Computer Vision

Course Code: MEAD-652

Lab Practical File

Submitted by

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Center for Development of Advanced Computing, Noida

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Exercise-1

i. Matrix Operations using Numpy:

Code:

```
import numpy as np

M = np.array(
    [
        [1, 2, 3],
        [4, 5, 6],
        [7, 8, 9],
        [0, 2, 2],
    ]
)

a = np.array(
    [
        [1],
        [1],
        [0],
    ]
)

b = np.array(
    [
        [-1],
        [2],
        [5],
    ]
)

c = np.array(
    [
        [0],
        [2],
        [3],
        [2],
    ]
)



print(np.dot(a.T, b))
print(np.multiply(a, b).T)
print(np.multiply(a, b).T)
print(M * a.T)
print(np.sort(M))
```

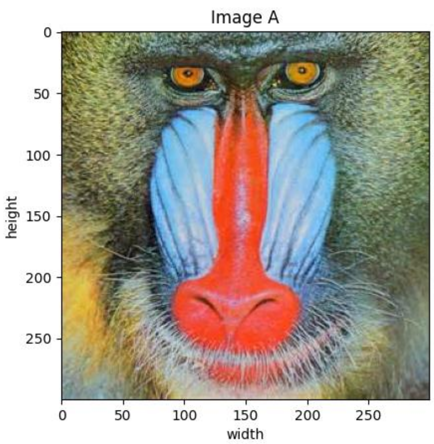
Output:

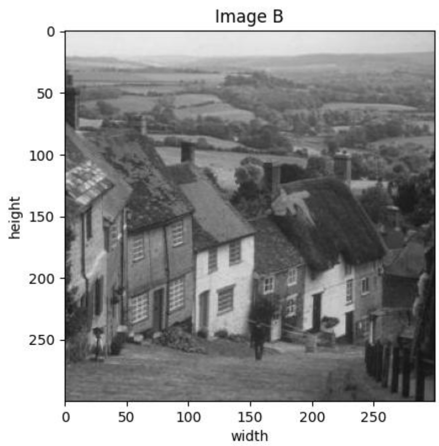
```
● (CV) vscode → /workspaces/cdac-labwork/sem-2/CV (main) $ python exercise-1/1.py
[[1]]
[[-1  2  0]]
[[-1  2  0]]
[[1 2 0]
 [4 5 0]
 [7 8 0]
 [0 2 0]]
[[1 2 3]
 [4 5 6]
 [7 8 9]
 [0 2 2]]
○ (CV) vscode → /workspaces/cdac-labwork/sem-2/CV (main) $ 
```

ii. Basic Image Manipulations:

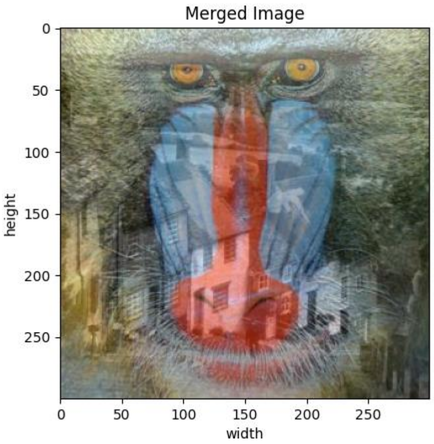
Code:

```python
import numpy as np
import matplotlib.pyplot as plt
import skimage as sk

imageA = sk.io.imread('./image1.jpg')
imageB = sk.io.imread('./image2.jpg')

plt.figure()
plt.title('Image A')
plt.xlabel('width')
plt.ylabel('height')
plt.imshow(imageA)

plt.figure()
plt.title('Image B')
plt.xlabel('width')
plt.ylabel('height')
plt.imshow(imageB)
```



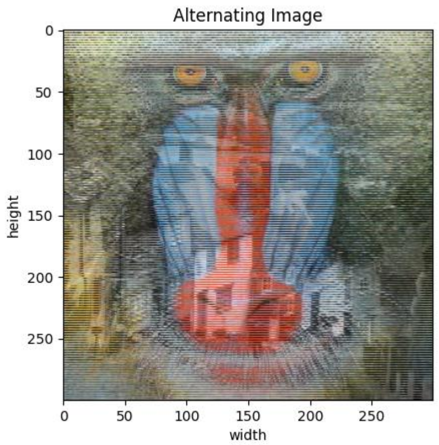


```
# Convert the images to double precision
imageA = imageA.astype(np.float64)
imageB = imageB.astype(np.float64)

# rescale them to stretch from minimum value 0 to maximum value 1
imageA = (imageA - np.min(imageA)) / (np.max(imageA) - np.min(imageA))
imageB = (imageB - np.min(imageB)) / (np.max(imageB) - np.min(imageB))

merged_image = imageA + imageB
merged_image = (merged_image - np.min(merged_image)) / (np.max(merged_image) -
np.min(merged_image))

# set size of the result image
merged_image = (merged_image * 255).astype(np.uint8)

# print merged image
plt.figure()
plt.title('Merged Image')
plt.xlabel('width')
plt.ylabel('height')
plt.imshow(merged_image)

# save merged image
sk.io.imsave('./merged.jpg', merged_image)
```



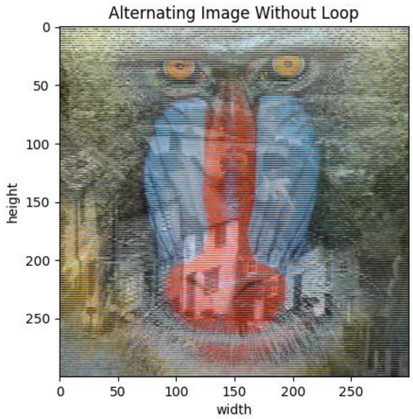

```
height, width, channels = imageA.shape
combined_image = np.zeros_like(imageA)

combined_image[:, :width//2, :] = imageA[:, :width//2, :]
combined_image[:, width//2:, :] = imageB[:, width//2:, :]

# print combined image
plt.figure()
plt.title('Combined Image')
plt.xlabel('width')
plt.ylabel('height')
plt.imshow(combined_image)

# set size of the result image
combined_image = (combined_image * 255).astype(np.uint8)

# save combined image
sk.io.imsave('./combined.jpg', combined_image)
```


```
alternating_image = np.zeros_like(imageA)
for i in range(height):
    if i % 2 == 0:
        alternating_image[i, :, :] = imageA[i, :, :]
    else:
        alternating_image[i, :, :] = imageB[i, :, :]

# set size of the result image
alternating_image = (alternating_image * 255).astype(np.uint8)

# print alternating image
plt.figure()
plt.title('Alternating Image')
plt.xlabel('width')
plt.ylabel('height')
plt.imshow(alternating_image)

sk.io.imsave('alternating_image.jpg', alternating_image)
```

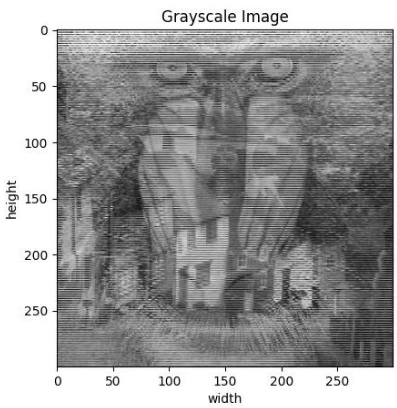



```
rows_imageA = imageA[::2, :, :]
rows_imageB = imageB[1::2, :, :]

alternating_image_without_loop = np.zeros_like(imageA)
alternating_image_without_loop[::2, :, :] = rows_imageA
alternating_image_without_loop[1::2, :, :] = rows_imageB
```

```
# print alternating image
plt.figure()
plt.title('Alternating Image Without Loop')
plt.xlabel('width')
plt.ylabel('height')
plt.imshow(alternating_image_without_loop)

# set size of the result image
alternating_image_without_loop = (alternating_image_without_loop * 255).astype(np.uint8)
sk.io.imsave('alternating_image_without_loop.jpg', alternating_image_without_loop)
```

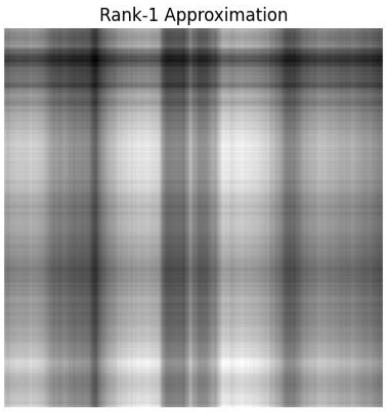



```
grayscale_image = sk.color.rgb2gray(alternating_image_without_loop)

# set size of the result image
grayscale_image = (grayscale_image * 255).astype(np.uint8)

# print grayscale image
plt.figure()
plt.title('Grayscale Image')
plt.xlabel('width')
plt.ylabel('height')
plt.imshow(grayscale_image, cmap='gray')
sk.io.imsave('grayscale_image.png', grayscale_image)
```

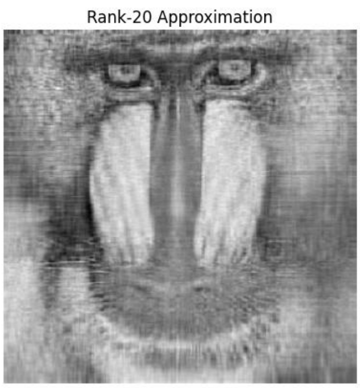


iii. Singular Value Decomposition

```
import numpy as np
import matplotlib.pyplot as plt
from skimage import io

imageA_grey = io.imread('./image1.jpg', as_gray=True)

U, S, Vt = np.linalg.svd(imageA_grey, full_matrices=False)
rank = 1
rank_1_approx = U[:, :rank] @ np.diag(S[:rank]) @ Vt[:rank, :]

# Save and display the rank-1 approximation
plt.imshow(rank_1_approx, cmap='gray')
plt.title(f'Rank-{rank} Approximation')
plt.axis('off')
plt.savefig('rank_1_approx.jpg', bbox_inches='tight', pad_inches=0)
plt.show()
```




```
rank = 20
rank_20_approx = U[:, :rank] @ np.diag(S[:rank]) @ Vt[:rank, :]

# Save and display the rank-20 approximation
plt.imshow(rank_20_approx, cmap='gray')
plt.title(f'Rank-{rank} Approximation')
plt.axis('off')
plt.savefig('rank_20_approx.png', bbox_inches='tight', pad_inches=0)
plt.show()
```



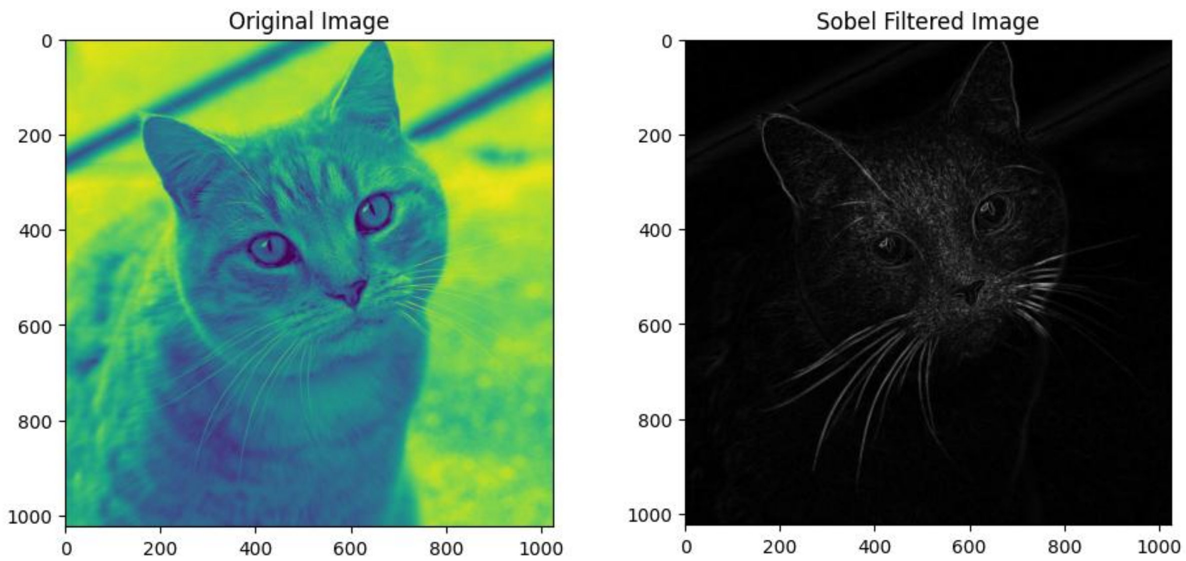
Exercise-2

Objective: Sobel Edge Detection

Code:

```python
import skimage as sk
import matplotlib.pyplot as plt

image = sk.io.imread("./image.png", sk.color.rgb2gray)
plt.imshow(image)
plt.title('Original Image')
plt.show()


edges = sk.filters.sobel(image)

plt.imshow(edges, cmap='gray')
plt.title('Sobel Filtered Image')
plt.show()
```

Output:



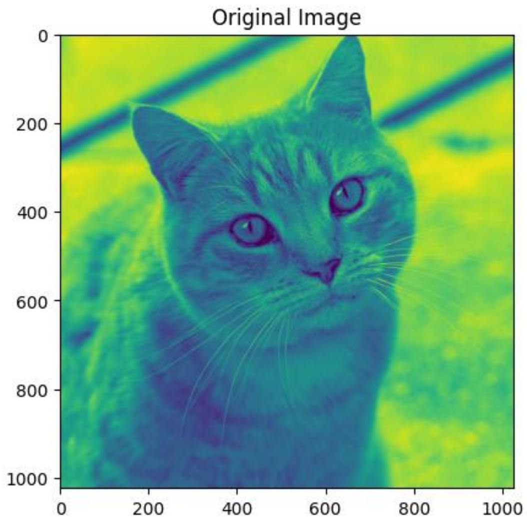
Exercise-3

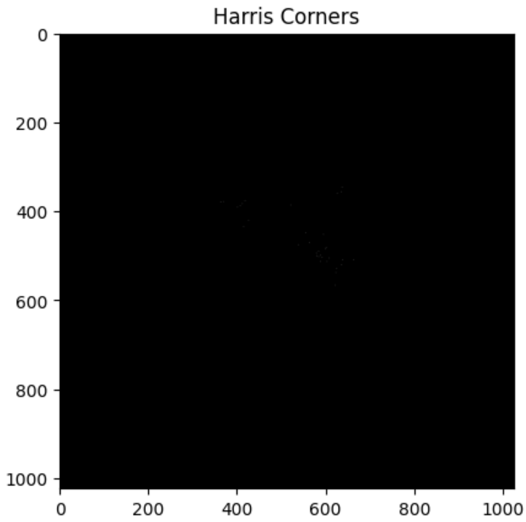
Objective: Harris Corner Detection

Code:

```python
import skimage as sk
import matplotlib.pyplot as plt
import numpy as np

image = sk.io.imread('./image.png', sk.color.rgb2gray)
plt.imshow(image)
plt.title('Original Image')
plt.show()

harris = sk.feature.corner_harris(image)
corners = sk.feature.corner_peaks(harris, min_distance=2, threshold_rel=0.02)

corner_image = np.zeros_like(image)
corner_image[corners[:, 0], corners[:, 1]] = 1

plt.imshow(corner_image, cmap='gray')
plt.title('Harris Corners')
plt.show()
```

Ouput:



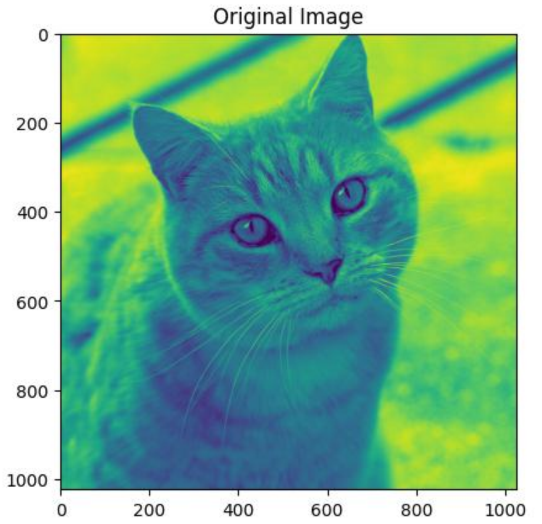


Exercise-4

Objective: 2D - Transformations on an image

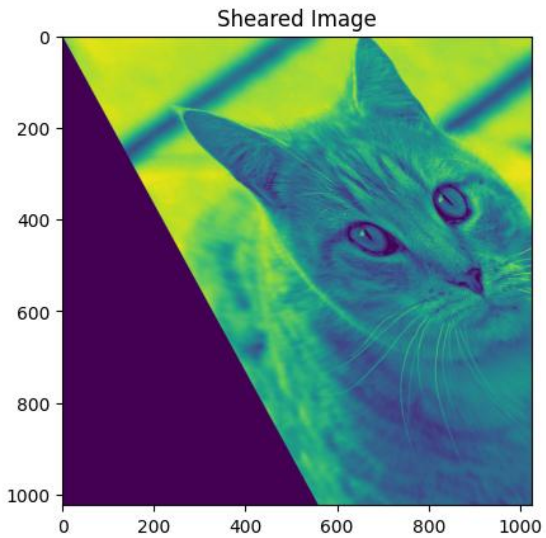
Code:

```
import skimage as sk
import matplotlib.pyplot as plt
image = sk.io.imread("../image.png", as_gray=True)
plt.title("Original Image")
plt.imshow(image)
```



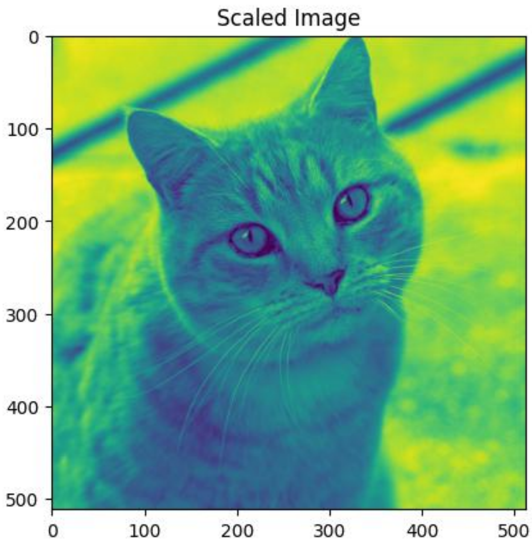
1. Shear

```
shear = sk.transform.warp(image,sk.transform.AffineTransform(shear=0.5))
plt.title("Sheared Image")
plt.imshow(shear)
```



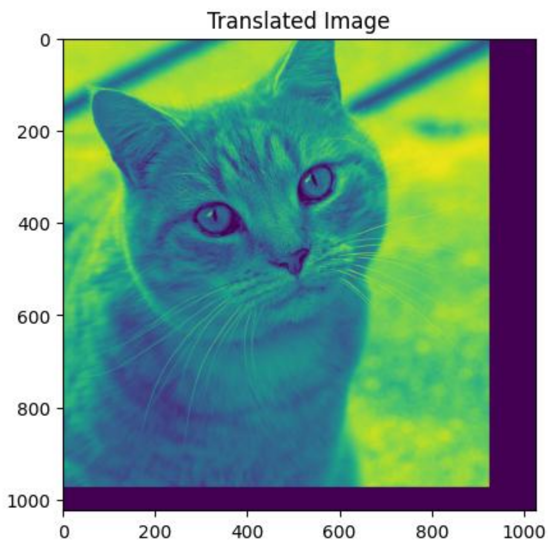
2. Scale

```
1. scaled = sk.transform.rescale(image, 0.5)
2. plt.title("Scaled Image")
3. plt.imshow(scaled)
4. plt.show()
```



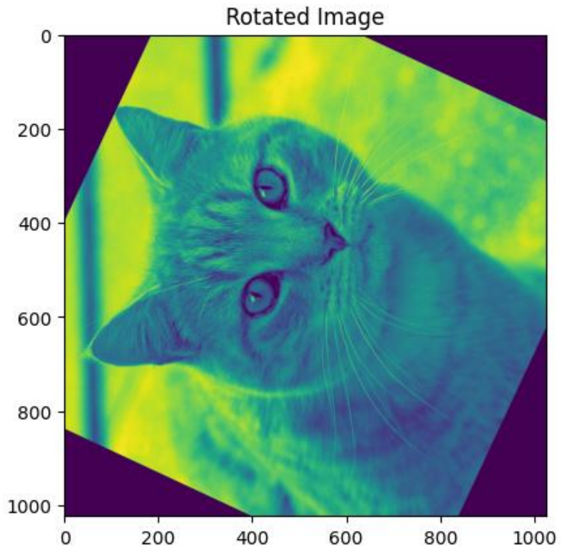
3. Transition

```
1. transition = sk.transform.warp(image,
sk.transform.AffineTransform(translation=(100, 50)))
2. plt.title("Translated Image")
3. plt.imshow(transition)
4. plt.show()
```



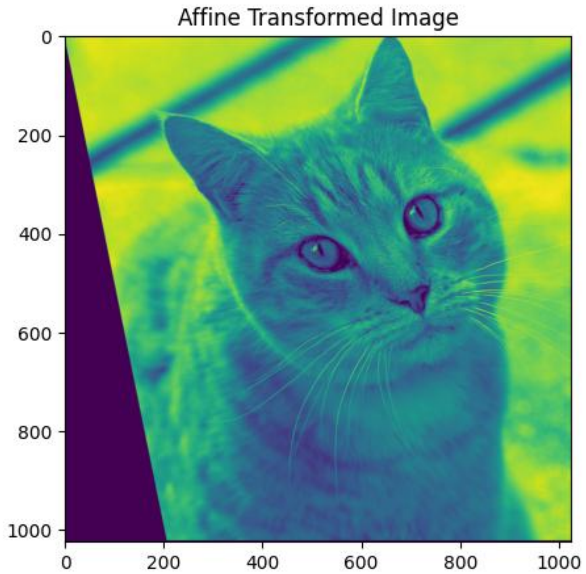
4. Rotation

```
1. rotated = sk.transform.rotate(image, 65)
2. plt.title("Rotated Image")
3. plt.imshow(rotated)
```



5. Affine

```
1. affined = sk.transform.warp(image,
sk.transform.AffineTransform(translation=(1,2), shear=0.2))
2.
3. plt.figure(figsize=(5, 5))
4. plt.title("Affine Transformed Image")
5. plt.imshow(affined)
6. plt.show()
```



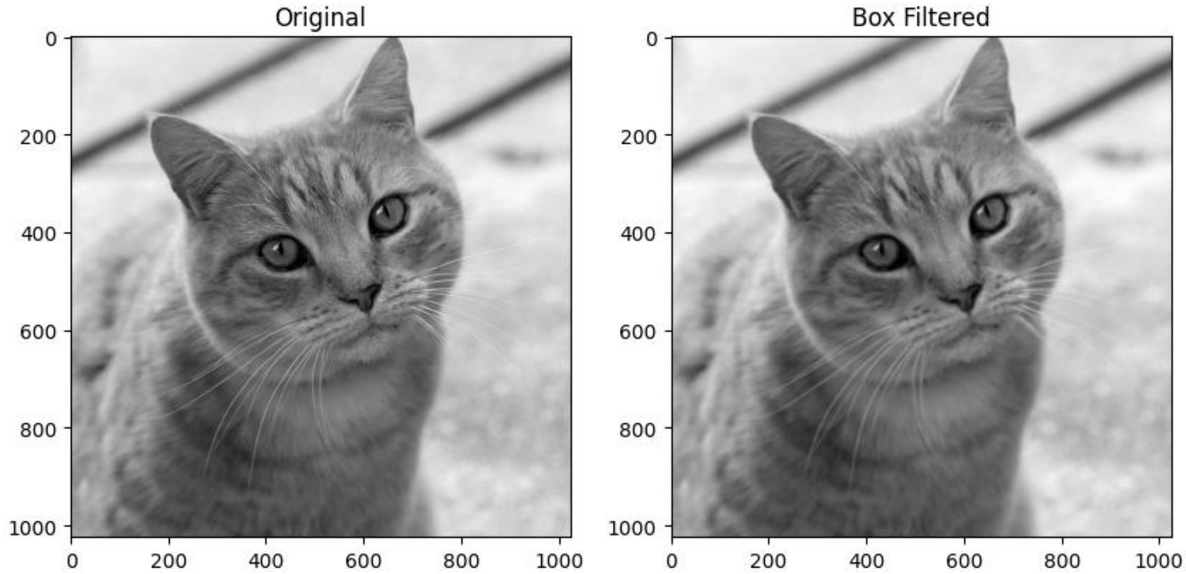
Exercise-5

Objective: Write a program to demonstrate Box Filter.

Code:

```
import cv2
import numpy as np
import matplotlib.pyplot as plt

img = cv2.imread("../image.png", cv2.IMREAD_GRAYSCALE)

# Apply box filter
box_filtered = cv2.boxFilter(img, ddepth=-1, ksize=(5, 5))

# Display original and filtered images
plt.figure(figsize=(10, 5))
plt.subplot(1, 2, 1)
plt.title('Original')
plt.imshow(img, cmap='gray')

plt.subplot(1, 2, 2)
plt.title('Box Filtered')
plt.imshow(box_filtered, cmap='gray')
plt.show()
```

Output:



Exercise-6

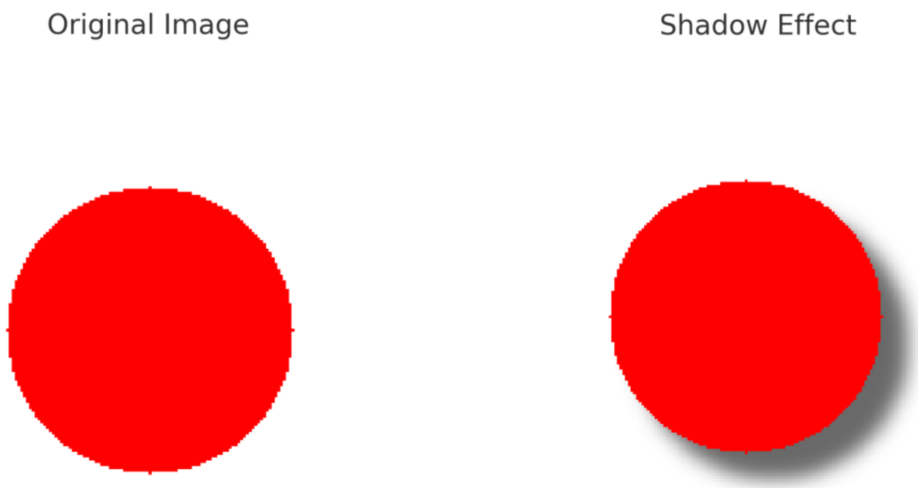
Objective: Write a program to create a shadow effect on an image.

Code:

```
import cv2
import numpy as np
import matplotlib.pyplot as plt

def shadow(image_path, shadow_offset=(10, 10), blur_ksize=(21, 21), shadow_color=(0, 0, 0, 10)):
    # read the image with alpha channel
    image = cv2.imread(image_path, cv2.IMREAD_UNCHANGED)
    plt.title("Original Image")
    plt.imshow(image)
    plt.show()

    if image.shape[2] != 4:
        raise ValueError("Image must have an alpha channel")

    h, w = image.shape[:2]

    # Create shadow base from alpha channel
    alpha = image[:, :, 3]
    shadow = np.zeros((h, w, 4), dtype=np.uint8)
    shadow[:, :, :3] = shadow_color[:3]
    shadow[:, :, 3] = alpha

    # Apply Gaussian blur to the shadow
    blurred_shadow = cv2.GaussianBlur(shadow, blur_ksize, 0)

    # Create a larger canvas to accommodate the shadow offset
    canvas_h = h + shadow_offset[1]
    canvas_w = w + shadow_offset[0]
    canvas = np.zeros((canvas_h, canvas_w, 4), dtype=np.uint8)

    # Print the blurred iamge
    canvas[shadow_offset[1]:shadow_offset[1]+h, shadow_offset[0]:shadow_offset[0]+w] = blurred_shadow

    # Overlay original image onto the canvas
    canvas[0:h, 0:w] = overlay_image_alpha(canvas[0:h, 0:w], image)

    return canvas

def overlay_image_alpha(background, foreground):
    alpha = foreground[:, :, 3] / 255.0
    for c in range(3):
        background[:, :, c] = (1 - alpha) * background[:, :, c] + alpha * foreground[:, :, c]
    background[:, :, 3] = np.clip(foreground[:, :, 3] + background[:, :, 3] * (1 - alpha), 0, 255)
```

```
    return background.astype(np.uint8)


result = shadow("../image1.png", shadow_offset=(10, 10), blur_ksize=(21, 21), shadow_color=(0, 0, 0, 10))
plt.title("Shadow Effect")
plt.imshow(result)
plt.show()
```

Output:



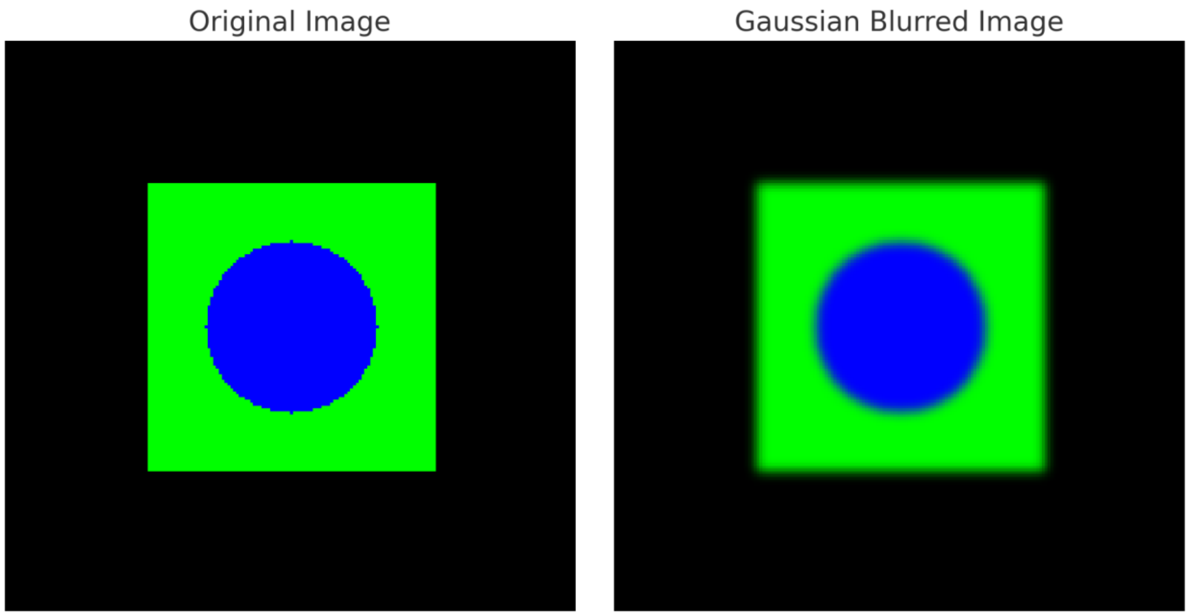
Exercise-7

Objective: Write a program to apply Gaussian Filtering to an image.

Code:

```
import cv2
import matplotlib.pyplot as plt

img = '../image1.png'

# Apply Gaussian filter
gaussian_filtered = cv2.GaussianBlur(img, ksize=(5, 5), sigmaX=0)

# Display original and filtered images
plt.figure(figsize=(10, 5))
plt.subplot(1, 2, 1)
plt.title('Original')
plt.imshow(img, cmap='gray')

plt.subplot(1, 2, 2)
plt.title('Gaussian Filtered')
plt.imshow(gaussian_filtered, cmap='gray')
plt.show()
```

Output:



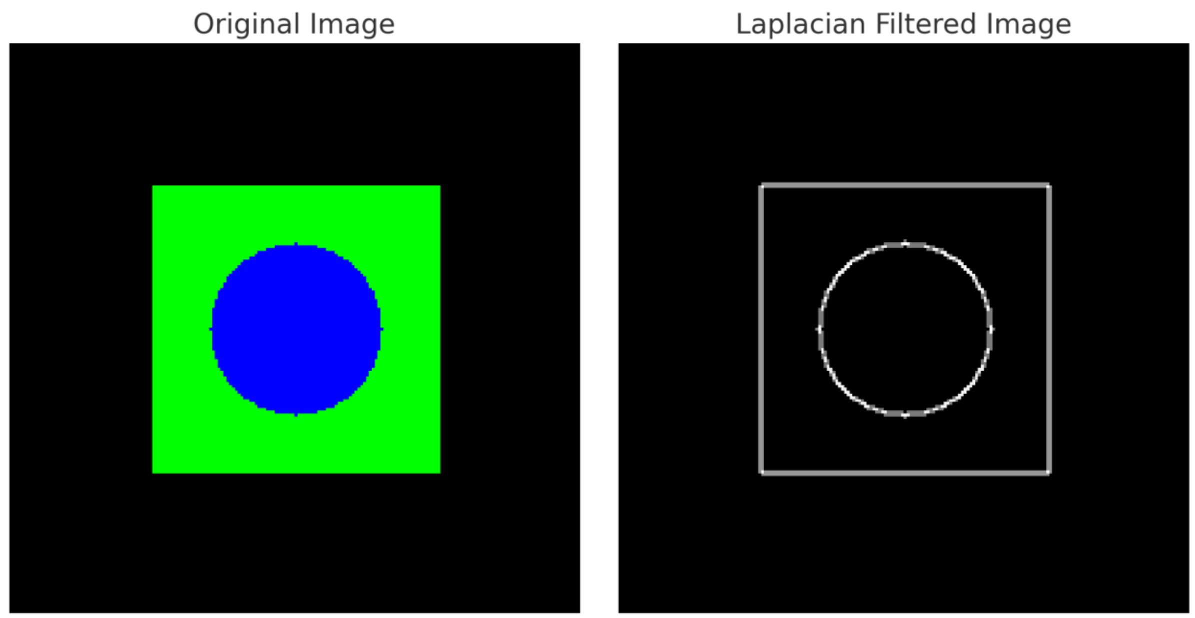
Exercise-8

Objective: Write a program to apply Laplacian Filtering to an image.

Code:

```
import cv2
import matplotlib.pyplot as plt

img = '../image1.png'

# Apply Laplacian filter
laplacian_filtered = cv2.Laplacian(img, ddepth=cv2.CV_64F)
# Display original and filtered images
plt.figure(figsize=(10, 5))
plt.subplot(1, 2, 1)
plt.title('Original')
plt.imshow(img, cmap='gray')
plt.subplot(1, 2, 2)
plt.title('Laplacian Filtered')
plt.imshow(laplacian_filtered, cmap='gray')
plt.show()
```

Output:



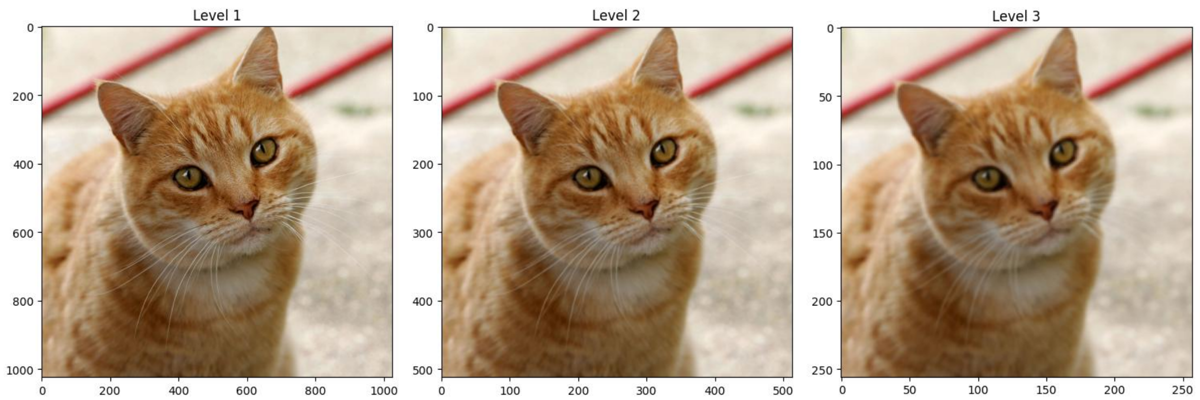
Exercise-9

Objective: Write a program to create a Gaussian Pyramid for an image.

Code:

```
import cv2
import numpy as np
import matplotlib.pyplot as plt

def create_gaussian_pyramid(image, levels=3):
    pyramid = [image]
    for i in range(levels - 1):
        # Apply Gaussian blur
        blurred = cv2.GaussianBlur(pyramid[i], (5, 5), 1)
        # Downsample the image
        downsampled = cv2.pyrDown(blurred)
        pyramid.append(downsampled)

    return pyramid

image = cv2.imread("../image.png")
image_rgb = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)

# Create Gaussian Pyramid with 3 levels
pyramid = create_gaussian_pyramid(image_rgb, levels=3)

# Plot the images in the pyramid
plt.figure(figsize=(15, 5))

for i, img in enumerate(pyramid):
    plt.subplot(1, len(pyramid), i + 1)
    plt.title(f"Level {i + 1}")
    plt.imshow(img)
plt.tight_layout()
plt.show()
```

Output:



Exercise-10

Objective: Multiclass Image Classification using CNN.

Code:

```
# IMPORTANT: RUN THIS CELL IN ORDER TO IMPORT YOUR KAGGLE DATA SOURCES,
# THEN FEEL FREE TO DELETE THIS CELL.

import kagglehub
path = kagglehub.dataset_download('puneet6060/intel-image-classification')

print('Data source import complete.')
print("Path:", path)
```

1. Import the Required Libraries

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

import cv2
import os
os.environ["TF_CPP_MIN_LOG_LEVEL"] = "2"
import warnings
warnings.filterwarnings('ignore')

from sklearn.metrics import confusion_matrix, classification_report

import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Activation, BatchNormalization, Conv2D
, Dense, Dropout, Flatten, MaxPooling2D
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.losses import CategoricalCrossentropy
from tensorflow.keras.regularizers import l2
from tensorflow.keras.callbacks import ReduceLROnPlateau
```

2. Load the Image Training and Validation Datasets

i. Get the Image Dataset Paths

```
train_dataset_path = path + '/seg_train/seg_train/'
validation_dataset_path = path + '/seg_test/seg_test/'
```

ii. Load Image Datasets and Apply Augmentations

Since the images present in the datasets are 150x150px in size, the image height and width are taken as 150, 150 respectively. The batch size value can be changed if required.

```
IMG_WIDTH = 150
IMG_HEIGHT = 150
BATCH_SIZE = 32
```

Loading the training dataset and applying augmentations on it.

```
train_datagen = ImageDataGenerator(rescale=1.0/255,
                                   zoom_range=0.2,
                                   width_shift_range=0.2,
                                   height_shift_range=0.2,
                                   fill_mode='nearest')
train_generator = train_datagen.flow_from_directory(train_dataset_path,
                                                    target_size=(IMG_WIDTH,
IMG_HEIGHT),
                                                    batch_size=BATCH_SIZE,
                                                    class_mode='categorical
',
                                                    shuffle=True)
```

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

Loading the validation dataset.

```
validation_datagen = ImageDataGenerator(rescale=1.0/255)
validation_generator = validation_datagen.flow_from_directory(validation_d
ataset_path,
                                                              target_size=(
IMG_WIDTH, IMG_HEIGHT),
                                                              batch_size=BA
TCH_SIZE,
                                                              class_mode='c
ategorical',
                                                              shuffle=True)
```

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

iii. Get the Label Mappings

The labels dictionary is made in order to retrive the class names against the label indices used for training the model

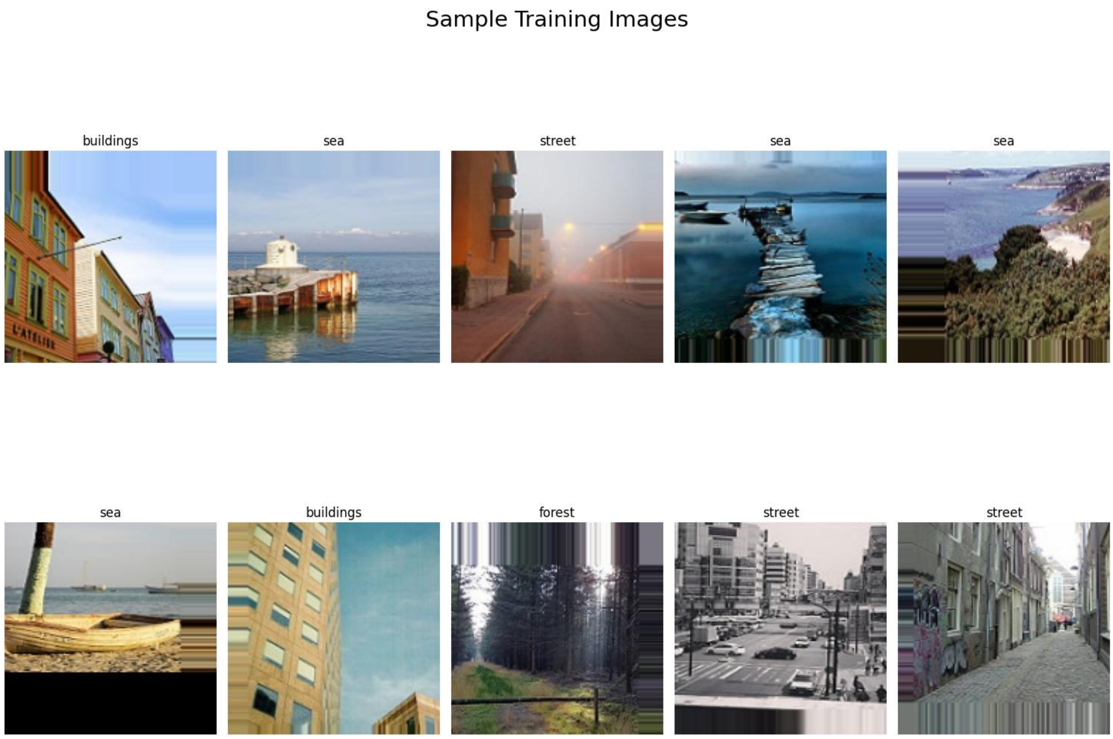
```
labels = {value: key for key, value in train_generator.class_indices.items
()}

print("Label Mappings for classes present in the training and validation d
atasets\n")
for key, value in labels.items():
    print(f"{key} : {value}")
```

```
Label Mappings for classes present in the training and validation datasets

0 : buildings
1 : forest
2 : glacier
3 : mountain
```

```
4 : sea
5 : street
```

3. Plotting Sample Training Images

```
fig, ax = plt.subplots(nrows=2, ncols=5, figsize=(15, 12))
idx = 0

for i in range(2):
    for j in range(5):
        label = labels[np.argmax(train_generator[0][1][idx])]
        ax[i, j].set_title(f"{label}")
        ax[i, j].imshow(train_generator[0][0][idx][:, :, :])
        ax[i, j].axis("off")
        idx += 1

plt.tight_layout()
plt.suptitle("Sample Training Images", fontsize=21)
plt.show()
```



4. Training a CNN Model

Since the training dataset is ready let's create a simple CNN Model to train on the image datasets

i. Create a CNN Model

```
def create_model():
    model = Sequential([
        Conv2D(filters=128, kernel_size=(5, 5), padding='valid', input_sha
pe=(IMG_WIDTH, IMG_HEIGHT, 3)),
        Activation('relu'),
        MaxPooling2D(pool_size=(2, 2)),
```

```
        BatchNormalization(),

        Conv2D(filters=64, kernel_size=(3, 3), padding='valid', kernel_reg
ularizer=l2(0.00005)),
        Activation('relu'),
        MaxPooling2D(pool_size=(2, 2)),
        BatchNormalization(),

        Conv2D(filters=32, kernel_size=(3, 3), padding='valid', kernel_reg
ularizer=l2(0.00005)),
        Activation('relu'),
        MaxPooling2D(pool_size=(2, 2)),
        BatchNormalization(),

        Flatten(),

        Dense(units=256, activation='relu'),
        Dropout(0.5),
        Dense(units=6, activation='softmax')
    ])

    return model

cnn_model = create_model()

print(cnn_model.summary())
```

```
Model: "sequential_1"
```

Layer (type)	Output Shape	Param #
conv2d_3 (Conv2D)	(None, 146, 146, 128)	9,728
activation_3 (Activation)	(None, 146, 146, 128)	0
max_pooling2d_3 (MaxPooling2D)	(None, 73, 73, 128)	0
batch_normalization_3 (BatchNormalization)	(None, 73, 73, 128)	512
conv2d_4 (Conv2D)	(None, 71, 71, 64)	73,792

activation_4 (Activation)	(None, 71, 71, 64)	0
max_pooling2d_4 (MaxPooling2D)	(None, 35, 35, 64)	0
batch_normalization_4 (BatchNormalization)	(None, 35, 35, 64)	256
conv2d_5 (Conv2D)	(None, 33, 33, 32)	18,464
activation_5 (Activation)	(None, 33, 33, 32)	0
max_pooling2d_5 (MaxPooling2D)	(None, 16, 16, 32)	0
batch_normalization_5 (BatchNormalization)	(None, 16, 16, 32)	128
flatten_1 (Flatten)	(None, 8192)	0
dense_2 (Dense)	(None, 256)	2,097,408
dropout_1 (Dropout)	(None, 256)	0
dense_3 (Dense)	(None, 6)	1,542

Total params: 2,201,830 (8.40 MB)

Trainable params: 2,201,382 (8.40 MB)

```
 Non-trainable params: 448 (1.75 KB)
```

None

ii. Defining Callbacks

A callback is an object that can perform actions at various stages of training (e.g. at the start or end of an epoch, before or after a single batch, etc)

a. Reduce Learning Rate on Plateau

Is used to reduce the learning rate when a metric has stopped improving.

```
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=np.sqrt(0.1), pat
ience=5, verbose=1)
```

iii. Defining the Optimizer

```
optimizer = Adam(learning_rate=0.001)
```

iv. Compile the Model

```
cnn_model.compile(optimizer=optimizer, loss=CategoricalCrossentropy(), met
rics=['accuracy'])
```

v. Training the Model

```
history = cnn_model.fit(train_generator, epochs=50, validation_data=valida
tion_generator,
                        verbose=2,
                        callbacks=[reduce_lr])
```

```
Epoch 1/50
439/439 - 65s - 149ms/step - accuracy: 0.4964 - loss: 2.1109 - val_accurac
y: 0.5127 - val_loss: 1.1990 - learning_rate: 1.0000e-03
Epoch 2/50
439/439 - 48s - 110ms/step - accuracy: 0.6131 - loss: 1.0702 - val_accurac
y: 0.5640 - val_loss: 1.3726 - learning_rate: 1.0000e-03
Epoch 3/50
439/439 - 48s - 110ms/step - accuracy: 0.6568 - loss: 0.9232 - val_accurac
y: 0.6773 - val_loss: 0.9458 - learning_rate: 1.0000e-03
Epoch 4/50
439/439 - 49s - 111ms/step - accuracy: 0.6912 - loss: 0.8486 - val_accurac
y: 0.7130 - val_loss: 0.8210 - learning_rate: 1.0000e-03
Epoch 5/50
439/439 - 48s - 109ms/step - accuracy: 0.7116 - loss: 0.8024 - val_accurac
y: 0.7020 - val_loss: 0.7868 - learning_rate: 1.0000e-03
Epoch 6/50
439/439 - 48s - 109ms/step - accuracy: 0.7282 - loss: 0.7564 - val_accurac
y: 0.7470 - val_loss: 0.7527 - learning_rate: 1.0000e-03
Epoch 7/50
439/439 - 48s - 110ms/step - accuracy: 0.7437 - loss: 0.7180 - val_accurac
y: 0.8000 - val_loss: 0.5946 - learning_rate: 1.0000e-03
Epoch 8/50
439/439 - 48s - 110ms/step - accuracy: 0.7542 - loss: 0.6940 - val_accurac
y: 0.7750 - val_loss: 0.6176 - learning_rate: 1.0000e-03
Epoch 9/50
439/439 - 48s - 110ms/step - accuracy: 0.7666 - loss: 0.6668 - val_accurac
y: 0.3233 - val_loss: 6.4530 - learning_rate: 1.0000e-03
```

```
Epoch 10/50
439/439 - 48s - 110ms/step - accuracy: 0.7772 - loss: 0.6363 - val_accurac
y: 0.8157 - val_loss: 0.5311 - learning_rate: 1.0000e-03
Epoch 11/50
439/439 - 48s - 110ms/step - accuracy: 0.7830 - loss: 0.6219 - val_accurac
y: 0.7837 - val_loss: 0.6171 - learning_rate: 1.0000e-03
Epoch 12/50
439/439 - 48s - 109ms/step - accuracy: 0.7861 - loss: 0.6130 - val_accurac
y: 0.7420 - val_loss: 0.7246 - learning_rate: 1.0000e-03
Epoch 13/50
439/439 - 48s - 109ms/step - accuracy: 0.7909 - loss: 0.5946 - val_accurac
y: 0.6197 - val_loss: 1.1284 - learning_rate: 1.0000e-03
Epoch 14/50
439/439 - 48s - 110ms/step - accuracy: 0.7971 - loss: 0.5837 - val_accurac
y: 0.8090 - val_loss: 0.5444 - learning_rate: 1.0000e-03
Epoch 15/50

Epoch 15: ReduceLROnPlateau reducing learning rate to 0.000316227781036850
84.
439/439 - 48s - 110ms/step - accuracy: 0.8096 - loss: 0.5662 - val_accurac
y: 0.7547 - val_loss: 0.7665 - learning_rate: 1.0000e-03
Epoch 16/50
439/439 - 49s - 112ms/step - accuracy: 0.8318 - loss: 0.4980 - val_accurac
y: 0.8703 - val_loss: 0.3983 - learning_rate: 3.1623e-04
Epoch 17/50
439/439 - 48s - 109ms/step - accuracy: 0.8394 - loss: 0.4691 - val_accurac
y: 0.8630 - val_loss: 0.4069 - learning_rate: 3.1623e-04
Epoch 18/50
439/439 - 48s - 110ms/step - accuracy: 0.8464 - loss: 0.4613 - val_accurac
y: 0.8727 - val_loss: 0.3951 - learning_rate: 3.1623e-04
Epoch 19/50
439/439 - 48s - 110ms/step - accuracy: 0.8440 - loss: 0.4555 - val_accurac
y: 0.8333 - val_loss: 0.5072 - learning_rate: 3.1623e-04
Epoch 20/50
439/439 - 48s - 110ms/step - accuracy: 0.8454 - loss: 0.4509 - val_accurac
y: 0.8790 - val_loss: 0.3827 - learning_rate: 3.1623e-04
Epoch 21/50
439/439 - 48s - 109ms/step - accuracy: 0.8499 - loss: 0.4347 - val_accurac
y: 0.8083 - val_loss: 0.6546 - learning_rate: 3.1623e-04
Epoch 22/50
439/439 - 48s - 110ms/step - accuracy: 0.8572 - loss: 0.4179 - val_accurac
y: 0.8757 - val_loss: 0.4188 - learning_rate: 3.1623e-04
Epoch 23/50
439/439 - 48s - 110ms/step - accuracy: 0.8546 - loss: 0.4227 - val_accurac
y: 0.8743 - val_loss: 0.4059 - learning_rate: 3.1623e-04
Epoch 24/50
439/439 - 49s - 111ms/step - accuracy: 0.8556 - loss: 0.4202 - val_accurac
y: 0.8563 - val_loss: 0.4641 - learning_rate: 3.1623e-04
Epoch 25/50
439/439 - 48s - 110ms/step - accuracy: 0.8575 - loss: 0.4151 - val_accurac
y: 0.8737 - val_loss: 0.3679 - learning_rate: 3.1623e-04
Epoch 26/50
439/439 - 48s - 110ms/step - accuracy: 0.8588 - loss: 0.4144 - val_accurac
y: 0.8707 - val_loss: 0.3899 - learning_rate: 3.1623e-04
```

```
Epoch 27/50
439/439 - 48s - 109ms/step - accuracy: 0.8598 - loss: 0.4095 - val_accurac
y: 0.8860 - val_loss: 0.3508 - learning_rate: 3.1623e-04
Epoch 28/50
439/439 - 49s - 111ms/step - accuracy: 0.8655 - loss: 0.4053 - val_accurac
y: 0.8560 - val_loss: 0.4347 - learning_rate: 3.1623e-04
Epoch 29/50
439/439 - 48s - 109ms/step - accuracy: 0.8625 - loss: 0.3991 - val_accurac
y: 0.8303 - val_loss: 0.5277 - learning_rate: 3.1623e-04
Epoch 30/50
439/439 - 48s - 109ms/step - accuracy: 0.8647 - loss: 0.3964 - val_accurac
y: 0.8847 - val_loss: 0.3669 - learning_rate: 3.1623e-04
Epoch 31/50
439/439 - 48s - 108ms/step - accuracy: 0.8645 - loss: 0.3888 - val_accurac
y: 0.8660 - val_loss: 0.4414 - learning_rate: 3.1623e-04
Epoch 32/50

Epoch 32: ReduceLROnPlateau reducing learning rate to 0.000100000006396061
99.
439/439 - 47s - 108ms/step - accuracy: 0.8720 - loss: 0.3785 - val_accurac
y: 0.8730 - val_loss: 0.4176 - learning_rate: 3.1623e-04
Epoch 33/50
439/439 - 48s - 109ms/step - accuracy: 0.8777 - loss: 0.3583 - val_accurac
y: 0.8903 - val_loss: 0.3283 - learning_rate: 1.0000e-04
Epoch 34/50
439/439 - 48s - 109ms/step - accuracy: 0.8813 - loss: 0.3551 - val_accurac
y: 0.8913 - val_loss: 0.3452 - learning_rate: 1.0000e-04
Epoch 35/50
439/439 - 47s - 108ms/step - accuracy: 0.8802 - loss: 0.3503 - val_accurac
y: 0.8847 - val_loss: 0.3761 - learning_rate: 1.0000e-04
Epoch 36/50
439/439 - 47s - 107ms/step - accuracy: 0.8833 - loss: 0.3446 - val_accurac
y: 0.8840 - val_loss: 0.3650 - learning_rate: 1.0000e-04
Epoch 37/50
439/439 - 47s - 107ms/step - accuracy: 0.8816 - loss: 0.3385 - val_accurac
y: 0.8917 - val_loss: 0.3435 - learning_rate: 1.0000e-04
Epoch 38/50

Epoch 38: ReduceLROnPlateau reducing learning rate to 3.1622778103685084e-
05.
439/439 - 48s - 108ms/step - accuracy: 0.8842 - loss: 0.3398 - val_accurac
y: 0.8650 - val_loss: 0.4605 - learning_rate: 1.0000e-04
Epoch 39/50
439/439 - 47s - 108ms/step - accuracy: 0.8845 - loss: 0.3349 - val_accurac
y: 0.8853 - val_loss: 0.3488 - learning_rate: 3.1623e-05
Epoch 40/50
439/439 - 47s - 108ms/step - accuracy: 0.8854 - loss: 0.3262 - val_accurac
y: 0.8820 - val_loss: 0.3739 - learning_rate: 3.1623e-05
Epoch 41/50
439/439 - 47s - 108ms/step - accuracy: 0.8901 - loss: 0.3225 - val_accurac
y: 0.8920 - val_loss: 0.3374 - learning_rate: 3.1623e-05
Epoch 42/50
439/439 - 48s - 108ms/step - accuracy: 0.8901 - loss: 0.3231 - val_accurac
y: 0.8940 - val_loss: 0.3280 - learning_rate: 3.1623e-05
```

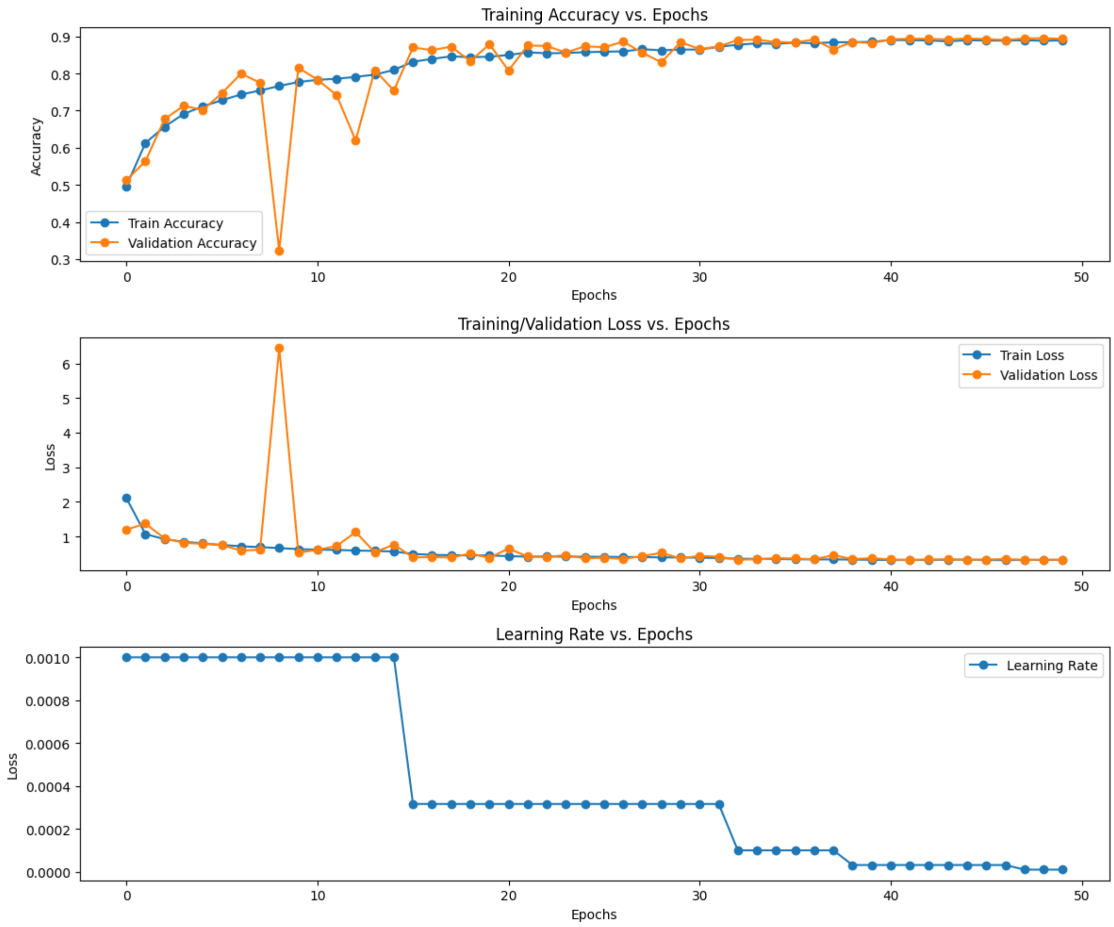
```
Epoch 43/50
439/439 - 47s - 107ms/step - accuracy: 0.8890 - loss: 0.3229 - val_accurac
y: 0.8933 - val_loss: 0.3381 - learning_rate: 3.1623e-05
Epoch 44/50
439/439 - 48s - 109ms/step - accuracy: 0.8868 - loss: 0.3286 - val_accurac
y: 0.8920 - val_loss: 0.3412 - learning_rate: 3.1623e-05
Epoch 45/50
439/439 - 48s - 108ms/step - accuracy: 0.8896 - loss: 0.3338 - val_accurac
y: 0.8943 - val_loss: 0.3311 - learning_rate: 3.1623e-05
Epoch 46/50
439/439 - 48s - 109ms/step - accuracy: 0.8891 - loss: 0.3221 - val_accurac
y: 0.8930 - val_loss: 0.3368 - learning_rate: 3.1623e-05
Epoch 47/50

Epoch 47: ReduceLROnPlateau reducing learning rate to 1.0000000409520217e-
05.
439/439 - 48s - 109ms/step - accuracy: 0.8886 - loss: 0.3198 - val_accurac
y: 0.8903 - val_loss: 0.3477 - learning_rate: 3.1623e-05
Epoch 48/50
439/439 - 48s - 110ms/step - accuracy: 0.8898 - loss: 0.3246 - val_accurac
y: 0.8947 - val_loss: 0.3303 - learning_rate: 1.0000e-05
Epoch 49/50
439/439 - 47s - 108ms/step - accuracy: 0.8882 - loss: 0.3241 - val_accurac
y: 0.8953 - val_loss: 0.3321 - learning_rate: 1.0000e-05
Epoch 50/50
439/439 - 48s - 108ms/step - accuracy: 0.8893 - loss: 0.3253 - val_accurac
y: 0.8933 - val_loss: 0.3319 - learning_rate: 1.0000e-05
```

5. Plotting the Model Metrics

i. Plotting training and validation accuracy, loss and learning rate

```
train_accuracy = history.history['accuracy']
val_accuracy = history.history['val_accuracy']

train_loss = history.history['loss']
val_loss = history.history['val_loss']

learning_rate = history.history['learning_rate']

fig, ax = plt.subplots(nrows=3, ncols=1, figsize=(12, 10))

ax[0].set_title('Training Accuracy vs. Epochs')
ax[0].plot(train_accuracy, 'o-', label='Train Accuracy')
ax[0].plot(val_accuracy, 'o-', label='Validation Accuracy')
ax[0].set_xlabel('Epochs')
ax[0].set_ylabel('Accuracy')
ax[0].legend(loc='best')

ax[1].set_title('Training/Validation Loss vs. Epochs')
ax[1].plot(train_loss, 'o-', label='Train Loss')
ax[1].plot(val_loss, 'o-', label='Validation Loss')
ax[1].set_xlabel('Epochs')
ax[1].set_ylabel('Loss')
ax[1].legend(loc='best')
```

```
ax[2].set_title('Learning Rate vs. Epochs')
ax[2].plot(learning_rate, 'o-', label='Learning Rate')
ax[2].set_xlabel('Epochs')
ax[2].set_ylabel('Loss')
ax[2].legend(loc='best')

plt.tight_layout()
plt.show()
```



6. Testing the Model on Test Set

Testing the model on the validation dataset because a seperate dataset for testing is not available.

```
test_dataset = path + '/seg_test/seg_test/'

test_datagen = ImageDataGenerator(rescale=1.0/255)

test_generator = test_datagen.flow_from_directory(test_dataset,
                                                  shuffle=False,
                                                  batch_size=BATCH_SIZE,
                                                  target_size = (IMG_WIDTH,
IMG_HEIGHT),
                                                  class_mode='categorical')
```

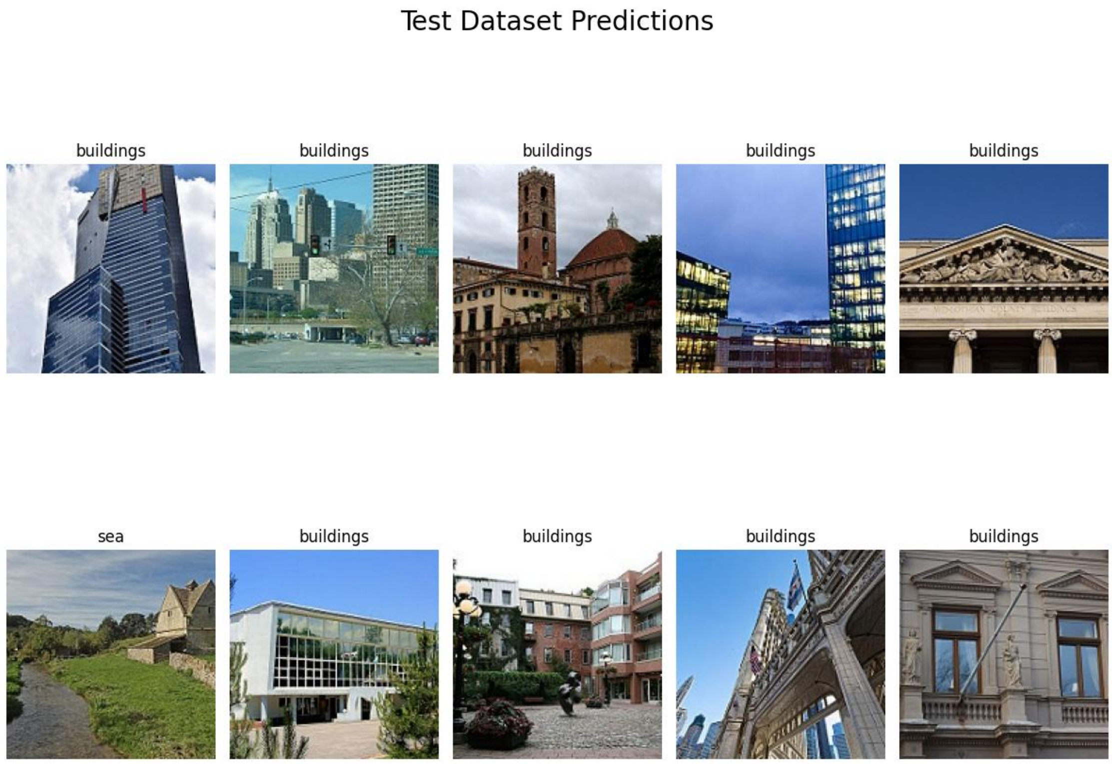
```
Found 3000 images belonging to 6 classes.
```

7. Model Prediction on the Test Dataset

```
predictions = cnn_model.predict(test_generator)
```

```
94/94 ━━━━━━━━━━━━━━━━━━━━ 4s 30ms/step
```

```
fig, ax = plt.subplots(nrows=2, ncols=5, figsize=(12, 10))
idx = 0

for i in range(2):
    for j in range(5):
        predicted_label = labels[np.argmax(predictions[idx])]
        ax[i, j].set_title(f"{predicted_label}")
        ax[i, j].imshow(test_generator[0][0][idx])
        ax[i, j].axis("off")
        idx += 1

plt.tight_layout()
plt.suptitle("Test Dataset Predictions", fontsize=20)
plt.show()
```




```
test_loss, test_accuracy = cnn_model.evaluate(test_generator, batch_size=B
ATCH_SIZE)
```

```
94/94 ━━━━━━━━━━━━━━━━━━━━ 2s 19ms/step - accuracy: 0.9104 - loss: 0.2821
```

```
print(f"Test Loss:     {test_loss}")
print(f"Test Accuracy: {test_accuracy}")
```

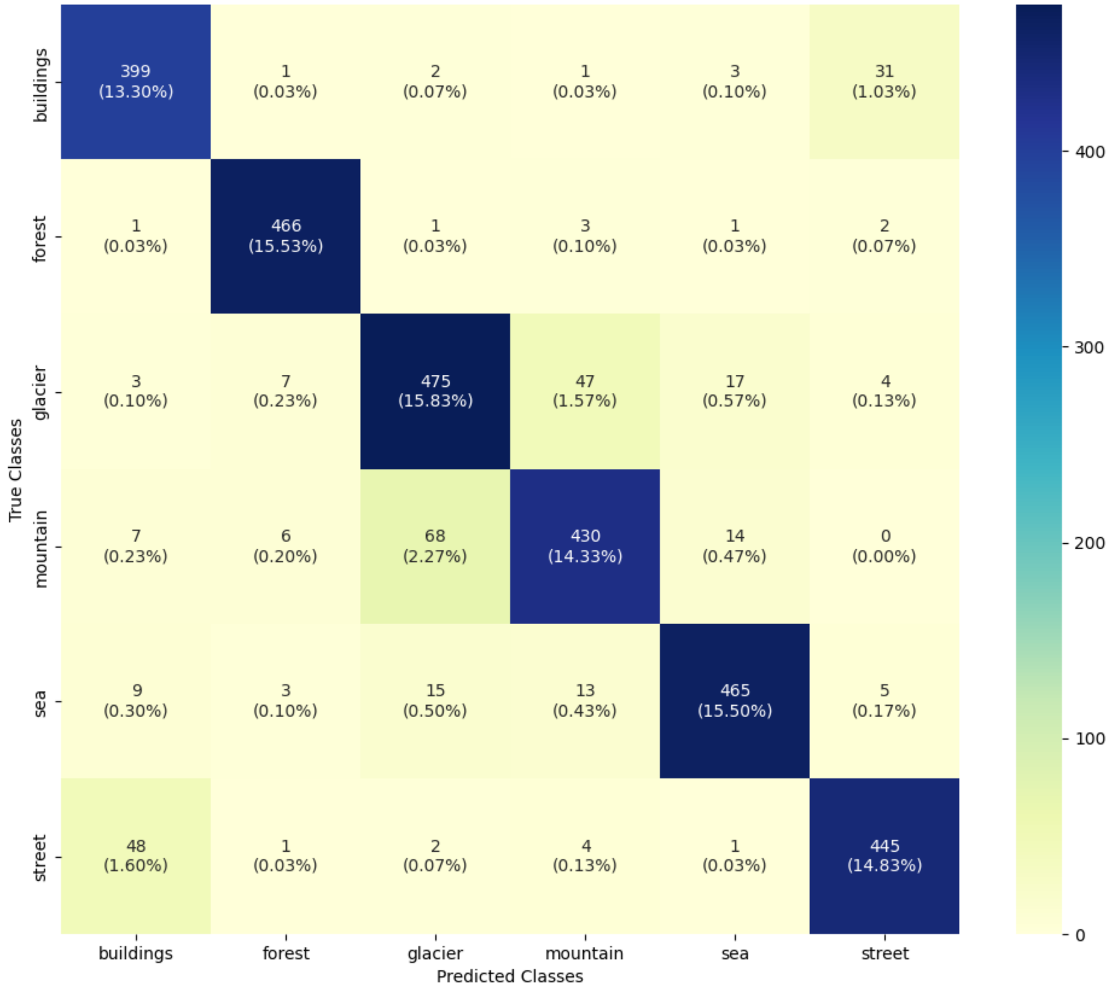
```
Test Loss:     0.3318774402141571
Test Accuracy: 0.8933333158493042
```

The test loss and test accuracy is the same as validation loss and validation accuracy at the last step since the testing and validation datasets are same.

8. Plotting the Classification Metrics

i. Confusion Matrix

```
y_pred = np.argmax(predictions, axis=1)
y_true = test_generator.classes

cf_mtx = confusion_matrix(y_true, y_pred)

group_counts = ["{0:0.0f}".format(value) for value in cf_mtx.flatten()]
group_percentages = ["{0:.2%}".format(value) for value in cf_mtx.flatten()
/np.sum(cf_mtx)]
box_labels = [f"{v1}\n({v2})" for v1, v2 in zip(group_counts, group_percen
tages)]
box_labels = np.asarray(box_labels).reshape(6, 6)

plt.figure(figsize = (12, 10))
sns.heatmap(cf_mtx, xticklabels=labels.values(), yticklabels=labels.values
(),
           cmap="YlGnBu", fmt="", annot=box_labels)
plt.xlabel('Predicted Classes')
plt.ylabel('True Classes')
plt.show()
```




```
print(classification_report(y_true, y_pred, target_names=labels.values()))
```

```
              precision    recall  f1-score   support

   buildings       0.85      0.91      0.88       437
      forest       0.96      0.98      0.97       474
     glacier       0.84      0.86      0.85       553
    mountain       0.86      0.82      0.84       525
         sea       0.93      0.91      0.92       510
      street       0.91      0.89      0.90       501

    accuracy                           0.89      3000
   macro avg       0.89      0.90      0.89      3000
weighted avg       0.89      0.89      0.89      3000
```

9. Wrong Predictions

Let's see where the model has given wrong predictions and what were the actual predictions on those images.

```
errors = (y_true - y_pred != 0)
y_true_errors = y_true[errors]
y_pred_errors = y_pred[errors]
```

```
test_images = test_generator.filenames
test_img = np.asarray(test_images)[errors]

fig, ax = plt.subplots(nrows=2, ncols=5, figsize=(12, 10))
idx = 0

for i in range(2):
    for j in range(5):
        idx = np.random.randint(0, len(test_img))
        true_index = y_true_errors[idx]
        true_label = labels[true_index]
        predicted_index = y_pred_errors[idx]
        predicted_label = labels[predicted_index]
        ax[i, j].set_title(f"True Label: {true_label} \n Predicted Label: {predicted_label}")
        img_path = os.path.join(test_dataset, test_img[idx])
        img = cv2.imread(img_path)
        img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
        ax[i, j].imshow(img)
        ax[i, j].axis("off")

plt.tight_layout()
plt.suptitle('Wrong Predictions made on test set', fontsize=20)
plt.show()
```