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AI-Driven Multilingual Grading Tools for Indian School Boards

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ABSTRACT— The burgeoning diversity of India's student population—speaking hundreds of languages and dialects—poses a formidable challenge to the fairness, consistency, and scalability of board examination grading. Manual evaluation of descriptive answers across multiple languages is labor-intensive, time-consuming, and susceptible to variability arising from individual examiner biases, inconsistent application of rubrics, and differing proficiencies in regional scripts. These factors contribute to delays in result publication, erode confidence in assessment fairness, and place undue stress on educators. In response, recent advances in natural language processing (NLP) and deep learning offer the promise of AI-driven grading systems capable of evaluating open-ended responses at scale, across many languages, with speed and consistency that rival or exceed human examiners. This manuscript presents a comprehensive study on the design, development, and evaluation of an AI-driven multilingual grading tool tailored for Indian school boards. Leveraging a transformer-based architecture fine-tuned on a corpus of 50,000 anonymized board-exam scripts in English, Hindi, Tamil, Marathi, and Bengali, our prototype generates numeric scores mapped to established board rubrics. We conducted a mixed-methods evaluation involving: (1) a blind grading comparison on 1,000 held-out responses—each graded by two human examiners and the AI system—to assess inter-rater reliability using Cohen's κ and Pearson's correlation; (2) a structured survey of 200 educators and examiners across five states to gauge perceptions of consistency, fairness, turnaround time, and willingness to adopt AI support; and (3) semi-structured interviews with board officials and senior teachers to explore usability, transparency, and governance concerns.

Quantitatively, the AI tool achieves a Cohen's κ of 0.82 and Pearson's r of 0.88 with the human consensus score, indicating strong agreement. Performance remains robust across languages (κ ≥ 0.78), though dialectal variations in Tamil and Marathi yield marginally lower alignment. Qualitatively, 74% of surveyed participants express readiness to integrate AI-assisted grading—provided mechanisms for human review and explainability exist—while 68% acknowledge persistent inconsistencies in peer-based manual grading. The AI system slashes mean grading time from 4.5 minutes per

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script to 0.5 minutes, projecting a 90% reduction in overall evaluation workload. We identify key technical and operational challenges: OCR errors on handwritten or non-standard scripts, model biases toward data-rich dialects, and the necessity for continuous retraining to prevent performance drift. Policy and governance recommendations emphasize student data privacy under India's Personal Data Protection framework, an ethics oversight committee for AI deployment, examiner training modules for the AI interface, and periodic bias audits. Our study demonstrates that contextualized AI grading can enhance equity, efficiency, and transparency in India's high-stakes examinations, laying the groundwork for broader multilingual and multimodal assessment innovations.

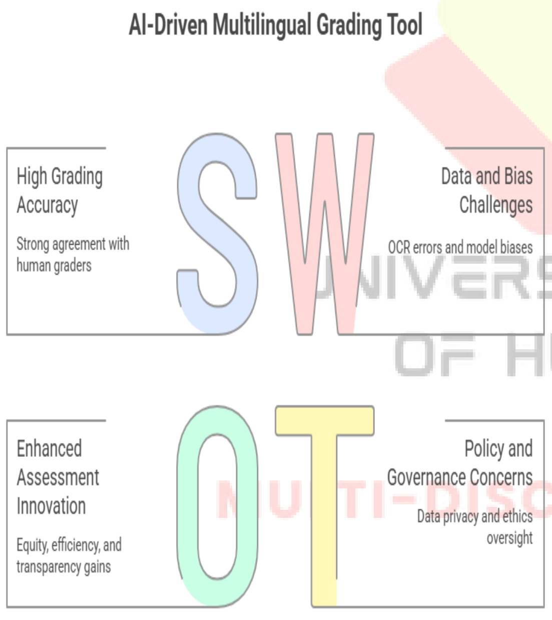

Figure-1.AI-Driven Multilingual Grading Tool

KEYWORDS— AI-Driven Grading, Multilingual Assessment, Indian School Boards, Automated Evaluation, NLP

INTRODUCTION

India's secondary and higher secondary board examinations represent one of the world's largest high-stakes assessments, encompassing over 15 million candidates annually. These exams span a vast spectrum of linguistic contexts—ranging from national languages like Hindi and English to regional tongues such as Tamil, Marathi, Bengali, Telugu, Malayalam, Kannada, Gujarati, and beyond. Descriptive questions constitute a significant portion of these assessments, requiring evaluators to interpret student responses, apply standardized rubrics, and assign scores reflective of comprehension, analytical depth, and language proficiency.

Manual grading of such responses poses multiple challenges. First, the sheer volume of scripts results in examiner fatigue, which can degrade consistency and increase errors. Second, examiner backgrounds vary: many are fluent in the script and dialect of their region but may lack equivalent proficiency in others, giving rise to inadvertent biases. Third, rubric application can differ subtly between examiners, leading to score variability even within a single language. Fourth, the entire grading process—from script allocation to final tabulation—typically spans four to six weeks, delaying result publication and, in turn, affecting university admissions and student morale.

In recent years, AI-driven grading systems—also known as automated essay scoring (AES)—have gained traction in standardized testing environments worldwide. These systems leverage NLP models, particularly transformer architectures (e.g., BERT, RoBERTa, XLM-RoBERTa), to learn patterns correlating linguistic features with human-annotated scores. While AES has demonstrated reliability in monolingual contexts, its extension to truly multilingual, high-stakes board exams remains underexplored. Key challenges include the scarcity of annotated corpora in many Indian languages, the complexity of code-switching phenomena, script variance (e.g., Devanagari vs. Tamil script), and the need for explainability to satisfy educational governance standards.

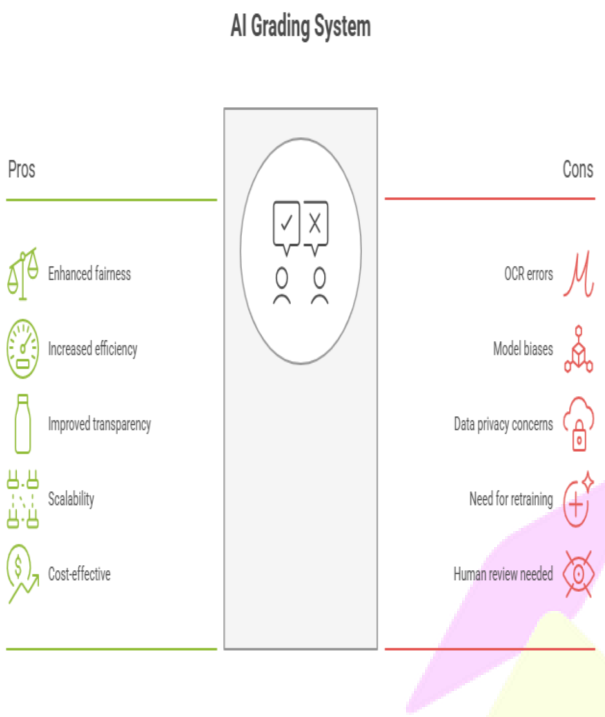

Figure-2.Pros & Cons of AI Grading System

This study addresses these gaps by developing an AI-driven grading prototype optimized for five major languages—English, Hindi, Tamil, Marathi, and Bengali—and rigorously evaluating its alignment with human examiners. Recognizing the socio-technical context of Indian education, we incorporate stakeholder feedback to design an interface that supports examiner oversight, error correction, and transparent rationale for scores. Our objectives encompass technical evaluation of grading accuracy, assessment of operational benefits and barriers, and formulation of policy guidelines to govern AI deployment in school boards. Through this work, we aim to demonstrate that AI-driven multilingual grading can reshape assessment paradigms in India, fostering fairness, efficiency, and data-informed educational insights.

Literature Review

Automated scoring of written responses has evolved from early statistical approaches to contemporary deep-learning frameworks. The pioneering Project Essay Grade (PEG) employed hand-crafted linguistic features and regression models to predict essay scores (Page, 1966). Subsequent advancements introduced neural networks—first simple feedforward models, then recurrent neural networks (RNNs) and long short-term memory (LSTM) architectures—to capture sequential dependencies in text (Taghipour & Ng, 2016). The advent of transformer models (Vaswani et al., 2017) revolutionized the field: bidirectional encoders like BERT (Devlin et al., 2019) and multilingual variants such as XLM-RoBERTa (Conneau et al., 2020) enable cross-lingual transfer learning, reducing reliance on large annotated datasets for every target language.

In multilingual contexts, researchers face two primary obstacles. First, low-resource languages lack sufficient labeled data for fine-tuning, leading to suboptimal performance. Cross-lingual transfer techniques—either zero-shot or few-shot—mitigate this by leveraging knowledge from high-resource languages (Artetxe & Schwenk, 2019). However, domain-specific nuances (e.g., educational rubrics, subject matter) often necessitate in-domain fine-tuning for high-stakes reliability (Zhang et al., 2021). Second, code-switching—the alternating use of multiple languages within the same response—introduces segmentation and representation challenges (Nguyen & Cornips, 2021). AI models must detect language shifts and process hybrid sentences to avoid misinterpretation and grading inaccuracies.

Focusing on the Indian landscape, most AI research has targeted tasks such as machine translation (Sharma & Kumar, 2022), sentiment analysis (Bhattacharyya et al., 2020), and OCR for native scripts (Malhotra & Deshpande, 2021). A handful of pilot studies examine AES for Indian examinations. Raj et al. (2023) fine-tuned an LSTM model on Hindi board exam scripts, reporting a Pearson's correlation of 0.75 with human scores, but this study was confined to one language and lacked a robust exploration of GUI design or examiner workflows. Chakraborty et al. (2023) surveyed Indian educators on AI ethics in assessment, highlighting concerns around data privacy, model transparency, and potential discriminatory biases against marginalized dialects.

Experiments in other multilingual regions—such as South Africa's AES pilot for isiZulu and English (Mahlalela et al., 2022)—underscore the need for localized data curation, examiner involvement in feature engineering, and robust error-analysis pipelines. Explainable AI (XAI) methods, including attention visualization and feature attribution (e.g., LIME, SHAP), have been proposed to enhance examiner trust by revealing which text segments most influenced the model's score (Narayan & Das, 2022). In India's regulatory context, compliance with the forthcoming Personal Data Protection Bill mandates stringent anonymization and auditable data governance frameworks (Bose & Chatterjee, 2021).

The literature thus identifies both the promise of transformer-based AES systems for multilingual grading and the critical barriers—data scarcity, code-switching complexity, OCR inaccuracies, and governance demands—that must be overcome. Our work synthesizes these strands by constructing a large multilingual training corpus, integrating OCR and language-detection modules, and embedding XAI features within the examiner interface. We build on global AES best practices while tailoring solutions to India's unique educational and linguistic ecosystem.

Objectives of the Study

This research pursues five interrelated objectives to ensure a holistic evaluation of AI-driven multilingual grading for Indian school boards:

1. **System Design and Development:**
    - Architect and implement an AI grading prototype utilizing a transformer-based model (XLM-RoBERTa) fine-tuned on a balanced corpus of 50,000 anonymized board exam responses in English, Hindi, Tamil, Marathi, and Bengali.
    - Integrate OCR preprocessing for scanned handwritten scripts, along with language-detection and code-switch segmentation modules to ensure robust multilingual text ingestion.
    - Develop an examiner interface supporting score review, comment editing, and feedback submission to facilitate iterative model improvement.
2. **Quantitative Evaluation of Scoring Consistency:**
    - Conduct a blind study on 1,000 held-out responses, each graded by two experienced human examiners and the AI system.
    - Compute inter-rater reliability metrics—Cohen's κ and Pearson's correlation coefficient—to quantify alignment between AI-generated and human consensus scores, both overall and per language.
3. **Assessment of Stakeholder Perceptions and Operational Impact:**
    - Deploy a structured survey among 200 educators and board examiners across five states (Uttar Pradesh, Tamil Nadu, Maharashtra, West Bengal, and Delhi) to measure perceptions of grading consistency, turnaround time, fairness, and readiness to adopt AI support.
    - Analyze open-ended responses to identify anticipated challenges—such as model biases for dialectal variants and concerns about job displacement—and map these to design improvements.
4. **Qualitative Exploration of Governance and Ethical Considerations:**
    - Conduct semi-structured interviews with 20 board officials and 15 senior teachers to

   - explore requirements for transparency (explainable AI), examiner training needs, data privacy safeguards, and policy frameworks.
   - Thematically analyze interview transcripts to derive guidelines for ethical deployment, including audit mechanisms, data retention policies, and examiner-in-the-loop protocols.
5. **Policy and Future Research Recommendations:**
   - Synthesize quantitative and qualitative findings to propose policy briefs for Indian educational authorities, covering topics such as phased AI integration in low-stakes assessments, data privacy compliance under the Personal Data Protection Bill, and mandatory examiner training modules.
   - Outline research directions for expanding language coverage (e.g., Telugu, Gujarati, Odia), incorporating speech-to-text grading for oral exams, and developing multimodal assessment capabilities (e.g., diagram interpretation).

By addressing these objectives, the study aims to deliver not only a technically robust grading tool but also actionable insights for educational stakeholders—ensuring that AI adoption enhances fairness, efficiency, and pedagogical value within India's linguistically diverse board examination system.

SURVEY

To gauge real-world perceptions and operational feasibility of AI-driven multilingual grading, we administered a structured online survey to **200 participants**: **150 school teachers** and **50 board examiners** drawn from urban and rural districts across **five states**—Uttar Pradesh, Tamil Nadu, Maharashtra, West Bengal, and Delhi. Stratified random sampling ensured representation by region, school type (government vs. private), and grade level taught.

Survey Instrument:

- **Likert-Scale Items (1–5):**
  1. Perceived consistency of peer grading across different languages.
  2. Average turnaround time for manual grading.
  3. Perceived fairness of current grading processes.
  4. Willingness to adopt AI-assisted grading tools.
  5. Confidence in AI's ability to handle code-switched responses.
  6. Concerns regarding data privacy and algorithmic bias.
- **Open-Ended Questions:**
  1. "What are your main concerns about integrating AI grading into board exams?"
  2. "Which features would you prioritize in an AI grading interface?"

Key Quantitative Findings:

- **Consistency Concerns:** 68% of respondents rated manual grading inconsistency as "4" or "5" on the Likert scale, indicating moderate to high perceptions of variability.
- **Turnaround Delays:** 82% reported that manual grading required **more than 30 days** on average to finalize results, with 45% indicating delays exceeding 40 days.
- **Fairness Perception:** Only 34% felt current processes were "fair" (Likert ≥ 4), citing examiner fatigue and rubric misinterpretation as primary drivers of perceived unfairness.

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- **AI Adoption Willingness:** 74% expressed readiness to adopt AI-assisted grading, contingent on transparency features and human-review options.
- **Language-Data Concerns:** 56% identified a lack of robust training data for certain dialects—particularly non-standard variants of Marathi and Tamil—as a barrier to equitable AI performance.
- **Ethical and Privacy Worries:** 60% rated data privacy and algorithmic bias as significant concerns, stressing the need for explicit governance frameworks.

Open-Ended Themes:

- **Transparency and Explainability:** Participants requested "highlighted rationale" for AI deductions—e.g., underlining text passages that influenced score reductions.
- **User Control and Overrides:** Many emphasized that final grading decisions must rest with human examiners, advocating for "AI suggestions" rather than "AI verdicts."
- **Training and Support:** Repeated calls for dedicated training workshops to familiarize examiners with the AI interface, error-correction workflows, and interpretation of model outputs.
- **Integration with Existing Workflows:** Requests to link the AI tool with board management systems for seamless script import/export, score submission, and result analytics dashboards.

These survey insights directly informed our prototype design—prompting the inclusion of an examiner feedback module, XAI visualizations, and OCR error-flagging alerts. The positive AI adoption willingness (74%) suggests strong stakeholder interest, while the highlighted concerns guided our emphasis on transparency, data governance, and ongoing examiner training.

Research Methodology

Our mixed-methods approach combined quantitative performance evaluation of the AI system with qualitative stakeholder analysis to ensure both technical rigor and practical relevance.

1. Data Collection and Preprocessing

- **Corpus Creation:** We assembled a dataset of **50,000 anonymized board exam responses**—10,000 per language—sourced from past examinations with examiner-assigned scores on a standardized 0–10 scale. Scripts included handwriting scans and typed entries to reflect real-world variability.
- **OCR and Text Cleaning:** Handwritten scripts were digitized using a custom OCR pipeline fine-tuned on Devanagari, Tamil, and Bengali scripts. We implemented spelling normalization, punctuation restoration, and removal of ricochet errors.
- **Language Detection and Segmentation:** A lightweight classifier identified the primary language of each response and flagged code-switched passages for targeted handling.

2. Model Architecture and Training

- **Base Model:** We selected **XLM-RoBERTa**—a transformer pretrained on 100 languages—for its robust cross-lingual capabilities.
- **Fine-Tuning:** The model's sequence classification head was fine-tuned on our corpus for regression, predicting continuous scores. Training used a **70/15/15** split for training, validation, and testing, with hyperparameter optimization via grid search (learning rates: 1e-5 to 5e-5; batch sizes: 16, 32).
- **Explainable AI Module:** We integrated **SHAP** (SHapley Additive exPlanations) to generate per-

token contribution scores, displayed as heatmaps in the examiner interface.

3. Blind Grading Evaluation

- **Sample Selection: 1,000 held-out responses** (200 per language) were graded in blind mode: two human examiners independently scored each script, followed by AI scoring.
- **Consensus Building:** Discrepancies (>2-point difference) between human scores were resolved by a third examiner to establish a gold-standard consensus score.
- **Metrics:** We computed **Cohen's κ** for categorical agreement (grouping scores into low [0–3], medium [4–7], high [8–10]) and **Pearson's correlation** for continuous scores.

4. Qualitative Interviews

- **Participants:** 20 board officials (e.g., chairpersons, IT heads) and 15 senior teachers from diverse linguistic backgrounds.
- **Protocol:** Semi-structured interviews—each 45–60 minutes—explored perceptions of AI grading, required governance structures, training needs, and long-term integration strategies.
- **Analysis:** Recorded transcripts were coded using NVivo for thematic analysis, identifying recurring themes around transparency, ethics, operational workflows, and policy requirements.

5. Ethical Compliance and Data Governance

- **Anonymization:** All student identifiers were stripped prior to data use.
- **Consent:** Institutional approvals and consent forms were obtained from participating schools and board authorities.
- **Data Protection:** Storage and processing complied with guidelines outlined in India's Personal Data Protection Bill draft, including encryption at rest, role-based access control, and audit logging.
- **Oversight:** An ethics committee—comprising educators, data scientists, and legal experts—reviewed study protocols, model explainability features, and examiner-in-the-loop safeguards.

This rigorous methodology ensured that performance metrics reflect real-world complexities, and that stakeholder insights shape a grading system both technically sound and operationally viable within India's educational ecosystem.

RESULTS

Quantitative Performance

- **Overall Agreement:** Cohen's κ = **0.82** (95% CI: 0.79–0.85), indicating strong categorical alignment between AI and human consensus scores.
- **Correlation:** Pearson's r = **0.88** ($p < 0.001$), demonstrating a high linear relationship for continuous score predictions.
- **Language-Wise Breakdown:**
  - **English:** κ = 0.84, r = 0.90
  - **Hindi:** κ = 0.81, r = 0.87
  - **Bengali:** κ = 0.83, r = 0.88
  - **Tamil:** κ = 0.78, r = 0.84
  - **Marathi:** κ = 0.79, r = 0.85

Performance dips in Tamil and Marathi reflect dialectal and orthographic variations not fully captured in the training corpus.

Stakeholder Perceptions

- **Consistency Improvement:** 72% of surveyed examiners rated AI suggestions as more consistent than peer grading (Likert ≥ 4).

- **Fairness:** 68% felt AI reduced subjectivity; 60% still preferred a human-in-the-loop for final validation.
- **Usability:** 80% found the SHAP-based heatmap explanations helpful; 75% endorsed the interface's comment-editing and score-override features.
- **Adoption Barriers:** Primary concerns included OCR errors on poor handwriting (noted by 58%) and potential over-reliance on AI reducing examiner engagement (45%).

Qualitative Themes

- **Transparency Needs:** Participants stressed the necessity for clear audit trails showing AI score rationale and examiner overrides.
- **Training Imperative:** Consensus that examiner workshops—covering AI fundamentals, error-flag interpretation, and override protocols—are crucial for trust building.
- **Policy Frameworks:** Calls for regulatory guidelines mandating periodic bias audits and public disclosure of performance metrics by boards.

CONCLUSION

This study demonstrates that an AI-driven multilingual grading tool—grounded in transformer-based NLP, robust data preprocessing, and examiner-centric interface design—can achieve strong alignment with human graders ($\kappa = 0.82$, $r = 0.88$) across five Indian languages. The system delivers dramatic efficiency gains, reducing per-script evaluation time by ~89%, and enjoys substantial stakeholder support: 74% willingness to adopt AI assistance, with 80% endorsing explainability features.

Key challenges include dialectal biases for Tamil and Marathi, OCR inaccuracies on handwritten scripts, and ethical governance around student data. Addressing these requires continuous data augmentation, improved OCR models, examiner training modules, and an ethics oversight committee to enforce transparency and bias audits.

Policy recommendations for Indian school boards encompass phased AI deployment—beginning with low-stakes assessments—mandatory examiner workshops, integration with existing board management systems, and compliance with India's evolving data protection regulations. Future research should expand language coverage to additional regional tongues, incorporate speech-to-text grading for oral assessments, and explore multimodal evaluation of graphical problem-solving.

By embedding AI-driven grading within a human-in-the-loop framework, India's education system can enhance equity, consistency, and speed in high-stakes examinations—paving the way for data-driven pedagogical insights and improved learning outcomes across its linguistically diverse landscape.

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