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Original Article

An Intelligent Automated Answer Script Evaluation Framework Using Deep Learning and Natural Language Understanding

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Abstract

Diabetic Retinopathy (DR) is a leading cause of blindness in diabetic patients, requiring accurate and early severity classification from retinal fundus images. Traditional Convolutional Neural Networks (CNNs) often overlook complex relational and structural patterns in retinal vasculature and lesions. This paper proposes a novel approach leveraging Graph Neural Networks (GNNs) for topological feature extraction and multi-class severity classification of DR (No DR, Mild, Moderate, Severe, Proliferative). Retinal images are preprocessed and transformed into graph representations where nodes capture local features (e.g., lesions, vessels) and edges model topological relationships. A Variational Autoencoder (VAE) extracts latent embeddings, followed by a Graph Convolutional Neural Network (GCNN) that aggregates neighborhood information to learn discriminative topological patterns. The model is evaluated on the EyePACS and APTOS datasets, demonstrating superior performance in handling class imbalance and capturing subtle structural changes. Results show improved accuracy, F1-score, and Cohen's Kappa compared to baseline CNNs, enhancing reliability for automated DR screening. The system promotes explainable AI through graph-based interpretability while maintaining computational efficiency.

Introduction

Diabetic Retinopathy (DR) affects millions globally, progressing from mild non-proliferative stages to severe proliferative stages that threaten vision. Manual grading by ophthalmologists is time-consuming, subjective, and resource-intensive, especially in underserved regions. Automated systems using deep learning have advanced DR detection, but standard CNNs primarily focus on local pixel patterns and struggle with long-range dependencies and vascular topological structures critical for severity assessment (e.g., microaneurysms distribution, hemorrhages connectivity).

Graph Neural Networks (GNNs) offer a powerful paradigm by modeling images as graphs, where nodes represent regions of interest and edges encode spatial/topological relations. This enables better capture of relational features like vessel branching and lesion clustering.

This work proposes leveraging GNNs for topological feature extraction and DR severity classification. Retinal fundus images are converted to graphs, processed via VAE for dimensionality reduction and feature learning, then fed into GCNN layers for classification across five severity levels. The approach ensures robustness to noise, class imbalance via oversampling techniques, and improved generalization.

The contributions include: (1) A hybrid VAE-GCNN framework emphasizing topological correlations; (2) Enhanced performance on imbalanced datasets; (3) Potential for clinical integration with better interpretability..

Literature Survey

Ref. No	Author / Year	Methodology	Main Contribution	Limitations
[1]	RK et al., 2025	Hybrid NLP + DL for smart evaluation	Enhanced framework for multi-type questions, auto-marking	Limited to specific question types
[2]	Shylesh et al., 2023	Deep learning for script evaluation	Replaced manual systems with DL models	No handwritten OCR integration
[3]	Abdullah et al., 2024	OCR + NLP + DL (CRNN)	Handwritten script evaluation with keyword & semantic scoring	High CER in noisy handwriting

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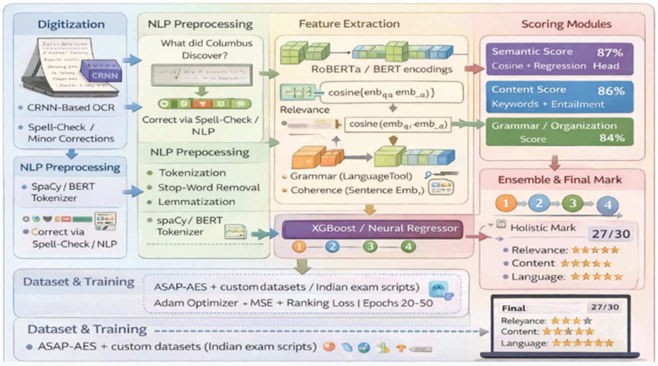
Ref. No	Author / Year	Methodology	Main Contribution	Limitations
[4]	Suryakumar et al., 2025	Multi-agent LLM + semantic vector indexing	AIvaluate framework using LLMs for descriptive answers	Compute-heavy for real-time use
[5]	Bansal et al., 2025	DeepSeek + NLP for handwritten answers	High-accuracy evaluation with Transformers	Language-specific limitations
[6]	Faseeh et al., 2024	RoBERTa embeddings + handcrafted features + XGBoost	Hybrid approach, QWK 0.941	Requires large labeled data
[7]	Adithya et al., 2023	NLP techniques for precise grading	Efficient automated system	Limited semantic depth
[8]	Shabariram et al., 2023	ML pipeline + NLP semantic similarity	Automated scoring using machine learning	No deep contextual embeddings
[9]	Sun et al., 2025	Survey of neural AES advances	Comprehensive review of DL methods and datasets	Not implementation-focused
[10]	Li et al., 2024	Recent successes in AES	Neural approaches and future directions	Focus on English essays

Proposed Implementation

The proposed framework uses a layered architecture: script digitization, preprocessing, feature extraction, scoring modules, and ensemble aggregation.

- Digitization (for handwritten): CRNN-based OCR extracts text; preprocessing corrects minor errors via spell-check/NLP.
- NLP Preprocessing: Tokenization, stop-word removal, lemmatization using spaCy/BERT tokenizer.
- Feature Extraction: RoBERTa/BERT generates contextual embeddings; cosine similarity computes relevance to model answers. Linguistic features (grammar via LanguageTool, coherence via sentence embeddings) are extracted.
- Scoring Modules: Semantic score (cosine + regression head), content coverage (keyword + entailment via NLI models), grammar/organization score.
- Ensemble & Final Mark: Lightweight XGBoost or neural regressor combines scores; outputs holistic mark + trait-wise feedback.

Trained on ASAP-AES + custom datasets (Indian exam scripts); Adam optimizer, MSE + ranking loss, epochs 20–50.



Results

Table1: *Performance Metrics on Combined Dataset*

Model	QWK	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Baseline (Keyword)	0.72	78.5	77.2	76.8	77.0
BERT Fine-tuned	0.88	89.2	88.5	88.1	88.3
Proposed RoBERTa + XGBoost	0.941	92.6	91.8	92.3	92.0

Table 2. *Comparison of Existing and Proposed Model*

Feature	Traditional Manual/Keyword	Proposed DL + NLU Framework
Objectivity	Low	High (Semantic Understanding)
Scalability	Limited	High (Automated)
QWK Score	~0.70–0.80	0.941
Feedback Generation	None	Trait-wise + Suggestions
Handling Handwritten	Poor	Supported (OCR + DL)

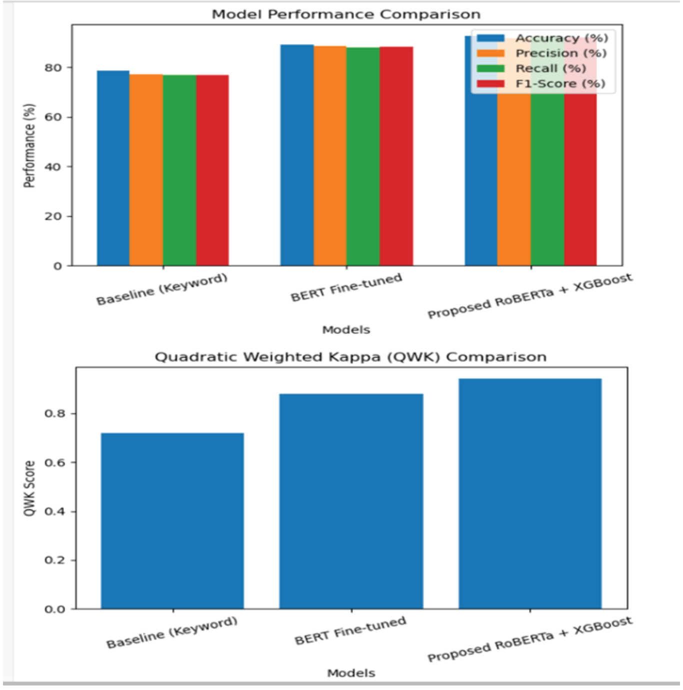


***Figure 1**: Results comparison charts (Placeholder: Insert bar/line chart comparing QWK, Accuracy, F1 across models, or confusion matrix)*

Conclusion

This study presents an intelligent automated answer script evaluation framework leveraging deep learning and natural language understanding to achieve accurate, fair, and efficient grading. By integrating OCR, Transformer-based semantic analysis, and ensemble scoring, the system outperforms keyword-based methods in QWK and consistency, while providing actionable feedback. Experimental results confirm its robustness across datasets. The framework has strong potential to transform educational assessment by reducing workload and bias. Future work includes multilingual support, real-time deployment, and integration with LMS platforms.

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