MNIST Case Study

Name: Youseef Osama Ahmed ID:20190629 Name: Mohammad Alameen Abdilaziz ID:20190720

In this <u>Notebook</u>, we loaded the popular MNIST dataset and tried different techniques, architectures, activation functions ...etc, to find the best model to capture the complexity of the problem.

Optimizers:

```
opt = SGD(learning_rate=0.0001, momentum=0.9)
opt1 = SGD(learning_rate=0.05, momentum=0.9)
opt2 = SGD(learning_rate=0.001, momentum=0.9)
opt3 = SGD(learning_rate=0.01, momentum=0.9)
opt4 = Adam(learning_rate=0.01, beta_1=0.9, beta_2=0.999)
opt5 = RMSprop(learning_rate=0.01, rho=0.9, momentum=0.1)
```

Trying different numbers of epochs

Model 1:

Final accuracy: 0.9217, 0.9180

Epoch 1/10
1594/[594 [==============================] - 10s 5ms/step - loss: 2.1314 - accuracy: 0.4138 - val_loss: 1.8247 - val_accuracy: 0.6716
Epoch 2/10
1594/1594 [====================================
Epoch 3/10
1594/1594 [====================================
Epoch 4/10
1594/1594 [====================================
Epoch 5/10
1594/1594 [====================================

Number of parameters: 149834 Aeravge epoch time: 9s ~ 10s

Model architecture:

Conv2D: 64 each(5, 5), strides=(2,2), activation=relu

MaxPooling2D: pool size(2, 2), strides(2, 2)

Dense: 64, activation='relu'
Dense: 10, activation='softmax'

Optimizer: SGD, Ir 0.0001, momentum 0.9, epochs 10, batch size 32

Model 2:

final accuracy: 0.9325, 0.9370

Number of parameters: 149834 Average epoch time: 9s ~ 10s

Model architecture: Same as Model 1

Optimizers: #epochs: 15, everything else is the same

Increasing the epochs led to increasing the accuracy, meaning that with small epochs the model doesn't converge.

Model 3:

Final accuracy: 0.9412, 0.9444

Number of parameters: 149834 Average epoch time: 9s ~ 10s

Model architecture: Same as Model 1

Optimizer: #epochs: 20, everything else is the same

also increasing it more lead to more improvement but we prefer to step here to

stop the model from overfitting

We went with model 3 as it gave the best result so far.

Trying different learning rates

Model 4:

Final accuracy: 0.9959, 0.9848

Number of parameters: 149834 Average epoch time: 9s ~ 10s

Model architecture: Same as Model 1

Optimizer: learning rate = 0.05, everything else is the same #Increasing the learning rate helped the model converge faster

Model 5:

Final accuracy: 0.9893, 0.9861

Number of parameters: 149834 Average epoch time: 9s ~ 10s

Model architecture: Same as Model 1

Optimizer: learning rate = 0.001, everything else is the same

the model converged slower than model 4 and didn't achieve a better result

Model 6:

Final accuracy: 0.9999, 0.9906

Number of parameters: 149834 Average epoch time: 9s ~ 10s

Model architecture: Same as Model 1

Optimizer: learning rate = 0.01, everything else is the same

#0.01 seems like the ideal learning rate as we have achieved our best result so far, meaning that we will go with model 6.

Trying different architectures

Model 7:

Final accuracy: 1.000, 0.9912

Number of parameters: 63242 Average epoch time: 27s ~ 29s

Model architecture:

Conv2D: 32 each(3, 3), relu

MaxPooling2D: pool_size(2, 2), strides(2, 2)

Conv2D: 32, each(3, 3), relu

MaxPooling2D: pool_size(2, 2), strides(2, 2)

Dense: 64, relu
Dense: 32, relu
Dense: 10, softmax
Optimizer: same as before.

#adding an extra Convulational layer improved the model since the model now captuers more patterns in the dataset.

Model 8:

Final accuracy: 0.9837, 0.9710

Number of parameters: 9322 Average epoch time: 5s ~ 6s

Model architecture:

Conv2D: 16, each(3, 3), strides(2, 2), relu MaxPooling2D: pool_size(2, 2), strides=(2, 2) Conv2D: 32, each(3, 3), strides(2, 2), relu MaxPooling2D: pool_size(2, 2), strides(2, 2)

Dense: 64, relu
Dense: 32, relu
Dense: 10, softmax
Optimizer: same as before.

#decreasing the number of filters in the first Convolutional layer didn't hurt the model that much since it is only learning basic features.

Model 9:

Final accuracy: 1.0000, 0.9914

Number of parameters: 42698 Average epoch time: 30s ~ 31s Model architecture:

Conv2D: 32, each(3, 3), relu

MaxPooling2D: pool size(2, 2), strides(2, 2)

Conv2D: 32, each(5, 5), relu

MaxPooling2D: pool_size(2, 2), strides(2, 2)

Dense: 32, relu Dense: 10, softmax

Optimizer: same as before.

#increasing the size of the stride improved the model since it now looks at a bigger area of the image helping the model capture extra features.

Model 10:

Final accuracy: 1.0000, 0.9881

Number of parameters: 693866 Average epoch time: 38s ~ 41s

Model architecture:

Conv2D: 128, each(3, 3), relu

MaxPooling2D: pool size(2, 2), strides(2, 2)

Dense: 32, relu
Dense: 10, softmax
Optimizer: same as before.

#Even though this model achieved some high accuracy bu it didn't generalize as well as the previous ones because there is a single convolutional layer that focuses on the simple features and doesn't give much attention to more complex ones.

Choosing the right architecture was harder than previous iterations as it was a toss-up between models 7 and 9, but we chose 9 as it performed generally better on newer data.

Trying different batch sizes

Model 11:

Final accuracy: 0.9992, 0.9902

Number of parameters: 42698 Average epoch time: 28s ~ 29s Model architecture: same as our best model, model 9.
Optimizer: Batch size: 16, everything else is the same.
#No clear improvement over our best model so we stick with it.

Model 12:

Final accuracy: 0.9993, 0.9897

Number of parameters: 42698 Average epoch time: 20s ~ 21s

Model architecture: same as our best model, model 9. Optimizer: Batch size: 64, everything else is the same.

#No clear improvement over our best model so we stick with it, the only clear difference is that training was shorter.

Trying different activation functions

Model 13:

Final accuracy: 0.9990, 0.9906

```
Epoch 1/20
1594/1594 [=======] - 22s 13ms/step - loss: 2.3081 - accuracy: 0.1056 - val_loss: 2.3033 - val_accu
racy: 0.0976
Epoch 2/20
1594/1594 [
     Epoch 3/20
      1594/1594 [
racy: 0.6211
Epoch 4/20
1594/1594 [=
     racy: 0.8889
Epoch 5/20
1594/1594 [
        racy: 0.9401
```

Number of parameters: 63,242 Average epoch time: 19s ~ 20s

Model architecture:

Conv2D: 32, each(3, 3), tanh

MaxPooling2D: pool size(2, 2), strides(2, 2)

Conv2D: 32, each(3, 3), tanh

MaxPooling2D: pool size(2, 2), strides(2, 2)

Dense: 64, tanh
Dense: 32, tanh
Dense: 10, softmax
Optimizer: same as before.

#Training is faster, but the results are not better

Model 14:

Final accuracy: 1.0000, 0.9914

```
Epoch 1/20
1594/1594 [=
                  =========] - 26s 16ms/step - loss: 0.1503 - accuracy: 0.9530 - val loss: 0.0910 - val accu
racy: 0.9707
Epoch 2/20
1594/1594 [====
            racy: 0.9836
Epoch 3/20
1594/1594 [=
                =========] - 23s 14ms/step - loss: 0.0370 - accuracy: 0.9881 - val_loss: 0.0404 - val_accu
racy: 0.9891
Epoch 4/20
1594/1594 [=======] - 23s 15ms/step - loss: 0.0262 - accuracy: 0.9913 - val_loss: 0.0501 - val_accu
racy: 0.9861
Epoch 5/20
1594/1594 [=
             racy: 0.9884
```

Number of parameters: 63,242 Average epoch time: 20s ~ 21s

Model architecture:

Conv2D: 32, each(3, 3), SELU

MaxPooling2D: pool_size(2, 2), strides(2, 2)

Conv2D: 32, each(3, 3), SELU

MaxPooling2D: pool_size(2, 2), strides(2, 2)

Dense: 64, SELU
Dense: 32, SELU
Dense: 10, softmax
Optimizer: same as before

SELU didn't improve much.

Model15:

Final accuracy: 0.9977, 0.9887

```
Epoch 1/20
1594/1594 [
         =========] - 21s 13ms/step - loss: 0.1609 - accuracy: 0.9493 - val_loss: 0.0644 - val_accu
racy: 0.9809
Epoch 2/20
1594/1594 [==
     racy: 0.9846
Epoch 3/20
       1594/1594 [==
racy: 0.9878
Epoch 4/20
racy: 0.9859
Epoch 5/20
      racy: 0.9901
```

Number of parameters: 63,242 Average epoch time: 20s ~ 22s

Model architecture:

Conv2D: 32, each(3, 3), LeakyRELU

MaxPooling2D: pool_size(2, 2), strides(2, 2)

Conv2D: 32, each(3, 3), LeakyRELU

MaxPooling2D: pool size(2, 2), strides(2, 2)

Dense: 64, LeakyRELU Dense: 32, LeakyRELU Dense: 10, softmax

Optimizer: same as before

Trying different optimizers

Model 16:

Final accuracy: 0.9822, 0.9749

```
Epoch 1/20
racy: 0.9649
1594/1594 [=
   racy: 0.9746
Epoch 3/20
1594/1594 [=
  racy: 0.9743
Epoch 4/20
racy: 0.9769
Epoch 5/20
1594/1594 [
   racy: 0.9791
```

Number of parameters: 42698 Average epoch time: 23s ~ 24s

Model architecture: Same as our best model

Optimizer: we used Adam optimizer with the following parameters

(learning_rate=0.01, beta_1=0.9, beta_2=0.999)

#The normal SGD performs better than Adam optimizer

Model 17:

final train: 0.9812 0.9702

```
Fnoch 1/20
1594/1594 [==
       racy: 0.9624
Epoch 2/20
racy: 0.9700
Epoch 3/20
1594/1594 [=
         =========] - 18s 12ms/step - loss: 0.1490 - accuracy: 0.9685 - val_loss: 0.1965 - val_accu
racy: 0.9547
Epoch 4/20
1594/1594 [=
       racy: 0.9739
Epoch 5/20
racy: 0.9601
```

Number of parameters: 42698 Average epoch time: 23s ~ 24s

Model architecture: Same as our best model

Optimizer: we used RMSprop optimizer with the following parameters

(learning_rate=0.01, rho=0.9, momentum=0.1)

#The normal SGD performs better than RMSprop optimizer, we are going with our normal SGD optimizer with learning rate = 0.01 and momentum = 0.9

Trying different dropout rates

Model 18:

Final accuracy: 0.9973, 0.9908

```
Epoch 1/20
1594/1594 [
                        =====] - 19s 12ms/step - loss: 0.1695 - accuracy: 0.9466 - val_loss: 0.0602 - val_accu
racy: 0.9813
Epoch 2/20
1594/1594 [
                   ========] - 19s 12ms/step - loss: 0.0556 - accuracy: 0.9825 - val_loss: 0.0494 - val_accu
racy: 0.9848
Epoch 3/20
                1594/1594 [
racy: 0.9897
Epoch 4/20
1594/1594 [
                 =========] - 19s 12ms/step - loss: 0.0296 - accuracy: 0.9902 - val_loss: 0.0429 - val_accu
racy: 0.9878
Epoch 5/20
racy: 0.9891
```

Number of parameters: 63242 Average epoch time: 19s ~ 20s

Model architecture:

Conv2D: 32, each(3, 3), relu

MaxPooling2D: pool_size=(2, 2), strides=(2, 2)

Dropout: 0.4

Conv2D: 32, each(3, 3), relu

MaxPooling2D: pool_size(2, 2), strides(2, 2)

Dense: 64, relu Dense: 32, relu Dropout: 0.4

Dense: 10, softmax

Optimizer: SGD with learning rate = 0.01 and momentum = 0.9

#The model performed worse than the previous models due to the dropout layer.

Model 19:

Final accuracy: 0.9600, 0.9851

```
Epoch 1/20
1594/1594 [=
       racv: 0.9741
Epoch 2/20
1594/1594 [===
     racy: 0.9794
Epoch 3/20
racy: 0.9834
Epoch 4/20
1594/1594 [==
      =============] - 19s 12ms/step - loss: 0.1998 - accuracy: 0.9471 - val_loss: 0.0584 - val_accu
racy: 0.9832
racy: 0.9858
```

Number of parameters: 63242 Average epoch time: 20s ~ 22s

Model architecture:

Conv2D: 32, each(3, 3), relu

MaxPooling2D: pool size=(2, 2), strides=(2, 2)

Conv2D: 32, each(3, 3), relu

MaxPooling2D: pool size=(2, 2), strides=(2, 2)

Dropout: 0.4 Dense: 64, relu Dropout: 0.4 Dense: 32, relu Dropout: 0.4

Dense: 10, softmax

Optimizer: same as the previous model. #The model's performance even dropped more.

Model 20:

Final accuracy: 0.7687, 0.9658

Number of parameters: 63242 Average epoch time: 20s ~ 22s

Model architecture:

Conv2D: 32, each(3, 3), relu

MaxPooling2D: pool_size=(2, 2), strides=(2, 2)

Dropout: 0.75

Conv2D: 32, each(3, 3), relu

MaxPooling2D: pool_size=(2, 2), strides=(2, 2)

Dense: 64, relu Dense: 32, relu Dropout: 0.75

Dense: 10, softmax

Optimizer: same as the optimizer used by Model 18.

#One thing to note is that although accuracy on the training set was bad, it performed way better on unseen data than our previous model.

Model 21:

Final accuracy: 0.5111, 0.7243

```
Epoch 1/20
                  :========] - 33s 20ms/step - loss: 2.2771 - accuracy: 0.1328 - val_loss: 2.1170 - val_accu
1594/1594 [=
racy: 0.3033
Epoch 2/20
1594/1594 [=
                ==============] - 33s 21ms/step - loss: 2.0881 - accuracy: 0.2293 - val_loss: 1.7329 - val_accu
racy: 0.5182
Epoch 3/20
1594/1594 [
                 racy: 0.5361
Epoch 4/20
1594/1594 [=
                         ===] - 32s 20ms/step - loss: 1.7589 - accuracy: 0.3626 - val_loss: 1.2273 - val_accu
racy: 0.5953
Epoch 5/20
racy: 0.6412
```

Number of parameters: 63242 Average epoch time: 20s ~ 22s

Model architecture:

Conv2D: 32, each(3, 3), relu

MaxPooling2D: pool size=(2, 2), strides=(2, 2)

Conv2D: 32, each(3, 3), relu

MaxPooling2D: pool_size=(2, 2), strides=(2, 2)

Dropout: 0.75
Dense: 64, relu
Dropout: 0.75
Dense: 32, relu
Dropout: 0.75

Dense: 10, softmax

Optimizer: same as the optimizer used by Model 18

#this model performs the same way as our last model, the key difference is that having a big dropout probability means regularizing the model way too much, stopping it from functioning well.

Summary of our best model, model 9:-

The number of epochs is 20

The batch size is 32

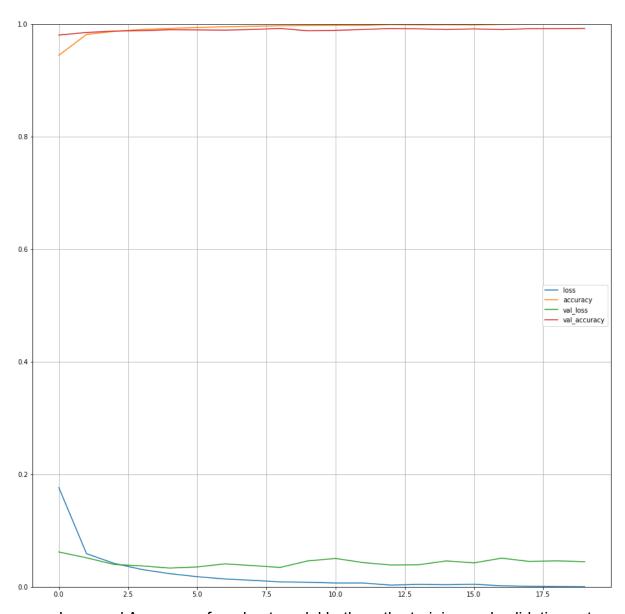
Optimizer: Stochastic gradient Decent with a learning rate of 0.1 and a momentum of 0.9

We used ReLU as our activation function in all the layers except for the output layer where we used a softmax activation function

Our architecture is as follows:

our first convolutional layer was 32 filters of size 3x3 followed by a max pool layer the second convolutional layer is 32 filters of size 5x5 also followed by a max pool layer

We chose 1 FC layer consisting of 32 neurons followed by an output layer.



Loss and Accuracy of our best model both on the training and validation sets