

```
In [1]: ### Satellite Images of Hurricane Damage
```

Overview

The data are satellite images from Texas after Hurricane Harvey divided into two groups (damage and no_damage). The goal is to make a model which can automatically identify if a given region is likely to contain flooding damage.

Source

Data originally taken from: <https://ieee-dataport.org/open-access/detecting-damaged-buildings-post-hurricane-satellite-imagery-based-customized> and can be cited with <http://dx.doi.org/10.21227/sdad-1e56> and the original paper is here: <https://arxiv.org/abs/1807.01688>

```
In [1]: ##!mkdir ~/.kaggle
```

```
In [2]: ##!cp /kaggle.json ~/.kaggle/
```

```
In [3]: ####!chmod 600 ~/.kaggle/kaggle.json
```

```
In [ ]: ####! pip install kaggle
```

```
In [ ]: ####!pip install keras-tuner
```

```
In [ ]: ####!kaggle datasets download -d kmader/satellite-images-of-hurricane-damage
```

```
In [ ]: ####! unzip /content/satellite-images-of-hurricane-damage.zip
```

```
In [8]: import tensorflow as tf
import tensorflow import keras
import numpy as np
```

```
In [9]: print(tf.__version__)
```

2.7.0

```
In [10]: # import the libraries as shown below

from tensorflow.keras.layers import Input, Lambda, Dense, Flatten, Conv2D
from tensorflow.keras.models import Model
from tensorflow.keras.applications.vgg19 import VGG19
from tensorflow.keras.applications.resnet50 import preprocess_input
from tensorflow.keras.preprocessing import image
from tensorflow.keras.preprocessing.image import ImageDataGenerator, load_img
from tensorflow.keras.models import Sequential
import numpy as np
from glob import glob
import matplotlib.pyplot as plt
```

```
In [11]: # re-size all the images to this
IMAGE_SIZE = [224, 224]

train_path = '/content/train_another'
valid_path = '/content/test_another'
valid_path2 = '/content/validation_another'
valid_path3 = '/content/test'
```

```
In [12]: # Import the Vgg 16 library as shown below and add preprocessing layer to the front of VGG
# Here we will be using imagenet weights

vggnet = VGG19(input_shape=IMAGE_SIZE + [3], weights='imagenet', include_top=False)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg19/vgg19_weights_tf_dim_ordering_tf_kernels_notop.h5
80142336/80134624 [=====] - 1s 0us/step
80150528/80134624 [=====] - 1s 0us/step
```

```
In [13]: # don't train existing weights
for layer in vggnet.layers:
    layer.trainable = False
```

```
In [14]: # useful for getting number of output classes
folders = glob('/content/train_another/*')
```

```
In [15]: folders
```

```
Out[15]: ['/content/train_another/no_damage', '/content/train_another/damage']
```

```
In [16]: # our layers - you can add more if you want
x = Flatten()(vggnet.output)
```

```
In [17]: prediction = Dense(len(folders), activation='softmax')(x)

# create a model object
model = Model(inputs=vggnet.input, outputs=prediction)
```

```
In [18]: # view the structure of the model
model.summary()
```

Model: "model"

Layer (type)	Output Shape	Param #
=====		
input_1 (InputLayer)	(None, 224, 224, 3)	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
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_conv4 (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_conv4 (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_conv4 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten (Flatten)	(None, 25088)	0
dense (Dense)	(None, 2)	50178
=====		

Total params: 20,074,562
Trainable params: 50,178
Non-trainable params: 20,024,384

```
In [19]: # tell the model what cost and optimization method to use
model.compile(
    loss='categorical_crossentropy',
    optimizer='adam',
    metrics=['accuracy']
)
```

```
In [20]: # Use the Image Data Generator to import the images from the dataset
from tensorflow.keras.preprocessing.image import ImageDataGenerator

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

test_datagen = ImageDataGenerator(rescale = 1./255)
```

```
In [21]: # Make sure you provide the same target size as initialied for the image size
training_set = train_datagen.flow_from_directory('/content/train_another',
                                                target_size = (224, 224),
                                                batch_size = 32,
                                                class_mode = 'categorical')
```

Found 10000 images belonging to 2 classes.

```
In [22]: training_set
```

```
Out[22]: <keras.preprocessing.image.DirectoryIterator at 0x7f9f110a3350>
```

```
In [23]: test_set = test_datagen.flow_from_directory('/content/test_another',
                                                    target_size = (224, 224),
                                                    batch_size = 32,
                                                    class_mode = 'categorical')
```

Found 9000 images belonging to 2 classes.

```
In [24]: # fit the model
# Run the cell. It will take some time to execute
r = model.fit_generator(
    training_set,
    validation_data=test_set,
    epochs=30,
    steps_per_epoch=len(training_set),
    validation_steps=len(test_set)
)
```

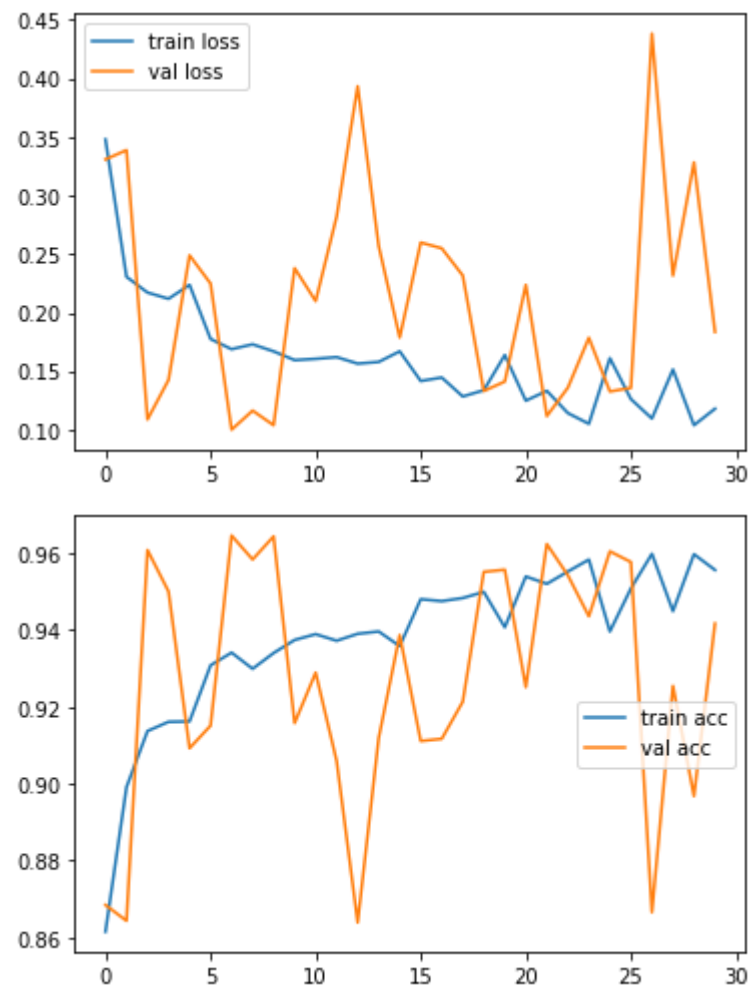
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:8: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Please use `Model.fit`, which

h supports generators.

```
Epoch 1/30
313/313 [=====] - 253s 747ms/step - loss: 0.3480 - accuracy: 0.8615 - val_loss: 0.3309 - val_accuracy: 0.8684
Epoch 2/30
313/313 [=====] - 223s 712ms/step - loss: 0.2306 - accuracy: 0.8991 - val_loss: 0.3388 - val_accuracy: 0.8643
Epoch 3/30
313/313 [=====] - 223s 714ms/step - loss: 0.2172 - accuracy: 0.9137 - val_loss: 0.1088 - val_accuracy: 0.9608
Epoch 4/30
313/313 [=====] - 218s 698ms/step - loss: 0.2118 - accuracy: 0.9161 - val_loss: 0.1425 - val_accuracy: 0.9500
Epoch 5/30
313/313 [=====] - 221s 705ms/step - loss: 0.2237 - accuracy: 0.9162 - val_loss: 0.2490 - val_accuracy: 0.9092
Epoch 6/30
313/313 [=====] - 221s 707ms/step - loss: 0.1775 - accuracy: 0.9308 - val_loss: 0.2248 - val_accuracy: 0.9151
Epoch 7/30
313/313 [=====] - 220s 702ms/step - loss: 0.1688 - accuracy: 0.9341 - val_loss: 0.1001 - val_accuracy: 0.9646
Epoch 8/30
313/313 [=====] - 219s 699ms/step - loss: 0.1730 - accuracy: 0.9299 - val_loss: 0.1163 - val_accuracy: 0.9583
Epoch 9/30
313/313 [=====] - 220s 703ms/step - loss: 0.1670 - accuracy: 0.9340 - val_loss: 0.1039 - val_accuracy: 0.9643
Epoch 10/30
313/313 [=====] - 219s 698ms/step - loss: 0.1595 - accuracy: 0.9374 - val_loss: 0.2380 - val_accuracy: 0.9158
Epoch 11/30
313/313 [=====] - 219s 700ms/step - loss: 0.1606 - accuracy: 0.9389 - val_loss: 0.2099 - val_accuracy: 0.9289
Epoch 12/30
313/313 [=====] - 219s 700ms/step - loss: 0.1620 - accuracy: 0.9372 - val_loss: 0.2822 - val_accuracy: 0.9059
Epoch 13/30
313/313 [=====] - 216s 690ms/step - loss: 0.1565 - accuracy: 0.9390 - val_loss: 0.3934 - val_accuracy: 0.8639
Epoch 14/30
313/313 [=====] - 223s 712ms/step - loss: 0.1579 - accuracy: 0.9396 - val_loss: 0.2569 - val_accuracy: 0.9119
Epoch 15/30
313/313 [=====] - 222s 709ms/step - loss: 0.1670 - accuracy: 0.9358 - val_loss: 0.1788 - val_accuracy: 0.9387
Epoch 16/30
313/313 [=====] - 224s 715ms/step - loss: 0.1417 - accuracy: 0.9480 - val_loss: 0.2599 - val_accuracy: 0.9111
Epoch 17/30
313/313 [=====] - 221s 707ms/step - loss: 0.1446 - accuracy: 0.9475 - val_loss: 0.2550 - val_accuracy: 0.9117
Epoch 18/30
313/313 [=====] - 221s 707ms/step - loss: 0.1284 - accuracy: 0.9483 - val_loss: 0.2317 - val_accuracy: 0.9213
Epoch 19/30
313/313 [=====] - 223s 714ms/step - loss: 0.1337 - accuracy: 0.9499 - val_loss: 0.1331 - val_accuracy: 0.9551
Epoch 20/30
313/313 [=====] - 221s 707ms/step - loss: 0.1638 - accuracy: 0.9407 - val_loss: 0.1412 - val_accuracy: 0.9557
Epoch 21/30
313/313 [=====] - 215s 687ms/step - loss: 0.1248 - accuracy: 0.9539 - val_loss: 0.2237 - val_accuracy: 0.9251
Epoch 22/30
313/313 [=====] - 213s 679ms/step - loss: 0.1332 - accuracy: 0.9520 - val_loss: 0.1117 - val_accuracy: 0.9623
Epoch 23/30
313/313 [=====] - 216s 690ms/step - loss: 0.1142 - accuracy: 0.9552 - val_loss: 0.1359 - val_accuracy: 0.9542
Epoch 24/30
313/313 [=====] - 218s 696ms/step - loss: 0.1051 - accuracy: 0.9583 - val_loss: 0.1786 - val_accuracy: 0.9436
Epoch 25/30
313/313 [=====] - 220s 702ms/step - loss: 0.1611 - accuracy: 0.9396 - val_loss: 0.1327 - val_accuracy: 0.9604
Epoch 26/30
313/313 [=====] - 219s 699ms/step - loss: 0.1262 - accuracy: 0.9508 - val_loss: 0.1358 - val_accuracy: 0.9577
Epoch 27/30
313/313 [=====] - 219s 699ms/step - loss: 0.1096 - accuracy: 0.9598 - val_loss: 0.4384 - val_accuracy: 0.8666
Epoch 28/30
313/313 [=====] - 218s 698ms/step - loss: 0.1514 - accuracy: 0.9449 - val_loss: 0.2316 - val_accuracy: 0.9254
Epoch 29/30
313/313 [=====] - 218s 696ms/step - loss: 0.1039 - accuracy: 0.9597 - val_loss: 0.3283 - val_accuracy: 0.8968
Epoch 30/30
313/313 [=====] - 219s 699ms/step - loss: 0.1179 - accuracy: 0.9556 - val_loss: 0.1836 - val_accuracy: 0.9417
```

```
In [25]: # plot the loss
plt.plot(r.history['loss'], label='train loss')
plt.plot(r.history['val_loss'], label='val loss')
plt.legend()
plt.show()
plt.savefig('LossVal_loss')

# plot the accuracy
plt.plot(r.history['accuracy'], label='train acc')
plt.plot(r.history['val_accuracy'], label='val acc')
plt.legend()
plt.show()
plt.savefig('AccVal_acc')
```



<Figure size 432x288 with 0 Axes>

```
In [26]: # save it as a h5 file

from tensorflow.keras.models import load_model

model.save('model_vgg19_new.h5')
```

```
In [27]: y_pred = model.predict(test_set)
```

```
In [28]: y_pred
```

```
Out[28]: array([[9.6935892e-01, 3.0641133e-02],
 [9.9955755e-01, 4.4239406e-04],
 [9.9619859e-01, 3.8013996e-03],
 ...,
 [9.8282832e-01, 1.7171687e-02],
 [8.3030403e-01, 1.6969596e-01],
 [5.7293600e-01, 4.2706403e-01]], dtype=float32)
```

```
In [29]: import numpy as np
y_pred = np.argmax(y_pred, axis=1)
```

```
In [30]: # Evaluating model on validation data
evaluate = model.evaluate(test_set)
print(evaluate)
```

```
282/282 [=====] - 80s 285ms/step - loss: 0.1836 - accuracy: 0.9417
[0.18358109891414642, 0.9416666626930237]
```

```
In [34]: from sklearn.metrics import classification_report, confusion_matrix
def give_accuracy():
    p=model.predict(test_set)
    cm=confusion_matrix(y_true=test_set.classes,y_pred=np.argmax(p,axis=-1))
    acc=cm.trace()/cm.sum()
    print('The Classification Report \n', cm)
    print(f'Accuracy: {acc*100}')
```

```
In [36]: give_accuracy()
```

```
The Classification Report
[[6768 1232]
 [ 837  163]]
Accuracy: 77.01111111111111
```

```
In [46]: import numpy as np
from tensorflow.keras.preprocessing import image
test_image = image.load_img('/content/test_another/damage/-93.560702_30.766426.jpeg', target_size = (224,224))
test_image = image.img_to_array(test_image)
test_image=test_image/255
test_image = np.expand_dims(test_image, axis = 0)
result = model.predict(test_image)
```

```
In [47]: test = np.array(test_image)
```

```
In [48]: # making predictions
#prediction = np.argmax(cnn.predict(test_image), axis=-1)
prediction = np.argmax(model.predict(test_image))
```

```
In [49]: prediction
```

```
Out[49]: 0
```

```
In [50]: OUTPUT = {0:'DAMAGE',1:'NON DAMAGE'}
```

```
In [51]: print("The prediction Of the Image is : ", OUTPUT[prediction])
```

The prediction Of the Image is : DAMAGE

```
In [52]: # show the image
import matplotlib.pyplot as plt
test_image = image.load_img('/content/test_another/damage/-93.560702_30.766426.jpeg', target_size = (224,224))
plt.axis('off')
plt.imshow(test_image)
plt.show()
```



```
In [53]: ##### Similarly
```

```
In [54]: import numpy as np
from tensorflow.keras.preprocessing import image
test_image = image.load_img('/content/validation_another/no_damage/-95.062123_30.056714000000003.jpeg', target_size = (224,224))
test_image = image.img_to_array(test_image)
test_image=test_image/255
test_image = np.expand_dims(test_image, axis = 0)
result = model.predict(test_image)
```

```
In [55]: test = np.array(test_image)
```

```
In [56]: # making predictions
#prediction = np.argmax(cnn.predict(test_image), axis=-1)
prediction = np.argmax(model.predict(test_image))
```



```
In [57]: prediction
```

```
Out[57]: 1
```

```
In [58]: OUTPUT = {0:'DAMAGE',1:'NON DAMAGE'}
```

```
In [59]: print("The prediction Of the Image is : ", OUTPUT[prediction])
```

The prediction Of the Image is : NON DAMAGE

```
In [60]: # show the image
import matplotlib.pyplot as plt
test_image = image.load_img('/content/validation_another/no_damage/-95.062123_30.0567140000000003.jpeg', target_size = (224,224))
plt.axis('off')
plt.imshow(test_image)
plt.show()
```

