# POC - Proof of Concept of Transfer Learning in ANN and CNN

```
# Importing some libraries
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
from sklearn.metrics import confusion_matrix, accuracy_score,precision_score
```

## MNIST DATASET

```
mnist = tf.keras.datasets.mnist
```

```
# segregation of Training and testing dataset
(X_train_full, y_train_full), (X_test, y_test) = mnist.load_data()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist_
11493376/11490434 [==============================] - 0s 0us/step
11501568/11490434 [==============================] - 0s 0us/step
```

```
X_train_full.shape  # training dataset
```

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

```
X_train_full[0].shape # shape of one single image
```

```
(28, 28)
```

```
y_train_full.shape  # shape of label or output dataset
```

```
(60000,)
```

```
y_train_full[0]    # output value corresponding the image data
```

```
5
```

```
X_test.shape    # shape of testing dataset
```

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

```
y_test.shape
```

```
(10000,)
```

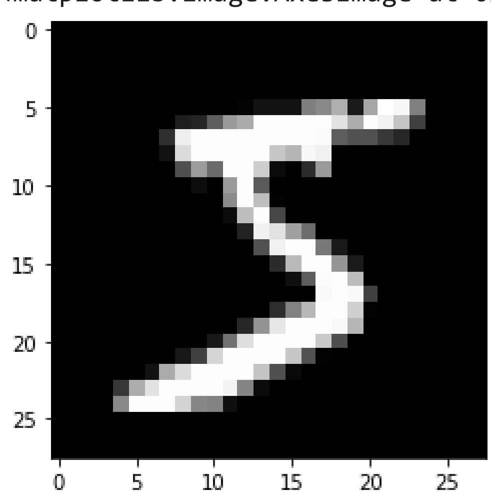
```
img = X_train_full[0]  # first image of training data
img
```

```
          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, 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]], dtype=uint8)
```

```
plt.imshow(img, cmap="gray")      # showing image
```

```
<matplotlib.image.AxesImage at 0x7f77e0df5510>
```

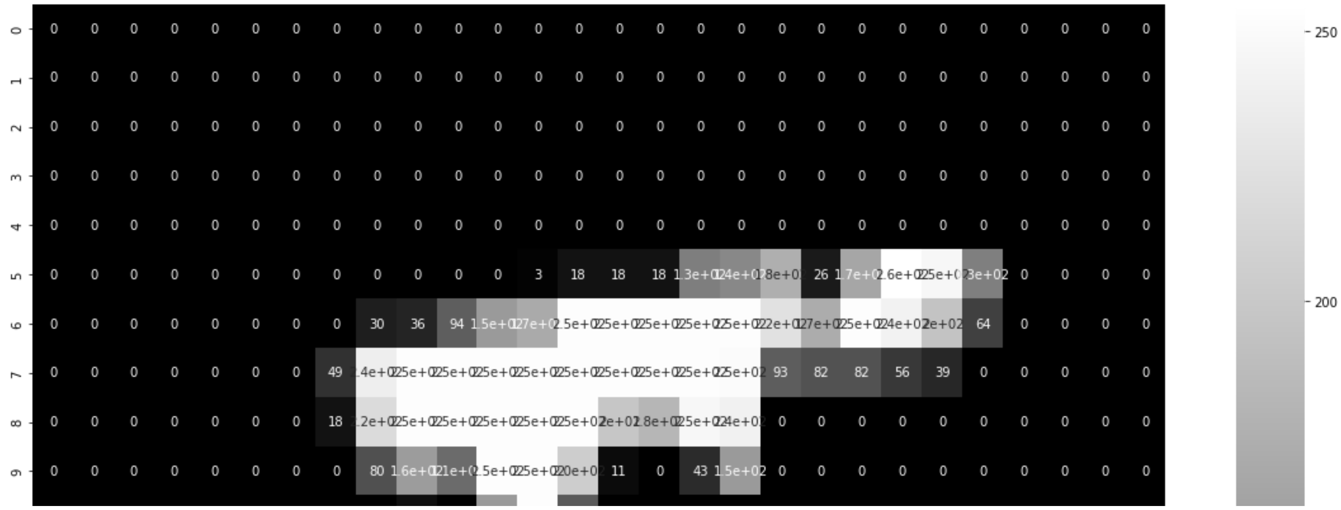



```
label = y_train_full[0]   # output label of the above shown image in y_train data
label
```

```
5
```

```
# plotting image with each pixel value in it
plt.figure(figsize=(20,20))    # setting plt figure size
sns.heatmap(img, annot=True, cmap="gray")    # using sns.heatmap, we can use img/255 to norma
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f77e2705c90>
```



```
print(1e+1, 1e+2, 1e+4, 1.5e+1, 1.5e+2)
```

```
10.0 100.0 10000.0 15.0 150.0
```

```
1.5e+2  # means 1.5 * (10**2)
```

```
150.0
```

1. *0 -> 255* => More computation time, and Search space is large for finding solution.
2. *0 -> 1* => Less computation time, and Search space is small for finding solution.

```
# segregating validation and training dataset

X_valid, X_train = X_train_full[:5000]/255, X_train_full[5000:]/255  # why divide by 255 reas
y_valid, y_train = y_train_full[:5000], y_train_full[5000:]

X_test = X_test/255
```

```
np.unique(y_train)     # different types of labels we have
```

```
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9], dtype=uint8)
```

```
len(np.unique(y_train))  # 10 different types of labels we have
```

```
10
```

```
CLASSES = len(np.unique(y_train))
CLASSES
```

```
10
```

# ANN - Artificial Neural Network Model

```
# Defining ANN Layers
LAYERS = [
    tf.keras.layers.Flatten(input_shape=(28, 28), name="inputLayer"), # 28*28 = 784 total num
    tf.keras.layers.Dense(300, activation="relu", name="hiddenLayer01"), # 300 layers
    tf.keras.layers.Dense(100, activation="relu", name="hiddenLayer02"), # 100 layers
    tf.keras.layers.Dense(CLASSES, activation="softmax", name="outputLayer"), # 10 output lab
]
```

```
ANN_model_clf = tf.keras.models.Sequential(LAYERS)  # creating model
```

```
ANN_model_clf.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 inputLayer (Flatten)        (None, 784)               0

 hiddenLayer01 (Dense)       (None, 300)               235500

 hiddenLayer02 (Dense)       (None, 100)               30100

 outputLayer (Dense)         (None, 10)                1010

=================================================================
Total params: 266,610
Trainable params: 266,610
Non-trainable params: 0
_________________________________________________________________
```

```
# Total trainable parameters at hidden layer01
784*300 + 300 # 784(input) * 300(weights of 300 neuron at hiddenLayer01) + 300 (biases)
```

```
235500
```

```
# Total trainable parameters at hidden layer02
300*100 + 100  #300(output Edges from 300 neuron at hiddenLayer01 ) * 100(weights of 100 neur
```

```
30100
```

```
# Total trainable parameters at output layer
100 * 10 + 10   # 100(100 neuron at hiddenLayer02 os 100 output edges)*10(neuron at output la
```

```
1010
```

```
# Total Number of parameters in ANN
235500 + 30100 + 1010
```

```
266610
```

```
# Compiling model
LOSS_FUNCTION = "sparse_categorical_crossentropy"
OPTIMIZERS = "SGD"
METRICS = ["accuracy"]

ANN_model_clf.compile(loss=LOSS_FUNCTION, optimizer=OPTIMIZERS, metrics=METRICS)
```

```
# Training the ANN model
EPOCHS = 30

VALIDATION = (X_valid, y_valid)

history = ANN_model_clf.fit(
    X_train,
    y_train,
    epochs = EPOCHS,
    batch_size=32,
    validation_data = VALIDATION
)
```

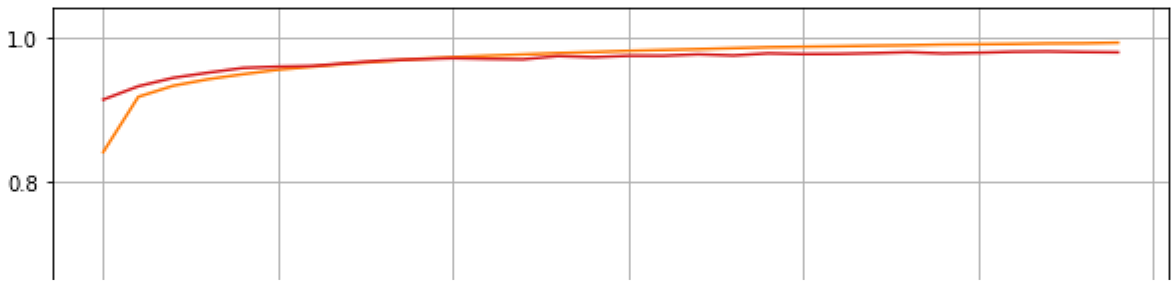
```
Epoch 2/30
1719/1719 [==============================] - 5s 3ms/step - loss: 0.2870 - accuracy: 0
Epoch 3/30
1719/1719 [==============================] - 5s 3ms/step - loss: 0.2358 - accuracy: 0
Epoch 4/30
1719/1719 [==============================] - 5s 3ms/step - loss: 0.2015 - accuracy: 0
Epoch 5/30
1719/1719 [==============================] - 4s 3ms/step - loss: 0.1761 - accuracy: 0
Epoch 6/30
1719/1719 [==============================] - 4s 3ms/step - loss: 0.1555 - accuracy: 0
Epoch 7/30
1719/1719 [==============================] - 5s 3ms/step - loss: 0.1389 - accuracy: 0
Epoch 8/30
1719/1719 [==============================] - 5s 3ms/step - loss: 0.1256 - accuracy: 0
Epoch 9/30
1719/1719 [==============================] - 4s 3ms/step - loss: 0.1138 - accuracy: 0
Epoch 10/30
1719/1719 [==============================] - 4s 3ms/step - loss: 0.1039 - accuracy: 0
Epoch 11/30
1719/1719 [==============================] - 5s 3ms/step - loss: 0.0955 - accuracy: 0
Epoch 12/30
1719/1719 [==============================] - 4s 3ms/step - loss: 0.0883 - accuracy: 0
Epoch 13/30
1719/1719 [==============================] - 4s 3ms/step - loss: 0.0815 - accuracy: 0
Epoch 14/30
1719/1719 [==============================] - 5s 3ms/step - loss: 0.0756 - accuracy: 0
Epoch 15/30
1719/1719 [==============================] - 5s 3ms/step - loss: 0.0704 - accuracy: 0
```

```
Epoch 16/30
1719/1719 [==============================] - 5s 3ms/step - loss: 0.0654 - accuracy: 0
Epoch 17/30
1719/1719 [==============================] - 5s 3ms/step - loss: 0.0610 - accuracy: 0
Epoch 18/30
1719/1719 [==============================] - 5s 3ms/step - loss: 0.0572 - accuracy: 0
Epoch 19/30
1719/1719 [==============================] - 5s 3ms/step - loss: 0.0536 - accuracy: 0
Epoch 20/30
1719/1719 [==============================] - 5s 3ms/step - loss: 0.0502 - accuracy: 0
Epoch 21/30
1719/1719 [==============================] - 5s 3ms/step - loss: 0.0472 - accuracy: 0
Epoch 22/30
1719/1719 [==============================] - 4s 3ms/step - loss: 0.0443 - accuracy: 0
Epoch 23/30
1719/1719 [==============================] - 4s 3ms/step - loss: 0.0417 - accuracy: 0
Epoch 24/30
1719/1719 [==============================] - 4s 3ms/step - loss: 0.0393 - accuracy: 0
Epoch 25/30
1719/1719 [==============================] - 4s 3ms/step - loss: 0.0371 - accuracy: 0
Epoch 26/30
1719/1719 [==============================] - 4s 3ms/step - loss: 0.0348 - accuracy: 0
Epoch 27/30
1719/1719 [==============================] - 5s 3ms/step - loss: 0.0329 - accuracy: 0
Epoch 28/30
1719/1719 [==============================] - 5s 3ms/step - loss: 0.0310 - accuracy: 0
Epoch 29/30
1719/1719 [==============================] - 5s 3ms/step - loss: 0.0292 - accuracy: 0
Epoch 30/30
```

```
pd.DataFrame(history.history)
```

| | loss | accuracy | val_loss | val_accuracy |
|---|---|---|---|---|
| **0** | 0.602583 | 0.841127 | 0.306945 | 0.9142 |
| **1** | 0.287045 | 0.918036 | 0.238777 | 0.9328 |
| **2** | 0.235803 | 0.933545 | 0.200872 | 0.9446 |
| **3** | 0.201510 | 0.942655 | 0.175132 | 0.9518 |
| **4** | 0.176078 | 0.949709 | 0.160087 | 0.9584 |
| **5** | 0.155475 | 0.955927 | 0.144078 | 0.9602 |
| **6** | 0.138908 | 0.960218 | 0.137016 | 0.9612 |
| **7** | 0.125565 | 0.964418 | 0.124601 | 0.9652 |
| **8** | 0.113823 | 0.967545 | 0.117422 | 0.9688 |
| **9** | 0.103897 | 0.971055 | 0.109604 | 0.9706 |
| **10** | 0.095522 | 0.973327 | 0.100909 | 0.9720 |
| **11** | 0.088304 | 0.975382 | 0.101532 | 0.9710 |
| **12** | 0.081504 | 0.977236 | 0.098050 | 0.9704 |
| **13** | 0.075611 | 0.979091 | 0.089285 | 0.9750 |
| **14** | 0.070446 | 0.980545 | 0.088075 | 0.9734 |
| **15** | 0.065376 | 0.982255 | 0.083710 | 0.9754 |
| **16** | 0.061048 | 0.983455 | 0.083467 | 0.9754 |
| **17** | 0.057232 | 0.984655 | 0.080478 | 0.9774 |

```
# plotting datafram
pd.DataFrame(history.history).plot(figsize=(10,7))
plt.grid(True)
plt.show()
```




```
# Evaluating the model for accuracy
ANN_model_clf.evaluate(X_test, y_test)
```

```
313/313 [==============================] - 1s 2ms/step - loss: 0.0704 - accuracy: 0.979
[0.07042375952005386, 0.9790999889373779]
```

```
ANN_model_clf.save("mnist_full.h5")
```

```
# Let's test how model is able to predict the output label from the input image data
X_new = X_test[:3]    # extracting 3 images data from test data

y_prob = ANN_model_clf.predict(X_new) # prediction of output label probabilites
y_prob.round(3)  # show probability of each output label
```

```
array([[0.   , 0.   , 0.   , 0.   , 0.   , 0.   , 0.   , 1.   , 0.   ,
        0.   ],
       [0.   , 0.   , 1.   , 0.   , 0.   , 0.   , 0.   , 0.   , 0.   ,
        0.   ],
       [0.   , 0.997, 0.   , 0.   , 0.   , 0.   , 0.   , 0.002, 0.   ,
        0.   ]], dtype=float32)
```

```
X_new.shape
```

```
(3, 28, 28)
```

```
y_prob.shape
```

```
(3, 10)
```

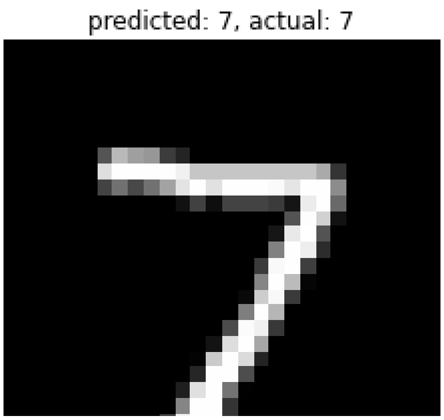
```
plt.imshow(X_new[0], cmap="gray") # image at 0th index o
```

```
<matplotlib.image.AxesImage at 0x7f77d0076190>
```


```
Y_pred = np.argmax(y_prob, axis=-1)
Y_pred[0]   # Predicted output label
```

```
7
```

```
# Testing the model with some actual and prediction
for img_array, pred, actual in zip(X_new, Y_pred, y_test[:3]):
    plt.imshow(img_array, cmap="gray")
    plt.title(f"predicted: {pred}, actual: {actual}")
    plt.axis("off")
    plt.show()
    print("--"*30)
```




**OBSERVATION:- Model is able to predict the number associated with image**

```
------------------------------------------------------------
```

```
# Make Prediction of X_test dataset
y_prob = ANN_model_clf.predict(X_test)
y_prob.shape
```

```
(10000, 10)
```

```
y_pred = np.argmax(y_prob,axis=-1)
y_pred
```

```
array([7, 2, 1, ..., 4, 5, 6])
```

```
# confusion matrix
confusion_matrix(y_test,y_pred)
```

```
array([[ 968,    0,    1,    2,    2,    2,    0,    1,    3,    1],
       [   0, 1124,    2,    1,    0,    2,    2,    1,    3,    0],
       [   4,    2, 1008,    5,    2,    0,    0,    7,    4,    0],
       [   0,    0,    4,  993,    0,    3,    0,    3,    5,    2],
       [   0,    0,    4,    1,  965,    0,    1,    2,    1,    8],
       [   2,    0,    0,    6,    2,  874,    4,    1,    2,    1],
       [   6,    3,    0,    1,    7,    8,  929,    0,    4,    0],
       [   0,    4,    9,    3,    0,    1,    0,  999,    4,    8],
       [   3,    0,    3,    6,    3,    3,    2,    2,  950,    2],
       [   2,    2,    1,    7,    9,    1,    0,    2,    4,  981]])
```

```
# Accuracy score using sklearn
accuracy_score(y_test,y_pred)
```

```
0.9791
```

```
# Precision
precision_score(y_test,y_pred,average='weighted')
```

```
0.9791474880189343
```

```
y_train.shape
```

```
(55000,)
```

```
y_train[1]
```

```
3
```

### y_train -

| data_points | label |
|---|---|
| 0 | 7 |
| 1 | 3 |

### X_train

| data_points | data |
|---|---|
| 0 | (28, 28) |
| 1 | (28, 28) |
| 2 | (28, 28) |
| 3 | (28, 28) |

### data

| data_points | data | label |
|---|---|---|
| 0 | (28, 28) | 7 |
| 1 | (28, 28) | 3 |
| 2 | (28, 28) | |
| 3 | (28, 28) | |

# Transfer learning in ANN

## New problem statement -

Classify handwritten digits into odd and even

```
pretrained_ANN_model = tf.keras.models.load_model("mnist_full.h5")  # loading the above saved
```

```
pretrained_ANN_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 inputLayer (Flatten)        (None, 784)               0
```

```
 hiddenLayer01 (Dense)       (None, 300)               235500

 hiddenLayer02 (Dense)       (None, 100)               30100

 outputLayer (Dense)         (None, 10)                1010

=================================================================
Total params: 266,610
Trainable params: 266,610
Non-trainable params: 0
_________________________________________________________________
```

```
# Checking for Trainable layers
for layer in pretrained_ANN_model.layers:
    print(f"{layer.name}: {layer.trainable}")
```

```
inputLayer: True
hiddenLayer01: True
hiddenLayer02: True
outputLayer: True
```

```
# Setting trainable features of layers
for layer in pretrained_ANN_model.layers[:-1]: # leave the last layer
    layer.trainable = False
```

```
for layer in pretrained_ANN_model.layers:
    print(f"{layer.name}: {layer.trainable}")
```

```
inputLayer: False
hiddenLayer01: False
hiddenLayer02: False
outputLayer: True
```

```
# Extraction of the layers whose Trainable features are disabled now
lower_pretrained_model = pretrained_ANN_model.layers[:-1]
```

```
# Creating new ANN model where output layer have two neurons one for odd and other for even
new_ANN_model = tf.keras.models.Sequential(lower_pretrained_model)
new_ANN_model.add(
    tf.keras.layers.Dense(2, activation="softmax")
)
```

```
new_ANN_model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 inputLayer (Flatten)        (None, 784)               0
```

```
 hiddenLayer01 (Dense)       (None, 300)               235500

 hiddenLayer02 (Dense)       (None, 100)               30100

 dense (Dense)               (None, 2)                 202

=================================================================
Total params: 265,802
Trainable params: 202
Non-trainable params: 265,600
_________________________________________________________________
```

```
# Trainable params at output layer for rest layers this is disabled
100*2 + 2
```

```
202
```

```
# function to update labels
def update_even_odd_labels(labels):
    for idx, label in enumerate(labels):
        labels[idx] = np.where(label%2 == 0, 1, 0) # 1 -> even, 0 -> odd
    return labels
```

```
ex_1 = np.array([1,2,3,4,5])
ex_1
```

```
array([1, 2, 3, 4, 5])
```

```
# showing enurmerate builtin function functionality
for idx, label in enumerate(ex_1):
    # print(idx, label)
    print(ex_1[idx], np.where(label%2 == 0, 1, 0))
```

```
1 0
2 1
3 0
4 1
5 0
```

```
# Updating labels in two classes 0 and 1
y_train_bin, y_test_bin, y_valid_bin = update_even_odd_labels([y_train, y_test, y_valid])
```

```
np.unique(y_train_bin)
```

```
array([0, 1])
```

```
new_ANN_model.compile(loss="sparse_categorical_crossentropy",
```

```
                  optimizer="SGD",
                  metrics=["accuracy"]
                  )


# Training the model
history = new_ANN_model.fit(
    X_train, y_train_bin, epochs=10, validation_data = (X_valid, y_valid_bin)
)
```

```
Epoch 1/10
1719/1719 [==============================] - 5s 3ms/step - loss: 0.1695 - accuracy: 0.93
Epoch 2/10
1719/1719 [==============================] - 4s 2ms/step - loss: 0.1162 - accuracy: 0.96
Epoch 3/10
1719/1719 [==============================] - 4s 2ms/step - loss: 0.1081 - accuracy: 0.96
Epoch 4/10
1719/1719 [==============================] - 4s 2ms/step - loss: 0.1037 - accuracy: 0.96
Epoch 5/10
1719/1719 [==============================] - 4s 2ms/step - loss: 0.1013 - accuracy: 0.96
Epoch 6/10
1719/1719 [==============================] - 4s 2ms/step - loss: 0.0991 - accuracy: 0.96
Epoch 7/10
1719/1719 [==============================] - 4s 2ms/step - loss: 0.0975 - accuracy: 0.96
Epoch 8/10
1719/1719 [==============================] - 4s 2ms/step - loss: 0.0963 - accuracy: 0.96
Epoch 9/10
1719/1719 [==============================] - 4s 3ms/step - loss: 0.0954 - accuracy: 0.96
Epoch 10/10
1719/1719 [==============================] - 4s 2ms/step - loss: 0.0945 - accuracy: 0.96
```

```
new_ANN_model.evaluate(X_test, y_test_bin)
```

```
313/313 [==============================] - 1s 2ms/step - loss: 0.1030 - accuracy: 0.9640
[0.10295837372541428, 0.9639999866485596]
```

```
X_new = X_test[:3]

y_prob = new_ANN_model.predict(X_new)
y_prob.round(3)  # probabilties output label of images X_new
```

```
array([[1.   , 0.   ],
       [0.   , 1.   ],
       [0.984, 0.016]], dtype=float32)
```

```
Y_pred = np.argmax(y_prob, axis=-1)
Y_pred
```

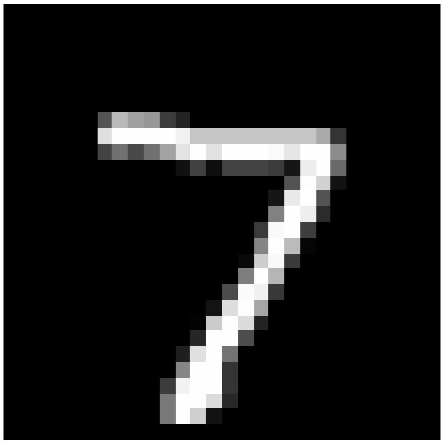
```
array([0, 1, 0])
```

```
y_test_bin[:3]
```

```
array([0, 1, 0])
```

```
# Testing of model for classification of image in even or odd
for img_array, pred, actual in zip(X_new, Y_pred, y_test_bin[:3]):
    if pred == 1:
        pred = "even"
    else:
        pred = "odd"

    if actual == 1:
        actual = "even"
    else:
        actual = "odd"
    plt.imshow(img_array, cmap="gray")
    plt.title(f"predicted: {pred}, actual: {actual}")
    plt.axis("off")
    plt.show()
    print("--"*30)
```




```
------------------------------------------------------------
```

**OBSERVATION:- Model created using Transfer learning technique is able to classify image as odd or even.**

```
# Make Prediction for X_test dataset
y_prob = new_ANN_model.predict(X_test)
y_prob.shape
```

```
(10000, 2)
```

```
y_pred = np.argmax(y_prob,axis=-1)
y_pred
```

```
array([0, 1, 0, ..., 1, 0, 1])
```

```
# confusion matrix
confusion_matrix(y_test_bin,y_pred)
```

```
array([[4901,  173],
       [ 187, 4739]])
```

```
# Accuracy score using sklearn
accuracy_score(y_test_bin,y_pred)
```

```
0.964
```

```
# Precision
precision_score(y_test_bin,y_pred)
```

```
0.9647801302931596
```

OBSERVATION: Accuracy score of the model created using Transfer learning is 0.96

# Train A CNN model on MNIST data

```
X_train[0].shape
```

```
(28, 28)
```

```
X_train[0]
```

```
         0.        , 0.44313725, 0.85882353, 0.99607843, 0.94901961,
         0.89019608, 0.45098039, 0.34901961, 0.12156863, 0.        ,
         0.        , 0.        , 0.        , 0.78431373, 0.99607843,
         0.94509804, 0.16078431, 0.        , 0.        , 0.        ,
         0.        , 0.        , 0.        ],
        [0.        , 0.        , 0.        , 0.        , 0.        ,
         0.        , 0.6627451 , 0.99607843, 0.69019608, 0.24313725,
         0.        , 0.        , 0.        , 0.        , 0.        ,
         0.        , 0.        , 0.18823529, 0.90588235, 0.99607843,
         0.91764706, 0.        , 0.        , 0.        , 0.        ,
         0.        , 0.        , 0.        ],
        [0.        , 0.        , 0.        , 0.        , 0.        ,
         0.        , 0.07058824, 0.48627451, 0.        , 0.        ,
         0.        , 0.        , 0.        , 0.        , 0.        ,
         0.        , 0.        , 0.32941176, 0.99607843, 0.99607843,
         0.65098039, 0.        , 0.        , 0.        , 0.        ,
         0.        , 0.        , 0.        ],
        [0.        , 0.        , 0.        , 0.        , 0.        ,
         0.        , 0.        , 0.        , 0.        , 0.        ,
         0.        , 0.        , 0.        , 0.        , 0.        ,
         0.        , 0.        , 0.54509804, 0.99607843, 0.93333333,
         0.22352941, 0.        , 0.        , 0.        , 0.        ,
         0.        , 0.        , 0.        ],
        [0.        , 0.        , 0.        , 0.        , 0.        ,
         0.        , 0.        , 0.        , 0.        , 0.        ,
         0.        , 0.        , 0.        , 0.        , 0.        ,
         0.        , 0.82352941, 0.98039216, 0.99607843, 0.65882353,
         0.        , 0.        , 0.        , 0.        , 0.        ,
         0.        , 0.        , 0.        ],
        [0.        , 0.        , 0.        , 0.        , 0.        ,
         0.        , 0.        , 0.        , 0.        , 0.        ,
         0.        , 0.        , 0.        , 0.        , 0.        ,
         0.        , 0.94901961, 0.99607843, 0.9372549 , 0.22352941,
         0.        , 0.        , 0.        , 0.        , 0.        ,
         0.        , 0.        , 0.        ],
        [0.        , 0.        , 0.        , 0.        , 0.        ,
         0.        , 0.        , 0.        , 0.        , 0.        ,
         0.        , 0.        , 0.        , 0.        , 0.        ,
         0.34901961, 0.98431373, 0.94509804, 0.3372549 , 0.        ,
         0.        , 0.        , 0.        , 0.        , 0.        ,
```

```
 0.        , 0.        , 0.        ],
[0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        , 0.        , 0.01960784,
 0.80784314, 0.96470588, 0.61568627, 0.        , 0.        ,
 0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        ],
[0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        , 0.        , 0.01568627,
 0.45882353, 0.27058824, 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.        ,
```

```
np.expand_dims(X_train, -1).shape  # showing example of working of np.expand_dims
```

```
(55000, 28, 28, 1)
```

```
np.expand_dims(X_train, -2).shape    # showing example of working of np.expand_dims
```

```
(55000, 28, 1, 28)
```

```
np.expand_dims(X_train, -3).shape      # showing example of working of np.expand_dims
```

```
(55000, 1, 28, 28)
```

```
np.expand_dims(X_train, 1).shape      # showing example of working of np.expand_dims
```

```
(55000, 1, 28, 28)
```

```
np.expand_dims(X_train, 3).shape     # showing example of working of np.expand_dims
```

```
(55000, 28, 28, 1)
```

```
# Adding one more dimension, this dimension signify number of channel of image data
X_train_CNN = np.expand_dims(X_train, -1)
X_test_CNN = np.expand_dims(X_test, -1)
X_valid_CNN = np.expand_dims(X_valid, -1)
```

```
X_train_CNN.shape
```

```
(55000, 28, 28, 1)
```

OBSERVATION:- The above you can see 5500 is number of image data, 28*28 is height and width, 1 is channel

```
X_train_CNN[0] # first image data
```

```
        [0.        ],
        [0.        ],
        [0.        ],
        [0.        ],
        [0.        ],
        [0.        ]],

       [[0.        ],
        [0.        ],
        [0.        ],
        [0.        ],
        [0.        ],
        [0.        ],
        [0.        ],
        [0.        ],
        [0.        ],
        [0.        ],
        [0.        ],
        [0.        ],
        [0.        ],
        [0.        ],
        [0.01568627],
        [0.45882353],
        [0.27058824],
        [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.        ],
```

```
X_train_CNN[0].shape  # first image data shape
```

```
(28, 28, 1)
```

```
# Creating Layers for the CNN Model
input_shape = (28, 28, 1) # (row, col, channels)
CLASSES = 10
LAYERS = [
    tf.keras.Input(shape=input_shape),
    tf.keras.layers.Conv2D(32, kernel_size=(3,3), activation="relu"),
    tf.keras.layers.MaxPooling2D(pool_size=(2,2)),
    tf.keras.layers.Conv2D(64, kernel_size=(3,3), activation="relu"),
    tf.keras.layers.MaxPooling2D(pool_size=(2,2)),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(CLASSES, activation="softmax")
]
```

```
# Creating CNN model
CNN_model = tf.keras.Sequential(
    LAYERS
)
```

```
CNN_model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_2 (Conv2D)           (None, 26, 26, 32)        320

 max_pooling2d_2 (MaxPooling  (None, 13, 13, 32)       0
 2D)

 conv2d_3 (Conv2D)           (None, 11, 11, 64)        18496

 max_pooling2d_3 (MaxPooling  (None, 5, 5, 64)         0
 2D)

 flatten_1 (Flatten)         (None, 1600)              0

 dense_2 (Dense)             (None, 10)                16010
```

```
=================================================================
Total params: 34,826
Trainable params: 34,826
Non-trainable params: 0
_________________________________________________________________
```

```
64*5*5  # Flatten input
```

```
1600
```

```
(3*3*1 + 1) * 32  # convo 1 params
```

```
320
```

```
(28 - 3) // 1 + 1 # After filter new image height or width
```

```
26
```

```
(26 - 2) // 2 + 1  # After max-pooling
```

```
13
```

```
(3*3*32 + 1) * 64  # convo 2 params
```

```
18496
```

```
1600 * 10 + 10
```

```
16010
```

```
CNN_model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_2 (Conv2D)           (None, 26, 26, 32)        320

 max_pooling2d_2 (MaxPooling  (None, 13, 13, 32)       0
 2D)

 conv2d_3 (Conv2D)           (None, 11, 11, 64)        18496

 max_pooling2d_3 (MaxPooling  (None, 5, 5, 64)         0
 2D)

 flatten_1 (Flatten)         (None, 1600)              0

 dense_2 (Dense)             (None, 10)                16010
```

```
=================================================================
Total params: 34,826
Trainable params: 34,826
Non-trainable params: 0
_________________________________________________________________
```

```
LOSS_FUNCTION = "sparse_categorical_crossentropy"
OPTIMIZERS = "SGD"
METRICS = ["accuracy"]

CNN_model.compile(loss=LOSS_FUNCTION, optimizer=OPTIMIZERS, metrics=METRICS)
```

```
# Training CNN Model
CNN_model.fit(X_train, y_train, epochs=10, validation_data = (X_valid, y_valid))
```

```
Epoch 1/10
1719/1719 [==============================] - 16s 4ms/step - loss: 0.6112 - accuracy: 0.8
Epoch 2/10
1719/1719 [==============================] - 9s 5ms/step - loss: 0.1878 - accuracy: 0.94
Epoch 3/10
1719/1719 [==============================] - 6s 3ms/step - loss: 0.1294 - accuracy: 0.96
Epoch 4/10
1719/1719 [==============================] - 8s 5ms/step - loss: 0.1051 - accuracy: 0.96
Epoch 5/10
1719/1719 [==============================] - 8s 5ms/step - loss: 0.0911 - accuracy: 0.97
Epoch 6/10
1719/1719 [==============================] - 7s 4ms/step - loss: 0.0804 - accuracy: 0.97
Epoch 7/10
1719/1719 [==============================] - 6s 3ms/step - loss: 0.0740 - accuracy: 0.97
Epoch 8/10
1719/1719 [==============================] - 6s 3ms/step - loss: 0.0682 - accuracy: 0.97
Epoch 9/10
1719/1719 [==============================] - 6s 3ms/step - loss: 0.0635 - accuracy: 0.98
Epoch 10/10
1719/1719 [==============================] - 6s 3ms/step - loss: 0.0600 - accuracy: 0.98
<keras.callbacks.History at 0x7f7718c18790>
```

```
# Extracting 3 images for testing purpose
X_new = X_test[:3]

y_prob = CNN_model.predict(X_new)
y_prob.round(3)
```

```
array([[0.   , 0.   , 0.   , 0.   , 0.   , 0.   , 0.   , 1.   , 0.   ,
        0.   ],
       [0.   , 0.001, 0.999, 0.   , 0.   , 0.   , 0.   , 0.   , 0.   ,
        0.   ],
       [0.   , 0.999, 0.   , 0.   , 0.   , 0.   , 0.   , 0.   , 0.   ,
        0.   ]], dtype=float32)
```

```
Y_pred = np.argmax(y_prob, axis=-1)
Y_pred    # prediction
```

```
array([7, 2, 1])
```

```
# comparing actual and prediction
for img_array, pred, actual in zip(X_new, Y_pred, y_test[:3]):
    plt.imshow(img_array, cmap="gray")
    plt.title(f"predicted: {pred}, actual: {actual}")
    plt.axis("off")
    plt.show()
    print("--"*30)
```


```
CNN_model.save("CNN_model.h5")
```

```
# Makeing prediction on whole test dataset
y_prob = CNN_model.predict(X_test)
y_prob.shape
```

```
(10000, 10)
```

```
y_pred = np.argmax(y_prob,axis=-1)
y_pred
```

```
array([7, 2, 1, ..., 4, 5, 6])
```

```
# confusion matrix
confusion_matrix(y_test,y_pred)
```

```
array([[ 972,    0,    0,    0,    0,    2,    1,    2,    3,    0],
       [   0, 1126,    1,    2,    1,    1,    1,    2,    1,    0],
       [   2,    3, 1011,    3,    1,    0,    0,    6,    5,    1],
       [   1,    0,    0, 1000,    0,    3,    0,    4,    2,    0],
       [   1,    0,    0,    1,  968,    0,    1,    1,    1,    9],
       [   2,    0,    0,    6,    0,  881,    1,    1,    1,    0],
       [   8,    2,    0,    1,    2,    5,  939,    0,    1,    0],
       [   1,    4,    6,    4,    0,    0,    0, 1008,    1,    4],
       [   7,    1,    2,    3,    2,    3,    1,    2,  951,    2],
       [   3,    5,    0,    3,    3,    4,    0,    2,    2,  987]])
```

```
# Accuracy score using sklearn
accuracy_score(y_test,y_pred)
```

```
0.9843
```

```
# Accuracy score using sklearn
accuracy_score(y_test,y_pred)
```

```
0.9843
```

OBSERVATION: CNN Model have accuracy score 0.98 which better than ANN

# Transfer Learning in CNN

## New problem statement -

Classify handwritten digits into odd and even

```
CNN_pretrained_model = tf.keras.models.load_model('CNN_model.h5')
```

```
CNN_pretrained_model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_2 (Conv2D)           (None, 26, 26, 32)        320

 max_pooling2d_2 (MaxPooling  (None, 13, 13, 32)       0
 2D)

 conv2d_3 (Conv2D)           (None, 11, 11, 64)        18496

 max_pooling2d_3 (MaxPooling  (None, 5, 5, 64)         0
 2D)

 flatten_1 (Flatten)         (None, 1600)              0

 dense_2 (Dense)             (None, 10)                16010

=================================================================
Total params: 34,826
Trainable params: 34,826
Non-trainable params: 0
_________________________________________________________________
```

```
# Checking Traininable parameter of CNN
for layer in CNN_pretrained_model.layers:
    print(f"{layer.name}: {layer.trainable}")
```

```
conv2d_2: True
max_pooling2d_2: True
conv2d_3: True
max_pooling2d_3: True
flatten_1: True
dense_2: True
```

```
for layer in CNN_pretrained_model.layers[:-1]: # leave the last layer
    layer.trainable = False  # disabling trainable params
```

```
for layer in CNN_pretrained_model.layers:
    print(f"{layer.name}: {layer.trainable}")
```

```
conv2d_2: False
max_pooling2d_2: False
conv2d_3: False
max_pooling2d_3: False
flatten_1: False
dense_2: True
```

```
# Extracting CNN leaving output layer
lower_CNN_pretrained_model = CNN_pretrained_model.layers[:-1]
```

```
lower_CNN_pretrained_model
```

```
[<keras.layers.convolutional.Conv2D at 0x7f7718898490>,
 <keras.layers.pooling.MaxPooling2D at 0x7f7718870490>,
 <keras.layers.convolutional.Conv2D at 0x7f7718bb9910>,
 <keras.layers.pooling.MaxPooling2D at 0x7f771889dbd0>,
 <keras.layers.core.flatten.Flatten at 0x7f771889df50>]
```

```
# Creating new CNN Model using Extracted layers hence doing Transfer learning
new_CNN_model = tf.keras.models.Sequential(lower_CNN_pretrained_model)
new_CNN_model.add(
    tf.keras.layers.Dense(2, activation="softmax")
)
```

```
#updating labels
def update_even_odd_labels(labels):
    for idx, label in enumerate(labels):
        labels[idx] = np.where(label%2 == 0, 1, 0) # 1 -> even, 0 -> odd
    return labels
```

```
y_train_bin, y_test_bin, y_valid_bin = update_even_odd_labels([y_train, y_test, y_valid])
```

```
# Expanding dimension
X_train_CNN = np.expand_dims(X_train, -1)
X_test_CNN = np.expand_dims(X_test, -1)
X_valid_CNN = np.expand_dims(X_valid, -1)
```

```
X_train_CNN.shape
```

```
(55000, 28, 28, 1)
```

```
np.unique(y_train_bin)
```

```
array([0, 1])
```

```
new_CNN_model.compile(loss="sparse_categorical_crossentropy",
                  optimizer="SGD",
                  metrics=["accuracy"]
                  )
```

```
# Building CNN Model by giving input layer shape
new_CNN_model.build(input_shape=(None,28,28,1))
```

```
new_CNN_model.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_2 (Conv2D)           (None, 26, 26, 32)        320

 max_pooling2d_2 (MaxPooling  (None, 13, 13, 32)       0
 2D)

 conv2d_3 (Conv2D)           (None, 11, 11, 64)        18496

 max_pooling2d_3 (MaxPooling  (None, 5, 5, 64)         0
 2D)

 flatten_1 (Flatten)         (None, 1600)              0

 dense_3 (Dense)             (None, 2)                 3202

=================================================================
Total params: 22,018
Trainable params: 3,202
Non-trainable params: 18,816
_________________________________________________________________
```

```
type(X_train_CNN)
```

```
numpy.ndarray
```

```
# Training new model
history = new_CNN_model.fit(X_train_CNN,
                            y_train_bin,
                            epochs=10,
                            validation_data=(X_valid_CNN,y_valid_bin)
                            )
```

```
Epoch 1/10
1719/1719 [==============================] - 5s 3ms/step - loss: 0.1750 - accuracy: 0.94
Epoch 2/10
1719/1719 [==============================] - 5s 3ms/step - loss: 0.0949 - accuracy: 0.96
Epoch 3/10
1719/1719 [==============================] - 5s 3ms/step - loss: 0.0838 - accuracy: 0.97
Epoch 4/10
1719/1719 [==============================] - 5s 3ms/step - loss: 0.0790 - accuracy: 0.97
Epoch 5/10
1719/1719 [==============================] - 5s 3ms/step - loss: 0.0753 - accuracy: 0.97
Epoch 6/10
1719/1719 [==============================] - 5s 3ms/step - loss: 0.0718 - accuracy: 0.97
Epoch 7/10
1719/1719 [==============================] - 5s 3ms/step - loss: 0.0696 - accuracy: 0.97
Epoch 8/10
1719/1719 [==============================] - 5s 3ms/step - loss: 0.0667 - accuracy: 0.97
Epoch 9/10
1719/1719 [==============================] - 5s 3ms/step - loss: 0.0654 - accuracy: 0.97
Epoch 10/10
1719/1719 [==============================] - 5s 3ms/step - loss: 0.0654 - accuracy: 0.97
```

```
new_CNN_model.evaluate(X_test_CNN, y_test_bin)
```

```
313/313 [==============================] - 1s 2ms/step - loss: 0.0534 - accuracy: 0.980
[0.05336078628897667, 0.98089998960495]
```

```
X_new = X_test_CNN[:3]
```

```
X_new = X_new.reshape((3,28,28))  # reshaping for prediction as model take 3 dimension image
```

```
X_new.shape
```

```
(3, 28, 28)
```

```
y_prob = new_CNN_model.predict(X_new)
y_prob.round(3)
```

```
array([[1.   , 0.   ],
       [0.   , 1.   ],
       [0.993, 0.007]], dtype=float32)
```

```
Y_pred = np.argmax(y_prob, axis=-1)
Y_pred
```

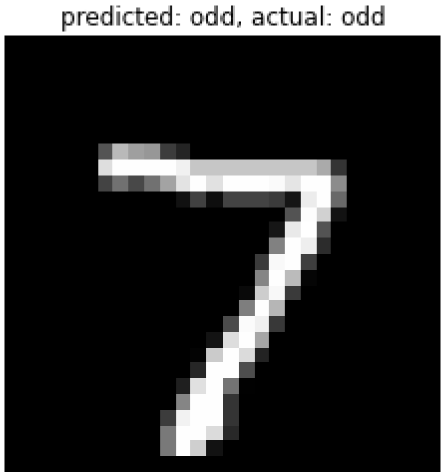
```
array([0, 1, 0])
```

```
y_test_bin[:3]
```

```
array([0, 1, 0])
```

```
# comparing actual and prediction of 3 images from test dataset
for img_array, pred, actual in zip(X_new, Y_pred, y_test_bin[:3]):
    if pred == 1:
        pred = "even"
    else:
        pred = "odd"

    if actual == 1:
        actual = "even"
    else:
        actual = "odd"
    plt.imshow(img_array, cmap="gray")
    plt.title(f"predicted: {pred}, actual: {actual}")
    plt.axis("off")
    plt.show()
    print("--"*30)
```




**OBSERVATION:- Model created using Transfer learning is able to classify image which numbers as even or odd.**

```
#Making Prediction on whole dataset
y_prob = new_CNN_model.predict(X_test)
y_prob.shape
```

```
(10000, 2)
```

```
y_pred = np.argmax(y_prob,axis=-1)
y_pred
```

```
array([0, 1, 0, ..., 1, 0, 1])
```

```
# confusion matrix
confusion_matrix(y_test_bin,y_pred)
```

```
array([[4943,  131],
       [  60, 4866]])
```

```
# Accuracy score using sklearn
accuracy_score(y_test_bin,y_pred)
```

```
0.9809
```

```
# Precision
precision_score(y_test_bin,y_pred,average='weighted')
```

```
0.9810009827683538
```

OBSERVATION:- Transfer Learning can be done in ANN and CNN both.