PROJECT BASED LEARNING (PBL-4) LAB (CSP392)

Optical Mark Recognition using Computer Vision

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DEPARTMENT OF COMPUTER SCIENCE &ENGINEERING

SHARDA UNIVERSITY, GREATER NOIDA

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Project Title
Optical Mark Recognition using Computer Vision.

This project focuses on providing a portable and convenient solution to the OMR sheet checking with the help of Computer Vision and proposing a web-based application made with python that allows you to upload OMR and get it evaluated accurately without the hassle of huge OMR scanners. We propose a software where you can post image of OMR sheet taken from different angles yet our application can detect the bubbles marked and evaluate the answers accordingly as per the answer scheme. It generates a *.csv* file as output with all the necessary fields such as roll no., question no., etc.

Team / Group Formation:

S. No	Student Name	Roll Number	System ID	Role
1	Avishek Thakur	200101079	2020502389	Developer
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3	Sumeet Dhiman	200101323	2020532155	Developer

Technologies to be used

Software Platform

a) **Front-end**
- Python 3

b) **OMR Checker**
- Pyhton 3
- Opencv
- Rich – table generation
- Numpy
- Pandas
- Matplotlib
- Jsonschema
- dotmerge

Hardware Platform
Camera for Capturing Images

Problem Statement

In today's world most of the competitive exams are based on MCQ (Multiple Choice Questions). For the convenience these exams are usually conducted with the help of OMR sheets that provides an easy way for the entry of necessary details as well as the MCQ answers. Even Surveys and Questionaries are conducted with the help of this technique these days. To evaluate these, we require special kind of sheets, with proper marking and margins and in some cases the special kind of paper as well which is suitable for the relevant hardware device i.e., OMR scanner.

OMR, also known as optical mark reader or optical mark recognition, is a method of acquiring data from people by identifying marks on a paper. A hardware tool (scanner) is used to perform OMR by detecting a reflection or a little amount of light transmittance on or through a sheet of paper. OMR analysis is the process of automatically examining human-marked answer sheets and deciphering the findings. Candidates use pencils or ballpoint pens to fill out their OMR papers. These hardware items are pricey to use and have poor portability. Thus, OMR utilization is severely constrained, which results in a lack of chances or, to put it another way, prevents us from getting the most out of this technology.

Some problems faced in traditional OMR checking are as follows

- Incomplete filling or erasing: Incomplete filling of bubbles or erasing marks can cause errors in the scanning process. These issues can be avoided by educating the users about how to correctly fill and erase the bubbles.

- Improper alignment: Improper alignment of OMR sheets during scanning can cause errors in the data, resulting in incorrect results. It is essential to ensure that the sheets are properly aligned with the scanning device.

- Low-quality printing: Low-quality printing can lead to smudging or incomplete printing of bubbles, which can lead to errors in the scanning process.

- Poor lighting conditions: Poor lighting conditions can cause issues in the scanning process, as the scanning device may not be able to accurately detect the marks. It is important to ensure proper lighting during scanning.

- Scanner issues: Scanner issues such as misalignment, paper jams, and scanning errors can also cause problems in the scanning and checking of OMR sheets.

- Misinterpretation of marks: There is also a chance of misinterpreting the marks due to various factors such as smudging or overlapping bubbles.

Literature 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

Feature extraction and selection play a vital role in the accuracy of OMR systems. Several techniques have been proposed for feature extraction and selection in OMR, including Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and Histogram of Oriented Gradients (HOG).

In their paper, "Automatic Optical Mark Recognition using PCA and SVM," Kim et al. [1] proposed a method for automatic OMR using PCA and Support Vector Machines (SVM). The authors used PCA to reduce the dimensionality of the feature space and SVM for classification. The proposed method achieved high accuracy in OMR detection, with an 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] proposed a method for automatic OMR using Random Forest. The authors used Random Forest for classification and achieved an average recognition rate of 98.5%.

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.

Li, L. L., & Sun, L. X. (2013) proposed an online examination system for computer basic operations, especially, Microsoft Office software operations. The system primarily accomplished functions such as intelligently creating exams, collecting and marking papers submitted automatically in the exam by the database, socket, ado, and VBA program methods. Their findings demonstrated that the method might assist professors in increasing job efficiency and students in improving software operations through online actual computer operation. The system has been working in the USTL university computer lab center for a while now, and it has already proven to be quite effective in solving the level evaluation problem for Microsoft Office software operations.

Project Description

We propose a fully working efficient and a continent way of OMR checking in form of a software that can read and evaluate OMR sheets scanned at any angle and having any color.

Table 1: Specifications

Specs	
Accuracy	Currently nearly 94% accurate on good quality document scans; and about 90% accurate on mobile images.
Robustness	Supports low resolution, xeroxed sheets. Minimum resolution **640x480**
Fast	Current processing speed without any optimization is 1**00 OMRs/minute.**
Customizable	Easily apply to custom OMR layouts, surveys, etc.
Visually Rich	Get insights to configure and debug easily.
Lightweight	Very minimal core code size.
Large Scale	Tested on a large scale.

Once the OMR layout and image have been captured and configured, all that is left to do is upload photos of the sheets to the software to retrieve the marked responses in an excel sheet.

Images can be taken from various angles as shown below

Figure 1: Input Images captured at various angles

Output generated would be of the form of a .csv file which can be later on taken into various applications such as data analysis, surveys, etc.

	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

Figure 2: Screenshot of Output .csv file generated from OMR sheet

Project Modules: Design/Algorithm and Methodology

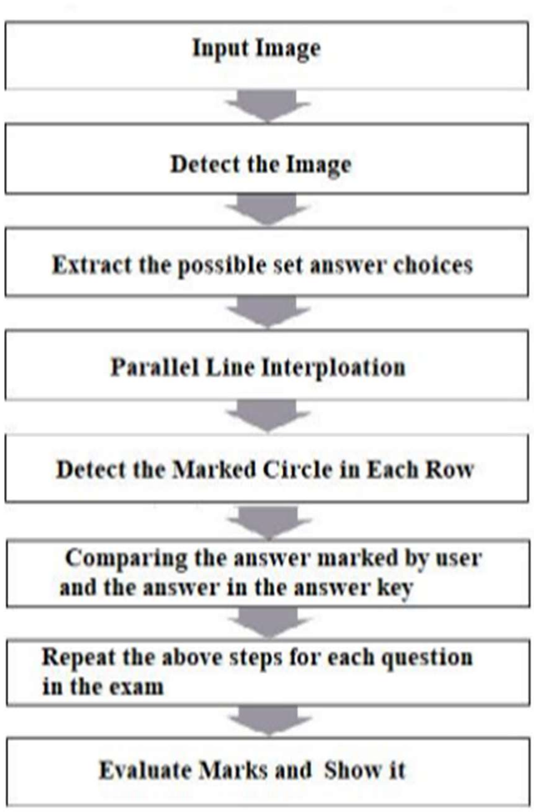

Figure 3: Workflow of the project

1. Input Image

We only need to invoke the cv2 module's imread function to read an image. An picture will be returned as a NumPy array. By invoking the type function and passing the object returned by the imread function as input, we can verify this.

“cv2.imshow('test.png',image)”.

2. Detect the Image:

We used an OMR sheet image to test the code. The OMR sheet was scanned several times and used in testing. The illustration used to test the strategy. Additionally, we test our code using various motivations. The current code only functions on OMR sheets with circles; other OMR sheets will not function with it. However, a modified version of our code that replaces the first step with the appropriate transformation for identifying the novel shapes will operate on it correctly.

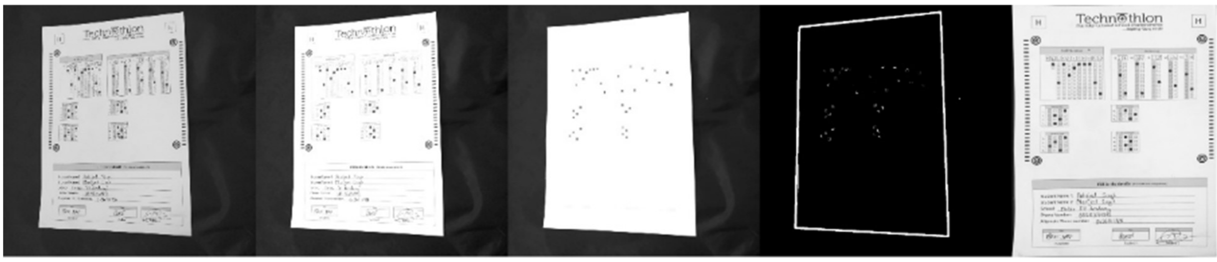

Figure 4: Finding the Region of Interest (ROI) i.e., paper in the image

3. Extract the possible answer choices

In order to detect the images of bubbles, we loop over each of the individual contours. Considering the aspect ratio of the contours we recognize a contour to be a bubble. Now, pre-process our input image as:

```
gray=cv2.cvtColor(image, cv2.COLOR_BGR2GRAY) blurred=cv2.GaussianBlur(gray,(5,5),0)
edged = cv2.Canny(blurred, 75, 200)
```

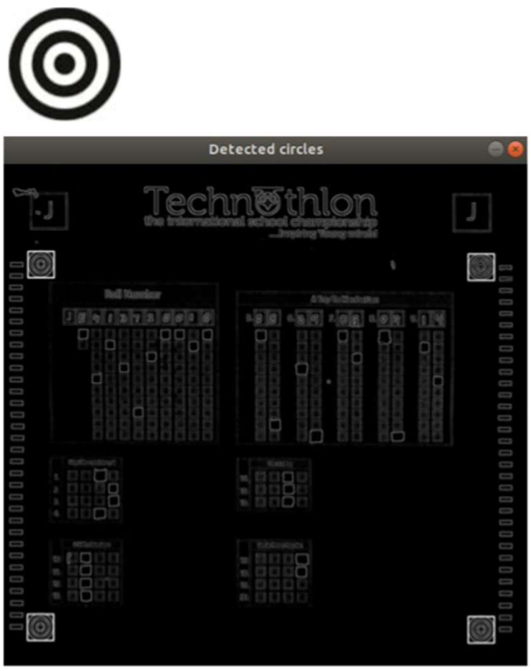

Figure 5: Detecting Markers on Image in order to align template layout in next step

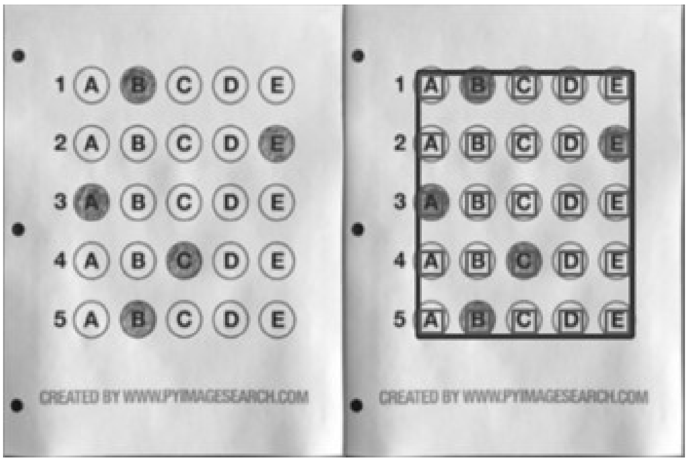

Figure 6.1: Template layout setting

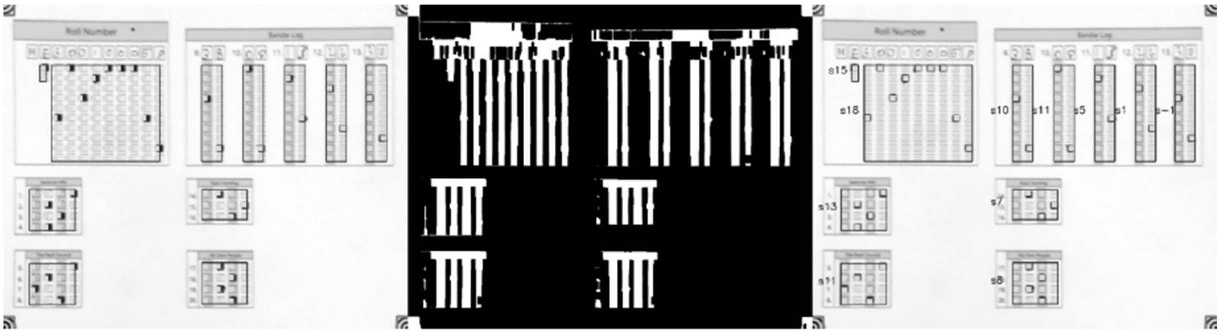

Figure 6.2: Template Layout Alignment

4. Parallel Line Interpolation:

When interpolating photographs, the image itself takes on the role of an interpolated function. As a result, if four parallel lines are interpolated and they pass through the centres of detected circles, they will also pass through the centres of missing circles. We develop an error minimization approach to locate the four parallel lines going through identified circles based on the aforementioned concept. The value representing the pixel's colour is then obtained. Pixels in an image are Points where the function's value (pixel colour) is known. The image does not necessarily get bigger since interpolation methods allow for arbitrary changes to the image's size and aspect ratio. Interpolation comprises intermediate values of the function (gives equation of lines).

Output module

Output module has the main task to generate an image of OMR with the bubbles and their respective interpretation merged over image as shown in figure after the correction as well as generate a csv files.

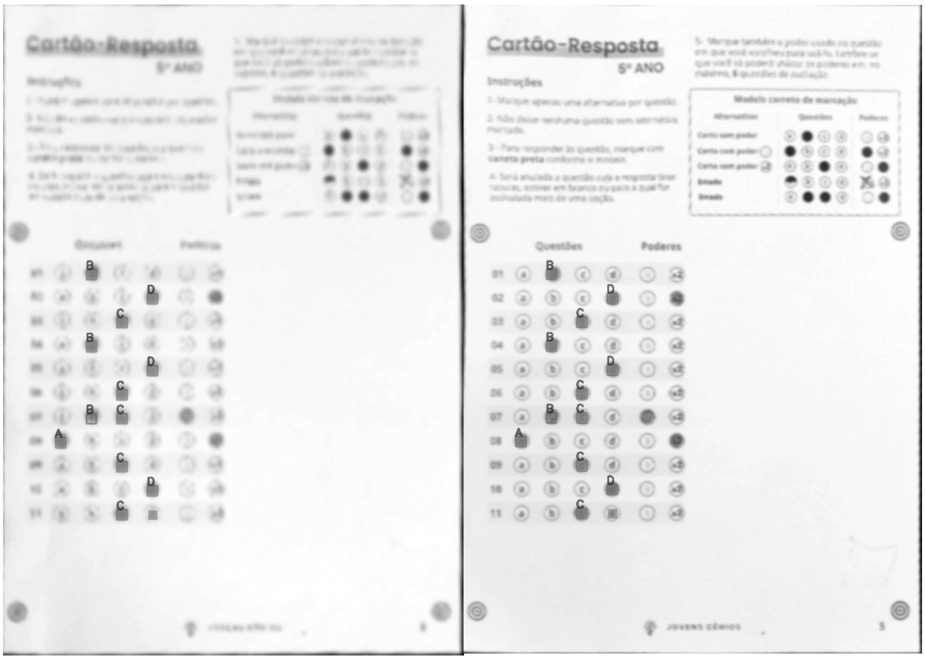

Figure 7: Output OMR generated after checking

	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

Figure 8: .csv file generated as output

Evaluation Explanation Table

Question	Marked	Answer(s)	Verdict	Delta	Score
q1	A	B	Incorrect	-1.0	-1.0
q2		D	Unmarked	0.0	-1.0
q3	D	C	Incorrect	-1.0	-2.0
q4	C	B	Incorrect	-1.0	-3.0
q5	AC	D	Incorrect	-1.0	-4.0
q6	A	C	Incorrect	-1.0	-5.0
q7	D	BC	Incorrect	-1.0	-6.0
q8	B	A	Incorrect	-1.0	-7.0
q9	C	C	Correct	3.0	-4.0
q10	D	D	Correct	3.0	-1.0
q11	D	C	Incorrect	-1.0	-2.0

Figure 9: summary of OMR generated by software

Data Acquisition and Pre-processing: Acquiring and pre-processing data is the initial stage in OMR identification utilising machine learning algorithms. Images or scanned papers can be used to store data. It is critical to ensure that the data is of good quality and free of any noise or distortion that could impair the OMR system's accuracy. The photographs should be excellent quality, and the text should be legible. diverse photographs from diverse settings have been acquired and pre-processed in order to make the best of the images and prepare them for the layout template to compare and analyse the OMR sheet.

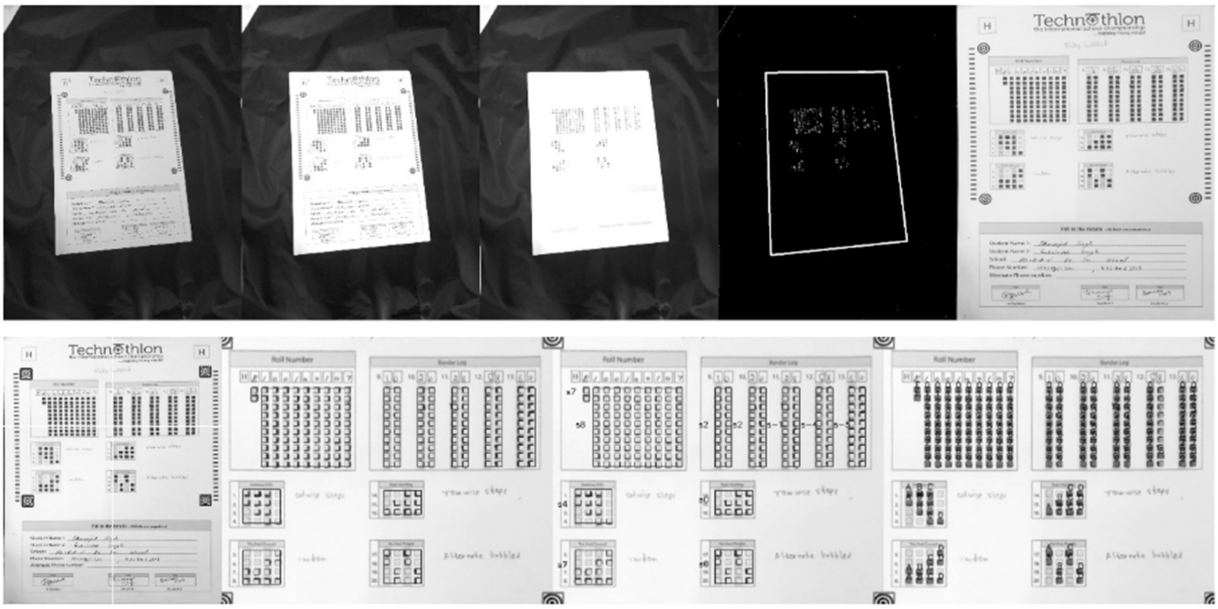

Figure 10: High Bubbling. Image captured ideally from a distance

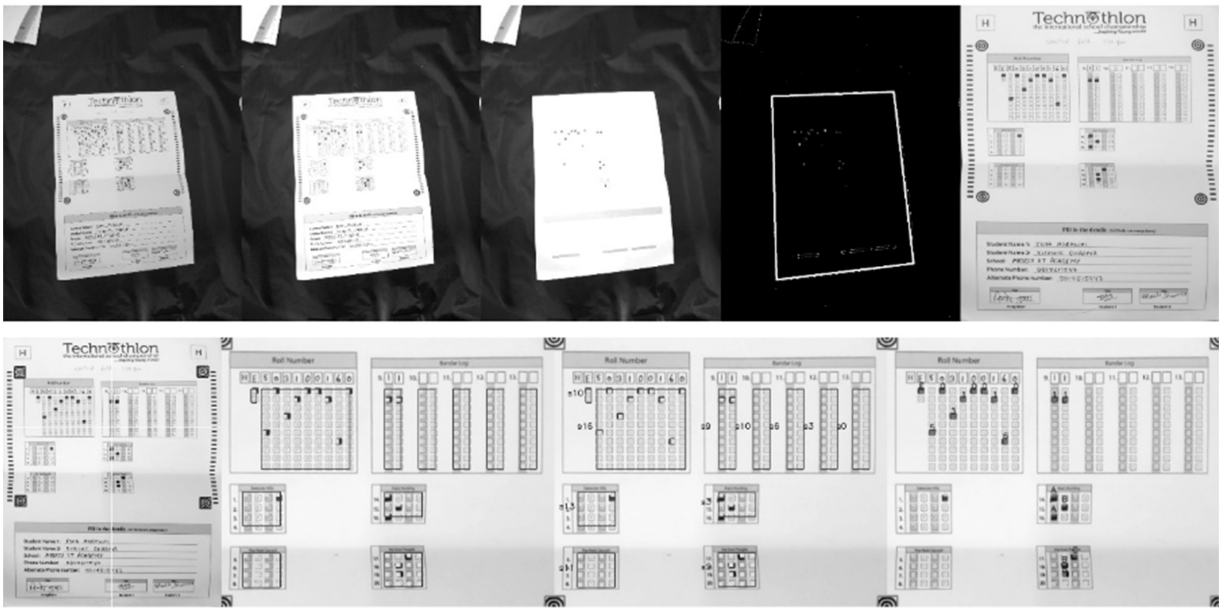

Figure 11: OMR sheet Folded from mid (Midfolding)

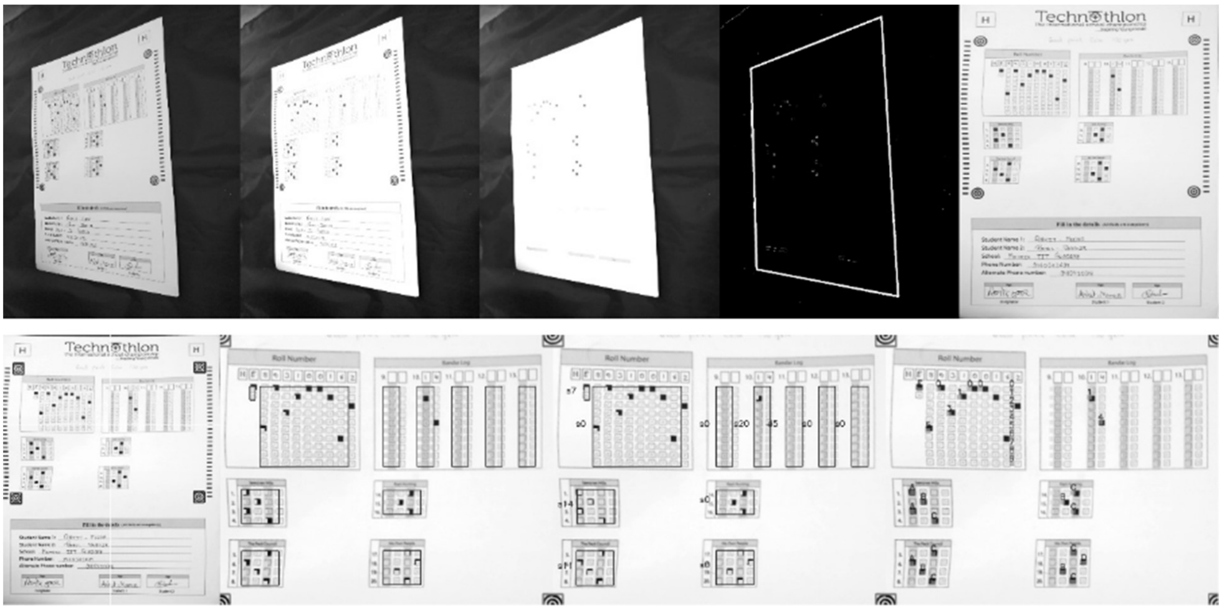

Figure 12: Image Captured from unusual angle

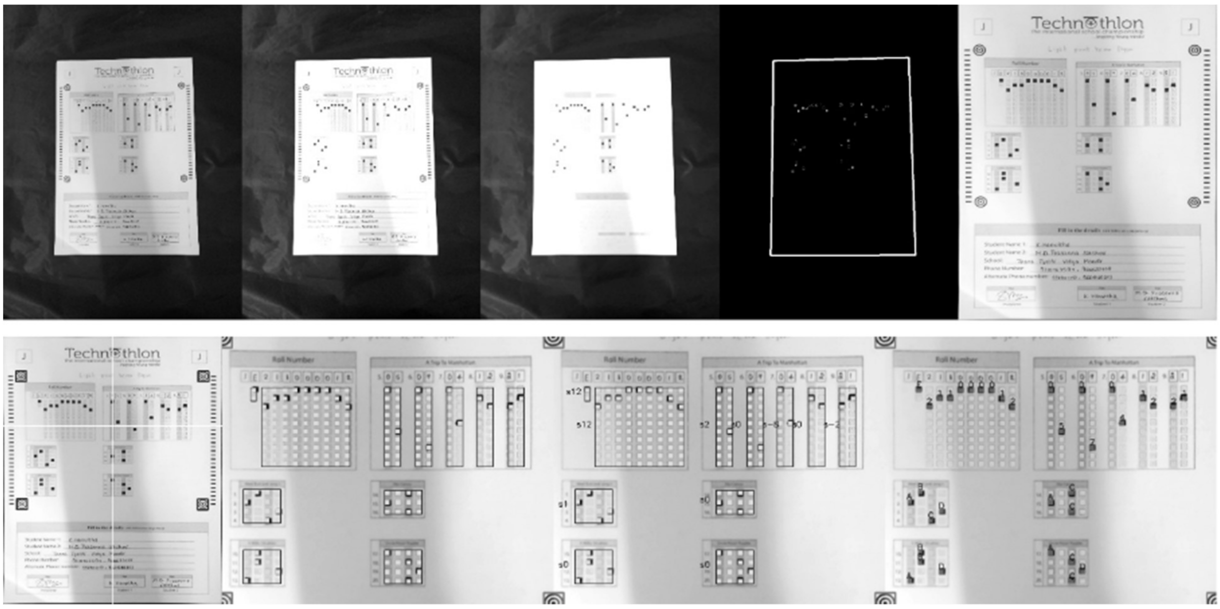

Figure 13: Shadow over the captured image

The pre-processing step involves cleaning the data and removing any unwanted elements that could interfere with the accuracy of the OMR system. This include removing noise, smoothing the image, and enhancing the contrast. Several techniques can be used for image pre-processing, including thresholding, edge detection, and morphological operations.

Threshold Detection is done as shown in the images below

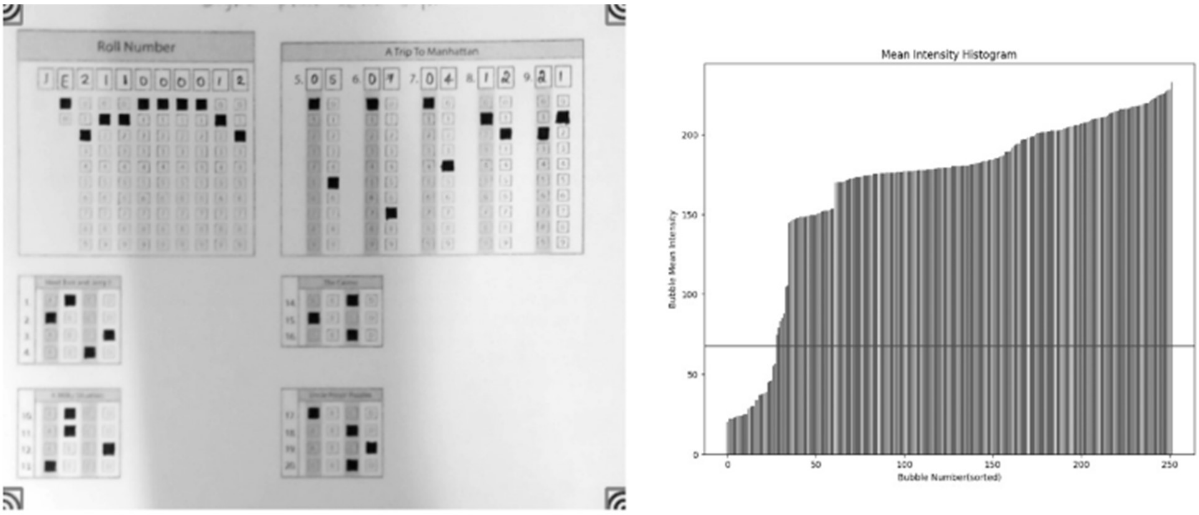

Figure 14.1: Global

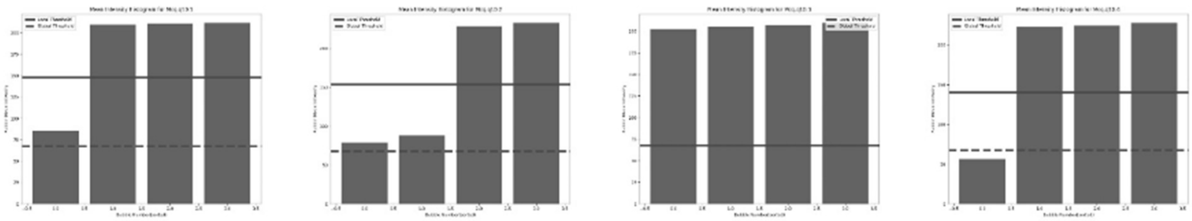

Figure 14.2: Local

Feature Extraction: The next step in OMR detection using machine learning techniques is feature extraction. This involves identifying and extracting relevant features from the input data that can be used to classify the marks on the document. Some of the features that can be extracted include the size, shape, and location of the marks.

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.

Plotting histogram of various different image inputs in order to understand images better and extract the relevant features.

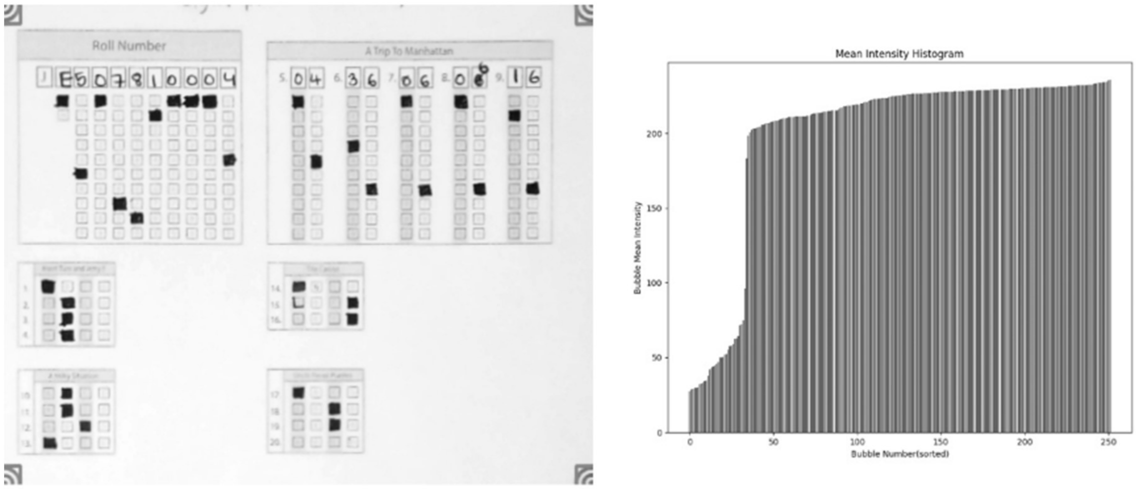

Figure 15: Histogram plotting: Coloured Image

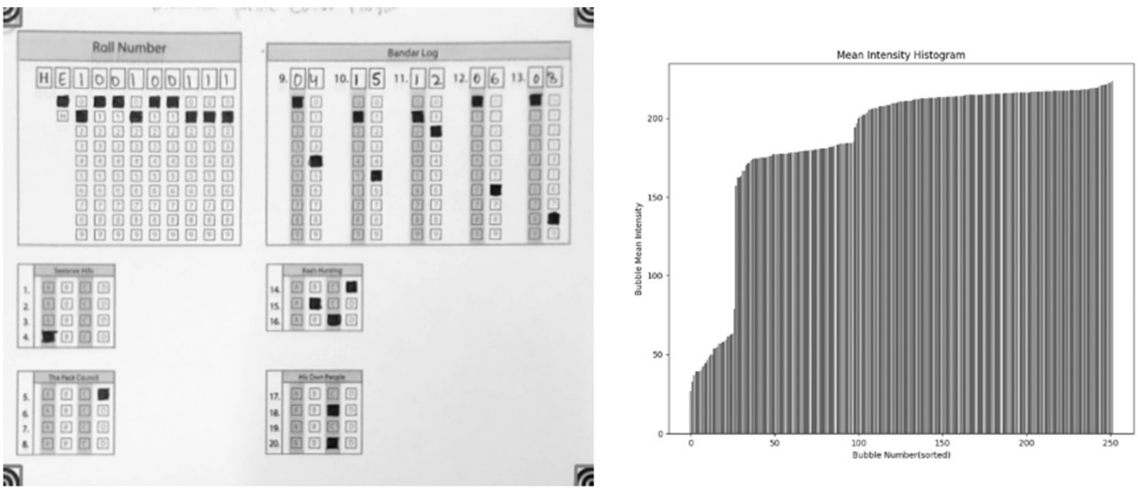

Figure 16: Histogram plotting: Xeroxed OMR Image

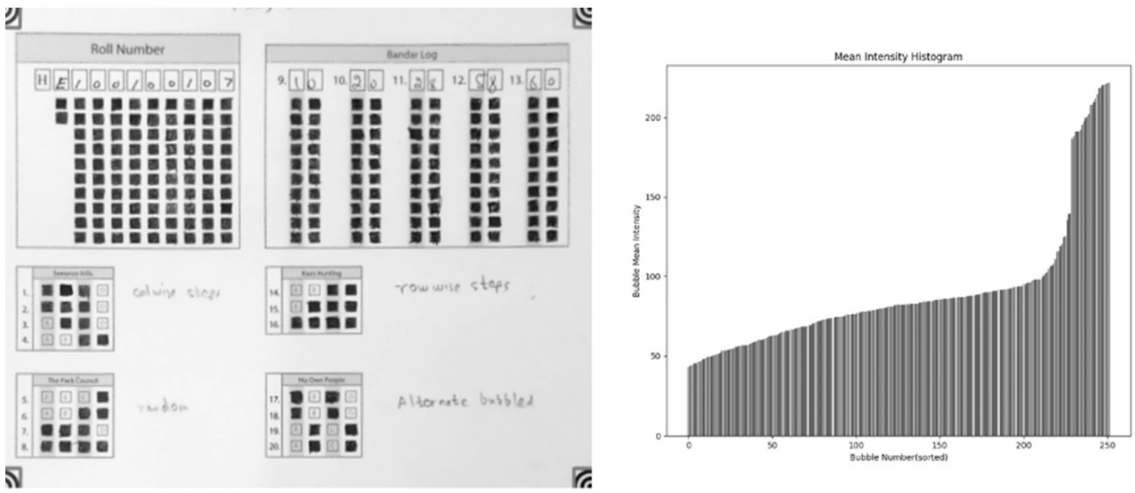

Figure 17: Histogram plotting: High Bubbling

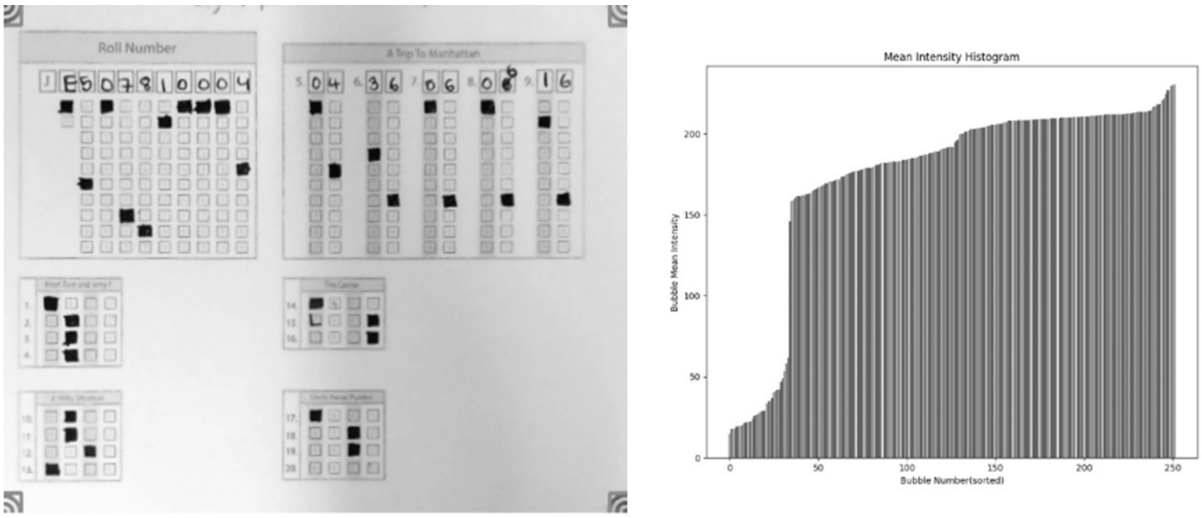

Figure 18: Histogram plotting: Image with shadow

Complete workflow of the OMR checker is summarised below with the help of block diagram

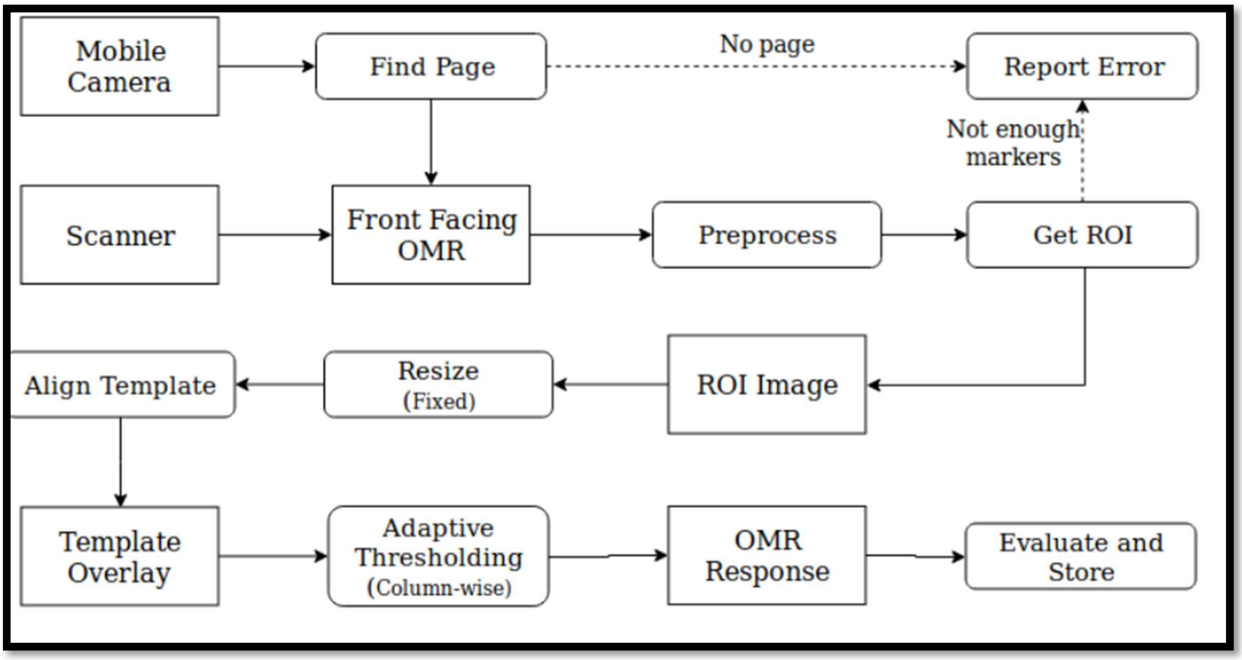

Figure 19: Block Diagram of the OMR Checker

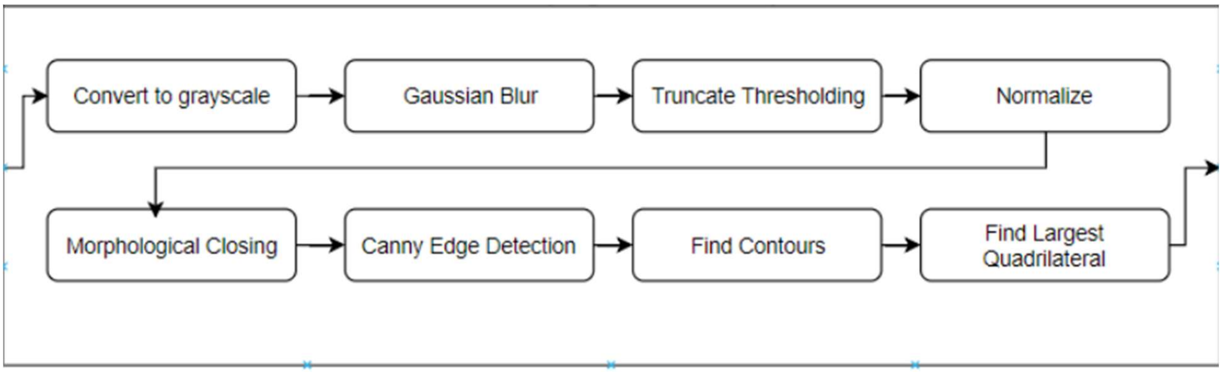

Figure 20.1: Block Diagram of Find Page Algorithm

Figure 20.2: Finding the Page algorithm application step by step

Result & Conclusion

Our Proposed model is Currently nearly 94% accurate on good quality document scans and about 90% accurate on mobile images.

OMR scanners are faster and more accurate than OCR scanners for processing OMR sheets, and that they can provide timely feedback to students. OMR scanning systems have been successfully implemented in various academic settings, with studies reporting high levels of accuracy and efficiency. These systems have the potential to save time and reduce the risk of errors compared to manual data entry or scanning. Additionally, OMR software that allows users to upload images directly without a scanner can offer convenience, flexibility, cost savings, improved accuracy, time savings, and data security. Overall, OMR checkers offer a reliable and efficient solution for grading multiple choice exams and evaluating student performance in large classes.

Future Scope of the Project

- The integration of artificial intelligence (AI) with OMR software can significantly improve the accuracy and speed of processing OMR sheets. With AI, the software can learn from past data and optimize the processing of future sheets.
- Cloud-based OMR solutions can offer more flexibility, accessibility, and scalability. Users can access the software from anywhere and scale up or down as per their requirements.
- With the increasing use of smartphones and tablets, mobile-based OMR applications can be developed. Users can scan the OMR sheets using their mobile devices and process the data in real-time.
- With globalization, there is a growing need for OMR software that supports multiple languages. Multi-lingual support can help to process OMR sheets in different languages without any errors.
- OMR software can be integrated with other software such as data analytics tools, reporting tools, and data visualization tools. This integration can provide more insights into the data and help in making better decisions.
- OMR software can be used for advanced data analytics to gain insights into the data. With the help of machine learning algorithms, the software can detect patterns, trends, and anomalies in the data.

Advantages of this Project

This project can offer several advantages, including convenience, flexibility, cost savings, improved accuracy, time savings, and data security.

- **Portable:** This project provides portability as it eliminates the need for huge hardware device such as scanners, one can use mobile application to get the OMR evaluated.
- **Convenience:** Users can easily upload images of OMR sheets without the need for a physical scanner. This can save time and effort, especially when working with large volumes of OMR sheets.
- **Flexibility:** Users can upload images from any location, as long as they have an internet connection. This can be particularly useful for remote work or when scanning OMR sheets from different locations.
- **Cost savings:** By eliminating the need for a physical scanner, users can save on the costs associated with purchasing, maintaining, and repairing scanners.
- **Improved accuracy:** OMR software that allows users to upload images directly can offer improved accuracy compared to manual data entry or scanning. This is because the software can automatically detect and interpret the marks on the OMR sheets with a high degree of accuracy.
- **Time savings:** By automating the scanning and processing of OMR sheets, users can save time and reduce the risk of errors. This can be particularly useful when processing large volumes of data.
- **Data security:** Uploading images directly to the OMR software can offer improved data security compared to physical scanners. This is because there is no risk of physical documents being lost, stolen, or damaged.

Outcome

- Research Paper Publication
- Project to Product Development

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