Supervised Learning (Assignment 3):

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Case 1:

For this case we test for the best number of epochs with batch size=32

Model 1: we use 10 epochs

Final accuracy: 98.47%

Number of parameters:

121.930

Average time: in the figure

Layers and activations:

2 conv layers with relu activation function and softmax for output layer

Learning rate: 0.01

Optimizers: **SGD with 0.01**

momentum

```
# Model 1

model = models.Sequential()
model.add(layers.Conv2D(32,(3,3), activation='relu', input_shape = (28,28,1)))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(layers.Conv2D(64,(3,3), activation='relu'))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(layers.Flatten())
model.add(layers.Dense(64,activation = 'relu'))
model.add(layers.Dense(10, activation= 'softmax'))
model.summary()
```

Model 2: we use 12 epochs

Final accuracy: 98.90%

Number of parameters: 121.930

Average time: in the figure

Layers and activations:

2 conv layers with relu activation function and softmax for output layer

Learning rate: 0.01

Optimizers: SGD with 0.01

momentum

Model 3: we use 15 epochs

Final accuracy: 99.25%

Number of parameters: 121.930

Average time: in the figure

Layers and activations: 2 conv

layers with relu activation

function and softmax for output

layer

Learning rate: 0.01

Optimizers: SGD with 0.01

momentum

So, as we see the best number of epochs is 15 with 121.930 parameters because it has the highest accuracy (99.25) and worst accuracy came with 10 epochs.

Case 2:

For this case we test for the best learning rate with batch size=32

Model 4: we use 0.001 learning rate

Final accuracy: 96.53%

Number of parameters: 121.930

Average time: in the figure

Layers and activations: 2 conv layers

with relu activation function and

softmax for output layer

Learning rate: 0.001

Optimizers: SGD with 0.01 momentum

Model 5: we use 0.1 learning rate

Final accuracy: 99.15%

Number of parameters: 121.930

Average time: in the figure Layers and activations: 2 conv

layers with relu activation

function and softmax for output

layer

Learning rate: 0.1

Optimizers: SGD with 0.01

momentum

Model 6: we use 0.5 learning rate

Final accuracy: 11.35%

Number of parameters: 121.930

Average time: in the figure Layers and activations: 2 conv

layers with relu activation function and softmax for output layer

Learning rate: 0.01

Optimizers: SGD with 0.01

momentum

At case 1 when we use 0.01 learning rate the accuracy was 99.25% so it is the best learning rate because the max accuracy in case 2 is 99.15%

Case 3:

For this case we change number of cnn and parameters with batch size=32, epochs=15 and learning rate= 0.01

```
model = models.Sequential()
model.add(layers.Conv2D(32,(3,3), activation='relu', input_shape = (28,28,1)))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(layers.Conv2D(64,(3,3), activation='relu'))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(layers.Conv2D(64,(3,3), activation='relu'))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(layers.Flatten())
model.add(layers.Dense(64,activation = 'relu'))
model.add(layers.Dense(10, activation= 'softmax'))
model.summary()
```

Model 7: we add another cnn layer with same size

Final accuracy: 98.22%
Number of parameters: 60.554
Average time: in the figure
Layers and activations: 3 conv
layers with relu activation
function and softmax for
output layer

Learning rate: 0.01

Optimizers: SGD with 0.01

momentum

Model 8: we remove a cnn layer

Final accuracy: 98.12%

Number of parameters: 347.146

Average time: in the figure

Layers and activations: 1 conv

layers with relu
activation function and
softmax for output layer

Learning rate: 0.01

Optimizers: SGD with 0.01

momentum

```
model = models.Sequential()
model.add(layers.Conv2D(32,(3,3), activation='relu', input_shape = (28,28,1)))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(layers.Flatten())
model.add(layers.Dense(64,activation = 'relu'))
model.add(layers.Dense(10, activation= 'softmax'))
model.summary()
```

```
model.compile(optimizer = tf.optimizers.SGD(learning_rate=0.01, momentum=0.01),
        loss = 'categorical_crossentropy',
        metrics = ['accuracy'] )
model.fit(x train, y train, epochs=15, batch size = 32)
Epoch 1/15
Epoch 2/15
1875/1875 [=
                 Epoch 3/15
1875/1875 [================== ] - 16s 8ms/step - loss: 0.1767 - accuracy: 0.9481
Epoch 4/15
         1875/1875 [=
Epoch 5/15
             ============== ] - 16s 8ms/step - loss: 0.1242 - accuracy: 0.9634
1875/1875 [======
```

Model 9: we change size of cnn layers to (2,2)

Final accuracy: 98.21%

Number of parameters: 156.586

Average time: in the figure

Layers and activations: 2 conv

layers with relu activation

function and softmax for output layer

Learning rate: 0.01

Optimizers: SGD with 0.01

momentum

```
model = models.Sequential()
model.add(layers.Conv2D(32,(2,2), activation='relu', input_shape = (28,28,1)))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(layers.Conv2D(64,(2,2), activation='relu'))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(layers.Flatten())
model.add(layers.Dense(64,activation = 'relu'))
model.add(layers.Dense(10, activation= 'softmax'))
model.summary()
```

```
model.compile(optimizer = tf.optimizers.SGD(learning_rate=0.01, momentum=0.01),
         loss = 'categorical_crossentropy',
         metrics = ['accuracy'] )
model.fit(x_train, y_train, epochs=15, batch_size = 32)
Epoch 1/15
1875/1875 [
            Epoch 2/15
1875/1875 [
                      =======] - 15s 8ms/step - loss: 0.2064 - accuracy: 0.9390
Epoch 3/15
1875/1875 [
                       =======] - 16s 9ms/step - loss: 0.1350 - accuracy: 0.9602
Epoch 4/15
1875/1875 [
             Epoch 5/15
                    ========] - 16s 9ms/step - loss: 0.0876 - accuracy: 0.9733
```

Model 10: we increase number of filters

Final accuracy: 98.47%

Number of parameters: 328.842

Average time: in the figure

Layers and activations: 2 conv

layers with relu activation

function and softmax for output layer

Learning rate: 0.01

Optimizers: SGD with

0.01 momentum

```
model = models.Sequential()
model.add(layers.Conv2D(64,(2,2), activation='relu', input_shape = (28,28,1)))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(layers.Conv2D(128,(2,2), activation='relu'))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(layers.Flatten())
model.add(layers.Dense(64,activation = 'relu'))
model.add(layers.Dense(10, activation= 'softmax'))
model.summary()
```

```
model.compile(optimizer = tf.optimizers.SGD(learning_rate=0.01, momentum=0.01),
         loss = 'categorical_crossentropy',
         metrics = ['accuracy'] )
model.fit(x_train, y_train, epochs=15, batch_size = 32)
Epoch 1/15
1875/1875 [=
                      =======] - 38s 20ms/step - loss: 0.6432 - accuracy: 0.8183
Epoch 2/15
Epoch 3/15
1875/1875 [=
            Epoch 4/15
1875/1875 [============] - 41s 22ms/step - loss: 0.1024 - accuracy: 0.9690
Epoch 5/15
1875/1875 [================= ] - 39s 21ms/step - loss: 0.0857 - accuracy: 0.9741
```

Model 11: we add another FC layer

Final accuracy: 98.62%

Number of parameters: 330.602

Average time: in the figure

Layers and activations: 2 conv

layers with relu activation function and softmax for output layer with another hidden layer

Learning rate: 0.01

Optimizers: **SGD with 0.01**

momentum

```
model = models.Sequential()
model.add(layers.Conv2D(64,(2,2), activation='relu', input_shape = (28,28,1)))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(layers.Conv2D(128,(2,2), activation='relu'))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(layers.Flatten())
model.add(layers.Dense(64,activation = 'relu'))
model.add(layers.Dense(32,activation = 'relu'))
model.add(layers.Dense(10, activation= 'softmax'))
model.summary()
```

```
model.compile(optimizer = tf.optimizers.SGD(learning_rate=0.01, momentum=0.01),
       loss = 'categorical_crossentropy',
      metrics = ['accuracy'] )
model.fit(x_train, y_train, epochs=15, batch_size = 32)
Epoch 1/15
1875/1875 [==:
       Epoch 2/15
1875/1875 [
        Epoch 3/15
             ========] - 43s 23ms/step - loss: 0.1280 - accuracy: 0.9601
1875/1875 [
Epoch 4/15
1875/1875 [=
         Epoch 5/15
```

From case 3 we see that when we add another hidden layer the accuracy increased to 98.62 which is better than the other models

But number of parameters became worst, until we add another cnn layer

So most suitable for accuracy and parameters that we add another cnn layers (98.22)

Case 4:

For this case we test different batch sizes with epochs=15 and learning rate= 0.01

Model 12: we try batch with size= **64**

Final accuracy: 98.20%

Number of parameters: **169.162** Average time: **in the figure**

Layers and activations: 3 conv layers with relu activation function and softmax for

output layer

Learning rate: 0.01

Optimizers: SGD with 0.01 momentum

Model 13: we try batch with size= **128**

Final accuracy: **97.87%** Number of parameters:

169.162

Average time: in the figure Layers and activations: 3 conv layers with relu activation function and softmax for output layer

Learning rate: 0.01

Optimizers: SGD with 0.01 momentum

Model 14: we try batch with size= **20**

Final accuracy: 98.77%

Number of parameters: 169.162
Average time: in the figure
Layers and activations: 3 conv
layers with relu activation
function and softmax for
output layer

Learning rate: 0.01

Optimizers: SGD with 0.01 momentum

As we see the best accuracy came with the batch size=20 but a lot of time

while the worst accuracy with size= 128 but it was the fastest

Case 5:

For this case we test different activation functions (with softmax in output layer) with epochs=15, learning rate= 0.01 and batch size= 20

```
Model 15: we try sigmoid activation function
```

Final accuracy: 36.27%

Number of parameters: 169.162

Average time: in the figure

```
model = models.Sequential()
model.add(layers.Conv2D(64,(2,2), activation='sigmoid', input_shape = (28,28,1)))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(layers.Conv2D(128,(2,2), activation='sigmoid'))
model.add(layers.Conv2D(64,(2,2), activation='sigmoid'))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(layers.Flatten())
model.add(layers.Dense(64,activation = 'sigmoid'))
model.add(layers.Dense(10, activation= 'softmax'))
model.summary()
```

```
Layers and activations: 3 conv layers with sigmoid activation function and softmax for output layer
```

Learning rate: **0.01** Optimizers: **SGD with**

0.01 momentum

```
Model 16: we try tanh activation function
```

3000/3000 [======

Final accuracy: 98.77%

Number of parameters: 169.162

Average time: in the figure

Layers and activations: 3 conv layers with tanh activation functions and softmax for output layer

Learning rate: 0.01

Optimizers: SGD with 0.01

momentum

```
model = models.Sequential()
model.add(layers.Conv2D(64,(2,2), activation='tanh', input_shape = (28,28,1)))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(layers.Conv2D(128,(2,2), activation='tanh'))
model.add(layers.Conv2D(64,(2,2), activation='tanh'))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(layers.Flatten())
model.add(layers.Dense(64,activation = 'tanh'))
model.add(layers.Dense(10, activation= 'softmax'))
model.summary()
```

Model 17: we try leaky_relu activation function

Final accuracy: 98.76%

Number of parameters: 169.162

Average time: in the figure Layers and activations: 3 conv

layers with leacky_relu activation

functions and softmax for output layer

Learning rate: **0.01**Optimizers: **SGD with**

0.01 momentum

```
model = models.Sequential()
model.add(layers.Conv2D(64,(2,2), activation='LeakyReLU', input_shape = (28,28,1)))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(layers.Conv2D(128,(2,2), activation='LeakyReLU'))
model.add(layers.Conv2D(64,(2,2), activation='LeakyReLU'))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(layers.Flatten())
model.add(layers.Dense(64,activation = 'LeakyReLU'))
model.add(layers.Dense(10, activation= 'softmax'))
model.summary()
```

```
model.compile(optimizer = tf.optimizers.SGD(learning_rate=0.01, momentum=0.01),
        loss = 'categorical_crossentropy',
       metrics = ['accuracy'] )
model.fit(x_train, y_train, epochs=15, batch_size = 20)
Fnoch 1/15
3000/3000 [====
                 ========] - 65s 22ms/step - loss: 0.4841 - accuracy: 0.8496
Epoch 2/15
3000/3000 [
           Epoch 3/15
             3000/3000 [
Epoch 4/15
3000/3000 [============ ] - 68s 23ms/step - loss: 0.0676 - accuracy: 0.9788
Epoch 5/15
```

So, we see that sigmoid activation function get the worst accuracy and it is not useful in the models, while the Relu activation function get the best accuracy (98.77%) but it take more time.

Case 6:

For this case we test different optimizers with epochs=15, learning rate= 0.01 and batch size= 20

Model 18: we use Adam optimizer

Final accuracy: **96.22%** Number of parameters:

169.162

Average time: in the

figure

```
model.compile(optimizer = tf.optimizers.Adam(learning rate=0.01),
         loss = 'categorical_crossentropy',
         metrics = ['accuracy'] )
model.fit(x_train, y_train, epochs=15, batch_size = 20)
Epoch 1/15
Epoch 2/15
3000/3000 [================= ] - 61s 20ms/step - loss: 0.1154 - accuracy: 0.9661
Epoch 3/15
```

Layers and activations: 3 conv layers with relu activation functions and softmax for output layer

model.compile(optimizer = tf.optimizers.Adadelta(learning_rate=0.01),

Epoch 4/15

Epoch 5/15

3000/3000 [==

Learning rate: 0.01

Optimizers: Adam with 0.01 learning rate

Model 19: we use Adadelta optimizer

Final accuracy: **97.65%** Number of parameters:

169,162

Average time: in the

figure

Lavers and activations:

loss = 'categorical_crossentropy', metrics = ['accuracy']) model.fit(x_train, y_train, epochs=15, batch_size = 20) Epoch 1/15 3000/3000 [==============] - 49s 16ms/step - loss: 0.1653 - accuracy: 0.9650 Epoch 2/15 3000/3000 [=======================] - 62s 21ms/step - loss: 0.1504 - accuracy: 0.9676 Epoch 3/15 3000/3000 [== Epoch 4/15 3000/3000 [=== Epoch 5/15

3000/3000 [==============] - 64s 21ms/step - loss: 0.1222 - accuracy: 0.9731

3 conv layers with relu activation functions and softmax for output layer

Learning rate: 0.01

Optimizers: Adadelta with 0.01 learning rate

So, as we see the best optimizer is SGD because Adam optimizer get worst accuracy and take a lot of time and Adadleta optimizer get medium accuracy and medium time.

Case 7:

For this case we put a dropout layer with different rates and in different places, with epochs=15, learning rate= 0.01 and batch size= 20

(dropout layer helps prevent overfitting by sets inputs unit to 0 with a frequency of rate)

```
Model 20: we use dropout layer with 0.1 rate
```

Final accuracy:

98.74%

Number of

parameters: **169.162**

Average time: in the figure

Layers and activations: 3 conv layers with relu activation functions and softmax

for output layer
Learning rate: 0.01
Optimizers: SGD with
0.01 learning rate

```
model = models.Sequential()
model.add(layers.Conv2D(64,(2,2), activation='relu', input_shape = (28,28,1)))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(Dropout(0.1))
model.add(layers.Conv2D(128,(2,2), activation='relu'))
model.add(layers.Conv2D(64,(2,2), activation='relu'))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(layers.Flatten())
model.add(layers.Dense(64,activation = 'relu'))
model.add(layers.Dense(10, activation= 'softmax'))
model.summary()
```

Model 21: we use dropout layer with 0.5 rate

Final accuracy: **98.80%**Number of parameters: **169.162**

Average time: in the figure
Layers and activations: 3
conv layers with relu
activation functions and
softmax for output layer

Learning rate: 0.01

Optimizers: SGD with 0.01

learning rate

```
model.compile(optimizer = tf.optimizers.SGD(learning rate=0.01),
    loss = 'categorical crossentropy',
    metrics = ['accuracy'] )
model.fit(x train, y train, epochs=15, batch size = 20)
Epoch 1/15
Epoch 2/15
Epoch 3/15
3000/3000 [=
     Epoch 4/15
      3000/3000 [=
Epoch 5/15
```

```
model = models.Sequential()
model.add(layers.Conv2D(64,(2,2), activation='relu', input_shape = (28,28,1)))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(Dropout(0.9))
model.add(layers.Conv2D(128,(2,2), activation='relu'))
model.add(layers.Conv2D(64,(2,2), activation='relu'))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(layers.Flatten())
model.add(layers.Dense(64,activation = 'relu'))
model.add(layers.Dense(10, activation= 'softmax'))
model.summary()
```

Model 22: we use dropout layer with 0.9 rate

Final accuracy: 97.67%

Number of parameters: 169.162

Average time: in the figure

Layers and activations: 3 conv layers with relu activation functions and softmax

Epoch 5/15

for output layer

Learning rate: **0.01**Optimizers: **SGD** with **0.01** learning rate

So, the best dropout rate is 0.5 as it get accuracy 98.80% and worst accuracy with rate 0.9

Model 23: we use dropout layer in different places, first place: after the first cnn layer

Final accuracy: **98.66%** Number of parameters:

169.162

Average time: in the

figure

Layers and activations: 3 conv layers with relu activation functions and softmax for output layer

Learning rate: 0.01

Optimizers: SGD with 0.01

learning rate

```
model = models.Sequential()
model.add(layers.Conv2D(64,(2,2), activation='relu', input_shape = (28,28,1)))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(Dropout(0.5))
model.add(layers.Conv2D(128,(2,2), activation='relu'))
model.add(layers.Conv2D(64,(2,2), activation='relu'))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(layers.Flatten())
model.add(layers.Dense(64,activation = 'relu'))
model.add(layers.Dense(10, activation= 'softmax'))
model.summary()
```

```
model.compile(optimizer = tf.optimizers.SGD(learning rate=0.01),
      loss = 'categorical_crossentropy',
      metrics = ['accuracy'] )
model.fit(x train, y train, epochs=15, batch size = 20)
3000/3000 [=
       Epoch 2/15
3000/3000 [=
      Epoch 3/15
Fnoch 4/15
3000/3000 [=
        ========= 0.9727 - 62s 21ms/step - loss: 0.0870 - accuracy: 0.9727
Epoch 5/15
```

Model 24: we use dropout layer in different places,

second place: after the fully

conected layer

Final accuracy: **98.80%** Number of parameters:

169,162

Average time: in the figure
Layers and activations: 3
conv layers with relu
activation functions and
softmax for output layer

Learning rate: 0.01

Optimizers: SGD with 0.01

```
model = models.Sequential()
model.add(layers.Conv2D(64,(2,2), activation='relu', input_shape = (28,28,1)))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(layers.Conv2D(128,(2,2), activation='relu'))
model.add(layers.Conv2D(64,(2,2), activation='relu'))
model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(layers.Flatten())
model.add(layers.Dense(64,activation = 'relu'))
model.add(Dropout(0.5))
model.add(layers.Dense(10, activation= 'softmax'))
model.summary()
```

```
model.compile(optimizer = tf.optimizers.SGD(learning_rate=0.01),
          loss = 'categorical_crossentropy',
          metrics = ['accuracy'] )
model.fit(x train, y train, epochs=15, batch size = 20)
Epoch 1/15
 Epoch 2/15
 3000/3000 [
                      =======] - 57s 19ms/step - loss: 0.2423 - accuracy: 0.9283
 Epoch 3/15
 3000/3000 [
                      :========] - 58s 19ms/step - loss: 0.1835 - accuracy: 0.9452
Epoch 4/15
 3000/3000
                     ========] - 61s 20ms/step - loss: 0.1564 - accuracy: 0.9539
Epoch 5/15
```

So as we see, when we put dropout layer after the hidden layer (FC layer) the accuracy increased and became (98.80%)

Till now best accuracy is 99.13 % but with 121.994 parameters which is quite large and it can be reduced, so the last way is to reduce number of neurons (filters) of the layers and see what will happen..

Model 25:

we reduce numbers of filters to 16 with 30 neurons and size 3*3 Final accuracy: **98.46%** Number of parameters: **12.820**

Average time: in the figure

Layers and activations:
3 conv layers with relu
activation functions
and softmax for
output layer

Learning rate: 0.01

Optimizers: SGD with 0.01

```
In [12]: model = models.Sequential()
         model.add(layers.Conv2D(16,(3,3), activation='relu', input shape = (28,28,1)))
         model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
         model.add(layers.Conv2D(16,(3,3), activation='relu'))
         model.add(layers.Conv2D(16,(3,3), activation='relu'))
         model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(layers.Flatten())
         model.add(layers.Dense(30,activation = 'relu'))
         model.add(Dropout(0.5))
         model.add(layers.Dense(10, activation= 'softmax'))
         model.summarv()
         Model: "sequential_9"
          Layer (type)
                                       Output Shape
                                                                  Param #
          conv2d_27 (Conv2D)
                                       (None, 26, 26, 16)
                                                                  160
          max_pooling2d_18 (MaxPoolin (None, 13, 13, 16)
          conv2d 28 (Conv2D)
                                       (None, 11, 11, 16)
                                                                  2329
          conv2d 29 (Conv2D)
                                       (None, 9, 9, 16)
                                                                  2320
          max_pooling2d_19 (MaxPoolin (None, 4, 4, 16)
          flatten 9 (Flatten)
                                       (None, 256)
          dense_18 (Dense)
                                       (None, 30)
          dropout_9 (Dropout)
                                       (None, 30)
          dense_19 (Dense)
                                      (None, 10)
                                                                  310
         Total params: 12,820
         Trainable params: 12,820
         Non-trainable params: 0
```

```
score = model.evaluate(x_test, y_test, verbose=0)
print('loss=', score[0])
print('accuracy=', score[1] * 100, '%')
loss= 0.04785200580954552
```

loss= 0.04785200580954552 accuracy= 98.46000075340271 %

Conclusion:

At the end after we test every parameter in the models we found that best accuracy with most suitable number of parameters and suitable time is **99.13%** and **121.994** parameters which is quite big, but when we reduce the number of filters (neurons), the number is greatly reduced and became **12.820** with accuracy= **98.65%** which is still suitable.

So the best final model came with:

Epochs= 15

Learning rate= **0.01**

3 CNN layers with **1** FC Layer and output with number of filters= **16** and **30** for neurons in hidden layer

Batch size= 20

Relu activation function

SGD optimizer

Dropout layer with rate= **0.5** and put it **after the FC layer**

As the final (best) accuracy= 98.65%

With number of parameters= 12.820

And this full Code for best model:

```
In [1]: import numpy as np
   import keras
   import tensorflow as tf
   from keras.datasets import mnist
   from keras.models import Sequential
   from keras.layers import Dense, Input
   from tensorflow.keras.utils import to_categorical
   from keras.layers import Dropout
   from keras import backend as k
   from keras import models
   from keras import layers
```

```
In [2]: #Loading and Processing the Data
         (x train, y train), (x test, y test) = mnist.load data()
        #Reshape Dataset to have a Single Channel
        x \text{ train} = x \text{ train.reshape}((60000, 28, 28, 1))
        x \text{ test} = x \text{ test.reshape}((10000, 28, 28, 1))
        #Convert from Integers to Floats
        x train = x train.astype('float32')/255
        x test = x test.astype('float32')/255
        # Convert Class Vectors to Binary Class Matrices OR one Hot Encode target values
        y train = to categorical(y train)
        y test = to categorical(y test)
        print('x train shape:', x train.shape)
        print('y train shape:', y train.shape)
        print(x train.shape[0], 'train samples')
        print(x test.shape[0], 'test samples')
        x train shape: (60000, 28, 28, 1)
        y train shape: (60000, 10)
        60000 train samples
         10000 test samples
```

```
In [3]: model = models.Sequential()
        model.add(layers.Conv2D(16,(3,3), activation='relu', input_shape = (28,28,1)))
        model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
        model.add(layers.Conv2D(16,(3,3), activation='relu'))
        model.add(layers.Conv2D(16,(3,3), activation='relu'))
        model.add(layers.MaxPooling2D(pool_size=(2,2), strides=(2,2)))
        model.add(layers.Flatten())
        model.add(layers.Dense(30,activation = 'relu'))
        model.add(Dropout(0.5))
        model.add(layers.Dense(10, activation= 'softmax'))
        model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 26, 26, 16)	160
<pre>max_pooling2d (MaxPooling2D)</pre>	(None, 13, 13, 16)	0
conv2d_1 (Conv2D)	(None, 11, 11, 16)	2320
conv2d_2 (Conv2D)	(None, 9, 9, 16)	2320
<pre>max_pooling2d_1 (MaxPooling 2D)</pre>	(None, 4, 4, 16)	0
flatten (Flatten)	(None, 256)	0
dense (Dense)	(None, 30)	7710
dropout (Dropout)	(None, 30)	0
dense_1 (Dense)	(None, 10)	310

Total params: 12,820 Trainable params: 12,820 Non-trainable params: 0

```
In [4]: model.compile(optimizer = tf.optimizers.SGD(learning_rate=0.01),
    loss = 'categorical_crossentropy',
    metrics = ['accuracy'] )
 model.fit(x_train, y_train, epochs=15, batch_size = 20)
 Epoch 1/15
 Epoch 2/15
 Epoch 3/15
 Epoch 4/15
 Epoch 5/15
 Epoch 6/15
 Epoch 7/15
 Epoch 8/15
 Epoch 9/15
 Epoch 12/15
 Epoch 13/15
 Epoch 14/15
 Epoch 15/15
 Out[4]: <keras.callbacks.History at 0x1825747a610>
```

```
In [5]: score = model.evaluate(x_test, y_test, verbose=0)
    print('loss=', score[0])
    print('accuracy=', score[1] * 100, '%')

loss= 0.0426531545817852
```

accuracy= 98.65999817848206 %