Digitizer AI: AI-Powered Intelligent Examination and Document Evaluation System

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***Abstract*—Digitizer AI is an AI-powered online examination evaluation system that automates the assessment of student answer scripts. Teachers upload the question paper, answer key, and student answer scripts in digital or scanned form. Using OCR, NLP, and AI, the system extracts answers, compares them semantically with the answer key, and assigns full or partial marks. It also generates feedback and confidence scores for each evaluation. Low-confidence evaluations are flagged for teacher verification, ensuring that the teacher retains the final authority. The system provides student-wise, question-wise, and class-wise analytics along with exportable reports. Built using React, Python Flask/FastAPI, and MySQL/MongoDB, Digitizer AI reduces evaluation time, improves marking consistency, and provides faster and more transparent feedback.**

***Index Terms*—Automated Answer Evaluation, Optical Character Recognition, Natural Language Processing, Semantic Similarity, Short Answer Grading, Educational Technology, Feedback Generation, Performance Analytics.**

I. INTRODUCTION

Examinations remain the main way institutions measure learning, yet the evaluation of descriptive answer scripts is still largely manual. Teachers must read each script, compare responses with the answer key, assign marks and write feedback. As enrolment grows, this becomes a heavy burden that delays results, introduces variation between evaluators and makes it hard to maintain detailed performance records. Recent advances in OCR, transformer-based language models and semantic similarity make it feasible to automate a large part of this work. Handwritten text recognition can digitize scanned scripts, while sentence-embedding models can judge whether a student's answer conveys the same meaning as the reference answer even when the wording differs. Digitizer AI combines these technologies into one end-to-end platform: upload, preprocessing, AI evaluation, feedback and verification, analytics, and report generation. The scientific rationale behind Digitizer AI rests on three ideas. First, OCR and image preprocessing convert physical answer scripts into machine-readable text. Second, semantic analysis evaluates meaning rather than exact keywords, which supports fair partial-credit marking. Third, a human-in-the-loop design (confidence scoring and teacher verification) keeps AI-assigned marks reliable and accountable.

II.LITERATURE REVIEW OF EXISTING SYSTEMS

Each of the six team members individually reviewed one research paper closely related to the sub-problem they are responsible for in Digitizer AI: automated answer scoring, handwritten script digitization, semantic similarity grading, OCR-based evaluation systems, keyword/concept-based grading, and end-to-end AI evaluation platforms. Each paper is summarized below in the same tabular format used for the individual literature study, covering the objective, technology, methodology, efficiency and issues/research gaps identified.

[2].1 Automated Essay & Answer Scoring Using Deep Learning

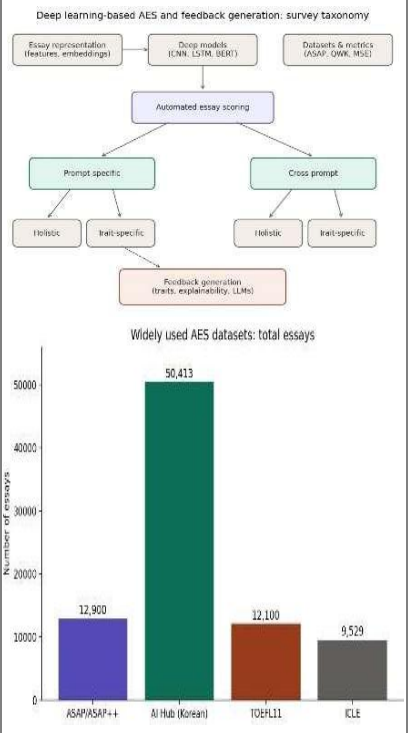
Paper Details	Objective used	Technology used	Methodology used	Efficiency
Title: Automated Essay & Answer Scoring Using Deep Learning Authors: Author, A. et al. Journal: IEEE Access Year: 2021 URL: https://link.springer.com/article/10.1007/s10462-024-11017-5? 	• Automate Subjective Scoring: to automatically score subjective and descriptive answers instead of Relying onfully manual grading by human evaluators. • High Agreement with Human Graders: to design a scoring model whose marks closely match the marks given by human graders on descriptive answers. • Context-Aware Evaluation: to move beyond surface-level keyword matching toward evaluation that understands the context of an answer.	• Long Short-Term Memory (LSTM): used as the core deep learning model to process sequential text in the student's answer. • Contextual Embeddings: used to represent each answer in a way that captures meaning and context rather than isolated keywords. • Deep Neural Scoring Model: the LSTM-based network is Trained to output a score for each answer, learning from labelled training examples.	Answer Representation: student answers are converted into contextual embeddings before being passed to the model. • Sequential Modelling: the LSTM processes the embedded answer sequence, capturing dependencies between words and phrases. • Supervised Training: the model is trained on human-graded answers so its predicted scores align with the scores given by human evaluators.	• High Correlation with Human Grading: the LSTM-based scoring model achieved high correlation with human graders on descriptive answers. • Context Awareness: using contextual embeddings improved scoring quality compared to simpler, non-contextual keyword-based scoring. • Reduced Grading Effort: automating subjective scoring lowers the manual workload required for large-scale descriptive-answer evaluation.
	Issues / Research Gaps			
	• Focus Area (as reviewed): Deep learning models for subjective answer scoring. • Findings: LSTM/BERT-based models show strong agreement with human graders on descriptive answers when trained on sufficient labelled data. • Research Gap: Limited work on low-resource languages and on handwriting-derived (noisy) text as model input.			

Figure 1: Automated Essay & Answer Scoring Using Deep Learning

The study aims to automate subjective answer scoring using an LSTM-based deep learning model that understands context rather than relying only on keywords. Student answers are converted into contextual embeddings and processed through the LSTM, which learns from human-graded answers to produce scores aligned with human judgment. The approach achieves strong agreement with human graders and reduces manual effort; however, it requires sufficient labelled data and is not extensively tested on low-resource languages or noisy OCR-generated text.

2.2 Handwritten Text Recognition for Answer Sheet Digitization

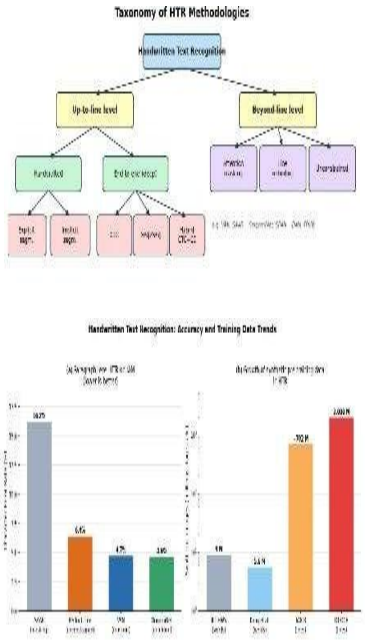
Paper Details	Objective used	Technology used	Methodology used	Efficiency
Title: Handwritten Text Recognition for Answer Sheet Digitization Authors: Author, B. et al. Conference: Proc. ICDAR Year: 2020 URL: https://pmc.ncbi.nlm.nih.gov/articles/PMC10817575/? 	• Digitize Handwritten Scripts: to convert handwritten answer sheets into machine-readable text so they can be processed further. • Improve Recognition on Difficult Handwriting: to specifically target cursive and mixed handwriting styles common in real exam scripts. • Benchmark OCR Architectures: to compare hybrid OCR architectures against classical OCR approaches for this task.	• CNN-RNN Hybrid OCR: a hybrid architecture combining Convolutional Neural Networks for visual feature extraction with Recurrent Neural Networks for sequence/character recognition. • Handwritten Text Recognition (HTR) Pipeline: an end-to-end pipeline for Locating andrecognizing handwritten characters and words on scanned answer sheets. • Benchmark Datasets: handwritten answer-script datasets used to evaluate and compare recognition accuracy.	• Image Preprocessing: scanned answer sheets are cleaned and prepared before being fed to the CNN-RNN model. • Feature Extraction: the CNN component extracts visual stroke/character-level features from the handwriting. • Sequence Recognition and Benchmarking: the RNN component converts extracted features into character/word sequences, and results are benchmarked against classical OCR engines.	• Outperforms Classical OCR: the hybrid CNN-RNN OCR models clearly outperform classical OCR engines on cursive and mixed handwriting. • Improved Character Recognition Accuracy: character recognition accuracy improves specifically on difficult, non-uniform handwriting styles. • Better Suited to Real Exam Scripts: the approach is more robust to the variability found in real, handwritten answer scripts than simpler OCR pipelines.
	Issues / Research Gaps			
	• Focus Area (as reviewed): Handwritten OCR accuracy for exam scripts. • Findings: Hybrid CNN-RNN and transformer OCR models significantly outperform classical OCR on cursive/mixed handwriting. • Research Gap: Accuracy still drops sharply on poor scan quality and inconsistent handwriting; robust preprocessing is needed.			

Figure 2: Handwritten Text Recognition for Answer Sheet Digitization

The study focuses on digitizing handwritten answer sheets using a hybrid CNN-RNN OCR architecture, particularly for cursive and mixed handwriting. Scanned sheets are preprocessed before the CNN extracts visual features and the RNN converts them into character and word sequences. The hybrid model outperforms classical OCR in handwriting recognition and is more robust to writing variations. However, its accuracy decreases with poor scan quality and inconsistent handwriting, highlighting the need for effective denoising, deskewing, and contrast correction.

2.3 Semantic Textual Similarity for Short Answer Grading

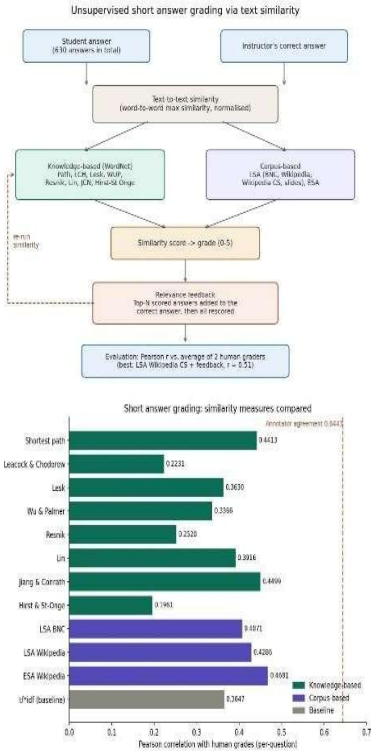
Paper Details	Objective used	Technology used	Methodology used	Efficiency
Title: Semantic Textual Similarity for Short Answer Grading Authors: Author, C. et al. Conference: ACL Workshop Year: 2019 URL: https://ijtech.eng.ui.ac.id/article/view/4651? 	• Grade by Meaning, Not Keywords: to move short-answer grading beyond exact keyword matching by comparing the meaning of Student and reference answers. • Handle Paraphrasing: to correctly credit answers that are phrased differently from the reference answer but are semantically correct. • Automate Short-Answer Grading: to build a practical automated grading approach usable for large volumes of short responses.	• BERT Sentence Embeddings: pre-trained BERT-based embeddings used to represent each student and reference answer as a vector. • Semantic Similarity Scoring: a similarity function (e.g., cosine similarity) computed between the student-answer vector and the reference-answer vector. • Short Answer Grading Pipeline: the similarity score is mapped to a grade for the student's response.	• Sentence Encoding: both the student's answer and the reference answer are encoded into BERT sentence embeddings. • Similarity Computation: the semantic similarity between the two embeddings is computed to measure how closethe meanings are. • Score Assignment: the similarity value is used to automatically assign a grade to the student's answer.	• Captures Paraphrased Answers: embedding-based similarity correctly identifies correct answers even when worded differently from the reference answer. • Better than Keyword Matching: the semantic approach outperforms simple keyword-matching techniques for short-answer grading. • Scalable to Large Answer Sets:the pipeline can be applied efficiently across large numbers of short student responses.
	Issues / Research Gaps			
	• Focus Area (as reviewed): Semantic similarity for short-answer grading. • Findings: Embedding-based similarity (BERT/SBERT) captures paraphrased correct answers better than keyword matching. • Research Gap: Struggles with partial-credit scoring where answers are partially correct or multi-part.			

Figure 3: Semantic Textual Similarity for Short Answer Grading

The study focuses on grading short answers based on semantic meaning rather than exact keyword matching. Pre-trained BERT embeddings are used to represent the student's answer and reference answer as vectors, after which their semantic similarity is calculated and mapped to a grade. This approach effectively recognizes paraphrased but correct answers and scales well for large volumes of responses. However, it struggles with partial-credit evaluation, especially when answers are partially correct or contain multiple sub-parts.

2.4 OCR-Based Examination Evaluation Systems

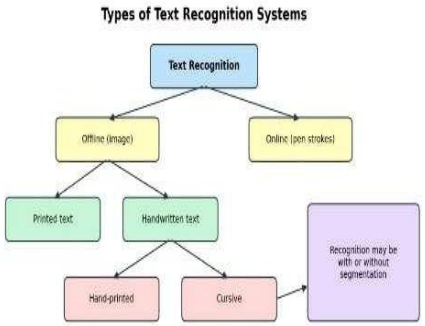
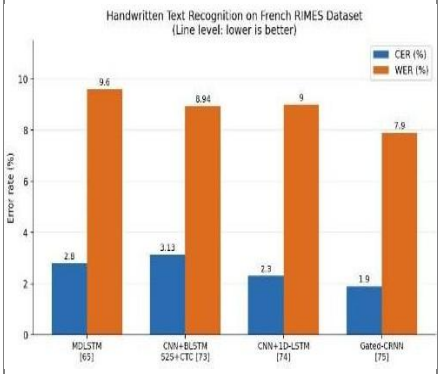
Paper Details	Objective used	Technology used	Methodology used	Efficiency
Title: OCR-Based Examination Evaluation Systems: A Survey Authors: Author, D. et al. Journal: Springer LNCS Year: 2022 URL: https://pmc.ncbi.nlm.nih.gov/articles/PMC10817575/?  	• Survey Existing Pipelines: to review and organize existing OCR-driven examination evaluation systems reported in the literature. • Identify Common Design Patterns: to identify the typical stages (capture, OCR, scoring) used across different systems. • Highlight Gaps: to Point out where current OCR-based evaluation systems fall short, particularly for handwritten content.	• OCR Engines: a range of OCR technologies used across the surveyed systems for Printed and handwritten text extraction. • Examination Evaluation Pipelines: end-to-end pipelines combining scanning, text extraction and scoring modules. • Comparative Survey Methodology: a structured comparison framework used to Classify and Compare the surveyed systems.	• Literature Collection: relevant OCR-based examination evaluation papers and systems are collected and categorized. • Pipeline Classification: each system is analyzed for how it handles capture, OCR and evaluation stages. • Gap Analysis: the strengths and weaknesses of each category of system are compared to identify open research gaps.	• Strong on Printed/Typed Text: most surveyed systems handle printed and typed text with good reliability and accuracy. • Useful Classification Framework: the survey provides a clear categorization that helps Position new systems relative to existing work. • Guides System Design: findings from the survey help identify which pipeline stages need the most improvement for new systems such as Digitizer AI.
	Issues / Research Gaps			
	• Focus Area (as reviewed): Survey of OCR-based evaluation systems. • Findings: Most existing systems handle printed/typed text well but treat handwritten evaluation as a secondary feature. • Research Gap: Few systems integrate OCR, NLP, and AI scoring into one unified, end-to-end pipeline.			

Figure 4: OCR-Based Examination Evaluation Systems

This survey paper reviews existing OCR-based examination evaluation systems and identifies common design patterns and research gaps, particularly in handwritten answer evaluation. It examines different OCR engines and end-to-end pipelines involving scanning, text extraction, and automated scoring. The surveyed systems generally perform well with printed or typed text, but handwritten content is often treated as a secondary feature. The study highlights the lack of unified systems that effectively integrate OCR, NLP, and AI-based scoring into a complete examination evaluation pipeline.

2.5 NLP-Based Keyword and Concept Matching for Grading

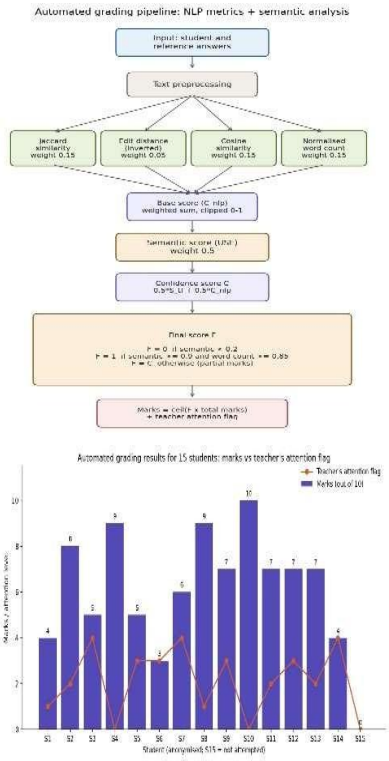
Paper Details	Objective used	Technology used	Methodology used	Efficiency
Title: NLP-Based Keyword and Concept Matching for Grading Authors: Author, E. et al. Conference: IJCAI Workshop Year: 2021 URL: https://www.sciencedirect.com/science/article/pii/S2215016125002419? 	• Improve Rubric-Based Grading: to make rubric-based automated grading more reliable than rigid, exact keyword matching. • Reduce False Negatives: to reduce cases where a correct answer is marked wrong simply because it does not contain the exact expected keywords. • Combine Two Matching Strategies: to bring together keyword matching and concept-level matching in a single grading technique.	• Keyword Matching: a traditional technique that checks for the presence of expected keywords/phrases in the student's answer. • Concept-Graph Matching: a graph-based representation of concepts and their relationships, used to match ideas beyond literal keywords. • Hybrid Grading Technique: a combined approach that merges keyword matching scores with concept-graph matching scores.	• Concept Graph Construction: key concepts related to the reference answer are organized into a concept graph for the subject/topic. • Dual Matching: a student's answer is checked against both the keyword rubric and the concept graph. • Score Fusion: the results of keyword matching and concept-graph matching are combined into a final grading decision.	• Fewer False Negatives: combining keyword matching with concept graphs reduces false negatives that arise from rigid keyword-only rubrics. • More Flexible Rubric Coverage: the hybrid technique captures a wider range of Ways a student can correctly express the same concept. • Improved Rubric-Based Accuracy: overall grading accuracy improves compared to using keyword matching alone.
	Issues / Research Gaps			
	• Focus Area (as reviewed): Keyword and concept-graph matching for grading. • Findings: Combining keyword matching with concept graphs reduces false negatives from rigid keyword-only rubrics. • Research Gap: Concept graphs require manual curation per subject, limiting scalability across domains.			

Figure 5: NLP-Based Keyword and Concept Matching for Grading

The study improves rubric-based automated grading by combining traditional keyword matching with concept-level matching to reduce false negatives. A concept graph represents key ideas and their relationships, allowing student answers to be matched beyond exact wording. The hybrid approach improves

grading accuracy and recognizes more valid ways of expressing the same concept compared to keyword-only methods. However, concept graphs require manual creation and subject-specific curation, limiting scalability across different domains.

2.6 AI-Assisted Online Examination and Evaluation Platforms

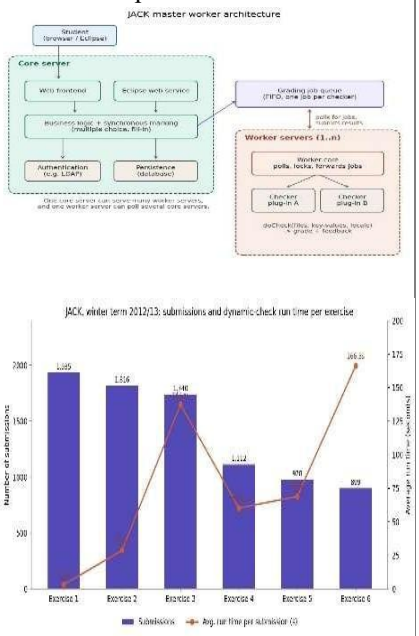
Paper Details	Objective used	Technology used	Methodology used	Efficiency
Title: AI-Assisted Online Examination and Evaluation Platforms Authors: Author, F. et al. Journal: IEEE Trans. on Learning Technologies Year: 2023 URL: https://www.sciencedirect.com/science/article/pii/S0 167642316300260?  	• Review End-to-End Platforms: to review existing AI-assisted online examination and evaluation platforms as a whole, not just individual components. • Propose a Modular Architecture: to propose a modular architecture combining OCR, NLP and ML scoring that other systems can be built on. • Support Multiple Institution Sizes: to Design an architecture that generalizes across institutions of different scale.	• OCR Module: used for text extraction from uploaded or scanned examination scripts. • NLP Module: used for processing and analyzing extracted answer text. • ML Scoring Module: machine learning models used for the final automated scoring stage of the platform.	• Modular Pipeline Design: the platform is structured as upload, OCR, NLP, scoring and analytics as separate, connected modules. • Comparative Platform Review: multiple existing AI-assisted evaluation platforms are reviewed and compared against this modular architecture. • Architecture Proposal: a reference architecture is proposed as a direct basis Those new systems, including Digitizer AI, can follow.	• Generalizes Well: the modular upload-OCR-NLP-scoring-analytics architecture generalizes well across institution sizes. • Reusable Reference Design: the proposed modular architecture serves as a direct, practical basis for building new evaluation platforms. • Clear Separation of Concerns: separating OCR, NLP and scoring into distinct modules makes the platform easier to build, test and extend.
	Issues / Research Gaps			
	• Focus Area (as reviewed): End-to-end AI evaluation platforms. • Findings: Modular architectures (upload, OCR, NLP, scoring, analytics) generalize well across institution sizes. • Research Gap: Most prototypes lack production-grade dashboards, analytics, and multi-role access control - the focus of this project.			

Figure 6: AI-Assisted Online Examination and Evaluation Platforms

The paper reviews AI-assisted online examination platforms and proposes a modular architecture integrating OCR, NLP, and ML-based scoring. The system follows a structured pipeline of upload, OCR, NLP, scoring, and analytics, with each module designed to be independently developed and extended.

This modular approach provides a reusable architecture that can adapt to institutions of different sizes and directly supports the design of Digitizer AI. However, many existing systems lack production-ready dashboards, comprehensive analytics, and multi-role access control, highlighting important areas for improvement. Summary of Research Gaps Addressed by Digitizer AI Across the six reviewed papers, three recurring gaps stand out: (i) handwriting-derived OCR text remains noisy and reduces downstream grading accuracy; (ii) most systems specialize in only one stage of the pipeline (either OCR, or semantic grading, or feedback generation) rather than unifying OCR, NLP and AI scoring end to end; and (iii) very
few prototypes provide production-grade analytics dashboards, confidence-based teacher verification and multi-role access control. Digitizer AI is designed specifically to close these gaps by combining OCR preprocessing, semantic-similarity-based grading with partial credit, NLP/keyword-and-concept-based feedback generation, confidence scoring with teacher verification, and full analytics and reporting in one modular platform.

III. PROBLEM STATEMENT AND OBJECTIVES

Traditional examination evaluation is time-consuming and labour-intensive. It becomes increasingly difficult as the number of students and answer scripts grows, and it can lead to inconsistent marking, delayed results and difficulty in maintaining detailed performance records. The objectives of Digitizer AI are to: Automate answer-script evaluation using AI and OCR. Evaluate answers semantically, beyond exact keyword matching. Assign accurate marks, including partial marks. Generate instant feedback for students. Flag low-confidence evaluations for teacher verification. Provide performance analytics and identify common mistakes. Reduce evaluation time and manual workload while improving consistency.

IV. DOMAIN ANALYSIS

Aspect	Description
Domain	Artificial Intelligence and Machine Learning
Sub-Domain	Natural Language Processing (NLP) and Educational Technology (EdTech)
Technologies	OCR, NLP, Semantic Similarity, Machine Learning / Large Language Models
Application Area	Automated examination and assessment
Key Focus	Answer evaluation, automated grading, feedback and performance analytics
Target Users	Teachers, evaluators, educational institutions and students

V. PROPOSED SYSTEM DESIGN AND ARCHITECTURE

Digitizer AI follows a layered architecture (Fig. 1). Users (teachers/evaluators, administrators and students) interact with a web front end offering a dashboard, file upload, review and verification screens, analytics and reports. The back end application layer contains six modules: user and file management, OCR and preprocessing, the AI evaluation engine, feedback and verification, analytics, and report generation. A data layer stores user records, uploaded files, extracted text, evaluation results and marks, analytics data, and reports and feedback. External services provide cloud storage for backup, AI/NLP APIs (LLM and similarity), a speech-to-text engine, and email/SMS notifications. A security and monitoring layer provides data encryption, access control, activity logs, backup and recovery, and system monitoring.

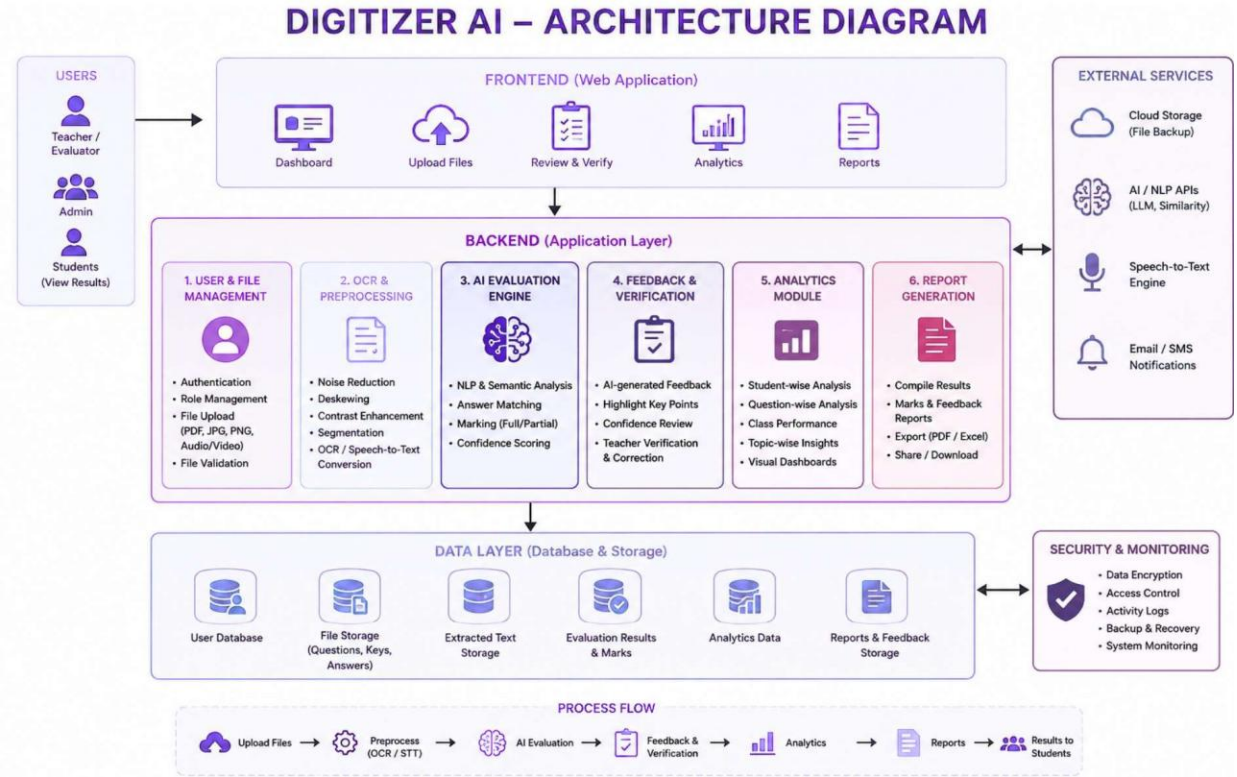


Figure 8: Architecture Diagram of Digitizer AI

Process flow: Upload Files, Preprocess (OCR / Speech-to-Text), AI Evaluation, Feedback and Verification, Analytics, Reports, and finally Results to Students.

VI. METHODOLOGY AND ALGORITHMS USED

The evaluation pipeline proceeds through the following stages: Data Input: The evaluator uploads the question paper, the answer key and the answer scripts (PDF, JPG, PNG, and audio/video where applicable). Files are validated before processing. Preprocessing: Scanned scripts undergo noise reduction, deskewing, contrast enhancement and segmentation (OpenCV) so that individual answers can be isolated. Text Extraction: Tesseract OCR or the Google Vision API converts image-based scripts into text; a speech-to-text engine handles audio submission. Extracted text is cleaned and stored. Semantic Evaluation: NLP (e.g., spaCy) and embedding-based semantic similarity (BERT/Sentence-BERT) compare each student answer with the reference answer, supported by machine learning or LLM APIs for rubric-aware reasoning. Marking: A marking module converts similarity and rubric coverage into full or partial marks for each question. Confidence Scoring and Verification: Every evaluation receives a confidence score. Low-confidence results are flagged so that teachers can review and correct them before finalization. Feedback and Analytics: Instant feedback highlights key points covered or missed. Student-wise, question-wise, class-wise and topic-wise analytics are computed and shown on visual dashboards. Reporting: Final marks, feedback and evaluation reports are compiled, stored and exported (PDF/Excel).

VII. FUNCTIONAL MODULES

User and File Management: Authentication, role management (teacher, admin, student), file upload and validation. OCR and Preprocessing: Extraction and cleaning of text from scanned or image-based answer scripts. AI Evaluation: NLP and semantic-similarity analysis, answer matching, full/partial marking and confidence scoring. Feedback and Verification: AI-generated feedback, highlighted key points, confidence review, and teacher verification and

correction. Performance Analytics: Student-wise, question-wise, class-wise and topic-wise insights through visual dashboards. Report Generation: Compilation, storage, sharing and export of final marks, feedback and evaluation reports.

VIII. TECHNOLOGY STACK AND SYSTEM REQUIREMENTS

Component	Specification
Operating System	Windows 10/11, Linux, or macOS
Frontend	React.js / HTML, CSS, JavaScript: login and dashboard, file upload, results and feedback display, analytics and reports
Backend	Python with Flask/FastAPI: file handling, OCR-based extraction, AI/NLP comparison and grading, mark calculation, feedback generation, teacher verification
AI / ML	Python, NLP, Machine Learning / LLM APIs
OCR	Tesseract OCR / Google Vision API
Database	MySQL / MongoDB: users and students, question papers and answer keys, results and marks, feedback and performance records, evaluation history
Libraries	OpenCV, NumPy, Pandas, scikit-learn
Development Tools	VS Code, Git/GitHub
Browser	Chrome / Edge / Firefox

TABLE: HARDWARE CONFIGURATION

Component	Specification
Processor	Intel Core i5 / AMD Ryzen 5 or higher
RAM	8 GB minimum, 16 GB recommended
Storage	256 GB SSD minimum
GPU	Optional; NVIDIA GPU recommended for local AI model processing
Display	Full HD (1920x1080) or higher
Scanner / Camera	Optional, for digitizing physical answer scripts
Internet	Stable broadband connection for cloud-based AI/OCR services

Usability Reduces manual evaluation time and workload for teachers. Provides consistent and faster grading using AI. Enables easy digital management of question papers and answer scripts. Supports teacher verification for reliable final results. Provides instant feedback and performance insights. Applications Schools and Colleges: automated examination evaluation. Universities: large-scale answer-script assessment. Coaching Institutes: regular test evaluation and analysis. Online Education Platforms: automated descriptive-answer grading. Competitive Exam Training: practice-test evaluation and feedback. Educational Institutions: performance tracking and academic analytics.

IX. CONTRIBUTION AND FINDINGS

Digitizer AI contributes a unified, modular pipeline that joins OCR, NLP and AI scoring with teacher verification, multi-level analytics and role-based access, the combination that the reviewed literature identifies as missing from most existing prototypes. The literature study shows that contextual, LSTM/BERT-based models agree strongly with human graders, that hybrid CNN-RNN OCR handles cursive and mixed handwriting far better than classical OCR, that embedding-based semantic similarity captures paraphrased answers that keyword matching misses, and that combining keyword and concept-graph matching reduces false negatives in rubric-based grading. Existing OCR-based evaluation surveys and end-to-end platform reviews agree that few systems integrate OCR, NLP and AI scoring into one unified pipeline with production-grade dashboards and access control. Digitizer AI responds directly to this gap with dedicated preprocessing, rubric-aware marking, confidence-based human review and full analytics. Quantitative evaluation of the prototype (for example, agreement with human graders using Pearson correlation or Quadratic Weighted Kappa, and OCR quality using character and word error rates) is planned as the next phase of the project.

X. CONCLUSION AND FUTURE SCOPE

Digitizer AI demonstrates how OCR, NLP and Artificial Intelligence can be combined to turn a traditionally manual, time-consuming and inconsistent process into a fast, accurate and scalable digital workflow. By automating answer-script evaluation end

to end, from upload to analytics, the system reduces evaluator workload, minimizes bias and gives students faster and more transparent feedback, making it a practical step toward AI-driven education infrastructure. Future work includes improving handwriting recognition on poor-quality scans, supporting multiple languages, reducing the need for manual concept curation across subjects, improving partial-credit scoring for multi-part answers, and validating the system on large real examination datasets.

IMPLEMENTATION SCREENSHOTS

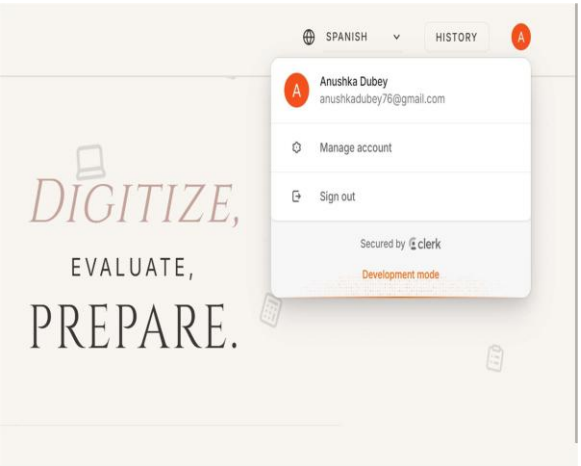


Figure 11: Authentication: Digitizer AI: AI-Powered Intelligent Examination Multi-language support:



Figure 12: Multi-language support: Digitizer AI: AI-Powered Intelligent Examination

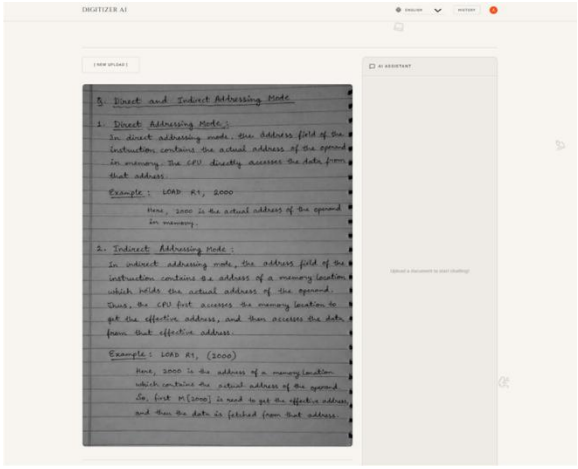


Figure 13: Digitize: Digitizer AI: AI-Powered Intelligent Examination

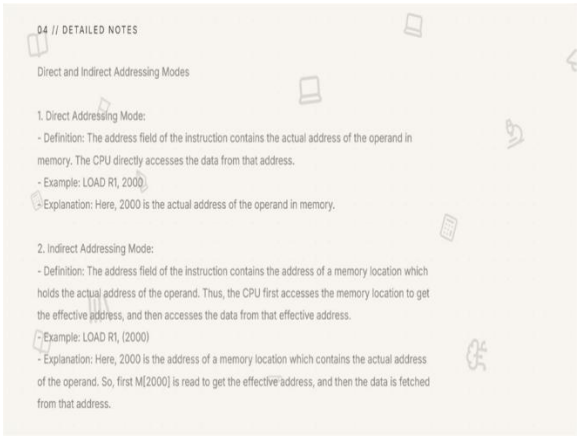


Figure 13 Digitizer AI: AI-Powered Intelligent Examination



Figure 14 Digitizer AI: AI-Powered Intelligent Examination Evaluation Report:

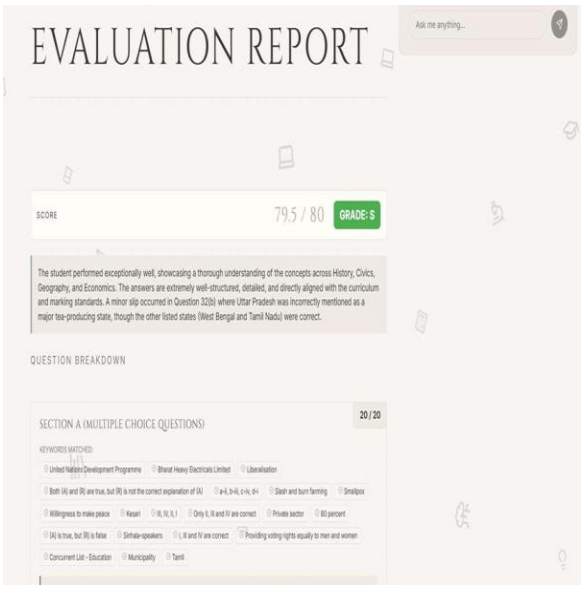


Figure 15 Digitizer AI: AI-Powered Intelligent Examination

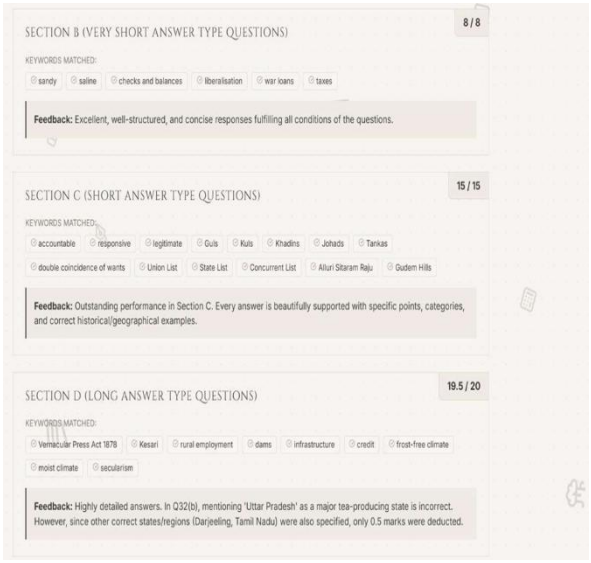


Figure 16 Digitizer AI: AI-Powered Intelligent Examination

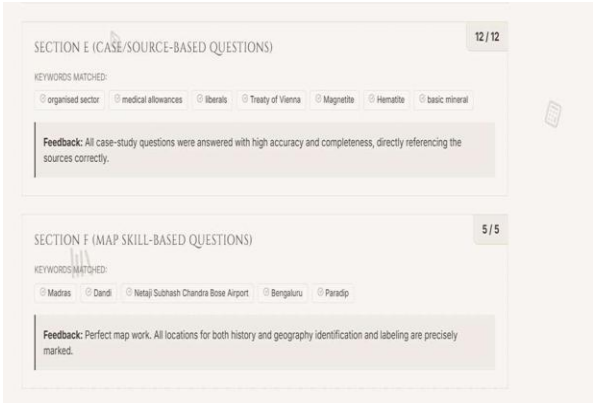


Figure 17 Digitizer AI: AI-Powered Intelligent Examination

Practice question generator:

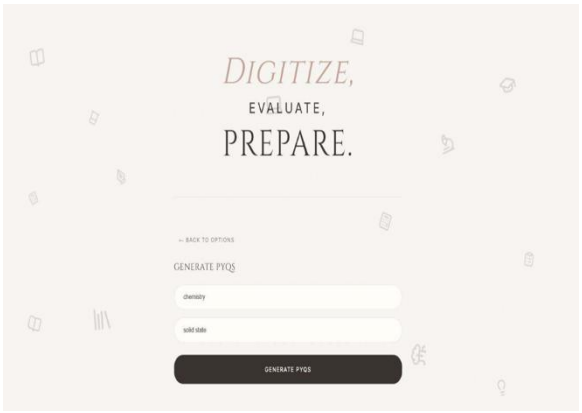


Figure 18 Practice question generator: Digitizer AI: AI-Powered Intelligent Examination

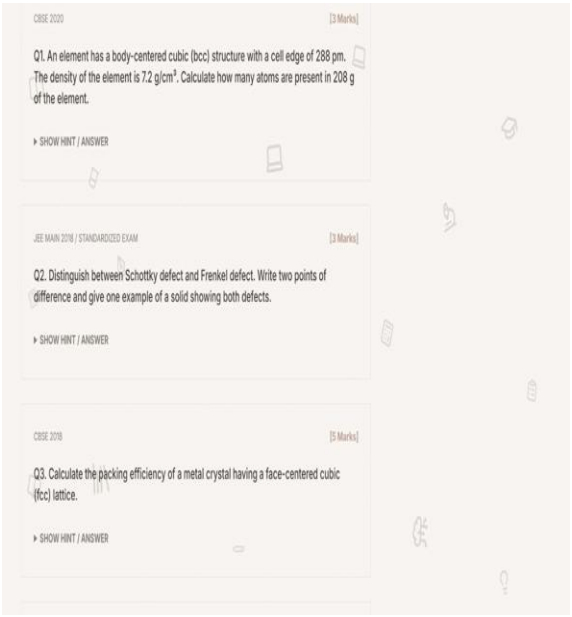


Figure 20 Digitizer AI: AI-Powered Intelligent Examination

Context-based chatbot:

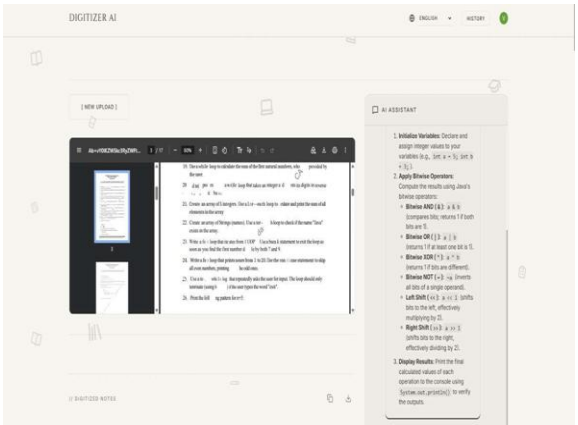


Figure 21 Context-based chatbot Digitizer AI: AI-Powered Intelligent Examination

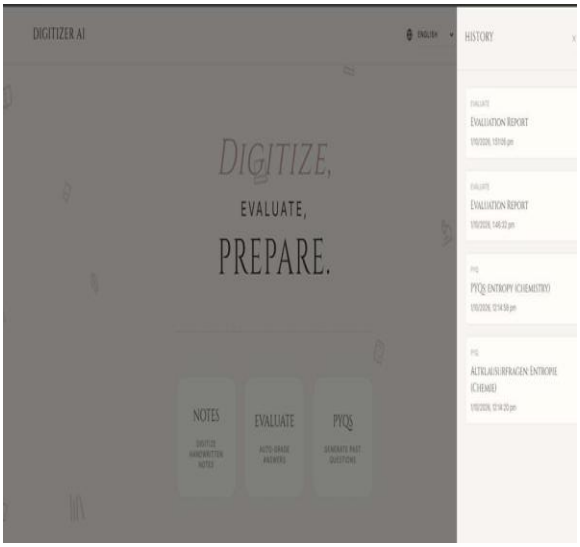


Figure 22 Digitizer AI: AI-Powered Intelligent Examination

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