1. Raw Data:

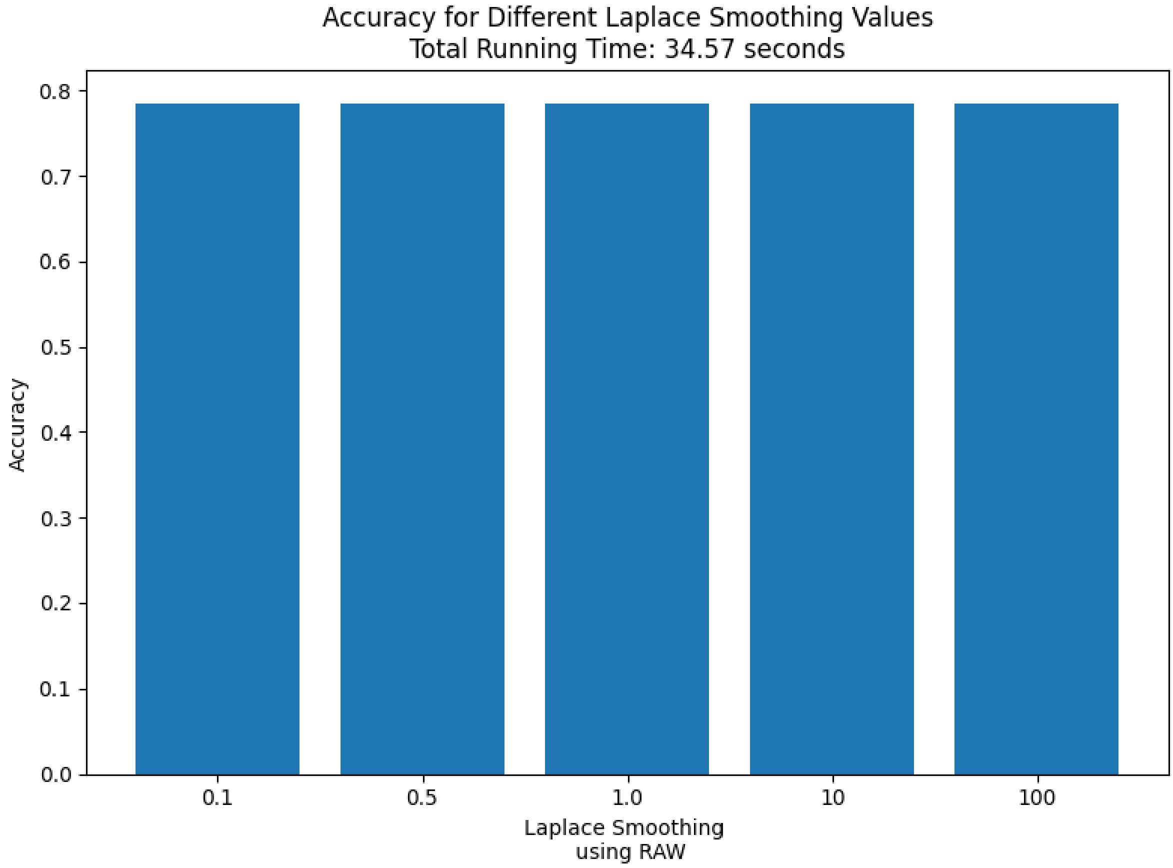
Raw data representation uses the pixel values of the input images without any preprocessing or feature extraction. It is the simplest and most straightforward way to represent the data.

When choosing raw data as a feature extraction method, the decision is based on the assumption that the raw pixel intensities contain sufficient discriminative information for the task at hand. The pixel values directly capture the visual appearance of the images, including color, texture, and intensity variations.

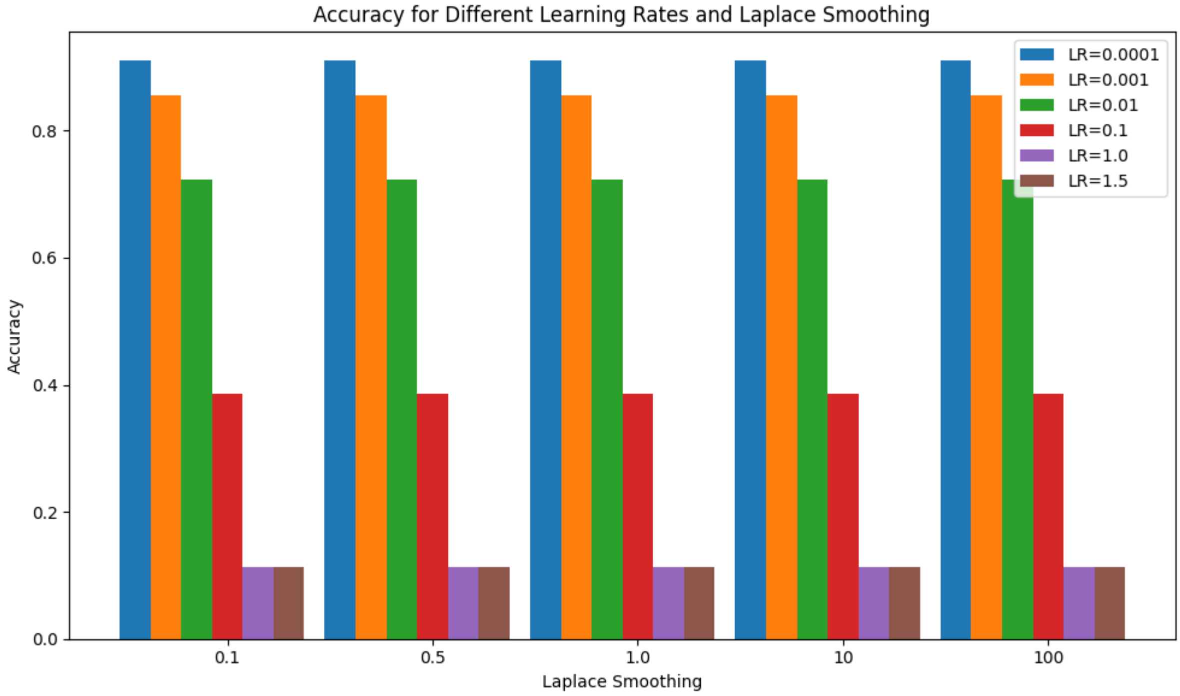
The working of raw data representation is quite intuitive. Each image is treated as a grid of pixels, with each pixel represented by its intensity value. By considering the pixel intensities as features, raw data preserves the fine details and local patterns present in the images. This can be advantageous in tasks where the pixel-level information plays a significant role, such as image classification or object recognition.

However, raw data may suffer from high dimensionality if the images are large or high-resolution. High dimensionality can lead to computational challenges and overfitting. Additionally, raw data may include noise or irrelevant features, which can impact the performance of machine learning models. Preprocessing techniques like normalization or scaling can be applied to mitigate these issues.

Using naive way:



Using Logical Regression:



2. Principal Component Analysis (PCA):

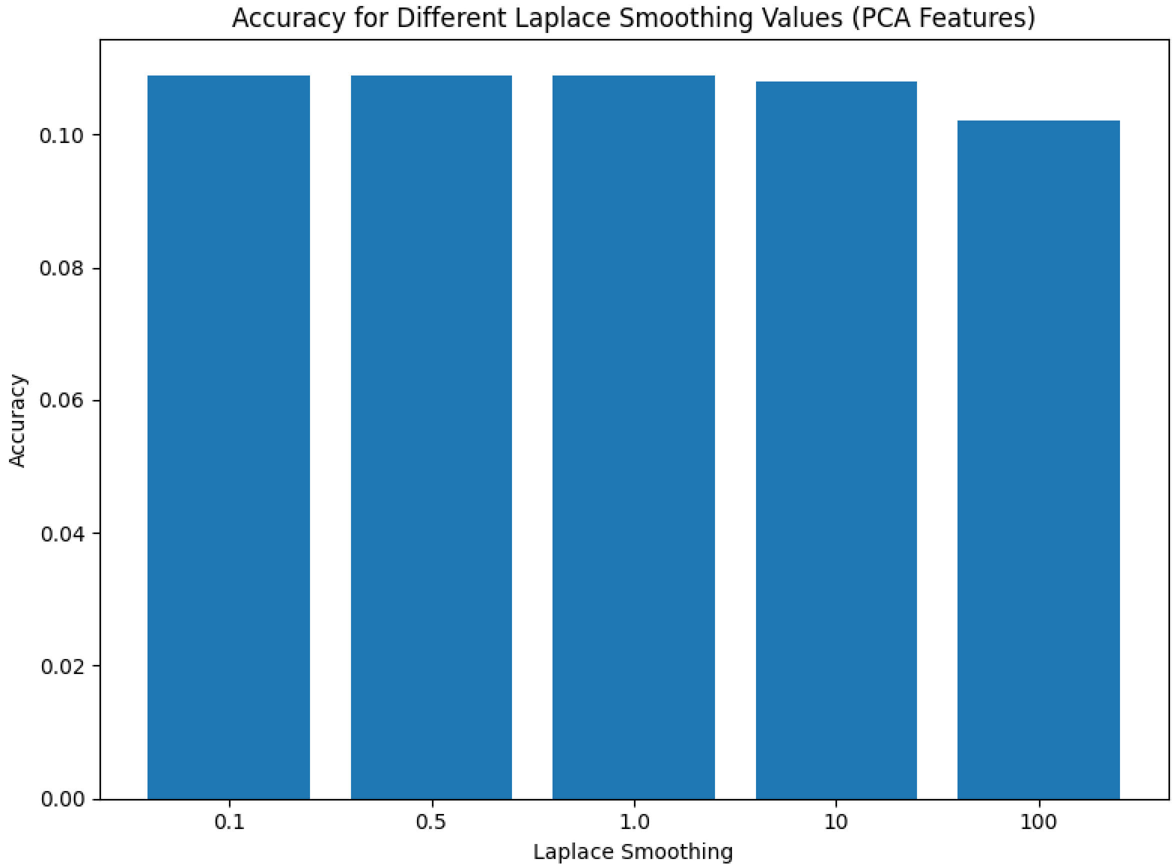
PCA is a widely used technique for dimensionality reduction and feature extraction. It aims to capture the most important variations in the data while reducing its dimensionality.

When choosing PCA as a feature extraction method, the main goal is to reduce the dimensionality of the data while preserving the most significant patterns or variations. PCA can be particularly useful when the input data has high dimensionality, making it computationally expensive or prone to overfitting.

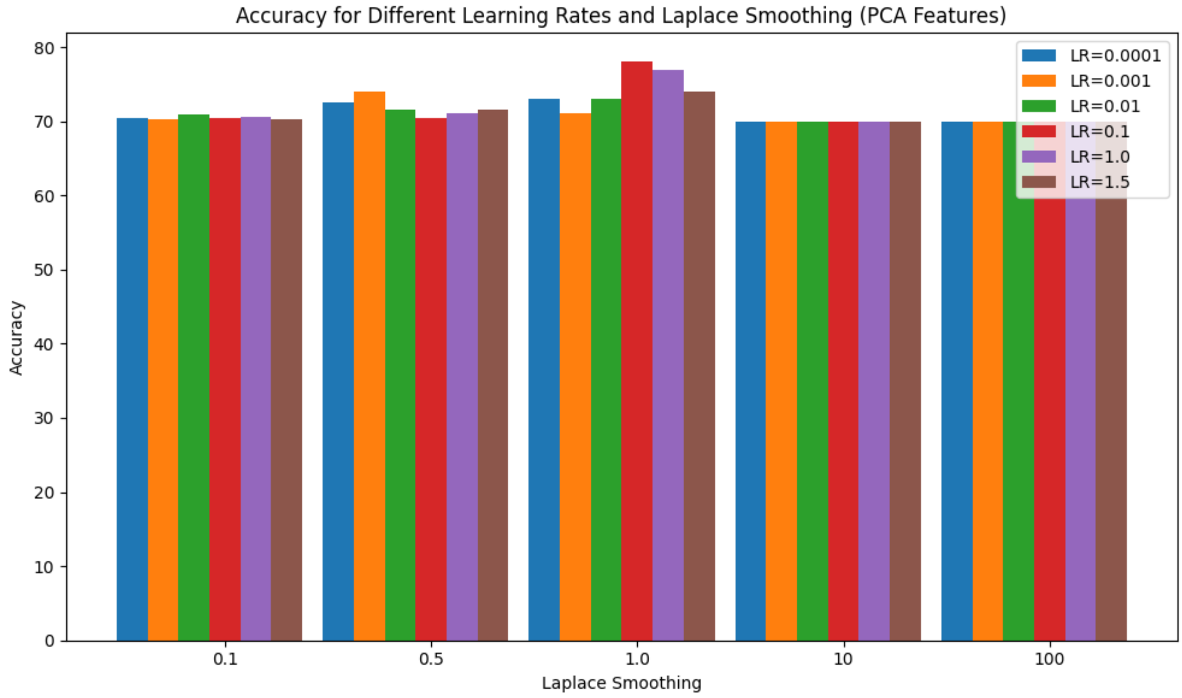
The working of PCA involves transforming the data into a new coordinate system defined by the principal components. The principal components are obtained through an eigenvalue decomposition of the covariance matrix of the input data. These components represent the directions in the data space along which the data varies the most. By selecting a subset of the top principal components that capture the most variance, PCA reduces the dimensionality while preserving the most important patterns.

PCA provides several benefits. It helps in reducing the computational complexity of the data by representing it in a lower-dimensional space. It also helps in removing noise or irrelevant features, as components with low variances can be discarded. Furthermore, PCA facilitates data visualization by projecting it onto a lower-dimensional subspace, enabling the exploration of the data's structure and patterns.

Using naive way:



Using Logical Regression:



3. Histogram of Oriented Gradients (HOG):

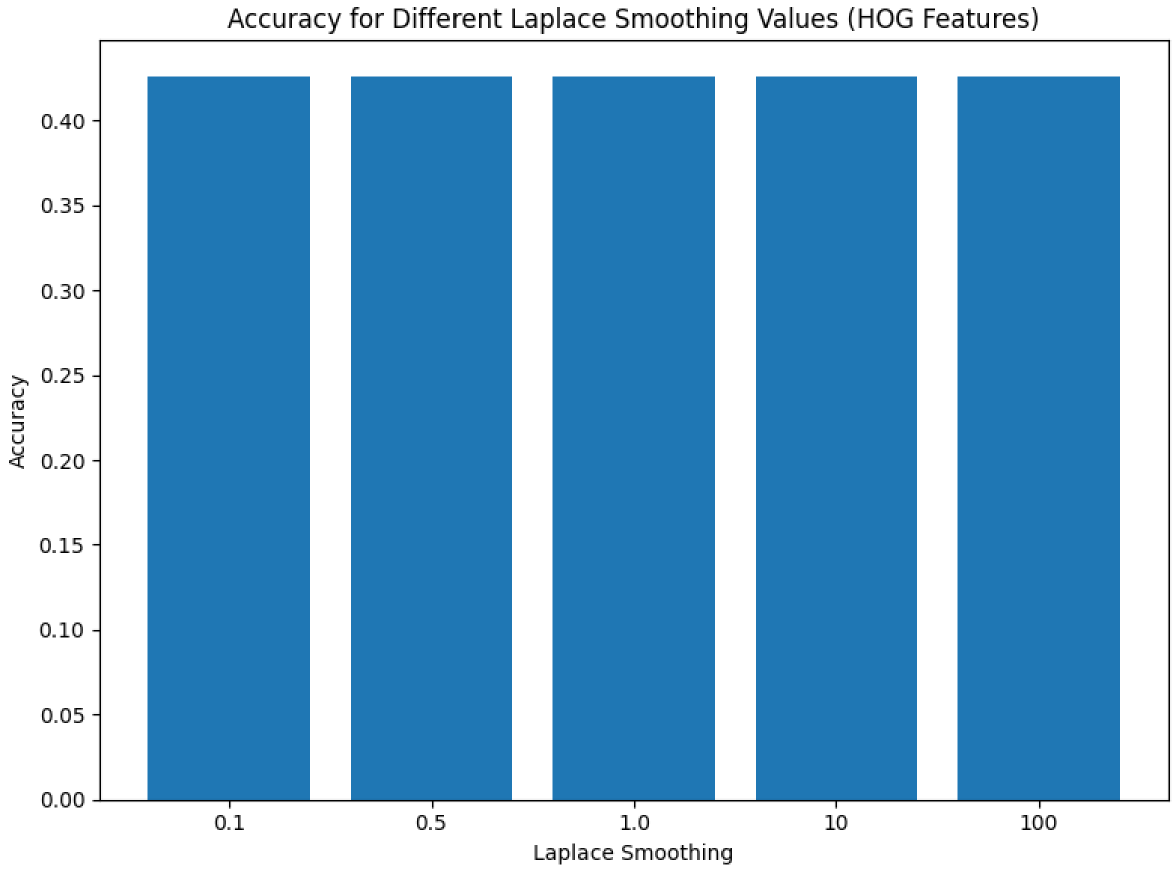
HOG captures local image structure and shape information through the distribution of gradient orientations.

When choosing HOG as a feature extraction method, the focus is on capturing the shape and structure of objects within the images. This makes it suitable for tasks where object appearance, texture, and spatial relationships are important.

The working of HOG involves calculating the gradients of the image pixels, representing the changes in pixel intensities. The gradients are computed in both the x and y directions using techniques such as Sobel operators. From the gradients, the magnitude and orientation of each pixel are determined. The image is divided into small cells, and within each cell, a histogram of gradient orientations is created, summarizing the distribution of orientations within that region. These histograms capture the texture and shape patterns within the image. To capture both local and global variations, the image is further divided into larger blocks, and the histograms are normalized.

The resulting HOG feature vector describes the distribution of gradient orientations in the image. It effectively represents object shape and structure, making it useful in tasks like object detection and recognition. The HOG features provide robustness to changes in lighting conditions, scale, and other factors that affect pixel intensities.

Using naive way:



Using Logical Regression: