Authentication

In [3]:

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount
("/content/drive", force_remount=True).
```

Unzipping the Datasets

In [ ]:

```
!unzip '/content/drive/MyDrive/FYP Project/GoodDatasets.zip'
print('done')
```

First we import all the necessary libraries

In [92]:

```
from keras.models import Sequential
import matplotlib.pyplot as plt
import tensorflow as tf
from keras.preprocessing.image import ImageDataGenerator
from keras.layers import Conv2D, MaxPooling2D, MaxPool2D
from keras.layers import Activation, Dropout, Flatten, Dense
```

Now we set the path for the datasets and also set the image details. Here, we have used custom made dataset which has already been divided into train, test and validation sets so we don't need to use the validation split here.

In [93]:

```
img_width, img_height = 32, 32

train_dir = 'GoodDatasets/training'
val_dir = 'GoodDatasets/validation'
nb_train_samples = 4000
nb_val_samples = 400
epochs = 25
batch_size = 8
```

The RGB values are in the range between 0-255 and this is not ideal for for a neural network. So, we will set the value between 0-1.

In [94]:

```
train_datagen = ImageDataGenerator(rescale = 1. / 255,)

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

Now, we read the datasets

In [95]:

```
train_generator = train_datagen.flow_from_directory(train_dir,
                                                     target_size =(img_width, img_height
),
                                                     batch_size = batch_size, class_mode
='categorical')

val_generator = test_datagen.flow_from_directory(
```

```
    val_dir,
    target_size =(img_width, img_height),
    batch_size = batch_size, class_mode ='categorical')
```

```
Found 4000 images belonging to 10 classes.
Found 400 images belonging to 10 classes.
```

In [96]:

```
test_data = 'GoodDatasets/testing'

test_datagen = ImageDataGenerator(
    rescale=1./255
)

testing_generator = test_datagen.flow_from_directory(test_data,
                                                     target_size =(img_width, img_height
),
                                                     batch_size = batch_size,
                                                      shuffle=False,
                                                     class_mode ='categorical')
```

```
Found 394 images belonging to 10 classes.
```

Now we create a model on which we train our datasets.

In [97]:

```
model1 = Sequential()
model1.add(Conv2D(32, (3, 3), input_shape = (img_width, img_height,3)))
model1.add(Activation('relu'))
model1.add(MaxPooling2D(pool_size =(2, 2)))

model1.add(Flatten())
model1.add(Dense(64))
model1.add(Activation('relu'))
model1.add(Dense(10))
model1.add(Activation('softmax'))

monitor = tf.keras.callbacks.EarlyStopping(monitor='val_loss',
                                           min_delta=0, patience=5,
                                           verbose=1, mode='auto',
                                           restore_best_weights=True)
```

In [98]:

```
model1.summary()
```

```
Model: "sequential_6"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_14 (Conv2D)           (None, 30, 30, 32)        896       
_________________________________________________________________
activation_24 (Activation)   (None, 30, 30, 32)        0         
_________________________________________________________________
max_pooling2d_14 (MaxPooling (None, 15, 15, 32)        0         
_________________________________________________________________
flatten_8 (Flatten)          (None, 7200)              0         
_________________________________________________________________
dense_14 (Dense)             (None, 64)                460864    
_________________________________________________________________
activation_25 (Activation)   (None, 64)                0         
_________________________________________________________________
dense_15 (Dense)             (None, 10)                650       
_________________________________________________________________
activation_26 (Activation)   (None, 10)                0         
=================================================================
Total params: 462,410
Trainable params: 462,410
Non-trainable params: 0
```

lets look at our classes

In [99]:

```
train_generator.class_indices
```

Out[99]:

```
{'Afganistan': 0,
 'America': 1,
 'Argentina': 2,
 'Bangladesh': 3,
 'Bhutan': 4,
 'India': 5,
 'Maldives': 6,
 'Nepal': 7,
 'Pakistan': 8,
 'SriLanka': 9}
```

Here, we are using the Adam optimizer and also using categorical croeesntropy as we are dealing with multiclass.

In [100]:

```
model1.compile(loss ='categorical_crossentropy',
              optimizer ='adam',
              metrics =['accuracy'])
```

In [101]:

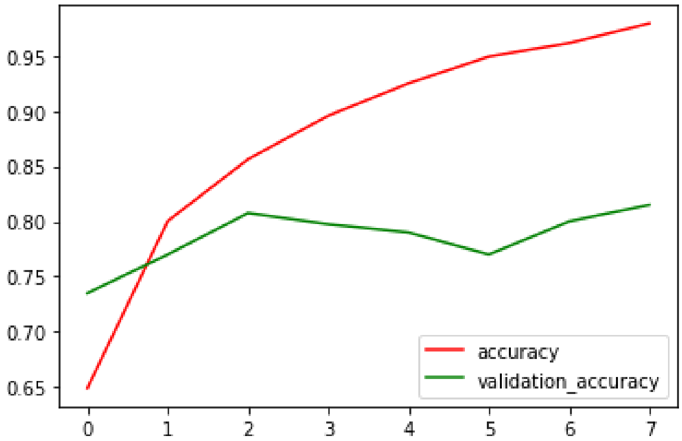
```
data = model1.fit(
    train_generator,
    steps_per_epoch = nb_train_samples // batch_size,
    validation_data=val_generator,
    epochs=epochs,
    callbacks = [monitor],
    validation_steps = nb_val_samples // batch_size
)

model1.save('data.h5')
```

```
Epoch 1/25
500/500 [==============================] - 7s 13ms/step - loss: 1.5684 - accuracy: 0.4944
- val_loss: 0.9205 - val_accuracy: 0.7350
Epoch 2/25
500/500 [==============================] - 6s 13ms/step - loss: 0.6742 - accuracy: 0.7992
- val_loss: 0.7218 - val_accuracy: 0.7700
Epoch 3/25
500/500 [==============================] - 6s 12ms/step - loss: 0.5124 - accuracy: 0.8550
- val_loss: 0.6458 - val_accuracy: 0.8075
Epoch 4/25
500/500 [==============================] - 6s 12ms/step - loss: 0.3477 - accuracy: 0.9042
- val_loss: 0.6542 - val_accuracy: 0.7975
Epoch 5/25
500/500 [==============================] - 6s 12ms/step - loss: 0.2819 - accuracy: 0.9217
- val_loss: 0.6780 - val_accuracy: 0.7900
Epoch 6/25
500/500 [==============================] - 6s 13ms/step - loss: 0.1826 - accuracy: 0.9507
- val_loss: 0.7694 - val_accuracy: 0.7700
Epoch 7/25
500/500 [==============================] - 6s 12ms/step - loss: 0.1563 - accuracy: 0.9632
- val_loss: 0.6753 - val_accuracy: 0.8000
Epoch 8/25
500/500 [==============================] - 6s 13ms/step - loss: 0.0912 - accuracy: 0.9812
- val_loss: 0.7093 - val_accuracy: 0.8150
Restoring model weights from the end of the best epoch.
Epoch 00008: early stopping
```

Here, we can see that the training set is too much perfect which is also not a good sign. When the model gets a small number of data, it starts to read the unexpected details of the images and starts to lack its knowledge to predict real life images. Here the model becomes fully dependent upon the train sets and becomes unable to recognize images outside of the training set.

In [102]:

```
plt.plot(data.history['accuracy'],c='r',label='accuracy')
plt.plot(data.history['val_accuracy'],c='g',label='validation_accuracy')
plt.legend(loc='lower right')
plt.show()
```



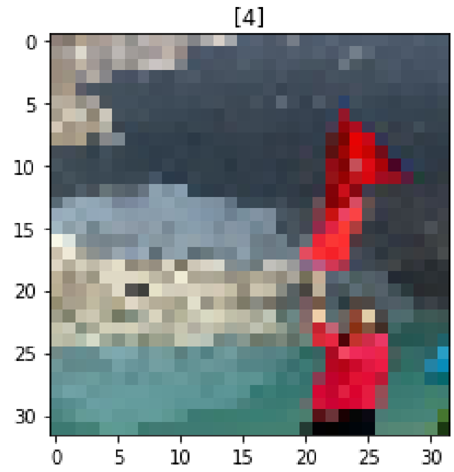
We try to predict Real life image this model.

In [103]:

```
from tensorflow.keras.preprocessing import image
import numpy as np
from keras.preprocessing.image import ImageDataGenerator, load_img, img_to_array
from keras.models import Sequential, load_model

image_path="SS_01.png"
img = image.load_img(image_path, target_size=(32, 32))
plt.imshow(img)
img = np.expand_dims(img, axis=0)
result=model1.predict_classes(img)
plt.title(result)
plt.show()

if result ==[0]:
    print("Classified: Afganistan")
elif result ==[1]:
    print("Classified: America")
elif result ==[2]:
    print("Classified: Argentina")
elif result ==[3]:
    print("Classified: Bangladesh")
elif result ==[4]:
    print("Classified: Bhutan")
elif result ==[5]:
    print("Classified: India")
elif result ==[6]:
    print("Classified: Maldives")
elif result ==[7]:
    print("Classified: Nepal")
elif result ==[8]:
    print("Classified: Pakistan")
else:
    print("Classified: SriLanka")
```

```
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/sequential.py:450:
UserWarning: `model.predict_classes()` is deprecated and will be removed after 2021-01-01
. Please use instead:* `np.argmax(model.predict(x), axis=-1)`,   if your model does multi
-class classification   (e.g. if it uses a `softmax` last-layer activation).* `(model.pre
dict(x) > 0.5).astype("int32")`,   if your model does binary classification   (e.g. if it
```

```
uses a `sigmoid` last-layer activation).
  warnings.warn('`model.predict_classes()` is deprecated and '
/usr/local/lib/python3.7/dist-packages/matplotlib/text.py:1165: FutureWarning: elementwis
e comparison failed; returning scalar instead, but in the future will perform elementwise
comparison
  if s != self._text:
```




```
Classified: Bhutan
```

Now, we can remove overfitting with various ways, for now we are using Data Augmentation and add Dropout to our model.

We are using the Data Augmentation Here.

In [104]:

```
train_aug = ImageDataGenerator(
    shear_range = 0.2,
    rotation_range = 90,
    brightness_range=[0.3,0.9],
    zoom_range = 0.2,
    horizontal_flip = True,
    vertical_flip = True
)
```

Selecting Random Image

In [105]:

```
import os
import random
random_gen = random.choice(os.listdir('GoodDatasets/training/Nepal'))
```

In [106]:

```
image_path = 'GoodDatasets/training/Nepal/' + random_gen
assert os.path.isfile(image_path)
```

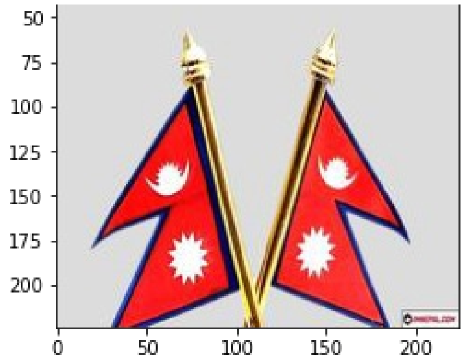
Visualizing the random image

In [107]:

```
import numpy as np
image = np.expand_dims(plt.imread(image_path),0)
plt.imshow(image[0])
```

Out[107]:

```
<matplotlib.image.AxesImage at 0x7f9070e28490>
```



function for plotting multiple images.

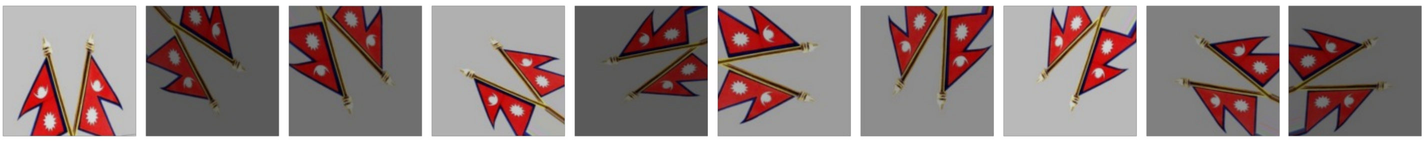
In [108]:

```
def plotImages(images_arr):
  flg, axes = plt.subplots(1, 10,figsize=(20,20))
  axes = axes.flatten()
  for img, ax in zip( images_arr, axes):
    ax.imshow(img)
    ax.axis('off')
  plt.tight_layout()
  plt.show()
```

Visualizing Augmented images.

In [109]:

```
aug_iter = train_aug.flow(image)
aug_images = [next(aug_iter)[0].astype(np.uint8) for i in range(10)]
plotImages(aug_images)
```



The RGB values are in the range between 0-255 and this is not ideal for for a neural network. So, we will set the value between 0-1. This will be done by calling the rescale method along with image augmentation.

In [110]:

```
training_datagen = ImageDataGenerator(
    rescale = 1./255,
    zoom_range = 0.8,
    shear_range=0.2,
    horizontal_flip = True,
    )

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

Flow from directory gathers all the images from inside the directories and also implements the data augmentation to all the images it finds. Here, it has found 4000 images for the training sets and 400 image for validation set.

In [111]:

```
training_generator = training_datagen.flow_from_directory(train_dir,
                                                     target_size =(img_width, img_height
),
                                                     batch_size = batch_size,
                                                     shuffle = True,
                                                     class_mode ='categorical')
```

```
validation_generator = validation_datagen.flow_from_directory(
    val_dir,
    target_size =(img_width, img_height),
    batch_size = batch_size, class_mode ='categorical')
```

```
Found 4000 images belonging to 10 classes.
Found 400 images belonging to 10 classes.
```

Now we will create a model with including the dropout layer.

In [112]:

```
model2 = Sequential()
model2.add(Conv2D(16, (3, 3), input_shape = (img_width,img_height,3)))
model2.add(Activation('relu'))
model2.add(MaxPooling2D(pool_size =(2, 2)))

model2.add(Conv2D(32, (3, 3)))
model2.add(Activation('relu'))
model2.add(MaxPooling2D(pool_size =(2, 2)))

model2.add(Conv2D(64, (3, 3)))
model2.add(Activation('relu'))
model2.add(MaxPooling2D(pool_size =(2, 2)))

model2.add(Flatten())
model2.add(Dense(128))
model2.add(Activation('relu'))
model2.add(Dropout(0.2))
model2.add(Dense(10))
model2.add(Activation('softmax'))

monitor = tf.keras.callbacks.EarlyStopping(monitor='val_loss', min_delta=0, patience=5,
verbose=1, mode='auto', restore_best_weights=True)
```

In [113]:

```
model2.compile(loss ='categorical_crossentropy',
              optimizer ='adam',
              metrics =['accuracy'])
```

Now we will train our model with the datsets

In [114]:

```
final_data = model2.fit(training_generator,
                 steps_per_epoch = nb_train_samples // batch_size,
                 epochs = 25, callbacks=[monitor], validation_data = validation_generato
r,
                 validation_steps = nb_val_samples // batch_size)
model2.save('today.h5')
len(final_data.history['loss'])
```

```
Epoch 1/25
500/500 [==============================] - 10s 19ms/step - loss: 1.9074 - accuracy: 0.309
0 - val_loss: 0.8251 - val_accuracy: 0.7625
Epoch 2/25
500/500 [==============================] - 9s 18ms/step - loss: 0.9855 - accuracy: 0.6753
- val_loss: 0.6596 - val_accuracy: 0.7750
Epoch 3/25
500/500 [==============================] - 9s 18ms/step - loss: 0.9144 - accuracy: 0.7166
- val_loss: 0.5799 - val_accuracy: 0.8100
Epoch 4/25
500/500 [==============================] - 9s 18ms/step - loss: 0.8472 - accuracy: 0.7312
- val_loss: 0.5554 - val_accuracy: 0.8225
Epoch 5/25
500/500 [==============================] - 9s 18ms/step - loss: 0.7198 - accuracy: 0.7633
- val_loss: 0.5242 - val_accuracy: 0.8175
Epoch 6/25
500/500 [==============================] - 9s 18ms/step - loss: 0.6980 - accuracy: 0.7821
```

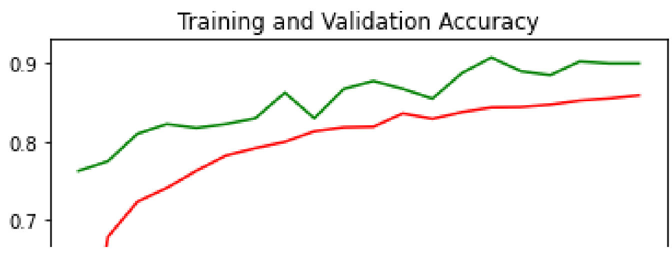
```
500/500 [==============================] - 9s 18ms/step - loss: 0.6980 - accuracy: 0.7821
- val_loss: 0.5171 - val_accuracy: 0.8225
Epoch 7/25
500/500 [==============================] - 9s 18ms/step - loss: 0.6244 - accuracy: 0.7997
- val_loss: 0.5150 - val_accuracy: 0.8300
Epoch 8/25
500/500 [==============================] - 9s 18ms/step - loss: 0.5977 - accuracy: 0.8064
- val_loss: 0.4338 - val_accuracy: 0.8625
Epoch 9/25
500/500 [==============================] - 9s 18ms/step - loss: 0.5993 - accuracy: 0.8069
- val_loss: 0.5528 - val_accuracy: 0.8300
Epoch 10/25
500/500 [==============================] - 9s 18ms/step - loss: 0.5377 - accuracy: 0.8292
- val_loss: 0.4299 - val_accuracy: 0.8675
Epoch 11/25
500/500 [==============================] - 9s 18ms/step - loss: 0.5468 - accuracy: 0.8267
- val_loss: 0.3957 - val_accuracy: 0.8775
Epoch 12/25
500/500 [==============================] - 9s 18ms/step - loss: 0.5297 - accuracy: 0.8274
- val_loss: 0.4179 - val_accuracy: 0.8675
Epoch 13/25
500/500 [==============================] - 9s 18ms/step - loss: 0.4955 - accuracy: 0.8333
- val_loss: 0.4825 - val_accuracy: 0.8550
Epoch 14/25
500/500 [==============================] - 9s 18ms/step - loss: 0.5078 - accuracy: 0.8431
- val_loss: 0.3502 - val_accuracy: 0.8875
Epoch 15/25
500/500 [==============================] - 9s 18ms/step - loss: 0.4729 - accuracy: 0.8450
- val_loss: 0.3138 - val_accuracy: 0.9075
Epoch 16/25
500/500 [==============================] - 9s 18ms/step - loss: 0.4719 - accuracy: 0.8438
- val_loss: 0.3508 - val_accuracy: 0.8900
Epoch 17/25
500/500 [==============================] - 9s 18ms/step - loss: 0.4732 - accuracy: 0.8536
- val_loss: 0.3612 - val_accuracy: 0.8850
Epoch 18/25
500/500 [==============================] - 9s 18ms/step - loss: 0.4403 - accuracy: 0.8541
- val_loss: 0.3148 - val_accuracy: 0.9025
Epoch 19/25
500/500 [==============================] - 9s 18ms/step - loss: 0.4816 - accuracy: 0.8467
- val_loss: 0.3184 - val_accuracy: 0.9000
Epoch 20/25
500/500 [==============================] - 9s 19ms/step - loss: 0.4564 - accuracy: 0.8497
- val_loss: 0.3148 - val_accuracy: 0.9000
Restoring model weights from the end of the best epoch.
Epoch 00020: early stopping
```

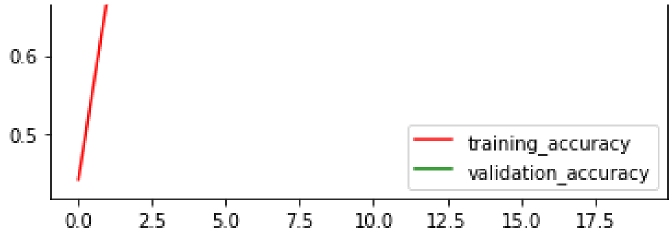
Out[114]:

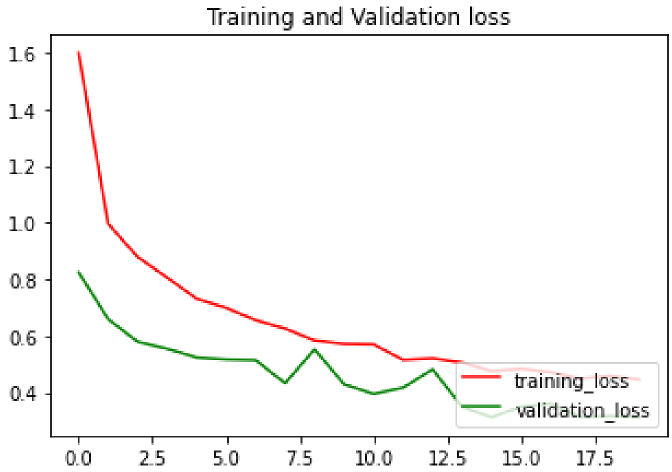
```
20
```

In [115]:

```
plt.plot(final_data.history['accuracy'],c='r',label='training_accuracy')
plt.plot(final_data.history['val_accuracy'],c='g',label='validation_accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')
plt.show()

plt.plot(final_data.history['loss'],c='r',label='training_loss')
plt.plot(final_data.history['val_loss'],c='g',label='validation_loss')
plt.legend(loc='lower right')
plt.title('Training and Validation loss')
plt.show()
```







Visualizing the results

Now we can see that the results have gone better than before after adding data augmentation and dropout layer. Now, the overfitting have been reduced by a noticable margin

Evaluating the model

In [116]:

```
saved_model_path = 'today.h5'
saved_model = load_model(saved_model_path)

train_evaluate=saved_model.evaluate(training_generator)
validation_evaluate=saved_model.evaluate(validation_generator)
```

```
500/500 [==============================] - 9s 17ms/step - loss: 0.4294 - accuracy: 0.8587
50/50 [==============================] - 1s 11ms/step - loss: 0.3138 - accuracy: 0.9075
```

Printing the accuracies

In [117]:

```
print('Training Accuracy  : %1.2f%%     Training loss  : %1.6f'%(train_evaluate[1]*100,t
rain_evaluate[0]))
print('Validation Accuracy: %1.2f%%     Validation loss: %1.6f'%(validation_evaluate[1]*
100,validation_evaluate[0]))
```

```
Training Accuracy  : 85.87%     Training loss  : 0.429379
Validation Accuracy: 90.75%     Validation loss: 0.313840
```

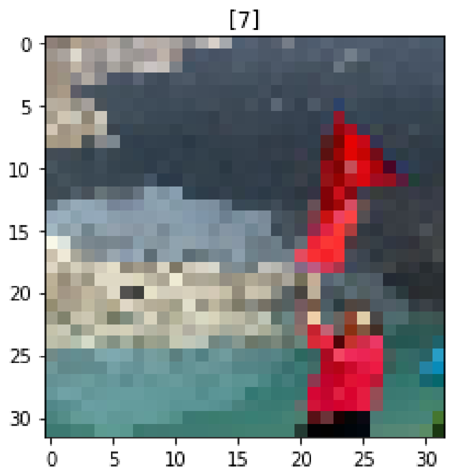
Making Predictions

In [118]:

```
from tensorflow.keras.preprocessing import image
import matplotlib.pyplot as plt
import numpy as np
from keras.preprocessing.image import ImageDataGenerator, load_img, img_to_array
from keras.models import Sequential, load_model

model_path='today.h5'
data1=load_model(model_path)
```

```
image_path="SS_01.png"
img = image.load_img(image_path, target_size=(img_width, img_height))
plt.imshow(img)
img = np.expand_dims(img, axis=0)
result=data1.predict_classes(img)
plt.title(result)
plt.show()

if result ==[0]:
    print("Classified: Afganistan")
elif result ==[1]:
    print("Classified: America")
elif result ==[2]:
    print("Classified: Argentina")
elif result ==[3]:
    print("Classified: Bangladesh")
elif result ==[4]:
    print("Classified: Bhutan")
elif result ==[5]:
    print("Classified: India")
elif result ==[6]:
    print("Classified: Maldives")
elif result ==[7]:
    print("Classified: Nepal")
elif result ==[8]:
    print("Classified: Pakistan")
else:
    print("Classified: SriLanka")
```

```
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/sequential.py:450: UserWarning: `model.predict_classes()` is deprecated and will be removed after 2021-01-01. Please use instead:* `np.argmax(model.predict(x), axis=-1)`,   if your model does multi-class classification   (e.g. if it uses a `softmax` last-layer activation).* `(model.predict(x) > 0.5).astype("int32")`,   if your model does binary classification   (e.g. if it uses a `sigmoid` last-layer activation).
  warnings.warn('`model.predict_classes()` is deprecated and '
/usr/local/lib/python3.7/dist-packages/matplotlib/text.py:1165: FutureWarning: elementwise comparison failed; returning scalar instead, but in the future will perform elementwise comparison
  if s != self._text:
```




```
Classified: Nepal
```

Now we check if the model is overfitting or not

Building a confusion matrix.

In [119]:

```
pred1=model2.predict_classes(testing_generator)
pred2 = testing_generator.classes

from sklearn.metrics import confusion_matrix
from sklearn import metrics
```

```
print(metrics.confusion_matrix(pred2, pred1))
print(metrics.classification_report(pred2, pred1, target_names = ['Afganistan (Class 0)'
,'America (Class 1)', 'Argentina (Class 2)','Bangladesh (Class 3)', 'Bhutan (Class 4)','
India (Class 5)', 'Maldives (Class 6)','Nepal (Class 7)', 'Pakistan (Class 8)','Srilanka
(Class 9)']))
```

```
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/sequential.py:450:
UserWarning: `model.predict_classes()` is deprecated and will be removed after 2021-01-01
. Please use instead:* `np.argmax(model.predict(x), axis=-1)`,   if your model does multi
-class classification   (e.g. if it uses a `softmax` last-layer activation).* `(model.pre
dict(x) > 0.5).astype("int32")`,   if your model does binary classification   (e.g. if it
uses a `sigmoid` last-layer activation).
  warnings.warn('`model.predict_classes()` is deprecated and '
```

```
[[32  0  0  2  0  1  3  0  0  2]
 [ 2 34  0  0  2  0  0  1  0  1]
 [ 0  0 30  0  2  3  0  1  2  2]
 [ 0  1  0 34  0  0  1  1  1  2]
 [ 0  0  0  0 36  0  0  0  0  4]
 [ 0  1  0  2  0 32  0  0  3  2]
 [ 0  0  0  0  0  0 33  0  0  1]
 [ 5  2  1  1  2  0  1 28  0  0]
 [ 0  0  0  0  1  0  0  3 35  1]
 [ 0  0  0  0  2  0  0  0  0 38]]
                      precision    recall  f1-score   support

Afganistan (Class 0)       0.82      0.80      0.81        40
   America (Class 1)       0.89      0.85      0.87        40
 Argentina (Class 2)       0.97      0.75      0.85        40
Bangladesh (Class 3)       0.87      0.85      0.86        40
    Bhutan (Class 4)       0.80      0.90      0.85        40
     India (Class 5)       0.89      0.80      0.84        40
  Maldives (Class 6)       0.87      0.97      0.92        34
     Nepal (Class 7)       0.82      0.70      0.76        40
  Pakistan (Class 8)       0.85      0.88      0.86        40
  Srilanka (Class 9)       0.72      0.95      0.82        40

            accuracy                           0.84       394
           macro avg       0.85      0.84      0.84       394
        weighted avg       0.85      0.84      0.84       394
```

Using SVM

In [120]:

```
import tensorflow as tf

svm = Sequential()
svm.add(Conv2D(16, (3, 3), input_shape = (32,32,3)))
svm.add(Activation('relu'))
svm.add(MaxPooling2D(pool_size =(2, 2)))

svm.add(Conv2D(32, (3, 3)))
svm.add(Activation('relu'))
svm.add(MaxPooling2D(pool_size =(2, 2)))

svm.add(Conv2D(64, (3, 3)))
svm.add(Activation('relu'))
svm.add(MaxPooling2D(pool_size =(2, 2)))

svm.add(Flatten())
svm.add(Dense(128))
svm.add(Activation('relu'))
svm.add(Dense(10, kernel_regularizer=tf.keras.regularizers.l2(0.01),activation='softmax'
))

monitor = tf.keras.callbacks.EarlyStopping(monitor='val_loss', min_delta=0, patience=5,
verbose=1, mode='auto', restore_best_weights=True)
```

In [121]:

```
svm.compile(optimizer='adam', loss = 'squared_hinge', metrics=['accuracy'])
```

In [122]:

```
svm.summary()
```

```
Model: "sequential_8"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_18 (Conv2D)           (None, 30, 30, 16)        448
_________________________________________________________________
activation_32 (Activation)   (None, 30, 30, 16)        0
_________________________________________________________________
max_pooling2d_18 (MaxPooling (None, 15, 15, 16)        0
_________________________________________________________________
conv2d_19 (Conv2D)           (None, 13, 13, 32)        4640
_________________________________________________________________
activation_33 (Activation)   (None, 13, 13, 32)        0
_________________________________________________________________
max_pooling2d_19 (MaxPooling (None, 6, 6, 32)          0
_________________________________________________________________
conv2d_20 (Conv2D)           (None, 4, 4, 64)          18496
_________________________________________________________________
activation_34 (Activation)   (None, 4, 4, 64)          0
_________________________________________________________________
max_pooling2d_20 (MaxPooling (None, 2, 2, 64)          0
_________________________________________________________________
flatten_10 (Flatten)         (None, 256)               0
_________________________________________________________________
dense_18 (Dense)             (None, 128)               32896
_________________________________________________________________
activation_35 (Activation)   (None, 128)               0
_________________________________________________________________
dense_19 (Dense)             (None, 10)                1290
=================================================================
Total params: 57,770
Trainable params: 57,770
Non-trainable params: 0
_________________________________________________________________
```

In [123]:

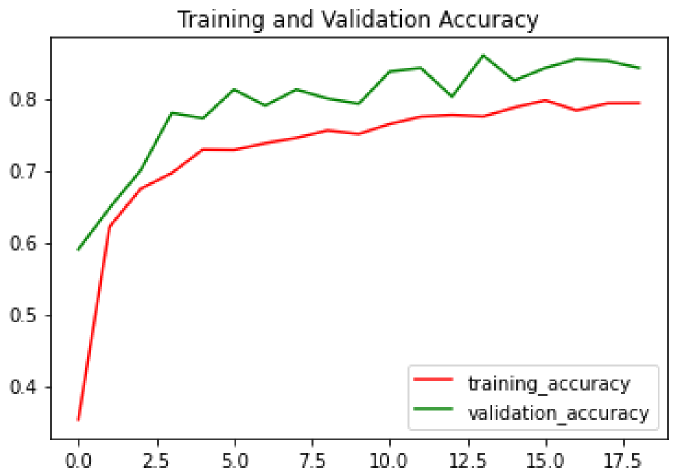
```
svm1 = svm.fit(x = training_generator, validation_data=validation_generator, epochs=epoch
s, callbacks=[monitor])

svm.save('svm_model.h5')
```

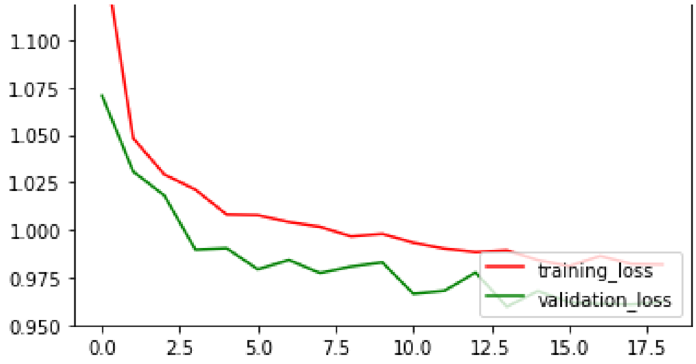
```
Epoch 1/25
500/500 [==============================] - 10s 19ms/step - loss: 1.2148 - accuracy: 0.230
0 - val_loss: 1.0707 - val_accuracy: 0.5900
Epoch 2/25
500/500 [==============================] - 9s 19ms/step - loss: 1.0553 - accuracy: 0.6008
- val_loss: 1.0307 - val_accuracy: 0.6475
Epoch 3/25
500/500 [==============================] - 9s 19ms/step - loss: 1.0374 - accuracy: 0.6494
- val_loss: 1.0181 - val_accuracy: 0.7000
Epoch 4/25
500/500 [==============================] - 9s 19ms/step - loss: 1.0194 - accuracy: 0.7050
- val_loss: 0.9895 - val_accuracy: 0.7800
Epoch 5/25
500/500 [==============================] - 9s 19ms/step - loss: 1.0119 - accuracy: 0.7174
- val_loss: 0.9903 - val_accuracy: 0.7725
Epoch 6/25
500/500 [==============================] - 9s 19ms/step - loss: 1.0129 - accuracy: 0.7133
- val_loss: 0.9792 - val_accuracy: 0.8125
Epoch 7/25
500/500 [==============================] - 9s 19ms/step - loss: 1.0052 - accuracy: 0.7360
- val_loss: 0.9841 - val_accuracy: 0.7900
Epoch 8/25
```

```
500/500 [==============================] - 9s 18ms/step - loss: 1.0029 - accuracy: 0.7416
- val_loss: 0.9773 - val_accuracy: 0.8125
Epoch 9/25
500/500 [==============================] - 9s 18ms/step - loss: 0.9955 - accuracy: 0.7595
- val_loss: 0.9807 - val_accuracy: 0.8000
Epoch 10/25
500/500 [==============================] - 9s 19ms/step - loss: 0.9970 - accuracy: 0.7555
- val_loss: 0.9829 - val_accuracy: 0.7925
Epoch 11/25
500/500 [==============================] - 9s 18ms/step - loss: 0.9885 - accuracy: 0.7799
- val_loss: 0.9663 - val_accuracy: 0.8375
Epoch 12/25
500/500 [==============================] - 9s 19ms/step - loss: 0.9910 - accuracy: 0.7710
- val_loss: 0.9679 - val_accuracy: 0.8425
Epoch 13/25
500/500 [==============================] - 9s 19ms/step - loss: 0.9884 - accuracy: 0.7777
- val_loss: 0.9776 - val_accuracy: 0.8025
Epoch 14/25
500/500 [==============================] - 9s 19ms/step - loss: 0.9908 - accuracy: 0.7697
- val_loss: 0.9595 - val_accuracy: 0.8600
Epoch 15/25
500/500 [==============================] - 9s 19ms/step - loss: 0.9860 - accuracy: 0.7829
- val_loss: 0.9678 - val_accuracy: 0.8250
Epoch 16/25
500/500 [==============================] - 9s 19ms/step - loss: 0.9803 - accuracy: 0.7984
- val_loss: 0.9619 - val_accuracy: 0.8425
Epoch 17/25
500/500 [==============================] - 9s 19ms/step - loss: 0.9887 - accuracy: 0.7750
- val_loss: 0.9611 - val_accuracy: 0.8550
Epoch 18/25
500/500 [==============================] - 10s 20ms/step - loss: 0.9839 - accuracy: 0.789
9 - val_loss: 0.9607 - val_accuracy: 0.8525
Epoch 19/25
500/500 [==============================] - 10s 19ms/step - loss: 0.9825 - accuracy: 0.794
0 - val_loss: 0.9622 - val_accuracy: 0.8425
Restoring model weights from the end of the best epoch.
Epoch 00019: early stopping
```

In [124]:

```
plt.plot(svm1.history['accuracy'],c='r',label='training_accuracy')
plt.plot(svm1.history['val_accuracy'],c='g',label='validation_accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')
plt.show()

plt.plot(svm1.history['loss'],c='r',label='training_loss')
plt.plot(svm1.history['val_loss'],c='g',label='validation_loss')
plt.legend(loc='lower right')
plt.title('Training and Validation loss')
plt.show()
```





In [125]:

```
model_path='svm_model.h5'
svm_model=load_model(model_path)

pred1=svm_model.predict_classes(testing_generator)
pred2 = testing_generator.classes

from sklearn.metrics import confusion_matrix
from sklearn import metrics

print(metrics.confusion_matrix(pred2, pred1))
print(metrics.classification_report(pred2, pred1, target_names = ['Afganistan (Class 0)'
,'America (Class 1)', 'Argentina (Class 2)','Bangladesh (Class 3)', 'Bhutan (Class 4)','
India (Class 5)', 'Maldives (Class 6)','Nepal (Class 7)', 'Pakistan (Class 8)','Srilanka
(Class 9)']))
```

```
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/sequential.py:450:
UserWarning: `model.predict_classes()` is deprecated and will be removed after 2021-01-01
. Please use instead:* `np.argmax(model.predict(x), axis=-1)`,   if your model does multi
-class classification   (e.g. if it uses a `softmax` last-layer activation).* `(model.pre
dict(x) > 0.5).astype("int32")`,   if your model does binary classification   (e.g. if it
uses a `sigmoid` last-layer activation).
  warnings.warn('`model.predict_classes()` is deprecated and '
```

```
[[28  0  0  7  0  2  2  0  0  1]
 [ 5 31  0  0  2  1  0  1  0  0]
 [ 1  1 27  1  1  3  0  2  2  2]
 [ 0  0  0 34  1  2  1  1  1  0]
 [ 0  0  2  0 35  0  0  0  0  3]
 [ 3  0  0  2  1 32  0  0  1  1]
 [ 1  0  0  1  0  0 32  0  0  0]
 [ 3  2  1  6  1  0  0 25  2  0]
 [ 1  0  1  2  0  1  0  1 33  1]
 [ 2  1  0  0  2  1  0  0  0 34]]
                      precision    recall  f1-score   support

Afganistan (Class 0)       0.64      0.70      0.67        40
   America (Class 1)       0.89      0.78      0.83        40
  Argentina (Class 2)      0.87      0.68      0.76        40
Bangladesh (Class 3)       0.64      0.85      0.73        40
    Bhutan (Class 4)       0.81      0.88      0.84        40
     India (Class 5)       0.76      0.80      0.78        40
  Maldives (Class 6)       0.91      0.94      0.93        34
     Nepal (Class 7)       0.83      0.62      0.71        40
  Pakistan (Class 8)       0.85      0.82      0.84        40
  Srilanka (Class 9)       0.81      0.85      0.83        40

            accuracy                           0.79       394
           macro avg       0.80      0.79      0.79       394
        weighted avg       0.80      0.79      0.79       394
```

Using a Pre Trained Model.

In [126]:

```
from keras.applications.vgg16 import VGG16
```

```
img_size = [32, 32]

vgg = VGG16(input_shape = img_size + [3], weights='imagenet', include_top = False)

for layer in vgg.layers:
  layer.trainable = False
```

In [127]:

```
from glob import glob
from keras.models import Model

folders = glob('GoodDatasets/training/*')

x = Flatten()(vgg.output)
prediction = Dense(len(folders), activation='softmax')(x)

model3 = Model(inputs=vgg.input, outputs=prediction)
monitor = tf.keras.callbacks.EarlyStopping(monitor='val_loss', min_delta=0, patience=5,
verbose=1, mode='auto', restore_best_weights=True)
```

In [128]:

```
model3.summary()
```

```
Model: "model_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_3 (InputLayer)         [(None, 32, 32, 3)]       0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 32, 32, 64)        1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 32, 32, 64)        36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 16, 16, 64)        0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 16, 16, 128)       73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 16, 16, 128)       147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 8, 8, 128)         0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 8, 8, 256)         295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 8, 8, 256)         590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 8, 8, 256)         590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 4, 4, 256)         0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 4, 4, 512)         1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 4, 4, 512)         2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 4, 4, 512)         2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 2, 2, 512)         0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 2, 2, 512)         2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 2, 2, 512)         2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 2, 2, 512)         2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 1, 1, 512)         0
_________________________________________________________________
flatten_11 (Flatten)         (None, 512)               0
_________________________________________________________________
dense_20 (Dense)             (None, 10)                5130
=================================================================
```

```
Total params: 14,719,818
Trainable params: 5,130
Non-trainable params: 14,714,688
_________________________________________________________________
```

In [129]:

```
model3.compile(
    loss='categorical_crossentropy',
    optimizer='adam',
    metrics=['accuracy']
)
```

In [130]:

```
t_data = ImageDataGenerator(
    rescale = 1./255,
    shear_range = 0.2,
    zoom_range = 0.2,
    horizontal_flip = True
)
v_data = ImageDataGenerator(rescale=1./255)
```

In [131]:

```
t_set = t_data.flow_from_directory(
    'GoodDatasets/training',
    target_size = (32,32),
    batch_size=2,
    class_mode='categorical'
)
v_set = t_data.flow_from_directory(
    'GoodDatasets/validation',
    target_size = (32,32),
    batch_size=2,
    class_mode='categorical'
)
```

```
Found 4000 images belonging to 10 classes.
Found 400 images belonging to 10 classes.
```

In [132]:

```
r = model3.fit_generator(
    t_set,
    validation_data = v_set,
    epochs = 20,
    steps_per_epoch = nb_train_samples // batch_size,
    validation_steps = nb_val_samples // batch_size,
    callbacks=[monitor]
)
```

```
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:1844: U
serWarning: `Model.fit_generator` is deprecated and will be removed in a future version.
Please use `Model.fit`, which supports generators.
  warnings.warn('`Model.fit_generator` is deprecated and '
```

```
Epoch 1/20
500/500 [==============================] - 8s 15ms/step - loss: 2.1664 - accuracy: 0.2248
- val_loss: 1.7259 - val_accuracy: 0.4300
Epoch 2/20
500/500 [==============================] - 7s 14ms/step - loss: 1.5582 - accuracy: 0.5152
- val_loss: 1.4812 - val_accuracy: 0.5300
Epoch 3/20
500/500 [==============================] - 7s 14ms/step - loss: 1.3644 - accuracy: 0.5779
- val_loss: 1.2301 - val_accuracy: 0.6400
Epoch 4/20
500/500 [==============================] - 7s 14ms/step - loss: 1.2748 - accuracy: 0.6088
- val_loss: 1.2301 - val_accuracy: 0.6000
Epoch 5/20
500/500 [==============================] - 7s 14ms/step - loss: 1.2223 - accuracy: 0.6337
- val_loss: 1.1731 - val_accuracy: 0.6200
```

```
- val_loss: 1.1751 - val_accuracy: 0.6200
Epoch 6/20
500/500 [==============================] - 7s 14ms/step - loss: 1.1328 - accuracy: 0.6561
- val_loss: 1.3169 - val_accuracy: 0.5800
Epoch 7/20
500/500 [==============================] - 7s 14ms/step - loss: 1.1190 - accuracy: 0.6770
- val_loss: 1.1324 - val_accuracy: 0.6200
Epoch 8/20
500/500 [==============================] - 7s 14ms/step - loss: 1.1357 - accuracy: 0.6494
- val_loss: 1.0936 - val_accuracy: 0.5900
Epoch 9/20
500/500 [==============================] - 7s 14ms/step - loss: 1.1102 - accuracy: 0.6478
- val_loss: 1.0696 - val_accuracy: 0.6300
Epoch 10/20
500/500 [==============================] - 7s 14ms/step - loss: 1.0478 - accuracy: 0.6700
- val_loss: 1.0913 - val_accuracy: 0.6600
Epoch 11/20
500/500 [==============================] - 7s 14ms/step - loss: 1.0546 - accuracy: 0.6900
- val_loss: 1.1751 - val_accuracy: 0.5700
Epoch 12/20
500/500 [==============================] - 7s 14ms/step - loss: 1.0051 - accuracy: 0.6814
- val_loss: 1.1301 - val_accuracy: 0.6300
Epoch 13/20
500/500 [==============================] - 7s 14ms/step - loss: 1.1370 - accuracy: 0.6610
- val_loss: 1.0334 - val_accuracy: 0.6600
Epoch 14/20
500/500 [==============================] - 7s 14ms/step - loss: 0.9804 - accuracy: 0.7013
- val_loss: 1.2173 - val_accuracy: 0.6200
Epoch 15/20
500/500 [==============================] - 7s 14ms/step - loss: 0.9548 - accuracy: 0.6872
- val_loss: 1.0694 - val_accuracy: 0.7200
Epoch 16/20
500/500 [==============================] - 7s 14ms/step - loss: 0.9510 - accuracy: 0.7017
- val_loss: 1.0639 - val_accuracy: 0.6600
Epoch 17/20
500/500 [==============================] - 7s 14ms/step - loss: 0.8364 - accuracy: 0.7500
- val_loss: 1.0687 - val_accuracy: 0.6400
Epoch 18/20
500/500 [==============================] - 7s 14ms/step - loss: 0.9764 - accuracy: 0.6779
- val_loss: 1.1574 - val_accuracy: 0.6400
Restoring model weights from the end of the best epoch.
Epoch 00018: early stopping
```

Visualizing the pre trained model's accuracy.

In [133]:

```python
plt.plot(r.history['accuracy'], label='training_accuracy')
plt.plot(r.history['val_accuracy'], label='validation_accuracy')
plt.legend()
plt.show()
```

In [133]:

```python

```