

BLG 453E – Computer Vision Homework 4

Student: Emil Huseynov

Student ID: 150210906

Course: BLG453E

Assignment: Homework 4

Due Date: January 27, 2025

Contents

1	Introduction	2
2	Q1 – Region-Growing	2
2.1	Problem Statement	2
2.2	Methodology	2
2.3	Code	3
2.4	Discussion	8
3	Q2 – Diffusion Models: Text-to-Image, Text-to-Video, Image-to-Image, Image-to-Video	8
3.1	Problem Statement	8
3.2	Methodology and Code	9
3.3	Discussion	11
4	Q3 – Optical Flow	11
4.1	Problem Statement	11
4.2	Methodology	12
4.3	Code	12
4.4	Discussion	15
5	Q4 – Principal Component Analysis (PCA) and Transfer Learning	15
5.1	Problem Statement	15
5.2	Methodology	15
5.3	Code	16
5.4	Discussion	22
6	Conclusion	22

1 Introduction

This report is prepared as the submission for **Assignment IV** of the *BLG 453E – Computer Vision* course.

The assignment is composed of four questions:

- **Q1 (20 pts):** Region-Growing Segmentation
- **Q2 (20 pts):** Diffusion Models for Text-to-Image, Text-to-Video, Image-to-Image, and Image-to-Video
- **Q3 (30 pts):** Optical Flow for Robot Arm Tracking
- **Q4 (30 pts):** Principal Component Analysis and Transfer Learning

In the following sections, each question is addressed with a detailed description of the methodology, the code, and relevant discussion of any results and issues encountered. All code listings are provided in separate code blocks for clarity.

2 Q1 – Region-Growing

2.1 Problem Statement

The task is to implement a simple region-growing algorithm for image segmentation. A single seed point (or multiple seeds) is selected in the `lion.jpg` image, and the region is grown by adding neighboring pixels based on a color similarity threshold. The goals are:

- Select a single seed point to segment the lion, annotating the seed with a red dot.
- Repeat the process with three separate seed points.
- Optionally, showcase three different scenarios using three seed points simultaneously and compare the results.

2.2 Methodology

The key steps in my solution are:

1. Read the input image using `OpenCV` in `BGR` format.

2. Define a `get_neighbors` function to retrieve the 8-connected neighbors of a given pixel.
3. Maintain a `visited` mask and a `queue` to perform a Breadth-First Search (BFS) type region growing:
 - Initialize the region with the seed pixel.
 - Compute color difference against the *current mean color* of the region; add neighbors if within threshold.
4. Create a visualization by zeroing out all pixels outside the region and placing a red circle on the seed coordinate.
5. Repeat the process for multiple seeds.

2.3 Code

```

1 import cv2 # For images
2 import matplotlib.pyplot as plt
3
4 def show_image_in_colab(image_bgr, title="Output"):
5     """
6     Displays a BGR image in Colab using Matplotlib (converted to
7     RGB).
8     """
9     image_rgb = cv2.cvtColor(image_bgr, cv2.COLOR_BGR2RGB)
10    plt.figure(figsize=(6, 6))
11    plt.imshow(image_rgb)
12    plt.title(title)
13    plt.axis('off')
14    plt.show()
15
16 def abs_value(a):
17     """Manual absolute value (since abs() is a built-in)."""
18     if a < 0:
19         return -a
20     return a
21
22 def color_difference(c1, c2):
23     """Difference between two BGR colors c1=(B1,G1,R1), c2=(B2,G2,
24     R2)."""
25     return (abs_value(c1[0] - c2[0]) +
26             abs_value(c1[1] - c2[1]) +
27             abs_value(c1[2] - c2[2]))
28
29 def get_neighbors(x, y, width, height):

```

```

28     """Return the 8-connected neighbors of (x,y) within image
        bounds."""
29     neighbors = []
30     for dx in [-1, 0, 1]:
31         for dy in [-1, 0, 1]:
32             if dx == 0 and dy == 0:
33                 continue
34             nx = x + dx
35             ny = y + dy
36             if 0 <= nx < width and 0 <= ny < height:
37                 neighbors.append((nx, ny))
38     return neighbors
39
40 def region_grow_segment(image, seed_x, seed_y, threshold=30):
41     """
42     Perform region growing on 'image' from seed (seed_x, seed_y).
43     Returns:
44     mask: 2D list of booleans
45     out_image: a copy of original image with region in color,
46     background black, and seed marked with a red
        circle.
47     """
48     height, width, _ = image.shape
49
50     # Prepare visited and mask
51     visited = []
52     mask = []
53     for _h in range(height):
54         visited.append([False]*width)
55         mask.append([False]*width)
56
57     # Initialize BFS queue
58     queue = []
59
60     # Starting color from seed
61     seed_color = image[seed_y, seed_x] # BGR
62     sum_b = int(seed_color[0])
63     sum_g = int(seed_color[1])
64     sum_r = int(seed_color[2])
65     region_size = 1
66
67     # Enqueue seed
68     queue.append((seed_x, seed_y))
69     visited[seed_y][seed_x] = True
70     mask[seed_y][seed_x] = True
71
72     # BFS
73     while len(queue) > 0:
74         x, y = queue.pop(0)

```

```

75
76     # Current region mean color
77     mean_b = sum_b // region_size
78     mean_g = sum_g // region_size
79     mean_r = sum_r // region_size
80
81     # Check neighbors
82     for nx, ny in get_neighbors(x, y, width, height):
83         if not visited[ny][nx]:
84             visited[ny][nx] = True
85             pix_color = image[ny, nx]
86             diff = color_difference(pix_color, (mean_b, mean_g,
87                                     mean_r))
88             if diff < threshold:
89                 # Accept into region
90                 mask[ny][nx] = True
91                 queue.append((nx, ny))
92
93                 # Update region color sums
94                 sum_b += int(pix_color[0])
95                 sum_g += int(pix_color[1])
96                 sum_r += int(pix_color[2])
97                 region_size += 1
98
99     # Prepare output visualization
100    out_image = image.copy()
101    for row_i in range(height):
102        for col_i in range(width):
103            if not mask[row_i][col_i]:
104                out_image[row_i, col_i] = [0, 0, 0] # black
105                background
106
107    # Draw a small red circle on the seed point
108    cv2.circle(out_image, (seed_x, seed_y), 5, (0, 0, 255), -1)
109
110    return mask, out_image
111
112    def region_grow_multiple_seeds(image, seeds, threshold=30):
113        """
114        Region growing with multiple initial seeds simultaneously.
115        seeds: list of (x, y) points
116        Returns:
117            mask: 2D list of booleans
118            out_image: region in color, background black, seeds in red
119                    circles.
120        """
121        height, width, _ = image.shape
122
123        visited = []

```

```

121 mask = []
122 for _h in range(height):
123     visited.append([False]*width)
124     mask.append([False]*width)
125
126 queue = []
127
128 # Initialize region color sums
129 sum_b, sum_g, sum_r = 0, 0, 0
130 region_size = 0
131
132 # Add seeds
133 for (sx, sy) in seeds:
134     seed_color = image[sy, sx]
135     sum_b += int(seed_color[0])
136     sum_g += int(seed_color[1])
137     sum_r += int(seed_color[2])
138     region_size += 1
139
140     visited[sy][sx] = True
141     mask[sy][sx] = True
142     queue.append((sx, sy))
143
144 # BFS
145 while len(queue) > 0:
146     x, y = queue.pop(0)
147
148     mean_b = sum_b // region_size
149     mean_g = sum_g // region_size
150     mean_r = sum_r // region_size
151
152     for nx, ny in get_neighbors(x, y, width, height):
153         if not visited[ny][nx]:
154             visited[ny][nx] = True
155             pix_color = image[ny, nx]
156             diff = color_difference(pix_color, (mean_b, mean_g,
157                                     mean_r))
158             if diff < threshold:
159                 mask[ny][nx] = True
160                 queue.append((nx, ny))
161                 sum_b += int(pix_color[0])
162                 sum_g += int(pix_color[1])
163                 sum_r += int(pix_color[2])
164                 region_size += 1
165
166 out_image = image.copy()
167 for row_i in range(height):
168     for col_i in range(width):
169         if not mask[row_i][col_i]:

```

```

169         out_image[row_i, col_i] = [0, 0, 0]
170
171     # Mark each seed with a small red circle
172     for (sx, sy) in seeds:
173         cv2.circle(out_image, (sx, sy), 5, (0, 0, 255), -1)
174
175     return mask, out_image
176
177 # Read input lion image
178 img = cv2.imread('Lion.jpg')
179 if img is None:
180     print("Could not find 'lion.jpg'. Please upload the image to Colab.")
181 else:
182     # 1) Single seed
183     seed_x, seed_y = 150, 250
184     mask_single, result_single = region_grow_segment(img, seed_x,
185                                                     seed_y, threshold=30)
186     show_image_in_colab(result_single, title="Single Seed Segmentation")
187
188     # 2) Three seeds, separate calls
189     seeds_individual = [(200, 400), (400, 200), (900, 600)]
190     for i, (sx, sy) in enumerate(seeds_individual):
191         msk_sep, res_sep = region_grow_segment(img, sx, sy,
192                                                 threshold=25)
193         show_image_in_colab(res_sep, title=f"Separate Seed {i+1} Segmentation")
194
195     # 3) BONUS: Multiple seeds in one run
196     seeds_scenario_1 = [(250, 280), (500, 210), (1050, 400)]
197     mask_multi_1, result_multi_1 = region_grow_multiple_seeds(img,
198                                                             seeds_scenario_1, threshold=30)
199     show_image_in_colab(result_multi_1, title="Multi-Seed Scenario 1")
200
201     seeds_scenario_2 = [(300, 620), (700, 500), (1100, 780)]
202     mask_multi_2, result_multi_2 = region_grow_multiple_seeds(img,
203                                                             seeds_scenario_2, threshold=30)
204     show_image_in_colab(result_multi_2, title="Multi-Seed Scenario 2")
205
206     seeds_scenario_3 = [(50, 100), (600, 400), (1150, 700)]
207     mask_multi_3, result_multi_3 = region_grow_multiple_seeds(img,
208                                                             seeds_scenario_3, threshold=50)
209     show_image_in_colab(result_multi_3, title="Multi-Seed Scenario 3")

```

Listing 1: Region-Growing Code for Q1.

2.4 Discussion

- The region-growing threshold is a sensitive parameter. Depending on the threshold value, more or fewer background pixels might be included.
- By selecting different seed points, we can segment slightly different portions of the image. For the lion, we focus on areas with similar fur color.
- The bonus scenario shows how using multiple seeds can expand or shrink the final segmented region depending on their initial positions and the threshold.

3 Q2 – Diffusion Models: Text-to-Image, Text-to-Video, Image-to-Image, Image-to-Video

3.1 Problem Statement

This question involves experimenting with modern diffusion models (e.g., Stable Diffusion, ZeroScope) to generate synthetic images and videos. Specifically, we:

- Generate images from text prompts (Text-to-Image).
- Generate videos from text prompts (Text-to-Video).
- Modify existing images via text prompts (Image-to-Image).
- Generate videos from input images (Image-to-Video).

We utilized publicly available models on Hugging Face, including:

- `runwayml/stable-diffusion-v1-5` for Text-to-Image and Image-to-Image
- `cerspense/zeroscope_v2.576w` for Text-to-Video
- `stabilityai/stable-video-diffusion-img2vid-xt` for Image-to-Video (optionally)

3.2 Methodology and Code

Below is the code used in Google Colab for the text-to-image, text-to-video, and image-to-image experiments. GPU acceleration (e.g., T4 runtime) is recommended due to the complexity of diffusion models.

```
1 import os
2 os.environ["HUGGINGFACE_TOKEN"] = "
    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"
3 import torch
4 import IPython
5 from PIL import Image
6 from IPython.display import display, Image as IPyImage
7
8 from diffusers import StableDiffusionPipeline
9
10 # 1) Load the Stable Diffusion text-to-image pipeline
11 pipe_t2i = StableDiffusionPipeline.from_pretrained(
12     "runwayml/stable-diffusion-v1-5", # or stable-diffusion-v1-5
13     torch_dtype=torch.float16,
14     use_auth_token=True
15 )
16 pipe_t2i.to("cuda")
17
18 # 2) Provide a prompt
19 prompt_t2i = "A student tries to fly using homemade wings in a
    sunny day from a mountain"
20
21 # 3) Generate the image
22 image_t2i = pipe_t2i(
23     prompt=prompt_t2i,
24     num_inference_steps=30,
25     guidance_scale=7.5
26 ).images[0]
27
28 # 4) Show result
29 display(image_t2i)
30
31
32 # -----
33 # TEXT TO VIDEO using ZeroScope
34 # -----
35 import torch
36 import imageio
37 import numpy as np
38 from IPython.display import Image as IPyImage, display
39 from diffusers import DiffusionPipeline
40
41 # Load ZeroScope
```

```

42 pipe_t2v = DiffusionPipeline.from_pretrained(
43     "cerspense/zeroscope_v2_576w",
44     torch_dtype=torch.float16,
45 )
46 pipe_t2v.to("cuda")
47
48 prompt = "A_cat_dancing_in_a_disco, neon_lights"
49
50 result = pipe_t2v(
51     prompt=prompt,
52     num_inference_steps=25,
53     guidance_scale=7.5,
54     num_frames=16,
55     width=576,
56     height=320
57 )
58
59 raw_frames = result.frames
60 arr_4d = raw_frames[0] # shape (16, 320, 576, 3)
61
62 video_frames = []
63 num_total_frames = arr_4d.shape[0]
64
65 for i in range(num_total_frames):
66     frame = arr_4d[i]
67     if frame.dtype != np.uint8:
68         frame = frame.astype(np.uint8)
69     video_frames.append(frame)
70
71 # Save frames as a GIF
72 gif_path = "zeroscope_output.gif"
73 imageio.mimsave(gif_path, video_frames, fps=4)
74 display(IPyImage(filename=gif_path))
75
76
77 # -----
78 # IMAGE-TO-IMAGE with Stable Diffusion
79 # -----
80 from diffusers import StableDiffusionImg2ImgPipeline
81
82 pipe_i2i = StableDiffusionImg2ImgPipeline.from_pretrained(
83     "runwayml/stable-diffusion-v1-5",
84     torch_dtype=torch.float16,
85     use_auth_token=True
86 ).to("cuda")
87
88 init_image_path = "tesla.jpg" # Example: some input image
89 init_img = Image.open(init_image_path).convert("RGB")
90 init_img = init_img.resize((512, 512)) # resize if needed

```

```

91
92 prompt_i2i = "Make_it_look_like_a_fantasy_landscape_by_Studio_
    Ghibli,_vibrant_colors"
93
94 image_i2i = pipe_i2i(
95     prompt=prompt_i2i,
96     image=init_img,
97     strength=0.7,
98     guidance_scale=8
99 ).images[0]
100
101 display(image_i2i)

```

Listing 2: Text-to-Image and Image-to-Image Diffusion Code.

3.3 Discussion

- The text-to-image task allows creative generation of images from pure text prompts.
- ZeroScope was used to convert text prompts into short video clips (Text-to-Video). The process can be slow but generates interesting, small video sequences.
- Image-to-image diffusion transforms a given image to match a text description in style or content.
- Depending on GPU resources and inference steps, results may vary significantly.

4 Q3 – Optical Flow

4.1 Problem Statement

Optical flow is a method to estimate motion between consecutive frames in a video. The assignment focuses on tracking the Baxter robot’s arm as it moves. The steps involve:

- Extract frames from a given video at a suitable frame rate.
- Detect feature points (e.g., via Shi–Tomasi corner detection) in the first frame.
- Use Lucas–Kanade optical flow to track these points across subsequent frames.

- Visualize the tracked points on the frames.

4.2 Methodology

1. A video file (e.g., `opticalflow_video.mp4`) is loaded. Frames are extracted at a rate of approximately 1 frame per second (or any suitable rate).
2. `cv2.goodFeaturesToTrack` is used on the first frame.
3. `cv2.calcOpticalFlowPyrLK` tracks the motion of these features.
4. For visualization, lines are drawn from old to new positions of each tracked feature.

4.3 Code

```

1 import cv2 as cv
2 import os
3 import numpy as np
4 from PIL import Image
5 import matplotlib.pyplot as plt
6 import glob
7
8 #####
9 # FRAME EXTRACTION PART
10 #####
11
12 path = "opticalflow_video.mp4"
13 frames_save_path = "/frames"
14
15 def frames_from_video(video_path):
16     cam = cv.VideoCapture(video_path) # read video file
17
18     if not os.path.exists(frames_save_path):
19         os.makedirs(frames_save_path)
20
21     original_fps = cam.get(cv.CAP_PROP_FPS)
22     # We want to save about 1 frame each second
23     extraction_rate = int(original_fps) if original_fps > 0 else
24         25
25
26     currframe = 0
27     while True:
28         ret, frame = cam.read()
29         if not ret:

```

```

29         break
30
31     if currframe % extraction_rate == 0:
32         frame_name = os.path.join(frames_save_path, f"frame_{
33             currframe}.png")
34         cv.imwrite(frame_name, frame)
35         print(f"Saved:_{frame_name}")
36         currframe += 1
37
38     cam.release()
39     cv.destroyAllWindows()
40 frames_from_video(path)
41
42 #####
43 # OPTICAL FLOW PART
44 #####
45 def optical_flow(frames_saved_path):
46     # 1) Gather & sort all frames
47     frames_path = sorted(glob.glob(os.path.join(frames_saved_path,
48         "*.png")),
49
50                         key=lambda x: int(os.path.splitext(os.path.
51                             basename(x))[0].split("_")[1]))
52     frames_images = [Image.open(f) for f in frames_path]
53
54     # 2) Parameters
55     feature_params = dict(
56         maxCorners=100,
57         qualityLevel=0.3,
58         minDistance=7,
59         blockSize=7
60     )
61
62     lk_params = dict(
63         winSize=(15, 15),
64         maxLevel=2,
65         criteria=(cv.TERM_CRITERIA_EPS | cv.TERM_CRITERIA_COUNT,
66             10, 0.03)
67     )
68
69     color = np.random.randint(0, 255, (100, 3))
70
71     # 3) Prepare the first frame
72     first_frame_pil = frames_images[0]
73     first_frame_pil = first_frame_pil.resize((244, 224))
74     first_frame = np.array(first_frame_pil)
75     first_frame_gray = cv.cvtColor(first_frame, cv.COLOR_RGB2GRAY)
76
77     # 4) Find corners in the first frame

```

```

74     p0 = cv.goodFeaturesToTrack(first_frame_gray, mask=None, **
75                                 feature_params)
76
77     # 5) Mask for drawing
78     mask = np.zeros_like(first_frame)
79     flow_points = []
80
81     # 6) Process subsequent frames
82     for idx in range(1, len(frames_images)):
83         frame_pil = frames_images[idx].resize((244, 224))
84         frame_np = np.array(frame_pil)
85         frame_gray = cv.cvtColor(frame_np, cv.COLOR_RGB2GRAY)
86
87         p1, st, err = cv.calcOpticalFlowPyrLK(first_frame_gray,
88                                             frame_gray, p0, None, **lk_params)
89
90         if p1 is not None and st is not None:
91             good_new = p1[st == 1]
92             good_old = p0[st == 1]
93
94             for i, (new, old) in enumerate(zip(good_new, good_old)):
95                 :
96                 a, b = new.ravel()
97                 c, d = old.ravel()
98                 mask = cv.line(mask, (int(a), int(b)), (int(c), int
99                                     (d)), color[i].tolist(), 2)
100                 frame_np = cv.circle(frame_np, (int(a), int(b)), 5,
101                                     color[i].tolist(), -1)
102
103                 img = cv.add(frame_np, mask)
104                 plt.figure(figsize=(6, 4))
105                 plt.imshow(img)
106                 plt.title(f"Optical_Flow_-_Frame_{idx}")
107                 plt.axis('off')
108                 plt.show()
109
110                 first_frame_gray = frame_gray.copy()
111                 p0 = good_new.reshape(-1, 1, 2)
112                 flow_points.append(p0)
113         else:
114             print("No_features_found_in_this_frame._Stopping.")
115             break
116
117     optical_flow(frames_save_path)

```

Listing 3: Optical Flow Tracking Code for Q3.

4.4 Discussion

- The number of features that remain trackable decreases as more frames are processed (some features move out of view or become occluded).
- If no features are detected in a frame, the process stops or must be reinitialized.
- The optical flow lines give an intuitive visualization of how points move from frame to frame, which helps track the robot arm effectively.

5 Q4 – Principal Component Analysis (PCA) and Transfer Learning

5.1 Problem Statement

We have a dataset of fruits and vegetables (Kaggle: Fruit-and-Vegetable Image Recognition). The task is split into two main parts:

1. **Basic Feature Extraction & PCA Visualization:** Flatten image pixels (RGB) into a vector and apply PCA to reduce dimensionality, then visualize in 2D.
2. **Transfer Learning & PCA Visualization:** Fine-tune a ResNet-50 model on the training set, then extract features from the penultimate layer, apply PCA, and compare the 2D visual clusters with the basic approach.

5.2 Methodology

Part 1: Basic Feature Extraction.

1. Resize the images to 224×224 .
2. Flatten each image into a vector of size $3 \times 224 \times 224$.
3. Perform PCA to reduce from $3 \times 224 \times 224$ to 2 dimensions.
4. Cluster the PCA-transformed data using `KMeans` and visualize.

Part 2: Transfer Learning.

1. Load a pre-trained ResNet-50 and replace the final fully-connected layer to match the number of classes.
2. Freeze most of the layers except the last block (layer4) and the new fc layer to allow partial fine-tuning.
3. Train on the `train` set, validate on the `validation` set, and save the best model.
4. Use the best model as a feature extractor by taking the output from the penultimate layer (pooling layer).
5. Again, perform PCA on these extracted features and compare the results to the basic features.

5.3 Code

```
1 import kagglehub
2
3 # Download dataset
4 path = kagglehub.dataset_download("kritikseth/fruit-and-vegetable-
   image-recognition")
5 print("Path to dataset files:", path)
6
7 import os
8 print(os.listdir("/root/.cache/kagglehub/datasets/kritikseth/fruit
   -and-vegetable-image-recognition/versions/8"))
9
10 import torch
11 import torch.nn as nn
12 import torch.optim as optim
13 from torchvision import models, transforms, datasets
14 from torch.utils.data import DataLoader
15 import numpy as np
16 import matplotlib.pyplot as plt
17 from sklearn.decomposition import PCA
18 from sklearn.cluster import KMeans
19
20 device = "cuda" if torch.cuda.is_available() else "cpu"
21 print("Using device:", device)
22
23 train_data_path = "/root/.cache/kagglehub/datasets/kritikseth/
   fruit-and-vegetable-image-recognition/versions/8/train"
24 val_data_path = "/root/.cache/kagglehub/datasets/kritikseth/fruit-
   and-vegetable-image-recognition/versions/8/validation"
```

```

25 test_data_path = "/root/.cache/kagglehub/datasets/kritikseth/fruit
    -and-vegetable-image-recognition/versions/8/test"
26
27 #####
28 # PART 1: BASIC FEATURE EXTRACTION
29 #####
30 basic_transform = transforms.Compose([
31     transforms.Resize((224, 224)),
32     transforms.ToTensor()
33 ])
34
35 test_dataset_basic = datasets.ImageFolder(test_data_path,
    transform=basic_transform)
36
37 basic_test_images = []
38 basic_test_labels = []
39
40 for img, label in test_dataset_basic:
41     flattened = img.view(-1).numpy() # shape (3*224*224,)
42     basic_test_images.append(flattened)
43     basic_test_labels.append(label)
44
45 basic_test_images = np.array(basic_test_images)
46 basic_test_labels = np.array(basic_test_labels)
47
48 print("Shape_of_raw_pixel_feature_matrix:", basic_test_images.
    shape)
49
50 # Apply PCA (2D)
51 pca_basic = PCA(n_components=2)
52 basic_test_pca = pca_basic.fit_transform(basic_test_images)
53
54 # KMeans
55 number_of_classes = len(test_dataset_basic.classes)
56 kmeans_basic = KMeans(n_clusters=number_of_classes, random_state
    =42)
57 clusters_basic = kmeans_basic.fit_predict(basic_test_pca)
58
59 # Visualization
60 plt.figure(figsize=(8,6))
61 scatter = plt.scatter(basic_test_pca[:, 0],
62                       basic_test_pca[:, 1],
63                       c=clusters_basic,
64                       cmap='tab10')
65 plt.title("PCA_of_Flattened-Pixel_Features_(Basic_Extraction)")
66 plt.xlabel("PC1")
67 plt.ylabel("PC2")
68 plt.colorbar(scatter, label="Cluster_ID")
69 plt.show()

```

```

70
71 # Optional function to visualize cluster images
72 def visualize_cluster_examples(basic_test_dataset, cluster_ids,
73                               kmeans_obj, k=3):
74     import random
75     unique_clusters = np.unique(cluster_ids)
76     for c in unique_clusters:
77         indices = np.where(cluster_ids == c)[0]
78         if len(indices) == 0:
79             continue
80         print(f"\nCluster_{c}:_showing_up_to_{k}_random_images")
81         chosen = np.random.choice(indices, size=min(k, len(indices)),
82                                     replace=False)
83
84         fig, axs = plt.subplots(1, max(1, len(chosen)), figsize
85                                 =(15, 3))
86         if len(chosen) == 1:
87             axs = [axs]
88
89         fig.suptitle(f"Cluster_{c}_sample_images", fontsize=16)
90         for i, idx in enumerate(chosen):
91             path, label_idx = basic_test_dataset.samples[idx]
92             img = plt.imread(path)
93             axs[i].imshow(img)
94             axs[i].axis('off')
95         plt.show()
96
97 visualize_cluster_examples(
98     test_dataset_basic,
99     clusters_basic,
100     kmeans_basic,
101     k=3
102 )
103
104 #####
105 # PART 2: TRANSFER LEARNING
106 #####
107 data_transforms = transforms.Compose([
108     transforms.Resize((224, 224)),
109     transforms.ToTensor(),
110     transforms.Normalize(mean=[0.485, 0.456, 0.406],
111                           std=[0.229, 0.224, 0.225])
112 ])
113
114 train_dataset = datasets.ImageFolder(train_data_path, transform=
115     data_transforms)
116 val_dataset = datasets.ImageFolder(val_data_path, transform=
117     data_transforms)

```

```

114 test_dataset = datasets.ImageFolder(test_data_path, transform=
    data_transforms)
115
116 train_loader = DataLoader(train_dataset, batch_size=32, shuffle=
    True)
117 val_loader = DataLoader(val_dataset, batch_size=32, shuffle=False)
118 test_loader = DataLoader(test_dataset, batch_size=32, shuffle=
    False)
119
120 num_classes = len(train_dataset.classes)
121
122 model = models.resnet50(pretrained=True)
123 for param in model.parameters():
124     param.requires_grad = False
125
126 # Unfreeze the last block
127 for name, param in model.layer4.named_parameters():
128     param.requires_grad = True
129
130 # Replace final FC layer
131 in_features = model.fc.in_features
132 model.fc = nn.Linear(in_features, num_classes)
133 for param in model.fc.parameters():
134     param.requires_grad = True
135
136 model.to(device)
137
138 criterion = nn.CrossEntropyLoss()
139 optimizer = optim.Adam(filter(lambda p: p.requires_grad, model.
    parameters()), lr=0.001)
140
141 def validate(model, val_loader):
142     model.eval()
143     val_loss = 0.0
144     correct = 0
145     total = 0
146     with torch.no_grad():
147         for inputs, labels in val_loader:
148             inputs, labels = inputs.to(device), labels.to(device)
149             outputs = model(inputs)
150             loss = criterion(outputs, labels)
151             val_loss += loss.item()
152
153             _, predicted = torch.max(outputs, 1)
154             correct += (predicted == labels).sum().item()
155             total += labels.size(0)
156     avg_loss = val_loss / len(val_loader)
157     accuracy = 100.0 * correct / total
158     return avg_loss, accuracy

```

```

159
160 def train_model(model, train_loader, val_loader, epochs=3):
161     best_val_acc = 0.0
162     for epoch in range(epochs):
163         model.train()
164         running_loss = 0.0
165         correct = 0
166         total = 0
167         for inputs, labels in train_loader:
168             inputs, labels = inputs.to(device), labels.to(device)
169             optimizer.zero_grad()
170             outputs = model(inputs)
171             loss = criterion(outputs, labels)
172             loss.backward()
173             optimizer.step()
174             running_loss += loss.item()
175
176             _, predicted = torch.max(outputs, 1)
177             correct += (predicted == labels).sum().item()
178             total += labels.size(0)
179
180         train_loss = running_loss / len(train_loader)
181         train_acc = 100.0 * correct / total
182
183         val_loss, val_acc = validate(model, val_loader)
184         print(f"[Epoch_{epoch+1}/{epochs}] ")
185             f"Train_Loss:_{train_loss:.4f},_Train_Acc:_{train_acc:.2f}%|"
186             f"Val_Loss:_{val_loss:.4f},_Val_Acc:_{val_acc:.2f}%")
187
188         if val_acc > best_val_acc:
189             best_val_acc = val_acc
190             print("_->_Saving_best_model...")
191             torch.save(model.state_dict(), "best_model.pth")
192
193 train_model(model, train_loader, val_loader, epochs=3)
194
195 # Load best model
196 best_model = models.resnet50(pretrained=False)
197 best_model.fc = nn.Linear(in_features, num_classes)
198 best_model.load_state_dict(torch.load("best_model.pth",
199                                     map_location=device))
200 best_model.to(device)
201 best_model.eval()
202
203 # Feature Extractor
204 feature_extractor = nn.Sequential(*list(best_model.children())
205                                   [:-1])
206 feature_extractor.to(device)

```

```

205 feature_extractor.eval()
206
207 features = []
208 test_labels = []
209
210 with torch.no_grad():
211     for imgs, lbls in test_loader:
212         imgs = imgs.to(device)
213         feats = feature_extractor(imgs)
214         feats = feats.view(feats.size(0), -1)
215         features.append(feats.cpu().numpy())
216         test_labels.extend(lbls.numpy())
217
218 features = np.concatenate(features, axis=0) # shape: [N, 2048]
219 test_labels = np.array(test_labels)
220
221 print("Shape of extracted features (ResNet_penultimate):",
222       features.shape)
223
224 # PCA
225 pca_resnet = PCA(n_components=2)
226 pca_features = pca_resnet.fit_transform(features)
227
228 kmeans_resnet = KMeans(n_clusters=num_classes, random_state=42)
229 clusters_resnet = kmeans_resnet.fit_predict(pca_features)
230
231 plt.figure(figsize=(8,6))
232 scatter = plt.scatter(pca_features[:, 0],
233                      pca_features[:, 1],
234                      c=clusters_resnet,
235                      cmap='tab10')
236 plt.title("PCA of Fine-Tuned ResNet-50 Features")
237 plt.xlabel("PC1")
238 plt.ylabel("PC2")
239 plt.colorbar(scatter, label="Cluster ID")
240 plt.show()
241
242 def visualize_cluster_examples_resnet(feature_dataset, cluster_ids,
243                                     kmeans_obj, k=3):
244     unique_clusters = np.unique(cluster_ids)
245     for c in unique_clusters:
246         indices = np.where(cluster_ids == c)[0]
247         if len(indices) == 0:
248             continue
249         print(f"\n[ResNet-FineTuned] Cluster {c}: showing up to {k}
250               random images")
251         chosen = np.random.choice(indices, size=min(k, len(indices)),
252                                   replace=False)

```

```

250     fig, axs = plt.subplots(1, max(1, len(chosen)), figsize
        =(15, 3))
251     if len(chosen) == 1:
252         axs = [axs]
253
254     fig.suptitle(f"Cluster_{c}_sample_images", fontsize=16)
255     for i, idx in enumerate(chosen):
256         path, label_idx = feature_dataset.samples[idx]
257         img = plt.imread(path)
258         axs[i].imshow(img)
259         axs[i].axis('off')
260     plt.show()
261
262 visualize_cluster_examples_resnet(test_dataset, clusters_resnet,
        kmeans_resnet, k=3)

```

Listing 4: PCA + Transfer Learning Code for Q4.

5.4 Discussion

- The raw pixel flattening often does not capture discriminative features effectively, leading to less cohesive clusters.
- Fine-tuned ResNet-50 features show significantly better cluster separation in PCA space.
- Transfer learning can improve classification accuracy and yield more meaningful embeddings.

6 Conclusion

This report covers four key topics in computer vision:

1. **Region-Growing Segmentation:** Demonstrated a BFS-based algorithm that expands a region from seed points. Different thresholds and multiple seeds can greatly influence the final segmentation outcome.
2. **Diffusion Models (Text-to-Image/Video, Image-to-Image/Video):** Explored the power of modern diffusion approaches for generative tasks using publicly available pipelines from Hugging Face.
3. **Optical Flow for Motion Tracking:** Implemented Lucas–Kanade optical flow to track feature points in a video, highlighting the movement of a robot arm.

4. **PCA and Transfer Learning:** Showed how PCA can visualize high-dimensional data, and how transfer learning (fine-tuning a ResNet-50) improves the feature representations compared to raw-pixel flattening.

Overall, each of these tasks demonstrates essential computer vision and deep learning techniques, ranging from classical segmentation and optical flow to state-of-the-art generative models and representation learning with deep neural networks.