

Ramaiah Institute of Technology

(Autonomous Institute Affiliated to VTU)

Department of Information Science and Engineering



DEEP LEARNING - ASSIGNMENT II

Course Code: ISE741

Credits: 3:0:0

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Satellite Image Classification as either waterbody,Forest, cloud or dessert.

Introduction

Satellite image classification is the most significant technique used in remote sensing for the computerized study and pattern recognition of satellite information, which is based on diversity structures of the image that involve rigorous validation of the training samples depending on the used classification algorithm.

EXECUTION OF THE PROGRAM :

Step 1: IMPORTING LIBRARIES and INITIALIZING

```
[ ] import tensorflow as tf
    from tensorflow.keras import models, layers
    import matplotlib.pyplot as plt
```

```
[ ] IMAGE_SIZE=256
    BATCH_SIZE=100
    CHANNELS=3
    EPOCHS=5
```

Step-2: Data Collection

```
dataset=tf.keras.preprocessing.image_dataset_from_directory(  
    r"C:\Users\chara\OneDrive\Documents\data",  
    shuffle=True,  
    image_size=(IMAGE_SIZE,IMAGE_SIZE),  
    batch_size=BATCH_SIZE  
)
```

Found 5600 files belonging to 4 classes.

```
class_names=dataset.class_names  
class_names
```

```
['cloudy', 'desert', 'green_area', 'water']
```

```
[ ] len(dataset)
```

56

Satellite image Classification Dataset-RSI-CB256 , This dataset has 4 different classes mixed from Sensors and google map snapshot.

Four classes are:

- 1)Cloudy
- 2)Desert
- 3)Green_area
- 4)water

Step-3

```

▶ plt.figure(figsize=(10,10))
  for image_batch,label_batch in dataset.take(1):

      print(image_batch.shape)
      print(label_batch.numpy())
      for i in range(12):
          ax=plt.subplot(3,4,i+1)
          plt.imshow(image_batch[i].numpy().astype("uint8"))
          plt.title(class_names[label_batch[i]])
          plt.axis("off")

```

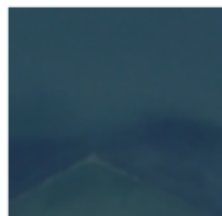
output:

```

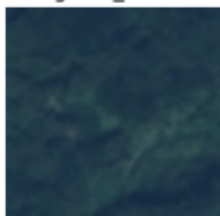
👤 (100, 256, 256, 3)
[3 2 0 3 0 0 1 3 0 2 2 2 1 2 0 0 2 3 0 2 2 2 0 3 3 3 2 0 0 2 2 0 0 3 1 2 3
 2 2 2 3 2 3 0 2 0 0 0 1 2 3 0 3 1 0 0 2 2 1 3 0 3 0 0 0 2 3 2 0 3 3 3 3 0
 3 1 1 1 1 3 2 1 3 0 0 1 0 2 1 2 3 1 1 3 1 3 1 2 3 0]

```

water



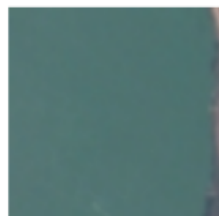
green_area



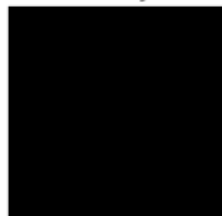
cloudy



water



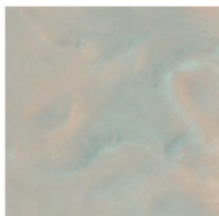
cloudy



cloudy



desert



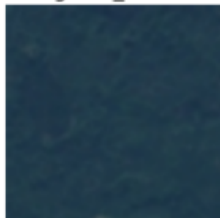
water



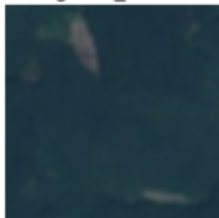
cloudy



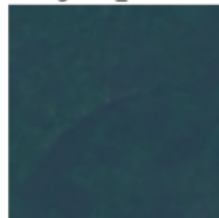
green_area



green_area



green_area



Step-4:Dividing Data into Train Test and Validation

```
def get_dataset_partitions_tf(ds,train_split=0.8,val_split=0.1,test_split=0.1,shuffle=True,shuffle_size=10000):  
    ds_size=len(ds)  
    if shuffle:  
        ds=ds.shuffle(shuffle_size,seed=12)  
    train_size=int(train_split*ds_size)  
    val_size=int(val_split*ds_size)  
    test_size=int(test_split*ds_size)  
    train_ds=dataset.take(train_size)  
    test_ds=dataset.skip(train_size)  
    val_ds=test_ds.take(val_size)  
    test_ds=test_ds.skip(val_size)  
    return train_ds,val_ds,test_ds
```

```
[ ] train_ds,val_ds,test_ds=get_dataset_partitions_tf(dataset)
```

```
[ ] len(train_ds)
```

44

```
[ ] len(val_ds)
```

5

```
[ ] len(test_ds)
```

7


Step -5 : Model Building


```
▶ input_shape=(BATCH_SIZE, IMAGE_SIZE, IMAGE_SIZE, CHANNELS)
n_classes=4
model=models.Sequential([
    resize_and_rescale,
    layers.Conv2D(32,(3,3),activation='relu',input_shape=input_shape),
    layers.MaxPooling2D((2,2)),
    layers.Conv2D(64,(3,3),activation='relu'),
    layers.MaxPooling2D((2,2)),
    layers.Conv2D(64,(3,3),activation='relu'),
    layers.MaxPooling2D((2,2)),
    layers.Conv2D(64,(3,3),activation='relu'),
    layers.MaxPooling2D((2,2)),
    layers.Conv2D(64,(3,3),activation='relu'),
    layers.MaxPooling2D((2,2)),
    layers.Flatten(),
    layers.Dense(64,activation='relu'),
    layers.Dense(n_classes,activation='softmax'),

])

model.build(input_shape=input_shape)
```

Step 6-Model Summary

 `model.summary()`

 Model: "sequential_3"

Layer (type)	Output Shape	Param #
=====		
sequential_2 (Sequential)	(100, 256, 256, 3)	0
conv2d_6 (Conv2D)	(100, 254, 254, 32)	896
max_pooling2d_6 (MaxPooling 2D)	(100, 127, 127, 32)	0
conv2d_7 (Conv2D)	(100, 125, 125, 64)	18496
max_pooling2d_7 (MaxPooling 2D)	(100, 62, 62, 64)	0
conv2d_8 (Conv2D)	(100, 60, 60, 64)	36928
max_pooling2d_8 (MaxPooling 2D)	(100, 30, 30, 64)	0
conv2d_9 (Conv2D)	(100, 28, 28, 64)	36928
max_pooling2d_9 (MaxPooling 2D)	(100, 14, 14, 64)	0
conv2d_10 (Conv2D)	(100, 12, 12, 64)	36928
max_pooling2d_10 (MaxPoolin g2D)	(100, 6, 6, 64)	0
conv2d_11 (Conv2D)	(100, 4, 4, 64)	36928
max_pooling2d_11 (MaxPoolin g2D)	(100, 2, 2, 64)	0
flatten_1 (Flatten)	(100, 256)	0
dense_2 (Dense)	(100, 64)	16448
dense_3 (Dense)	(100, 4)	260
=====		
Total params: 183,812		
Trainable params: 183,812		
Non-trainable params: 0		

```
▶ history=model.fit(  
    train_ds,  
    epochs=EPOCHS,  
    batch_size=BATCH_SIZE,  
    verbose=1,  
    validation_data=val_ds  
)
```

```
● Epoch 1/5  
44/44 [=====] - 274s 6s/step - loss: 0.6923 - accuracy: 0.6630 - val_loss: 0.3780 - val_accuracy: 0.8240  
Epoch 2/5  
44/44 [=====] - 259s 6s/step - loss: 0.3066 - accuracy: 0.8541 - val_loss: 0.3824 - val_accuracy: 0.8100  
Epoch 3/5  
44/44 [=====] - 244s 6s/step - loss: 0.2591 - accuracy: 0.8814 - val_loss: 0.3784 - val_accuracy: 0.7340  
Epoch 4/5  
44/44 [=====] - 247s 6s/step - loss: 0.2528 - accuracy: 0.8816 - val_loss: 0.2563 - val_accuracy: 0.9000  
Epoch 5/5  
44/44 [=====] - 239s 5s/step - loss: 0.2331 - accuracy: 0.8950 - val_loss: 0.2219 - val_accuracy: 0.9160
```

Step 7-Model Evaluation:

```
scores=model.evaluate(test_ds)
```

```
7/7 [=====] - 15s 1s/step - loss: 0.1791 - accuracy: 0.9271
```

```
scores
```

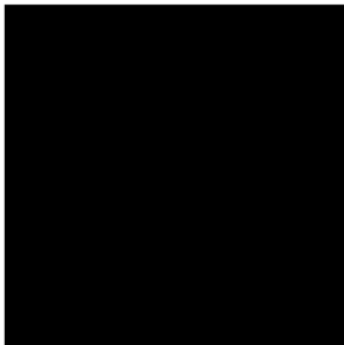
```
[0.17912176251411438, 0.927142858505249]
```


Step 8-Prediction:

```
def predict(model,img):  
    img_array=tf.keras.preprocessing.image.img_to_array(images[i].numpy())  
    img_array=tf.expand_dims(img_array,0)  
  
    predictions=model.predict(img_array)  
  
    predicted_class=class_names[np.argmax(predictions[0])]  
    confidence=round(100*(np.max(predictions[0])),2)  
  
    return predicted_class,confidence
```

```
plt.figure(figsize=(15,15))  
for images,labels in test_ds.take(1):  
    for i in range(9):  
        ax=plt.subplot(3,3,i+1)  
        plt.imshow(images[i].numpy().astype('uint8'))  
  
        predicted_class,confidence=predict(model,images[i].numpy())  
        actual_class=class_names[labels[i]]  
  
        plt.title(f"Actual: {actual_class},\n Predicted:{predicted_class},\nconfidence:{confidence}")  
  
    plt.axis('off')
```

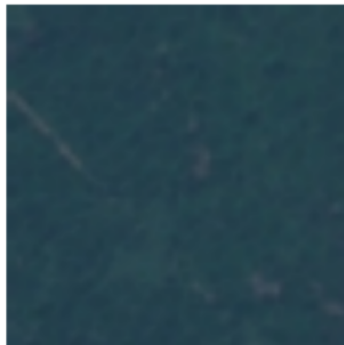
Actual: cloudy,
Predicted:cloudy,
confidence:99.99



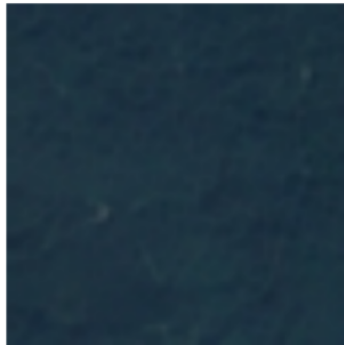
Actual: cloudy,
Predicted:cloudy,
confidence:99.99



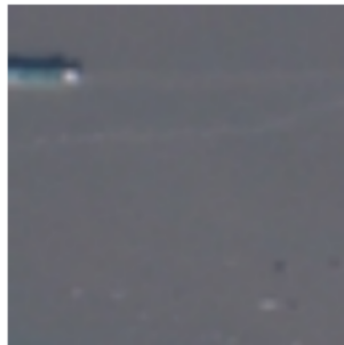
Actual: green_area,
Predicted:green_area,
confidence:77.93



Actual: green_area,
Predicted:green_area,
confidence:54.66

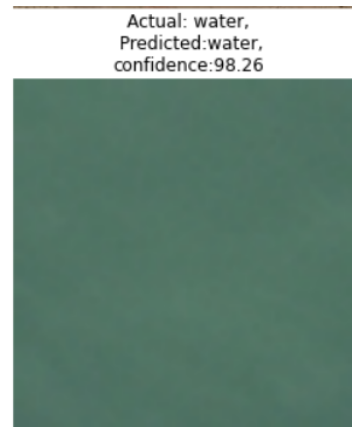
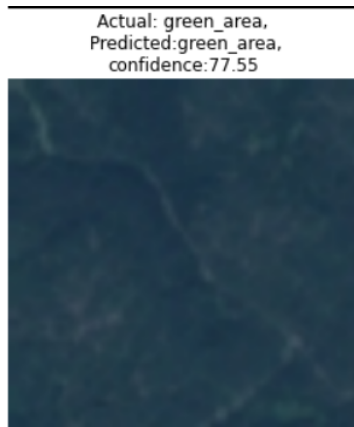


Actual: water,
Predicted:water,
confidence:98.86



Actual: desert,
Predicted:desert,
confidence:99.99





conclusion

Regions in the satellite images are not understandable every time by eye site. So Satellite image classification is very helpful to gather information about a particular region. Similar structures of different class of images and environmental variations makes the work difficult. Images used for testing is checked to determine the accuracy.