

Configuration Manual

MSc Research Project Data Analytics

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National College of Ireland



MSc Project Submission Sheet

School of Computing

Student Name: Vrushali Atul Surve **Student ID:** X19212712 2021-22 **Programme: Data Analytics** Year: Module: MSc Research Project Lecturer: Paul Stynes, Pramod Pathak, Rejwanul Haque **Submission Due Date:** 16/12/2021 **Project Title:** An Image-based Transfer Learning Framework for Classification of E-Commerce Products. 821 Page Count: 14 Word Count:

I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own contribution will be fully referenced and listed in the relevant bibliography section at the rear of the project.

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Date: 16th December 2021

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Configuration Manual

Vrushali Surve Student ID: x19212712

1 Hardware/Software Requirements

This configuration manual describes the procedures taken while running the scripts adopted in this research. These instructions will help you run the code successfully. This manual also includes information on the machine's hardware configuration in which the code was executed. The minimal setup required for the system is also described. The process flow of a Convolutional Neural Network (CNN) is covered in this manual, as well as VGG19, InceptionV3, MobileNet, and ResNet50 are image classification algorithms that use transfer learning.

2 System Specification

2.1 Hardware Requirements

The hardware specifications for the system on which the research project is executed are as follows:

- Processor: AMD Ryzen 5 3500U
- Storage: 100 GB.
- RAM: 8GB.

2.2 Software Requirements

The following software is necessary to carry out the experiments:

- Windows Edition: Windows 10 Home.
- Integrated Development Environment: Google Colab
- Scripting Language: Python 3.7
- Cloud Storage: Google Drive.
- Microsoft Tools: Microsoft Excel
- Other Tool: Jupyter Notebook, Anaconda Navigator (64 bit), Notepad ++

3 Setting up environment

3.1 Anaconda Setup

Anaconda Navigator 64-bit configuration is required. First, open anaconda cmd to create an environment for this research using the below statement.

(base) C:\Users\vrushali>conda create -n ecommerce python=3.7

Then type anaconda navigator into the start menu. Launch Anaconda Navigator by searching for it. The next screen you will see is as fig 1. select e-commerce environment. On the Anaconda platform, there are a variety of navigations and applications. Jupyter Notebook

will be utilized for this project. The Jupyter notebook will open in Chrome on port 8888 by default.

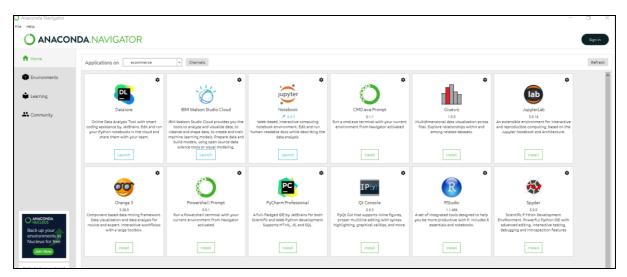


Figure 1 Anaconda Navigator

3.2 Colab Setup

Google Colaboratory environment settled. Fig 2 below can help grasp that concept better.

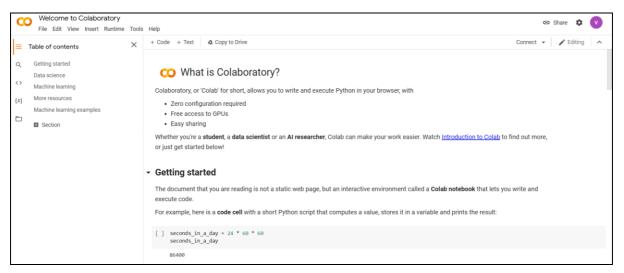


Figure 2 Google Colaboratory

4 Data Selection

The data collection can be found on Kaggle's dataset repository¹ This experiment uses the 'Flipkart Products' dataset shown in below figure 3. This dataset repository has the raw data CSV file and has around unique 20000*15 records.

¹ PromptCloud (2017) Flipkart Products. Available at: https://kaggle.com/PromptCloudHQ/flipkart-products (Accessed: 9 December 2021).

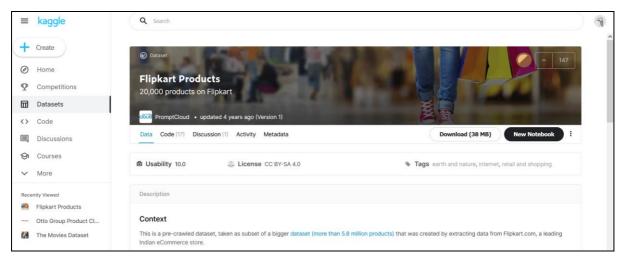


Figure 3 Kaggle Flipkart Dataset

5 Database Creation

Images are imported from the CSV downloaded from Kaggle using the escaping method. BeautifulSoup tool was used for this. First, to create a dataset, we must activate the e-commerce environment, as shown in fig 4. Then scape.py file needs to be run to import the image. Filescrap code is as illustrated in fig 5.

(base) C:\Users\vrushali>conda activate ecommerce
(ecommerce) C:\Users\vrushali>d:
(ecommerce) D:\>cd D:\thesis-project\code\flipscrap
(ecommerce) D:\thesis-project\code\flipscrap>python scrape.py
inside 0 http://img5a.flixcart.com/image/short/u/4/a/altht-3p-21-alisha-38-original-imaeh2d5vm5zbtgg.jpeg 1 http://img5a.flixcart.com/image/short/p/j/z/altght4p-26-alisha-38-original-imaeh2d5kbufss6n.jpeg 2 http://img5a.flixcart.com/image/short/p/j/z/altght4p-26-alisha-38-original-imaeh2d5npdybzyt.jpeg 3 http://img5a.flixcart.com/image/short/z/j/7/altght-7-alisha-38-original-imaeh2d5jsz2ghd6.jpeg
inside 0 http://img6a.flixcart.com/image/sofa-bed/j/f/y/fhd112-double-foam-fabhomedecor-leatherette-black-leatherette-1100x11
-imaeh3gemjjcg9ta.jpeg
1 http://img6a.flixcart.com/image/sofa-bed/j/f/y/fhd112-double-foam-fabhomedecor-leatherette-black-leatherette-origin -imaeh3gemjjcg9ta.jpeg
2 http://img6a.flixcart.com/image/sofa-bed/j/f/y/fhd112-double-foam-fabhomedecor-leatherette-black-leatherette-origin -imaeh3genfxkqvuv.jpeg
<pre>imachSgcNrAcqvvv.pcg http://img5a.flixcart.com/image/sofa-bed/j/f/y/fhd112-double-foam-fabhomedecor-leatherette-black-leatherette-origin -imaeh3ge2sfeczef.jpeg</pre>
4 http://img5a.flixcart.com/image/sofa-bed/j/f/y/fhd112-double-foam-fabhomedecor-leatherette-black-leatherette-origin
-imaeh3geuy7d74g2.jpeg 5 http://img5a.flixcart.com/image/sofa-bed/j/f/y/fhd112-double-foam-fabhomedecor-leatherette-black-leatherette-origin -imaeh3gerfhdxzwj.jpeg
inside
0 http://img5a.flixcart.com/image/shoe/7/z/z/red-as-454-aw-11-original-imaeebfwsdf6jdf6.jpeg 1 http://img6a.flixcart.com/image/shoe/7/z/z/red-as-454-aw-11-original-imaeebfwsdf6jdf6.jpeg

Figure 4 Image Scrap



Figure 5 Web scrapping Code

The crawlers gathered data from the column image URL content in this CSV and imported the picture path. That image was saved in the correct folder for the category. It produced a log folder with a log file containing failure warnings while downloading images by using the logger function.

```
import logging
from os import path, mkdir
if not path.exists("logs"):
    mkdir("logs")

logging.basicConfig(filename="./logs/log.log",
    format='%(asctime)s %(message)s',
    filemode='a', level=logging.INFO)

logger = logging.getLogger()

def saveLog(msg):
    logger.info(msg)
```

Figure 6 Log Code

After that count, check for better understanding using the below fig 7 command.

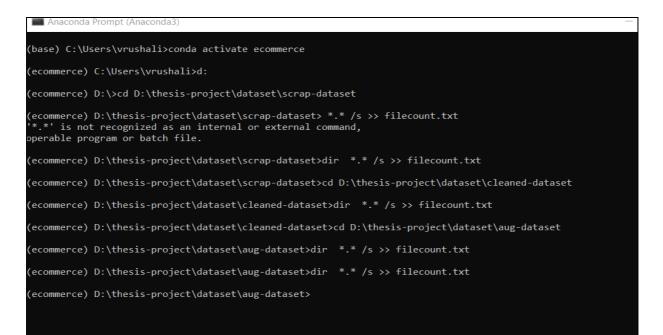


Figure 7 File Count To Check

There was 27 category after this. Categories were manually split for more apparent appreciation since there were multiple levels of categorization. So after cleaning, there are 15 categories with fewer images, so using the augmentation process, images are imported. Image augmentation is shown in 8. Count of cleaned categories and after augmentation process is given in snip no 9. Then these image data are saved, zipped and uploaded on google drive.

In [2]:	# Import Libraries
	import cv2 as cv
	import glob
	import numpy as np
	from scipy import misc
	import imageio
	import os
	import sys
	import imgaug as ia
	from imgaug import augmenters as iaa
T- (0).	# Specify folder images to be augmented
IN [3]:	# Specify folder images to be augmented images = []
	<pre>images = [1] files = glob.glob("D://thesis-project//dataset//cleaned-dataset//wrist-watches//*.jpeg")</pre>
	Tites - glob.glob(D.//thesis-project//dataset//teaned-dataset//wrist-watches//".jpeg /
Tp [4] -	# Reading Images from the folder
	for myFile in files:
	image = cv.imread (myFile,1)
	image rgb = cv.cvtColor(image, cv.COLOR BGR2RGB) #change from BRG to RGB
	images.append(image rgb)
In [5]:	# Augementing Images sometimes = lambda aug: iaa.Sometimes(0.5, aug)
	sometimes - lambda aug: laa.Sometimes(0.5, aug)
	seg = iaa.Seguential(
	iaa.Fliplr(0.4), # horizontally flip 50% of all images
	iaa.Flipud(0.1), # vertically flip 20% of all images
	sometimes(iaa,Affine(
	rotate=(-10, 10),
	iaa.OneOf([
	iaa.GaussianBlur((0, 3.0)),
	iaa.AverageBlur $(k=(2, 7))$.
	iaa.MedianBlur(k=(3, 11)),
	1)1,
	random_order=True)
IN [6]:	# Folder Fath were images to be augmented
	<pre>write_to_dir = "D://thesis-project//dataset//aug-dataset//wrist-watches//"</pre>
	# Specifying Number of images per image to be augmented
	# specifying Number of images per image to be augmented n augs per image = 20
	wTendle_herTrundle = ==
In [7]:	# Saving Augmented Images
	for i, image in enumerate(images):
	image augs = seq.augment images([image] * n augs per image)
	for 1. image aug in enumerate(image augs):
	image_io_imwrite(os.path.join(write to dir, "%03d %02d.jpg" % (i, j)), image aug)
	print(os.path.join(write_to_dir, "\$03d_\$02d.jpg" % (i, j)))
	D://thesis-project//dataset//aug-dataset//wrist-watches//000 00.jpg
	D://thesis_project//dataset//aug_dataset//wrist_watches//000_01.pg
	D://thesis-project//dataset//aug-dataset//wrist-watches//000 02.jpg
	D://thesis-project//dataset//aug-dataset//wrist-watches//000 03.jpg
	D://thesis-project//dataset//aug-dataset//wrist-watches//000 04.pg

Figure 8 Augmentation Code

Cleaned Count	Augmented Count
189	1134
160	1120
589	1178
279	1116
336	1008
493	<mark>986</mark>
173	1038
1239	1239
225	1125
557	1114
692	1384
445	890
1230	1230
1097	1097
51	1020
	189 160 589 279 336 493 173 1239 225 557 692 445 1230 1097

Figure 9 Count

6 Implementation The libraries in fig 10 need to develop in this project are below.



Figure 10 Library List

6.1 Importing Data

As seen in figure 11, mounting the google drive to the colab notebook. Select the Gmail account from the URL and enter the authentication code.



Figure 11 Google Drive Mount

Figure 12, Keras & TensorFlow library imported.

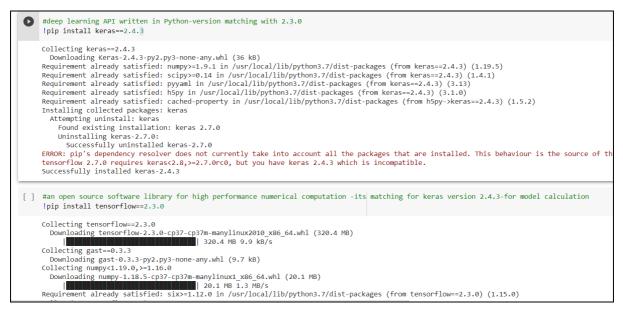


Figure 12 Keras-Tensorflow import

Test directory, train directory, image size and classes are set in figure 13. then a training dataset was created.



Figure 13 Dataset create

Dataset is split into training and testing ration 70:30, as shown in figure 14.

```
[] print('Total number images for training -', len(training_data))
    # Randomly Shuffling Data
    random.shuffle(training_data)
    x = []
    y = []
    # Assign Features and Labels
    for features, label in training_data:
        x.append(features)
        y.append(label)
    # Reshapping Image Arrays
    x = np.array(x).reshape(-1,img_size,img_size,3)
    x[0].shape
    # Split Dataset Ratio (70:30)
    x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.3,random_state=96)
    # Deleting Variables
    del x,y
    # Converting Variables to Categories
    Y_train = utils.to_categorical(y_train,num_classes=15)
    Y_test = utils.to_categorical(y_test,num_classes=15)
    Total number images for training - 16679
```

Figure 14 Split DS for Model Training

There were three experiments conducted in this research to archive the aim.

6.2 Experiment 1: Effectivity of CNN Model

The CNN model is shown in figures 15 a and 15b.





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[] 1 1 1 1 1 1 1 1 1 1
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wight_path = ' <u>icontent/drive/hight-iwo/wight-iworwi</u> ght_ingcon'
d_erry_stoppe - trajtoppeq(most)r - 'vilos', pattere - erry_stopped(most) d_errespinet - modoRespinet((Teller) - migl_errespinet - mig
results = sy_wold. Htt(v_train, bit(0_train=bat(0_train=q_spots, wrstosci,
validation_data=(_tetst_V_test), calibatis=(_data=y_tetst_V_test),
prin(result.history.key())
Robel: "separatial"
Layer (type) Output Shape Paras #
Convold (Convold) (Nore, 222, 222, 32) 896
max_pooling2d (Min#Gooling2D) (Minme, 111, 112) 0
dropout (Brogout) (Nerw, III, III, J2) 0
conv2d_1 (Conv20) (Nore, 189, 189, 64) 18496
max_pooling2d_1 (ManApooling2 (Ma
dropost_1 (Bropost) (None, 54, 54, 64) 0
conv2d_2 (Conv2D) (Nove, 51, 52, 128) 73856
max_pooling2d_2 (MaxMooling2 (Maxm, 6, 6, 128) 0
dropout,2 (Dropout) (None, 6, 6, 128) 0
flatten (flatten) (Nove, 408) 0
dense (Dense) (None, 12) 69125
activation (Activation) (Nowe, 15) 0
Teta peren: 142,343 Triababe peren: 142,343 Kon-draiable peren: 6
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17/17 / 17/17/17/17/17/17/17/17/17/17/17/17/17/1
and the address for the second s

Figure 15. b CNN

6.3 Experiment 2: Effectiveness of transfer learning models like VGG19 and InceptionV3.

In this experiment, both models use pre-trained ImageNet weights shown in VGG19 in fig 16 and InceptionV3 in fig 17.

0			lse,input_ten:	sor=Input(shape=(224, 224, 3)))
	headModel = my_model.build	<pre>() () ()</pre>	4)	
	<pre># replace the FC with head my_model = Model(inputs=ba</pre>	Model: seModel.input, outputs=hea	dModel)	
	<pre># unfreezing some of conv for layer in baseModel.lay layer.trainable = Fals</pre>	ens[:]:		
0		<pre>s://storage.googleapis.com] -</pre>		eras-applications/vgg19/vgg19 weights tf dim ordering tf kernels notop.h5
[]	<pre>] my_model.compile(loss='categorical_crossentropy',metrics=['accuracy'],optimizer='adam') print(my_model.summary())</pre>			
	<pre>weight_path = '/content/drive/MyDrive/weights/vgg19/' cb_early_stopper = EarlyStopping(monitor = 'val_loss', patience = early_stop_patience) cb_checkpointer = ModelCheckpoint(filepath = weight_path, monitor = 'val_loss', save_best_only = True, mode = 'auto')</pre>			
	<pre>results = my_model.fit(x_train,Y_train,</pre>)
	<pre>print(results.history.keys</pre>	())		
	Model: "functional_1"			
	Layer (type)	Output Shape	Param #	
	input_1 (InputLayer)	[(None, 224, 224, 3)]	0	
	block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792	
	block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928	
	<pre>block1_pool (MaxPooling2D)</pre>	(None, 112, 112, 64)	0	
	block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856	

Figure 16 VGG19



Figure 17 InceptionV3

6.4 Experiment 3: Effectivity of transfer learning models like ResNet50 and MobileNet model.

Transfer learning models are better as they save time. Below fig 18 and 19 shows an implementation of model ResNet50 and MobileNet, respectively.

0	#MobileNet				
	<pre># load pretrained model:</pre>				
	<pre>baseModel = MobileNet(weights='imagenet', include_top=False,input_tensor=Input(shape=(224, 224, 3)))</pre>				
# initialize head of network					
	<pre>my_model = MyModel(baseMode</pre>		56)		
	<pre>headModel = my_model.build</pre>	0			
	# replace the FC with head	Model:			
	<pre>my_model = Model(inputs=bas</pre>	seModel.input, outputs=hea	dModel)		
	# unfreezing some of conv i	lavers:			
	for layer in baseModel.laye				
	layer.trainable = True				
Θ			-square, or `rows` is not in [128, 160, 192, 224]. Weights for input shape (224, 224) will be loaded as the default.		
	17227776/17225924 [======		/tensorflow/keras-applications/mobilenet/mobilenet 1 0 224 tf no top.h5 0s 0us/step		
[]	batch_size = 50				
	n_epochs = 10				
	<pre>my_model.compile(loss='categorical_crossentropy',metrics=['accuracy'],optimizer='adam')</pre>				
	my_model.complet(loss= categoital_crossentropy ,metrics=[acturacy],optimizer= adam) print(my.model.summary())				
	weight_path = '/content/drive/MyDrive/weights/mobilenet/'				
	cb early stopper = EarlyStopping(monitor = 'val loss', patience = early stop patience)				
	cc_enty_scuper = caryscupying(municum = val_uss, patence = caryscup_patence) cc_checkpointer = Modelheckpoint("filepath = weight_path, monitor = 'val_loss', save_best_only = True, mode = 'auto')				
	<pre>results = my_model.fit(x_train,Y_train, batch_size=batch_size,epochs=n_epochs,</pre>				
	verbose		pochs,		
		tion_data=(x_test,Y_test),			
	<pre>volucion_ocuto(xccs,y_c</pre>				
	Layer (type)	Output Shape	Param #		
	input_4 (InputLayer)	[(None, 224, 224, 3)]	0		
	inpuc_+ (inpuccayer)		·		
	<pre>conv1_pad (ZeroPadding2D)</pre>	(None, 225, 225, 3)	0		
	conv1 (Conv2D)	(None, 112, 112, 32)	864		
1					

Figure 18 MobileNet

[] #ResNet50					
	# load pretrained model:				
basenoue.	<pre>baseModel = ResNet50(weights='imagenet', include_top=False,input_tensor=Input(shape=(224, 224, 3)))</pre>				
# initia	ize head of network				
my_model	= MyModel(baseModel, classes=n_classes, D=256)				
headMode:	= my_model.build()				
	the FC with headModel:				
my_model	= Model(inputs=baseModel.input, outputs=headModel)				
# unfree:	ing some of conv layers:				
	in baseModel.layers[15:]:				
	layer trainable = True				
	g data from https://storage.googleapis.com/tensorflow/keras-applications/resnet/resnet50 weights tf dim ordering tf kernels notop.h5				
94773248/	4765736 [====================================				
	[] batch_size = 50				
n_epocns	n_epochs = 10				
my model	compile(loss='categorical crossentropy',metrics=['accuracy'],optimizer='adam')				
	my_model.cumary()) print(my.model.summary())				
weight_pa	<pre>weight_path = '/content/drive/MyDrive/weights/ResNet50/'</pre>				
	<pre>cb_early_stopper = EarlyStopping(monitor = 'val_loss', patience = early_stop_patience)</pre>				
cb_check	<pre>cb_checkpointer = ModelCheckpoint(filepath = weight_path, monitor = 'val_loss', save_best_only = True, mode = 'auto')</pre>				
results :	results = my_model.fit(x_train,Y_train,				
	bath_icebath_ice_path_ice_pochs_n_epochs,				
	verbose1,				
	<pre>validation_data=(x_test,Y_test),</pre>				
	callbacks=[cb_checkpointer, cb_early_stopper])				
print(res	ults.history.kevs())				
Model: "	Model: "functional_5"				
Layer (ty	be) Output Shape Param # Connected to				
input_3 (InputLayer) [(None, 224, 224, 3) 0				
conv1_pac	(ZeroPadding2D) (None, 230, 230, 3) 0 input_3[0][0]				
conv1_cor	/ (Conv2D) (None, 112, 112, 64) 9472 conv1_pad[0][0]				
conv1_bn	[BatchNormalization) (None, 112, 112, 64) 256 conv1_conv[0][0]				

Figure 19 ResNet50

7 Evaluation & Result

In these steps, graphs are created using performance measures like Confusion matrix, classification Report and loss/accuracy versus epochs graph. Code for these graphs is shown in Figures 20,21 and 22.

```
# Plot training & validation accuracy values
plt.plot(results.history['accuracy'])
plt.plot(results.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='lower right')
plt.show()
# Plot training & validation loss values
plt.plot(results.history['loss'])
plt.plot(results.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper right')
plt.show()
```

Figure 20 Accuracy\Loss verses Epoch

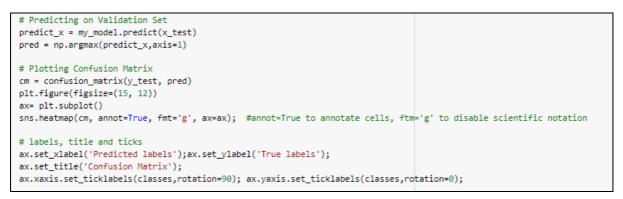


Figure 21 Confusion Matrix

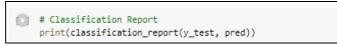


Figure 22 Classification Report

Inferencing on testing data is done to check model flow.

```
# Inferencing on Testing Data
images = []
titles = []
for img in glob.glob(test_directory + "*.jpeg"):
    start_time = time.time()
    img_name = os.path.split(img)[-1]
   im = cv2.imread(img)
   im = cv2.cvtColor(im, cv2.COLOR_BGR2RGB)
    img_og = image.load_img(img,target_size=(224,224))
    img = np.asarray(img_og)
   img = np.expand_dims(img, axis=0)
    prediction = my_model.predict(img)
   MaxPosition=np.argmax(prediction)
   prediction_label=classes[MaxPosition]
   print(prediction_label)
   org = (50, 50)
   fontScale = 1
    color = (255, 0, 0)
    thickness = 2
   cv2.putText(im, prediction_label, org, cv2.FONT_HERSHEY_SIMPLEX,
                   fontScale, color, thickness, cv2.LINE_AA)
   end_time = time.time()
   infer_timne = end_time - start_time
    print('Time Requirted: ',{infer_timne})
    plt.imshow(im)
   plt.show()
cv2.destroyAllWindows()
```

Figure 23 Inferencing Code