Logo

Description automatically generatedA picture containing text, soup, dish, food

Description automatically generated

**Grade Auto Filler**

**Team Members**

|  |  |  |
| --- | --- | --- |
| Name | Sec | BN |
| Ahmed Alaa | 1 | 7 |
| Beshoy Morad | 1 | 20 |
| Zeyad Tarek | 1 | 28 |
| Waleed Hesham | 2 | 36 |

**Project Needs**

1. Python 3.10
2. OpenCV
3. Numpy
4. Skimage
5. Imutils
6. Pytesseract
7. Xlsxwriter

**Project Description**

The main idea of (Grade Auto Filler) is to give an image of a table with some data to the program and get an output of excel sheet containing the data that was in that image after mapping the symbols to the wanted grades.

The main idea of (Bubble sheet correction) is …

**Constraints**

1. The image should be clear, and the light distribution is appropriate and not too bad.
2. Handwritten numbers and symbols should be clear.
3. Bubble sheet must consist of 2 columns or 3 columns only.
4. The paper should be fully visible.
5. The background of the paper should be dark.
6. The paper should be flat (not bent).

**Used algorithms**

[Module 1]: Grade Auto Filler

To detect cells with normal image processing:

1. Enhance the image of the cell to remove the noises
2. Get the angle of lines in that cell and if it was in a certain range then this cell is **correct mark**
3. Perform opening operation on the cell with vertical and horizontal kernels to get the number of vertical and horizontal lines in that cell.
4. Get the contours and calculate the area then check if it was higher that a certain value then this cell is **Box**
5. Perform houghCircles with a certain value for min and max radius to check if that cell is **Question mark**
6. If it was nothing from the above, then check if it was **horizontal lines or vertical lines** cell
7. If it was not horizontal or vertical, then it is an empty cell

To detect cells using HOG and KNN:

1. We have to train the HOG, KNN models using a set of images with different scales and different shapes.
2. We can use that model to predict the upcoming cells.

To extract cells:

1. Apply gaussian blur + canny edge detection
2. Get contours of the edged image and sort them by area and select largest one (paper)
3. Apply four point transform to this contour to correct skewness
4. Apply morphological opening using row structure element to remove anything except horizontal lines
5. Apply HoughLines transform to detect horizontal lines and remove unwanted lines (not perfectly horizontal)
6. Apply step 4, 5 again for vertical lines
7. Draw the detected lines in a fully white image with same size of original one
8. Get contours of this image and sort them from top to bottom
9. Filter contours based on its size to eliminate false cells
10. Extract cells from original image from these contours’ coordinates

[Module 2]: Bubble Sheet Auto Corrector

1. Apply skew correction which is implemented in the previous module (Module 1).
2. Crop the student’s information ticket.
3. Convert the image into grayscale.
4. Apply Canny Edge Detector.
5. Detect all the circles (whatever filled or not) using Hough Circle, which is represented in center (a, b) and radius (r).
6. Sort the circles according to Y values.
7. Sort each row’s circles according to X values.
8. Resolve each question’s circles and take rectangle over each circle and binarize it.
9. If the number of white pixels (value = 255) is less than specified threshold value, then this circle is classified as filled pixel.
10. If the student’s ID is included, then separate the 1st 10 elements and extract the ID from it by comparing it by the choice’s orders.
11. Compare the detected answers with the model answer, then create a list of True/False.
12. Send a JSON object containing “id”, and “answers”
13. Use the JSON object to generate the excel sheet to summarize the results of the student.

[BONUS] Extra Feature:

1. Our model can adapt with multi-answer per question which is meaning that if the question has more than one choice, it will detect it and report it as true and false.
2. Create [configBubble.conf] to customize your own constraints on the model like (if there is ID or not) or (number of questions, number of choices, etc)
3. Load students’ IDs from file.
4. Export the autocorrected answer paper on the hard disk.

**Experiment results**

We used 15 samples with different angles of capturing (Skewing, orientation, scale) and with different hand-writing fillings.

The results:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Sample Number | Number of wrong detected symbols with normal image processing | Number of wrong detected codes with OCR | Number of wrong detected numeric values with OCR | Number of wrong detected numeric values with features + classifier |
| 1 | 1 | 0 | 2 | 2 |
| 2 | 0 | 0 | 4 | 3 |
| 3 | 2 | 1 | 4 | 2 |
| 4 | 1 | 0 | 5 | 1 |
| 5 | 1 | 0 | 1 | 0 |
| 6 | 1 | 3 | 1 | 1 |
| 7 | 0 | 0 | 1 | 2 |
| 8 | 0 | 1 | 1 | 0 |
| 9 | 1 | 1 | 6 | 0 |
| 10 | 0 | 0 | 4 | 1 |
| 11 | 0 | 0 | 7 | 0 |
| 12 | 0 | 0 | 2 | 1 |
| 13 | 0 | 0 | 4 | 0 |
| 14 | 0 | 0 | 2 | 0 |
| 15 | 0 | 0 | 2 | 0 |

**Accuracy of Symbols**

Number of test cases = 17 cell \* 2 columns \* 15 samples = 510

Number of wrong detected symbols = 7

Accuracy of symbols detection with normal image processing techniques

= (510 - 7) / 510 = **98.6%**

Accuracy of symbols detection with HOG model = **100%**

**Accuracy of code and numeric values detection using OCR**

Number of test cases = 17 cell \* 15 sample = 255

Number of wrong detected codes = 6

Number of wrong detected numeric values = 46

Accuracy of code detection = (255 - 6) / 255 = **97.6%**

Accuracy of numeric values detection = (255 - 46) / 255 = **82%**

**Accuracy of code and numeric values detection using features and classifier**

Number of test cases = 17 cell \* 15 sample = 255

Number of wrong detected numeric values = 13

Accuracy of numeric values detection = (255 - 13) / 255 = **94.9%**

**Analysis**

After testing the program with a lot of samples we noticed that OCR is good with codes but not very efficient with numeric values, also most of wrong numeric values detected was (**digit 1**) and sometimes (**digit 7**), but the KNN model is very good with the handwritten numeric values and not very efficient with the codes, so we decided to make a hybrid model to use the OCR to get the codes and the KNN to get the handwritten numeric values.

For symbols, most of wrong detected cells were right mark and question mark because the angle of lines of right marks sometimes gets out of the specified range, also question marks sometimes the radius of the circle gets out of the specified range.