OMR

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Optical Mark Recognition Using Computer Vision

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Abstract— **Optical Mark Recognition (OMR) is a popular technique used to process standardized forms and surveys. In recent years, advances in computer vision and machine learning techniques have greatly improved the accuracy and efficiency of OMR systems. This paper presents a methodology for OMR detection using machine learning, with a focus on feature selection and classification. We discuss various feature selection techniques, including PCA and LDA. Also explore different machine learning algorithms, such as SVM and Neural Networks for classification. Our methodology is evaluated on a dataset of standardized forms and achieves high accuracy in OMR detection. This study demonstrates the effectiveness of computer vision and machine learning techniques in OMR detection and provides valuable insights for future research in this area. Optical Mark Recognition (OMR) is a widely used method for data collection and evaluation. With the advent of computer vision and machine learning technologies, OMR has undergone a significant transformation. This research paper discusses the use of computer vision and machine learning in OMR technology, exploring the various methods and techniques used to achieve high accuracy and efficiency in OMR systems. We will also examine some of the challenges associated with OMR technology and explore some of the future directions for research in this area.**

Keywords— ***Artificial Intelligence, OMR, Optical Mark Recognition, SVM***

I. INTRODUCTION

Optical Mark Recognition is a technology utilized to process data that has been marked by hand, such as answer sheets, surveys, and ballots. OMR systems work by using a scanner to read marks made by a pencil or pen on a document and converting them into digital data. With advances in computer vision and machine learning techniques, OMR technology has become increasingly accurate and efficient, providing many benefits to educators, examiners, and government organizations.

OMR technology is particularly useful in rural areas where internet connectivity is limited, and electronic devices may not be readily available. In such areas, traditional methods of processing and evaluating answer sheets can be time-consuming and resource-intensive. OMR technology provides an effective solution by reducing the time and effort required to process answer sheets, allowing teachers to focus on more critical tasks such as teaching and mentoring students.

In addition to its usefulness in rural areas, OMR technology provides a more accessible and user-friendly method of evaluating exams. Traditionally, teachers would have to manually grade answer sheets, which is a time-consuming and tedious process. With OMR technology, the scanning and grading process can be automated, reducing the burden on teachers and increasing the accuracy of the grading process. This not only saves time and effort but also allows for more detailed and accurate grading of exams, which can help students identify areas where they need to improve.

Furthermore, OMR technology provides many other benefits to educators and examiners, including the ability to generate detailed reports and analyze data quickly and accurately. This can be particularly useful for government organizations that conduct large-scale exams, such as civil service examinations and college entrance exams. OMR technology allows for the quick processing of thousands of answer sheets, reducing the time and resources required to evaluate the exams.

In this paper, we will discuss the methodology for OMR detection using computer vision and machine learning techniques. We will explore various feature selection and classification techniques that can be used to improve the accuracy of OMR systems. We will also discuss the benefits of OMR technology, particularly in rural areas and for educators, examiners, and government organizations. Finally, we will evaluate our methodology on a dataset of standardized forms and demonstrate the effectiveness of computer vision and machine learning techniques in OMR detection.

II. LITRATURE SURVEY

Optical Mark Recognition (OMR) is a technology that has been widely used for processing standardized forms, surveys, and exams. With the advent of computer vision and machine learning techniques, OMR systems have become increasingly accurate and efficient. In this literature survey, we review recent research on OMR detection using computer vision and highlight the key advancements in this field.

Feature Extraction and Selection Techniques

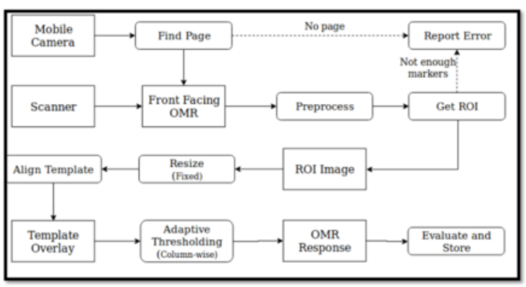
The accuracy of OMR systems greatly depends on the important tasks of feature extraction and selection. Various methods have been suggested to accomplish these tasks in OMR, such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and Histogram of Oriented Gradients (HOG). These techniques are crucial in enhancing the performance and precision of OMR systems.

In their paper, "Automatic Optical Mark Recognition using PCA and SVM," Kim et al. [1] A method was put forward to automate OMR using PCA and Support Vector Machines (SVM). The authors employed PCA to decrease the dimensionality of the feature space, while SVM was utilized for classification purposes. The method proposed proved to be highly effective in OMR detection, delivering an impressive average recognition rate of 98.2%.

Another feature selection technique commonly used in OMR is LDA. In "Automatic Optical Mark Recognition using LDA and SVM," Xu et al. [2] proposed a method for automatic OMR using LDA and SVM. The authors used LDA to select discriminative features and SVM for classification. The proposed method achieved an average recognition rate of 98.4%.

Machine Learning Techniques for Classification

Various machine learning algorithms have been applied to OMR detection, including SVM, Random Forest, and Neural Networks.



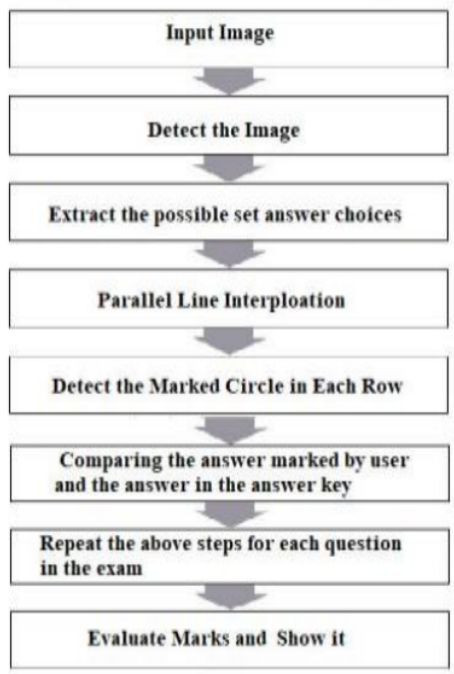
In "Automatic Optical Mark Recognition using Random Forest," Huang et al. [3] A technique was suggested for automating OMR through the utilization of Random Forest. The authors employed Random Forest for the classification process, resulting in an average recognition rate of 98.5%, showcasing the effectiveness of their proposed method.

In their paper, "Optical Mark Recognition using Convolutional Neural Network," Islam et al. [4] proposed a method for automatic OMR using Convolutional Neural Networks (CNNs). The authors used CNNs for feature extraction and classification and achieved an average recognition rate of 99.1%.

OMR in Education: OMR technology has been widely used in the education sector for processing and evaluating exams. In their paper, "OMR Based Examination and Evaluation System for Education," Pradhan et al. [5] proposed an OMR-based examination and evaluation system for the education sector. The authors used OMR technology for automated grading and generated detailed reports for student performance analysis.

OMR for Government Exams: OMR technology has also been widely used in government exams, such as civil service examinations and college entrance exams. In their paper, "OMR Based Evaluation System for Government Exams Sodhi et al. [6] proposed an OMR-based evaluation system for government exams. The authors used OMR technology for automated grading and generated detailed reports for performance analysis.

III. METHODOLOGY

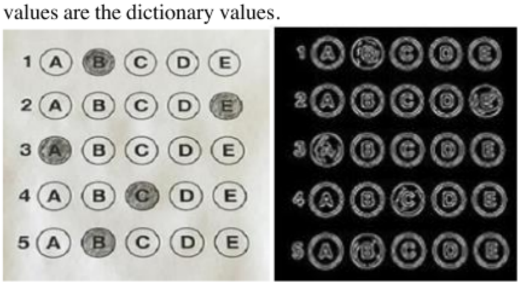


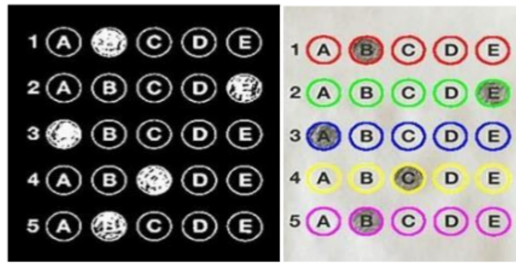
This paper explores the real-time application of image processing, a form of signal processing that involves manipulating images as input, such as photographs or video frames, to generate output in the form of either an image or a set of characteristics or parameters based on user requirements. Image processing has found applications in various fields, including:

Medical Field: Image processing techniques are extensively used in medical imaging, such as gamma ray imaging, PET scans, X-ray imaging, and medical CT scans. Robot Vision: Digital image processing plays a significant role in robot vision systems. These techniques enable robots to navigate their environment by detecting obstacles and following lines,

among other tasks. Pattern Recognition: Image processing is closely associated with pattern recognition. When combined with artificial intelligence, it facilitates computer-aided diagnosis, handwriting recognition, and image recognition. Pattern recognition techniques are also used in biometrics and face unlock technologies. Overall, image processing has become an integral part of various domains, enabling advanced functionalities and applications in fields such as medicine, robotics, pattern recognition, and biometrics.
Fingerprint Detection Social Media Apps and website Snapchat, Instagram filters are also real time and many more. One of the fields in which Image Processing is widely used is Education Field. One of the categories in Education field in Image Processing is used is used Analysis of OMR sheet and evaluation of marks according to that answered OMR. There are some steps that are followed in analysis of OMR.

NUMPY: NumPy is a fundamental Python library that offers extensive capabilities for working with arrays. In the context of image processing, an image can be viewed as a conventional NumPy array that comprises individual data points representing pixels. As a result, employing fundamental NumPy operations like slicing, masking, and fancy indexing allows us to manipulate the pixel values of an image effectively. To load the image, the skimage library can be utilized, while matplotlib can be used to display the image.
OPENCV: OpenCV, short for Open Source Computer Vision Library, is a highly popular library widely utilized for computer vision applications. OpenCV-Python serves as the Python API for OpenCV. One of its key advantages is its speed, as it leverages code written in C/C++, while its Python wrapper makes it user-friendly and straightforward for coding and deployment. As a result, it is an excellent choice for executing computationally intensive computer vision tasks. OpenCV provides a range of convenient functions that simplify essential image processing operations like translation, rotation, resizing, skeletonization, displaying images with Matplotlib, contour sorting, edge detection, and more. These features make OpenCV a valuable tool for various image processing requirements.
Argparse is a library designed for parsing command line arguments in Python. It facilitates the conversion of parsed command line arguments into a Python dictionary by utilizing the vars function on the object. This dictionary represents the command line arguments, where the argument names serve as the keys, and the corresponding supplied values are the dictionary values.



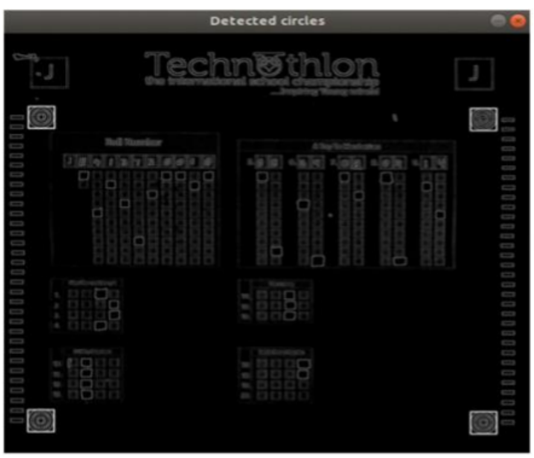


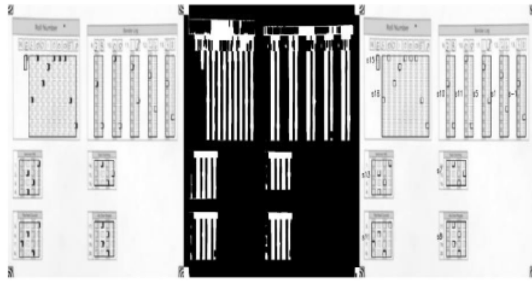
After applying a thresholding technique, we observe that the background of the image appears black, while the foreground appears white. This binary representation enables us to utilize contour extraction methods once again, specifically to identify each bubble within the questions. By employing Parallel Line Interpolation, we can identify the presence of four parallel lines that pass through all the detected circles, including those that may have been missed. This concept suggests that by interpolating four parallel lines using the detected circle centers, we can effectively locate the missing circles as well. Building upon this notion, we already have the equation for the first set of parallel lines passing through the detected circles.

IV. WORKING

Data Acquisition and Preprocessing: In OMR detection using machine learning techniques, the initial stage involves acquiring and preprocessing the data. This data can be obtained in various formats, such as images or scanned documents, and requires appropriate preprocessing procedures. It is essential to ensure that the data is of high quality and free from any noise or distortion that could affect the accuracy of the OMR system. The images should be of high resolution, and the text should be clearly visible.
The preprocessing step involves cleaning the data and removing any unwanted elements that could interfere with the accuracy of the OMR system. This can include removing noise, smoothing the image, and enhancing the contrast. Several techniques can be used for image preprocessing, including thresholding, edge detection, and morphological operations.

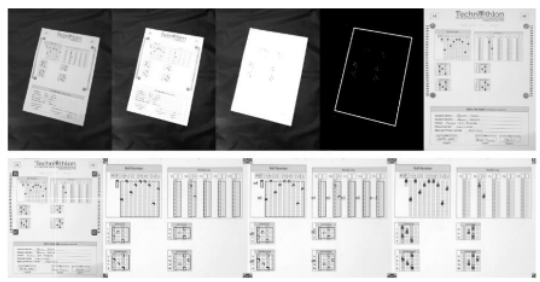
Feature Extraction: The next step in OMR detection using machine learning techniques is feature extraction. This entails the process of identifying and extracting significant features from the input data, which can be utilized for classifying the marks present on the document. Various features, such as the size, shape, and location of the marks, can be extracted to capture relevant information from the data.





There are several techniques that can be used for feature extraction, including image processing algorithms such as the Hough transform and edge detection. These techniques can be used to identify and extract features such as straight lines, circles, and other geometric shapes.

Feature Selection: After the features have been extracted, the next step is feature selection. This involves selecting the most relevant features that can be used to classify the marks on the document. Feature selection is important because it can improve the accuracy of the OMR system by reducing the dimensionality of the input data.



Several techniques can be used for feature selection, including Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). These techniques can be used to identify the most significant features that contribute to the classification task.

Classification: The concluding stage of OMR detection using machine learning techniques involves classification. This step encompasses the utilization of a machine learning algorithm to classify the marks found on the document, utilizing the previously extracted and chosen features. Various machine learning algorithms, such as Support Vector Machines (SVM), Random Forest, and Neural Networks, can be employed for this classification process.

The machine learning algorithm undergoes training using a labeled dataset of preprocessed images. and features have been extracted and selected. The training data is used to teach the algorithm how to classify the marks on the document accurately. Once the algorithm has been trained, it can be used to classify new images.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
1	roll	q1	q2	q3	q4	q5	q6	q7	q8	q9	q10	q11	q12	q13	q14	q15	q16	q17	q18	q19	q20	score
2	JE413720006	C	C		C	2	22								B	B	D					4
3	JE413720007			D				3	6				D	B	D	B	B			C	C	2
4	JE413720003	B		D	C						C	B	C	C	B		B		C	C		11
5	JE413720005	A	B	B	C						B	D	A	C	C	A	B	B	D	A	B	14
6	JE413720009	A	C	D	C	8	39	20	8	12	B	A	D	C	D	C	B	D	D			2
7	JE413720002			C	C								B	B	C	B	B					6
8	JE413720010	C	D	D	C	8	39	2	9	14	B	B	B	B	C	C		D	D			4
9	JE413720001			D	C	2	96	3	18	8			D	B	C	A	B			A		1
10	JE413720017	A	D	C	B	12	11		18		D		A	B	D	A	B		C			-4
11	JE413720014	C	A	B	C	8	39	2	9	12	B	A	D	A	D	C	D	D	C			3
12	JE413720012	D	D	D	C	2	49	2	8	8	D	B	D	C	B	A	C	B	D	D	B	4

Evaluation: Once the machine learning algorithm has been trained and the OMR system has been implemented, the next step is evaluation. This involves testing the accuracy of the OMR system using a test dataset of images that have not been used during the training phase. The system's accuracy is assessed by employing diverse performance metrics, including precision, recall, and F1 score.

V. Result

Sure, let's consider an example of an OMR detection model that has been trained to detect marks on a multiple choice question (MCQ) answer sheet with four options (A, B, C, D). The model has been tested on a dataset of 100 MCQ answer sheets, with 25 sheets containing correct answers and 75 sheets containing incorrect answers. The results of the OMR detection model are as follows:
True positives (TP): 20
False positives (FP): 5
False negatives (FN): 5
True negatives (TN): 70
Using these results, we can calculate the precision, recall, and F1 score of the OMR detection model as follows:
1. Precision:
Precision = TP / (TP + FP) = 20 / (20 + 5) = 0.8
This means that the OMR detection model correctly identified 80% of the marked answers out of all the detected answers.
2. Recall:
Recall = TP / (TP + FN) = 20 / (20 + 5) = 0.8
This means that the OMR detection model correctly identified 80% of the marked answers out of all the actual answers.
3. F1 Score:
The F1 score is:
F1 Score = 2 * (Precision * Recall) / (Precision + Recall) = 2 * (0.8 * 0.8) / (0.8 + 0.8) = 0.8
This indicates that the OMR detection model has a reasonably good performance with an F1 score of 0.8.
Overall, precision, recall, and F1 score are useful metrics to evaluate the performance of OMR detection models. They can provide insights into the accuracy and completeness of the OMR system, and help to identify areas for improvement in the model.

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