

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 = ['CarLabel'] )

#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
4          Acura TSX Sedan 2012

   ImageName  X1  Y1  X2  Y2  Class
0  00001.jpg   39 116 569 375    14
1  00002.jpg   36 116 868 587     3
2  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   181
1  00002.jpg  100  19 576 203   103
2  00003.jpg   51 105 968 659   145
3  00004.jpg   67  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

173

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', right_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', 'honda', 'hyundai', 'infiniti', 'isuzu', 'jaguar', 'jeep', 'lamborghini', 'land', 'rover', 'lincoln', 'mini', 'cooper', 'maybach', 'mazda', 'mclaren', 'mercedes-benz', 'mitsubishi', 'nissan', 'plymouth', 'porsche', 'ram', 'rolls-royce', 'scion', 'spyker', 'suzuki', 'tesla', 'toyota', 'volkswagen', 'volvo', 'smart']
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():
            words1 = word_tokenize(row[col].lower())
            print(index, words1)

            if len(words1)>1:
                year = re.findall(pattern, words1[len(words1)-1]) #row[0]
                if year:
                    eda_df.loc[index, 'year'] = year[0]
                body = list(set(words1).intersection(car_body_type))
                if body:
                    eda_df.loc[index, 'body'] = body[0]
                make = list(set(words1).intersection(car_make))
                if make:
```

```

eda_df.loc[index, 'make'] = ' '.join(make)
iden=year + body + make
print(iden)
model = list(set(words1).difference(iden))
print(model)
if model:
    eda_df.loc[index, 'model'] = ' '.join(model)

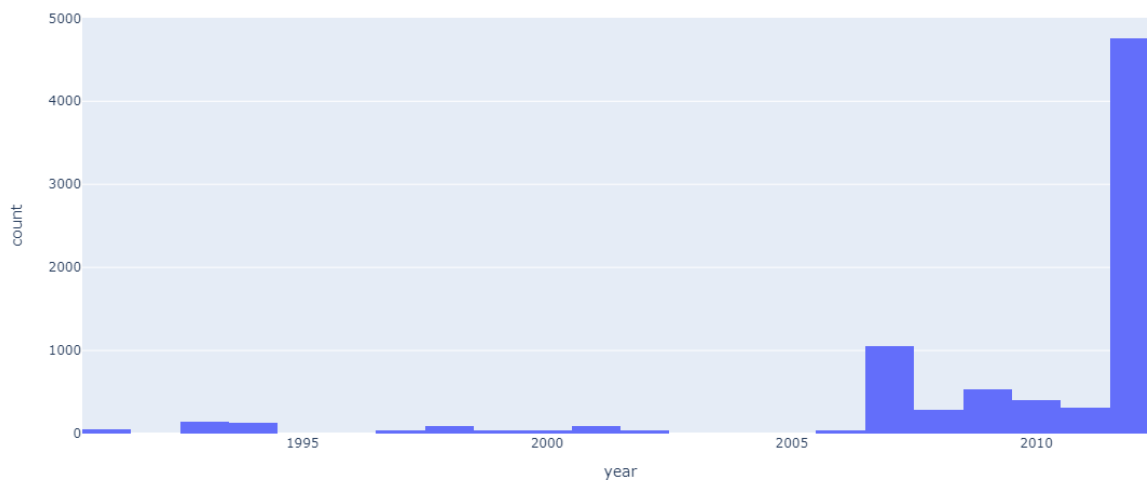
```

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

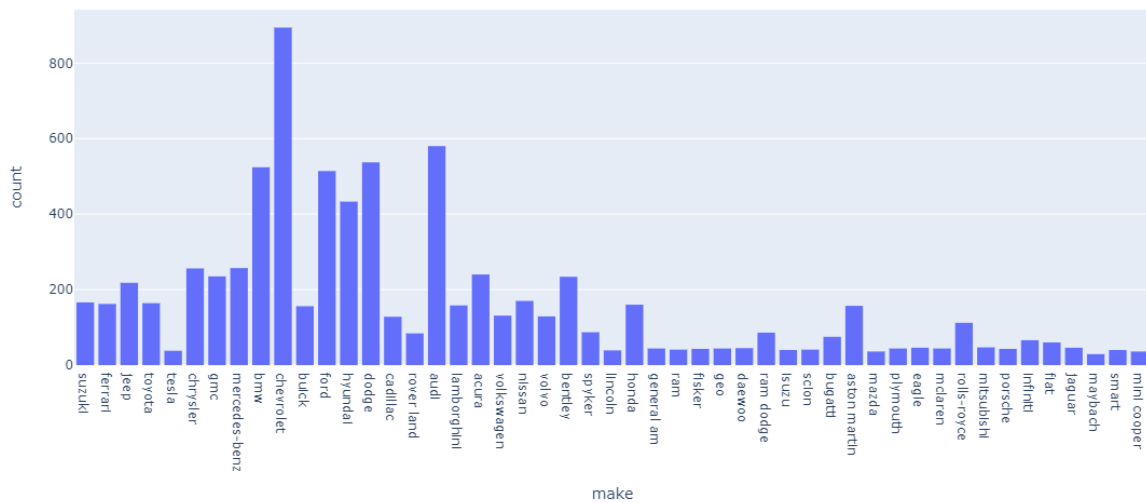
- Display bar charts for different columns

➤ Count of different cars by year



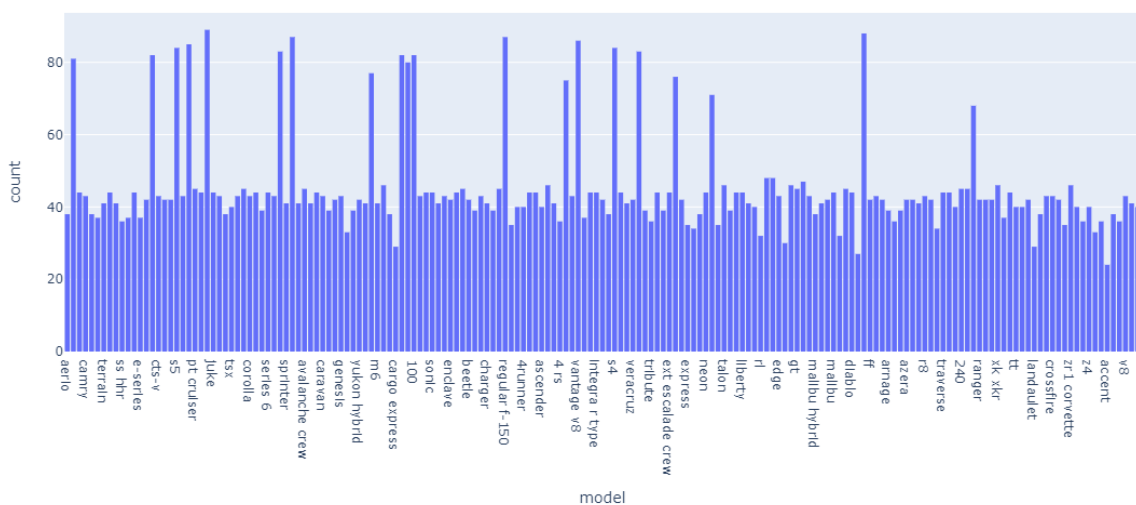
As seen, most of cars are of make year between 2007 – 2012

➤ Count of different cars by make



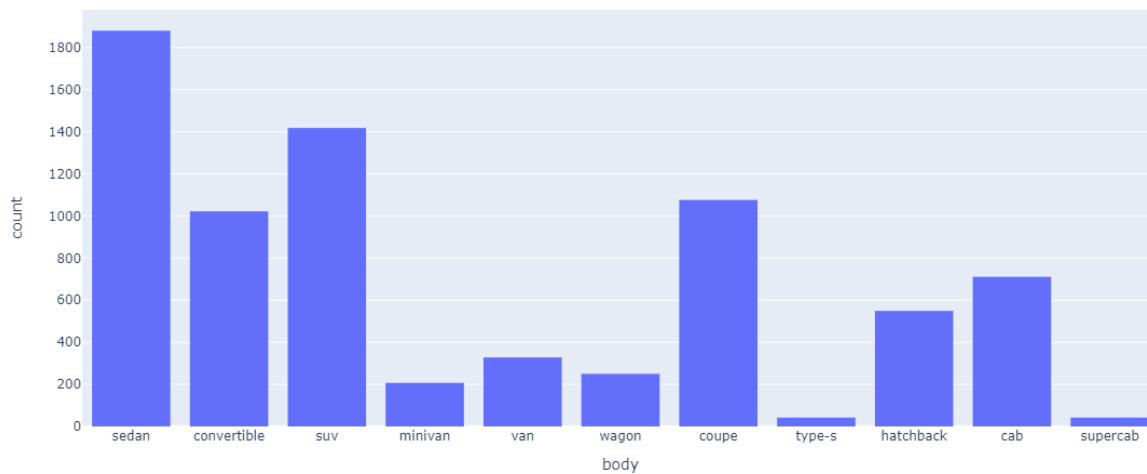
As seen, most of cars are of make Chevrolet, audi, bmw and dodge. ‘Mini Cooper’, ‘Smart’ and ‘Jaguar’ are less represented. Therefore, an effective model would be the one which can identify cars belonging to these classes.

➤ 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 ]

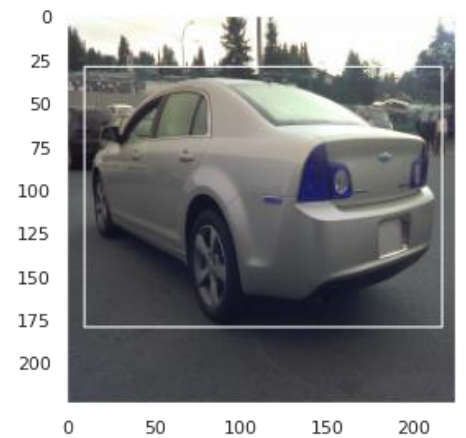
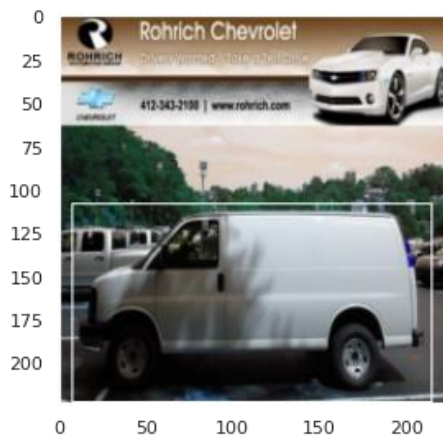
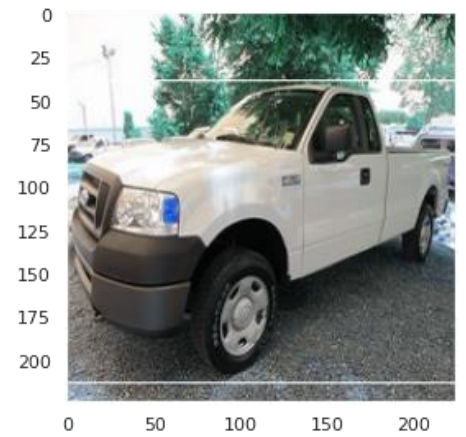
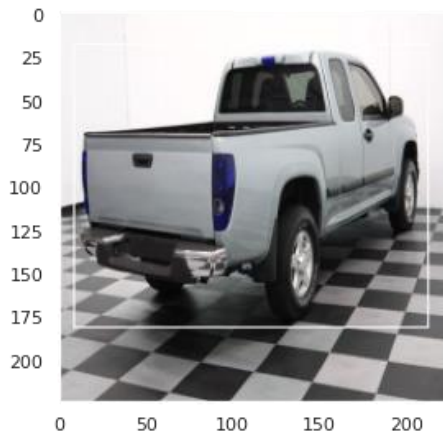
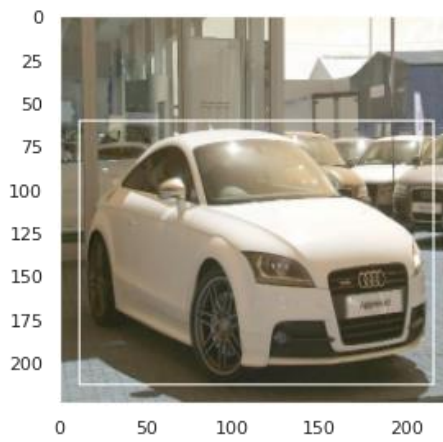
path = 'Car Images/Train Images/{0}/{1}'.format( eg_car['CarLabel'], eg
_car['ImageName'] )
img = cv2.imread( path )
img_shape = img.shape
img = cv2.resize(img, dsize = (IMAGE_SIZE, IMAGE_SIZE), interpolation=c
v2.INTER_AREA)

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
y2 = int(eg_car['Y2'] * IMAGE_SIZE / img_shape[0] + 3 ) # No
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 Annotated/{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 Annotated/{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 Annotated/{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 Annotated/{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 Annotated'

test_path = 'Car Images/Test Images Annotated'

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 ReLU
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 function 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 function 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 (MaxPooling2D)	(None, 112, 112, 32)	0
conv2d_4 (Conv2D)	(None, 112, 112, 32)	9248
max_pooling2d_4 (MaxPooling2D)	(None, 56, 56, 32)	0
conv2d_5 (Conv2D)	(None, 56, 56, 32)	9248
max_pooling2d_5 (MaxPooling2D)	(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

254/254 [=====] - 2523s 10s/step - loss: 5.2871 - accuracy: 0.0048 - val_loss: 5.2809 - val_accuracy: 0.0085

Epoch 2/20

254/254 [=====] - 188s 739ms/step - loss: 5.2378 - accuracy: 0.0094 - val_loss: 5.1779 - val_accuracy: 0.0108

Epoch 3/20

254/254 [=====] - 187s 736ms/step - loss: 5.1521 - 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

254/254 [=====] - 182s 719ms/step - loss: 5.0102 - accuracy: 0.0221 - val_loss: 4.9850 - val_accuracy: 0.0253

Epoch 7/20

254/254 [=====] - 184s 726ms/step - loss: 4.9130 - accuracy: 0.0303 - val_loss: 4.8883 - val_accuracy: 0.0408

Epoch 8/20

254/254 [=====] - 184s 724ms/step - loss: 4.7473 - accuracy: 0.0477 - val_loss: 4.6899 - val_accuracy: 0.0603

Epoch 9/20

254/254 [=====] - 184s 725ms/step - loss: 4.5756 - accuracy: 0.0664 - val_loss: 4.5243 - val_accuracy: 0.0706

Epoch 10/20

254/254 [=====] - 184s 725ms/step - loss: 4.3834 - accuracy: 0.0867 - val_loss: 4.3964 - val_accuracy: 0.0820

Epoch 11/20

```

254/254 [=====] - 184s 725ms/step - loss: 4.2401 -
accuracy: 0.0987 - val_loss: 4.2711 - val_accuracy: 0.0999
Epoch 12/20
254/254 [=====] - 183s 723ms/step - loss: 4.0806 -
accuracy: 0.1187 - val_loss: 4.2011 - val_accuracy: 0.1048
Epoch 13/20
254/254 [=====] - 183s 722ms/step - loss: 3.9654 -
accuracy: 0.1387 - val_loss: 4.2050 - val_accuracy: 0.1112
Epoch 14/20
254/254 [=====] - 184s 727ms/step - loss: 3.8438 -
accuracy: 0.1456 - val_loss: 4.0591 - val_accuracy: 0.1213
Epoch 15/20
254/254 [=====] - 185s 728ms/step - loss: 3.7540 -
accuracy: 0.1610 - val_loss: 4.0304 - val_accuracy: 0.1300
Epoch 16/20
254/254 [=====] - 184s 726ms/step - loss: 3.6654 -
accuracy: 0.1700 - val_loss: 3.9678 - val_accuracy: 0.1376
Epoch 17/20
254/254 [=====] - 183s 722ms/step - loss: 3.5846 -
accuracy: 0.1811 - val_loss: 3.9020 - val_accuracy: 0.1416
Epoch 18/20
254/254 [=====] - 183s 723ms/step - loss: 3.5153 -
accuracy: 0.2046 - val_loss: 3.8804 - val_accuracy: 0.1493
Epoch 19/20
254/254 [=====] - 184s 725ms/step - loss: 3.4546 -
accuracy: 0.2061 - val_loss: 3.8908 - val_accuracy: 0.1504
Epoch 20/20
254/254 [=====] - 184s 725ms/step - loss: 3.3658 -
accuracy: 0.2226 - val_loss: 3.8429 - val_accuracy: 0.1584

```

5. Accuracy and Loss for Training and Validation

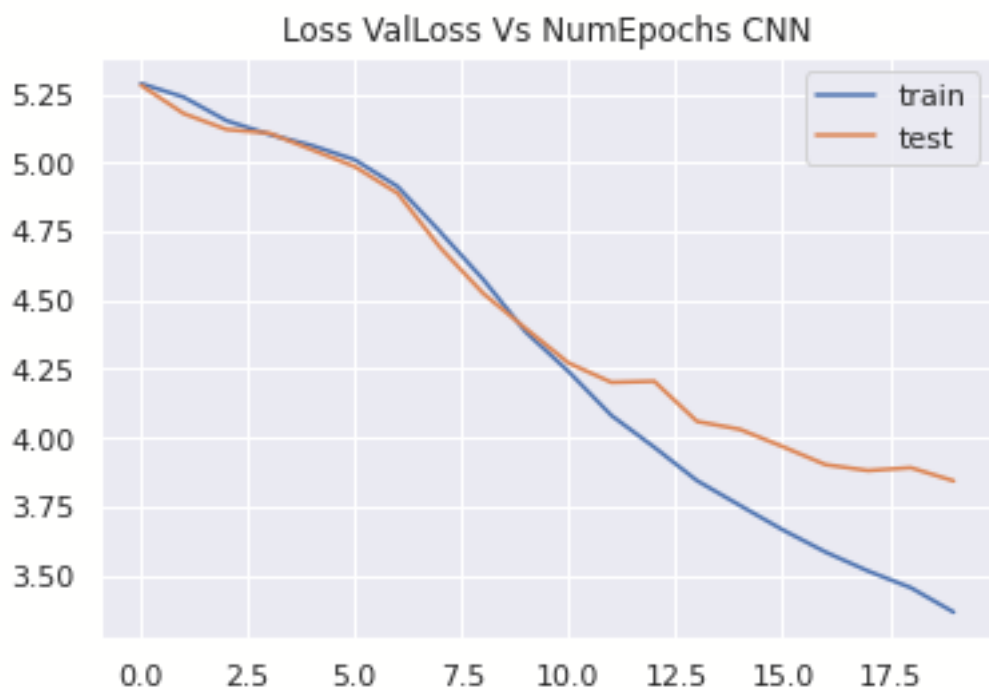
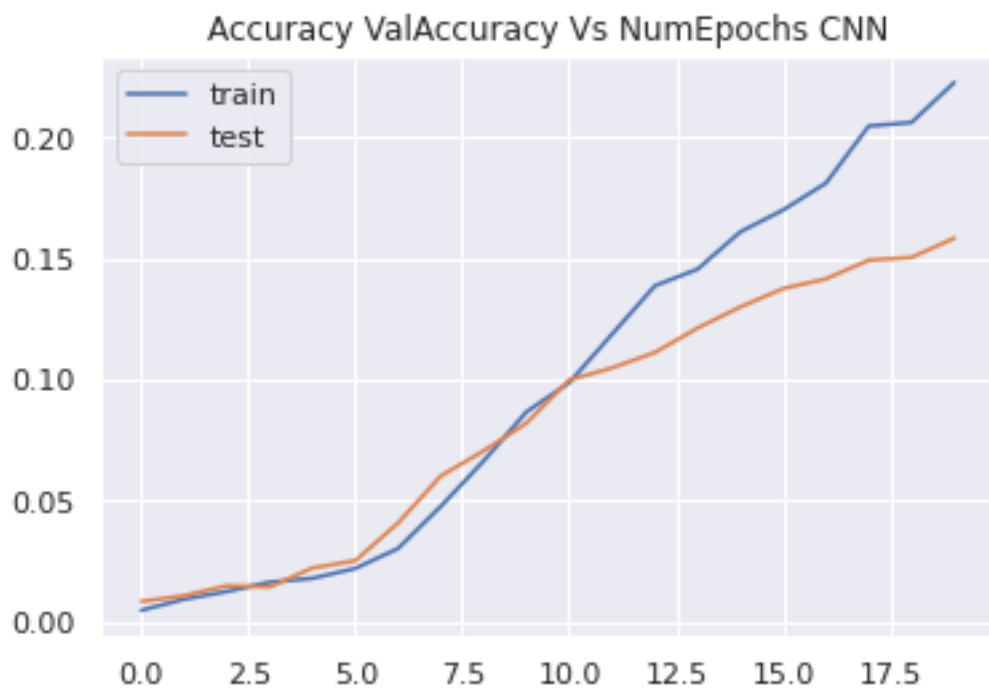
```

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

```



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_generator.samples/BATCH_SIZE))  
val_acc = classifier.evaluate_generator(validation_generator, steps = int(validation_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

```
#Store the Performance Matrix for each model in a dataframe for final comparison
resultsDf = pd.DataFrame({'Model': ['CNN'], 'Train_Accuracy': train_acc[1], 'Test_Accuracy': val_acc[1],
                           })
resultsDf = resultsDf[['Model', 'Train_Accuracy', 'Test_Accuracy']]
resultsDf
```

	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	(None, 56, 56, 64)	256	conv2_block1_1_conv[0][0]
=====			
conv2_block1_1_relu (Activation	(None, 56, 56, 64)	0	conv2_block1_1_bn[0][0]
=====			
conv2_block1_2_conv (Conv2D)	(None, 56, 56, 64)	36928	conv2_block1_1_relu[0][0]
=====			

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

conv2_block2_3_bn (BatchNormali (None, 56, 56, 256) 1024
conv2_block2_3_conv[0][0]

conv2_block2_add (Add) (None, 56, 56, 256) 0
conv2_block1_out[0][0]

conv2_block2_3_bn[0][0]

conv2_block2_out (Activation) (None, 56, 56, 256) 0
conv2_block2_add[0][0]

conv2_block3_1_conv (Conv2D) (None, 56, 56, 64) 16448
conv2_block2_out[0][0]

conv2_block3_1_bn (BatchNormali (None, 56, 56, 64) 256
conv2_block3_1_conv[0][0]

conv2_block3_1_relu (Activation (None, 56, 56, 64) 0
conv2_block3_1_bn[0][0]

conv2_block3_2_conv (Conv2D) (None, 56, 56, 64) 36928
conv2_block3_1_relu[0][0]

conv2_block3_2_bn (BatchNormali (None, 56, 56, 64) 256
conv2_block3_2_conv[0][0]

conv2_block3_2_relu (Activation (None, 56, 56, 64) 0
conv2_block3_2_bn[0][0]

conv2_block3_3_conv (Conv2D) (None, 56, 56, 256) 16640
conv2_block3_2_relu[0][0]

conv2_block3_3_bn (BatchNormali (None, 56, 56, 256) 1024
conv2_block3_3_conv[0][0]

conv2_block3_add (Add) (None, 56, 56, 256) 0
conv2_block2_out[0][0]

conv2_block3_3_bn[0][0]

conv2_block3_out (Activation) (None, 56, 56, 256) 0
conv2_block3_add[0][0]

conv3_block1_1_conv (Conv2D) (None, 28, 28, 128) 32896
conv2_block3_out[0][0]

conv3_block1_1_bn (BatchNormali	(None, 28, 28, 128)	512
conv3_block1_1_conv[0][0]		
<hr/>		
conv3_block1_1_relu (Activation	(None, 28, 28, 128)	0
conv3_block1_1_bn[0][0]		
<hr/>		
conv3_block1_2_conv (Conv2D)	(None, 28, 28, 128)	147584
conv3_block1_1_relu[0][0]		
<hr/>		
conv3_block1_2_bn (BatchNormali	(None, 28, 28, 128)	512
conv3_block1_2_conv[0][0]		
<hr/>		
conv3_block1_2_relu (Activation	(None, 28, 28, 128)	0
conv3_block1_2_bn[0][0]		
<hr/>		
conv3_block1_0_conv (Conv2D)	(None, 28, 28, 512)	131584
conv2_block3_out[0][0]		
<hr/>		
conv3_block1_3_conv (Conv2D)	(None, 28, 28, 512)	66048
conv3_block1_2_relu[0][0]		
<hr/>		
conv3_block1_0_bn (BatchNormali	(None, 28, 28, 512)	2048
conv3_block1_0_conv[0][0]		
<hr/>		
conv3_block1_3_bn (BatchNormali	(None, 28, 28, 512)	2048
conv3_block1_3_conv[0][0]		
<hr/>		
conv3_block1_add (Add)	(None, 28, 28, 512)	0
conv3_block1_0_bn[0][0]		
conv3_block1_3_bn[0][0]		
<hr/>		
conv3_block1_out (Activation)	(None, 28, 28, 512)	0
conv3_block1_add[0][0]		
<hr/>		
conv3_block2_1_conv (Conv2D)	(None, 28, 28, 128)	65664
conv3_block1_out[0][0]		
<hr/>		
conv3_block2_1_bn (BatchNormali	(None, 28, 28, 128)	512
conv3_block2_1_conv[0][0]		
<hr/>		
conv3_block2_1_relu (Activation	(None, 28, 28, 128)	0
conv3_block2_1_bn[0][0]		
<hr/>		
conv3_block2_2_conv (Conv2D)	(None, 28, 28, 128)	147584
conv3_block2_1_relu[0][0]		

conv3_block2_2_bn (BatchNormali	(None, 28, 28, 128)	512
conv3_block2_2_conv[0][0]		

conv3_block2_2_relu (Activation	(None, 28, 28, 128)	0
conv3_block2_2_bn[0][0]		

conv3_block2_3_conv (Conv2D)	(None, 28, 28, 512)	66048
conv3_block2_2_relu[0][0]		

conv3_block2_3_bn (BatchNormali	(None, 28, 28, 512)	2048
conv3_block2_3_conv[0][0]		

conv3_block2_add (Add)	(None, 28, 28, 512)	0
conv3_block1_out[0][0]		
conv3_block2_3_bn[0][0]		

conv3_block2_out (Activation)	(None, 28, 28, 512)	0
conv3_block2_add[0][0]		

conv3_block3_1_conv (Conv2D)	(None, 28, 28, 128)	65664
conv3_block2_out[0][0]		

conv3_block3_1_bn (BatchNormali	(None, 28, 28, 128)	512
conv3_block3_1_conv[0][0]		

conv3_block3_1_relu (Activation	(None, 28, 28, 128)	0
conv3_block3_1_bn[0][0]		

conv3_block3_2_conv (Conv2D)	(None, 28, 28, 128)	147584
conv3_block3_1_relu[0][0]		

conv3_block3_2_bn (BatchNormali	(None, 28, 28, 128)	512
conv3_block3_2_conv[0][0]		

conv3_block3_2_relu (Activation	(None, 28, 28, 128)	0
conv3_block3_2_bn[0][0]		

conv3_block3_3_conv (Conv2D)	(None, 28, 28, 512)	66048
conv3_block3_2_relu[0][0]		

conv3_block3_3_bn (BatchNormali	(None, 28, 28, 512)	2048
conv3_block3_3_conv[0][0]		

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

conv4_block1_1_relu	(Activation	(None, 14, 14, 256)	0
conv4_block1_1_bn[0][0]			
<hr/>			
conv4_block1_2_conv	(Conv2D)	(None, 14, 14, 256)	590080
conv4_block1_1_relu[0][0]			
<hr/>			
conv4_block1_2_bn	(BatchNormali	(None, 14, 14, 256)	1024
conv4_block1_2_conv[0][0]			
<hr/>			
conv4_block1_2_relu	(Activation	(None, 14, 14, 256)	0
conv4_block1_2_bn[0][0]			
<hr/>			
conv4_block1_0_conv	(Conv2D)	(None, 14, 14, 1024)	525312
conv3_block4_out[0][0]			
<hr/>			
conv4_block1_3_conv	(Conv2D)	(None, 14, 14, 1024)	263168
conv4_block1_2_relu[0][0]			
<hr/>			
conv4_block1_0_bn	(BatchNormali	(None, 14, 14, 1024)	4096
conv4_block1_0_conv[0][0]			
<hr/>			
conv4_block1_3_bn	(BatchNormali	(None, 14, 14, 1024)	4096
conv4_block1_3_conv[0][0]			
<hr/>			
conv4_block1_add	(Add)	(None, 14, 14, 1024)	0
conv4_block1_0_bn[0][0]			
conv4_block1_3_bn[0][0]			
<hr/>			
conv4_block1_out	(Activation)	(None, 14, 14, 1024)	0
conv4_block1_add[0][0]			
<hr/>			
conv4_block2_1_conv	(Conv2D)	(None, 14, 14, 256)	262400
conv4_block1_out[0][0]			
<hr/>			
conv4_block2_1_bn	(BatchNormali	(None, 14, 14, 256)	1024
conv4_block2_1_conv[0][0]			
<hr/>			
conv4_block2_1_relu	(Activation	(None, 14, 14, 256)	0
conv4_block2_1_bn[0][0]			
<hr/>			
conv4_block2_2_conv	(Conv2D)	(None, 14, 14, 256)	590080
conv4_block2_1_relu[0][0]			
<hr/>			
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)	(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)	1024
conv4_block4_1_conv[0][0]		

conv4_block4_1_relu (Activation	(None, 14, 14, 256)	0
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)	0
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]		

conv4_block4_add (Add)	(None, 14, 14, 1024)	0
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)	0
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_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]

conv4_block6_2_conv (Conv2D) (None, 14, 14, 256) 590080
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)	(None, 14, 14, 1024)	0
conv4_block5_out[0][0]		
conv4_block6_3_bn[0][0]		
conv4_block6_out (Activation)	(None, 14, 14, 1024)	0
conv4_block6_add[0][0]		
conv5_block1_1_conv (Conv2D)	(None, 7, 7, 512)	524800
conv4_block6_out[0][0]		
conv5_block1_1_bn (BatchNormali	(None, 7, 7, 512)	2048
conv5_block1_1_conv[0][0]		
conv5_block1_1_relu (Activation	(None, 7, 7, 512)	0
conv5_block1_1_bn[0][0]		
conv5_block1_2_conv (Conv2D)	(None, 7, 7, 512)	2359808
conv5_block1_1_relu[0][0]		
conv5_block1_2_bn (BatchNormali	(None, 7, 7, 512)	2048
conv5_block1_2_conv[0][0]		
conv5_block1_2_relu (Activation	(None, 7, 7, 512)	0
conv5_block1_2_bn[0][0]		
conv5_block1_0_conv (Conv2D)	(None, 7, 7, 2048)	2099200
conv4_block6_out[0][0]		
conv5_block1_3_conv (Conv2D)	(None, 7, 7, 2048)	1050624
conv5_block1_2_relu[0][0]		
conv5_block1_0_bn (BatchNormali	(None, 7, 7, 2048)	8192
conv5_block1_0_conv[0][0]		
conv5_block1_3_bn (BatchNormali	(None, 7, 7, 2048)	8192
conv5_block1_3_conv[0][0]		
conv5_block1_add (Add)	(None, 7, 7, 2048)	0
conv5_block1_0_bn[0][0]		
conv5_block1_3_bn[0][0]		
conv5_block1_out (Activation)	(None, 7, 7, 2048)	0
conv5_block1_add[0][0]		

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

conv5_block3_2_bn (BatchNormali	(None, 7, 7, 512)	2048	
conv5_block3_2_conv[0][0]			
conv5_block3_2_relu (Activation	(None, 7, 7, 512)	0	
conv5_block3_2_bn[0][0]			
conv5_block3_3_conv (Conv2D)	(None, 7, 7, 2048)	1050624	
conv5_block3_2_relu[0][0]			
conv5_block3_3_bn (BatchNormali	(None, 7, 7, 2048)	8192	
conv5_block3_3_conv[0][0]			
conv5_block3_add (Add)	(None, 7, 7, 2048)	0	
conv5_block2_out[0][0]			
conv5_block3_3_bn[0][0]			
conv5_block3_out (Activation)	(None, 7, 7, 2048)	0	
conv5_block3_add[0][0]			
flatten_5 (Flatten)	(None, 100352)	0	
conv5_block3_out[0][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
2/2 [=====] - 11s 2s/step - loss: 5.3621 - accuracy:
0.0000e+00 - val_loss: 5.5525 - val_accuracy: 0.0000e+00
Epoch 2/30
2/2 [=====] - 2s 914ms/step - loss: 5.4601 -
accuracy: 0.0000e+00 - val_loss: 5.7100 - val_accuracy: 0.0000e+00
Epoch 3/30
2/2 [=====] - 2s 1s/step - loss: 5.4117 - accuracy:
0.0000e+00 - val_loss: 5.5345 - val_accuracy: 0.0000e+00
Epoch 4/30
2/2 [=====] - 2s 993ms/step - loss: 5.3791 -
accuracy: 0.0000e+00 - val_loss: 5.5610 - val_accuracy: 0.0000e+00
Epoch 5/30
2/2 [=====] - 2s 1s/step - loss: 5.5947 - accuracy:
0.0000e+00 - val_loss: 5.6320 - val_accuracy: 0.0000e+00
Epoch 6/30
2/2 [=====] - 2s 1s/step - loss: 5.3780 - accuracy:
0.0000e+00 - val_loss: 5.4623 - val_accuracy: 0.0000e+00
Epoch 7/30
2/2 [=====] - 2s 1s/step - loss: 5.4169 - accuracy:
0.0000e+00 - val_loss: 5.5907 - val_accuracy: 0.0000e+00
Epoch 8/30
2/2 [=====] - 2s 1s/step - loss: 5.4999 - accuracy:
0.0000e+00 - val_loss: 5.4237 - val_accuracy: 0.0000e+00
Epoch 9/30
2/2 [=====] - 2s 965ms/step - loss: 5.4621 -
```

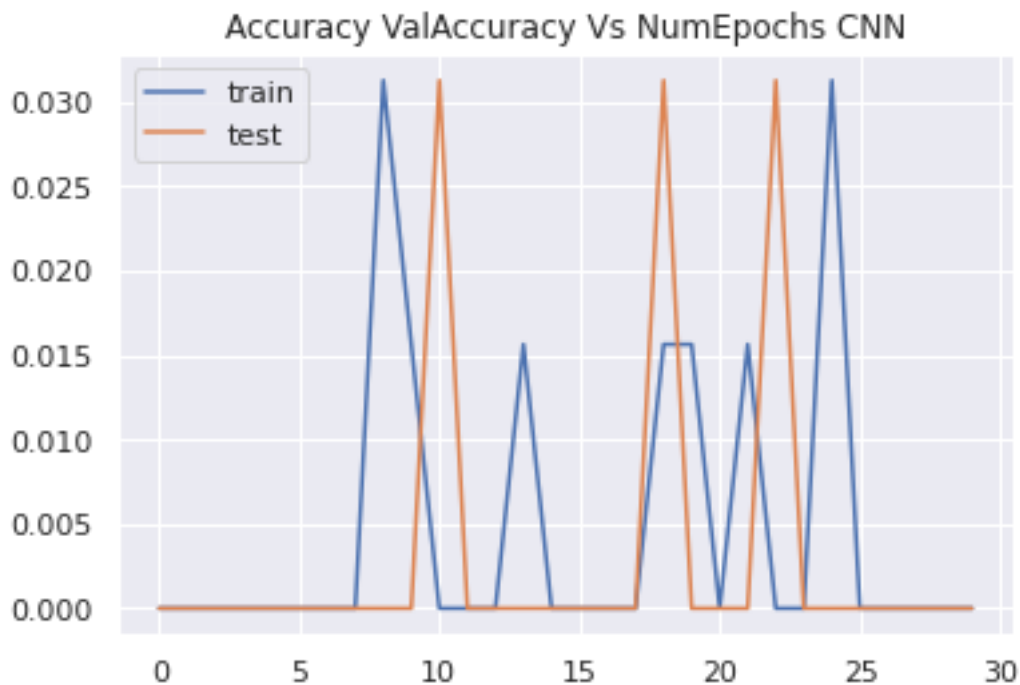
accuracy: 0.0312 - val_loss: 5.4819 - val_accuracy: 0.0000e+00
Epoch 10/30
2/2 [=====] - 2s 1s/step - loss: 5.4418 - accuracy:
0.0156 - val_loss: 5.4853 - val_accuracy: 0.0000e+00
Epoch 11/30
2/2 [=====] - 2s 1s/step - loss: 5.5179 - accuracy:
0.0000e+00 - val_loss: 5.3407 - val_accuracy: 0.0312
Epoch 12/30
2/2 [=====] - 2s 955ms/step - loss: 5.3203 -
accuracy: 0.0000e+00 - val_loss: 5.5048 - val_accuracy: 0.0000e+00
Epoch 13/30
2/2 [=====] - 2s 1s/step - loss: 5.3476 - accuracy:
0.0000e+00 - val_loss: 5.3331 - val_accuracy: 0.0000e+00
Epoch 14/30
2/2 [=====] - 2s 954ms/step - loss: 5.2757 -
accuracy: 0.0156 - val_loss: 5.3322 - val_accuracy: 0.0000e+00
Epoch 15/30
2/2 [=====] - 2s 1s/step - loss: 5.3678 - accuracy:
0.0000e+00 - val_loss: 5.4033 - val_accuracy: 0.0000e+00
Epoch 16/30
2/2 [=====] - 2s 1s/step - loss: 5.4252 - accuracy:
0.0000e+00 - val_loss: 5.3253 - val_accuracy: 0.0000e+00
Epoch 17/30
2/2 [=====] - 2s 1s/step - loss: 5.4463 - accuracy:
0.0000e+00 - val_loss: 5.3175 - val_accuracy: 0.0000e+00
Epoch 18/30
2/2 [=====] - 2s 1s/step - loss: 5.4036 - accuracy:
0.0000e+00 - val_loss: 5.3590 - val_accuracy: 0.0000e+00
Epoch 19/30
2/2 [=====] - 2s 987ms/step - loss: 5.3229 -
accuracy: 0.0156 - val_loss: 5.3885 - val_accuracy: 0.0312
Epoch 20/30
2/2 [=====] - 2s 1s/step - loss: 5.2921 - accuracy:
0.0156 - val_loss: 5.3115 - val_accuracy: 0.0000e+00
Epoch 21/30
2/2 [=====] - 2s 957ms/step - loss: 5.3349 -
accuracy: 0.0000e+00 - val_loss: 5.2952 - val_accuracy: 0.0000e+00
Epoch 22/30
2/2 [=====] - 2s 993ms/step - loss: 5.3338 -
accuracy: 0.0156 - val_loss: 5.3405 - val_accuracy: 0.0000e+00
Epoch 23/30
2/2 [=====] - 2s 994ms/step - loss: 5.3303 -
accuracy: 0.0000e+00 - val_loss: 5.3367 - val_accuracy: 0.0312
Epoch 24/30
2/2 [=====] - 2s 1s/step - loss: 5.3819 - accuracy:
0.0000e+00 - val_loss: 5.2927 - val_accuracy: 0.0000e+00
Epoch 25/30
2/2 [=====] - 2s 1s/step - loss: 5.3205 - accuracy:
0.0312 - val_loss: 5.3621 - val_accuracy: 0.0000e+00
Epoch 26/30
2/2 [=====] - 2s 1s/step - loss: 5.3144 - accuracy:
0.0000e+00 - val_loss: 5.3109 - val_accuracy: 0.0000e+00
Epoch 27/30
2/2 [=====] - 2s 1s/step - loss: 5.3487 - accuracy:
0.0000e+00 - val_loss: 5.2597 - val_accuracy: 0.0000e+00
Epoch 28/30
2/2 [=====] - 2s 958ms/step - loss: 5.3365 -
accuracy: 0.0000e+00 - val_loss: 5.3778 - val_accuracy: 0.0000e+00
Epoch 29/30
2/2 [=====] - 2s 1s/step - loss: 5.3138 - accuracy:
0.0000e+00 - val_loss: 5.3392 - val_accuracy: 0.0000e+00

Epoch 30/30

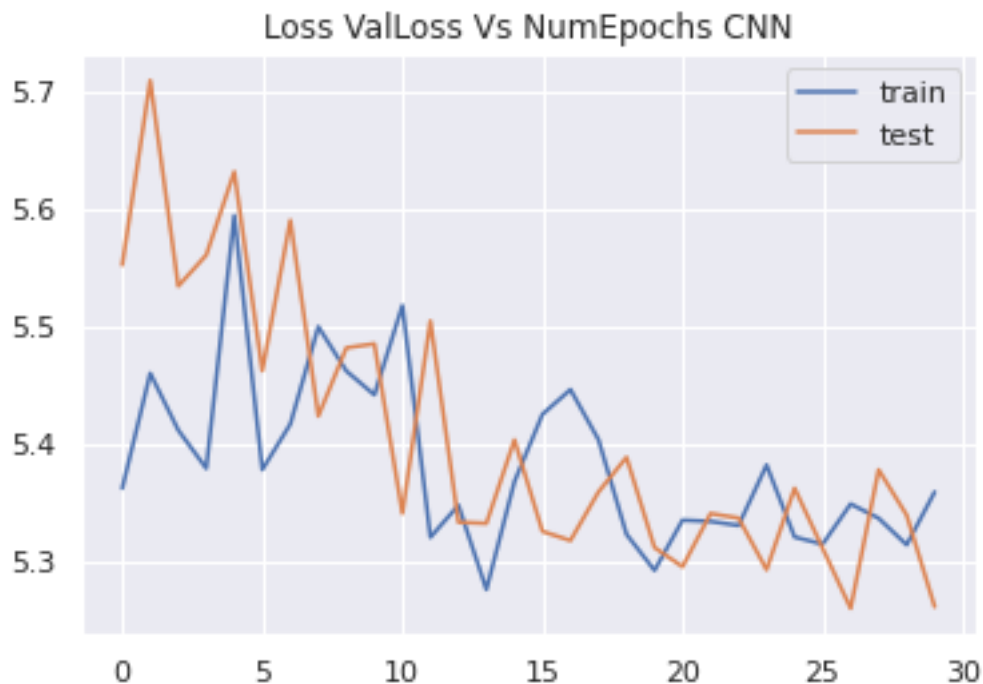
2/2 [=====] - 2s 1s/step - loss: 5.3589 -
accuracy: 0.0000e+00 - val_loss: 5.2610 - val_accuracy: 0.0000e+00

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_generator.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_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

C. VGG16

1. Creating the model

```
print ( 'VGG with custom FC Layers')
vgg_conv = VGG16(weights='imagenet', include_top=False, input_shape= (224,224,
3))
# Freeze all the layers except for the last layer:
for layer in vgg_conv.layers:
    layer.trainable = False

x = Flatten() (vgg_conv.output)
x = Dense(197, activation='softmax') (x)
vgg_model = Model(vgg_conv.input, x)
```

VGG with custom FC Layers

Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5
58892288/58889256 [=====] - 1s 0us/step

58900480/58889256 [=====] - 1s 0us/step

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_crossentropy', metrics = ['accuracy'])
```

```
early = EarlyStopping(monitor='val_accuracy',min_delta=0.01,patience=20,verbose=1,mode='auto')
```

```
#Training
```

```
vgg_classifier = vgg_model.fit_generator(train_generator, epochs =30, validation_data = validation_generator, callbacks = [early] )
```

```
Epoch 1/30
```

```
255/255 [=====] - 187s 731ms/step - loss: 0.3102 - accuracy: 0.9467 - val_loss: 4.6444 - val_accuracy: 0.5884
```

```
Epoch 2/30
```

```
255/255 [=====] - 183s 718ms/step - loss: 0.3438 - accuracy: 0.9422 - val_loss: 4.7269 - val_accuracy: 0.5948
```

```
Epoch 3/30
```

```
255/255 [=====] - 181s 711ms/step - loss: 0.3808 - 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
```

```
255/255 [=====] - 181s 709ms/step - loss: 0.3306 - accuracy: 0.9473 - val_loss: 5.1069 - val_accuracy: 0.5900
```

```
Epoch 6/30
```

```
255/255 [=====] - 180s 707ms/step - loss: 0.4257 - accuracy: 0.9353 - val_loss: 5.2278 - val_accuracy: 0.5865
```

```
Epoch 7/30
```

```
255/255 [=====] - 180s 708ms/step - loss: 0.2552 - accuracy: 0.9565 - val_loss: 5.8028 - val_accuracy: 0.5659
```

```
Epoch 8/30
```

```
255/255 [=====] - 180s 707ms/step - loss: 0.3380 - accuracy: 0.9474 - val_loss: 5.7594 - val_accuracy: 0.5743
```

```
Epoch 9/30
```

```
255/255 [=====] - 180s 705ms/step - loss: 0.3781 - accuracy: 0.9398 - val_loss: 6.2191 - val_accuracy: 0.5476
```

```
Epoch 10/30
```

```
255/255 [=====] - 180s 706ms/step - loss: 0.3021 - accuracy: 0.9546 - val_loss: 4.9970 - val_accuracy: 0.6029
```

```
Epoch 11/30
```

```
255/255 [=====] - 181s 709ms/step - loss: 0.2226 - accuracy: 0.9634 - val_loss: 5.5075 - val_accuracy: 0.5799
```

```
Epoch 12/30
```

```
255/255 [=====] - 181s 708ms/step - loss: 0.3211 - 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
```

```
255/255 [=====] - 183s 717ms/step - loss: 0.3017 - accuracy: 0.9538 - val_loss: 6.6898 - val_accuracy: 0.5348
```

```
Epoch 15/30
```

```
255/255 [=====] - 182s 715ms/step - loss: 0.3076 - accuracy: 0.9554 - val_loss: 5.8260 - val_accuracy: 0.5806
```

```
Epoch 16/30
```

```
255/255 [=====] - 183s 717ms/step - loss: 0.2479 - accuracy: 0.9602 - val_loss: 5.4916 - val_accuracy: 0.6008
```

```
Epoch 17/30
```



```

255/255 [=====] - 184s 723ms/step - loss: 0.3149 -
accuracy: 0.9558 - val_loss: 6.3606 - val_accuracy: 0.5646
Epoch 18/30
255/255 [=====] - 184s 720ms/step - loss: 0.3615 -
accuracy: 0.9506 - val_loss: 5.5514 - val_accuracy: 0.6050
Epoch 19/30
255/255 [=====] - 181s 711ms/step - loss: 0.2693 -
accuracy: 0.9570 - val_loss: 6.3985 - val_accuracy: 0.5748
Epoch 20/30
255/255 [=====] - 182s 715ms/step - loss: 0.3107 -
accuracy: 0.9543 - val_loss: 5.9179 - val_accuracy: 0.5907
Epoch 21/30
255/255 [=====] - 182s 713ms/step - loss: 0.2523 -
accuracy: 0.9629 - val_loss: 6.2966 - val_accuracy: 0.5783
Epoch 22/30
255/255 [=====] - 182s 713ms/step - loss: 0.2820 -
accuracy: 0.9635 - val_loss: 5.8626 - val_accuracy: 0.6010
Epoch 23/30
255/255 [=====] - 181s 709ms/step - loss: 0.2569 -
accuracy: 0.9630 - val_loss: 6.3886 - val_accuracy: 0.5886
Epoch 24/30
255/255 [=====] - 181s 711ms/step - loss: 0.3322 -
accuracy: 0.9564 - val_loss: 6.0438 - val_accuracy: 0.5994
Epoch 25/30
255/255 [=====] - 182s 714ms/step - loss: 0.2849 -
accuracy: 0.9592 - val_loss: 6.7721 - val_accuracy: 0.5663
Epoch 26/30
255/255 [=====] - 181s 710ms/step - loss: 0.2081 -
accuracy: 0.9680 - val_loss: 5.9842 - val_accuracy: 0.6064
Epoch 27/30
255/255 [=====] - 183s 717ms/step - loss: 0.2362 -
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
255/255 [=====] - 182s 713ms/step - loss: 0.2329 -
accuracy: 0.9684 - val_loss: 6.0159 - val_accuracy: 0.6081
Epoch 30/30
255/255 [=====] - 180s 707ms/step - loss:
0.2903 - accuracy: 0.9608 - val_loss: 6.4375 - val_accuracy: 0.5978

```

4. Plot Accuracy and Loss

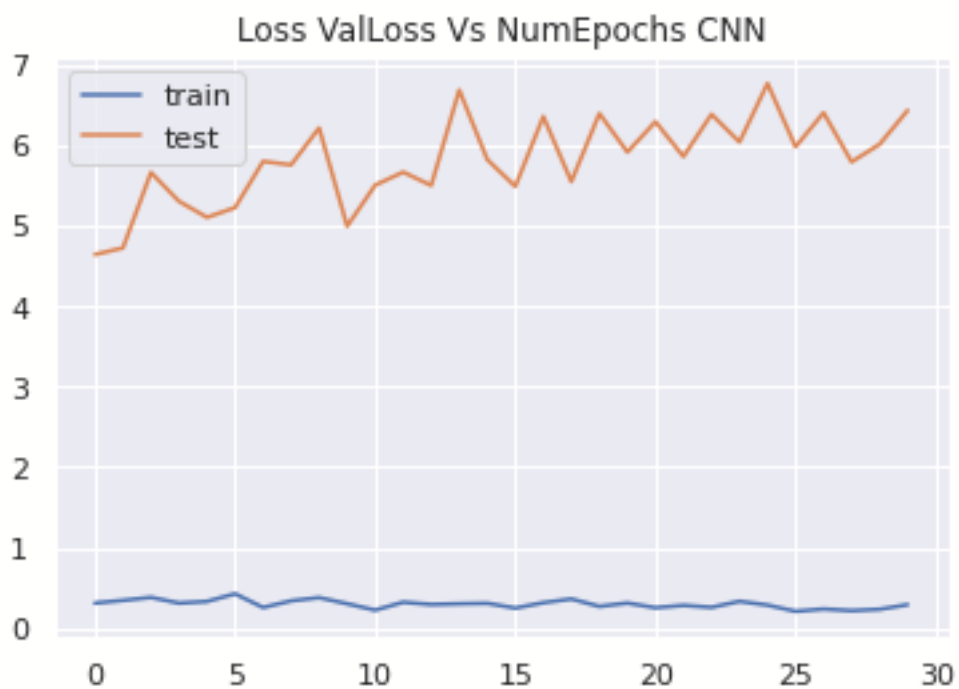
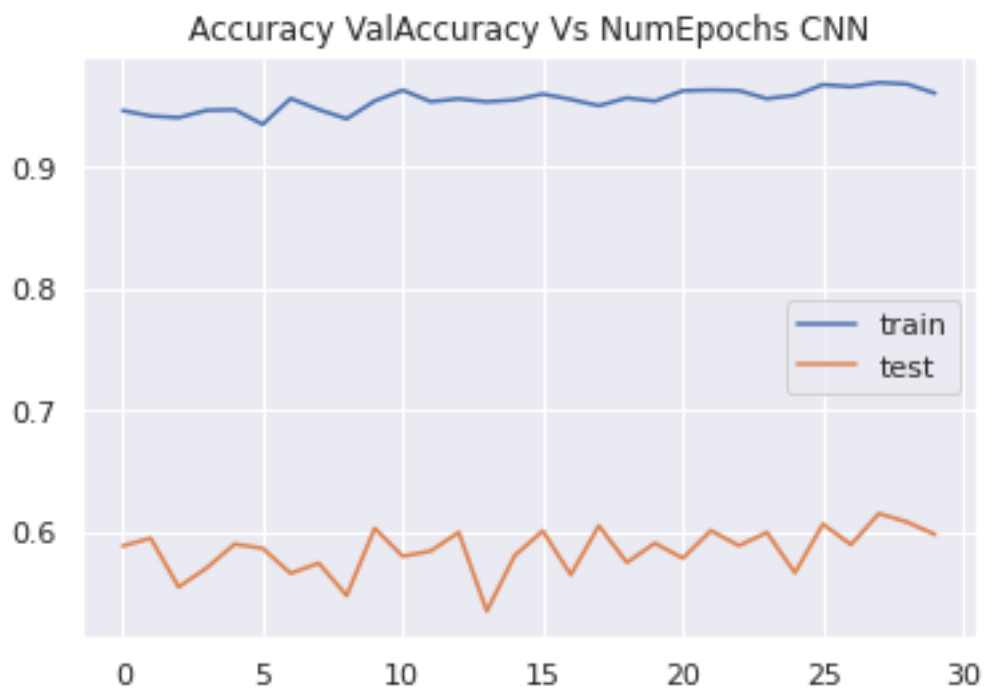
```

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
```



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()
```

```
Model: "model_4"
```

Layer (type)	Output Shape	Param #	Connected to
input_5 (InputLayer)	[(None, 224, 224, 3)]	0	
conv1_pad (ZeroPadding2D)	(None, 230, 230, 3)	0	input_5[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	(None, 56, 56, 64)	256
conv2_block1_1_conv[0][0]		
conv2_block1_1_relu (Activation	(None, 56, 56, 64)	0
conv2_block1_1_bn[0][0]		
conv2_block1_2_conv (Conv2D)	(None, 56, 56, 64)	36928
conv2_block1_1_relu[0][0]		
conv2_block1_2_bn (BatchNormali	(None, 56, 56, 64)	256
conv2_block1_2_conv[0][0]		
conv2_block1_2_relu (Activation	(None, 56, 56, 64)	0
conv2_block1_2_bn[0][0]		
conv2_block1_0_conv (Conv2D)	(None, 56, 56, 256)	16640
pool1_pool[0][0]		
conv2_block1_3_conv (Conv2D)	(None, 56, 56, 256)	16640
conv2_block1_2_relu[0][0]		
conv2_block1_0_bn (BatchNormali	(None, 56, 56, 256)	1024
conv2_block1_0_conv[0][0]		
conv2_block1_3_bn (BatchNormali	(None, 56, 56, 256)	1024
conv2_block1_3_conv[0][0]		

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

conv2_block3_1_relu (Activation (None, 56, 56, 64)	0
conv2_block3_1_bn[0][0]	
<hr/>	
conv2_block3_2_conv (Conv2D) (None, 56, 56, 64)	36928
conv2_block3_1_relu[0][0]	
<hr/>	
conv2_block3_2_bn (BatchNormali (None, 56, 56, 64)	256
conv2_block3_2_conv[0][0]	
<hr/>	
conv2_block3_2_relu (Activation (None, 56, 56, 64)	0
conv2_block3_2_bn[0][0]	
<hr/>	
conv2_block3_3_conv (Conv2D) (None, 56, 56, 256)	16640
conv2_block3_2_relu[0][0]	
<hr/>	
conv2_block3_3_bn (BatchNormali (None, 56, 56, 256)	1024
conv2_block3_3_conv[0][0]	
<hr/>	
conv2_block3_add (Add) (None, 56, 56, 256)	0
conv2_block2_out[0][0]	
<hr/>	
conv2_block3_3_bn[0][0]	
<hr/>	
conv2_block3_out (Activation) (None, 56, 56, 256)	0
conv2_block3_add[0][0]	
<hr/>	
conv3_block1_1_conv (Conv2D) (None, 28, 28, 128)	32896
conv2_block3_out[0][0]	
<hr/>	
conv3_block1_1_bn (BatchNormali (None, 28, 28, 128)	512
conv3_block1_1_conv[0][0]	
<hr/>	
conv3_block1_1_relu (Activation (None, 28, 28, 128)	0
conv3_block1_1_bn[0][0]	
<hr/>	
conv3_block1_2_conv (Conv2D) (None, 28, 28, 128)	147584
conv3_block1_1_relu[0][0]	
<hr/>	
conv3_block1_2_bn (BatchNormali (None, 28, 28, 128)	512
conv3_block1_2_conv[0][0]	
<hr/>	
conv3_block1_2_relu (Activation (None, 28, 28, 128)	0
conv3_block1_2_bn[0][0]	
<hr/>	
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	(None, 28, 28, 128)	512
conv3_block2_2_conv[0][0]		
conv3_block2_2_relu (Activation	(None, 28, 28, 128)	0
conv3_block2_2_bn[0][0]		
conv3_block2_3_conv (Conv2D)	(None, 28, 28, 512)	66048
conv3_block2_2_relu[0][0]		
conv3_block2_3_bn (BatchNormali	(None, 28, 28, 512)	2048
conv3_block2_3_conv[0][0]		
conv3_block2_add (Add)	(None, 28, 28, 512)	0
conv3_block1_out[0][0]		
conv3_block2_3_bn[0][0]		

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

conv3_block4_2_conv (Conv2D)	(None, 28, 28, 128)	147584
conv3_block4_1_relu[0][0]		
<hr/>		
conv3_block4_2_bn (BatchNormali	(None, 28, 28, 128)	512
conv3_block4_2_conv[0][0]		
<hr/>		
conv3_block4_2_relu (Activation	(None, 28, 28, 128)	0
conv3_block4_2_bn[0][0]		
<hr/>		
conv3_block4_3_conv (Conv2D)	(None, 28, 28, 512)	66048
conv3_block4_2_relu[0][0]		
<hr/>		
conv3_block4_3_bn (BatchNormali	(None, 28, 28, 512)	2048
conv3_block4_3_conv[0][0]		
<hr/>		
conv3_block4_add (Add)	(None, 28, 28, 512)	0
conv3_block3_out[0][0]		
<hr/>		
conv3_block4_3_bn[0][0]		
<hr/>		
conv3_block4_out (Activation)	(None, 28, 28, 512)	0
conv3_block4_add[0][0]		
<hr/>		
conv4_block1_1_conv (Conv2D)	(None, 14, 14, 256)	131328
conv3_block4_out[0][0]		
<hr/>		
conv4_block1_1_bn (BatchNormali	(None, 14, 14, 256)	1024
conv4_block1_1_conv[0][0]		
<hr/>		
conv4_block1_1_relu (Activation	(None, 14, 14, 256)	0
conv4_block1_1_bn[0][0]		
<hr/>		
conv4_block1_2_conv (Conv2D)	(None, 14, 14, 256)	590080
conv4_block1_1_relu[0][0]		
<hr/>		
conv4_block1_2_bn (BatchNormali	(None, 14, 14, 256)	1024
conv4_block1_2_conv[0][0]		
<hr/>		
conv4_block1_2_relu (Activation	(None, 14, 14, 256)	0
conv4_block1_2_bn[0][0]		
<hr/>		
conv4_block1_0_conv (Conv2D)	(None, 14, 14, 1024)	525312
conv3_block4_out[0][0]		
<hr/>		
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)	(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)	1024
conv4_block4_1_conv[0][0]		

conv4_block4_1_relu (Activation	(None, 14, 14, 256)	0
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) 0
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]

conv4_block4_add (Add) (None, 14, 14, 1024) 0
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) 0
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_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]

conv4_block6_2_conv (Conv2D) (None, 14, 14, 256) 590080
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) (None, 14, 14, 1024) 0
conv4_block5_out[0][0]

conv4_block6_3_bn[0][0]

conv4_block6_out (Activation) (None, 14, 14, 1024) 0
conv4_block6_add[0][0]

conv5_block1_1_conv (Conv2D) (None, 7, 7, 512) 524800
conv4_block6_out[0][0]

conv5_block1_1_bn (BatchNormali (None, 7, 7, 512) 2048
conv5_block1_1_conv[0][0]

conv5_block1_1_relu (Activation (None, 7, 7, 512) 0
conv5_block1_1_bn[0][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] conv5_block1_3_bn[0][0]	(None, 7, 7, 2048)	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 (None, 7, 7, 512)	0
conv5_block2_2_bn[0][0]	
<hr/>	
conv5_block2_3_conv (Conv2D) (None, 7, 7, 2048)	1050624
conv5_block2_2_relu[0][0]	
<hr/>	
conv5_block2_3_bn (BatchNormali (None, 7, 7, 2048)	8192
conv5_block2_3_conv[0][0]	
<hr/>	
conv5_block2_add (Add) (None, 7, 7, 2048)	0
conv5_block1_out[0][0]	
<hr/>	
conv5_block2_3_bn[0][0]	
<hr/>	
conv5_block2_out (Activation) (None, 7, 7, 2048)	0
conv5_block2_add[0][0]	
<hr/>	
conv5_block3_1_conv (Conv2D) (None, 7, 7, 512)	1049088
conv5_block2_out[0][0]	
<hr/>	
conv5_block3_1_bn (BatchNormali (None, 7, 7, 512)	2048
conv5_block3_1_conv[0][0]	
<hr/>	
conv5_block3_1_relu (Activation (None, 7, 7, 512)	0
conv5_block3_1_bn[0][0]	
<hr/>	
conv5_block3_2_conv (Conv2D) (None, 7, 7, 512)	2359808
conv5_block3_1_relu[0][0]	
<hr/>	
conv5_block3_2_bn (BatchNormali (None, 7, 7, 512)	2048
conv5_block3_2_conv[0][0]	
<hr/>	
conv5_block3_2_relu (Activation (None, 7, 7, 512)	0
conv5_block3_2_bn[0][0]	
<hr/>	
conv5_block3_3_conv (Conv2D) (None, 7, 7, 2048)	1050624
conv5_block3_2_relu[0][0]	
<hr/>	
conv5_block3_3_bn (BatchNormali (None, 7, 7, 2048)	8192
conv5_block3_3_conv[0][0]	
<hr/>	
conv5_block3_add (Add) (None, 7, 7, 2048)	0
conv5_block2_out[0][0]	
<hr/>	
conv5_block3_3_bn[0][0]	
<hr/>	

conv5_block3_out (Activation)	(None, 7, 7, 2048)	0
conv5_block3_add[0][0]		
<hr/>		
flatten_5 (Flatten)	(None, 100352)	0
conv5_block3_out[0][0]		
<hr/>		
dense_14 (Dense)	(None, 197)	19769541
flatten_5[0][0]		
<hr/>		
=====		
Total params: 43,357,253		
Trainable params: 19,769,541		
Non-trainable params: 23,587,712		
<hr/>		

3. Training [Forward pass and Backpropagation]

```
#Compile with optimizer
resnet.compile(optimizer = Adam(learning_rate=0.001), loss = 'categorical_crossentropy', 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, validation_data = validation_generator, callbacks = [early] )
```

```
Epoch 1/30
255/255 [=====] - 188s 726ms/step - loss: 25.5408 - accuracy: 0.0128 - val_loss: 14.5744 - val_accuracy: 0.0285
Epoch 2/30
255/255 [=====] - 182s 716ms/step - loss: 13.3197 - accuracy: 0.0379 - val_loss: 14.4397 - val_accuracy: 0.0420
Epoch 3/30
255/255 [=====] - 183s 718ms/step - loss: 12.8443 - accuracy: 0.0561 - val_loss: 13.0493 - val_accuracy: 0.0451
Epoch 4/30
255/255 [=====] - 183s 718ms/step - loss: 12.7389 - 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']
```

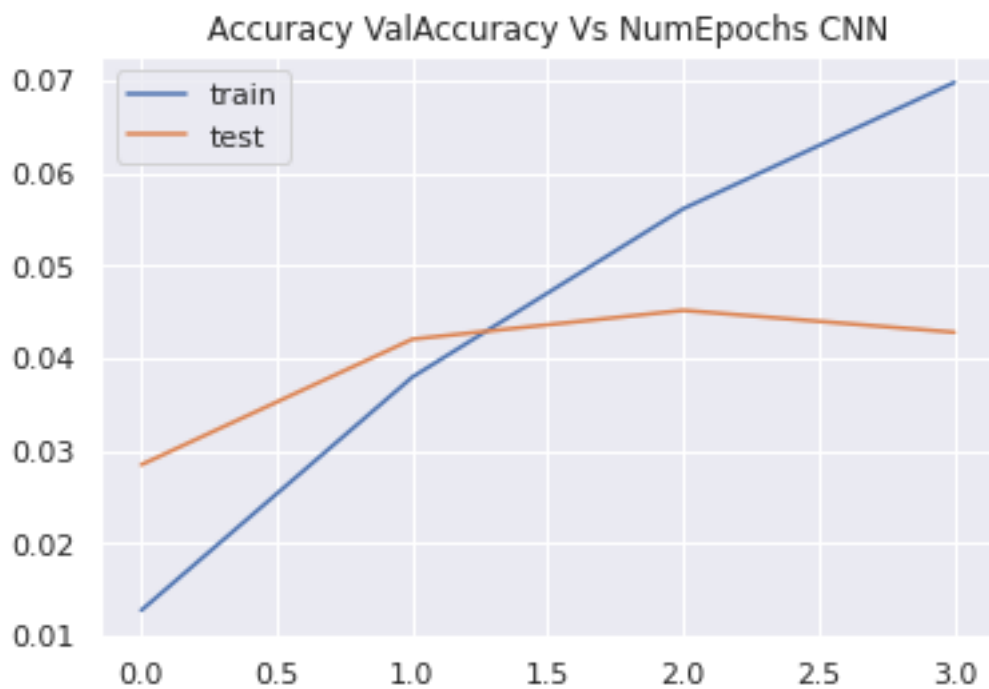
```

val_loss    = resnet_classifier.history['val_loss']

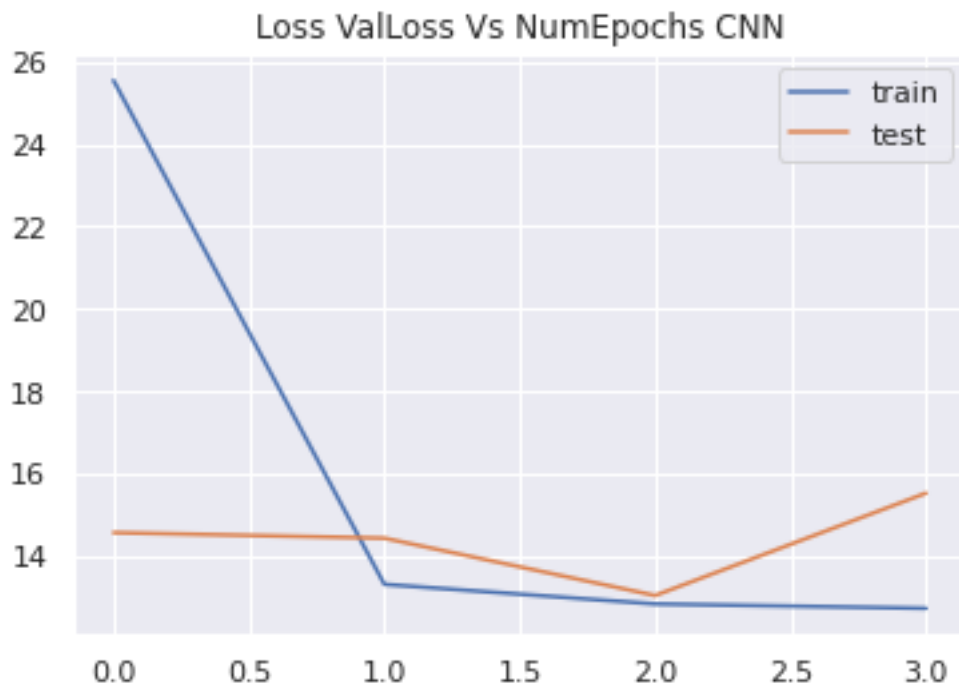
xc = resnet_classifier.epoch
plt.title("Accuracy ValAccuracy Vs NumEpochs CNN")
plt.plot(xc,resnet_classifier.history['accuracy'], label='train')
plt.plot(xc,resnet_classifier.history['val_accuracy'], label='test')
plt.legend()
plt.show()

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_generator.samples/BATCH_SIZE))
val_acc = resnet.evaluate_generator(validation_generator, steps = int(validation_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

```
base_model = InceptionResNetV2(include_top=False, input_shape = INPUT_SIZE)
```

Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/inception_resnet_v2/inception_resnet_v2_weights_tf_dim_ordering_tf_kernels_notop.h5

```
219062272/219055592 [=====] - 2s 0us/step
```

```
219070464/219055592 [=====] - 2s 0us/step
```

```
classification_model = tf.keras.Sequential([
    base_model,
    tf.keras.layers.GlobalAveragePooling2D(),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.Dropout(0.2),
```

```
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 (Function)	(None, 5, 5, 1536)	54336736
global_average_pooling2d (GlobalAveragePooling2D)	(None, 1536)	0
dense_15 (Dense)	(None, 128)	196736
batch_normalization_203 (Batch Normalization)	(None, 128)	512
dropout_1 (Dropout)	(None, 128)	0
dense_16 (Dense)	(None, 197)	25413
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(lr=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=True, 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
255/255 [=====] - 219s 774ms/step - loss: 5.0064 - accuracy: 0.0424 - val_loss: 4.8299 - val_accuracy: 0.0622
Epoch 2/30
255/255 [=====] - 193s 756ms/step - loss: 3.0798 - accuracy: 0.3256 - val_loss: 3.7128 - val_accuracy: 0.1919
Epoch 3/30
255/255 [=====] - 192s 754ms/step - loss: 1.4914 - accuracy: 0.6661 - val_loss: 1.6520 - val_accuracy: 0.5869
Epoch 4/30
255/255 [=====] - 193s 755ms/step - loss: 0.7913 - accuracy: 0.8196 - val_loss: 1.7750 - val_accuracy: 0.5655

Epoch 00004: ReduceLROnPlateau reducing learning rate to 0.00050000000237487257.
Epoch 5/30
255/255 [=====] - 190s 745ms/step - loss: 0.3456 - accuracy: 0.9209 - val_loss: 0.5200 - val_accuracy: 0.8710
Epoch 6/30
255/255 [=====] - 193s 753ms/step - loss: 0.2035 - accuracy: 0.9573 - val_loss: 0.5306 - val_accuracy: 0.8605

Epoch 00006: ReduceLROnPlateau reducing learning rate to 0.00025000000118743628.
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
255/255 [=====] - 193s 755ms/step - loss: 0.0785 - accuracy: 0.9877 - val_loss: 0.3624 - val_accuracy: 0.9042
Epoch 9/30
255/255 [=====] - 193s 756ms/step - loss: 0.0683 - accuracy: 0.9882 - val_loss: 0.3795 - val_accuracy: 0.8957

Epoch 00009: ReduceLROnPlateau reducing learning rate to 0.00012500000059371814.
Epoch 10/30
161/255 [=====>.....] - ETA: 50s - loss: 0.0471 - accuracy: 0.9930
```

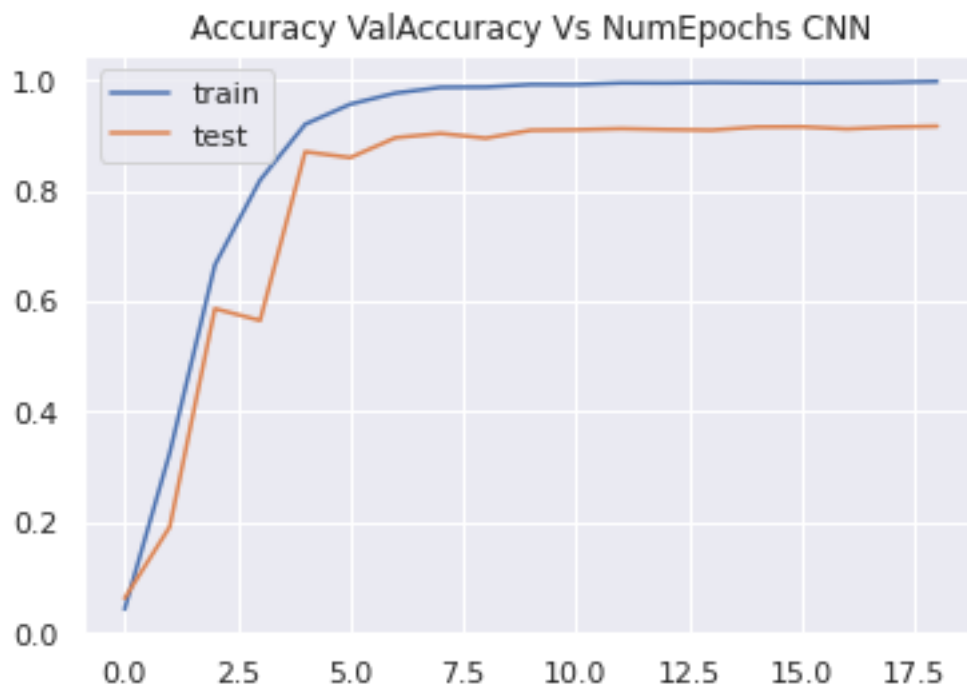
6. Plot Accuracy and Loss for Training and Validation

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

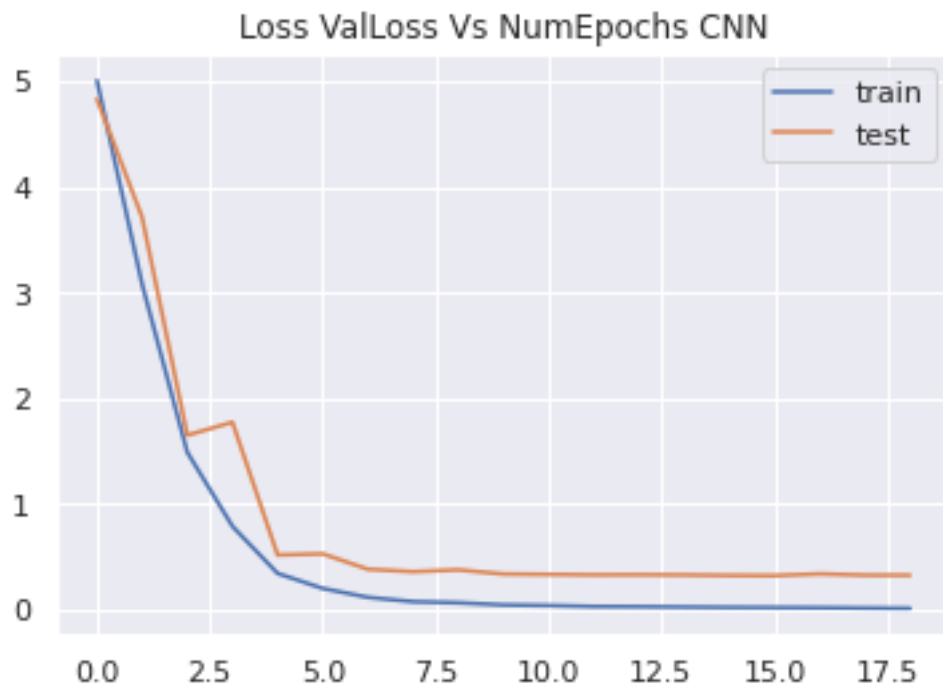
xc = history.epoch
plt.title("Accuracy ValAccuracy Vs NumEpochs CNN")
```

```
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.



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 = int(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
```

	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

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)
```



```
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