An Efficient Read and Mark Mechanism for Multiple-choice Questions Using Optical Character Recognition

Muhammad Usman[1], Shah Khalid*[1], Aftab Alam[1], Muhammad Ubaid[2], Fakhrud Din[1], Muhammad Raees[3]
[1]Department of Computer Science and IT, University of Malakand, Chakdara, Pakistan,
[2]Department of Computer Science and IT, University of Bahria, Islamabad, Pakistan,
[3]Governament Degree College Totakan, Higher Education Department, Kim Pakistan
*Correspondence: musman11662@gmail.com; khaliddir@gmail.com; alam@uom.edu.pk; muhammadubaid8@gmail.com; fakhruddincs@gmail.com; visitrais@gmail.com

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This research paper focuses on modifying the grading of multiple-choice questions (MCQs) to better the efficiency and incorrectness of educational tests. Conventional grading systems, such as optical mark recognition (OMR), have fundamental drawbacks, excluding the necessity for precise shading, time-wasting, and the use of special OMR sheets and OMR scanners. This conceptualization can be expensive and error-prone, especially if the MCQs papers are folded or unmarked. In comparison, the suggested OCR-based approach gives fundamental benefits in all necessary areas. It is less costly to use a simple scanner and software alternatively to costly OMR equipment. The method is motivated to be simple to set up and use. It importantly reduces error rates and marking time by employing precise OCR algorithms and processing greater amounts of answer sheets quickly. Moreover, the system is extremely accurate and scalable, allowing it to handle a rising amount of paper efficiently. It also has limited trust in external tools and is highly flexible and adaptable to different MCQ formats and grading settings. In General, the OCR-based approach outperforms existing methods by eliminating their shortcomings and delivering a trustworthy, time-saving alternative for automated MCQ grading.

Keywords: Multiple Choice Questions, Optical Mark Recognition, Optical Character Recognition, International Business Machines, Computer Vision 2, Identification, Pakistani Rupee and Personal Computers.

Introduction:

Technology positively impacts various sectors of education, including assessments. With the advancement of technology, assessments can now be conducted and evaluated with greater ease and efficiency. Numerous tools are available these days, to support the development of the assessments, their administration, and even the automation of the grading process.

Multiple-choice questions (MCQs) are one of the common forms of tests within schools and universities as they substantially save of time required for grading [1]. Frederick J. Kelly developed multiple-choice questions and answers in 1914 as a technique for conducting mass screenings during World War I to determine talented workers [2]. With the increased adoption of MCQ-based exams in educational institutions, the test is not as accurate when comparing a student's performance to that of a written exam. Nevertheless, the majority of educators continue to use MCQs primarily for the simple reason that it takes less time to grade them [2].

Technological tools can further streamline the grading process. For example, a computer-based test can automate scoring, and in the case of paper-based exams, an MCQ scoring machine can efficiently handle the grading.

However, to date, there are still considerations on employing computers instead of the paper and pencil tests due to (a) the logistic costs associated with administering the computer-based test, namely where a large student number (greater than 100) is anticipated (c2) and (b) the hardware and software that does not fail during the test administration [3]. On the other hand, paper-based tests that employ MCQ scoring machines are very popular due to their ability to grade papers quickly and accurately. Paper and pen MCQ tests are more accurate even though computerized tests are still in practice in most educational institutions but only limited to a few students. This has led researchers to focus on advancing traditional MCQ tests through computer technologies while still maintaining the paper-based version. This may be done using a credible automatic MCQ scoring platform. The concept of having an automated MCQ scoring system is simply to identify a unique answer sheet and then match it with the key answer sheet to arrive at an overall score mark. This system is by far the trade-off to mark a large number of exam papers due to the computer-based disadvantages [4].

Objectives:

This study introduces an innovative OCR-based system for automated multiple-choice sheet grading, featuring: (1) optimized image preprocessing combining adaptive noise reduction and dynamic contrast enhancement for reliable text extraction from poor-quality scans; (2) an intelligent validation mechanism that cross-checks results while detecting scanning artifacts; and (3) fully automated Excel integration for instant result compilation. The solution outperforms manual grading in both speed (processing thousands of sheets rapidly) and accuracy, while adapting to various sheet designs - offering educational institutions a practical, scalable assessment tool that eliminates manual errors and delivers immediate feedback. This paper seeks to add improvement to the existing system. To replace the conventional method of hand-checking multiple-choice questions and optical mark recognition. We propose a system, which is called optical character recognition. This technique relies on handwriting in designated segments instead of shading. We introduced an efficient MCQ generator using a mobile camera and OCR technique which is more cost-effective, less time-consuming, user-friendly, efficient in terms of light conditions, marks small part of the given option, may use any type of marking, and is used for more than 100 plus languages as compared to the methods and techniques presented in the literature.

The organization of this paper is as follows. After the introduction, the related work is discussed in section II. Section III explains the proposed system while the experimental

result can be found in section IV. Lastly, the conclusion and the future work are presented in Section V.

Related Works:

IBM was the first company to invent a test-scoring machine, with their initial invention being the IBM 805 Test Scoring Machine, developed in 1937. This marked a revolutionary advancement in educational technology. The machine reads the pencil marks by detecting pencil lead, which conducts electricity and establishes a connection with the contact plates when exposed to electrical charges. The correct and incorrect answers are identified using a "scoring key" to support the connectivity of the shaded answer. Then, the total score is indicated on an inductor of the machine. It has been observed that the machine cannot score multiple test cards (answer sheets) and requires human intervention again at this stage. IBM 805 Test Scoring Machine was succeeded later at the beginning of the 1960s by the optical mark recognition (IBM 1230). IBM started using optical mark recognition which was designed successfully by Everett Franklin Lindquist.

Lindquist's mechanism is that a light beam is used on the mark positions of the answer sheet to recognize the selected choice against the acquired marks. The machine identifies the marked areas as shaded marks on the answer sheet representing less light than the unshaded mark [5].

Presently several other corporations offer scoring machines including the Scantron Corporation. The last big company in optical mark recognition machines is Scantron Corporation. While IBM sold the concept of optical readers for optical mark recognition machines, Scantron patented the concept of the optical mark recognition system. This characteristic also sets Scantron Corporation apart from other companies, as it serves the educational market with a range of optical mark readers.

According to the research conducted by Scantron its products are used by 98 % of the best schools in America, 94 leading universities in the country, and educational institutions across 56 countries worldwide. Scantron says that the increase in the need for Scantron's products proves that optically marked recognition solutions from Scantron are satisfactory for the assessors.

However, despite the high-reliability rating in some of these institutions, Scantron's products and maintenance costs are relatively expensive, making them less affordable for small-scale institutes.

The prices of the Scantron machines depend on the model of the machines. Their machines' prices vary from USD 5,400 to USD 17,275. Additionally, these scoring machines require special transoptic paper for answer sheets, costing USD 0.15 each, and allow only limited pen colors for marking.

In the last two decades, an effective method, which has evolved on image processing technology has opened a new PC-based Optical Mark Recognition system to minimize the constraints of such scoring machines. Region symbol and optical character recognition were used to bring the new method of optical mark recognition system of automated multiple-choice test as stated by Sandh et al., [6]. The new solution targets a low-cost and high-speed optical mark recognition system with a flexible answer sheet.

Earlier in 1999, Chinnasarn and Rangsanseri [7] designed the first PC-based marking system that scans printable answer sheets from an ordinary optical scanner. The answer sheet has to be read initially as a learning model first before being used to identify interests, for example; unit and student code. Subsequently, within the operation model, a set of answer sheets is subjected to an answer model. Nguyen et al [8] implemented a consistent approach, so the camera could take the place of an optical scanner since they wanted to make it easier to mark multiple-choice questions. Using a camera to capture answer sheets is faster and more mobile than an optical scanner. Additionally, a camera is more portable and offers greater

mobility compared to a standard scanner. Čupić [9] designed an open-source Java-based marking system. The offline application is designed to mark two sets of test answer sheets: training tests and self-checking test forms that provide multiple choices without the test questions in the sheets, multiple-choice tests, and answer sheets, which include answer sheets, but with few multiple choices. The application also provides student ID and unit code information recognition with different types, including bar code type and matrix type. Čupić et al. [10] performed further with more focus on the student ID identifier matrix in the same answer sheets to a 100% recognition rate where high rotation and skewing were witnessed. Furthermore, the study by Bonačić et al. [11] expanded on Čupić's earlier research on information decoding for student ID design by incorporating optical character recognition (OCR) of digits encoded in a seven-segment display format. Each digit is outlined by a 7-segment display where students can sharpen to complete the outline. Locations of digits and digit segments (regions of interest) are assumed to be fixed to identify the numbers from zero to nine about the input patterns. While the method appears to be rigid and hand-drawn instead of handwritten, it is far less complex and more conceptually intuitive for a student to encode than an identifier matrix as evidenced by return rates exceeding 90 percent. Additionally, Čupić et al. [12] developed a strategy that allows students to revise their responses if they answered incorrectly on the first, second, or even third attempt. If students change their response, they simply circle the mistake made and write the required letter next to the answer box. Later during processing if the error circle has been filled in; it is possible to immediately identify the characters A, B, C, E, or F which have been written by hand.

Sattayakawee [13] provided three types of grid-based answer sheets that yielded an average accuracy of 0.999. She used only tick marks instead of coloring entire answer boxes completely. Last, Chai proposed an automated marking algorithm that pays much attention to the resulting feedback. The proposed method involves adding prints of the pupil answers sheets and sending the scanned answer sheet back to the student with highlights on the right/wrong answers besides every answer this is done by emailing the annotated response again to the student. The results demonstrate that the method operates with high efficiency, processing each sheet in as little as 1.4 seconds while maintaining optimal accuracy.

Proposed Methodology:

A review of related works revealed that most implemented algorithms primarily focus on a single aspect of test scoring: mark registration and detection. This section outlines the methods and strategies used to create and assess an automated MCQ marking system that utilizes optical character recognition (OCR) technology. Smartphone camera or scanner images of MCQs are automatically read and marked by OCR to enhance current practices of manual marking and grading as well as optical mark recognition. This section provides a detailed overview of the study process involved in developing, implementing, and evaluating the proposed framework. The key technologies used to implement the automatic marking system include Open CV (CV2), an image processing and computer vision library, and Pytesseract, a Python OCR tool powered by the Tesseract engine. The implementation of the proposed framework has also used Pytesseract and CV2 Combined with the smartphone camera to capture and process the MCQ answers.

The framework includes conducting tests to evaluate the OCR method. During the testing phase, the automated system's results are compared with those of manual marking to assess its accuracy and efficiency. Thorough testing in a variety of settings ensures the strength and dependability of the system, including different lighting conditions, handwriting styles, and image distortions.

By identifying and addressing any limits, this iterative testing helps to improve the system's performance.

Flow Chart:

The flowchart in Figure 1 elaborates on an automated MCQ evaluation process using OCR technology. The process begins with system initialization, followed by capturing images of MCQs, extracting text using OCR, comparing the extracted text with a master copy, and ultimately saving and displaying the results.

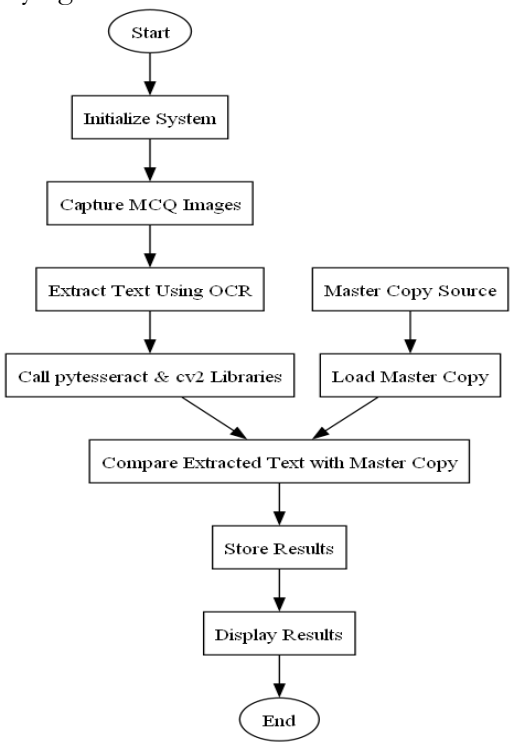


Figure 1: Flow Chart

Integration of Tools:

Open CV is a Python toolkit for doing image processing and computer vision tasks. It offers various functions, such as object detection, face recognition, and tracking. By exploiting these libraries' complementing features, the system can efficiently process MCQ answer sheets collected from multiple sources. Pytesseract performs word extraction, while CV2 assists with picture preprocessing and segmentation. This integration ensures that the OCR engine and image processing functions operate smoothly together, creating a unified and reliable system for automating the grading of multiple-choice questions. Furthermore, the substantial documentation and community support for Pytesseract and CV2 make development and debugging easier, increasing the automatic marking system's dependability and scalability.

This entails establishing the proper infrastructure, and segregating the Pytesseract and CV2 libraries for image preprocessing, text extraction, and answer judgment. The framework implementation stage of the approach aims to transform the abstract design into a functional system.

Python has been selected as the leading programming language because of its simplicity, ability, and wide support for libraries like Pytesseract and CV2. The CV2 and Pytesseract libraries are enclosed in the Python environment. This user interface modifies easy communication between the OCR engine (Pytesseract) and the image processing ability (CV2).

Image Prepossessing:

The photos of the collected MCQ answer sheet are prepossessed before text extraction can begin. This process uses noise reduction, contrast improvement, and scaling to improve image quality and clarity.

Text Extraction:

For text extraction, we used pytesseract to process the images captured from MCQs. Pytesseract analyzes the picture and extracts text information, including MCQ response, before converting them to machine-readable text format.

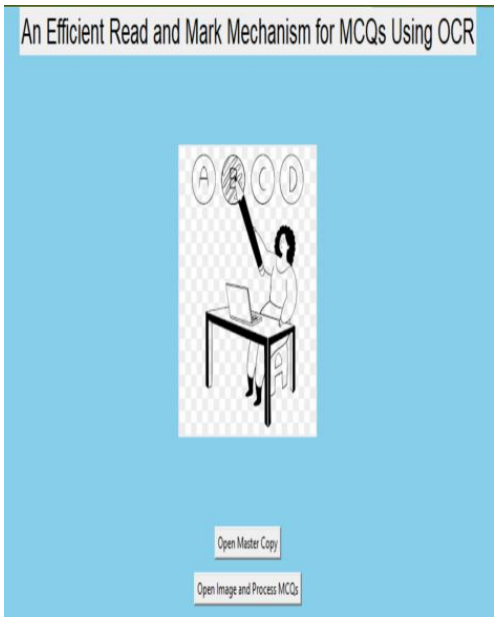
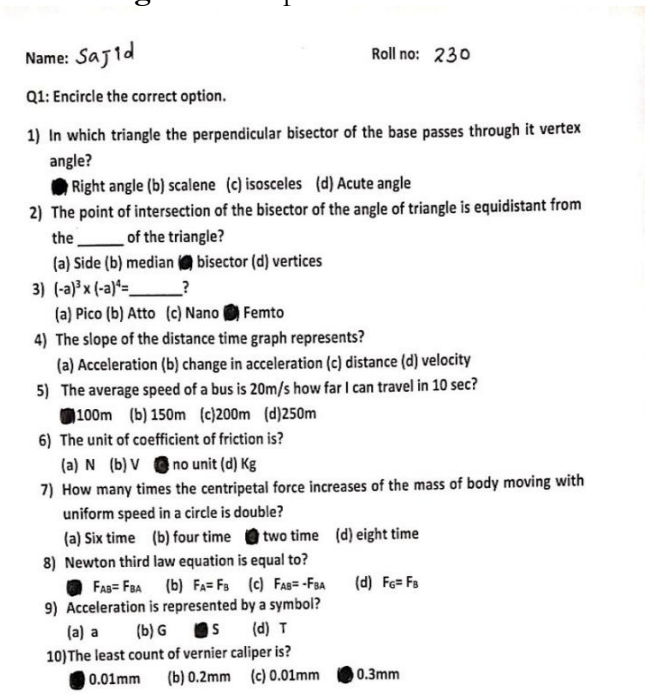


Figure:2: Graphical User Interface



Name: Sajid Roll no: 230

Q1: Encircle the correct option.

1) In which triangle the perpendicular bisector of the base passes through it vertex angle?
   ● Right angle (b) scalene (c) isosceles (d) Acute angle
2) The point of intersection of the bisector of the angle of triangle is equidistant from the _____ of the triangle?
   (a) Side (b) median ● bisector (d) vertices
3) $(-a)^3 \times (-a)^4 =$ _____?
   (a) Pico (b) Atto (c) Nano ● Femto
4) The slope of the distance time graph represents?
   (a) Acceleration (b) change in acceleration (c) distance (d) velocity
5) The average speed of a bus is 20m/s how far I can travel in 10 sec?
   ●100m (b) 150m (c)200m (d)250m
6) The unit of coefficient of friction is?
   (a) N (b) V ● no unit (d) Kg
7) How many times the centripetal force increases of the mass of body moving with uniform speed in a circle is double?
   (a) Six time (b) four time ● two time (d) eight time
8) Newton third law equation is equal to?
   ● $F_{AB} = F_{BA}$ (b) $F_A = F_B$ (c) $F_{AB} = -F_{BA}$ (d) $F_G = F_B$
9) Acceleration is represented by a symbol?
   (a) a (b) G ● S (d) T
10) The least count of vernier caliper is?
   ● 0.01mm (b) 0.2mm (c) 0.01mm ● 0.3mm

Figure 3: Sample Paper for Text Extraction

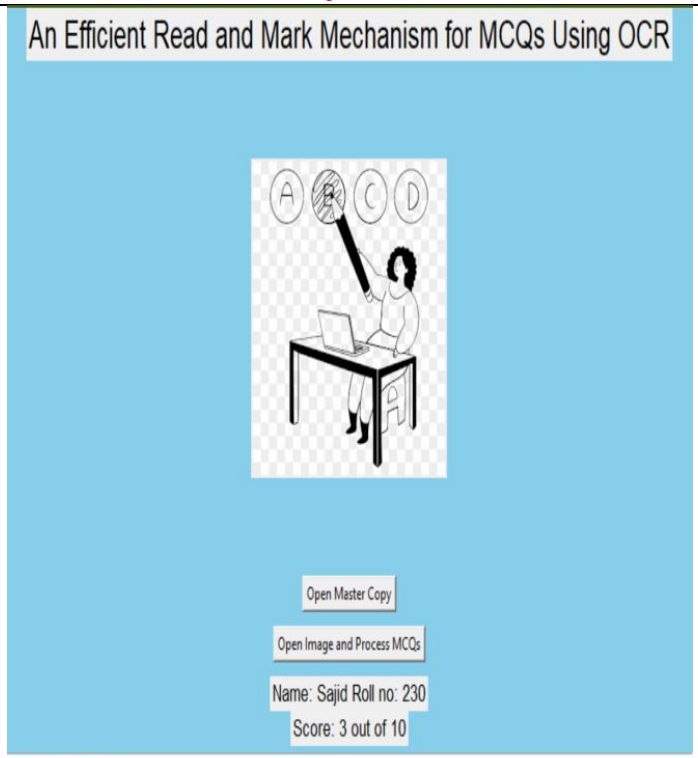


Figure 4: Extracted Text of Student and Master Answer

Student Marked Copy:

[' A', 'C', 'D', 'Incorrect', 'A', 'C', 'C', 'A', 'C', 'Incorrect']

As Master copy:

[' A', 'B', 'B', 'C', 'C', 'B', 'A', 'A', 'C', 'B']

Total score:

Result image: Name: sajid Roll No. 23

The total obtained marks is 3 out of 10.

Testing Procedure:

Objective: To evaluate the effectiveness and functionality of the automated marking system.

Procedure:

- The captured images were processed using the developed framework to extract text and analyze the responses.
- Responses were checked against the manually coded answers to ensure they were correct.
- Marking precision, time, and frequency of occurrence of errors were used to evaluate the outcomes of running the different systems.

Result and Discussion:

The main goal of this project was to use OCR technology to provide a dependable and effective system for automating the grading of multiple-choice questions (MCQs). The study presented a new approach that used mobile cameras to reliably read and evaluate MCQ-based answer sheets. This system addresses the limitations of manual grading and OCR, including time inefficiency and susceptibility to human errors. **Comparative Analysis of OMR, OCR, and Manual Hand Checking:**

Table 1 presents three techniques for MCQ evaluation. OMR, OCR, and manual hand checking.

Table 1: Comparative Analysis of OMR, OCR, and Manual Hand Checking

Parameter	Manual Hand Checking	OMR	OCR
Cost	Low (labor cost)	9 lakh price in 2017, now 22 lakh	Pocket mobile with mobile app CamScanner (20,000 to 30,000)
Ease of Use	Moderate	High (easy to use, automated)	Moderate to High (depends on software)
Error Rate	Medium(human error)	Higher than OCR (low-end scanner, light or inconsistent mark, dust, humidity, damaged pages)	Low (depends on image quality)
Time	Low(time-consuming)	2 seconds on scanning, then quality checking, and report generation (10 to 15 seconds)	5-7 seconds per paper on scanned image
Accuracy	High (depends on human)	99% with scanner	99.5% with scanner and 98% without scanner
Scalability	Low (not scalable for large volumes)	High (scalable for large volumes)	High (scalable for large volumes)
Dependency	Human resources	Specialized equipment (OMR scanner, OMR sheet)	General equipment (mobile camera, mobile cam scanner)
Flexibility	High (can handle various formats)	Low (requires specific forms)	High (can handle various formats)
Setup Complexity	None (simple, manual)	Moderate (requires setup of OMR system)	Moderate (requires setup of OCR system)
Adaptability	High	Low (requires predefined templates)	High (software can be adapted for different formats)

Cost Analysis:

The following table no 1 lists the costs of three different methods for grading including MCQs, OMR, OCR, and manual hand checking. The cost of each method was converted into a simplified score to reflect its relative affordability and resource requirements.

Table 2: Cost Analysis for Manual, OMR, and OCR

System Type	Requirements	Price	Frequency
Manual checking	Staff, stationary, space, grading sheet	Rs 5 per paper (500,000 x 5 = 2,500,000 per exam)	For one time
OMR	Computer or laptop, OMR Scanner	Rs 9,00,000 – 22,00,000	For lifetime
OCR (with Scanner)	Computer or laptop, Scanner	Rs 1,10,000	For lifetime
OCR (with Mobile Cam scanner)	Computer or laptop, Mobile Camera	Rs 70,000	For lifetime

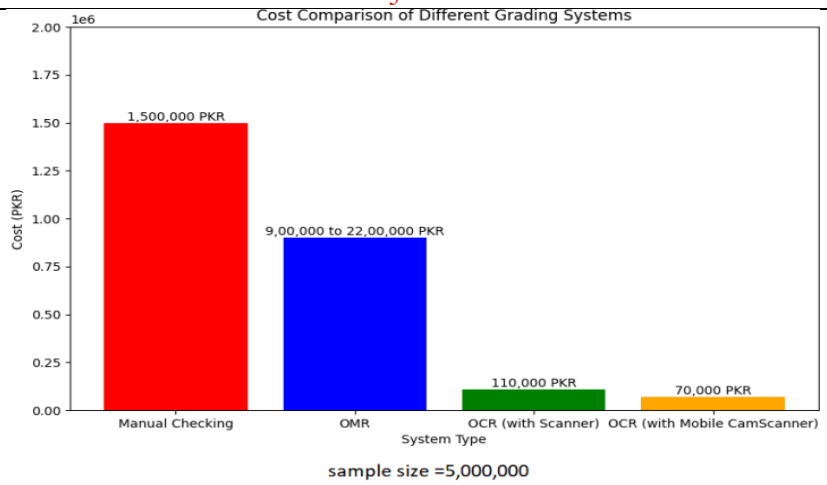


Figure 5: Cost comparison of grading system

Figure 5 shows the cost of Manual hand checking, OMR, and OCR techniques for the MCQs marking system. The expense of manually checking multiple-choice questions is PKR 25, 00,000 for 500,000 papers at a rate of 5 Rs per paper. Large volumes render this approach unfeasible because of its high cost, extended processing times, and higher error rates. If the exam needs to be rescheduled for the following year, the same amount, PKR 2,500,000, would be required to process the same number of papers. However, if the number of papers is small, manual grading is a better option. For larger volumes, OCR and OMR systems are the more efficient and cost-effective choices. OMR grading system for the said number of papers is RS 500,000. It provides efficiency and accuracy for extensive assessments at an initial cost ranging from PKR 900,000 to PKR 2,200,000 for a 5,000,000 MCQ sheet.

The amount remains the same for the subsequent numbers of papers. The initial cost of the OMR software and equipment is not affected by subsequent examinations. Initial expenses ranged from PKR 70,000 to PKR 110,000 for OCR offering a versatile and affordable alternative for MCQ grading. The cost remains unchanged whether grading 500,000 papers in a single batch or across multiple batches. The first OCR setup cost remained the same if the test had taken place in the second year; however, operational expenses for each batch were spent in a manner consistent with the first setup.

Ease of Use:

The ease of usage of three distinct grading methods manual checking, OMR, and OCR based on user feedback on the Likert scale is shown in Table 3, 4, and Figure 6.

Table 3: Grading techniques for OMR and OCR and Manual

Grading Technique	Question	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
Manual Checking	Ease of Setup	10%	20%	30%	25%	15%
Manual Checking	User-Friendliness	5%	15%	35%	30%	15%
Manual Checking	Speed of Grading	25%	30%	20%	15%	10%
Manual Checking	Fatigue	30%	25%	20%	15%	10%
Manual Checking	Flexibility	10%	20%	30%	30%	10%
OMR	Ease of Setup	5%	15%	25%	35%	20%
OMR	User-Friendliness	10%	20%	25%	30%	15%
OMR	Speed of Grading	5%	15%	30%	30%	20%
OMR	Fatigue	15%	20%	25%	25%	15%
OMR	Flexibility	10%	20%	30%	25%	15%
OCR	Ease of Setup	0%	5%	10%	35%	50%
OCR	User-Friendliness	0%	5%	10%	35%	50%
OCR	Speed of Grading	0%	10%	15%	35%	40%
OCR	Fatigue	0%	5%	10%	30%	55%
OCR	Flexibility	0%	5%	10%	30%	55%

Table 4: Likert Percentage of Grading Techniques

Grading Technique	Average Score	Likert Percentage
Manual Checking	3.2	64%
OMR	3.2	64%
OCR	4.6	94%

The manual checking received 64% positive feedback on aspects including easiness in setting up, the friendliness, speed, fatigue, and flexibility of the system. It can be done without any special tools and owes its operation time and personnel. Again, at 64% OMR was least friendly to the users because of its special sheets and devices and more complicated to set. Although less complex than manual grading, OMR is less user-friendly and may take more time compared to OCR.

OCR topped the list with 94% user-friendliness, making it the most user-friendly method. The fact that it is compatible with everyday gadgets such as phones and PCs demonstrated the effectiveness of the system and its simplicity thereby making it the most preferred grading method.

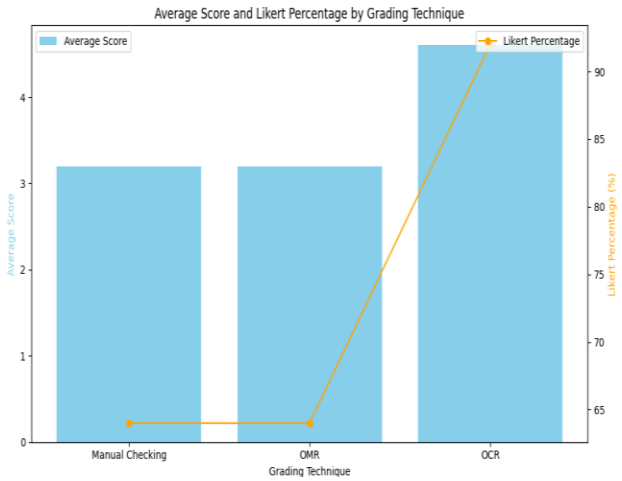


Figure 6: Average scale and Likert percentage by grading techniques

Error Analysis:

The Average scale and Likert percentage clearly showed that the error rate is an important factor in determining the precision and reliability of any grading method. From Figure 6, OCR has the lowest error rate of 0.3 out of 1, because of its ability to process different types of text forms and provide guidance to the user. Even though handwriting and the quality of images may affect OCR, its versatility and user-friendliness remain better than other solutions. However, OMR has inherent limitations affecting its accuracy, primarily due to issues like missing sheets and incorrect calibration during scanning. As a result, the method achieves only 90% accuracy, with an error rate of 0.5%. The highest error rate is encountered with the manual checking of exams, which has an error rate of 0.7%, resulting from stress or fatigue as well as a probable misreading of the question.

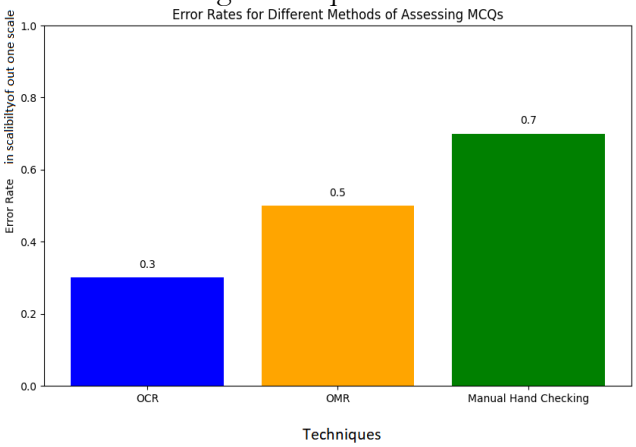


Figure 7: Error rates of different grading systems

Time Analysis:

In today's context, efficiency is crucial for institutions managing large-scale testing. Manual checking takes 15 minutes to check 15 papers; it involves human verification, is time-consuming, and demands significant labor. OMR takes 5 minutes because it uses pr-developed answer sheets and automation but setup time and accurate filling may hamper its efficiency. The OCR-based approach takes 3 minutes, and it is the fastest one but it requires high-quality images and additional preprocessing. This makes OCR suitable for large-scale grading where time is a very important factor to be considered. Figure 8 shows the completion times for grading 15 sample papers.

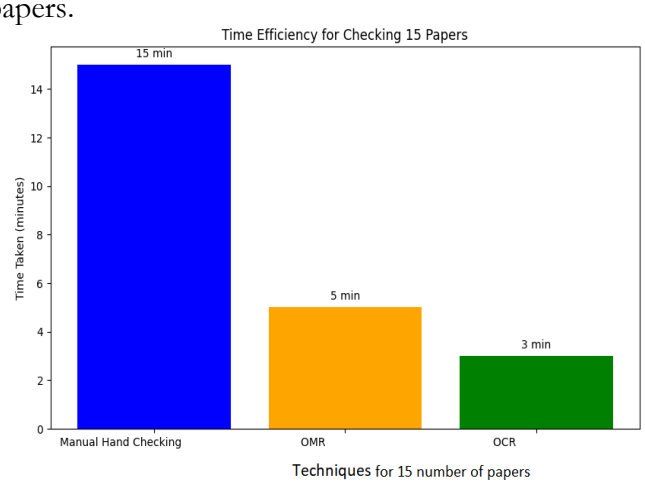


Figure 8: Time Efficiency for 15 Number of Papers

Accuracy:

Manual checking can be as accurate as automated methods but sample-checking time depends on the number of samples, error rate, and fatigue. Using scanner-readable sheets,

OMR is reliable; it attained about 98 percent accuracy. Overall, OCR achieved up to 99.5% accuracy when using scanners, while its accuracy stands at around 98% when no scanner is used; there are no major troubles with different formats. For this reason, OCR is especially suitable for various forms of tests and assessments. The credibility concentrates on the criteria for choosing the assessment methods: The closer an assessment is to perfection, the better. However, accuracy should be balanced with practicality and scalability, allowing institutions to select assessment methods based on their specific needs.

OCR Analysis with Android and Apple Mobile Phones:

According to Table 5, OCR accuracy for reading 10 questions on 5 answer sheets on an Android smartphone without a scanner was 98%, while with a scanner, it was 100%. Almost 100% accuracy was attained in both cases using an iPhone mobile with or without a scanner. This indicates that using a scanner enhances the accuracy of Android devices, bringing it on par with the iPhone's reliable 100% accuracy.

Table 5: OCR Analysis with Android and Apple mobile phones

Number of Papers	Number of Questions	Android Mobile (Without Scanner)	Android Mobile (With Scanner)	iPhone Mobile (Without Scanner)	iPhone Mobile (With Scanner)	Android Accuracy (Without Scanner) (%)	Android Accuracy (With Scanner) (%)	iPhone Accuracy (Without Scanner) (%)	iPhone Accuracy (With Scanner) (%)
15	150	149/150	150/150	150/150	150/150	98%	100%	100%	100%

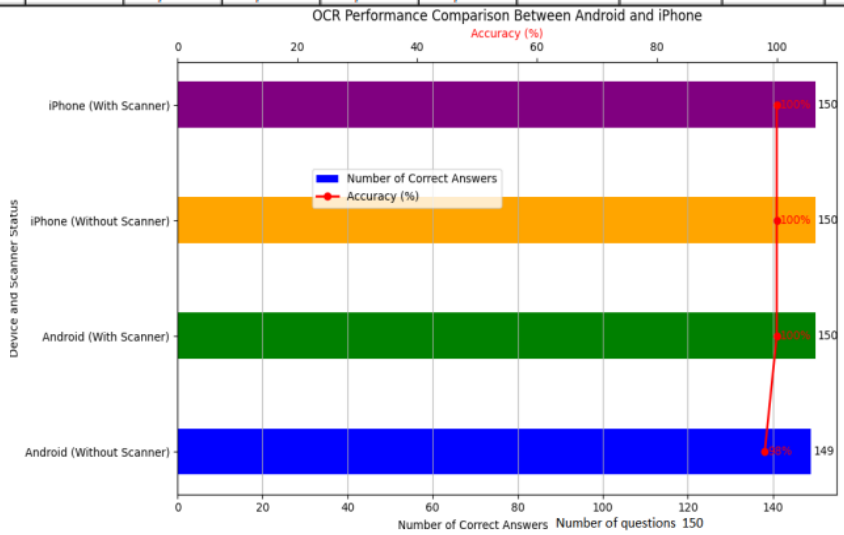


Figure 9 OCR performance between Android and iPhone

Accuracy of Different Marking Options:

The "Accuracy of Different Marking Options" Figure 10 to 13 shows how the system identifies accurate marks on MCQs where students can only mark one correct response. The system recognizes multiple markings by a pupil as a mistake and classifies the response as wrong. The graphic illustrates several scenarios:

All options Marked:

According to this scenario, the OCR system aims to identify a student's marking all possibilities as an erroneous response for a single question. Since marking every option goes against the principle of choosing just one right response, the accuracy is zero, as shown in Fig 10.

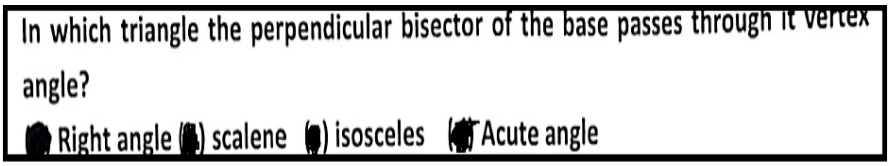


Figure 10: All option mark scenario

No Option Marked:

The system also marks it as incorrect if the options are left blank. Although this kind of mistake is distinct from marking more than one option, it nonetheless leads to the question being marked incorrectly, as depicted in (Fig 11).

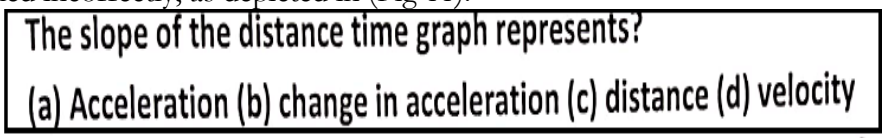


Figure 11: No option mark scenario

Three Marked Options:

Marking three options is also considered wrong by the system. The response is labeled as incorrect even if there are fewer marked possibilities than in the prior scenario shown in (fig 12).

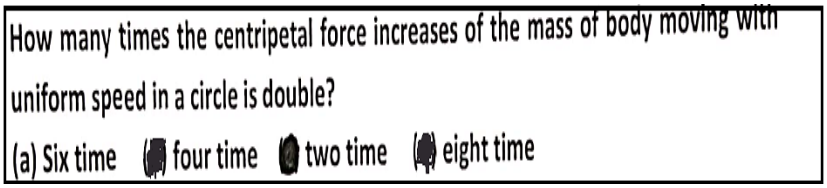


Figure 12: Three option mark scenario

Two options marked:

Lastly, marking only two selections is also considered incorrect. The system shows an error, and the question is marked incorrect (fig 13)

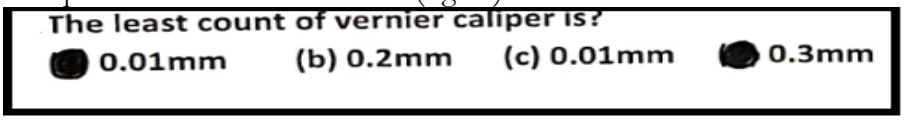


Figure 13: Two option mark scenario

Accuracy of Different Marking Types:

This indicates that the system accurately detects and recognizes the student's markings 100% of the time, regardless of whether they are made with a check mark, shading, line, or circle.

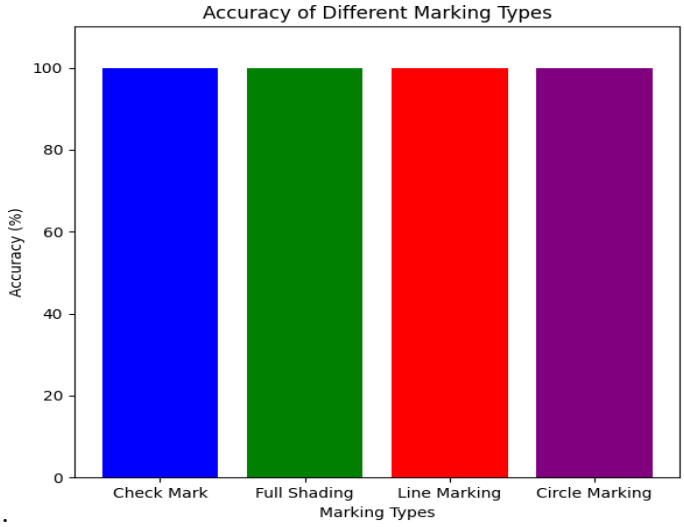


Figure 14: Accuracy of different marking types

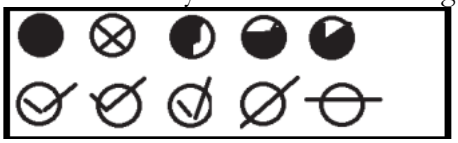


Figure 15: Marking of different marking types

Conclusion:

This research proposed and implemented an OCR-based MCQ answer sheets reading and marking system for enhancing the grading process. The results indicated that Tesseract OCR could be used to obtain answer recognition and was complemented by image processing techniques, including edge detection and noise reduction. Special scripts were developed for analysis of the various answer markers like filled bubbles and ticks where the findings showed high levels of accuracy. With the use of this system, grading may be reduced to a very small amount of time, which the teachers will have to spend; such a system is capable of handling large exams; cost may also be slashed since manual checking is not required. Expected enhancement includes extending the system for grading entire papers including handwritten sections and introducing machine learning for higher accuracy in cases of insignificance in marks. The system should also be more versatile concerning support to an increase in different formats of answer sheets and also support to more languages usage. The current system does not include real-time processing and a mobile app could give immediate feedback. Lastly, the idea of Modified structures should include security to maintain the integrity of the exam. Users' interfaces will be more enhanced and compatibility with other academic tools like LMS will help improve the grading management by making data transfer seamless making it more useful in the education sector.

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