FACIAL EXPRESSION RECOGNITION USING PCA

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CSC 481

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OUTLINE

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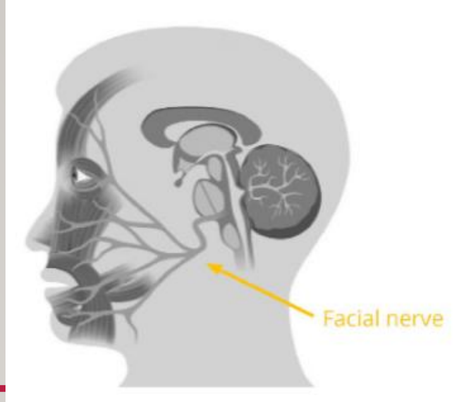
PROBLEM STATEMENT



- Facial expressions are movements of the numerous muscles supplied by the facial nerve that are attached to and move the facial skin.
- Humans can recognize differences between facial expressions, so patterns must be present that can determine a facial expression
- Given an image of a face, how can we classify a facial expression?

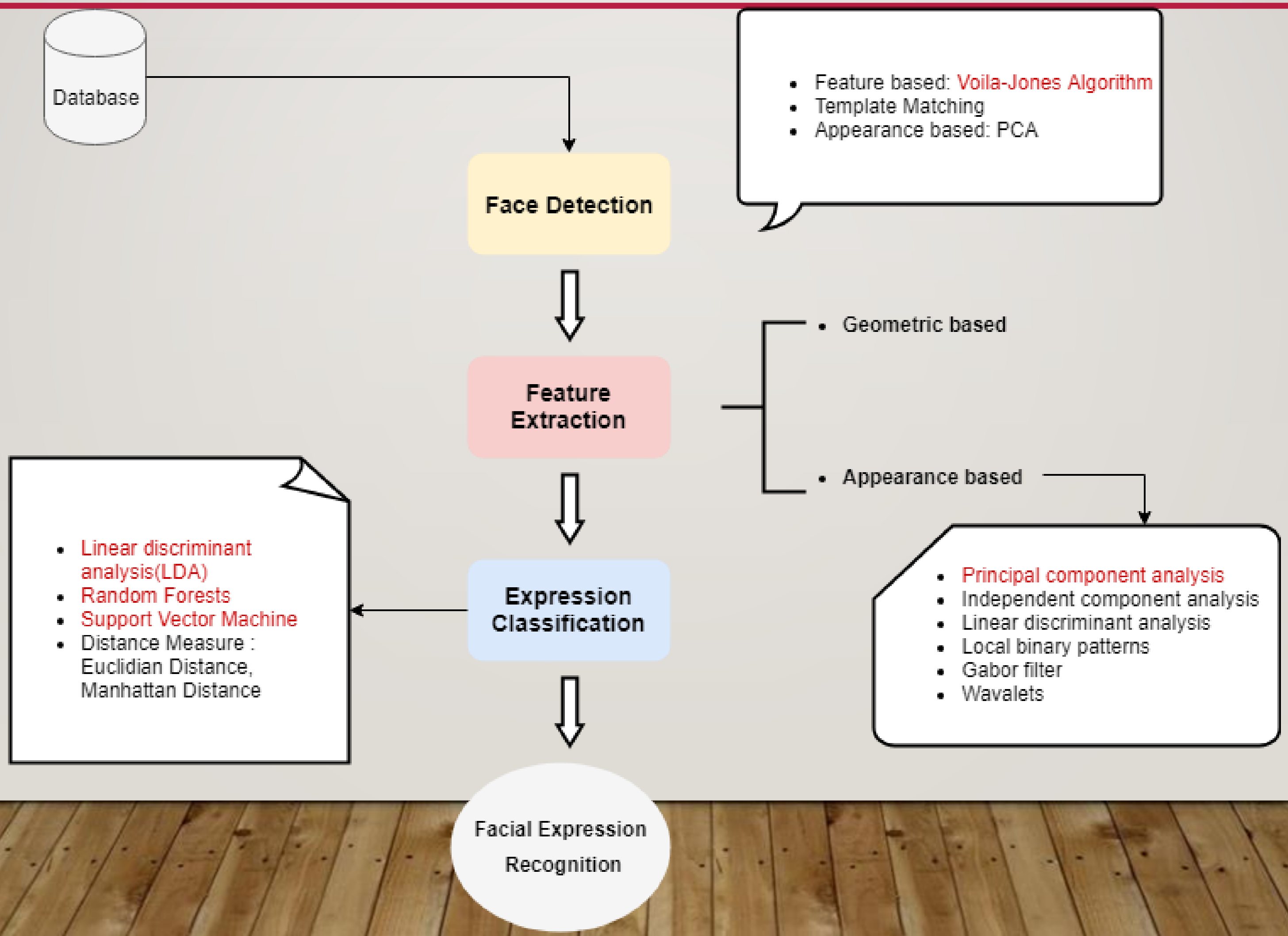
MOTIVATION

- Facial expression recognition has many important potential applications
  - Consumer neuroscience and neuromarketing
  - Media testing & advertisement
  - Psychological research
  - Clinical psychology and psychotherapy
  - Medical applications & plastic surgery
  - Software UI & website design
  - Engineering of artificial social agents (avatars)

RELATED WORK

Reference	Feature Extraction	Classifier	Database	Sample size	Performance
Kotsia and Pitas, 2007	Geometric displacement of Candide nodes	SVM	Cohn-Kanade	Whole DB	99.7% for facial expression recognition 95.1% for facial expression recognition based on AU detection
Kotsia et al., 2008	Gabor features, DNMF algorithm and by Geometric displacement vectors extracted using Candide tracker	Multiclass SVM and MLP	Cohn-Kanade and JAFFE		Using JAFFE: with Gabor: 88.1%, with DNMF: 85.2% Using Cohn-Kanade: with Gabor: 91.6%, with DNMF: 86.7%, with SVM: 91.4%
Gosavi and Khot 2013	PCA	Euclidian Distance	JAFFE	70 JAFFE test samples	Accuracy using JAFFE: with PCA: 91.63%, Recognition rate: 67.14%

METHOD
Facial Expression Recognition System

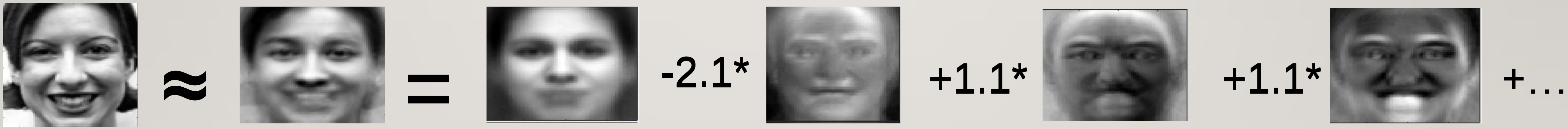


METHOD
PCA/Eigenfaces: key idea(Turk and Pendland,1991)

- Assume that most face images lie on a low-dimensional subspace determined by the first K (k<<d) directions of maximum variance
- Use PCA to determine the vectors or “eigenfaces” e_1,e_2,.....e_k that span that subspace
- Represent all face images in the dataset as linear combinations of eigenfaces. Find the coefficients by dot product.

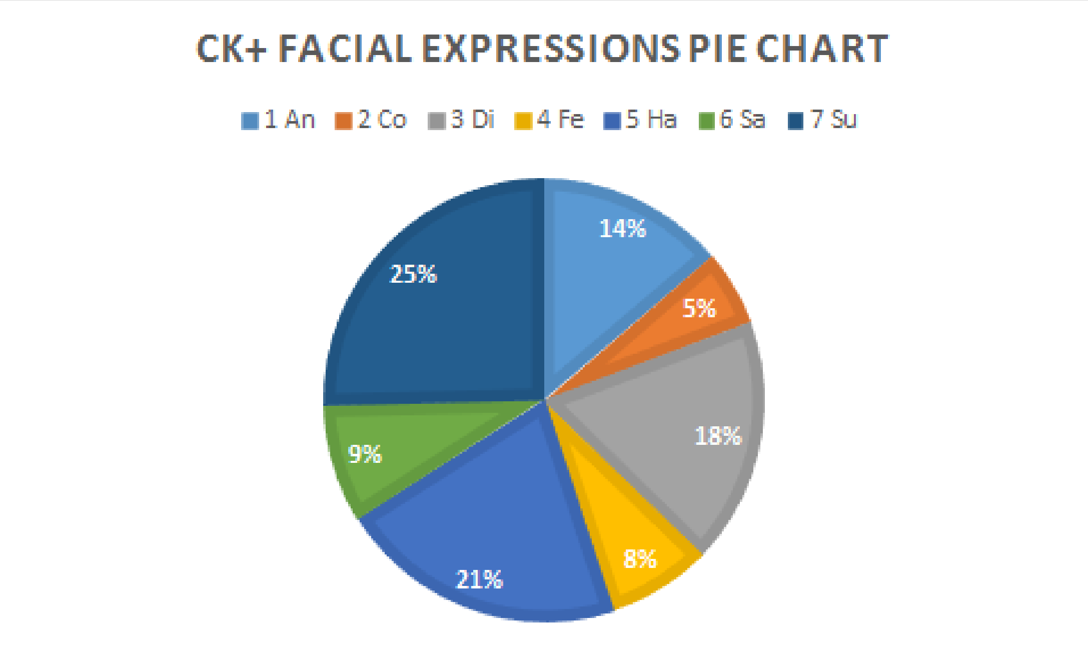
METHOD
PCA/Eigenfaces

- Face images can be economically represented by their projection onto a small number of basis images that are derived by finding the most significant eigenvectors of the pixelwise covariance matrix for a set of training images.



METHOD
Raw Data

- Extended Cohn-Kanade Dataset (CK+)
  - 123 subjects
  - 327 images with emotion labels
  - Male and female
  - Various ethnic backgrounds
- Japanese Female Facial Expression Dataset (JAFFE)
  - 10 subjects
  - 213 images with emotion label

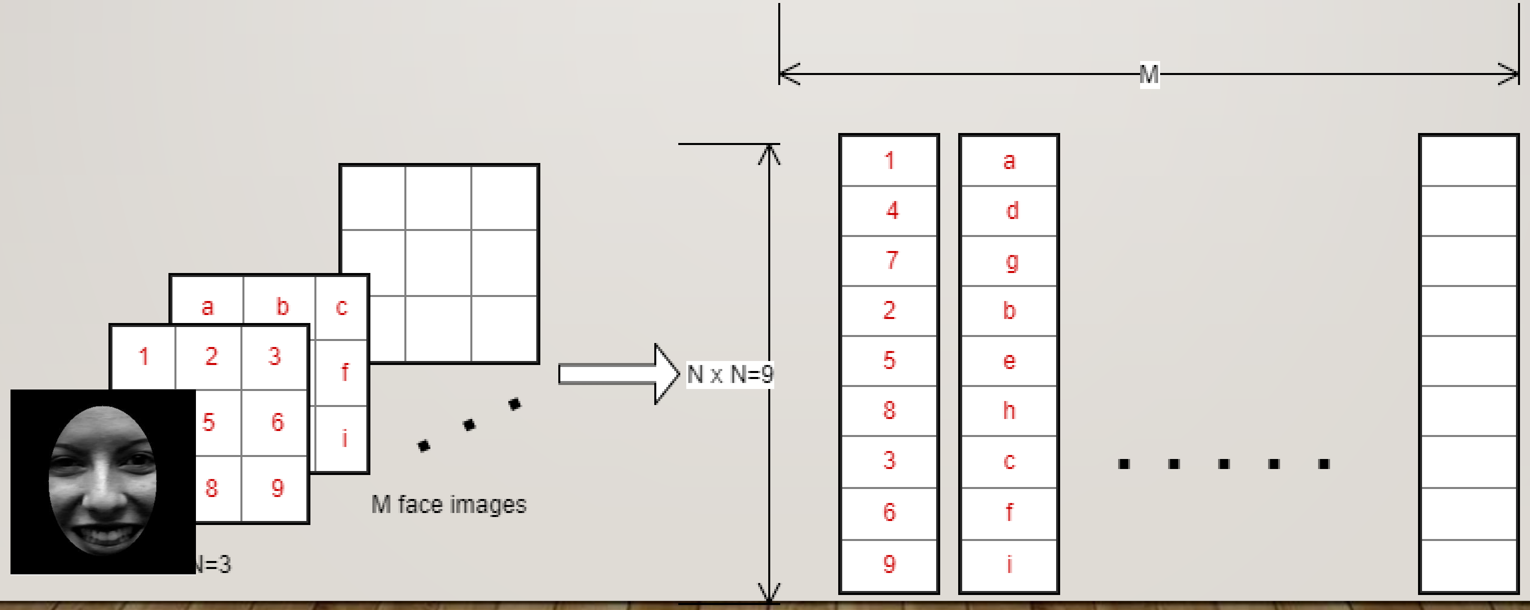


METHOD
PREPROCESSING-Loading the images

- Convert to grayscale
- Face detection
  - Important for centering the faces: aligned based on facial features
  - Method – Voila-Jones Algorithm
- Crop the image based on face detection
- Use an oval mask to further isolate the face
- Histogram Equalization

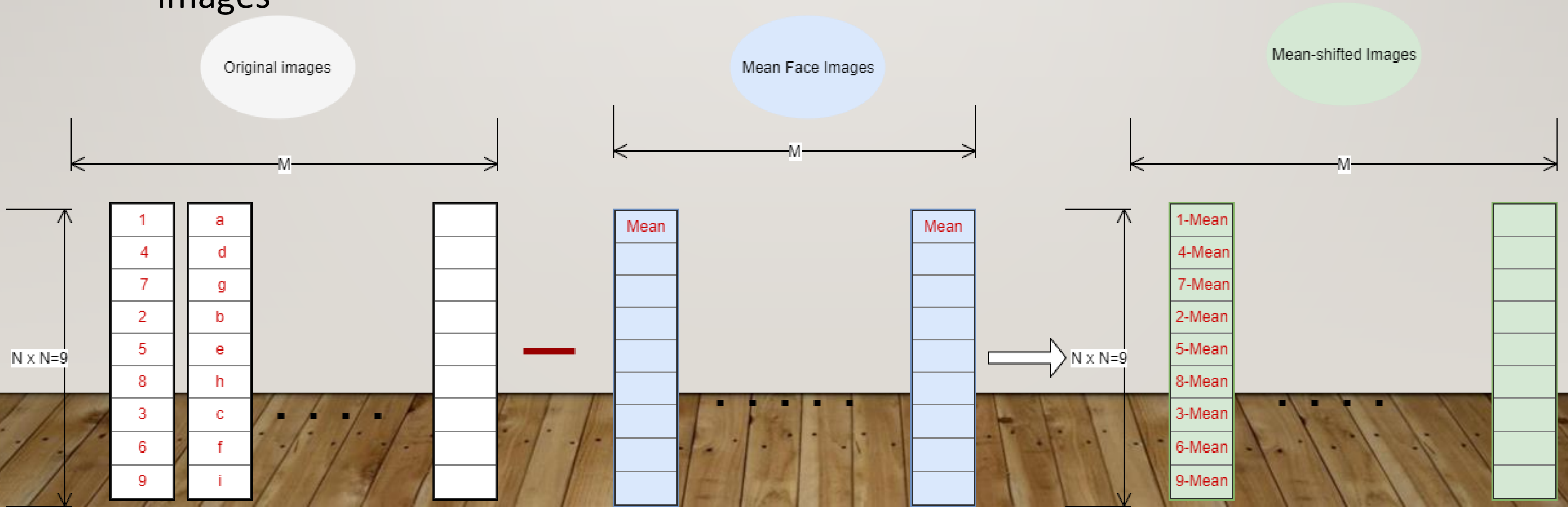
METHOD
PREPROCESSING - Loading the images

- Convert image matrix to column vector
- Create matrix where each column represents a different picture



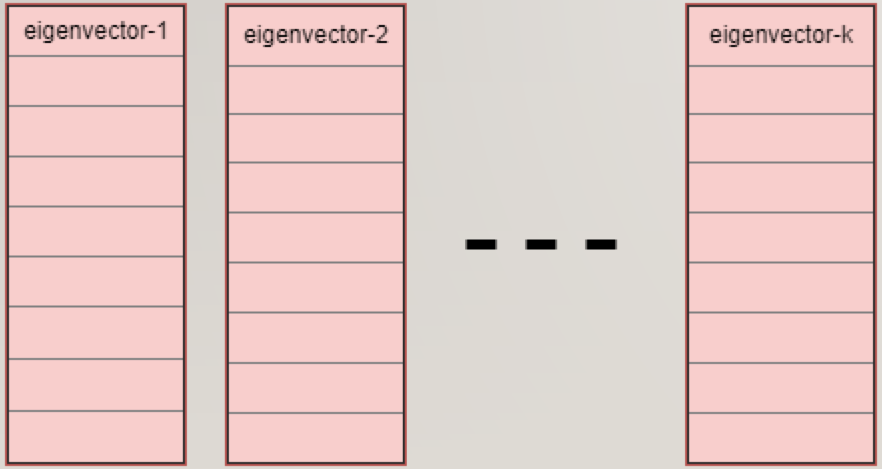
METHOD
Training-PCA

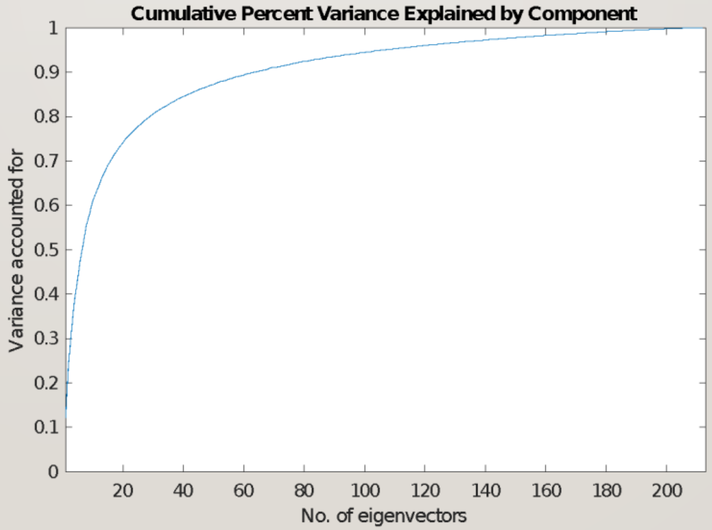
- Calculate the mean of the input face images
- Subtract the mean from the input images to obtain the mean-shifted images
- Calculate the eigenvectors and eigenvalues of the mean shifted images



METHOD
Training-Eigenvectors

- Order the eigenvectors by their corresponding eigenvalues
- Retain only the eigenvectors with the largest eigenvalues

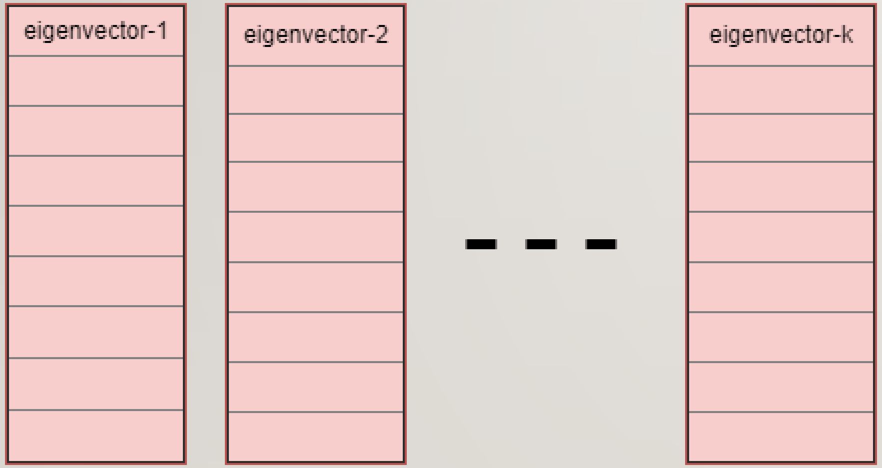


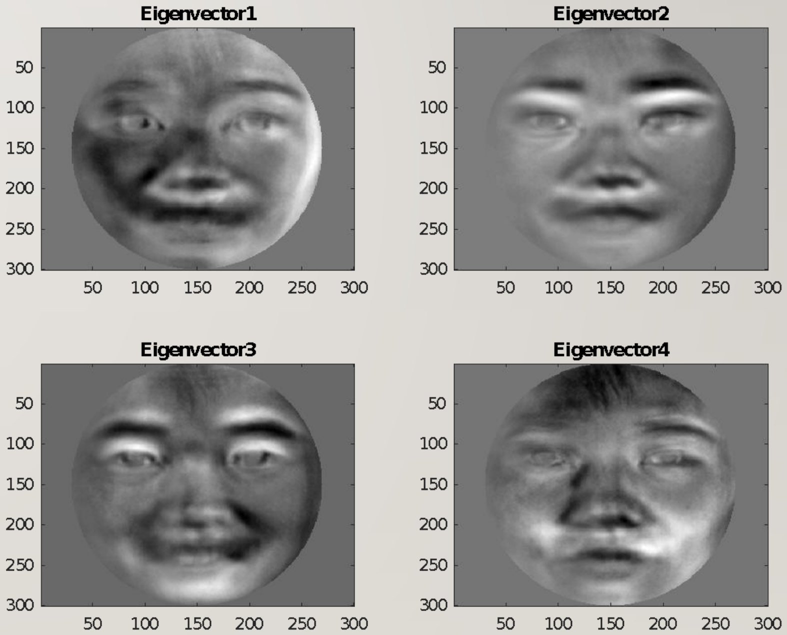


Selected enough to represent 90% of the variance in the original Data.

- JAFFE = 60 eigenvectors
- CK+ = 80 eigenvectors

METHOD
Training-Eigenfaces



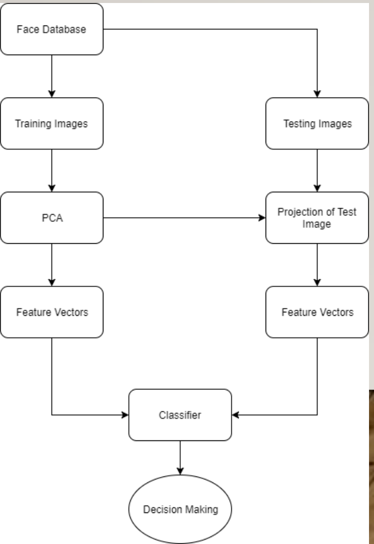


METHOD
Training-Projection

- Project the mean-shifted images into the eigenspace using the retained eigenvectors.
- Represent input image as a linear combination of eigenfaces

METHOD
FEATURE EXTRACTION

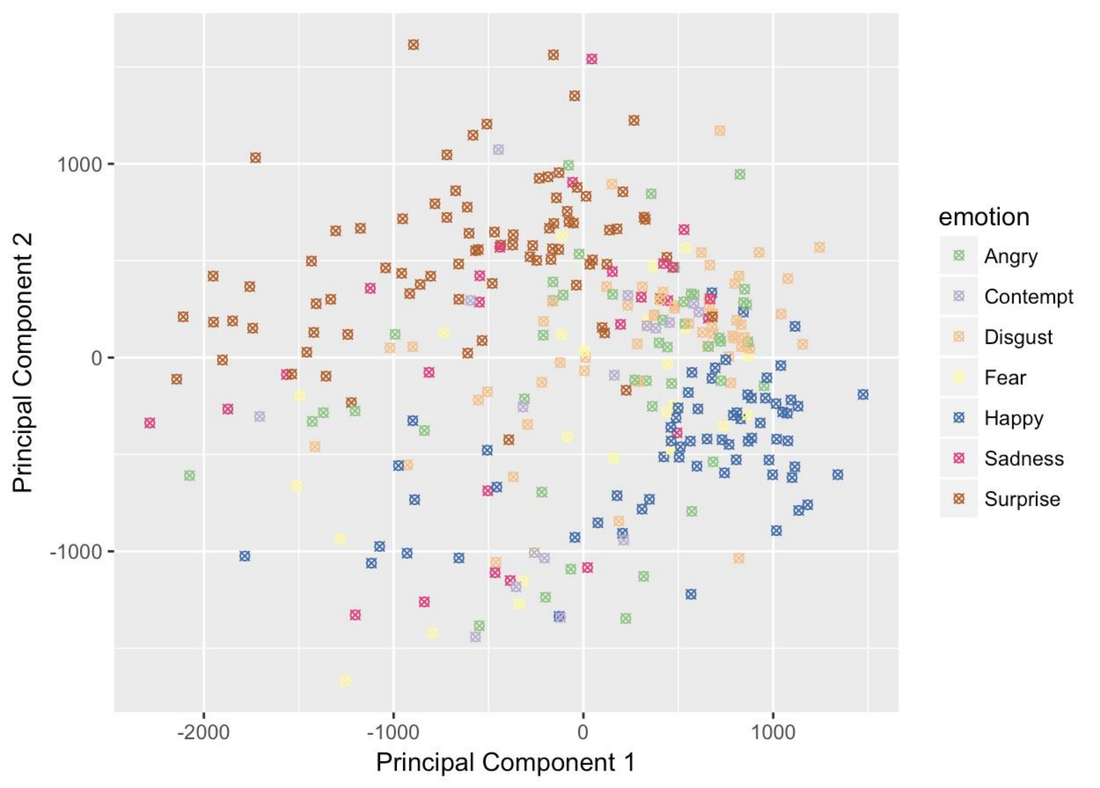
- Once the number of eigenvectors has been selected the original data is first subtracted from the “mean face” and then can be projected onto the subspace to extract a coefficient for each eigenvector for each image.
- The assumption is that combinations of the eigenvectors can be used to predict facial expressions
- Below is an example from the CK+ dataset showing the first 8 eigenvectors and the emotion label.



emotion	X1	X2	X3	X4	X5	X6	X7	X8
3	-460.93	-1056.7	-463.38	290.68	138.74	563.94	-414.58	-4.4586
7	-609.64	22.931	-499.6	194.22	-1015.4	210.44	223.16	-173.87
1	-310.8	-213.5	-608.97	-236.98	-349.63	319.96	414.48	108.7
5	347.85	-731.31	217.83	620.92	-802.2	220.08	22.439	-185.07
7	-393.32	-424.03	-1131.9	108.6	-270.27	-110.72	24.816	-14.22
6	-503.29	-687.19	-952.08	-268.99	-53.427	5.436	213.11	81.124

METHOD CLASSIFICATION

By plotting the values for the first two principal components we can see some rough patterns begin to emerge.

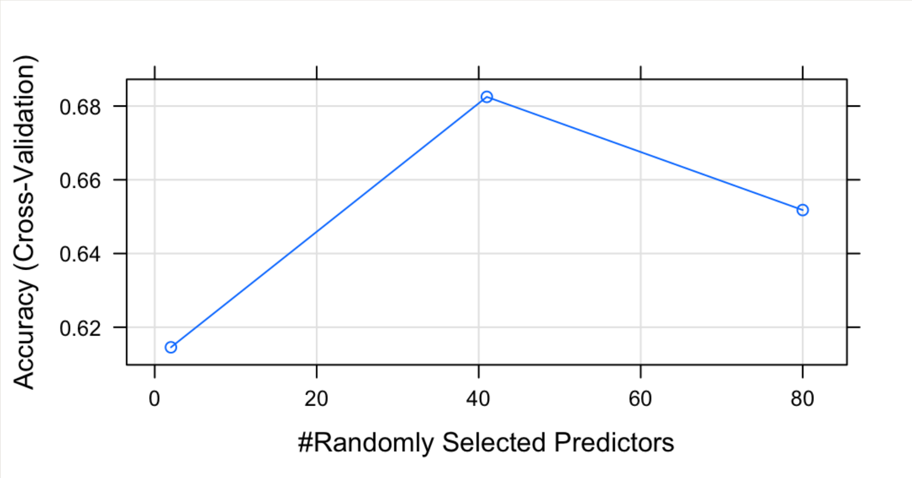


METHOD
CLASSIFICATION

- 10 fold cross-validation was used
  - Split the data into 10 subsets (folds) using stratified sampling
  - 9 folds are used for training and the last fold for testing
  - A different 9 folds are used for training and different fold for testing
  - This is repeated until all the data has been used for both training and testing
- 3 Model types were used:
  - Random Forest
  - Support Vector Machine – Linear Kernel
  - Linear Discriminant Analysis

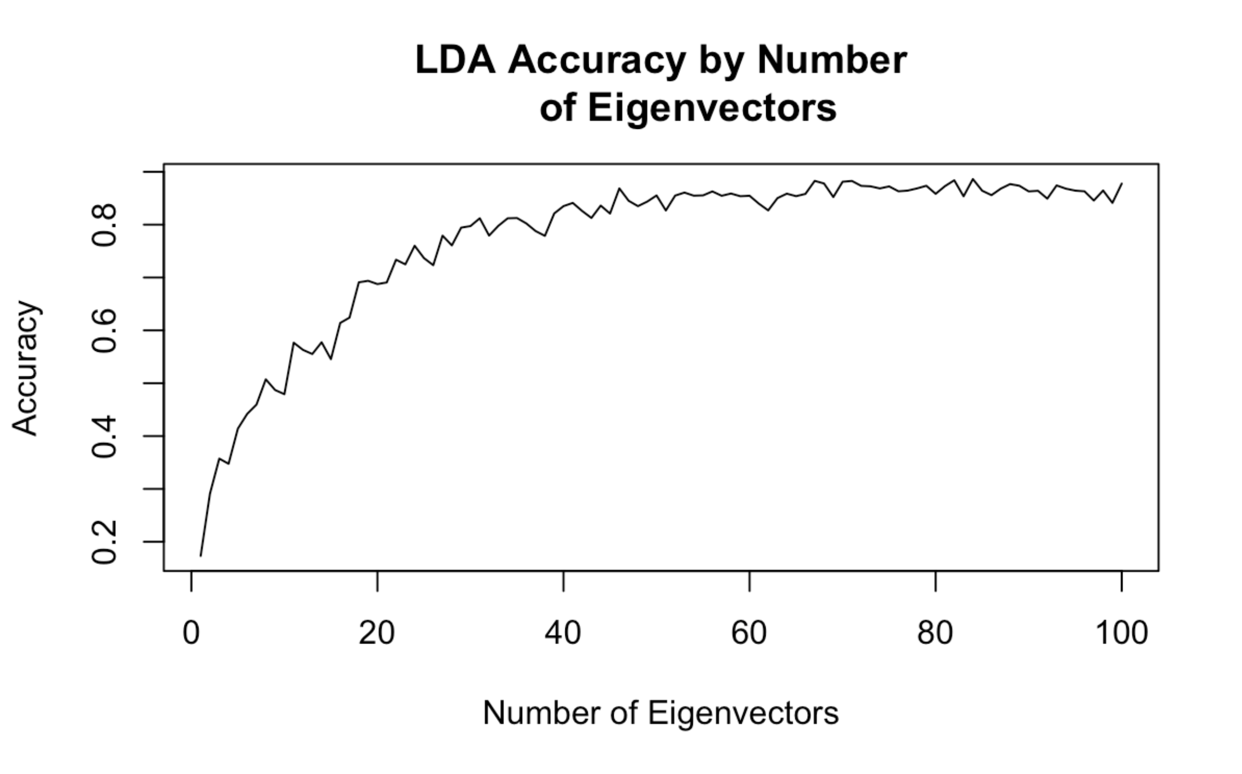
METHOD CLASSIFICATION

- Models parameters were tuned for some models to increase classification accuracy.
  - Example for Random Forest



Method
Classification - Number of Eigenvectors to Use - JAFFE

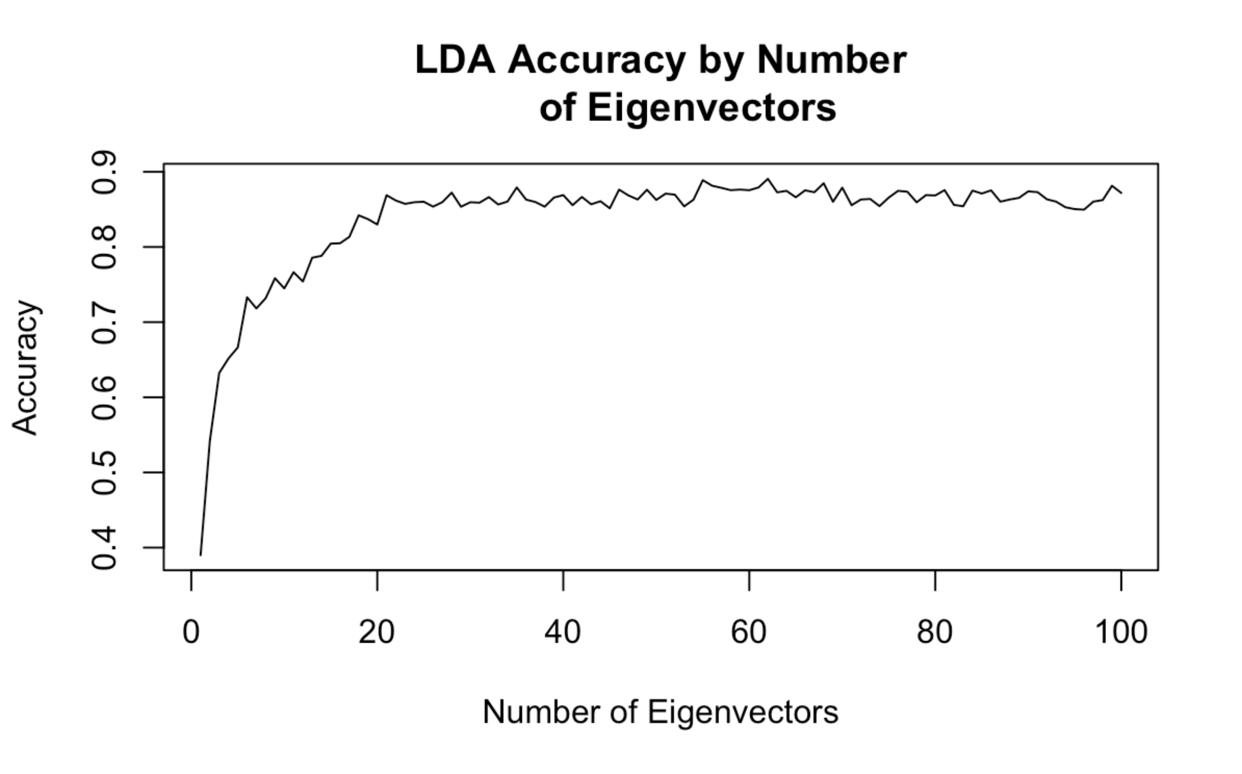
For JAFFE using LDA The max accuracy stops increasing between 40 and 60 eigenvectors



Method
Classification - Number of Eigenvectors to Use - CK+

For CK+ using LDA, the accuracy stops increasing between 20 and 40 eigenvectors.

Lesson Learned- the number of eigenvectors needed depends on the dataset



RESULTS

Model	CK+ Accuracy	JAFFE Accuracy
Linear Discriminant Analysis	88%	86%
Support Vector Machine	78%	78%
Random Forest	67%	79%

Results
CK+ Accuracy by Expression - LDA

- The model performs well when predicting disgust, happy, and surprise
- The model doesn't perform well when predicting contempt, fear, and sadness
- There appears to be correlation between the record count per expression and the accuracy

Expression	Count	True Positive Rate	Precision
Angry	45	87%	76%
Contempt	17	65%	65%
Disgust	58	95%	100%
Fear	25	68%	77%
Happy	68	97%	94%
Sadness	26	62%	70%
Surprise	82	94%	93%

Results
JAFFE Accuracy by Expression - LDA

- The model performs well across emotions, with the exceptions of sadness and fear

Expression	**Count**	**True Positive Rate**	**Precision**
Angry	30	87%	93%
Disgust	29	79%	88%
Fear	32	81%	79%
Happy	31	90%	97%
Neutral	30	97%	85%
Sadness	31	84%	74%
Surprise	30	83%	89%

Evaluation
Comparisons with other Methods

Feature Extraction	**Classifier**	**CK/CK+ Accuracy**	**JAFFE Accuracy**
Geometric displacement of Candide nodes	SVM	99.7%	-
Gabor features	SVM and MLP	91.6%	88.1%
PCA - Our Method	LDA	87.0%	86.0%

CONCLUSION

- Using PCA as a feature extraction method does allow us to detect patterns in facial expressions and classify them with a decent degree of accuracy
- Advantages
  - It provides a decent degree of accuracy and is easy implement
  - It provides “eigenfaces” which help to see how PCA is extracting features
  - Quick Speed
- Disadvantages
  - There are more accurate ways to extract features
  - PCA is a global method - it may be better to isolate facial regions (eg. eyes, mouth)
  - Face must facing forward with no inclination or occlusion
  - Outliers will cause problems, such as lighting
  - When classifying new faces and expressions, they must be similar to the training set

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