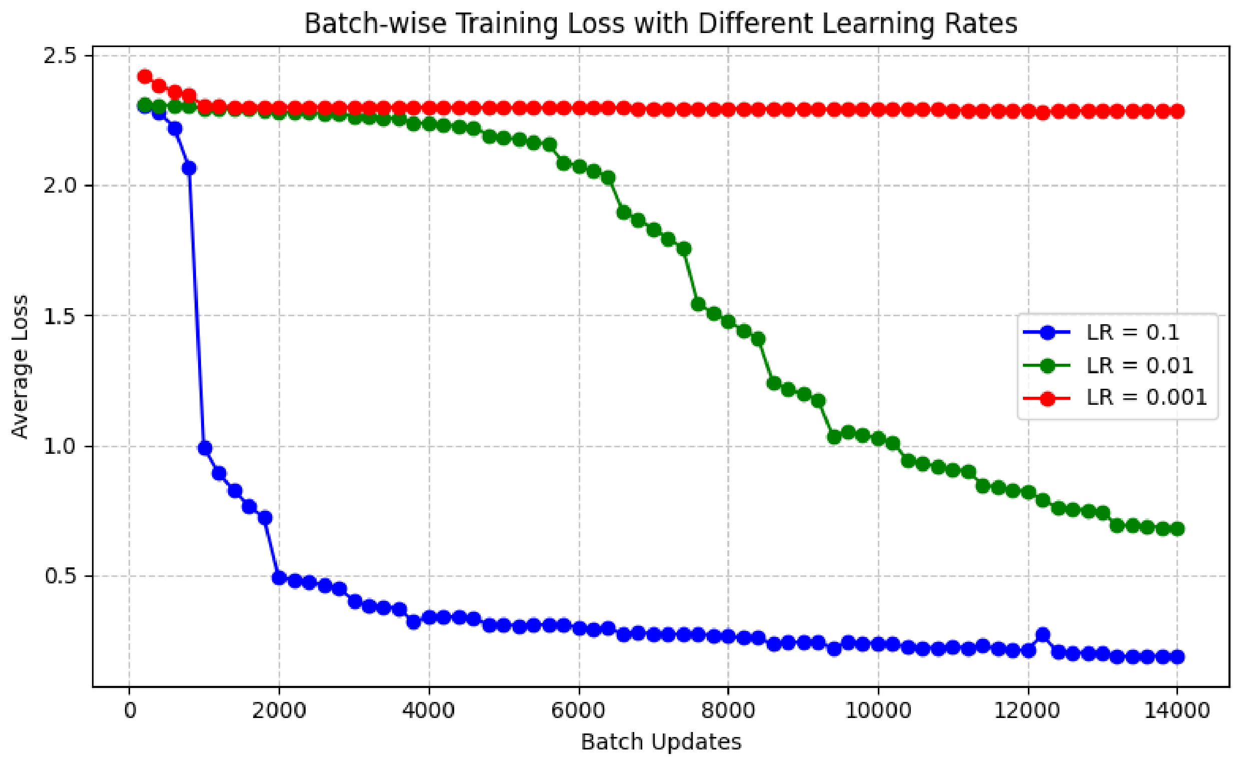
```
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/
_classification.py:1565: UndefinedMetricWarning: Precision is ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classificatio
n.py:1565: UndefinedMetricWarning: Precision is ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classificatio
n.py:1565: UndefinedMetricWarning: Precision is ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
```

```
np.float64(0.1156)
```

```
plt.figure(figsize=(8,5))
plt.plot(range(1, len(loss_history_sigmoid_1)+1),
loss_history_sigmoid_1, marker='o', color='b', label="LR = 0.1")
plt.plot(range(1, len(loss_history)+1), loss_history, marker='o',
color='g', label="LR = 0.01")
plt.plot(range(1, len(loss_history_sigmoid_2)+1),
loss_history_sigmoid_2, marker='o', color='r', label="LR = 0.001")
plt.title("Epoch-wise Training Loss with Different Learning Rates")
plt.xlabel("Epochs")
plt.ylabel("Average Loss")
plt.legend()
plt.grid(True, linestyle="--", alpha=0.7)
plt.tight_layout()
plt.show()
```




```
plt.figure(figsize=(8,5))
plt.plot(iter_sigmoid_1, iter_loss_sigmoid_1, marker='o', color='b',
label="LR = 0.1")
plt.plot(iter_tanh, iter_loss, marker='o', color='g', label="LR =
0.01")
plt.plot(iter_sigmoid_2, iter_loss_sigmoid_2, marker='o', color='r',
label="LR = 0.001")
plt.title("Batch-wise Training Loss with Different Learning Rates")
plt.xlabel("Batch Updates")
plt.ylabel("Average Loss")
plt.legend()
plt.grid(True, linestyle="--", alpha=0.7)
plt.tight_layout()
plt.show()
```



Observations and Conclusions for different learning rates for the baseline model using Sigmoid Activation

- Test Accuracy with learning rate = 0.001 -> **11.56%**
- Test Accuracy with learning rate = 0.01 -> **82.30%** (Baseline model)
- Test Accuracy with learning rate = 0.1 -> **94.25%**

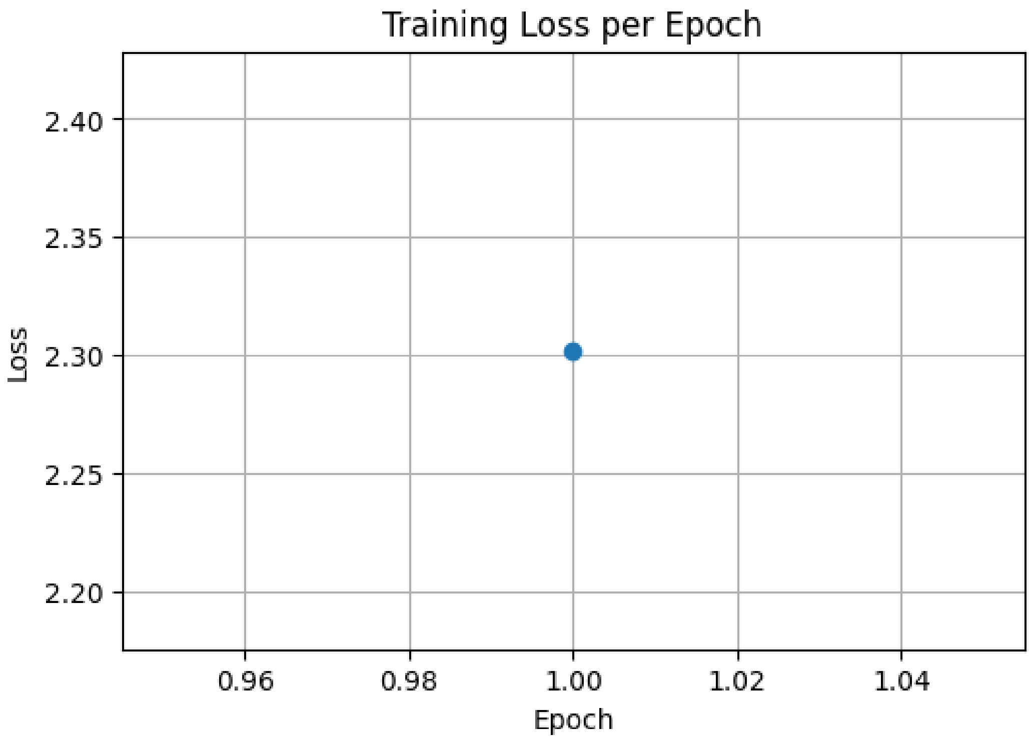
Higher Learning rate leads to better test accuracy and lesser loss in training. Increasing the learning rate helped in improving the baseline model quite drastically

Analyzing the MLP baseline model for different num of epochs using Sigmoid activation function

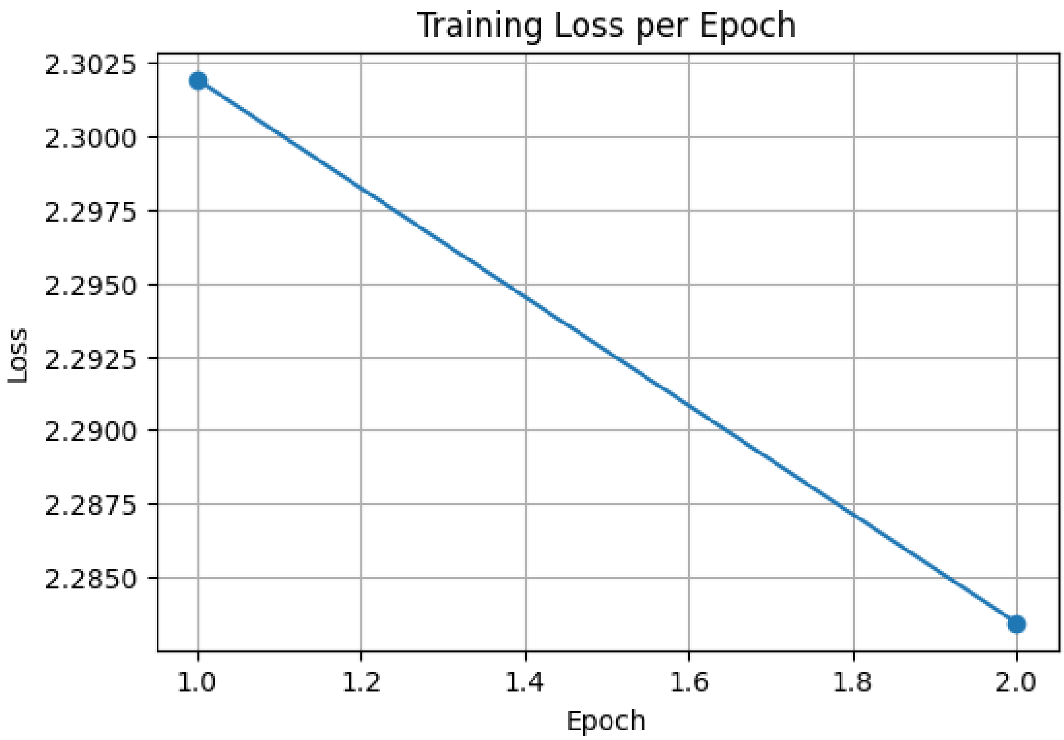
Number of Epochs = 10

```
model_3 = MLP()
loss_history_sigmoid_3, iter_sigmoid_3, iter_loss_sigmoid_3 =
train(model_3, train_loader, 10, 0.01)
```

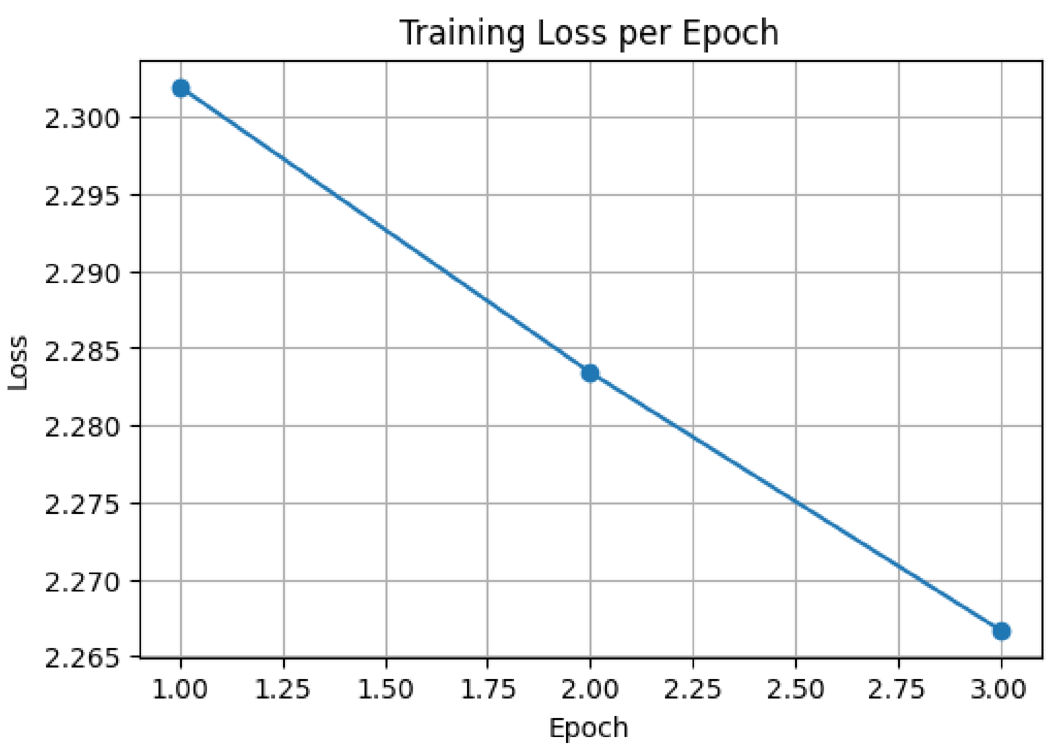
```
Epoch 1/10, Loss: 2.3019
```



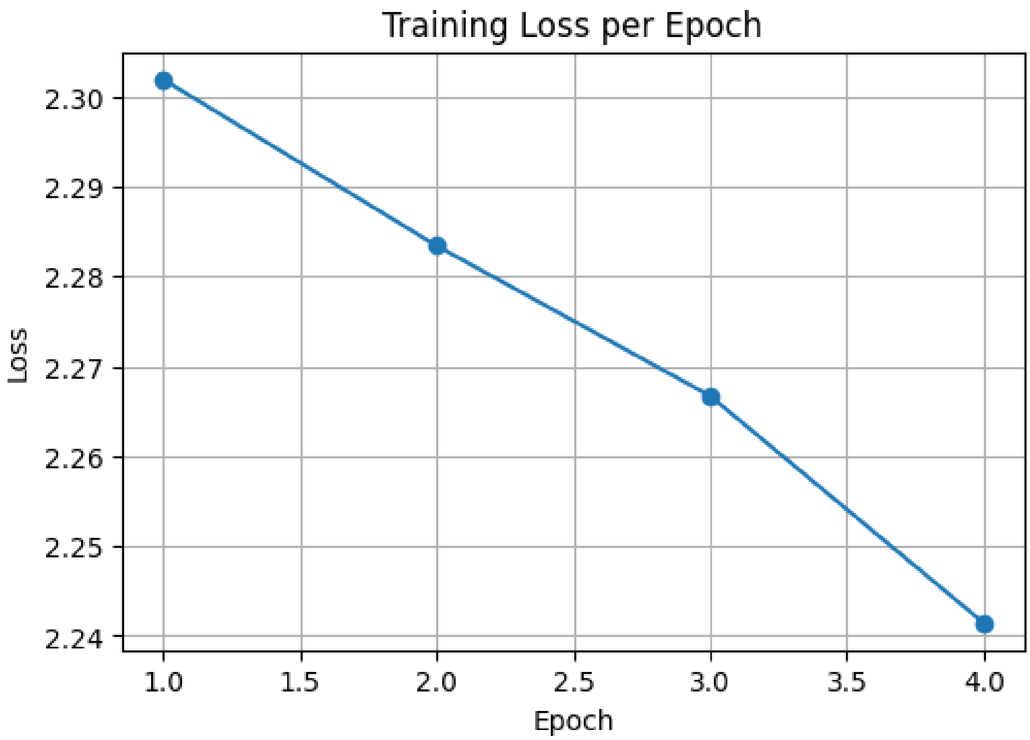

```
Epoch 2/10, Loss: 2.2834
```



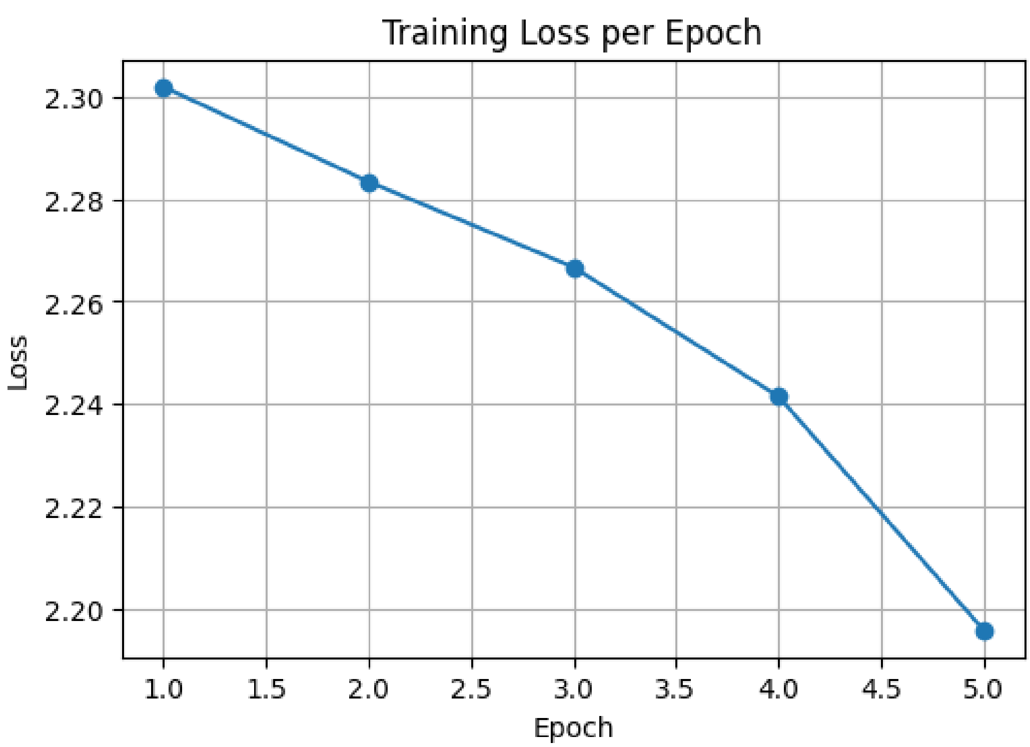

```
Epoch 3/10, Loss: 2.2667
```



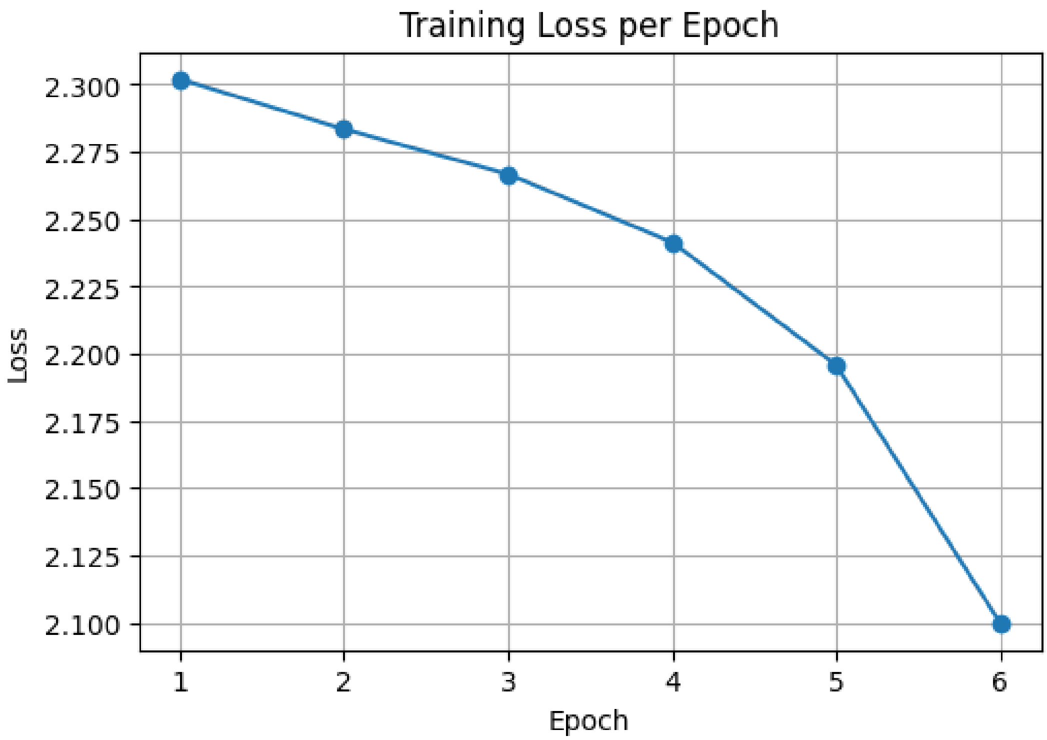

```
Epoch 4/10, Loss: 2.2415
```



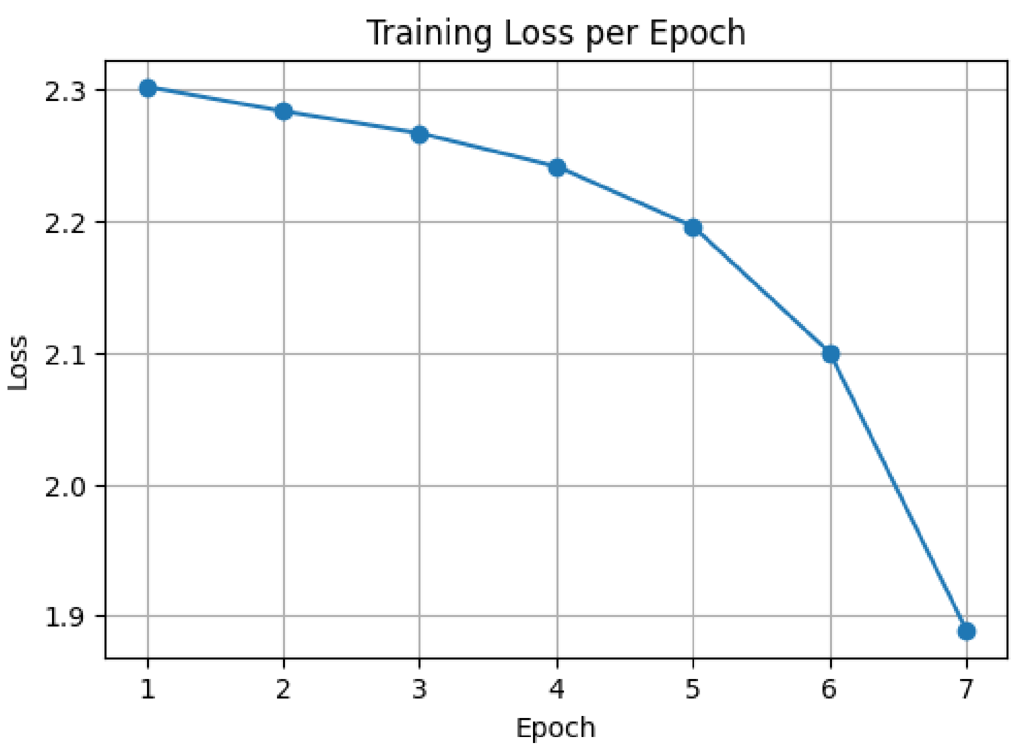

```
Epoch 5/10, Loss: 2.1958
```



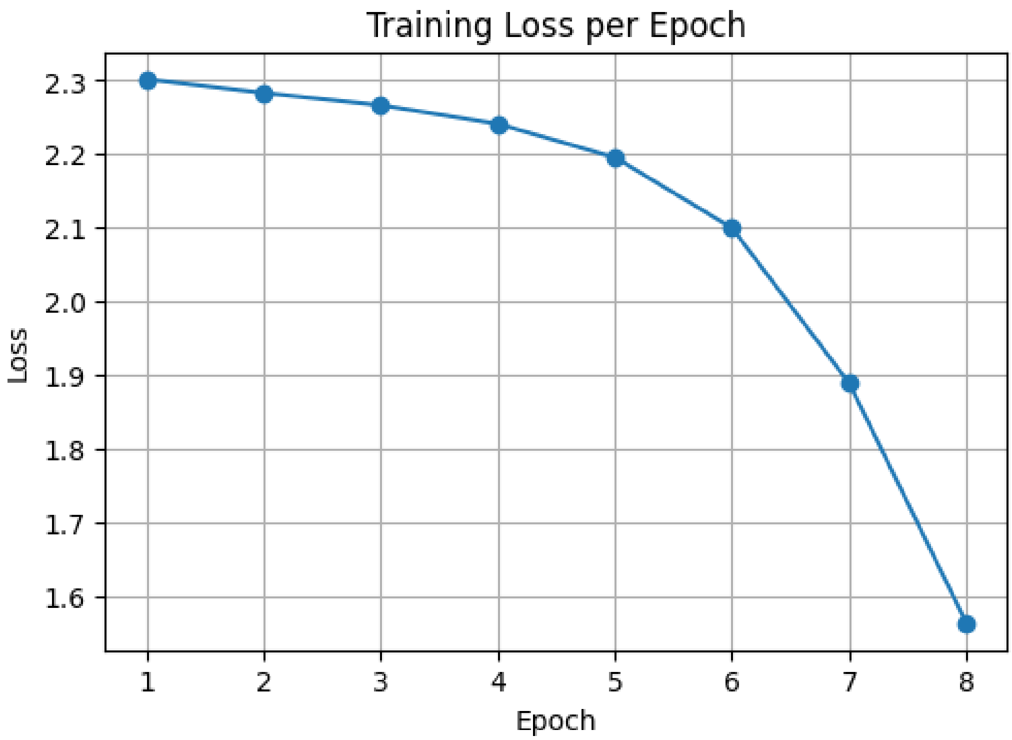

```
Epoch 6/10, Loss: 2.1000
```



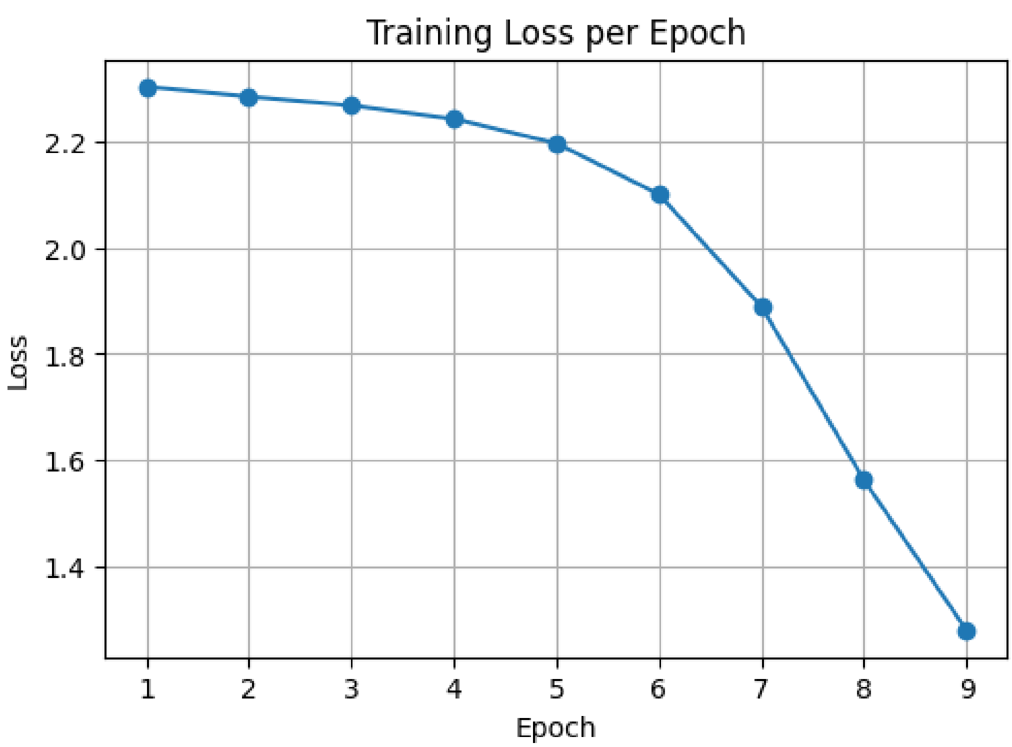

```
Epoch 7/10, Loss: 1.8891
```



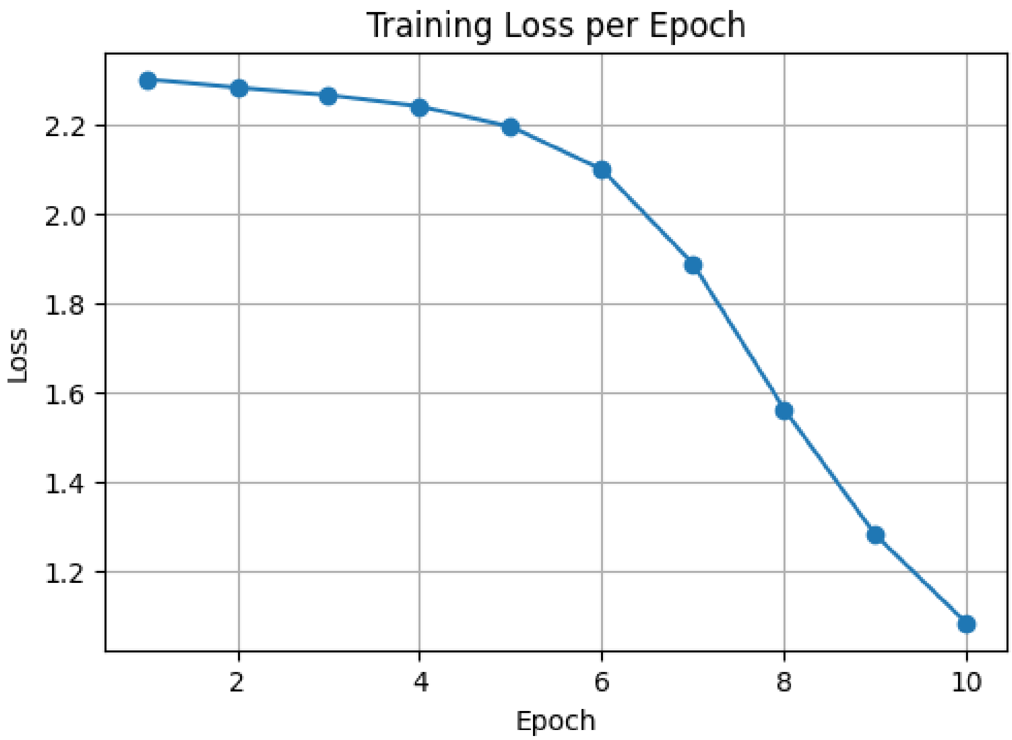

```
Epoch 8/10, Loss: 1.5635
```

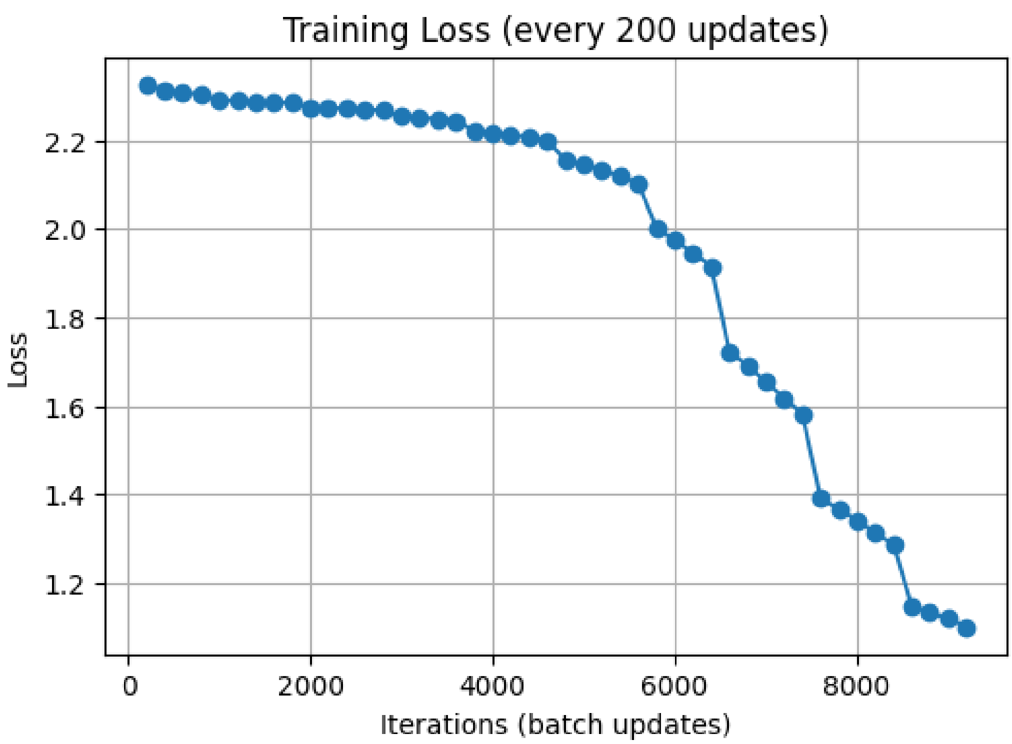



```
Epoch 9/10, Loss: 1.2815
```

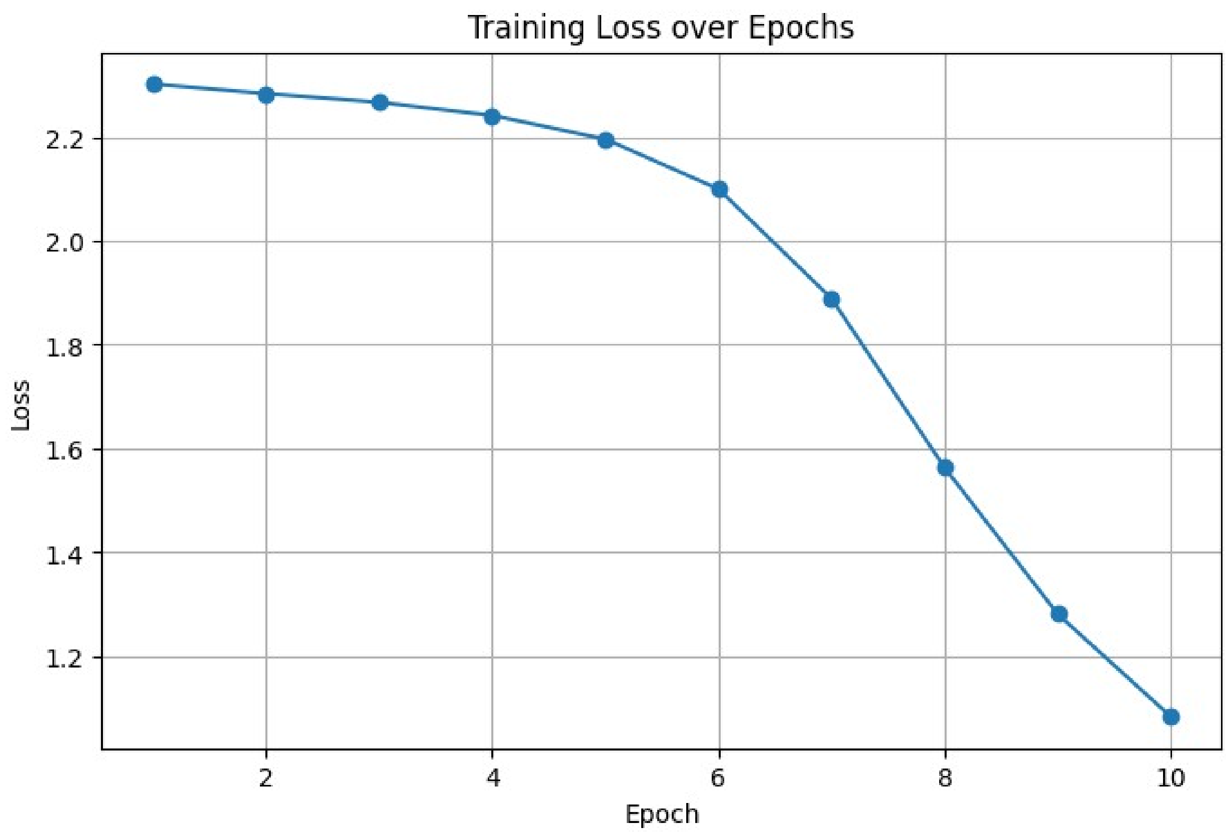



```
Epoch 10/10, Loss: 1.0842
```






```
plot_training_curves(loss_history_sigmoid_3)
```



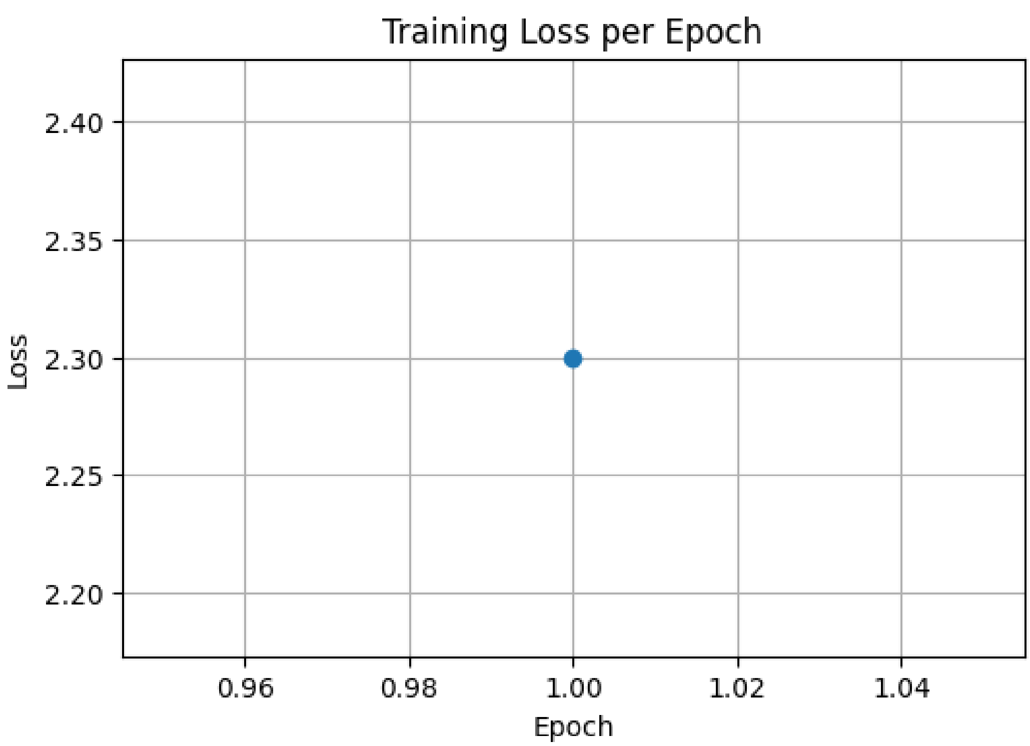

```
X_test_np = mnist_testset.data.numpy().reshape(-1, 28*28) / 255.0
y_test_np = mnist_testset.targets.numpy()

print("Test Set Evaluation for 10 epochs")
evaluate(model_3, X_test_np, y_test_np)

Test Set Evaluation for 10 epochs
Accuracy: 69.7600%
Confusion Matrix:
[[ 942    0    1    4    1   21    8    1    2    0]
 [   0 1121    4    5    0    0    1    0    3    1]
 [  34   42  705   67   30   10  114    7   20    3]
 [   8   32   53  829    3   41    1   17   18    8]
 [   1   28    2    0  607    0   50   20    1  273]
 [  57   16   35  269   18  353   34   56   36   18]
 [  39    7   61    0   18    8  815    0   10    0]
 [   4   71    8    2   14    9    1  852    8   59]
 [  40  127  114  292   15   42   21   24  262   37]
 [  16   26    1   11  185    9    8  263    0  490]]

Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.96      0.89       980
```

```
           1       0.76      0.99      0.86      1135
           2       0.72      0.68      0.70      1032
           3       0.56      0.82      0.67      1010
           4       0.68      0.62      0.65       982
           5       0.72      0.40      0.51       892
           6       0.77      0.85      0.81       958
           7       0.69      0.83      0.75      1028
           8       0.73      0.27      0.39       974
           9       0.55      0.49      0.52      1009

    accuracy                           0.70     10000
   macro avg       0.70      0.69      0.67     10000
weighted avg       0.70      0.70      0.68     10000


np.float64(0.6976)
```

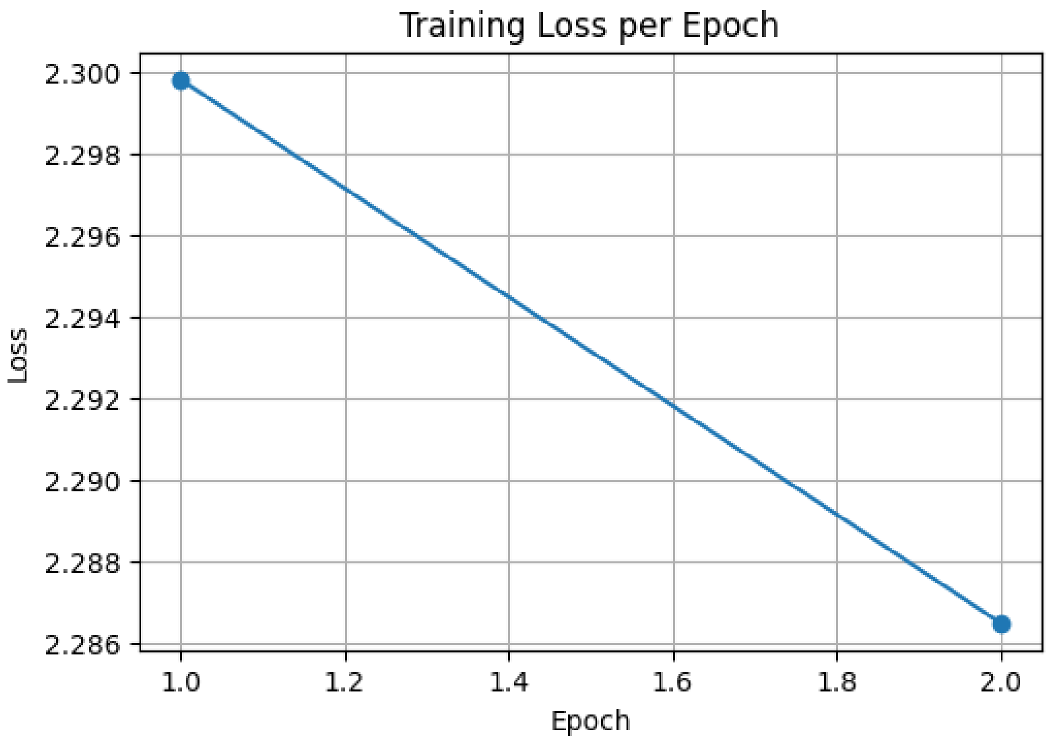
Number of Epochs = 20

```
model_4 = MLP()
loss_history_sigmoid_4, iter_sigmoid_4, iter_loss_sigmoid_4 =
train(model_4, train_loader, 20, 0.01)
```

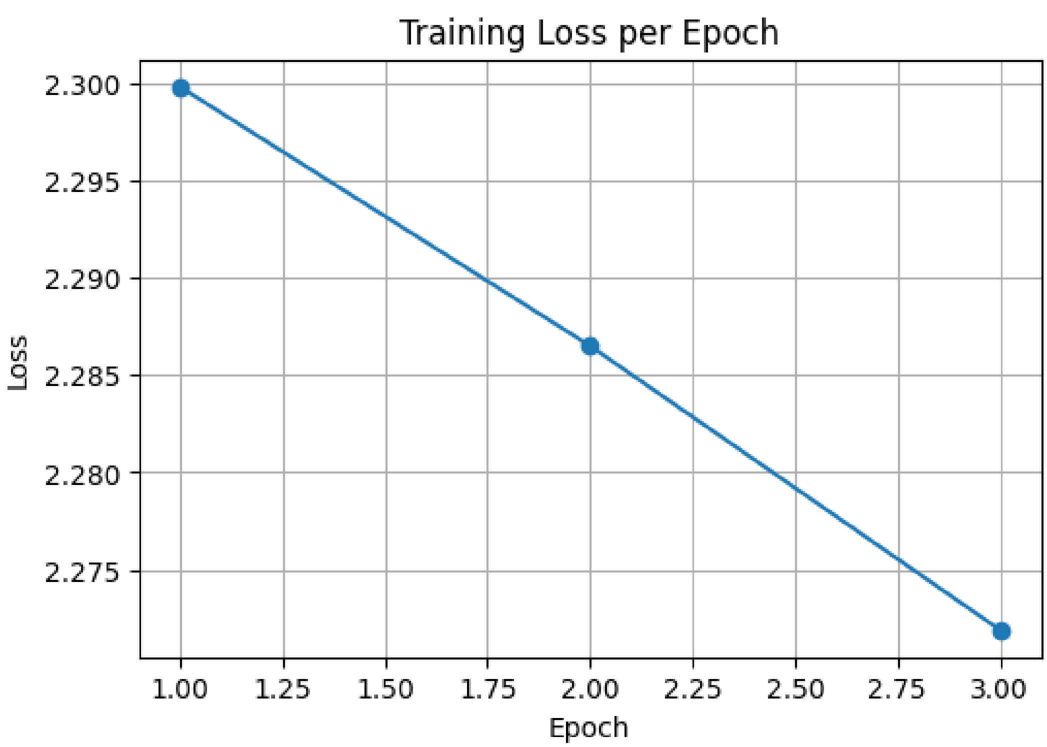
```
Epoch 1/20, Loss: 2.2998
```



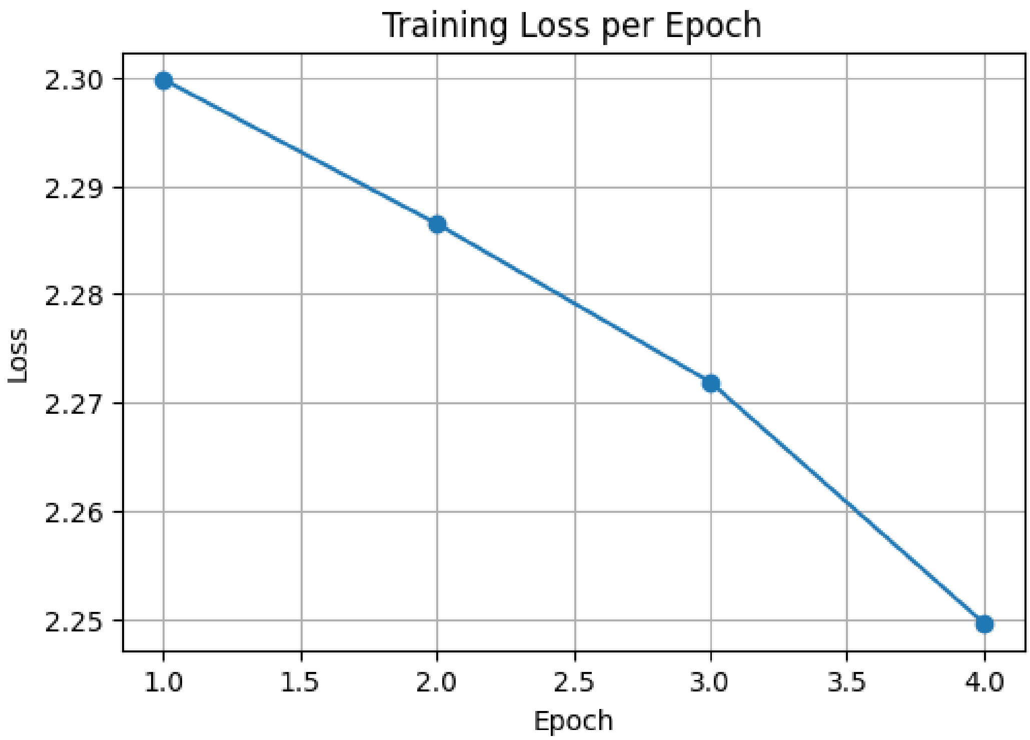

```
Epoch 2/20, Loss: 2.2865
```



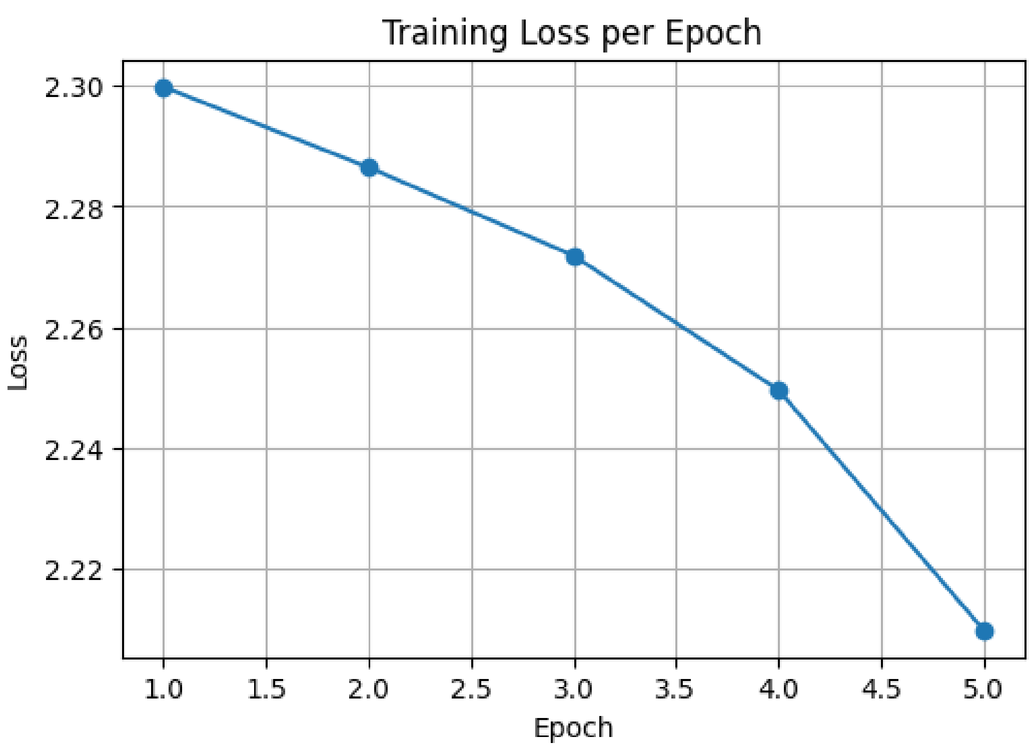

```
Epoch 3/20, Loss: 2.2719
```



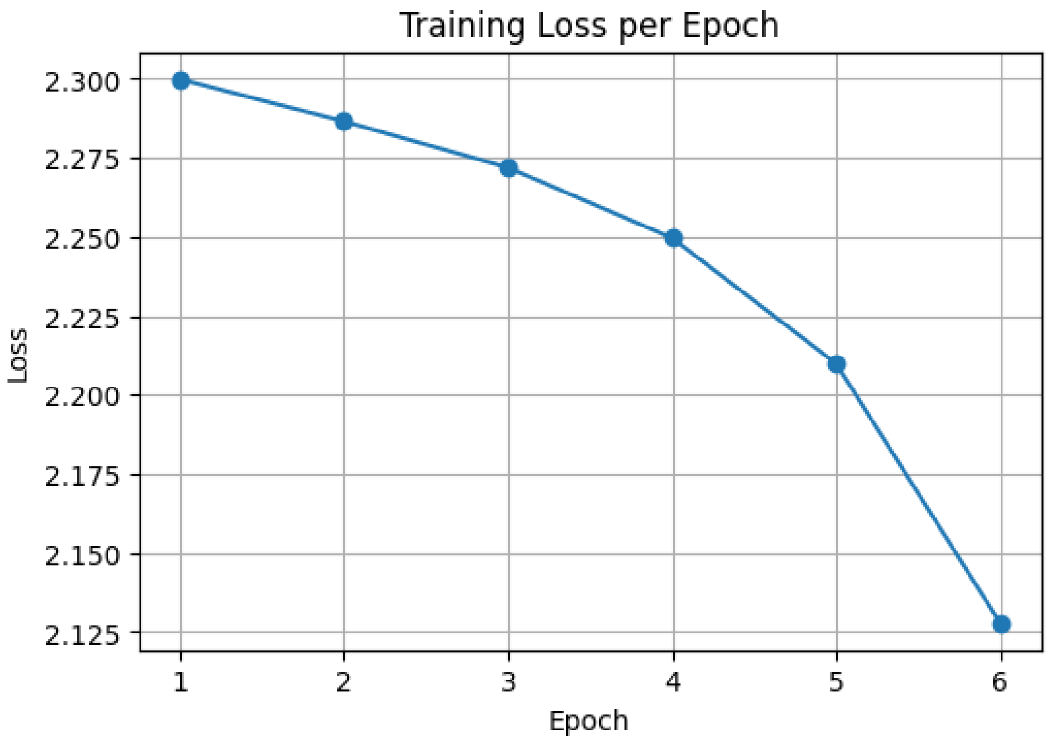

```
Epoch 4/20, Loss: 2.2496
```



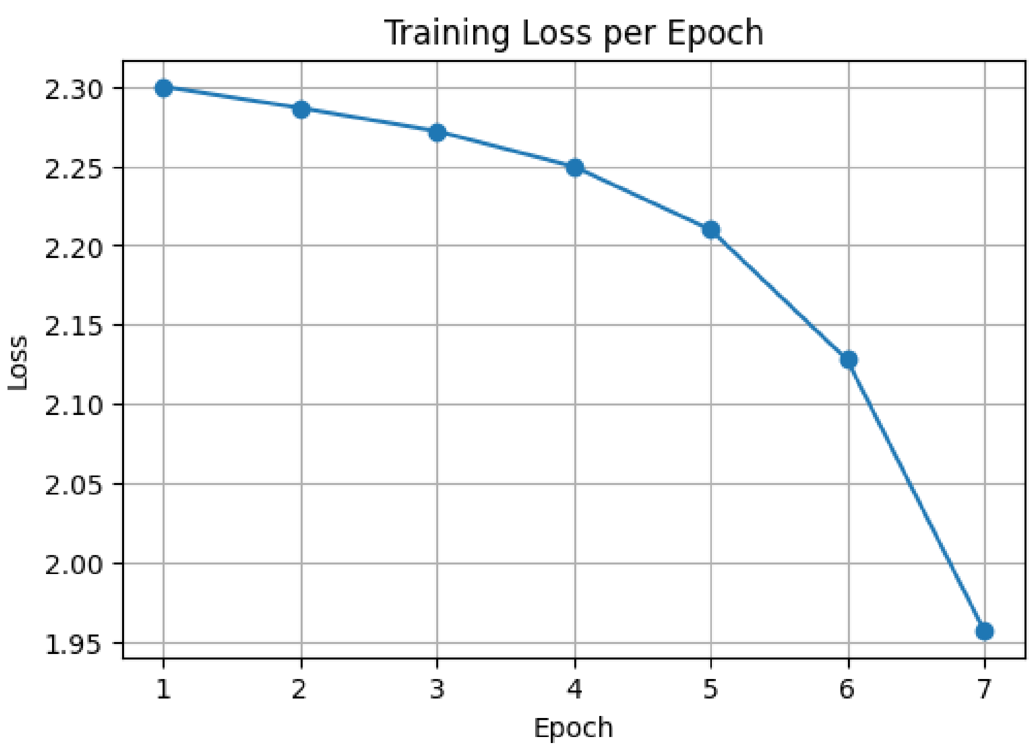

```
Epoch 5/20, Loss: 2.2099
```



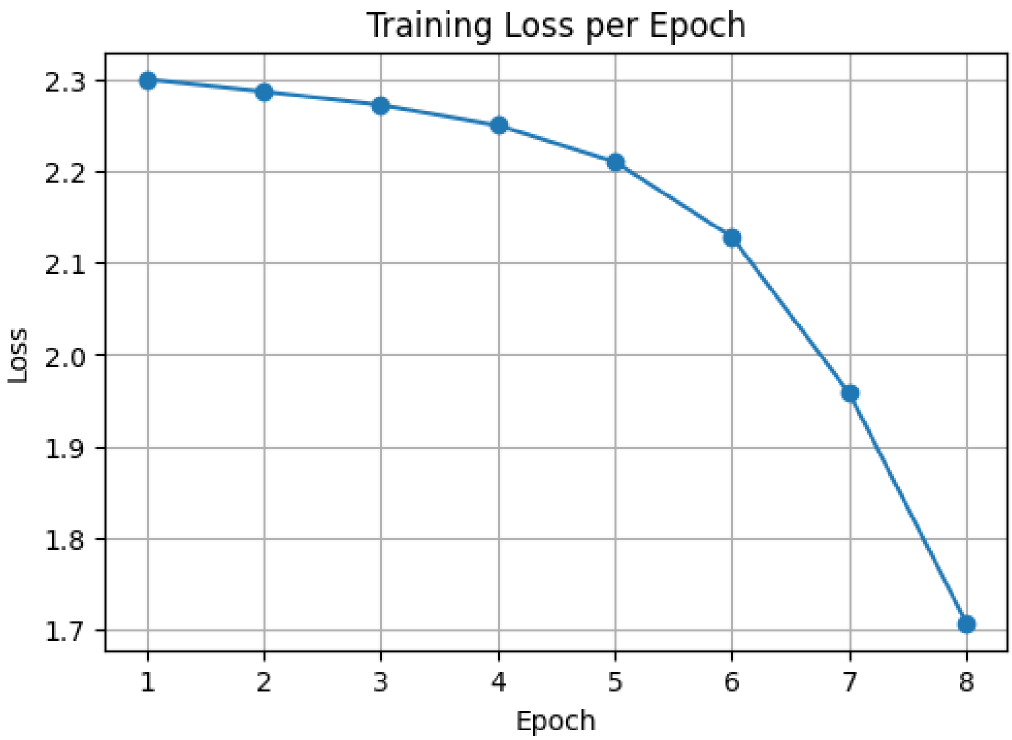

```
Epoch 6/20, Loss: 2.1279
```



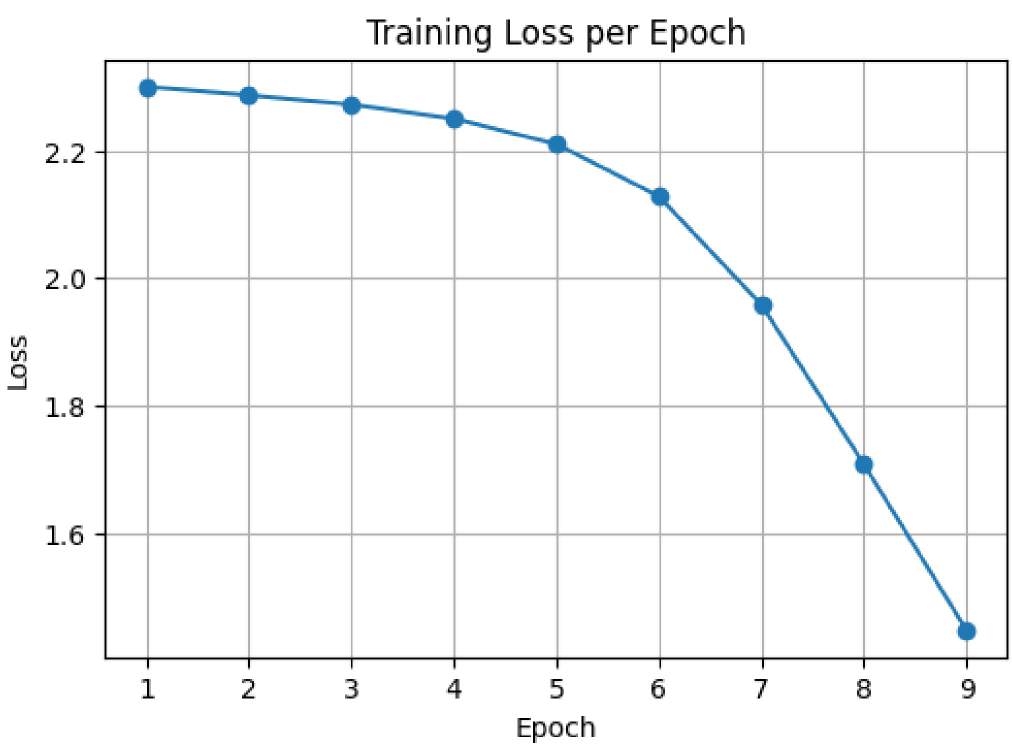

```
Epoch 7/20, Loss: 1.9578
```



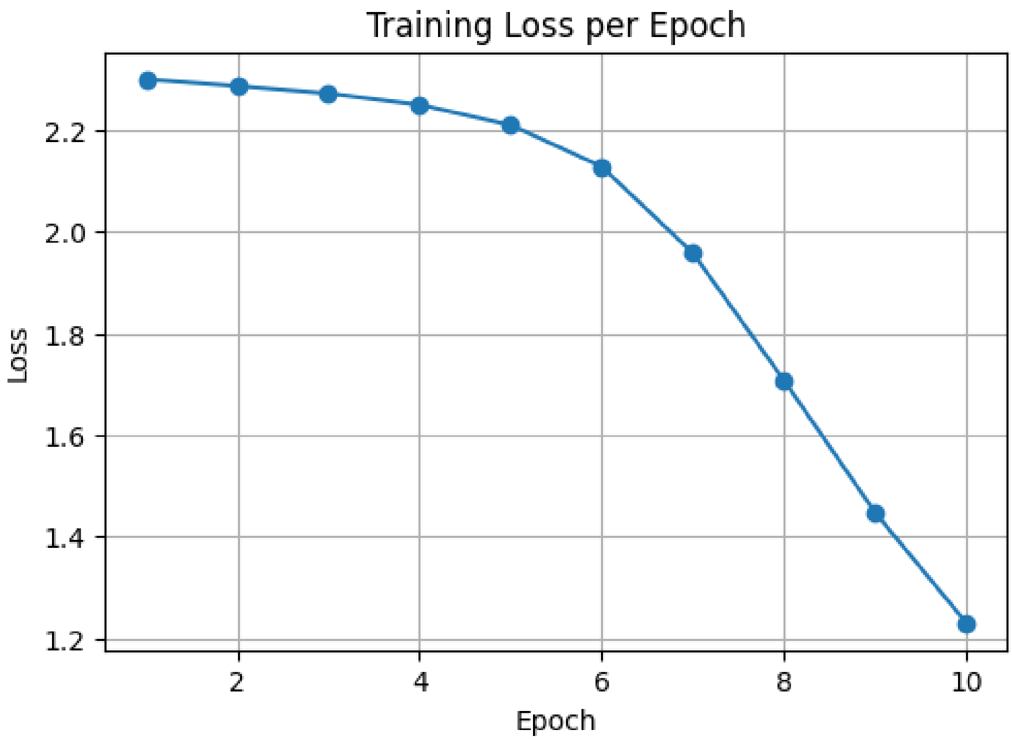

```
Epoch 8/20, Loss: 1.7073
```



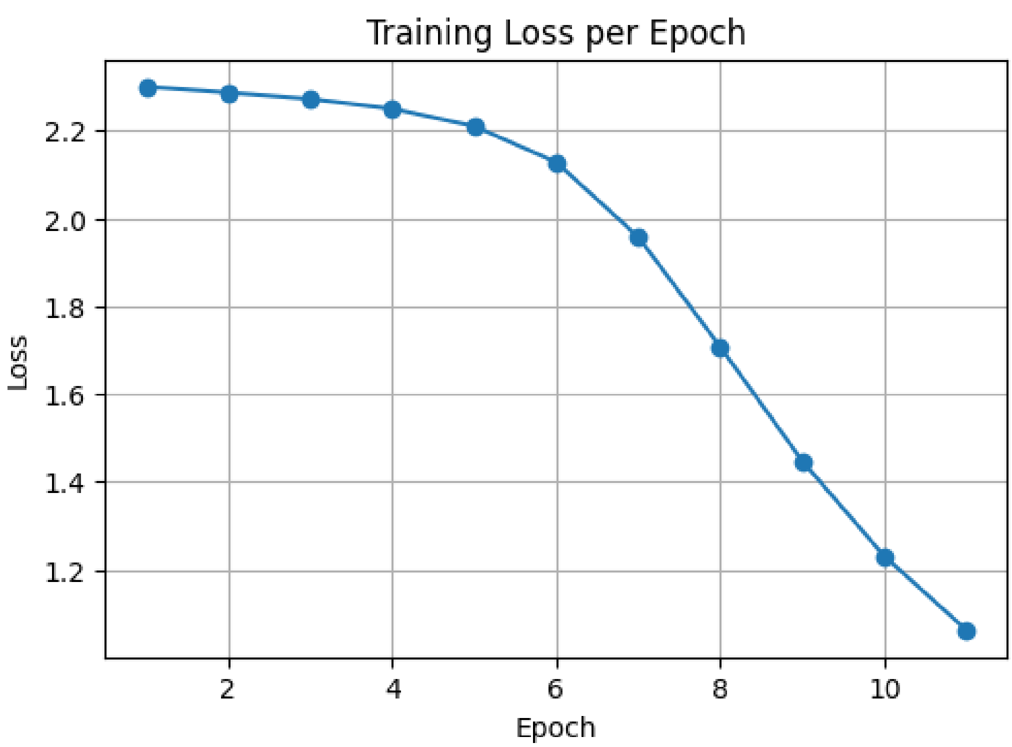

```
Epoch 9/20, Loss: 1.4472
```



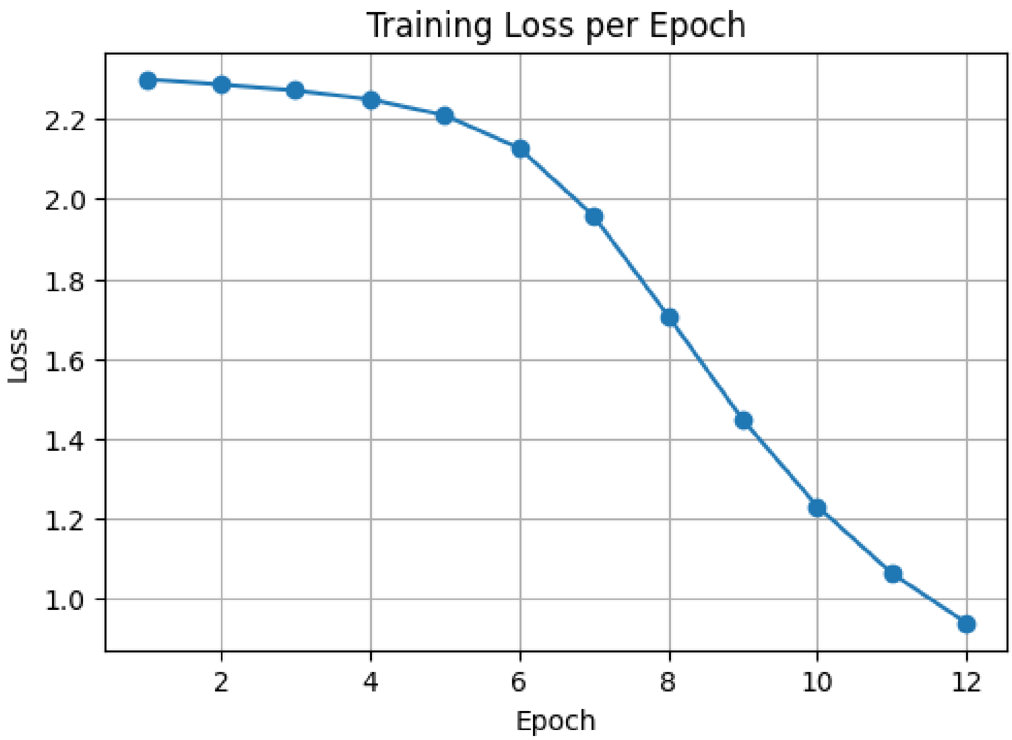

```
Epoch 10/20, Loss: 1.2305
```



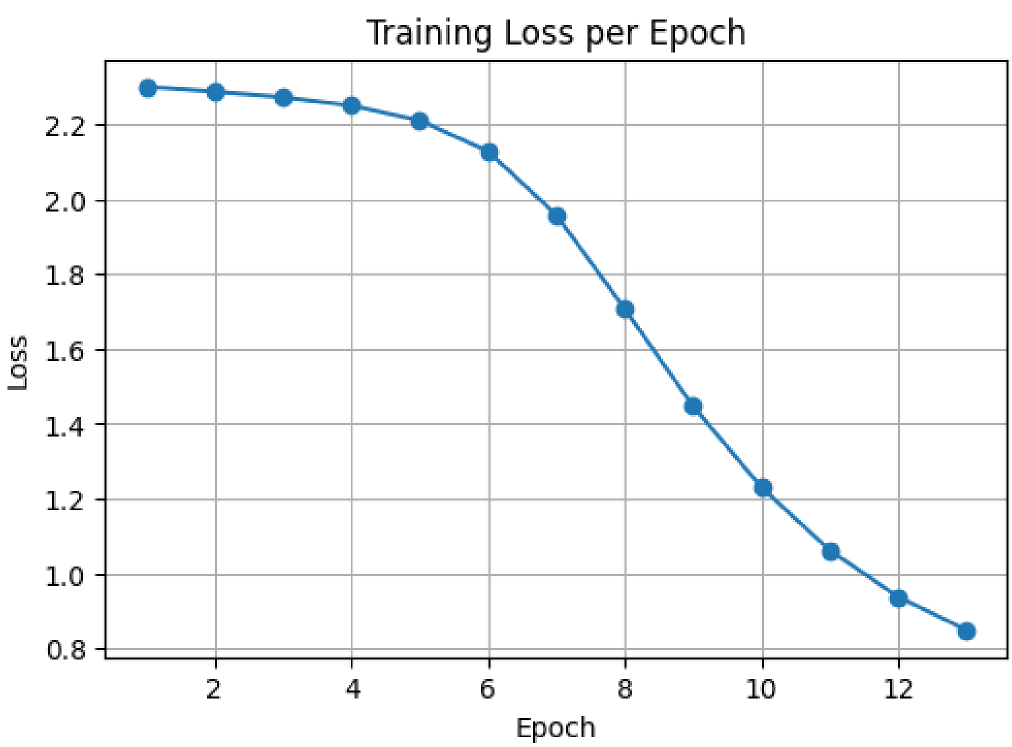

```
Epoch 11/20, Loss: 1.0625
```



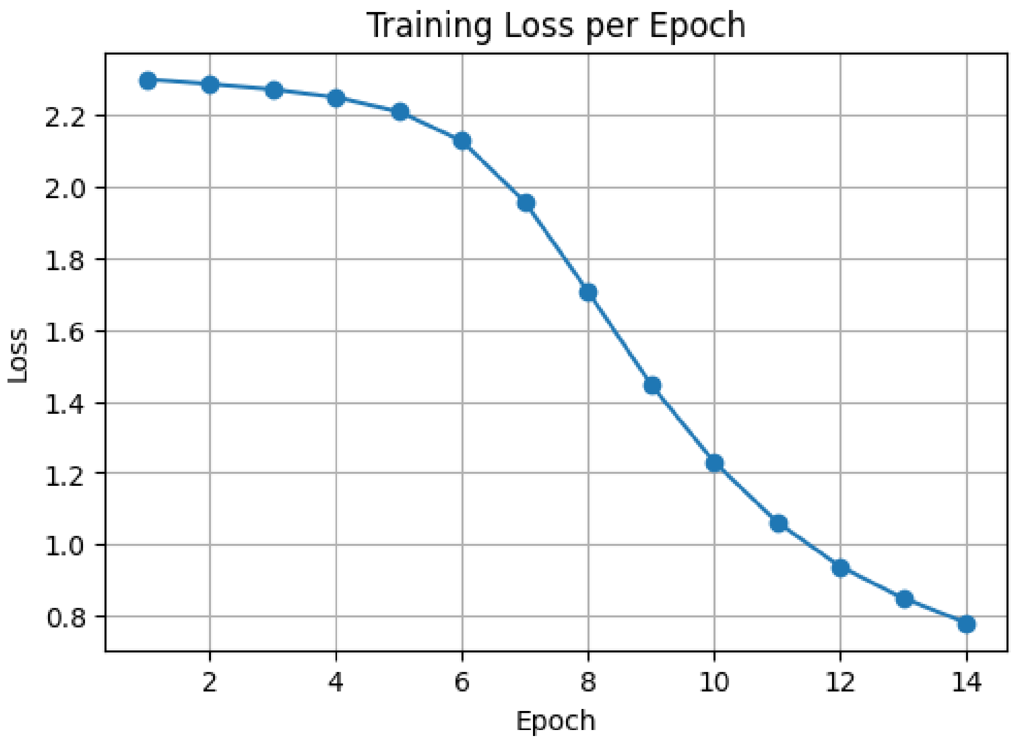

```
Epoch 12/20, Loss: 0.9382
```



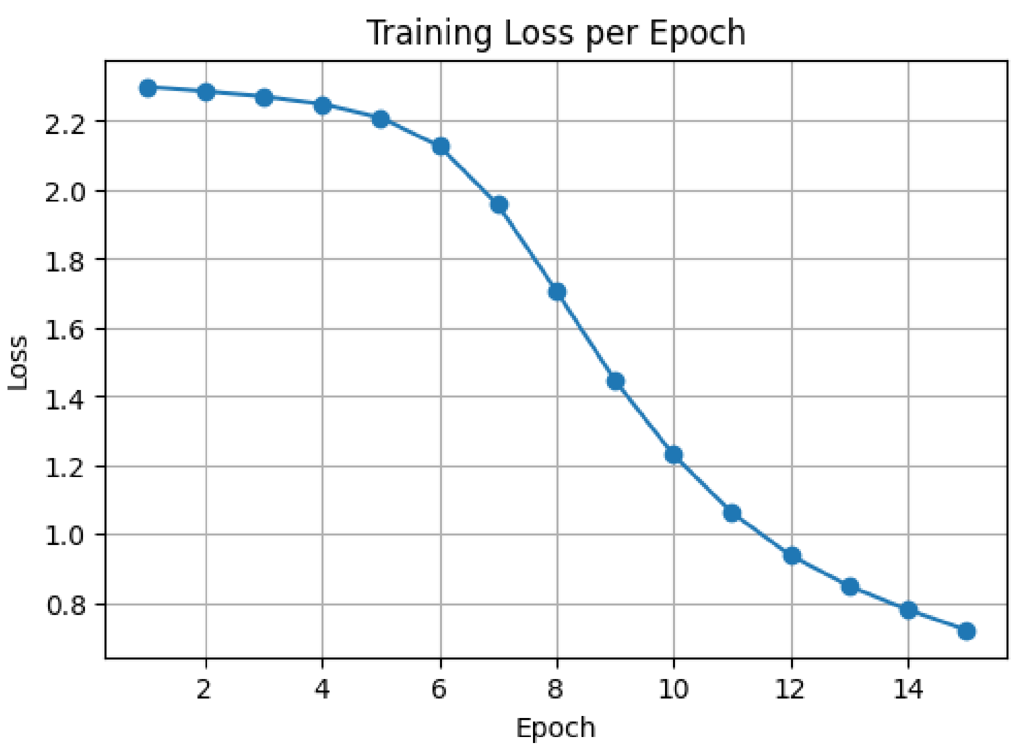

```
Epoch 13/20, Loss: 0.8494
```



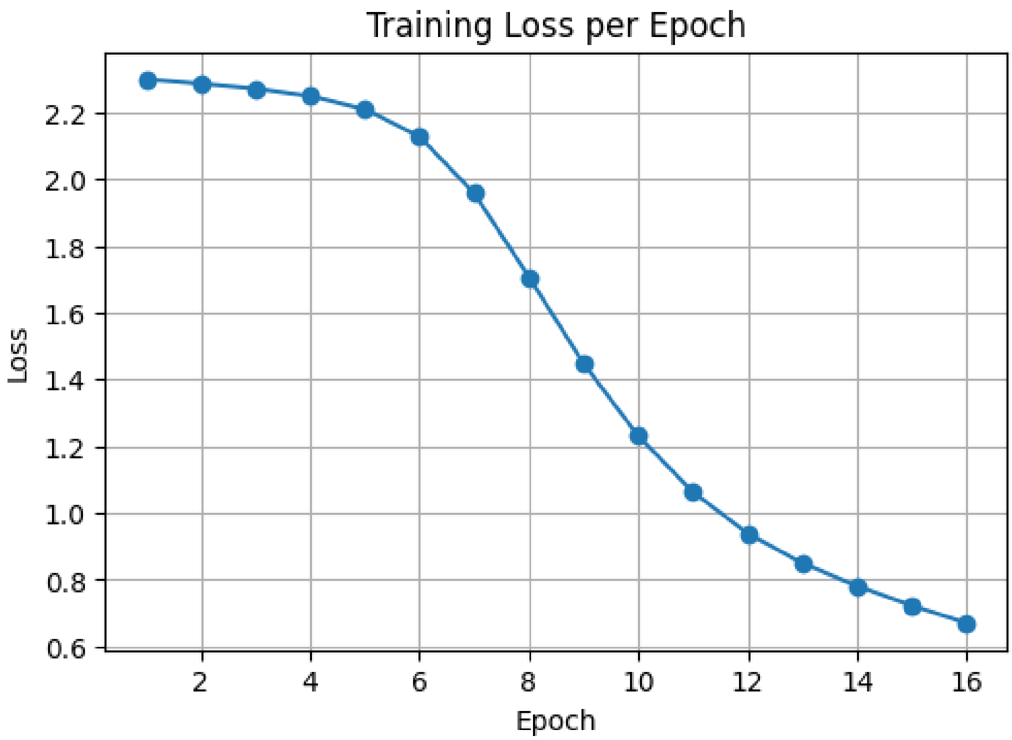

```
Epoch 14/20, Loss: 0.7807
```



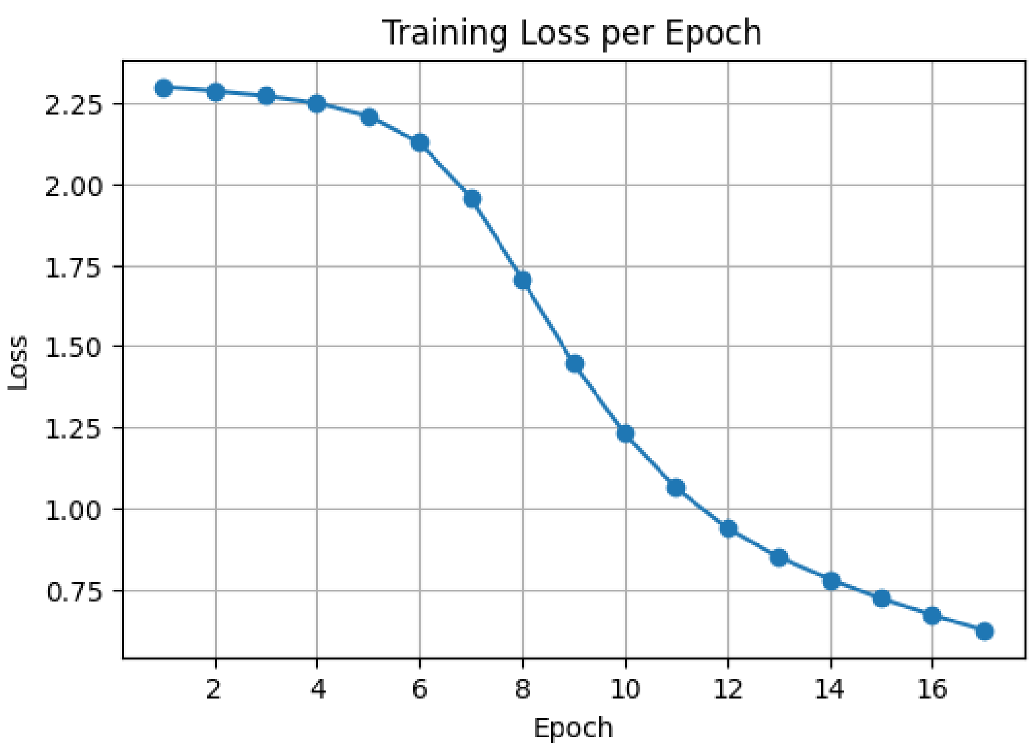

```
Epoch 15/20, Loss: 0.7219
```



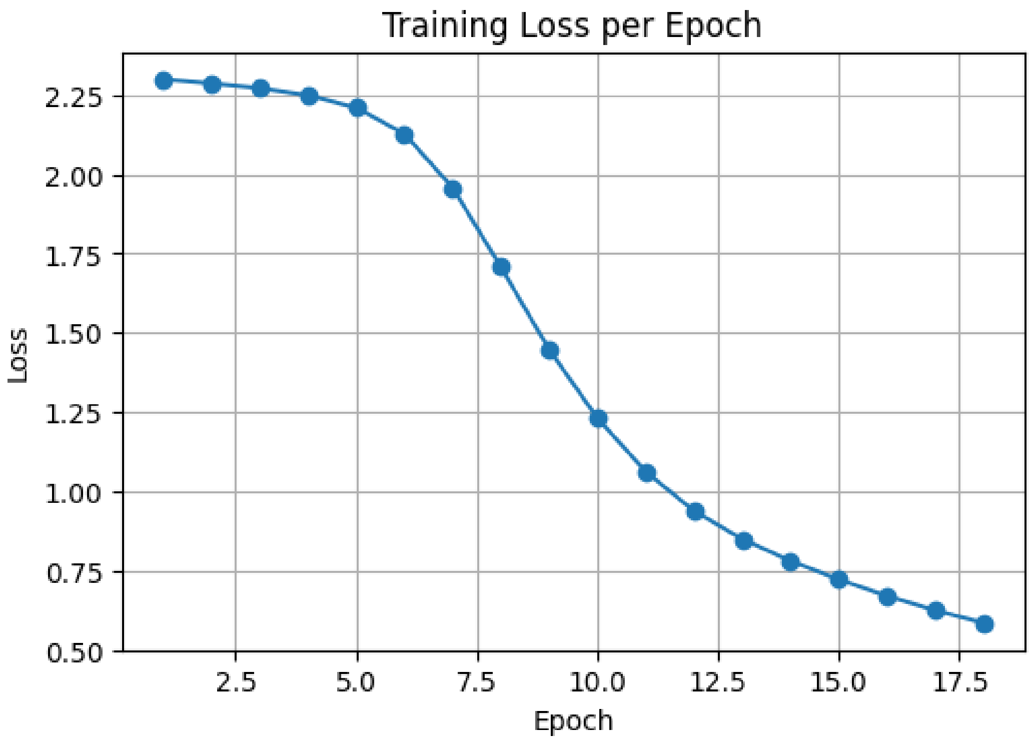

```
Epoch 16/20, Loss: 0.6701
```



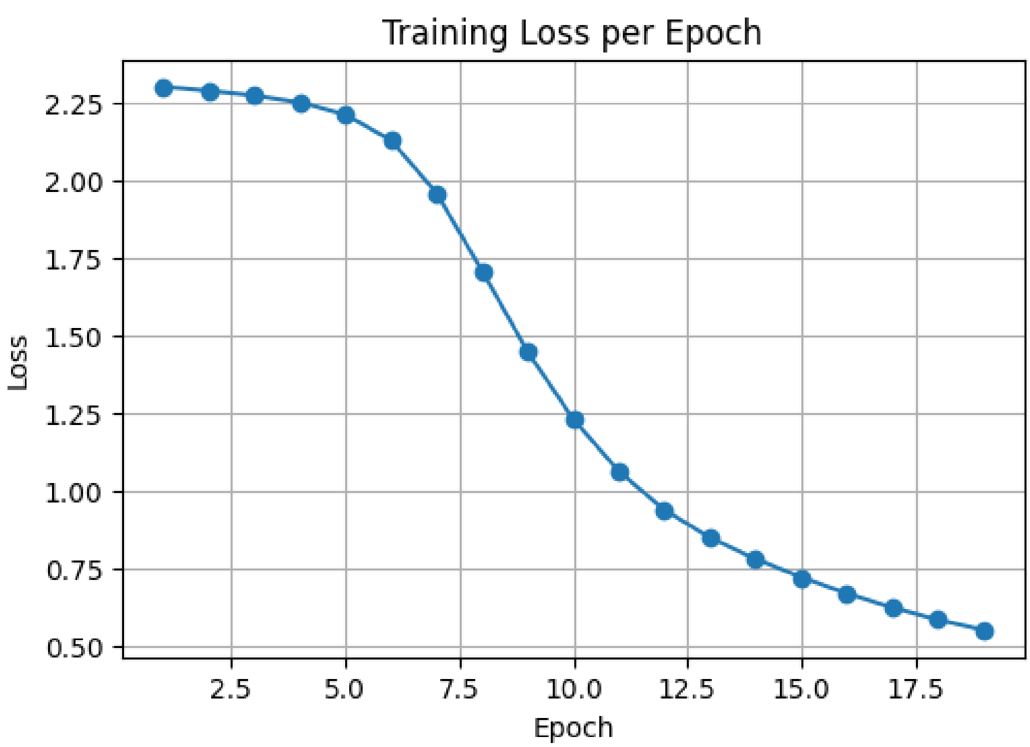

```
Epoch 17/20, Loss: 0.6244
```



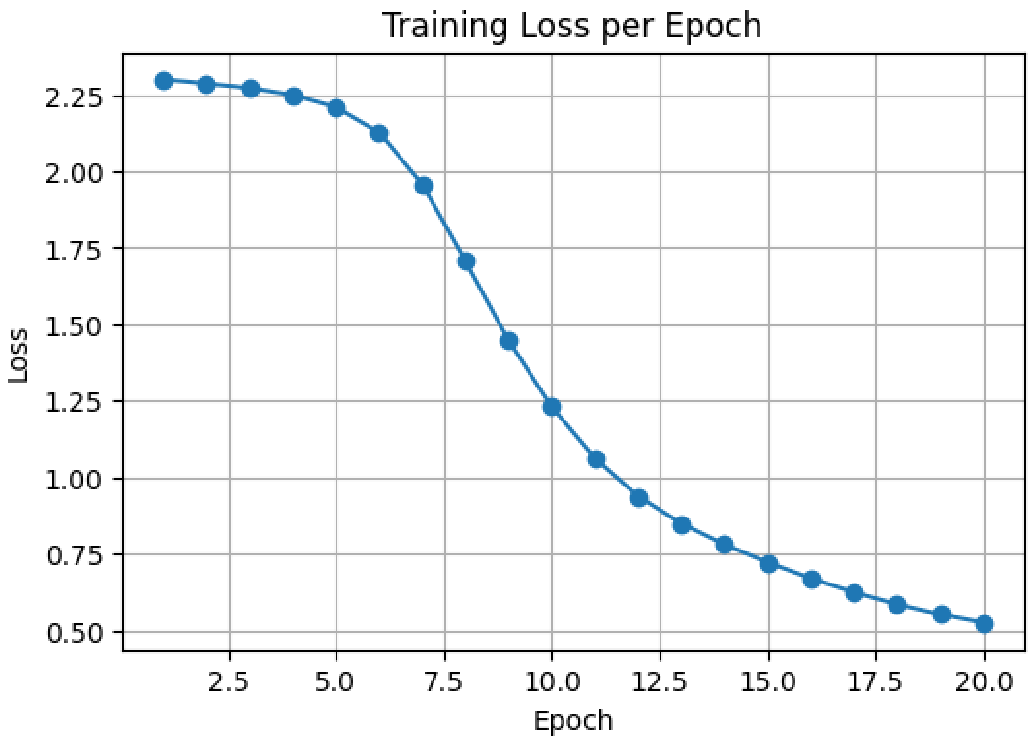

```
Epoch 18/20, Loss: 0.5850
```

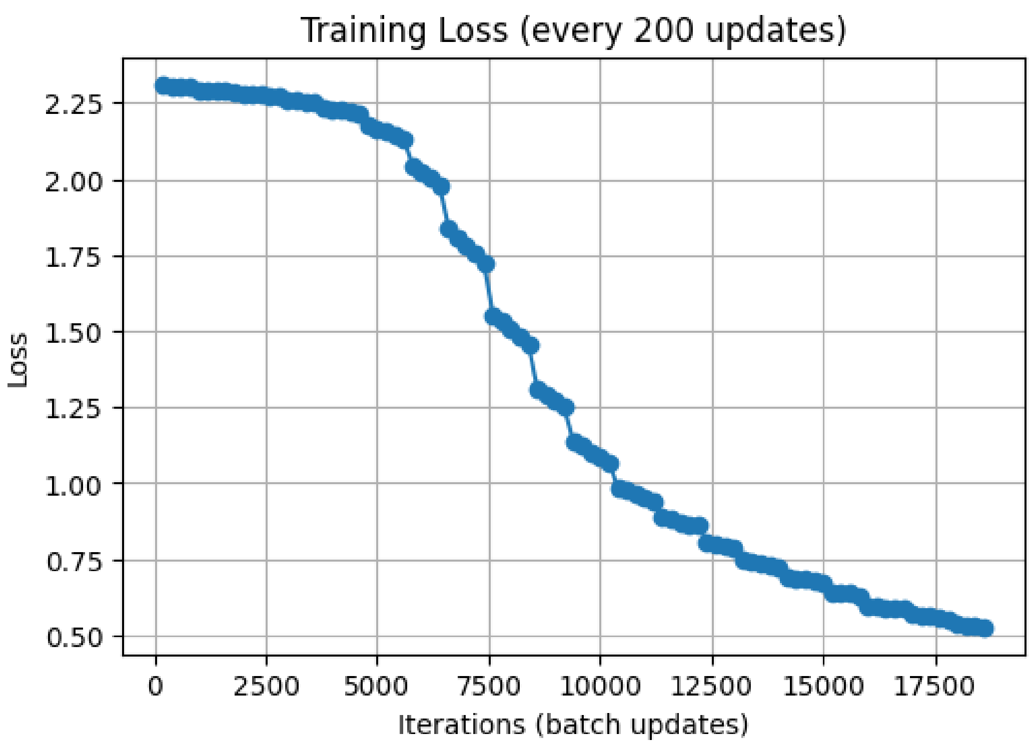



```
Epoch 19/20, Loss: 0.5523
```

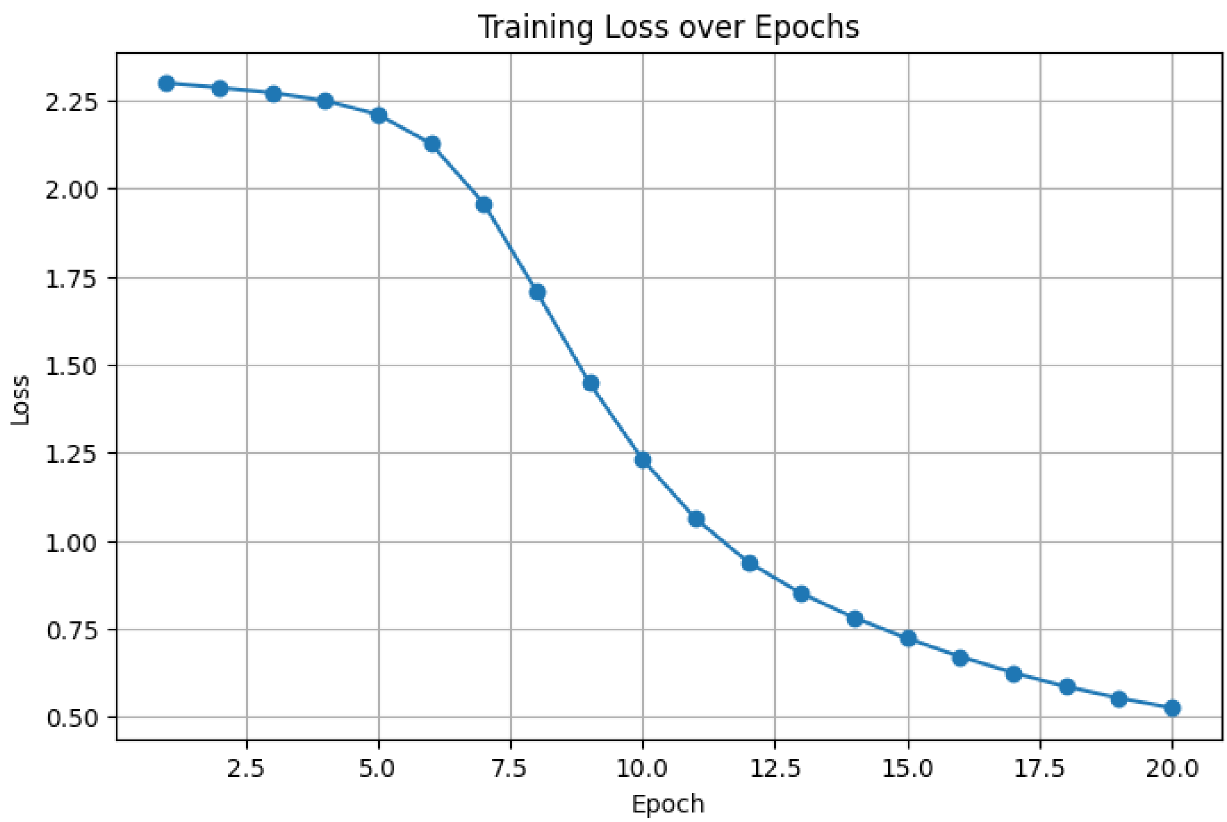



```
Epoch 20/20, Loss: 0.5247
```






```
plot_training_curves(loss_history_sigmoid_4)
```

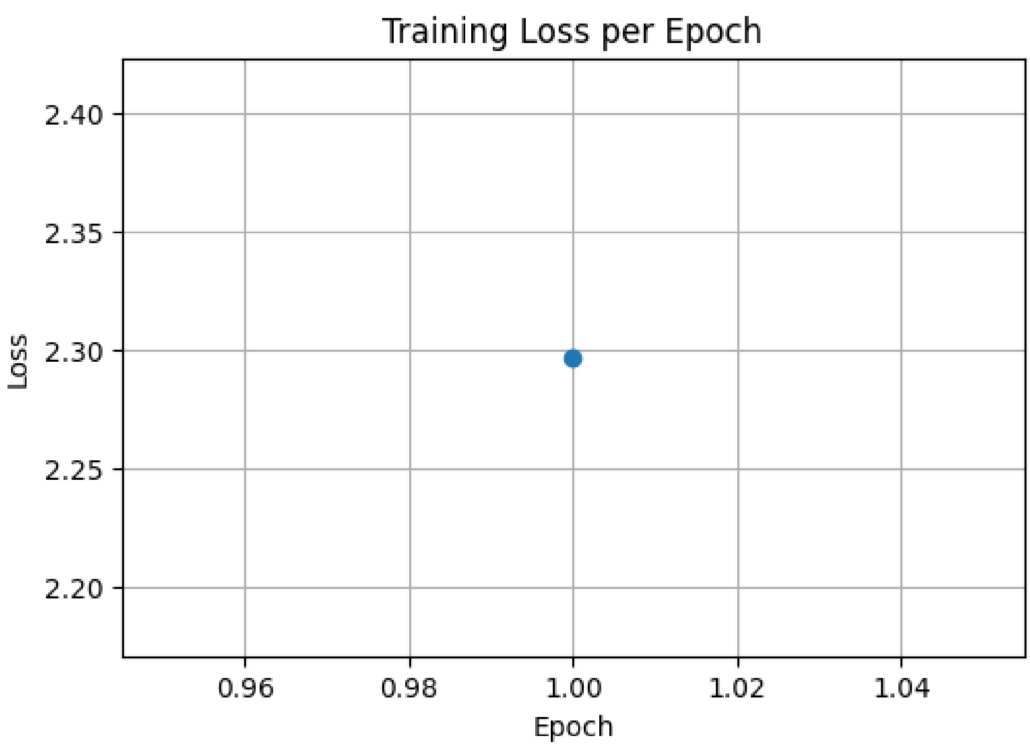



```
X_test_np = mnist_testset.data.numpy().reshape(-1, 28*28) / 255.0
y_test_np = mnist_testset.targets.numpy()

print("Test Set Evaluation for 20 epochs")
evaluate(model_4, X_test_np, y_test_np)

Test Set Evaluation for 20 epochs
Accuracy: 85.3900%
Confusion Matrix:
[[ 951    0    2    3    0   13   10    1    0    0]
 [   0 1112    1    6    0    2    3    1    9    1]
 [  14   11  866   58   24    2   23   10   19    5]
 [   3    7   46  842    0   48    1   18   39    6]
 [   1    8    5    0  804    0   23    0    8  133]
 [  22    3   12   90   11  656   29    8   46   15]
 [  24    4   12    1   15   21  878    0    3    0]
 [   6   32   27    7    1    1    0  888    5   61]
 [   9   21   21   45   27   51   17    9  743   31]
 [  13    8    7    5   99   15    0   51   12  799]]

Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.97      0.94       980
           1       0.92      0.98      0.95      1135
```

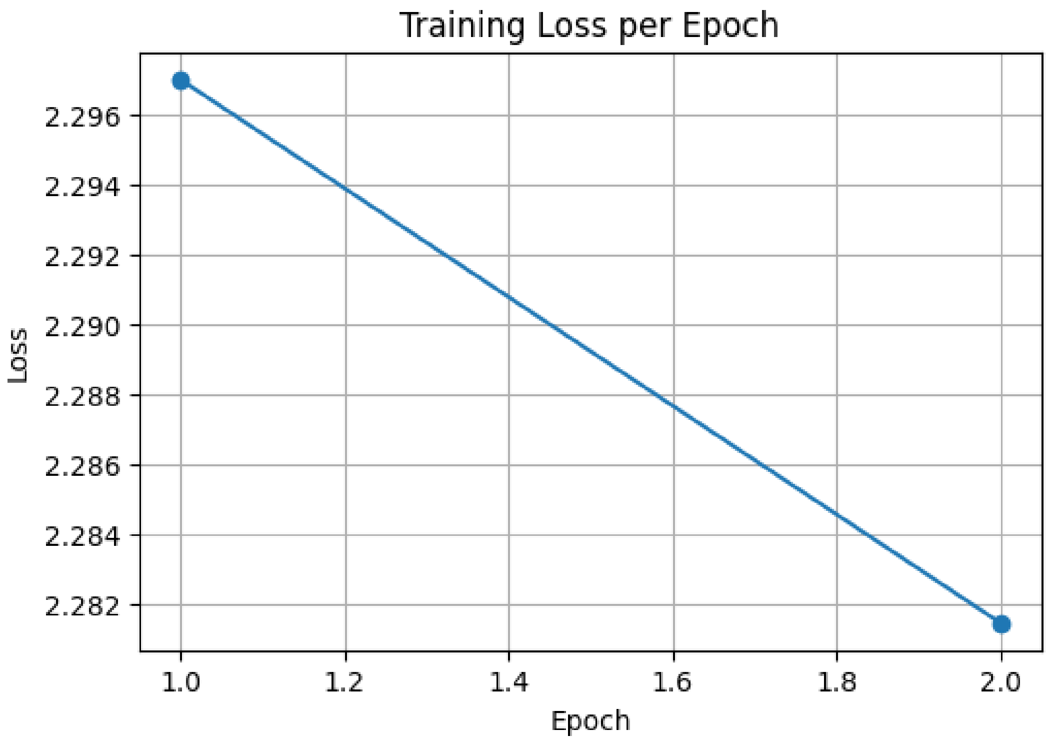
```
           2       0.87      0.84      0.85      1032
           3       0.80      0.83      0.81      1010
           4       0.82      0.82      0.82       982
           5       0.81      0.74      0.77       892
           6       0.89      0.92      0.90       958
           7       0.90      0.86      0.88      1028
           8       0.84      0.76      0.80       974
           9       0.76      0.79      0.78      1009

    accuracy                           0.85     10000
   macro avg       0.85      0.85      0.85     10000
weighted avg       0.85      0.85      0.85     10000


np.float64(0.8539)
```

Number of Epochs = 25

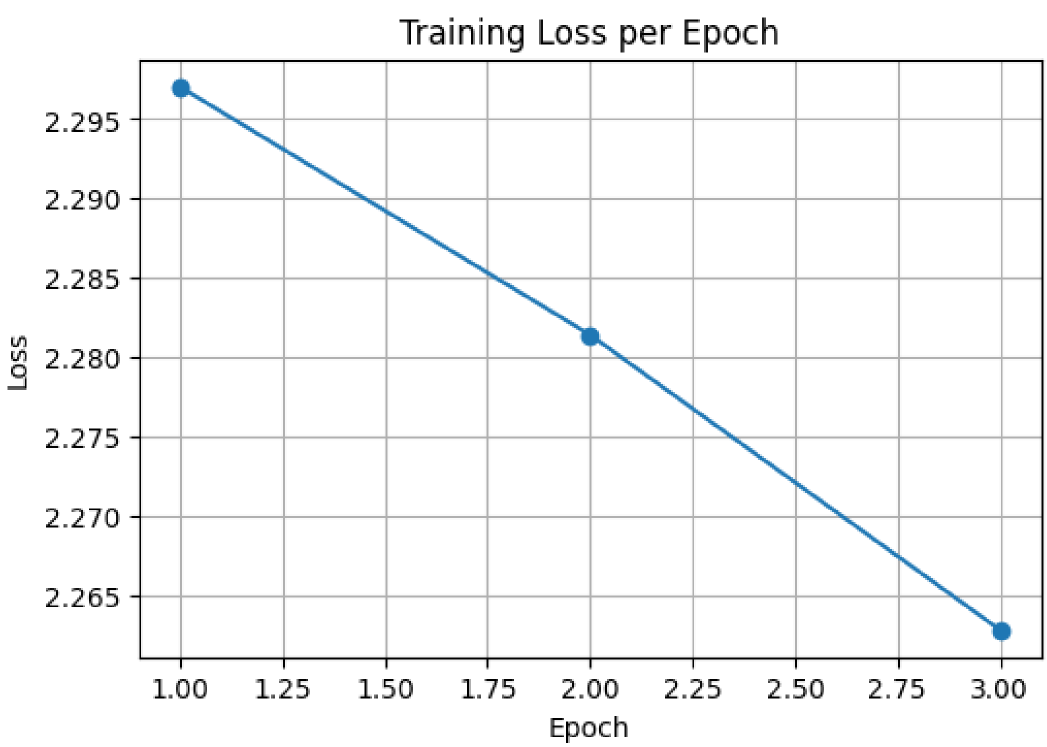
```
model_5 = MLP()
loss_history_sigmoid_5, iter_sigmoid_5, iter_loss_sigmoid_5 =
train(model_5, train_loader, 25, 0.01)

Epoch 1/25, Loss: 2.2970
```



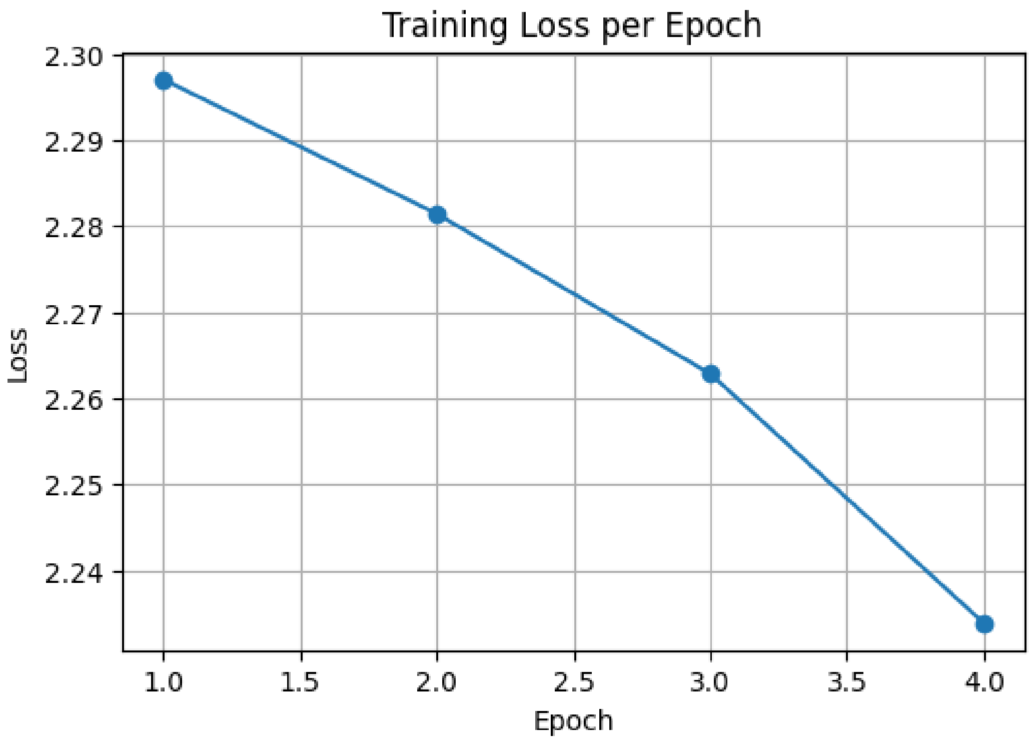

```
Epoch 2/25, Loss: 2.2814
```



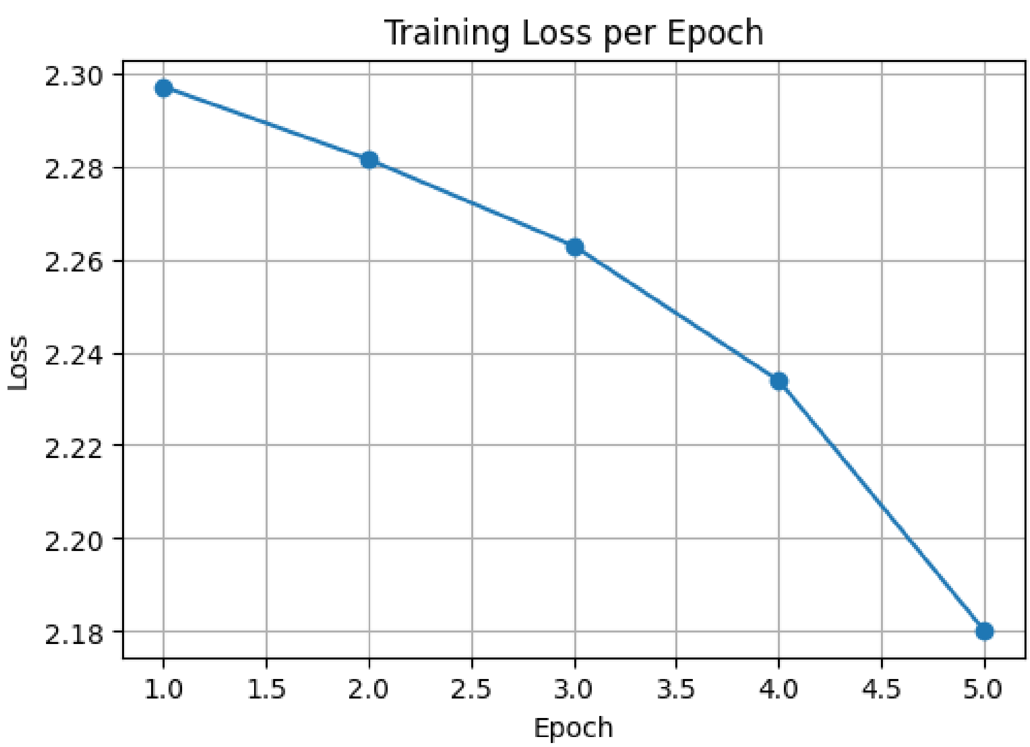

```
Epoch 3/25, Loss: 2.2629
```



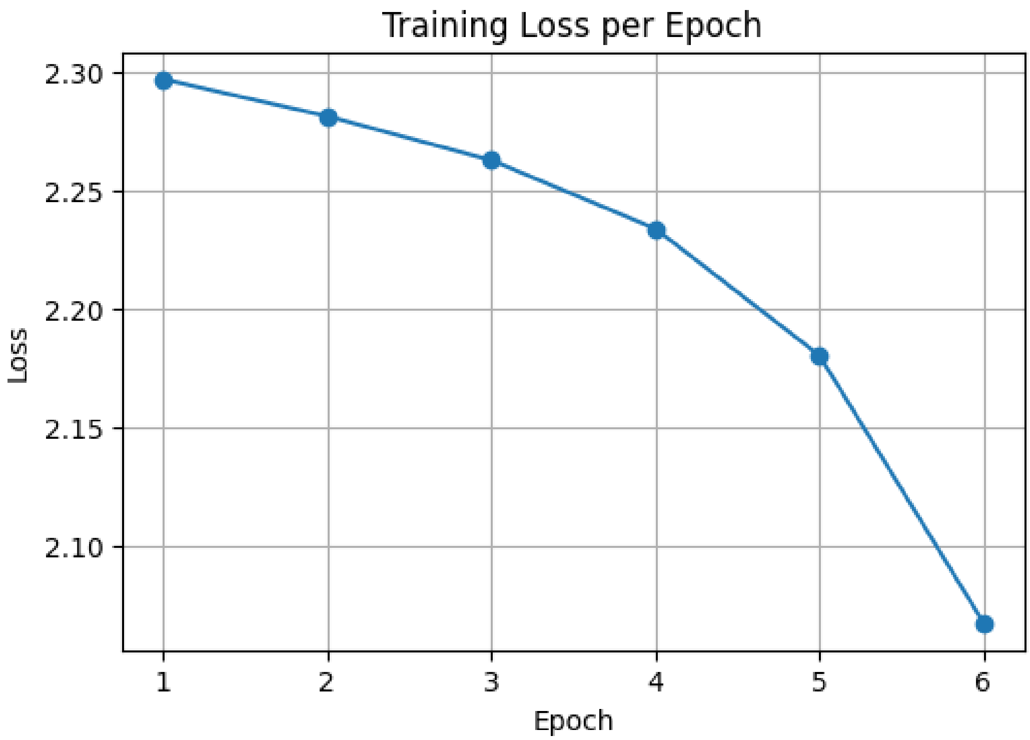

```
Epoch 4/25, Loss: 2.2339
```



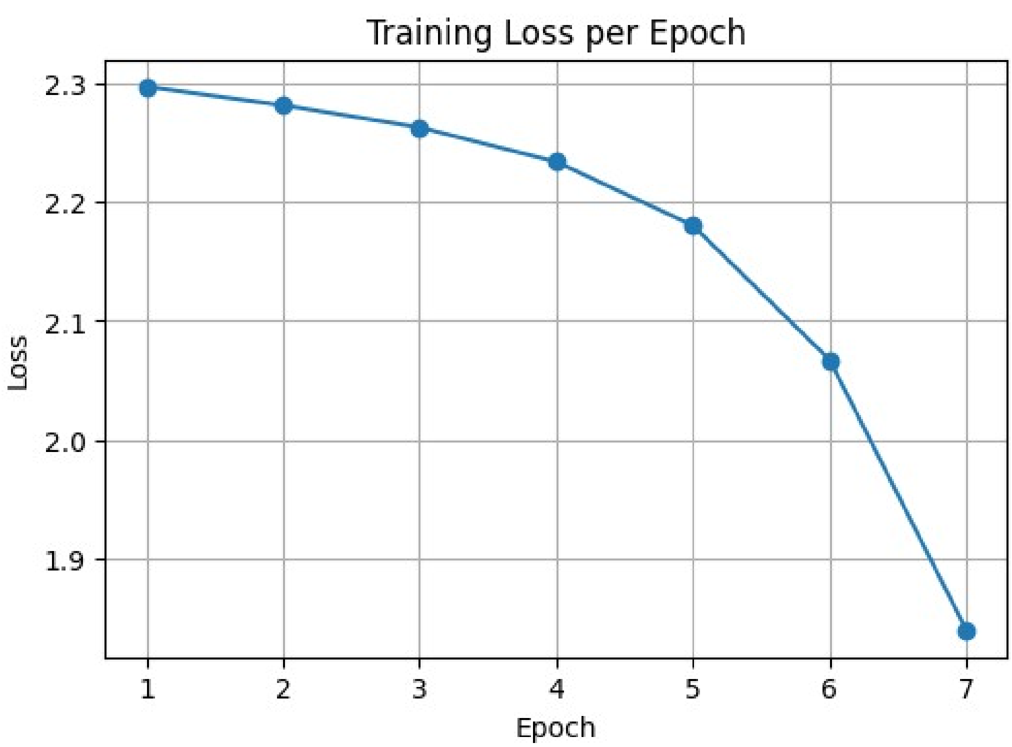

```
Epoch 5/25, Loss: 2.1803
```



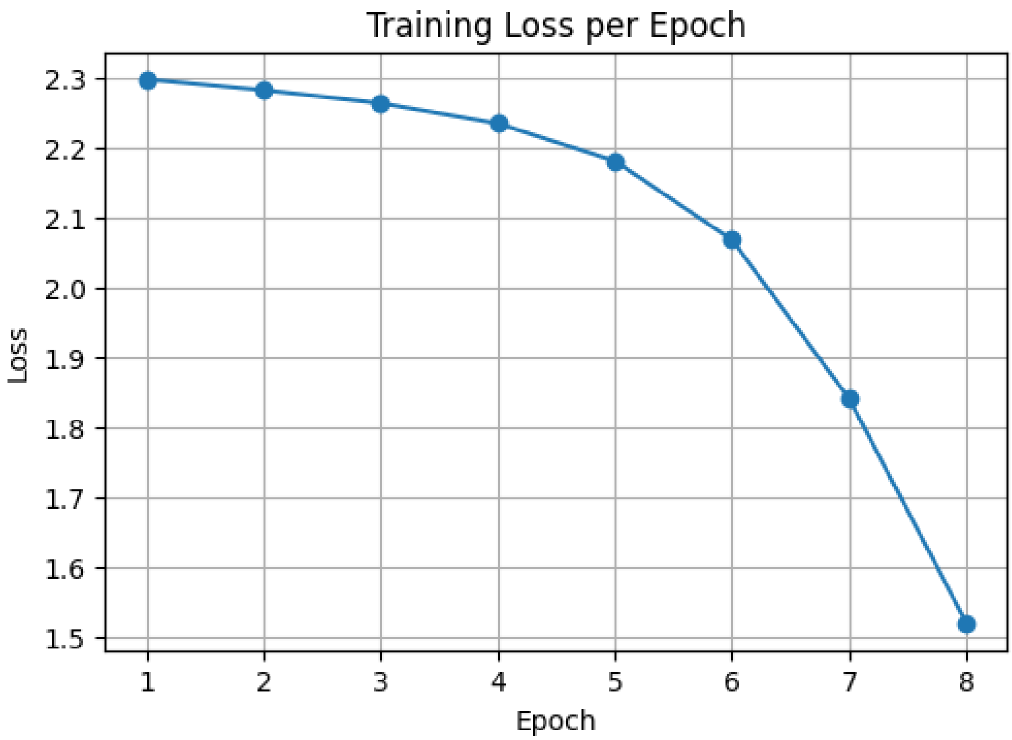

```
Epoch 6/25, Loss: 2.0673
```



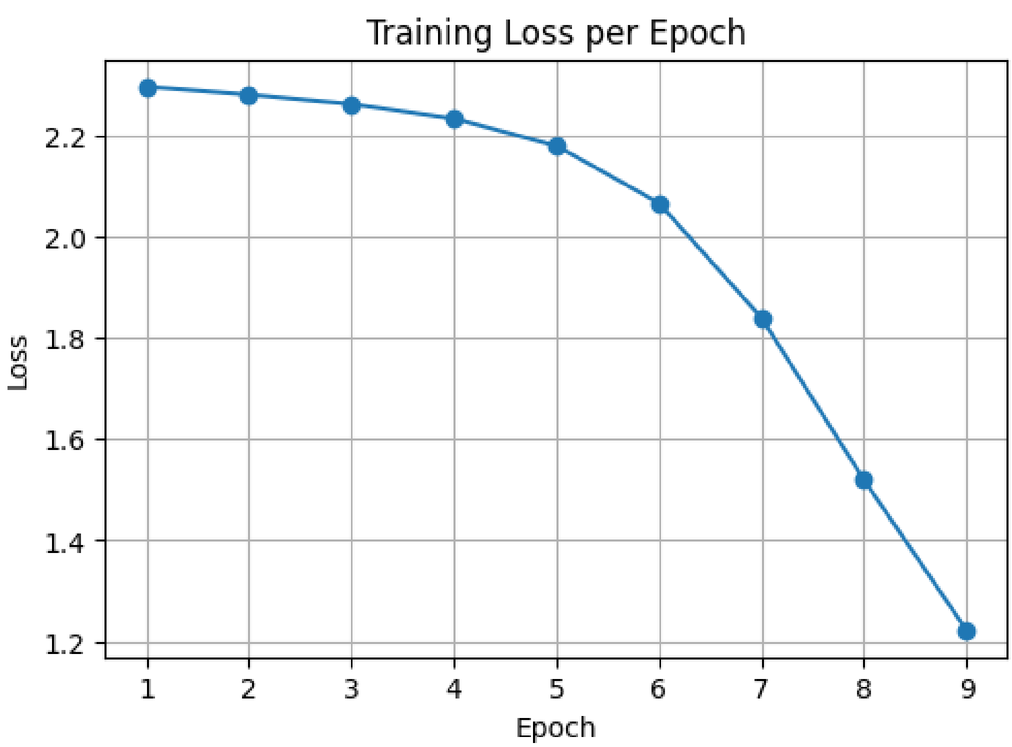

```
Epoch 7/25, Loss: 1.8402
```



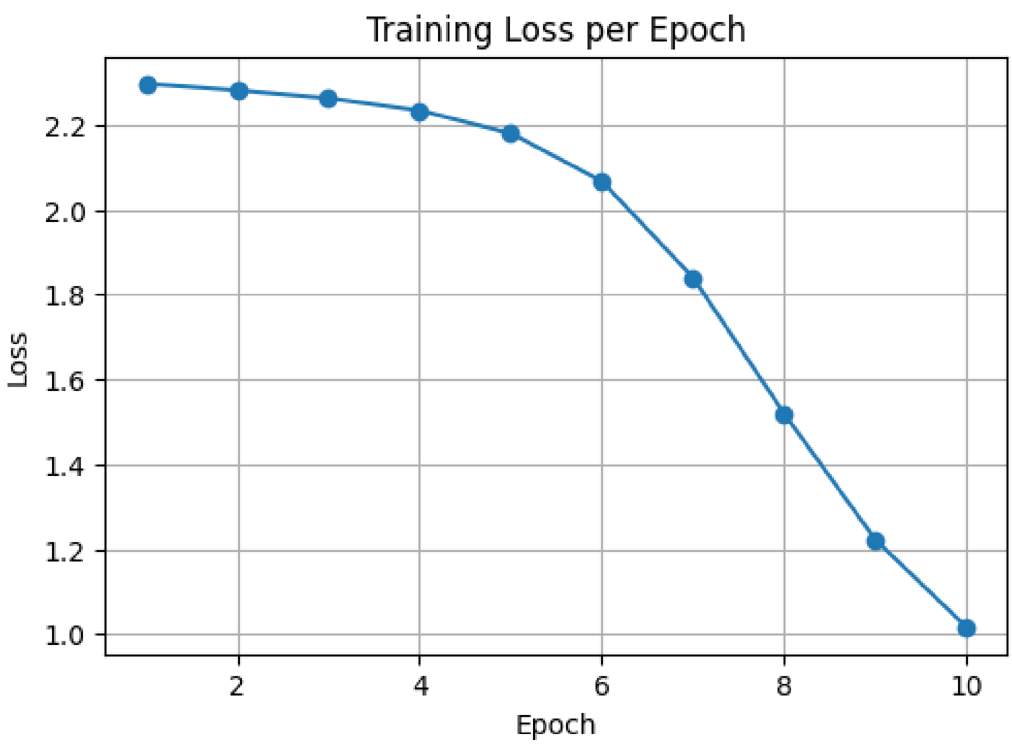

```
Epoch 8/25, Loss: 1.5197
```



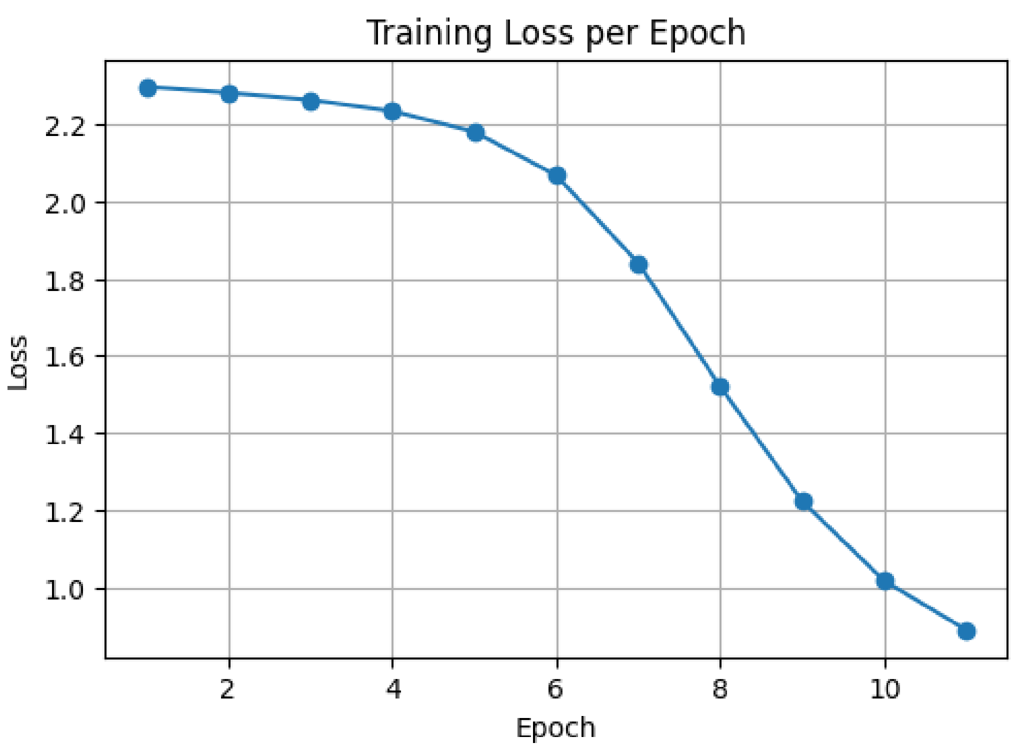

```
Epoch 9/25, Loss: 1.2224
```



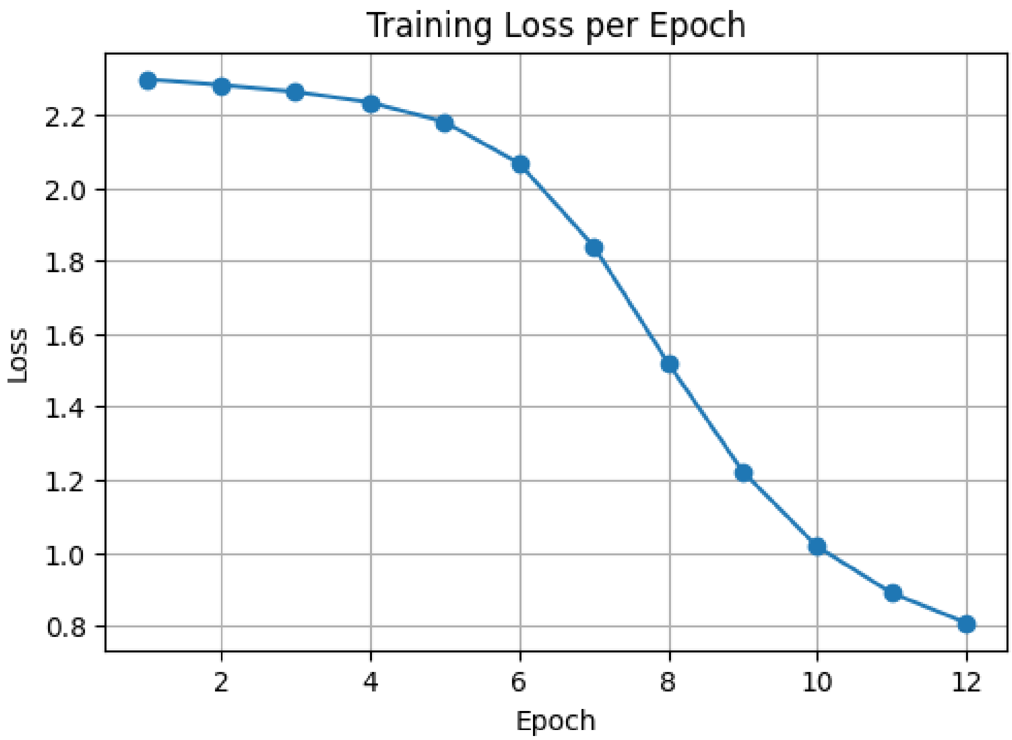

```
Epoch 10/25, Loss: 1.0162
```



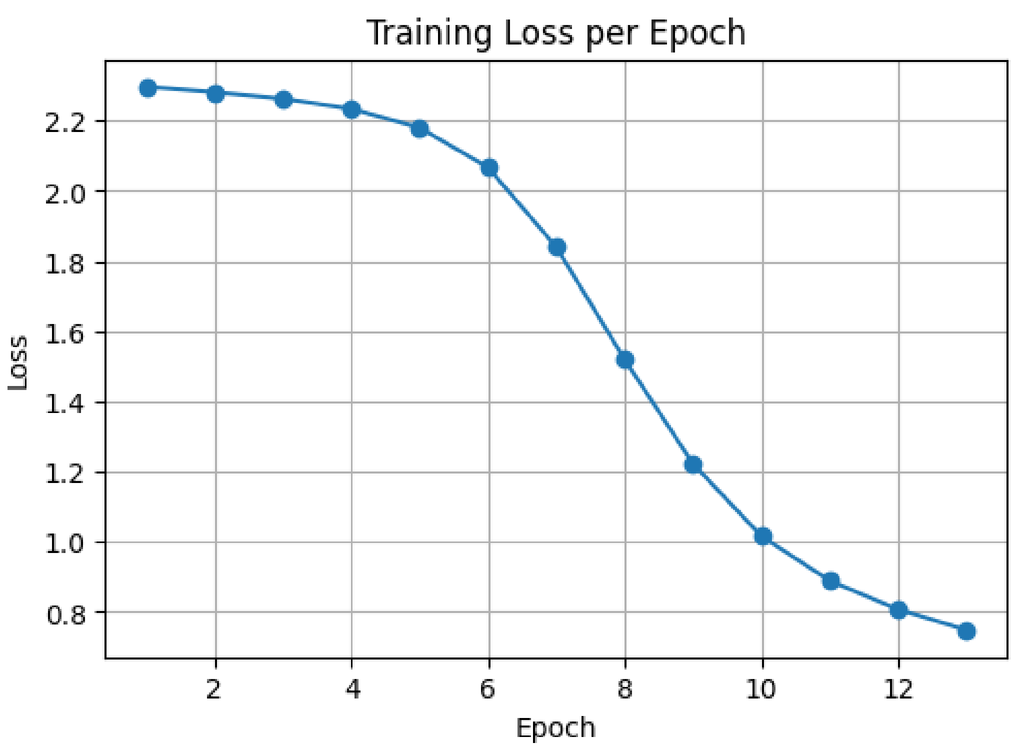

```
Epoch 11/25, Loss: 0.8891
```



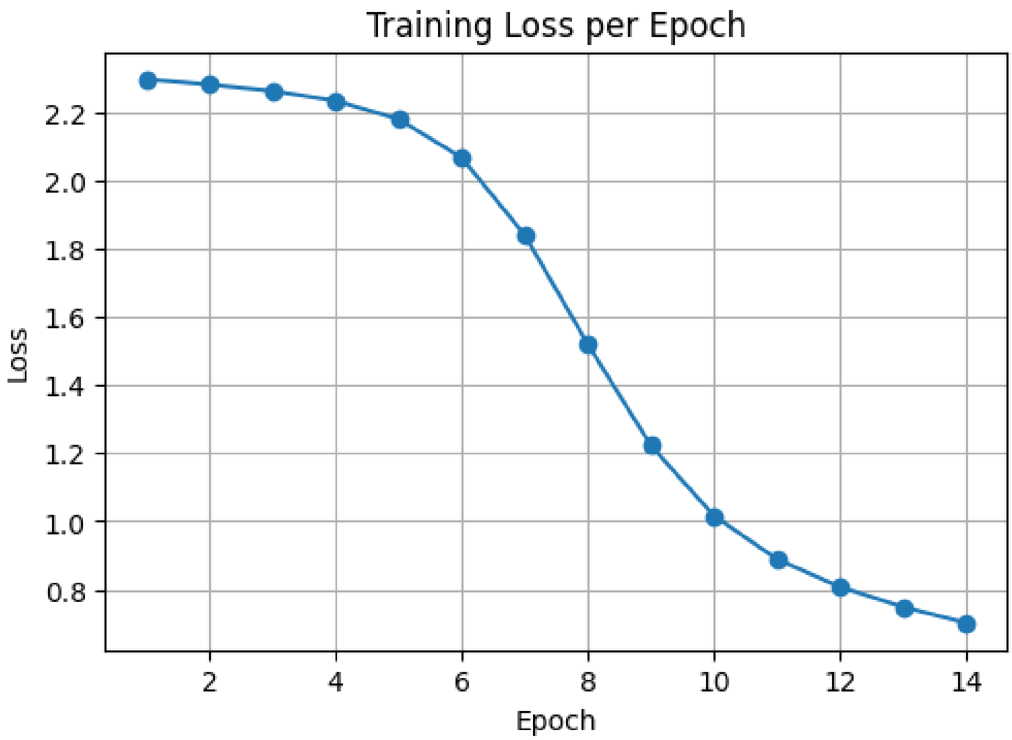

```
Epoch 12/25, Loss: 0.8073
```



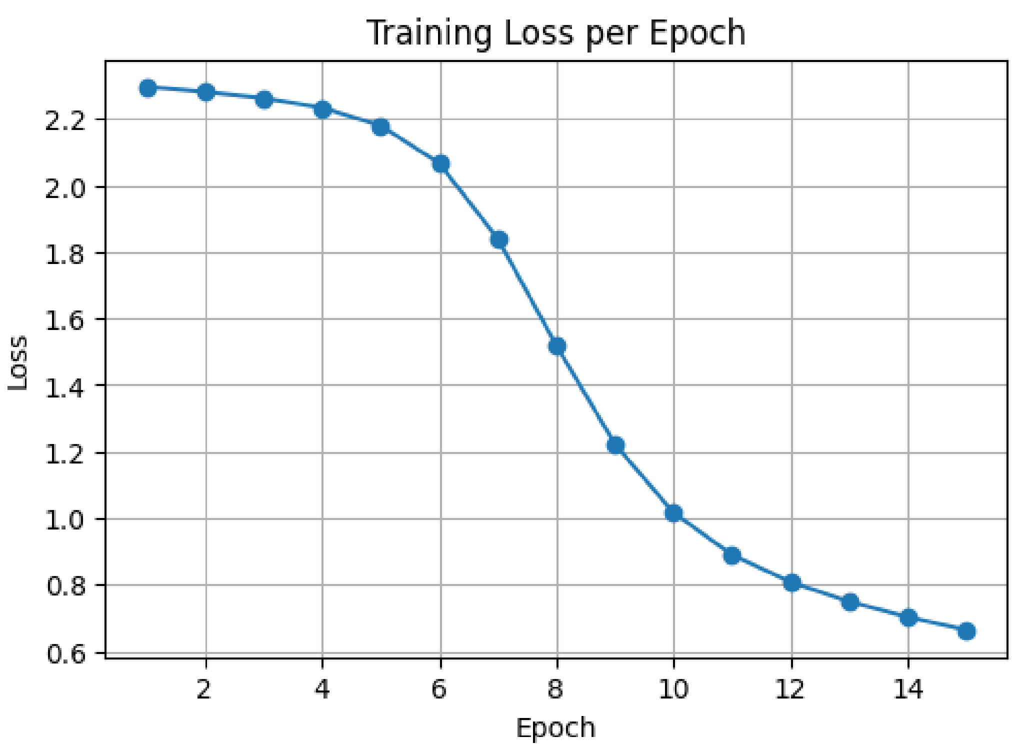

```
Epoch 13/25, Loss: 0.7487
```



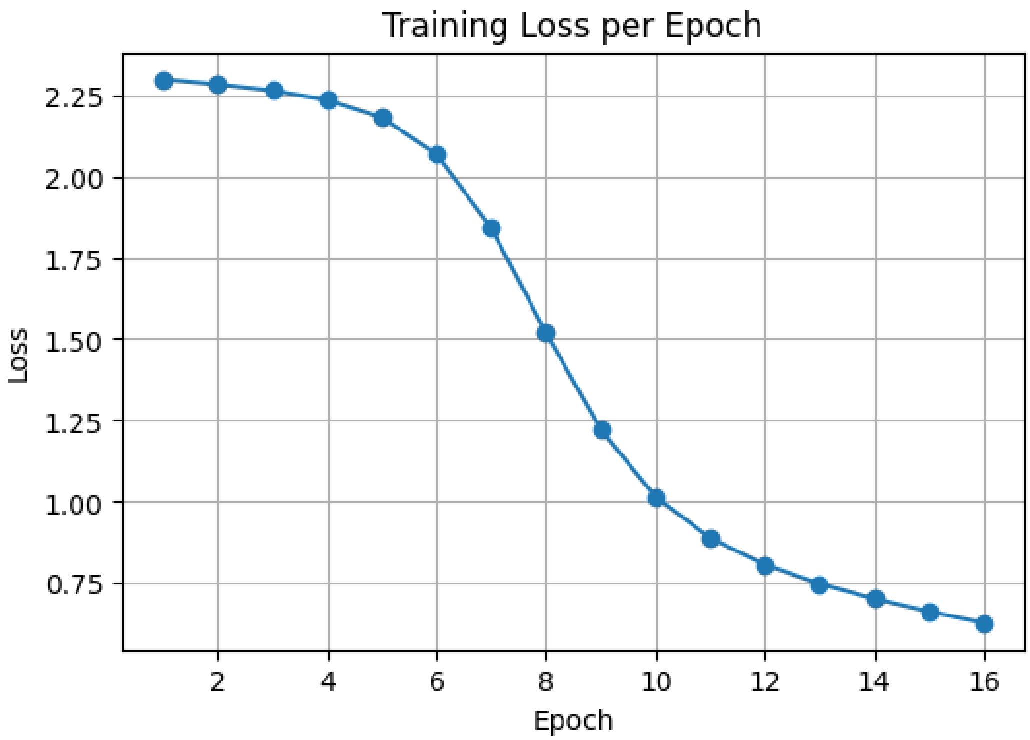

```
Epoch 14/25, Loss: 0.7022
```



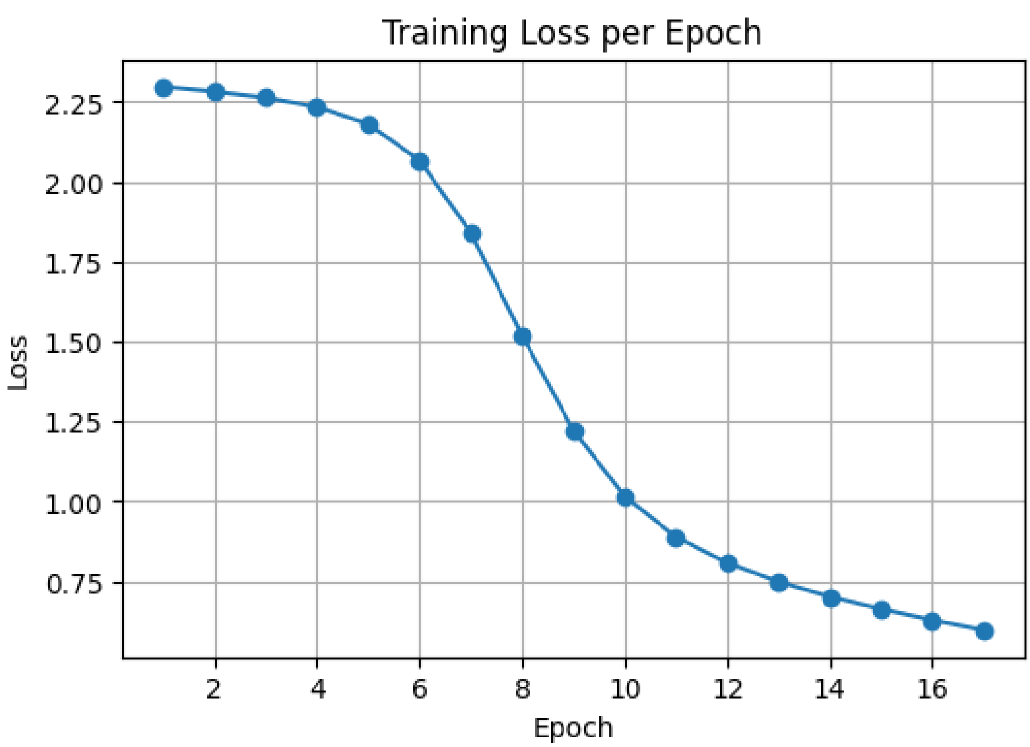

```
Epoch 15/25, Loss: 0.6632
```



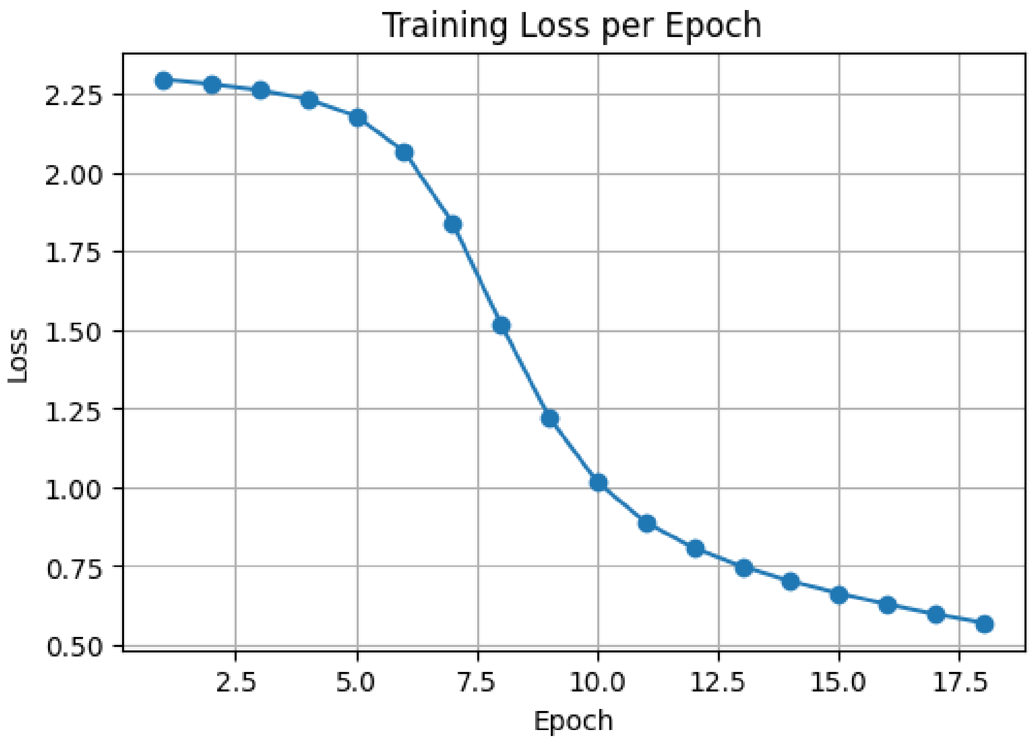

```
Epoch 16/25, Loss: 0.6288
```



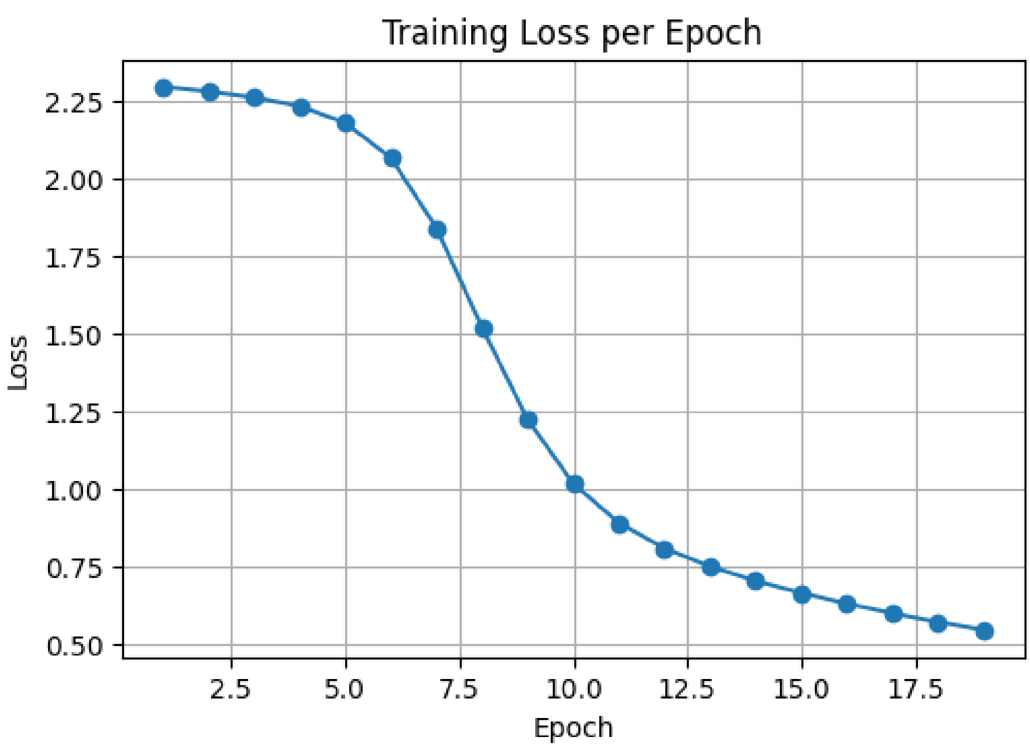

```
Epoch 17/25, Loss: 0.5977
```



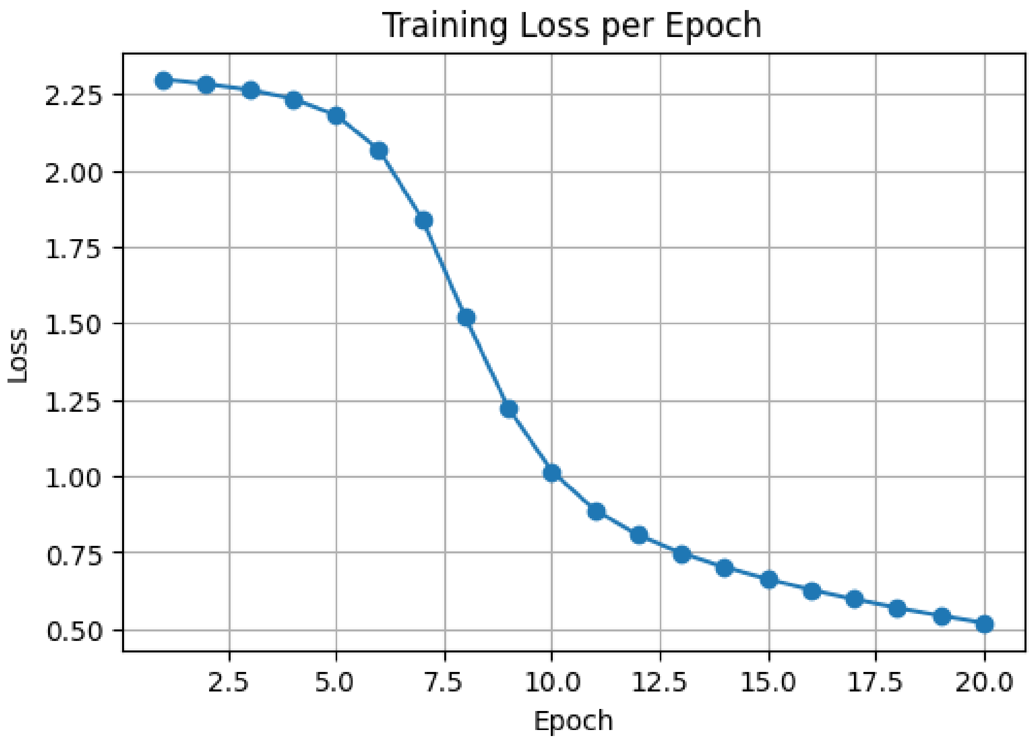

```
Epoch 18/25, Loss: 0.5694
```



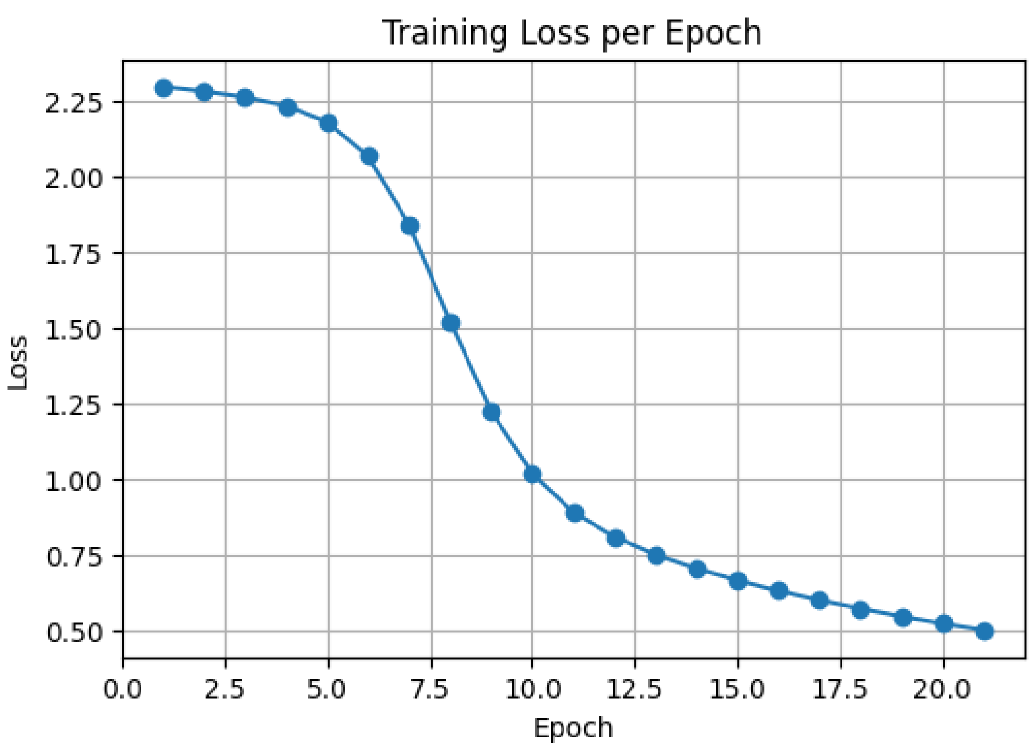

```
Epoch 19/25, Loss: 0.5437
```



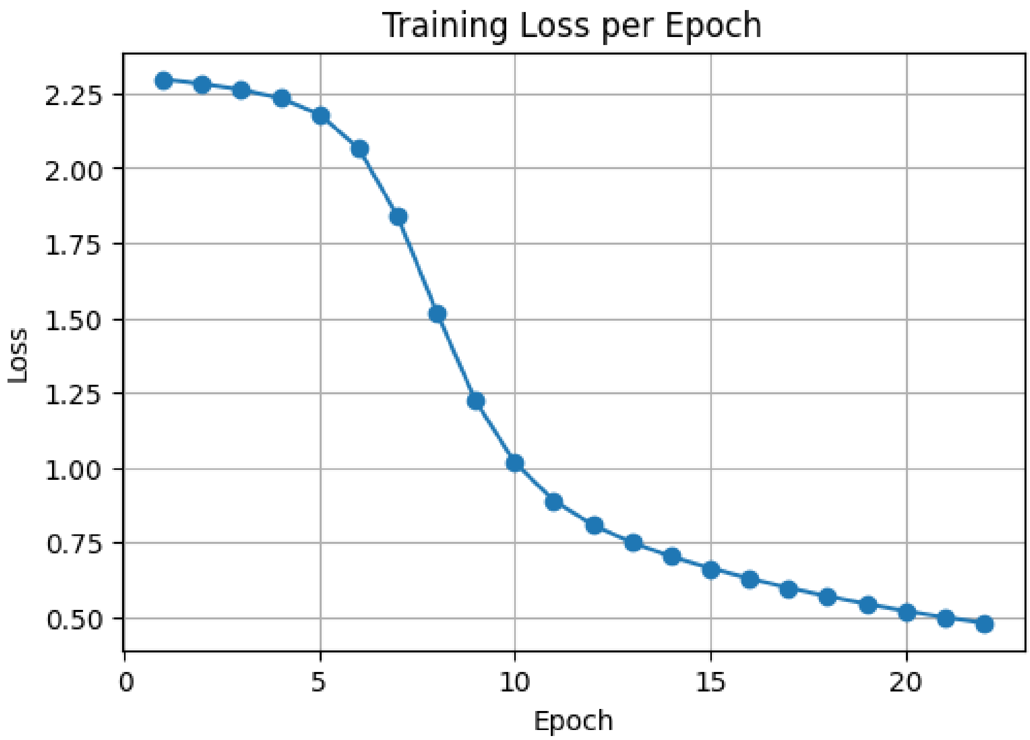

```
Epoch 20/25, Loss: 0.5201
```



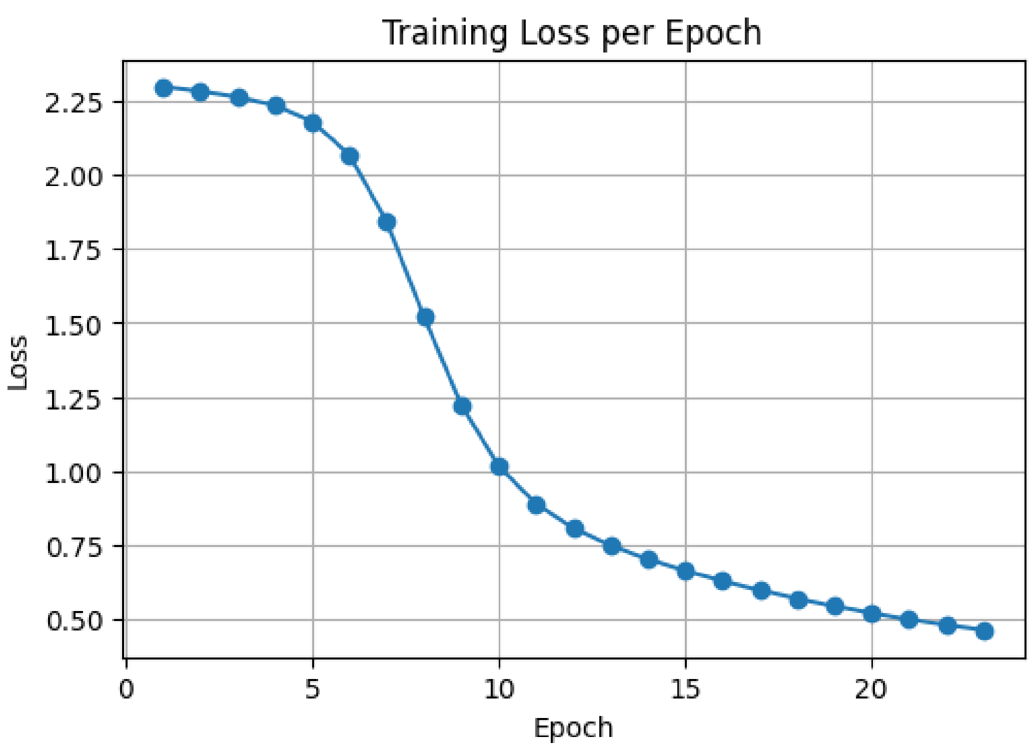

```
Epoch 21/25, Loss: 0.4989
```



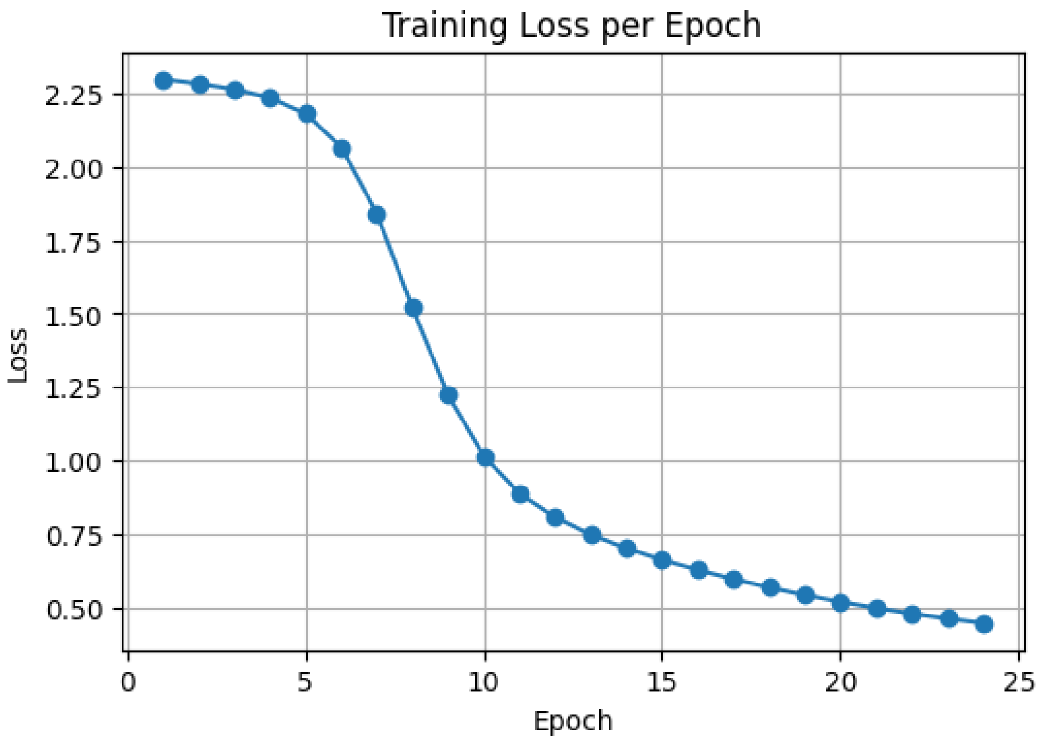

```
Epoch 22/25, Loss: 0.4801
```



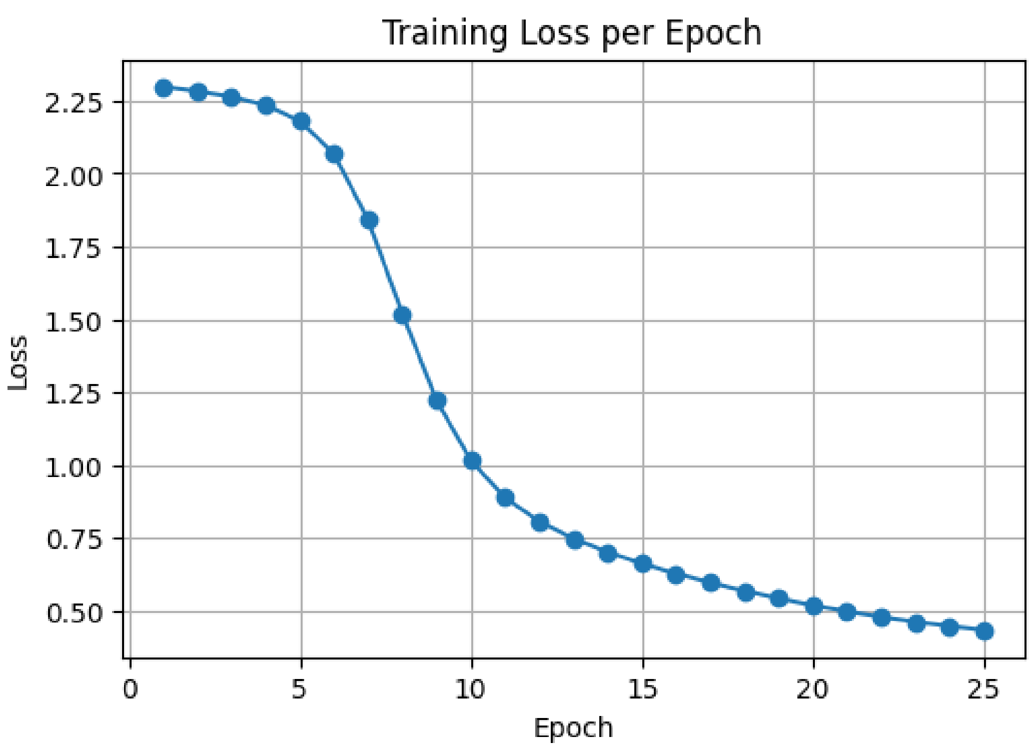

```
Epoch 23/25, Loss: 0.4632
```

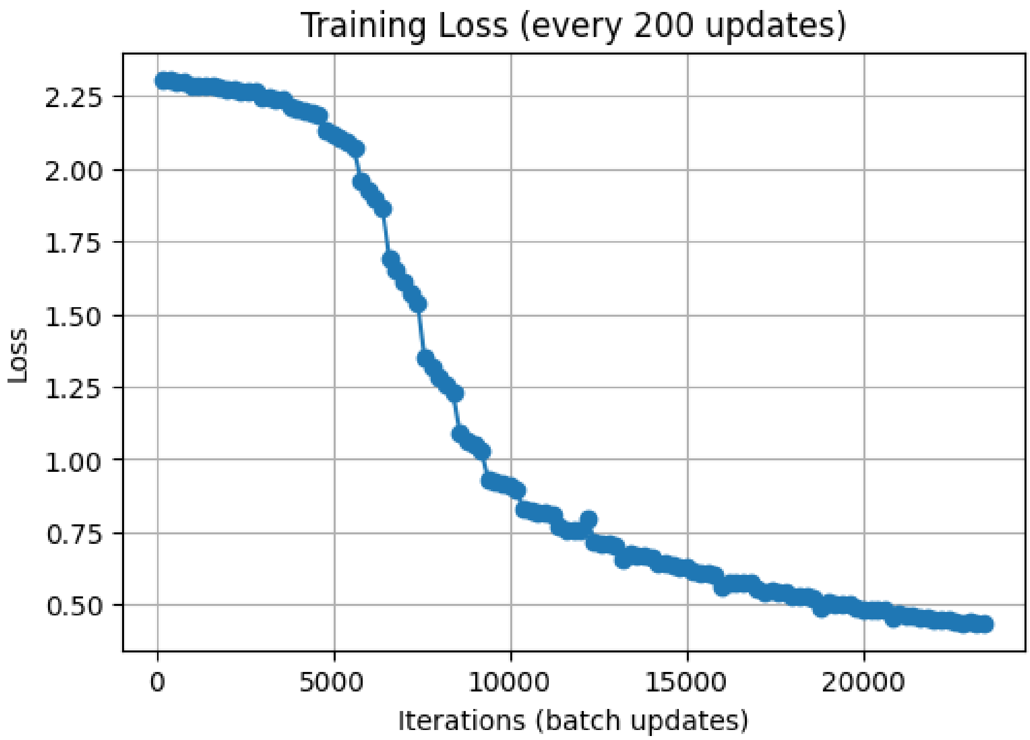



```
Epoch 24/25, Loss: 0.4486
```

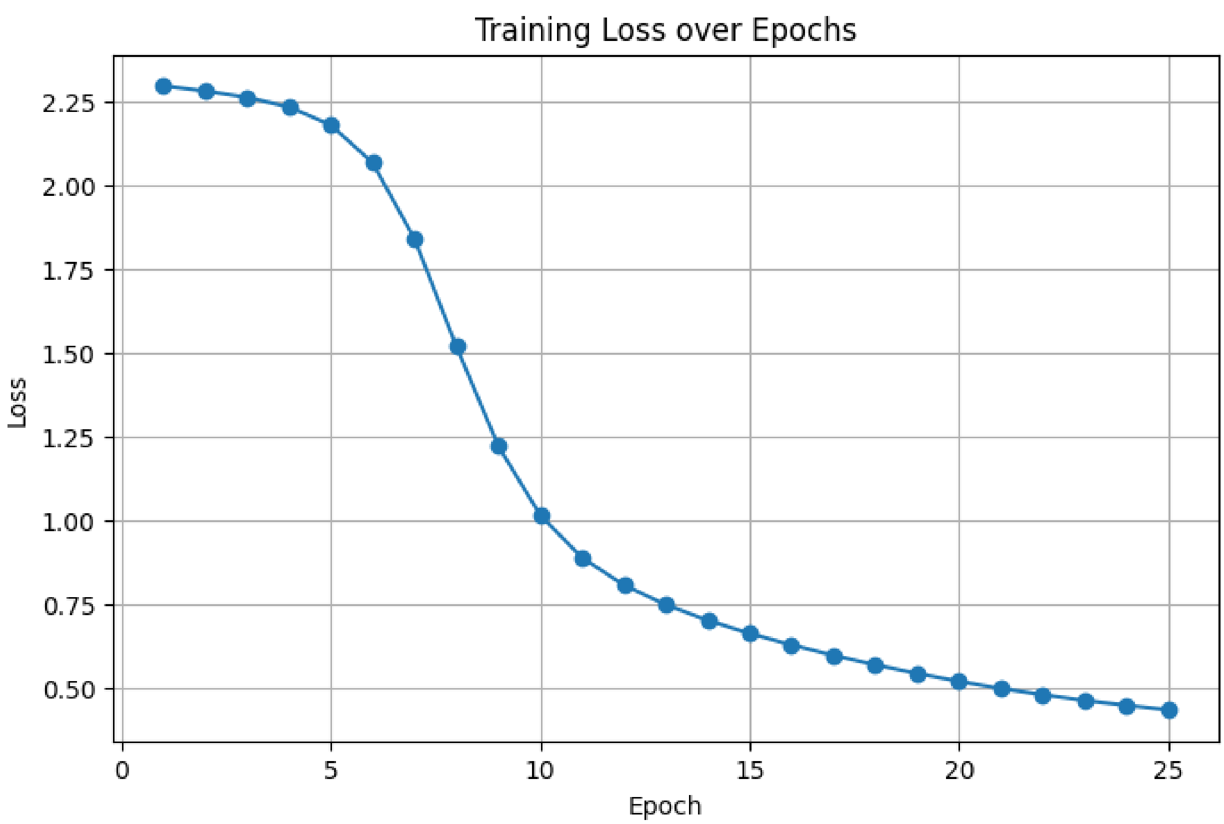



```
Epoch 25/25, Loss: 0.4352
```






```
plot_training_curves(loss_history_sigmoid_5)
```

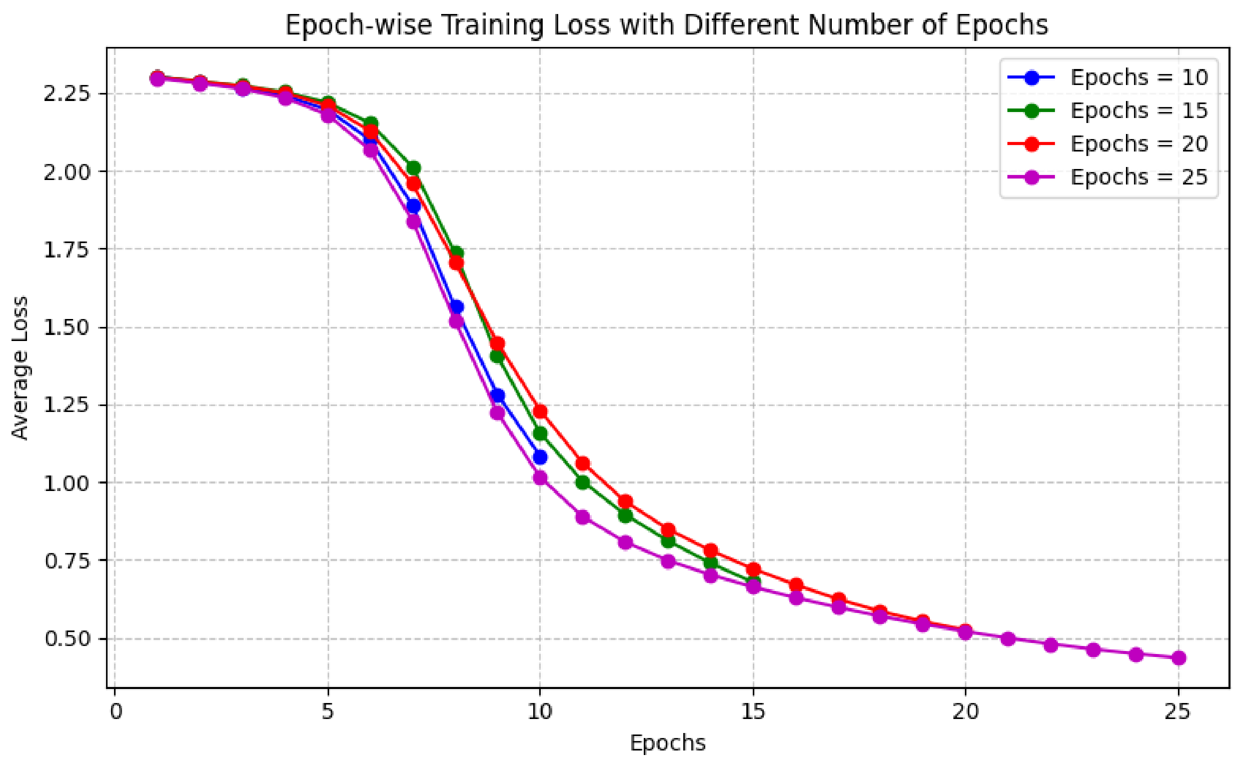


```python
X_test_np = mnist_testset.data.numpy().reshape(-1, 28*28) / 255.0
y_test_np = mnist_testset.targets.numpy()

print("Test Set Evaluation for 25 epochs")
evaluate(model_5, X_test_np, y_test_np)
```

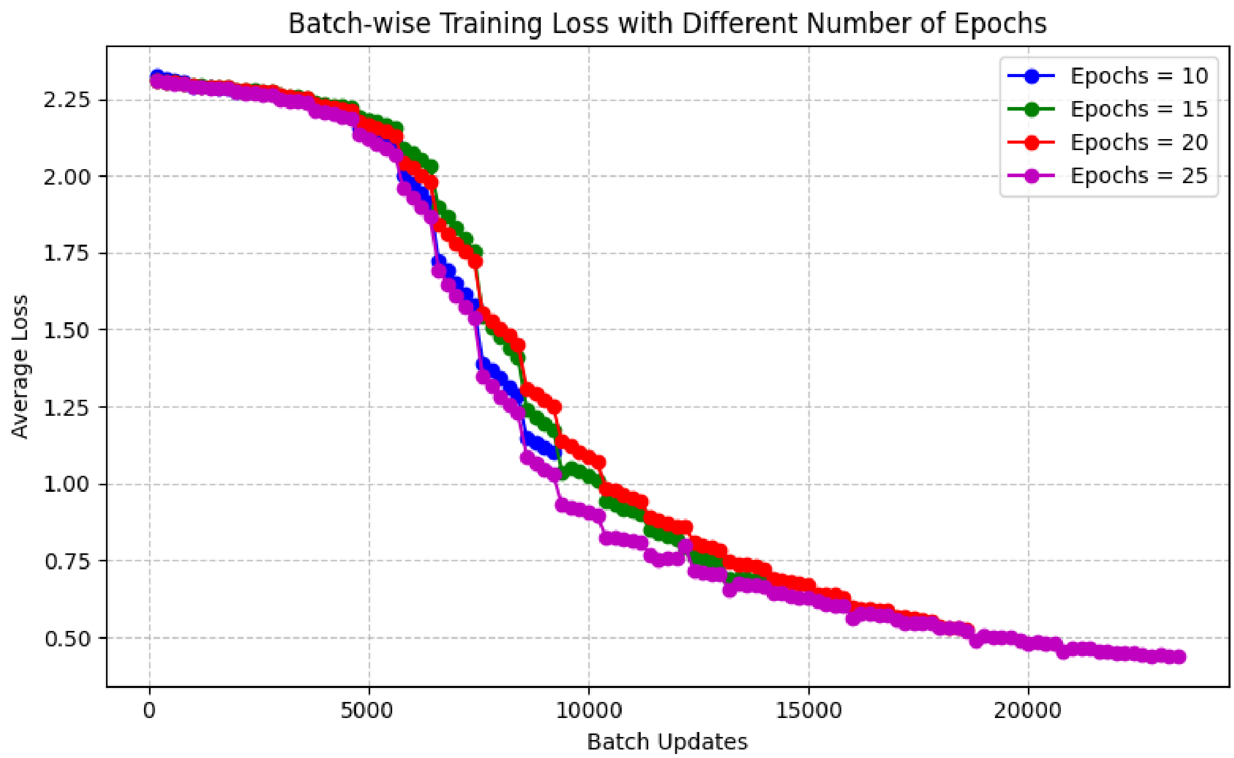
```
Test Set Evaluation for 25 epochs
Accuracy: 87.7500%
Confusion Matrix:
[[ 948    0    2    3    0   18    6    2    1    0]
 [   0 1094    1    6    1    3    3    1   26    0]
 [  16   13  861   41   21    4   21    9   38    8]
 [   4    1   35  849    1   58    0   24   32    6]
 [   1    2    6    0  885    1   12    1    9   65]
 [  14    3    8   49   11  723   26   14   36    8]
 [  25    2   12    0   24   22  869    0    4    0]
 [   7   16   20   11    5    1    0  907    5   56]
 [   5    5   12   28   16   46   19    6  818   19]
 [  10    3    3    6   93   16    1   42   14  821]]

Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.97      0.94       980
           1       0.96      0.96      0.96      1135
           2       0.90      0.83      0.86      1032
           3       0.85      0.84      0.85      1010
           4       0.84      0.90      0.87       982
           5       0.81      0.81      0.81       892
           6       0.91      0.91      0.91       958
           7       0.90      0.88      0.89      1028
           8       0.83      0.84      0.84       974
           9       0.84      0.81      0.82      1009

    accuracy                           0.88     10000
   macro avg       0.88      0.88      0.88     10000
weighted avg       0.88      0.88      0.88     10000


np.float64(0.8775)
```

```python
plt.figure(figsize=(8,5))
plt.plot(range(1, len(loss_history_sigmoid_3)+1),
loss_history_sigmoid_3, marker='o', color='b', label="Epochs = 10")
plt.plot(range(1, len(loss_history)+1), loss_history, marker='o',
color='g', label="Epochs = 15")
plt.plot(range(1, len(loss_history_sigmoid_4)+1),
loss_history_sigmoid_4, marker='o', color='r', label="Epochs = 20")
plt.plot(range(1, len(loss_history_sigmoid_5)+1),
loss_history_sigmoid_5, marker='o', color='m', label="Epochs = 25")
```

```
plt.title("Epoch-wise Training Loss with Different Number of Epochs")
plt.xlabel("Epochs")
plt.ylabel("Average Loss")
plt.legend()
plt.grid(True, linestyle="--", alpha=0.7)
plt.tight_layout()
plt.show()
```




```
plt.figure(figsize=(8,5))
plt.plot(iter_sigmoid_3, iter_loss_sigmoid_3, marker='o', color='b',
label="Epochs = 10")
plt.plot(iter_tanh, iter_loss, marker='o', color='g', label="Epochs =
15")
plt.plot(iter_sigmoid_4, iter_loss_sigmoid_4, marker='o', color='r',
label="Epochs = 20")
plt.plot(iter_sigmoid_5, iter_loss_sigmoid_5, marker='o', color='m',
label="Epochs = 25")
plt.title("Batch-wise Training Loss with Different Number of Epochs")
plt.xlabel("Batch Updates")
plt.ylabel("Average Loss")
plt.legend()
plt.grid(True, linestyle="--", alpha=0.7)
plt.tight_layout()
plt.show()
```



Observation and Conclusions based on variation in number of epochs

- Test accuracy for 10 epochs = **69.76%**
- Test accuracy for 15 epochs = **82.30%**
- Test accuracy for 20 epochs = **85.39%**
- Test accuracy for 25 epochs = **87.75%**

Increasing the number of epochs gives more time for the network to learn and hence postively helps in improving the accuracy in testing phase.

The overall training loss per epoch is roughly the same and independent of number of epochs, that is the training at the nth epoch is roughly same in each case of having different number of epochs for the overall training