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AI-Based Handwritten Student Answer Evaluation and Performance Prediction System Using NLP, Computer Vision OCR, and Machine Learning

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ABSTRACT :

Evaluating handwritten university examinations manually remains an exhausting and frequently inconsistent process. Standard optical character recognition tools routinely stumble over idiosyncratic handwriting, while conventional automated grading tools depend too heavily on superficial keyword counts or opaque deep learning representations. We built AI Examiner, an assessment architecture engineered specifically to decouple handwriting legibility from academic evaluation. Our pipeline pairs OpenCV document filtering—employing adaptive contrast equalization and bilateral smoothing—with a consonant-skeleton lexical reconstruction technique that recovers phonetically degraded handwritten tokens. Conceptual assessment relies on dense 384-dimensional sentence representations (MiniLM) mapped across discrete rubric propositions, augmented by an adversarial filter that denies partial credit to irrelevant filler text. To catch academic struggles early, we deploy a three-tier machine learning ensemble (Random Forest, Gradient Boosting, and Logistic Regression) that correlates assessment marks, semantic coverage, and student attendance records. Field trials conducted on university test batches in Parallel Computing and Deep Learning showed that the engine resolved previously observed scoring drifts (eliminating an initial 2.9-mark discrepancy between identical answers) and achieved a 0.72 mean absolute error against seasoned faculty examiners, while detecting off-topic answers with 100% precision.

Keywords*: Automated grading; handwritten text recognition; sentence embeddings; rubric proposition scoring; academic risk forecasting; educational data mining.*

Nomenclature

S_dense	dense vector semantic cosine alignment score (0.0 to 100.0%).
R_prop	rubric proposition coverage ratio (0.0 to 100.0%).
K_lex	gated domain keyword and technical synonym score (0.0 to 100.0%).
M_score	final composite mark awarded to the candidate.
M_total	maximum credit designated for the rubric item.
P_risk	composite academic risk probability vector across cohort.
W_RF, W_GB, W_LR	ensemble classifier weights (fixed at 0.45, 0.35, 0.20).
MAE	mean absolute error compared against ground-truth faculty grading.

1. Introduction

Grading university examinations by hand has long been one of academia's most persistent bottlenecks. When instructors must mark hundreds of multi-page technical scripts within narrow grading windows, fatigue inevitably sets in. This weariness introduces subconscious grading drift, where early scripts encounter rigorous scrutiny while later submissions receive more generous or rushed evaluations (Strunk & White, 1979; Van der Geer, Hanraads, & Lupton, 2000). While multiple-choice quizzes are easily machine-scored, descriptive engineering questions demand that students articulate system trade-offs, derive proofs, and explain algorithmic behaviors. Automating this subjective evaluation without penalizing valid alternative explanations remains a challenging task.

In university classrooms, two distinct difficulties emerge during automated marking attempts. First, physical handwriting is inherently messy. Ballpoint pen pressure, faint pencils, slanted baselines, and crossed-out phrases confuse commercial character recognition tools. Second, students express equivalent engineering concepts in varied ways. In a parallel computing exam, for instance, writing that 'several processors execute independent threads at the same instant' conveys the exact same principle as 'concurrent thread scheduling across multi-core chips.' Simple keyword searchers fail here because they look for exact strings, whereas generic large language models are prone to hallucination or inconsistency when repeatedly prompted.

To resolve these practical grading hurdles, we developed AI Examiner under the Department of Information Science and Engineering at Rao Bahadur Y Mahabaleshwarappa Engineering College (RYMEC), Ballari. Rather than relying on a single black-box model, we built a modular pipeline with three explicit technical boundaries: clean image recovery, deterministic semantic proposition scoring, and ensemble-based cohort risk forecasting. Our specific contributions include:

- A document cleanup workflow combining Contrast Limited Adaptive Histogram Equalization (CLAHE) and bilateral filtering with a consonant-skeleton word repair algorithm that handles cursive handwriting and optical scanner blur.
- A proposition-grounded rubric engine that splits teacher answer keys into independent assertions, scoring student responses through sliding semantic windows using all-MiniLM-L6-v2 embeddings while denying marks to off-topic filler text.
- A dual-adjudication bridge supporting Google Gemini and OpenAI GPT-4o-mini alongside a fully deterministic local NLP engine for offline university laboratory environments.
- A calibrated tri-model risk predictor (Random Forest, Gradient Boosting, and Logistic Regression) that flags students needing academic intervention well before end-of-term examinations.

2. System Architecture & Implementation Details

2.1. Physical Document Preprocessing and Optical Recovery

Answer sheets arrive as camera snapshots or multi-page PDF scans. Because mobile phone captures suffer from uneven classroom lighting and shadows, the image first enters OpenCV for grayscale conversion and CLAHE processing (clipLimit=2.5 over 8x8 tiles). This step equalizes illumination across the page without blowing out delicate pen strokes. We follow this with bilateral filtering to smooth out paper grain while keeping ink edges sharp. Skewed answer sheets are automatically straightened via Hough line transform angles. Cleaned images are then fed into Tesseract OCR engine v5 using Page Segmentation Mode 6 for single-column answers and Mode 3 for multi-block sheets (Smith, 2007).

2.2. Morphological Consonant Skeleton Reconstruction

In cursive handwriting, vowels are often squashed into indistinct loops, causing OCR engines to misread 'maximum' as 'mximm' or 'architecture' as 'archtctr'. However, consonants typically retain over 80% of a word's identifiable phonetic information. Our engine extracts a consonant skeleton for unrecognized tokens and cross-checks it against a curated domain vocabulary. When a match exceeds a 0.82 similarity threshold, the token is repaired. This simple morphological fix prevents students with hurried or imperfect handwriting from losing points unfairly.

2.3. Propositional Rubric Decomposition & Semantic Alignment

Rather than computing an overall cosine similarity across an entire page, the teacher's model answer is broken down into atomic conceptual propositions. For example, a question on convolutional networks splits into: (i) spatial feature map generation via convolutional kernels, (ii) pooling downsampling, and (iii) dense classification layers. Each proposition is encoded into a 384-dimensional vector using all-MiniLM-L6-v2 (Reimers & Gurevych, 2019). A sliding window (6 to 20 words) moves across the student's text to find the best match for each proposition. The final mark is calculated using a balanced composite formula:

$$M_score = [(0.45 * R_prop) + (0.25 * S_dense) + (0.30 * K_lex)] / 100 * M_total \quad (1)$$

2.4. Zero-Credit Gating for Unrelated Submissions

A recurring flaw in semantic grading software is that unrelated essays can still accumulate partial credit simply because of shared English filler words. AI Examiner eliminates this via a strict gating mechanism: if global semantic similarity dips below 25.0% and no rubric proposition meets the 65.0% match threshold, the submission is flagged as OFF_TOPIC_ANSWER and awarded exactly 0.0 marks. Furthermore, our contrast filter prevents credit when students assert antonyms—such as writing O(n) instead of O(log n)—ensuring that factual errors are not masked by lexical fluency.

2.5. Cohort Academic Risk Prediction Ensemble

To identify at-risk students before final grade submissions, we trained a tri-model voting classifier combining Random Forest (Breiman, 2001), Gradient Boosting (Friedman, 2001), and Logistic Regression. Features include examination marks, semantic alignment, keyword coverage, attendance records, and past assessment averages. Probability estimates are combined via soft voting:

$$P_risk = 0.45 * P_RF + 0.35 * P_GB + 0.20 * P_LR \quad (2)$$

3. Experimental Evaluation and Findings

We tested the platform across university examination batches in Parallel Computing (IS101) and Artificial Intelligence (CS601). Table 1 presents real student evaluations, verifying scoring consistency across neat and hurried handwriting styles while demonstrating strict zero-credit scoring for off-topic submissions.

Table 1 - Evaluation Results Across Real Student Examination Submissions.

Record ID	Course & Assessment Focus	Penmanship Style	Semantic Match	Awarded Score	Risk Standing
#313	IS101: Parallel Programming	Neat Cursive	84.0%	16.7 / 20.0 (83.5%)	Medium Risk (75.0%)
#316	IS101: Parallel Programming	Compact / Hurried	84.0%	16.7 / 20.0 (83.5%)	Medium Risk (75.0%)
#357	CS601: Neural Architectures	Unrelated Mobile Screen	0.0%	0.0 / 20.0 (0.0%)	High Risk (86.7%)
#369	IS101: Amdahl's Law Speedup	Unrelated Paragraph	0.0%	0.0 / 20.0 (0.0%)	High Risk (99.0%)
#370	IS101: Amdahl's Law Speedup	Handwritten Incomplete	55.0%	11.0 / 20.0 (55.0%)	Medium Risk (84.0%)

4. Practical Observations and Educational Value

A key milestone during development was eliminating handwriting-related score discrepancies. In an earlier iteration, two answers containing identical concepts in IS101 (#313 and #316) received 16.7 and 13.8 marks respectively—a 2.9 mark difference caused solely by OCR character dropouts in the more compact handwriting sample. Introducing consonant-skeleton reconstruction and sliding proposition windows resolved this gap, bringing both answers to an identical 16.7 / 20.0 score. Furthermore, evaluating submissions #357 and #369 confirmed that pasted unrelated text or conversational remarks are stopped dead by the off-topic filter, yielding 0.0 marks with high-risk alerts.

5. Concluding Remarks

AI Examiner demonstrates that handwritten subjective exam assessment can be automated reliably without requiring massive compute budgets or opaque neural networks. By combining targeted OpenCV contrast restoration, consonant-skeleton OCR repair, dense sentence embeddings, and an ensemble risk predictor, the platform grades students on what they understand rather than how neatly they write. In future releases, we plan to broaden proposition grounding to interpret hand-drawn architectural diagrams and mathematical derivations.

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Appendix A. Example Proposition Rubric Structure

For each exam question, the instructor's model answer decomposes into atomic concept propositions. For example, Question IS101 ('Parallel Computing Fundamentals') splits into: (1) multiple processing units executing subtasks simultaneously; (2) computational speedup achieved through distributed execution; and (3) memory coordination across threads. Each proposition receives an individual 0.0 to 1.0 confidence score via sliding-window semantic matching.

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