Basic Steps to be followed

1. Importing Required Libraries
2. Load the Data
3. Preprocess the data
4. Define the Model
5. Compile the model
6. Fit the model
7. Evaluate

1. Importing Required Libraries

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow as tf
from tensorflow import keras
from keras.utils import np_utils
from keras.models import Sequential
from keras.layers import Dense, Dropout, BatchNormalization, Flatten
```

In [2]:

```
# Checking the versions of tensorflow and keras
print(tf.__version__)
print(keras.__version__)
```

```
2.12.0
2.12.0
```

2. Loading The MNIST Dataset

In [3]:

```
from keras.datasets import mnist
```

In [4]:

```
(x_train,y_train),(x_test,y_test) = mnist.load_data()
```

In [5]:

```
x_train.shape
```

Out[5]:

```
(60000, 28, 28)
```

In [6]:

```
x_test.shape
```

Out[6]:

```
(10000, 28, 28)
```

Observation:

- Train data has 60000 images of 28x28 dimension
- Test data has 10000 images of 28x28 dimension
- The images are in black and white

In [7]:

```python
print(x_train[0])
```

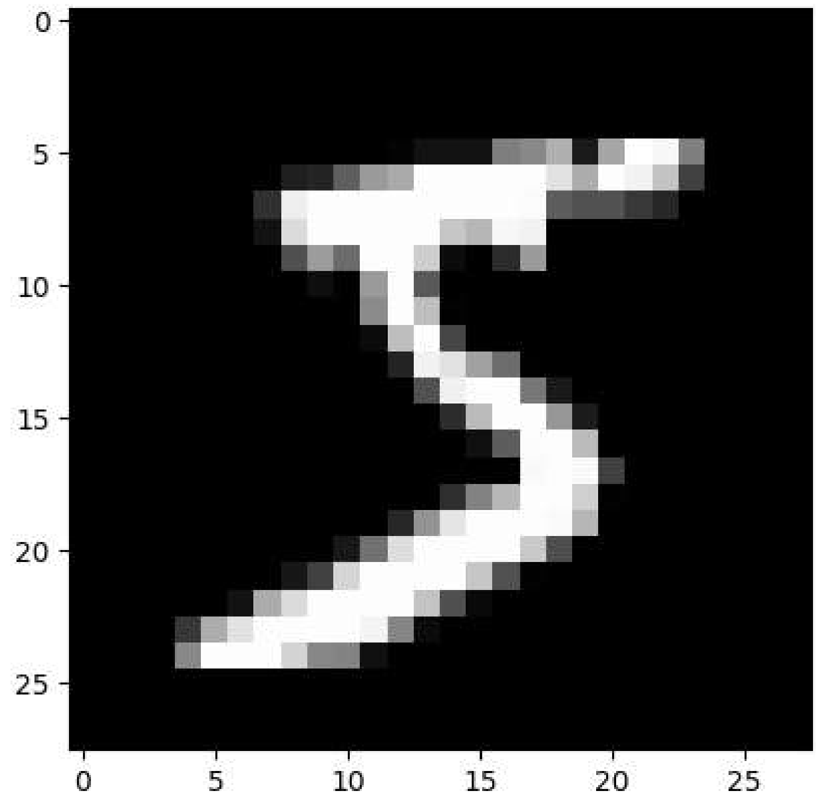
```
[[  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   3  18  18  18 126 136
  175  26 166 255 247 127   0   0   0   0]
 [  0   0   0   0   0   0   0   0  30  36  94 154 170 253 253 253 253 253
  225 172 253 242 195  64   0   0   0   0]
 [  0   0   0   0   0   0   0  49 238 253 253 253 253 253 253 253 253 251
   93  82  82  56  39   0   0   0   0   0]
 [  0   0   0   0   0   0   0  18 219 253 253 253 253 253 198 182 247 241
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0  80 156 107 253 253 205  11   0  43 154
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0  14   1 154 253  90   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0 139 253 190   2   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0  11 190 253  70   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0  35 241 225 160 108   1
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0  81 240 253 253 119
   25   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0  45 186 253 253
  150  27   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0  16  93 252
  253 187   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 249
  253 249  64   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0  46 130 183 253
  253 207   2   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0  39 148 229 253 253 253
  250 182   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0  24 114 221 253 253 253 253 201
   78   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0  23  66 213 253 253 253 253 198  81   2
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0  18 171 219 253 253 253 253 195  80   9   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0  55 172 226 253 253 253 253 244 133  11   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0 136 253 253 253 212 135 132  16   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]]
```

In [8]:

```
plt.imshow(x_train[0],cmap="gray")
```

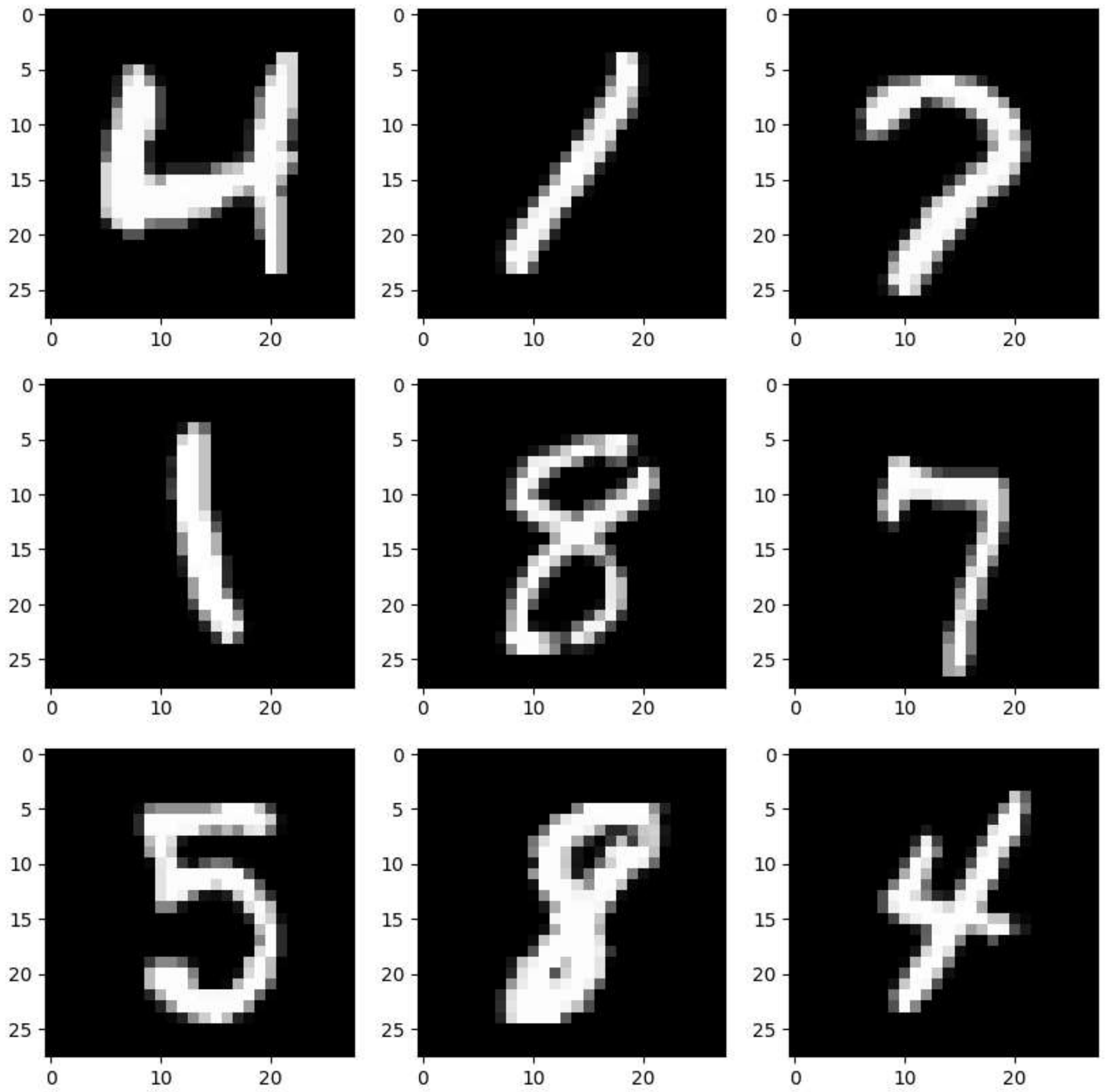
Out[8]:

```
<matplotlib.image.AxesImage at 0x7aa5234ba9b0>
```



In [9]:

```
# Viewing few random images from the data
plt.figure(figsize=(10,10))
np.random.seed(0)
index = np.random.randint(0,60000,9)
for i in range(len(index)):
  plt.subplot(3,3,i+1)
  plt.imshow(x_train[index[i]],cmap="gray")
```



3. Data Preprocessing

In [10]:

```
# Min Max Scaling without using the library
# x - x_min/ x_max - x_min
# x_min = 0 (The smallest Pixel value)
# x_max = 255 (The maximum pixel value)

x_train_scaled = x_train/255      #x_train - 0 / 255 - 0
x_test_scaled = x_test/255
```

In [11]:

```
# Converting 2d to 1d using numpy reshape
# 60000 data points will remain the same
# The next dimension will be 28x28 = 784
x_train_flattened = x_train_scaled.reshape(60000,784)
```

In [12]:

```
# Similarly for test data
x_test_flattened = x_test_scaled.reshape(10000,784)
```

In [13]:

```
# Checking the datatype of scaled df
x_train_scaled.dtype
```

Out[13]:

```
dtype('float64')
```

In [14]:

```
x_train_flattened.shape
```

Out[14]:

```
(60000, 784)
```

In [15]:

```
# Converting the output to One Hot Encoding using np_utils from keras
y_train_encoded = np_utils.to_categorical(y_train,10)
y_test_encoded = np_utils.to_categorical(y_test,10)
# 10 Because in our dataset there are 10 classes(0 to 9)
```

In [16]:

```
print(y_train[0])
print(y_train_encoded[0])
```

```
5
[0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]
```

4. Define the model - Softmax Classifier

In [17]:

```
model = Sequential()
# Sequential: Simple feedforward Network Where the neurons of the layers are connected
model.add(Dense(10,input_dim=784,activation="softmax"))
```

In [18]:

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 dense (Dense)               (None, 10)                7850      
                                                                 
=================================================================
Total params: 7,850
Trainable params: 7,850
Non-trainable params: 0
_________________________________________________________________
```

5. Compile the model

In [19]:

```
model.compile(optimizer="sgd",
              loss="categorical_crossentropy",
              metrics=["accuracy"])
```

6. Fit the model

In [20]:

```
model.fit(x_train_flattened,y_train_encoded,batch_size=128,epochs=10)
```

```
Epoch 1/10
469/469 [==============================] - 5s 7ms/step - loss: 1.3031 - ac
curacy: 0.6993
Epoch 2/10
469/469 [==============================] - 2s 5ms/step - loss: 0.7209 - ac
curacy: 0.8406
Epoch 3/10
469/469 [==============================] - 2s 4ms/step - loss: 0.5890 - ac
curacy: 0.8597
Epoch 4/10
469/469 [==============================] - 3s 6ms/step - loss: 0.5262 - ac
curacy: 0.8694
Epoch 5/10
469/469 [==============================] - 4s 8ms/step - loss: 0.4881 - ac
curacy: 0.8758
Epoch 6/10
469/469 [==============================] - 4s 9ms/step - loss: 0.4619 - ac
curacy: 0.8801
Epoch 7/10
469/469 [==============================] - 3s 6ms/step - loss: 0.4426 - ac
curacy: 0.8834
Epoch 8/10
469/469 [==============================] - 3s 5ms/step - loss: 0.4276 - ac
curacy: 0.8866
Epoch 9/10
469/469 [==============================] - 2s 4ms/step - loss: 0.4155 - ac
curacy: 0.8887
Epoch 10/10
469/469 [==============================] - 1s 3ms/step - loss: 0.4054 - ac
curacy: 0.8912
```

Out[20]:

```
<keras.callbacks.History at 0x7aa51d959d80>
```

7. Evaluate the model

In [21]:

```
model.evaluate(x_test_flattened,y_test_encoded)
```

```
313/313 [==============================] - 1s 2ms/step - loss: 0.3804 - ac
curacy: 0.8986
```

Out[21]:

```
[0.3803711533546448, 0.8985999822616577]
```

In [22]:

```
model.evaluate(x_test_flattened,y_test_encoded,verbose=0)
```

Out[22]:

```
[0.3803711533546448, 0.8985999822616577]
```

4. Define The Model - Sigmoid Activation

In [23]:

```
model = Sequential()
model.add(Dense(512,input_dim=784,
                activation="sigmoid"))# First Input Layer + First Hidden Layer
model.add(Dense(128,activation="sigmoid")) # Second Layer
model.add(Dense(64,activation="sigmoid")) # Third Layer
model.add(Dense(10,activation="softmax")) # Output Layer
```

In [24]:

```
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_1 (Dense)             (None, 512)               401920

 dense_2 (Dense)             (None, 128)               65664

 dense_3 (Dense)             (None, 64)                8256

 dense_4 (Dense)             (None, 10)                650

=================================================================
Total params: 476,490
Trainable params: 476,490
Non-trainable params: 0
_________________________________________________________________
```

5. Compile The Model

In [25]:

```
model.compile(optimizer="adam",loss="categorical_crossentropy",metrics=["accuracy"])
```

6. Fit the Model

In [26]:

```
model.fit(x_train_flattened,y_train_encoded,batch_size=128,epochs=10)
```

```
Epoch 1/10
469/469 [==============================] - 8s 14ms/step - loss: 0.7092 - a
ccuracy: 0.8201
Epoch 2/10
469/469 [==============================] - 7s 15ms/step - loss: 0.2248 - a
ccuracy: 0.9363
Epoch 3/10
469/469 [==============================] - 6s 14ms/step - loss: 0.1515 - a
ccuracy: 0.9564
Epoch 4/10
469/469 [==============================] - 7s 15ms/step - loss: 0.1114 - a
ccuracy: 0.9681
Epoch 5/10
469/469 [==============================] - 6s 13ms/step - loss: 0.0874 - a
ccuracy: 0.9743
Epoch 6/10
469/469 [==============================] - 7s 16ms/step - loss: 0.0689 - a
ccuracy: 0.9795
Epoch 7/10
469/469 [==============================] - 7s 14ms/step - loss: 0.0551 - a
ccuracy: 0.9842
Epoch 8/10
469/469 [==============================] - 7s 15ms/step - loss: 0.0434 - a
ccuracy: 0.9877
Epoch 9/10
469/469 [==============================] - 7s 14ms/step - loss: 0.0369 - a
ccuracy: 0.9894
Epoch 10/10
469/469 [==============================] - 9s 18ms/step - loss: 0.0296 - a
ccuracy: 0.9918
```

Out[26]:

```
<keras.callbacks.History at 0x7aa51d77ee30>
```

7. Evaluate The Model

In [27]:

```
model.evaluate(x_test_flattened,y_test_encoded)
```

```
313/313 [==============================] - 1s 4ms/step - loss: 0.0685 - ac
curacy: 0.9794
```

Out[27]:

```
[0.06854818016290665, 0.9793999791145325]
```

4. Define The Model - ReLU Activation

In [28]:

```
model = Sequential()
model.add(Dense(512,input_dim=784,
                activation="relu"))# First Input Layer + First Hidden Layer
model.add(BatchNormalization())
model.add(Dropout(0.3))
model.add(Dense(128,activation="relu")) # Second Layer
model.add(BatchNormalization())
model.add(Dropout(0.3))
model.add(Dense(64,activation="relu")) # Third Layer
model.add(BatchNormalization())
model.add(Dropout(0.3))
model.add(Dense(10,activation="softmax")) # Output Layer
```

In [29]:

```
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_5 (Dense)             (None, 512)               401920

 batch_normalization (BatchN  (None, 512)              2048
 ormalization)

 dropout (Dropout)           (None, 512)               0

 dense_6 (Dense)             (None, 128)               65664

 batch_normalization_1 (Batc  (None, 128)              512
 hNormalization)

 dropout_1 (Dropout)         (None, 128)               0

 dense_7 (Dense)             (None, 64)                8256

 batch_normalization_2 (Batc  (None, 64)               256
 hNormalization)

 dropout_2 (Dropout)         (None, 64)                0

 dense_8 (Dense)             (None, 10)                650

=================================================================
Total params: 479,306
Trainable params: 477,898
Non-trainable params: 1,408
_________________________________________________________________
```

5. Compile the Model

In [30]:

```
model.compile(optimizer="adam",loss="categorical_crossentropy",metrics=["accuracy"])
```

6. Fit the Model

In [31]:

```
model.fit(x_train_flattened,y_train_encoded,batch_size=128,epochs=10)
```

```
Epoch 1/10
469/469 [==============================] - 11s 18ms/step - loss: 0.3871 -
accuracy: 0.8861
Epoch 2/10
469/469 [==============================] - 9s 19ms/step - loss: 0.1714 - a
ccuracy: 0.9501
Epoch 3/10
469/469 [==============================] - 10s 20ms/step - loss: 0.1299 -
accuracy: 0.9612
Epoch 4/10
469/469 [==============================] - 8s 17ms/step - loss: 0.1089 - a
ccuracy: 0.9671
Epoch 5/10
469/469 [==============================] - 10s 21ms/step - loss: 0.0936 -
accuracy: 0.9724
Epoch 6/10
469/469 [==============================] - 9s 18ms/step - loss: 0.0854 - a
ccuracy: 0.9741
Epoch 7/10
469/469 [==============================] - 8s 17ms/step - loss: 0.0752 - a
ccuracy: 0.9769
Epoch 8/10
469/469 [==============================] - 9s 19ms/step - loss: 0.0715 - a
ccuracy: 0.9786
Epoch 9/10
469/469 [==============================] - 9s 19ms/step - loss: 0.0634 - a
ccuracy: 0.9809
Epoch 10/10
469/469 [==============================] - 8s 18ms/step - loss: 0.0578 - a
ccuracy: 0.9823
```

Out[31]:

```
<keras.callbacks.History at 0x7aa5001a0df0>
```

7. Evaluate The Model

In [32]:

```
model.evaluate(x_test_flattened,y_test_encoded)
```

```
313/313 [==============================] - 2s 4ms/step - loss: 0.0641 - ac
curacy: 0.9812
```

Out[32]:

```
[0.06406933069229126, 0.9811999797821045]
```