

Load data from kaggle we used kaggle api to download [intel image classification](#)

About the data sets

Context

This is image data of Natural Scenes around the world.

Content

This Data contains around 25k images of size 150x150 distributed under 6 categories.

{'buildings' -> 0,

'forest' -> 1,

'glacier' -> 2,

'mountain' -> 3,

'sea' -> 4,

'street' -> 5 }

The Train, Test and Prediction data is separated in each zip files. There are around 14k images in Train, 3k in Test and 7k in Prediction.***

Load data from the kaggle

```
#load data set from the kaggle
! pip install -q kaggle
#Make a directory named “.kaggle”
! mkdir ~/.kaggle
from google.colab import files
! cp /content/kaggle.json ~/.kaggle/
! cp /content/kaggle.json ~/.kaggle/
! kaggle datasets download -d puneet6060/intel-image-classification
```

```
mkdir: cannot create directory '/root/.kaggle': File exists
Warning: Your Kaggle API key is readable by other users on this system! To fix this, you can run 'chmod 600 /root/.kaggle/kaggl
Downloading intel-image-classification.zip to /content
 97% 337M/346M [00:12<00:00, 42.2MB/s]
100% 346M/346M [00:13<00:00, 27.8MB/s]
```

Unzip the data sets

```
#create the directory of the data
! mkdir data
```

```
#unzip train data there
```

```
! unzip /content/intel-image-classification.zip -d data
```

```
inflating: data/seg_train/seg_train/street/9484.jpg
inflating: data/seg_train/seg_train/street/9489.jpg
inflating: data/seg_train/seg_train/street/9516.jpg
inflating: data/seg_train/seg_train/street/9521.jpg
inflating: data/seg_train/seg_train/street/9530.jpg
inflating: data/seg_train/seg_train/street/9535.jpg
inflating: data/seg_train/seg_train/street/9581.jpg
inflating: data/seg_train/seg_train/street/9595.jpg
inflating: data/seg_train/seg_train/street/9600.jpg
inflating: data/seg_train/seg_train/street/9609.jpg
inflating: data/seg_train/seg_train/street/9649.jpg
inflating: data/seg_train/seg_train/street/9652.jpg
inflating: data/seg_train/seg_train/street/9655.jpg
inflating: data/seg_train/seg_train/street/9662.jpg
inflating: data/seg_train/seg_train/street/9685.jpg
inflating: data/seg_train/seg_train/street/9687.jpg
inflating: data/seg_train/seg_train/street/9690.jpg
inflating: data/seg_train/seg_train/street/9693.jpg
inflating: data/seg_train/seg_train/street/970.jpg
inflating: data/seg_train/seg_train/street/9704.jpg
inflating: data/seg_train/seg_train/street/9707.jpg
inflating: data/seg_train/seg_train/street/971.jpg
inflating: data/seg_train/seg_train/street/9717.jpg
```

```
inflating: data/seg_train/seg_train/street/9717.jpg
inflating: data/seg_train/seg_train/street/9720.jpg
inflating: data/seg_train/seg_train/street/9733.jpg
inflating: data/seg_train/seg_train/street/9734.jpg
inflating: data/seg_train/seg_train/street/974.jpg
inflating: data/seg_train/seg_train/street/9744.jpg
inflating: data/seg_train/seg_train/street/9749.jpg
inflating: data/seg_train/seg_train/street/9760.jpg
inflating: data/seg_train/seg_train/street/9770.jpg
inflating: data/seg_train/seg_train/street/9798.jpg
inflating: data/seg_train/seg_train/street/9817.jpg
inflating: data/seg_train/seg_train/street/9843.jpg
inflating: data/seg_train/seg_train/street/9846.jpg
inflating: data/seg_train/seg_train/street/9847.jpg
inflating: data/seg_train/seg_train/street/9863.jpg
inflating: data/seg_train/seg_train/street/9867.jpg
inflating: data/seg_train/seg_train/street/9872.jpg
inflating: data/seg_train/seg_train/street/9875.jpg
inflating: data/seg_train/seg_train/street/9878.jpg
inflating: data/seg_train/seg_train/street/9879.jpg
inflating: data/seg_train/seg_train/street/9885.jpg
inflating: data/seg_train/seg_train/street/9891.jpg
inflating: data/seg_train/seg_train/street/9895.jpg
inflating: data/seg_train/seg_train/street/9903.jpg
inflating: data/seg_train/seg_train/street/9911.jpg
inflating: data/seg_train/seg_train/street/992.jpg
inflating: data/seg_train/seg_train/street/9926.jpg
inflating: data/seg_train/seg_train/street/9931.jpg
inflating: data/seg_train/seg_train/street/9934.jpg
inflating: data/seg_train/seg_train/street/994.jpg
inflating: data/seg_train/seg_train/street/9953.jpg
inflating: data/seg_train/seg_train/street/9959.jpg
inflating: data/seg_train/seg_train/street/9961.jpg
inflating: data/seg_train/seg_train/street/9967.jpg
inflating: data/seg_train/seg_train/street/9978.jpg
inflating: data/seg_train/seg_train/street/9989.jpg
inflating: data/seg_train/seg_train/street/999.jpg
```

```
#import library
import tensorflow.keras.layers as Layers
import tensorflow.keras.activations as Actications
..
```

```
import tensorflow.keras.models as Models
import tensorflow.keras.optimizers as Optimizer
import tensorflow.keras.metrics as Metrics
import tensorflow.keras.utils as Utils
from keras.utils.vis_utils import model_to_dot
import os
import matplotlib.pyplot as plot
import cv2
import numpy as np
from sklearn.utils import shuffle
from sklearn.metrics import confusion_matrix as CM
from random import randint
import matplotlib.gridspec as gridspec
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt

def get_images(file_directory):
    Images = []
    Labels = []
    label = 0
    for labels in os.listdir(file_directory):
        if labels == 'glacier':
            label = 2
        elif labels == 'sea':
            label = 4
        elif labels == 'buildings':
            label = 0
        elif labels == 'forest':
            label = 1
        elif labels == 'street':
            label = 5
        elif labels == 'mountain':
            label = 3
    for image_file in os.listdir(file_directory+labels):
        #Extracting the file name of the image from Class Label folder
        image = cv2.imread(file_directory+labels+r'/' +image_file)
        #Reading the image (OpenCV)
```

```
        image = cv2.resize(image,(150,150))
        #Resize the image, Some images are different sizes. (Resizing is very Important)
        Images.append(image)
        Labels.append(label)
    return shuffle(Images,Labels,random_state=0) #Shuffle the dataset you just prepared.

def get_classlabel(class_code):
    labels = {2:'glacier', 4:'sea', 0:'buildings', 1:'forest', 5:'street', 3:'mountain'}

    return labels[class_code]
Images, Labels = get_images('data/seg_train/seg_train/')
#Extract the training images

Images = np.array(Images)
#converting the list of images to numpy array
Labels = np.array(Labels)

print("Shape of Images:",Images.shape)
print("Shape of Labels:",Labels.shape)

    Shape of Images: (14034, 150, 150, 3)
    Shape of Labels: (14034,)

f,ax = plot.subplots(5,5)
f.subplots_adjust(0,0,3,3)
for i in range(0,5,1):
    for j in range(0,5,1):
        rnd_number = randint(0,len(Images))
        ax[i,j].imshow(Images[rnd_number])
        ax[i,j].set_title(get_classlabel(Labels[rnd_number]))
        ax[i,j].axis('off')
```

mountain



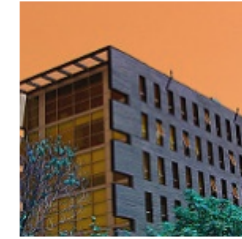
glacier



street



buildings



forest



sea



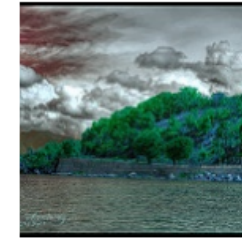
sea



mountain



sea



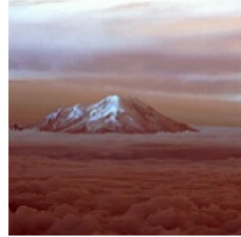
glacier



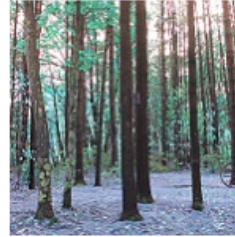
street



mountain



forest



street



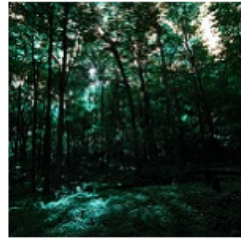
buildings



mountain



forest



street



street



glacier



mountain



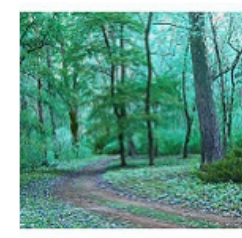
glacier



buildings



forest



buildings



```

model = Models.Sequential()

model.add(Layers.Conv2D(200,kernel_size=(3,3),activation='relu',input_shape=(150,150,3)))
model.add(Layers.Conv2D(180,kernel_size=(3,3),activation='relu'))
model.add(Layers.MaxPool2D(5,5))
model.add(Layers.Conv2D(180,kernel_size=(3,3),activation='relu'))
model.add(Layers.Conv2D(140,kernel_size=(3,3),activation='relu'))
model.add(Layers.Conv2D(100,kernel_size=(3,3),activation='relu'))
model.add(Layers.Conv2D(50,kernel_size=(3,3),activation='relu'))
model.add(Layers.MaxPool2D(5,5))
model.add(Layers.Flatten())
model.add(Layers.Dense(180,activation='relu'))
model.add(Layers.Dense(100,activation='relu'))
model.add(Layers.Dense(50,activation='relu'))
model.add(Layers.Dropout(rate=0.5))
model.add(Layers.Dense(6,activation='softmax'))

model.compile(optimizer=Optimizer.Adam(lr=0.0001),loss='sparse_categorical_crossentropy',metrics=['accuracy'])

model.summary()

```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 148, 148, 200)	5600
conv2d_1 (Conv2D)	(None, 146, 146, 180)	324180
max_pooling2d (MaxPooling2D)	(None, 29, 29, 180)	0
conv2d_2 (Conv2D)	(None, 27, 27, 180)	291780
conv2d_3 (Conv2D)	(None, 25, 25, 140)	226940
conv2d_4 (Conv2D)	(None, 23, 23, 100)	126100

conv2d_5 (Conv2D)	(None, 21, 21, 50)	45050
max_pooling2d_1 (MaxPooling2D)	(None, 4, 4, 50)	0
flatten (Flatten)	(None, 800)	0
dense (Dense)	(None, 180)	144180
dense_1 (Dense)	(None, 100)	18100
dense_2 (Dense)	(None, 50)	5050
dropout (Dropout)	(None, 50)	0
dense_3 (Dense)	(None, 6)	306

```

=====
Total params: 1,187,286
Trainable params: 1,187,286
Non-trainable params: 0

```

```

/usr/local/lib/python3.7/dist-packages/keras/optimizer_v2/optimizer_v2.py:356: UserWarning: The `lr` argument is deprecated, use
`The `lr` argument is deprecated, use `learning_rate` instead.")

```

```
train_data = model.fit(Images,Labels,epochs=5,validation_split=0)
```

```

Epoch 1/5
439/439 [=====] - 241s 549ms/step - loss: 1.1474 - accuracy: 0.5613
Epoch 2/5
439/439 [=====] - 234s 534ms/step - loss: 0.9514 - accuracy: 0.6526
Epoch 3/5
439/439 [=====] - 234s 534ms/step - loss: 0.8191 - accuracy: 0.7165
Epoch 4/5
439/439 [=====] - 234s 533ms/step - loss: 0.7315 - accuracy: 0.7505
Epoch 5/5
439/439 [=====] - 234s 533ms/step - loss: 0.6599 - accuracy: 0.7714

```

Here we get 77 percent accuracy if we increase the epoch accuracy also increase

**Thank you ** link off the colab:- (<https://colab.research.google.com/drive/1KhqmF-kmKZhtesian-sO5qgnc0I3hF9?usp=sharing>)

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