

```

Epoch 6/50
858/858 [=====] - 1s 745us/step - loss: 2.0956 - accuracy: 0.5528 - val_loss: 2.2952 - val_accuracy: 0.4939
Epoch 7/50
858/858 [=====] - 1s 744us/step - loss: 1.9923 - accuracy: 0.5703 - val_loss: 2.2566 - val_accuracy: 0.4872
Epoch 8/50
858/858 [=====] - 1s 738us/step - loss: 1.9127 - accuracy: 0.5834 - val_loss: 2.1353 - val_accuracy: 0.5301
Epoch 9/50
858/858 [=====] - 1s 743us/step - loss: 1.8525 - accuracy: 0.5965 - val_loss: 2.0467 - val_accuracy: 0.5544
Epoch 10/50
858/858 [=====] - 1s 749us/step - loss: 1.8147 - accuracy: 0.6072 - val_loss: 1.9657 - val_accuracy: 0.5728
Epoch 11/50
858/858 [=====] - 1s 743us/step - loss: 1.7740 - accuracy: 0.6170 - val_loss: 2.0392 - val_accuracy: 0.5259
Epoch 12/50
858/858 [=====] - 1s 736us/step - loss: 1.7549 - accuracy: 0.6162 - val_loss: 1.9834 - val_accuracy: 0.5508
Epoch 13/50
858/858 [=====] - 1s 742us/step - loss: 1.7356 - accuracy: 0.6211 - val_loss: 2.5880 - val_accuracy: 0.4041
Epoch 14/50
858/858 [=====] - 1s 738us/step - loss: 1.6971 - accuracy: 0.6358 - val_loss: 1.9187 - val_accuracy: 0.5862
Epoch 15/50
858/858 [=====] - 1s 745us/step - loss: 1.7018 - accuracy: 0.6343 - val_loss: 2.1135 - val_accuracy: 0.5159
Epoch 16/50
858/858 [=====] - 1s 747us/step - loss: 1.6857 - accuracy: 0.6414 - val_loss: 1.9186 - val_accuracy: 0.5686
Epoch 17/50
858/858 [=====] - 1s 741us/step - loss: 1.6772 - accuracy: 0.6405 - val_loss: 1.8645 - val_accuracy: 0.6138
Epoch 18/50
858/858 [=====] - 1s 748us/step - loss: 1.6606 - accuracy: 0.6424 - val_loss: 2.4435 - val_accuracy: 0.4467
Epoch 19/50
858/858 [=====] - 1s 746us/step - loss: 1.6460 - accuracy: 0.6514 - val_loss: 2.2045 - val_accuracy: 0.4880
Epoch 20/50
858/858 [=====] - 1s 751us/step - loss: 1.6392 - accuracy: 0.6536 - val_loss: 2.0044 - val_accuracy: 0.5577
Epoch 21/50
858/858 [=====] - 1s 760us/step - loss: 1.6299 - accuracy: 0.6547 - val_loss: 1.9098 - val_accuracy: 0.5884
Epoch 22/50
858/858 [=====] - 1s 748us/step - loss: 1.6325 - accuracy: 0.6532 - val_loss: 1.9898 - val_accuracy: 0.5240

```

According to the performance of this best densely connected model after using L2 Regularizer, after epoch 22, its training accuracy is about 0.6532 and its validation accuracy is about 0.524. The difference between these two values is about 0.13. Hence, this method of L2 Regularization just can slightly reduce the overfitting problem of this model since the gap between these two values of this model before apply L2 regularization is about 0.2. However, the validation accuracy of this model after applying L2 Regularization is much lower than its original validation accuracy since the model's validation accuracy before applying this L2 regularization method is about 0.73.

```

In [34]: # Try using Weight Initialization for the best densely connect model
model_dense_wi = keras.models.Sequential()
model_dense_wi.add(keras.layers.Flatten(input_shape = [28, 28, 1]))
model_dense_wi.add(keras.layers.Dense(64, activation = 'elu', kernel_initializer = 'he_normal'))
for n in hiddensizes[1:]:
    model_dense_wi.add(keras.layers.Dense(n, activation = 'selu'))
model_dense_wi.add(keras.layers.Dense(24, activation = "softmax"))
model_dense_wi.compile(loss="sparse_categorical_crossentropy", optimizer=keras.optimizers.SGD(learning_rate=0.01), metrics=['accuracy'])
history_dense_wi = model_dense_wi.fit(X_train, y_train, epochs=50, callbacks = early_stopping_cb, validation_data=(X_val, y_val))
max_val_acc_dense_wi = np.max(history_dense_wi.history['val_accuracy'])

Epoch 1/50
858/858 [=====] - 1s 851us/step - loss: 2.4767 - accuracy: 0.2469 - val_loss: 2.0876 - val_accuracy: 0.3001
Epoch 2/50
858/858 [=====] - 1s 747us/step - loss: 1.6745 - accuracy: 0.4679 - val_loss: 1.7099 - val_accuracy: 0.4674
Epoch 3/50
858/858 [=====] - 1s 742us/step - loss: 1.2962 - accuracy: 0.5767 - val_loss: 1.4403 - val_accuracy: 0.5198
Epoch 4/50
858/858 [=====] - 1s 760us/step - loss: 1.0809 - accuracy: 0.6441 - val_loss: 1.3226 - val_accuracy: 0.5563
Epoch 5/50
858/858 [=====] - 1s 747us/step - loss: 0.9198 - accuracy: 0.6972 - val_loss: 1.3666 - val_accuracy: 0.5555
Epoch 6/50
858/858 [=====] - 1s 752us/step - loss: 0.8026 - accuracy: 0.7372 - val_loss: 1.3986 - val_accuracy: 0.5717
Epoch 7/50
858/858 [=====] - 1s 751us/step - loss: 0.7075 - accuracy: 0.7696 - val_loss: 1.1941 - val_accuracy: 0.6291
Epoch 8/50
858/858 [=====] - 1s 746us/step - loss: 0.6068 - accuracy: 0.8032 - val_loss: 1.1448 - val_accuracy: 0.6576
Epoch 9/50
858/858 [=====] - 1s 752us/step - loss: 0.5400 - accuracy: 0.8260 - val_loss: 1.2350 - val_accuracy: 0.6431
Epoch 10/50
858/858 [=====] - 1s 759us/step - loss: 0.4729 - accuracy: 0.8477 - val_loss: 1.1406 - val_accuracy: 0.6746
Epoch 11/50
858/858 [=====] - 1s 749us/step - loss: 0.4407 - accuracy: 0.8629 - val_loss: 1.1842 - val_accuracy: 0.6603
Epoch 12/50
858/858 [=====] - 1s 771us/step - loss: 0.3714 - accuracy: 0.8840 - val_loss: 1.1757 - val_accuracy: 0.6882
Epoch 13/50
858/858 [=====] - 1s 750us/step - loss: 0.3145 - accuracy: 0.9050 - val_loss: 1.4618 - val_accuracy: 0.6302
Epoch 14/50
858/858 [=====] - 1s 755us/step - loss: 0.2825 - accuracy: 0.9168 - val_loss: 1.4035 - val_accuracy: 0.6489
Epoch 15/50
858/858 [=====] - 1s 767us/step - loss: 0.2430 - accuracy: 0.9289 - val_loss: 1.1950 - val_accuracy: 0.7022

```

According to the performance of this best densely connected model after using Weight initialization method, after epoch 15, this model converges with its training accuracy is about 0.9289 and its validation accuracy is about 0.7022. The difference between these two values is about 0.23. Hence, this method of Weight initialization does not reduce the gap between the training accuracy and the validation accuracy of the model since the difference between these two values before applying Weight initialization is about 0.2.

```
In [35]: # Try using Dropout Regularization for the best densely connect model
model_dense_dr = keras.models.Sequential()
model_dense_dr.add(keras.layers.Flatten(input_shape = [28, 28, 1]))
for n in hiddensizes:
    model_dense_dr.add(keras.layers.Dense(n, activation = 'elu'))
    model_dense_dr.add(keras.layers.Dropout (0.05))
model_dense_dr.add(keras.layers.Dense(24, activation = "softmax"))
model_dense_dr.compile(loss="sparse_categorical_crossentropy", optimizer=keras.optimizers.SGD(learning_rate=0.01), metrics=[accuracy])
history_dense_dr = model_dense_dr.fit(X_train, y_train, epochs=50, callbacks = early_stopping_cb, validation_data=(X_val, y_val))
max_val_acc_dense_dr = np.max(history_dense_dr.history['val_accuracy'])

Epoch 1/50
858/858 [=====] - 1s 894us/step - loss: 2.9185 - accuracy: 0.1554 - val_loss: 2.6923 - val_accuracy: 0.2181
Epoch 2/50
858/858 [=====] - 1s 801us/step - loss: 2.2142 - accuracy: 0.3331 - val_loss: 1.9673 - val_accuracy: 0.3879
Epoch 3/50
858/858 [=====] - 1s 837us/step - loss: 1.7477 - accuracy: 0.4443 - val_loss: 1.7352 - val_accuracy: 0.4526
Epoch 4/50
858/858 [=====] - 1s 809us/step - loss: 1.4906 - accuracy: 0.5182 - val_loss: 1.4266 - val_accuracy: 0.5694
Epoch 5/50
858/858 [=====] - 1s 822us/step - loss: 1.3086 - accuracy: 0.5742 - val_loss: 1.3576 - val_accuracy: 0.5904
Epoch 6/50
858/858 [=====] - 1s 814us/step - loss: 1.1739 - accuracy: 0.6153 - val_loss: 1.3680 - val_accuracy: 0.5669
Epoch 7/50
858/858 [=====] - 1s 848us/step - loss: 1.0610 - accuracy: 0.6532 - val_loss: 1.2966 - val_accuracy: 0.5973
Epoch 8/50
858/858 [=====] - 1s 815us/step - loss: 0.9655 - accuracy: 0.6806 - val_loss: 1.2189 - val_accuracy: 0.6037
Epoch 9/50
858/858 [=====] - 1s 810us/step - loss: 0.8752 - accuracy: 0.7104 - val_loss: 1.1290 - val_accuracy: 0.6617
Epoch 10/50
858/858 [=====] - 1s 815us/step - loss: 0.8072 - accuracy: 0.7341 - val_loss: 1.0966 - val_accuracy: 0.6347
Epoch 11/50
858/858 [=====] - 1s 808us/step - loss: 0.7452 - accuracy: 0.7521 - val_loss: 1.0968 - val_accuracy: 0.6492
Epoch 12/50
858/858 [=====] - 1s 810us/step - loss: 0.6987 - accuracy: 0.7675 - val_loss: 1.1331 - val_accuracy: 0.6598
Epoch 13/50
858/858 [=====] - 1s 818us/step - loss: 0.6528 - accuracy: 0.7821 - val_loss: 1.0886 - val_accuracy: 0.6662
Epoch 14/50
858/858 [=====] - 1s 806us/step - loss: 0.5888 - accuracy: 0.8040 - val_loss: 1.0324 - val_accuracy: 0.7002
Epoch 15/50
858/858 [=====] - 1s 830us/step - loss: 0.5649 - accuracy: 0.8106 - val_loss: 1.1694 - val_accuracy: 0.6718
Epoch 16/50
858/858 [=====] - 1s 810us/step - loss: 0.5300 - accuracy: 0.8212 - val_loss: 1.0503 - val_accuracy: 0.7223
Epoch 17/50
858/858 [=====] - 1s 805us/step - loss: 0.4836 - accuracy: 0.8381 - val_loss: 1.0324 - val_accuracy: 0.7306
Epoch 18/50
858/858 [=====] - 1s 812us/step - loss: 0.4562 - accuracy: 0.8448 - val_loss: 1.4071 - val_accuracy: 0.6202
Epoch 19/50
858/858 [=====] - 1s 814us/step - loss: 0.4384 - accuracy: 0.8548 - val_loss: 1.0183 - val_accuracy: 0.7231
Epoch 20/50
858/858 [=====] - 1s 815us/step - loss: 0.4091 - accuracy: 0.8633 - val_loss: 1.0445 - val_accuracy: 0.7181
Epoch 21/50
858/858 [=====] - 1s 814us/step - loss: 0.3818 - accuracy: 0.8733 - val_loss: 1.1317 - val_accuracy: 0.7131
Epoch 22/50
858/858 [=====] - 1s 820us/step - loss: 0.3630 - accuracy: 0.8774 - val_loss: 1.0987 - val_accuracy: 0.7292
Epoch 23/50
858/858 [=====] - 1s 808us/step - loss: 0.3477 - accuracy: 0.8833 - val_loss: 1.2303 - val_accuracy: 0.6704
Epoch 24/50
858/858 [=====] - 1s 820us/step - loss: 0.3210 - accuracy: 0.8912 - val_loss: 1.0704 - val_accuracy: 0.7292
```

According to the performance of this best densely connected model after using Dropout regularization method, after epoch 24, this model converges with its training accuracy is about 0.8912 and its validation accuracy is about 0.7292. The difference between these two values is about 0.16. Hence, this method of Dropout regulation also just slightly reduce the gap between the training accuracy and the validation accuracy of the model since the gap between these two values of this model before apply Dropout regularization is about 0.2, but it does not improve the validation accuracy much.

3.2 Train and optimize a Convolutional Neural Network (CNN) model

The CNN model is built with Convolutional layers 3x3, strides equal to 1, Max Pooling layers 2x2, 1 Flatten layer, and 1 Dense layer including 24 neurons for the output. The used loss function is Sparse categorical crossentropy since labels are encoding as integers (from 0 to 23). Early stopping is also defined with patience of 5, and monitored by validation loss values. Early stopping is used to prevent model from overfitting.

```
In [37]: hiddensizes = [64,32,16]
batch_size = 32
n_epochs = 50

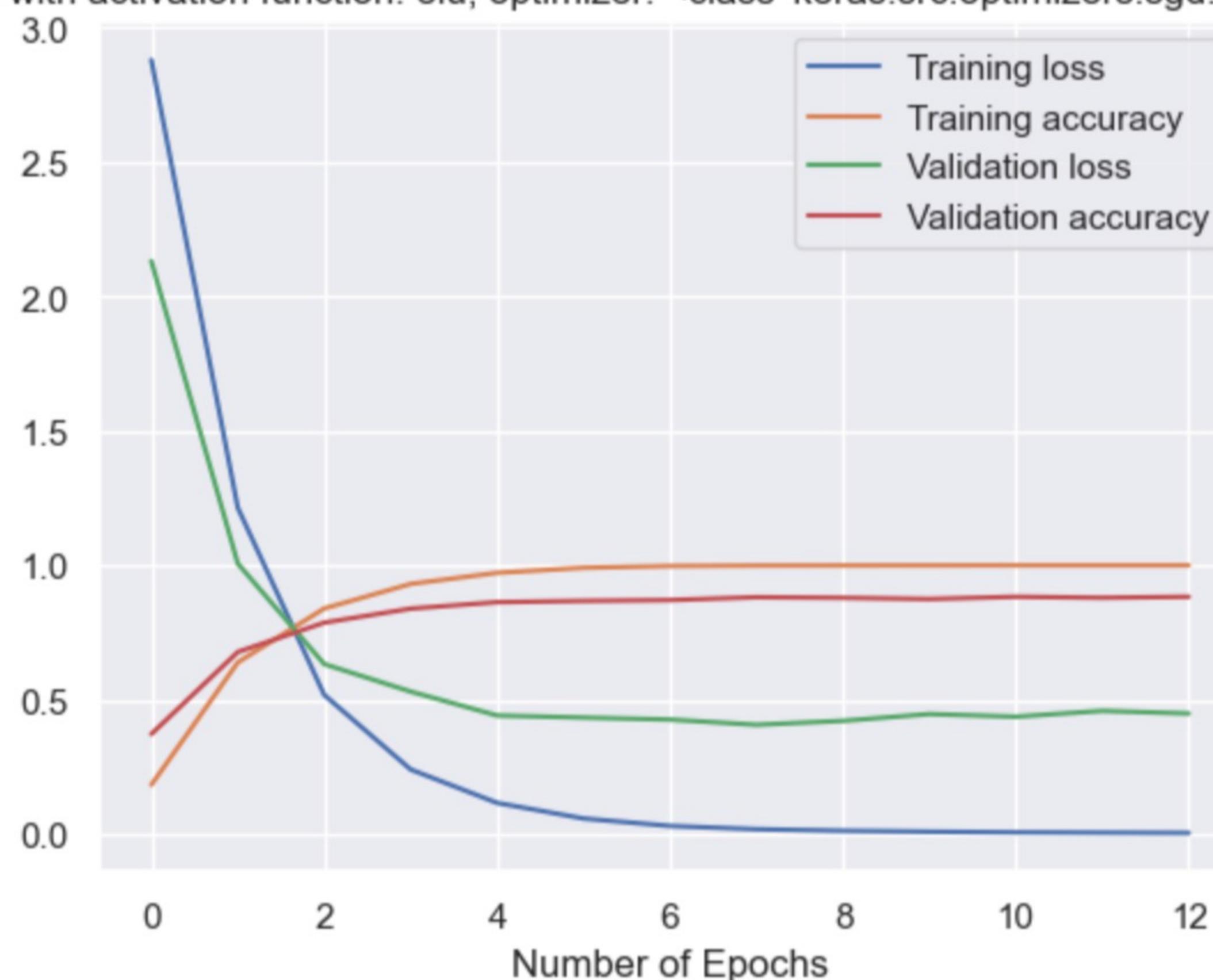
def model_cnn_factory(hiddensizes, actfn, optimizer, learningrate=0):
    model = keras.models.Sequential()
    model.add(keras.layers.Conv2D(filters=hiddensizes[0], kernel_size=3, strides=1, activation=actfn, padding="same",
                                 input_shape=[28, 28, 1]))
    model.add(keras.layers.MaxPooling2D(pool_size=2))
    for n in hiddensizes[1:-1]:
        model.add(keras.layers.Conv2D(filters=n, kernel_size=3, strides=1, padding="same", activation=actfn))
        model.add(keras.layers.MaxPooling2D(pool_size=2))
    model.add(keras.layers.Conv2D(filters=hiddensizes[-1], kernel_size=3, strides=1, padding="same",
                                 activation=actfn))
    model.add(keras.layers.Flatten())
    model.add(keras.layers.Dense(24, activation = "softmax"))
    model.compile(loss="sparse_categorical_crossentropy", optimizer=optimizer(learning_rate=learningrate),
                  metrics=["accuracy"])
    return model

def build_cnn(hiddensizes, actfn, optimizer, learningrate, n_epochs, batch_size, further_callbacks=[]):
    if further_callbacks != []:
        callbacks = further_callbacks
    else:
        callbacks = [early_stopping_cb]
    model = model_cnn_factory(hiddensizes, actfn, optimizer, learningrate)
    history = model.fit(X_train, y_train, epochs=n_epochs, callbacks = callbacks,
                         validation_data=(X_val, y_val))
    max_val_acc = np.max(history.history['val_accuracy'])
    return (max_val_acc, history, model)

res_cnn = []
for i in learningrate:
    for o in optimizer:
        for a in actfn:
            max_val_acc_cnn, history_cnn, model_cnn = build_cnn(hiddensizes, a, o, i, n_epochs, batch_size)
            pd.DataFrame(history_cnn.history).plot()
            plt.xlabel("Number of Epochs")
            plt.title(f'Plot of the CNN model with activation function: {a}, optimizer: {o} and learning rate: {i}')
            plt.legend(['Training loss', 'Training accuracy', 'Validation loss', 'Validation accuracy'])
            plt.show()
            res_cnn += [[i, o, a, max_val_acc_cnn]]
```

```
Epoch 1/50
858/858 [=====] - 16s 18ms/step - loss: 2.8795 - accuracy: 0.1839 - val_loss: 2.1314 - val_accuracy: 0.3726
Epoch 2/50
858/858 [=====] - 15s 18ms/step - loss: 1.2141 - accuracy: 0.6392 - val_loss: 1.0068 - val_accuracy: 0.6779
Epoch 3/50
858/858 [=====] - 16s 18ms/step - loss: 0.5182 - accuracy: 0.8397 - val_loss: 0.6327 - val_accuracy: 0.7869
Epoch 4/50
858/858 [=====] - 16s 18ms/step - loss: 0.2408 - accuracy: 0.9309 - val_loss: 0.5305 - val_accuracy: 0.8391
Epoch 5/50
858/858 [=====] - 15s 18ms/step - loss: 0.1165 - accuracy: 0.9722 - val_loss: 0.4416 - val_accuracy: 0.8631
Epoch 6/50
858/858 [=====] - 15s 18ms/step - loss: 0.0585 - accuracy: 0.9910 - val_loss: 0.4339 - val_accuracy: 0.8678
Epoch 7/50
858/858 [=====] - 15s 18ms/step - loss: 0.0309 - accuracy: 0.9975 - val_loss: 0.4265 - val_accuracy: 0.8709
Epoch 8/50
858/858 [=====] - 16s 18ms/step - loss: 0.0186 - accuracy: 0.9992 - val_loss: 0.4069 - val_accuracy: 0.8815
Epoch 9/50
858/858 [=====] - 16s 18ms/step - loss: 0.0129 - accuracy: 0.9995 - val_loss: 0.4217 - val_accuracy: 0.8793
Epoch 10/50
858/858 [=====] - 15s 18ms/step - loss: 0.0096 - accuracy: 0.9997 - val_loss: 0.4469 - val_accuracy: 0.8748
Epoch 11/50
858/858 [=====] - 15s 18ms/step - loss: 0.0071 - accuracy: 0.9999 - val_loss: 0.4371 - val_accuracy: 0.8832
Epoch 12/50
858/858 [=====] - 15s 18ms/step - loss: 0.0058 - accuracy: 0.9999 - val_loss: 0.4587 - val_accuracy: 0.8795
Epoch 13/50
858/858 [=====] - 16s 18ms/step - loss: 0.0048 - accuracy: 0.9999 - val_loss: 0.4490 - val_accuracy: 0.8832
```

Plot of the CNN model with activation function: elu, optimizer: <class 'keras.src.optimizers.sgd.SGD'> and learning rate: 0.01



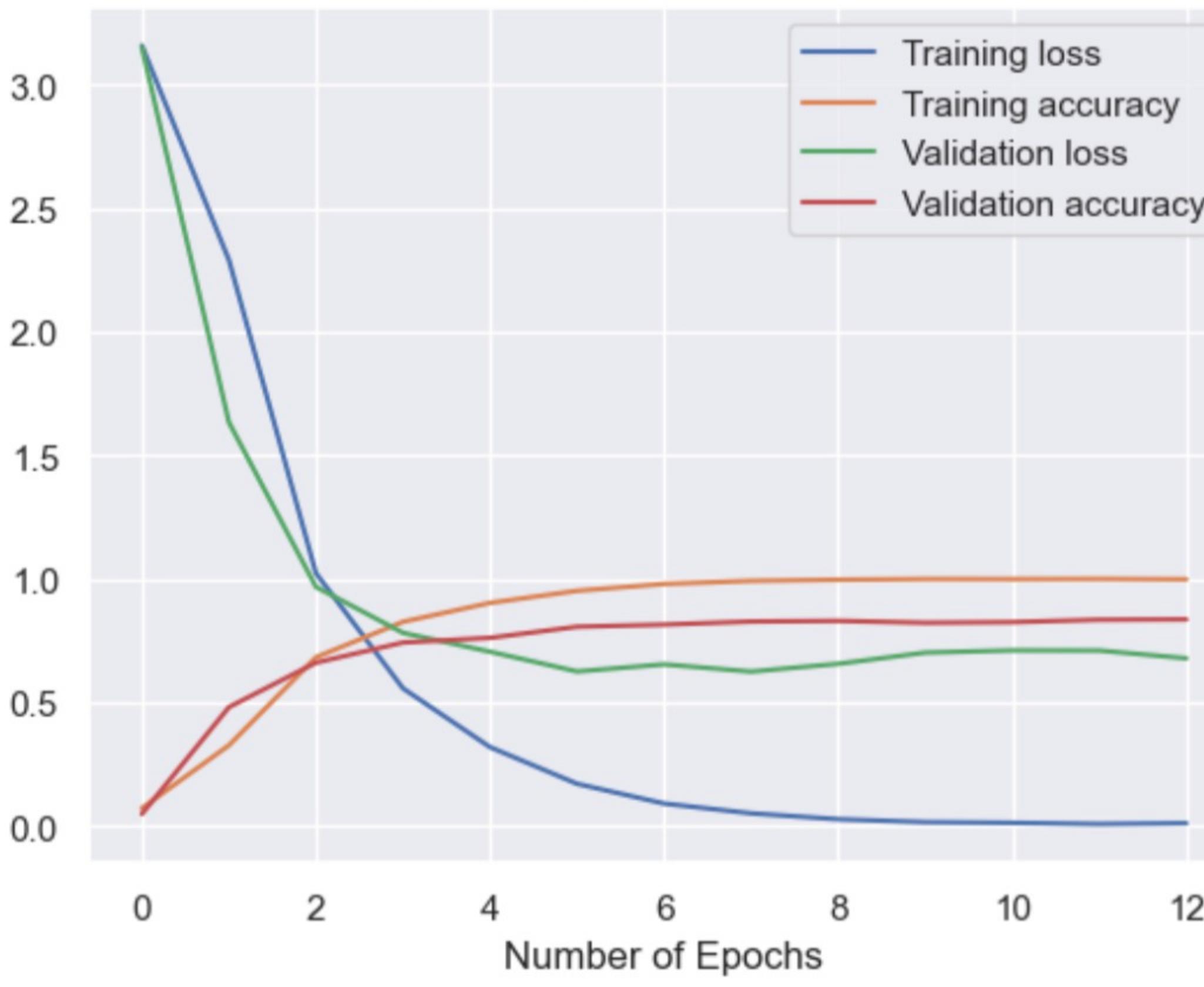
```
Epoch 1/50
858/858 [=====] - 14s 16ms/step - loss: 3.1578 - accuracy: 0.0720 - val_loss: 3.1513 - val_accuracy: 0.0485
Epoch 2/50
858/858 [=====] - 14s 16ms/step - loss: 2.2905 - accuracy: 0.3265 - val_loss: 1.6336 - val_accuracy: 0.3265
```

```

accuracy: 0.4808
Epoch 3/50
858/858 [=====] - 14s 16ms/step - loss: 1.0229 - accuracy: 0.6828 - val_loss: 0.9674 - val_accuracy: 0.6609
Epoch 4/50
858/858 [=====] - 14s 17ms/step - loss: 0.5568 - accuracy: 0.8263 - val_loss: 0.7815 - val_accuracy: 0.7423
Epoch 5/50
858/858 [=====] - 14s 16ms/step - loss: 0.3191 - accuracy: 0.9027 - val_loss: 0.7051 - val_accuracy: 0.7613
Epoch 6/50
858/858 [=====] - 14s 16ms/step - loss: 0.1706 - accuracy: 0.9516 - val_loss: 0.6253 - val_accuracy: 0.8062
Epoch 7/50
858/858 [=====] - 14s 16ms/step - loss: 0.0908 - accuracy: 0.9794 - val_loss: 0.6540 - val_accuracy: 0.8148
Epoch 8/50
858/858 [=====] - 14s 16ms/step - loss: 0.0512 - accuracy: 0.9919 - val_loss: 0.6248 - val_accuracy: 0.8274
Epoch 9/50
858/858 [=====] - 14s 16ms/step - loss: 0.0274 - accuracy: 0.9965 - val_loss: 0.6562 - val_accuracy: 0.8299
Epoch 10/50
858/858 [=====] - 14s 16ms/step - loss: 0.0156 - accuracy: 0.9993 - val_loss: 0.7015 - val_accuracy: 0.8224
Epoch 11/50
858/858 [=====] - 14s 16ms/step - loss: 0.0129 - accuracy: 0.9991 - val_loss: 0.7106 - val_accuracy: 0.8249
Epoch 12/50
858/858 [=====] - 14s 16ms/step - loss: 0.0081 - accuracy: 0.9997 - val_loss: 0.7100 - val_accuracy: 0.8346
Epoch 13/50
858/858 [=====] - 14s 16ms/step - loss: 0.0114 - accuracy: 0.9984 - val_loss: 0.6785 - val_accuracy: 0.8360

```

Plot of the CNN model with activation function: LeakyReLU, optimizer: <class 'keras.src.optimizers.sgd.SGD'> and learning rate: 0.01

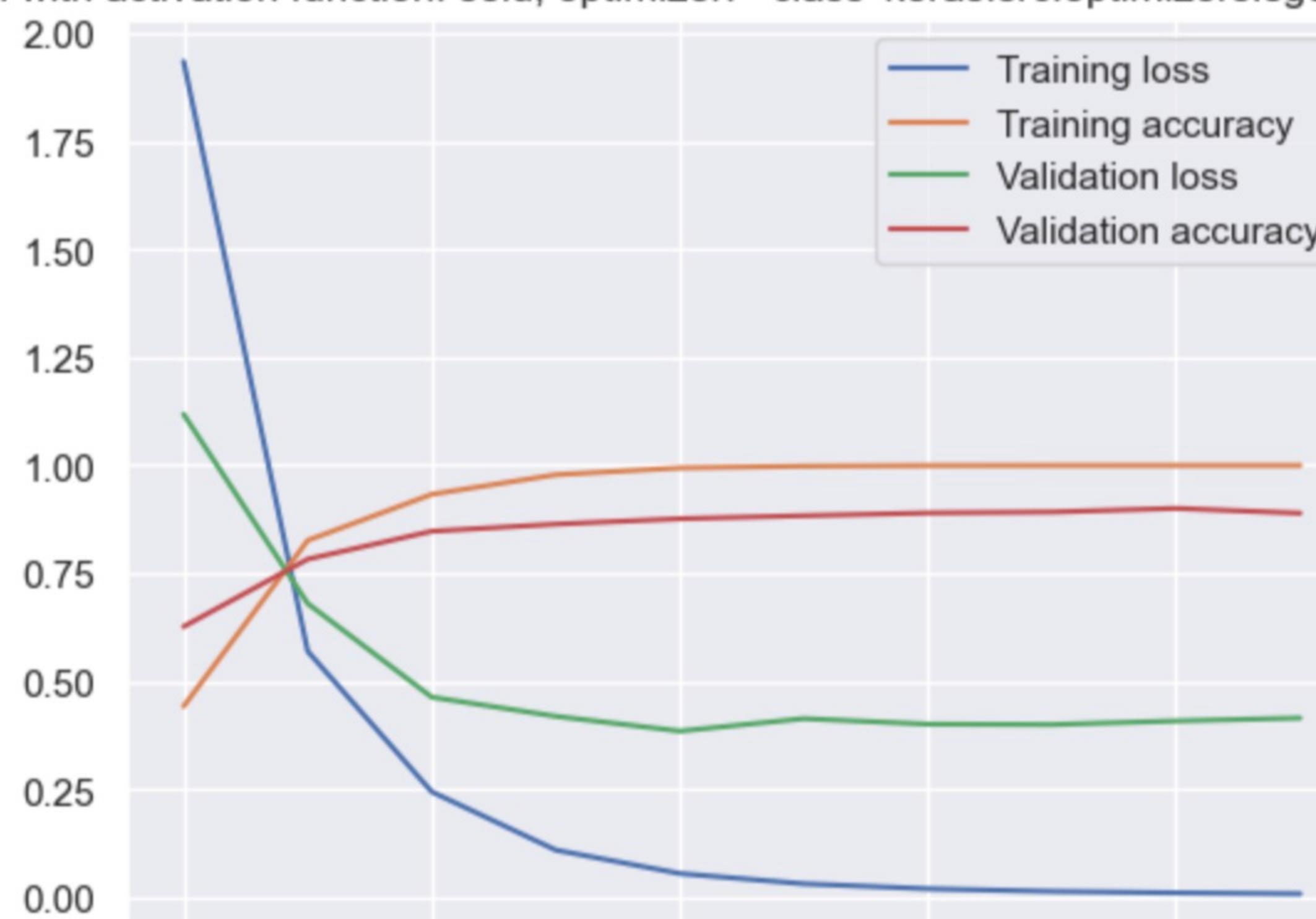


```

Epoch 1/50
858/858 [=====] - 16s 18ms/step - loss: 1.9353 - accuracy: 0.4421 - val_loss: 1.1185 - val_accuracy: 0.6266
Epoch 2/50
858/858 [=====] - 16s 19ms/step - loss: 0.5696 - accuracy: 0.8263 - val_loss: 0.6801 - val_accuracy: 0.7828
Epoch 3/50
858/858 [=====] - 16s 18ms/step - loss: 0.2442 - accuracy: 0.9330 - val_loss: 0.4633 - val_accuracy: 0.8475
Epoch 4/50
858/858 [=====] - 16s 18ms/step - loss: 0.1092 - accuracy: 0.9783 - val_loss: 0.4190 - val_accuracy: 0.8639
Epoch 5/50
858/858 [=====] - 16s 18ms/step - loss: 0.0548 - accuracy: 0.9941 - val_loss: 0.3846 - val_accuracy: 0.8765
Epoch 6/50
858/858 [=====] - 16s 18ms/step - loss: 0.0311 - accuracy: 0.9981 - val_loss: 0.4136 - val_accuracy: 0.8834
Epoch 7/50
858/858 [=====] - 16s 19ms/step - loss: 0.0195 - accuracy: 0.9995 - val_loss: 0.4007 - val_accuracy: 0.8898
Epoch 8/50
858/858 [=====] - 16s 18ms/step - loss: 0.0135 - accuracy: 0.9998 - val_loss: 0.3997 - val_accuracy: 0.8921
Epoch 9/50
858/858 [=====] - 16s 19ms/step - loss: 0.0101 - accuracy: 0.9998 - val_loss: 0.4082 - val_accuracy: 0.9004
Epoch 10/50
858/858 [=====] - 16s 18ms/step - loss: 0.0079 - accuracy: 0.9998 - val_loss: 0.4149 - val_accuracy: 0.8893

```

Plot of the CNN model with activation function: selu, optimizer: <class 'keras.src.optimizers.sgd.SGD'> and learning rate: 0.01



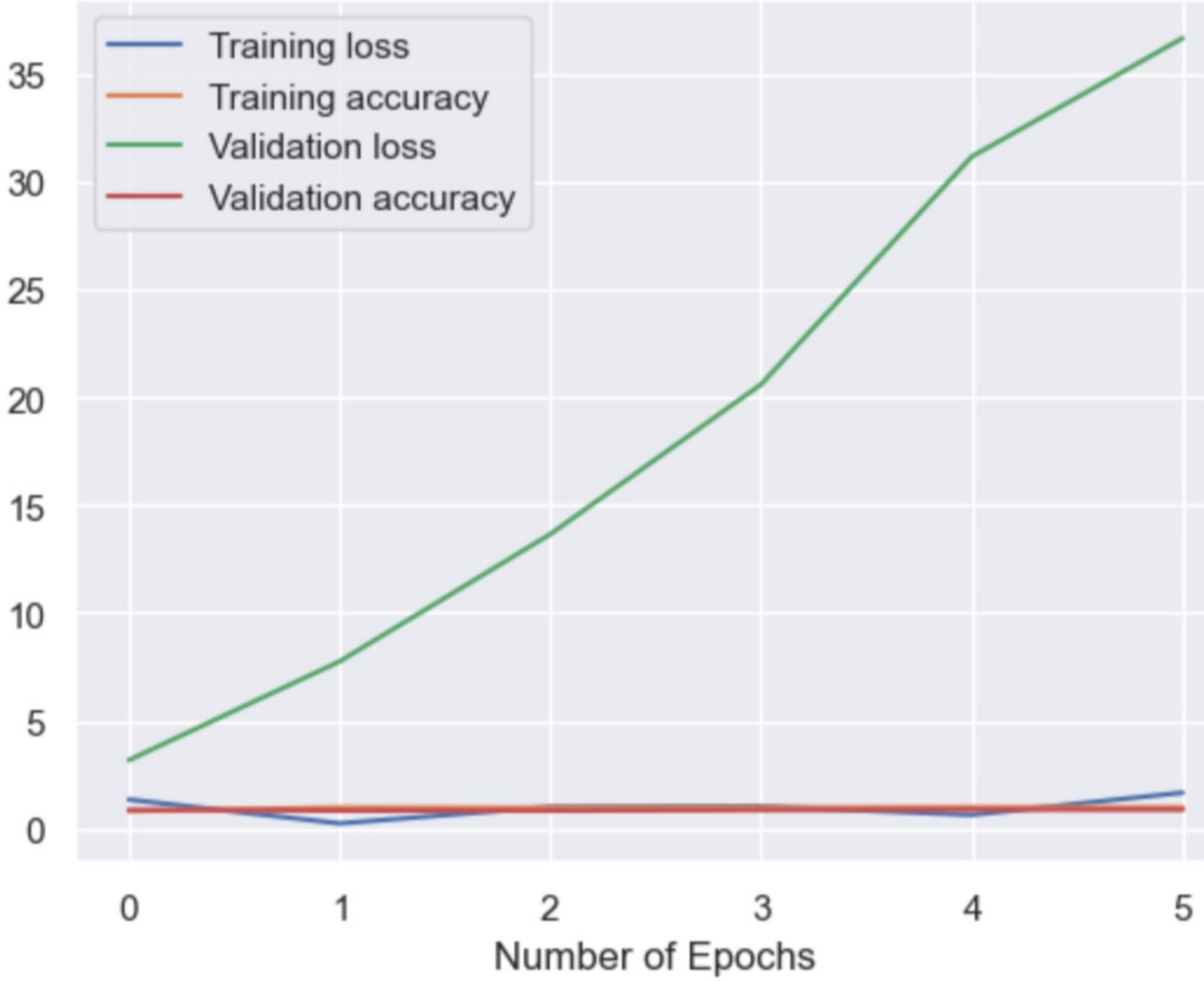


```

Epoch 1/50
858/858 [=====] - 17s 19ms/step - loss: 1.3477 - accuracy: 0.8103 - val_loss: 3.1771 - val_accuracy: 0.8779
Epoch 2/50
858/858 [=====] - 16s 19ms/step - loss: 0.2401 - accuracy: 0.9822 - val_loss: 7.7578 - val_accuracy: 0.8349
Epoch 3/50
858/858 [=====] - 16s 19ms/step - loss: 1.0093 - accuracy: 0.9658 - val_loss: 13.6655 - val_accuracy: 0.8330
Epoch 4/50
858/858 [=====] - 16s 19ms/step - loss: 1.0300 - accuracy: 0.9786 - val_loss: 20.6149 - val_accuracy: 0.8611
Epoch 5/50
858/858 [=====] - 17s 19ms/step - loss: 0.6397 - accuracy: 0.9903 - val_loss: 31.1856 - val_accuracy: 0.8862
Epoch 6/50
858/858 [=====] - 16s 19ms/step - loss: 1.6665 - accuracy: 0.9851 - val_loss: 36.6808 - val_accuracy: 0.8745

```

Plot of the CNN model with activation function: elu, optimizer: <class 'keras.src.optimizers.adam.Adam'> and learning rate: 0.01

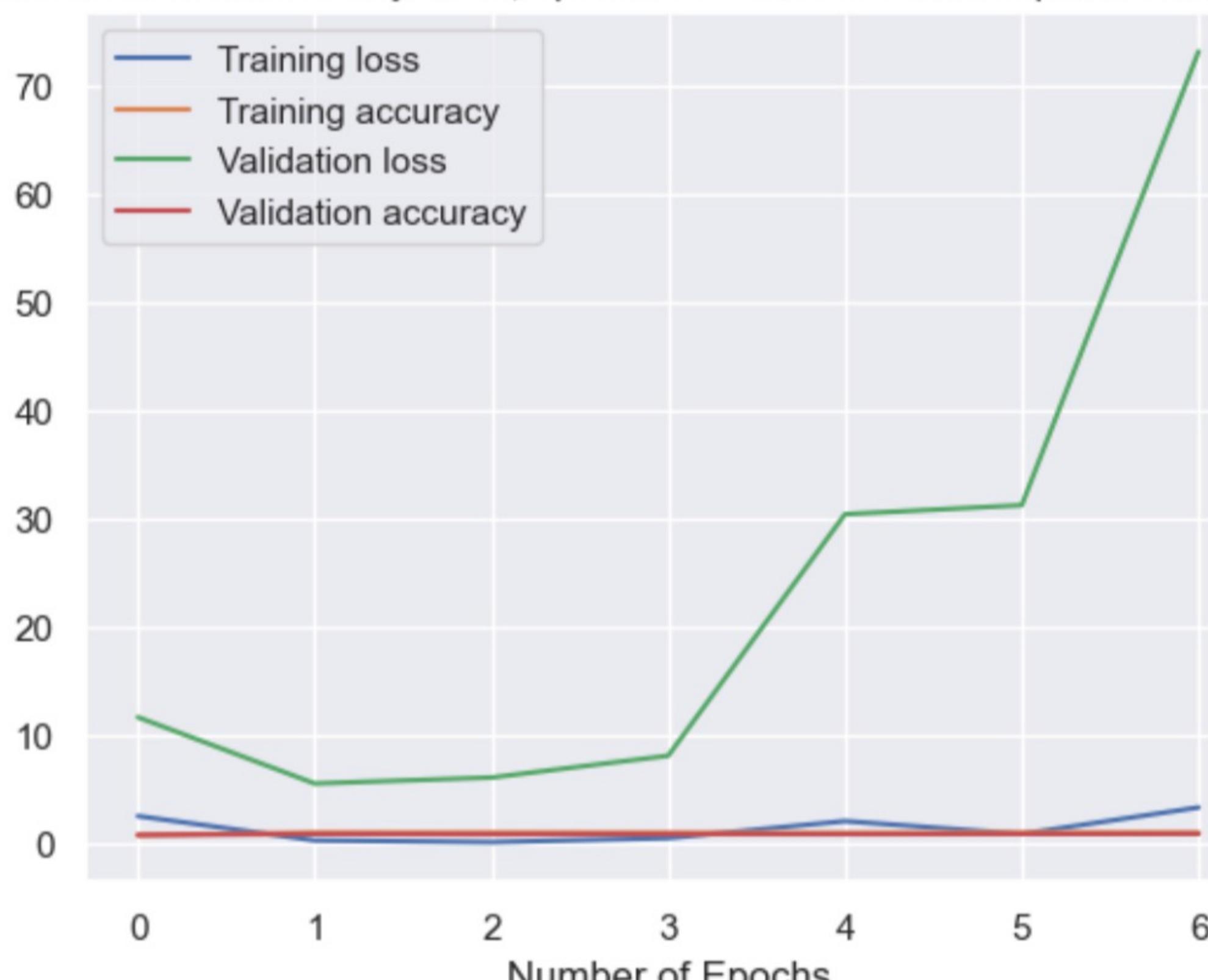


```

Epoch 1/50
858/858 [=====] - 14s 16ms/step - loss: 2.5116 - accuracy: 0.7588 - val_loss: 11.6346 - val_accuracy: 0.7557
Epoch 2/50
858/858 [=====] - 14s 16ms/step - loss: 0.2642 - accuracy: 0.9811 - val_loss: 5.5127 - val_accuracy: 0.8578
Epoch 3/50
858/858 [=====] - 15s 17ms/step - loss: 0.1033 - accuracy: 0.9890 - val_loss: 6.0678 - val_accuracy: 0.8271
Epoch 4/50
858/858 [=====] - 15s 17ms/step - loss: 0.4755 - accuracy: 0.9721 - val_loss: 8.0769 - val_accuracy: 0.8514
Epoch 5/50
858/858 [=====] - 14s 16ms/step - loss: 2.0433 - accuracy: 0.9617 - val_loss: 30.3714 - val_accuracy: 0.8397
Epoch 6/50
858/858 [=====] - 14s 16ms/step - loss: 0.8565 - accuracy: 0.9879 - val_loss: 31.2023 - val_accuracy: 0.8564
Epoch 7/50
858/858 [=====] - 14s 16ms/step - loss: 3.3077 - accuracy: 0.9793 - val_loss: 73.0682 - val_accuracy: 0.8731

```

Plot of the CNN model with activation function: LeakyReLU, optimizer: <class 'keras.src.optimizers.adam.Adam'> and learning rate: 0.01



```

Epoch 1/50
858/858 [=====] - 17s 20ms/step - loss: 9.1001 - accuracy: 0.3966 - val_loss: 6.2461 - val_accuracy: 0.0368
Epoch 2/50
858/858 [=====] - 16s 19ms/step - loss: 7.2546 - accuracy: 0.0411 - val_loss: 10.1235 - val_accuracy: 0.0544
Epoch 3/50
858/858 [=====] - 16s 18ms/step - loss: 7.1465 - accuracy: 0.0436 - val_loss: 5.0743 - val_accuracy: 0.0435
Epoch 4/50
858/858 [=====] - 16s 18ms/step - loss: 7.1383 - accuracy: 0.0421 - val_loss: 6.3165 - val_accuracy: 0.0613
Epoch 5/50
858/858 [=====] - 16s 18ms/step - loss: 7.5356 - accuracy: 0.0443 - val_loss: 9.4454 - val_accuracy: 0.0301
Epoch 6/50
858/858 [=====] - 16s 18ms/step - loss: 7.2638 - accuracy: 0.0412 - val_loss: 5.8915 - val_accuracy: 0.0435

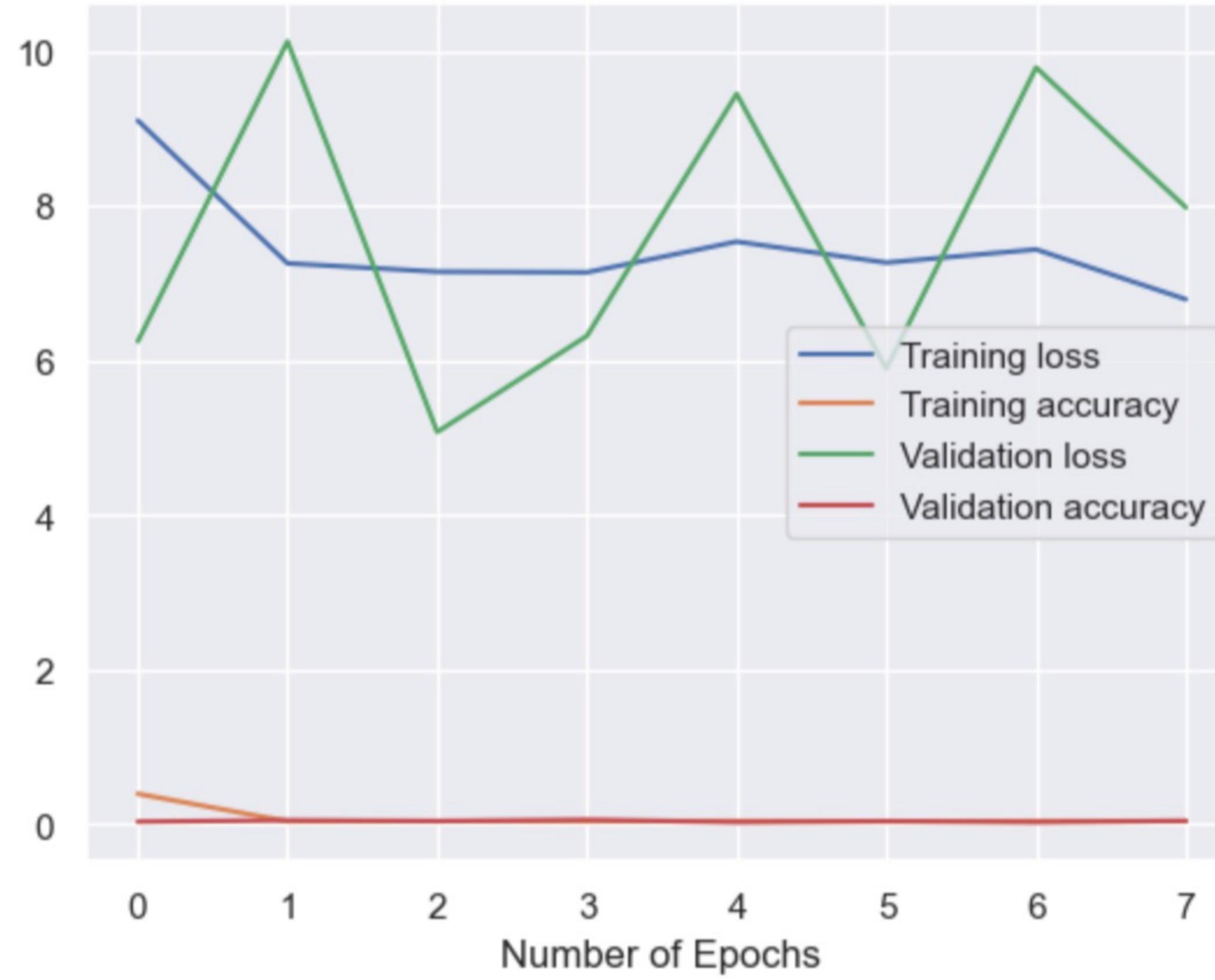
```

```

Epoch 7/50
858/858 [=====] - 16s 18ms/step - loss: 7.4342 - accuracy: 0.0437 - val_loss: 9.7864 - val_accuracy: 0.0307
Epoch 8/50
858/858 [=====] - 16s 18ms/step - loss: 6.7898 - accuracy: 0.0433 - val_loss: 7.9770 - val_accuracy: 0.0477

```

Plot of the CNN model with activation function: selu, optimizer: <class 'keras.src.optimizers.adam.Adam'> and learning rate: 0.01

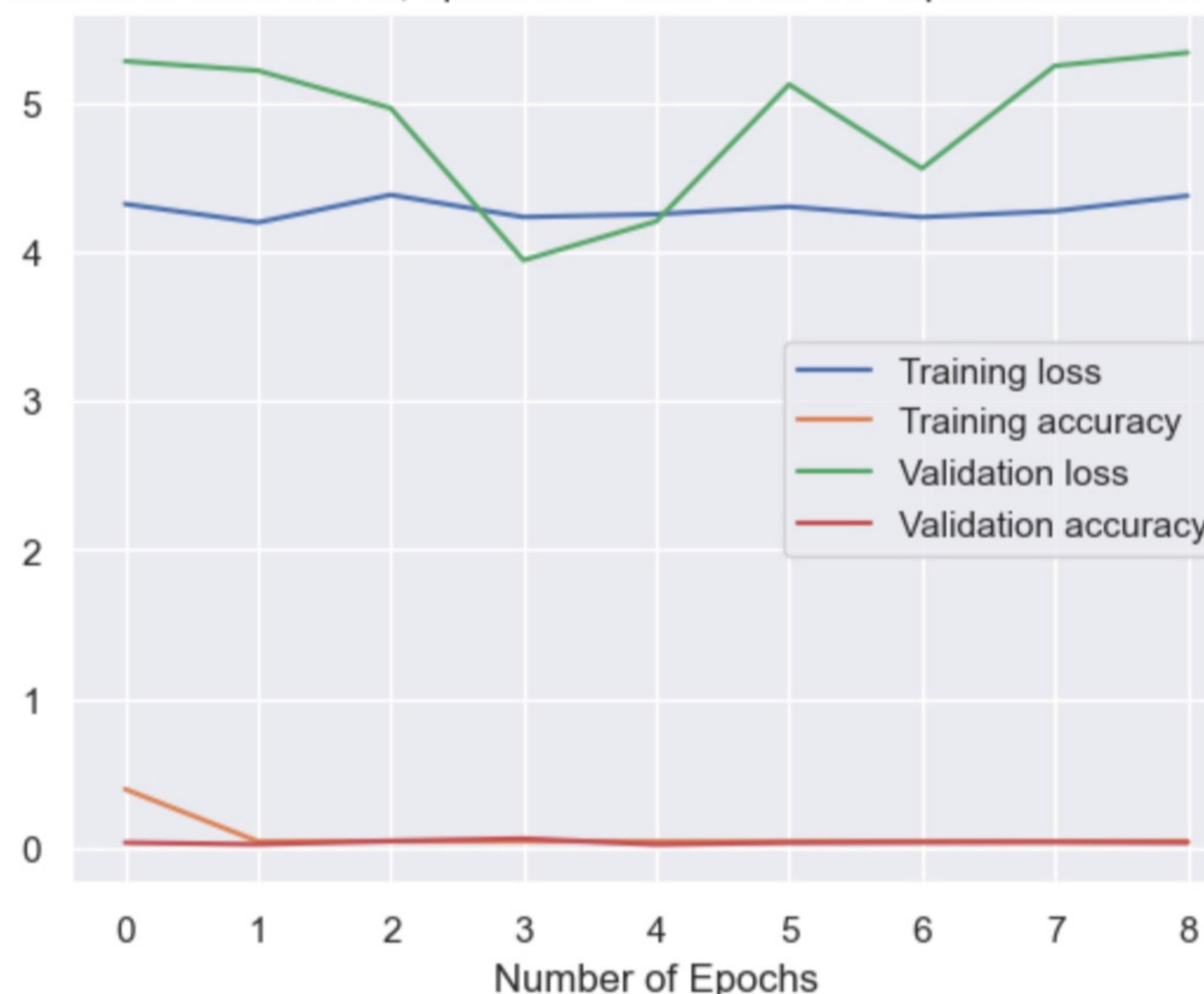


```

Epoch 1/50
858/858 [=====] - 17s 19ms/step - loss: 4.3176 - accuracy: 0.3932 - val_loss: 5.2754 - val_accuracy: 0.0346
Epoch 2/50
858/858 [=====] - 16s 18ms/step - loss: 4.1939 - accuracy: 0.0425 - val_loss: 5.2123 - val_accuracy: 0.0226
Epoch 3/50
858/858 [=====] - 16s 18ms/step - loss: 4.3789 - accuracy: 0.0425 - val_loss: 4.9607 - val_accuracy: 0.0457
Epoch 4/50
858/858 [=====] - 16s 18ms/step - loss: 4.2300 - accuracy: 0.0430 - val_loss: 3.9408 - val_accuracy: 0.0613
Epoch 5/50
858/858 [=====] - 16s 19ms/step - loss: 4.2492 - accuracy: 0.0425 - val_loss: 4.2017 - val_accuracy: 0.0215
Epoch 6/50
858/858 [=====] - 15s 18ms/step - loss: 4.2996 - accuracy: 0.0415 - val_loss: 5.1193 - val_accuracy: 0.0346
Epoch 7/50
858/858 [=====] - 15s 18ms/step - loss: 4.2296 - accuracy: 0.0433 - val_loss: 4.5558 - val_accuracy: 0.0368
Epoch 8/50
858/858 [=====] - 15s 18ms/step - loss: 4.2698 - accuracy: 0.0409 - val_loss: 5.2444 - val_accuracy: 0.0390
Epoch 9/50
858/858 [=====] - 15s 18ms/step - loss: 4.3726 - accuracy: 0.0434 - val_loss: 5.3330 - val_accuracy: 0.0346

```

Plot of the CNN model with activation function: elu, optimizer: <class 'keras.src.optimizers.nadam.Nadam'> and learning rate: 0.01

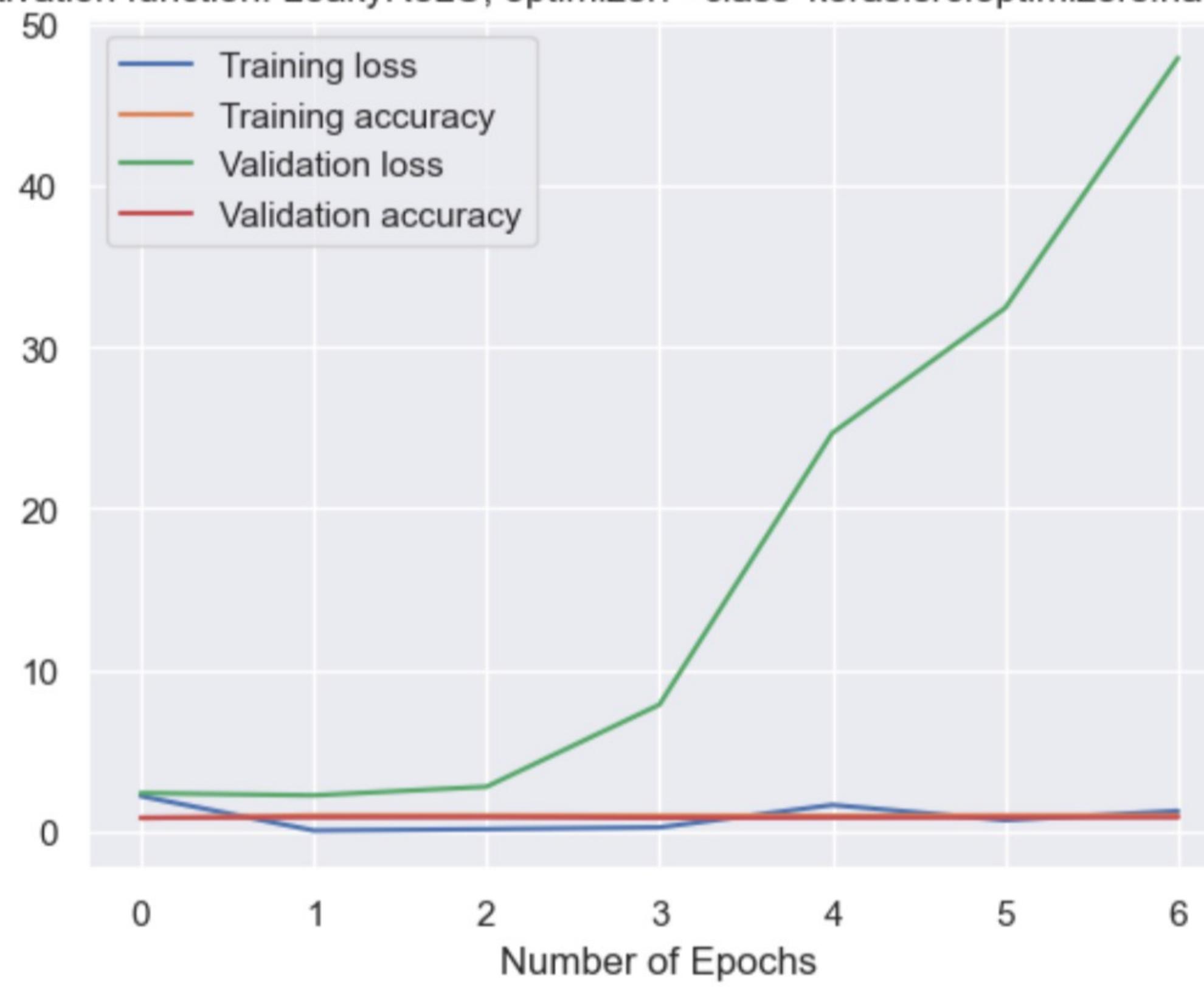


```

Epoch 1/50
858/858 [=====] - 14s 16ms/step - loss: 2.1886 - accuracy: 0.8094 - val_loss: 2.3757 - val_accuracy: 0.8489
Epoch 2/50
858/858 [=====] - 15s 17ms/step - loss: 0.0544 - accuracy: 0.9916 - val_loss: 2.2289 - val_accuracy: 0.8678
Epoch 3/50
858/858 [=====] - 14s 16ms/step - loss: 0.1378 - accuracy: 0.9862 - val_loss: 2.7661 - val_accuracy: 0.8756
Epoch 4/50
858/858 [=====] - 15s 17ms/step - loss: 0.2461 - accuracy: 0.9819 - val_loss: 7.8486 - val_accuracy: 0.8307
Epoch 5/50
858/858 [=====] - 14s 17ms/step - loss: 1.6349 - accuracy: 0.9668 - val_loss: 24.6761 - val_accuracy: 0.8477
Epoch 6/50
858/858 [=====] - 14s 16ms/step - loss: 0.6927 - accuracy: 0.9905 - val_loss: 32.4254 - val_accuracy: 0.8569
Epoch 7/50
858/858 [=====] - 14s 16ms/step - loss: 1.2636 - accuracy: 0.9883 - val_loss: 47.9220 - val_accuracy: 0.8675

```

Plot of the CNN model with activation function: LeakyReLU, optimizer: <class 'keras.src.optimizers.nadam.Nadam'> and learning rate: 0.01

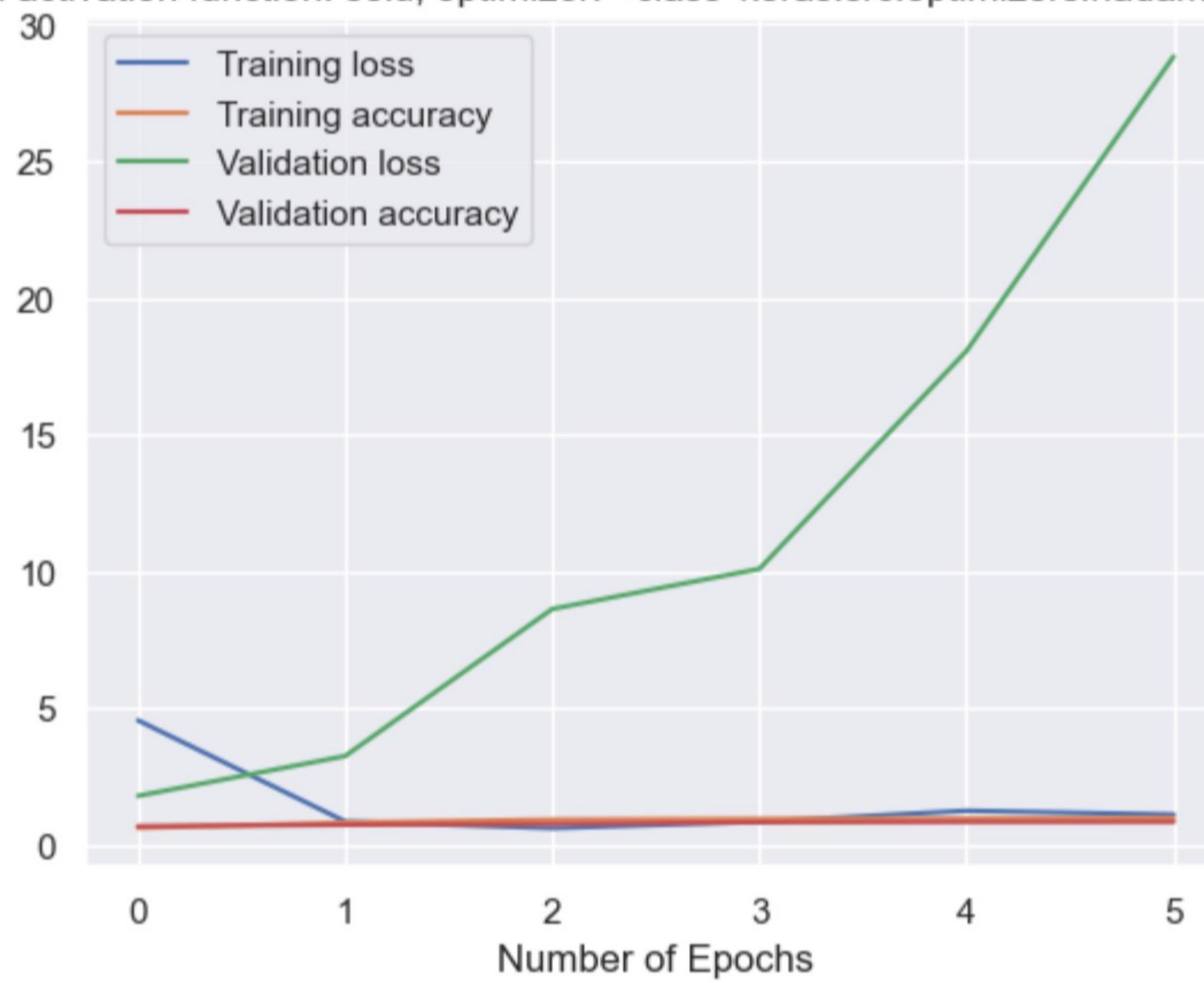


```

Epoch 1/50
858/858 [=====] - 16s 18ms/step - loss: 4.5521 - accuracy: 0.6202 - val_loss: 1.7903 - val_accuracy: 0.6788
Epoch 2/50
858/858 [=====] - 16s 18ms/step - loss: 0.8560 - accuracy: 0.8152 - val_loss: 3.2479 - val_accuracy: 0.7345
Epoch 3/50
858/858 [=====] - 17s 20ms/step - loss: 0.6119 - accuracy: 0.9252 - val_loss: 8.6254 - val_accuracy: 0.7705
Epoch 4/50
858/858 [=====] - 17s 19ms/step - loss: 0.8456 - accuracy: 0.9500 - val_loss: 10.0914 - val_accuracy: 0.8293
Epoch 5/50
858/858 [=====] - 16s 19ms/step - loss: 1.2485 - accuracy: 0.9625 - val_loss: 18.0585 - val_accuracy: 0.8424
Epoch 6/50
858/858 [=====] - 16s 19ms/step - loss: 1.1085 - accuracy: 0.9769 - val_loss: 28.8274 - val_accuracy: 0.8447

```

Plot of the CNN model with activation function: selu, optimizer: <class 'keras.src.optimizers.nadam.Nadam'> and learning rate: 0.01



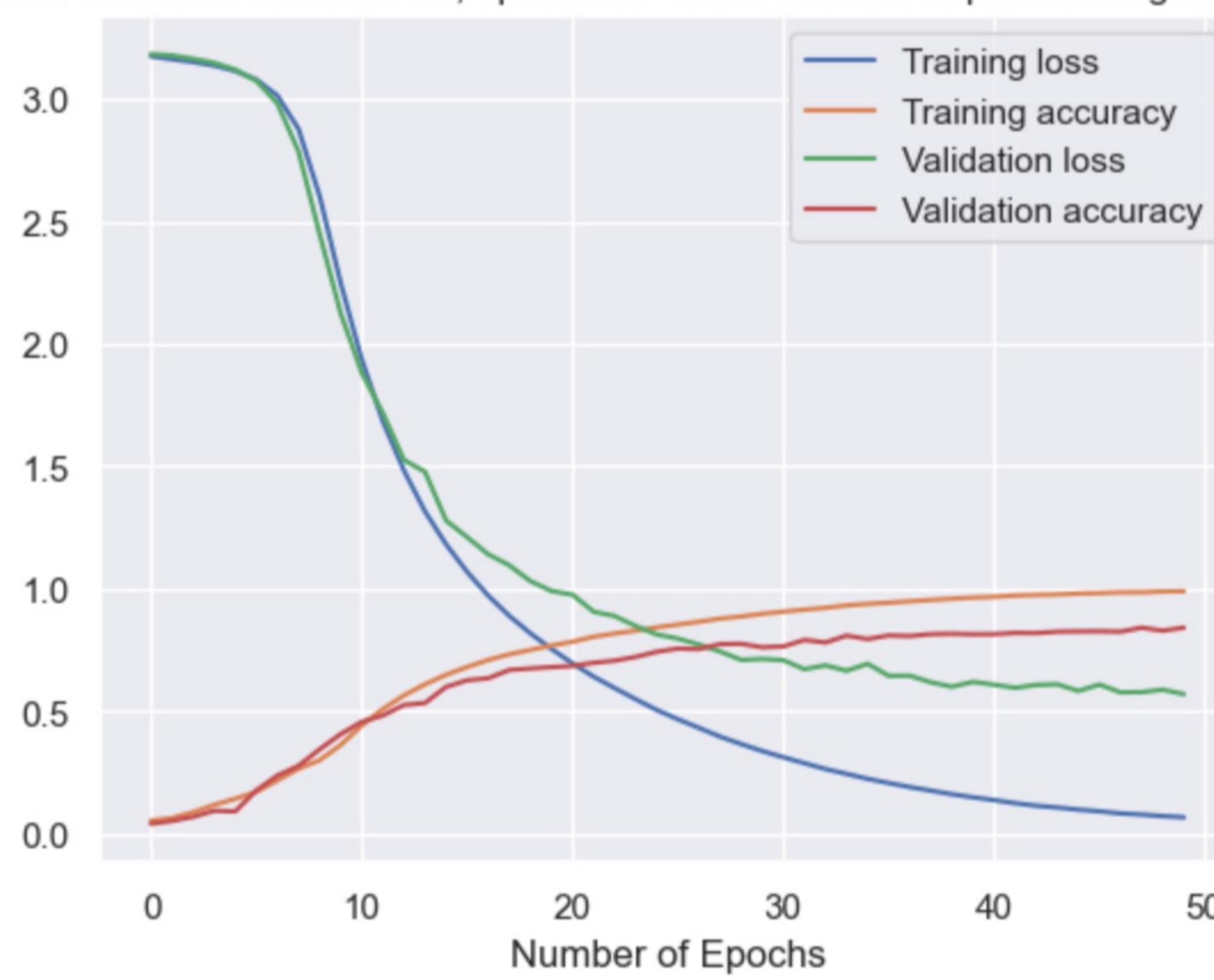
```

Epoch 1/50
858/858 [=====] - 15s 18ms/step - loss: 3.1738 - accuracy: 0.0549 - val_loss: 3.1831 - val_accuracy: 0.0421
Epoch 2/50
858/858 [=====] - 16s 18ms/step - loss: 3.1617 - accuracy: 0.0653 - val_loss: 3.1770 - val_accuracy: 0.0538
Epoch 3/50
858/858 [=====] - 16s 18ms/step - loss: 3.1506 - accuracy: 0.0897 - val_loss: 3.1636 - val_accuracy: 0.0706
Epoch 4/50
858/858 [=====] - 16s 18ms/step - loss: 3.1359 - accuracy: 0.1195 - val_loss: 3.1470 - val_accuracy: 0.0954
Epoch 5/50
858/858 [=====] - 16s 18ms/step - loss: 3.1140 - accuracy: 0.1445 - val_loss: 3.1193 - val_accuracy: 0.0929
Epoch 6/50
858/858 [=====] - 16s 18ms/step - loss: 3.0786 - accuracy: 0.1726 - val_loss: 3.0736 - val_accuracy: 0.1788
Epoch 7/50
858/858 [=====] - 16s 18ms/step - loss: 3.0131 - accuracy: 0.2193 - val_loss: 2.9810 - val_accuracy: 0.2390
Epoch 8/50
858/858 [=====] - 16s 18ms/step - loss: 2.8772 - accuracy: 0.2670 - val_loss: 2.7854 - val_accuracy: 0.2789
Epoch 9/50
858/858 [=====] - 15s 18ms/step - loss: 2.6043 - accuracy: 0.3017 - val_loss: 2.4494 - val_accuracy: 0.3461
Epoch 10/50
858/858 [=====] - 16s 18ms/step - loss: 2.2492 - accuracy: 0.3636 - val_loss: 2.1250 - val_accuracy: 0.4080
Epoch 11/50
858/858 [=====] - 16s 18ms/step - loss: 1.9366 - accuracy: 0.4433 - val_loss: 1.8819 - val_accuracy: 0.4582
Epoch 12/50
858/858 [=====] - 16s 19ms/step - loss: 1.6844 - accuracy: 0.5104 - val_loss: 1.7181 - val_accuracy: 0.4844
Epoch 13/50
858/858 [=====] - 16s 18ms/step - loss: 1.4840 - accuracy: 0.5659 - val_loss: 1.5265 - val_accuracy: 0.5268
Epoch 14/50
858/858 [=====] - 15s 18ms/step - loss: 1.3167 - accuracy: 0.6111 - val_loss: 1.4782 - val_accuracy: 0.5351
Epoch 15/50
858/858 [=====] - 15s 18ms/step - loss: 1.1825 - accuracy: 0.6502 - val_loss: 1.2797 - val_accuracy: 0.5351

```

```
accuracy: 0.6007
Epoch 16/50
858/858 [=====] - 15s 18ms/step - loss: 1.0700 - accuracy: 0.6819 - val_loss: 1.2118 - val_accuracy: 0.6277
Epoch 17/50
858/858 [=====] - 15s 18ms/step - loss: 0.9728 - accuracy: 0.7106 - val_loss: 1.1417 - val_accuracy: 0.6361
Epoch 18/50
858/858 [=====] - 15s 18ms/step - loss: 0.8903 - accuracy: 0.7338 - val_loss: 1.0967 - val_accuracy: 0.6698
Epoch 19/50
858/858 [=====] - 15s 18ms/step - loss: 0.8194 - accuracy: 0.7515 - val_loss: 1.0327 - val_accuracy: 0.6760
Epoch 20/50
858/858 [=====] - 15s 18ms/step - loss: 0.7556 - accuracy: 0.7696 - val_loss: 0.9919 - val_accuracy: 0.6813
Epoch 21/50
858/858 [=====] - 15s 18ms/step - loss: 0.6968 - accuracy: 0.7851 - val_loss: 0.9771 - val_accuracy: 0.6863
Epoch 22/50
858/858 [=====] - 15s 18ms/step - loss: 0.6425 - accuracy: 0.8053 - val_loss: 0.9075 - val_accuracy: 0.6991
Epoch 23/50
858/858 [=====] - 15s 18ms/step - loss: 0.5957 - accuracy: 0.8186 - val_loss: 0.8898 - val_accuracy: 0.7078
Epoch 24/50
858/858 [=====] - 15s 18ms/step - loss: 0.5503 - accuracy: 0.8302 - val_loss: 0.8489 - val_accuracy: 0.7231
Epoch 25/50
858/858 [=====] - 17s 20ms/step - loss: 0.5063 - accuracy: 0.8436 - val_loss: 0.8146 - val_accuracy: 0.7443
Epoch 26/50
858/858 [=====] - 16s 19ms/step - loss: 0.4688 - accuracy: 0.8550 - val_loss: 0.7977 - val_accuracy: 0.7571
Epoch 27/50
858/858 [=====] - 16s 18ms/step - loss: 0.4334 - accuracy: 0.8667 - val_loss: 0.7736 - val_accuracy: 0.7552
Epoch 28/50
858/858 [=====] - 16s 19ms/step - loss: 0.3978 - accuracy: 0.8792 - val_loss: 0.7452 - val_accuracy: 0.7752
Epoch 29/50
858/858 [=====] - 16s 19ms/step - loss: 0.3675 - accuracy: 0.8879 - val_loss: 0.7109 - val_accuracy: 0.7766
Epoch 30/50
858/858 [=====] - 16s 18ms/step - loss: 0.3389 - accuracy: 0.8989 - val_loss: 0.7146 - val_accuracy: 0.7624
Epoch 31/50
858/858 [=====] - 16s 19ms/step - loss: 0.3136 - accuracy: 0.9079 - val_loss: 0.7097 - val_accuracy: 0.7658
Epoch 32/50
858/858 [=====] - 15s 18ms/step - loss: 0.2895 - accuracy: 0.9160 - val_loss: 0.6729 - val_accuracy: 0.7922
Epoch 33/50
858/858 [=====] - 15s 18ms/step - loss: 0.2657 - accuracy: 0.9233 - val_loss: 0.6888 - val_accuracy: 0.7819
Epoch 34/50
858/858 [=====] - 15s 18ms/step - loss: 0.2459 - accuracy: 0.9331 - val_loss: 0.6666 - val_accuracy: 0.8098
Epoch 35/50
858/858 [=====] - 15s 18ms/step - loss: 0.2256 - accuracy: 0.9396 - val_loss: 0.6949 - val_accuracy: 0.7959
Epoch 36/50
858/858 [=====] - 15s 18ms/step - loss: 0.2084 - accuracy: 0.9443 - val_loss: 0.6461 - val_accuracy: 0.8107
Epoch 37/50
858/858 [=====] - 16s 18ms/step - loss: 0.1921 - accuracy: 0.9499 - val_loss: 0.6463 - val_accuracy: 0.8081
Epoch 38/50
858/858 [=====] - 15s 18ms/step - loss: 0.1775 - accuracy: 0.9553 - val_loss: 0.6195 - val_accuracy: 0.8160
Epoch 39/50
858/858 [=====] - 16s 18ms/step - loss: 0.1627 - accuracy: 0.9607 - val_loss: 0.6016 - val_accuracy: 0.8176
Epoch 40/50
858/858 [=====] - 19s 22ms/step - loss: 0.1502 - accuracy: 0.9653 - val_loss: 0.6213 - val_accuracy: 0.8154
Epoch 41/50
858/858 [=====] - 22s 26ms/step - loss: 0.1389 - accuracy: 0.9681 - val_loss: 0.6096 - val_accuracy: 0.8160
Epoch 42/50
858/858 [=====] - 16s 19ms/step - loss: 0.1263 - accuracy: 0.9736 - val_loss: 0.5969 - val_accuracy: 0.8210
Epoch 43/50
858/858 [=====] - 15s 17ms/step - loss: 0.1159 - accuracy: 0.9759 - val_loss: 0.6087 - val_accuracy: 0.8204
Epoch 44/50
858/858 [=====] - 16s 18ms/step - loss: 0.1085 - accuracy: 0.9778 - val_loss: 0.6113 - val_accuracy: 0.8260
Epoch 45/50
858/858 [=====] - 15s 17ms/step - loss: 0.1001 - accuracy: 0.9817 - val_loss: 0.5841 - val_accuracy: 0.8271
Epoch 46/50
858/858 [=====] - 15s 17ms/step - loss: 0.0930 - accuracy: 0.9836 - val_loss: 0.6103 - val_accuracy: 0.8279
Epoch 47/50
858/858 [=====] - 15s 18ms/step - loss: 0.0845 - accuracy: 0.9864 - val_loss: 0.5783 - val_accuracy: 0.8260
Epoch 48/50
858/858 [=====] - 16s 18ms/step - loss: 0.0798 - accuracy: 0.9867 - val_loss: 0.5795 - val_accuracy: 0.8424
Epoch 49/50
858/858 [=====] - 18s 21ms/step - loss: 0.0736 - accuracy: 0.9898 - val_loss: 0.5895 - val_accuracy: 0.8299
Epoch 50/50
858/858 [=====] - 16s 19ms/step - loss: 0.0685 - accuracy: 0.9909 - val_loss: 0.5710 - val_accuracy: 0.8424
```

Plot of the CNN model with activation function: elu, optimizer: <class 'keras.src.optimizers.sgd.SGD'> and learning rate: 0.001



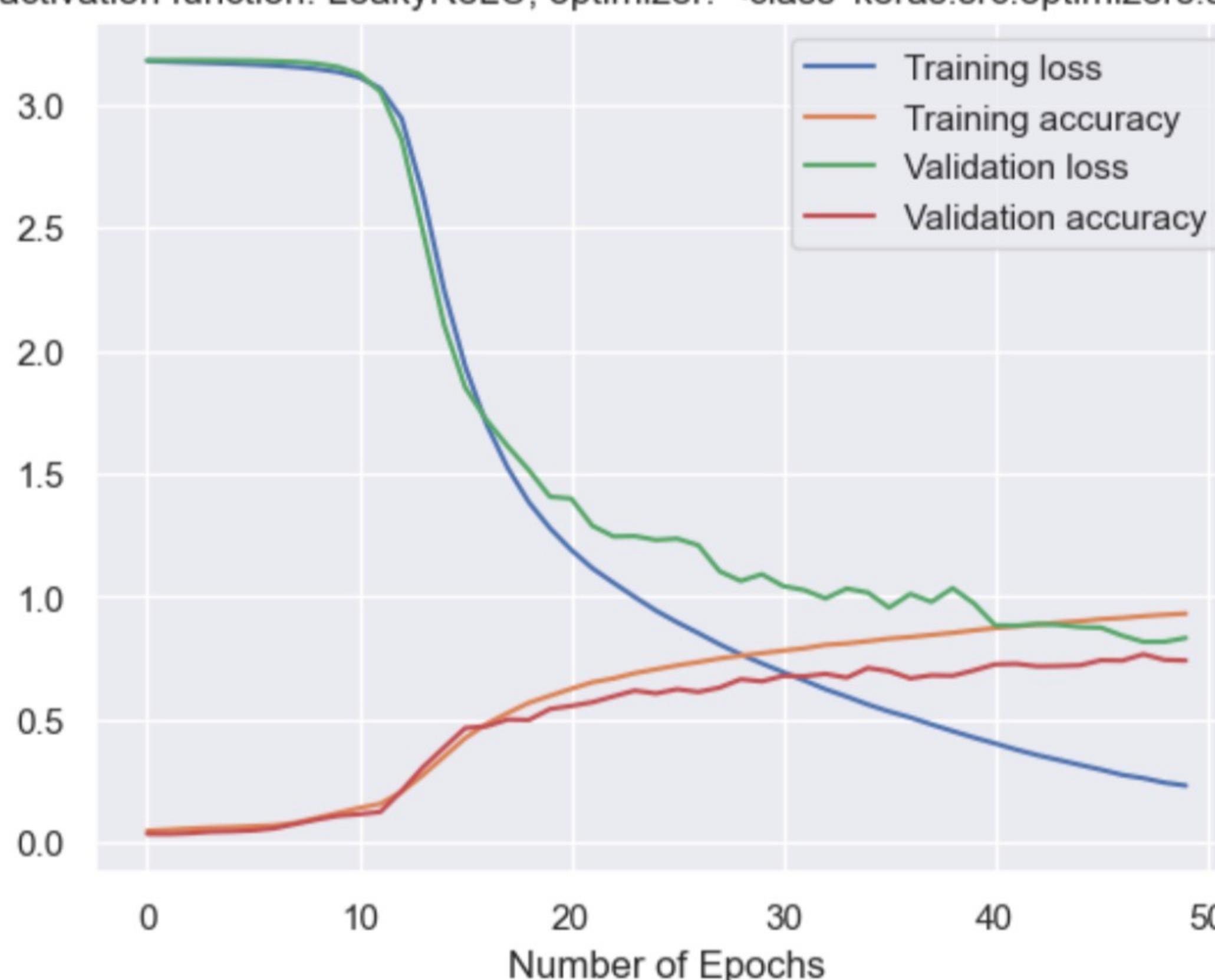
```
Epoch 1/50
858/858 [=====] - 15s 17ms/step - loss: 3.1781 - accuracy: 0.0463 - val_loss: 3.1799 - val_accuracy: 0.0340
Epoch 2/50
858/858 [=====] - 14s 17ms/step - loss: 3.1744 - accuracy: 0.0504 - val_loss: 3.1808 - val_accuracy: 0.0337
Epoch 3/50
858/858 [=====] - 14s 17ms/step - loss: 3.1716 - accuracy: 0.0554 - val_loss: 3.1807 - val_accuracy: 0.0368
Epoch 4/50
858/858 [=====] - 15s 17ms/step - loss: 3.1690 - accuracy: 0.0591 - val_loss: 3.1804 - val_accuracy: 0.0427
Epoch 5/50
858/858 [=====] - 14s 17ms/step - loss: 3.1661 - accuracy: 0.0614 - val_loss: 3.1795 - val_accuracy: 0.0446
Epoch 6/50
858/858 [=====] - 14s 17ms/step - loss: 3.1627 - accuracy: 0.0651 - val_loss: 3.1784 - val_accuracy: 0.0482
Epoch 7/50
858/858 [=====] - 14s 17ms/step - loss: 3.1584 - accuracy: 0.0685 - val_loss: 3.1766 - val_accuracy: 0.0566
Epoch 8/50
858/858 [=====] - 14s 16ms/step - loss: 3.1526 - accuracy: 0.0790 - val_loss: 3.1736 - val_accuracy: 0.0745
Epoch 9/50
858/858 [=====] - 14s 17ms/step - loss: 3.1446 - accuracy: 0.0985 - val_loss: 3.1667 - val_accuracy: 0.0923
Epoch 10/50
858/858 [=====] - 15s 17ms/step - loss: 3.1325 - accuracy: 0.1188 - val_loss: 3.1532 - val_accuracy: 0.1074
Epoch 11/50
858/858 [=====] - 14s 17ms/step - loss: 3.1112 - accuracy: 0.1394 - val_loss: 3.1249 - val_accuracy: 0.1141
Epoch 12/50
858/858 [=====] - 14s 17ms/step - loss: 3.0653 - accuracy: 0.1564 - val_loss: 3.0525 - val_accuracy: 0.1235
Epoch 13/50
858/858 [=====] - 14s 16ms/step - loss: 2.9439 - accuracy: 0.2050 - val_loss: 2.8585 - val_accuracy: 0.2086
Epoch 14/50
858/858 [=====] - 14s 17ms/step - loss: 2.6383 - accuracy: 0.2729 - val_loss: 2.4853 - val_accuracy: 0.3045
Epoch 15/50
858/858 [=====] - 14s 16ms/step - loss: 2.2467 - accuracy: 0.3484 - val_loss: 2.1048 - val_accuracy: 0.3851
Epoch 16/50
858/858 [=====] - 14s 16ms/step - loss: 1.9353 - accuracy: 0.4236 - val_loss: 1.8494 - val_accuracy: 0.4643
Epoch 17/50
858/858 [=====] - 14s 16ms/step - loss: 1.7008 - accuracy: 0.4806 - val_loss: 1.7178 - val_accuracy: 0.4716
Epoch 18/50
858/858 [=====] - 14s 16ms/step - loss: 1.5231 - accuracy: 0.5253 - val_loss: 1.6111 - val_accuracy: 0.4992
Epoch 19/50
858/858 [=====] - 14s 16ms/step - loss: 1.3831 - accuracy: 0.5666 - val_loss: 1.5138 - val_accuracy: 0.4972
Epoch 20/50
858/858 [=====] - 14s 16ms/step - loss: 1.2772 - accuracy: 0.5957 - val_loss: 1.4054 - val_accuracy: 0.5418
Epoch 21/50
858/858 [=====] - 14s 16ms/step - loss: 1.1890 - accuracy: 0.6239 - val_loss: 1.3978 - val_accuracy: 0.5544
Epoch 22/50
858/858 [=====] - 14s 16ms/step - loss: 1.1143 - accuracy: 0.6506 - val_loss: 1.2871 - val_accuracy: 0.5694
Epoch 23/50
858/858 [=====] - 14s 16ms/step - loss: 1.0549 - accuracy: 0.6661 - val_loss: 1.2436 - val_accuracy: 0.5934
Epoch 24/50
858/858 [=====] - 14s 16ms/step - loss: 0.9972 - accuracy: 0.6876 - val_loss: 1.2452 - val_accuracy: 0.6168
Epoch 25/50
858/858 [=====] - 14s 16ms/step - loss: 0.9420 - accuracy: 0.7036 - val_loss: 1.2294 - val_accuracy: 0.6051
Epoch 26/50
858/858 [=====] - 14s 16ms/step - loss: 0.8942 - accuracy: 0.7192 - val_loss: 1.2346 - val_accuracy: 0.6224
Epoch 27/50
858/858 [=====] - 14s 17ms/step - loss: 0.8505 - accuracy: 0.7326 - val_loss: 1.2078 - val_accuracy: 0.6113
Epoch 28/50
858/858 [=====] - 15s 17ms/step - loss: 0.8049 - accuracy: 0.7472 - val_loss: 1.1019 - val_accuracy: 0.6286
Epoch 29/50
858/858 [=====] - 15s 18ms/step - loss: 0.7639 - accuracy: 0.7585 - val_loss: 1.0626 - val_accuracy: 0.6629
Epoch 30/50
858/858 [=====] - 14s 17ms/step - loss: 0.7271 - accuracy: 0.7690 - val_loss: 1.0899 - val_accuracy: 0.6286
```

```

accuracy: 0.6542
Epoch 31/50
858/858 [=====] - 14s 17ms/step - loss: 0.6919 - accuracy: 0.7792 - val_loss: 1.0420 - val_accuracy: 0.6762
Epoch 32/50
858/858 [=====] - 14s 17ms/step - loss: 0.6580 - accuracy: 0.7888 - val_loss: 1.0255 - val_accuracy: 0.6748
Epoch 33/50
858/858 [=====] - 14s 17ms/step - loss: 0.6223 - accuracy: 0.8027 - val_loss: 0.9915 - val_accuracy: 0.6846
Epoch 34/50
858/858 [=====] - 14s 17ms/step - loss: 0.5923 - accuracy: 0.8085 - val_loss: 1.0318 - val_accuracy: 0.6693
Epoch 35/50
858/858 [=====] - 15s 18ms/step - loss: 0.5600 - accuracy: 0.8177 - val_loss: 1.0153 - val_accuracy: 0.7089
Epoch 36/50
858/858 [=====] - 15s 18ms/step - loss: 0.5316 - accuracy: 0.8281 - val_loss: 0.9539 - val_accuracy: 0.6958
Epoch 37/50
858/858 [=====] - 14s 17ms/step - loss: 0.5073 - accuracy: 0.8346 - val_loss: 1.0098 - val_accuracy: 0.6665
Epoch 38/50
858/858 [=====] - 15s 17ms/step - loss: 0.4791 - accuracy: 0.8432 - val_loss: 0.9777 - val_accuracy: 0.6790
Epoch 39/50
858/858 [=====] - 16s 18ms/step - loss: 0.4519 - accuracy: 0.8516 - val_loss: 1.0333 - val_accuracy: 0.6771
Epoch 40/50
858/858 [=====] - 15s 17ms/step - loss: 0.4259 - accuracy: 0.8619 - val_loss: 0.9714 - val_accuracy: 0.6988
Epoch 41/50
858/858 [=====] - 14s 16ms/step - loss: 0.4018 - accuracy: 0.8709 - val_loss: 0.8822 - val_accuracy: 0.7234
Epoch 42/50
858/858 [=====] - 14s 17ms/step - loss: 0.3767 - accuracy: 0.8773 - val_loss: 0.8811 - val_accuracy: 0.7256
Epoch 43/50
858/858 [=====] - 16s 18ms/step - loss: 0.3541 - accuracy: 0.8855 - val_loss: 0.8874 - val_accuracy: 0.7153
Epoch 44/50
858/858 [=====] - 16s 19ms/step - loss: 0.3346 - accuracy: 0.8931 - val_loss: 0.8841 - val_accuracy: 0.7167
Epoch 45/50
858/858 [=====] - 15s 17ms/step - loss: 0.3146 - accuracy: 0.8987 - val_loss: 0.8751 - val_accuracy: 0.7195
Epoch 46/50
858/858 [=====] - 17s 19ms/step - loss: 0.2951 - accuracy: 0.9072 - val_loss: 0.8726 - val_accuracy: 0.7401
Epoch 47/50
858/858 [=====] - 15s 18ms/step - loss: 0.2739 - accuracy: 0.9122 - val_loss: 0.8402 - val_accuracy: 0.7387
Epoch 48/50
858/858 [=====] - 17s 20ms/step - loss: 0.2605 - accuracy: 0.9195 - val_loss: 0.8150 - val_accuracy: 0.7644
Epoch 49/50
858/858 [=====] - 17s 20ms/step - loss: 0.2422 - accuracy: 0.9252 - val_loss: 0.8153 - val_accuracy: 0.7418
Epoch 50/50
858/858 [=====] - 17s 20ms/step - loss: 0.2305 - accuracy: 0.9297 - val_loss: 0.8310 - val_accuracy: 0.7390

```

Plot of the CNN model with activation function: LeakyReLU, optimizer: <class 'keras.src.optimizers.sgd.SGD'> and learning rate: 0.001



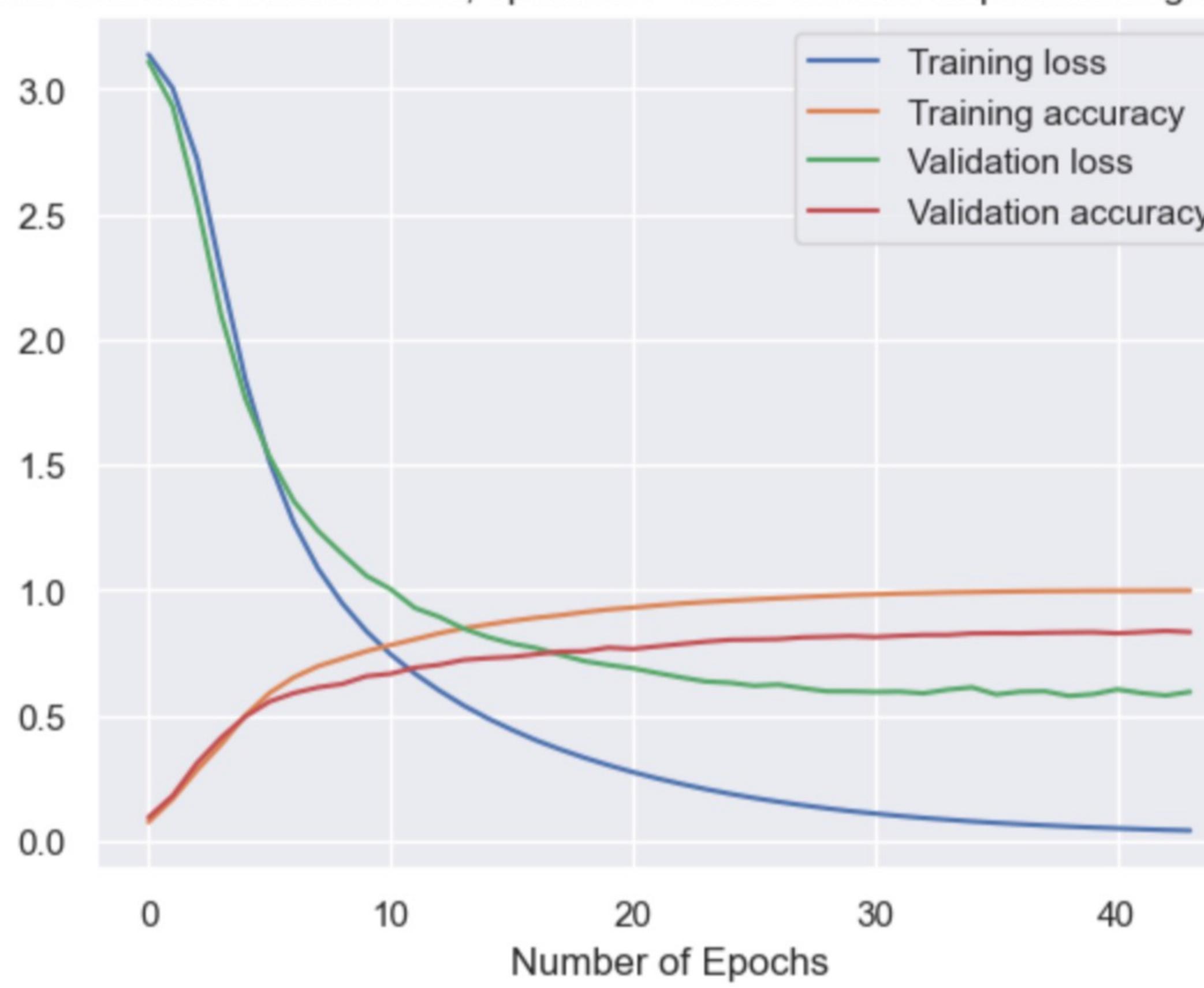
```

Epoch 1/50
858/858 [=====] - 20s 23ms/step - loss: 3.1377 - accuracy: 0.0751 - val_loss: 3.1095 - val_accuracy: 0.0937
Epoch 2/50
858/858 [=====] - 23s 26ms/step - loss: 3.0029 - accuracy: 0.1674 - val_loss: 2.9303 - val_accuracy: 0.1804
Epoch 3/50
858/858 [=====] - 25s 29ms/step - loss: 2.7222 - accuracy: 0.2821 - val_loss: 2.5505 - val_accuracy: 0.3101
Epoch 4/50
858/858 [=====] - 24s 28ms/step - loss: 2.2668 - accuracy: 0.3850 - val_loss: 2.0969 - val_accuracy: 0.4116
Epoch 5/50
858/858 [=====] - 23s 27ms/step - loss: 1.8400 - accuracy: 0.5005 - val_loss: 1.7642 - val_accuracy: 0.4964
Epoch 6/50
858/858 [=====] - 26s 30ms/step - loss: 1.5123 - accuracy: 0.5903 - val_loss: 1.5317 - val_accuracy: 0.5561
Epoch 7/50
858/858 [=====] - 23s 27ms/step - loss: 1.2682 - accuracy: 0.6524 - val_loss: 1.3555 - val_accuracy: 0.5898
Epoch 8/50
858/858 [=====] - 21s 24ms/step - loss: 1.0866 - accuracy: 0.6969 - val_loss: 1.2367 - val_accuracy: 0.6124
Epoch 9/50
858/858 [=====] - 22s 26ms/step - loss: 0.9479 - accuracy: 0.7273 - val_loss: 1.1447 - val_accuracy: 0.6260
Epoch 10/50

```

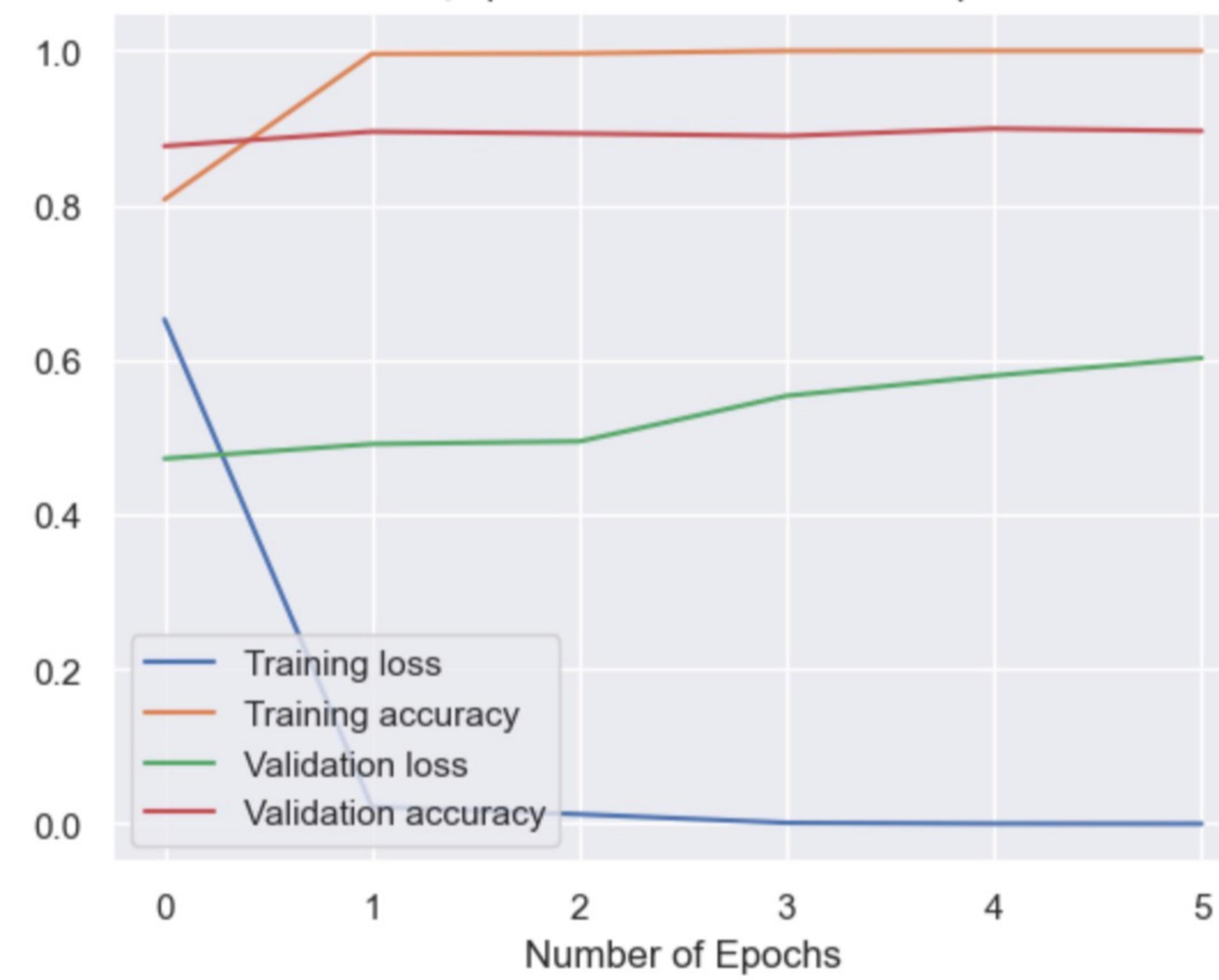
```
858/858 [=====] - 23s 27ms/step - loss: 0.8363 - accuracy: 0.7569 - val_loss: 1.0575 - val_accuracy: 0.6573
Epoch 11/50
858/858 [=====] - 23s 26ms/step - loss: 0.7440 - accuracy: 0.7813 - val_loss: 1.0040 - val_accuracy: 0.6668
Epoch 12/50
858/858 [=====] - 21s 24ms/step - loss: 0.6670 - accuracy: 0.8044 - val_loss: 0.9291 - val_accuracy: 0.6910
Epoch 13/50
858/858 [=====] - 22s 26ms/step - loss: 0.6002 - accuracy: 0.8282 - val_loss: 0.8941 - val_accuracy: 0.7025
Epoch 14/50
858/858 [=====] - 22s 26ms/step - loss: 0.5408 - accuracy: 0.8480 - val_loss: 0.8474 - val_accuracy: 0.7220
Epoch 15/50
858/858 [=====] - 23s 27ms/step - loss: 0.4892 - accuracy: 0.8631 - val_loss: 0.8135 - val_accuracy: 0.7292
Epoch 16/50
858/858 [=====] - 22s 25ms/step - loss: 0.4433 - accuracy: 0.8778 - val_loss: 0.7875 - val_accuracy: 0.7340
Epoch 17/50
858/858 [=====] - 22s 25ms/step - loss: 0.4014 - accuracy: 0.8902 - val_loss: 0.7696 - val_accuracy: 0.7448
Epoch 18/50
858/858 [=====] - 23s 27ms/step - loss: 0.3650 - accuracy: 0.9002 - val_loss: 0.7428 - val_accuracy: 0.7552
Epoch 19/50
858/858 [=====] - 23s 27ms/step - loss: 0.3317 - accuracy: 0.9128 - val_loss: 0.7172 - val_accuracy: 0.7566
Epoch 20/50
858/858 [=====] - 22s 26ms/step - loss: 0.3018 - accuracy: 0.9232 - val_loss: 0.7018 - val_accuracy: 0.7711
Epoch 21/50
858/858 [=====] - 22s 25ms/step - loss: 0.2744 - accuracy: 0.9310 - val_loss: 0.6884 - val_accuracy: 0.7660
Epoch 22/50
858/858 [=====] - 23s 27ms/step - loss: 0.2495 - accuracy: 0.9394 - val_loss: 0.6697 - val_accuracy: 0.7761
Epoch 23/50
858/858 [=====] - 20s 23ms/step - loss: 0.2272 - accuracy: 0.9471 - val_loss: 0.6522 - val_accuracy: 0.7856
Epoch 24/50
858/858 [=====] - 25s 29ms/step - loss: 0.2066 - accuracy: 0.9531 - val_loss: 0.6360 - val_accuracy: 0.7948
Epoch 25/50
858/858 [=====] - 23s 26ms/step - loss: 0.1880 - accuracy: 0.9583 - val_loss: 0.6311 - val_accuracy: 0.8020
Epoch 26/50
858/858 [=====] - 21s 24ms/step - loss: 0.1713 - accuracy: 0.9632 - val_loss: 0.6190 - val_accuracy: 0.8034
Epoch 27/50
858/858 [=====] - 21s 25ms/step - loss: 0.1563 - accuracy: 0.9681 - val_loss: 0.6237 - val_accuracy: 0.8051
Epoch 28/50
858/858 [=====] - 20s 23ms/step - loss: 0.1424 - accuracy: 0.9726 - val_loss: 0.6094 - val_accuracy: 0.8120
Epoch 29/50
858/858 [=====] - 19s 22ms/step - loss: 0.1300 - accuracy: 0.9769 - val_loss: 0.5968 - val_accuracy: 0.8143
Epoch 30/50
858/858 [=====] - 20s 23ms/step - loss: 0.1187 - accuracy: 0.9810 - val_loss: 0.5966 - val_accuracy: 0.8173
Epoch 31/50
858/858 [=====] - 18s 21ms/step - loss: 0.1090 - accuracy: 0.9835 - val_loss: 0.5942 - val_accuracy: 0.8134
Epoch 32/50
858/858 [=====] - 21s 24ms/step - loss: 0.0999 - accuracy: 0.9870 - val_loss: 0.5957 - val_accuracy: 0.8182
Epoch 33/50
858/858 [=====] - 19s 22ms/step - loss: 0.0916 - accuracy: 0.9887 - val_loss: 0.5888 - val_accuracy: 0.8218
Epoch 34/50
858/858 [=====] - 19s 23ms/step - loss: 0.0846 - accuracy: 0.9912 - val_loss: 0.6037 - val_accuracy: 0.8218
Epoch 35/50
858/858 [=====] - 19s 22ms/step - loss: 0.0778 - accuracy: 0.9927 - val_loss: 0.6126 - val_accuracy: 0.8279
Epoch 36/50
858/858 [=====] - 20s 23ms/step - loss: 0.0719 - accuracy: 0.9944 - val_loss: 0.5842 - val_accuracy: 0.8288
Epoch 37/50
858/858 [=====] - 21s 25ms/step - loss: 0.0667 - accuracy: 0.9955 - val_loss: 0.5954 - val_accuracy: 0.8282
Epoch 38/50
858/858 [=====] - 21s 25ms/step - loss: 0.0620 - accuracy: 0.9965 - val_loss: 0.5971 - val_accuracy: 0.8305
Epoch 39/50
858/858 [=====] - 19s 23ms/step - loss: 0.0576 - accuracy: 0.9969 - val_loss: 0.5783 - val_accuracy: 0.8316
Epoch 40/50
858/858 [=====] - 20s 24ms/step - loss: 0.0535 - accuracy: 0.9977 - val_loss: 0.5854 - val_accuracy: 0.8327
Epoch 41/50
858/858 [=====] - 20s 23ms/step - loss: 0.0501 - accuracy: 0.9979 - val_loss: 0.6044 - val_accuracy: 0.8282
Epoch 42/50
858/858 [=====] - 19s 23ms/step - loss: 0.0467 - accuracy: 0.9981 - val_loss: 0.5899 - val_accuracy: 0.8330
Epoch 43/50
858/858 [=====] - 21s 24ms/step - loss: 0.0438 - accuracy: 0.9986 - val_loss: 0.5802 - val_accuracy: 0.8377
Epoch 44/50
858/858 [=====] - 20s 23ms/step - loss: 0.0414 - accuracy: 0.9987 - val_loss: 0.5946 - val_accuracy: 0.8332
```

Plot of the CNN model with activation function: selu, optimizer: <class 'keras.src.optimizers.sgd.SGD'> and learning rate: 0.001



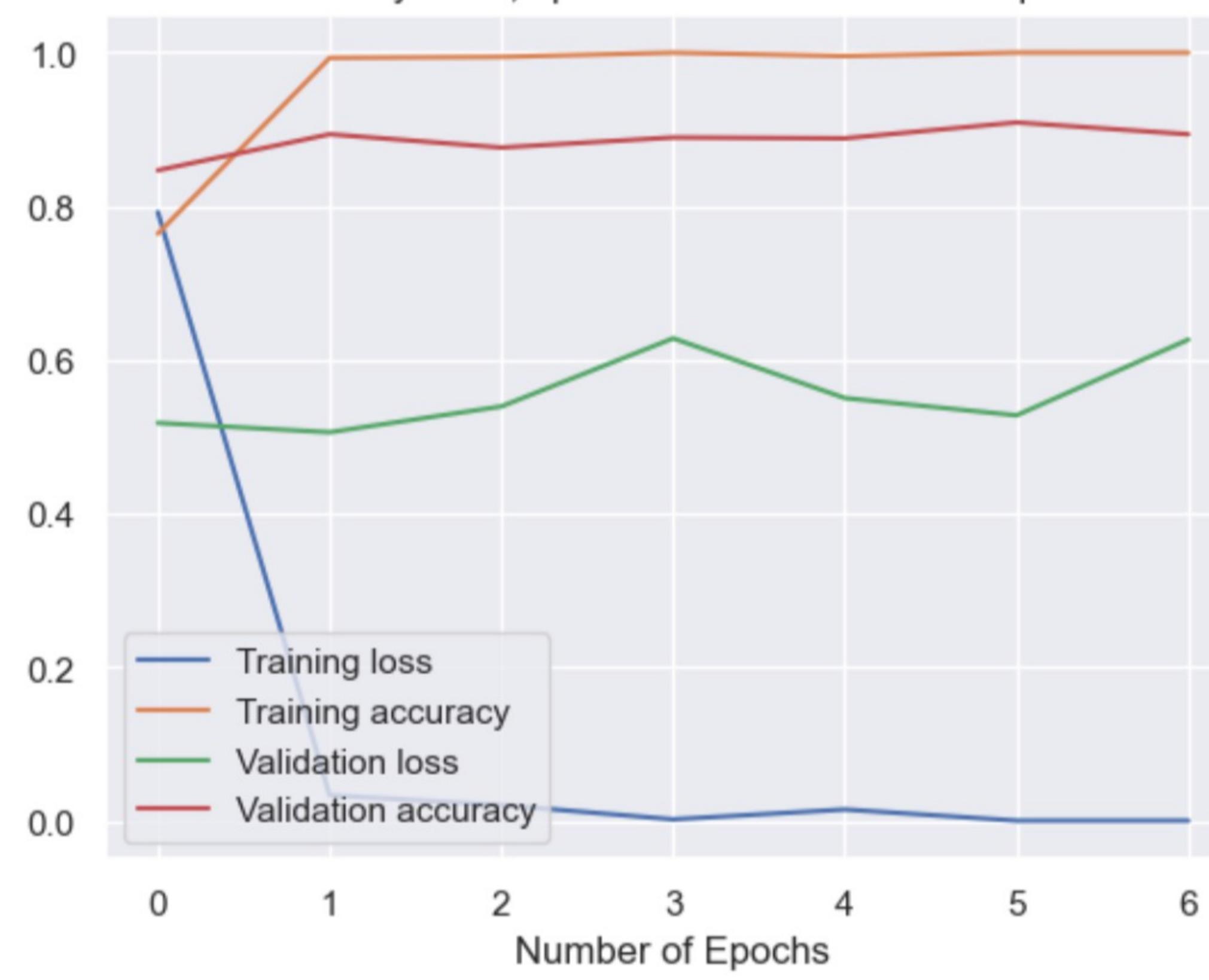
```
Epoch 1/50
858/858 [=====] - 21s 24ms/step - loss: 0.6524 - accuracy: 0.8076 - val_loss: 0.4725 - val_accuracy: 0.8767
Epoch 2/50
858/858 [=====] - 22s 26ms/step - loss: 0.0221 - accuracy: 0.9961 - val_loss: 0.4913 - val_accuracy: 0.8954
Epoch 3/50
858/858 [=====] - 22s 25ms/step - loss: 0.0125 - accuracy: 0.9967 - val_loss: 0.4947 - val_accuracy: 0.8929
Epoch 4/50
858/858 [=====] - 22s 26ms/step - loss: 0.0013 - accuracy: 0.9999 - val_loss: 0.5537 - val_accuracy: 0.8898
Epoch 5/50
858/858 [=====] - 22s 26ms/step - loss: 2.9921e-04 - accuracy: 1.0000 - val_loss: 0.5799 - val_accuracy: 0.8993
Epoch 6/50
858/858 [=====] - 24s 28ms/step - loss: 1.4849e-04 - accuracy: 1.0000 - val_loss: 0.6025 - val_accuracy: 0.8963
```

Plot of the CNN model with activation function: elu, optimizer: <class 'keras.src.optimizers.adam.Adam'> and learning rate: 0.001



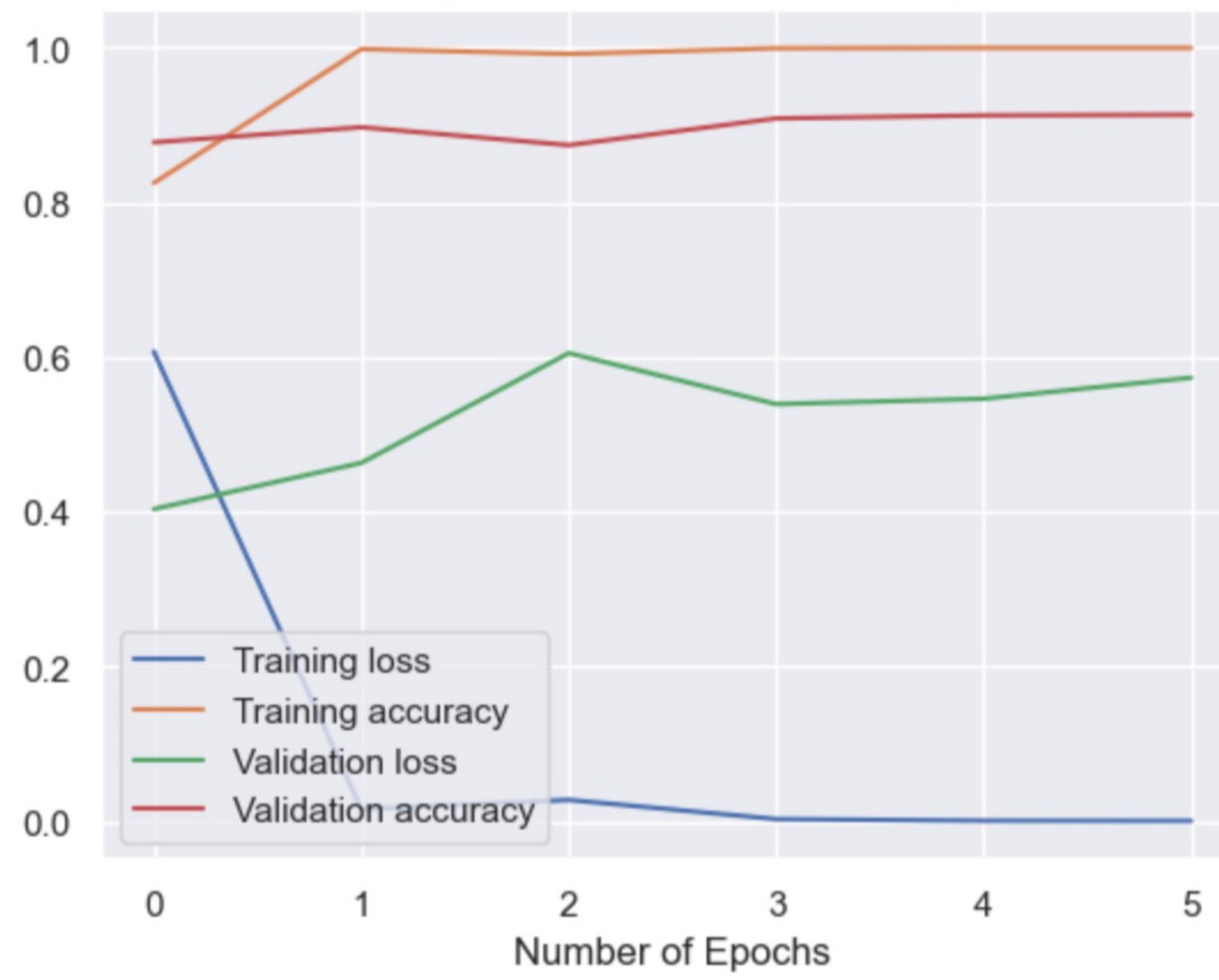
```
Epoch 1/50
858/858 [=====] - 20s 23ms/step - loss: 0.7923 - accuracy: 0.7645 - val_loss: 0.5183 - val_accuracy: 0.8469
Epoch 2/50
858/858 [=====] - 20s 23ms/step - loss: 0.0339 - accuracy: 0.9931 - val_loss: 0.5061 - val_accuracy: 0.8938
Epoch 3/50
858/858 [=====] - 20s 23ms/step - loss: 0.0212 - accuracy: 0.9944 - val_loss: 0.5397 - val_accuracy: 0.8765
Epoch 4/50
858/858 [=====] - 20s 23ms/step - loss: 0.0025 - accuracy: 0.9999 - val_loss: 0.6283 - val_accuracy: 0.8896
Epoch 5/50
858/858 [=====] - 21s 25ms/step - loss: 0.0154 - accuracy: 0.9954 - val_loss: 0.5506 - val_accuracy: 0.8885
Epoch 6/50
858/858 [=====] - 20s 23ms/step - loss: 8.6169e-04 - accuracy: 0.9999 - val_loss: 0.5281 - val_accuracy: 0.9091
Epoch 7/50
858/858 [=====] - 20s 23ms/step - loss: 8.3940e-04 - accuracy: 0.9999 - val_loss: 0.6266 - val_accuracy: 0.8938
```

Plot of the CNN model with activation function: LeakyReLU, optimizer: <class 'keras.src.optimizers.adam.Adam'> and learning rate: 0.001



```
Epoch 1/50
858/858 [=====] - 22s 26ms/step - loss: 0.6071 - accuracy: 0.8253 - val_loss: 0.4035 - val_accuracy: 0.8779
Epoch 2/50
858/858 [=====] - 22s 26ms/step - loss: 0.0154 - accuracy: 0.9985 - val_loss: 0.4632 - val_accuracy: 0.8974
Epoch 3/50
858/858 [=====] - 21s 24ms/step - loss: 0.0273 - accuracy: 0.9922 - val_loss: 0.6052 - val_accuracy: 0.8742
Epoch 4/50
858/858 [=====] - 22s 25ms/step - loss: 0.0025 - accuracy: 0.9996 - val_loss: 0.5393 - val_accuracy: 0.9088
Epoch 5/50
858/858 [=====] - 22s 25ms/step - loss: 3.7741e-04 - accuracy: 1.0000 - val_loss: 0.5462 - val_accuracy: 0.9127
Epoch 6/50
858/858 [=====] - 21s 25ms/step - loss: 2.0934e-04 - accuracy: 1.0000 - val_loss: 0.5734 - val_accuracy: 0.9136
```

Plot of the CNN model with activation function: selu, optimizer: <class 'keras.src.optimizers.adam.Adam'> and learning rate: 0.001



```
Epoch 1/50
858/858 [=====] - 23s 26ms/step - loss: 0.6488 - accuracy: 0.8127 - val_loss: 0.4897 - val_accuracy: 0.8751
Epoch 2/50
858/858 [=====] - 22s 26ms/step - loss: 0.0218 - accuracy: 0.9964 - val_loss: 0.5584 - val_accuracy: 0.8840
Epoch 3/50
858/858 [=====] - 22s 25ms/step - loss: 0.0115 - accuracy: 0.9974 - val_loss: 0.4865 - val_accuracy: 0.8924
Epoch 4/50
858/858 [=====] - 21s 24ms/step - loss: 0.0022 - accuracy: 0.9996 - val_loss: 0.7391 - val_accuracy: 0.8522
Epoch 5/50
858/858 [=====] - 23s 27ms/step - loss: 0.0156 - accuracy: 0.9953 - val_loss: 0.5686 - val_accuracy: 0.9069
Epoch 6/50
858/858 [=====] - 21s 25ms/step - loss: 3.0463e-04 - accuracy: 1.0000 - val_loss: 0.5880 - val_accuracy: 0.9052
Epoch 7/50
858/858 [=====] - 20s 24ms/step - loss: 1.3558e-04 - accuracy: 1.0000 - val_loss: 0.6189 - val_accuracy: 0.9055
Epoch 8/50
858/858 [=====] - 22s 26ms/step - loss: 7.9281e-05 - accuracy: 1.0000 - val_loss: 0.6443 - val_accuracy: 0.9060
```

Plot of the CNN model with activation function: elu, optimizer: <class 'keras.src.optimizers.nadam.Nadam'> and learning rate: 0.001

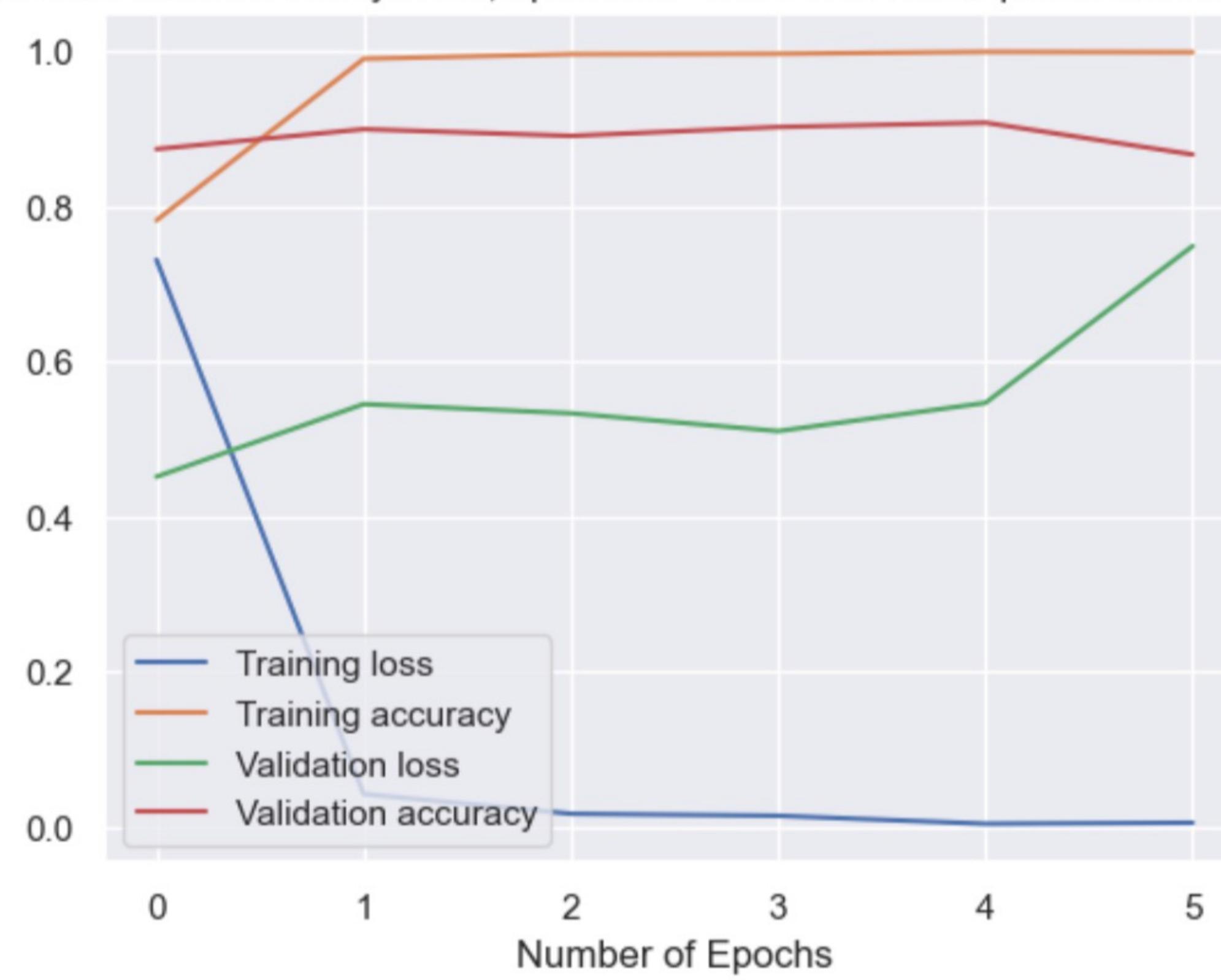


```

Epoch 1/50
858/858 [=====] - 20s 23ms/step - loss: 0.7310 - accuracy: 0.7818 - val_loss: 0.4513 - val_accuracy: 0.8737
Epoch 2/50
858/858 [=====] - 19s 22ms/step - loss: 0.0421 - accuracy: 0.9901 - val_loss: 0.5449 - val_accuracy: 0.8993
Epoch 3/50
858/858 [=====] - 18s 21ms/step - loss: 0.0168 - accuracy: 0.9961 - val_loss: 0.5330 - val_accuracy: 0.8907
Epoch 4/50
858/858 [=====] - 19s 22ms/step - loss: 0.0142 - accuracy: 0.9966 - val_loss: 0.5101 - val_accuracy: 0.9021
Epoch 5/50
858/858 [=====] - 19s 23ms/step - loss: 0.0038 - accuracy: 0.9991 - val_loss: 0.5464 - val_accuracy: 0.9077
Epoch 6/50
858/858 [=====] - 19s 23ms/step - loss: 0.0051 - accuracy: 0.9986 - val_loss: 0.7486 - val_accuracy: 0.8667

```

Plot of the CNN model with activation function: LeakyReLU, optimizer: <class 'keras.src.optimizers.nadam.Nadam'> and learning rate: 0.001

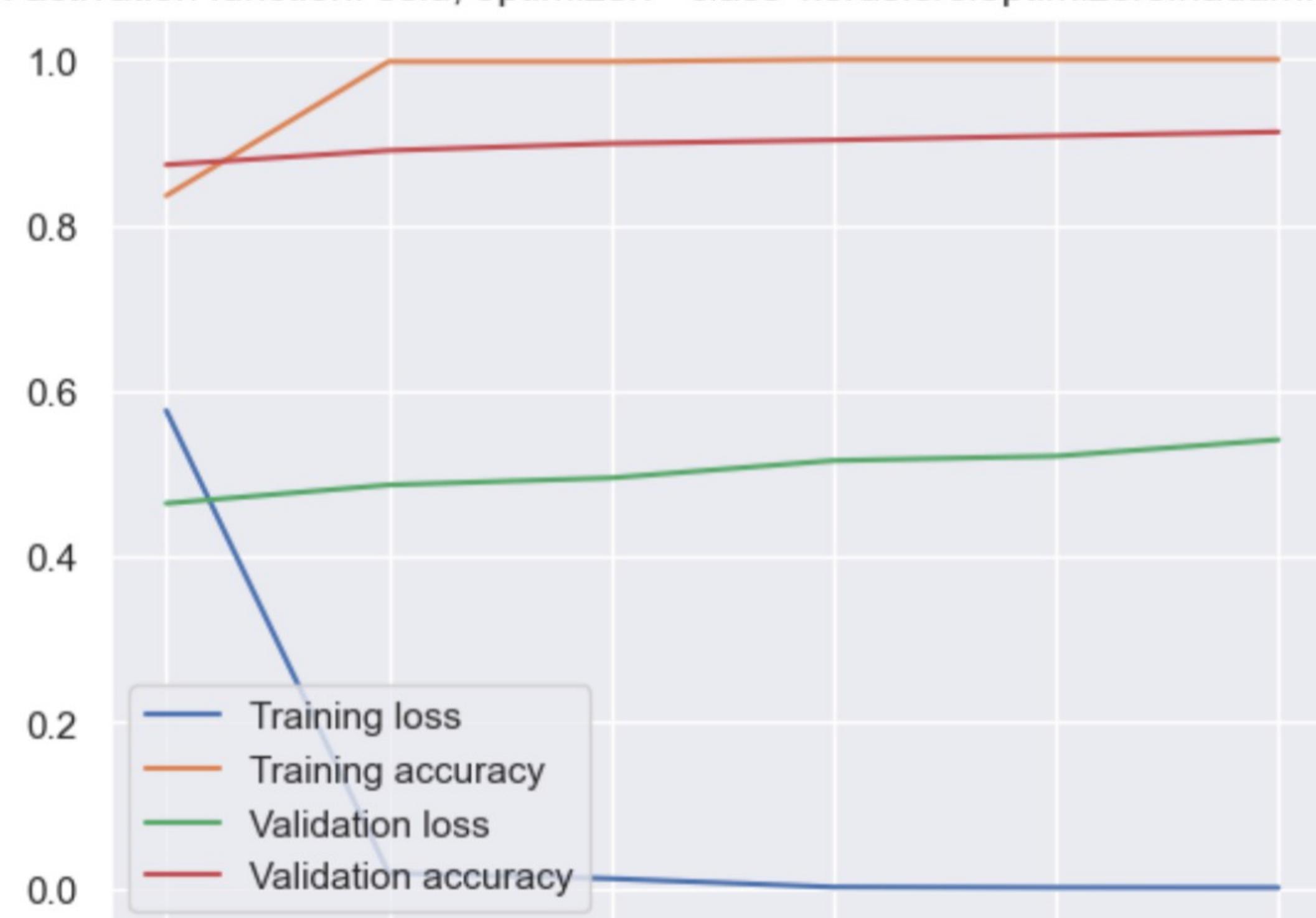


```

Epoch 1/50
858/858 [=====] - 23s 26ms/step - loss: 0.5762 - accuracy: 0.8355 - val_loss: 0.4641 - val_accuracy: 0.8728
Epoch 2/50
858/858 [=====] - 24s 28ms/step - loss: 0.0179 - accuracy: 0.9975 - val_loss: 0.4863 - val_accuracy: 0.8901
Epoch 3/50
858/858 [=====] - 23s 27ms/step - loss: 0.0111 - accuracy: 0.9975 - val_loss: 0.4948 - val_accuracy: 0.8985
Epoch 4/50
858/858 [=====] - 24s 28ms/step - loss: 9.0320e-04 - accuracy: 1.0000 - val_loss: 0.5157 - val_accuracy: 0.9027
Epoch 5/50
858/858 [=====] - 24s 27ms/step - loss: 3.2747e-04 - accuracy: 1.0000 - val_loss: 0.5211 - val_accuracy: 0.9077
Epoch 6/50
858/858 [=====] - 23s 26ms/step - loss: 1.8214e-04 - accuracy: 1.0000 - val_loss: 0.5409 - val_accuracy: 0.9124

```

Plot of the CNN model with activation function: selu, optimizer: <class 'keras.src.optimizers.nadam.Nadam'> and learning rate: 0.001



```
In [38]: lr_cnn = []
opt_cnn = []
act_cnn = []
val_acc_cnn = []
for i in range(0, len(res_cnn)):
    lr_cnn.append(res_cnn[i][0])
    opt_cnn.append(res_cnn[i][1])
    act_cnn.append(res_cnn[i][2])
    val_acc_cnn.append(res_cnn[i][3])

print('Table of the maximum validation accuracy for each combination of activation function, optimizer and learning rate')
val_cnn = pd.DataFrame({'Learning rate': lr_cnn, 'Optimizer': opt_cnn, 'Activation function': act_cnn,
                        'Max validation accuracy': val_acc_cnn})
val_cnn = val_cnn.sort_values('Max validation accuracy')
val_cnn
```

Table of the maximum validation accuracy for each combination of activation function, optimizer and learning rate for the CNN model:

Out[38]:

	Learning rate	Optimizer	Activation function	Max validation accuracy
5	0.010	<class 'keras.src.optimizers.adam.Adam'>	selu	0.061350
6	0.010	<class 'keras.src.optimizers.nadam.Nadam'>	elu	0.061350
10	0.001	<class 'keras.src.optimizers.sgd.SGD'>	LeakyReLU	0.764361
1	0.010	<class 'keras.src.optimizers.sgd.SGD'>	LeakyReLU	0.836029
11	0.001	<class 'keras.src.optimizers.sgd.SGD'>	selu	0.837702
9	0.001	<class 'keras.src.optimizers.sgd.SGD'>	elu	0.842443
8	0.010	<class 'keras.src.optimizers.nadam.Nadam'>	selu	0.844674
4	0.010	<class 'keras.src.optimizers.adam.Adam'>	LeakyReLU	0.873118
7	0.010	<class 'keras.src.optimizers.nadam.Nadam'>	LeakyReLU	0.875627
0	0.010	<class 'keras.src.optimizers.sgd.SGD'>	elu	0.883157
3	0.010	<class 'keras.src.optimizers.adam.Adam'>	elu	0.886224
12	0.001	<class 'keras.src.optimizers.adam.Adam'>	elu	0.899331
2	0.010	<class 'keras.src.optimizers.sgd.SGD'>	selu	0.900446
15	0.001	<class 'keras.src.optimizers.nadam.Nadam'>	elu	0.906860
16	0.001	<class 'keras.src.optimizers.nadam.Nadam'>	LeakyReLU	0.907697
13	0.001	<class 'keras.src.optimizers.adam.Adam'>	LeakyReLU	0.909091
17	0.001	<class 'keras.src.optimizers.nadam.Nadam'>	selu	0.912437
14	0.001	<class 'keras.src.optimizers.adam.Adam'>	selu	0.913553

In general, these CNN models gain better performance since their maximum validation accuracy are larger than the figures for other densely connected models. Most of the maximum validation accuracy scores of these CNN models range from about 0.76 to 0.91. Additionally, the differences between training accuracy and validation accuracy of these CNN models are not large as the figures for other densely connected models, since they are only from around 0.1 to 0.2. Although these differences are not large, they still can indicate overfitting problem, therefore, in order to solve this problem, three methods such as Regularization, Weight initialization and Dropout regularization are used.

The best CNN model is the model with Selu activation function, Adam optimizer and learning rate of 0.001. Its training accuracy is 1, and its maximum validation accuracy is around 0.9136. The difference between its validation accuracy and training accuracy is about 0.0864. The second best CNN model is the model with Selu activation function, Nadam optimizer and learning rate of 0.001. Its training accuracy is 1, and its maximum validation accuracy is about 0.9124. The difference between its validation accuracy and training accuracy is also about 0.0876. These two best models are chosen to apply some regularization methods to mitigate overfitting problem.

Apply Regularization methods on the second best CNN model (Selu activation function, Nadam optimizer and learning rate 0.001)

```
In [39]: # Try using Regularization for the second best CNN model with Selu activation function, Nadam optimizer and learning rate
model_cnn_reg_1 = keras.models.Sequential()
model_cnn_reg_1.add(keras.layers.Conv2D(filters=hiddensizes[0], kernel_size=3, strides=1,
                                         activation='selu', padding="same", input_shape=[28, 28, 1],
                                         kernel_regularizer=keras.regularizers.l2(0.01),
                                         bias_regularizer=keras.regularizers.l2(0.01)))
model_cnn_reg_1.add(keras.layers.MaxPooling2D(pool_size=2))
for n in hiddensizes[1:-1]:
    model_cnn_reg_1.add(keras.layers.Conv2D(filters=n, kernel_size=3, strides=1, padding="same", activation='selu'))
    model_cnn_reg_1.add(keras.layers.MaxPooling2D(pool_size=2))
model_cnn_reg_1.add(keras.layers.Conv2D(filters=hiddensizes[-1], kernel_size=3, strides=1,
                                         padding="same", activation='selu'))
model_cnn_reg_1.add(keras.layers.Flatten())
model_cnn_reg_1.add(keras.layers.Dense(24, activation = "softmax"))
model_cnn_reg_1.compile(loss="sparse_categorical_crossentropy", optimizer=keras.optimizers.Nadam(learning_rate=0.001),
                        metrics=['accuracy'])
history_cnn_reg_1 = model_cnn_reg_1.fit(X_train, y_train, epochs=50,
                                         callbacks = early_stopping_cb, validation_data=(X_val, y_val))
```

```
Epoch 1/50
858/858 [=====] - 23s 26ms/step - loss: 0.6340 - accuracy: 0.8266 - val_loss: 0.4913 - val_accuracy: 0.8561
Epoch 2/50
858/858 [=====] - 22s 25ms/step - loss: 0.0543 - accuracy: 0.9969 - val_loss: 0.4549 - val_accuracy: 0.8832
Epoch 3/50
858/858 [=====] - 23s 27ms/step - loss: 0.0274 - accuracy: 0.9997 - val_loss: 0.5510 - val_accuracy: 0.8759
Epoch 4/50
858/858 [=====] - 22s 26ms/step - loss: 0.0275 - accuracy: 0.9967 - val_loss: 0.4342 - val_accuracy: 0.9002
Epoch 5/50
858/858 [=====] - 22s 26ms/step - loss: 0.0184 - accuracy: 0.9975 - val_loss: 0.7784 - val_accuracy: 0.8274
Epoch 6/50
858/858 [=====] - 23s 27ms/step - loss: 0.0222 - accuracy: 0.9964 - val_loss: 0.4775 - val_accuracy: 0.9147
Epoch 7/50
858/858 [=====] - 23s 27ms/step - loss: 0.0074 - accuracy: 1.0000 - val_loss: 0.4289 - val_accuracy: 0.9197
Epoch 8/50
858/858 [=====] - 22s 25ms/step - loss: 0.0160 - accuracy: 0.9964 - val_loss: 0.7902 - val_accuracy: 0.9197
```

```

accuracy: 0.8572
Epoch 9/50
858/858 [=====] - 22s 25ms/step - loss: 0.0178 - accuracy: 0.9970 - val_loss: 0.5568 - val_accuracy: 0.9105
Epoch 10/50
858/858 [=====] - 24s 28ms/step - loss: 0.0056 - accuracy: 1.0000 - val_loss: 0.5342 - val_accuracy: 0.9024
Epoch 11/50
858/858 [=====] - 22s 26ms/step - loss: 0.0036 - accuracy: 1.0000 - val_loss: 0.4938 - val_accuracy: 0.8940
Epoch 12/50
858/858 [=====] - 22s 26ms/step - loss: 0.0026 - accuracy: 1.0000 - val_loss: 0.4704 - val_accuracy: 0.9027

```

According to the performance of the second best CNN model (with Selu activation function, Nadam optimizer and learning rate of 0.001) after using l2 Regularizer, this model converges after epoch 12. Its training accuracy is 1 and its validation accuracy is about 0.9027. The difference between these two values is about 0.0973. Hence, the method of l2 Regularization does not reduce the gap between the training accuracy and validation accuracy of this second best CNN model since the difference between these two values before applying l2 Regularization is 0.0876.

In [40]: # Try using Weight Initialization for the second best CNN model with Selu activation function, Nadam optimizer and learning rate of 0.001

```

model_cnn_wi_1 = keras.models.Sequential()
model_cnn_wi_1.add(keras.layers.Conv2D(filters=hiddensizes[0], kernel_size=3, strides=1,
                                      activation='selu', padding="same",
                                      input_shape=[28, 28, 1], kernel_initializer = 'lecun_normal'))
model_cnn_wi_1.add(keras.layers.MaxPooling2D(pool_size=2))
for n in hiddensizes[1:-1]:
    model_cnn_wi_1.add(keras.layers.Conv2D(filters=n, kernel_size=3, strides=1, padding="same", activation='selu'))
    model_cnn_wi_1.add(keras.layers.MaxPooling2D(pool_size=2))
model_cnn_wi_1.add(keras.layers.Conv2D(filters=hiddensizes[-1], kernel_size=3,
                                      strides=1, padding="same", activation='selu'))
model_cnn_wi_1.add(keras.layers.Flatten())
model_cnn_wi_1.add(keras.layers.Dense(24, activation = "softmax"))
model_cnn_wi_1.compile(loss="sparse_categorical_crossentropy",
                      optimizer=keras.optimizers.Nadam(learning_rate=0.001), metrics=[ "accuracy"])
history_cnn_wi_1 = model_cnn_wi_1.fit(X_train, y_train, epochs=50,
                                       callbacks = early_stopping_cb, validation_data=(X_val, y_val))

```

```

Epoch 1/50
858/858 [=====] - 24s 27ms/step - loss: 0.5053 - accuracy: 0.8583 - val_loss: 0.4194 - val_accuracy: 0.8765
Epoch 2/50
858/858 [=====] - 22s 26ms/step - loss: 0.0143 - accuracy: 0.9989 - val_loss: 0.4313 - val_accuracy: 0.8949
Epoch 3/50
858/858 [=====] - 22s 25ms/step - loss: 0.0116 - accuracy: 0.9972 - val_loss: 0.4673 - val_accuracy: 0.8820
Epoch 4/50
858/858 [=====] - 24s 28ms/step - loss: 0.0043 - accuracy: 0.9989 - val_loss: 0.4709 - val_accuracy: 0.8988
Epoch 5/50
858/858 [=====] - 22s 25ms/step - loss: 0.0083 - accuracy: 0.9974 - val_loss: 0.4828 - val_accuracy: 0.9016
Epoch 6/50
858/858 [=====] - 22s 26ms/step - loss: 1.3925e-04 - accuracy: 1.0000 - val_loss: 0.4783 - val_accuracy: 0.9080

```

According to the performance of the second best CNN model (with Selu activation function, Nadam optimizer and learning rate of 0.001) after using Weight Initialization, this model converges after epoch 6, its training accuracy is about 1 and its validation accuracy is about 0.908. The difference between these two values is about 0.092. Hence, the method of Weight Initialization also does not reduce the difference between the training accuracy and the validation accuracy of this second best CNN model since the difference between these two values before applying Weight Initialization is 0.0876.

In [41]: # Try using Dropout Regularization for the second best CNN model with Selu activation function, Nadam optimizer and learning rate of 0.001

```

model_cnn_dr_1 = keras.models.Sequential()
model_cnn_dr_1.add(keras.layers.Conv2D(filters=hiddensizes[0], kernel_size=3, strides=1,
                                      activation='selu', padding="same", input_shape=[28, 28, 1]))
model_cnn_dr_1.add(keras.layers.MaxPooling2D(pool_size=2))
model_cnn_dr_1.add(keras.layers.Dropout (0.05))
for n in hiddensizes[1:-1]:
    model_cnn_dr_1.add(keras.layers.Conv2D(filters=n, kernel_size=3, strides=1, padding="same", activation='selu'))
    model_cnn_dr_1.add(keras.layers.MaxPooling2D(pool_size=2))
    model_cnn_dr_1.add(keras.layers.Dropout (0.05))
model_cnn_dr_1.add(keras.layers.Conv2D(filters=hiddensizes[-1], kernel_size=3,
                                      strides=1, padding="same", activation='selu'))
model_cnn_dr_1.add(keras.layers.Flatten())
model_cnn_dr_1.add(keras.layers.Dense(24, activation = "softmax"))
model_cnn_dr_1.compile(loss="sparse_categorical_crossentropy", optimizer=keras.optimizers.Nadam(learning_rate=0.001),
                      metrics=[ "accuracy"])
history_cnn_dr_1 = model_cnn_dr_1.fit(X_train, y_train, epochs=50,
                                       callbacks = early_stopping_cb, validation_data=(X_val, y_val))

```

```

Epoch 1/50
858/858 [=====] - 26s 29ms/step - loss: 0.6450 - accuracy: 0.8121 - val_loss: 0.3691 - val_accuracy: 0.8820
Epoch 2/50
858/858 [=====] - 25s 29ms/step - loss: 0.0269 - accuracy: 0.9953 - val_loss: 0.3271 - val_accuracy: 0.9088
Epoch 3/50
858/858 [=====] - 26s 31ms/step - loss: 0.0133 - accuracy: 0.9970 - val_loss: 0.4485 - val_accuracy: 0.8918
Epoch 4/50
858/858 [=====] - 25s 29ms/step - loss: 0.0127 - accuracy: 0.9967 - val_loss: 0.4957 - val_accuracy: 0.8985
Epoch 5/50
858/858 [=====] - 25s 29ms/step - loss: 0.0079 - accuracy: 0.9979 - val_loss: 0.6247 - val_accuracy: 0.8918
Epoch 6/50
858/858 [=====] - 25s 29ms/step - loss: 0.0046 - accuracy: 0.9987 - val_loss: 0.3954 - val_accuracy: 0.9225
Epoch 7/50
858/858 [=====] - 26s 30ms/step - loss: 0.0078 - accuracy: 0.9979 - val_loss: 0.5070 - val_accuracy: 0.9021

```

According to the performance of the second best CNN model (with Selu activation function, Nadam optimizer and learning rate of 0.001) after using Dropout Regularization, this model converges after epoch 7, its training accuracy is about 0.9979 and its validation accuracy is about 0.9021. The difference between these two values is about 0.0958. Hence, the method of Dropout Regularization also does not reduce the difference between the training accuracy and the validation accuracy of this second best CNN model since the difference between these two values before applying Dropout Regularization is 0.0876.

Apply Regularization methods on the best CNN model (Selu activation function, Adam optimizer and learning rate 0.001)

```
In [42]: # Try using Regularization for the best CNN model with Selu activation function, Adam optimizer and learning rate of 0.
model_cnn_reg_2 = keras.models.Sequential()
model_cnn_reg_2.add(keras.layers.Conv2D(filters=hiddensizes[0], kernel_size=3, strides=1,
                                         activation='selu', padding="same", input_shape=[28, 28, 1],
                                         kernel_regularizer=keras.regularizers.l2(0.01),
                                         bias_regularizer=keras.regularizers.l2(0.01)))
model_cnn_reg_2.add(keras.layers.MaxPooling2D(pool_size=2))
for n in hiddensizes[1:-1]:
    model_cnn_reg_2.add(keras.layers.Conv2D(filters=n, kernel_size=3, strides=1, padding="same", activation='selu'))
    model_cnn_reg_2.add(keras.layers.MaxPooling2D(pool_size=2))
model_cnn_reg_2.add(keras.layers.Conv2D(filters=hiddensizes[-1], kernel_size=3,
                                         strides=1, padding="same", activation='selu'))
model_cnn_reg_2.add(keras.layers.Flatten())
model_cnn_reg_2.add(keras.layers.Dense(24, activation = "softmax"))
model_cnn_reg_2.compile(loss="sparse_categorical_crossentropy", optimizer=keras.optimizers.Adam(learning_rate=0.001),
                        metrics=["accuracy"])
history_cnn_reg_2 = model_cnn_reg_2.fit(X_train, y_train, epochs=50,
                                         callbacks = early_stopping_cb, validation_data=(X_val, y_val))
```

Epoch 1/50
858/858 [=====] - 24s 27ms/step - loss: 0.6275 - accuracy: 0.8290 - val_loss: 0.3969 - val_accuracy: 0.8904
Epoch 2/50
858/858 [=====] - 22s 25ms/step - loss: 0.0486 - accuracy: 0.9976 - val_loss: 0.4046 - val_accuracy: 0.9055
Epoch 3/50
858/858 [=====] - 22s 25ms/step - loss: 0.0279 - accuracy: 0.9990 - val_loss: 0.3782 - val_accuracy: 0.9080
Epoch 4/50
858/858 [=====] - 23s 27ms/step - loss: 0.0378 - accuracy: 0.9929 - val_loss: 0.5874 - val_accuracy: 0.8659
Epoch 5/50
858/858 [=====] - 23s 27ms/step - loss: 0.0165 - accuracy: 0.9990 - val_loss: 0.3790 - val_accuracy: 0.9255
Epoch 6/50
858/858 [=====] - 22s 26ms/step - loss: 0.0094 - accuracy: 1.0000 - val_loss: 0.3470 - val_accuracy: 0.9286
Epoch 7/50
858/858 [=====] - 22s 26ms/step - loss: 0.0067 - accuracy: 1.0000 - val_loss: 0.4123 - val_accuracy: 0.9127
Epoch 8/50
858/858 [=====] - 22s 26ms/step - loss: 0.0406 - accuracy: 0.9906 - val_loss: 0.4843 - val_accuracy: 0.9041
Epoch 9/50
858/858 [=====] - 23s 27ms/step - loss: 0.0068 - accuracy: 1.0000 - val_loss: 0.4421 - val_accuracy: 0.9124
Epoch 10/50
858/858 [=====] - 23s 27ms/step - loss: 0.0054 - accuracy: 1.0000 - val_loss: 0.4143 - val_accuracy: 0.9161
Epoch 11/50
858/858 [=====] - 23s 26ms/step - loss: 0.0042 - accuracy: 1.0000 - val_loss: 0.3985 - val_accuracy: 0.9191

According to the performance of the best CNN model (with Selu activation function, Adam optimizer and learning rate of 0.001) after using L2 Regularizer, this model converges after epoch 11, its training accuracy is about 1 and its validation accuracy is about 0.9191. The difference between these two values is about 0.0809. Hence, the method of L2 Regularization can slightly reduce the difference between the training accuracy and the validation accuracy of this best CNN model since the difference between these two values before applying L2 Regularization is 0.0864. However, it does not improve the validation accuracy much because the original validation accuracy is 0.9136.

```
In [43]: # Try using Weight Initialization for the best CNN model with Selu activation function, Adam optimizer and learning rate of 0.001
model_cnn_wi_2 = keras.models.Sequential()
model_cnn_wi_2.add(keras.layers.Conv2D(filters=hiddensizes[0], kernel_size=3, strides=1,
                                         activation='selu', padding="same", input_shape=[28, 28, 1],
                                         kernel_initializer = 'lecun_normal'))
model_cnn_wi_2.add(keras.layers.MaxPooling2D(pool_size=2))
for n in hiddensizes[1:-1]:
    model_cnn_wi_2.add(keras.layers.Conv2D(filters=n, kernel_size=3, strides=1, padding="same", activation='selu'))
    model_cnn_wi_2.add(keras.layers.MaxPooling2D(pool_size=2))
model_cnn_wi_2.add(keras.layers.Conv2D(filters=hiddensizes[-1], kernel_size=3, strides=1,
                                         padding="same", activation='selu'))
model_cnn_wi_2.add(keras.layers.Flatten())
model_cnn_wi_2.add(keras.layers.Dense(24, activation = "softmax"))
model_cnn_wi_2.compile(loss="sparse_categorical_crossentropy", optimizer=keras.optimizers.Adam(learning_rate=0.001),
                        metrics=["accuracy"])
history_cnn_wi_2 = model_cnn_wi_2.fit(X_train, y_train, epochs=50,
                                         callbacks = early_stopping_cb, validation_data=(X_val, y_val))
```

Epoch 1/50
858/858 [=====] - 22s 26ms/step - loss: 0.5768 - accuracy: 0.8359 - val_loss: 0.3951 - val_accuracy: 0.8781
Epoch 2/50
858/858 [=====] - 21s 25ms/step - loss: 0.0159 - accuracy: 0.9986 - val_loss: 0.3748 - val_accuracy: 0.8974
Epoch 3/50
858/858 [=====] - 22s 26ms/step - loss: 0.0116 - accuracy: 0.9975 - val_loss: 0.4356 - val_accuracy: 0.8921
Epoch 4/50
858/858 [=====] - 23s 27ms/step - loss: 0.0149 - accuracy: 0.9955 - val_loss: 0.4787 - val_accuracy: 0.8979
Epoch 5/50
858/858 [=====] - 23s 26ms/step - loss: 4.5626e-04 - accuracy: 1.0000 - val_loss: 0.4567 - val_accuracy: 0.9013
Epoch 6/50
858/858 [=====] - 22s 26ms/step - loss: 1.5869e-04 - accuracy: 1.0000 - val_loss: 0.4449 - val_accuracy: 0.9096
Epoch 7/50
858/858 [=====] - 22s 26ms/step - loss: 9.6578e-05 - accuracy: 1.0000 - val_loss: 0.4586 - val_accuracy: 0.9094

According to the performance of the best CNN model (with Selu activation function, Adam optimizer and learning rate of 0.001) after using Weight Initialization, after epoch 7, its training accuracy is about 1 and its validation accuracy is about 0.9094. The difference between these two values is about 0.0906. Hence, the method of Weight Initialization does not reduce the difference between training accuracy and validation accuracy of this best CNN model since the gap between these two values before applying Weight Initialization is 0.0864.

```
In [44]: # Try using Dropout Regularization for the best CNN model with Selu activation function, Adam optimizer and learning rate of 0.001
model_cnn_dr_2 = keras.models.Sequential()
model_cnn_dr_2.add(keras.layers.Conv2D(filters=hiddensizes[0], kernel_size=3, strides=1,
                                         activation='selu', padding="same", input_shape=[28, 28, 1]))
model_cnn_dr_2.add(keras.layers.MaxPooling2D(pool_size=2))
model_cnn_dr_2.add(keras.layers.Dropout (0.05))
for n in hiddensizes[1:-1]:
    model_cnn_dr_2.add(keras.layers.Conv2D(filters=n, kernel_size=3, strides=1, padding="same", activation='selu'))
    model_cnn_dr_2.add(keras.layers.MaxPooling2D(pool_size=2))
    model_cnn_dr_2.add(keras.layers.Dropout (0.05))
model_cnn_dr_2.add(keras.layers.Conv2D(filters=hiddensizes[-1], kernel_size=3,
                                         strides=1, padding="same", activation='selu'))
model_cnn_dr_2.add(keras.layers.Flatten())
model_cnn_dr_2.add(keras.layers.Dense(24, activation = "softmax"))
model_cnn_dr_2.compile(loss="sparse_categorical_crossentropy", optimizer=keras.optimizers.Adam(learning_rate=0.001),
                        metrics=["accuracy"])
history_cnn_dr_2 = model_cnn_dr_2.fit(x_train, y_train, epochs=50,
                                       callbacks = early_stopping_cb, validation_data=(x_val, y_val))
```

```
Epoch 1/50
858/858 [=====] - 25s 28ms/step - loss: 0.5971 - accuracy: 0.8245 - val_loss: 0.4035 - val_accuracy: 0.8756
Epoch 2/50
858/858 [=====] - 25s 29ms/step - loss: 0.0298 - accuracy: 0.9942 - val_loss: 0.4644 - val_accuracy: 0.8798
Epoch 3/50
858/858 [=====] - 26s 31ms/step - loss: 0.0201 - accuracy: 0.9944 - val_loss: 0.4454 - val_accuracy: 0.9071
Epoch 4/50
858/858 [=====] - 26s 30ms/step - loss: 0.0026 - accuracy: 0.9996 - val_loss: 0.4577 - val_accuracy: 0.9102
Epoch 5/50
858/858 [=====] - 25s 29ms/step - loss: 6.2306e-04 - accuracy: 1.0000 - val_loss: 0.4802 - val_accuracy: 0.9194
Epoch 6/50
858/858 [=====] - 24s 28ms/step - loss: 0.0308 - accuracy: 0.9908 - val_loss: 0.6384 - val_accuracy: 0.8804
```

According to the performance of the best CNN model (with Selu activation function, Adam optimizer and learning rate of 0.001) after using Dropout Regularization, this model converges after epoch 6, its training accuracy is about 0.9908 and its validation accuracy is about 0.8804. The difference between these two values is about 0.1104. Hence, the method of Dropout Regularization also does not reduce the gap between the training accuracy and the validation accuracy of this best CNN model since the difference between these two values before applying Dropout Regularization is 0.0864.

In conclusion, in comparison with the best densely connected model, the best CNN model (with Selu activation function, Adam optimizer and learning rate of 0.001), and the second best CNN model (with Selu activation function, Nadam optimizer and learning rate of 0.001) obtain better validation accuracy score. Therefore, these two best models are used in prediction process. In addition, three methods (Regularization, Weight initialization and Dropout regularization) do not reduce the difference between training accuracy and validation accuracy, hence they can not mitigate the overfitting problem. Therefore, these two best CNN models are used to generate predictions without applying any regularization methods.

3.3 Perform a statistical test between the best and the second best models

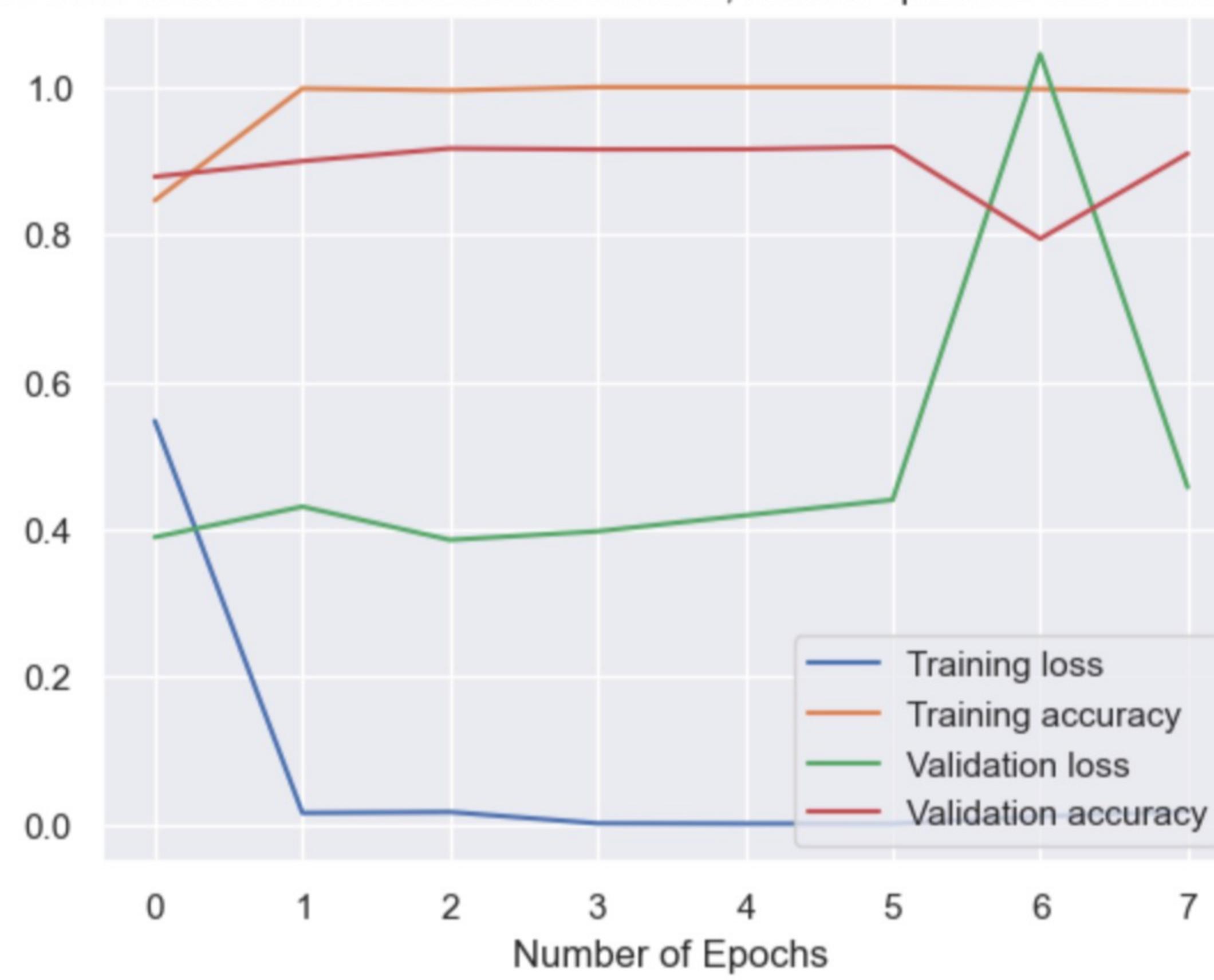
Fitting the second best CNN model (Selu activation function, Nadam optimizer and learning rate of 0.001) on training data

```
In [45]: # Training the second best CNN model with Selu activation function, Nadam optimizer and learning rate of 0.001 on the training data
model_cnn_final_1 = keras.models.Sequential()
model_cnn_final_1.add(keras.layers.Conv2D(filters=hiddensizes[0], kernel_size=3,
                                         strides=1, activation='selu', padding="same", input_shape=[28, 28, 1]))
model_cnn_final_1.add(keras.layers.MaxPooling2D(pool_size=2))
for n in hiddensizes[1:-1]:
    model_cnn_final_1.add(keras.layers.Conv2D(filters=n, kernel_size=3, strides=1, padding="same", activation='selu'))
    model_cnn_final_1.add(keras.layers.MaxPooling2D(pool_size=2))
model_cnn_final_1.add(keras.layers.Conv2D(filters=hiddensizes[-1], kernel_size=3, strides=1,
                                         padding="same", activation='selu'))
model_cnn_final_1.add(keras.layers.Flatten())
model_cnn_final_1.add(keras.layers.Dense(24, activation = "softmax"))
model_cnn_final_1.compile(loss="sparse_categorical_crossentropy",
                        optimizer=keras.optimizers.Nadam(learning_rate=0.001), metrics=["accuracy"])
history_cnn_final_1 = model_cnn_final_1.fit(x_train, y_train, epochs=50,
                                             callbacks = early_stopping_cb, validation_data=(x_val, y_val))
```

```
Epoch 1/50
858/858 [=====] - 22s 25ms/step - loss: 0.5470 - accuracy: 0.8462 - val_loss: 0.3893 - val_accuracy: 0.8784
Epoch 2/50
858/858 [=====] - 24s 28ms/step - loss: 0.0150 - accuracy: 0.9982 - val_loss: 0.4306 - val_accuracy: 0.8996
Epoch 3/50
858/858 [=====] - 24s 28ms/step - loss: 0.0162 - accuracy: 0.9956 - val_loss: 0.3856 - val_accuracy: 0.9169
Epoch 4/50
858/858 [=====] - 23s 27ms/step - loss: 7.7819e-04 - accuracy: 1.0000 - val_loss: 0.3972 - val_accuracy: 0.9155
Epoch 5/50
858/858 [=====] - 21s 25ms/step - loss: 3.5748e-04 - accuracy: 1.0000 - val_loss: 0.4188 - val_accuracy: 0.9158
Epoch 6/50
858/858 [=====] - 22s 26ms/step - loss: 2.0846e-04 - accuracy: 1.0000 - val_loss: 0.4398 - val_accuracy: 0.9189
Epoch 7/50
858/858 [=====] - 23s 27ms/step - loss: 0.0102 - accuracy: 0.9975 - val_loss: 1.0450 - val_accuracy: 0.7942
Epoch 8/50
858/858 [=====] - 23s 27ms/step - loss: 0.0169 - accuracy: 0.9948 - val_loss: 0.4569 - val_accuracy: 0.9099
```

```
In [47]: # Plot of the second best CNN model with Selu activation function, Nadam optimizer and learning rate of 0.001
pd.DataFrame(history_cnn_final_1.history).plot()
plt.xlabel("Number of Epochs")
plt.title(f'Plot of the CNN model with Selu activation function, Nadam optimizer and learning rate of 0.001')
plt.legend(['Training loss', 'Training accuracy', 'Validation loss', 'Validation accuracy'], loc = 'lower right')
plt.show()
```

Plot of the CNN model with Selu activation function, Nadam optimizer and learning rate of 0.001



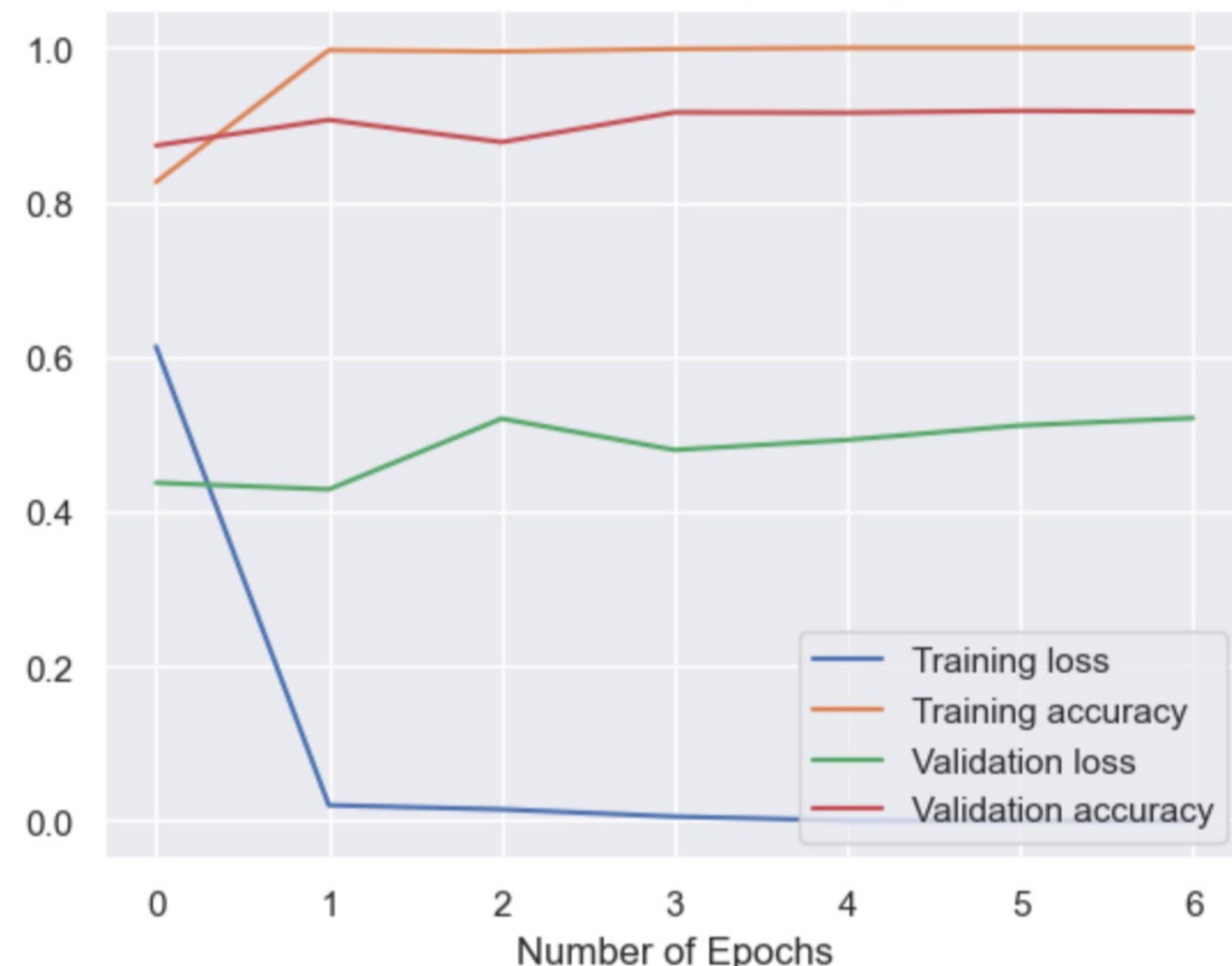
Fitting the best CNN model (Selu activation function, Adam optimizer and learning rate of 0.001) on training data

```
In [46]: # Training the best CNN model with Selu activation function, Adam optimizer and learning rate of 0.001 on the training
model_cnn_final_2 = keras.models.Sequential()
model_cnn_final_2.add(keras.layers.Conv2D(filters=hiddensizes[0], kernel_size=3, strides=1, activation='selu', padding='same', input_shape=[28, 28, 1]))
model_cnn_final_2.add(keras.layers.MaxPooling2D(pool_size=2))
for n in hiddensizes[1:-1]:
    model_cnn_final_2.add(keras.layers.Conv2D(filters=n, kernel_size=3, strides=1, padding="same", activation='selu'))
    model_cnn_final_2.add(keras.layers.MaxPooling2D(pool_size=2))
model_cnn_final_2.add(keras.layers.Conv2D(filters=hiddensizes[-1], kernel_size=3, strides=1, padding="same", activation='selu'))
model_cnn_final_2.add(keras.layers.Flatten())
model_cnn_final_2.add(keras.layers.Dense(24, activation = "softmax"))
model_cnn_final_2.compile(loss="sparse_categorical_crossentropy", optimizer=keras.optimizers.Adam(learning_rate=0.001), history_cnn_final_2 = model_cnn_final_2.fit(X_train, y_train, epochs=50, callbacks = early_stopping_cb, validation_data=(X_val, y_val))

Epoch 1/50
858/858 [=====] - 22s 25ms/step - loss: 0.6135 - accuracy: 0.8265 - val_loss: 0.4373 - val_accuracy: 0.8737
Epoch 2/50
858/858 [=====] - 23s 27ms/step - loss: 0.0202 - accuracy: 0.9972 - val_loss: 0.4288 - val_accuracy: 0.9069
Epoch 3/50
858/858 [=====] - 23s 27ms/step - loss: 0.0148 - accuracy: 0.9956 - val_loss: 0.5204 - val_accuracy: 0.8781
Epoch 4/50
858/858 [=====] - 24s 28ms/step - loss: 0.0054 - accuracy: 0.9987 - val_loss: 0.4798 - val_accuracy: 0.9166
Epoch 5/50
858/858 [=====] - 24s 28ms/step - loss: 3.2926e-04 - accuracy: 1.0000 - val_loss: 0.4928 - val_accuracy: 0.9161
Epoch 6/50
858/858 [=====] - 22s 26ms/step - loss: 1.8261e-04 - accuracy: 1.0000 - val_loss: 0.5115 - val_accuracy: 0.9186
Epoch 7/50
858/858 [=====] - 22s 25ms/step - loss: 1.1708e-04 - accuracy: 1.0000 - val_loss: 0.5211 - val_accuracy: 0.9175
```

```
In [48]: # Plot of the best CNN model with Selu activation function, Adam optimizer and learning rate of 0.001
pd.DataFrame(history_cnn_final_2.history).plot()
plt.xlabel("Number of Epochs")
plt.title(f'Plot of the CNN model with Selu activation function, Adam optimizer and learning rate of 0.001')
plt.legend(['Training loss', 'Training accuracy', 'Validation loss', 'Validation accuracy'], loc = 'lower right')
plt.show()
```

Plot of the CNN model with Selu activation function, Adam optimizer and learning rate of 0.001



Perform a statistical test between the best CNN model and the second best CNN model

```
In [49]: # Making prediction from the best CNN model (with Selu activation function, Adam optimizer and learning rate of 0.001), # and the second best CNN model (with Selu activation function, Nadam optimizer and learning rate of 0.001) on the validation
y_val_pred = []
y_val_pred += [np.argmax(model_cnn_final_2.predict(X_val),axis=1)]
y_val_pred += [np.argmax(model_cnn_final_1.predict(X_val),axis=1)]
print(y_val_pred)
```

```
113/113 [=====] - 1s 7ms/step
113/113 [=====] - 1s 7ms/step
[array([ 6,  5,  9, ..., 23,  7, 17]), array([ 6,  5,  9, ..., 23,  7, 13])]
```

```
In [50]: from sklearn.metrics import accuracy_score
from mlxtend.evaluate import permutation_test
# Perform statistical test between the best and second-best models, to see if there is any significant difference in performance
p_value = permutation_test(y_val_pred[0], y_val_pred[1], paired=True,
                            func=lambda x, y: np.abs(accuracy_score(y_val,x) - accuracy_score(y_val,y)),
                            method="approximate", seed=1, num_rounds=1000)
print(f'With the threshold of 0.05, the P-value in comparing the two best models is {p_value}, which is below the threshold of 0.05')

With the threshold of 0.05, the P-value in comparing the two best models is 0.028971028971028972, which is below the threshold, hence the difference in performance between these two best models is significant.
```

The best CNN model with Selu activation function, Adam optimizer and learning rate of 0.001 converges with the validation accuracy of 0.9175, and the second best CNN model with Selu activation function, Nadam optimizer and learning rate of 0.001 converges with the validation accuracy is 0.9099. Additionally, the difference in the performance of these two best models is significant because the p-value in comparing these two best models is below 0.05, therefore, the CNN model with Selu activation function, Adam optimizer and learning rate of 0.001 is chosen to make predictions on the testing data.

4. Model predictions

```
In [51]: # Evaluating the final CNN model with Selu activation function, Adam optimizer and learning rate of 0.001 on the testing data
testres_1 = model_cnn_final_2.evaluate(X_test, y_test)
print('The testing loss of the final CNN model is: ', testres_1[0])
print('The testing accuracy of the final CNN model is: ', testres_1[1])
```

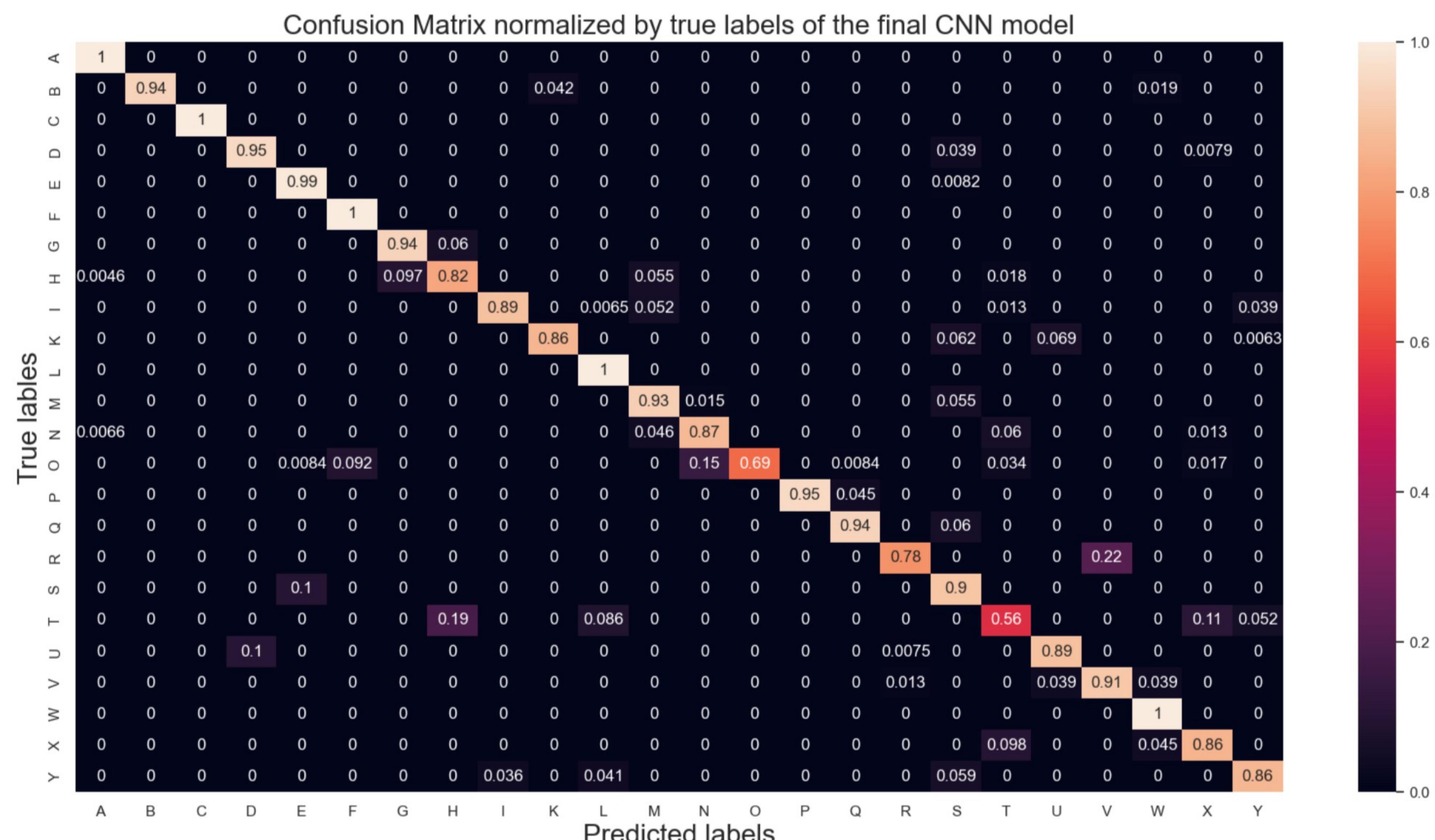
```
113/113 [=====] - 1s 7ms/step - loss: 0.4283 - accuracy: 0.9044
The testing loss of the final CNN model is:  0.4282926917076111
The testing accuracy of the final CNN model is:  0.9043502807617188
```

```
In [52]: # Making predictions from the final CNN model with Elu activation function, Nadam optimizer and learning rate of 0.001
y_pred = np.argmax(model_cnn_final_2.predict(X_test, verbose = 0),axis=1)
```

```
In [53]: from sklearn.metrics import accuracy_score, confusion_matrix
import seaborn as sns

y_test_label = y_test.apply(lambda x: class_names[x])
y_pred_label = pd.Series(y_pred).apply(lambda x: class_names[x])

conf_mat_norm = confusion_matrix(y_test_label, y_pred_label, normalize = 'true')
conf_mat_norm = pd.DataFrame(conf_mat_norm, index = class_names, columns = class_names)
f, ax = plt.subplots(figsize=(20, 10))
sns.heatmap(conf_mat_norm, annot = True)
plt.xlabel('Predicted labels', fontsize = 20)
plt.ylabel('True labels', fontsize = 20)
plt.title('Confusion Matrix normalized by true labels of the final CNN model', fontsize = 20, loc = "center")
plt.show()
```



According to the confusion matrix normalized by true labels, only 56% observations of the letter 'T' are predicted correctly. In addition, the letter 'O' has only 69% observations which are predicted correctly, and the letter 'R' has only 78% observations which are predicted correctly. The remaining letters have around 80% observations or more being predicted correctly. The letters 'A', 'C', 'F', 'L', 'W' are completely predicted correctly.

```
In [54]: # Accuracy score for each individual letter
acc = pd.DataFrame({'Predicted labels': y_pred_label, 'True labels':y_test_label})
acc_v = acc[acc['Predicted labels'] == acc['True labels']]
acc_v = pd.DataFrame(acc_v.drop('True labels', axis = 1).value_counts(),
                      columns = ["Number of correct prediction"]).sort_values('Predicted labels')
count_pred = pd.DataFrame({'Predicted labels': y_pred_label}).value_counts()
count_pred = pd.DataFrame(count_pred, columns = ["Total number of prediction"]).sort_values('Predicted labels')
acc_total = pd.concat([acc_v, count_pred], axis=1)
acc_total['Accuracy_score'] = acc_total['Number of correct prediction']/acc_total['Total number of prediction']

print('The table of accuracy score of the final CNN model:')
acc_total.sort_values('Accuracy_score')
```

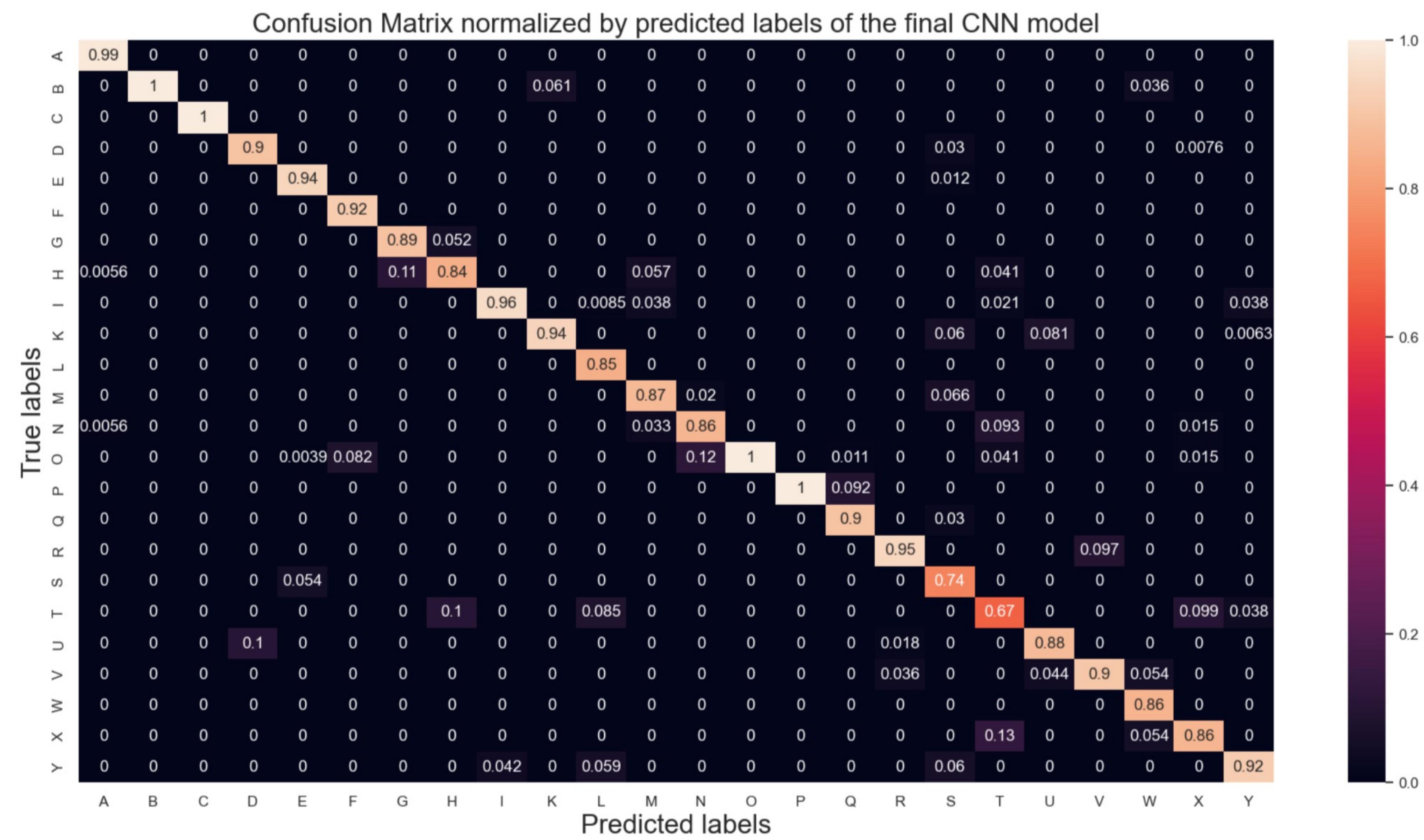
The table of accuracy score of the final CNN model:

```
Out[54]:
```

<table border="1

T	65	97	0.670103
S	124	167	0.742515
H	179	212	0.844340
L	100	118	0.847458
W	96	112	0.857143
X	113	131	0.862595
N	132	153	0.862745
M	185	212	0.872642
U	119	136	0.875000
G	173	194	0.891753
D	121	135	0.896296
Q	78	87	0.896552
V	140	155	0.903226
F	123	134	0.917910
Y	146	159	0.918239
K	138	147	0.938776
E	242	257	0.941634
R	52	55	0.945455
I	137	143	0.958042
A	177	179	0.988827
O	82	82	1.000000
C	154	154	1.000000
B	199	199	1.000000
P	168	168	1.000000

```
In [55]: conf_mat = confusion_matrix(y_test, y_pred, normalize = "pred")
conf_mat = pd.DataFrame(conf_mat, index = class_names, columns = class_names)
f, ax = plt.subplots(figsize=(20, 10))
sns.heatmap(conf_mat, annot = True)
plt.xlabel('Predicted labels', fontsize = 20)
plt.ylabel('True labels', fontsize = 20)
plt.title('Confusion Matrix normalized by predicted labels of the final CNN model', fontsize = 20, loc = "center")
plt.show()
```



According to the confusion matrix normalized by predicted labels and the table of accuracy score of the final CNN model above, the letter 'T' has the lowest accuracy score (only 0.67) because among all letters are predicted as 'T', only 67% observations are truly 'T'. The letter 'S' has the second lowest accuracy score because among all letters are predicted as 'S', only about 74% observations are truly 'S'.

```
In [56]: # The most common misclassification
diff = pd.DataFrame({'True labels':y_test_label, 'Predicted labels': y_pred_label})
diff = diff.loc[diff['True labels'] != diff['Predicted labels']].reset_index(drop = True)
nrow = len(diff)
diff_v = pd.DataFrame(diff.groupby("True labels").value_counts(), columns = ["Count"])
diff_v['Proportion'] = diff_v['Count']/nrow
count_v = diff_v.groupby("True labels").sum('Proportion')
```

```
In [57]: print("Table shows the count and the proportion of misclassification for each letter: \n")
count_v.sort_values('Proportion')
```

Table shows the count and the proportion of misclassification for each letter:

Out[57]:

True labels	Count	Proportion
E	2	0.005831
Q	5	0.014577
D	6	0.017493
P	8	0.023324
G	11	0.032070
B	13	0.037901

S	14	0.040816
V	14	0.040816
M	14	0.040816
R	15	0.043732
U	15	0.043732
I	17	0.049563
N	19	0.055394
X	19	0.055394
K	22	0.064140
Y	23	0.067055
O	37	0.107872
H	38	0.110787
T	51	0.148688

```
In [58]: print('Table shows the count and the proportion of misclassification for each combination of True labels and Predicted labels:')

Table shows the count and the proportion of misclassification for each combination of True labels and Predicted labels:
```

Out[58]:

True labels	Predicted labels	Count	Proportion
B	K	9	0.026239
	W	4	0.011662
D	S	5	0.014577
	X	1	0.002915
E	S	2	0.005831
G	H	11	0.032070
H	G	21	0.061224
	M	12	0.034985
	T	4	0.011662
	A	1	0.002915
I	M	8	0.023324
	Y	6	0.017493
	T	2	0.005831
	L	1	0.002915
K	U	11	0.032070
	S	10	0.029155
	Y	1	0.002915
M	S	11	0.032070
	N	3	0.008746
N	T	9	0.026239
	M	7	0.020408
	X	2	0.005831
	A	1	0.002915
O	N	18	0.052478
	F	11	0.032070
	T	4	0.011662
	X	2	0.005831
	Q	1	0.002915
	E	1	0.002915
P	Q	8	0.023324
Q	S	5	0.014577
R	V	15	0.043732
S	E	14	0.040816
T	H	22	0.064140
	X	13	0.037901
	L	10	0.029155
	Y	6	0.017493
U	D	14	0.040816
	R	1	0.002915
V	U	6	0.017493
	W	6	0.017493
	R	2	0.005831
X	T	13	0.037901
	W	6	0.017493
Y	S	10	0.029155
	L	7	0.020408
	I	6	0.017493

According to the table illustrating the number of the proportion of misclassification for each letter above, the letter 'T' is the most common letter which are predicted incorrectly. Because in all of misclassifications of this final CNN model, the number of missification of the letter 'T' is 51 (accounts for around 15% of total number of misclassification). Particularly, the letter 'T' is misclassified as 'H', 'X', 'L', and 'Y' according to the table showing the count and the proportion of misclassification for each combination of True labels and Predicted labels above. The second most common letter which are misclassified is the letter 'H' with about 11% of total number of misclassification. This letter 'H' is more misclassified as 'G' and 'N'. The third most misclassified letter is the letter 'O' with about 10.8% of total number of misclassification, and this letter is more likely to be predicted as 'N' and 'F'.

Although the accuracy of this final Convolutional Neural Network (CNN) model is high, this accuracy score does not meet the required accuracy score of 96% since its accuracy score is only about 90.4%. Therefore, for further improvement, the number of hidden layers and the size of these hidden layers should be tuned to examine if they can improve the performance of this model, since there are only three hyperparameters that are currently tuned for this CNN model (the activation function, the optimizer and its learning rate). In addition, some other methods such as Batch Normalization and Residual Unit should be considered, since Residual Unit can mitigate overfitting problem, which means that it can reduce the gap between training accuracy and validation accuracy of this model. Last, the training dataset and the testing dataset may not comprehensive since the letter 'J' and 'Z' do not appear in these datasets, which can lead to some misclassifications and a decrease in the overall accuracy of the model.

In []: