Own_Data_Training

February 16, 2019

0.0.1 Description Generation for Images

Description Generation for Images included Two Major Domains Image Processing as well as NLTP [Natural Language and Text Processing]

- Image Processing used to Blob Detection in the Sense Object Detection and Recognition.
- NLTK [Natural Language and Text Processing] is used to Generate Text for the Blob We Detected in Image.

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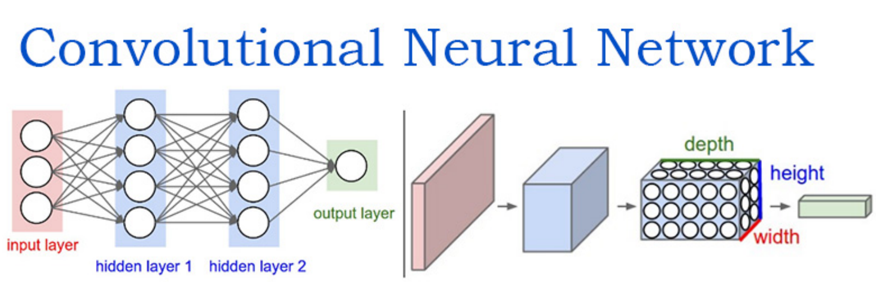
0.0.2 Training of Images for Object prediction using Keras Using TensorFlow Backend.

Importing Basic Packages Required for the Program.

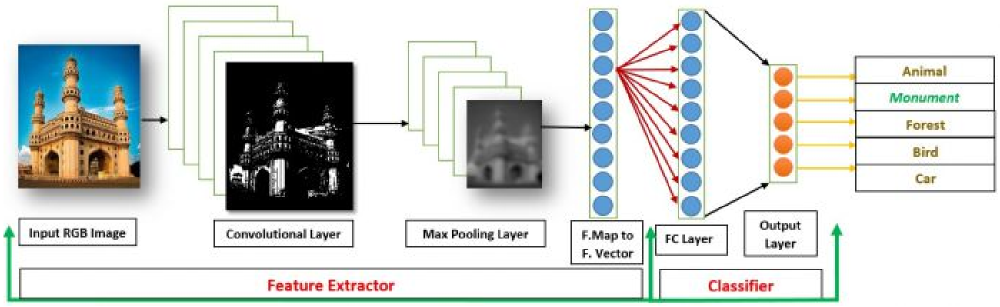
```
In [1]: import os
        import cv2
        import numpy as np
        import matplotlib.pyplot as plt
```

Importing Machine learning Libraries Required for the Program. We're using sklearn Tools for Machine Learning.



Left: A regular 3-layer Neural Network. Right: A ConvNet arranges its neurons in three dimensions (width, height, depth), as visualized in one of the layers. Every layer of a ConvNet transforms the 3D input volume to a 3D output volume of neuron activations. In this example, the red input layer holds the image, so its width and height would be the dimensions of the image, and the depth would be 3 (Red, Green, Blue channels).

title



title

```
In [4]: from sklearn.utils import shuffle
        from sklearn.model_selection  import train_test_split
```

Importing Deep learning Libraries for Training Images. We're using Keras with Tensor Flow BackGround

```
In [5]: from keras import backend as K
        K.set_image_dim_ordering('th')
```

```
Using TensorFlow backend.
```

```
In [6]: from keras.utils import np_utils
        from keras.models import Sequential
        from keras.layers.core import Dense, Dropout, Activation, Flatten
        from keras.layers.convolutional import Conv2D, MaxPooling2D
        from keras.optimizers import SGD, RMSprop,adam
```

Reading paths

```
In [26]: PATH = os.getcwd()
         print(PATH)

         DATA_PATH = PATH + '\data'
         print(DATA_PATH)

         DATA_DIR_LIST = os.listdir(DATA_PATH)
         print(DATA_DIR_LIST)
```

```
C:\Users\Rajath Kumar K S\Downloads\CaptionGenerationandObjectDetection
C:\Users\Rajath Kumar K S\Downloads\CaptionGenerationandObjectDetection\data
['cats', 'dogs', 'horses', 'Humans']
```

Defining Configurations for Training Model

```
In [27]: img_rows = 128
         img_cols = 128
         num_channel = 1
         num_epoch = 25
```

Defining Number of Classes * Classification of Images Different Type of Images in Different Folder * In this Case Right Now I've Taken Four Classes of Images like 1. Dogs, 2. Cats, 3. Humans, 4. Horses

```
In [28]: num_classes = 4
```

```
In [29]: img_data_list = []
```

```
In [30]: for dataset in DATA_DIR_LIST:
             img_list = os.listdir(DATA_PATH+'\\'+dataset)
             print('Loaded the images of Dataset - '+' {}\n'.format(dataset))
             for img in img_list:
                 input_img=cv2.imread(DATA_PATH + '\\'+ dataset + '\\'+ img )
                 input_img=cv2.cvtColor(input_img, cv2.COLOR_BGR2GRAY)
                 input_img_resize=cv2.resize(input_img,(128,128))
                 img_data_list.append(input_img_resize)
```

```
Loaded the images of Dataset -  cats

Loaded the images of Dataset -  dogs

Loaded the images of Dataset -  horses

Loaded the images of Dataset -  Humans
```

```
In [31]: img_data = np.array(img_data_list)
         img_data = img_data.astype('float32')
         img_data /= 255
         print (img_data.shape)
```

```
(808, 128, 128)
```

```
In [32]: if num_channel==1:
             if K.image_dim_ordering()=='th':
                 img_data= np.expand_dims(img_data, axis=1)
                 print (img_data.shape)
             else:
                 img_data= np.expand_dims(img_data, axis=4)
                 print (img_data.shape)
         else:
             if K.image_dim_ordering()=='th':
                 img_data=np.rollaxis(img_data,3,1)
                 print (img_data.shape)
```

```
(808, 1, 128, 128)
```

```
In [33]: num_of_samples = img_data.shape[0]
         labels = np.ones((num_of_samples,),dtype='int64')
```

```
In [34]: labels[0:202]=0
         labels[202:404]=1
         labels[404:606]=2
         labels[606:]=3
```

```
In [35]: labels
```

```
Out[35]: array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
                1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
                1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
                1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
                1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
                1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
                1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
                1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
                1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
                1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
                2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
                2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
                2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
                2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
                2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
                2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
                2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
                2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
                2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
                3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
                3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
                3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
                3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
                3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
                3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
                3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
                3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
                3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3], dtype=int64)
```

```
In [36]: names = ['cats','dogs','horses','humans']
```

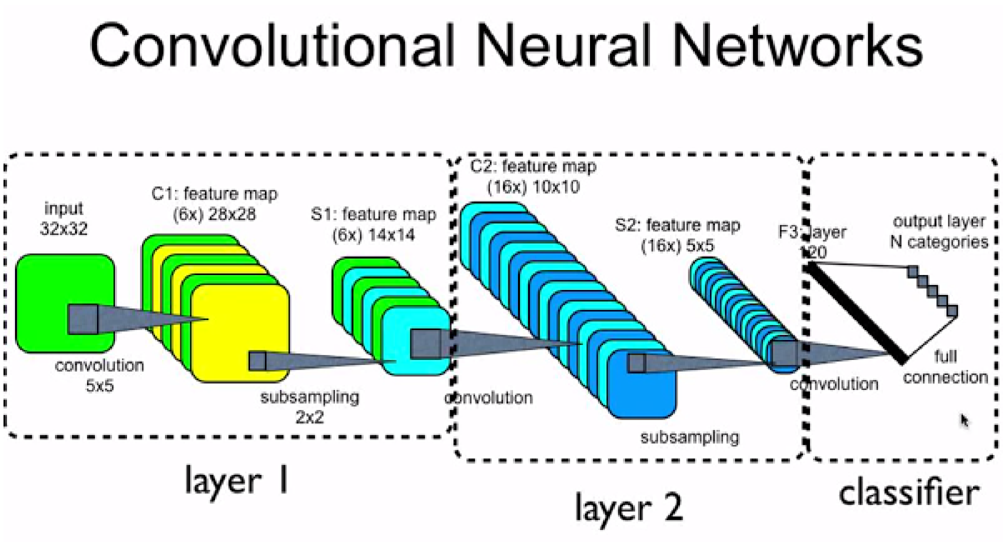
In [37]:
```
# convert class labels to on-hot encoding
Y = np_utils.to_categorical(labels, num_classes)
```

In [38]:
```
Y
```

Out[38]:
```
array([[1., 0., 0., 0.],
       [1., 0., 0., 0.],
       [1., 0., 0., 0.],
       ...,
       [0., 0., 0., 1.],
       [0., 0., 0., 1.],
       [0., 0., 0., 1.]], dtype=float32)
```

In [39]:
```
#Shuffle the dataset
x,y = shuffle(img_data,Y, random_state=2)
# Split the dataset
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=
```

In [40]:
```
# Defining the model

# dimensions of our images.
#img_width, img_height = 224, 224

#if K.image_data_format() == 'channels_first':
#    input_shape = (3, img_width, img_height)
#else:
#    input_shape = (img_width, img_height, 3)

input_shape=img_data[0].shape

model = Sequential()

model.add(Conv2D(32, (3,3), input_shape=input_shape))
model.add(Activation('relu'))
model.add(Conv2D(32, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.5))

model.add(Conv2D(64, (3, 3)))
model.add(Activation('relu'))
#model.add(Convolution2D(64, 3, 3))
#model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.5))

model.add(Flatten())
model.add(Dense(64))
model.add(Activation('relu'))
```

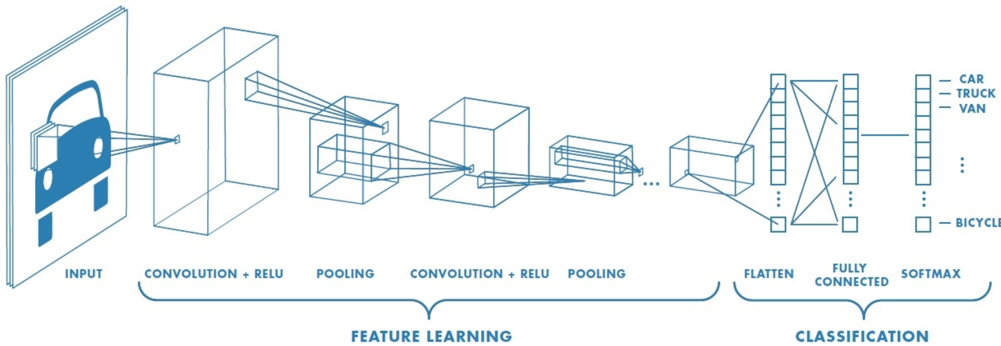


title

```
model.add(Dropout(0.5))
model.add(Dense(num_classes))
model.add(Activation('softmax'))

model.compile(loss='categorical_crossentropy', optimizer='rmsprop',metrics=["accuracy'
```

In [41]:
```
# Viewing model_configuration

model.summary()
model.get_config()
model.layers[0].get_config()
model.layers[0].input_shape
model.layers[0].output_shape
model.layers[0].get_weights()
np.shape(model.layers[0].get_weights()[0])
model.layers[0].trainable
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 32, 126, 126)      320
_________________________________________________________________
activation_1 (Activation)    (None, 32, 126, 126)      0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 32, 124, 124)      9248
_________________________________________________________________
activation_2 (Activation)    (None, 32, 124, 124)      0
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 32, 62, 62)        0
```



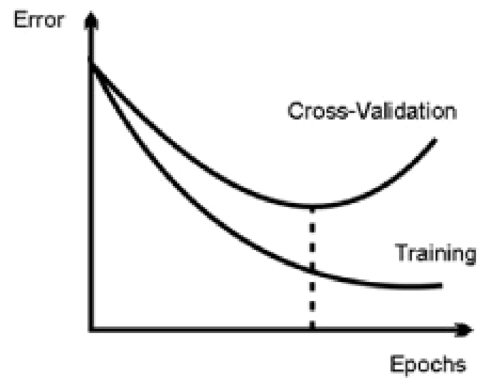
title

```
_________________________________________________________________
dropout_1 (Dropout)          (None, 32, 62, 62)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 64, 60, 60)        18496
_________________________________________________________________
activation_3 (Activation)    (None, 64, 60, 60)        0
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 64, 30, 30)        0
_________________________________________________________________
dropout_2 (Dropout)          (None, 64, 30, 30)        0
_________________________________________________________________
flatten_1 (Flatten)          (None, 57600)             0
_________________________________________________________________
dense_1 (Dense)              (None, 64)                3686464
_________________________________________________________________
activation_4 (Activation)    (None, 64)                0
_________________________________________________________________
dropout_3 (Dropout)          (None, 64)                0
_________________________________________________________________
dense_2 (Dense)              (None, 4)                 260
_________________________________________________________________
activation_5 (Activation)    (None, 4)                 0
=================================================================
Total params: 3,714,788
Trainable params: 3,714,788
Non-trainable params: 0
_________________________________________________________________
```

```
Out[41]: True
```

```
In [42]: print("Model Training Started Wait a While Until It's Get Completed")
         hist = model.fit(X_train, y_train, batch_size=16, epochs=num_epoch, verbose=1, valida
         print("Model Training Completed")
```

```
Model Training Started Wait a While Until It's Get Completed
Train on 646 samples, validate on 162 samples
Epoch 1/25
646/646 [==============================] - 148s 229ms/step - loss: 1.5379 - acc: 0.2647 - val_
Epoch 2/25
646/646 [==============================] - 161s 249ms/step - loss: 1.3407 - acc: 0.3669 - val_
Epoch 3/25
646/646 [==============================] - 157s 244ms/step - loss: 1.2209 - acc: 0.4489 - val_
Epoch 4/25
646/646 [==============================] - 160s 247ms/step - loss: 1.1311 - acc: 0.5015 - val_
Epoch 5/25
646/646 [==============================] - 156s 241ms/step - loss: 1.0138 - acc: 0.5789 - val_
Epoch 6/25
646/646 [==============================] - 175s 271ms/step - loss: 0.9134 - acc: 0.6146 - val_
Epoch 7/25
646/646 [==============================] - 210s 325ms/step - loss: 0.8291 - acc: 0.6641 - val_
Epoch 8/25
646/646 [==============================] - 208s 322ms/step - loss: 0.7303 - acc: 0.6981 - val_
Epoch 9/25
646/646 [==============================] - 237s 367ms/step - loss: 0.7043 - acc: 0.6997 - val_
Epoch 10/25
646/646 [==============================] - 194s 300ms/step - loss: 0.6630 - acc: 0.7399 - val_
Epoch 11/25
646/646 [==============================] - 188s 292ms/step - loss: 0.5428 - acc: 0.7755 - val_
Epoch 12/25
646/646 [==============================] - 182s 281ms/step - loss: 0.4983 - acc: 0.7972 - val_
Epoch 13/25
646/646 [==============================] - 215s 332ms/step - loss: 0.4879 - acc: 0.8127 - val_
Epoch 14/25
646/646 [==============================] - 206s 319ms/step - loss: 0.4364 - acc: 0.8158 - val_
Epoch 15/25
646/646 [==============================] - 164s 254ms/step - loss: 0.4112 - acc: 0.8344 - val_
Epoch 16/25
646/646 [==============================] - 198s 306ms/step - loss: 0.3708 - acc: 0.8406 - val_
Epoch 17/25
646/646 [==============================] - 191s 296ms/step - loss: 0.3884 - acc: 0.8344 - val_
Epoch 18/25
646/646 [==============================] - 173s 267ms/step - loss: 0.3980 - acc: 0.8344 - val_
Epoch 19/25
646/646 [==============================] - 181s 280ms/step - loss: 0.3480 - acc: 0.8700 - val_
Epoch 20/25
646/646 [==============================] - 183s 283ms/step - loss: 0.3674 - acc: 0.8545 - val_
Epoch 21/25
646/646 [==============================] - 181s 280ms/step - loss: 0.3628 - acc: 0.8607 - val_
Epoch 22/25
646/646 [==============================] - 190s 295ms/step - loss: 0.3599 - acc: 0.8545 - val_
Epoch 23/25
646/646 [==============================] - 195s 302ms/step - loss: 0.3776 - acc: 0.8622 - val_
```



Reference for Training and Accuracy Curve

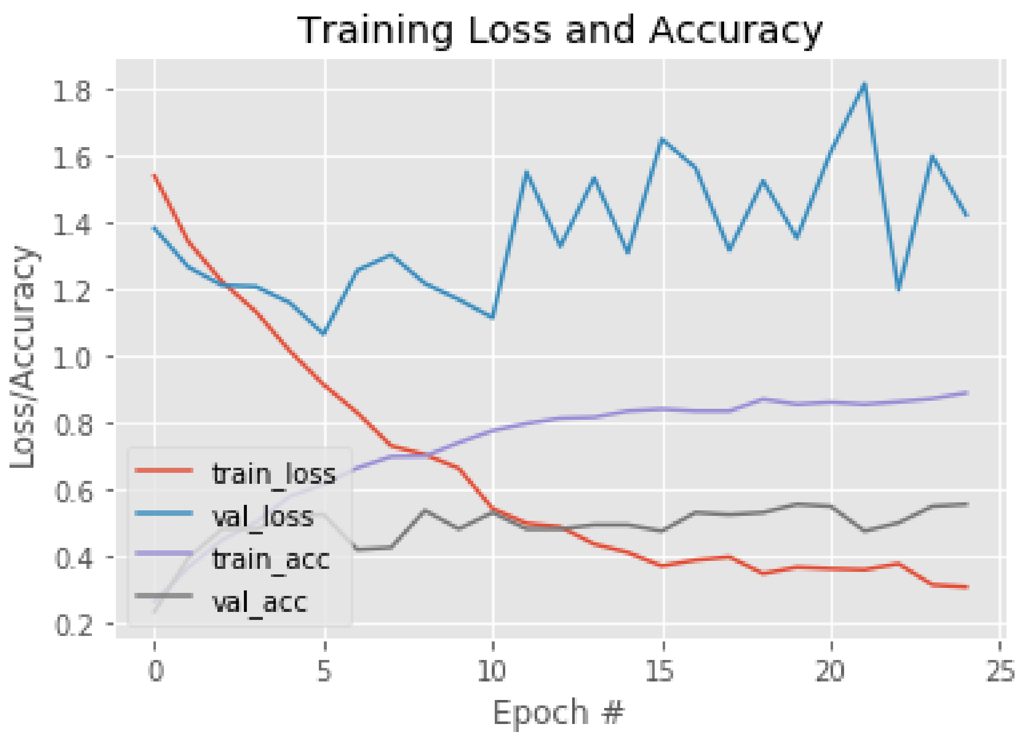
```
Epoch 24/25
646/646 [==============================] - 191s 296ms/step - loss: 0.3145 - acc: 0.8715 - val_l
Epoch 25/25
646/646 [==============================] - 191s 295ms/step - loss: 0.3080 - acc: 0.8885 - val_l
Model Training Completed
```

In [43]:
```
%matplotlib inline
```

0.0.3 Training and Accuracy Curve

In [44]:
```
plt.style.use("ggplot")
plt.figure()
N = num_epoch
plt.plot(np.arange(0, N), hist.history["loss"], label="train_loss")
plt.plot(np.arange(0, N), hist.history["val_loss"], label="val_loss")
plt.plot(np.arange(0, N), hist.history["acc"], label="train_acc")
plt.plot(np.arange(0, N), hist.history["val_acc"], label="val_acc")
plt.title("Training Loss and Accuracy")
plt.xlabel("Epoch #")
plt.ylabel("Loss/Accuracy")
plt.legend(loc="lower left")
#plt.savefig(args["plot"])
```

Out[44]:
```
<matplotlib.legend.Legend at 0x1ca4f471908>
```




```
In [45]: # Training with callbacks
         from keras import callbacks

In [46]: filename='model_train_new.csv'
         csv_log=callbacks.CSVLogger(filename, separator=',', append=False)

In [47]: early_stopping=callbacks.EarlyStopping(monitor='val_loss', min_delta=0, patience=2, ve

In [48]: filepath="Best-weights-my_model-{epoch:03d}-{loss:.4f}-{acc:.4f}.hdf5"

In [49]: checkpoint = callbacks.ModelCheckpoint(filepath, monitor='val_loss', verbose=1, save_b

In [50]: callbacks_list = [csv_log,early_stopping,checkpoint]

In [51]: print("Model Training Started Wait a While Until It's Get Completed")
         hist = model.fit(X_train, y_train, batch_size=16, epochs=num_epoch, verbose=1, valida
         print("Model Training Completed")
```

```
Model Training Started Wait a While Until It's Get Completed
Train on 646 samples, validate on 162 samples
Epoch 1/25
646/646 [==============================] - 179s 277ms/step - loss: 0.3625 - acc: 0.8390 - val_l

Epoch 00001: val_loss improved from inf to 1.62075, saving model to Best-weights-my_model-001-0
```

```
Epoch 2/25
646/646 [==============================] - 203s 314ms/step - loss: 0.3510 - acc: 0.8669 - val_l

Epoch 00002: val_loss did not improve from 1.62075
Epoch 3/25
646/646 [==============================] - 159s 247ms/step - loss: 0.3829 - acc: 0.8437 - val_l

Epoch 00003: val_loss improved from 1.62075 to 1.45247, saving model to Best-weights-my_model-0
Epoch 4/25
646/646 [==============================] - 182s 281ms/step - loss: 0.4143 - acc: 0.8514 - val_l

Epoch 00004: val_loss improved from 1.45247 to 1.43439, saving model to Best-weights-my_model-0
Epoch 5/25
646/646 [==============================] - 166s 257ms/step - loss: 0.3867 - acc: 0.8700 - val_l

Epoch 00005: val_loss did not improve from 1.43439
Epoch 6/25
646/646 [==============================] - 168s 260ms/step - loss: 0.3529 - acc: 0.8622 - val_l

Epoch 00006: val_loss did not improve from 1.43439
Model Training Completed
```

In [66]:
```
train_loss=hist.history['loss']
val_loss=hist.history['val_loss']
train_acc=hist.history['acc']
val_acc=hist.history['val_acc']
xc=range(6)
```

In [67]:
```
train_loss
```

Out[67]:
```
[0.3625010556019497,
 0.3510149658741228,
 0.3829233427719435,
 0.41431847592994525,
 0.3867188396837689,
 0.35288972326845575]
```

In [68]:
```
train_acc
```

Out[68]:
```
[0.8390092877411621,
 0.8668730650154799,
 0.8436532505894593,
 0.8513931886699546,
 0.8699690402476781,
 0.8622291019826481]
```

In [69]:
```
val_loss
```

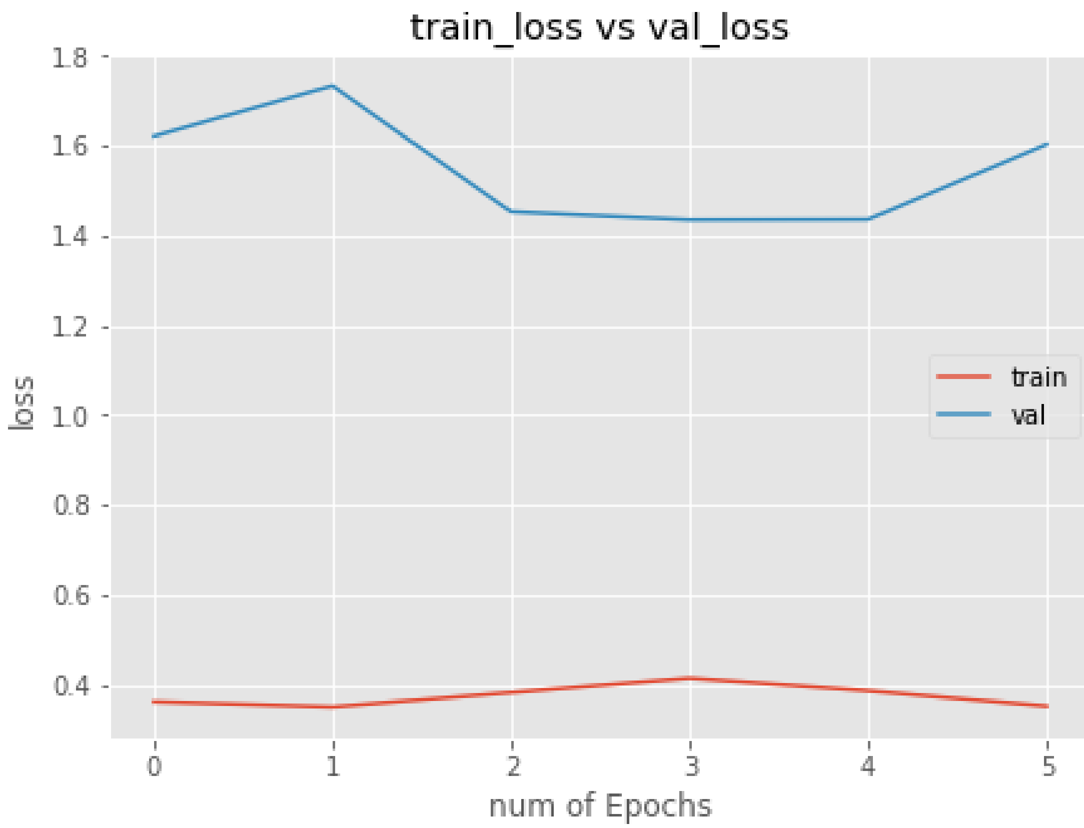
Out[69]: [1.62075396526007,
 1.7326229766563133,
 1.4524739759939689,
 1.4343875484702029,
 1.4353121563240334,
 1.602714595971284]

In [70]: val_acc

Out[70]: [0.49382716049382713,
 0.49382716049382713,
 0.5493827160493827,
 0.5061728395061729,
 0.5493827160493827,
 0.5]

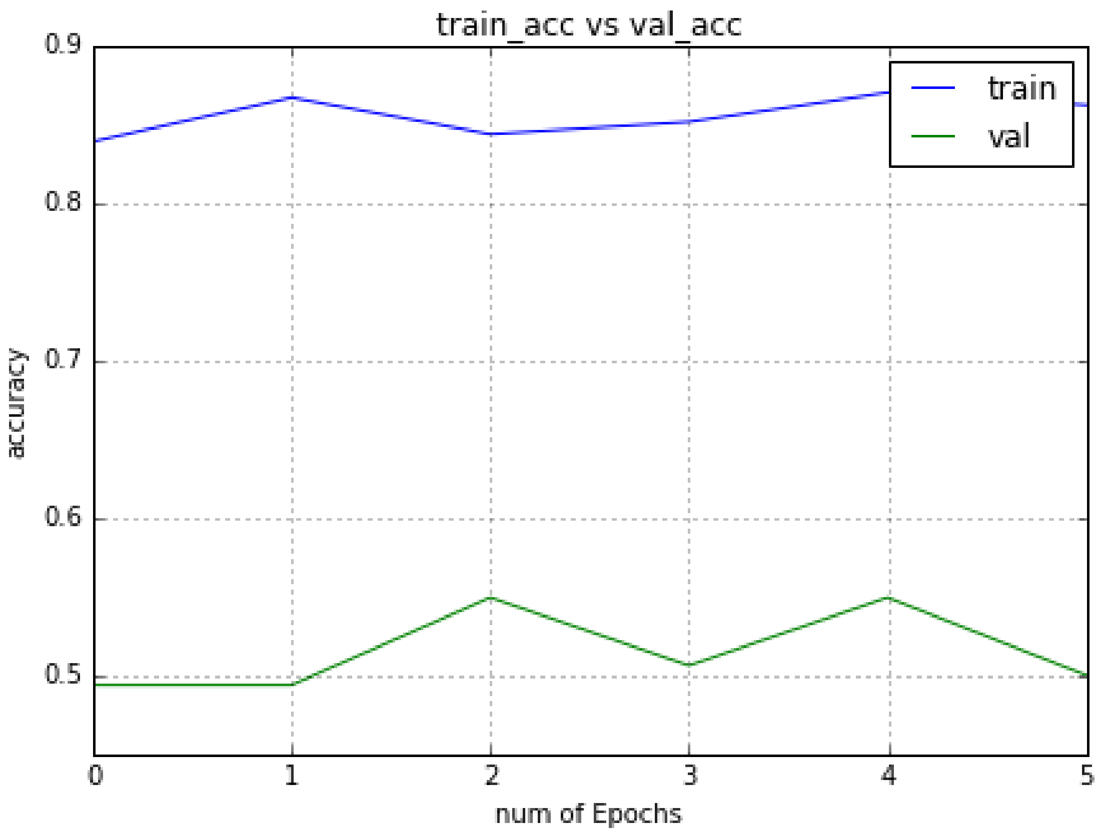
In [71]: %matplotlib inline

In [72]:
```
plt.figure(1,figsize=(7,5))
plt.plot(xc,train_loss)
plt.plot(xc,val_loss)
plt.xlabel('num of Epochs')
plt.ylabel('loss')
plt.title('train_loss vs val_loss')
plt.grid(True)
plt.legend(['train','val'])
plt.style.use(['classic'])
```




```
In [73]: %matplotlib inline
```

```
In [74]: plt.figure(2,figsize=(7,5))
         plt.plot(xc,train_acc)
         plt.plot(xc,val_acc)
         plt.xlabel('num of Epochs')
         plt.ylabel('accuracy')
         plt.title('train_acc vs val_acc')
         plt.grid(True)
         plt.legend(['train','val'])
         plt.style.use(['classic'])
```




```
In [75]: score = model.evaluate(X_test, y_test, verbose=0)
         print('Test Loss:', score[0])
         print('Test accuracy:', score[1])
```

```
Test Loss: 1.6027146077450412
Test accuracy: 0.5
```

```
In [76]: test_image = X_test[0:1]
         print (test_image.shape)
```

```
(1, 1, 128, 128)
```

```
In [77]: print(model.predict(test_image))
         print(model.predict_classes(test_image))
         print(y_test[0:1])
```

```
[[6.9700298e-05 2.0247183e-03 9.9627352e-01 1.6321237e-03]]
[2]
[[0. 0. 1. 0.]]
```

In [78]:
```
test_image = cv2.imread('data/Humans/rider-8.jpg')
test_image=cv2.cvtColor(test_image, cv2.COLOR_BGR2GRAY)
test_image=cv2.resize(test_image,(128,128))
test_image = np.array(test_image)
test_image = test_image.astype('float32')
test_image /= 255
print (test_image.shape)
```

```
(128, 128)
```

In [79]:
```
if num_channel==1:
    if K.image_dim_ordering()=='th':
        test_image= np.expand_dims(test_image, axis=0)
        test_image= np.expand_dims(test_image, axis=0)
        print (test_image.shape)
    else:
        test_image= np.expand_dims(test_image, axis=3)
        test_image= np.expand_dims(test_image, axis=0)
        print (test_image.shape)
else:
    if K.image_dim_ordering()=='th':
        test_image=np.rollaxis(test_image,2,0)
        test_image= np.expand_dims(test_image, axis=0)
        print (test_image.shape)
    else:
        test_image= np.expand_dims(test_image, axis=0)
        print (test_image.shape)
```

```
(1, 1, 128, 128)
```

In [80]:
```
print((model.predict(test_image)))
```

```
[[0.00778023 0.0074342  0.00173834 0.9830472 ]]
```

In [81]:
```
print(model.predict_classes(test_image))
```

```
[3]
```

In [ ]: