**National University of Computer
and Emerging Sciences**

Department: Data Science

Name of Assignment: ASSIGNMENT # 2

Name: Muhammad Haziq Ijaz i21-2692

Section: "DS-N"

Subject: Data Mining

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Interactive Foreground Segmentation Using K-Means Clustering

Abstract

This report describes the development and implementation of an interactive image segmentation system, which leverages K-Means clustering to distinguish foreground elements from the background. The system utilizes human-annotated seed points to guide the segmentation process, enhancing accuracy and interactivity.

Introduction

The task of image segmentation is a fundamental operation in the field of computer vision, with applications ranging from medical imaging to autonomous vehicles. The goal of segmentation is to partition an image into segments, or sets of pixels, that correspond to different objects or regions of interest. Our approach introduces a semi-automatic segmentation method known as "Interactive Foreground Segmentation", which incorporates user input in the form of seed points to improve the precision of the segmentation task.

Methodology

Data Preprocessing

The original and auxiliary images were preprocessed with the following steps:

- Gaussian Blur: Applied to the original and auxiliary images to reduce noise and facilitate more accurate seed extraction.
- HSV Conversion: The auxiliary images were converted from BGR to HSV color space to more reliably detect the seed pixels marked by the user.

Seed Pixel Extraction

Seed pixels for the foreground and background were extracted using predefined color thresholds in the HSV space. These seeds were utilized as initial data points for the K-Means clustering algorithm.

K-Means Clustering

K-Means was implemented from scratch, consisting of the following steps:

1. Initialization: Centroids were initialized using random seed pixels from the dataset.

2. Assignment: Each pixel was assigned to the nearest centroid based on Euclidean distance.

3. Update: Centroids were recalculated as the mean of the assigned pixels.

This process iterated until convergence or a maximum number of iterations was reached.

Likelihood Computation

For each pixel in the image, a likelihood score was computed based on its distance from each centroid, using a non-squared exponential function to mitigate the downsides of small distance values.

Post-Processing

After segmentation, the following post-processing steps were applied:

- Morphological Operations: Used to clean up the segmentation mask, closing holes and eliminating noise.

- Connected Component Analysis: Small, disconnected components likely to be noise were removed from the segmentation mask.

- Contour Analysis: Contours were used to fill in gaps within the segmented regions.

Results

The segmentation system was tested on a variety of images with different complexities. The system was able to accurately segment the foreground from the background, as evidenced by the visual comparison between the original images and the segmentation results. The addition of post-processing techniques notably improved the quality of the segmentation by reducing noise.
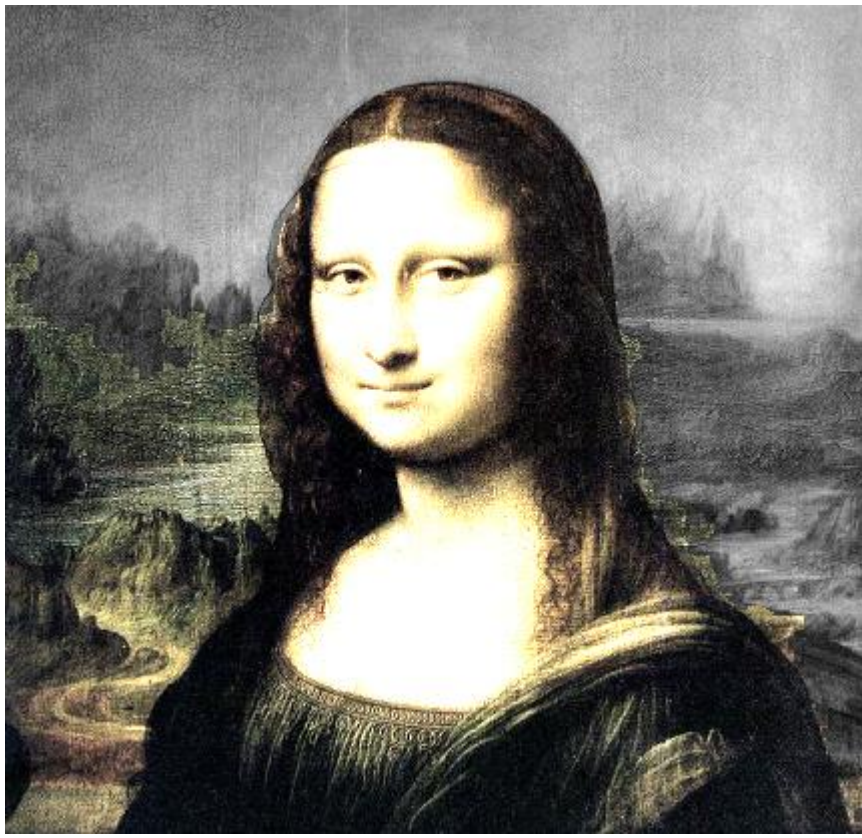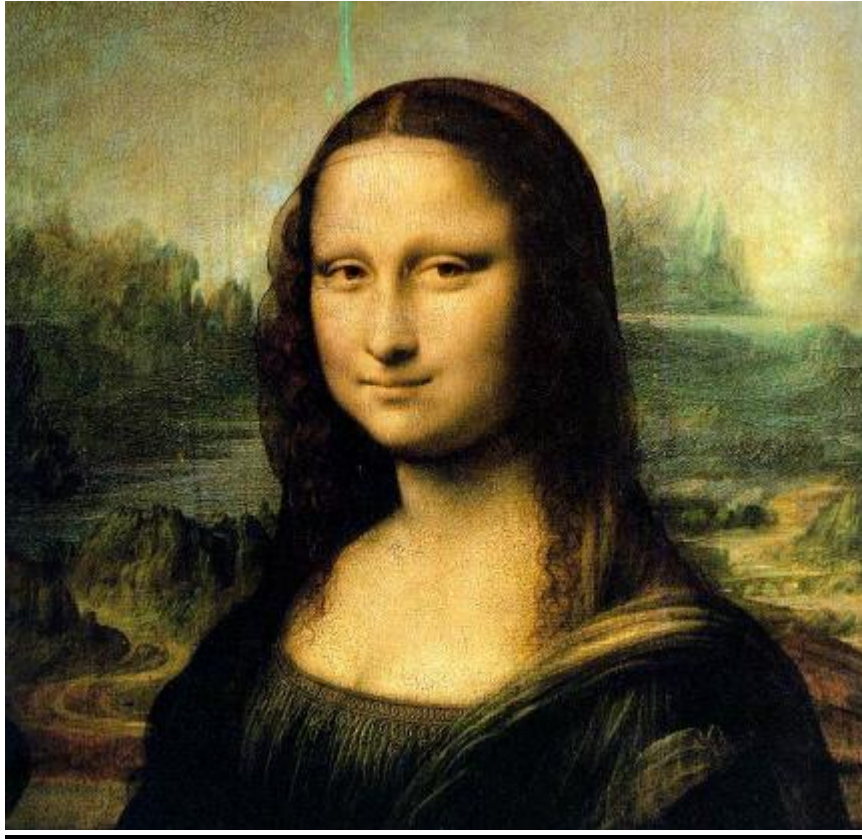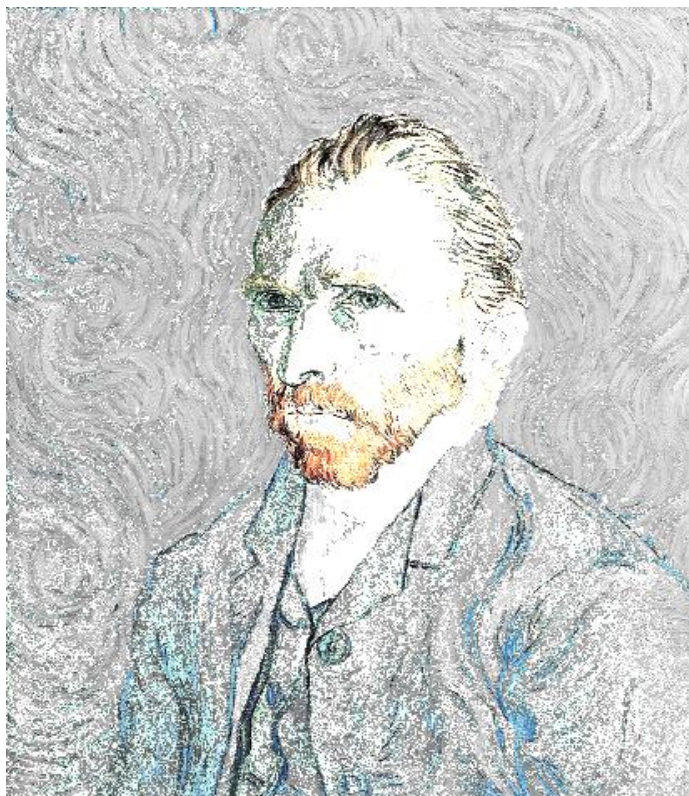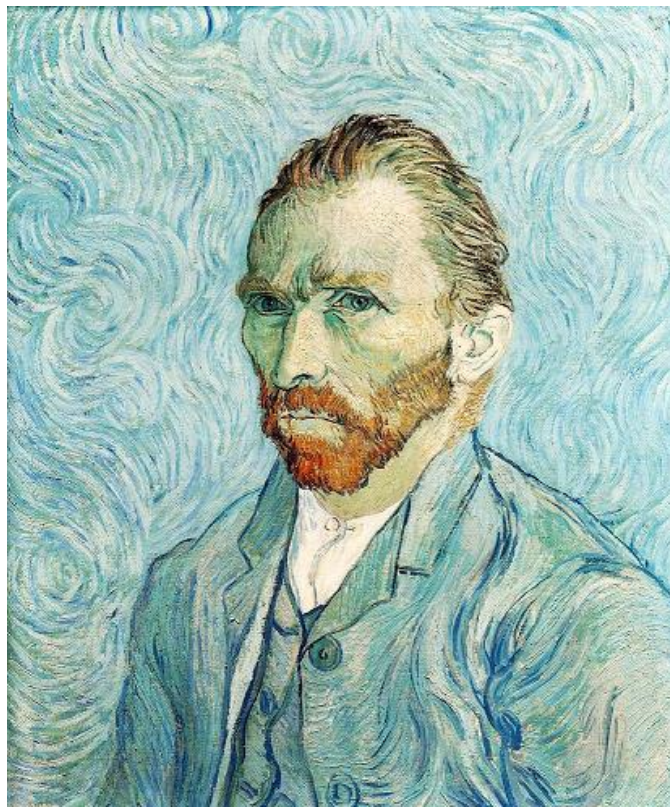
BEFORE

AFTER

Mona-Lisa

Mona-Lisa

Van-Gogh

Question 2

Accuracy:

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Accuracy of k-NN: 0.94
Accuracy of SVM: 1.00
Accuracy of GaussianNB: 0.51
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PCA Analysis:

PCA Visualization of Training and Testing Data