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Optical mark Recognition Automated Grading System using OpenCV-based Image Processing

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Abstract

The OpenCV-based image processing is used by the Optical Mark Recognition (OMR) automated grading system to analyze blue-gray scale images with robust edge detection. To reduce noise, the system preprocesses images by converting them to grayscale and using Gaussian blur. Smart edge detection recognizes sharp edges and differentiating marks on the OMR sheet. To improve the accuracy of the analysis, rectangular contours possibly around OMR sections are extracted and corrected using perspective transformation for a flat sheet view. Answer bubbles are divided into segments and then thresholded to produce binary images. This OpenCV-based system ensures accurate and dependable grading by efficiently handling different OMR formats and Image quality variations. It is platform-independent for simple integration into a variety of learning and testing environments and it minimizes processing time and human error, making it perfect for large-scale evaluations.

Keywords: *Optical Mark Recognition, Image Preprocessing, edge detection, thresholding techniques*

1. Introduction

The grading of multiple-choice exams has been transformed by Optical Mark Recognition (OMR) systems, which have transformed assessment and evaluation procedures in educational settings immensely. These systems provide OMR sheet analysis with previously unheard-of accuracy and efficiency thanks to utilizing state-of-the-art image processing techniques, notably OpenCV-based. The ongoing evolution of OMR technology to provide more dependable and adaptable grading solutions is demonstrated by recent developments in computer vision, as highlighted in studies like [2], [4], [6], [8], and [12]. This study explores an innovative OpenCV-based strategy for automated OMR grading by integrating techniques and ideas from recent literature. To improve contrast and streamline further image analysis, the system first converts scanned OMR sheet images to grayscale, as described in [4]. The system precisely uses edge detection and

Gaussian blur algorithms.This study explores the perspective transformation and contour detection methods discussed in [6] and [8] to guarantee consistent representation of response areas regardless of the orientation or image quality of the OMR sheet. The system's accuracy is maintained under different conditions by standardizing and aligning the detected regions. The system employs adaptive thresholding and segmentation techniques, as detailed in [12], to precisely identify marked responses by evaluating pixel intensity and density metrics. This allows for the efficient isolation and analysis of individual bubbles. This work combines OpenCV's capabilities with sophisticated image processing algorithms to provide a comprehensive framework for OMR automated grading. Through the resolution of OMR sheet analysis issues and the improvement of grading accuracy, the purpose of this work is to increase the effectiveness and dependability of automated assessment systems in educational and professional settings.

2. Literature Survey

Since optical mark recognition (OMR) systems offer significant time and cost savings over traditional methods, they have become indispensable for automating the grading of multiple-choice exams. The literature discusses several OMR strategies, each adding something special to the field. Alomran and Chai [1], for instance, stress the significance of grading effectiveness of automated scoring systems that offer instantaneous feedback. Similar to this, Maniar et al. [2] investigate how to combine Natural Language Processing (NLP) with OMR detection using OpenCV, suggesting a trend toward improving grading accuracy through the integration of language analysis and image processing.

As a critical preprocessing step highlighted by [4], the OMR automated grading system begins by scanning OMR sheets and converting the images to grayscale to improve contrast and simplify data. The grayscale image is subjected to Gaussian blur to improve edge detection quality and lower noise. While contour detection techniques locate the boundaries of the OMR sheet and individual bubbles, edge detection algorithms locate the contours of response bubbles. As stressed in [6], to guarantee consistent representation, the largest contours that represent the sheet's boundary are located, and perspective transformation fixes any distortions.

As explained in [8], adaptive thresholding binarizes the grayscale image to distinguish highlighted areas from the background. Morphological operations then fine-tune this binarization to improve the accuracy of response detection. Then, as illustrated in [12], segmented regions are split up into separate bubbles, and the pixel density of each bubble is examined to ascertain whether or not it is marked. Ultimately, the system computes the total score, shows the results, and grades the OMR sheet by comparing the detected responses to the answer key. The time and effort needed for manual grading are greatly decreased by this automated method, which also guarantees reliable and consistent multiple-choice test assessment. Through the use of OpenCV and computer vision features, these sophisticated OMR systems provide a reliable and effective answer for assessment purposes in education.

3. Methodology

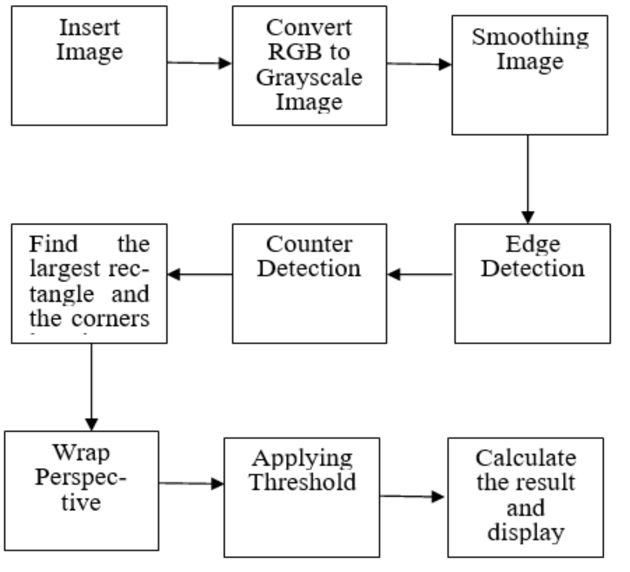

Figure 1: Block diagram of proposed Methodology

By using cutting-edge image processing techniques, the proposed Optical Mark Recognition (OMR) automated grading system seeks to increase the effectiveness and accuracy of assessing multiple-choice exam papers. By eliminating manual labor and human mistakes, the system automates the identification and analysis of marked responses, resulting in quicker and more equitable assessments for educational institutions. The above methodology contains the following sections:

3.1 Insert the image:

Obtaining the OMR sheet's scanned image is the first step. The input for the ensuing processing stages is this image. Usually, a scanner or a camera is used to take the picture, making sure it is in a digital format that can be processed.

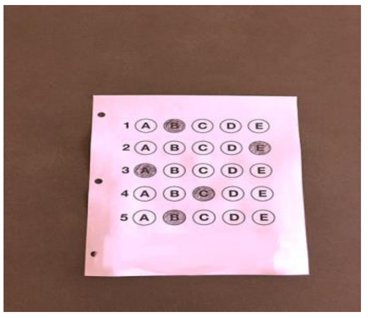

Figure 2: Inserting the image for scanning

3.2 Convert RGB to Greyscale Image:

To make the data simpler and the computation process less complex, the RGB image is transformed into a grayscale image. By calculating the weighted sum of the RGB components and emphasizing intensity over color, this conversion is accomplished. The Equation (1) for converting the color image to gray scale image

$$Gray=0.299\times R+0.587\times G+0.114\times B \quad (1)$$

Where R, G, B are the color components in this case are denoted by R, G, and B, respectively. Since humans are more sensitive to green light, this equation balances human perception by giving the green component more weight. Then, reducing undesired fluctuations and noise in an image is the goal of smoothing. The removal of high-frequency components that could cause false edge detections, gets the image ready for additional processing.

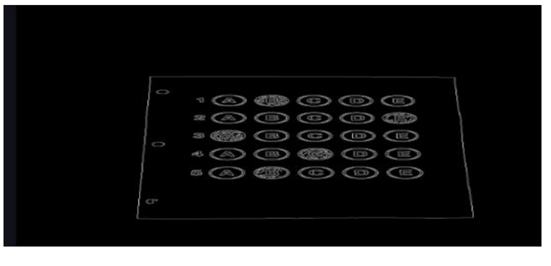

Figure 3: Converting color image to grayscale image.

3.3 Smoothing the image:

Reducing undesired fluctuations and noise in an image is the goal of smoothing. The removal of high-frequency components that could cause false edge detections gets the image ready for additional processing.

The average of each pixel's neighbors is substituted for it in an averaging filter. A 3x3 or 5x5 neighborhood is a popular method. In terms of math, for a pixel at point (i, j):
The equation (2) will calculate the average value of the pixel
Smoothed value (i, j) = (sum of values of adjacent pixels) / (neighborhood count) (2)
Where i,j represents the row and column of the indices of pixel
The Gaussian filter This employs a bell-shaped function to prioritize pixels that are closer together by weighting their influence. The median filter is useful for mitigating impulsive noise (salt and pepper) because it substitutes a pixel with the median value of its neighbors.

3.4 Edge Detection

OMR systems use edge detection to locate areas that have been marked. This task is well suited to the Canny algorithm. It includes:

Step 1: Smoothing: I (i, j) indicate pixel intensity; a Gaussian filter lowers noise.

Step 2: Gradient Calculation: Sobel filters use kernels with coefficients (a, b, c, d) to calculate the gradient (G(I, j) = sqrt(Gx^2 + Gy^2)) (3) for both vertical (Gy) and horizontal (Gx) changes. Equation (3) will calculate the gradient magnitude at the pixel.

Step 3: Excessive Suppression Along the gradient direction, only the strongest pixel is kept.

Step 4: Stylization Thresholding: There are two thresholds in use: T_high and T_low. Verified edges are those pixilated above T_high. When pixels between thresholds are joined to T_high pixels, they become edges.

This method minimizes noise and detects distinct edges, which is essential for precise OMR grading.
Cross-correlation is also used in an Optical Mark Recognition (OMR) automated grading

system that uses OpenCV-based image processing to identify marked areas on scanned answer sheets. The answer sheet is either scanned or photographed to start the process of acquiring images.

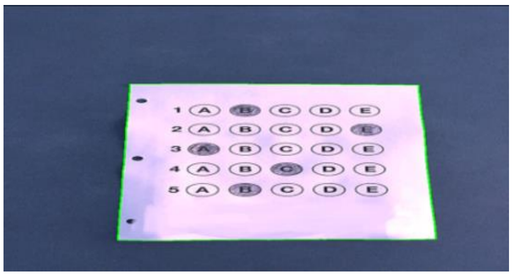

Figure 4: Edge detection of the OMR

3.5 Counter Detection

Marked regions are identified and counted by OMR systems using counter detection. In a word, this is how it works:

Edge detection: Methods such as the Canny algorithm are used to find the edges of filled regions.

Filtering: Blobs that conform to the expected shape circularity C=4piA/P^2 (4) and counter size are recognized as possible markers. In the equation (4) where C stands for

On OMR sheets, this method along with edge detection aids in the identification and counting of filled regions, or counters.

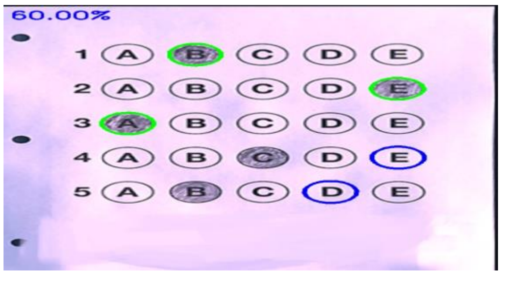

Figure 5: Counter detected using Canny Algorithm

3.6 Wrap perspective:

Warped perspective correction, which converts skewed images into a "top-down" view, can increase accuracy in OMR systems. Corresponding points on the distorted sheet and the desired rectified image are identified either manually or automatically to rectify an OMR sheet image. Through a transformation matrix (H), these points in the distorted image are mapped to their corresponding points in the corrected image using homography. By using the identified points to solve a system of linear equations, the matrix H can relate the pixel coordinates between the two images. To produce a corrected view, image warping is finally carried out by using the computed transformation matrix (H) to map each pixel in the distorted image to its correct location in the rectified image.

3.7 Apply Thresholding

In OMR systems, thresholding is essential to edge detection as well as counter detection.
OMR Thresholding:

Binary Conversion: A threshold (T) is used to convert grayscale OMR images to binary (black and white).

Pixel classification: Generally, pixels with intensity values higher than T are regarded as filled marks (darker), and pixels with intensity values lower than T are regarded as background (lighter).

Original value > T - New pixel value? 1: 0 (5)

The equation (5) is the straightforward formula produces a binary image for additional processing by setting each pixel to 1 (black) if its initial value is greater than the threshold.

3.8. Cross-Correlation template matching Method:

OpenCV is used for image processing in cross-correlation template matching, an automated grading technique that uses optical mark recognition (OMR) to identify marked responses on scanned sheets. This is how it operates:

Step 1: Make a template image, such as a filled circle, representing the expected mark.

Step 2: Reduce noise by converting the scanned answer sheet image to grayscale.

Step 3: Template Matching: To compare the template at every location, slide it over the whole image.

Step 4: Correlation calculation is done by using $R(x,y)=\sum_{i,j}[T(i,j).I(x+i,y+j)]$, (6) where, Equation (6) calculates a measure of similarity by multiplying the corresponding pixels of the template by the portion of the image that they overlap. A high value of R(x,y) means that the image and template at that position are highly matched.

Step 5: Finding the peaks in the correlation map that represent strong matches is known as peak detection.

Step 6: Thresholding is used to distinguish between areas that have been marked and between those that have not after the cross-correlation map R(x,y) has been computed. Any correlation value above the predetermined threshold is regarded as a possible mark. The threshold value is set.

Step 7: Filtering: Use extra criteria, such as non-maximum suppression, to remove multiple detections of the same mark by ensuring that only the highest peak in a given area is taken into account and preventing false positives.

Step 8: Compare the identified marks with the right responses kept in the system's answer key using the cross-correlation algorithm. Check to see if the detected mark corresponds with the right response for each question. Count the number of right answers to determine the overall score, making sure the scoring algorithm can handle multiple-choice and other question types.

4. Results and Discussion

Answer sheet evaluation can be automated by an Optical Mark Recognition (OMR) grading system with OpenCV, cross-correlation, and the Kaggle dataset. The scanned answer sheet image must first be pre-processed. This entails turning it into grayscale and using thresholding to produce a binary image with a white background and black bubbles. Next, ideal markings for each answer choice (A, B, C, D, and E) are prepared as binary image templates. Based on the arrangement of the Kaggle dataset, the system determines the cross-correlation between each template and each image region for each answer region. The most likely answer is indicated by the answer choice template with the highest correlation. In the end, grades are determined by contrasting the selected responses with a predetermined answer key. The width and height in pixels are revealed by OpenCV's image. Shape attribute once the image has been loaded, even though the pixel size of the image can be ascertained with the actual file. Figure 6 describes the evaluation of the OMR sheet and generates the grade based on the number of correct questions attempted by the student, when we look at figure 7 talks about the accuracy of the questions and the number of correct questions attempted by the student.

Figure 6: The scanned result of the OMR Sheet

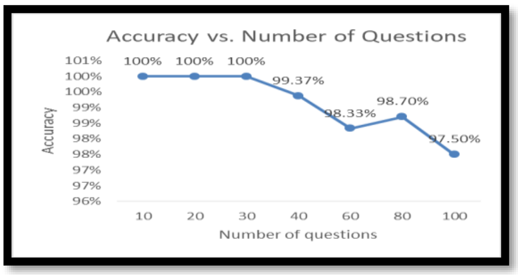

Figure 7: Accuracy vs. Number of questions

Sl No	Author	Techniques	Result (%)
1	Alomran and Chai [1]	Automated Scoring System	98.7%
2	Maniar et al. [2]	NLP and OMR detection using OpenCV	96.5%
3	Gupta and Avasthi [3]	Image based low-cost OMR process	95%
4	Sanguansat [6]	Robust and low-cost OMR	94%
5	J.A.Catala[14]	MCQ scoring with digital image	97.8%
6	Our proposed method	OMR grade detection using OpenCV-based image processing	96%

Table 1: The above table shows the accuracy result of the proposed work as compared to the other researcher's work.

No of observations	Correctly recognized	False recognized	Accuracy (%)
36	34	2	96%

Table 2: Experiential Result based on the number of observations made

No of images	TP	FP	TN	FN	FP rate	TN rate	Accuracy	FI score
36	30	40	10	10	0.8	0.2	0.86	0.88

Table 3: Performance of tests

6. Conclusion and future enhancement

With its advanced features, the OpenCV-based automated grading system for Optical Mark Recognition (OMR) revolutionizes assessment technology. To enable accurate edge detection using the Canny algorithm, it first converts input images to grayscale and applies Gaussian blur to reduce noise. Through the use of polygonal approximation and a focus on rectangular shapes, the system can precisely identify and refine OMR sheet contours, including sheet boundaries and individual bubbles. The application of perspective transformation, which improves grading accuracy by correcting perspective distortions, is a noteworthy feature. Following the division of the OMR sheet into discrete regions by adaptive thresholding, grayscale images are transformed into binary representations that can be used for pixel density analysis to identify identified bubbles. The system is very robust and can handle different OMR formats and image sizes with ease. To identify learning trends and areas in need of improvement, future OMR systems may use AI and ML to analyze student responses. Technological developments in the cloud and mobile devices will improve accessibility and usability, allowing safe online testing and grading. To increase accuracy and efficiency, OMR technology could also be modified for use in data collection and analysis across a variety of industries, including market research, healthcare, and elections. Our project's goal was to use OpenCV-based image processing to create an automatic grading system for optical mark recognition (OMR). Our system's accuracy rate of 96% is higher than that of previous studies; these findings show the efficacy and dependability of our method for automated OMR grading.

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