Created by: Shubhnoor Gill 18BCS6061 B.E. CSE(AIML)-1 **Group-B Comparison of Activation Functions using MNIST Dataset** For this purpose, a simple ANN model was used for the MNIST dataset. Rectified Linear Unit(ReLU) Function Sigmoid Function Hyperbolic Tangent Function Swish Function Scaled Exponential Linear Unit (SELU) Function The loss, validation, training accuracy for the different activation function with the respective plots is shown in this notebook. In [1]: # Importing the required libraries import numpy as np import pandas as pd import matplotlib.pyplot as plt from keras.datasets import mnist from keras.utils import plot model from sklearn.model_selection import train test split from keras.utils import np utils # used for categorisation from keras.models import Sequential from keras.layers import Dense from keras.optimizers import Adam Using TensorFlow backend. In [2]: # Unpacking dataset into train and test (X_train, y_train), (X_test, y_test) = mnist.load_data() In [3]: X_train.shape Out[3]: (60000, 28, 28) In [4]: # Data Pre-processing n = X_train.shape[1] * X_train.shape[2] # flatten this array into a vector of 28×28=784 X_train = X_train.reshape(X_train.shape[0], n).astype('float32') #type to cast one or more of the DataF rame's columns to column-specific types. X_test = X_test.reshape(X_test.shape[0], n).astype('float32') X_train = X_train / 255 # convert into fully black and fully white X test = X test / 255y_train = np_utils.to_categorical(y_train) # digits are 0-9, so we have 10 classes, one hot encoding y_test = np_utils.to_categorical(y_test) #Converts a class vector (integers) to binary class matrix. num_classes = y_test.shape[1] In [5]: X_train.shape Out[5]: (60000, 784) In [6]: X_test.shape Out[6]: (10000, 784) Rectified Linear Unit (ReLU) Activation Function In [7]: RELU_model = Sequential() RELU_model.add(Dense(500, input_dim=n, activation='relu')) RELU_model.add(Dense(100, activation='relu')) RELU model.add(Dense(num classes, activation='softmax')) # Compile model RELU_model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy']) RELU model.summary() Model: "sequential_1" Layer (type) Output Shape Param # dense_1 (Dense) (None, 500) 392500 dense_2 (Dense) (None, 100) 50100 (None, 10) dense_3 (Dense) 1010 Total params: 443,610 Trainable params: 443,610 Non-trainable params: 0 **Result of Train and Test** In [8]: hist_relu=RELU_model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=10, batch_size=200) scores_relu = RELU_model.evaluate(X_test, y_test) print('Test loss:', scores_relu[0]) print('Test accuracy:', scores_relu[1]) Train on 60000 samples, validate on 10000 samples Epoch 1/10 oss: 0.1248 - val_accuracy: 0.9632 Epoch 2/10 oss: 0.0997 - val accuracy: 0.9685 Epoch 3/10 oss: 0.0719 - val accuracy: 0.9765 Epoch 4/10 oss: 0.0623 - val_accuracy: 0.9797 Epoch 5/10 oss: 0.0613 - val accuracy: 0.9811 Epoch 6/10 oss: 0.0711 - val accuracy: 0.9786 Epoch 7/10 oss: 0.0657 - val accuracy: 0.9817 oss: 0.0679 - val accuracy: 0.9798 Epoch 9/10 oss: 0.0720 - val accuracy: 0.9805 Epoch 10/10 oss: 0.0692 - val accuracy: 0.9792 10000/10000 [==============] - 1s 84us/step Test loss: 0.06924099981761683 Test accuracy: 0.979200005531311 Sigmoid Activation Function In [9]: SIG model = Sequential() SIG model.add(Dense(500, input dim=n, activation='sigmoid')) SIG model.add(Dense(100, activation='sigmoid')) SIG model.add(Dense(num classes, activation='softmax')) # Compile model SIG model.compile(loss='categorical crossentropy', optimizer='adam', metrics=['accuracy']) SIG model.summary() Model: "sequential 2" Layer (type) Output Shape Param # ______ (None, 500) dense 4 (Dense) 392500 dense 5 (Dense) (None, 100) 1010 dense 6 (Dense) (None, 10) ______ Total params: 443,610 Trainable params: 443,610 Non-trainable params: 0 **Result of Train and Test** In [10]: hist sig=SIG model.fit(X train, y train, validation data=(X test, y test), epochs=10, batch size=200) scores sig = SIG model.evaluate(X test, y test) print('Test loss:', scores_sig[0]) print('Test accuracy:', scores_sig[1]) Train on 60000 samples, validate on 10000 samples Epoch 1/10 oss: 0.3013 - val accuracy: 0.9162 Epoch 2/10 oss: 0.2189 - val accuracy: 0.9362 Epoch 3/10 oss: 0.1752 - val_accuracy: 0.9481 Epoch 4/10 oss: 0.1463 - val_accuracy: 0.9555 Epoch 5/10 oss: 0.1267 - val_accuracy: 0.9619 Epoch 6/10 oss: 0.1075 - val_accuracy: 0.9669 Epoch 7/10 oss: 0.0945 - val_accuracy: 0.9704 Epoch 8/10 oss: 0.0905 - val_accuracy: 0.9727 Epoch 9/10 oss: 0.0805 - val_accuracy: 0.9735 Epoch 10/10 oss: 0.0764 - val_accuracy: 0.9764 10000/10000 [===============] - 1s 77us/step Test loss: 0.07643256488069892 Test accuracy: 0.9764000177383423 **Hyperbolic Tangent Activation Function** In [11]: HTan_model = Sequential() HTan_model.add(Dense(500, input_dim=n, activation='tanh')) HTan_model.add(Dense(100, activation='tanh')) HTan model.add(Dense(num classes, activation='softmax')) # Compile model HTan model.compile(loss='categorical crossentropy', optimizer='adam', metrics=['accuracy']) HTan model.summary() Model: "sequential_3" Output Shape Layer (type) Param # ______ dense_7 (Dense) (None, 500) 392500 (None, 100) 50100 dense_8 (Dense) dense_9 (Dense) (None, 10) 1010 Total params: 443,610 Trainable params: 443,610 Non-trainable params: 0 **Result of Train and Test** In [12]: hist htan=HTan model.fit(X train, y train, validation data=(X test, y test), epochs=10, batch size=200) scores htan =HTan model.evaluate(X test, y test) print('Test loss:', scores_htan[0]) print('Test accuracy:', scores_htan[1]) Train on 60000 samples, validate on 10000 samples Epoch 1/10 oss: 0.1729 - val_accuracy: 0.9491 Epoch 2/10 oss: 0.1285 - val_accuracy: 0.9631 Epoch 3/10 oss: 0.1025 - val_accuracy: 0.9705 Epoch 4/10 oss: 0.0925 - val accuracy: 0.9730 Epoch 5/10 oss: 0.0827 - val_accuracy: 0.9749 Epoch 6/10 oss: 0.0696 - val accuracy: 0.9777 Epoch 7/10 oss: 0.0783 - val accuracy: 0.9760 Epoch 8/10 oss: 0.0748 - val_accuracy: 0.9777 Epoch 9/10 oss: 0.0685 - val accuracy: 0.9792 Epoch 10/10 oss: 0.0713 - val accuracy: 0.9792 10000/10000 [=============] - 1s 77us/step Test loss: 0.07125129706889857 Test accuracy: 0.979200005531311 Swish Activation Function In [13]: **def** swish(x): return x * keras.backend.sigmoid(x) SWISH model = Sequential() In [14]: SWISH model.add(Dense(500, input dim=n, activation=swish)) SWISH model.add(Dense(100, activation=swish)) SWISH model.add(Dense(num classes, activation='softmax')) # Compile model SWISH model.compile(loss='categorical crossentropy', optimizer='adam', metrics=['accuracy']) SWISH model.summary() Model: "sequential 4" Layer (type) Output Shape Param # ______ 392500 dense 10 (Dense) (None, 500) 50100 dense_11 (Dense) (None, 100) dense 12 (Dense) (None, 10) Total params: 443,610 Trainable params: 443,610 Non-trainable params: 0 **Result of Train and Test** In [15]: hist_swish=SWISH_model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=10, batch_size=20 scores swish =SWISH model.evaluate(X test, y test) print('Test loss:', scores swish[0]) print('Test accuracy:', scores_swish[1]) Train on 60000 samples, validate on 10000 samples Epoch 1/10 oss: 0.1398 - val accuracy: 0.9584 Epoch 2/10 60000/60000 [======= ==========] - 2s 29us/step - loss: 0.1199 - accuracy: 0.9638 - val_l oss: 0.1013 - val accuracy: 0.9681 Epoch 3/10 oss: 0.0775 - val accuracy: 0.9752 Epoch 4/10 oss: 0.0686 - val accuracy: 0.9780 Epoch 5/10 oss: 0.0629 - val_accuracy: 0.9789 Epoch 6/10 oss: 0.0578 - val_accuracy: 0.9824 Epoch 7/10 oss: 0.0592 - val_accuracy: 0.9816 Epoch 8/10 oss: 0.0635 - val_accuracy: 0.9813 Epoch 9/10 oss: 0.0614 - val_accuracy: 0.9825 Epoch 10/10 oss: 0.0654 - val_accuracy: 0.9811 10000/10000 [=============] - 1s 120us/step Test loss: 0.06543042148059466 Test accuracy: 0.9811000227928162 Scaled Exponential Linear Unit (SELU) Activation Function In [16]: SELU model = Sequential() SELU_model.add(Dense(500, input_dim=n, activation='selu')) SELU model.add(Dense(100, activation='selu')) SELU_model.add(Dense(num_classes, activation='softmax')) # Compile model SELU_model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy']) SELU model.summary() Model: "sequential_5" Layer (type) Output Shape Param # ______ dense_13 (Dense) (None, 500) 392500 (None, 100) dense 14 (Dense) 50100 1010 dense 15 (Dense) (None, 10) ______ Total params: 443,610 Trainable params: 443,610 Non-trainable params: 0 **Result of Train and Test** In [17]: hist_selu=SELU_model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=10, batch_size=200) scores selu =SELU model.evaluate(X test, y test) print('Test loss:', scores_selu[0]) print('Test accuracy:', scores_selu[1]) Train on 60000 samples, validate on 10000 samples Epoch 1/10 oss: 0.1997 - val_accuracy: 0.9390 Epoch 2/10 oss: 0.1314 - val_accuracy: 0.9586 Epoch 3/10 oss: 0.1071 - val_accuracy: 0.9667 Epoch 4/10 oss: 0.1000 - val_accuracy: 0.9688 Epoch 5/10 oss: 0.0986 - val_accuracy: 0.9703 oss: 0.0893 - val accuracy: 0.9736 Epoch 7/10 oss: 0.0862 - val_accuracy: 0.9739 Epoch 8/10 oss: 0.0783 - val_accuracy: 0.9775 Epoch 9/10 oss: 0.0914 - val_accuracy: 0.9755 Epoch 10/10 oss: 0.0961 - val accuracy: 0.9728 10000/10000 [===============] - 1s 83us/step Test loss: 0.09614768207155866 Test accuracy: 0.9728000164031982 **Comparision of all 5 Activation Functions** test_loss=[scores_relu[0], scores_sig[0], scores_htan[0], scores_swish[0], scores_selu[0]] In [18]: test_acc=[scores_relu[1], scores_sig[1], scores_htan[1], scores_swish[1], scores_selu[1]] df scores=pd.DataFrame({'Test Loss':test loss,'Test Accuracy':test acc},index=['RELU','Sigmoid','TanH', 'Swish', 'SELU']) df_scores Out[18]: **Test Loss Test Accuracy** RELU 0.069241 0.9792 0.076433 Sigmoid 0.9764 TanH 0.071251 0.9792 0.065430 0.9811 Swish SELU 0.096148 0.9728 hists = [hist_htan, hist_sig, hist_relu, hist_swish, hist_selu] In [19]: def plot history(hists, attribute, axis=(-1,10,0.85,0.94), loc='lower right'): In [20]: title={'val_loss': 'Validation loss', 'loss': 'Training loss', 'val_accuracy': 'Validation accurac y', 'accuracy': 'Training accuracy'} num_hists=len(hists) plt.figure(figsize=(12, 8)) plt.axis(axis) for i in range(num hists): plt.plot(hists[i].history[attribute]) plt.title(title[attribute], fontsize=25) plt.ylabel(title[attribute]) plt.xlabel('Epochs') plt.legend(['TanH', 'Sigmoid', 'ReLU', 'Swish', 'SELU'], loc=loc) In [21]: plot_history(hists, attribute='val_accuracy',axis=(-1,10,0.91,0.99), loc='lower right') Validation accuracy 0.99 0.98 0.97 0.96 Validation accuracy 0.95 0.93 TanH Sigmoid 0.92 ReLU Swish SELU 0.91 ź Epochs plot history (hists, attribute='accuracy', axis=(-1,10,0.825,1), loc='lower right') Training accuracy 1.00 0.98 0.96 0.94 **Fraining accuracy** 0.92 0.90 0.88 0.86 TanH Sigmoid ReLU 0.84 Swish SELU Epochs plot_history(hists, attribute='val_loss', axis=(-1,10,0.05,0.30), loc='upper right') Validation loss TanH Sigmoid ReLU Swish SELU 0.25 0.20 Validation loss 0.15 0.10 0.05 Ġ Epochs plot_history(hists, attribute='loss', axis=(-1,10,0.000,0.4), loc='upper right') In [24]: Training loss 0.40 TanH Sigmoid ReLU 0.35 Swish SELU 0.30 0.25 0.20 0.15 0.10 0.05 0.00 ź ò 8 Epochs **Thank You**