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1.About the model

In deep learning, a convolutional neural network (CNN) is class of the deep neural networks, which is applied to analyze visual images.

Generally, multiple layers of artificial neurons make up convolutional neural networks. Artificial neurons are mathematical functions that calculate the weighted sum of various inputs and output an activation value, similar to their biological counterparts. Each layer creates many activation functions that are passed on to the next layer when you input an image into a Convolution Network.

Basic characteristics such as horizontal or diagonal edges are generally extracted by the first layer. This information is passed on to the next layer, which is responsible for detecting more complicated features like corners and combinational edges. As we go further into the network, it can recognize increasingly more complex elements like objects, faces, and so on.

The classification layer generates a series of confidence ratings based on the activation map of the final convolution layer, which indicate how it belongs to a class. This is how CNN works.

2.Dataset

Details of given dataset are as follows :

This is image data of Natural Scenes around the world. 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 are separated in zip files. There are around 14k images in Train, 3k in Test, and 7k in Prediction.

Here we are importing necessary packages

```
import pandas as pd
```

```
import pandas as pd
from pathlib import Path
import cv2
from PIL import Image
from random import randint
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np


import tensorflow.keras.optimizers as Optimizer
import tensorflow.keras.layers as Layers
import tensorflow.keras.models as Models


from sklearn.model_selection import train_test_split
from keras.callbacks import ModelCheckpoint, EarlyStopping
from keras.layers import Dense, Conv2D, Activation, Dropout, Flatten, MaxPooling2D
from keras.models import Sequential, load_model, Model
import matplotlib.gridspec as gridspec
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sn
import tensorflow as tf
from tensorflow.keras import optimizers


from zipfile import ZipFile
```

3.Data Pre-Processing

Here we are reading images and then we are resizing it to 150*150. Then we are returning images & their category.

```
def rd_image(dataset_dir, img_cat):
    images=[]
    classes =[]
    if len(img_cat)!=0:
      for dir_image in img_cat:
          for path in Path(dataset_dir+'/'+dir_image).iterdir():
              if path.name.endswith('.jpg'):
                      image = cv2.imread(str(path))
                      image = cv2.resize(image,(150,150))
                      images.append(image)
                      classes.append(dir_image)
    elif len(img_cat) == 0:
      for path in Path(dataset_dir).iterdir():
```

```
            if path.name.endswith('.jpg'):
                    image = cv2.imread(str(path))
                    image = cv2.resize(image,(150,150))
                    images.append(image)
    return images, classes

#Displaying image
def image_under_display(images, classes, rows, columns):
    plt.subplots_adjust(0,0,3,3)
    for i in range(0,rows*columns):
        random_no = randint(0, len(train_img))
        image = images[random_no]
        plt.subplot(rows,columns,i+1)
        plt.title(classes[random_no])
        plt.axis('off')
        plt.imshow(image)
```

Here we are encoding

```
def encoder(classes):
  class_cat ={'buildings':0, 'forest':1, 'glacier':2, 'mountain':3, 'sea':4, 'street':5}
  label = [class_cat[item] for item in classes]
  return label
```

Here we are decoding

```
def decoder(class_code):
    label = {2:'glacier', 4:'sea', 0:'buildings', 1:'forest', 5:'street', 3:'mountain', 6:'un
    return label[class_code]
```

Here we are unzipping the files

```
def unzipfile(zipfile):
  with ZipFile(zipfile, 'r') as zipObj:
    zipObj.extractall()
```

Here we are setting stopping point

```
early_stp = EarlyStopping(monitor='val_loss', patience=2, verbose=1)
```

Here we are assigning checkpoint to the model so that we can keep saving the model as physical file

```
model_cpt = ModelCheckpoint('fas_mnist_1.h5', verbose=1, save_best_only=True)
```

Here we are cross validating function

```
def cross_validation(n_folds, X, y, model):
  mod_hist = []
  for i in range(n_folds):
      print("Training on Fold: ",i+1)
      mod_hist.append(model.fit(X, y, epochs=20, callbacks=[early_stp],
              verbose=1, validation_split=0.1))
      print("======="*12, end="\n\n\n")

  return mod_hist
```

Here we are defining category list

```
img_cat = ['buildings','forest','glacier','mountain','sea','street']
train_cat = 'seg_train'
```

Here we are unzipping training file

```
unzipfile('seg_train.zip')
```

Here we are reading images in training set

```
train_img, train_cls = rd_image('/content/seg_train/seg_train', img_cat)
```

Here we are converting images to numpy array so that we make fast operations

```
train_img = np.array(train_img)
train_cls = np.array(train_cls)
```

4.Data visualization

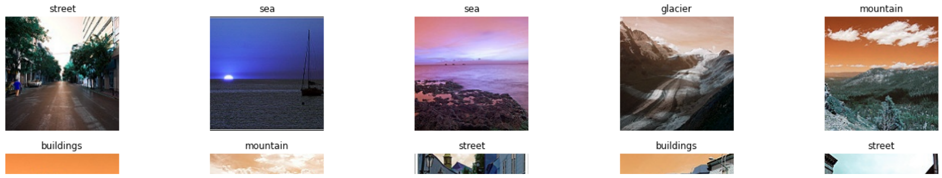
Here we are obtaining the shape of images and classes

```
print('Shape of Images:', train_img.shape)
print('Shape of Classes:', train_cls.shape)
```

```
Shape of Images: (14034, 150, 150, 3)
Shape of Classes: (14034,)
```

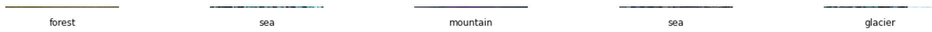
Here we are exhibiting 25 random images from the given training set

```
image_under_display(train_img, train_cls, 5, 5)
```



4. CNN model


```
train_lbls = encoder(train_cls)
train_lbls = np.array(train_lbls)
```



Here we are developing CNN model for Image classification using activation capacity i.e., relu, Pooling capacity i.e., MaxPool2D and Filter Function i.e., Conv2D

```
model=Models.Sequential()

model.add(Layers.Conv2D(200,kernel_size=(3,3),activation='relu',inp_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(learning_rate=0.0001),loss='sparse_categorical_crossen
```

```
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 (MaxPooling  (None, 4, 4, 50)         0
 2D)

 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
_________________________________________________________________
```

5.Applying the model

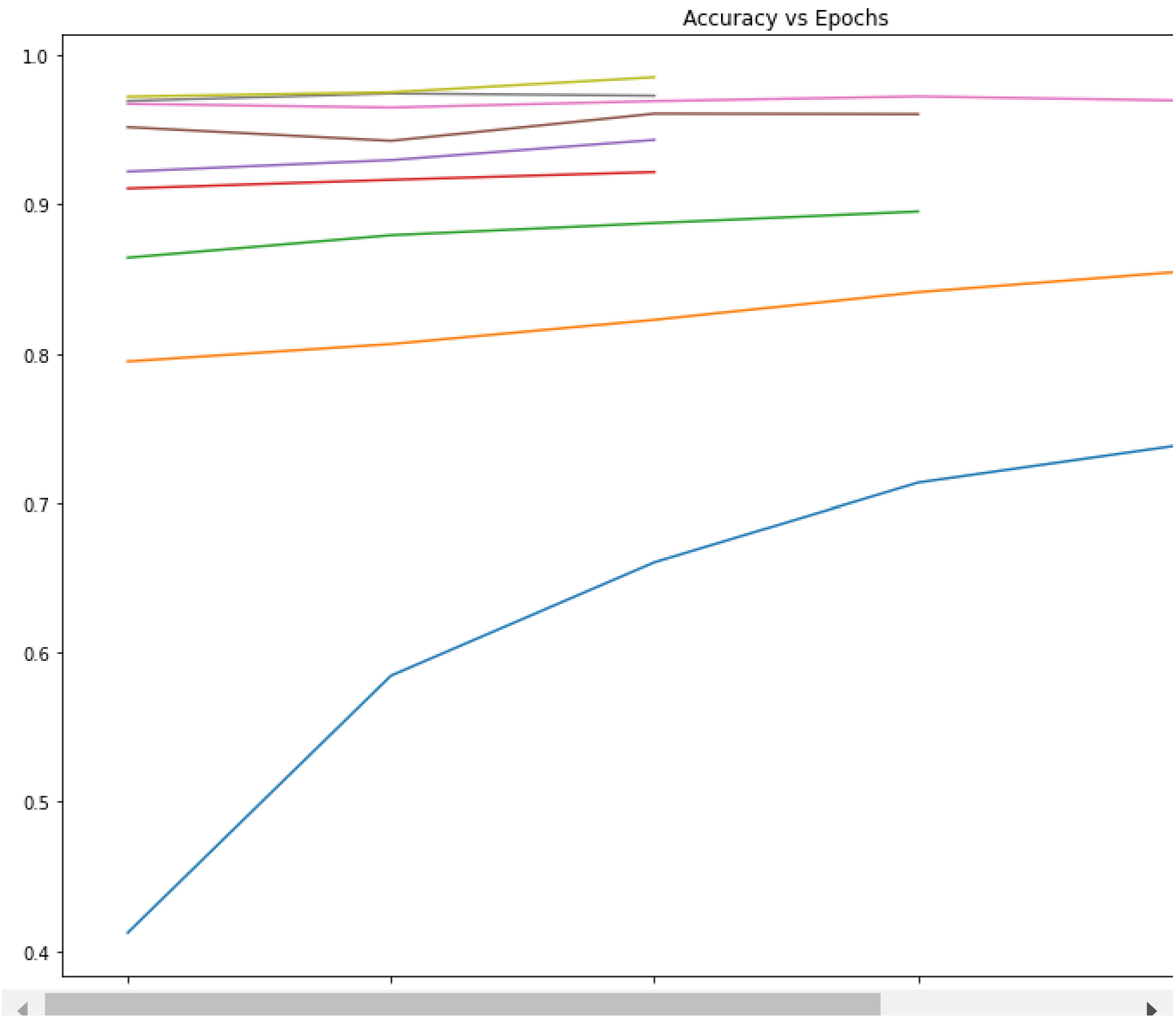
As discussed earlier in CNN we have multiple layers. Here we using 10 layers where in each layer the model exactness and approval precision are recorded and then train information is parted into train and approval set. Through this procvess for every layer the preparation is stopped after 2 nonstop ages where the approval misfortune isn't moved along. In the end, the after effects of cross approval are obtained.

```
mod_hist = cross_validation(10, train_img, train_lbls, model)
```

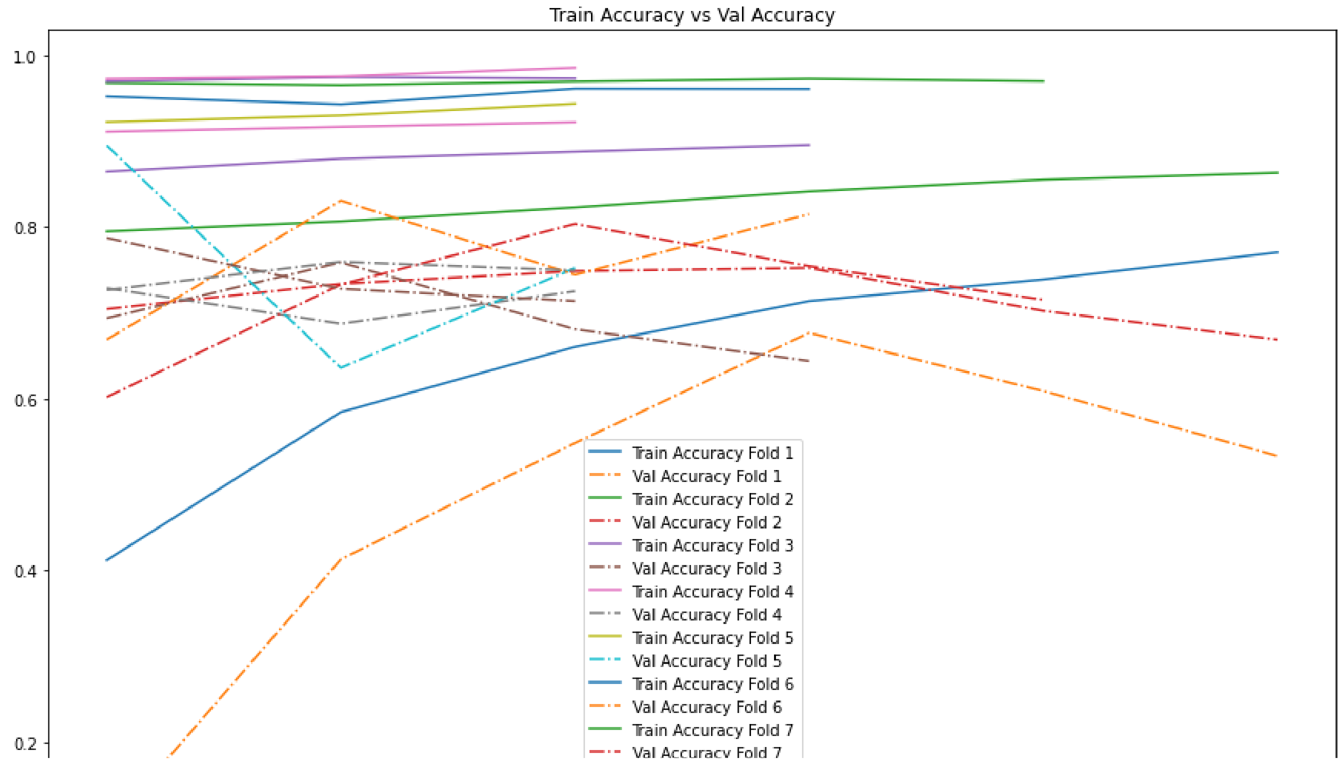
```
Training on Fold:  1
Epoch 1/20
395/395 [==============================] - 130s 236ms/step - loss: 1.7019 - accuracy
Epoch 2/20
395/395 [==============================] - 90s 228ms/step - loss: 1.1643 - accuracy:
Epoch 3/20
395/395 [==============================] - 91s 231ms/step - loss: 0.9530 - accuracy:
Epoch 4/20
395/395 [==============================] - 92s 234ms/step - loss: 0.8553 - accuracy:
Epoch 5/20
395/395 [==============================] - 93s 235ms/step - loss: 0.7504 - accuracy:
Epoch 6/20
```

```
395/395 [==============================] - 93s 235ms/step - loss: 0.6694 - accuracy:
Epoch 00006: early stopping
==================================================================================


Training on Fold:  2
Epoch 1/20
395/395 [==============================] - 93s 236ms/step - loss: 0.6204 - accuracy:
Epoch 2/20
395/395 [==============================] - 93s 236ms/step - loss: 0.5690 - accuracy:
Epoch 3/20
395/395 [==============================] - 93s 236ms/step - loss: 0.5338 - accuracy:
Epoch 4/20
395/395 [==============================] - 93s 236ms/step - loss: 0.4872 - accuracy:
Epoch 5/20
395/395 [==============================] - 93s 236ms/step - loss: 0.4529 - accuracy:
Epoch 6/20
395/395 [==============================] - 93s 235ms/step - loss: 0.4189 - accuracy:
Epoch 00006: early stopping
==================================================================================


Training on Fold:  3
Epoch 1/20
395/395 [==============================] - 93s 236ms/step - loss: 0.4111 - accuracy:
Epoch 2/20
395/395 [==============================] - 93s 236ms/step - loss: 0.3673 - accuracy:
Epoch 3/20
395/395 [==============================] - 93s 236ms/step - loss: 0.3421 - accuracy:
Epoch 4/20
395/395 [==============================] - 93s 235ms/step - loss: 0.3125 - accuracy:
Epoch 00004: early stopping
==================================================================================


Training on Fold:  4
Epoch 1/20
395/395 [==============================] - 93s 236ms/step - loss: 0.2778 - accuracy:
Epoch 2/20
395/395 [==============================] - 93s 235ms/step - loss: 0.2519 - accuracy:
Epoch 3/20
395/395 [==============================] - 93s 235ms/step - loss: 0.2408 - accuracy:
Epoch 00003: early stopping
==================================================================================
```

```
plt.figure(figsize=(15,10))
plt.title('Accuracy vs Epochs')
for i in range(0,9):
  plt.plot(mod_hist[i].history['accuracy'], label='Training Fold '+str(i+1))

plt.legend()
plt.show()
```




```
plt.figure(figsize=(15,10))
plt.title('Train Accuracy vs Val Accuracy')
for i in range(0,9):
  plt.plot(mod_hist[i].history['accuracy'], label='Train Accuracy Fold '+str(i+1))
  plt.plot(mod_hist[i].history['val_accuracy'], label='Val Accuracy Fold '+str(i+1), linestyl
plt.legend()
plt.show()
```



6.Validation of test data

```
# Here we are finding model accuracy using test data, at first we are reading test images and
unzipfile('seg_test.zip')
test_img, test_cls= rd_image('/content/seg_test/seg_test', img_cat)
```

```
#Here we are converting test images into numpy array
test_img = np.array(test_img)
test_cls = np.array(test_cls)
```

```
#Here we are obtaining the shape of images and labels
print('Shape of Images:', test_img.shape)
print('Shape of Classes:', test_cls.shape)
```

```
Shape of Images: (3000, 150, 150, 3)
Shape of Classes: (3000,)
```

```
#Here we are doing Label encoding for the test classes
test_lbls = encoder(test_cls)
test_lbls = np.array(test_lbls)
```

Here we are loading the model that was saved by ModelCheckpoint

```
model.evaluate(test_img, test_lbls)
```

```
94/94 [==============================] - 9s 94ms/step - loss: 1.1157 - accuracy: 0.8473
[1.1156854629516602, 0.8473333120346069]
```

7.Prediction result

Here we are Predicting the labels for the images that are new

```
unzipfile('seg_pred.zip')
img_prediction, unknown = rd_image('/content/seg_pred/seg_pred', [])
```

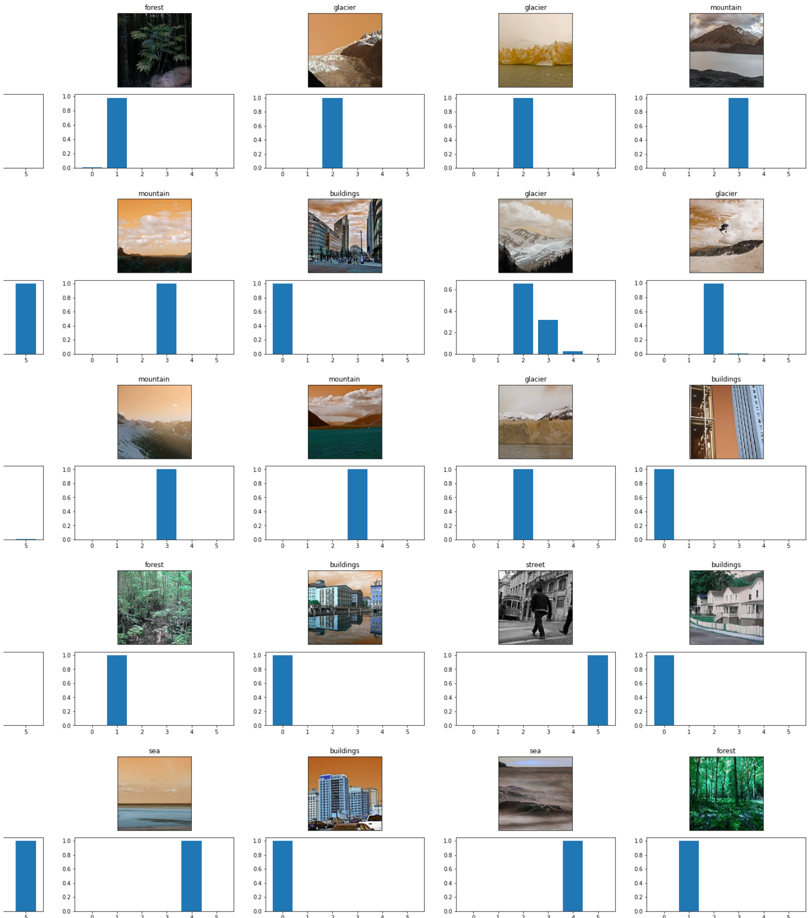
```
img_prediction = np.array(img_prediction)
img_prediction.shape
```

```
(7301, 150, 150, 3)
```

```
def get_clslbl(class_code):
    labels = {2:'glacier', 4:'sea', 0:'buildings', 1:'forest', 5:'street', 3:'mountain'}
    return labels[class_code]
```

```
# Herw we are visualizing the predicted classes.
fig = plt.figure(figsize=(30, 30))
outer = gridspec.GridSpec(5, 5, wspace=0.2, hspace=0.2)

for i in range(25):
    inner = gridspec.GridSpecFromSubplotSpec(2, 1,subplot_spec=outer[i], wspace=0.1, hspace=0
    random_num = randint(0,len(img_prediction))
    img_pred = np.array([img_prediction[random_num]])
    pred_class = get_clslbl(model.predict_classes(img_pred)[0])
    pred_prob = model.predict(img_pred).reshape(6)
    for j in range(2):
        if (j%2) == 0:
            ax = plt.Subplot(fig, inner[j])
            ax.imshow(img_pred[0])
            ax.set_title(pred_class)
            ax.set_xticks([])
            ax.set_yticks([])
            fig.add_subplot(ax)
        else:
            ax = plt.Subplot(fig, inner[j])
            ax.bar([0,1,2,3,4,5],pred_prob)
            fig.add_subplot(ax)


fig.show()
```

```
l/lib/python3.7/dist-packages/tensorflow/python/keras/engine/s
s.warn('`model.predict_classes()` is deprecated and '
```



8.Metrics

```
pred = model.predict(test_img)
```

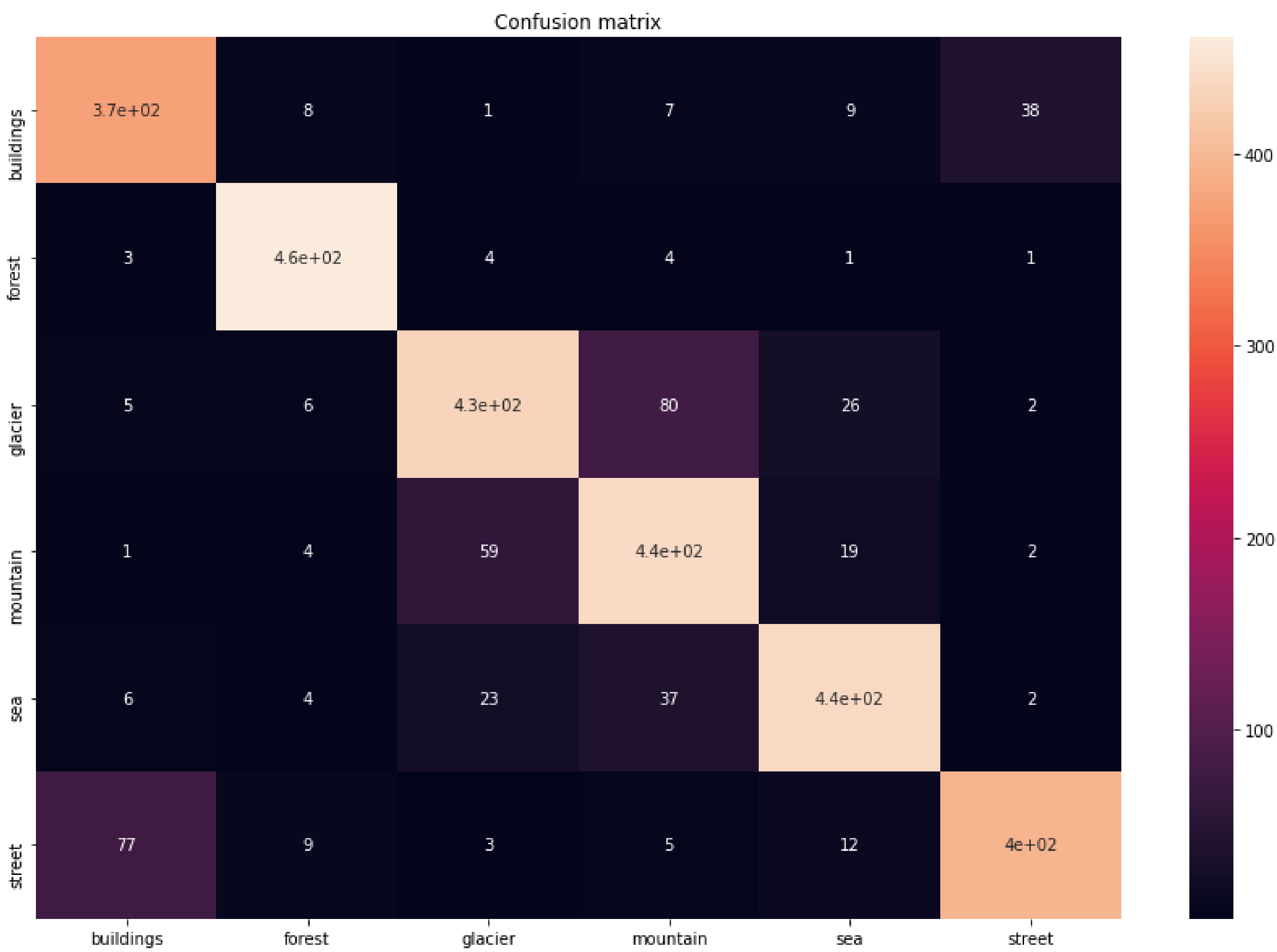
```
prediction_lbl = np.argmax(pred, axis = 1)
```

```
import sklearn.metrics as metrics
import seaborn as sn
```

Heatmap

Here we are plotting heat map

```
ConfMat = confusion_matrix(test_lbls, prediction_lbl)
fig, ax = plt.subplots(figsize =(15,10))
ax = plt.axes()
sn.heatmap(ConfMat, annot=True,
           annot_kws={"size": 10},
           xticklabels=img_cat,
           yticklabels=img_cat, ax = ax)
ax.set_title('Confusion matrix')
plt.show()
```



```
cls_names = ['mountain', 'street', 'glacier', 'buildings', 'sea', 'forest']

def mislabld_image(cls_names, test_img, test_lbls, prediction_lbl):
    indi = (test_lbls == prediction_lbl)
    mislabld_ind = np.where(indi == 0)
    mislabld_img = test_img[mislabld_ind]
    mislabld_lbl = prediction_lbl[mislabld_ind]

    title = "Some examples of mislabeled images by the classifier:"
    display_examples(cls_names,  mislabld_img, mislabld_lbl)
```

Transfer learning process

VGG i.e., visual geometry group is used.

```
data_gen = ImageDataGenerator(rescale=1/255.,
                              horizontal_flip=True,
                              width_shift_range=0.1,
                              height_shift_range=0.1)

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

```
#Here the data generators are assigned
from tensorflow.keras.preprocessing.image import ImageDataGenerator

inp_shp = (150,150)
batch_sz = 16
train_gen = data_gen.flow_from_directory('/content/seg_train/seg_train',
                                         target_size = inp_shp,
                                         class_mode='categorical',
                                         batch_size=batch_sz,
                                         shuffle=False)

test_gen = test_datagen.flow_from_directory('/content/seg_test/seg_test',
                                         target_size = inp_shp,
                                         class_mode='categorical',
                                         batch_size=batch_sz,
                                         shuffle=False)
```

```
Found 14034 images belonging to 6 classes.
Found 3000 images belonging to 6 classes.
```

```
model = Sequential()
L2 = tf.keras.regularizers.l2(0.001)
inp_shape = (150,150,3)
```

```
model = tf.keras.applications.VGG19(include_top=False, input_shape=inp_shape)
for layer in model.layers:
    layer.trainable=False
flat = Flatten()(model.layers[-1].output)
hidden1 = Dense(128,activation='relu')(flat)
output = Dense(6,activation='softmax')(hidden1)

model = Model(inputs=model.inputs, outputs=output)
model.summary()
```

```
Model: "model_4"
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
input_7 (InputLayer)        [(None, 150, 150, 3)]     0

block1_conv1 (Conv2D)       (None, 150, 150, 64)      1792

block1_conv2 (Conv2D)       (None, 150, 150, 64)      36928

block1_pool (MaxPooling2D)  (None, 75, 75, 64)        0

block2_conv1 (Conv2D)       (None, 75, 75, 128)       73856

block2_conv2 (Conv2D)       (None, 75, 75, 128)       147584

block2_pool (MaxPooling2D)  (None, 37, 37, 128)       0

block3_conv1 (Conv2D)       (None, 37, 37, 256)       295168

block3_conv2 (Conv2D)       (None, 37, 37, 256)       590080

block3_conv3 (Conv2D)       (None, 37, 37, 256)       590080

block3_conv4 (Conv2D)       (None, 37, 37, 256)       590080

block3_pool (MaxPooling2D)  (None, 18, 18, 256)       0

block4_conv1 (Conv2D)       (None, 18, 18, 512)       1180160

block4_conv2 (Conv2D)       (None, 18, 18, 512)       2359808

block4_conv3 (Conv2D)       (None, 18, 18, 512)       2359808

block4_conv4 (Conv2D)       (None, 18, 18, 512)       2359808

block4_pool (MaxPooling2D)  (None, 9, 9, 512)         0

block5_conv1 (Conv2D)       (None, 9, 9, 512)         2359808

block5_conv2 (Conv2D)       (None, 9, 9, 512)         2359808

block5_conv3 (Conv2D)       (None, 9, 9, 512)         2359808

```

```
block5_conv4 (Conv2D)        (None, 9, 9, 512)         2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 4, 4, 512)         0
_________________________________________________________________
flatten_7 (Flatten)          (None, 8192)              0
_________________________________________________________________
dense_16 (Dense)             (None, 128)               1048704
_________________________________________________________________
dense_17 (Dense)             (None, 6)                 774
=================================================================
Total params: 21,073,862
Trainable params: 1,049,478
Non-trainable params: 20,024,384
```

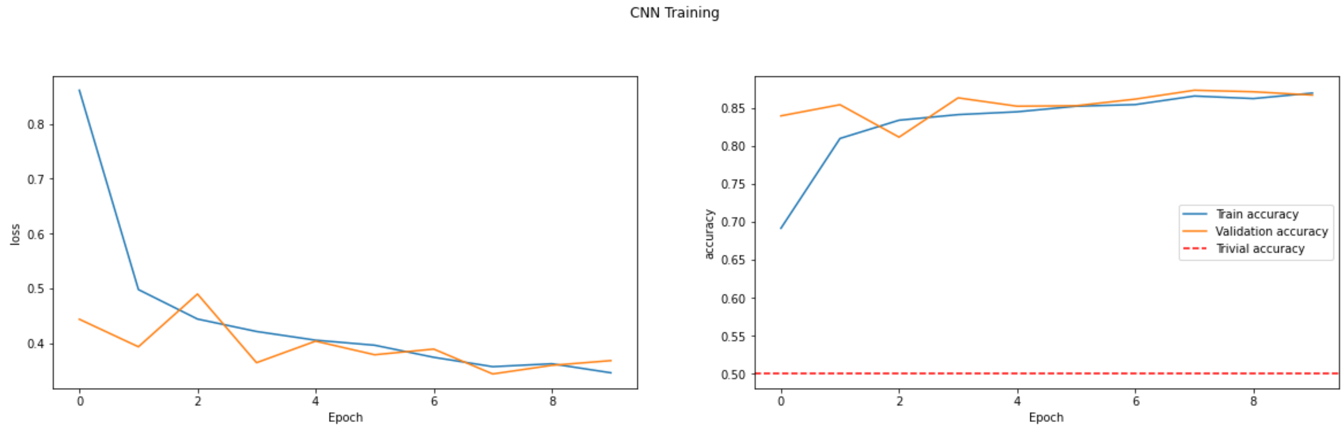
```
model.compile(loss = 'categorical_crossentropy', optimizer= optimizers.Adam(0.001), metrics=[
```

```
history = model.fit(train_gen,
                   epochs=10,
                   validation_data = test_gen, )
```

```
Epoch 1/10
878/878 [==============================] - 104s 118ms/step - loss: 1.3438 - accuracy: 0
Epoch 2/10
878/878 [==============================] - 93s 106ms/step - loss: 0.5176 - accuracy: 0.8
Epoch 3/10
878/878 [==============================] - 94s 107ms/step - loss: 0.4460 - accuracy: 0.8
Epoch 4/10
878/878 [==============================] - 94s 107ms/step - loss: 0.4076 - accuracy: 0.8
Epoch 5/10
878/878 [==============================] - 94s 106ms/step - loss: 0.4063 - accuracy: 0.8
Epoch 6/10
878/878 [==============================] - 93s 106ms/step - loss: 0.3882 - accuracy: 0.8
Epoch 7/10
878/878 [==============================] - 94s 107ms/step - loss: 0.3842 - accuracy: 0.8
Epoch 8/10
878/878 [==============================] - 93s 106ms/step - loss: 0.3580 - accuracy: 0.8
Epoch 9/10
878/878 [==============================] - 96s 110ms/step - loss: 0.3549 - accuracy: 0.8
Epoch 10/10
878/878 [==============================] - 94s 107ms/step - loss: 0.3365 - accuracy: 0.8
```

```
fig, ax = plt.subplots(1,2, figsize=(20,5))
for i, m in enumerate(['loss', 'accuracy']):
    ax[i].plot(history.history[m], label=('Train '+m))
    ax[i].plot(history.history['val_'+m], label='Validation '+m)
    if m == 'accuracy': ax[i].axhline(0.5, c='r', ls='--', label='Trivial accuracy')
    ax[i].set_xlabel('Epoch')
    ax[i].set_ylabel(m)
plt.suptitle('CNN Training', y=1.05)
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f37c4790ad0>
```



9. Conclusion

```
m = model.evaluate(test_gen)
print(f'The Loss of evluation is: {m[0]}')
print(f'The Accuracy of evluation is: {m[1]:.2%}')
```

```
188/188 [==============================] - 8s 44ms/step - loss: 0.3686 - accuracy: 0.866
The Loss of evluation is: 0.36861076951026917
The Accuracy of evluation is: 86.67%
```

CNN Model has same accuracy,predicted image is 86% correct and 14% incorrect

Transfer learning model also has same accuracy,predicted image is 86% correct and 14% incorrect.