Pattern Recognition and Neural Networks

Project Document

Writer Identification System

Team no. 7

Team members

Khaled Amgad
Section:1, B.N.:15
khaled.mohamed98@eng-st.cu.edu.eg

Sofyan Mahmoud
Section:1, B.N.:25
sofyan.alsayed98@eng-st.cu.edu.eg

Mohamed Mokhtar
Section:2, B.N.:17
mohamed.mahmoud98@eng-st.cu.edu.eg

Nour Nasser
Section:2, B.N.:30
nour.mohamed98@eng-st.cu.edu.eg

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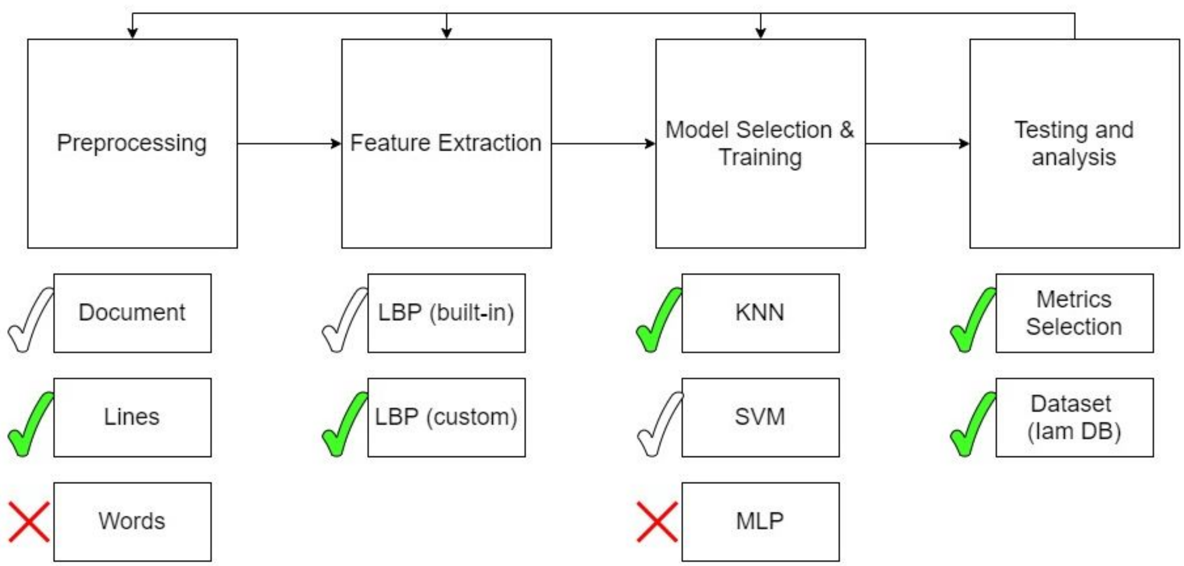
Project Pipeline

The system consists of four main modules: pre-processing module(handwritten lines), feature extractions module (LBP), and classification module (KNN) and Testing and analysis module. We first load all seven images, we run the pre-processing module then feature extractions module on all the images at once, using seven threads, we wait for them to finish then we pass a list of features to the classification module(KNN) then we make the prediction.
In each thread we give an image to the pre-processing module which divide it into handwritten lines (array of lines grayscale and binary formats),we give this array to feature extractions module, it calculates an array of histograms for the lines then, we collect all histograms from all threads to be given input to classification module(KNN).



Pre-processing Module

It takes an image as an input, it first detects the handwritten part, crops it and performs
Line segmentation.
The outputs are an array of images each containing one line.
Steps:

1. We first trim the image by cropping the bordes to remove border noise.
2. Median blur to remove noise (window size 5).
3. Create a binary image from the blurred image by thresholding with threshold equal 200.
4. Anding black and white image with blurred image store it in variable img.
5. Get contours of the binary image.

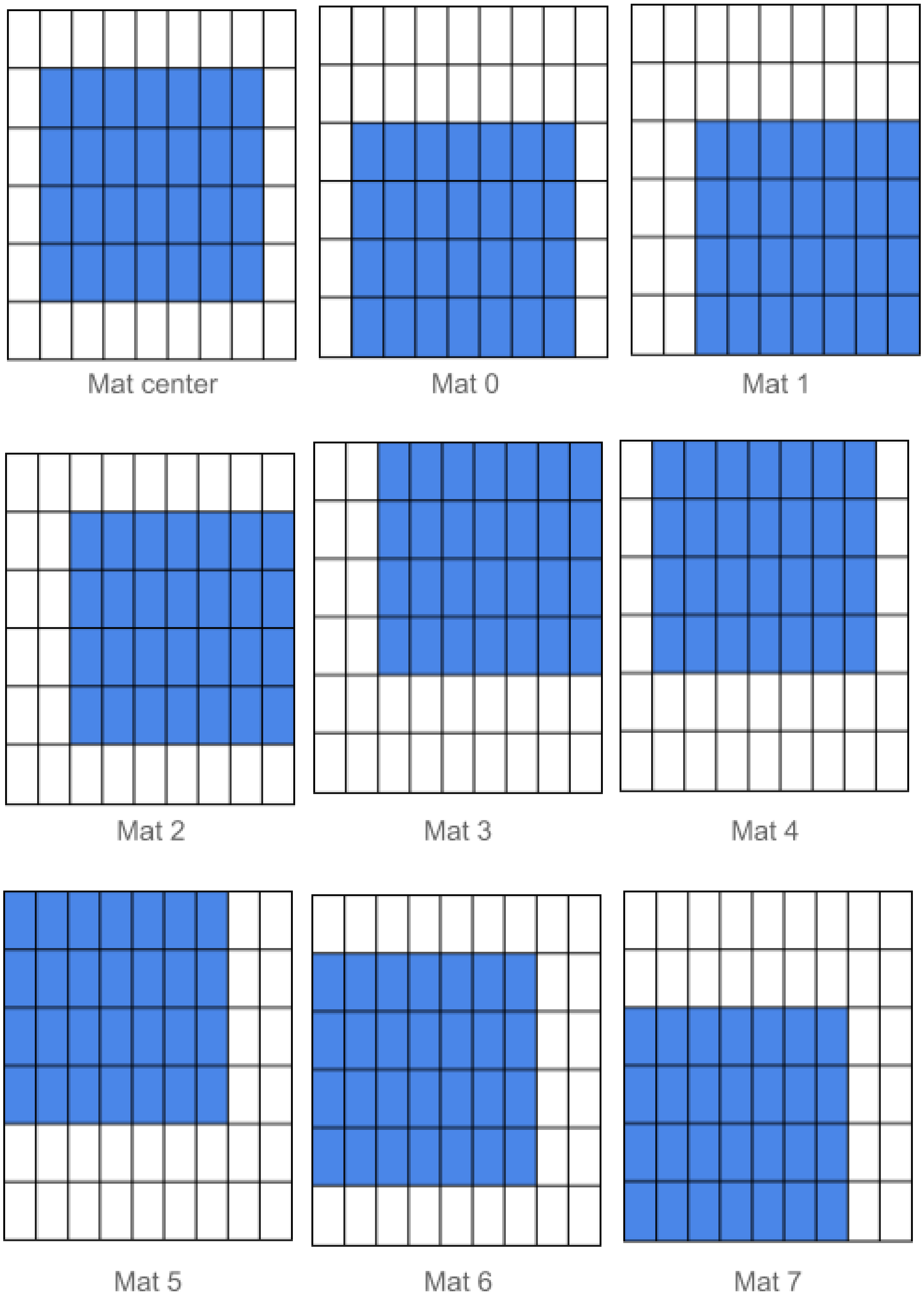
6. Detect two lines to isolate the handwritten part from the shape of contours.
7. Remove all white borders.
8. Eroding the result binary image with kernel equal one pixel X 0.8 of the image width.
9. Get contours of the eroded image, each contour now contains a line
10. We divide (img) & (binaryImg) images into several images each one containing a single line,Using the contours bounding box

Feature Extraction Module

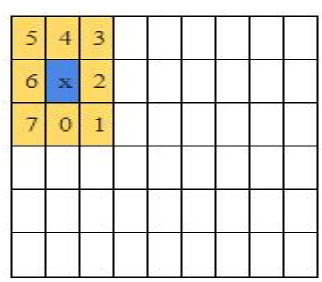
We are using local binary patterns as a feature, it's considered to be one of the most powerful texture descriptors.
LBP is a local descriptor that based on the neighbourhood for any given pixel, it assigns a decimal value for each pixel the way it calculates this value is by comparing the center pixel to all its neighbours, if the center pixel > neighbour pixel , this neighbour pixel takes value one else zero, this gives an 8-digit binary number (which is usually converted to decimal), compute the histogram of the calculated image.
We implemented our own LBP(r=3)
Steps

1. In this approach we extract 9 matrices from the image as shown in the following figures.
2. We compare the center matrix to all 8 matrices,the result of this comparison are 8 binary matrices.
3. Multiply each matrix by $2^{index\ of\ the\ matrix}$
4. We sum results of previous step,the results of the sum is now the LBP image of the center matrix
5. Calculate the histogram of the LBP

In the following figures we consider this matrix to be our image and we calculate LBP to it with r = 1. In our algorithm we ignore the borders with width equal to r so we will be actually calculating LBP for the center matrix using all eight other matrices.



Here if we consider the pixel in the left upper corner of each matrix. We will find the neighbours of the pixel x (first pixel) in the center matrix to have the same as it in the other eight matrices.



For an example its right neighbour would be the first pixel in Mat
0 ,etc. So when we execute steps 3 and 4 we calculate LBP matrix for the center matrix.

Classification Module

We use K nearest Neighbors classifier with k=7.

Training:

The inputs are two arrays, first one is feature vector array and second one is features labels.

The feature vector contains histograms of all LBP images, one for each line and the corresponding label is the number of the writer.

We fit the model with the input data.

Prediction:

The input is one array containing the histogram of all LBP images of the lines of the test image.

We use our module to predict the label of each line then we take the majority vote to be considered our final prediction.

Performance Analysis Module & Results

Writing the times and outputs in the files:

The performance depends on the time of the three modules (**preprocessing, feature extraction and classifier module**) and the accuracy of the output itself. We write the output of each test case and the taking time in files and calculate the accuracy if there is an expected output (Optional)

Stepes:

1. Before each test case - before pre-processing module - we start a timer
2. After this test case - after the knn module - we end this timer
3. Take the difference between start timer and end timer and save the result in a file in path (output/time.txt).
4. Take the output from the knn module after each test case and save it in a file in path (output/results.txt)

Calculate the accuracy (Optional):

We have created a module to calculate the accuracy if the output

Steps:

1. Fill the file in path (output/results.txt) with the expected outputs.
2. At the start of running the code, we read those expected outputs and save them in a list. After each test case we save the actual output in a list too
3. After finishing all test cases we compare the actual outputs with the expected outputs
4. To calculate the accuracy.
5. The calculated accuracy printed in the console and if there is no expected outputs it will print a message for no accuracy

The average time and the accuracy:

We have tried the module on **1000** test case and the result was as follow

- Average Time: **1.4 sec**
- The accuracy is: **97.3 %**

Any other developed modules

Test cases generator Module:

We have created a module to generate test cases from **IAM-DATABASE,** That it takes a path of the input directory - the directory contains the dataset of **IAM-DATABASE -** and the path of the output directory - the directory of the output test cases - and then it create random test cases in this architecture

\output_directory

– \01

∗ \writer1_name

· 1.png

· 2.png

∗ \writer2_name

· 1.png

· 2.png

∗ \writer3_name

· 1.png

· 2.png

∗ test.png (A random image from one of those three writers)

– \02 (and so on….)

Other trials

1. LBP(Skimage) with KNN (K=1) on the handwritten part(grayscale)
2. We tried different r (1,3,5,6,9) in LBP, we found r=3 gives the best accuracy
3. We also tried black and white image but the grayscale is better
4. We found skimage LBP takes a lot of time, so we tried other libraries such as mahotas and opencv. We couldn't integrate them in our system because of the poor interface and encapsulated implementation so we implemented our own implementation.
5. LBP(Skimage) with minimum distance classifier on the handwritten part(grayscale)
6. LBP(Skimage) with SVM on the handwritten part(grayscale)
7. LBP(Skimage) with SVM on the handwritten lines(grayscale)
8. LBP(Skimage) with KNN (K=7) on the handwritten lines(grayscale)

   None of the first seven trials exceeded 90% accuracy and average time 5 seconds.
   The last trial (trial-8) has the same accuracy as our final implementation with average time 5 seconds. The current implementation has an average time 1.4 second.

Future work

We can increase this accuracy in many ways such as:

1. One of them is to change our feature extraction module and try to detect the morphological features which require an accurate character segmentation. Or mix with texture based features as the one we used.
2. Or we can change our classifier module and use a deep neural network which will result in better accuracy. To input handwritten parts(grayscale) as input to CNN.
3. We could also use an extended version of LBP which is local ternary patterns (LTP) that gives the pixel values of (-1,0,1) and the results in extracting two histograms of the same image instead of one which means more features for our model.
4. Construct a texture block before feature extraction as used in https://drive.google.com/drive/u/2/folders/1XAxfaSELMh6Y08la2tIYm-Yx9zHhg5FX .
5. If more data is needed, RNN may be used for generating more samples.

Workload division

Khaled Amged	- Pipeline & Architecture - Pre-processing Module
Nour Nasser	- Pipeline & Architecture - Feature Extraction Module
Mohamed Mokhtar	- Pipeline & Architecture - Classification Module - Test cases generator Module
Sofyan Mahmoud	- Pipeline & Architecture - Main IO - Performance Analysis Module & Results - Test cases generator Module