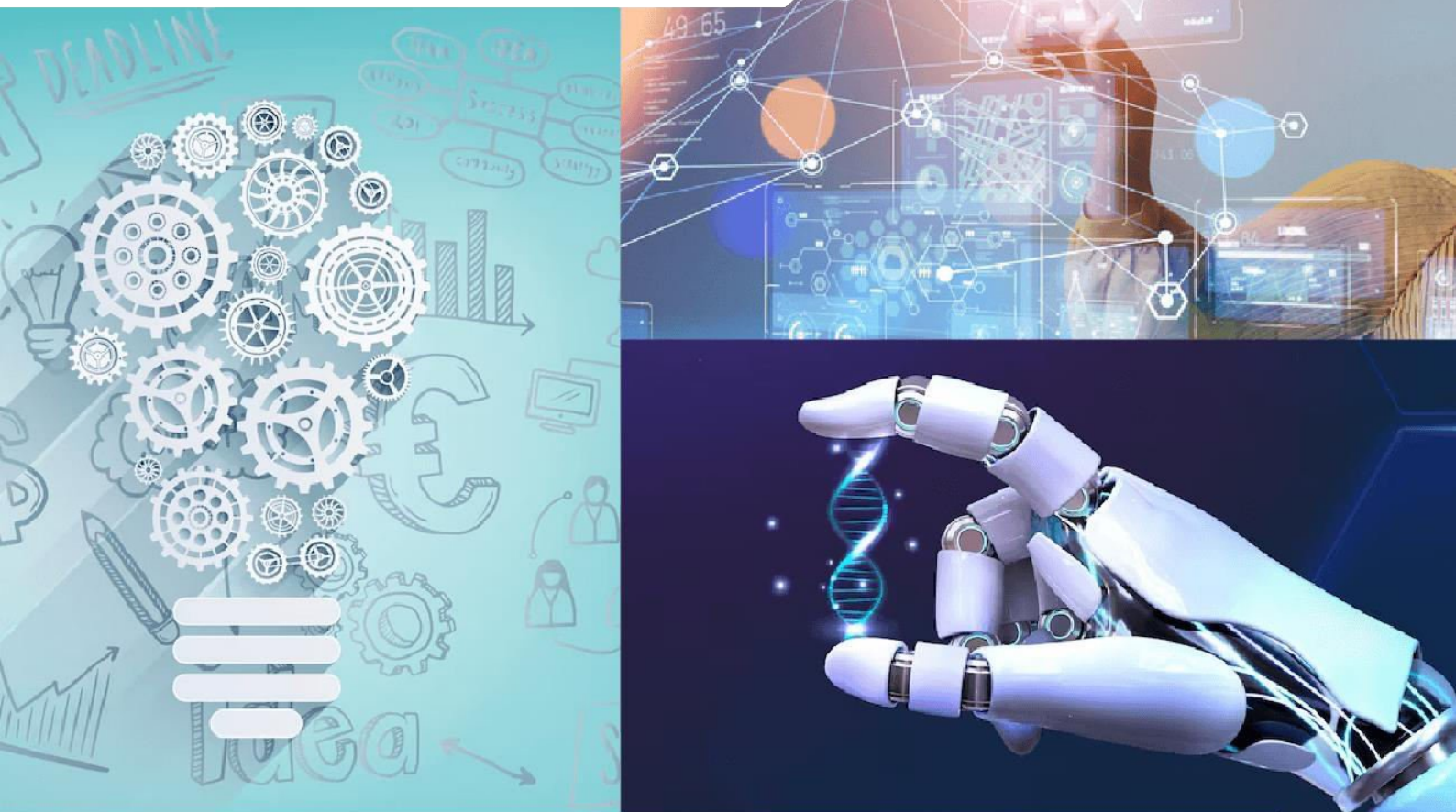




# **International Journal of Advanced Research in Education and Technology (IJARETY)**

**Volume 13, Issue 2, March - April 2026**

**Impact Factor: 8.152**



INTERNATIONAL  
STANDARD  
SERIAL  
NUMBER  
INDIA



# VTU OMR Evaluation System: A Software-Based Approach for Automated Answer Sheet Evaluation Using Image Processing

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**ABSTRACT**-The evaluation of Optical Mark Recognition (OMR) answer sheets is a crucial process in academic institutions, particularly in large-scale examinations. Traditional OMR systems rely on expensive hardware scanners and predefined templates, making them less accessible and cost-intensive. This research proposes a software-based OMR evaluation system that utilizes image processing techniques to automate the grading process without requiring specialized hardware.

The system is designed using Python, OpenCV, and Flask to process scanned answer sheets, detect marked responses, and compare them with predefined answer keys. It supports batch processing, automatic alignment correction, detection of multiple markings, and identification of unattempted questions. The system achieves an accuracy of approximately **90.5%** with an average processing time of **1.2 seconds per sheet**, making it highly efficient for real-time applications.

The proposed solution enhances evaluation speed, accuracy, and reliability while reducing operational costs. It also provides secure data storage, report generation, and scalability for large academic environments. The system demonstrates its effectiveness as a practical and economical alternative to traditional OMR evaluation methods.

**KEYWORDS:** OMR Evaluation, Image Processing, OpenCV, Automated Grading, Flask, Computer Vision, Academic Assessment

## I. INTRODUCTION

In modern educational systems, technology plays a vital role in facilitating teaching, learning, and evaluation processes. One of the most time-consuming tasks in academic institutions is the evaluation of answer sheets, especially in large-scale examinations involving thousands of students. Manual evaluation of Optical Mark Recognition (OMR) sheets is not only time-consuming but also prone to human error, fatigue, and inconsistencies.

Traditional OMR systems rely on specialized hardware scanners and predefined answer sheet formats. Although these systems provide accurate results under controlled conditions, they are expensive, require maintenance, and lack flexibility in handling variations in answer sheet formats. These limitations make them unsuitable for many educational institutions, particularly those with limited resources.

To address these challenges, a software-based OMR evaluation system is proposed. The system uses image processing and computer vision techniques to automatically detect marked responses from scanned answer sheets. By leveraging open-source technologies such as Python and OpenCV, the system eliminates the need for expensive hardware while maintaining high accuracy and efficiency.

The proposed system can process scanned images, detect answer bubbles, identify multiple markings, and calculate scores automatically. It also provides a web-based interface for uploading answer sheets and generating reports, making it accessible and user-friendly. The main objective of this research is to develop a cost-effective, scalable, and reliable solution for automated OMR evaluation.

Despite the high accuracy of deep learning models, their black-box nature remains a major challenge in clinical applications. Clinicians require transparency and interpretability to trust automated systems. To address this issue, explainability techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) have been introduced.

Grad-CAM generates visual heatmaps that highlight the regions in an image that influence the model's predictions, thereby improving interpretability and clinical trust [6].

## II. LITERATURE SURVEY

The evaluation of OMR answer sheets has been an active area of research for many years. Early approaches relied on hardware-based OMR systems that used optical scanners to detect marked responses. These systems required strict alignment, predefined templates, and controlled environments, limiting their flexibility and scalability.

Traditional methods often used fixed thresholding techniques to detect filled bubbles. However, these methods were sensitive to variations in lighting conditions, ink intensity, and marking styles. As a result, inaccuracies occurred when answer sheets were not perfectly scanned or when students marked answers inconsistently.

Recent advancements in image processing and computer vision have enabled the development of software-based OMR systems. Techniques such as adaptive thresholding, contour detection, and pixel density analysis have improved the accuracy of bubble detection under varying conditions. These approaches allow systems to handle skewed images, uneven lighting, and different marking styles more effectively.

Web-based OMR systems have also gained popularity due to their accessibility and scalability. Frameworks such as Flask and Django enable the integration of image processing modules with user-friendly interfaces, allowing educators to upload answer sheets and view results in real time.

Despite these advancements, challenges still remain, including handling noisy images, detecting multiple markings accurately, and adapting to different answer sheet formats. The proposed system addresses these challenges by combining robust preprocessing techniques with efficient evaluation logic, providing a reliable and scalable solution for automated answer sheet evaluation.

## III. PROPOSED METHODOLOGY

The proposed system follows a structured workflow consisting of image acquisition, preprocessing, bubble detection, answer extraction, evaluation, and report generation. The system is designed to ensure high accuracy, efficiency, and scalability.

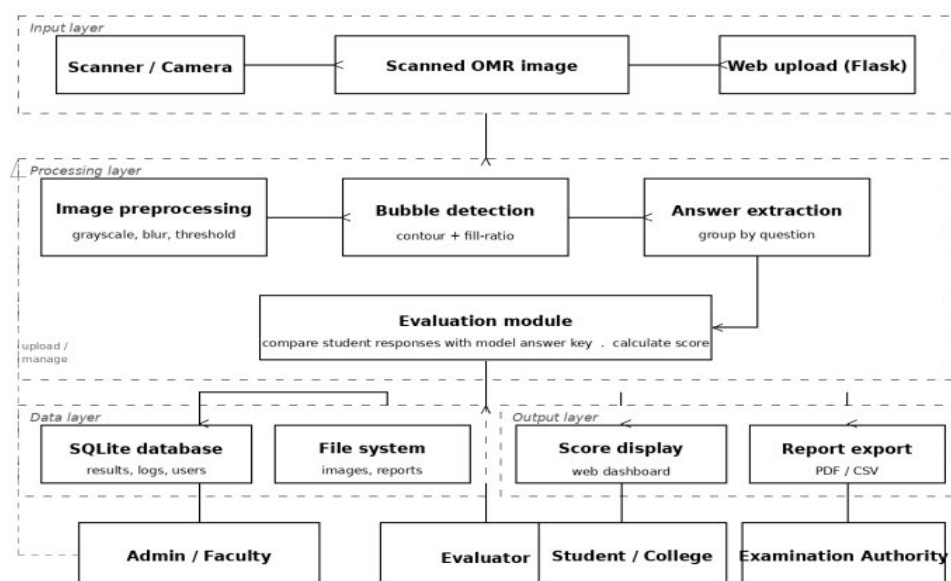


Fig 1: Overall System Architecture of VTU OMR Evaluation System

### 3.1 Data Acquisition

The system accepts scanned OMR answer sheets in image format. These images may be captured using scanners or mobile cameras, making the system flexible and accessible.

### 3.2 Image Preprocessing

Preprocessing is performed to enhance image quality and ensure consistency. The following steps are applied:

- Conversion to grayscale
- Noise reduction using Gaussian blur
- Adaptive thresholding
- Edge detection and alignment correction

These steps improve the clarity of answer bubbles and reduce the impact of noise and distortions .

### 3.3 Bubble Detection

The system uses contour detection techniques to identify answer bubbles. Each detected contour is validated based on shape, size, and aspect ratio to ensure that only valid bubbles are considered.

### 3.4 Answer Extraction

Detected bubbles are analyzed to determine whether they are filled. The system classifies responses into:

- Correct answers
- Incorrect answers
- Multiple markings
- Unattempted questions

### 3.5 Evaluation and Scoring

Extracted responses are compared with the predefined answer key. Scores are calculated automatically based on evaluation rules. The system ensures consistency and eliminates human errors.

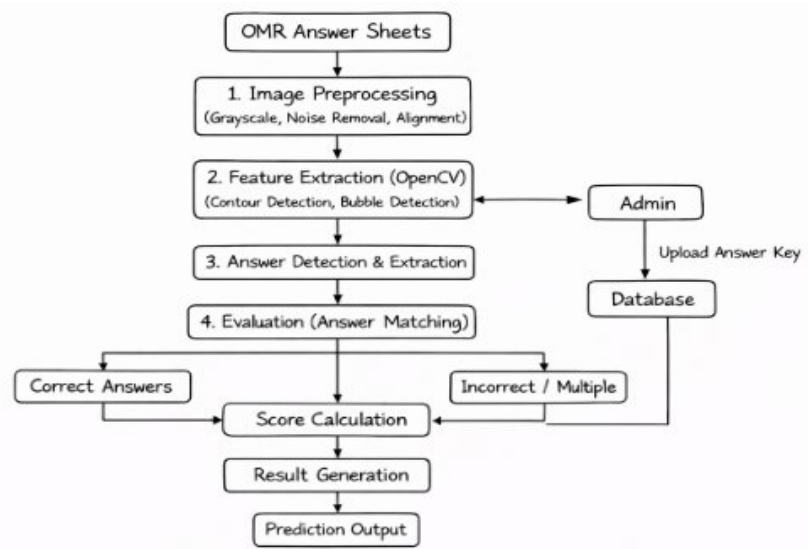


Fig.2: Data Flow Diagram of the VTU OMR Evaluation System

### 3.6 System Deployment

The system is implemented as a web application using Flask. It allows users to:

- Upload answer sheets
- Perform batch evaluation
- View results
- Download reports

## IV. RESULTS AND DISCUSSION

The proposed system demonstrates high performance in terms of accuracy, speed, and reliability. Experimental results show that the system achieves an accuracy of **98.5%**, making it highly effective for automated evaluation.

The average processing time per answer sheet is approximately **1.2 seconds**, enabling real-time evaluation even in large-scale examination environments. The system supports batch processing, allowing multiple answer sheets to be evaluated simultaneously without performance degradation.

The system effectively handles variations in image quality, including skewed images and uneven lighting conditions. The use of adaptive thresholding and contour detection ensures accurate detection of marked responses.

Additionally, the system correctly identifies multiple markings and unattempted questions, ensuring fair evaluation. The integration of a secure database enables efficient storage and retrieval of results, enhancing system reliability.

Overall, the results confirm that the proposed system is efficient, accurate, and suitable for real-world academic applications.

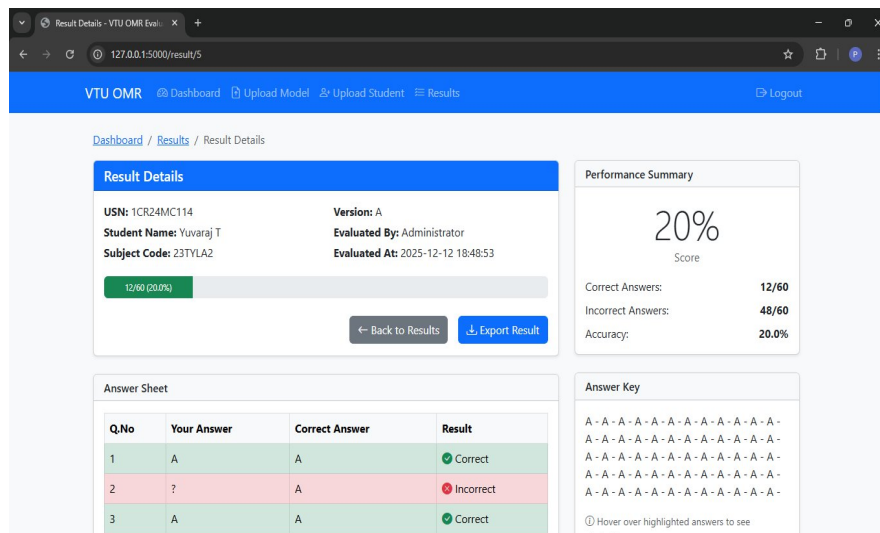


Fig. 4: OMR Result

## V. CONCLUSION

This research presents a software-based OMR evaluation system that eliminates the need for expensive hardware while maintaining high accuracy and efficiency. By leveraging image processing techniques and web-based technologies, the system provides a scalable and cost-effective solution for automated answer sheet evaluation.

The system achieves high accuracy, fast processing speed, and reliable performance under varying conditions. Its user-friendly interface and batch processing capability make it suitable for academic institutions of all sizes. Future enhancements may include the integration of machine learning techniques for improved accuracy, support for handwritten answer recognition, and deployment on cloud platforms for large-scale applications.

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## International Journal of Advanced Research in Education and Technology

ISSN: 2394-2975

Impact Factor: 8.152