Introduction

In this kernel,we will be learning about Convolution neural networks.We will learn

- how to prepare your data to feed to a neural network
- how convolution neural network works
- how to implement cnn in keras
- how to evaluvate your results
- how to use keras pretrained network to improve your model
- how to predict and create a submission

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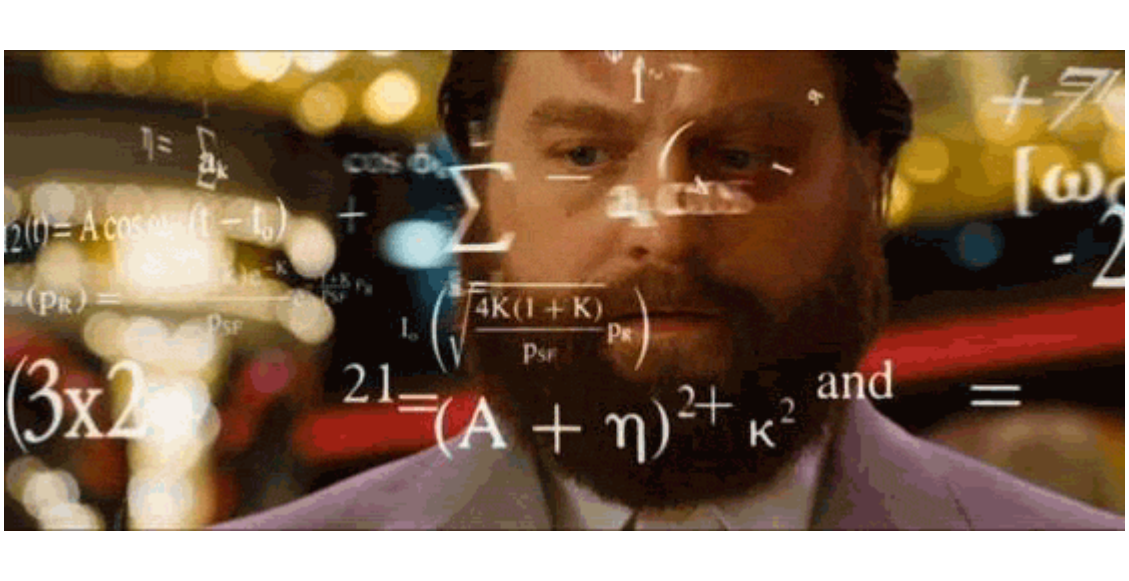


and it's no rocket science,its fun.

Loading required libraries

In [1]:
```
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import os,cv2
from IPython.display import Image
from keras.preprocessing import image
from keras import optimizers
from keras import layers,models
from keras.applications.imagenet_utils import preprocess_input
import matplotlib.pyplot as plt
import seaborn as sns
from keras import regularizers
from keras.preprocessing.image import ImageDataGenerator
from keras.applications.vgg16 import VGG16
print(os.listdir("../input"))

import numpy as np
```

```
Using TensorFlow backend.
['test', 'train', 'train.csv', 'sample_submission.csv']
```

Setting our directories

In [2]:
```
train_dir="../input/train/train"
test_dir="../input/test/test"
train=pd.read_csv('../input/train.csv')

df_test=pd.read_csv('../input/sample_submission.csv')
```

Getting a basic idea

In [3]:
```
train.head(5)
train.has_cactus=train.has_cactus.astype(str)
```

In [4]:
```
print('out dataset has {} rows and {} columns'.format(train.shape[0],train.shape[1]))
```

```
out dataset has 17500 rows and 2 columns
```

In [5]:
```
train['has_cactus'].value_counts()
```

Out[5]:
```
1    13136
0     4364
Name: has_cactus, dtype: int64
```

In [6]:
```
print("The number of rows in test set is %d"%(len(os.listdir('../input/test/test'))))
```

```
The number of rows in test set is 4000
```

Displaying an image

In [7]:
```
Image(os.path.join("../input/train/train",train.iloc[0,0]),width=250,height=250)
```

Out[7]:

Data preparation

As you know,data should be processed into appropriatly pre-processed floating point tensors before being fed to our network.So the steps for getting it into our network are roughly

- Read the picture files
- Decode JPEG content to RGB pixels
- Convert this into floating tensors
- Rescale pixel values (between 0 to 255) to [0,1] interval.

we will make use of ImageDataGenerator method available in keras to do all the preprocessing.

In [8]:
```
datagen=ImageDataGenerator(rescale=1./255)
batch_size=150
```

flow_from_dataframe Method

This method is useful when the images are clustered in only one folder. To put in other words images from different class/labels reside in only one folder. Generally, with such kind of data, some text files containing information on class and other parameters are provided. In this case, we will create a dataframe using pandas and text files provided, and create a meaningful dataframe with columns having file name (only the file names, not the path) and other classes to be used by the model. For this method, arguments to be used are:

```
dataframe value : Dataframe having meaningful data (file name, class columns are a must)
directory value : The path to the parent directory containing all images.
x_col value : which will be the name of column(in dataframe) having file names
y_col value : which will be the name of column(in dataframe) having class/label
```

In [9]:
```
train_generator=datagen.flow_from_dataframe(dataframe=train[:15001],directory=train_dir,x_col='id',
                                            y_col='has_cactus',class_mode='binary',batch_size=batch_siz
e,
                                            target_size=(150,150))


validation_generator=datagen.flow_from_dataframe(dataframe=train[15000:],directory=train_dir,x_col='id'
,
                                                y_col='has_cactus',class_mode='binary',batch_size=50,
                                                target_size=(150,150))
```

```
Found 15001 images belonging to 2 classes.
Found 2500 images belonging to 2 classes.
```

Splitting our train and validation dataset

Now,after preprocessing is done with our data we will split our dataset to training and validation for training our model and validating the result repectively. We will take first 15000 images to train our data and last 2500 images to validate our model later.

A brief intro to CNN

The convolution operation is the building block of a convolutional neural network as the name suggests it. Now, in the field of computer vision, an image can be expressed as a matrix of RGB values. Therefore, let's consider the 6x6 matrix below as a part of an image:

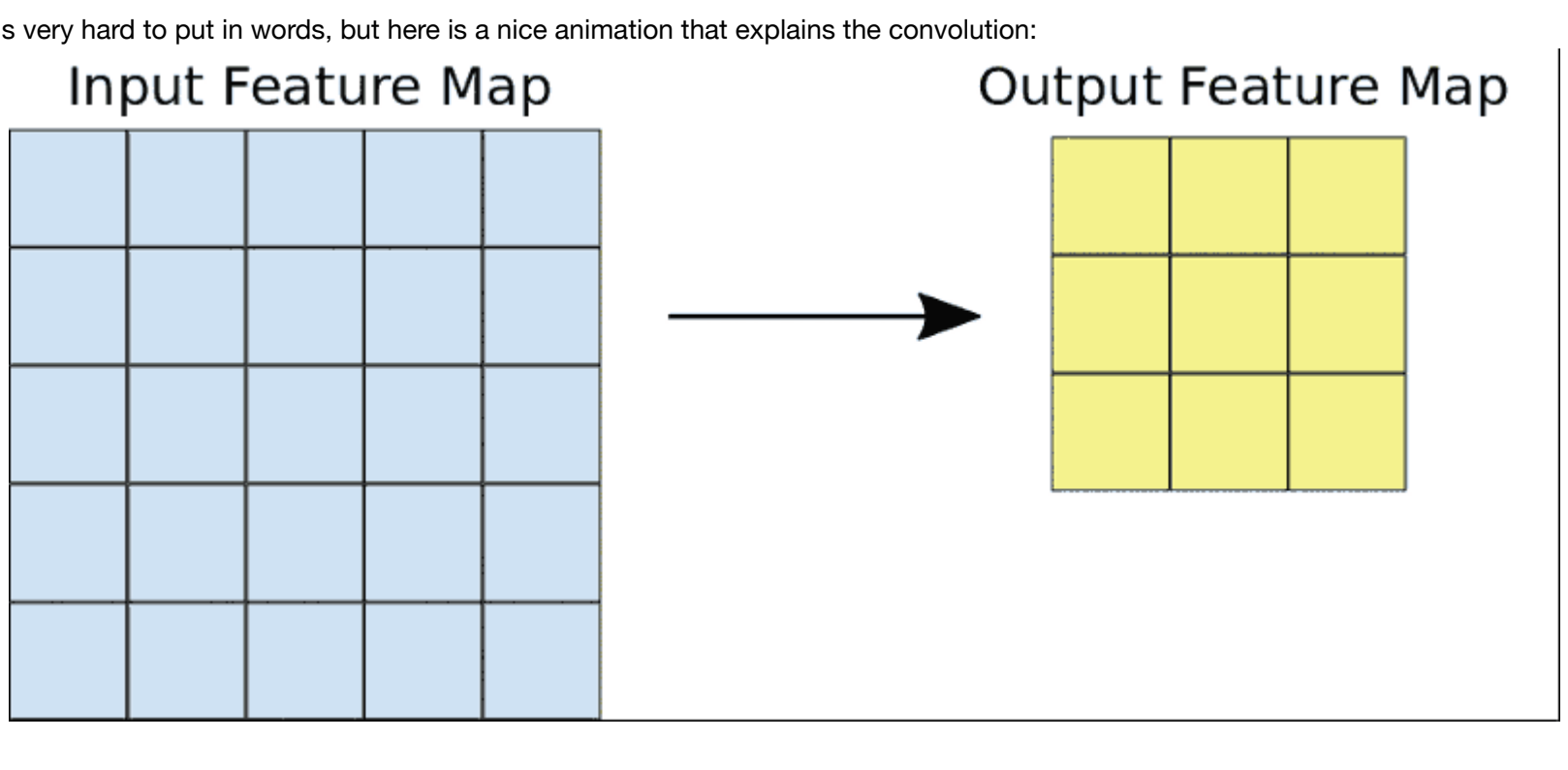
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

And the filter will be the following matrix:

1	0	-1
1	0	-1
1	0	-1

Then, the convolution involves superimposing the filter onto the image matrix, adding the product of the values from the filter and and the values from the image matrix, which will generate a 4x4 convoluted layer.

This is very hard to put in words, but here is a nice animation that explains the convolution:

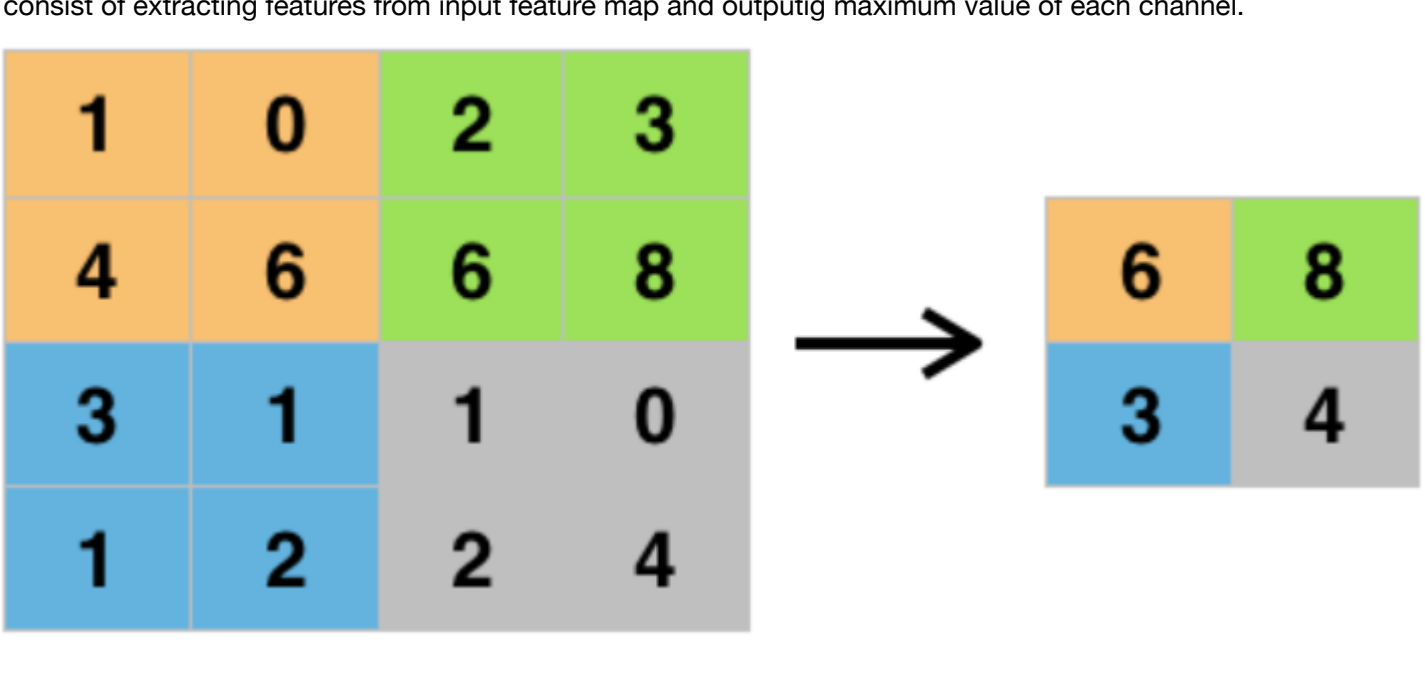


Convolutions are defined on two key parameters

- The size of patches that are extracted from input feature map..ie here 3x3
- The number of filters computed from convolutions

Maxpooling

Maxpooling consist of extracting features from input feature map and outputig maximum value of each channel.



Building our model

Now we will build our network.We will build our model such that it contains 5 **Conv2D + Maxpooling2D stages** with **relu** activation function.

In [10]:
```
model=models.Sequential()
model.add(layers.Conv2D(32,(3,3),activation='relu',input_shape=(150,150,3)))
model.add(layers.MaxPool2D((2,2)))
model.add(layers.Conv2D(64,(3,3),activation='relu',input_shape=(150,150,3)))
model.add(layers.MaxPool2D((2,2)))
model.add(layers.Conv2D(128,(3,3),activation='relu',input_shape=(150,150,3)))
model.add(layers.MaxPool2D((2,2)))
model.add(layers.Conv2D(128,(3,3),activation='relu',input_shape=(150,150,3)))
model.add(layers.MaxPool2D((2,2)))
model.add(layers.Flatten())
model.add(layers.Dense(512,activation='relu'))
model.add(layers.Dense(1,activation='sigmoid'))
```

```
WARNING:tensorflow:From /opt/conda/lib/python3.6/site-packages/tensorflow/python/framework/op_def_lib
rary.py:263: colocate_with (from tensorflow.python.framework.ops) is deprecated and will be removed i
n a future version.
Instructions for updating:
Colocations handled automatically by placer.
```

Displaying summary of our network

In [11]:
```
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 148, 148, 32)      896
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 74, 74, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 72, 72, 64)        18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 36, 36, 64)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 34, 34, 128)       73856
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 17, 17, 128)       0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 15, 15, 128)       147584
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 7, 7, 128)         0
_________________________________________________________________
flatten_1 (Flatten)          (None, 6272)              0
_________________________________________________________________
dense_1 (Dense)              (None, 512)               3211776
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 513
=================================================================
Total params: 3,453,121
Trainable params: 3,453,121
Non-trainable params: 0
_________________________________________________________________
```

Compiling our model

In [12]:
```
```

In this step we will specify 3 important things related to our model

- loss: we will set our loss as binary_crossentropy since we are attacking a binary classification problem
- optimizer : optimizers shape and mold your model into its most accurate possible form by futzing with the weights.
- metrics : This is the evaluation criteria that we choose to evaluate our model

In [12]:
```
model.compile(loss='binary_crossentropy',optimizer=optimizers.rmsprop(),metrics=['acc'])
```

Fitting our model

Here we will use keras fit_generator() method instead of fit() method because we have used ImageDataGenerator to generate values.

In [13]:
```
epochs=10
history=model.fit_generator(train_generator,steps_per_epoch=100,epochs=10,validation_data=validation_ge
nerator,validation_steps=50)
```

```
WARNING:tensorflow:From /opt/conda/lib/python3.6/site-packages/tensorflow/python/ops/math_ops.py:306
6: to_int32 (from tensorflow.python.ops.math_ops) is deprecated and will be removed in a future versi
on.
Instructions for updating:
Use tf.cast instead.
Epoch 1/10
100/100 [==============================] - 39s 394ms/step - loss: 0.5635 - acc: 0.8113 - val_loss: 0.
2326 - val_acc: 0.9188
Epoch 2/10
100/100 [==============================] - 24s 237ms/step - loss: 0.2046 - acc: 0.9185 - val_loss: 0.
1487 - val_acc: 0.9388
Epoch 3/10
100/100 [==============================] - 24s 237ms/step - loss: 0.1487 - acc: 0.9436 - val_loss: 0.
2846 - val_acc: 0.9080
Epoch 4/10
100/100 [==============================] - 24s 240ms/step - loss: 0.1286 - acc: 0.9531 - val_loss: 0.
2111 - val_acc: 0.9156
Epoch 5/10
100/100 [==============================] - 24s 237ms/step - loss: 0.1029 - acc: 0.9589 - val_loss: 0.
1168 - val_acc: 0.9592
Epoch 6/10
100/100 [==============================] - 24s 237ms/step - loss: 0.0864 - acc: 0.9678 - val_loss: 0.
1003 - val_acc: 0.9592
Epoch 7/10
100/100 [==============================] - 24s 236ms/step - loss: 0.0872 - acc: 0.9716 - val_loss: 0.
1817 - val_acc: 0.9388
Epoch 8/10
100/100 [==============================] - 24s 239ms/step - loss: 0.0801 - acc: 0.9773 - val_loss: 0.
0626 - val_acc: 0.9820
Epoch 9/10
100/100 [==============================] - 24s 239ms/step - loss: 0.0571 - acc: 0.9751 - val_loss: 0.
0681 - val_acc: 0.9840
Epoch 10/10
100/100 [==============================] - 24s 237ms/step - loss: 0.0459 - acc: 0.9845 - val_loss: 0.
0636 - val_acc: 0.9852
```

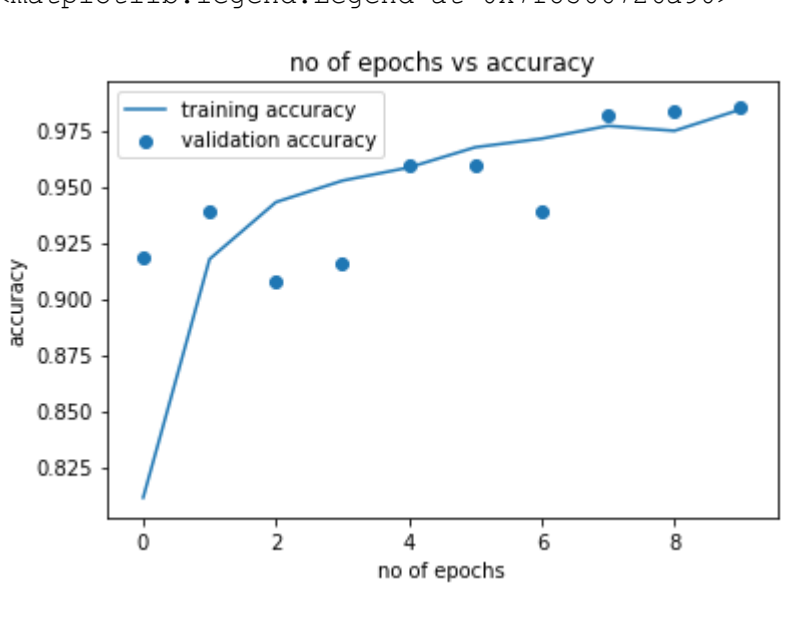
Evaluating our model

we will plot our results using matplotlib.first we will plot training and validation accuracy.

In [14]:
```
acc=history.history['acc']  ##getting  accuracy of each epochs
epochs_=range(0,epochs)
plt.plot(epochs_,acc,label='training accuracy')
plt.xlabel('no of epochs')
plt.ylabel('accuracy')

acc_val=history.history['val_acc']  ##getting validation accuracy of each epochs
plt.scatter(epochs_,acc_val,label="validation accuracy")
plt.title("no of epochs vs accuracy")
plt.legend()
```

Out[14]: `<matplotlib.legend.Legend at 0x7f8566726a90>`

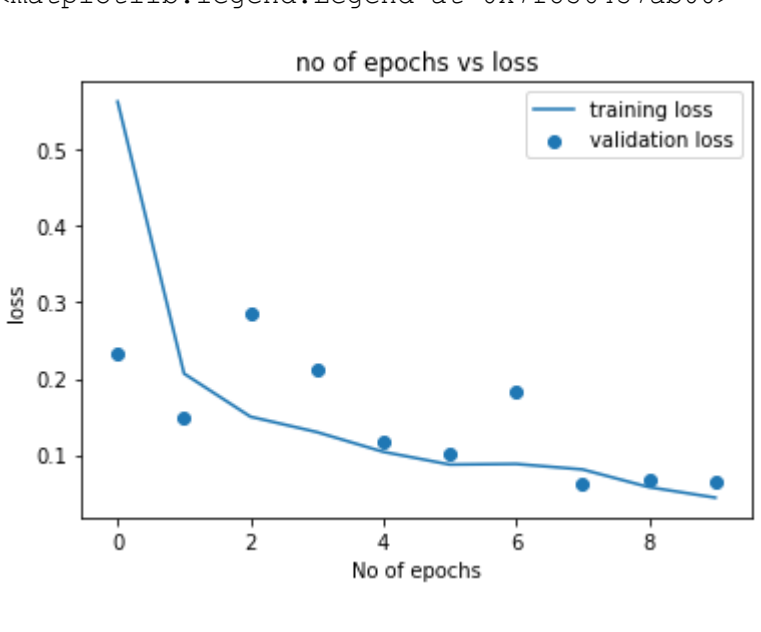


Now we will plot training loss and validation loss vs number of epochs

In [15]:
```
acc=history.history['loss']    ##getting  loss of each epochs
epochs_=range(0,epochs)
plt.plot(epochs_,acc,label='training loss')
plt.xlabel('No of epochs')
plt.ylabel('loss')

acc_val=history.history['val_loss']  ## getting validation loss of each epochs
plt.scatter(epochs_,acc_val,label="validation loss")
plt.title('no of epochs vs loss')
plt.legend()
```

Out[15]: `<matplotlib.legend.Legend at 0x7f856457ab00>`



Improving our model using VGG16

- Instantiating the VGG16 convolution base

In [16]:
```
model_vg=VGG16(weights='imagenet',include_top=False)
model_vg.summary()
```

```
Downloading data from https://github.com/fchollet/deep-learning-models/releases/download/v0.1/vgg16_w
eights_tf_dim_ordering_tf_kernels_notop.h5
58892288/58889256 [==============================] - 1s 0us/step
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (None, None, None, 3)     0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, None, None, 64)    1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, None, None, 64)    36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, None, None, 64)    0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, None, None, 128)   73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, None, None, 128)   147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, None, None, 128)   0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, None, None, 256)   295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, None, None, 256)   590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, None, None, 256)   590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, None, None, 256)   0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, None, None, 512)   1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, None, None, 512)   2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, None, None, 512)   2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, None, None, 512)   0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, None, None, 512)   2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, None, None, 512)   2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, None, None, 512)   2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, None, None, 512)   0
=================================================================
Total params: 14,714,688
Trainable params: 14,714,688
Non-trainable params: 0
_________________________________________________________________
```

Extracting features using VGG16

In [17]:
```
def extract_features(directory,samples,df):


    features=np.zeros(shape=(samples,4,4,512))
    labels=np.zeros(shape=(samples))
    generator=datagen.flow_from_dataframe(dataframe=df,directory=directory,x_col='id',
                                          y_col='has_cactus',class_mode='other',batch_size=batch_size
,
                                          target_size=(150,150))
    i=0
    for input_batch,label_batch in generator:
        feature_batch=model_vg.predict(input_batch)
        features[i*batch_size:(i+1)*batch_size]=feature_batch
        labels[i*batch_size:(i+1)*batch_size]=label_batch
        i+=1
        if(i*batch_size>samples):
            break
    return(features,labels)

train.has_cactus=train.has_cactus.astype(int)
features,labels=extract_features(train_dir,17500,train)
train_features=features[:15001]
train_labels=labels[:15001]

validation_features=features[15000:]
validation_labels=labels[15000:]
```

```
Found 17500 images.
```

Reshaping our features to feed into our dense layers

In [18]:
```
#df_test.has_cactus=df_test.has_cactus.astype(str)
test_features,test_labels=extract_features(test_dir,4000,df_test)
```

```
Found 4000 images.
```

In [19]:
```
train_features=train_features.reshape((15001,4*4*512))
validation_features=validation_features.reshape((2500,4*4*512))

test_features=test_features.reshape((4000,4*4*512))
```

Define a densely connected network

In [20]:
```
model=models.Sequential()
model.add(layers.Dense(212,activation='relu',kernel_regularizer=regularizers.l1_l2(.001),input_dim=(4*4
*512)))
model.add(layers.Dropout(0.2))
model.add(layers.Dense(1,activation='sigmoid'))
```

```
WARNING:tensorflow:From /opt/conda/lib/python3.6/site-packages/keras/backend/tensorflow_backend.py:34
45: calling dropout (from tensorflow.python.ops.nn_ops) with keep_prob is deprecated and will be remo
ved in a future version.
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - keep_prob`.
```

In [21]:
```
model.compile(optimizer=optimizers.rmsprop(),loss='binary_crossentropy',metrics=['acc'])
```

In [22]:
```
history=model.fit(train_features,train_labels,epochs=30,batch_size=15,validation_data=(validation_featu
res,validation_labels))
```

```
Train on 15001 samples, validate on 2500 samples
Epoch 1/30
15001/15001 [==============================] - 5s 352us/step - loss: 1.4906 - acc: 0.8940 - val_loss:
1.2673 - val_acc: 0.8724
Epoch 2/30
15001/15001 [==============================] - 5s 317us/step - loss: 1.1491 - acc: 0.9299 - val_loss:
1.2668 - val_acc: 0.8636
Epoch 3/30
15001/15001 [==============================] - 5s 318us/step - loss: 1.1200 - acc: 0.9368 - val_loss:
1.0743 - val_acc: 0.9672
Epoch 4/30
15001/15001 [==============================] - 5s 330us/step - loss: 1.1101 - acc: 0.9398 - val_loss:
1.0446 - val_acc: 0.9608
Epoch 5/30
15001/15001 [==============================] - 5s 316us/step - loss: 1.1045 - acc: 0.9389 - val_loss:
1.0382 - val_acc: 0.9692
Epoch 6/30
15001/15001 [==============================] - 5s 320us/step - loss: 1.1008 - acc: 0.9397 - val_loss:
1.1922 - val_acc: 0.8924
Epoch 7/30
15001/15001 [==============================] - 5s 317us/step - loss: 1.1012 - acc: 0.9401 - val_loss:
1.1909 - val_acc: 0.8972
Epoch 8/30
15001/15001 [==============================] - 5s 315us/step - loss: 1.0972 - acc: 0.9407 - val_loss:
1.0379 - val_acc: 0.9652
Epoch 9/30
15001/15001 [==============================] - 5s 317us/step - loss: 1.0961 - acc: 0.9403 - val_loss:
1.0513 - val_acc: 0.9632
Epoch 10/30
15001/15001 [==============================] - 5s 314us/step - loss: 1.0897 - acc: 0.9437 - val_loss:
1.0397 - val_acc: 0.9596
Epoch 11/30
15001/15001 [==============================] - 5s 315us/step - loss: 1.0926 - acc: 0.9412 - val_loss:
1.0649 - val_acc: 0.9540
Epoch 12/30
15001/15001 [==============================] - 5s 315us/step - loss: 1.0878 - acc: 0.9423 - val_loss:
1.0963 - val_acc: 0.9420
Epoch 13/30
15001/15001 [==============================] - 5s 315us/step - loss: 1.0902 - acc: 0.9445 - val_loss:
1.0148 - val_acc: 0.9676
Epoch 14/30
15001/15001 [==============================] - 5s 316us/step - loss: 1.0897 - acc: 0.9429 - val_loss:
1.0140 - val_acc: 0.9716
Epoch 15/30
15001/15001 [==============================] - 5s 315us/step - loss: 1.0902 - acc: 0.9419 - val_loss:
1.0251 - val_acc: 0.9656
Epoch 16/30
15001/15001 [==============================] - 5s 316us/step - loss: 1.0906 - acc: 0.9424 - val_loss:
1.1232 - val_acc: 0.9244
Epoch 17/30
15001/15001 [==============================] - 5s 316us/step - loss: 1.0907 - acc: 0.9425 - val_loss:
1.0979 - val_acc: 0.9324
Epoch 18/30
15001/15001 [==============================] - 5s 316us/step - loss: 1.0910 - acc: 0.9405 - val_loss:
1.0147 - val_acc: 0.9720
Epoch 19/30
15001/15001 [==============================] - 5s 318us/step - loss: 1.0908 - acc: 0.9407 - val_loss:
1.0156 - val_acc: 0.9704
Epoch 20/30
15001/15001 [==============================] - 5s 317us/step - loss: 1.0907 - acc: 0.9391 - val_loss:
1.0193 - val_acc: 0.9724
Epoch 21/30
15001/15001 [==============================] - 5s 315us/step - loss: 1.0965 - acc: 0.9395 - val_loss:
1.0619 - val_acc: 0.9604
Epoch 22/30
15001/15001 [==============================] - 5s 316us/step - loss: 1.0938 - acc: 0.9399 - val_loss:
1.0146 - val_acc: 0.9732
Epoch 23/30
15001/15001 [==============================] - 5s 316us/step - loss: 1.0966 - acc: 0.9417 - val_loss:
1.0270 - val_acc: 0.9652
Epoch 24/30
15001/15001 [==============================] - 5s 316us/step - loss: 1.0896 - acc: 0.9427 - val_loss:
1.1422 - val_acc: 0.9204
Epoch 25/30
15001/15001 [==============================] - 5s 316us/step - loss: 1.0941 - acc: 0.9416 - val_loss:
1.0247 - val_acc: 0.9620
Epoch 26/30
15001/15001 [==============================] - 5s 316us/step - loss: 1.0956 - acc: 0.9426 - val_loss:
1.0180 - val_acc: 0.9696
Epoch 27/30
15001/15001 [==============================] - 5s 315us/step - loss: 1.0876 - acc: 0.9452 - val_loss:
1.0229 - val_acc: 0.9696
Epoch 28/30
15001/15001 [==============================] - 5s 316us/step - loss: 1.0907 - acc: 0.9441 - val_loss:
1.1160 - val_acc: 0.9284
Epoch 29/30
15001/15001 [==============================] - 5s 315us/step - loss: 1.0879 - acc: 0.9435 - val_loss:
1.0241 - val_acc: 0.9636
Epoch 30/30
15001/15001 [==============================] - 5s 316us/step - loss: 1.0930 - acc: 0.9423 - val_loss:
1.2741 - val_acc: 0.8884
```

making prediction

In [23]:
```
y_pre=model.predict_proba(test_features)
```

Making a submission

In [24]:
```
df=pd.DataFrame({'id':df_test['id'] })
df['has_cactus']=y_pre
df.to_csv("submission.csv",index=False)
```

If you guys like my kernel,please do consider upvoting it.

In [25]:
```
```