AIML Capstone Project: CV - Car Detection

Interim Report

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Summary and Problem Statement

Computer vision can be used to automate supervision and generate action appropriate action trigger if the event is predicted from the image of interest. For example a car moving on the road can be easily identified by a camera as make of the car, type, colour, number plates etc.

DATA DESCRIPTION:

The dataset contains 16,185 images of 196 classes of cars. The data is split into 8,144 training images and 8,041 testing images, where each class has been split roughly in a 50-50 split.

Classes are typically at the level of Make, Model, Year, e.g. 2012 Tesla Model S or 2012 BMW M3 coupe.

- > Train Images: Consists of real images of cars as per the make and year of the car
- Test Images: Consists of real images of cars as per the make and year of the car.
- > Train Annotation: Consists of bounding box region for training images.
- ➤ Test Annotation: Consists of bounding box region for testing images.

Dataset:

https://drive.google.com/drive/folders/1y6JWx2CpsOuka00uePe72jNgr7F9sK45?usp=s haring,

PROJECT OBJECTIVE: Design a DL based car identification model

EDA and Pre-processing

Step #1: Importing the dataset in dataframes

```
#Different car labels
car_names = pd.read_csv( 'Car names and make.csv', header=None, names = ['CarLabe
1'] )

#Train data
train_data = pd.read_csv( 'Annotations/Train Annotations.csv', skiprows=1, names
= ['ImageName', 'X1', 'Y1', 'X2', 'Y2', 'Class'] )

#Test data
test_data = pd.read_csv( 'Annotations/Test Annotation.csv', skiprows=1, names =
['ImageName', 'X1', 'Y1', 'X2', 'Y2', 'Class'])
```

Display few records

```
CarLabel
0 AM General Hummer SUV 2000
1
         Acura RL Sedan 2012
2
         Acura TL Sedan 2012
3
        Acura TL Type-S 2008
        Acura TSX Sedan 2012
  ImageName X1 Y1
                        X2
                             Y2 Class
0 00001.jpg 39 116 569 375
1 00002.jpg 36 116 868 587
                                  14
                                     3
  00003.jpg 85 109
                      601
                             381
                                     91
3 00004.jpg 621 393 1484 1096
                                    134
4 00005.jpg 14 36 133 99
                                    106
  ImageName X1 Y1 X2
                           Y2 Class
0 00001.jpg 30 52 246 147
1 00002.jpg 100 19 576 203
                                  103
2 00003.jpg 51 105 968 659
3 00004.jpg 67 84 581 407
                                  145
                 84 581 407
                                  187
4 00005.jpg 140 151 593 339
                                  185
```

Problem faced: While trying to read few images using cv2, we were getting return type as None. After troubleshooting, we found that this is due to folder name of images. Some of folder names have a '/' in it. Therefore, we decided to update such names as part of pre-processing step.

Step #2: Find class name with '/' and update

```
for i in range(len(car_names)):
    if '/' in car_names.loc[i,"CarLabel"]:
        print(car_names.loc[i,"CarLabel"])
        print(i)

Ram C/V Cargo Van Minivan 2012
```

Thus, there was only 1 class with '/' in it's name.

```
#Replace '/' with '-' in the name
car_names.loc[173,'CarLabel'] = 'Ram C-V Cargo Van Minivan 2012'
```

Step #3: Map training and test images to corresponding classes and annotations.

```
car_names['Class'] = car_names.index + 1
car_train_df = pd.merge(train_data, car_names, how = 'left', left_on='Class', rig
ht_on='Class')
car_train_df.head()

car_test_df = pd.merge(test_data, car_names, how = 'left', left_on='Class', right_on='Class')
car_test_df.head()
```

Display few records

ImageName	X1	Y1	X2	Y2	Class	CarLabel	
0	00001.jpg	30	52	246	147	181	Suzuki Aerio Sedan 2007
1	00002.jpg	100	19	576	203	103	Ferrari 458 Italia Convertible 2012
2	00003.jpg	51	105	968	659	145	Jeep Patriot SUV 2012
3	00004.jpg	67	84	581	407	187	Toyota Camry Sedan 2012
4	00005.jpg	140	151	593	339	185	Tesla Model S Sedan 2012

Step #4: Exploratory Data Analysis

For each car image label, separate year, make, model and body

```
import nltk
nltk.download('punkt')
#Different body types
car body type = ["suv", "sedan", "type-s", "type-
r", "convertible", "coupe", "wagon", "hatchback", "cab", "supercab", "van", "minivan"]
car body type = [item.lower() for item in car body type]
#Different car make
car_make = ['am', 'general', 'acura', 'aston', 'martin', 'audi', 'bmw', 'bentley',
'bugatti', 'buick', 'cadillac', 'chevrolet', 'chrysler', 'daewoo',
            'dodge', 'eagle', 'fiat', 'ferrari', 'fisker', 'ford', 'gmc', 'geo', 'h
onda', 'hyundai', 'infiniti', 'isuzu',
            'jaguar', 'jeep', 'lamborghini', 'land', 'rover', 'lincoln', 'mini', 'c
ooper', 'maybach', 'mazda', 'mclaren', 'mercedes-benz',
            'mitsubishi', 'nissan', 'plymouth', 'porsche', 'ram', 'rolls-
royce', 'scion', 'spyker', 'suzuki', 'tesla', 'toyota', 'volkswagen', 'volvo', 'sma
rt']
car make = [item.lower() for item in car make]
#Define dataframe to store results
eda df = car test df.copy()
eda df["year"] = None
eda df["make"] = None
eda df["model"] = None
eda df["body"] = None
pattern="[0-9][0-9][0-9][0-9]"
for col in eda df.columns:
    if col == 'CarLabel':
        for index, row in eda df.iterrows():
            wordsl = word tokenize(row[col].lower())
            print(index, wordsl)
            if len(wordsl)>1:
                year = re.findall(pattern, wordsl[len(wordsl)-1]) #row[0])
                if year:
                    eda_df.loc[index, 'year'] = year[0]
                body = list(set(wordsl).intersection(car body type))
                if body:
                    eda df.loc[index, 'body'] = body[0]
                make = list(set(wordsl).intersection(car make))
                if make:
```

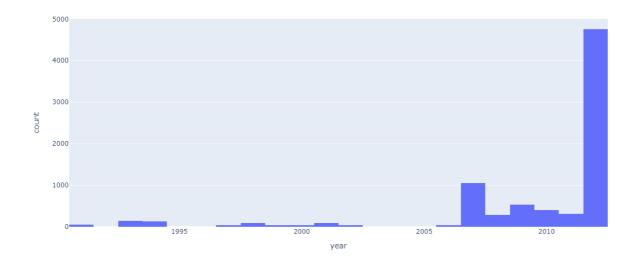
```
eda_df.loc[index, 'make'] = ' '.join(make)
iden=year + body + make
print(iden)
model = list(set(wordsl).difference(iden))
print(model)
if model:
    eda_df.loc[index, 'model'] = ' '.join(model)
```

Display Few records:

	ImageName	X1	Y1	X2	Y2	Class	CarLabel	year	make	model	body
0	00001.jpg	30	52	246	147	181	Suzuki Aerio Sedan 2007	2007	suzuki	aerio	sedan
1	00002.jpg	100	19	576	203	103	Ferrari 458 Italia Convertible 2012	2012	ferrari	458 italia	convertible
2	00003.jpg	51	105	968	659	145	Jeep Patriot SUV 2012	2012	jeep	patriot	suv
3	00004.jpg	67	84	581	407	187	Toyota Camry Sedan 2012	2012	toyota	camry	sedan
4	00005.jpg	140	151	593	339	185	Tesla Model S Sedan 2012	2012	tesla	s model	sedan

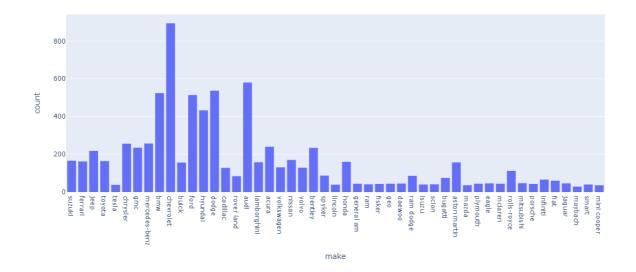
• Display bar charts for different columns

> Count of different cars by year



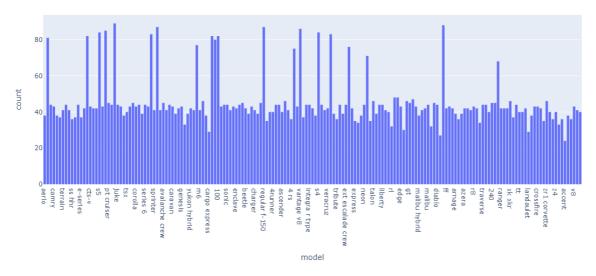
As seen, most of cars are of make year between 2007 – 2012

> Count of different cars by make



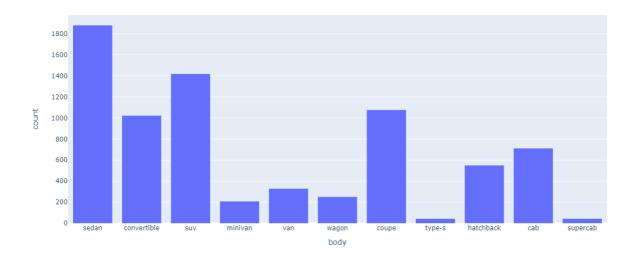
As seen, most of cars are of make Chevrolet, audi, bmw and dodge. 'Mini Cooper', 'Smart' and 'Jaguar' are less represented. Therefore, an effective model would be the one which can identify cars belonging to these classes.

Count of different cars by model



As seen, cars evenly belong to different models, with some models having more number of cars.

> Count of cars by different body types



As seen, most of cars are of type Sedan

• Display images with bounding box.

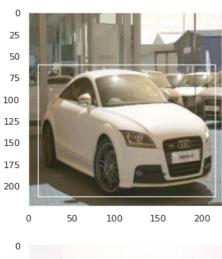
```
IMAGE_SIZE = 224
IMAGE_HEIGHT = IMAGE_SIZE
IMAGE_WIDTH = IMAGE_SIZE

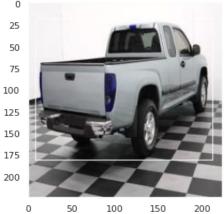
HEIGHT_CELLS = 28
WIDTH_CELLS = 28

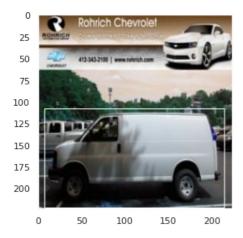
print ( 'Generating bounding boxes images for Eg Train Data')

i = 1
    plt.figure(figsize=(20,20))
    for no in [0 , 6, 67, 89 , 99, 340 ]:
```

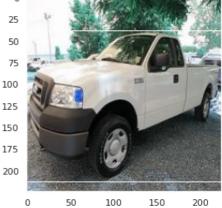
```
eg car = car train df.iloc[ no ]
    path = 'Car Images/Train Images/{0}/{1}'.format( eg_car['CarLabel'], eg
car['ImageName'] )
    img = cv2.imread( path )
    img shape = img.shape
    img = cv2.resize(img, dsize = (IMAGE SIZE, IMAGE SIZE), interpolation=c
v2.INTER AREA)
   x1 = int(eg car['X1'] * IMAGE SIZE / img shape[1] -
3 )  # Normalize bounding box by image size
   y1 = int(eg car['Y1'] * IMAGE SIZE / img shape[0] - 3 ) # Norm
alize bounding box by image size
   x2 = int(eg car['X2'] * IMAGE SIZE / img shape[1] + 3)
                                                                     # No
rmalize bounding box by image size
                                                                     # No
   y2 = int(eg_car['Y2'] * IMAGE_SIZE / img_shape[0] + 3)
rmalize bounding box by image size
   cv2.rectangle(img, (x1, y1), (x2, y2), (255,255,255))
   i +=1
   plt.subplot(4,2,i+1)
   plt.grid(False)
   plt.imshow(img);
```

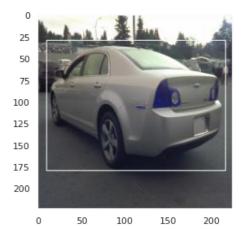












• Save training images with bounding box.

We will extract bounding boxes and then save those as images

```
for i in range(len(car_train_df)):
    eg_car = car_train_df.iloc[i]
    source_path = 'Car Images/Train Images/{0}/{1}'.format( eg_car['CarLabel'], eg_car['ImageName'] )
```

```
dest path = 'Car Images/Train Images Annoted/{0}/{1}'.format( eg car['CarLabel'
], eg car['ImageName'] )
 image = cv2.imread(source path)
 if image is None:
   print(source_path)
 x1 = int(eg car['X1'])
 y1 = int(eg car['Y1'])
 x2 = int(eg_car['X2'])
 y2 = int(eg car['Y2'])
 im2 = image[y1:y2,x1:x2]
 im2 = cv2.resize(im2, (IMAGE_SIZE, IMAGE_SIZE))
 destdirname = 'Car Images/Train Images Annoted/{0}'.format( eg car['CarLabel'])
 destfilename= eg_car['ImageName']
 if not os.path.exists(destdirname):
    os.mkdir(destdirname)
 cv2.imwrite(os.path.join(destdirname, destfilename), im2)
```

Display few cropped training images

```
eg_car = car_train_df.iloc[8]
path = 'Car Images/Train Images Annoted/{0}/{1}'.format( eg_car['CarLabel'], eg_c
ar['ImageName'] )
img = cv2.imread( path )
plt.grid(False)
plt.imshow(img)
```



```
eg_car = car_train_df.iloc[16]
path = 'Car Images/Train Images Annoted/{0}/{1}'.format( eg_car['CarLabel'], eg_c
ar['ImageName'] )
img = cv2.imread( path )
plt.grid(False)
plt.imshow(img)
```



Do the same for test images.

• Load the cropped train & test images using ImageDataGenerator

```
train_path = 'Car Images/Train Images Annoted'

test_path = 'Car Images/Test Images Annoted'

BATCH_SIZE = 32
IMG_SIZE = (224, 224)

train_datagen = ImageDataGenerator(
    rescale=1./255,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True)

test_datagen = ImageDataGenerator(rescale=1./255)

train_generator = train_datagen.flow_from_directory(
    train_path,
    target_size=IMG_SIZE,
```

```
batch_size=BATCH_SIZE,
    class_mode='categorical')

validation_generator = test_datagen.flow_from_directory(
    test_path,
    target_size=IMG_SIZE,
    batch_size=BATCH_SIZE,
    class_mode='categorical')

Found 8144 images belonging to 197 classes.
```

Found 8041 images belonging to 197 classes.

Train Different Models

For this problem, we tried following models:

- 1) Custom CNN Classifier
- 2) ResNet50 (with multiple layers)
- 3) VGG16
- 4) ResNet50 (without multiple layers)
- 5) InceptionResNetV2

A. Custom CNN Classifier

1. Create the model

```
# Initialising the CNN classifier
classifier = Sequential()
INPUT SIZE = (224, 224, 3)
# Add a Convolution layer with 32 kernels of 3X3 shape with activation function R
classifier.add(Conv2D(32, (3, 3), input shape = INPUT SIZE, activation = 'relu',
padding = 'same'))
# Add a Max Pooling layer of size 2X2
classifier.add(MaxPooling2D(pool size = (2, 2)))
# Add another Convolution layer with 32 kernels of 3X3 shape with activation func
tion ReLU
classifier.add(Conv2D(32, (3, 3), activation = 'relu', padding = 'same'))
# Adding another pooling layer
classifier.add(MaxPooling2D(pool size = (2, 2)))
# Add another Convolution layer with 32 kernels of 3X3 shape with activation func
tion ReLU
classifier.add(Conv2D(32, (3, 3), activation = 'relu', padding = 'same'))
# Adding another pooling layer
classifier.add(MaxPooling2D(pool size = (2, 2)))
# Flattening the layer before fully connected layers
classifier.add(Flatten())
```

```
# Adding a fully connected layer with 512 neurons
classifier.add(Dense(units = 512, activation = 'relu'))

# Adding dropout with probability 0.5
classifier.add(Dropout(0.5))

# Adding a fully connected layer with 128 neurons
classifier.add(Dense(units = 128, activation = 'relu'))

# The final output layer with output size 197 classes for the categorical classification
classifier.add(Dense(units = 197, activation = 'softmax'))
```

2. Summary

Model: "sequential 1"

Layer (type)	Output	Shape	Param #
conv2d_3 (Conv2D)	(None,	224, 224, 32)	896
max_pooling2d_3 (MaxPooling2	(None,	112, 112, 32)	0
conv2d_4 (Conv2D)	(None,	112, 112, 32)	9248
max_pooling2d_4 (MaxPooling2	(None,	56, 56, 32)	0
conv2d_5 (Conv2D)	(None,	56, 56, 32)	9248
max_pooling2d_5 (MaxPooling2	(None,	28, 28, 32)	0
flatten_1 (Flatten)	(None,	25088)	0
dense_3 (Dense)	(None,	512)	12845568
dropout_1 (Dropout)	(None,	512)	0
dense_4 (Dense)	(None,	128)	65664
dense_5 (Dense)	(None,	197) ========	25413

Total params: 12,956,037
Trainable params: 12,956,037

Non-trainable params: 0

3. Define Optimizer

```
opt = Adam(learning_rate=0.001, beta_1=0.9, beta_2=0.999, epsilon=None, decay=
0.001, amsgrad=False)
classifier.compile(optimizer = opt, loss = 'categorical_crossentropy', metrics
= ['accuracy'])
```

4. Training [Forward pass and Backpropagation]

```
#Early stopping
early = EarlyStopping(monitor='val accuracy', min delta=0, patience=40, verbose=1, mo
de='auto')
# There are 3823 training images and 500 test images in total
hist CNNClassifier = classifier.fit generator(train generator,
              steps per epoch = int(train generator.samples/BATCH SIZE),
              epochs = 20,
              validation data = validation generator,
              validation steps = int(validation generator.samples/BATCH SIZE
             ),
              callbacks = [early])
Epoch 1/20
accuracy: 0.0048 - val loss: 5.2809 - val accuracy: 0.0085
Epoch 2/20
accuracy: 0.0094 - val loss: 5.1779 - val accuracy: 0.0108
Epoch 3/20
accuracy: 0.0126 - val loss: 5.1202 - val_accuracy: 0.0149
Epoch 4/20
254/254 [==
                         =====] - 185s 728ms/step - loss: 5.1024 -
accuracy: 0.0164 - val loss: 5.1068 - val accuracy: 0.0144
Epoch 5/20
254/254 [===========
                       =======] - 184s 724ms/step - loss: 5.0617 -
accuracy: 0.0180 - val_loss: 5.0464 - val_accuracy: 0.0223
Epoch 6/20
accuracy: 0.0221 - val_loss: 4.9850 - val_accuracy: 0.0253
Epoch 7/20
                       =======] - 184s 726ms/step - loss: 4.9130 -
254/254 [======
accuracy: 0.0303 - val loss: 4.8883 - val accuracy: 0.0408
Epoch 8/20
accuracy: 0.0477 - val loss: 4.6899 - val accuracy: 0.0603
Epoch 9/20
accuracy: 0.0664 - val loss: 4.5243 - val accuracy: 0.0706
Epoch 10/20
                           ===] - 184s 725ms/step - loss: 4.3834 -
254/254 [==
accuracy: 0.0867 - val loss: 4.3964 - val accuracy: 0.0820
Epoch 11/20
```

```
accuracy: 0.0987 - val loss: 4.2711 - val accuracy: 0.0999
Epoch 12/20
                 =======] - 183s 723ms/step - loss: 4.0806 -
254/254 [===
accuracy: 0.1187 - val loss: 4.2011 - val accuracy: 0.1048
Epoch 13/20
        254/254 [==
accuracy: 0.1387 - val loss: 4.2050 - val accuracy: 0.1112
Epoch 14/20
accuracy: 0.1456 - val loss: 4.0591 - val_accuracy: 0.1213
Epoch 15/20
                    =====] - 185s 728ms/step - loss: 3.7540 -
254/254 [====
accuracy: 0.1610 - val_loss: 4.0304 - val_accuracy: 0.1300
Epoch 16/20
accuracy: 0.1700 - val loss: 3.9678 - val_accuracy: 0.1376
Epoch 17/20
accuracy: 0.1811 - val loss: 3.9020 - val accuracy: 0.1416
Epoch 18/20
accuracy: 0.2046 - val loss: 3.8804 - val accuracy: 0.1493
Epoch 19/20
accuracy: 0.2061 - val loss: 3.8908 - val accuracy: 0.1504
Epoch 20/20
   accuracy: 0.2226 - val loss: 3.8429 - val accuracy: 0.1584
```

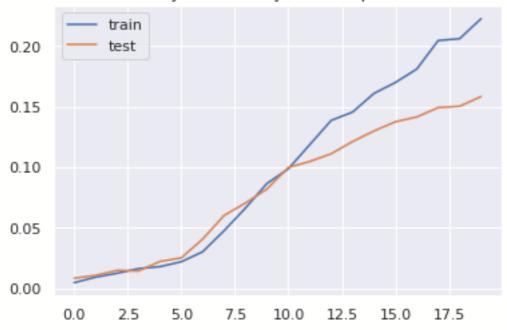
5. Accuracy and Loss for Training and Validation

```
train_loss = hist_CNNClassifier.history['loss']
val_loss = hist_CNNClassifier.history['val_loss']

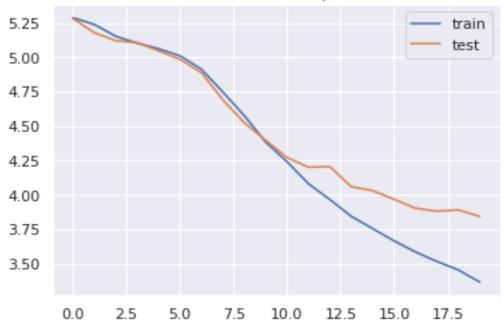
xc = hist_CNNClassifier.epoch
plt.title("Accuracy ValAccuracy Vs NumEpochs CNN")
plt.plot(xc,hist_CNNClassifier.history['accuracy'], label='train')
plt.plot(xc,hist_CNNClassifier.history['val_accuracy'], label='test')
plt.legend()
plt.show()

plt.figure()
plt.title("Loss ValLoss Vs NumEpochs CNN")
plt.plot(xc, train_loss,label='train')
plt.plot(xc, val_loss,label='test')
plt.legend()
plt.show
```

Accuracy ValAccuracy Vs NumEpochs CNN







Graph shows that model tends to increase both training and validation accuracy, and decrease training and validation loss with each epoch.

6. Evaluation

train_acc = classifier.evaluate_generator(train_generator, steps = int(train_ge
nerator.samples/BATCH_SIZE))
val_acc = classifier.evaluate_generator(validation_generator, steps = int(vali
dation_generator.samples/BATCH_SIZE))

```
print(train_acc[1])
print(val_acc[1])

0.3591289222240448
0.15861554443836212
```

Final evaluation shows that overall training accuracy is only around 36% and validation accuracy is around 16%. Therefore, this reveals both high bias and high variance issues.

7. Store result in a dataframe for final comparison of different models

Model Train_Accuracy Test_Accuracy

0	CNN	0.359129	0.158616
---	-----	----------	----------

8. Pickle the model for future use

```
classifier.save('./classifier.h5')
classifier.save weights('./classifier weights.h5')
```

B. ResNet50 (with multiple layers)

1. Creating the model

```
resnet50 = resnet50
conv_model = resnet50.ResNet50(weights='imagenet', include_top=False, input_shape
=(224,224,3))
x = Flatten()(conv_model.layers[-1].output)
x = Dense(512, activation='relu')(x)
x = Dense(224, activation='relu')(x)
```

```
x = Dense(224, activation='relu')(x)
x = Dense(224, activation='relu')(x)
x = Dense(224, activation='relu')(x)
x = Dense(224, activation='sigmoid')(x)
x = Dense(224, activation='sigmoid')(x)
predictions = Dense(197, activation='softmax')(x)

full_model = Model(inputs=conv_model.input, outputs=predictions)
```

2. Summary of model

full model.summary()

Model: "model 1"

Layer (type)	Output Shape	Param #	Connected to
input_3 (InputLayer)	[(None, 224, 224, 3)	0	
conv1_pad (ZeroPadding2D)	(None, 230, 230, 3)	0	input_3[0][0]
conv1_conv (Conv2D)	(None, 112, 112, 64)	9472	conv1_pad[0][0]
conv1_bn (BatchNormalization)	(None, 112, 112, 64)	256	conv1_conv[0][0]
conv1_relu (Activation)	(None, 112, 112, 64)	0	conv1_bn[0][0]
pool1_pad (ZeroPadding2D)	(None, 114, 114, 64)	0	conv1_relu[0][0]
pool1_pool (MaxPooling2D)	(None, 56, 56, 64)	0	pool1_pad[0][0]
conv2_block1_1_conv (Conv2D)	(None, 56, 56, 64)	4160	pool1_pool[0][0]
conv2_block1_1_bn (BatchNormali conv2_block1_1_conv[0][0]	(None, 56, 56, 64)	256	
conv2_block1_1_relu (Activation conv2_block1_1_bn[0][0]	(None, 56, 56, 64)	0	
conv2_block1_2_conv (Conv2D) conv2_block1_1_relu[0][0]	(None, 56, 56, 64)	36928	

<pre>conv2_block1_2_bn (BatchNormali conv2_block1_2_conv[0][0]</pre>	(None,	56,	56,	64)	256	
conv2_block1_2_relu (Activation conv2_block1_2_bn[0][0]	(None,	56,	56,	64)	0	
conv2_block1_0_conv (Conv2D)	(None,	56,	56,	256)	16640	pool1_pool[0][0]
conv2_block1_3_conv (Conv2D) conv2_block1_2_relu[0][0]	(None,	56,	56,	256)	16640	
conv2_block1_0_bn (BatchNormali conv2_block1_0_conv[0][0]	(None,	56,	56,	256)	1024	
conv2_block1_3_bn (BatchNormali conv2_block1_3_conv[0][0]	(None,	56,	56,	256)	1024	
conv2_block1_add (Add) conv2_block1_0_bn[0][0]	(None,	56,	56,	256)	0	
conv2_block1_3_bn[0][0]						
conv2_block1_out (Activation) conv2_block1_add[0][0]	(None,	56,	56,	256)	0	
conv2_block2_1_conv (Conv2D) conv2_block1_out[0][0]	(None,	56,	56,	64)	16448	
conv2_block2_1_bn (BatchNormali conv2_block2_1_conv[0][0]	(None,	56,	56,	64)	256	
conv2_block2_1_relu (Activation conv2_block2_1_bn[0][0]	(None,	56,	56,	64)	0	
conv2_block2_2_conv (Conv2D) conv2_block2_1_relu[0][0]	(None,	56,	56,	64)	36928	
conv2_block2_2_bn (BatchNormali conv2_block2_2_conv[0][0]	(None,	56,	56,	64)	256	
conv2_block2_2_relu (Activation conv2_block2_2_bn[0][0]	(None,	56,	56,	64)	0	
conv2_block2_3_conv (Conv2D) conv2_block2_2_relu[0][0]	(None,	56,	56,	256)	16640	

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<pre>conv2_block2_3_bn (BatchNormali conv2_block2_3_conv[0][0]</pre>	(None,	56,	56,	256)	1024
conv2_block2_add (Add) conv2_block1_out[0][0]	(None,	56,	56,	256)	0
conv2_block2_3_bn[0][0]					
conv2_block2_out (Activation) conv2_block2_add[0][0]	(None,	56,	56,	256)	0
conv2_block3_1_conv (Conv2D) conv2_block2_out[0][0]	(None,	56,	56,	64)	16448
conv2_block3_1_bn (BatchNormali conv2_block3_1_conv[0][0]	(None,	56,	56,	64)	256
conv2_block3_1_relu (Activation conv2_block3_1_bn[0][0]	(None,	56,	56,	64)	0
conv2_block3_2_conv (Conv2D) conv2_block3_1_relu[0][0]	(None,	56,	56,	64)	36928
<pre>conv2_block3_2_bn (BatchNormali conv2_block3_2_conv[0][0]</pre>	(None,	56,	56,	64)	256
conv2_block3_2_relu (Activation conv2_block3_2_bn[0][0]	(None,	56,	56,	64)	0
conv2_block3_3_conv (Conv2D) conv2_block3_2_relu[0][0]	(None,	56,	56,	256)	16640
<pre>conv2_block3_3_bn (BatchNormali conv2_block3_3_conv[0][0]</pre>	(None,	56,	56,	256)	1024
conv2_block3_add (Add) conv2_block2_out[0][0]	(None,	56,	56,	256)	0
conv2_block3_3_bn[0][0]					
conv2_block3_out (Activation) conv2_block3_add[0][0]	(None,	56,	56,	256)	0
conv3_block1_1_conv (Conv2D) conv2_block3_out[0][0]	(None,	28,	28,	128)	32896

```
conv3 block1 1 bn (BatchNormali (None, 28, 28, 128) 512
conv3 block1 1 conv[0][0]
conv3_block1_1_relu (Activation (None, 28, 28, 128) 0
conv3_block1_1_bn[0][0]
conv3 block1 2 conv (Conv2D)
                              (None, 28, 28, 128) 147584
conv3 block1 1 relu[0][0]
conv3 block1 2 bn (BatchNormali (None, 28, 28, 128) 512
conv3_block1_2_conv[0][0]
conv3 block1 2 relu (Activation (None, 28, 28, 128) 0
conv3 block1 2 bn[0][0]
conv3 block1 0 conv (Conv2D)
                              (None, 28, 28, 512) 131584
conv2_block3_out[0][0]
conv3 block1_3_conv (Conv2D)
                              (None, 28, 28, 512) 66048
conv3 block1 2 relu[0][0]
conv3 block1 0 bn (BatchNormali (None, 28, 28, 512) 2048
conv3 block1 0 conv[0][0]
conv3 block1 3 bn (BatchNormali (None, 28, 28, 512) 2048
conv3 block1 3 conv[0][0]
conv3 block1 add (Add)
                               (None, 28, 28, 512) 0
conv3 block1 0 bn[0][0]
conv3 block1 3 bn[0][0]
conv3 block1 out (Activation) (None, 28, 28, 512) 0
conv3 block1 add[0][0]
conv3 block2 1 conv (Conv2D)
                             (None, 28, 28, 128) 65664
conv3 block1 out[0][0]
conv3 block2 1 bn (BatchNormali (None, 28, 28, 128) 512
conv3 block2 1 conv[0][0]
conv3 block2 1 relu (Activation (None, 28, 28, 128) 0
conv3_block2_1_bn[0][0]
conv3_block2_2_conv (Conv2D) (None, 28, 28, 128) 147584
conv3 block2 1 relu[0][0]
```

conv3_block2_2_bn (BatchNormali conv3_block2_2_conv[0][0]	(None,	28,	28,	128)	512
conv3_block2_2_relu (Activation conv3_block2_2_bn[0][0]	(None,	28,	28,	128)	0
conv3_block2_3_conv (Conv2D) conv3_block2_2_relu[0][0]	(None,	28,	28,	512)	66048
conv3_block2_3_bn (BatchNormali conv3_block2_3_conv[0][0]	(None,	28,	28,	512)	2048
conv3_block2_add (Add) conv3_block1_out[0][0]	(None,	28,	28,	512)	0
conv3_block2_3_bn[0][0]					
conv3_block2_out (Activation) conv3_block2_add[0][0]	(None,	28,	28,	512)	0
conv3_block3_1_conv (Conv2D) conv3_block2_out[0][0]	(None,	28,	28,	128)	65664
conv3_block3_1_bn (BatchNormali conv3_block3_1_conv[0][0]	(None,	28,	28,	128)	512
conv3_block3_1_relu (Activation conv3_block3_1_bn[0][0]	(None,	28,	28,	128)	0
conv3_block3_2_conv (Conv2D) conv3_block3_1_relu[0][0]	(None,	28,	28,	128)	147584
conv3_block3_2_bn (BatchNormali conv3_block3_2_conv[0][0]	(None,	28,	28,	128)	512
conv3_block3_2_relu (Activation conv3_block3_2_bn[0][0]	(None,	28,	28,	128)	0
conv3_block3_3_conv (Conv2D) conv3_block3_2_relu[0][0]	(None,	28,	28,	512)	66048
conv3_block3_3_bn (BatchNormali conv3_block3_3_conv[0][0]	(None,	28,	28,	512)	2048

<pre>conv3_block3_add (Add) conv3_block2_out[0][0]</pre>	(None,	28,	28,	512)	0
conv3_block3_3_bn[0][0]					
conv3_block3_out (Activation) conv3_block3_add[0][0]	(None,	28,	28,	512)	0
conv3_block4_1_conv (Conv2D) conv3_block3_out[0][0]	(None,	28,	28,	128)	65664
conv3_block4_1_bn (BatchNormali conv3_block4_1_conv[0][0]	(None,	28,	28,	128)	512
conv3_block4_1_relu (Activation conv3_block4_1_bn[0][0]	(None,	28,	28,	128)	0
conv3_block4_2_conv (Conv2D) conv3_block4_1_relu[0][0]	(None,	28,	28,	128)	147584
conv3_block4_2_bn (BatchNormali conv3_block4_2_conv[0][0]	(None,	28,	28,	128)	512
conv3_block4_2_relu (Activation conv3_block4_2_bn[0][0]	(None,	28,	28,	128)	0
conv3_block4_3_conv (Conv2D) conv3_block4_2_relu[0][0]	(None,	28,	28,	512)	66048
conv3_block4_3_bn (BatchNormali conv3_block4_3_conv[0][0]	(None,	28,	28,	512)	2048
conv3_block4_add (Add) conv3_block3_out[0][0]	(None,	28,	28,	512)	0
conv3_block4_3_bn[0][0]					
conv3_block4_out (Activation) conv3_block4_add[0][0]	(None,	28,	28,	512)	0
conv4_block1_1_conv (Conv2D) conv3_block4_out[0][0]	(None,	14,	14,	256)	131328
conv4_block1_1_bn (BatchNormali conv4_block1_1_conv[0][0]	(None,	14,	14,	256)	1024

```
conv4 block1 1 relu (Activation (None, 14, 14, 256) 0
conv4 block1 1 bn[0][0]
conv4_block1_2_conv (Conv2D)
                               (None, 14, 14, 256) 590080
conv4_block1_1_relu[0][0]
conv4 block1 2 bn (BatchNormali (None, 14, 14, 256) 1024
conv4 block1 2 conv[0][0]
conv4 block1 2 relu (Activation (None, 14, 14, 256) 0
conv4_block1_2_bn[0][0]
                               (None, 14, 14, 1024) 525312
conv4 block1 0 conv (Conv2D)
conv3 block4 out[0][0]
conv4 block1 3 conv (Conv2D)
                               (None, 14, 14, 1024) 263168
conv4_block1_2_relu[0][0]
conv4 block1 0 bn (BatchNormali (None, 14, 14, 1024) 4096
conv4 block1 0 conv[0][0]
conv4 block1 3 bn (BatchNormali (None, 14, 14, 1024) 4096
conv4 block1 3 conv[0][0]
conv4 block1 add (Add)
                              (None, 14, 14, 1024) 0
conv4 block1 0 bn[0][0]
conv4 block1 3 bn[0][0]
conv4 block1 out (Activation)
                               (None, 14, 14, 1024) 0
conv4 block1 add[0][0]
conv4 block2 1 conv (Conv2D)
                              (None, 14, 14, 256) 262400
conv4 block1 out[0][0]
conv4 block2 1 bn (BatchNormali (None, 14, 14, 256) 1024
conv4 block2 1 conv[0][0]
conv4 block2 1 relu (Activation (None, 14, 14, 256) 0
conv4 block2 1 bn[0][0]
conv4 block2 2 conv (Conv2D)
                              (None, 14, 14, 256) 590080
conv4_block2_1_relu[0][0]
conv4_block2_2_bn (BatchNormali (None, 14, 14, 256) 1024
conv4 block2 2 conv[0][0]
```

```
conv4 block2 2 relu (Activation (None, 14, 14, 256) 0
conv4_block2_2_bn[0][0]
conv4_block2_3_conv (Conv2D)
                              (None, 14, 14, 1024) 263168
conv4 block2_2_relu[0][0]
conv4 block2 3 bn (BatchNormali (None, 14, 14, 1024) 4096
conv4_block2_3_conv[0][0]
conv4 block2 add (Add)
                               (None, 14, 14, 1024) 0
conv4 block1 out[0][0]
conv4 block2 3 bn[0][0]
conv4 block2 out (Activation)
                                (None, 14, 14, 1024) 0
conv4_block2_add[0][0]
conv4 block3_1_conv (Conv2D)
                               (None, 14, 14, 256) 262400
conv4 block2 out[0][0]
conv4_block3_1_bn (BatchNormali (None, 14, 14, 256) 1024
conv4 block3 1 conv[0][0]
conv4 block3 1 relu (Activation (None, 14, 14, 256) 0
conv4 block3 1 bn[0][0]
conv4_block3_2_conv (Conv2D)
                               (None, 14, 14, 256) 590080
conv4 block3 1 relu[0][0]
conv4_block3_2_bn (BatchNormali (None, 14, 14, 256) 1024
conv4_block3_2_conv[0][0]
conv4_block3_2_relu (Activation (None, 14, 14, 256) 0
conv4_block3_2_bn[0][0]
conv4_block3_3_conv (Conv2D)
                              (None, 14, 14, 1024) 263168
conv4_block3_2_relu[0][0]
conv4 block3 3 bn (BatchNormali (None, 14, 14, 1024) 4096
conv4 block3 3 conv[0][0]
conv4_block3_add (Add)
                               (None, 14, 14, 1024) 0
conv4_block2_out[0][0]
conv4 block3 3 bn[0][0]
```

conv4_block3_out (Activation) conv4_block3_add[0][0]	(None,	14,	14,	1024)	0
conv4_block4_1_conv (Conv2D) conv4_block3_out[0][0]	(None,	14,	14,	256)	262400
conv4_block4_1_bn (BatchNormali conv4_block4_1_conv[0][0]	(None,	14,	14,	256)	1024
conv4_block4_1_relu (Activation conv4_block4_1_bn[0][0]	(None,	14,	14,	256)	0
conv4_block4_2_conv (Conv2D) conv4_block4_1_relu[0][0]	(None,	14,	14,	256)	590080
conv4_block4_2_bn (BatchNormali conv4_block4_2_conv[0][0]	(None,	14,	14,	256)	1024
conv4_block4_2_relu (Activation conv4_block4_2_bn[0][0]	(None,	14,	14,	256)	0
conv4_block4_3_conv (Conv2D) conv4_block4_2_relu[0][0]	(None,	14,	14,	1024)	263168
conv4_block4_3_bn (BatchNormali conv4_block4_3_conv[0][0]	(None,	14,	14,	1024)	4096
conv4_block4_add (Add) conv4_block3_out[0][0]	(None,	14,	14,	1024)	0
conv4_block4_3_bn[0][0]					
conv4_block4_out (Activation) conv4_block4_add[0][0]	(None,	14,	14,	1024)	0
conv4_block5_1_conv (Conv2D) conv4_block4_out[0][0]	(None,	14,	14,	256)	262400
conv4_block5_1_bn (BatchNormali conv4_block5_1_conv[0][0]	(None,	14,	14,	256)	1024
conv4_block5_1_relu (Activation conv4_block5_1_bn[0][0]	(None,	14,	14,	256)	0

```
(None, 14, 14, 256) 590080
conv4 block5 2 conv (Conv2D)
conv4 block5 1 relu[0][0]
conv4_block5_2_bn (BatchNormali (None, 14, 14, 256) 1024
conv4_block5_2_conv[0][0]
conv4 block5 2 relu (Activation (None, 14, 14, 256) 0
conv4 block5 2 bn[0][0]
conv4 block5 3 conv (Conv2D)
                            (None, 14, 14, 1024) 263168
conv4_block5_2_relu[0][0]
conv4 block5 3 bn (BatchNormali (None, 14, 14, 1024) 4096
conv4 block5 3 conv[0][0]
                               (None, 14, 14, 1024) 0
conv4 block5 add (Add)
conv4_block4_out[0][0]
conv4 block5 3 bn[0][0]
conv4 block5 out (Activation) (None, 14, 14, 1024) 0
conv4_block5_add[0][0]
conv4 block6 1 conv (Conv2D) (None, 14, 14, 256) 262400
conv4_block5_out[0][0]
conv4 block6 1 bn (BatchNormali (None, 14, 14, 256) 1024
conv4 block6 1 conv[0][0]
conv4 block6 1 relu (Activation (None, 14, 14, 256) 0
conv4 block6 1 bn[0][0]
                              (None, 14, 14, 256) 590080
conv4 block6 2 conv (Conv2D)
conv4 block6 1 relu[0][0]
conv4 block6 2 bn (BatchNormali (None, 14, 14, 256) 1024
conv4_block6_2_conv[0][0]
conv4 block6 2 relu (Activation (None, 14, 14, 256) 0
conv4_block6_2_bn[0][0]
conv4 block6 3 conv (Conv2D) (None, 14, 14, 1024) 263168
conv4_block6_2_relu[0][0]
conv4_block6_3_bn (BatchNormali (None, 14, 14, 1024) 4096
```

conv4 block6 3 conv[0][0]

conv4_block6_add (Add) conv4_block5_out[0][0]	(None, 14, 14, 1024)	0
conv4_block6_3_bn[0][0]		
conv4_block6_out (Activation) conv4_block6_add[0][0]	(None, 14, 14, 1024)	0
conv5_block1_1_conv (Conv2D) conv4_block6_out[0][0]	(None, 7, 7, 512)	524800
conv5_block1_1_bn (BatchNormali conv5_block1_1_conv[0][0]	(None, 7, 7, 512)	2048
conv5_block1_1_relu (Activation conv5_block1_1_bn[0][0]	(None, 7, 7, 512)	0
conv5_block1_2_conv (Conv2D) conv5_block1_1_relu[0][0]	(None, 7, 7, 512)	2359808
conv5_block1_2_bn (BatchNormali conv5_block1_2_conv[0][0]	(None, 7, 7, 512)	2048
conv5_block1_2_relu (Activation conv5_block1_2_bn[0][0]	(None, 7, 7, 512)	0
conv5_block1_0_conv (Conv2D) conv4_block6_out[0][0]	(None, 7, 7, 2048)	2099200
conv5_block1_3_conv (Conv2D) conv5_block1_2_relu[0][0]	(None, 7, 7, 2048)	1050624
conv5_block1_0_bn (BatchNormali conv5_block1_0_conv[0][0]	(None, 7, 7, 2048)	8192
conv5_block1_3_bn (BatchNormali conv5_block1_3_conv[0][0]	(None, 7, 7, 2048)	8192
conv5_block1_add (Add) conv5_block1_0_bn[0][0]	(None, 7, 7, 2048)	0
conv5_block1_3_bn[0][0]		
conv5_block1_out (Activation) conv5_block1_add[0][0]	(None, 7, 7, 2048)	0

conv5_block2_1_conv (Conv2D) conv5_block1_out[0][0]	(None,	7,	7,	512)	1049088
conv5_block2_1_bn (BatchNormali conv5_block2_1_conv[0][0]	(None,	7,	7,	512)	2048
conv5_block2_1_relu (Activation conv5_block2_1_bn[0][0]	(None,	7,	7,	512)	0
conv5_block2_2_conv (Conv2D) conv5_block2_1_relu[0][0]	(None,	7,	7,	512)	2359808
conv5_block2_2_bn (BatchNormali conv5_block2_2_conv[0][0]	(None,	7,	7,	512)	2048
conv5_block2_2_relu (Activation conv5_block2_2_bn[0][0]	(None,	7,	7,	512)	0
conv5_block2_3_conv (Conv2D) conv5_block2_2_relu[0][0]	(None,	7,	7,	2048)	1050624
conv5_block2_3_bn (BatchNormali conv5_block2_3_conv[0][0]	(None,	7,	7,	2048)	8192
conv5_block2_add (Add) conv5_block1_out[0][0]	(None,	7,	7,	2048)	0
conv5_block2_3_bn[0][0]					
conv5_block2_out (Activation) conv5_block2_add[0][0]	(None,	7,	7,	2048)	0
conv5_block3_1_conv (Conv2D) conv5_block2_out[0][0]	(None,	7,	7,	512)	1049088
<pre>conv5_block3_1_bn (BatchNormali conv5_block3_1_conv[0][0]</pre>	(None,	7,	7,	512)	2048
conv5_block3_1_relu (Activation conv5_block3_1_bn[0][0]	(None,	7,	7,	512)	0
conv5_block3_2_conv (Conv2D) conv5_block3_1_relu[0][0]	(None,	7,	7,	512)	2359808

<pre>conv5_block3_2_bn (BatchNormali conv5_block3_2_conv[0][0]</pre>	(None,	7, 7, 512)	2048	
conv5_block3_2_relu (Activation conv5_block3_2_bn[0][0]	(None,	7, 7, 512)	0	
conv5_block3_3_conv (Conv2D) conv5_block3_2_relu[0][0]	(None,	7, 7, 2048)	1050624	
conv5_block3_3_bn (BatchNormali conv5_block3_3_conv[0][0]	(None,	7, 7, 2048)	8192	
conv5_block3_add (Add) conv5_block2_out[0][0]	(None,	7, 7, 2048)	0	
conv5_block3_3_bn[0][0]				
conv5_block3_out (Activation) conv5_block3_add[0][0]	(None,	7, 7, 2048)	0	
flatten_5 (Flatten) conv5_block3_out[0][0]	(None,	100352)	0	
dense_18 (Dense)	(None,	512)	51380736	flatten_5[0][0]
dense_19 (Dense)	(None,	224)	114912	dense_18[0][0]
dense_20 (Dense)	(None,	224)	50400	dense_19[0][0]
dense_21 (Dense)	(None,	224)	50400	dense_20[0][0]
dense_22 (Dense)	(None,	224)	50400	dense_21[0][0]
dense_23 (Dense)	(None,	224)	50400	dense_22[0][0]
dense_24 (Dense)	(None,	224)	50400	dense_23[0][0]
dense_25 (Dense)	(None,	197) =======	44325 =======	dense_24[0][0]
============				

Total params: 75,379,685
Trainable params: 75,326,565
Non-trainable params: 53,120

3. Define optimizer

```
opt= Adam(learning rate=0.001)
```

4. Training [Forward pass and Backpropagation]

```
#Compile
full model.compile(optimizer= opt, loss = 'categorical crossentropy', metrics
= ['accuracy'])
#Early stopping
early = EarlyStopping (monitor='val accuracy', min delta=0, patience=40, verbose=1
, mode='auto')
res classifier=full model.fit generator(train generator, steps per epoch = 2, e
pochs =30, validation data = validation generator,
       validation steps = 1, callbacks = [early])
Epoch 1/30
0.0000e+00 - val_loss: 5.5525 - val_accuracy: 0.0000e+00
Epoch 2/30
accuracy: 0.0000e+00 - val loss: 5.7100 - val accuracy: 0.0000e+00
Epoch 3/30
2/2 [======
           0.0000e+00 - val loss: 5.5345 - val accuracy: 0.0000e+00
accuracy: 0.0000e+00 - val_loss: 5.5610 - val_accuracy: 0.0000e+00
Epoch 5/30
            0.0000e+00 - val loss: 5.6320 - val accuracy: 0.0000e+00
Epoch 6/30
0.0000e+00 - val loss: 5.4623 - val accuracy: 0.0000e+00
Epoch 7/30
0.0000e+00 - val_loss: 5.5907 - val_accuracy: 0.0000e+00
Epoch 8/30
                    ====] - 2s 1s/step - loss: 5.4999 - accuracy:
2/2 [=======
0.0000e+00 - val_loss: 5.4237 - val_accuracy: 0.0000e+00
Epoch 9/30
```

```
accuracy: 0.0312 - val loss: 5.4819 - val_accuracy: 0.0000e+00
Epoch 10/30
0.0156 - val loss: 5.4853 - val accuracy: 0.0000e+00
Epoch 11/30
0.0000e+00 - val_loss: 5.3407 - val_accuracy: 0.0312
Epoch 12/30
accuracy: 0.0000e+00 - val loss: 5.5048 - val accuracy: 0.0000e+00
Epoch 13/30
0.0000e+00 - val loss: 5.3331 - val accuracy: 0.0000e+00
Epoch 14/30
accuracy: 0.0156 - val loss: 5.3322 - val accuracy: 0.0000e+00
Epoch 15/30
0.0000e+00 - val loss: 5.4033 - val accuracy: 0.0000e+00
Epoch 16/30
      0.0000e+00 - val_loss: 5.3253 - val_accuracy: 0.0000e+00
Epoch 17/30
     2/2 [====
0.0000e+00 - val_loss: 5.3175 - val_accuracy: 0.0000e+00
Epoch 18/30
0.0000e+00 - val_loss: 5.3590 - val_accuracy: 0.0000e+00
Epoch 19/30
accuracy: 0.0156 - val loss: 5.3885 - val_accuracy: 0.0312
Epoch 20/30
0.0156 - val loss: 5.3115 - val accuracy: 0.0000e+00
Epoch 21/30
accuracy: 0.0000e+00 - val loss: 5.2952 - val accuracy: 0.0000e+00
Epoch 22/30
accuracy: 0.0156 - val_loss: 5.3405 - val_accuracy: 0.0000e+00
Epoch 23/30
           =========] - 2s 994ms/step - loss: 5.3303 -
accuracy: 0.0000e+00 - val loss: 5.3367 - val accuracy: 0.0312
Epoch 24/30
         2/2 [======
0.0000e+00 - val_loss: 5.2927 - val_accuracy: 0.0000e+00
Epoch 25/30
0.0312 - val_loss: 5.3621 - val_accuracy: 0.0000e+00
Epoch 26/30
          0.0000e+00 - val loss: 5.3109 - val accuracy: 0.0000e+00
Epoch 27/30
0.0000e+00 - val loss: 5.2597 - val accuracy: 0.0000e+00
Epoch 28/30
accuracy: 0.0000e+00 - val loss: 5.3778 - val accuracy: 0.0000e+00
Epoch 29/30
         2/2 [========
0.0000e+00 - val_loss: 5.3392 - val_accuracy: 0.0000e+00
```

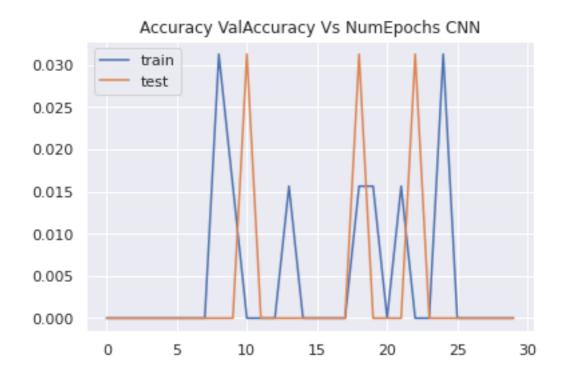
```
Epoch 30/30
```

5. Plot Accuracy and Loss for Training and Validation

```
train_loss = res_classifier.history['loss']
val_loss = res_classifier.history['val_loss']

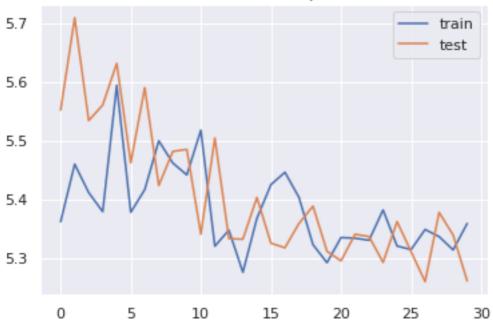
xc = res_classifier.epoch
plt.title("Accuracy ValAccuracy Vs NumEpochs CNN")
plt.plot(xc,res_classifier.history['accuracy'], label='train')
plt.plot(xc,res_classifier.history['val_accuracy'], label='test')
plt.legend()
plt.show()

plt.figure()
plt.title("Loss ValLoss Vs NumEpochs CNN")
plt.plot(xc, train_loss,label='train')
plt.plot(xc, val_loss,label='test')
plt.legend()
plt.show
```



Plot shows that model tries to touch peaks and troughs with increasing epochs.





Plot shows that model tries to reduce loss for both training and validation dataset with each epoch.

6. Evaluation

```
train_acc = full_model.evaluate_generator(train_generator, steps = int(train_ge
nerator.samples/BATCH_SIZE))
val_acc = full_model.evaluate_generator(validation_generator, steps = int(validation_generator.samples/BATCH_SIZE))

print(train_acc[1])
print(val acc[1])
```

- 0.005290354136377573
- 0.005229083821177483

Thus, this model performs very poorly on both training and validation dataset.

7. Adding results to dataframe for final comparison

```
#Adding Performance metrics of ResNet50 to the list
tempResultsDf = pd.DataFrame({'Model':['ResNet50'], 'Train_Accuracy': train_a
cc[1],'Test_Accuracy': val_acc[1]})
resultsDf = pd.concat([resultsDf, tempResultsDf])
resultsDf = resultsDf[['Model', 'Train_Accuracy','Test_Accuracy']]
resultsDf
```

Model Train_Accuracy Test_Accuracy

0	CNN	0.359129	0.158616
0	ResNet50	0.005290	0.005229

C. VGG16

1. Creating the model

2. Summary of model

```
vgg_model.summary()
Model: "model 3"
```

Layer (type)	Output Shape	Param #
input_5 (InputLayer)	[(None, 224, 224, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten_7 (Flatten)	(None, 25088)	0
dense_27 (Dense)	(None, 197)	4942533

Total params: 19,657,221 Trainable params: 4,942,533 Non-trainable params: 14,714,688

3. Training [Forward pass and Backpropagation]

```
#Compile the model with Adam optimizer
vgg_model.compile(optimizer = Adam(learning_rate=0.001), loss = 'categorical_c
rossentropy', metrics = ['accuracy'])
```

```
early = EarlyStopping(monitor='val accuracy', min delta=0.01, patience=20, verbos
e=1, mode='auto')
#Training
vgg classifier = vgg model.fit generator(train generator, epochs =30, validati
on data = validation generator, callbacks = [early] )
Epoch 1/30
accuracy: 0.9467 - val loss: 4.6444 - val_accuracy: 0.5884
Epoch 2/30
accuracy: 0.9422 - val loss: 4.7269 - val accuracy: 0.5948
Epoch 3/30
accuracy: 0.9408 - val loss: 5.6650 - val accuracy: 0.5547
Epoch 4/30
255/255 [============= ] - 180s 708ms/step - loss: 0.3101 -
accuracy: 0.9468 - val loss: 5.3064 - val accuracy: 0.5703
Epoch 5/30
accuracy: 0.9473 - val loss: 5.1069 - val accuracy: 0.5900
Epoch 6/30
       255/255 [==
accuracy: 0.9353 - val_loss: 5.2278 - val_accuracy: 0.5865
Epoch 7/30
accuracy: 0.9565 - val loss: 5.8028 - val accuracy: 0.5659
Epoch 8/30
accuracy: 0.9474 - val loss: 5.7594 - val accuracy: 0.5743
Epoch 9/30
accuracy: 0.9398 - val loss: 6.2191 - val accuracy: 0.5476
Epoch 10/30
```

```
accuracy: 0.9546 - val loss: 4.9970 - val accuracy: 0.6029
Epoch 11/30
accuracy: 0.9634 - val loss: 5.5075 - val_accuracy: 0.5799
Epoch 12/30
                  =======] - 181s 708ms/step - loss: 0.3211 -
255/255 [====
accuracy: 0.9540 - val loss: 5.6694 - val accuracy: 0.5843
Epoch 13/30
255/255 [============
                  =======] - 182s 715ms/step - loss: 0.2927 -
accuracy: 0.9563 - val_loss: 5.5035 - val_accuracy: 0.5997
Epoch 14/30
accuracy: 0.9538 - val_loss: 6.6898 - val_accuracy: 0.5348
Epoch 15/30
255/255 [======
           accuracy: 0.9554 - val loss: 5.8260 - val accuracy: 0.5806
Epoch 16/30
accuracy: 0.9602 - val loss: 5.4916 - val accuracy: 0.6008
Epoch 17/30
```

```
accuracy: 0.9558 - val loss: 6.3606 - val accuracy: 0.5646
Epoch 18/30
                   =======] - 184s 720ms/step - loss: 0.3615 -
255/255 [=============
accuracy: 0.9506 - val loss: 5.5514 - val accuracy: 0.6050
Epoch 19/30
         255/255 [==
accuracy: 0.9570 - val loss: 6.3985 - val accuracy: 0.5748
Epoch 20/30
accuracy: 0.9543 - val_loss: 5.9179 - val_accuracy: 0.5907
Epoch 21/30
                   ======] - 182s 713ms/step - loss: 0.2523 -
255/255 [======
accuracy: 0.9629 - val loss: 6.2966 - val accuracy: 0.5783
Epoch 22/30
accuracy: 0.9635 - val loss: 5.8626 - val accuracy: 0.6010
Epoch 23/30
accuracy: 0.9630 - val loss: 6.3886 - val accuracy: 0.5886
Epoch 24/30
accuracy: 0.9564 - val loss: 6.0438 - val_accuracy: 0.5994
Epoch 25/30
accuracy: 0.9592 - val loss: 6.7721 - val accuracy: 0.5663
Epoch 26/30
                   =======] - 181s 710ms/step - loss: 0.2081 -
255/255 [============
accuracy: 0.9680 - val loss: 5.9842 - val accuracy: 0.6064
Epoch 27/30
accuracy: 0.9662 - val loss: 6.4080 - val_accuracy: 0.5895
Epoch 28/30
255/255 [=======
                   =======] - 182s 713ms/step - loss: 0.2165 -
accuracy: 0.9697 - val loss: 5.7963 - val accuracy: 0.6151
Epoch 29/30
accuracy: 0.9684 - val loss: 6.0159 - val accuracy: 0.6081
Epoch 30/30
     0.2903 - accuracy: 0.9608 - val_loss: 6.4375 - val_accuracy: 0.5978
```

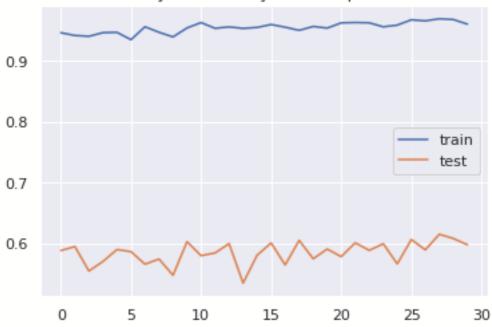
4. Plot Accuracy and Loss

```
train_loss = vgg_classifier.history['loss']
val_loss = vgg_classifier.history['val_loss']

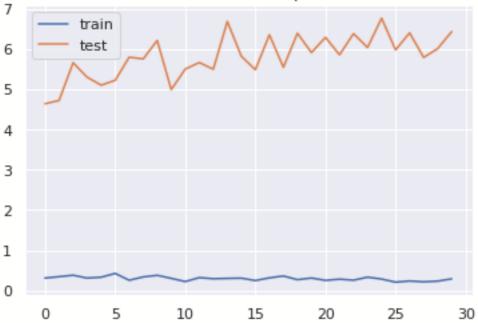
xc = vgg_classifier.epoch
plt.title("Accuracy ValAccuracy Vs NumEpochs CNN")
plt.plot(xc,vgg_classifier.history['accuracy'], label='train')
plt.plot(xc,vgg_classifier.history['val_accuracy'], label='test')
plt.legend()
plt.show()
```

```
plt.figure()
plt.title("Loss ValLoss Vs NumEpochs CNN")
plt.plot(xc, train_loss,label='train')
plt.plot(xc, val_loss,label='test')
plt.legend()
plt.show
```

Accuracy ValAccuracy Vs NumEpochs CNN



Loss ValLoss Vs NumEpochs CNN



Plot shows that both training and validation accuracy, and training and validation loss remains more or less constant over epochs.

5. Evaluation

```
train_acc = vgg_model.evaluate_generator(train_generator, steps = int(train_generator.samples/BATCH_SIZE))
val_acc = vgg_model.evaluate_generator(validation_generator, steps = int(validation_generator.samples/BATCH_SIZE))
print(train_acc[1])
print(val_acc[1])
0.9386072754859924
0.5639940500259399
```

Therefore, model shows a high training accuracy of around 94%. But validation accuracy is low at 56%. This shows a high variance problem.

6. Add result to dataframe for final comparison

```
#Adding Performance metrics of ResNet50 to the list
tempResultsDf = pd.DataFrame({'Model':['VGG16'], 'Train_Accuracy': train_acc[
1],'Test_Accuracy': val_acc[1]})
resultsDf = pd.concat([resultsDf, tempResultsDf])
resultsDf = resultsDf[['Model', 'Train_Accuracy','Test_Accuracy']]
resultsDf
```

	Model	Train_Accuracy	Test_Accuracy
0	CNN	0.359129	0.158616
0	ResNet50	0.005290	0.005229
0	VGG16	0.938607	0.563994

7. Save model for future use

```
vgg_model.save('./vgg.h5')
vgg_model.save_weights('./vgg_weights.h5')
```

D. ResNet50 (without multiple layers)

1. Creating the model

```
resnet_conv = ResNet50(weights='imagenet', include_top=False, input_shape=(224
,224,3))

# Freeze all the layers except for the last layer:
for layer in resnet_conv.layers:
    layer.trainable = False

x2 = Flatten()(resnet_conv.output)
x2 = Dense(197, activation='sigmoid')(x2)
resnet = Model(resnet_conv.input, x2)
```

2. Summary of model

resnet.summary()

conv1_conv (Conv2D) conv1_pad[0][0]	(None,	112, 112	2, 64)	9472
conv1_bn (BatchNormalization) conv1_conv[0][0]	(None,	112, 112	2, 64)	256
conv1_relu (Activation) conv1_bn[0][0]	(None,	112, 112	2, 64)	0
pool1_pad (ZeroPadding2D) conv1_relu[0][0]	(None,	114, 114	4, 64)	0
pool1_pool (MaxPooling2D) pool1_pad[0][0]	(None,	56, 56,	64)	0
conv2_block1_1_conv (Conv2D) pool1_pool[0][0]	(None,	56, 56,	64)	4160
conv2_block1_1_bn (BatchNormaliconv2_block1_1_conv[0][0]	(None,	56, 56,	64)	256
conv2_block1_1_relu (Activation conv2_block1_1_bn[0][0]	(None,	56, 56,	64)	0
conv2_block1_2_conv (Conv2D) conv2_block1_1_relu[0][0]	(None,	56, 56,	64)	36928
conv2_block1_2_bn (BatchNormaliconv2_block1_2_conv[0][0]	(None,	56, 56,	64)	256
conv2_block1_2_relu (Activation conv2_block1_2_bn[0][0]	(None,	56, 56,	64)	0
conv2_block1_0_conv (Conv2D) pool1_pool[0][0]	(None,	56, 56,	256)	16640
conv2_block1_3_conv (Conv2D) conv2_block1_2_relu[0][0]	(None,	56, 56,	256)	16640
conv2_block1_0_bn (BatchNormali conv2_block1_0_conv[0][0]	(None,	56, 56,	256)	1024
conv2_block1_3_bn (BatchNormali conv2_block1_3_conv[0][0]	(None,	56, 56,	256)	1024

<pre>conv2_block1_add (Add) conv2_block1_0_bn[0][0] conv2_block1_3_bn[0][0]</pre>	(None,	56,	56,	256)	0
conv2_block1_out (Activation) conv2_block1_add[0][0]	(None,	56,	56,	256)	0
conv2_block2_1_conv (Conv2D) conv2_block1_out[0][0]	(None,	56,	56,	64)	16448
conv2_block2_1_bn (BatchNormaliconv2_block2_1_conv[0][0]	(None,	56,	56,	64)	256
conv2_block2_1_relu (Activation conv2_block2_1_bn[0][0]	(None,	56,	56,	64)	0
conv2_block2_2_conv (Conv2D) conv2_block2_1_relu[0][0]	(None,	56,	56,	64)	36928
conv2_block2_2_bn (BatchNormaliconv2_block2_2_conv[0][0]	(None,	56,	56,	64)	256
conv2_block2_2_relu (Activation conv2_block2_2_bn[0][0]	(None,	56,	56,	64)	0
conv2_block2_3_conv (Conv2D) conv2_block2_2_relu[0][0]	(None,	56,	56,	256)	16640
conv2_block2_3_bn (BatchNormali conv2_block2_3_conv[0][0]	(None,	56,	56,	256)	1024
conv2_block2_add (Add) conv2_block1_out[0][0]	(None,	56,	56,	256)	0
conv2_block2_3_bn[0][0]					
conv2_block2_out (Activation) conv2_block2_add[0][0]	(None,	56,	56,	256)	0
conv2_block3_1_conv (Conv2D) conv2_block2_out[0][0]	(None,	56,	56,	64)	16448
conv2_block3_1_bn (BatchNormali conv2_block3_1_conv[0][0]	(None,	56,	56,	64)	256

<pre>conv2_block3_1_relu (Activation conv2_block3_1_bn[0][0]</pre>	(None,	56,	56,	64)	0
conv2_block3_2_conv (Conv2D) conv2_block3_1_relu[0][0]	(None,	56,	56,	64)	36928
conv2_block3_2_bn (BatchNormali conv2_block3_2_conv[0][0]	(None,	56,	56,	64)	256
conv2_block3_2_relu (Activation conv2_block3_2_bn[0][0]	(None,	56,	56,	64)	0
conv2_block3_3_conv (Conv2D) conv2_block3_2_relu[0][0]	(None,	56,	56,	256)	16640
conv2_block3_3_bn (BatchNormaliconv2_block3_3_conv[0][0]	(None,	56,	56,	256)	1024
conv2_block3_add (Add) conv2_block2_out[0][0]	(None,	56,	56,	256)	0
conv2_block3_3_bn[0][0]					
conv2_block3_out (Activation) conv2_block3_add[0][0]	(None,	56,	56,	256)	0
conv3_block1_1_conv (Conv2D) conv2_block3_out[0][0]	(None,	28,	28,	128)	32896
conv3_block1_1_bn (BatchNormali conv3_block1_1_conv[0][0]	(None,	28,	28,	128)	512
conv3_block1_1_relu (Activation conv3_block1_1_bn[0][0]	(None,	28,	28,	128)	0
conv3_block1_2_conv (Conv2D) conv3_block1_1_relu[0][0]	(None,	28,	28,	128)	147584
conv3_block1_2_bn (BatchNormali conv3_block1_2_conv[0][0]	(None,	28,	28,	128)	512
conv3_block1_2_relu (Activation conv3_block1_2_bn[0][0]	(None,	28,	28,	128)	0
conv3_block1_0_conv (Conv2D) conv2_block3_out[0][0]	(None,	28,	28,	512)	131584

conv3_block1_3_conv (Conv2D) conv3_block1_2_relu[0][0]	(None,	28,	28,	512)	66048
conv3_block1_0_bn (BatchNormali conv3_block1_0_conv[0][0]	(None,	28,	28,	512)	2048
conv3_block1_3_bn (BatchNormali conv3_block1_3_conv[0][0]	(None,	28,	28,	512)	2048
conv3_block1_add (Add) conv3_block1_0_bn[0][0]	(None,	28,	28,	512)	0
conv3_block1_3_bn[0][0]					
conv3_block1_out (Activation) conv3_block1_add[0][0]	(None,	28,	28,	512)	0
conv3_block2_1_conv (Conv2D) conv3_block1_out[0][0]	(None,	28,	28,	128)	65664
conv3_block2_1_bn (BatchNormali conv3_block2_1_conv[0][0]	(None,	28,	28,	128)	512
conv3_block2_1_relu (Activation conv3_block2_1_bn[0][0]	(None,	28,	28,	128)	0
conv3_block2_2_conv (Conv2D) conv3_block2_1_relu[0][0]	(None,	28,	28,	128)	147584
conv3_block2_2_bn (BatchNormali conv3_block2_2_conv[0][0]	(None,	28,	28,	128)	512
conv3_block2_2_relu (Activation conv3_block2_2_bn[0][0]	(None,	28,	28,	128)	0
conv3_block2_3_conv (Conv2D) conv3_block2_2_relu[0][0]	(None,	28,	28,	512)	66048
conv3_block2_3_bn (BatchNormali conv3_block2_3_conv[0][0]	(None,	28,	28,	512)	2048
conv3_block2_add (Add) conv3_block1_out[0][0]	(None,	28,	28,	512)	0
conv3_block2_3_bn[0][0]					

conv3_block2_out (Activation) conv3_block2_add[0][0]	(None,	28,	28,	512)	0
conv3_block3_1_conv (Conv2D) conv3_block2_out[0][0]	(None,	28,	28,	128)	65664
conv3_block3_1_bn (BatchNormali conv3_block3_1_conv[0][0]	(None,	28,	28,	128)	512
conv3_block3_1_relu (Activation conv3_block3_1_bn[0][0]	(None,	28,	28,	128)	0
conv3_block3_2_conv (Conv2D) conv3_block3_1_relu[0][0]	(None,	28,	28,	128)	147584
conv3_block3_2_bn (BatchNormali conv3_block3_2_conv[0][0]	(None,	28,	28,	128)	512
conv3_block3_2_relu (Activation conv3_block3_2_bn[0][0]	(None,	28,	28,	128)	0
conv3_block3_3_conv (Conv2D) conv3_block3_2_relu[0][0]	(None,	28,	28,	512)	66048
conv3_block3_3_bn (BatchNormali conv3_block3_3_conv[0][0]	(None,	28,	28,	512)	2048
conv3_block3_add (Add) conv3_block2_out[0][0]	(None,	28,	28,	512)	0
conv3_block3_3_bn[0][0]					
conv3_block3_out (Activation) conv3_block3_add[0][0]	(None,	28,	28,	512)	0
conv3_block4_1_conv (Conv2D) conv3_block3_out[0][0]	(None,	28,	28,	128)	65664
conv3_block4_1_bn (BatchNormali conv3_block4_1_conv[0][0]	(None,	28,	28,	128)	512
conv3_block4_1_relu (Activation conv3_block4_1_bn[0][0]	(None,	28,	28,	128)	0

<pre>conv3_block4_2_conv (Conv2D) conv3_block4_1_relu[0][0]</pre>	(None,	28,	28,	128)	147584
conv3_block4_2_bn (BatchNormali conv3_block4_2_conv[0][0]	(None,	28,	28,	128)	512
conv3_block4_2_relu (Activation conv3_block4_2_bn[0][0]	(None,	28,	28,	128)	0
conv3_block4_3_conv (Conv2D) conv3_block4_2_relu[0][0]	(None,	28,	28,	512)	66048
conv3_block4_3_bn (BatchNormali conv3_block4_3_conv[0][0]	(None,	28,	28,	512)	2048
conv3_block4_add (Add) conv3_block3_out[0][0]	(None,	28,	28,	512)	0
conv3_block4_3_bn[0][0]					
conv3_block4_out (Activation) conv3_block4_add[0][0]	(None,	28,	28,	512)	0
conv4_block1_1_conv (Conv2D) conv3_block4_out[0][0]	(None,	14,	14,	256)	131328
conv4_block1_1_bn (BatchNormali conv4_block1_1_conv[0][0]	(None,	14,	14,	256)	1024
conv4_block1_1_relu (Activation conv4_block1_1_bn[0][0]	(None,	14,	14,	256)	0
conv4_block1_2_conv (Conv2D) conv4_block1_1_relu[0][0]	(None,	14,	14,	256)	590080
conv4_block1_2_bn (BatchNormali conv4_block1_2_conv[0][0]	(None,	14,	14,	256)	1024
conv4_block1_2_relu (Activation conv4_block1_2_bn[0][0]	(None,	14,	14,	256)	0
conv4_block1_0_conv (Conv2D) conv3_block4_out[0][0]	(None,	14,	14,	1024)	525312
conv4_block1_3_conv (Conv2D) conv4_block1_2_relu[0][0]	(None,	14,	14,	1024)	263168

```
conv4 block1 0 bn (BatchNormali (None, 14, 14, 1024) 4096
conv4 block1 0 conv[0][0]
conv4 block1 3 bn (BatchNormali (None, 14, 14, 1024) 4096
conv4 block1 3 conv[0][0]
conv4 block1 add (Add)
                               (None, 14, 14, 1024) 0
conv4_block1_0_bn[0][0]
conv4_block1_3_bn[0][0]
conv4 block1 out (Activation)
                              (None, 14, 14, 1024) 0
conv4 block1 add[0][0]
conv4 block2 1 conv (Conv2D)
                               (None, 14, 14, 256) 262400
conv4_block1_out[0][0]
conv4 block2 1 bn (BatchNormali (None, 14, 14, 256)
                                                     1024
conv4 block2 1 conv[0][0]
conv4 block2_1_relu (Activation (None, 14, 14, 256) 0
conv4 block2 1 bn[0][0]
                              (None, 14, 14, 256)
conv4 block2 2 conv (Conv2D)
                                                    590080
conv4 block2 1 relu[0][0]
conv4 block2 2 bn (BatchNormali (None, 14, 14, 256) 1024
conv4 block2 2 conv[0][0]
conv4_block2_2_relu (Activation (None, 14, 14, 256)
conv4_block2_2_bn[0][0]
conv4 block2 3 conv (Conv2D)
                               (None, 14, 14, 1024) 263168
conv4 block2 2 relu[0][0]
conv4_block2_3_bn (BatchNormali (None, 14, 14, 1024) 4096
conv4_block2_3_conv[0][0]
conv4 block2 add (Add)
                               (None, 14, 14, 1024) 0
conv4 block1 out[0][0]
conv4 block2 3 bn[0][0]
conv4 block2 out (Activation) (None, 14, 14, 1024) 0
```

conv4 block2 add[0][0]

```
conv4 block3 1 conv (Conv2D)
                               (None, 14, 14, 256)
                                                     262400
conv4 block2 out[0][0]
conv4 block3 1 bn (BatchNormali (None, 14, 14, 256)
                                                     1024
conv4 block3 1 conv[0][0]
conv4 block3 1 relu (Activation (None, 14, 14, 256) 0
conv4_block3_1_bn[0][0]
conv4 block3 2 conv (Conv2D)
                               (None, 14, 14, 256)
                                                     590080
conv4 block3 1 relu[0][0]
conv4 block3 2 bn (BatchNormali (None, 14, 14, 256)
                                                     1024
conv4_block3_2_conv[0][0]
conv4_block3_2_relu (Activation (None, 14, 14, 256)
conv4 block3 2 bn[0][0]
conv4 block3 3 conv (Conv2D)
                               (None, 14, 14, 1024) 263168
conv4_block3_2_relu[0][0]
conv4 block3 3 bn (BatchNormali (None, 14, 14, 1024) 4096
conv4 block3 3 conv[0][0]
conv4 block3 add (Add)
                               (None, 14, 14, 1024) 0
conv4 block2 out[0][0]
conv4 block3 3 bn[0][0]
conv4_block3_out (Activation)
                               (None, 14, 14, 1024) 0
conv4_block3_add[0][0]
conv4_block4_1_conv (Conv2D)
                               (None, 14, 14, 256) 262400
conv4 block3 out[0][0]
conv4_block4_1_bn (BatchNormali (None, 14, 14, 256)
conv4 block4 1 conv[0][0]
conv4 block4 1 relu (Activation (None, 14, 14, 256)
conv4 block4 1 bn[0][0]
conv4_block4_2_conv (Conv2D)
                               (None, 14, 14, 256)
                                                    590080
conv4_block4_1_relu[0][0]
```

```
conv4 block4 2 bn (BatchNormali (None, 14, 14, 256) 1024
conv4 block4 2 conv[0][0]
conv4_block4_2_relu (Activation (None, 14, 14, 256)
conv4_block4_2_bn[0][0]
conv4 block4 3 conv (Conv2D)
                               (None, 14, 14, 1024) 263168
conv4 block4 2 relu[0][0]
conv4 block4 3 bn (BatchNormali (None, 14, 14, 1024) 4096
conv4_block4_3_conv[0][0]
                               (None, 14, 14, 1024) 0
conv4 block4 add (Add)
conv4 block3 out[0][0]
conv4_block4_3_bn[0][0]
conv4_block4_out (Activation)
                               (None, 14, 14, 1024) 0
conv4 block4 add[0][0]
conv4 block5 1 conv (Conv2D)
                              (None, 14, 14, 256) 262400
conv4_block4_out[0][0]
conv4 block5 1 bn (BatchNormali (None, 14, 14, 256)
                                                     1024
conv4 block5 1 conv[0][0]
conv4 block5 1 relu (Activation (None, 14, 14, 256)
conv4 block5 1 bn[0][0]
conv4 block5 2_conv (Conv2D)
                               (None, 14, 14, 256)
                                                    590080
conv4_block5_1_relu[0][0]
conv4 block5 2 bn (BatchNormali (None, 14, 14, 256) 1024
conv4 block5 2 conv[0][0]
conv4 block5 2 relu (Activation (None, 14, 14, 256) 0
conv4_block5_2_bn[0][0]
conv4 block5 3 conv (Conv2D)
                               (None, 14, 14, 1024) 263168
conv4 block5 2 relu[0][0]
conv4 block5 3 bn (BatchNormali (None, 14, 14, 1024) 4096
conv4_block5_3_conv[0][0]
conv4 block5 add (Add)
                               (None, 14, 14, 1024) 0
```

conv4 block4 out[0][0]

conv4_block5_out (Activation) conv4_block5_add[0][0]	(None,	14,	14,	1024)	0
conv4_block6_1_conv (Conv2D) conv4_block5_out[0][0]	(None,	14,	14,	256)	262400
conv4_block6_1_bn (BatchNormaliconv4_block6_1_conv[0][0]	(None,	14,	14,	256)	1024
conv4_block6_1_relu (Activation conv4_block6_1_bn[0][0]	(None,	14,	14,	256)	0
conv4_block6_2_conv (Conv2D) conv4_block6_1_relu[0][0]	(None,	14,	14,	256)	590080
conv4_block6_2_bn (BatchNormali conv4_block6_2_conv[0][0]	(None,	14,	14,	256)	1024
conv4_block6_2_relu (Activation conv4_block6_2_bn[0][0]	(None,	14,	14,	256)	0
conv4_block6_3_conv (Conv2D) conv4_block6_2_relu[0][0]	(None,	14,	14,	1024)	263168
conv4_block6_3_bn (BatchNormali conv4_block6_3_conv[0][0]	(None,	14,	14,	1024)	4096
conv4_block6_add (Add) conv4_block5_out[0][0]	(None,	14,	14,	1024)	0
conv4_block6_3_bn[0][0]					
conv4_block6_out (Activation) conv4_block6_add[0][0]	(None,	14,	14,	1024)	0
conv5_block1_1_conv (Conv2D) conv4_block6_out[0][0]	(None,	7,	7, 5	12)	524800
conv5_block1_1_bn (BatchNormali conv5_block1_1_conv[0][0]	(None,	7,	7, 5:	12)	2048
conv5_block1_1_relu (Activation conv5_block1_1_bn[0][0]	(None,	7,	7, 5	12)	0

conv5_block1_2_conv (Conv2D) conv5_block1_1_relu[0][0]	(None,	7,	7,	512)	2359808
conv5_block1_2_bn (BatchNormali conv5_block1_2_conv[0][0]	(None,	7,	7,	512)	2048
conv5_block1_2_relu (Activation conv5_block1_2_bn[0][0]	(None,	7,	7,	512)	0
conv5_block1_0_conv (Conv2D) conv4_block6_out[0][0]	(None,	7,	7,	2048)	2099200
conv5_block1_3_conv (Conv2D) conv5_block1_2_relu[0][0]	(None,	7,	7,	2048)	1050624
conv5_block1_0_bn (BatchNormali conv5_block1_0_conv[0][0]	(None,	7,	7,	2048)	8192
conv5_block1_3_bn (BatchNormali conv5_block1_3_conv[0][0]	(None,	7,	7,	2048)	8192
conv5_block1_add (Add) conv5_block1_0_bn[0][0]	(None,	7,	7,	2048)	0
conv5_block1_3_bn[0][0]					
conv5_block1_out (Activation) conv5_block1_add[0][0]	(None,	7,	7,	2048)	0
conv5_block2_1_conv (Conv2D) conv5_block1_out[0][0]	(None,	7,	7,	512)	1049088
conv5_block2_1_bn (BatchNormali conv5_block2_1_conv[0][0]	(None,	7,	7,	512)	2048
conv5_block2_1_relu (Activation conv5_block2_1_bn[0][0]	(None,	7,	7,	512)	0
conv5_block2_2_conv (Conv2D) conv5_block2_1_relu[0][0]	(None,	7,	7,	512)	2359808
conv5_block2_2_bn (BatchNormali conv5_block2_2_conv[0][0]	(None,	7,	7,	512)	2048

<pre>conv5_block2_2_relu (Activation conv5_block2_2_bn[0][0]</pre>	(None,	7,	7,	512)	0
conv5_block2_3_conv (Conv2D) conv5_block2_2_relu[0][0]	(None,	7,	7,	2048)	1050624
conv5_block2_3_bn (BatchNormali conv5_block2_3_conv[0][0]	(None,	7,	7,	2048)	8192
conv5_block2_add (Add) conv5_block1_out[0][0]	(None,	7,	7,	2048)	0
conv5_block2_3_bn[0][0]					
conv5_block2_out (Activation) conv5_block2_add[0][0]	(None,	7,	7,	2048)	0
conv5_block3_1_conv (Conv2D) conv5_block2_out[0][0]	(None,	7,	7,	512)	1049088
conv5_block3_1_bn (BatchNormali conv5_block3_1_conv[0][0]	(None,	7,	7,	512)	2048
conv5_block3_1_relu (Activation conv5_block3_1_bn[0][0]	(None,	7,	7,	512)	0
conv5_block3_2_conv (Conv2D) conv5_block3_1_relu[0][0]	(None,	7,	7,	512)	2359808
conv5_block3_2_bn (BatchNormali conv5_block3_2_conv[0][0]	(None,	7,	7,	512)	2048
conv5_block3_2_relu (Activation conv5_block3_2_bn[0][0]	(None,	7,	7,	512)	0
conv5_block3_3_conv (Conv2D) conv5_block3_2_relu[0][0]	(None,	7,	7,	2048)	1050624
conv5_block3_3_bn (BatchNormali conv5_block3_3_conv[0][0]	(None,	7,	7,	2048)	8192
conv5_block3_add (Add) conv5_block2_out[0][0]	(None,	7,	7,	2048)	0
conv5_block3_3_bn[0][0]					

3. Training [Forward pass and Backpropagation]

```
#Compile with optimizer
resnet.compile(optimizer = Adam(learning rate=0.001), loss = 'categorical cros
sentropy', metrics = ['accuracy'])
early = EarlyStopping(monitor='val accuracy',min delta=0.01,patience=2,verbose
=1, mode='auto')
#Training
resnet classifier = resnet.fit generator(train generator, epochs = 30, validatio
n data = validation generator, callbacks = [early] )
Epoch 1/30
accuracy: 0.0128 - val loss: 14.5744 - val accuracy: 0.0285
Epoch 2/30
             255/255 [======
accuracy: 0.0379 - val_loss: 14.4397 - val_accuracy: 0.0420
Epoch 3/30
accuracy: 0.0561 - val_loss: 13.0493 - val_accuracy: 0.0451
Epoch 4/30
         255/255 [==
accuracy: 0.0697 - val_loss: 15.5320 - val_accuracy: 0.0428
      Epoch 00004: early stopping
```

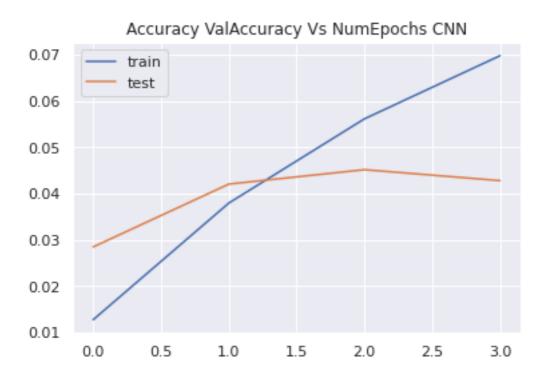
4. Plot Accuracy and Loss

```
train_loss = resnet_classifier.history['loss']
```

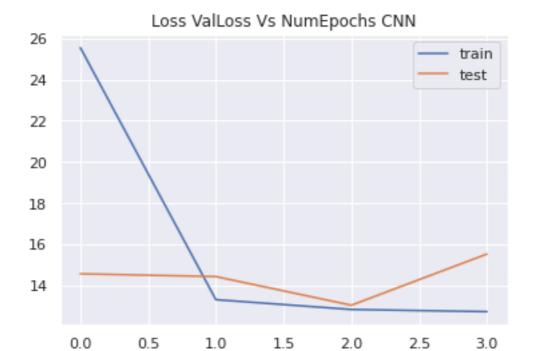
```
val_loss = resnet_classifier.history['val_loss']

xc = resnet_classifier.epoch
plt.title("Accuracy ValAccuracy Vs NumEpochs CNN")
plt.plot(xc,resnet_classifier.history['accuracy'], label='train')
plt.plot(xc,resnet_classifier.history['val_accuracy'], label='test')
plt.legend()
plt.show()

plt.figure()
plt.title("Loss ValLoss Vs NumEpochs CNN")
plt.plot(xc, train_loss,label='train')
plt.plot(xc, val_loss,label='test')
plt.legend()
plt.show
```



As seen in the graph, training set accuracy continue to increase with each epoch. However, validation set accuracy doesn't change after few epochs.



As seen above, training dataset loss shows a sharp drop after initial few epochs and then becomes constant. Validation dataset loss shows a marginal drop after few epochs and then starts to increase again.

5. Evaluation

```
train_acc = resnet.evaluate_generator(train_generator, steps = int(train_genera
tor.samples/BATCH_SIZE))
val_acc = resnet.evaluate_generator(validation_generator, steps = int(validati
on_generator.samples/BATCH_SIZE))

print(train_acc[1])
print(val_acc[1])
0.07221949100494385
0.04282868653535843
```

As seen, this model gives a very low training and validation accuracy of 7% and 4% respectively.

6. Adding result to dataframe for comparison

```
#Adding Performance metrics of Custom ResNet50 to the list
tempResultsDf = pd.DataFrame({'Model':['ResNet Custom FC'], 'Train_Accuracy':
    train_acc[1],'Test_Accuracy': val_acc[1]})
```

```
resultsDf = pd.concat([resultsDf, tempResultsDf])
resultsDf = resultsDf[['Model', 'Train_Accuracy', 'Test_Accuracy']]
resultsDf
```

	Model	Train_Accuracy	Test_Accuracy
0	CNN	0.359129	0.158616
0	ResNet50	0.005290	0.005229
0	VGG16	0.938607	0.563994
0	ResNet Custom FC	0.072219	0.042829

7. Save model for future use

```
resnet.save('./resnet.h5')
resnet.save_weights('./resnet_weights.h5')
```

E. InceptionResNetV2

1. Creating the model

```
tf.keras.layers.Dense(197, activation='softmax')
])
```

2. Summary of model

```
classification_model.summary()
```

Model: "sequential 1"

Layer (type)	Output	Shape	Param #
inception_resnet_v2 (Functio	(None,	5, 5, 1536)	54336736
global_average_pooling2d (Gl	(None,	1536)	0
dense_15 (Dense)	(None,	128)	196736
batch_normalization_203 (Bat	(None,	128)	512
dropout_1 (Dropout)	(None,	128)	0
dense_16 (Dense)	(None,	197)	25413
Total params: 54,559,397			

Total params: 54,559,397 Trainable params: 54,498,597 Non-trainable params: 60,800

3. Define optimizer

```
lr=0.001
classification_model.compile(loss='categorical_crossentropy', optimizer=Adam(l
r=lr), metrics=['accuracy'])
```

4. Early stopping and Model Checkpoint

```
patience = 1
stop_patience = 3
factor = 0.5

callbacks = [
    tf.keras.callbacks.ModelCheckpoint("classify_model.h5", save_best_only=Tru
e, verbose = 0),
    tf.keras.callbacks.EarlyStopping(patience=stop_patience, monitor='val_loss
', verbose=1),
    tf.keras.callbacks.ReduceLROnPlateau(monitor='val_loss', factor=factor, patience=patience, verbose=1)
]
```

5. Training [Forward pass and Backpropagation]

```
epochs = 30
history = classification model.fit(train generator, validation data=validation
generator, epochs=epochs, callbacks=callbacks, verbose=1)
Epoch 1/30
accuracy: 0.0424 - val_loss: 4.8299 - val_accuracy: 0.0622
Epoch 2/30
accuracy: 0.3256 - val loss: 3.7128 - val accuracy: 0.1919
Epoch 3/30
accuracy: 0.6661 - val loss: 1.6520 - val accuracy: 0.5869
Epoch 4/30
accuracy: 0.8196 - val loss: 1.7750 - val accuracy: 0.5655
Epoch 00004: ReduceLROnPlateau reducing learning rate to
0.0005000000237487257.
Epoch 5/30
accuracy: 0.9209 - val_loss: 0.5200 - val_accuracy: 0.8710
accuracy: 0.9573 - val loss: 0.5306 - val accuracy: 0.8605
Epoch 00006: ReduceLROnPlateau reducing learning rate to
0.0002500000118743628.
Epoch 7/30
255/255 [============ ] - 191s 748ms/step - loss: 0.1194 -
accuracy: 0.9773 - val loss: 0.3848 - val accuracy: 0.8965
Epoch 8/30
accuracy: 0.9877 - val loss: 0.3624 - val accuracy: 0.9042
Epoch 9/30
accuracy: 0.9882 - val loss: 0.3795 - val accuracy: 0.8957
Epoch 00009: ReduceLROnPlateau reducing learning rate to
0.0001250000059371814.
Epoch 10/30
161/255 [========>.....] - ETA: 50s - loss: 0.0471 - accuracy:
0.9930
```

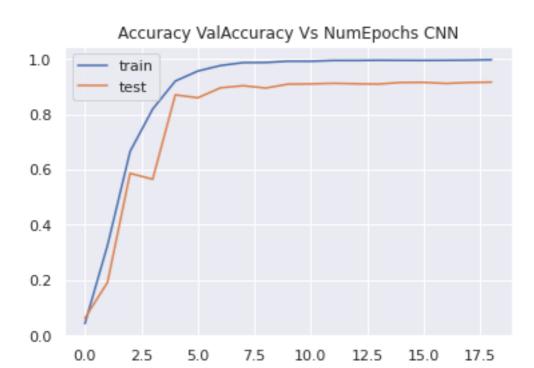
6. Plot Accuracy and Loss for Training and Validation

```
train_loss = history.history['loss']
val_loss = history.history['val_loss']

xc = history.epoch
plt.title("Accuracy ValAccuracy Vs NumEpochs CNN")
```

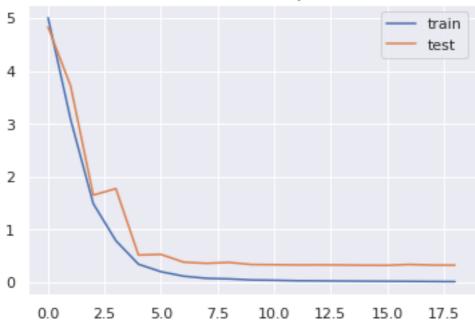
```
plt.plot(xc,history.history['accuracy'], label='train')
plt.plot(xc,history.history['val_accuracy'], label='test')
plt.legend()
plt.show()

plt.figure()
plt.title("Loss ValLoss Vs NumEpochs CNN")
plt.plot(xc, train_loss,label='train')
plt.plot(xc, val_loss,label='test')
plt.legend()
plt.show
```



As seen from the graph above, both training and validation accuracy continue to increase for initial epochs and then becomes constant after reaching near 100%. This shows that we could have probably trained model for lesser number of epochs.

Loss ValLoss Vs NumEpochs CNN



As seen from the graph above, both training and validation loss continue to decrease for initial epochs and then becomes constant after reaching near 0. This shows that we could have probably trained model for lesser number of epochs.

7. Evaluation

```
train_acc = classification_model.evaluate_generator(train_generator,steps = in
t(train_generator.samples/BATCH_SIZE))
val_acc = classification_model.evaluate_generator(validation_generator, steps
= int(validation_generator.samples/BATCH_SIZE))

print(train_acc[1])
print(val_acc[1])
0.9977854490280151
0.9172061681747437
```

Thus model works really great and shows a near perfect accuracy of 99.77% for training dataset, and very high accuracy of 91.7% for validation dataset.

8. Adding result to dataframe for comparison

```
#Adding Performance metrics of InceptionResNetv2 to the list
tempResultsDf = pd.DataFrame({'Model':['InceptionResNetv2'], 'Train_Accuracy'
: train_acc[1],'Test_Accuracy': val_acc[1]})
resultsDf = pd.concat([resultsDf, tempResultsDf])
resultsDf = resultsDf[['Model', 'Train_Accuracy','Test_Accuracy']]
resultsDf
```

0 CNN 0.359129 0.15861
0 DooNotEO 0.00E200 0.00E220
0 ResNet50 0.005290 0.005229
0 VGG16 0.938607 0.56399
0 ResNet Custom FC 0.072219 0.04282
0 InceptionResNetv2 0.997785 0.91720

Comparing Models

resultsDf

	Model	Train_Accuracy	Test_Accuracy
0	CNN	0.359129	0.158616
0	ResNet50	0.005290	0.005229
0	VGG16	0.938607	0.563994
0	ResNet Custom FC	0.072219	0.042829
0	InceptionResNetv2	0.997785	0.917206

As seen from the table above, we tried different models for this classification problem. InceptionResNetv2 gives the best accuracy. Therefore, it is our final selected model.

```
final_model = classification_model
```

• Pickle model for future use

```
final_model.save('./final_model.h5')
```

Predictions

Let us use final model to predict some test car images

```
final_model = keras.models.load_model('final_model.h5')
from google.colab import files
uploaded = files.upload()
Saving test4.jpg to test4.jpg
path = 'test1.jpg'
img = cv2.imread( path )
plt.grid(False)
plt.imshow(img)
   0
  25
  50
  75
 100
 125
 150
 175
      0
              50
                       100
                                150
                                         200
                                                  250
from tensorflow.keras.utils import img_to_array, load_img
import cv2
img = cv2.resize(img, (224,224),)
img.shape
(224, 224, 3)
pixels = img.astype('float32')
pixels /= 255.0
```

```
print(pixels.shape)
(224, 224, 3)
#Expanding the dimensions of the numpy array to match the dimension expected by
predict method
pixels = np.expand_dims(pixels, axis=0)
print(pixels.shape)
(1, 224, 224, 3)
prediction = final model.predict(pixels)
prediction = np.argmax(prediction, axis = 1)
print(prediction)
[135]
predicted_label = car_names[car_names['Class'] == prediction[0]]
print(predicted label)
                       CarLabel Class
134 Hyundai Elantra Sedan 2007
                                   135
```

Thus our model is able to make correct prediction.

Next Steps:

For next milestone, we will work on following steps:

- 1) Try to fine tune our selected model to reduce variance.
- 2) Design a clickable UI which can automate tasks performed under milestone 1
- 3) Design a clickable UI which can automate tasks performed under milestone 2
- 4) Design a clickable UI based interface which can allow the user to browse & input the image, output the class and the bounding box or mask
- 5) Create final report