# EDU-CIRCUIT-HW: Evaluating Multimodal Large Language Models on Real-World University-Level STEM Student Handwritten Solutions

**Anonymous ACL submission**


## Abstract

Multimodal Large Language Models (MLLMs) hold significant promise for revolutionizing traditional education and reducing teachers' workload. However, accurately interpreting unconstrained STEM student handwritten solutions with intertwined mathematical formulas, diagrams, and textual reasoning poses a significant challenge due to the lack of authentic and domain-specific benchmarks. Additionally, current evaluation paradigms predominantly rely on the outcomes of downstream tasks (e.g., auto-grading), which often probe only a subset of the recognized content, thereby failing to capture the MLLMs' understanding of complex handwritten logic as a whole. To bridge this gap, we release `EDU-CIRCUIT-HW`, a dataset consisting of 1,300+ authentic student handwritten solutions from a university-level STEM course. Utilizing the expert-verified verbatim transcriptions and grading reports of student solutions, we simultaneously evaluate various MLLMs' upstream recognition fidelity and downstream auto-grading performance. Our evaluation uncovers an astonishing scale of latent failures within MLLM-recognized student handwritten content, highlighting the models' insufficient reliability for auto-grading and other understanding-oriented applications in high-stakes educational settings. In solution, we present a case study demonstrating that leveraging identified error patterns to preemptively detect and rectify recognition errors, with only minimal human intervention (approximately 4% of the total solutions), can significantly enhance the robustness of the deployed AI-enabled grading system on unseen student solutions.


## 1 Introduction

Recent cutting-edge multimodal large language models (MLLMs) have demonstrated near-human performance over a wide range of low-stakes, daily visual understanding tasks. However, as the focus shifts to high-stakes, precision-critical domains, the visual understanding of these MLLMs remains insufficiently robust and inadequately evaluated. One particularly challenging and underexplored setting is university-level STEM (Science, Technology, Engineering, and Mathematics) student handwritten solution understanding, where the model must interpret the complex, interleaved "visual language" consisting of unconstrained handwriting,

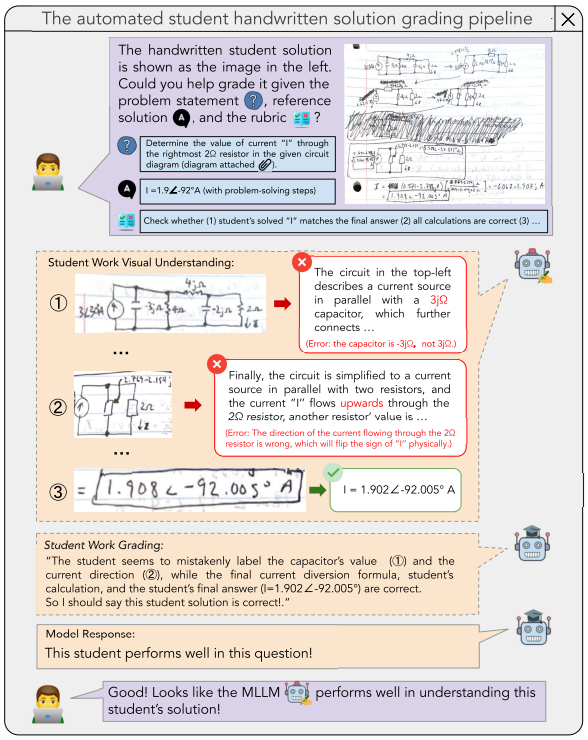


Figure 1: An exemplary STEM student handwritten solution auto-grading workflow: MLLM (e.g., `Gemini-2.5-Pro`) recognizes ①, ②, ③, and other visual contents of the solution, which serve as inputs for the consequent AI grading. Notably, recognition errors (① and ②) may not influence the grading if they fall outside the specific grading criteria. As a result, this successful grading masks underlying recognition failures, leading users to overestimate the MLLM's visual understanding performance on the student solution.

intricate mathematical derivations, and hand-drawn diagrams. The interpreted content further serves as input to consequent downstream tasks such as auto-grading (Kortemeyer et al., 2024; Khrulev, 2025) as shown in Figure 1. To this end, a reliable and trustworthy MLLM-based workflow to understand student handwritten solutions is a longstanding ambition in AI-enabled education.

Despite the potential of MLLMs, evaluating their effectiveness in real-world university settings faces two critical hurdles. First is the scarcity of proper authentic data. Most existing benchmarks fall short of capturing the complexity of real-world student handwritten work. For instance, many benchmarks (Xie et al., 2023; Gervais et al., 2025) focus on isolated visual elements (e.g., a single mathematical expression in Figure 1 ③) rather than the tightly interleaved reasoning processes characteristic of authentic student works (e.g., the entire input student solution in Figure 1). In addition, these benchmarks often omit or oversimplify hand-drawn diagrammatic understanding (e.g., ① and ② in Figure 1), despite diagrams playing a critical role in many STEM domains. Moreover, many prior benchmarks (Baral et al., 2025) target relatively low-difficulty settings such as K–12-level math. As a result, they fail to reflect the challenges posed by college STEM handwritten assignments. Consequently, such benchmarks provide limited insight into the true visual understanding and reasoning capabilities of MLLMs under realistic, high-stakes educational conditions.

Second, there is a fundamental misalignment in evaluation paradigms. Most existing benchmarks for student handwritten solution understanding focus on a single downstream objective (e.g., VQA (Baral et al., 2025) or auto-grading). While these task-specific evaluations are valuable, such downstream tasks often probe only a subset of the recognized content, leaving many recognition errors unobserved if they do not affect the specific task outcome. One such example is shown in Figure 1, where recognition errors in ① and ② are not reflected in the final grading report due to the rubric limitations. Crucially, these "negligible" errors in the auto-grading task may be catastrophic for other downstream tasks, such as circuit-to-netlist transformation (Xu et al., 2025).

To bridge the abovementioned gaps, we introduce `EDU-CIRCUIT-HW`, a diagnostic dataset grounded in real-world university STEM education, which comprises 1334 authentic student handwritten solutions to complex circuit analysis problems. To enable fine-grained MLLM visual recognition ability analysis, we curated near-verbatim transcriptions for a data subset and utilize them as the reference to capture different MLLMs' errors in their recognized student solutions. Moreover, we build a taxonomy for these captured errors and evaluate their cascading impact on a downstream auto-grading task.

Our evaluation reveals a pervasive presence of latent recognition errors beneath current grading outcomes. Although these failures may remain dormant under coarse assessment criteria (e.g., binary correctness check), they become increasingly detrimental as grading granularity refines (e.g., specific, targeted score deduction), where higher precision inevitably exposes these underlying defects and degrades grading quality. This finding indicates that reliable student solution understanding and its applications remain a distant goal. In solution, we demonstrate the feasibility to detect and suppress unseen potential recognition failures via our identified error patterns in a case study.

Overall, our contributions are summarized as follows:

i) We release `EDU-CIRCUIT-HW`, a dataset of 1300+ authentic university-level STEM solutions, facilitating the evaluation of MLLMs' visual understanding capabilities in real-world educational scenarios.

ii) We conduct a comprehensive evaluation of various cutting-edge MLLMs' capabilities in handwriting understanding and downstream auto-grading on `EDU-CIRCUIT-HW` via a proposed automated diagnostic workflow. By establishing a fine-grained taxonomy of visual perception failures, we systematically analyze the cascading impact of recognition errors on the downstream auto-grading, which uncovers the latent risks concealed by seemingly robust downstream performance.

iii) We conduct a targeted case study to demonstrate that the identified error patterns can be leveraged to detect and prevent MLLMs' recognition failures over unseen student solutions, thereby enhancing the reliability of deployed grading systems.

## 2 The `EDU-CIRCUIT-HW` Dataset

This section introduces the `EDU-CIRCUIT-HW` dataset for evaluating MLLMs' capabilities on university-level STEM handwritten solution recognition and downstream auto-grading tasks.

## 2.1 Handwritten Solution Collection

The EDU-CIRCUIT-HW dataset consists of 1334 handwritten homework solutions from 29 students in an undergraduate-level circuit analysis course at a large, public, research-intensive institution in the Southeast United States during the Spring 2025 semester. The homework problems are all from the textbook (Svoboda and Dorf, 2013) with the topics varying from the basic circuit concepts and elements to advanced topics such as the first- and second-order circuit analyses. Each handwritten solution figure in this dataset corresponds to one student's submission to a specific homework problem. In the pre-processing step, we removed the personally identifiable information of students, including students' names and university IDs, from the solution images. All the students' solutions are associated with expert-labeled reference grades in five different aspects, making the dataset able to be used to verify the performance of MLLM-enabled auto-graders, as illustrated in Section 3.2. Since students may leverage matrix theory, calculus, complex operations, and hand-drawn diagrams when solving the circuit problem, the benchmarks and analyses built on the EDU-CIRCUIT-HW can also be extended to other related STEM areas beyond circuit analyses.

## 2.2 Dataset Statistics

There are two data groups in the EDU-CIRCUIT-HW dataset: observation set and test set. The observation set consists of 513 handwritten solutions from 11 students. Each solution in the observation set is associated with detailed grades and image recognition results, of which both are verified and proofread manually by experts, as detailed in Section 3. Particularly, the expert-proofread recognition contains a near-verbatim transcription of all student-handwritten content, including natural-language descriptions for any non-textual elements such as hand-drawn circuit diagrams with annotations or function graphs. Since the recognized content is manually verified, the observation set can be regarded and utilized as a "training set" from which we can summarize the recognition patterns and use them to further improve the performance of both recognition and automated grading, as illustrated in Sections 3–5. In addition to the observation set, the 821 samples from the remaining 18 students constitute the test set, in which each handwritten solution is associated with a ground truth grade but not expert-verified recognition. Table 1 summarizes some key attributes of these two data groups.

| Attribute | Observation Set | Test Set |
|---|---|---|
| Number of Unique Questions | 62 | 62 |
| Number of Students | 11 | 18 |
| Number of Samples | 513 | 821 |
| w/ Verified Recognition | ✓ | ✗ |
| w/ Ground Truth Grade | ✓ | ✓ |
| Student's Solution Accuracy | 72.12% | 71.86% |

Table 1: Key attributes of the observation and test sets in EDU-CIRCUIT-HW.

# 3 Handwritten Solution Recognition and Automated Grading Framework

Section 2 describes the collection and basic statistics of the EDU-CIRCUIT-HW dataset. In this section, we first detail how the handwritten solution can be effectively recognized by prompting MLLMs strategically. We then describe how the recognition errors can be classified into four well-defined categories and propose a method to investigate their impact on the downstream auto-grading task.

## 3.1 Handwritten Solution Recognition

Reliable handwritten solution recognition is essential and further affects the downstream task, such as homework auto-grading. However, even the most cutting-edge MLLMs perform poorly on STEM handwritten homework solution recognition tasks (Baral et al., 2025; Caraeni et al., 2024).

In this section, we analyze MLLMs' recognition performance in a more fine-grained view. To this end, after obtaining MLLMs' recognition results for the observation set, we build an LLM-as-a-judge pipeline to locate all potential recognition errors, which directly reflect the handwritten segments that the MLLM has trouble recognizing, as shown in Figure 2. Specifically, we first prompt Gemini-2.5-Pro to recognize the image-based students' solution submissions and output the resulting textual descriptions in the Markdown format. In this process, the equations and texts are prompted to be recognized verbatim, and the diagrams, if existing, are interpreted in natural language that contains the full diagram information, such as the circuit topology and students' annotations. The recognition results are then manually proofread against the original handwritten images by experts who are also responsible for rectifying the identified recognition errors, such as wrong diagram

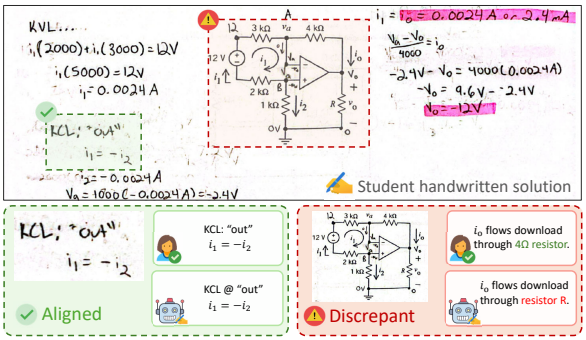


Figure 2: The demonstration on our recognition error detection. Given a handwritten solution, the MLLM's recognition result is compared with the expert-verified transcriptions in a full-text level, after which all discrepant items within the recognition result are listed as recognition errors. Note that we regard two items as aligned when they are semantically equivalent in engineering education (e.g., KCL: "out" and KCL: @ "out" are regarded as semantically aligned despite the additional "@").

depictions or equations, by saving the rectified version in new Markdown files.

The expert-proofread Markdown files serve as the ground truth to assist an LLM-judger, which we use `Gemini-2.5-Pro`, to capture the potential recognition errors from the evaluated MLLM. Specifically, for each handwritten solution, we provide the LLM-judger with both the verified recognition and the evaluated MLLM's recognition and ask the LLM-judger to list all potential discrepant recognition items between them. Note that an item in this scenario can be either a sentence or an equation. Some item examples can be found in Figure 17 in Appendix D.

### 3.1.1 LLM-as-a-Judge Method Validation

In order to verify the LLM-judger's reliability, we further manually check the recognition discrepancies and compare the identified discrepancies with those listed by the LLM-judger. The comparisons are made at two levels: sample level and item level. The sample level aims to measure the agreement between the LLM-judger and human experts in determining whether a handwritten recognition result contains any recognition errors. We use a binary indicator to describe this agreement. The item level focuses on whether each individual recognition error annotated by human experts (e.g., the discrepant case shown in Figure 2) can be detected by the LLM-as-a-judge method. At this level, we evaluate error detection performance using the precision,

| Model | Sample | Item-Level Metrics | | | | | |
|---|---|---|---|---|---|---|---|
| | Accuracy | TP | FP | FN | Precision | Recall | F1 Score |
| GPT-5.1 | 0.9516 | 97 | 6 | 10 | 0.9417 | 0.9065 | 0.9238 |
| Claude-4.5-Sonnet | 0.9839 | 137 | 13 | 15 | 0.9133 | 0.9013 | 0.9073 |
| Qwen3-VL-Plus | 0.9516 | 62 | 7 | 5 | 0.8986 | 0.9254 | 0.9118 |
| **Total** | **0.9624** | **296** | **26** | **30** | **0.9193** | **0.9080** | **0.9136** |

Table 2: Validation results of the automated recognition error detection via LLM-judgers against expert annotations across 186 handwritten solutions from three MLLMs.

recall, and the F1 score, i.e.,

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (1)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (2)$$

$$\text{F1 Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (3)$$

where true positives (TP) are recognition errors identified by both the human expert and the LLM-judger, false positives (FP) are errors reported by the LLM-judger but not annotated by the human experts, and false negatives (FN) are errors annotated by the human experts but missed by the automated LLM-judger.

The comparison is conducted with over 186 recognized handwritten solution samples containing more than 5000 items. Specifically, we sample one student's solution randomly for all the 62 problems in our dataset and prompt 3 commercial MLLMs (`GPT-5.1`, `Claude-4.5-Sonnet`, and `Qwen3-VL-PLUS`) to make recognitions. For each recognized result, an expert manually annotates all recognition errors (like those discrepant items in Figure 2). These annotations are then used to evaluate the performance of LLM-judger at both sample and item levels. The results are shown in Table 2, which indicates both high sample-level accuracy (larger than 0.95 on all three models) and item-level consistency (precision, recall, and the F1 score are all close to or larger than 0.9 on three models). A closer inspection also indicates that false positives and false negatives are predominantly associated with ambiguous items rather than reflecting systematic misjudgments. These results suggest that the LLM-as-a-judge pipeline is highly reliable and thus enables automated evaluation of handwritten recognition performance of different MLLMs with human-level consistency.

| Category | Introduction & Example |
|---|---|
| **Symbolic & Character** | Misreading alphanumeric glyphs, operators, or units. Example: $20000 \rightarrow 2a000$; $-V \rightarrow V$ |
| **Structural & Notational** | Wrong mathematical layout or variable consistency. Example: $\mathrm{R} = \frac{\frac{1}{8}}{\frac{1}{8}+\frac{1}{16}}\Omega \rightarrow \mathrm{R} = \frac{8}{8+16}\Omega$ |
| **Diagrammatic** | Misinterpretation of diagram space attributes or annotations. Example: Erroneous circuit topology. |
| **Textual & Logical** | Mislabeling context or sequence of reasoning. Example: Omission of critical derivation steps |

Table 3: Taxonomy of recognition errors. More examples with image illustrations are available in Tables 8–11 in Appendix D.5.

### 3.1.2 Taxonomy on Recognition Errors

Recognition errors vary from trivial character mistakes to severe logical misunderstandings. To gain detailed insights, we further divide the recognition errors into four categories in Table 3. An LLM is prompted with clear category definitions to categorize all discrepant items in an automated way. With this taxonomy, we can observe the distribution of errors among different recognitions, which reveals the weaknesses of current MLLMs.

## 3.2 Downstream Task: Automated Grading

Section 3.1 described the methods of handwritten solution recognition and detection for recognition errors. In this section, we will explore how the upstream recognition errors affect the downstream task, which is helpful to minimize the negative effect of the recognition errors and boost the downstream task performance.

In this work, we consider auto-grading as the downstream task, a process widely implemented across educational institutions worldwide. Specifically, we use an LLM-based grader, which is provided with MLLM-recognized student solutions and the problem context to assess student performance on the given problem. In our settings, the problem context includes the problem description, reference solution, and grading rubrics. The auto-grader's reports are then compared with expert-verified reference grades available in the dataset, as described in Section 2.1.

In the `EDU-CIRCUIT-HW` dataset, each student's handwritten solution was evaluated by a human expert based on a multi-dimensional rubric that covers five distinct perspectives of assessment as shown in Table 4. With these five grading aspects, the rubrics are defined to be problem-specific by using a unique rubric for each problem in our dataset. Given the rubric, the human expert will deduct scores for those students' submissions violating the rubric per perspective. For example, "`{E:0.02pts, U:0.01pts}`" indicates that the student might use a wrong equation (e.g., incorrect Ohm's Law "$R = \frac{I}{V}$") and an incompatible unit (e.g., using "voltage" instead of "ampere" to describe a current). These expert-verified grading results can serve as ground truth to evaluate the performance of the auto-grading pipeline.

| Type | Description |
|---|---|
| **E** | Equation Error: Incorrect or inapplicable equations |
| **M** | Method Error: Flawed problem-solving logic |
| **U** | Unit Error: Missing or incorrect units |
| **C** | Calculation Error: Wrong arithmetic with the correct equation |
| **NC** | Incomplete Solution: Incomplete answer or missing steps |

Table 4: The rubric for grading students' work. A student's solution can violate multiple standards in the table and get scores deducted separately. A rubric example can be found in Figure 19 in Appendix D.

# 4 Experiments

This section shows the experiments on the observation set that includes the expert-proofread recognition results. Specifically, we conduct detailed analyses of recognition errors across various cutting-edge MLLMs and examine their relationship to downstream auto-grading performance.

## 4.1 Experiment Setup

In this experiment, we analyze the recognition capabilities of different cutting-edge MLLMs on students' handwritten solutions in the observation set of `EDU-CIRCUIT-HW`. Specifically, we use the LLM-as-a-judge detector (introduced and validated in Section 3.1) to identify recognition errors in the "MLLM recognized text" as illustrated in Figure 3. For each model, we count the number of recognition errors, categorize their types, and examine their relationship with downstream grading outcomes. All grading results are obtained using the vanilla grading pipeline in Figure 3.

We evaluate five closed-source commercial models (`Gemini-3-Pro-Preview`, `Gemini-2.5-Pro`, `Qwen3-VL-PLUS`, `Claude-4.5-Sonnet`, and `GPT-5.1`) and one open-source model (`Qwen3-VL-8B-Thinking`) as MLLM recognizers in Figure 3. Additionally, we include an oracle baseline in which expert-proofread transcriptions are provided to the LLM grader, representing grading performance under perfect recognition. We use

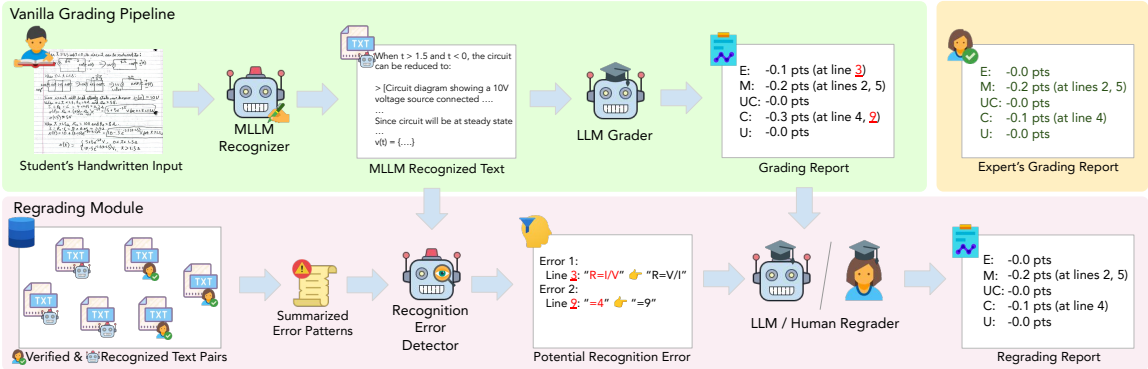


Figure 3: The proposed auto-grading pipeline. The "vanilla grading pipeline" in green box is a widely-used auto-grading paradigm in AI-enabled education field. In our experiment (Section 4), we detect and analyze recognition errors within "MLLM Recognized Text" utilizing the automated pipeline introduced in Section 3.1, and further evaluate "Grading Report" by benchmarking it against the "Expert's Grading Report" in yellow box. In pink box, we present an exemplary regrading module where we summarize the detected recognition error patterns and leverage it to filter out potential recognition errors within "MLLM Recognized Text", and let LLM/human regraders to reassess those solutions flagged with containing potential recognition error, more details can be found in Section 5.

| Grader | Visual Recognizer | Recognition Quality | | Grading Performance | | | EIR (%)↓ |
|---|---|---|---|---|---|---|---|
| | | SER (%)↓ | AEC↓ | Binary (%)↑ | Type (%)↑ | Point (%)↑ | |
| Graduate | – | – | – | 83.63 | **82.46** | **81.29** | – |
| GPT-5.1 | Human Expert | – | – | **89.47** | 78.36 | 74.46 | – |
| | Gemini-3-Preview | **37.62** | **0.61** | 87.91 | 78.17 | 74.27 | 7.60% |
| | Gemini-2.5-Pro | 53.52 | 1.23 | 85.58 | 73.68 | 69.40 | 14.72% |
| | GPT-5.1 | 71.54 | 2.05 | 77.78 | 65.50 | 61.99 | 17.89% |
| | Qwen3-VL-Plus | 61.72 | 1.38 | 80.90 | 68.62 | 65.11 | 16.67% |
| | Claude-4.5-Sonnet | 80.70 | 2.76 | 77.58 | 63.16 | 59.84 | 18.05% |
| | Qwen3-VL-8B-Thinking | 85.43 | 2.79 | 75.05 | 61.01 | 56.92 | 19.60% |

Table 5: Overall evaluation results of different MLLMs' recognition quality on student handwritten works in EDU-CIRCUIT-HW (the observation set), and their impact (i.e., Error Impact Rate (EIR)) on the downstream grading performance. We further add two baselines: (1) A Graduate student grades directly on all handwritten samples and (2) Human Expert recognizes and provides the "gold standard" recognized text for the LLM grader for reference. For metrics, we adopt Sample Error Rate (SER) and Average Error Count (AEC) to evaluate recognition quality, and binary, type, and point agreements to evaluate grading performance. The **bold** values are the best scores across different metrics. The detailed taxonomic EIR analysis over different error categories is detailed in Figure 4.

GPT-5.1 as the LLM grader in all settings. More details can be found in Appendix D.

**Comparison With Human Grader** In addition, we include the grades assigned by the graduate teaching assistant (denoted as Graduate in Table 5) in the data collection course. This serves as a strong baseline, enabling us to assess how far current cutting-edge MLLM-based auto-graders have progressed in handling relatively challenging university-level problems.

**Recognition Quality and Grading Metrics** We evaluate recognition performance at two granularities: Sample Error Rate (SER) and Average Error Count (AEC). SER measures the proportion of recognized texts containing at least one recognition error, while AEC represents the item-level average number of errors per handwritten solution.

To evaluate grading performance, based on the rubric introduced in Table 4, we measure the agreement between the LLM and expert grading reports at three levels: (1) Binary Agreement: Evaluates whether the model correctly identifies the presence of any student mistakes; (2) Type Agreement: Requires consistency in the flagged error types (E, M, U, C, NC); (3) Point Agreement: The strictest metric that requires exact matches in both error types and their corresponding point deductions. For example, given an LLM grading report {E:-0.1pts,M:-0.3pts} and an expert grading report {E:-0.1pts,M:-0.2pts}, binary agreement is satisfied since both identify errors, and type agreement is also satisfied since both flag the same

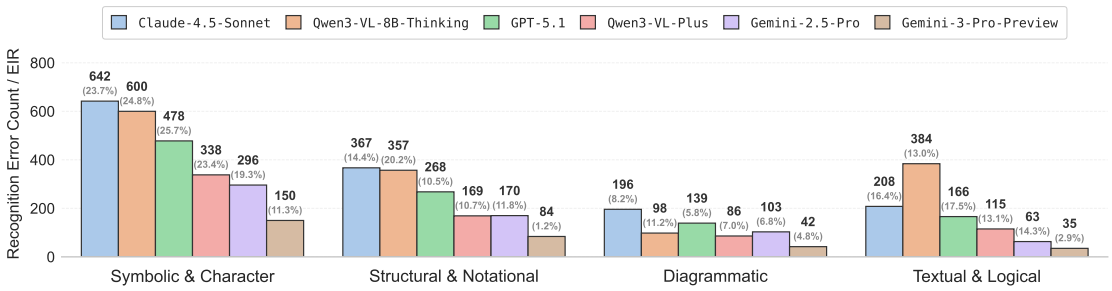


Figure 4: Comparisons of different MLLMs' recognition error counts over 4 error categories (defined in Table 3) and the corresponding error impact rate (EIR) to the downstream LLM grading performance in Table 5. The annotation above each bar presents the error count (line 1) and the EIR (line 2 in gray) of this model in the category.

error types ("E" and "M"). However, point agreement is not satisfied due to the discrepancy in the deducted score for perspective "M".

**Error Impact Analysis** To further investigate the propagation of errors from visual recognition to the final grading, we introduce the Error Impact Rate (EIR). This metric quantifies the proportion of item-level recognition errors that directly lead to a downstream grading discrepancy. It is calculated as the number of recognition errors that result in a grading error divided by the total number of item-level recognition errors identified.

### 4.2 Results and Findings

The experimental results in Table 5 reveal several key insights. First, the findings empirically support our argument that task-centric evaluation alone fails to expose the full spectrum of visual recognition errors. Although automated grading is a multi-faceted downstream task, it inherently masks a significant portion of recognition failures. For instance, while `Gemini-3-Preview` exhibits a Sample Error Rate (SER) of 37.62%, its Error Impact Rate (EIR) is merely 7.60%. Nevertheless, the recognition errors have amplified negative impacts on the downstream fine-grained auto-grading tasks. According to Table 5, with SER and EIR increasing from `Gemini-3-Preview` to `Qwen3-VL-8B-Thinking`, the grading performance gaps increase from 12.86% in the binary agreement to 17.16% and 17.35% in the type and point agreements which require the correct identification of error types and precise point deductions. Additionally, as the overall recognition deteriorates, the EIR increases from 7.60% to 19.60%. These trends imply that stronger visual understanding captures more contextually significant information from student work, thereby reducing the likelihood of catastrophic error propagation.

Second, when comparing LLM-based graders with the human graduate grader, we observe a clear divergence between coarse-grained and fine-grained assessments. State-of-the-art MLLMs (e.g., the `Gemini` series) outperform the graduate grader in the binary agreement. However, this advantage diminishes when facing more strict criteria. On the type and point agreements, even the strongest MLLMs lag behind the human grader with non-negligible performance gaps. This indicates that current MLLMs still struggle to reliably capture and reason over critical, fine-grained details in handwritten solutions, highlighting a persistent challenge in deploying LLM-based systems for precision-critical educational evaluation.

**Recognition Error Taxonomy** Based on the taxonomy defined in Table 3, we categorize the identified recognition errors to analyze their distribution and impact, as summarized in Figure 4. Unsurprisingly, recognition errors are most prevalent at the surface level, particularly in the *Symbolic & Character* category, while more complex *Diagrammatic* and *Textual & Logical* errors are less frequent. Beyond this, we observe that different MLLMs exhibit heterogeneous visual recognition capabilities. For instance, despite its smaller scale, `Qwen3-VL-8B-Thinking` demonstrates competitive performance in the *Diagrammatic* category (98 errors), even surpassing larger models like `Gemini-2.5-Pro` (103 errors). Conversely, commercial models generally excel in the *Textual & Logical* category, showcasing their superior ability to interpret high-level semantic relations and textual explanations.

In addition, the Error Impact Rates (EIRs) in Figure 4 reveal the sensitivity of grading to different error types. Notably, surface-level errors in *Symbolic & Character* have a more direct impact on grading

outcomes, with EIRs consistently around 20%. In contrast, identification failures in more complex *Diagrammatic* and *Textual & Logical* categories generally exhibit lower EIRs, frequently falling below 10%. This suggests that current auto-grading pipelines remain heavily reliant on symbolic matching rather than structural or diagrammatic reasoning. However, while diagrammatic errors appear less "impactful" for simple grading, they remain catastrophic for downstream STEM-specific tasks such as circuit-to-netlist generation (Rachala and Panicker, 2022) or complex problem solving (Chen et al., 2025; Skelic et al., 2025). These findings underscore that achieving truly robust and comprehensive STEM handwriting understanding still remains a significant challenge.

## 5 Case Study

To assess the practical utility of our recognition error analysis, we conduct a deployment-oriented case study that integrates our empirical recognition error diagnostics into a realistic human-in-the-loop grading workflow (i.e., the "regrading module" in Figure 3). Specifically, we first collect identified recognition errors from the observation set and summarize their patterns. These patterns are then used to prompt the LLM to identify potential errors within the MLLM-recognized student solutions in the test set, which simulate unseen scenarios in practice. Meanwhile, considering that the distinction between genuine recognition errors and students' own mistakes can sometimes be ambiguous (due to handwriting or logical issues), we further ask the LLM to provide a confidence level ("high" or "low") for each identified error. Solutions flagged with low-confidence errors are routed directly to the course teaching assistant for manual grading, while the remaining solutions are regraded by the LLM grader given the detector's error report. More details can be found in Appendix D.3.

**Deployment Setup** We use the "vanilla grading pipeline" in Figure 3 for the first round student solution grading, where `GPT-5.1` and `Gemini-2.5-Pro` are tested as the visual recognizer separately. Subsequently, we apply the "regrading module" to regrade all solutions that received point deductions in the first round. This design is motivated by both error characteristics and deployment costs: recognition errors primarily result in false positive grading penalties, and cases with point deductions generally constitute a small fraction of student solutions. The LLM grader, LLM re-grader, and recognition error detector are all implemented using `GPT-5.1`.

| Workflow | Visual Recognizer | Grading Perf. (%) ↑ | | | Regrading Rate (%) | |
|---|---|---|---|---|---|---|
| | | Binary | Type | Point | LLM | Human |
| Vanilla | `Gemini-2.5-Pro` | 85.02 | 74.91 | 69.91 | – | – |
| | `GPT-5.1` | 82.34 | 72.23 | 66.87 | – | – |
| w/ Regrading | `Gemini-2.5-Pro` | 86.48 | 77.34 | 74.42 | 20.6 | 3.3 |
| | `GPT-5.1` | 86.60 | 78.93 | 75.76 | 25.1 | 4.4 |

Table 6: Performance and regrading statistics before and after applying the regrading module for student solutions in the test set. **LLM** and **Human** columns denote the percentage of solutions assigned to LLM and teaching assistant for regrading, respectively.

**Performance Gain from Regrading** Table 6 indicates that the "regrading module" significantly improves grading performance, particularly in type and point agreement, which necessitate precise alignment of fine-grained details. Notably, with fewer than 5% solutions requiring human intervention, the regrading achieves performance comparable to the setting where human experts serve as visual recognizers for all solutions in Table 5. This demonstrates that despite the low error impact ratio, targeted recognition error suppression remains indispensable for achieving expert-level accuracy in complex STEM evaluation.

## 6 Conclusions

In this work, we introduce `EDU-CIRCUIT-HW`, a real-world benchmark comprising over 1,300 authentic university-level STEM handwritten student solutions. Leveraging expert-verified verbatim handwritten solution transcriptions and grading reports, we comprehensively evaluate the visual understanding capability of MLLMs and their cascading impact on downstream auto-grading. The evaluation uncovers a substantial volume of latent recognition errors that may be exposed when rubrics become stricter and more professional, highlighting the significant challenges in deploying reliable MLLM-based educational applications. Furthermore, in response to these challenges, we propose and validate a human-in-the-loop grading workflow to mitigate the impact of recognition failures, which significantly enhances system robustness with minimal human intervention. We hope our work can serve as a cornerstone for developing more trustworthy AI-enabled educational technologies.

## 7 Limitations

This work focuses on the analysis on handwritten solution visual understanding capability in a university-level circuit analysis course. Although such a course represents a comprehensive STEM subject that integrates concepts from mathematics, physics, and engineering, the problem set and accompanying diagrams are mainly centered on circuit-related analysis. Other diagram types strongly associated with abstract mathematics (e.g., complex geometric graphs) are underrepresented in our dataset. Therefore, the conclusions drawn in this study may not fully generalize to handwritten recognition tasks involving substantially different diagram modalities.

In addition, in our analysis of how upstream recognition errors propagate to downstream tasks, we mainly consider auto-grading as the primary downstream application. Although auto-grading is a practical and representative task in educational settings, we do not investigate the impact of recognition errors on other downstream tasks, such as visual question answering (VQA), which may exhibit different sensitivity patterns to recognition inaccuracies.

Finally, the grading labels and rubrics in our dataset are provided by few doctoral experts with extensive familiarity with the course content. However, human evaluation and rubric-crafting in open-ended STEM problem-solving are inherently subjective to some extent. Despite our efforts to ensure consistency through detailed grading criteria and rigorous verification grounded in mathematical logic and domain expertise, potential subtle subjective biases may still exist in the grading scores.

Overall, we view these limitations as opportunities for future work to extend the analysis to broader subject domains, additional downstream tasks, and alternative assessment protocols.

## 8 Ethics Considerations

**Data Collection** Prior to data collection, all participating students and experts (teaching assistants, rubric- and grade-annotators, etc) signed informed consent forms, authorizing the collection and usage of their homework solutions and grading records for research and publication purposes. All data were anonymized to remove Personally Identifiable Information (PII) of students (e.g., we identify students in our dataset via "student + index" (student 1, student 6, etc) instead of their true names for privacy protection.), and the collection was approved by the Institutional Review Board (IRB).

**Copyright and Licensing** The 62 questions used in this study are sourced from the textbook (Svoboda and Dorf, 2013), with their corresponding IDs listed in Table 7. To comply with copyright regulations, `EDU-CIRCUIT-HW` does not distribute and publicize the original problem statements, figures, or image-based hints. Researchers who wish to replicate our experiments involving the original question content are advised to consult the textbook themselves using the provided IDs. However, for all questions listed in Table 7, we have independently developed the reference solutions and comprehensive grading rubrics (as exemplified in Figure 19). These annotations are original contributions and are fully included in `EDU-CIRCUIT-HW`.

**Reliability Risks in Educational Settings** As analyzed in our work, MLLMs adopted in current auto-grading systems present unreliable recognition qualities on university-level STEM student solutions, which could propagate to downstream grading performance and thereby lead to unfair or incorrect assessments if deployed without sufficient human oversight. We emphasize that our dataset and analysis are intended for diagnostic and research purposes, and that any practical deployment should include human-in-the-loop verification and error detection mechanisms, as shown in the case study.

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# A Related Work

## A.1 Handwriting Text Recognition

Despite the prevalence of MLLMs, they still face several challenges. One notable issue is the difficulty in accurately recognizing students' handwriting and converting it into clean, machine-readable text. Although Optical Character Recognition (OCR) (Hamad and Kaya, 2016) and visual understanding techniques can reliably process standard text and simple, one-line mathematical expressions (Wu et al., 2022), their performance degrades when confronted with complex deductions, hand-drawn auxiliary plots, and uncommon symbol combinations. This leads to low confidence in the automated evaluation of student work (Yang et al., 2025; Caraeni et al., 2024), thereby increasing the need for manual verification (Yang et al., 2025). Consequently, it is meaningful to analyze in detail the impact of recognition errors on auto-grading systems and to develop targeted solutions for these shortcomings.

## A.2 Handwriting Text Recognition Correction

Handwriting Text Recognition (HTR) correction plays a crucial role in identifying and rectifying recognition errors, thereby improving the overall performance of the recognition pipeline. For example, Pavlopoulos et al. (2023) demonstrated that a sequential "detect-then-rectify" approach could enhance Greek text recognition accuracy to 97%. Similarly, Chen et al. (2023) employed an external LLM to automatically correct mathematical formulas by leveraging LaTeX grammar and semantic context, achieving an approximate 6% improvement in expression recognition accuracy on the CROHME dataset (Mouchère et al., 2014).

Methods for error detection vary, including BERT-based models (Peng et al., 2021) and confidence-based approaches (Gupta et al., 2021). However, their effectiveness remains underexplored in the context of complex student handwriting, especially when accounting for practical constraints such as minimizing API call frequency and ensuring high-recall error detection (i.e., identifying as many errors as possible). This paper introduces a specialized error detection and correction pipeline tailored to student handwriting, developed and evaluated within the context of a university-level circuit analysis course, as detailed in the case study in Section 5.

## A.3 Automated Grading

Recent auto-grading agents primarily leverage the capabilities of foundation models such as Gemini and GPT. For handwriting input, some researchers have explored end-to-end grading approaches that process handwritten submissions directly (Caraeni et al., 2024; Khrulev, 2025; Nath et al., 2025). However, the opaque nature and relatively lower performance of these models render them unreliable at the current stage. Alternatively, a more interpretable approach involves first recognizing the student's handwritten solution and converting it into a structured text format (e.g., LaTeX or Markdown), which is then used as input for the grading model along with a prompt and predefined rubric. For instance, Liu et al. (2024) utilized GPT-4 to automatically grade a university-level mock mathematics exam. Kortemeyer et al. (2024) combined GPT-4V and Mathpix to evaluate student performance on a high-stakes thermodynamics exam. Similarly, Parsaeifard et al. (2025) developed a pipeline to automatically grade economics-related mathematics courses at a Swiss distance university. Yang et al. (2025) introduced an online auto-grading platform[1] that supports various academic institutions across subjects such as Computer Science, Mathematics, and Chemistry.

# B Dataset Details and Ethics Statements

The `EDU-CIRCUIT-HW` dataset consists of the following components: (1) 1334 authentic student handwritten solutions collected from a university-level STEM course during the Spring 2025 term; (2) 62 reference answers and corresponding grading rubrics; (3) 513 expert-crafted, near-verbatim transcriptions of student solutions within the observation set; and (4) detailed records of recognition errors, categorized according to the taxonomy presented in Table 3. Further descriptions of these components are provided below.

(1) **Student Handwritten Solution Collection.** As summarized in Table 1, data were collected from 29 students enrolled in the course. Prior to data collection, all participants signed an informed consent form permitting the use of their homework submissions and grading scores for research purposes. All data were anonymized to remove Personally Identifiable Information (PII), and the collection process was approved by the Institutional Review Board (IRB). Handwritten assignments

[1] See `https://www.pensieve.co/schools`.

**Prompt for categorizing the recognition errors based on the error taxonomy**

```
As an expert in Electronic Engineering education and OCR quality assessment, categorize the following
     recognition error into one of the four major types:

Category 1: Symbol & Character Errors (Low-level OCR)
- Includes: Misreading numbers/letters (e.g., '20000' as '2a000'), missing negative signs, operator
     misrecognition, and unit/prefix errors (e.g., '\muF' as 'mF' or 'MF').

Category 2: Structural & Mathematical Notation Errors
- Includes: Broken formula structures (e.g., fractions split across lines), missing parentheses, inconsistent
     variables (e.g., 'vc' becoming 'vo' mid-derivation), and dimensional inconsistencies.

Category 3: Visual & Diagrammatic Reasoning Errors
- Includes: Incorrect circuit topology (e.g., identifying parallel as series), misaligning attributes to wrong
      components, reversed polarity/direction, and hallucinations regarding diagram elements.

Category 4: Textual & Logical Flow Errors
- Includes: Omission of critical steps, mislabeling physics laws (e.g., writing KVL when KCL was used), and
     boundary condition mismatches (e.g., 't < 0' misread as 't > 0').

---
Error Item Content:
{item_content}
---

Task: Output ONLY the category number (1, 2, 3, or 4). Do not include any other text.
```

Figure 5: Prompt used to categorize recognition errors according to the taxonomy defined in Table 3, where the four categories correspond to "Symbol & Character", "Structural & Notational", "Diagrammatic", and "Textual & Logical" errors.

and corresponding grading reports were gathered throughout the Spring 2025 term. Notably, some students occasionally submitted assignments in LaTeX or other digital formats; these were excluded from the dataset. As a result, not all students in EDU-CIRCUIT-HW have handwritten solutions for every question.

(2) **Questions, Reference Solutions, and Rubrics.** The IDs of all 62 questions, sourced from the textbook (Svoboda and Dorf, 2013), are listed in Table 7. Due to copyright restrictions, EDU-CIRCUIT-HW does not include the original problem statements, figures, or image-based hints. Researchers wishing to replicate experiments involving the original content are encouraged to consult the textbook using the provided question IDs. For all questions listed in Table 7, we developed corresponding reference answers and comprehensive grading rubrics, both of which are included in EDU-CIRCUIT-HW. An example rubric is shown in Figure 19.

(3) **Expert-Rectified Student Solution Recognitions.** This component is described in greater detail in Appendix C and was previously introduced in Section 3.1.

(4) **Recognition Errors and Taxonomy.** As detailed in Section 3.1 and Appendix C, human experts identified recognition errors in the transcriptions produced by Gemini-2.5-Pro on the observation set within EDU-CIRCUIT-HW. These errors were then categorized using the taxonomy defined in Table 3, with classification performed by prompting Gemini-2.5-Pro using the prompt shown in Figure 5. In addition, we will release the recognition errors identified across all evaluated models (as shown in Figure 4), flagged by the LLM-based error detector and organized according to the same taxonomy, to support further research.

## C Expert Handwriting Recognition

This section outlines the procedure for generating expert-verified handwritten recognition results, referred to as the "gold standard", for student solutions. For all data in the EDU-CIRCUIT-HW observation set, we initially employed Gemini-2.5-Pro to recognize and transcribe the handwritten submissions into Markdown format, using the prompt shown in Figure 14. Subsequently, human experts carefully reviewed each transcription against the original handwritten images. Any recognition errors identified during this verification process were manually corrected by the experts. The resulting set of transcriptions serves as the gold standard and is assumed to be error-free for the experiments reported in Table 5.

To better illustrate the expert rectification pro-

| Chapter Index | Problem Indexes |
|---|---|
| 1 | P1.5-2, P1.5-3 |
| 2 | P2.4-6, P2.4-7, P2.5-1, P2.5-2 |
| 3 | P3.2-1, P3.2-2, P3.2-6, P3.4-4, P3.6-1 |
| 4 | P4.2-2, P4.2-5, P4.3-3, P4.4-1, P4.4-6, P4.5-2, P4.6-2, P4.7-1, P4.7-2, P4.7-6 |
| 6 | P6.3-2, P6.3-3, P6.4-1, P6.4-2, P6.4-4, P6.4-5, P6.4-6 |
| 7 | P7.2-2, P7.2-4, P7.3-2, P7.4-1, P7.4-3, P7.5-4, P7.5-5, P7.6-2, P7.7-2, P7.8-2 |
| 8 | P8.3-1, P8.3-2, P8.3-4, P8.3-5, P8.3-9, P8.3-10, P8.4-1, P8.7-3, P8.7-5 |
| 9 | P9.2-1, P9.3-3, P9.4-1, P9.4-2, P9.5-1, P9.6-1, P9.7-2 |
| 10 | P10.3-2, P10.3-3, P10.4-1, P10.4-6, P10.6-1, P10.6-4, P10.7-1, P10.10-4 |

Table 7: Index of problems from (Svoboda and Dorf, 2013) corresponding to the data included in EDU-CIRCUIT-HW.

cess, we provide a representative example. Figure 6 presents the original student handwritten submission; Figure 10 shows the initial transcription generated by Gemini-2.5-Pro; and Figure 11 displays the expert-rectified version based on the model's output. In these figures, recognition errors in the original transcription are highlighted in red, while the corresponding corrections in the expert-verified version are marked in green.

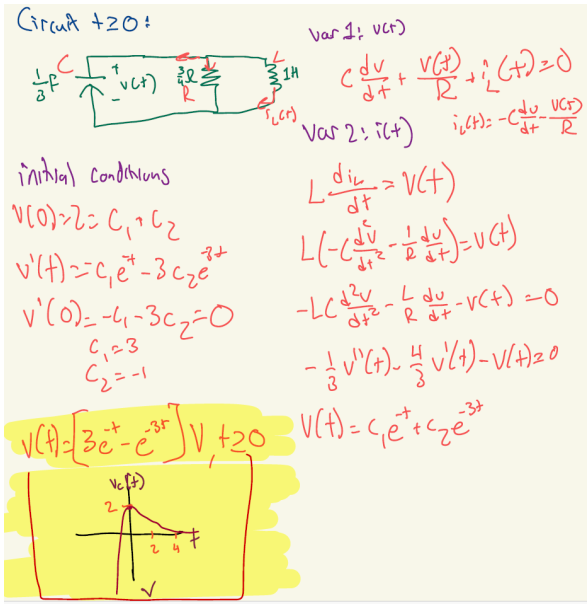



Figure 6: Screenshot of a handwritten solution from Student 16 for question P9.4-2, included in the observation set.

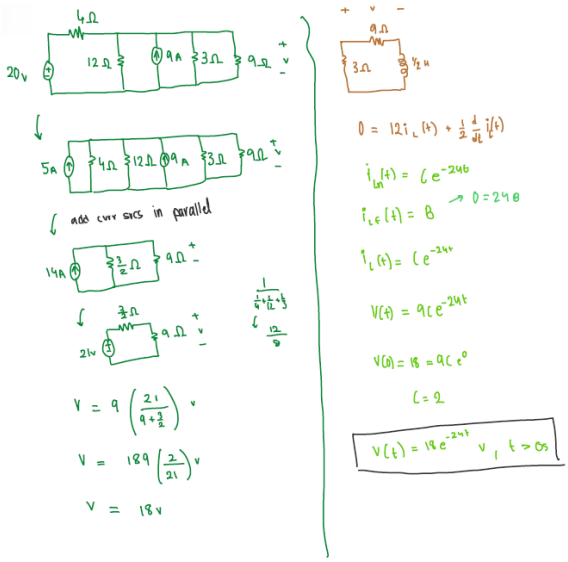



Figure 7: Screenshot of a student handwritten solution for question P8.3-10 from the test set. This example is used as the one-shot demonstration in the LLM-based recognition error detector described in Section 3.1 for evaluating the observation set.

## D Experiment Details

### D.1 Automated LLM-Enabled Recognition Error Detector

This section describes the implementation of the LLM-enabled automated recognition error detector, as introduced in Section 3.1. Leveraging the expert-verified transcriptions as the "gold standard", we use Gemini-2.5-Pro to detect discrepancies between the recognition outputs produced by various MLLMs and the corresponding reference texts. The prompt used for this comparison process is illustrated in Figure 16, and consists of the following components:

- **target_content**: The Markdown transcription generated by the target MLLM for a specific student handwritten solution.
- **label_content**: The expert-verified Markdown transcription of the same student solution, generated through the pipeline described in Section C. This serves as the gold-standard reference for evaluating recognition accuracy.
- **examples['target']**: A sample transcrip-

tion generated by GPT-5.1 for the student submission shown in Figure 7, with the transcribed output illustrated in Figure 12. To ensure fair evaluation (e.g., in Tables 2 and 5) and prevent data leakage, this example, corresponding to question P8.3-10 from Student 19, was selected from the test set, which lies outside the EDU-CIRCUIT-HW observation set.

- **examples['gt']**: The expert-rectified transcription corresponding to the student submission shown in Figure 7, as illustrated in Figure 13.
- **examples['result']**: A list of sample recognition errors and their corresponding corrections, derived by comparing examples['target'] with examples['gt']. This list is shown in Figure 17, and the detector's output follows the same structure.
- **examples['evidence']**: Detailed justifications for each recognition error identified in examples['target'], based on comparisons with examples['gt']. These justifications are illustrated in Figure 18.

This prompt utilizes a one-shot strategy based on a representative example from the test set. Specifically, we intentionally paired a transcription produced by GPT-5.1 with an expert-rectified ground truth originally derived from Gemini-2.5-Pro. By incorporating outputs from different MLLMs in the one-shot example, the detector is exposed to the natural variability in how models represent the same visual content, for instance, through differing LaTeX notations for equivalent formulas or alternative phrasings for diagrammatic descriptions. This cross-model pairing enhances the robustness of the LLM-based detector by helping it distinguish between benign structural or stylistic differences and true recognition errors.

### D.2 Vanilla Grading Pipeline

The "vanilla grading pipeline", illustrated in Figure 3, comprises two main stages: (1) transcription of the student handwritten solution by an MLLM, such as Gemini-2.5-Pro, and (2) automated evaluation by an LLM-based grader. In the transcription stage, we utilize different MLLMs to convert handwritten student responses into structured text, guided by prompts specific to each model series (see Figures 14 and 15).

In the second stage, the LLM grader (i.e., GPT-5.1), configured with a "high" reasoning effort setting, evaluates the transcribed content through a two-round dialogue process. In the first round, the grader employs the prompt shown in Figure 20 to assess the submission based on four question-specific attributes: problem_statement, images_hint, final_answer (the reference solution), and rubric_snippet. Within EDU-CIRCUIT-HW, we provide the latter two components, developed by domain experts, while the problem_statement and images_hint can be retrieved from the textbook (Svoboda and Dorf, 2013) using the corresponding question indexes. The student_markdown field contains the transcribed student solution, which may originate from an MLLM (e.g., Figure 12) or a human expert, depending on the experimental setting. After the first round, the grader outputs an overall score deduction report (e.g., {E: -0.04 pts, C: -0.01 pts}).

In the second round, the LLM grader is prompted (as shown in Figure 21) to provide detailed justifications for the score deductions identified in the first round. The input to this stage includes the raw_scoring_json (e.g., {E: -0.04 pts, C: -0.01 pts}) generated earlier. This round concludes with the generation of a final grading report. A representative example is shown in Figure 9, which presents the LLM grader's feedback on the student submission in Figure 8, evaluated using the rubric provided in Figure 19.

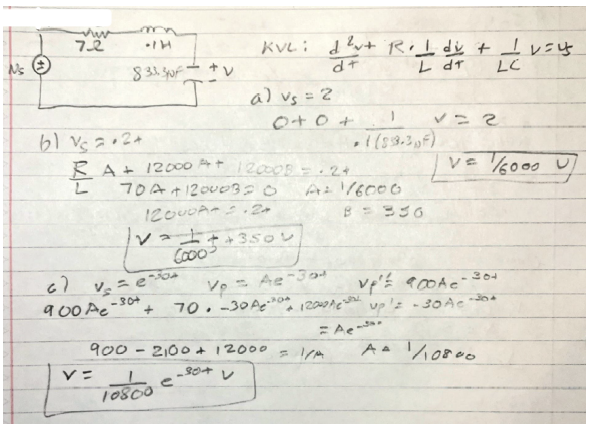


Figure 8: Screenshot of a student handwritten solution for question P9.7-2. A grading report example for this submission, generated by the LLM grader, is presented in Figure 9, based on the rubric shown in Figure 19.

**A grading report example**

```
E: EE1 (0.04) - The governing ODE is written with
     v_s on the right-hand side instead of (1/LC)
     v_s, so the source term is incorrectly scaled,
      making the ODE relating v and v_s wrong. |
     evidence: $$\frac{d^2v}{dt} + R \cdot \frac
     {1}{L} \frac{dv}{dt} + \frac{1}{LC} v = v_s$$

C: CC1 (0.01) - From 70A + 12000B = 0 and 12000A =
     0.2, solving gives a small negative B, not
     350; this is an algebra error in solving for
     the ramp-case constant B. | evidence: $$B =
     350$$
```

Figure 9: Grading report for a student submission on question P9.7-2. The report includes score deductions in the categories of "Equation" (E) and "Calculation" (C), along with detailed explanations for each deduction and the corresponding evidence (e.g., `evidence: $$B = 350$$`) from the transcribed student solution.

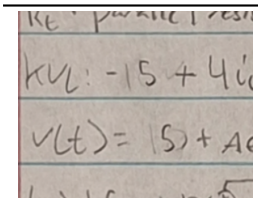
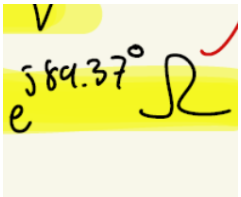
| Image | Error Details |
|---|---|
|  | KVL: $-5 + 4i_1$ ... ↓ KVL: $-15 + 4i_1$ ... |
|  | $e^{j89.37°}$ ↓ $e^{j84.37°}$ |

Table 8: Examples of the recognition errors in the "Symbolic & Character" category in Table 3. The incorrect recognitions are marked in red and the rectified versions are marked in green.

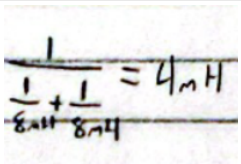
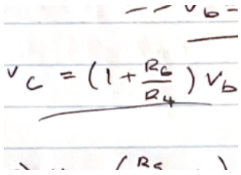
| Image | Error Details |
|---|---|
|  | $\frac{1}{\frac{1}{8\text{ mH}}+\frac{1}{8\text{ mH}}} = 4\text{ mH}$ ↓ $\frac{1}{8\text{ mH}+8\text{ mH}} = 4\text{ mH}$ |
|  | $v_c = (1 + \frac{R_6}{R_4})v_b$ ↓ $v_c = (\frac{1+R_6}{R_4})v_b$ |

Table 9: Examples of the recognition errors in the "Structural & Notational" category in Table 3. The incorrect recognitions are marked in red and the rectified versions are marked in green.

## D.3 Regrading Module

This section provides additional details on the "regrading module" in Figure 3, which was implemented as part of the case study described in Section 5.

To implement this module, we first aggregated all recognition errors flagged by human experts within the observation set; the process for collecting these errors is detailed in Section C. Leveraging this prior knowledge, experts distilled a set of empirical criteria, presented in Figures 23 and 24, to guide the detection of potential recognition errors in the test set. These criteria were then integrated into the recognition error detector, which identifies likely transcription failures in student responses that received score deductions in the initial grading stage. For the case study, we use `GPT-5.1` as the detector. Based on its output, the LLM regrader re-evaluates the affected student work using the prompt shown in Figure 22. During this process, the regrader is explicitly instructed to disregard any content flagged as a recognition error, even if it introduces discrepancies with the reference solution.

In cases where the detector is unable to definitively distinguish between a recognition error and a genuine student mistake (i.e., segments marked as "[uncertain]" in Figure 23), the corresponding solution is referred to a human grader for final evaluation. In our case study, this human grader is the doctoral teaching assistant for the course from which `EDU-CIRCUIT-HW` was derived.

## D.4 Human and MLLM API Settings

**Experts and Human Graders** The graduate grader referenced in Table 5 is a graduate student who previously completed the course associated with `EDU-CIRCUIT-HW` and has also served as a teaching assistant for the class. All experts and human graders involved in the student work regrading are doctoral students with comprehensive mastery and deep subject-matter expertise in the course content.

**Model Configurations** All MLLMs used in our visual recognition experiments are accessed exclusively through their official API interfaces. To ensure reproducibility and reduce output variability, we set the temperature parameter to 0 for all models, except for `GPT-5.1`, whose temperature is fixed at 1 by the official setting[2]. Unless otherwise spec-

[2]

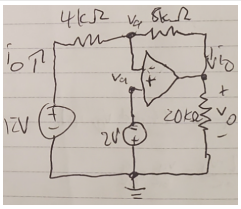
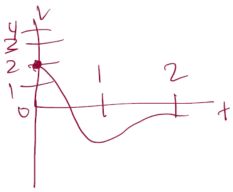
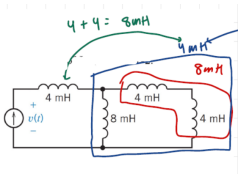
| Image | Error Details |
|---|---|
|  | $i_o$ follows downwards through 8 kΩ resistor.<br>↓<br>$i_o$ follows downwards through 20 kΩ resistor. |
|  | The curve has a minimum between $t$=0 and $t$=1.<br>↓<br>The curve has a minimum between $t$=1 and $t$=2. |
|  | The student circles two 4mH inductors (top right & rightmost) in red.<br>↓<br>The student circles the rightmost 4mH inductor in red. |

Table 10: Examples of the recognition errors in the "Diagrammatic" category in Table 3. The incorrect recognitions are marked in red and the rectified versions are marked in green.

ified, all other hyperparameters (e.g., reasoning effort for `GPT-5.1`) remain at their default API settings. Given the low-temperature configurations, which result in highly stable outputs, and the practical constraints of deployment, where inference is typically conducted only once to control costs, we report experimental results based on a single run per model.

### D.5 Examples about Recognition Error Taxonomy

In this section, we present several examples of recognition errors, categorized according to the taxonomy defined in Table 3. The examples are organized as follows:

- **Symbolic & Character:** Representative recognition errors in this category are provided in Table 8.
- **Structural & Notational:** Examples of errors involving equation structure or notation are shown in Table 9.
- **Diagrammatic:** Recognition errors related to diagrams are illustrated in Table 10.

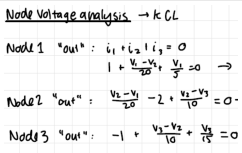
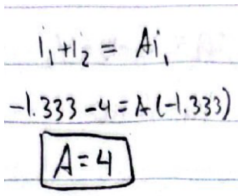
| Image | Error Details |
|---|---|
|  | Node voltage analysis → KCL ...<br>↓<br>Node voltage analysis → KVL ... |
|  | $i_1 + i_2 = \mathrm{A}i_1$.<br>$-1.333 - 4 = \mathrm{A}(-1.333)$<br>...<br>↓<br>[Missing Equation].<br>$-1.333 - 4 = \mathrm{A}(-1.333)$<br>... |

Table 11: Examples of the recognition errors in the "Textual & Logical" category in Table 3. The incorrecrt recognitions are marked in red and the rectified versions are marked in green.

- **Textual & Logical:** Examples of misinterpretations involving textual descriptions or logical reasoning appear in Table 11.

**Example: Gemini-2.5-Pro transcribed student handwritten solution in Figure 6**

```
> A circuit diagram for ‘t >= 0‘ is drawn, showing a capacitor, resistor, and inductor connected in a series
    loop The capacitor is labeled ‘1/3 F‘ and ‘C‘, with the voltage across it marked as ‘v(t)‘ (positive on
    the left ). The resistor is labeled ‘R‘ and ‘3/4 \Omega‘. The inductor is labeled ‘1H‘. A clockwise
    current is indicated, with the label ‘i_L(t)‘ pointing downwards through the inductor.

**Circuit t>=0:**

**Var 1: v(t)**
$$C \frac{dv}{dt} + \frac{V(t)}{R} + i_L(t) = 0$$

**Var 2: i(t)**
$$i_c(t) = -C \frac{dv}{dt} - \frac{v(t)}{R}$$

$$L \frac{di_L}{dt} = v(t)$$

$$L(-C \frac{d^2v}{dt^2} - \frac{1}{R} \frac{dv}{dt}) = v(t)$$

$$-LC \frac{d^2v}{dt^2} - \frac{L}{R} \frac{dv}{dt} - v(t) = 0$$

$$- \frac{1}{3} v''(t) - \frac{4}{3} v'(t) - v(t) = 0$$

$$v(t) = c_1 e^{-t} + c_2 e^{-3t}$$

**initial conditions**
$$v(0)=2 = c_1 + c_2$$

$$v'(t) = c_1 e^{-t} - 3 c_2 e^{-3t}$$

$$v'(0) = c_1 - 3c_2 = 0$$

$$c_1 = 3$$

$$c_2 = -1$$

$$v(t) = [3e^{-t} - e^{-3t}]V + 20$$

> A graph is drawn with ‘v_c(t)‘ on the vertical axis and ‘t‘ on the horizontal axis. The vertical axis is
    labeled ‘V‘ and has a tick mark at ‘2‘. The horizontal axis has tick marks at ‘2‘ and ‘4‘. The plotted
    curve starts at ‘(0, 2)‘, increases to a peak value at approximately ‘t=0.5‘, and then decays ,
    approaching zero.
```

Figure 10: Transcription generated by Gemini-2.5-Pro from the student handwritten solution shown in Figure 6. Expert-identified recognition errors are highlighted in red .

**Example: Expert-rectified `Gemini-2.5-Pro` transcribed student handwritten solution in Figure 6**

```
> A circuit diagram for ‘t >= 0‘ is drawn, showing a capacitor, resistor, and inductor connected in parallel.
    The capacitor is labeled ‘1/3 F‘ and ‘C‘, with the voltage across it marked as ‘v(t)‘ (positive on the
    top). The resistor is labeled ‘R‘ and ‘3/4 \Omega‘. The inductor is labeled ‘1H‘. A clockwise current is
    indicated, with the label ‘i_L(t)‘ pointing downwards through the inductor.

**Circuit t>=0:**

**Var 1: v(t)**
$$C \frac{dv}{dt} + \frac{V(t)}{R} + i_L(t) = 0$$

**Var 2: i(t)**
$$i_c(t) = -C \frac{dv}{dt} - \frac{v(t)}{R}$$

$$L \frac{di_L}{dt} = v(t)$$

$$L(-C \frac{d^2v}{dt^2} - \frac{1}{R} \frac{dv}{dt}) = v(t)$$

$$-LC \frac{d^2v}{dt^2} - \frac{L}{R} \frac{dv}{dt} - v(t) = 0$$

$$- \frac{1}{3} v''(t) - \frac{4}{3} v'(t) - v(t) = 0$$

$$v(t) = c_1 e^{-t} + c_2 e^{-3t}$$

**initial conditions**
$$v(0)=2 = c_1 + c_2$$

$$v'(t) = -c_1 e^{-t} - 3 c_2 e^{-3t}$$

$$v'(0) = -c_1 - 3c_2 = 0$$

$$c_1 = 3$$

$$c_2 = -1$$

$$v(t) = [3e^{-t} - e^{-3t}]V , t \ge 0$$

> A graph is drawn with ‘v_c(t)‘ on the vertical axis and ‘t‘ on the horizontal axis. The vertical axis is
    labeled ‘V‘ and has a tick mark at ‘2‘. The horizontal axis has tick marks at ‘2‘ and ‘4‘.
    The plotted curve starts from negative ‘t‘, increases to a peak value ‘2‘ at ‘t=0‘, and then decays,
    approaching zero.
```

Figure 11: Expert-rectified version of the `Gemini-2.5-Pro` transcription from the student handwritten solution shown in Figure 6. Corrections corresponding to the original recognition errors are highlighted in green.

**Example: GPT-5.1 transcribed student handwritten solution in Figure 7**

```
> [On the left, the student redraws the original circuit but with the inductor removed (open-circuited) to
     find the initial voltage across where the inductor will be. From left to right there is a 20 V source in
     series with a 4 \Omega resistor, followed by a node that branches downward to a 12 \Omega resistor, then
     to a 9 A current source, then to a 3 \Omega resistor, all in parallel. To the right of this parallel
     network is a 9 \Omega resistor whose right terminal is labeled with $+$ at the top and $-$ at the bottom
     as $v$.
> The student then replaces the 4 \Omega, 12 \Omega, and 3 \Omega resistors and the 9 A current source with
     equivalent sources/resistances: first, turning the 20 V source and 4 \Omega resistor into an equivalent 5
      A current source in parallel with 4 \Omega, then showing that 5 A source in parallel with the 12 \Omega
     resistor, the 9 A source, and the 3 \Omega resistor, all feeding the 9 \Omega resistor where $v$ is
     measured.
> Next, the two current sources (5 A and 9 A) are added in parallel to yield a single 14 A source in parallel
     with an equivalent resistance made from the 4 \Omega, 12 \Omega, and 3 \Omega resistors in parallel.
> Finally, these parallel resistors are combined into a single 3 \Omega resistor in series with the 9 \Omega
     resistor to the right, still labeled $v$ with $+$ at the top and $-$ at the bottom.
> On the right side of the page, the student draws the circuit for $t>0$ where the inductor is connected: a 3
     \Omega resistor in series with a 9 \Omega resistor, and a $1/2$ H inductor in series with them, with the
     voltage across the 9 \Omega resistor labeled $v$.]

---

**Left side (initial conditions and equivalent circuit)**

$$\text{(top node currents)} \Rightarrow 5\text{A} \quad 4\Omega \quad 12\Omega \quad 9\text{A} \quad 3\Omega
     \quad 9\Omega \; v^+$$

*add curr srcs in parallel*

$$14\text{A} \quad \boxed{\frac{3}{2}\,\Omega} \quad 9\Omega^{+}_{-}$$

$$\boxed{3\Omega} \quad 9\Omega^{+}_{-}$$

$$\frac{1}{\frac{1}{4} + \frac{1}{12} + \frac{1}{3}} \Rightarrow \frac{12}{8}$$

$$V = 9\left(\frac{21}{9 + \frac{3}{2}}\right)\,V$$

$$V = \frac{189}{\frac{21}{2}}\,V$$

$$V = 18\,V$$

---

**Right side (differential equation and solution)**

> [Small circuit: a 3 \Omega resistor in series with a $1/2$ H inductor and a 9 \Omega resistor, with $+$ at
     the left of the 9 \Omega and $-$ at the right labeled $v$.]

$$0 = 12\,i_L(t) + \tfrac {1}{2}\frac {d}{dt} i(t)$$

$$i_L'(t) = C e^{-24t}$$

$$i_{L,c}(t) = B \quad \Rightarrow 0 = 24 B$$

$$i_L(t) = C e^{-24t}$$

$$V(t) = 9 C e^{-24t}$$

$$V(0) = 18 = 9 C e^{0}$$

$$C = 2$$

$$\boxed {V(t) = 18 e^{-24t},\quad t>0}$$
```

Figure 12: Transcription generated by GPT-5.1 from the student handwritten solution shown in Figure 7. Expert-identified recognition errors are highlighted in red.

**Example: Expert-rectified `Gemini-2.5-Pro` transcribed student handwritten solution in Figure 7**

```
> [A sequence of circuit diagrams shows the simplification of the circuit for t < 0 to find an initial
     condition. The inductor is omitted and the switch is treated as a short circuit.]
>
> 1.  **Initial Diagram:** A redrawing of the original circuit components relevant for t < 0. A 20V source is
     in series with a 4\Omega resistor. This is in parallel with a 12\Omega resistor, a 9A current source, a
     3\Omega resistor, and a 9\Omega resistor. The voltage ‘v‘ is marked across the 9\Omega resistor.
> 2.  **Source Transformation:** ‘=>‘ The 20V source and 4\Omega series resistor are transformed into a 5A
     current source in parallel with a 4\Omega resistor.
> 3.  **Combine Parallel Elements:** ‘=>‘ The parallel current sources (5A and 9A) are combined into a single
     14A source. The parallel resistors (4\Omega, 12\Omega, and 3\Omega) are combined into
     a single ‘3/2 \Omega ‘ resistor. The circuit is now a 14A source in parallel with a ‘3/2 \Omega‘
     resistor, connected to the 9\Omega resistor.
> 4.  **Final Source Transformation:** ‘=>‘ The 14A source and ‘3/2 \Omega‘ parallel resistor are transformed
     into a 21V voltage source in series with a ‘3/2 \Omega‘ resistor. This is connected to the 9\Omega
     resistor.

$$
\begin{aligned}
v &= 9 \left( \frac{21}{9 + \frac{3}{2}} \right) v \\
v &= 189 \left( \frac{2}{21} \right) v \\
v &= 18V
\end{aligned}
$$

---
> [A circuit diagram for t > 0 is drawn. It shows a 3\Omega resistor, a 9\Omega resistor, and a 1/2 H inductor
      connected in a series loop. The voltage ‘v‘ is labeled across the 9\Omega resistor with the positive
     terminal on the left.]

$$0 = 12 i_L(t) + \frac {1}{2} \frac {di_L}{dt}(t)$$

$$i_{Ln}(t) = C e^{-24t}$$

$$i_{L_F}(t) = B \rightarrow 0 = 24B$$

$$i_L(t) = C e^{-24t}$$

$$V(t) = 9 C e^{-24t}$$

$$V(0) = 18 = 9 C e^0$$

$$C = 2$$

$$\boxed {V(t) = 18e^{-24t} V, \quad t > 0s}$$
```

Figure 13: Expert-rectified transcription from `Gemini-2.5-Pro` for the student handwritten solution shown in Figure 7. The highlighted segments in green correspond to parts where `GPT-5.1` (used here as the target model for diversity in few-shot learning) produced recognition errors, as shown in Figure 12. The LLM-based error detector is expected to produce a recognition error report similar to that shown in Figure 17 when comparing these transcriptions.

## Prompt for student handwritten solution transcription

```
You are an expert OCR (Optical Character Recognition) assistant specializing in student-submitted work for
     engineering and physics problems.
Your primary goal is to accurately transcribe the content from an image of a student's handwritten work,
     including text, mathematical formulas, and diagrams.
To provide you with the necessary context to improve accuracy, I am giving you the original problem statement
     (text and any associated images) that the student was working on.

---

## 1. Context: The Original Problem
This is the problem the student was asked to solve. Use this information to better interpret their handwriting,
      especially for technical terms, symbols, numbers, and to compare against any diagrams they draw.

**Original Problem Statement Text:**
{problem_statement}

**Original Problem Images:**
(If any images are associated with the original problem, they will be provided as input right after this
     prompt.)

---

## 2. Your Task: Transcribe the Student's Work
Now, analyze the **final image provided**, which contains the **student's handwritten work**.

**Instructions:**
1.  **Identify the Core Content**: Focus on the student's actual work (the text, equations, diagrams, and code
     ) in their image.

2.  **Analyze and Describe Circuit Diagrams**: This is a critical step. Students often redraw circuits to aid
     their analysis. You must analyze any circuit diagrams drawn by the student and describe them **only if
     they add new information** compared to the original problem's diagram.
    *   **A. For Annotations:** If the student redraws the circuit and adds labels like node names ('A', 'B', '
     v_1'), current arrows ('i_x', 'i_1'), or voltage polarities ('+ V_o -'), describe these additions in
     natural language. Frame your description inside a Markdown blockquote.
        > **Example Output for Annotations:**
        > '[A circuit diagram is drawn with a current source, a voltage source, and a resistor in series. The
     current source is labeled 2A. The voltage source is labeled 10V. The resistor is labeled 5\Omega, and the
      voltage across it is labeled V1 with the positive terminal on the left.]'

    *   **B. For Simplifications or Transformations:** If the student shows a sequence of diagrams
     representing circuit simplification (e.g., combining resistors, source transformation, finding Thévenin/
     Norton equivalents), describe this process step-by-step. Use arrows '=>' to show the progression. Frame
     your description inside a Markdown blockquote.
        > **Example Output for Simplifications:**
        > '[Circuit with the two rightmost 1\Omega resistors in series is combined into a single 2\Omega
     resistor] => [The new 2\Omega resistor is now in parallel with the existing 2\Omega resistor, which are
     combined into a 1\Omega equivalent resistor] => [Final equivalent circuit with a 12V source and a 3\Omega
      resistor]'

3.  **Accurate Text Transcription**: Transcribe all other handwritten text as accurately as possible. For code,
      preserve indentation and syntax.

4.  **Mathematical Formula Formatting**:
    *   Convert all mathematical expressions, equations, and formulas to proper LaTeX syntax.
    *   Use inline math with single dollar signs: '$formula$' for simple expressions.
    *   Use display math with double dollar signs: '$$formula$$' for equations that should be centered on
     their own line.
    *   Ensure all mathematical symbols, subscripts, superscripts, fractions, integrals, derivatives, etc. are
      properly formatted in LaTeX.
    *   Examples: '$x^2 + y^2 = z^2$', '$$\int_0^1 f(x) dx$$', '$\frac{a}{b}$', '$\sum_{i=1}^n x_i$'

5.  **Formatting**: Use appropriate Markdown formatting (headings, lists, bold text) for clarity while
     preserving the student's original organization.

6.  **Output**: Return only the final Markdown content of the student's transcribed work. Do not include any
     introductory phrases or explanations about the transcription process.
```

Figure 14: Prompt used to instruct `Gemini-3-Pro-Preview`, `Gemini-2.5-Pro`, `GPT-5.1`, and `Claude-4.5-Sonnet` to transcribe student handwritten solutions into Markdown format.

**Prompt for student handwritten solution transcription (for `Qwen3-VL` series)**

```
You are a **Strict Verbatim OCR Transcription System** specializing in digitizing handwritten student work for
      engineering and physics.
Your **SOLE** purpose is to convert the pixels of the student's handwriting into digital text and LaTeX.
You are **NOT** a tutor or a solver. Do not attempt to solve the problem, correct the student's math, or fill
     in missing steps.

To provide you with context for ambiguous handwriting, I am giving you the original problem statement.

---

## 1. Context: The Original Problem
(Use this ONLY to recognize messy handwriting. **DO NOT** transcribe or describe this content as the student's
      work.)

**Original Problem Statement Text:**
{problem_statement}

**Original Problem Images:**
(Provided as input if available)

---

## 2. Your Task: Transcribe the Student's Work
Now, analyze the **final image provided**, which contains the **student's handwritten work**.

**CRITICAL RULES (Anti-Hallucination):**
*   **NO AUTO-COMPLETION**: If the student wrote ‘F = m‘, do NOT output ‘F = ma‘. Output exactly ‘F = m‘.
*   **NO INFERENCE**: Do not generate intermediate mathematical steps that are not explicitly written on the
     paper.
*   **NO GHOST DIAGRAMS**: If the student did not draw a circuit diagram with their pen/pencil, **do not
     output any diagram description**. Do not describe the printed diagrams from the original problem.
*   **PRESERVE ERRORS**: If the student made a mistake, transcribe the mistake exactly as written.

**Instructions:**

1.  **Identify the Student's Ink**: Ignore printed text from the worksheet/exam paper unless the student has
     written over it. Focus only on the handwritten content.

2.  **Analyze Student-Drawn Diagrams (STRICTLY CONDITIONAL)**:
    *   **Check First**: Did the student actually **redraw** or **annotate** a circuit diagram by hand?
    *   **If NO**: Skip this step entirely. Do not describe the printed problem image.
    *   **If YES (and only if new information is added)**:
        *   **For Annotations**: If the student added labels or arrows to a drawn circuit, describe them
     inside a Markdown blockquote.
            > **Example:** ‘[Student's hand-drawn circuit: Labeled node A and B, added current arrow i_x
     pointing right.]‘
        *   **For Simplifications**: If the student drew a sequence of simplified circuits, describe the
     progression using arrows ‘=>‘.
            > **Example:** ‘[Hand-drawn diagram showing 2\Omega and 3\Omega resistors combined] => [Final
     simplified circuit with source transformation]‘

3.  **Strict Text Transcription**: Transcribe handwritten text exactly as it appears.

4.  **Mathematical Formula Formatting**:
    *   Convert handwritten math to proper LaTeX.
    *   Use inline math ‘$...$‘ and display math ‘$$...$$‘ appropriately.
    *   **Verify against the image**: Ensure every symbol in your LaTeX output exists in the student's
     handwriting.

5.  **Output Format**: Return **only** the Markdown content of the transcription. Start directly with the
     content.
```

Figure 15: Prompt used to instruct `Qwen3-VL-Plus` and `Qwen3-VL-8B-Thinking` to transcribe student handwritten solutions into Markdown format.

**One-shot prompt for the LLM detector to find recognition errors in the MLLM recognized text**

```
You are an expert OCR (Optical Character Recognition) Quality Assurance Judge.
Your task is to compare a [TARGET MODEL OUTPUT] against a verified [GROUND TRUTH].

### GENERAL COMPARISON RULES:
1. **IGNORE Syntax Differences:** Do not report benign LaTeX variations (e.g., ‘\\frac‘ vs ‘\\dfrac‘, extra
     whitespaces) if the rendered mathematical meaning is identical.
2. **IGNORE Minor Wording:** Do not report missing conversational filler words (e.g., "So," "Therefore")
     unless they change the logic. Ignore case differences (e.g., $v$ vs $V$).
3. **ABOUT Redrawn Diagrams:** If the OCR result depicts a student’s redrawn diagram, ignore layout
     differences unless the values, units, or directions (e.g., 2\Omega vs 3\Omega, clockwise vs
     counterclockwise) are clearly incorrect compared to the Ground Truth logic.

### OUTPUT FORMAT:
If errors are found, list them in the following structured format:
1.
Source: [Exact snippet from TARGET that is wrong]
Rectified Version: [Correct snippet from GROUND TRUTH]
Reason: [Brief explanation of the error]

If no meaningful errors are found, output: "No significant errors found."

### ONE-SHOT EXAMPLE:
**[EXAMPLE TARGET]:**
{examples['target']}

**[EXAMPLE GROUND TRUTH]:**
{examples['gt']}

**[EXAMPLE EXPECTED JUDGEMENT]:**
{examples['result']}

**[EXAMPLE CORRECTION LOGIC]:**
{examples['evidence']}

---

### CURRENT TASK:

**[TARGET MODEL OUTPUT]:**
{target_content}

**[GROUND TRUTH]:**
{label_content}

**[CAUTION]:**
You should report the differences in the formula formatting if they break the formula’s mathematical meaning,
     e.g., "\int tdt" vs "\int t\tau" (the dummy variable changes from t to \tau will lead to a different
     numerical result), "di/dt + i = 0" vs "di/dt + i_L = 0", etc.

Again, you can ignore the following differences:
1. The differences in the crossed-out or cancelled content, unless only one of the ground truth/target’s
     content is crossed-out or cancelled.
2. Capitalization differences (e.g., $v$ vs $V$, $v_0$ vs $V_o$, $w$ and $W$) **unless** they break the
     formula’s mathematical meaning (e.g., both $v$ vs $V$ expressing the same physical quantity in a single
     formula like $dv/dt + V = 0$, "\int tdt" vs "\intt\tau", etc.).
3.  Formating or presenting differences which won’t change the formula’s mathematical meaning/result (e.g.,
     $j2$ vs $2j$, $3A$ vs $3(B-2)$ where it’s written that A=B-2 before, "5e^7" vs "5 e^7.0", "100mH vs 0.1H",
      "A = 3" vs "A -> 3", "cos 2t" vs "cos(2t)", -$\frac{1}{2/3}$ vs $\frac{-3}{2}$, etc.) should be ignored.
      They make the formula/sentence looks different, but they are mathematically/numerically equivalent.

**Your Judgement:**
```

Figure 16: Prompt used by the LLM-enabled recognition error detector to identify potential recognition errors in the target transcription (i.e., `target_content`) by comparing it with the expert-verified gold standard (i.e., `label_content`). To enhance detection performance, a one-shot learning approach is employed by providing an example that includes expert-annotated recognition errors and their corresponding rectifications.

**One-shot example for LLM recognition error detector: errors and their rectified versions**

```
1.
Source:
On the left, the student redraws the original circuit but with the inductor removed \colorbox{softred}{(open-
     circuited)} to find the initial voltage across where the inductor will be.

Rectified Version:
On the left, the student redraws the original circuit but with the inductor removed (short-circuited) to find
     the initial voltage across where the inductor will be.

2
Source:
> Finally, these parallel resistors are combined into a single 3 \Omega resistor in series with the 9 \Omega
     resistor to the right, still labeled $v$ with $+$ at the top and $-$ at the bottom.

Rectified Version:
> Finally, these parallel resistors are combined into a single 3/2 \Omega resistor in series with the 9 \Omega
      resistor to the right, still labeled $v$ with $+$ at the top and $-$ at the bottom.

3.
Source:
$$
0 = 12\,i_L(t) + \tfrac{1}{2}\frac{d}{dt} i(t)
$$

Rectified Version:
$$
0 = 12\,i_L(t) + \tfrac{1}{2}\frac{d}{dt} i_L(t)
$$

4.
Source:
$$
i_L'(t) = C e^{-24t}
$$

Rectified Version:
$$
i_{Ln}(t) = C e^{-24t}
$$

5.
Source:
$$
i_{L,c}(t) = B \quad \Rightarrow 0 = 24 B
$$

Rectified Version:
$$
i_{Lf}(t) = B \quad \Rightarrow 0 = 24 B
$$

6.
Source:
\boxed{V(t) = 18 e^{-24t},\quad t>0}

Rectified Version:
\boxed{V(t) = 18 e^{-24t},\quad t>0 s}
```

Figure 17: Recognition errors and their corresponding rectifications for the sample shown in Figure 7, based on the comparison between the MLLM-generated transcription and the expert-verified gold standard. In this example, six item-level recognition errors were identified and corrected. The output format of the LLM-based recognition error detector follows this same structure.

**One-shot example for LLM recognition error detector: explanations for capturing some errors**

```
Items 1 and 2 represent entirely different scenarios for the target diagram (e.g., "open-circuited" vs. "short-
     circuited", or "3 \Omega resistor in series with 9 \Omega" vs. "3/2 \Omega resistor in series with 9 \
     Omega"). These must be flagged as errors. Other variations such as minor grammatical differences or
     descriptions that are slightly more or less detailed can be ignored as long as they do not convey
     incorrect information.

In Item 3, changing $i_L(t)$ to $i(t)$ leads to a misunderstanding of the function; symbols representing the
     same physical quantity must remain consistent throughout the formula. Similarly, errors that will
     significantly change the formulas meaning must be pointed out, for example, if the ground truth uses $q =
      \int_{-\infty}^{t} i(\tau) \, d\tau$ but the target uses $dt$ instead of $d\tau$, this totally changes
     the mathematical meaning. Nevertheless, it is acceptable to ignore differences that do not change the
     underlying meaning, such as $v_0$ vs. $V_o$ (capitalization), $10^{-7}$ vs. $E^{-7}$, $\int_{0}^{1}d\tau$
      vs. $\int_{0}^{1}dx$, $10^\circ$ vs. $10 \text{ degrees}$, $sin 2t$ vs $sin(2t)$, $\frac{1}{3/2}$ vs. $\
     frac{2}{3}$, etc. These are simply diverse ways of expression that lead to the same result without
     causing confusion.

Items 4 and 5 represent standard errors. However, note that errors involving symbols for widely used physical
     quantities (such as natural response and forced response) must be treated strictly. For instance, $I_n$
     should not be misidentified as $I_e, I_x$, or $I_t$; $V_f$ should not be $V_{eq}$ or $V_h$; the steady-
     state value $k$ or $K$ should not be altered; and Thevenin resistance ($R_t, R_T, R_{th}$) should not be
     labeled as $R_x$.

Item 6 involves unit errors. It is acceptable to be lenient with unit issues in intermediate steps; however,
     for final answers, any missing units or the addition of incorrect units (those that do not match the
     ground truth) must be treated as errors.

The **sentence order** (e.g., "first A then B" vs. "first B then A") and **layout sketches** in the OCR
     results, such as:

"
---

**Left side (initial conditions and equivalent circuit)**

$$
\text{(top node currents)} \Rightarrow 5\text{A} \quad 4\Omega \quad 12\Omega \quad 9\text{A} \quad 3\Omega \
     quad 9\Omega \; v^+
$$

*add curr srcs in parallel*

$$
14\text{A} \quad \boxed{\frac{3}{2}\,\Omega} \quad 9\Omega^{+}_{-}
$$

$$
\boxed{3\Omega} \quad 9\Omega^{+}_{-}
$$

$$
\frac{1}{\frac{1}{4} + \frac{1}{12} + \frac{1}{3}} \Rightarrow \frac{12}{8}
$$

"

can be ignored. Focus solely on information present in the ground truth that the OCR results lack (excluding
     sketch-like elements), especially missing critical variables, key derivation steps, and algebraic
     expressions used for substitution.

Formulas may be presented in different algebraic forms, such as:

$$
V = \frac{189}{\frac{21}{2}}\,V
$$

and

$$
v = 189 \left( \frac{2}{21} \right) v
$$

These should be treated as identical.
```

Figure 18: Explanations for each item-level recognition error presented in Figure 17. These justifications serve as reference examples to guide the LLM-based detector in identifying and interpreting recognition errors.

**A rubric example for question P9.7-2 in EDU-CIRCUIT-HW**

```
### M - Method
Uses an appropriate method to find the forced (particular) response for v_f for each input (constant, ramp,
     exponential). Acceptable methods include time-domain particular-solution ansatz, or Laplace-domain
     solution; should clearly target the forced response (not the homogeneous/natural response).
- **Typical deduction**: 0.01
- **Max deduction**: 0.04
**Deduction rules:**
- **M1**: Solves only the homogeneous/natural response or mixes total response with initial conditions instead
      of isolating the forced response. - deduct 0.01. _e.g.,_ Gives v(t)=C1 e^{s1 t}+C2 e^{s2 t} only; Uses
     ICs to determine constants for natural response but no particular solution
- **M2**: Chooses an incompatible particular form for the input type (e.g., uses sinusoidal trial for a ramp
     or exponential input). - deduct 0.01. _e.g.,_ Assumes v_f=Ae^{jwt} for vs=0.2 t; Assumes v_f=K (constant)
      for vs=e^{-30 t}


### C - Calculation
Carries out algebra, differentiation, and numeric substitution correctly (e.g., R/L=70 s^-1, 1/LC=12000 s^-2)
     and solves for constants in the particular solution accurately.
- **Typical deduction**: 0.01
- **Max deduction**: 0.04
**Deduction rules:**
- **C1**: Arithmetic or algebra mistakes in solving for particular-solution constants (e.g., A, B) after
     correct setup. - deduct 0.01. _e.g.,_ Incorrect A from 2400=12000A; Wrong B from 70A+12000B=0
- **C2**: Differentiation errors for the chosen trial (wrong sign or power). - deduct 0.01. _e.g.,_ d/dt(e
     ^{-30t})=+30e^{-30t}
- **C3**: Numerical parameter errors (e.g., wrong 1/LC or R/L) that affect the final constants. - deduct 0.01.
      _e.g.,_ Uses 1/LC=1200 instead of 12000

### E - Equation
Sets up correct governing equations (KVL and i=C dv/dt) and the correct linear ODE relating v and v_s, with
     proper coefficients (R/L, 1/LC), and applies the chosen particular form correctly in the equation.
- **Typical deduction**: 0.01
- **Max deduction**: 0.04
**Deduction rules:**
- **E1**: Incorrect or incomplete differential equation relating v and v_s for the given RLC (e.g., wrong
     coefficients, sign errors, or omits a term). - deduct 0.01. _e.g.,_ Uses R/C instead of R/L; Misses the
     1/LCv term
- **E2**: Misapplies element laws in equations (e.g., i!=C dv/dt or KVL written inconsistently with polarity).
      - deduct 0.01. _e.g.,_ Writes i= (1/C) dv/dt; Drops the inductor voltage term in KVL
- **E3**: Does not correctly substitute the trial particular form into the ODE for the given input. - deduct
     0.01. _e.g.,_ Uses v_f=At+B but substitutes derivatives inconsistently

### U - Units
Includes correct units for final voltage answers and consistent time units. Voltages should be labeled in V;
     time assumed in seconds unless otherwise stated.
- **Typical deduction**: 0.01
- **Max deduction**: 0.02
**Deduction rules:**
- **U1**: Missing or incorrect units on final v_f(t) answers. - deduct 0.01. _e.g.,_ Reports v_f(t)=...
     without 'V'
- **U2**: Inconsistent time units that contradict given data (e.g., mixing ms and s without conversion). -
     deduct 0.01.

### NC - Not complete
Solution is missing required parts (a), (b), or (c), or does not present the final forced response expression(
     s) clearly.
- **Typical deduction**: 0.05
- **Max deduction**: 0.2
**Deduction rules:**
- **NC1**: Omits the forced response for any one of the three source cases. - deduct 0.05. _e.g.,_ Only
     provides (a) and (b)
- **NC2**: Shows work but does not state the final v_f(t) expression(s). - deduct 0.05.
- **NC3**: Provides only intermediate transforms/ODE without returning to time-domain forced response. -
     deduct 0.05.

## Notes
Full credit solutions typically: derive or state the correct second-order ODE for v and v_s for the given RLC
     (or an equivalent Laplace-domain relation), choose an appropriate particular form for each input (
     constant: v_f=K; ramp: v_f=At+B; exponential: v_f=Ae^{-30t}), solve for constants correctly using the
     circuit parameters (R=7 \Omega, L=0.1 H, C=833.3 \muF so R/L=70 s^-1 and 1/LC=12000 s^-2), and report v_f
     (t) with units of volts. Alternative correct methods (time-domain or Laplace) are acceptable as long as
     they target the forced solution.
```

Figure 19: Grading rubric for question P9.7-2, outlining how to identify student mistakes and assign score deductions across five categories: "E", "M", "C", "U", and "NC", as defined in Table 4.

## Prompt (Round 1) for LLM grading (generate deducted scores if any)

```
You are a meticulous TA grader.
You will receive: (1) the problem statement (+ optional images), (2) a student's solution in Markdown recognized from their handwriting, and (3) a
      compact rubric snippet.
Your job: identify which rubric criteria apply and produce strictly valid JSON with per-criterion deductions and short justifications.

Rules:
- Judge only using the provided materials. If the recognized text seems partially wrong or noisy, rely on clear evidence.
- Use the rubric snippet's rules (codes M, E, C, U, NC). If multiple rules under the same code apply, you may include multiple items for that code.
- Do not exceed the rubric's typical intentions; avoid double-counting the same mistake under different rules unless they are clearly distinct.
- Use conservative rounding and keep messages concise.
- Output strictly valid JSON matching the schema provided below. No extra keys, no Markdown fences.

Schema (you MUST follow this exactly):
{
  "per_criterion": {
    "M": {
      "applied": [ {"rule_id": "string or empty", "deduct": number, "comment": "short justification"} ],
      "subtotal": number
    },
    "E": { "applied": [ ... ], "subtotal": number },
    "C": { "applied": [ ... ], "subtotal": number },
    "U": { "applied": [ ... ], "subtotal": number },
    "NC": { "applied": [ ... ], "subtotal": number }
  },
  "overall_comment": "1-3 sentences summary"
}

Notes:
- 'rule_id' can be empty if you cannot map to a specific micro-rule, but prefer using it when obvious from rubric snippet.
- 'subtotal' is the model's suggested deduction for that code BEFORE any external capping.
- Do not include total score; it will be post-processed with rubric caps externally.
"""

SCORING_USER_TEMPLATE = """PROBLEM STATEMENT:
{problem_statement}

OFFICIAL PROBLEM SOLUTION (ground truth, optional):
{final_answer}

PROBLEM IMAGES (optional base64 PNGs): count={num_images}
{images_hint}

STUDENT RECOGNIZED SOLUTION (Markdown):
{student_markdown}

RUBRIC SNIPPET (compact):
{rubric_snippet}

IMPORTANT:
- Apply deductions only if clearly supported by the content in the student solution.
- When students don't add unit for calculated values, you should not deduct for that criterion "U" (such as $V(t)$, $I(t)$, $R$, $L$, $C$, $\tau$,
      $Z_L$, $Z_C$, etc.). Only deducting when students clearly provide the wrong unit (such as $V(t)$ is given in $A$).
- If the student uses some values that are not stated in the problem solving process, try to find some clues from the PROBLEM IMAGES (such as the
      current $i_2$ labeled in the schematic). If you cannot find any clues, then you can deduct for that criterion "NC".
- If evidence is insufficient, set zero deductions for that criterion.
- It is fine for students not to simply a value (such as not turning 150/350 into 3/7) if the value is correct numerically or to simply a value (
      such as turn 4000/3998 into 1) when they are very close.
- It is fine for students to use different precision's answer (e.g., 3.33, 3.333, 3.3, 10/3) or different units (e.g., mA vs A, mH vs H, \mu F vs F
       once they can be converted to the same value) for the same problem (e.g., 1.33 mA instead of 1.333 mA). Importantly, the rounding errors
      within a reasonable range should not be considered as calculation errors.
- You should recognize the equivalences between different number formats (e.g., decimal, fraction, scientific notation) and between different
      values under unit conversions when comparing student answers with the final answer or checking intermediate steps.
- Even though the student use different types of KCL/KVL equations to solve the problem (such as 'sum of currents leaving = 0' and 'in=out'), which
       might looks inconsistent, you should not deduct for that criterion "E".
- The circuit diagram descriptions in the student solution may also contain important information. Thus, the circuit diagram descriptions should
      also be considered as part of the solution.
- Fill all five keys M,E,C,U,NC in "per_criterion" (empty 'applied' list and subtotal=0 if no issues).
- If there is any deleted or crossed-out content in the student's Markdown, you should NOT consider it as part of the solution.
- If there is some content in a box, you should consider it as part of the solution and carefully check it.
- For the problems involving passive sign convention, if the final numerical answer is correct but the student did not make the passive sign
      convention explicit in their solution, you should NOT deduct any points.
- If the method or intermediate equations used by the student is different from the one in the reference solution but is valid and leads to correct
       results, you should NOT deduct any points.

Return ONLY JSON per the schema.
```

Figure 20: First-round prompt used by the LLM grader to generate point deductions based on detected mistakes in the student's solution.

**Prompt (Round 2) for LLM grading (explaining the score deductions)**

```
You are a careful grading explainer.
You will receive:
- The original student solution (Markdown),
- The rubric snippet,
- And the model's raw scoring JSON from the prior turn.

Your job:
1) For EVERY applied deduction (any code M/E/C/U/NC with subtotal > 0 or non-empty 'applied'), explain *why*
     with short, specific reasons tied to the student's content.
2) Show a concrete EVIDENCE SNIPPET: an exact, short substring copied from the student's Markdown that
     motivated the deduction (when possible).
3) Provide a single OVERALL CONFIDENCE label: "high" or "low". Use "low" when OCR noise/ambiguity/insufficient
      evidence could materially affect the scoring; otherwise "high".
4) Produce an EDITED MARKDOWN where ONLY the problematic parts are visually flagged **in-place**, keeping all
     other text untouched:
   - Wrap error spans with: <span style="background-color:#ffd6d6;color:#b00020;font-weight:bold"> ... </span>
   - Immediately after the span, append a small bracket note like: [deduct -0.03, reason: ...]
   - Do not move or rewrite surrounding text; preserve original formatting as much as possible.

Return strictly valid JSON with this schema:
{
  "reasons": {
    "M": [ {"rule_id": "string or empty", "deduct": number, "evidence_snippet": "short exact copy from student'
     s text", "why": "short reason"} ],
    "E": [ ... ],
    "C": [ ... ],
    "U": [ ... ],
    "NC": [ ... ]
  },
  "confidence": "high" | "low",
  "edited_markdown": "FULL edited student Markdown with inline highlights"
}

Notes:
- If a code has no deductions, return an empty list for that code in "reasons".
- Keep 'evidence_snippet' short (a phrase or one sentence); if truly impossible, use an empty string.
- The edited_markdown must remain valid Markdown and keep all original content except the inline inserts for
     flagged parts.
"""

EXPLANATION_USER_TEMPLATE = """CONTEXT:
RUBRIC SNIPPET:
{rubric_snippet}

STUDENT MARKDOWN (original):
{student_markdown}

RAW SCORING JSON FROM PRIOR TURN:
{raw_scoring_json}

TASK:
- Explain deductions with concise reasons and evidence snippets.
- Output ONLY the JSON per the schema (no Markdown fences).
```

Figure 21: Prompt for the second round in which the LLM grader explains the reasons for score deductions and identifies their locations within the student's transcribed Markdown solution.

**Prompt for the LLM regrader to grade student solutions given the flagged recognition errors**

```
You are regrading a student's Markdown solution using the rubric and recognition-error triage. Return ONLY a
     single compact JSON object.

Context:
- Problem statement (possibly with illustrative images (e.g., schematics for the problem) if provided) and the
      student's Markdown solution (may contain some recognition errors or student's own mistakes) are provided.

- The correct final answer is provided.
- The rubric is summarized below and includes examples and max deduction caps.
- You also get the previous AI grader's outcome (per_code and deduction_reason) and the recognition-error
     triage (reasoning + error_details), both of which are based on the student's Markdown solution and you
     can locate the corresponding parts in the student's Markdown solution.

Regrade rules:
1) If recognition_errors likely caused the previous deductions (e.g., a wrong symbol/value that is
     inconsistent with context and appears only once),
   then IGNORE those recognition-induced issues in the second grading (do NOT deduct for them).
2) If there are student_own_mistakes in the recognition-error triage, determine (a) whether the first grading
     properly accounted for them or (b) whether there are also recognition errors based on the previous AI
     grader's outcome, the student's Markdown solution, and, the problem information. If a reasonable student
     mistake was NOT considered and it materially affects correctness *be conservative when making this
     judgement*, deduct accordingly this time. If you think some student mistakes are just recognition errors,
      then do not deduct for them like 1).
3) If neither applies materially, keep the original deductions (or return empty if none).
4) Only deduct among M/E/C/U/NC. Follow the rubric_snippet; do not exceed each code's max deduction (caps will
      also be applied downstream).

Provide brief, concrete justification tied to the student's Markdown (and final answer), referencing
     recognition triage details where needed.

--- INPUTS ---
Problem statement:
{problem_statement}

Correct final answer (concise):
{final_answer}

Student's Markdown solution:
{markdown_content}

Rubric snippet (abbrev):
{rubric_snippet}

Recognition-error triage:
- reasoning: {recog_reasoning}
- error_details: {json.dumps(recog_error_details, ensure_ascii=False)[:2000]}

Previous AI grader:
- per_code: {json.dumps(orig_pred_per_code, ensure_ascii=False)}
- deduction_reason: {orig_deduction_reason}

--- OUTPUT (return only this JSON, no extra text) ---
{{
  "per_code": {{}},                // e.g., {{ "E": 0.02, "M": 0.03 }}; empty object means no deductions after
      regrade
  "deduction_reason": "one or two sentences explaining the deductions kept/added/removed, why, and where in
     the student's Markdown solution"
}}
```

Figure 22: Prompt used to instruct the LLM regrader (`GPT-5.1`) to evaluate student solutions while accounting for recognition errors flagged by the recognition error detector.

**Prompt for heuristically identifying recognition errors from the target recognized text (Part I)**

```
You are an expert assistant specializing in university-entry-level circuit analysis education and handwriting
     recognition analysis.
You are given a student's solution converted from handwriting to Markdown. Your task is to analyze this
     solution and decide, for each detected issue,
whether it is a handwriting recognition error, a student's own mistake, or uncertain.

Heuristic Principles:
- Recognition errors typically affect a local line/region; before and after that line the values/logic remain
     consistent.
  Student mistakes often propagate downstream and cause multiple subsequent inconsistencies.
- A single wrong line amid otherwise consistent derivation (e.g., 'vb'=4V appears once while context uses 9V)
     suggests recognition error.
- Spurious variables that never appear in problem statement/diagram nor the student's own circuit description
     -> recognition_error.
- If final answer disagrees with a correct derivation at the end, triage per rules below.
- When sign or direction conventions differ but are internally consistent within the student's equations,
     treat them as non-errors. Only mismatched internal usage counts as error.
- Always preserve and verify all sign symbols (''-'') during recognition. Missing or faint minus signs should
     default to ''-'' rather than being dropped.
- When recognizing handwritten math, never reinterpret ''-'' as a hyphen or spacing artifact. If uncertain,
     mark it as [possible -] rather than omitting it.

Rules for Labeling Each Issue:
1) [student_own_mistake]
   When there is no contextual support to disambiguate AND the recognized value/result is completely
     unreasonable or far from
   the expected magnitude (e.g., should be 1.2 but shows 3457; or drastic unit/number mismatch).
   Moreover, if the ''mistake'' appears mid-derivation but the final answer matches the correct final answer,
     it is empirically not a student's own mistake.
   Note: Differences in current or voltage sign due solely to opposite reference directions are not student
     mistakes if equations are self-consistent.

2) [recognition_error]
   If context above and below is consistent and only a single line is wrong, label recognition_error.
   Also label recognition_error when a variable/value conflicts with provided diagrams or a variable never
     appears in the statement/diagram/description but suddenly shows up (spurious).
   Include possible OCR sign loss: if removing or adding a ''-'' restores numerical or logical consistency,
     label as recognition_error (missing_minus).

3) [uncertain]
   In the same ''no-context'' setting as (1), but the recognized number is close to or easily confusable with
     the expected value (e.g., 4 vs 9, faint minus, 1/x vs x).
   In these ambiguous cases you cannot rule out recognition vs student error, so label the issue as uncertain.
      Use sparingly.

4) General Consistency Checks
   - Logical/Numerical inconsistency: symbol/number changes meaning without justification (e.g., Va=5V becomes
      -5V/5A).
   - Malformed formulas: e.g., parallel resistors written as R1 + R2; KCL/KVL sign violations.
```

Figure 23: Prompt (Part I) for heuristically identifying potential recognition errors in transcriptions of student handwritten work from EDU-CIRCUIT-HW. The prompt includes a set of rules to help the detector exclude genuine student mistakes from flagged recognition errors. If the detector is uncertain about a particular case, it labels it as "uncertain". During the regrading phase, all such cases are reviewed by a human expert (the doctoral teaching assistant in our case study).

**Prompt for heuristically identifying recognition errors from the target recognized text (Part II)**

```
--- INPUT DATA ---

1) Problem Statement:
{problem_statement}

2) Correct Final Answer (for reference):
{final_answer}

3) Recognized Student Solution (Markdown):
{markdown_content}

--- TASK ---
Read the solution and identify issues. For each issue, provide:
- a precise location_snippet from the Markdown,
- a short diagnostic,
- a tags array containing exactly one of: ["recognition_error"], ["student_own_mistake"], or ["uncertain"],
- any image indices used (e.g., "#S0", "#P1"),
- and the rule(s) applied. Also add an overall summary for human-in-the-loop routing.

--- OUTPUT FORMAT (MUST be a single valid JSON object, no extra text) ---
{{
  "issue_summary": {{
    "recognition_errors": integer,
    "student_own_mistakes": integer,
    "uncertain": integer
  }},
  "contains_recognition_error": boolean,
  "reasoning": "A concise justification of the overall decision. When applicable, cite #S*/#P* and briefly
     note ambiguity.",
  "error_details": [
    {{
      "location_snippet": "Exact snippet from the Markdown where the issue occurs.",
      "explanation": "Why this is an issue; reference the applied rule(s).",
      "tags": ["recognition_error" | "student_own_mistake" | "uncertain"],
      "support": {{
        "image_refs": ["#S0", "#P1"],
        "context_check": "Describe local-consistency or lack thereof (e.g., above/below lines use 9V while
     this line is 4V).",
        "impact_scope": "local | propagating"
      }}
    }}
  ]
}}
Return only that JSON object and nothing else.
```

Figure 24: Prompt (Part II) for heuristically identifying potential recognition errors in transcriptions of student handwritten work from EDU-CIRCUIT-HW. The `markdown_content` field contains the MLLM-generated transcription to be analyzed, while `problem_statement` and `final_answer` provide question-specific context (as introduced in Appendix B) to support accurate error detection.