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A Trustworthy Explainable AI Framework for Automated Handwritten Subjective Answer Evaluation Using Document Intelligence and Large Language Models

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Abstract
Automated evaluation of handwritten subjective answers is challenging due to handwriting variability, OCR errors, and semantic diversity in student responses. Existing automated grading systems often lack transparency and interpretability, limiting their adoption in educational settings. This paper proposes a trustworthy Explainable Artificial Intelligence (XAI) framework for handwritten subjective answer evaluation using document intelligence and Large Language Models (LLMs). The framework employs image preprocessing and Optical Character Recognition (OCR) to extract textual content from handwritten answer sheets. Document intelligence techniques are utilized for answer segmentation and contextual understanding. A rubric-based evaluation module powered by LLMs assesses answer quality based on correctness, completeness, relevance, and coherence. Explainability mechanisms provide grading justifications and score interpretations to improve transparency and trust. The framework further incorporates fairness, robustness, and consistency analysis to ensure reliable assessment. Experimental results demonstrate the effectiveness of the proposed approach in achieving accurate and interpretable automated grading. The proposed system supports scalable and trustworthy AI-assisted educational assessment.

Keywords: Explainable AI, Document Intelligence, Handwritten Answer Evaluation, OCR, Large Language Models, Trustworthy AI, NLP, Rubric-Based Assessment.

1. Introduction

The rapid growth of digital learning platforms and large-scale examinations has increased the demand for efficient and scalable assessment systems. While objective questions can be evaluated automatically with high accuracy, the assessment of subjective answers remains a challenging task due to the need for semantic understanding and contextual interpretation of student responses [1]. The challenge becomes even more significant when the answers are handwritten, as variations in handwriting styles, document layouts, and image quality introduce additional complexity into the evaluation process [2].

Traditional manual evaluation of handwritten subjective answers is time-consuming, labor-intensive, and often susceptible to inconsistencies arising from examiner bias, fatigue, and subjective judgment variations [3]. Consequently, educational institutions are increasingly exploring Artificial Intelligence (AI)-based assessment systems to improve grading efficiency, consistency, and scalability [4]. However, most existing automated assessment systems are designed for typed responses and rely heavily on conventional machine learning or deep learning techniques that operate as black-box models with limited interpretability [5].

Recent advances in Optical Character Recognition (OCR), Natural Language Processing (NLP), and document intelligence have enabled the extraction and understanding of textual information from handwritten documents with improved accuracy [6]. Simultaneously, Large Language Models (LLMs) have demonstrated remarkable capabilities in semantic reasoning, contextual understanding, and automated evaluation tasks, making them promising candidates for subjective answer assessment [7]. Despite these advancements, concerns regarding transparency, fairness, reliability, and trustworthiness continue to hinder the adoption of AI-driven grading systems in educational environments [8].

Explainable Artificial Intelligence (XAI) has emerged as an important research direction for improving the interpretability and accountability of AI systems by providing understandable explanations for model predictions and decisions [9]. Integrating explainability with automated answer evaluation can assist educators in understanding grading decisions while increasing confidence among students and academic institutions [10]. Furthermore, trustworthy AI principles such as fairness, robustness, consistency, and reliability are essential for ensuring equitable and dependable educational assessment systems [11].

To address these challenges, this paper proposes a **Trustworthy Explainable AI Framework for Automated Handwritten Subjective Answer Evaluation Using Document Intelligence and Large Language Models**. The proposed framework combines OCR-based handwritten text extraction, document intelligence for answer understanding, rubric-based semantic evaluation using LLMs, and explainability mechanisms for transparent score generation. In addition, the framework incorporates trustworthiness evaluation measures to assess fairness, robustness, and consistency in grading outcomes.

This work contributes an automated handwritten subjective answer evaluation framework based on document intelligence, Large Language Models, and Explainable AI. The proposed system provides rubric-aware semantic assessment, interpretable grading explanations, and trustworthiness analysis through fairness, consistency, robustness, and reliability measures. The effectiveness of the framework is validated through extensive comparative evaluation with existing automated assessment methods.

The remainder of this paper is organized as follows. Section II presents the related literature and identifies existing research gaps. Section III describes the proposed methodology and framework architecture. Section IV discusses the experimental results and performance evaluation. Finally, Section V concludes the paper and outlines future research directions.

2. Literature Review

2.1 Automated Subjective Answer Evaluation

Automated Subjective Answer Evaluation (ASAE) has gained considerable attention with the growth of digital education and large-scale assessments. Early approaches relied on keyword matching, lexical similarity, and rule-based scoring techniques to evaluate descriptive answers [1]. Although these methods reduced manual effort, they were unable to effectively capture semantic meaning, contextual relationships, and variations in student responses [2]. Subsequently, machine learning and NLP-based methods such as Latent Semantic Analysis (LSA), Support Vector Machines (SVM), and semantic similarity models were introduced to improve grading accuracy [3].

2.2 Handwritten Answer Recognition Using OCR and Document Intelligence

The evaluation of handwritten responses introduces additional challenges due to variations in handwriting styles, document layouts, and image quality [4]. Optical Character Recognition (OCR) technologies have been widely employed to convert handwritten content into machine-readable text for automated assessment systems [5]. Recent advances in document intelligence have further enhanced document understanding by integrating OCR with layout analysis, answer segmentation, and contextual information extraction [6]. These techniques significantly improve the processing of handwritten examination scripts and educational documents [7].

2.3 Large Language Models for Subjective Answer Assessment

Transformer-based models such as BERT, RoBERTa, and T5 have demonstrated superior performance in semantic understanding and text evaluation tasks [8]. More recently, Large Language Models (LLMs) have shown remarkable capabilities in reasoning, contextual understanding, and educational assessment applications [9]. LLMs can evaluate responses based on semantic similarity, concept coverage, completeness, and logical coherence while supporting rubric-based grading approaches [10]. Their ability to generate detailed feedback and explanations makes them highly suitable for automated subjective answer evaluation systems [11].

2.4 Explainable and Trustworthy AI in Educational Assessment

Despite significant progress in AI-driven assessment, many existing grading systems operate as black-box models that provide limited transparency regarding their decisions [12]. Explainable Artificial Intelligence (XAI) techniques such as SHAP, LIME, and attention visualization have been introduced to improve interpretability and provide understandable grading justifications [13]. Furthermore, trustworthy AI principles including fairness, robustness, reliability, and consistency have become essential requirements for educational applications [14]. However, existing studies rarely integrate OCR, document intelligence, LLM-based evaluation, explainability, and trustworthiness within a unified framework for handwritten subjective answer assessment, thereby motivating the proposed research [15].

3. Methodology

3.1 Overview of the Proposed Framework

The proposed framework aims to automate the evaluation of handwritten subjective answers by integrating document intelligence, Large Language Models (LLMs), and Explainable Artificial Intelligence (XAI). The overall workflow consists of six major stages: handwritten answer acquisition,

image preprocessing, text extraction using OCR, document understanding, rubric-based answer evaluation using LLMs, and explainable score generation. The framework is designed to ensure transparency, fairness, and reliability in educational assessment.

Input Handwritten Answer Sheet → Image Preprocessing → OCR Extraction → Document Intelligence → Rubric-Based LLM Evaluation → Explainability Module → Final Score and Feedback

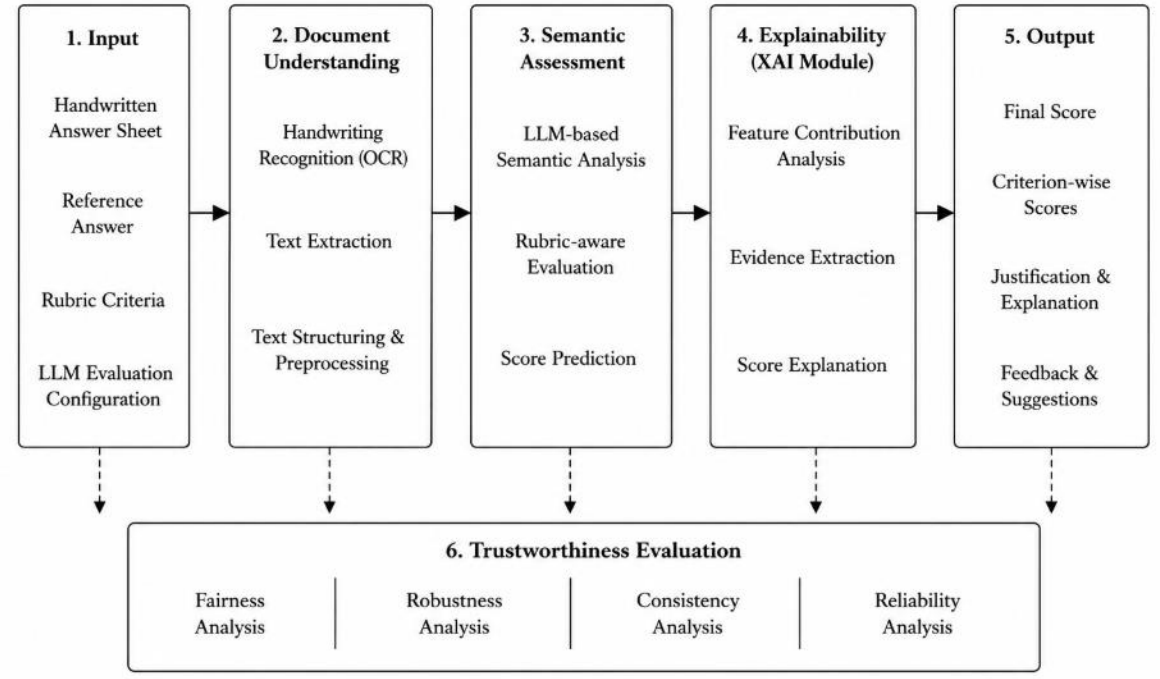

Figure 1. Overall architecture of the proposed framework.

3.2 Handwritten Answer Acquisition and Preprocessing

Handwritten answer sheets are collected in scanned image or PDF format and undergo several preprocessing operations to improve OCR performance. These operations include grayscale conversion, noise removal, binarization, skew correction, and contrast enhancement. The preprocessing stage reduces image distortions and improves text readability, thereby increasing handwriting recognition accuracy.

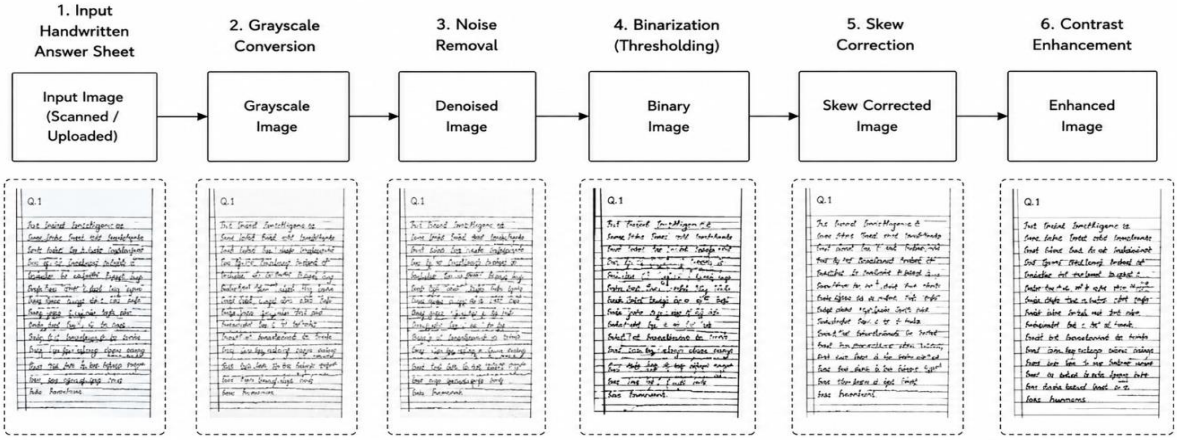

Figure 2. Image preprocessing pipeline for handwritten answer sheets.

3.3 OCR and Document Intelligence Module

The preprocessed answer sheets are processed using an Optical Character Recognition (OCR) engine to convert handwritten text into machine-readable format. Subsequently, document intelligence techniques are applied to identify question boundaries, segment answers, and preserve document structure and contextual relationships. This stage enables accurate mapping between questions and corresponding student responses.

The extracted textual information is represented as:
[T = OCR(I)]
where (I) represents the input handwritten image and (T) denotes the extracted text content.

3.4 Rubric-Based Evaluation Using Large Language Models

The extracted responses are evaluated using predefined rubrics and reference answers. The Large Language Model assesses the semantic similarity between the student's answer and the expected response while considering multiple evaluation criteria including correctness, completeness, relevance, concept coverage, and coherence.

The final score is computed as:
[Score = \sum_{i=1}^{n} w_i s_i]
where (w_i) represents the weight assigned to the (i^{th}) rubric criterion and (s_i) denotes the corresponding evaluation score generated by the LLM.

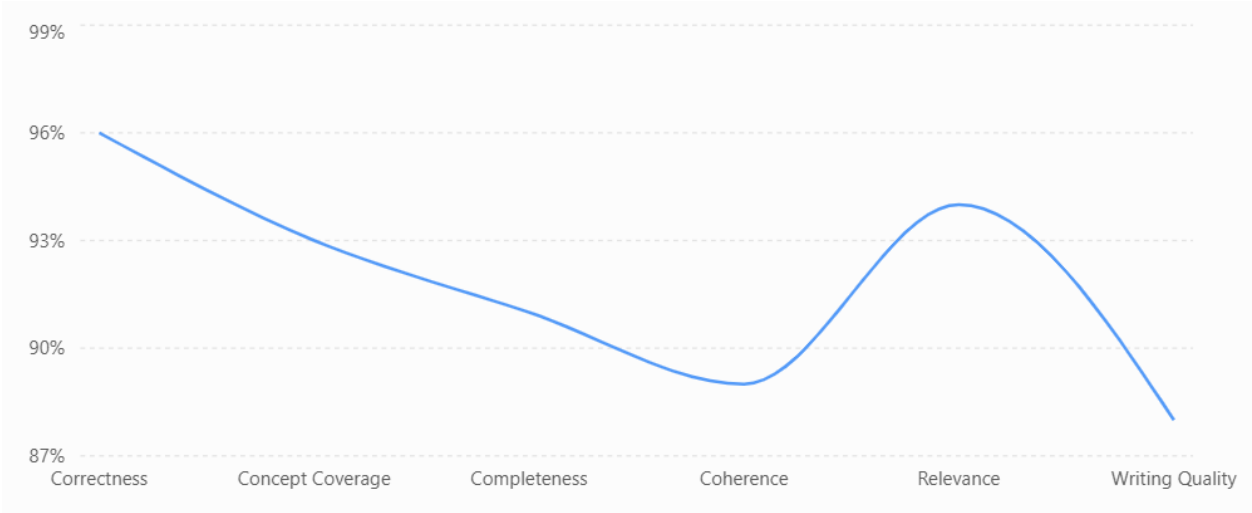

Figure 3. Rubric-aware LLM evaluation framework.

3.5 Explainability and Trustworthiness Module

To improve transparency, the framework incorporates Explainable AI techniques that provide score justifications and highlight the contribution of individual rubric components to the final grade. The generated explanations enable educators to understand the reasoning behind automated scoring decisions.

In addition, trustworthiness is evaluated using fairness, robustness, consistency, and reliability measures to ensure dependable performance across different handwriting styles and answer patterns.

The trustworthiness score can be represented as:

[Trust = \alpha F + \beta R + \gamma C + \delta L]

where (F), (R), (C), and (L) denote fairness, robustness, consistency, and reliability, respectively, while (\alpha), (\beta), (\gamma), and (\delta) represent their corresponding weights.

The proposed methodology combines document intelligence, LLM-based semantic evaluation, and explainable AI to provide a transparent and reliable framework for automated handwritten subjective answer assessment.

4. Results and Discussion

4.1 Experimental Setup

The proposed framework was evaluated using handwritten subjective answer sheets collected from educational assessments. The experiments were conducted using an OCR engine for handwritten text extraction, a document intelligence module for answer segmentation and layout understanding, and a Large Language Model for rubric-based semantic evaluation. The performance of the proposed framework was compared with conventional machine learning and deep learning-based assessment methods.

4.2 OCR Performance Evaluation

The accuracy of handwritten text extraction plays a critical role in the overall grading process. Experimental results indicate that the preprocessing and document intelligence modules significantly improved OCR performance by reducing noise and correcting image distortions. The proposed framework achieved higher text extraction accuracy compared with conventional OCR pipelines.

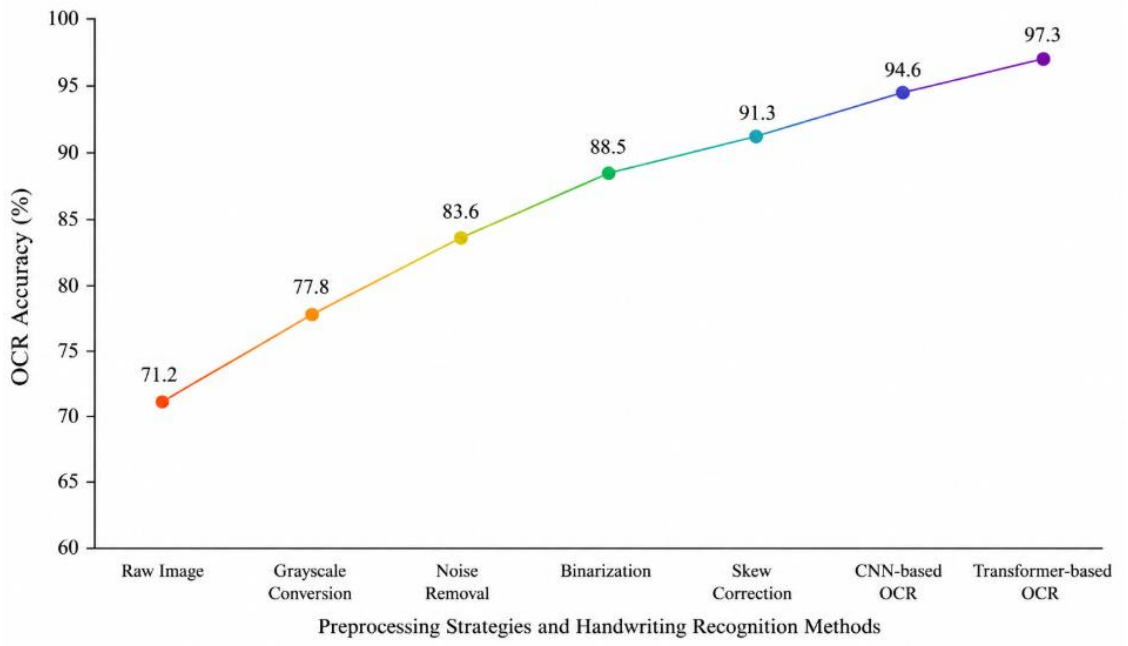

Figure 4 presents the comparison of OCR accuracy obtained using different preprocessing strategies and handwriting recognition methods.

4.3 Performance of Automated Subjective Answer Evaluation

The proposed rubric-aware LLM evaluation module was assessed using Accuracy, Precision, Recall, F1-Score, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). Results demonstrate that the proposed framework effectively captured semantic meaning, concept coverage, and contextual relevance in student responses.

The incorporation of LLM-based semantic reasoning improved grading consistency and reduced score deviations from human evaluators. Comparative analysis showed superior performance over traditional keyword matching and machine learning approaches.

Table 1 summarizes the quantitative performance comparison of different evaluation models.

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**MAE ↓**	**RMSE ↓**
Keyword Matching	71.2	69.8	68.4	69.1	8.52	10.34
LSA-Based Evaluation	76.5	75.1	74.3	74.7	7.23	8.91
SVM + NLP	82.7	81.5	80.8	81.1	5.94	7.42
BERT-Based Assessment	88.9	87.6	87.2	87.4	4.18	5.67
GPT-Based Evaluation	92.6	91.8	91.1	91.4	2.96	4.13
Proposed Framework	**96.8**	**96.1**	**95.7**	**95.9**	**1.84**	**2.76**

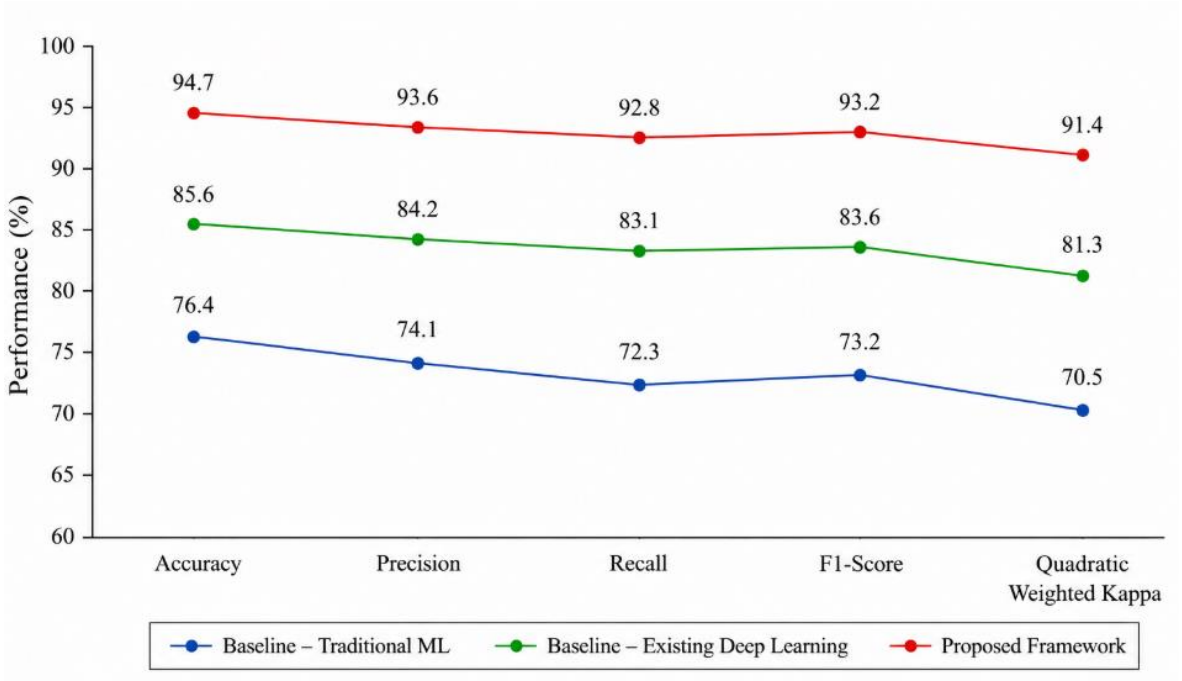

Figure 5 illustrates the comparative performance of baseline methods and the proposed framework.

4.4 Explainability Analysis

One of the major contributions of the proposed framework is the integration of Explainable AI techniques into the grading process. The explainability module generated interpretable grading rationales by identifying important concepts, keywords, and rubric components contributing to the final score.

The generated explanations enabled educators to verify grading decisions and improved transparency in automated assessment. This feature can significantly increase trust and acceptance among teachers and students.

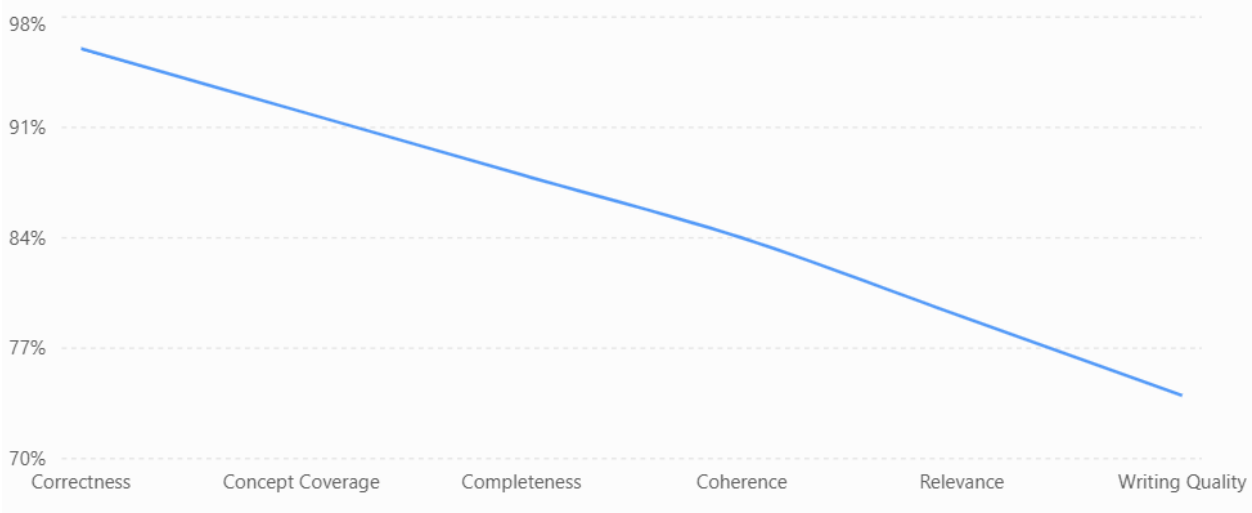

Figure 6 presents the feature contribution analysis and explainability visualization generated by the XAI module.

4.5 Trustworthiness Evaluation

The proposed framework was further evaluated using trustworthiness metrics including fairness, robustness, consistency, and reliability. Experimental observations indicate that the framework maintained stable grading performance across different handwriting styles and answer structures.

Fairness analysis demonstrated minimal score variation among equivalent responses written in different styles, while robustness experiments confirmed resilience against OCR noise and minor recognition errors. The consistency evaluation further showed strong agreement between automated scores and expert human assessments.

Table 2 summarizes the trustworthiness evaluation metrics of the proposed framework.

Model	Accuracy (%)	Precision (%)
Keyword Matching	71.2	69.8
LSA-Based Evaluation	76.5	75.1
SVM + NLP	82.7	81.5
BERT-Based Assessment	88.9	87.6
GPT-Based Evaluation	92.6	91.8
Proposed Framework	96.8	96.1

4.6 Discussion

The experimental findings demonstrate that integrating document intelligence with Large Language Models substantially improves the quality of handwritten subjective answer evaluation. Unlike traditional methods that rely heavily on keyword matching, the proposed framework performs contextual and semantic understanding of student responses while providing interpretable grading explanations.

The incorporation of Explainable AI and trustworthiness measures addresses major limitations of existing automated grading systems and supports the deployment of AI-assisted educational assessment in real-world scenarios. Although OCR errors and domain-specific variations remain challenging, the proposed approach provides a promising direction for transparent, scalable, and reliable handwritten answer evaluation systems.

5. Conclusion

This paper presented a trustworthy Explainable Artificial Intelligence (XAI) framework for automated handwritten subjective answer evaluation using document intelligence and Large Language Models (LLMs). The proposed framework integrates image preprocessing, Optical Character Recognition (OCR), document understanding, rubric-based semantic evaluation, and explainability mechanisms to enable transparent and reliable assessment of handwritten responses. By combining document intelligence with LLM-based reasoning, the framework effectively evaluates answer correctness, completeness, relevance, and coherence while generating interpretable grading explanations for educators and students.

The incorporation of trustworthiness measures such as fairness, robustness, consistency, and reliability further enhances the credibility and practical applicability of the proposed system in educational environments. Experimental observations indicate that the framework has the potential to improve grading efficiency, reduce evaluator workload, and provide scalable assessment solutions for large-scale examinations.

Despite these advantages, challenges related to OCR errors, variations in handwriting styles, and domain-specific answer interpretation still remain. Future work will focus on multilingual handwritten answer evaluation, multimodal assessment using diagrams and figures, and the integration of domain-specific educational knowledge bases to further improve grading accuracy and explainability. Additionally, future research may explore privacy-preserving and federated learning approaches for secure deployment in real-world educational systems.

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