```
#import libraries
import cv2
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import keras
from keras.datasets import fashion mnist #
import keras.models as models
import keras.layers as layers
from keras import regularizers
from keras.layers import Dropout
#from keras.engine.sequential import Sequential
#tensor flow-> layers
import tensorflow as tf
from tensorflow.keras.models import Sequential, Model ##squnce of process
from tensorflow.keras.layers import Dense, Activation, Flatten, Dropout, Conv2D, MaxPooling2D
                                                                                           #bipertate graph
from keras.layers.advanced activations import LeakyReLU
from tensorflow.keras.utils import to categorical #for catagorical data
from google.colab import drive
drive.mount('/content/drive')
     Mounted at /content/drive
cd /content/drive/"MyDrive/dataset ml/Train set"
     /content/drive/MyDrive/dataset ml/Train set
dataset = pd.read_csv('train.csv')
dataset.shape
```

(7095, 3)

dataset

	ImageId	ClassId	EncodedPixels
0	0002cc93b.jpg	1	29102 12 29346 24 29602 24 29858 24 30114 24 3
1	0007a71bf.jpg	3	18661 28 18863 82 19091 110 19347 110 19603 11
2	000a4bcdd.jpg	1	37607 3 37858 8 38108 14 38359 20 38610 25 388
3	000f6bf48.jpg	4	131973 1 132228 4 132483 6 132738 8 132993 11
4	0014fce06.jpg	3	229501 11 229741 33 229981 55 230221 77 230468
7090	ffcf72ecf.jpg	3	121911 34 122167 101 122422 169 122678 203 122
7091	fff02e9c5.jpg	3	207523 3 207777 9 208030 15 208283 22 208537 2
7092	fffe98443.jpg	3	105929 5 106177 14 106424 24 106672 33 106923
7093	ffff4eaa8.jpg	3	16899 7 17155 20 17411 34 17667 47 17923 60 18
7094	ffffd67df.jpg	3	30931 43 31103 127 31275 211 31489 253 31745 2
7095 rows × 3 columns			
<pre>data=dataset.values[:7095,0:2]#5000·image·for·train print(data.shape) data</pre>			
<pre>(7095, 2) array([['0002cc93b.jpg', 1], ['0007a71bf.jpg', 3], ['000a4bcdd.jpg', 1],</pre>			

['fffe98443.jpg', 3],

```
['ffff4eaa8.jpg', 3],
            ['ffffd67df.jpg', 3]], dtype=object)
#code for taking class 2 only
i=0
j=0
k=0
democlasses=[]
demoimage=[]
while(i!=245):
 if(data[j][1]==2):
    democlasses.append(data[j][1])
    demoimage.append(data[j][0])
    i+=1
   j+=1
  else:
    j+=1
#code for taking class 1 only
i=0
j=0
while(i!=245):
 if(data[j][1]==1):
    democlasses.append(data[j][1])
    demoimage.append(data[j][0])
    i+=1
   j+=1
  else:
    j+=1
#code for taking class 3 only
i=0
j=0
while(i!=245):
 if(data[j][1]==3):
    democlasses.append(data[j][1])
```

```
demoimage.append(data[i][0])
    i+=1
   j+=1
  else:
    j+=1
#code for taking class 4 only
i=0
j=0
while(i!=245):
 if(data[j][1]==4):
    democlasses.append(data[j][1])
    demoimage.append(data[j][0])
    i+=1
   j+=1
  else:
    j+=1
#democlasses = np.array(democlasses)
print(len(demoimage))
print(type(democlasses))
print(len(democlasses))
     980
     <class 'list'>
     980
image=[]
classes=[]
for i in range(980):
 img=cv2.imread(data[i][0])#read 5000 setof image
 img2=cv2.cvtColor(img,cv2.COLOR BGR2GRAY)
  image.append(img2)#append all the image in imge
  classes.append(data[i][1])#append all the class in classes
#px.imshow(img2,binary_string=True)
```

```
print(type(image))
print(type(classes))
image=np.array(image)
classes=np.array(classes)
print(type(image))
print(type(classes))
image
     <class 'list'>
     <class 'list'>
     <class 'numpy.ndarray'>
     <class 'numpy.ndarray'>
     array([[[ 70, 70, 68, ..., 48, 48, 50],
            [ 66, 68, 68, ..., 48, 49, 51],
            [61, 64, 65, ..., 49, 51, 54],
            . . . ,
            [155, 133, 131, ..., 51, 51,
                                          50],
            [160, 111, 100, ..., 55, 54,
                                          48],
            [155, 114, 98, ..., 58, 58, 50]],
           [[ 47, 49, 49, ..., 65, 67, 63],
            [49, 51, 52, ..., 64, 66, 67],
            [49, 51, 51, \ldots, 61, 62, 67],
            . . . ,
            [106, 109, 100, ..., 98, 86, 85],
            [103, 110, 106, ..., 86, 85, 85],
            [103, 111, 107, \ldots, 83, 90, 90],
           [[52, 51, 51, \ldots, 45, 45, 44],
            [53, 50, 49, ..., 48, 48, 47],
            [54, 51, 50, ..., 47, 47, 47],
            . . . ,
            [ 77, 78, 78, ..., 76, 75, 79],
            [72, 79, 78, ..., 76, 75, 78],
            [ 69, 79, 78, ..., 74, 74, 78]],
           . . . ,
           [[ 62, 69, 64, ..., 59, 57, 56],
            [69, 68, 59, ..., 58, 58, 58],
```

```
[ 68, 69, 63, ..., 55, 54, 56],
            . . . ,
           [72, 75, 78, ..., 68, 69, 68],
            [ 70, 71, 75, ..., 66, 65,
                                         63],
            [ 74, 71, 71, ..., 65, 65,
                                         64]],
           [[ 51, 53, 54, ..., 0,
                                          0],
           [ 52, 53, 53, ..., 0, 0,
                                          0],
           [51, 52, 52, ...,
                                          0],
            . . . ,
            [ 62,
                                          1],
                  62, 62, ..., 1,
                               1,
            [ 60, 59, 56, ...,
                                    1,
                                          1],
           [ 58, 59, 58, ..., 1,
                                         1]],
           [[ 46, 46, 47, ..., 50, 49, 44],
           [50, 50, 50, ..., 47, 49, 48],
           [49, 49, 50, ..., 46, 47, 48],
            . . . ,
            [106, 110, 112, ..., 113, 116, 109],
            [108, 112, 116, ..., 115, 120, 110],
            [105, 108, 116, ..., 114, 119, 109]]], dtype=uint8)
plt.imshow(image[0])
print(image[0])
    [ 70 70 68 ... 48 48
     [ 66 68 68 ... 48 49
                             51]
     [ 61 64 65 ... 49 51 54]
     [155 133 131 ... 51
                             50]
     [160 111 100 ... 55 54
                             48]
     [155 114 98 ... 58 58 50]]
```

#model training task

0

200

400

600

. . .

0 -

200

1000

1200 1400

800

```
#split into validation and train
from sklearn.model selection import train test split
train x,test x,train y,test y=train test split(image,classes,test size=0.2,random state=13)
print(train x.shape,train y.shape)
     (784, 256, 1600) (784,)
print(test x.shape,test y.shape)
     (196, 256, 1600) (196,)
classes=np.unique(train y)
nclasses=len(classes)
print(classes)
print(nclasses)
     [1 2 3 4]
classes=np.unique(test y)
nclasses=len(classes)
print(classes)
print(nclasses)
     [1 2 3 4]
#reshape image
train x=train x.reshape(-1,256,1600,1)
test x=test x.reshape(-1,256,1600,1)
```

```
print(train x.shape,train y.shape)
print(test x.shape,test y.shape)
     (784, 256, 1600, 1) (784,)
     (196, 256, 1600, 1) (196,)
train y.shape[0]
     784
#converting value 0-1
#type convertion to avoid integer
train x=train x.astype('float32')
test x=test x.astype('float32')
train x=train x/255
test x=test x/255
train_x
             [[0.30002/40],
              [0.3529412],
              [0.34509805],
              [0.02352941],
              [0.02352941],
              [0.02352941]]],
            [[[0.00392157],
              [0.00392157],
              [0.00392157],
              . . . ,
              [0.2509804],
              [0.24313726],
              [0.23529412]],
             [[0.00392157],
```

```
[0.00392157],
 [0.00392157],
 [0.23921569],
 [0.23921569],
 [0.23921569]],
[[0.00392157],
[0.00392157],
[0.00392157],
 . . . ,
 [0.23921569],
 [0.23921569],
 [0.24313726]],
. . . ,
[[0.00392157],
[0.00392157],
[0.00392157],
 . . . ,
 [0.28627452],
 [0.2901961],
 [0.29803923]],
[[0.00392157],
[0.00392157],
 [0.00392157],
 . . . ,
 [0.28627452],
 [0.28627452],
 [0.2901961]],
[[0.00392157],
[0.00392157],
 [0.00392157],
 . . . ,
 [0.29411766],
 [0.29411766],
 [0.29411766]]]], dtype=float32)
```

```
train one hot=to categorical(train y)
test one hot=to categorical(test y)
print(train one hot[777])
print(train one hot)
     [0. 0. 0. 0. 1.]
     [[0. 0. 0. 0. 1.]
      [0. 0. 0. 0. 1.]
      [0. 0. 0. 1. 0.]
      . . .
      [0. 0. 0. 1. 0.]
      [0. 0. 0. 1. 0.]
      [0. 0. 0. 1. 0.]]
train y one hot = []
#train y one hot = np.append(train y one hot, np.array([[11, 21, 31, 41]]), axis=0)
print(train y one hot)
#train_y_one_hot=np.array(train y one hot)
test y one hot=[]
#test y one hot=np.array(test y one hot)
     []
for i in range(0,784):
 train=np.delete(train one hot[i],0)
 train y one hot.append(train)
 #train y one hot = np.append(train y one hot, train, axis=0)
  #print(train)
for i in range(0,196):
 test=np.delete(test one hot[i],0)
 test y one hot.append(test)
  #train y one hot = np.append(train y one hot, train, axis=0)
```

#print(train)

```
train y one hot
```

```
[array([0., 0., 0., 1.], dtype=float32),
array([0., 0., 0., 1.], dtype=float32),
array([0., 0., 1., 0.], dtype=float32),
array([1., 0., 0., 0.], dtype=float32),
array([0., 0., 1., 0.], dtype=float32),
array([0., 0., 1., 0.], dtype=float32),
array([0., 0., 1., 0.], dtype=float32),
array([0., 0., 0., 1.], dtype=float32),
array([0., 0., 1., 0.], dtype=float32),
array([1., 0., 0., 0.], dtype=float32),
array([0., 0., 1., 0.], dtype=float32),
array([0., 1., 0., 0.], dtype=float32),
array([0., 0., 1., 0.], dtype=float32),
array([0., 0., 0., 1.], dtype=float32),
array([1., 0., 0., 0.], dtype=float32),
array([0., 0., 0., 1.], dtype=float32),
array([0., 0., 0., 1.], dtype=float32),
array([0., 0., 1., 0.], dtype=float32).
array([0., 0., 0., 1.], dtype=float32),
array([0., 0., 1., 0.], dtype=float32),
```

```
array([0., 0., 1., 0.], dtype=float32),
      array([0., 0., 0., 1.], dtype=float32),
      array([1., 0., 0., 0.], dtype=float32),
      array([0., 1., 0., 0.], dtype=float32),
      array([1., 0., 0., 0.], dtype=float32),
      array([0., 0., 1., 0.], dtype=float32),
      array([1., 0., 0., 0.], dtype=float32),
      array([0., 0., 1., 0.], dtype=float32),
      array([0., 0., 0., 1.], dtype=float32),
      array([0., 0., 1., 0.], dtype=float32),
train y one hot=np.array(train y one hot)
test y one hot=np.array(test y one hot)
print(train v one hot)
print(type(train y one hot))
     [[0. 0. 0. 1.]
      [0. 0. 0. 1.]
      [0. 0. 1. 0.]
      . . .
      [0. 0. 1. 0.]
      [0. 0. 1. 0.]
```

```
[0. 0. 1. 0.]]
     /class 'numny ndannay's
print(train y one hot[1])
print(type(train y one hot))
     [0. 0. 0. 1.]
     <class 'numpy.ndarray'>
test y one hot
     array([[1., 0., 0., 0.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
            [1., 0., 0., 0.],
            [0., 0., 1., 0.],
            [1., 0., 0., 0.],
            [0., 0., 1., 0.],
            [0., 0., 0., 1.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
            [0., 0., 0., 1.],
            [0., 0., 1., 0.],
            [0., 1., 0., 0.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
            [1., 0., 0., 0.],
            [1., 0., 0., 0.],
            [0., 0., 1., 0.],
            [0., 0., 0., 1.],
            [1., 0., 0., 0.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
```

```
[1., 0., 0., 0.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
            [1., 0., 0., 0.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
            [1., 0., 0., 0.],
            [0., 1., 0., 0.],
            [1., 0., 0., 0.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
            [0., 0., 0., 1.],
            [0., 0., 0., 1.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
            [1., 0., 0., 0.],
            [0., 0., 1., 0.],
            [0., 0., 1., 0.],
            [0., 0., 0., 1.],
classes=np.unique(test y one hot)
nclasses=len(classes)
print(classes)
print(nclasses)
     [0. 1.]
test_y_one_hot[1]
```

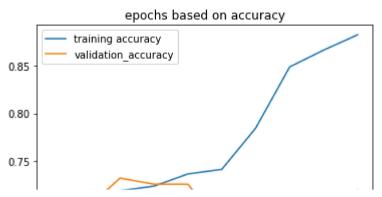
https://colab.research.google.com/drive/1ORS6exyUurqoXq7gtg_vSi76FNmwNGpq#scrollTo=OERNklzabzql&printMode=true

```
array([0., 0., 1., 0.], dtype=float32)
train y one hot[1]
     array([0., 0., 0., 1.], dtype=float32)
#model training task
#split into validation and train
from sklearn.model selection import train test split
train x, valid x, train label, valid label=train test split(train x, train y one hot, test size=0.2, random state=13)
train x.shape, valid x.shape, train label.shape, valid label.shape
     ((627, 256, 1600, 1), (157, 256, 1600, 1), (627, 4), (157, 4))
batch size=10#there is total 48000 image from that we are taking 64 student batch
epochs=20
num classes=4
#declaration of Sequential model
model=tf.keras.Sequential()
#1 hidden layer
model.add(tf.keras.layers.Conv2D(32,(3,3),activation="linear",padding="same"))#valid->not any padding,same=same size
model.add(tf.keras.layers.LeakyReLU(alpha=0.1))#alpha is slop of line in nagative part
model.add(tf.keras.layers.MaxPooling2D(pool size=(2,2),padding="same"))
#2 hidden layer
model.add(tf.keras.layers.Conv2D(64,(3,3),activation="linear",padding="same"))#valid->not any padding,same=same size
model.add(tf.keras.layers.LeakyReLU(alpha=0.1))#alpha is slop of line in nagative part
model.add(tf.keras.layers.MaxPooling2D(pool size=(2,2),padding="same"))
```

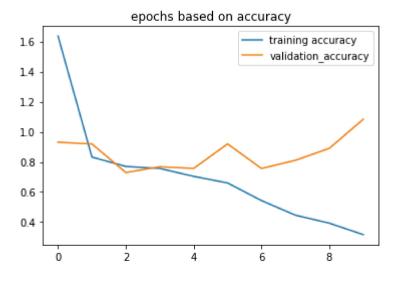
#3 hidden layer

```
model.add(tf.keras.layers.Conv2D(128,(3,3),activation="linear",padding="same"))#valid->not any padding,same=same size
model.add(tf.keras.layers.LeakyReLU(alpha=0.1))#alpha is slop of line in nagative part
model.add(tf.keras.layers.MaxPooling2D(pool size=(2,2),padding="same"))
model.add(tf.keras.layers.Flatten())
model.add(tf.keras.layers.Dense(128,activation="linear"))
model.add(tf.keras.layers.LeakyReLU(alpha=0.1))
#output final layer
model.add(tf.keras.layers.Dense(num classes,activation='softmax'))#softmax because we want probabbility of all 10 class
model.compile(loss=tf.keras.losses.categorical crossentropy.optimizer=tf.keras.optimizers.Adam(),metrics=['accuracy'])
print(valid x.shape)
print(valid label.shape)
    (157, 256, 1600, 1)
    (157, 4)
model train=model.fit(train x,train label,batch size=10,epochs=10,verbose=1,validation data=(valid x,valid label))#verbose·is·show·pr
    Epoch 1/10
    63/63 [============== ] - 37s 405ms/step - loss: 1.6357 - accuracy: 0.6858 - val loss: 0.9312 - val accuracy: 0.
    Epoch 2/10
    Epoch 3/10
    63/63 [============== ] - 25s 392ms/step - loss: 0.7699 - accuracy: 0.7193 - val loss: 0.7294 - val accuracy: 0.
    Epoch 4/10
    63/63 [============= ] - 24s 379ms/step - loss: 0.7567 - accuracy: 0.7241 - val loss: 0.7680 - val accuracy: 0.
    Epoch 5/10
    63/63 [============= ] - 24s 379ms/step - loss: 0.7043 - accuracy: 0.7368 - val loss: 0.7567 - val accuracy: 0.
    Epoch 6/10
    63/63 [============= ] - 24s 381ms/step - loss: 0.6603 - accuracy: 0.7416 - val loss: 0.9199 - val accuracy: 0.
```

```
Epoch 7/10
     63/63 [============= ] - 24s 379ms/step - loss: 0.5431 - accuracy: 0.7847 - val loss: 0.7564 - val accuracy: 0.
     Epoch 8/10
     63/63 [============= ] - 24s 380ms/step - loss: 0.4463 - accuracy: 0.8485 - val loss: 0.8107 - val accuracy: 0.
     Epoch 9/10
     63/63 [============= ] - 24s 379ms/step - loss: 0.3932 - accuracy: 0.8660 - val loss: 0.8904 - val accuracy: 0.
     Epoch 10/10
     63/63 [============= ] - 24s 380ms/step - loss: 0.3169 - accuracy: 0.8820 - val loss: 1.0832 - val accuracy: 0.
testing evaluation=model.evaluate(test x,test y one hot)
     7/7 [============== ] - 4s 350ms/step - loss: 1.1085 - accuracy: 0.6786
testing evaluation #loss,accuracy
     [1.1085442304611206, 0.6785714030265808]
accuracy=model train.history['accuracy']
val accuracy=model train.history['val accuracy']
loss=model train.history['loss']
val loss=model train.history['val loss']
epochs=range(len(accuracy))
plt.plot(epochs,accuracy,label='training accuracy')
plt.plot(epochs, val accuracy, label='validation accuracy')
plt.title('epochs based on accuracy')
plt.legend()
plt.show()
```



plt.plot(epochs,loss,label='training accuracy')
plt.plot(epochs,val_loss,label='validation_accuracy')
plt.title('epochs based on accuracy')
plt.legend()
plt.show()



#based on graph we can said that over model is overfitting #so we have to do regularization

#declaration of Sequential model
regmodel=tf.keras.Sequential()

```
#1 hidden layer
regmodel.add(tf.keras.layers.Conv2D(32,(3,3),activation="linear",padding="same"))#valid->not any padding,same=same size
regmodel.add(tf.keras.layers.LeakyReLU(alpha=0.1))#alpha is slop of line in nagative part
regmodel.add(tf.keras.layers.MaxPooling2D(pool size=(2,2),padding="same"))
regmodel.add(tf.keras.layers.Dropout(0.25))
#2 hidden layer
regmodel.add(tf.keras.layers.Conv2D(64,(3,3),activation="linear",padding="same"))#valid->not any padding,same=same size
regmodel.add(tf.keras.layers.LeakyReLU(alpha=0.1))#alpha is slop of line in nagative part
regmodel.add(tf.keras.layers.MaxPooling2D(pool size=(2,2),padding="same"))
regmodel.add(tf.keras.layers.Dropout(0.25))
#3 hidden layer
regmodel.add(tf.keras.layers.Conv2D(128,(3,3),activation="linear",padding="same"))#valid->not any padding,same=same size
regmodel.add(tf.keras.layers.LeakyReLU(alpha=0.1))#alpha is slop of line in nagative part
regmodel.add(tf.keras.layers.MaxPooling2D(pool_size=(2,2),padding="same"))
regmodel.add(tf.keras.layers.Dropout(0.40))
regmodel.add(tf.keras.layers.Flatten())
regmodel.add(tf.keras.layers.Dense(128,activation="linear"))
regmodel.add(tf.keras.layers.LeakyReLU(alpha=0.1))
regmodel.add(tf.keras.layers.Dropout(0.3))
#output final layer
regmodel.add(tf.keras.layers.Dense(num classes,activation='softmax'))#softmax because we want probabbility of all 10 class
regmodel.compile(loss=tf.keras.losses.categorical crossentropy,optimizer=tf.keras.optimizers.Adam(),metrics=['accuracy'])
reg model train=regmodel.fit(train x,train label,batch size=10,epochs=10,verbose=1,validation data=(valid x,valid label))#verbose⋅is⋅
     Epoch 1/10
     63/63 [============= ] - 27s 404ms/step - loss: 4.5404 - accuracy: 0.6459 - val loss: 1.6078 - val accuracy: 0.
     Epoch 2/10
     63/63 [============= ] - 25s 401ms/step - loss: 0.9042 - accuracy: 0.7193 - val loss: 1.7586 - val accuracy: 0.
     Epoch 3/10
```

```
63/63 [============= ] - 25s 405ms/step - loss: 0.8485 - accuracy: 0.7209 - val loss: 1.7532 - val accuracy: 0.
  Epoch 4/10
  Epoch 5/10
  Epoch 6/10
  Epoch 7/10
  63/63 [============= ] - 25s 403ms/step - loss: 0.7783 - accuracy: 0.7209 - val loss: 1.1269 - val accuracy: 0.
  Epoch 8/10
  Epoch 9/10
  Epoch 10/10
  testing evaluation rg=regmodel.evaluate(test x,test y one hot)
  7/7 [============== ] - 2s 260ms/step - loss: 0.8574 - accuracy: 0.6735
testing evaluation rg #loss,accuracy
  [0.8574106097221375, 0.6734693646430969]
reg model train.history
  {'accuracy': [0.6459330320358276,
   0.719298243522644,
   0.720893144607544,
   0.7177033424377441,
   0.7129186391830444,
   0.7256778478622437,
   0.720893144607544,
```

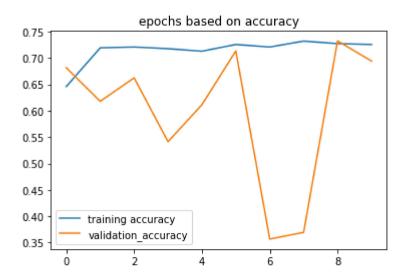
https://colab.research.google.com/drive/1ORS6exyUurqoXq7gtg vSi76FNmwNGpq#scrollTo=OERNklzabzql&printMode=true

0.7320573925971985, 0.7272727489471436, 0.7256778478622437],

'loss': [4.540424346923828,

```
0.9041980504989624.
       0.8485251665115356,
       0.8329122066497803,
       0.8432847857475281,
       0.8041791319847107,
       0.7783027291297913,
       0.802110493183136,
       0.7607107758522034,
       0.7575175762176514],
      'val accuracy': [0.6815286874771118,
       0.6178343892097473.
       0.662420392036438,
       0.5414012670516968,
       0.6114649772644043,
       0.7133758068084717,
       0.35668790340423584,
       0.36942675709724426,
       0.7324841022491455,
       0.6942675113677979],
      'val loss': [1.607753038406372,
       1.7585843801498413,
       1.7532382011413574,
       1.245573878288269,
       1.8855507373809814,
       0.794147789478302,
       1.1268559694290161,
       1.0811797380447388,
       0.7879035472869873,
       0.8270518183708191]}
accuracy reg=reg model train.history['accuracy']
val accuracy reg=reg model train.history['val accuracy']
loss reg=reg model train.history['loss']
val loss reg=reg model train.history['val loss']
epochs reg=range(len(accuracy reg))
plt.plot(epochs reg,accuracy reg,label='training accuracy')
plt.plot(epochs_reg,val_accuracy_reg,label='validation_accuracy')
```

```
plt.title('epochs based on accuracy')
plt.legend()
plt.show()
```



```
plt.plot(epochs_reg,loss_reg,label='training.accuracy')
plt.plot(epochs_reg,val_loss_reg,label='validation_accuracy')
plt.title('epochs.based.on.accuracy')
plt.legend()
plt.show()
```

https://colab.research.google.com/drive/1ORS6exyUurqoXq7gtg_vSi76FNmwNGpq#scrollTo=OERNklzabzql&printMode=true

