AIUB

Assignment

Course Name : COMPUTER VISION AND PATTERN RECOGNITION

Assignment No : 1 [MID TERM]

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1. Importing the libraries needed to build our k-NN model.

```
In [4]: import os
        import random
        import cv2
        from tqdm import tqdm
        import numpy as np
        import matplotlib.pyplot as plt
```

2. The CIFAR-10 training dataset is loaded.

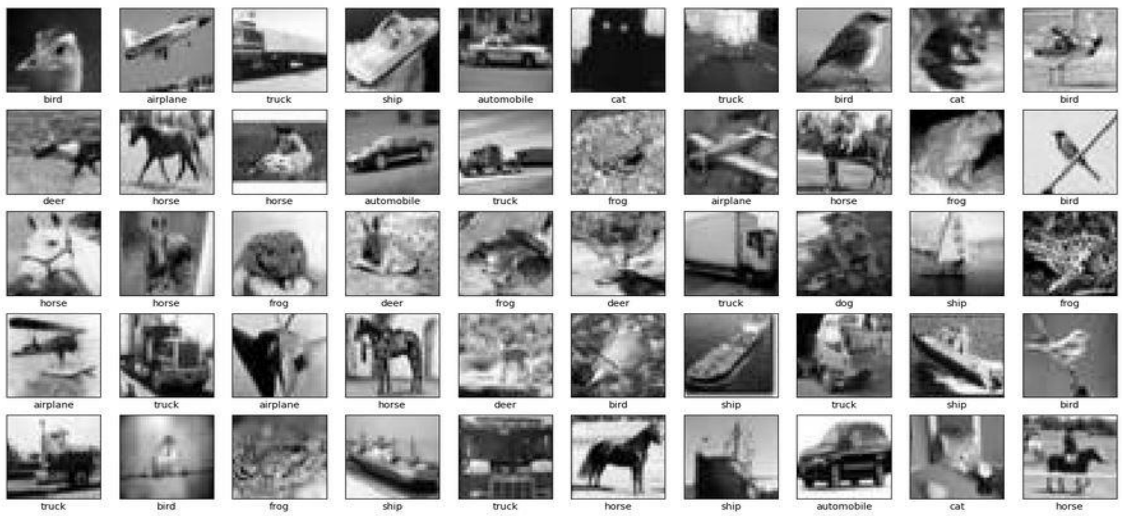
```
In [5]: TRAIN_DIR = 'G:/Dataset/train'
        CATEGORIES = []
        for c in os.listdir(TRAIN_DIR):
            CATEGORIES.append(c)
        print(CATEGORIES)

        ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck']
```

3. Reading and storing all images from each class by recording them.

```
In [6]: TRAIN_DATA = []
        for c in CATEGORIES:
            path = os.path.join(TRAIN_DIR,c)
            class_num = CATEGORIES.index(c)
            for img in tqdm(os.listdir(path)):
                img_arr = cv2.imread(os.path.join(path,img))
                TRAIN_DATA.append([img_arr, class_num])
        print(len(TRAIN_DATA))

        100%|██████████| 5000/5000 [00:33<00:00, 150.27it/s]
        100%|██████████| 5000/5000 [00:33<00:00, 150.25it/s]
        100%|██████████| 5000/5000 [00:35<00:00, 141.53it/s]
        100%|██████████| 5000/5000 [00:34<00:00, 146.26it/s]
        100%|██████████| 5000/5000 [00:35<00:00, 139.39it/s]
        100%|██████████| 5000/5000 [00:38<00:00, 130.58it/s]
        100%|██████████| 5000/5000 [00:40<00:00, 123.80it/s]
        100%|██████████| 5000/5000 [00:39<00:00, 127.89it/s]
        100%|██████████| 5000/5000 [00:44<00:00, 111.89it/s]
        100%|██████████| 5000/5000 [00:38<00:00, 128.29it/s]

        50000
```

4. Changing all of the images to grayscale.

```
In [7]: random.shuffle(TRAIN_DATA)
        plt.figure(figsize=(20,10))
        for i in range(50):
            plt.subplot(5,10,i+1)
            image = TRAIN_DATA[i][0]
            image_gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
            plt.imshow(image_gray, cmap="gray")
            plt.xlabel(CATEGORIES[TRAIN_DATA[i][1]])
            plt.xticks([])
            plt.yticks([])
            if i==50:
                break
        plt.show()
```



5. Defining 5 folds of data and dividing them into 1000 photos per fold.

```
In [8]: f0 = TRAIN_DATA[0:1000]
        f1 = TRAIN_DATA[1000:2000]
        f2 = TRAIN_DATA[2000:3000]
        f3 = TRAIN_DATA[3000:4000]
        f4 = TRAIN_DATA[4000:5000]
```

6. Establishing L1 and L2 distances

```
In [16]: def by_l1_dist(list):
             return list[2]["l1"]

         def by_l2_dist(list):
             return list[2]["l2"]
```

7. Training the model and computing L1 and L2 distance accuracies, as well as visualizing the results of L1 and L2 distance accuracies.

In [17]:
```
top_filter = 20
def distance_calc(train_fold, valid_fold):
    l1_result = []
    l2_result = []
    for valid in tqdm(valid_fold):
        temp_dist_list = []
        for train in train_fold:
            l1_dist = np.sum(np.abs(valid[0]-train[0]))
            l2_dist = np.sqrt(np.sum(valid[0]-train[0]**2))
            temp_dist_list.append([valid[1],  train[1], {"l1": l1_dist, "l2": l2_dist}])
        temp_dist_list.sort(key=by_l1_dist)
        l1_result.append(temp_dist_list[:top_filter])
        temp_dist_list.sort(key=by_l2_dist)
        l2_result.append(temp_dist_list[:top_filter])
    return [l1_result, l2_result]
```

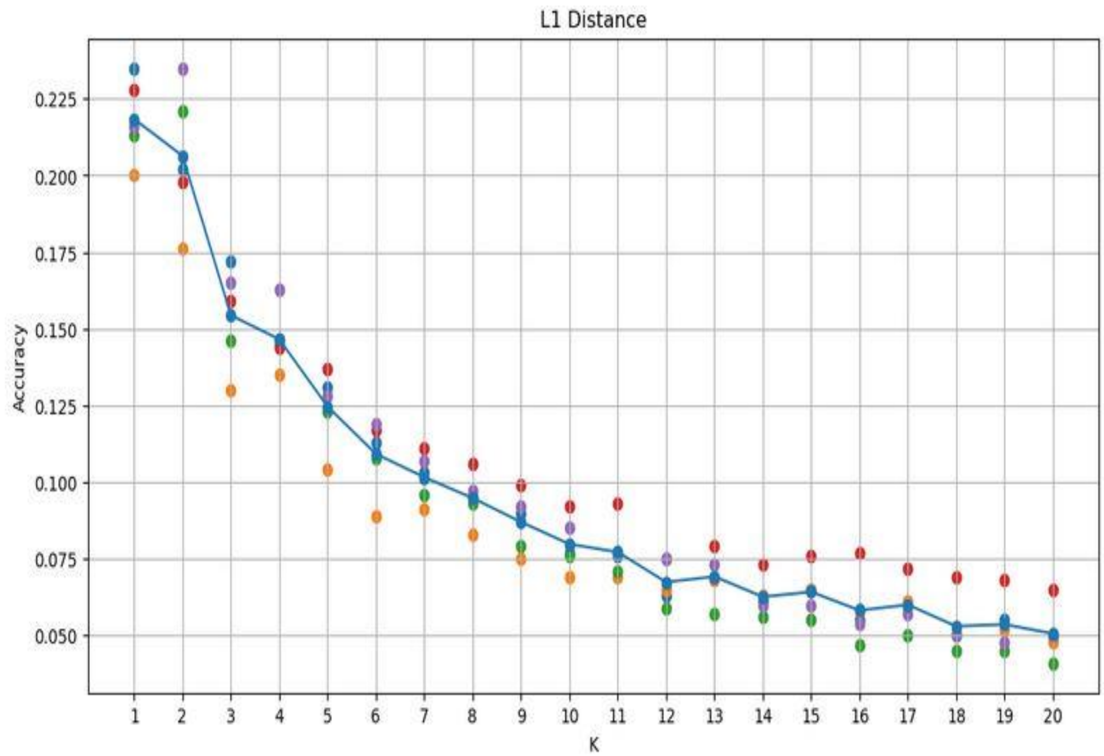
In [18]:
```
k_range = 20
def cal_accuracy(dist_result, dist_term):
    k_accuracies = []
    for k in range(1, k_range+1):
        img_accuracy = 0
        for valid_img in dist_result:
            nn = valid_img[:k]
            same_class = [n for n in nn if n[0] == n[1]]
            same_class_len = len(same_class)
            if k % 2 != 0:
                if ((k-1) / 2) < same_class_len:
                    img_accuracy += 1
            else:
                diff_class = [n for n in nn if n[0] != n[1]]
                if same_class_len > len(diff_class):
                    img_accuracy += 1
                elif same_class_len == len(diff_class): # tie
                    same_class_dist = sum([n[2][dist_term] for n in same_class])
                    diff_class_dist = sum([n[2][dist_term] for n in diff_class])
                    if same_class_dist > diff_class_dist:
                        img_accuracy += 1
        k_accuracies.append(img_accuracy/len(dist_result))
    return k_accuracies
```

In [19]:
```
dist_by_fold = []
import math
for i in range(5):
    if i==0:
        train = f1+f2+f3+f4
        validation = f0
    elif i==1:
        train = f0+f2+f3+f4
        validation = f1
    elif i==2:
        train = f1+f0+f3+f4
        validation = f2
    elif i==3:
        train = f1+f2+f0+f4
        validation = f3
    elif i==4:
        train = f1+f2+f3+f0
        validation = f4

    dist_by_fold.append(distance_calc(train, validation))
```

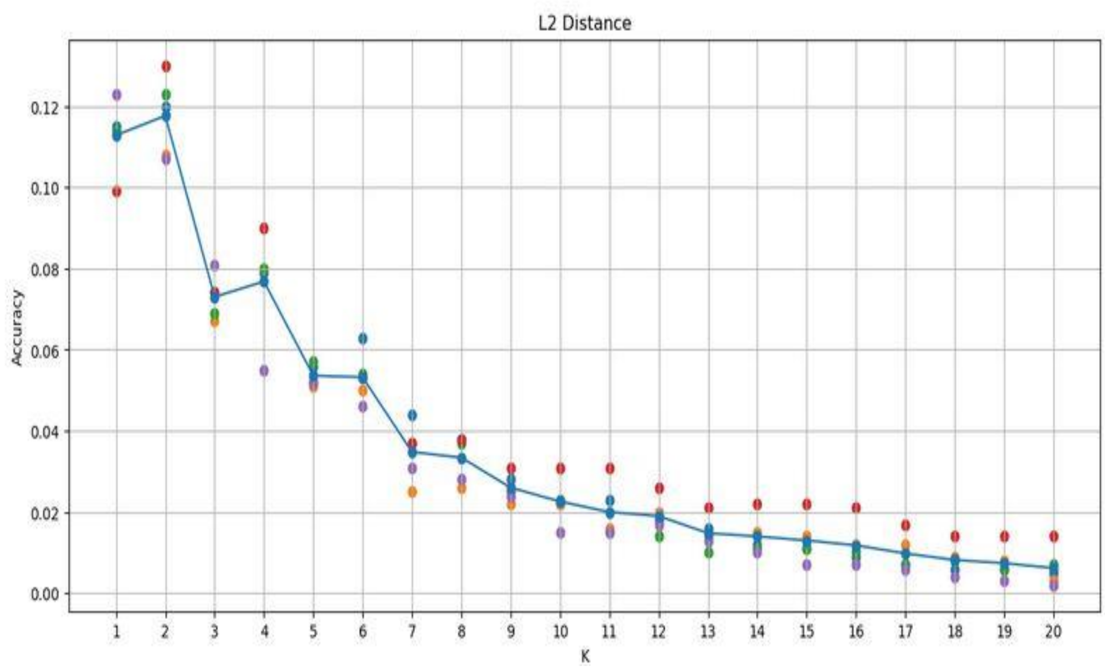
```
100%|██████████| 1000/1000 [01:56<00:00,  8.60it/s]
100%|██████████| 1000/1000 [01:56<00:00,  8.61it/s]
100%|██████████| 1000/1000 [01:57<00:00,  8.54it/s]
100%|██████████| 1000/1000 [01:56<00:00,  8.58it/s]
100%|██████████| 1000/1000 [01:57<00:00,  8.48it/s]
```

In [20]:
```
accuracies = []

for result in dist_by_fold:
    l1_accuracy = cal_accuracy(result[0], "l1")
    l2_accuracy = cal_accuracy(result[1], "l2")
    accuracies.append([l1_accuracy, l2_accuracy])
```

In [23]:
```

x_list = list(range(1, k_range+1))
plt.figure(figsize=(12, 6))

for fold in accuracies:
  y_list = fold[0]
  plt.scatter(x_list, y_list)
arr = []
for i in range(k_range):
  arr.append([fold[0][i] for fold in accuracies])
trend = [np.mean(a) for a in arr]
plt.errorbar(x_list, trend,fmt='-o')
plt.title('L1 Distance')
plt.xticks(x_list)
plt.grid(True)
plt.xlabel('K')
plt.ylabel('Accuracy')
plt.show()

x_list = list(range(1, k_range+1))
plt.figure(figsize=(14, 6))

for fold in accuracies:
  y_list = fold[1]
  plt.scatter(x_list, y_list)
arr = []
for i in range(k_range):
  arr.append([fold[1][i] for fold in accuracies])
trend = [np.mean(a) for a in arr]
plt.errorbar(x_list, trend,fmt='-o')
plt.title('L2 Distance')
plt.xticks(x_list)
plt.grid(True)
plt.xlabel('K')
plt.ylabel('Accuracy')
plt.show()
```



L1 Distance
Accuracy
0.225
0.200
0.175
0.150
0.125
0.100
0.075
0.050
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
K



L2 Distance
Accuracy
0.12
0.10
0.08
0.06
0.04
0.02
0.00
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
K

8. Predicting the top five photos based on L1 and L2 distances. Each Prediction will provide the class name predicted by the KNN model as well as the distance determined for that value.

```
In [31]: def l1_dist(image1, image2):
             return np.sum(np.abs(image1 - image2))

         def l2_dist(image1, image2):
             return np.sqrt(np.sum((image1 - image2) ** 2))

         random.shuffle(TRAIN_DATA)
         plt.figure(figsize=(20, 10))
         for i in range(50):
             plt.subplot(5, 10, i+1)
             image = TRAIN_DATA[i][0]
             image_gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
             plt.imshow(image_gray, cmap="gray")
             plt.xlabel(CATEGORIES[TRAIN_DATA[i][1]])
             plt.xticks([])
             plt.yticks([])
             if i == 49:
                 break
         test_images = []

         for i in range(2000):
             test_image = TRAIN_DATA[i][0]
             test_image_gray = cv2.cvtColor(test_image, cv2.COLOR_BGR2GRAY)
             test_images.append(test_image_gray)

         print("Top 5 Predictions for L1 Distance:")
         for test_image_gray in test_images:
             distances1 = []
             for train_image, class_num in TRAIN_DATA:
                 train_image_gray = cv2.cvtColor(train_image, cv2.COLOR_BGR2GRAY)
                 dist1 = l1_dist(test_image_gray, train_image_gray)
                 distances1.append((dist1, class_num))
             distances1.sort(key=lambda x: x[0])

             for i, (dist1, class_num) in enumerate(distances1[:5]):
                 predicted_class = CATEGORIES[class_num]
                 print(f"Prediction {i+1}: Class '{predicted_class}' with L1 distance {dist1/100:.2f}")
             break


         print("\nTop 5 Predictions for L2 Distance:")
         for test_image_gray in test_images:
             distances2 = []
             for train_image, class_num in TRAIN_DATA:
                 train_image_gray = cv2.cvtColor(train_image, cv2.COLOR_BGR2GRAY)
                 dist2 = l2_dist(test_image_gray, train_image_gray)
                 distances2.append((dist2, class_num))
             distances2.sort(key=lambda x: x[0])

             for i, (dist2, class_num) in enumerate(distances2[:5]):
                 predicted_class = CATEGORIES[class_num]
                 print(f"Prediction {i+1}: Class '{predicted_class}' with L2 distance {dist2:.2f}")
             break
```

```
Top 5 Predictions for L1 Distance:
Prediction 1: Class 'frog' with L1 distance 0.00
Prediction 2: Class 'frog' with L1 distance 518.24
Prediction 3: Class 'airplane' with L1 distance 742.61
Prediction 4: Class 'cat' with L1 distance 750.62
Prediction 5: Class 'frog' with L1 distance 767.43

Top 5 Predictions for L2 Distance:
Prediction 1: Class 'frog' with L2 distance 0.00
Prediction 2: Class 'frog' with L2 distance 264.80
Prediction 3: Class 'dog' with L2 distance 297.18
Prediction 4: Class 'airplane' with L2 distance 300.15
Prediction 5: Class 'airplane' with L2 distance 301.15
```

Discussion:

The performance of Manhattan (L1) and Euclidean (L2) distances was tested using the CIFAR-10 dataset, which contains 60,000 32x32x3 color pictures in ten different classes. The goal was to identify which distance calculation technique was best suited to the given gray-scale dataset. In terms of accuracy, the L1 distance outperformed the L2 distance, according to the analysis. The Manhattan (L1) and Euclidean (L2) distance comparisons demonstrated the need of considering dataset characteristics and feature nature when deciding on a distance computation approach.