

# Iris Recognition

Using PCA and Fischer LDA

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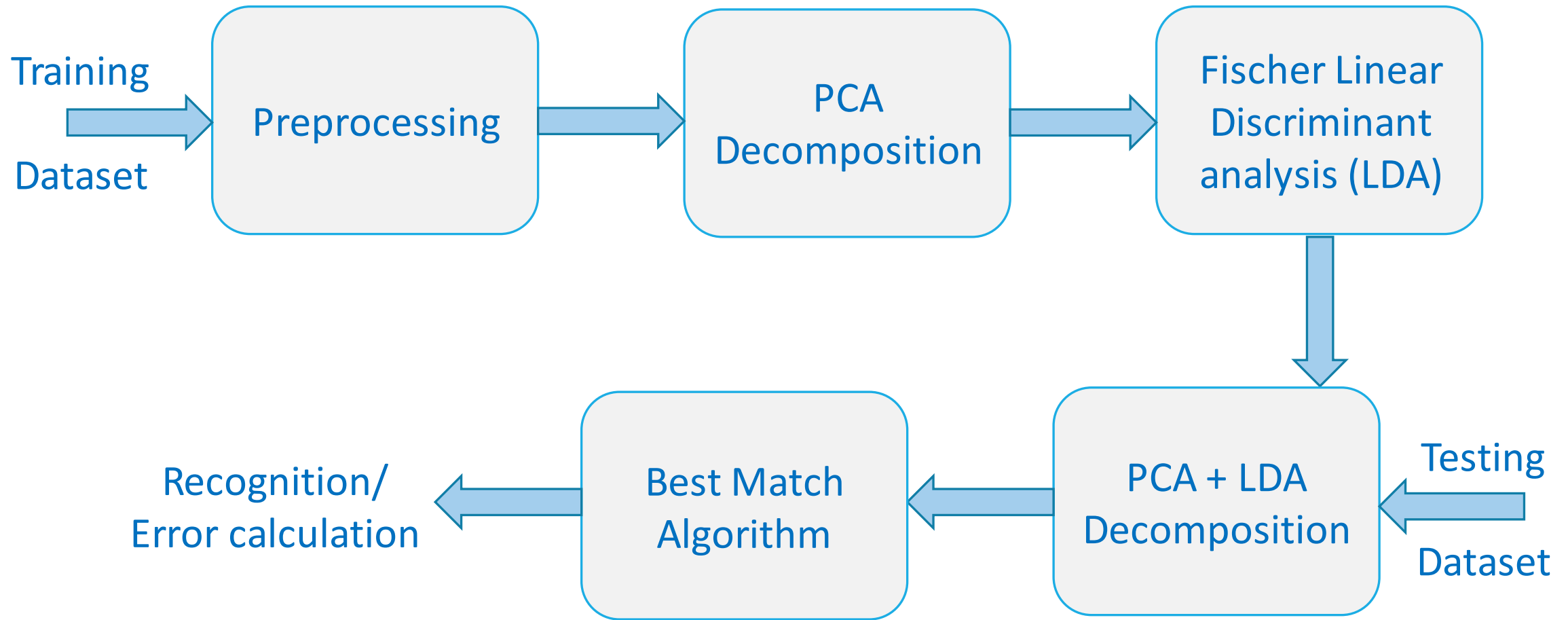
-ANIKET BHATIA

-SHUBHANG BHATNAGAR

-VINEET ASHOK KOTARIYA

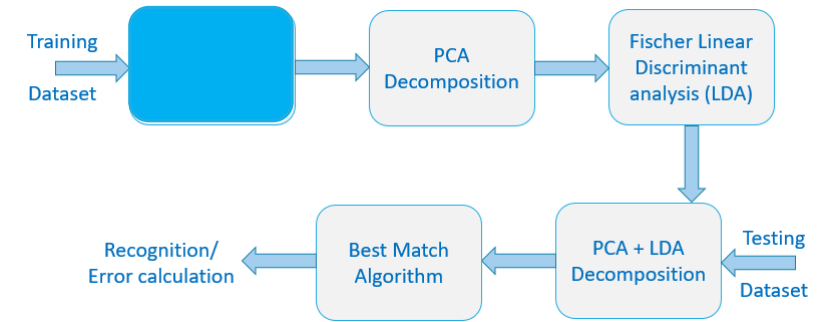
A solid blue horizontal bar at the bottom of the slide.

# Block Diagram

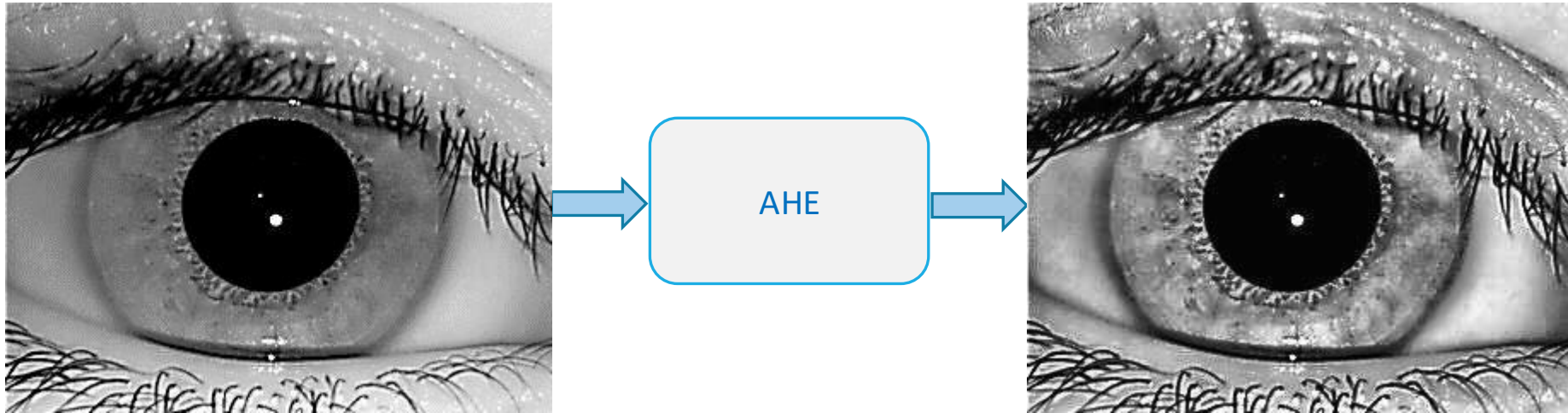


# Preprocessing

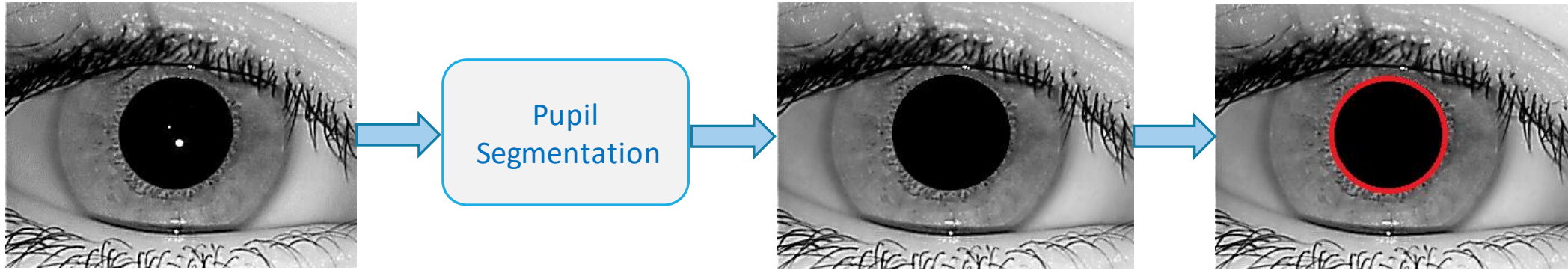
1. No Preprocessing of data
2. Enhanced Dataset images
3. Normalization of Dataset images
4. Occlusion Removal of Normalized images
  - I. Remove the complete right half
  - II. Eyelash Detection and Removal



# Enhancement of the Images



# Normalization of the Images



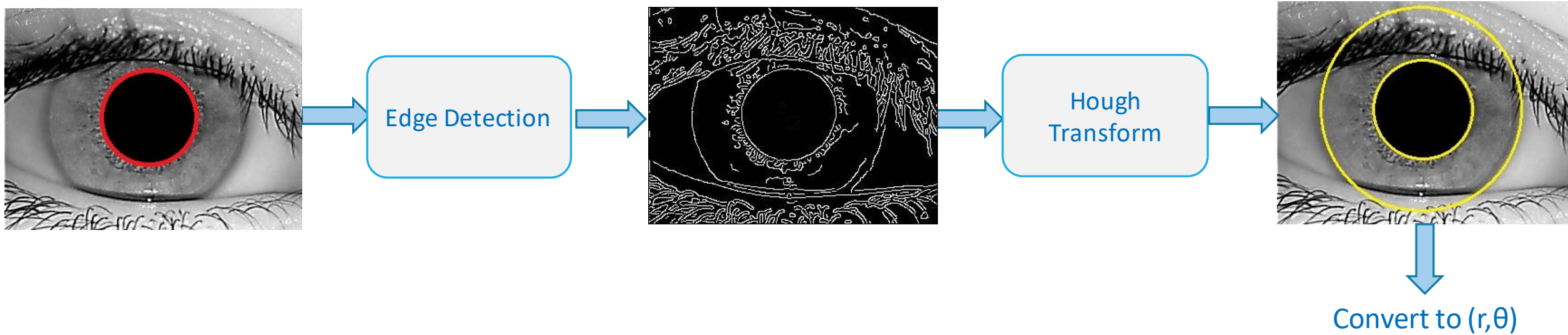
→ We use segmentation to cluster images and then use thresholding to identify pupil. The longest black row and column gives us the centre coordinate and diameter of the pupil.

→  $X_c = (X_1 + X_2)/2$

→  $Y_c = (Y_1 + Y_2)/2$

→  $\text{Radius} = ((X_1 - X_2)^2 + (Y_1 - Y_2)^2)^{1/2}$

# Normalization(Contd.)



- We use “Canny” Edge detection to demarcate a rough boundary circle for the Iris
- Hough transform is then used to get the outer radius of the iris (and outer radius of the pupil)
- We convert the image between the two radii into  $(r,\theta)$  format to get the “Rubber Sheet model” or the Normalized Image.

# Occlusion Removal

- ✓ Keep left Side of Normalized Image only



→ Here we do get rid of a major portion the irrelevant features, but we also lose some desired features

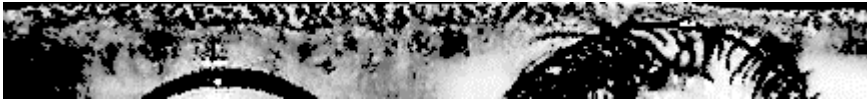
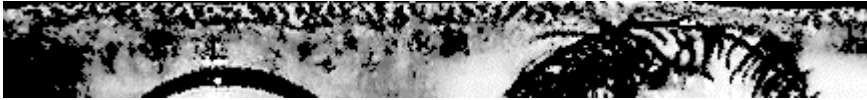
- ✓ Eyelash Detection and Removal



→ Here we detect the outline of the eyelash and try to remove it, hence trying to preserve the relevant data.

→ This mask is for the detected eyelash (on the right) and was multiplied with the original image to remove the effect of the eyelashes

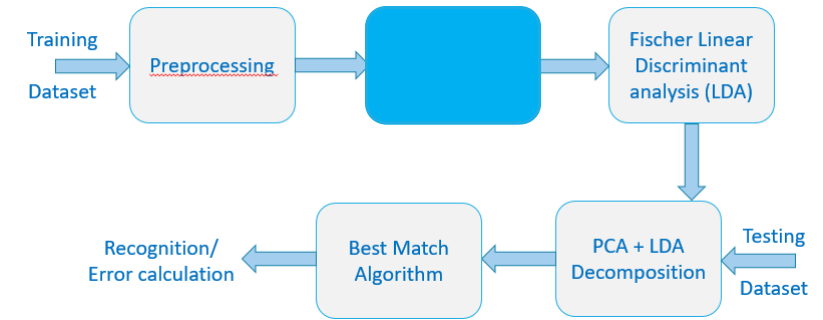
# Left Side of Normalized Image + Median Filter+CLAHE





# Principal Component Analysis (PCA)

- PCA is an algorithm which is used to effectively reduce the dimensionality of the input data. This is achieved by first getting the covariance matrix of the data and then getting its eigenvectors.
- The covariance matrix  $C$  is-  
$$C = XX^T$$
 ( $X$  is the mean subtracted data)  
We then Solve the eigenvalue problem-  
$$CV = \lambda V$$
- Now the 'kp' eigenvector's corresponding to the kp largest eigenvalues of  $C$  are chosen as the dimensions in which we will project our data. They are the kp orthogonal directions in which the variance of the data is maximum. Also, our reconstruction error is minimum if we project our data in these directions



# Benefits of using PCA before LDA

- It helps reduce the dimensionality of the input data to the LDA so that the LDA can work faster with a reduced number of dimensions. It also helps to filter out the data to give only the important features only.
- Also PCA is critical in the fisher 'iris' algorithm as the within the class scatter matrix  $S_w$  of LDA becomes almost singular if the dimensions of the input to it is much higher than the number of training examples given to it (if  $d \gg n$ ). This is a problem as we need to calculate  $\text{inverse}(S_w)$  in the LDA algorithm. To overcome this, we project our data to a lower dimensional sub space which is given by PCA

# Linear Discriminant Analysis (LDA)

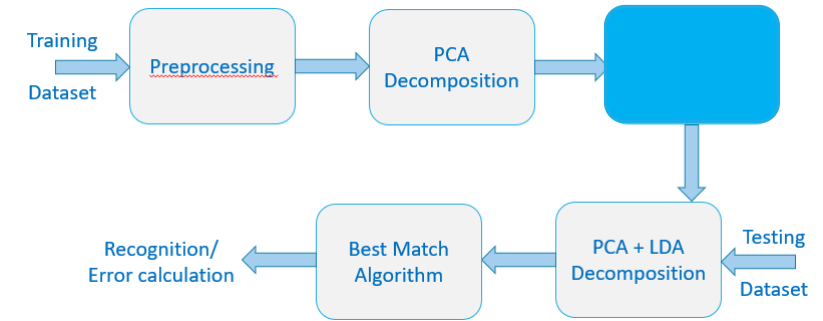
- LDA is a supervised classification algorithm, with a linear decision boundary (hence the name). It too involves getting a set of directions (like PCA) in which we project the data. It is better than PCA as it considers the class labels of data in getting the best directions for projecting the data.
- For calculating the LDA directions, we calculate 2 matrices-  
The between the class scatter matrix-

$$S_b = \sum_{j=1}^C (\mu_j - \mu)(\mu_j - \mu)'$$

The within the class scatter matrix is given by-

$$S_w = \sum_{j=1}^C \sum_{i=1}^{n_j} (x_{ij} - \mu_j)(x_{ij} - \mu_j)^T$$

Where C is the number of classes and  $n_j$  is the number of elements in the  $j^{\text{th}}$  class



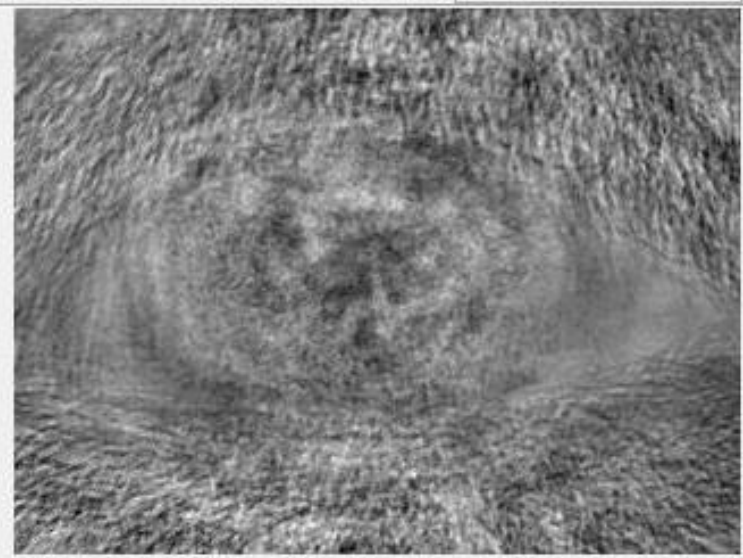
→ Then the directions which give the maximum separation of data are given by maximizing-

$$J(v) = \frac{v^T S_b v}{v^T S_w v}$$

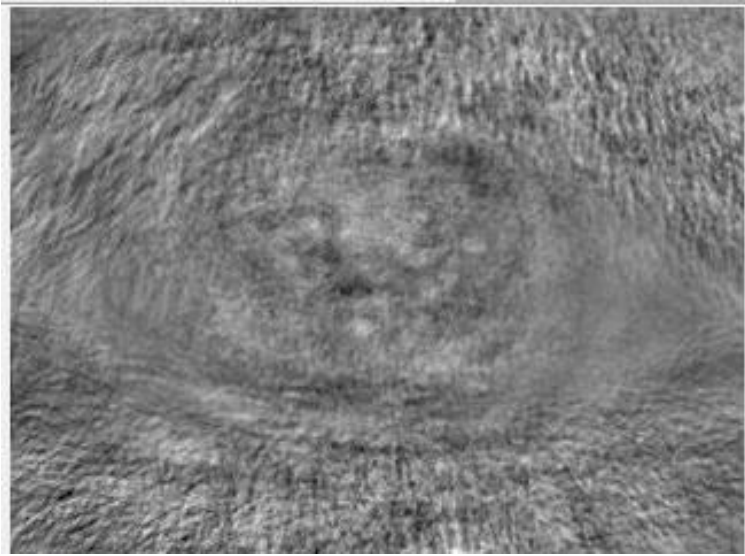
→ The solution to this problem is given by solving-

$$S_b v = \lambda S_w v$$

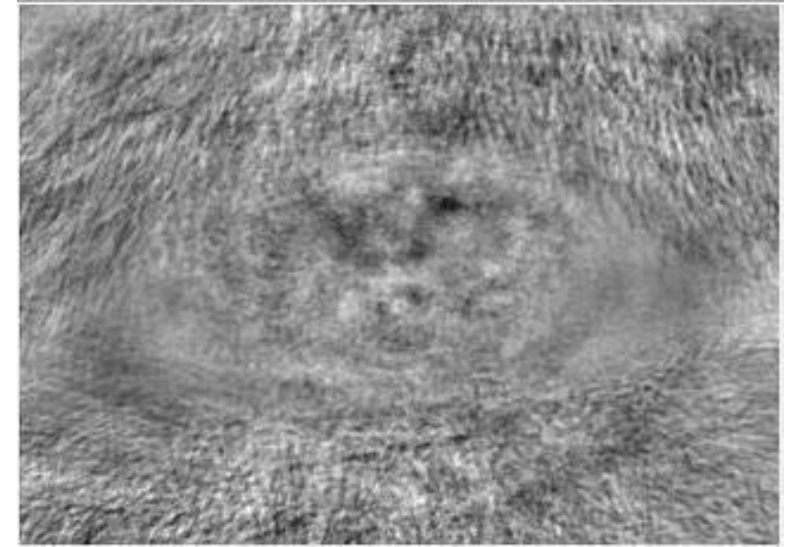
The first  $k$  values with the highest eigenvalues give the directions in which we get the maximum separation of classes on projecting the data.



Fisher Iris 1



Fisher Iris 2

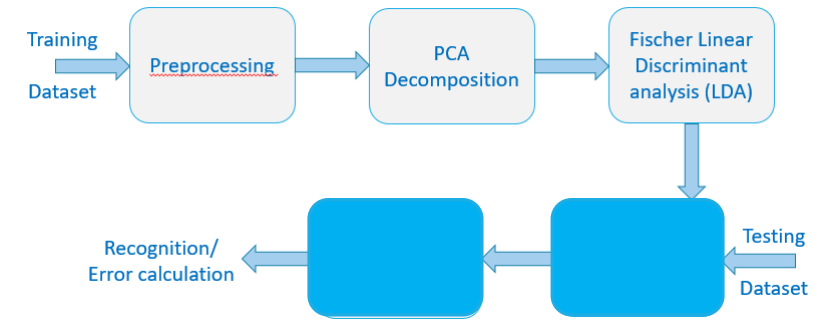


Fisher Iris 3

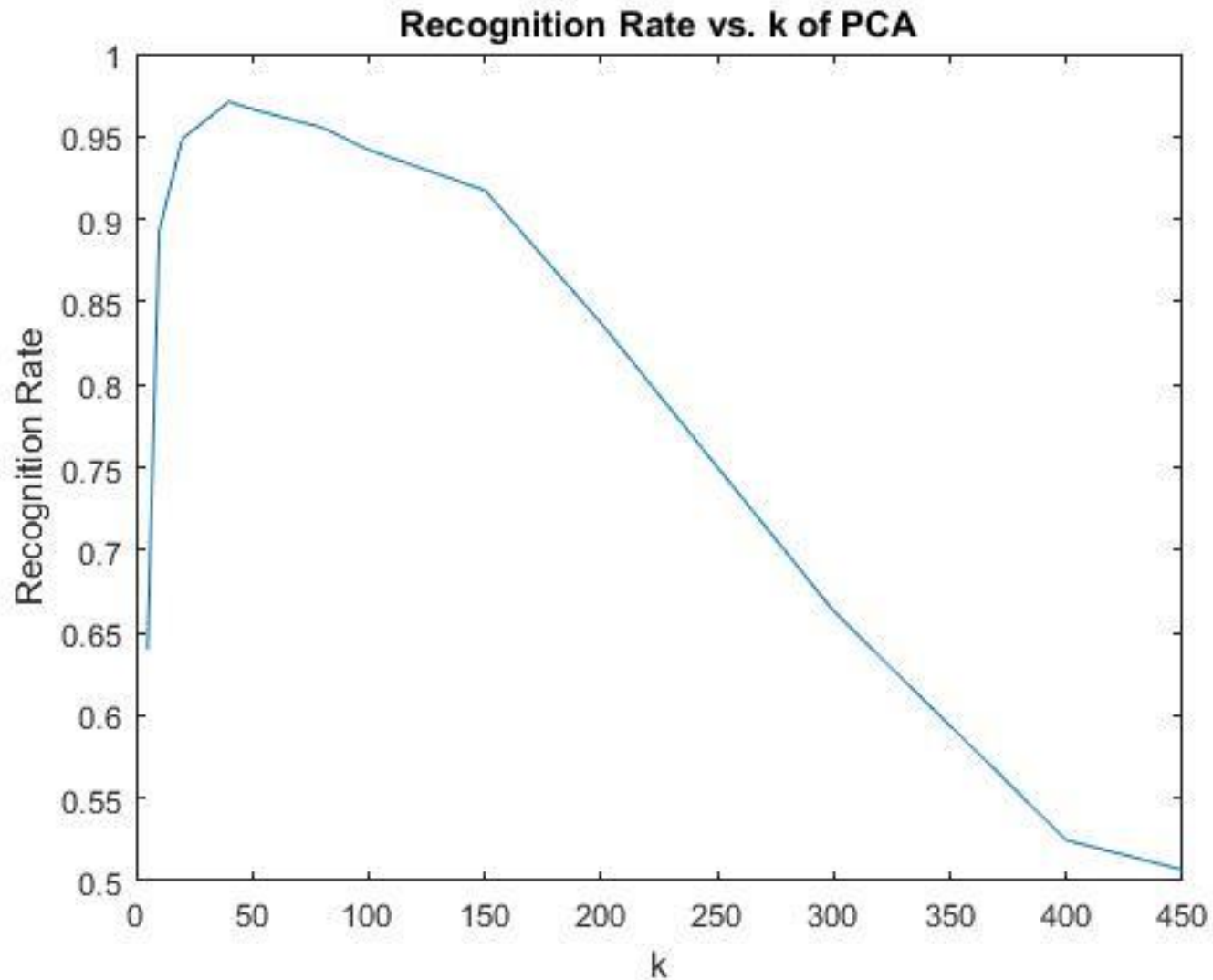
→ The LDA eigenvectors which we get are called Fisher Iris and represent the direction's. After getting the set of directions, we project our training data in this direction to get a set of coefficients (of the LDA directions). This set of coefficients is compared with the test inputs coefficients to give the correct output class for the test data.

# Testing and Matching

- ✓ In the fisher iris algorithm we perform LDA on the reduced dimension representation of the training dataset to get the LDA vectors. So, for testing too we have to follow:
  - Calculate the PCA eigenvector's coefficients for the mean subtracted test input.
  - Calculate the LDA eigenvector's coefficients for the calculated PCA eigenvectors of the test data.
  - We compare the test inputs with the stored training data's LDA coefficients and select the training sample which is the closest in terms of Euclidean distance to the test input.
  - Also, if the distance between the nearest training sample and the test input is too high (determined through hit and try) we reject the input and give a null match.



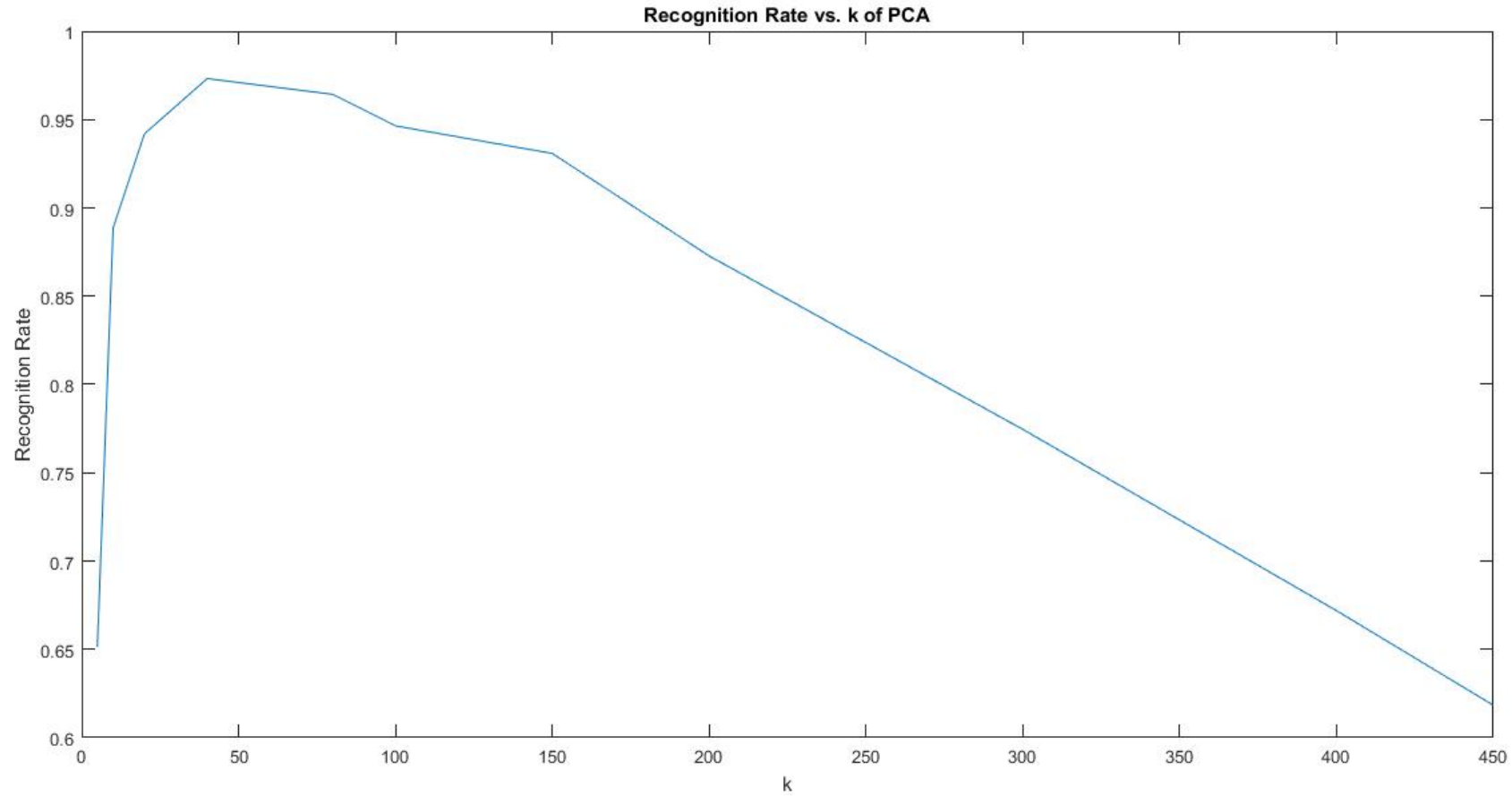
# Unprocessed Training Data



- The Dataset was used as it is without any pre-processing on it
- As the k increases the recognition rate decreases sharply.
- For smaller k only the desired “features” with higher spread (important ones) are included. (Iris has maximum variance)
- The extra (undesired) features (Eyelashes/pupil etc.) when included more, due to higher k, begin to dominate and the accuracy plummets

→ Maximum Accuracy : 97.10%

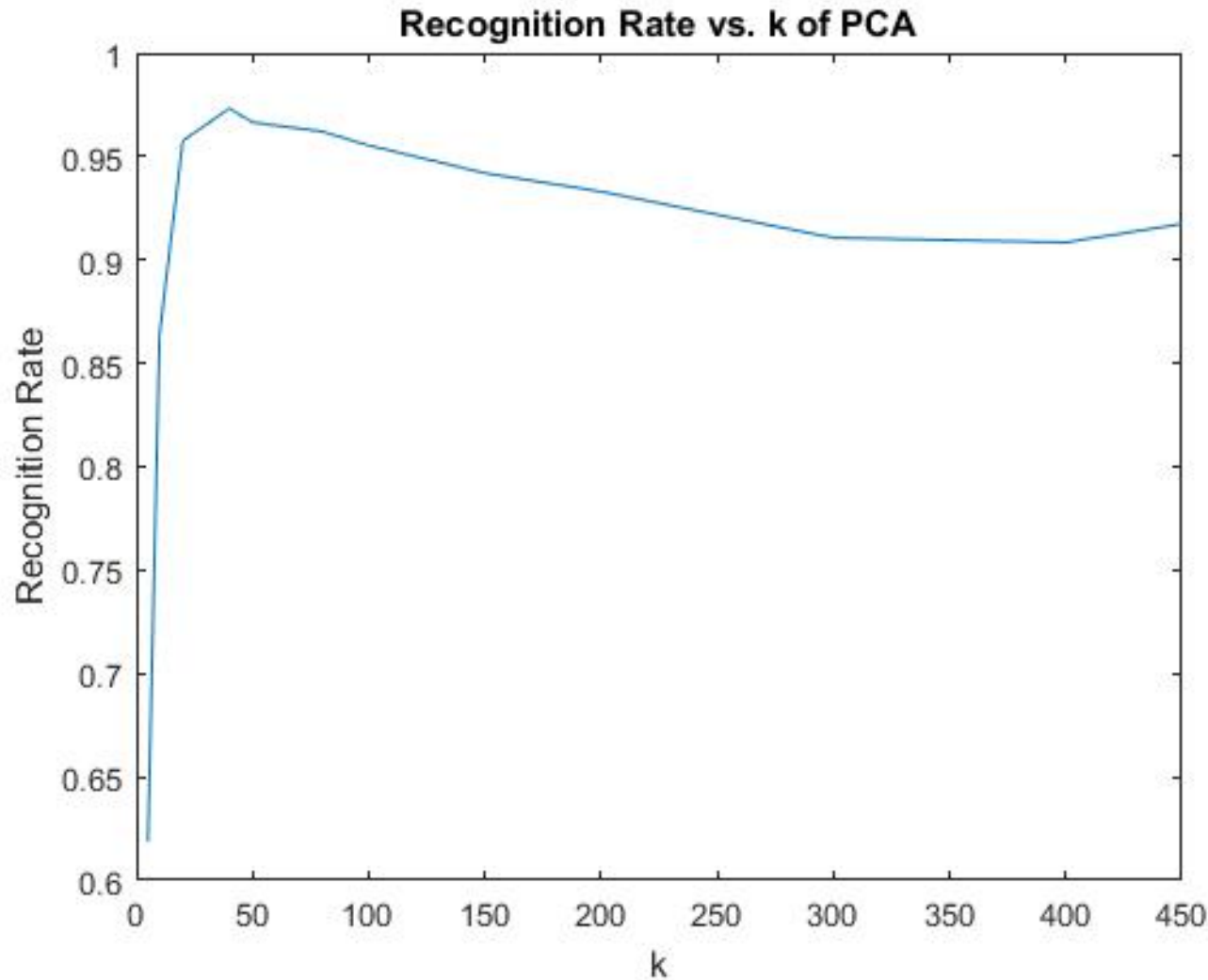
# Median Filtered Training Data



→ Maximum Accuracy : 97.32%



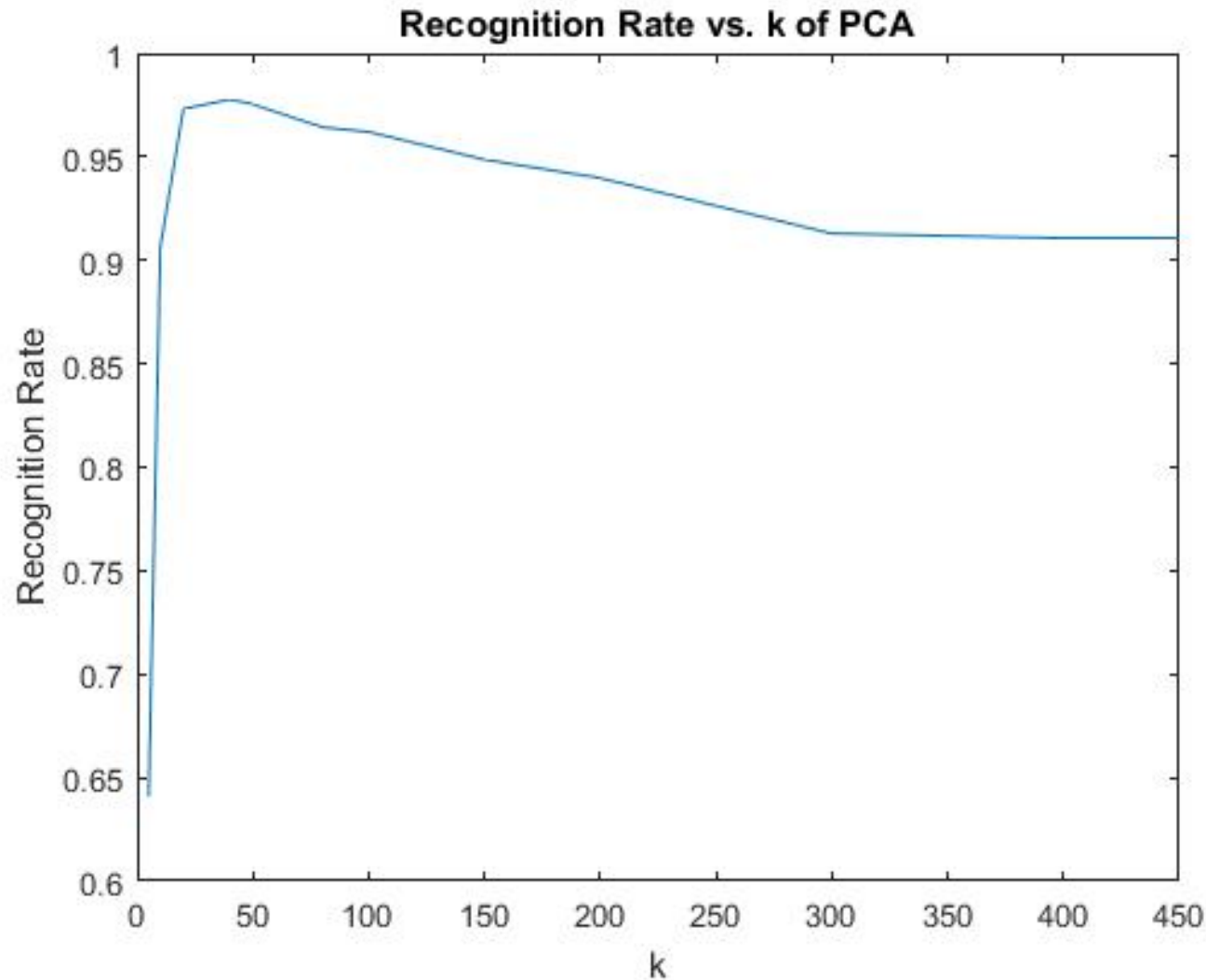
# Normalized Training Data



- Each image was transformed into a “Rubber sheet” model of itself.
- Only the Iris had to be “extracted” from each image. Segmentation, thresholding, inversion, edge detection and Hough transform have to be used to achieve that.
- A lot of undesired features are removed and only the significant “information is retained”. This is why it gives us a higher recognition rate than unprocessed images.

→ Maximum Accuracy : 97.32%

# Right Half-Removed Normalized Training Data



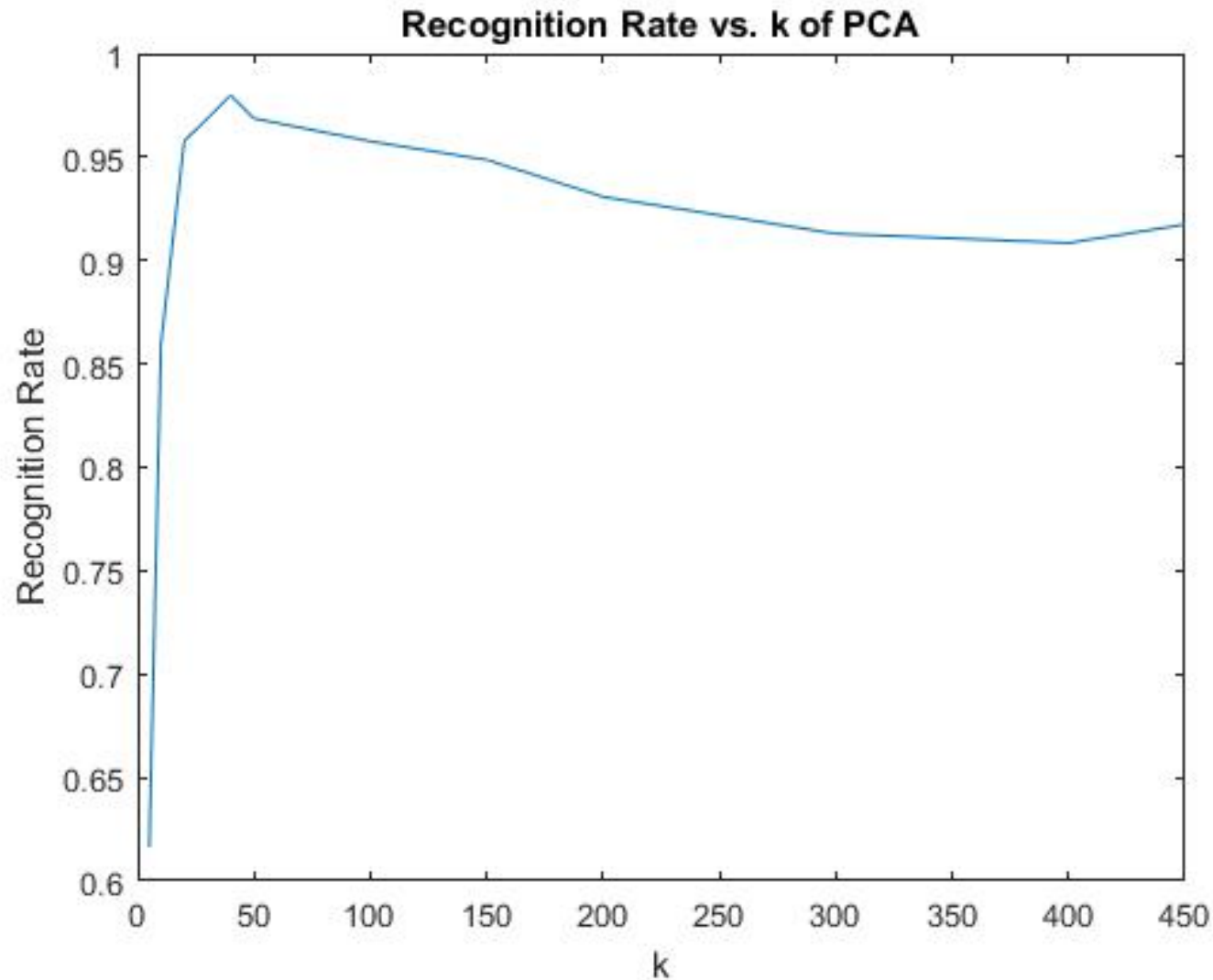
→  $\theta \in (\pi, 2\pi]$  contains the eyelashes almost completely.

→ And its removal gives us a higher recognition rate than unprocessed images as the undesired information is removed.

→ However, it removes some of the relevant data as well

→ Maximum Accuracy : 97.70%

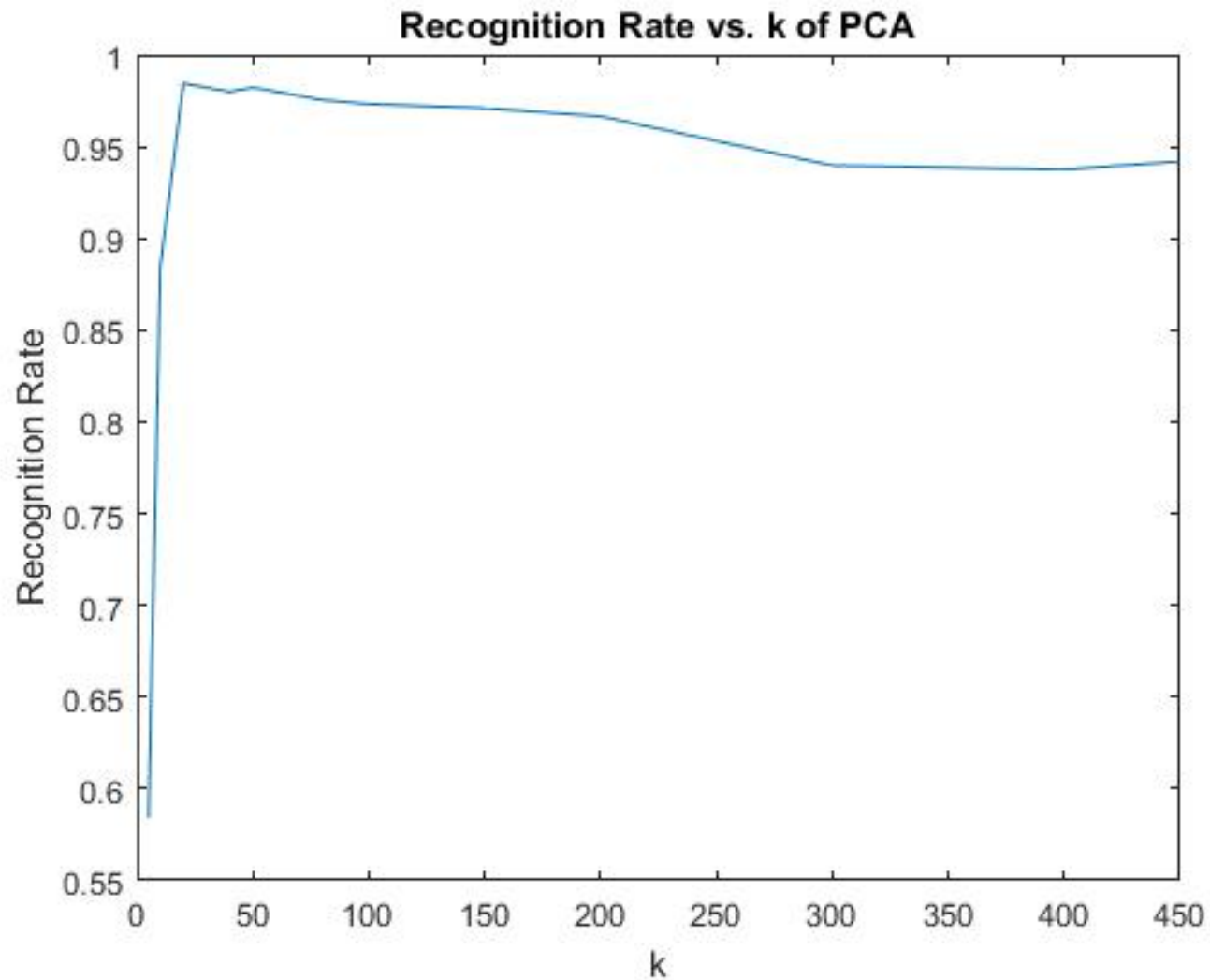
# Eyelash-Removed Normalized Training Data



- $\theta \in (\pi, 2\pi]$  contains the eyelashes almost completely.
- Complete removal of the right part removes the eyelashes but it removes some of the relevant data as well
- So, we try to remove only the eyelashes part from the images which involves eyelash detection
- This increases the recognition rate even further.

→ Maximum Accuracy : 97.99%

# Right Half-Removed Normalized+Median+AHE Training Data

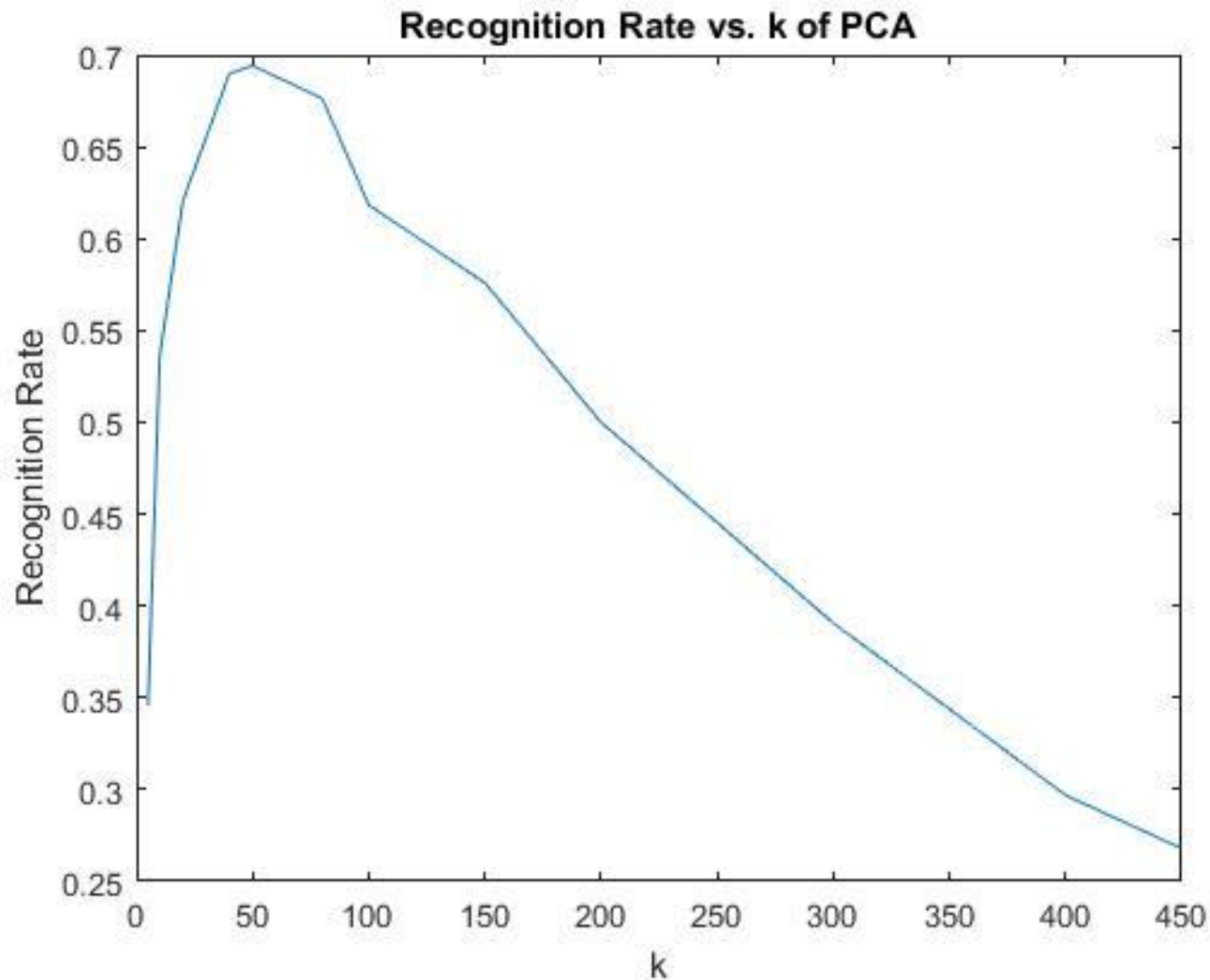


→ Applying Median Filter and Adaptive Histogram equalization (AHE) on the further increases the recognition rate.

→ The Iris is now better contrast enhanced and as a result the classification is slightly better.

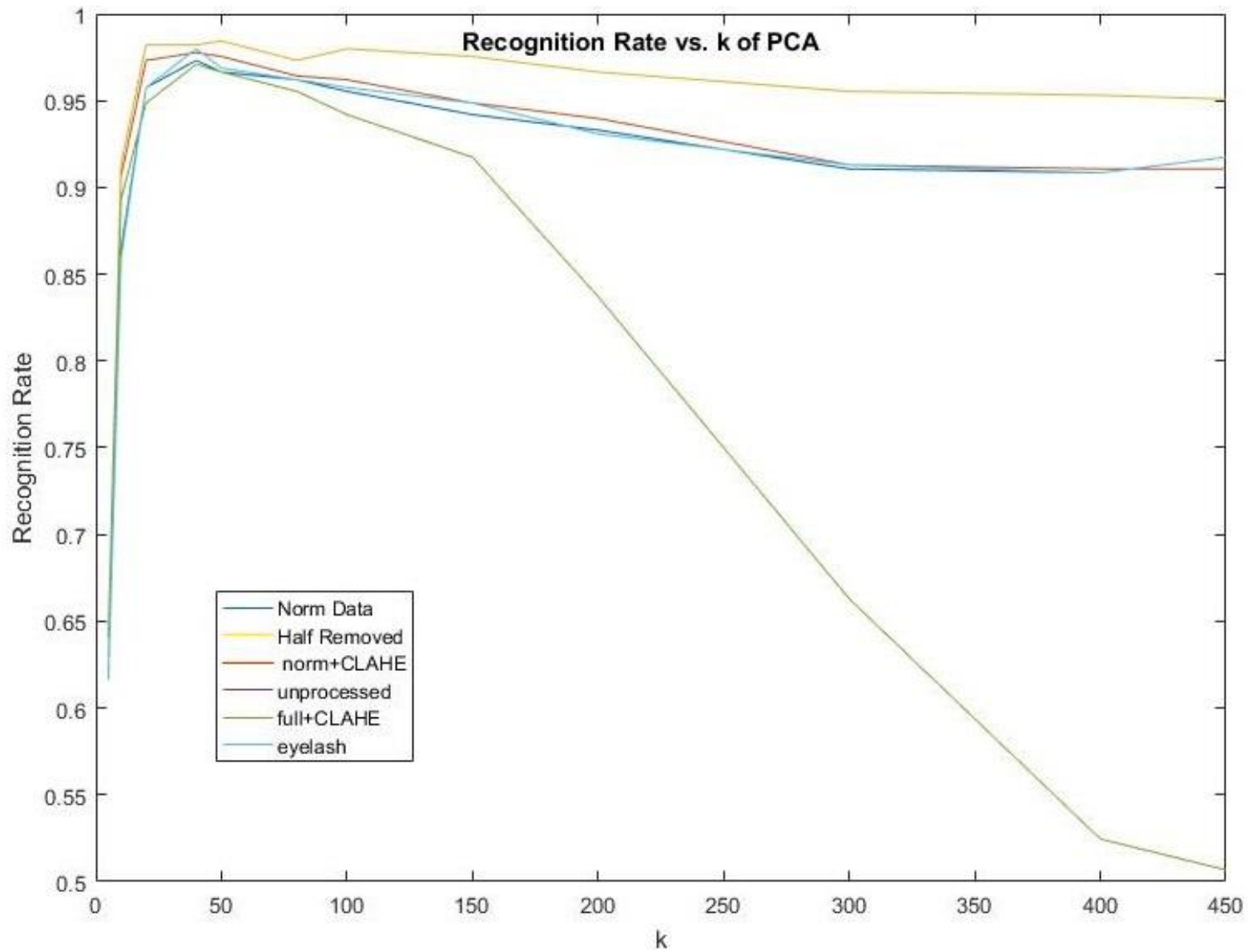
→ Maximum Accuracy : 98.44%

# Median Filter + CLAHE on Training Data



- Applying Median Filter and Adaptive Histogram equalization (AHE) on the decreases the recognition rate.
- This is in contrast with Median + AHE in Normalized training data case as the unwanted features (predominantly the eyelashes) are much better enhanced than the Iris, further reducing the recognition rate.

→ Maximum Accuracy : 69.42%



→ Our algorithm takes on an average 0.077 seconds to test an input against our training dataset.

# References

- Emad ul Haq, Q.; Javed, M.Y.; Sami ul Haq, Q., "Efficient and robust approach of iris recognition through Fisher Linear Discriminant Analysis method and Principal Component Analysis method," in Multitopic Conference, 2008. INMIC 2008. IEEE International ,pp.218-225, 23-24 Dec. 2008
- "Principal Components Analysis Based Iris Recognition and Identification System", E. Mattar, International Journal of Soft Computing and Engineering (IJSCE), ISSN: 2231-2307, Volume-3, Issue-2, May 2013.

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*“ There is no real ending.  
It’s just the place where  
you stop the story. ”*

-Frank Herbert