# SMAI Assignment 2

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## 1 Problem-1

# 1.1 Eigenfaces

Eigenfaces are the eigenvectors of the covariance matrix of face images, and are used in the field of computer vision in facial recognition, and in general pattern recognition.

These eigen vectors form the basis of all the images and are used to reduce the dimensionality and reconstruct the matrix.

# 1.2 Number of Eigenfaces required

The number of eigenfaces required to satisfactorily represent the images in each of the datasets is as follows:-

IMFDB :- 61

Yale Face Database :- 46

IIIT-CFW:- 113

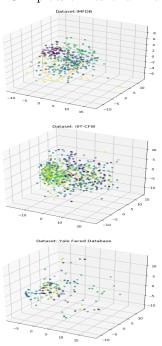
The numbers were determined by analysing the plotted eigen value spectrum of the the dataset, all the values above the and taking the number of eigen values that are above a threshold.

These numbers came by comparing the sum ratio of the eigenvalues in the eigenvalue spectrum. i.e. the sum of eigenvalues taken to be important should be comparable (0.95) to the sum of all eigenvalues. However I have taken 100 eigenvalues for all the datasets to be on a safer side.

# 1.3 Reconstructed Images and related problems

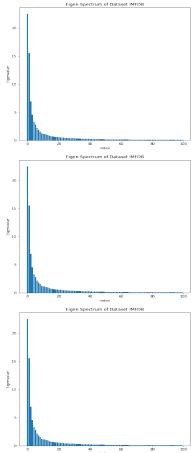
The most difficult dataset to represent, based on the eigenvalue spectrum, is IIIT-CFW dataset. This is because the variation in the images of this dataset is quite high. Therefore, the spread in the eigenvalues

Figure 1: 3-D plots of Pca of all Datasets



is quite high. Also, in IMFDB, the most difficult persons to repre- sent is AkshayKumar,Shilpa Shetty, in Yale Face Database, it is the one with class id 0, and in IIIT-CFW it is Narendra Modi,Manmohan Singh. This was determined empirically, by calculating reconstruction error for each class separately.

Figure 2: Eigen Value Spectrum for all Dataset



# 2 Problem 2

#### 2.1 Classification Results

I have used MLP classifer for all of the features and found different results for all the datasets to have an ease of comparision.

It can be seen from figure 5 that ResNet features perform best in all three Datasets.

#### 2.2 Confusion Matrix

The Confusion matrices for the best models for each dataset is shown in figure 4:

Figure 3: Some of the Reconstructed Images



Figure 4: Confusion matrix for different Dataset

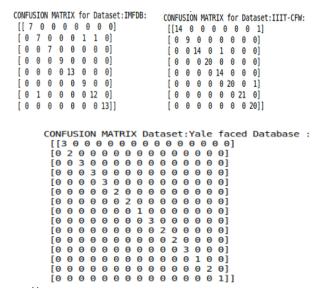


Figure 5: Results for classification using different features and MLP classifier. Table 1: IMFDB, Table 2:IMFDB, Table 3: Yale face dataset

5 resnet with mlp

	,				
	Feature Used	Reduced Dimension Space	Classification Error /	Accuracy F	1-Score
0	pca with mlp	100	0.1750	0.8250	0.8250
1	kpca with mlp	100	0.1500	0.8500	0.8500
2	lda with mlp	7	0.2500	0.7500	0.7500
3	klda with mlp	7	0.2500	0.7500	0.7500
4	vgg with mlp	4096	0.1375	0.8625	0.8625
5	resnet with mlp	2048	0.0375	0.9625	0.9625
b	Feature Used	Reduced Dimension Space	Classification Error	Accuracy	F1-Score
0	pca with mlp	100	0.397059	0.602941	0.602941
1	kpca with mlp	100	0.397059	0.602941	0.602941
2	lda with mlp	7	0.705882	0.294118	0.294118
3	klda with mlp	7	0.882353	0.117647	0.117647
4	vgg with mlp	4096	0.325926	0.674074	0.674074
5	resnet with mlp	2048	0.029630	0.970370	0.970370
	Feature Used	Reduced Dimension Space	Classification Erro	r Accuracy	/ F1-Scor
0	pca with mlp	100	0.00000	1.000000	1.00000
1	kpca with mlp	100	0.00000	1.000000	1.00000
2	lda with mlp	14	0.00000	1.000000	1.00000
3	klda with mlp	14	0.00000	1.000000	1.00000
4	vgg with mlp	4096	0.51515	2 0.484848	0.48484
_		20.40	0.00000	1 00000	1 00000

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0.000000 1.000000 1.000000

2048

## 3 Problem 3

#### 3.1 t-SNE Plots

TSNE for different features and their scatter plot are shown in fig 6,7,8 respectively

## 3.2 Observations

It is observed that, with the exception of a few outliers, the data points with the same classes are closer and are clustered in the t-SNE.

# 4 Problem 4

#### 4.1 Formulation

a.) For the problem, we first compute different features (using PCA, LDA, or other variants), and train a KNN classifier. Then, given a data point X and the corresponding class ID, we find the predicted ID (using our KNN classifier), and return yes or no according to whether it matches the given class ID or not.

b.) Metric used to compare performance is accuracy

$$Accuracy = \frac{No.ofCorrectPredicitions}{TotalSamples} \quad \ (1)$$

Another metric that used is precision

$$Precision = \sum_{C \in Classes} \frac{TP(C)}{TP(C) + FN(C)}$$
 (2)

$$Precision = \frac{Precision}{No.ofClasses}$$
 (3)

#### 4.2 Results

Results for classification using different features is Shown in Fig 9 and Fig 10

Figure 6: TSNE Plots for Dataset:IMFDB

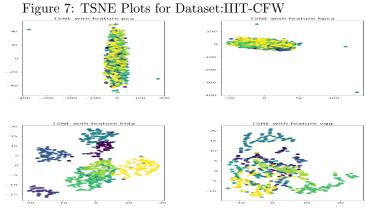
TSNE with feature pea

TSNE with feature kida

TSNE with feature vgg

TSNE with feature vgg

TSNE with feature vgg



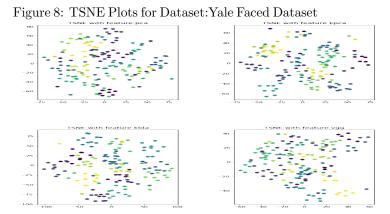
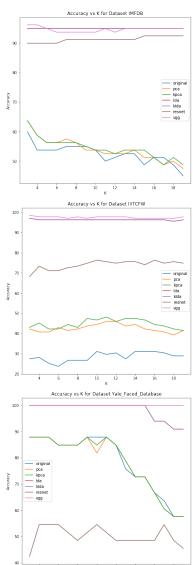


Figure 9: Results for classification using different features and MLP classifier. Table 1: IMFDB

Figure 10: Accuracy vs K for Neighbour Classifier for KNN

	Feature Used	Reduced Dimension Space	Classification Error	Accuracy	Precision
0	pca with k=7	100	42.50	57.50	0.5750
1	kpca with k=7	100	43.75	56.25	0.5625
2	lda with k=7	7	5.00	95.00	0.9500
3	klda with k=7	7	5.00	95.00	0.9500
4	vgg with k=7	2048	6.25	93.75	0.9375
5	resnet with k=7	4096	8.75	91.25	0.9125

	Feature Used	Reduced Dimension Space	Classification Error	Accuracy	Precision
0	pca with k=7	100	58.518519	41.481481	0.414815
1	kpca with k=7	100	55.55556	44.44444	0.444444
2	lda with k=7	7	3.703704	96.296296	0.962963
3	klda with k=7	7	3.703704	96.296296	0.962963
4	vgg with k=7	2048	2.962963	97.037037	0.970370
5	resnet with k=7	4096	27.407407	72.592593	0.725926
	Feature Used	Reduced Dimension Space	Classification Error	Accuracy	Precisio
0	Feature Used pca with k=7	Reduced Dimension Space	Classification Error 15.151515	Accuracy 84.848485	
0		· ·			0.84848
	pca with k=7	100	15.151515	84.848485	0.84848 0.84848
1	pca with k=7 kpca with k=7	100	15.151515 15.151515	84.848485 84.848485	0.84848 0.84848 1.00000
1	pca with k=7 kpca with k=7 Ida with k=7	100 100 14	15.151515 15.151515 0.000000	84.848485 84.848485 100.000000	0.848483 0.848483 0.000000 0.00000000000000000000000000



## 5 Problem 5

#### 5.1 Problem Statement

I have chosen the application/extension problem of gender prediction i.e. given an image, predict if the person in the image is Male or Female. This is problem is difficult to solve with classical non-machine learning methods because it is difficult to predict the features which result in Male-Female prediction through explicit mathematical models.

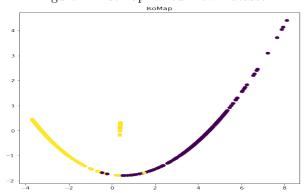
subsectionPipeline

- I have taken the IIIT-CFW and IMFDB datasets and changed their labels so that the label is 1 for males and 0 for females. I have then concatenated the two datasets to form a single dataset.
- I have used klda features as my training set.
- I have Splited the data into training and validation sets, then trained my classifier. I have used MLP classifier as my classifier.

5.2 Results

The accuracies for our classifier is in the range [99-100]

Figure 11: Isomap for our new Dataset



Some Wrongly Classified Images:

Figure 12: TSNE plot for our new Dataset

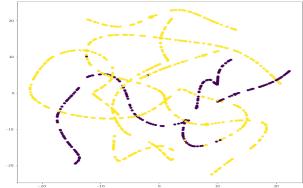


Figure 13: Some Wrongly Classified Images

