Computer Department
Faculty of Engineering
Cairo University

CMPN450

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Pattern Recognition and Neural Networks

Report

Evram Yousef **Sec : 1** **B.N : 8**

Omar Ahmed **Sec : 1** **B.N : 36**

Kareem Osama **Sec : 2** **B.N : 5**

Muhammad Sayed **Sec : 2** **B.N : 14**

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PROJECT PIPELINE

1. Read images.
2. Preprocess images and extract features.
3. Perform PCA on returned features to extract less features.
4. Fit the classifiers on the tuning images and classify the test image.
5. Take votes of classifiers when confidence of SVM is less than 50%.

PREPROCESSING MODULE

- Convert image into **grayscale**.
- Apply binary **"otsu"** threshold.
- Find largest line in the image (get it's coordinates)
- Crop image and take only the handwritten part using largest lines.
- Segment the image into lines using closing and opening image processing techniques.
- Return list of images, each image contains a line of the handwriting.

FEATURE EXTRACTION MODULE

Local Binary Pattern Histogram(LBPH) [1], [3]

The Local binary pattern(LBP) is a hidden texture based feature in image. Where each pixel has a binary code, This binary code depends on the intensity of the 8 neighbour pixels in comparison to the intensity of the center pixel.

A histogram is then applied to the image of binary codes. The histogram is a feature of the image.

Center Symmetric Local Binary Pattern with greyscale co-occurrence matrix(CSLBCop) [1]

The Center Symmetric Local Binary Pattern(CSLBP) is a hidden texture based feature in image. Where each pixel has a binary code, This binary code depends on the comparison between intensity of the corresponding pixels of the surrounding window(centered at center pixel).

Grey Scale Co-occurrence matrix(GLCM) is applied to the image of binary codes. The extracted matrix from the image is a feature of the image.

Frequency Domain Histogram(FDH)

The image is converted to frequency domain. Then applying a log function on the resulting image and scaling with a factor enhances the output.

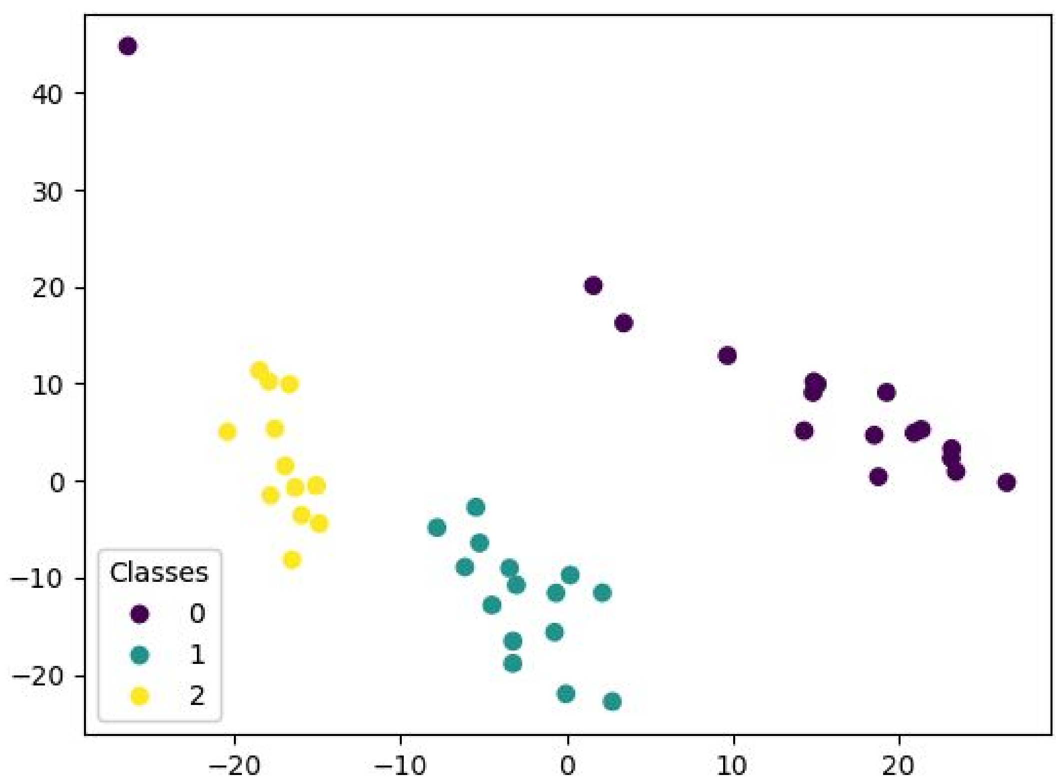
A histogram is applied to the resultant image in frequency domain. This extracted histogram is considered as another feature of the image.

PCA

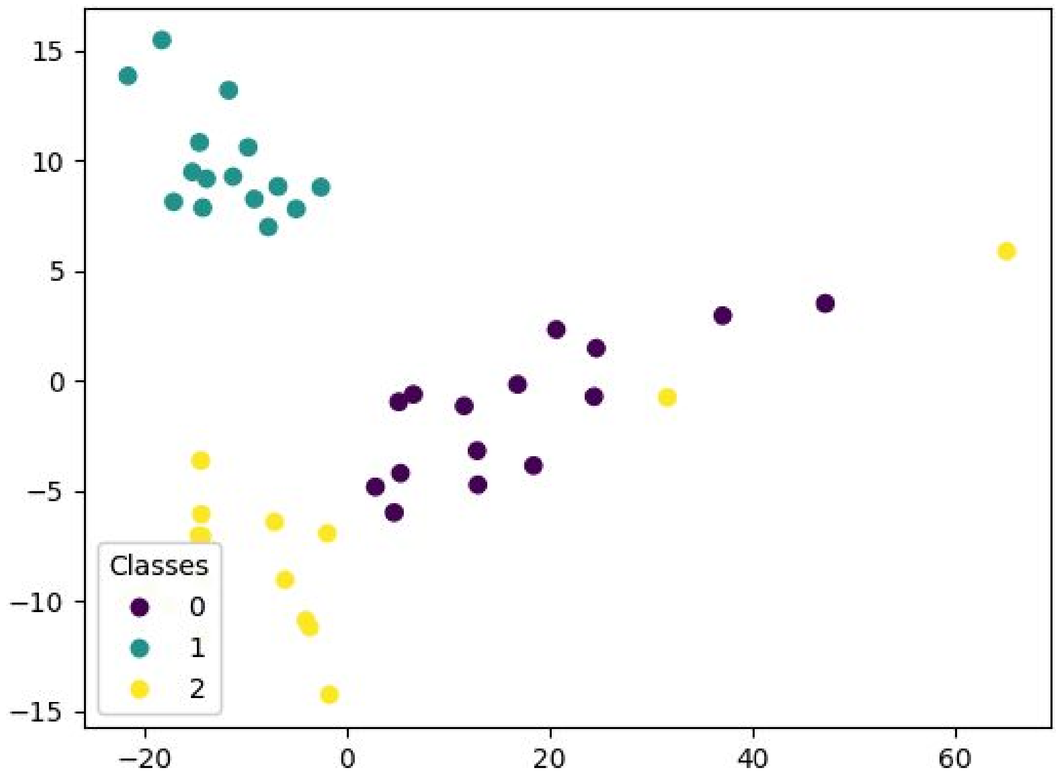
Using principal component analysis we managed to enhance timing and also plot features extracted from the CSLBCOP in two dimensional space.

We tuned the number of components extracted from the *X_tune* matrix to be exactly 39 columns, thus this is the average number in which 90% of variance is contained.

Plotting features extracted guided us to pick the appropriate classifier, and to tune parameters involved in LBPH and CSLBCOP.

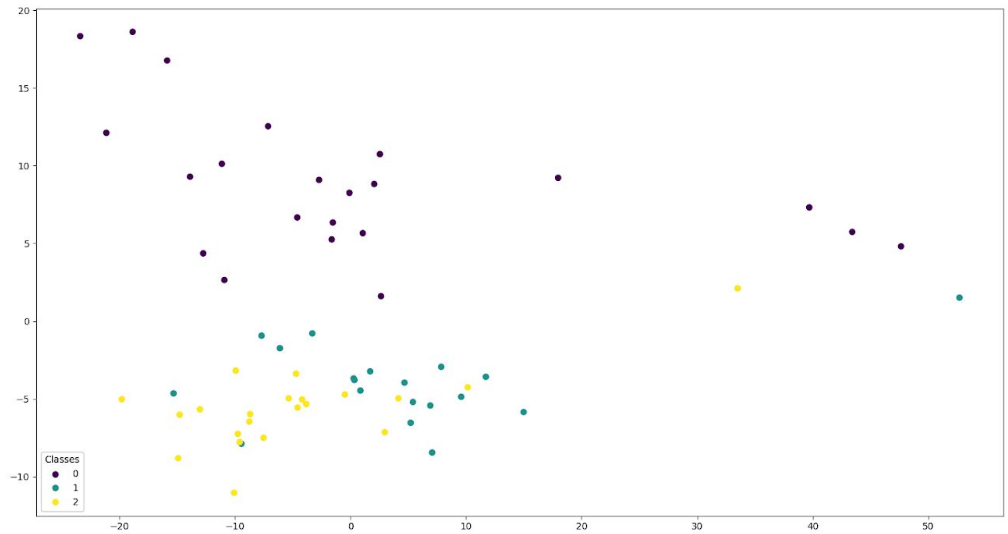


(Figure 1: 2D representation of the LBPH extracted feature



(Figure 2: 2D representation of the CSLBCoP *extracted features)*

In addition to that, PCA shows how misclassified cases are overlapped when presented in 2D.

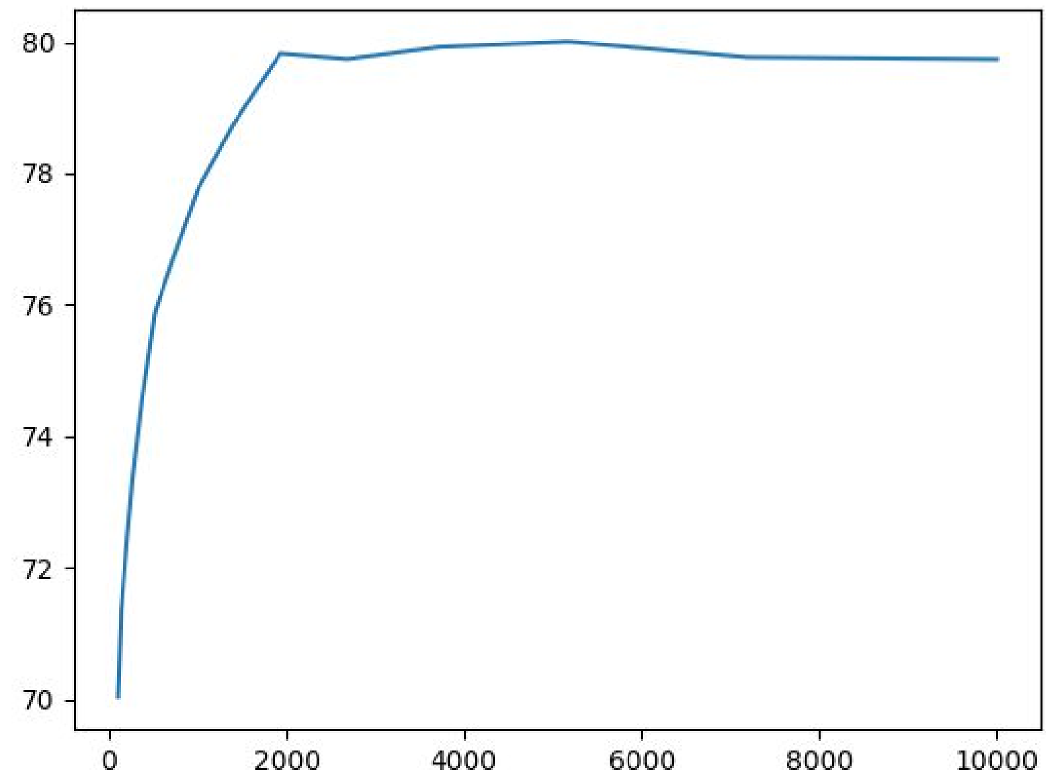


(Figure3: Classes 1 and 2 are overlapped)

CLASSIFICATION

SVM

Our initial guess was using Support Vector Machine; as it shows compatibility with features extracted using LBPH. So our first goal was to tune the regularization parameter in SVM *-named C in sklearn-* so we tested values within the range [100:10000] and as it turns out from the graph the value 4000 is the most appropriate one.



(Figure 4: Regularization parameter vs. accuracy)

Second tuning parameter was the kernel used in svm, at first 'linear' and 'poly' kernels didn't differ significantly, but after using PCA to reduce dimensionality, 'linear' kernel improved results slightly.

ADABOOST

Second classification technique we used was adaptive boosting, the intuition behind using it was that most of our random tests are linearly separable, but due to the non linearly separable tests, adaboost failed to meet our expectations.

We tried to make use of it, by only considering classifying using adaboost if SVM is not confident with its best pick by a percentage like (70%). But as it turned out that when SVM correctly classifies authors its percentage of confidence is greater than 80%ز

PERFORMANCE ANALYSIS MODULE

The data set of IAM consists of 657 writers; only 159 of them have more than or equal 3 forms.

The total number of forms of the 159 writers is 899.

We tried an experiment to take each of the 899 forms as a test and randomly choose two other forms from the set of forms of the same writer, Then randomly choose two other writers and foreach choose randomly 2 forms from their set of forms.

On carrying out this experiment with the three features each with three classifiers. We got these results.

	SVM			Adaboost			KNN		
	fails	acc %	avg time(s)	fails	acc %	avg time(s)	fails	acc %	avg time(s)
CSLBCop	5	99.44	1.7	94	89.54	2.32	9	99.	1.69
LBP	6	99.33	1.84	126	85.98	2.57	17	98.1	1.94
FDH	67	92.55	1.82	288	67.96	2.47	157	82.54	1.99

So the best results came from the CSLBCop feature combined with SVM classifier with only 5 fails in the 899 test forms.

So our best performance is 99.44% as an identification accuracy and 1.7 secs as execution time per test.

ENHANCEMENT AND FUTURE WORK

- We can optimize the execution time by resizing the image into smaller one BUT we need to tune the parameters of segmentation
- We can use non texture based features like height and width of the handwriting.
- We can use data augmentation and use the other authors that have less than 3 forms.
- We can make use of multiple features combination together and solve the ties with weighted votes, But we had no time for that

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NAME	WORKLOAD
Evram Youssef	Classification (SVM & Adaboost) - PCA
Omar Ahmed	Preprocessing - Features(Local Binary Pattern Histogram).
Kareem Osama	Classification (Knn) -Features(LBPH tuning - freq histogram)
Muhammad Sayed	Features(LTPH - CSLBCoP)

References

1. Heikkilä M, Pietikäinen M, Schmid C. Description of interest regions with center-symmetric local binary patterns. ICVGIP. 6. Springer; 2006. p. 58–69.
2. Priyanka Singh , Partha Pratim Roy, Balasubramanian Raman. Writer identification using texture features: A comparative study
3. Yaacoub Hannad, Imran Siddiqi, Mohamed El Youssfi El Kettani, Writer identification using texture descriptors of handwritten fragments,