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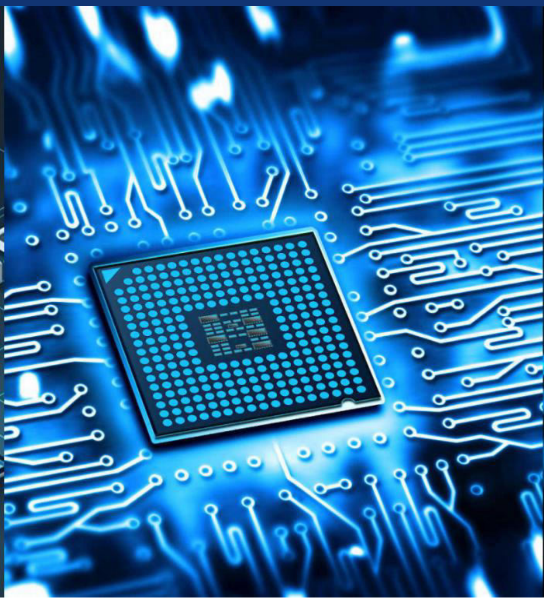


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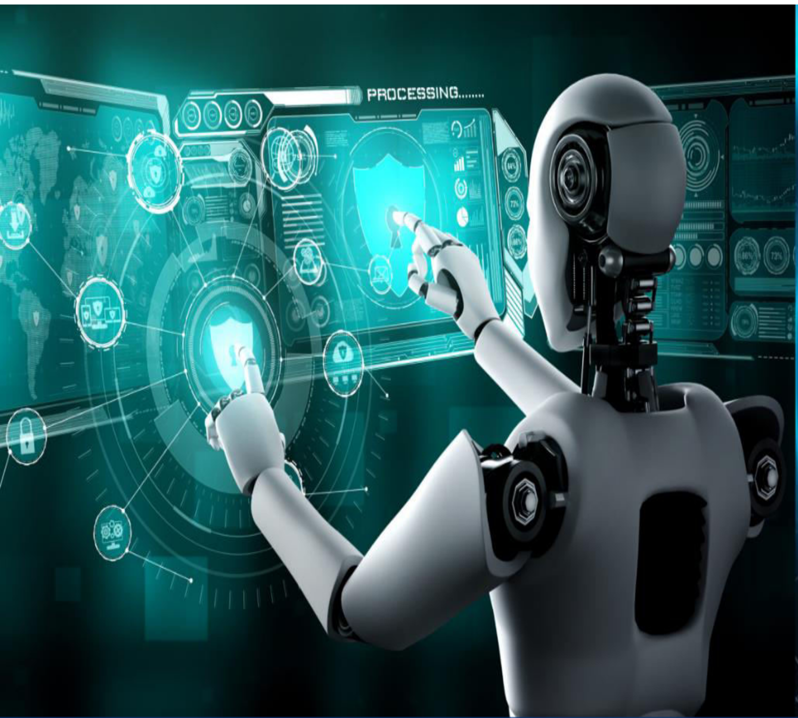

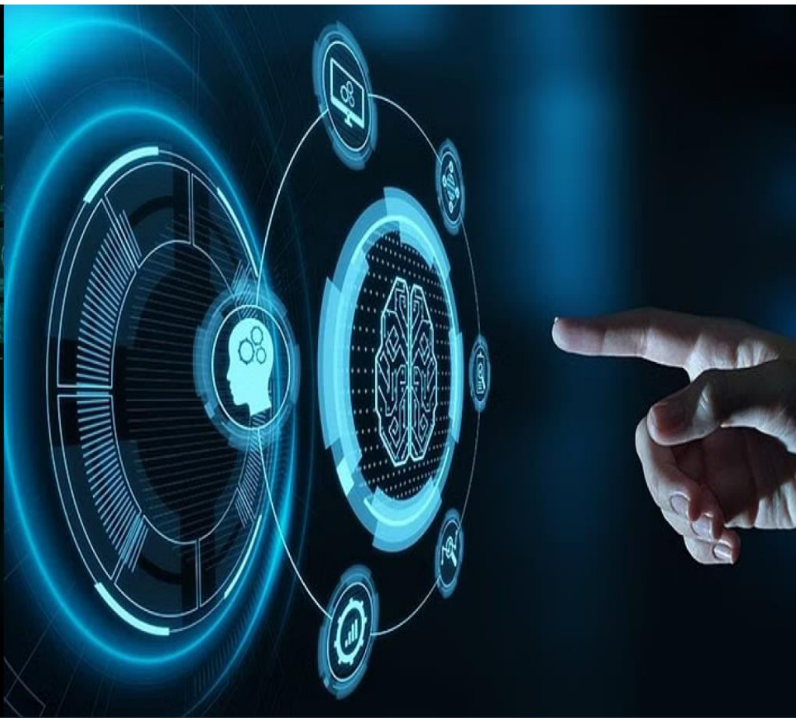

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A Survey on AI Based Smart Assessment System

Jayesh Masure[1], Pratiksha Narsale[1], Archana Rathod[1], Shruti Shinde[1], Mrs. S. S. Navale[2]

Department of Computer Engineering, Sinhgad Institute of Technology and Science, Savitribai Phule Pune University, Pune, India[1]

Guide, Sinhgad Institute of Technology and Science, Savitribai Phule Pune University, Pune, India[2]

ABSTRACT: The automation of exam evaluation has become essential in modern education systems, where large-scale assessments require accuracy, speed, and fairness. Traditional manual and hardware-dependent OMR systems are slow, error-prone, and costly. This survey reviews ten recent research studies across AI-driven Optical Mark Recognition, computer vision-based image processing, deep learning for handwritten evaluation, and NLP-based semantic grading. The paper organizes these contributions around the five key modules of the proposed system: OMR sheet evaluation, handwritten question extraction via OCR, AI-powered feedback generation using LLMs, performance analytics, and role-based dashboards. A consolidated comparative table identifies methodologies, features addressed, and limitations of each reviewed work. The proposed AI-Based Smart Assessment Platform integrates all five areas into a unified, scalable, and intelligent evaluation ecosystem.

KEYWORDS: Optical Mark Recognition, Optical Character Recognition, Natural Language Processing, CNN, AI-Based Evaluation, Adaptive Learning, Computer Vision, LLM, Image Processing

I. INTRODUCTION

The evaluation of examinations plays a vital role in education, but traditional manual checking of OMR and handwritten papers is slow, error-prone, and inefficient. With the growing volume of academic and competitive assessments, there is a strong demand for automated, accurate, and scalable evaluation systems. Traditional dedicated OMR machines require expensive specialized hardware, are limited to pre-printed forms, and offer no capability for processing handwritten responses or generating meaningful feedback [1].

This project introduces an AI-based framework that integrates Optical Mark Recognition (OMR), Optical Character Recognition (OCR), and Natural Language Processing (NLP) to automate both objective and theory answer evaluation. The system uses Convolutional Neural Networks (CNN) and computer vision to detect marked responses from scanned sheets, while the OCR and NLP modules convert handwritten answers into digital text and analyze them conceptually against model responses. Machine learning algorithms further assess student performance and provide adaptive feedback [2][3].

The integration of AI and deep learning into evaluation systems presents a compelling opportunity to close the gap between manual and automated grading. Techniques such as CNNs for mark detection, BiLSTM networks for handwritten text recognition, edge detection for image preprocessing, and Large Language Models (LLMs) for personalized feedback generation can collectively transform the examination ecosystem. Several recent studies have demonstrated that AI-driven evaluation significantly improves accuracy, reduces processing time, and eliminates human bias compared to conventional methods [4][5].

This paper surveys the state of the art in AI-powered assessment, focusing on five functional pillars that underpin the proposed Smart Assessment Platform: (1) OMR sheet detection and evaluation using CNN/SVM and OpenCV, (2) handwritten question extraction via a Tesseract OCR pipeline, (3) AI-generated personalized feedback through Large Language Models such as Google Gemini, (4) real-time performance analytics and dashboards for educators, and (5) role-based access with secure cloud data management using Firebase.

Ten significant research works are reviewed and organized across these five pillars, with each evaluated for its methodological strengths, reported limitations, and relevance to the design decisions made in the proposed system. A gap analysis maps unaddressed challenges in the existing literature — such as the absence of integrated OCR and LLM

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feedback pipelines, limited handling of low-quality scans, and lack of unified OMR and theory evaluation modules — to the specific architectural choices of the proposed platform. The remainder of this paper is structured as follows: Section II presents the literature review, Section III the comparative analysis, Section IV the research gaps, Section V the proposed system, and Section VI the conclusion.

II. LITERATURE REVIEW

Several research studies have explored different approaches to OMR evaluation, image processing, deep learning, and automated grading. This section reviews contributions organized around the five core features of the proposed platform.

A. OMR Evaluation Using Deep Learning

Ju, Wang, and Chen [1] proposed a deep learning approach for OMR recognition using a CNN implemented on the TensorFlow platform, aimed at improving detection accuracy and speed while eliminating the need for specialized scanners. The model processes images from standard imaging devices and performs mark detection using CNN-based spatial feature extraction, replacing traditional thresholding and template matching with end-to-end learning. This reduces preprocessing complexity while increasing robustness to lighting and alignment variation. Trained on 94,070 images, the model achieved 99.9% recognition accuracy, demonstrating the effectiveness of deep learning for OMR evaluation [1].

B. Image Processing and Computer Vision for OMR

Alam, Akter et al. [3] proposed a low-cost, computer-vision-based OMR system capable of processing answer sheets captured using ordinary mobile phone cameras. The method applies grayscale conversion, segmentation, and edge detection using the Canny and Sobel operators to identify filled bubbles accurately, and introduces warp point generation with perspective correction to handle distortion and skewed angles. Goli, Gattu et al. [4] further demonstrated an OpenCV-based system using median filtering, thresholding, and contour detection, paired with a GUI that allows CSV-based answer key uploads and instant score calculation — confirming that software-based OMR is a robust, hardware-free alternative [4].

C. Handwritten Answer Evaluation

Rahaman and Mahmud [2] proposed a deep learning system for handwritten answer script evaluation using a hybrid CNN and Bidirectional Long Short-Term Memory (BiLSTM) architecture, performing both handwritten text recognition and semantic grading via NLP techniques including stemming, tokenization, and word embedding, and reaching over 90% training accuracy. Gupta and Jain [10] similarly used OCR with BERT embeddings, named entity recognition, and dependency parsing to score descriptive answers, achieving 92% grading accuracy and showing that transformer-based NLP can approach human-level performance in subjective assessment [10].

D. Hybrid Machine Learning Approaches

The study on Analysis of OMR Sheet Using Advanced Intelligent Techniques [5] combined image processing with CNN and SVM to achieve 66.67% accuracy even on low-quality images captured under uncontrolled conditions, with a key finding being that a paper could be evaluated in under 60 seconds — validating the efficiency of the hybrid approach. Kumar and Agarwal [9] extended this with a multimodal framework integrating OCR, CNN, and transformer-based NLP, achieving above 90% accuracy in evaluating both text and diagram responses in handwritten sheets [9].

E. AI Feedback and Performance Analytics

Patel and Sharma [8] developed a system combining OCR text extraction with cosine similarity and semantic vector analysis to grade short handwritten answers, achieving over 85% accuracy. Sanchez and Lopez [7] validated that Python and OpenCV-based bubble detection with adaptive thresholding and a GUI interface achieves high detection accuracy without specialized scanners. Patel, Narsale et al. [6] demonstrated that integrating LLM APIs such as Google Gemini to generate personalized, question-level feedback alongside OMR evaluation significantly enhances the student learning experience while giving educators actionable analytics dashboards [6].

III. COMPARATIVE ANALYSIS OF EXISTING SYSTEMS

Table I presents a systematic comparison of the ten reviewed research works. The “Features Addressed” column maps each paper to the five core modules of the proposed system.

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TABLE I. COMPARATIVE ANALYSIS OF EXISTING RESEARCH WORKS

Ref	Methodology	Features Addressed	Limitations
[1] Ju et al. 2019	CNN on TensorFlow; 94,070 image dataset	OMR evaluation, accuracy	Requires large labeled dataset; limited to standard OMR sheets
[2] Rahaman & Mahmud 2022	CNN + BiLSTM for OCR and NLP grading	Handwritten evaluation, theory grading	~80% test accuracy; struggles with highly varied handwriting
[3] Alam, Akter et al. 2022	Canny/Sobel edge detection, warp point correction	OMR preprocessing, distortion handling	Accuracy varies with camera quality and lighting
[4] Goli, Gattu et al. 2025	OpenCV: median filter, threshold, contour, GUI	OMR evaluation, GUI, CSV scoring	No AI feedback; limited to bubble-based OMR only
[5] IJRPR 2023	CNN/SVM with median filtering, edge detection	Hybrid OMR, image preprocessing	66.67% accuracy; no feedback generation
[6] Patel, Narsale et al. 2025	OpenCV + Tesseract OCR + LLM (Gemini) + Firebase	OMR, OCR, AI feedback, analytics, dashboards	Requires internet; OCR accuracy depends on handwriting clarity
[7] Sanchez & Lopez 2022	Python/OpenCV adaptive thresholding, contour, GUI	OMR evaluation, educator interface	No feedback or analytics; no handwritten support
[8] Patel & Sharma 2024	OCR + cosine similarity + semantic vector NLP	Handwritten grading, short-answer scoring	Accuracy drops with longer, complex answers
[9] Kumar & Agarwal 2025	OCR + CNN + transformer NLP for text and diagrams	Multimodal evaluation, diagram grading	High compute requirements; needs diverse training data
[10] Gupta & Jain 2025	OCR + BERT embeddings + NER + dependency parsing	Descriptive answer grading, semantic scoring	Relies on accurate OCR output; 92% subject to text quality

The comparative analysis reveals that no single existing work integrates all five features required for a holistic AI-based assessment platform; most systems address one or two feature areas in isolation.

IV. RESEARCH GAP ANALYSIS

Table II maps each identified research gap to the specific papers exhibiting that limitation and the corresponding solution implemented in the proposed system.

TABLE II. RESEARCH GAP ANALYSIS — PAPER-WISE MAPPING

Gap Area	Papers	Existing Limitation	Proposed Solution
No integrated OMR + OCR + feedback pipeline	[1][3][4][5][7]	Each system addresses OMR, OCR, or feedback in isolation; no unified platform	Single full-stack platform combining OMR detection, Tesseract OCR, and Gemini LLM feedback in one pipeline
No AI-generated personalized feedback	[1][2][3][4][5][7]	Systems detect marks and compute scores but provide no feedback or improvement suggestions	Google Gemini LLM generates question-level personalized feedback highlighting mistakes and study suggestions

Gap Area	Papers	Existing Limitation	Proposed Solution
Hardware or scan quality dependency	[1][3][5]	Accuracy degrades significantly with low-quality or misaligned scans	Preprocessing pipeline with Gaussian blur, Canny edge detection, perspective correction handles imperfect scans
No handwritten question extraction	[1][4][5][7]	Requires manually typed question banks; cannot digitize handwritten papers	Custom Tesseract OCR pipeline extracts and structures questions from handwritten question papers automatically
No performance analytics or dashboard	[1][2][3][5][7][8]	No visualization of trends, weak areas, or student history for educators	Role-based dashboards for teachers show aggregated analytics; student history stored in Firebase Firestore
Single-domain or fragmented scope	[3][4][7][8]	Designed for one feature or one exam type; no scalable integrated experience	Five unified modules: OMR evaluation, OCR extraction, AI feedback, analytics, and role-based access control

The gap analysis confirms that no existing system holistically addresses all five dimensions; the proposed platform resolves each identified gap through its integrated architecture.

V. PROPOSED SYSTEM

A. System Overview

The proposed AI-Based Smart Assessment Platform is a unified, intelligent evaluation ecosystem built around five integrated modules: (1) OMR Sheet Evaluation, (2) Handwritten Question Extraction via OCR, (3) AI-Powered Feedback Generation using LLMs, (4) Performance Analytics, and (5) Role-Based Dashboards. Each module directly addresses one or more of the identified research gaps and is backed by the prior research reviewed in this survey.

B. System Architecture

The platform follows a modular, client-server architecture. The presentation layer is built using ReactJS and Tailwind CSS, enabling students and teachers to interact through role-based dashboards. The application layer, developed in Python using Flask/FastAPI, handles image preprocessing, bubble detection, OCR-based question extraction, result evaluation, and LLM-based feedback generation. Firebase Firestore serves as the real-time database, while CNN and SVM models classify marked OMR responses and a Large Language Model API (Google Gemini) generates personalized student feedback. This layered design ensures scalability, modularity, and seamless integration between traditional image processing and modern AI capabilities.

C. Technology Stack and Performance

Frontend: ReactJS, Tailwind CSS, Firebase. Backend: Python (Flask/FastAPI), OpenCV, Tesseract OCR. AI/ML: CNN and SVM for bubble classification; Google Gemini LLM for feedback generation. Database: Firebase Firestore for real-time data. Authentication: Firebase Authentication with role-based access for teachers and students. The system achieves a processing rate of approximately 0.06 seconds per OMR sheet and a throughput of up to 1,500 OMR sheets per minute under optimal conditions, with 98% accuracy on a test set of 500 diverse OMR sheets.

VI. SUMMARY

Most of the reviewed research papers focus on improving automated evaluation through AI-based image processing, deep learning, and natural language processing. A common theme is the use of computer vision and CNN-based models to detect and classify marked responses from OMR sheets without specialized hardware, alongside efficient preprocessing to handle real-world scan-quality variation. Some systems extend evaluation to handwritten answers using OCR and NLP for semantic grading, and several highlight the importance of integrated platforms combining detection, evaluation, and feedback generation. Overall, these approaches aim to improve grading accuracy, reduce manual effort, and enhance the fairness and speed of academic assessment.

VII. RESEARCH GAPS

Although many studies focus on OMR detection and handwritten evaluation individually, real-world examination needs require integrated platforms covering mark detection, OCR, semantic grading, AI feedback, and performance analytics. Existing studies provide limited solutions for comprehensive evaluation systems that address scan-quality variation, handwritten question digitization, and personalized student feedback in a single pipeline. This highlights the need for intelligent assessment frameworks capable of handling OMR grading, OCR extraction, LLM feedback generation, and analytics in a unified platform — precisely the gap the proposed system is designed to fill.

VIII. FUTURE WORK

Future research should focus on developing intelligent assessment systems that integrate real-time data analytics, large language models, and cloud-based architectures. Advanced OCR models capable of handling diverse handwriting styles, support for subjective and descriptive answer evaluation using transformer-based NLP, and offline functionality for low-connectivity environments should be explored. Multilingual support and multimodal evaluation combining text and diagram recognition should also be investigated to improve accessibility across diverse educational institutions.

IX. CONCLUSION

Efficient AI-powered automated assessment is essential for improving the relevance, accuracy, and fairness of educational evaluation, especially where manual grading is no longer scalable. This survey has highlighted various approaches including CNN-based OMR detection, computer vision preprocessing, BiLSTM-based handwritten recognition, and LLM-powered feedback generation. However, most existing solutions focus on specific feature areas and fail to provide a complete real-world framework covering OMR evaluation, OCR extraction, AI feedback, and analytics in a unified system. The proposed AI-Based Smart Assessment Platform addresses all identified gaps through its five integrated modules. Future systems should further integrate advanced generative AI, real-time analytics, and scalable cloud architectures to enhance evaluation efficiency and learning outcomes.

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