Neural Networks - Image Recognition

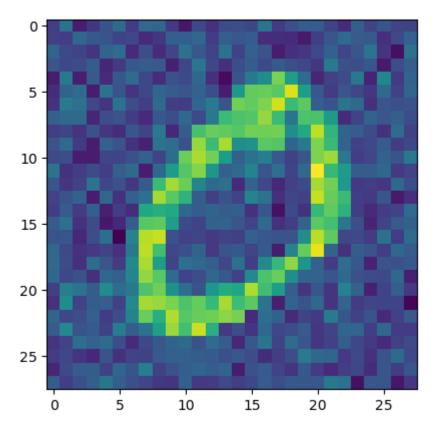
```
In [1]: import keras
         from keras.datasets import mnist
         from keras.models import Sequential
         from keras.optimizers import RMSprop
         from keras.layers import Dense, Dropout, Flatten
         from keras.layers import Conv2D, MaxPooling2D
         from keras import backend
        import matplotlib.pyplot as plt
In [2]:
         %matplotlib inline
In [3]: # the data, shuffled and split between train and test sets
         (x_train, y_train), (x_test, y_test) = mnist.load_data()
         x train = x train.reshape(60000, 784)
         x_{\text{test}} = x_{\text{test.reshape}}(10000, 784)
         x_train = x_train.astype('float32')
         x_test = x_test.astype('float32')
         x train /= 255
         x test /= 255
         print(x_train.shape[0], 'train samples')
         print(x_test.shape[0], 'test samples')
        60000 train samples
        10000 test samples
```

1. Add random noise (see below on size parameter on np.random.normal) to the images in training and testing. Make sure each image gets a different noise feature added to it. Inspect by printing out several images. Note - the size parameter should match the data.

```
In [4]: # Noise is added here
        # Generate random noise with the same shape as the image
        import numpy as np
        mean = .5
        stddev = .16
        noise = np.random.normal(mean, stddev, x train[1].shape)
        # Add the noise to the image
        image noise added = x train[1] + noise
        image_noise_added
        # The max value of the noise should not grossly surpass 1.0
        max(noise)
        1.000400027849817
Out[4]:
        # Max of noise is less than .1002; very slightly over 1
```

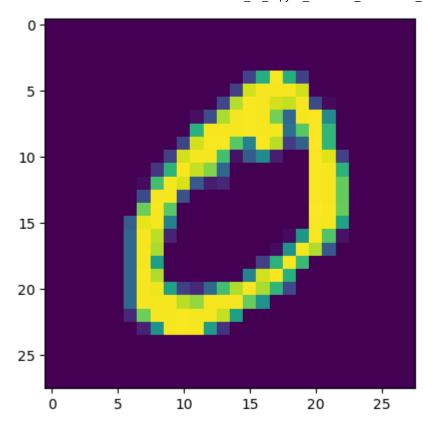
```
In [6]:
        # New Image vs Old
        # New Image with noise added
        plt.imshow(image_noise_added.reshape(28, 28))
```

<matplotlib.image.AxesImage at 0x267d288a9e0> Out[6]:



```
In [7]:
        # Old Image without noise added
        plt.imshow(x_train[1].reshape(28, 28))
```

<matplotlib.image.AxesImage at 0x2678d3ebbe0> Out[7]:



```
# Normalization
In [8]:
        mean = np.mean(x_train)
         std = np.std(x_train)
         x_train_norm = (x_train - mean) / std
         mean = np.mean(x_test)
         std = np.std(x_test)
         x_{test_norm} = (x_{test} - mean) / std
```

```
### Add noise to whole set of images
In [9]:
        # Noise is added here
        # Generate random noise with the same shape as the image
        import numpy as np
        mean = .0
        stddev = 2.0
        # noise = np.random.normal(mean, stddev, x_train.shape)
        # Generate random noise with the same shape as the image
        # test_noise = np.random.normal(mean, stddev, x_test.shape)
        x_train_noise = np.random.normal(mean, stddev, x_train.shape)
        x_test_noise = np.random.normal(mean, stddev, x_test.shape)
        # Add noise
        x_train_noise_added = x_train_norm + x_train_noise
        x_test_noise_added = x_test_norm + x_test_noise
        # y_train_noise = y_train + y_train_noise
        # y_test_noise = y_test + y_test_noise
        # Add noise
        x_test_noise[1]
```

```
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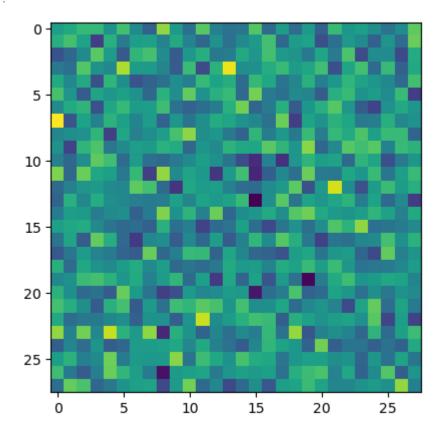
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-4.97271464e+00, -3.67050280e-01, -1.34134816e+00, 9.59558649e-01,
-6.12018273e-01, -4.80938489e-01, -3.57087546e+00, -2.76209600e+00,
5.02872179e-02,
                 1.13830270e-01, -2.61090499e+00, 3.23256000e+00,
4.03603298e+00, -1.94963850e+00, 2.70997673e+00, -2.95580273e-01,
8.77840966e-01, 1.78284126e+00, -4.16936090e+00, -1.87141672e+00,
-1.24722444e+00, 2.07211240e+00, -4.44212381e+00, 1.40826211e+00,
-2.17718867e+00, -3.46292437e-02, 1.45459799e+00, -1.10595510e+00,
-1.21584142e+00, -5.77601508e-01, -1.15135249e+00, -3.70065738e-01,
7.40347092e-01, 3.35329450e+00, -4.87795480e-01, 8.00202268e-01,
-2.31027615e+00,
                 4.34550368e+00, 3.69414086e+00, 3.89241130e+00,
-2.68274851e+00, 4.37192470e+00, 1.76901968e+00, 2.28860584e+00,
-3.42288779e+00, 7.87254274e-01, 6.50906456e-01,
                                                   5.15458210e-01,
                 1.42229094e-02, 1.18868263e+00, 6.35880274e-01,
-4.08233522e-01,
-1.69164097e+00, -5.26696606e-01, 1.79027910e+00, 1.51925002e+00,
-1.37507793e+00, 3.00375281e+00, 5.73601186e-01, -3.40245156e+00,
                 1.20551566e+00, -1.63067972e+00, 4.14710747e-01,
-1.44041484e+00,
-5.94337788e-01, 1.24214939e+00, -1.47142467e+00, -4.79015548e-01,
-8.49983629e-01, -1.69511851e+00, -9.44350614e-01, 7.81777747e-01,
-6.47976679e-01, -4.94554077e+00, 1.25869319e+00, -2.57331946e+00,
```

```
2.91115501e+00, 1.53627230e+00, 7.95663228e-01, -6.49879035e-01,
                 5.78016164e-01, -9.35640854e-01, 7.06282749e-01,
2.47322911e+00,
7.59100656e-01, -2.08039361e+00, 1.07705670e+00, -3.15859978e+00,
2.36673955e+00, 2.13134044e+00, 8.01320448e-01, -4.11869548e-01,
-4.29252739e-01, 3.79287819e+00, 2.68601173e+00, -1.71729191e-02,
8.74836584e-01, -6.90105117e-01, -3.73782991e-01, 1.15029076e-01,
1.76076156e+00, -2.40512317e+00, -8.91663751e-01, -3.88712580e+00,
2.61109615e+00, -1.71419144e+00, -1.52867955e+00, -3.06506129e+00,
-2.01102502e-01, 5.61763729e-01, 5.06148012e+00, -2.49460669e+00,
-6.48952380e-01, -6.14372085e-01, -9.96071107e-01, -3.32742161e+00,
2.72131263e+00, -3.97473527e+00, -6.32709553e-01, -7.73707871e-01,
-7.54186900e-01, 3.48942809e-01, -2.48242842e-01, -1.83642218e-01,
3.82953379e-01, -2.66003652e+00, 4.49717641e-01, 3.07856272e-01,
2.36621262e+00, -3.23380139e-01, 5.83108060e-01, 2.95828334e+00,
-2.82613732e+00, -1.03981455e+00, -3.36464120e-01, 1.84188986e+00,
6.90461758e-01, -2.19475851e+00, 8.27730946e-01, -6.12220266e-01])
```

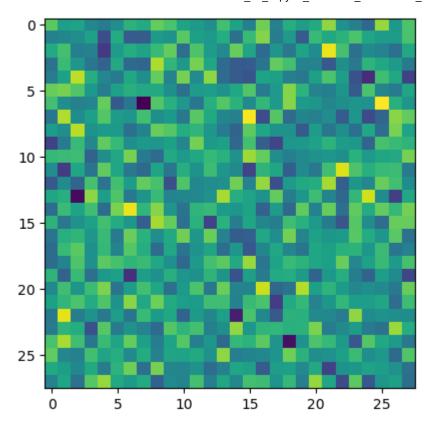
```
# Compare Noises to Ensure they are Different
In [10]:
         # Noise on Image 122
         plt.imshow(x train noise[122].reshape(28, 28))
```

<matplotlib.image.AxesImage at 0x2678d459b10> Out[10]:



```
In [11]:
         # Noise on Image 124
         plt.imshow(x train noise[124].reshape(28, 28))
```

<matplotlib.image.AxesImage at 0x2678d4de380> Out[11]:



As the two visual representations (images) of the noise show different patterns, they are indicating different noise levels for each image

1. Compare the accuracy of train and val after N epochs for MLNN with and without noise.

```
In [12]:
         %%capture
         ## Code From Base for Creating Neural Network Without Noise
         def neural_network(batch_size, num_classes, epochs, x_train, x_test, y_train, y_test)
             # convert class vectors to binary class matrices
             y_train = keras.utils.to_categorical(y_train, num_classes)
             y_test = keras.utils.to_categorical(y_test, num_classes)
             model = Sequential()
             model.add(Dense(512, activation='relu', input_shape=(784,)))
             model.add(Dropout(0.2))
             model.add(Dense(512, activation='relu'))
             model.add(Dropout(0.2))
             model.add(Dense(10, activation='softmax'))
             model.summary()
             model.compile(loss='categorical_crossentropy',
                            optimizer="adam",
                            metrics=['accuracy'])
             history = model.fit(x_train, y_train,
                                  batch_size=batch_size,
                                  epochs=epochs,
                                  verbose=1,
                                  validation_data=(x_test, y_test))
```

```
score = model.evaluate(x_test, y_test, verbose=0)
             print('Test loss:', score[0])
             print('Test accuracy:', score[1])
             return score
In [13]: import pandas as pd
         np.max(x_train_noise),
         np.min(x_train_noise),
         np.max(x_train),
         np.min(x_train)
         )
         (10.62403342399543, -11.502094450839351, 1.0, 0.0)
Out[13]:
In [14]: batch_size = 128
         num_classes = 10
         epochs = 20
         # NN With Noise
         neural_network(batch_size, num_classes, epochs, x_train_noise_added, x_test_noise_added
         # NN Without Noise
         neural_network(batch_size, num_classes, epochs, x_train, x_test, y_train, y_test)
```

Param #

Output Shape

Model: "sequential"

Layer (type)

```
______
            (None, 512)
dense (Dense)
                        401920
dropout (Dropout)
            (None, 512)
dense_1 (Dense)
            (None, 512)
                        262656
            (None, 512)
dropout 1 (Dropout)
dense 2 (Dense)
            (None, 10)
                        5130
______
Total params: 669706 (2.55 MB)
Trainable params: 669706 (2.55 MB)
Non-trainable params: 0 (0.00 Byte)
Epoch 1/20
7568 - val_loss: 0.4324 - val_accuracy: 0.8569
Epoch 2/20
8888 - val loss: 0.3739 - val accuracy: 0.8772
Epoch 3/20
9293 - val loss: 0.3616 - val accuracy: 0.8841
Epoch 4/20
9553 - val loss: 0.4020 - val accuracy: 0.8861
Epoch 5/20
9639 - val loss: 0.4299 - val accuracy: 0.8849
Epoch 6/20
9722 - val_loss: 0.4744 - val_accuracy: 0.8830
Epoch 7/20
9737 - val loss: 0.4915 - val accuracy: 0.8847
9769 - val loss: 0.5140 - val accuracy: 0.8910
Epoch 9/20
9788 - val loss: 0.5464 - val accuracy: 0.8889
Epoch 10/20
9808 - val loss: 0.5866 - val accuracy: 0.8845
Epoch 11/20
9815 - val loss: 0.6281 - val accuracy: 0.8823
Epoch 12/20
9828 - val_loss: 0.6033 - val_accuracy: 0.8864
Epoch 13/20
9832 - val loss: 0.6275 - val accuracy: 0.8866
Epoch 14/20
```

```
9829 - val loss: 0.6465 - val accuracy: 0.8913
Epoch 15/20
9847 - val loss: 0.6660 - val accuracy: 0.8896
Epoch 16/20
9853 - val loss: 0.6574 - val accuracy: 0.8917
Epoch 17/20
9847 - val loss: 0.6506 - val accuracy: 0.8936
Epoch 18/20
9863 - val_loss: 0.6902 - val_accuracy: 0.8907
Epoch 19/20
9879 - val loss: 0.7065 - val accuracy: 0.8918
Epoch 20/20
9871 - val loss: 0.7421 - val accuracy: 0.8897
Test loss: 0.7421275973320007
Test accuracy: 0.8896999955177307
Model: "sequential_1"
```

Layer (type)	Output	Shape	Param #
dense_3 (Dense)	(None,	512)	401920
dropout_2 (Dropout)	(None,	512)	0
dense_4 (Dense)	(None,	512)	262656
dropout_3 (Dropout)	(None,	512)	0
dense_5 (Dense)	(None,	10)	5130

Total params: 669706 (2.55 MB) Trainable params: 669706 (2.55 MB) Non-trainable params: 0 (0.00 Byte)

```
Epoch 1/20
9263 - val loss: 0.1069 - val accuracy: 0.9669
Epoch 2/20
9685 - val loss: 0.0781 - val accuracy: 0.9759
Epoch 3/20
9785 - val loss: 0.0716 - val accuracy: 0.9782
Epoch 4/20
9821 - val loss: 0.0731 - val accuracy: 0.9780
Epoch 5/20
9857 - val_loss: 0.0613 - val_accuracy: 0.9818
Epoch 6/20
9871 - val loss: 0.0709 - val accuracy: 0.9794
Epoch 7/20
```

```
9883 - val loss: 0.0731 - val accuracy: 0.9790
    Epoch 8/20
    9903 - val_loss: 0.0612 - val_accuracy: 0.9831
    Epoch 9/20
    9913 - val loss: 0.0659 - val accuracy: 0.9820
    Epoch 10/20
    9912 - val loss: 0.0771 - val accuracy: 0.9797
    Epoch 11/20
    9920 - val_loss: 0.0812 - val_accuracy: 0.9815
    Epoch 12/20
    9928 - val loss: 0.0775 - val accuracy: 0.9828
    Epoch 13/20
    9926 - val loss: 0.0726 - val accuracy: 0.9820
    Epoch 14/20
    9934 - val_loss: 0.0784 - val_accuracy: 0.9811
    Epoch 15/20
    9932 - val loss: 0.0831 - val accuracy: 0.9820
    Epoch 16/20
    9931 - val loss: 0.0812 - val accuracy: 0.9817
    Epoch 17/20
    9952 - val_loss: 0.0703 - val_accuracy: 0.9838
    Epoch 18/20
    9947 - val loss: 0.0785 - val accuracy: 0.9838
    Epoch 19/20
    9944 - val_loss: 0.0825 - val_accuracy: 0.9833
    Epoch 20/20
    9949 - val_loss: 0.0730 - val_accuracy: 0.9852
    Test loss: 0.0729510709643364
    Test accuracy: 0.9851999878883362
    [0.0729510709643364, 0.9851999878883362]
Out[14]:
```

Looking at the above two models generated by neural nets, we see that the model with noise reached a final accuracy of .889, while the one without noise reached a final accuracy of .985. All other elements of the model, besides noise, are held constant (the function defines the same number of layers, and batch size/number of classes/epochs are also constant.) Therefore, we see a noticeable dropoff in accuracy as a result of adding noise to the dataset.

1. Vary the amount of noise by changing the scale parameter in np.random.normal by a factor. Use .1, .5, 1.0, 2.0, 4.0 for the scale and keep track of the accuracy for training and validation and plot these results.

```
In [15]: def neural_network_with_noise(mean, stddev, batch_size, num_classes, epochs, x_train,
             # noise = np.random.normal(mean, stddev, x train.shape)
             # Generate random noise with the same shape as the image
             # test noise = np.random.normal(mean, stddev, x test.shape)
             x_train_noise = np.random.normal(mean, stddev, x_train.shape)
             x test noise = np.random.normal(mean, stddev, x test.shape)
             # Add noise
             x_train_noise_added = x_train_norm + x_train_noise
             x_test_noise_added = x_test_norm + x_test_noise
             score = neural_network(batch_size, num_classes, epochs, x_train_noise_added, x_tes
             # Append Loss & Accuracy To List
             test loss = score[0]
             test_accuracy = score[1]
             loss values.append(test loss)
             accuracy values.append(test accuracy)
```

```
In [16]: # %%capture
         ## Combining Noise Code with Model-Running code for a single, repeatable block:
         # Listing Scale (i.e. Standard Deviation) Values over which to train models
          stddev values = [0.1, 0.5, 1.0, 2.0, 4.0] # Values given
          # Initializing Lists
         loss_values = []
          accuracy values = []
          batch size = 128
          num classes = 10
         epochs = 20
         mean = 0
         # Loop:
         for stddev in stddev values:
             neural_network_with_noise(mean, stddev, batch_size, num_classes, epochs, x_train,
```

Param #

Output Shape

Model: "sequential 2"

Layer (type)

```
______
            (None, 512)
dense 6 (Dense)
                        401920
dropout 4 (Dropout)
            (None, 512)
dense_7 (Dense)
            (None, 512)
                        262656
            (None, 512)
dropout 5 (Dropout)
dense 8 (Dense)
            (None, 10)
                        5130
______
Total params: 669706 (2.55 MB)
Trainable params: 669706 (2.55 MB)
Non-trainable params: 0 (0.00 Byte)
Epoch 1/20
9262 - val_loss: 0.1186 - val_accuracy: 0.9622
Epoch 2/20
9660 - val loss: 0.0886 - val accuracy: 0.9717
Epoch 3/20
9749 - val loss: 0.0802 - val accuracy: 0.9761
Epoch 4/20
9798 - val loss: 0.0711 - val accuracy: 0.9793
Epoch 5/20
9818 - val loss: 0.0683 - val accuracy: 0.9799
Epoch 6/20
9852 - val loss: 0.0767 - val accuracy: 0.9780
Epoch 7/20
9858 - val loss: 0.0727 - val accuracy: 0.9780
9874 - val loss: 0.0802 - val accuracy: 0.9794
Epoch 9/20
9872 - val loss: 0.0801 - val accuracy: 0.9790
Epoch 10/20
9879 - val loss: 0.0717 - val accuracy: 0.9814
Epoch 11/20
9896 - val loss: 0.0704 - val accuracy: 0.9818
Epoch 12/20
9905 - val_loss: 0.0825 - val_accuracy: 0.9791
Epoch 13/20
9902 - val loss: 0.0913 - val accuracy: 0.9803
Epoch 14/20
```

```
9904 - val loss: 0.0758 - val accuracy: 0.9824
Epoch 15/20
9911 - val loss: 0.0851 - val accuracy: 0.9829
Epoch 16/20
9920 - val loss: 0.0837 - val accuracy: 0.9819
Epoch 17/20
9924 - val loss: 0.0807 - val accuracy: 0.9819
Epoch 18/20
9923 - val_loss: 0.1018 - val_accuracy: 0.9799
Epoch 19/20
9926 - val loss: 0.0854 - val accuracy: 0.9834
Epoch 20/20
9940 - val loss: 0.0910 - val accuracy: 0.9823
Test loss: 0.09101765602827072
Test accuracy: 0.9822999835014343
Model: "sequential_3"
```

_				
	Layer (type)	Output	Shape	Param #
•	dense_9 (Dense)	(None,	512)	401920
	dropout_6 (Dropout)	(None,	512)	0
	dense_10 (Dense)	(None,	512)	262656
	dropout_7 (Dropout)	(None,	512)	0
	dense_11 (Dense)	(None,	10)	5130

Total params: 669706 (2.55 MB) Trainable params: 669706 (2.55 MB) Non-trainable params: 0 (0.00 Byte)

Epoch 1/20 9122 - val loss: 0.1246 - val accuracy: 0.9610 Epoch 2/20 9664 - val loss: 0.1049 - val accuracy: 0.9679 Epoch 3/20 9772 - val loss: 0.0926 - val accuracy: 0.9720 Epoch 4/20 9849 - val loss: 0.1047 - val accuracy: 0.9696 Epoch 5/20 9865 - val_loss: 0.1101 - val_accuracy: 0.9687 Epoch 6/20 9870 - val loss: 0.1136 - val accuracy: 0.9689 Epoch 7/20

```
9902 - val loss: 0.1009 - val accuracy: 0.9735
Epoch 8/20
9915 - val loss: 0.1080 - val accuracy: 0.9743
Epoch 9/20
9917 - val loss: 0.1426 - val accuracy: 0.9680
Epoch 10/20
9919 - val loss: 0.1264 - val accuracy: 0.9726
Epoch 11/20
9930 - val loss: 0.1437 - val accuracy: 0.9698
Epoch 12/20
9917 - val loss: 0.1331 - val accuracy: 0.9720
Epoch 13/20
9941 - val loss: 0.1346 - val accuracy: 0.9737
Epoch 14/20
9926 - val_loss: 0.1297 - val_accuracy: 0.9743
Epoch 15/20
9938 - val loss: 0.1399 - val accuracy: 0.9729
Epoch 16/20
9937 - val loss: 0.1222 - val accuracy: 0.9763
Epoch 17/20
469/469 [============== ] - 5s 10ms/step - loss: 0.0182 - accuracy: 0.
9948 - val loss: 0.1423 - val accuracy: 0.9749
Epoch 18/20
9940 - val loss: 0.1558 - val accuracy: 0.9738
Epoch 19/20
9956 - val_loss: 0.1599 - val_accuracy: 0.9743
Epoch 20/20
9950 - val loss: 0.1560 - val accuracy: 0.9754
Test loss: 0.15600836277008057
Test accuracy: 0.9753999710083008
Model: "sequential 4"
```

Layer (type)	Output Shape	 Param #
=======================================		
dense_12 (Dense)	(None, 512)	401920
dropout_8 (Dropout)	(None, 512)	0
dense_13 (Dense)	(None, 512)	262656
duanant O (Duanant)	(Name 512)	0
dropout_9 (Dropout)	(None, 512)	0
dense_14 (Dense)	(None, 10)	5130

Total params: 669706 (2.55 MB) Trainable params: 669706 (2.55 MB) Non-trainable params: 0 (0.00 Byte)

```
Epoch 1/20
8780 - val loss: 0.1948 - val accuracy: 0.9382
Epoch 2/20
9541 - val loss: 0.1660 - val accuracy: 0.9468
Epoch 3/20
9740 - val loss: 0.1656 - val accuracy: 0.9499
Epoch 4/20
9822 - val_loss: 0.1733 - val_accuracy: 0.9531
Epoch 5/20
9857 - val loss: 0.1802 - val accuracy: 0.9551
Epoch 6/20
9880 - val loss: 0.2054 - val accuracy: 0.9519
9878 - val_loss: 0.2002 - val_accuracy: 0.9522
Epoch 8/20
9898 - val loss: 0.2361 - val accuracy: 0.9533
Epoch 9/20
9897 - val loss: 0.2237 - val_accuracy: 0.9536
Epoch 10/20
9911 - val_loss: 0.2388 - val_accuracy: 0.9549
Epoch 11/20
9914 - val loss: 0.2580 - val accuracy: 0.9525
Epoch 12/20
9923 - val_loss: 0.2539 - val_accuracy: 0.9541
Epoch 13/20
9929 - val loss: 0.2700 - val accuracy: 0.9537
9926 - val loss: 0.2607 - val accuracy: 0.9555
Epoch 15/20
9924 - val loss: 0.2821 - val accuracy: 0.9547
Epoch 16/20
9932 - val loss: 0.2635 - val accuracy: 0.9561
Epoch 17/20
9945 - val loss: 0.2725 - val accuracy: 0.9557
Epoch 18/20
9930 - val_loss: 0.3139 - val_accuracy: 0.9499
Epoch 19/20
9939 - val loss: 0.2683 - val accuracy: 0.9569
Epoch 20/20
```

9943 - val_loss: 0.2939 - val_accuracy: 0.9562

Test loss: 0.29390591382980347 Test accuracy: 0.9562000036239624

Model: "sequential_5"

Layer (type)	Output Shape	Param #
dense_15 (Dense)	(None, 512)	401920
dropout_10 (Dropout)	(None, 512)	0
dense_16 (Dense)	(None, 512)	262656
dropout_11 (Dropout)	(None, 512)	0
dense_17 (Dense)	(None, 10)	5130

Total params: 669706 (2.55 MB) Trainable params: 669706 (2.55 MB) Non-trainable params: 0 (0.00 Byte)

Epoch 1/20 7565 - val loss: 0.4416 - val accuracy: 0.8556 Epoch 2/20 8869 - val loss: 0.3733 - val accuracy: 0.8791 Epoch 3/20 9302 - val_loss: 0.3729 - val_accuracy: 0.8886 Epoch 4/20 9537 - val loss: 0.3961 - val accuracy: 0.8871 Epoch 5/20 9656 - val loss: 0.4312 - val accuracy: 0.8845 Epoch 6/20 9715 - val loss: 0.4945 - val accuracy: 0.8839 9744 - val loss: 0.4691 - val accuracy: 0.8870 Epoch 8/20 9786 - val loss: 0.5123 - val accuracy: 0.8865 Epoch 9/20 9792 - val loss: 0.4948 - val accuracy: 0.8902 Epoch 10/20 9802 - val loss: 0.5283 - val accuracy: 0.8908 Epoch 11/20 9805 - val_loss: 0.5619 - val_accuracy: 0.8915 Epoch 12/20 9826 - val loss: 0.5962 - val accuracy: 0.8840 Epoch 13/20

```
9825 - val loss: 0.5892 - val accuracy: 0.8900
Epoch 14/20
9852 - val_loss: 0.5928 - val_accuracy: 0.8901
Epoch 15/20
9865 - val loss: 0.6508 - val accuracy: 0.8928
Epoch 16/20
9854 - val loss: 0.6707 - val accuracy: 0.8869
Epoch 17/20
9834 - val_loss: 0.6592 - val_accuracy: 0.8868
Epoch 18/20
9861 - val loss: 0.6673 - val accuracy: 0.8913
Epoch 19/20
9862 - val loss: 0.6828 - val accuracy: 0.8872
9874 - val loss: 0.6794 - val accuracy: 0.8881
Test loss: 0.6794248819351196
Test accuracy: 0.8881000280380249
Model: "sequential_6"
```

Layer (type)	Output	Shape	Param #
dense_18 (Dense)	(None,	512)	401920
dropout_12 (Dropout)	(None,	512)	0
dense_19 (Dense)	(None,	512)	262656
dropout_13 (Dropout)	(None,	512)	0
dense_20 (Dense)	(None,	10)	5130

Total params: 669706 (2.55 MB) Trainable params: 669706 (2.55 MB) Non-trainable params: 0 (0.00 Byte)

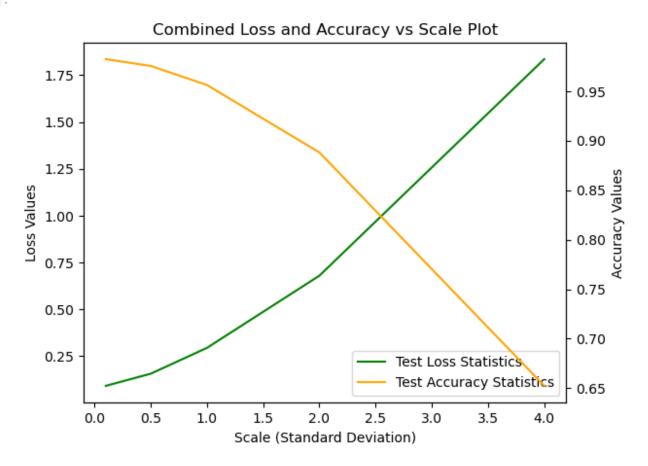
```
Epoch 1/20
4954 - val loss: 1.0872 - val accuracy: 0.6321
Epoch 2/20
6605 - val loss: 1.0231 - val accuracy: 0.6496
Epoch 3/20
7224 - val loss: 1.0059 - val accuracy: 0.6597
7731 - val_loss: 1.0209 - val_accuracy: 0.6565
Epoch 5/20
8143 - val loss: 1.0954 - val accuracy: 0.6571
Epoch 6/20
```

```
8466 - val loss: 1.1370 - val accuracy: 0.6536
    Epoch 7/20
    8707 - val_loss: 1.2539 - val_accuracy: 0.6518
    Epoch 8/20
    8855 - val loss: 1.2811 - val accuracy: 0.6530
    Epoch 9/20
    9006 - val loss: 1.3865 - val accuracy: 0.6484
    Epoch 10/20
    9101 - val_loss: 1.4220 - val_accuracy: 0.6516
    Epoch 11/20
    9180 - val loss: 1.4670 - val accuracy: 0.6514
    Epoch 12/20
    9252 - val loss: 1.5364 - val accuracy: 0.6553
    9280 - val_loss: 1.5795 - val_accuracy: 0.6548
    Epoch 14/20
    9316 - val loss: 1.6368 - val accuracy: 0.6538
    Epoch 15/20
    9366 - val loss: 1.6660 - val accuracy: 0.6554
    Epoch 16/20
    9379 - val_loss: 1.7188 - val_accuracy: 0.6529
    Epoch 17/20
    9413 - val loss: 1.7691 - val accuracy: 0.6571
    Epoch 18/20
    9427 - val loss: 1.8267 - val accuracy: 0.6528
    Epoch 19/20
    9452 - val loss: 1.7963 - val accuracy: 0.6553
    9477 - val loss: 1.8360 - val accuracy: 0.6524
    Test loss: 1.8360189199447632
    Test accuracy: 0.652400016784668
In [17]: accuracy values
    [0.9822999835014343,
Out[17]:
     0.9753999710083008,
     0.9562000036239624,
     0.8881000280380249,
     0.652400016784668]
    # Compile Loss and Accuracy statistics for the models into a single data frame
In [18]:
     accuracy loss results dataframe = pd.DataFrame({'stddev values': stddev values, 'loss'
     accuracy_loss_results_dataframe
```

Out[18]:		stddev_values	loss_values	accuracy_values
	0	0.1	0.091018	0.9823
	1	0.5	0.156008	0.9754
	2	1.0	0.293906	0.9562
	3	2.0	0.679425	0.8881
	4	4.0	1.836019	0.6524

```
In [19]: # Plotting Results
         fig, ax1 = plt.subplots()
         loss_line = ax1.plot(stddev_values, loss_values, color = 'green', label = 'Test Loss S
         # Loss line Plot
         ax1.set_xlabel('Scale (Standard Deviation)')
          ax1.set ylabel('Loss Values')
          ax1.set_title('Combined Loss and Accuracy vs Scale Plot')
         # Accuracy line Plot
         ax2 = ax1.twinx()
         accuracy_line = ax2.plot(stddev_values, accuracy_values, color='orange', label='Test /
          ax2.set_ylabel('Accuracy Values')
         # Combine Both Lines Into One Plot
         lines = loss_line + accuracy_line
          labels = [l.get_label() for l in lines]
          ax1.legend(lines, labels, loc='lower right')
```

<matplotlib.legend.Legend at 0x2678d4c6950> Out[19]:



The plot shows an inverse relationship between the scale of the noise and the accuracy of the model; in other words, noise makes the models less predictive.