

Natural scene image classification

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Introduction

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
- 14k images in Train, 3k in Test and 7k in Prediction

Exploratory Data Analysis (EDA)

```
import numpy as np
import os
from sklearn.metrics import confusion_matrix
import seaborn as sn; sn.set(font_scale=1.4)
from sklearn.utils import shuffle
import matplotlib.pyplot as plt
import cv2
import tensorflow as tf
from tqdm import tqdm
```

```
class_names = ['mountain', 'street', 'glacier', 'buildings', 'sea', 'forest']  
class_names_label = {class_name:i for i, class_name in enumerate(class_names)}  
  
nb_classes = len(class_names)  
  
IMAGE_SIZE = (150, 150)
```

```
datasets = ['../input/seg_train/seg_train', '../input/seg_test/seg_test']
output = []

# Iterate through training and test sets
for dataset in datasets:

    images = []
    labels = []

    print("Loading {}".format(dataset))

    # Iterate through each folder corresponding to a category
    for folder in os.listdir(dataset):
        label = class_names_label[folder]

        # Iterate through each image in our folder
        for file in tqdm(os.listdir(os.path.join(dataset, folder))):

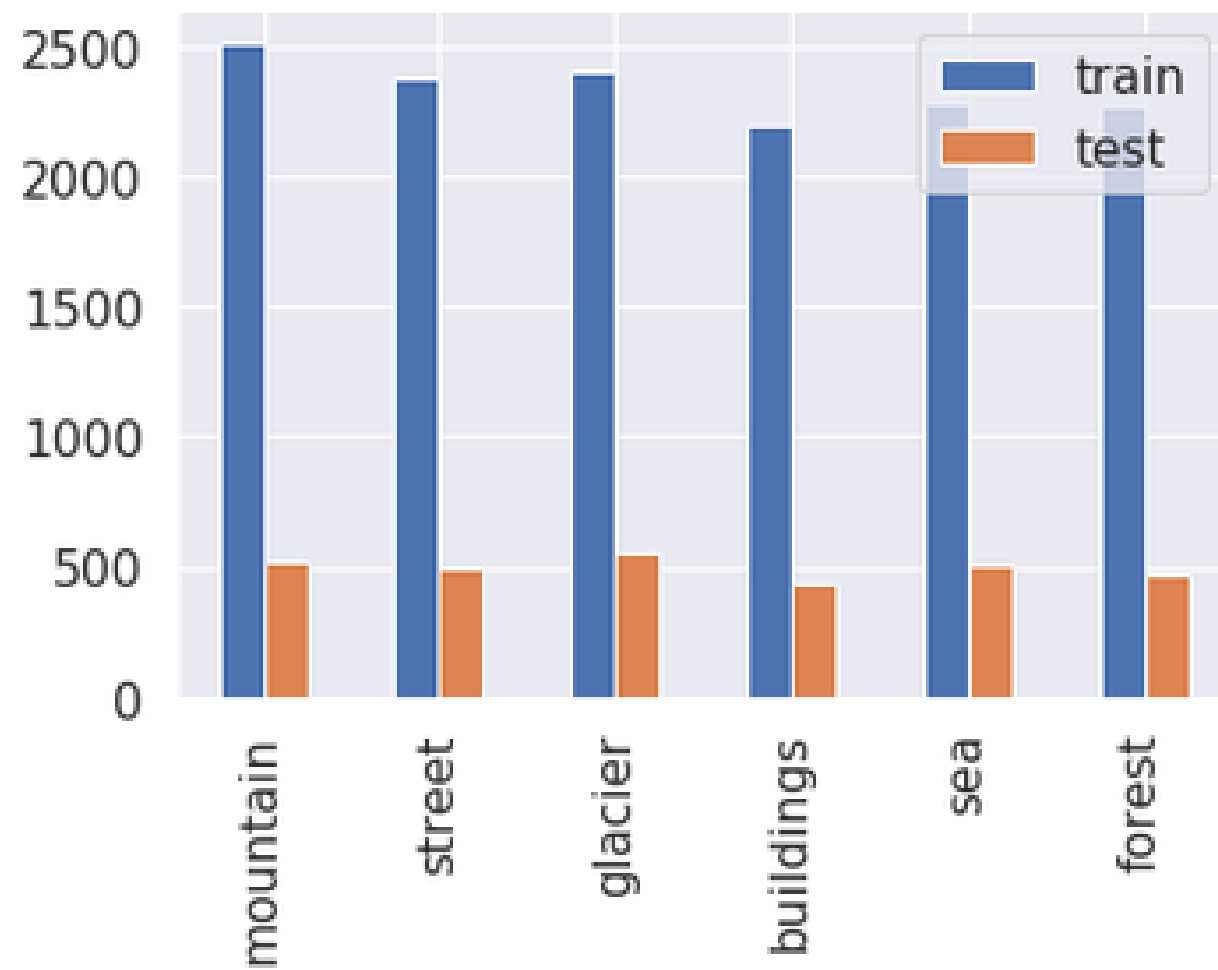
            # Get the path name of the image
            img_path = os.path.join(os.path.join(dataset, folder), file)

            # Open and resize the img
            image = cv2.imread(img_path)
            image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
            image = cv2.resize(image, IMAGE_SIZE)

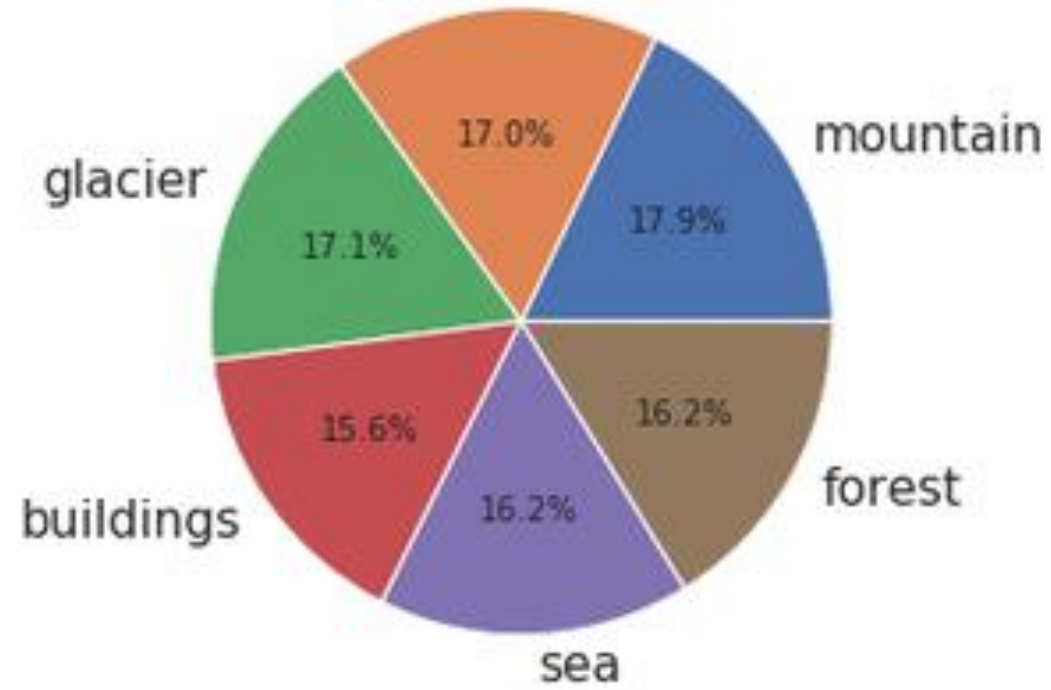
            # Append the image and its corresponding label to the output
            images.append(image)
            labels.append(label)

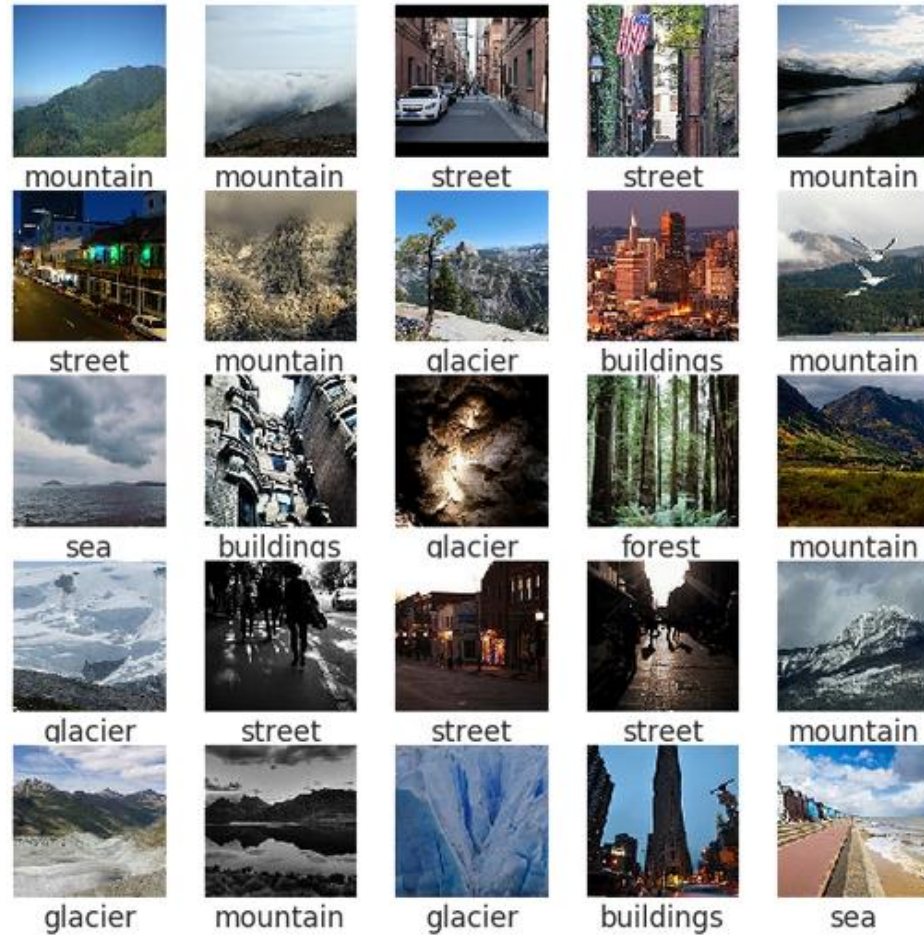
    images = np.array(images, dtype = 'float32')
    labels = np.array(labels, dtype = 'int32')

    output.append((images, labels))
```



Proportion of each observed category
street





Model configuration

```
model = tf.keras.Sequential([
    tf.keras.layers.Conv2D(32, (3, 3), activation = 'relu', input_shape = (150, 150, 3)),
    tf.keras.layers.MaxPooling2D(2,2),
    tf.keras.layers.Conv2D(32, (3, 3), activation = 'relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(128, activation=tf.nn.relu),
    tf.keras.layers.Dense(6, activation=tf.nn.softmax)
])
```

Model compilation and training

```
model.compile(optimizer = 'adam', loss = 'sparse_categorical_crossentropy', metrics=['accuracy'])
```

```
history = model.fit(train_images, train_labels, batch_size=128, epochs=20, validation_split = 0.2)
```

Model evaluation- 78%

```
test_loss = model.evaluate(test_images, test_labels)
```

```
3000/3000 [=====] - 1s 264us/sample - loss: 1.0085 - acc: 0.7837
```

```
predictions = model.predict(test_images)    # Vector of probabilities
pred_labels = np.argmax(predictions, axis = 1) # We take the highest probability

display_random_image(class_names, test_images, pred_labels)
```

Image #1888 : glacier





mountain



glacier



glacier



glacier



glacier



mountain



mountain



mountain



glacier



mountain



mountain



glacier



mountain



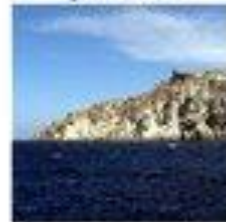
glacier



mountain



glacier



mountain



glacier



street



mountain



glacier



glacier



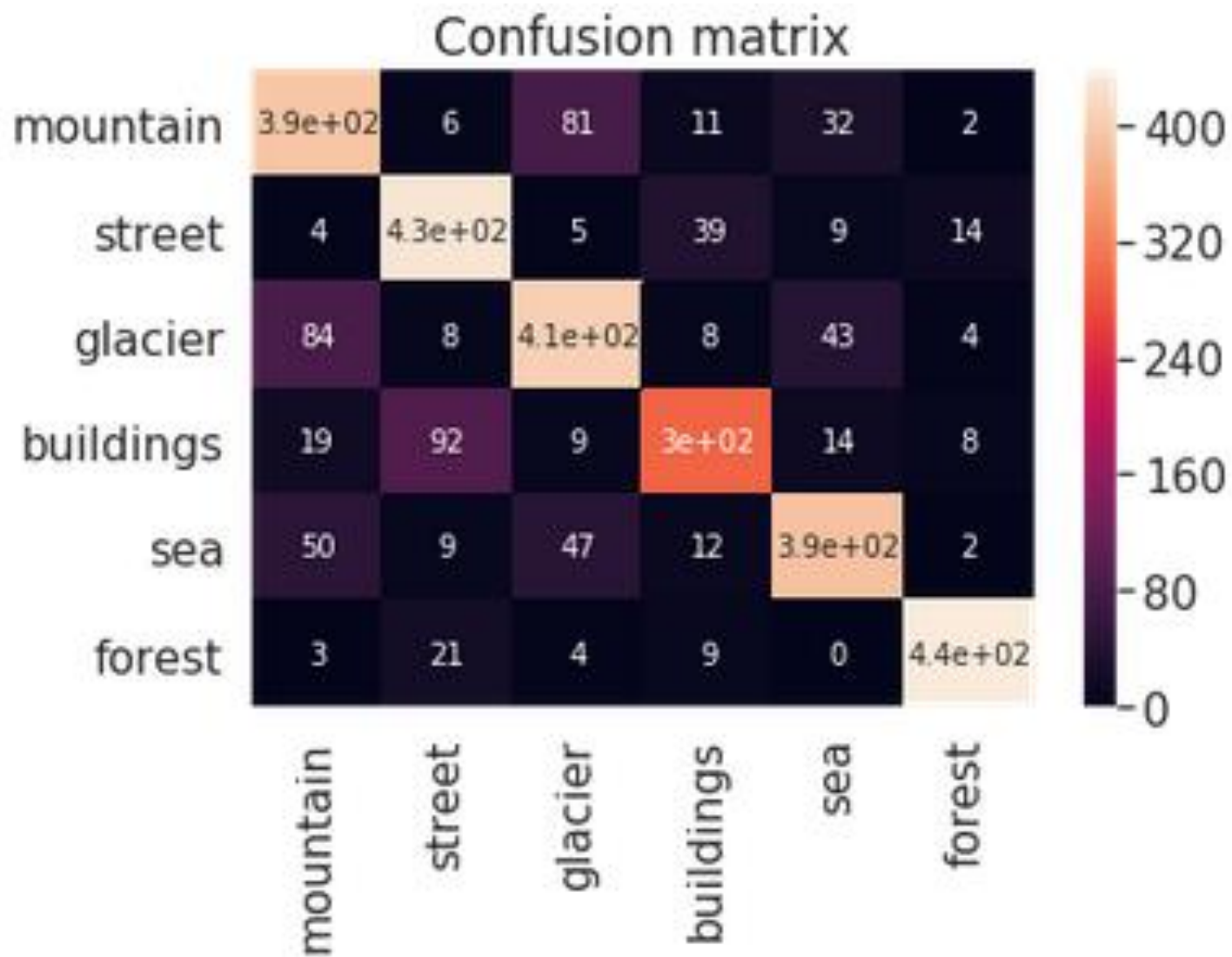
buildings



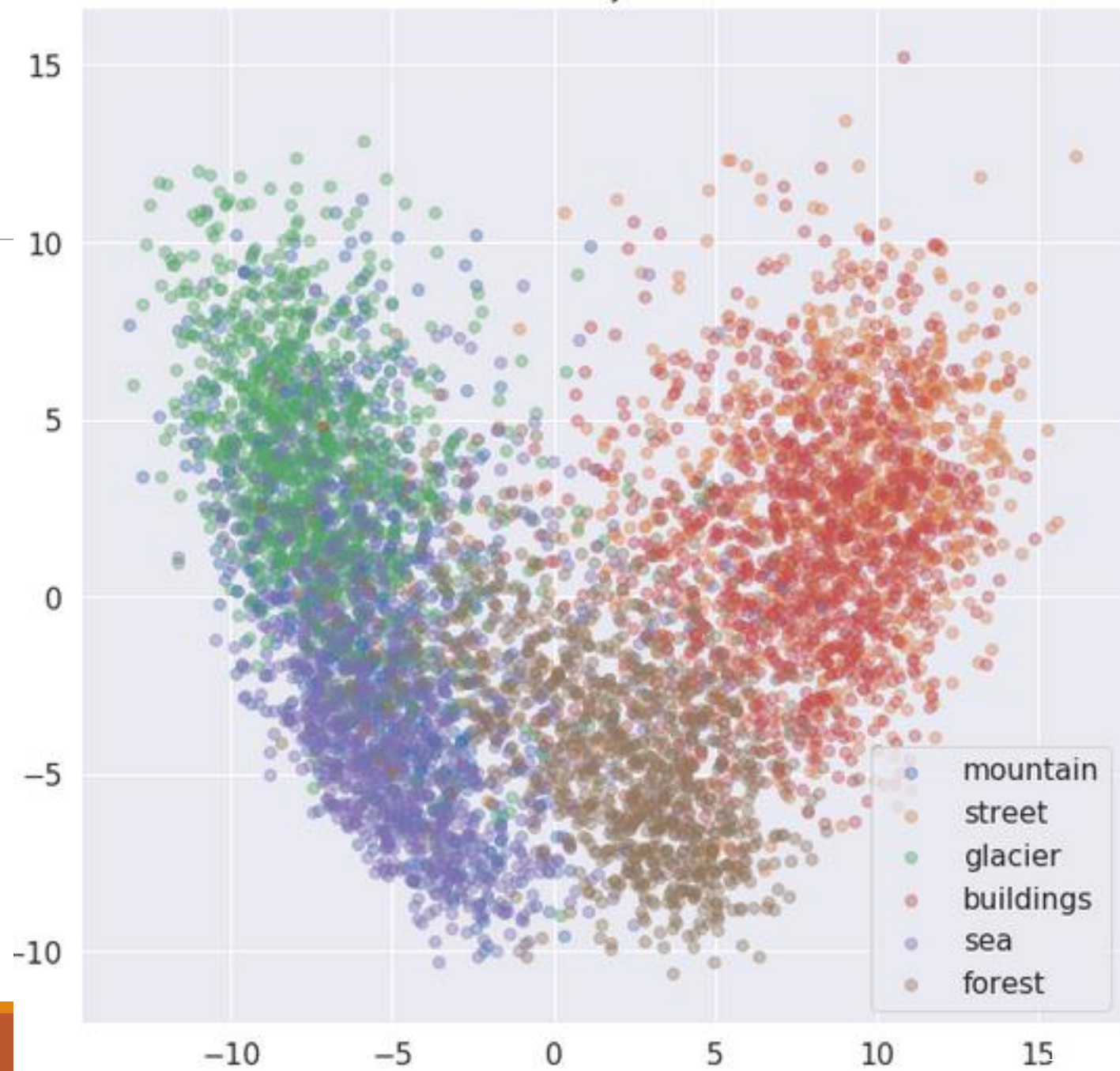
mountain



mountain



PCA Projection



VGG Model

imports

```
from keras.applications.vgg16 import VGG16  
from keras.preprocessing import image  
from keras.applications.vgg16 import preprocess_input
```

```
model2 = tf.keras.Sequential([
    tf.keras.layers.Flatten(input_shape = (x, y, z)),
    tf.keras.layers.Dense(50, activation=tf.nn.relu),
    tf.keras.layers.Dense(6, activation=tf.nn.softmax)
])

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

history2 = model2.fit(train_features, train_labels, batch_size=128, epochs=15, validation_split = 0.2)
```

VGG evaluation – 87%

```
test_loss = model2.evaluate(test_features, test_labels)
```

```
3000/3000 [=====] - 0s 90us/sample - loss: 0.4345 - acc: 0.8730
```

```
from keras.layers import Input, Dense, Conv2D, Activation, MaxPooling2D, Flatten

model2 = VGG16(weights='imagenet', include_top=False)

input_shape = model2.layers[-4].get_input_shape_at(0) # get the input shape of desired layer
layer_input = Input(shape = (9, 9, 512)) # a new input tensor to be able to feed the desired layer
# https://stackoverflow.com/questions/52800025/keras-give-input-to-intermediate-layer-and-get-final-output

x = layer_input
for layer in model2.layers[-4::1]:
    x = layer(x)

x = Conv2D(64, (3, 3), activation='relu')(x)
x = MaxPooling2D(pool_size=(2, 2))(x)
x = Flatten()(x)
x = Dense(100, activation='relu')(x)
x = Dense(6, activation='softmax')(x)

# create the model
new_model = Model(layer_input, x)
```

Model compilation and training

```
new_model.compile(optimizer = 'adam', loss = 'sparse_categorical_crossentropy',  
metrics=['accuracy'])
```

```
history = new_model.fit(train_features, train_labels, batch_size=128, epochs=10,  
validation_split = 0.2)
```



```
from sklearn.metrics import accuracy_score

predictions = new_model.predict(test_features)
pred_labels = np.argmax(predictions, axis = 1)
print("Accuracy : {}".format(accuracy_score(test_labels, pred_labels)))
```

```
Accuracy : 0.8933333333333333
```

| Model | CNN | VGG | VGG(fine-tune) |
|-----------|-----|-----|----------------|
| Accouracy | 78% | 87% | 89% |

conclusion

Firstly, the dataset is analyzed

A basic CNN is trained and tested but the model has an error while predicting mountain and glacier and the accuracy is 78%

PCA is used to understand the behavior of data

Then, VGG is trained to resolve the aforementioned errors and accuracy is improved to 87%

For further enhancement in accuracy, the model is fine-tuned

The comparison results shows that with fine-tuned VGG the accuracy is improved up to 89%

Thank You