### Literature Review: Automated Grading Systems with Inbuilt Plagiarism Detection

#### 1. \*\*Introduction to Automated Grading Systems\*\*

Automated grading systems (AGS) leverage technology to evaluate student submissions, such as essays, code, or assignments. The systems aim to reduce the manual effort required by educators while ensuring consistent and timely feedback. AGS often utilize machine learning (ML), natural language processing (NLP), and artificial intelligence (AI) to analyze submissions. As educational institutions increasingly adopt online learning platforms, the demand for robust automated grading tools has grown significantly.

#### 2. \*\*Core Technologies in Automated Grading Systems\*\*

AGS rely heavily on advancements in AI and ML. Techniques such as NLP enable these systems to evaluate textual assignments by analyzing grammar, syntax, and coherence. Research by Shermis and Burstein (2013) highlighted that automated essay scoring (AES) systems like E-Rater and IntelliMetric utilize NLP models to assess essays with performance comparable to human graders.

For non-textual assignments, such as coding tasks, automated graders like AutoGrader or Gradescope use static and dynamic analysis to evaluate code quality, correctness, and efficiency. Emerging deep learning techniques further enhance grading by identifying patterns and anomalies in student responses.

#### 3. \*\*Plagiarism Detection in Grading Systems\*\*

Inbuilt plagiarism detection is a critical feature of AGS. These tools ensure academic integrity by identifying similarities between student submissions and existing content in databases or online sources. Advanced plagiarism detection systems, such as Turnitin, PlagScan, and Grammarly, employ algorithms like shingling, hashing, and sequence matching to detect overlaps in text.

A study by Maurer et al. (2006) emphasized the importance of integrating plagiarism detection in AGS, noting its effectiveness in curbing unethical practices. Modern systems extend their capabilities by using AI to paraphrase detection, which captures subtle forms of plagiarism.

#### 4. \*\*Benefits of Automated Grading with Plagiarism Detection\*\*

Combining grading and plagiarism detection streamlines the evaluation process, offering multiple advantages:

- \*\*Efficiency\*\*: Automated grading significantly reduces the time educators spend on grading, especially in large-scale assessments.

- \*\*Consistency\*\*: AI-based grading ensures objective evaluation, minimizing human bias.

- \*\*Integrity\*\*: Integrated plagiarism detection upholds academic standards by identifying and addressing copied content.

- \*\*Scalability\*\*: AGS can handle large volumes of submissions, making them ideal for Massive Open Online Courses (MOOCs).

#### 5. \*\*Challenges and Limitations\*\*

While AGS with plagiarism detection offer numerous advantages, challenges remain:

- \*\*Contextual Understanding\*\*: Automated systems may misinterpret nuanced arguments, cultural contexts, or creative writing styles.

- \*\*False Positives\*\*: Plagiarism detection tools occasionally flag original content as plagiarized due to common phrases or technical jargon.

- \*\*Dependence on Training Data\*\*: ML-based systems require extensive, high-quality training data to function effectively.

- \*\*Ethical Concerns\*\*: Overreliance on automated tools may undermine the role of educators in providing personalized feedback.

#### 6. \*\*Recent Advances and Future Directions\*\*

Recent studies focus on improving the interpretability and accuracy of AGS. Research by Phandi et al. (2015) explored deep learning models that outperform traditional AES systems in contextual understanding. Similarly, hybrid approaches combining human and machine grading are gaining traction to address limitations.

Future advancements could include adaptive systems capable of learning from educator feedback, enhancing their grading accuracy. Additionally, integrating blockchain technology could improve the transparency and traceability of plagiarism detection.

#### 7. \*\*Conclusion\*\*

Automated grading systems with inbuilt plagiarism detection represent a transformative approach to academic evaluation. By leveraging AI, ML, and NLP, these systems address the growing demand for efficient, scalable, and fair assessment tools. However, ongoing research and innovation are essential to overcome challenges and ensure these systems remain robust, ethical, and adaptable in diverse educational contexts.

#### References

- Shermis, M. D., & Burstein, J. (2013). \*Handbook of automated essay evaluation: Current applications and new directions\*.

- Maurer, H. A., Kappe, F., & Zaka, B. (2006). Plagiarism—a survey. \*Journal of Universal Computer Science\*, 12(8), 1050-1084.

- Phandi, P., Chai, K. M. A., & Ng, H. T. (2015). Flexible domain adaptation for automated essay scoring using a Bayesian framework. \*Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing\*.

### CHAPTER TWO: LITERATURE REVIEW

#### \*\*2.1 Introduction\*\*

The integration of automated grading systems (AGS) with inbuilt plagiarism detection has become a critical area of research in educational technology. As digital learning platforms expand, there is an increasing need for efficient, scalable, and reliable tools to assess student work while ensuring academic integrity. This chapter explores the historical context, foundational concepts, methodologies, empirical studies, and debates surrounding this topic, providing a comprehensive understanding of the subject.

#### \*\*2.2 Historical Context of the Research Topic\*\*

The concept of automated grading emerged in the mid-20th century with early efforts to create machine-readable answer sheets for multiple-choice questions. Over time, technological advancements enabled the evaluation of complex student work, such as essays and coding assignments. Pioneering systems like Page and Peterson's Project Essay Grade (PEG) in the 1960s laid the groundwork for modern automated essay scoring.

Plagiarism detection, on the other hand, gained prominence in the 1990s with the rise of digital content. Tools like Turnitin revolutionized how academic institutions addressed plagiarism by comparing submissions against vast databases of texts. The convergence of AGS and plagiarism detection began in the early 2000s, driven by the growing need for holistic assessment tools.

#### \*\*2.3 Key Concepts and Definitions\*\*

1. \*\*Automated Grading Systems (AGS)\*\*: Software systems that use algorithms and artificial intelligence to evaluate and score student submissions.

2. \*\*Plagiarism Detection\*\*: Techniques used to identify similarities between a submitted work and existing content to ensure originality.

3. \*\*Natural Language Processing (NLP)\*\*: A branch of AI that focuses on the interaction between computers and human language, essential for analyzing textual submissions in AGS.

4. \*\*Academic Integrity\*\*: Adherence to ethical standards in academic work, including the avoidance of plagiarism.

#### \*\*2.4 Review of Related Literature\*\*

\*\*Automated Grading Systems\*\*: Research by Shermis and Burstein (2013) demonstrated that AES tools like E-Rater use NLP to evaluate essays with accuracy comparable to human graders. Other tools, such as Gradescope, extend this functionality to diverse assignment types, including programming tasks.

\*\*Plagiarism Detection\*\*: Maurer et al. (2006) highlighted the evolution of plagiarism detection algorithms, from basic string matching to advanced AI techniques for identifying paraphrased content. Tools like Grammarly and PlagScan integrate these methods to ensure comprehensive detection.

\*\*Integration of Grading and Plagiarism Detection\*\*: Studies emphasize the importance of combining these functionalities. For instance, hybrid systems like WriteCheck evaluate assignments while detecting unoriginal content, streamlining the assessment process.

#### \*\*2.5 Methodology\*\*

Research methodologies in this field include:

- \*\*Quantitative Analysis\*\*: Evaluating the performance of AGS and plagiarism detection tools using metrics like precision, recall, and accuracy.

- \*\*Qualitative Analysis\*\*: Assessing user satisfaction and system effectiveness through educator and student feedback.

- \*\*Comparative Studies\*\*: Comparing automated systems with human evaluation to identify strengths and limitations.

- \*\*Case Studies\*\*: Documenting the adoption of integrated AGS tools in educational institutions to understand their impact.

#### \*\*2.6 Empirical Review\*\*

Empirical studies reveal that automated systems significantly reduce grading time while maintaining accuracy. For instance, Phandi et al. (2015) demonstrated that Bayesian frameworks outperform traditional scoring models in understanding essay context. Additionally, plagiarism detection tools like Turnitin report detection rates exceeding 90% for copied content. However, challenges such as false positives and contextual misinterpretations persist.

#### \*\*2.7 Conceptual Review\*\*

The conceptual framework of integrated AGS systems is rooted in AI and educational psychology. The systems aim to replicate human grading by evaluating content quality, coherence, and originality. Key elements include:

- \*\*Grading Algorithms\*\*: Designed to assess specific criteria, such as grammar, content relevance, and formatting.

- \*\*Similarity Detection Algorithms\*\*: Techniques like fingerprinting and semantic analysis used for plagiarism detection.

- \*\*User Interfaces\*\*: Intuitive platforms that enable educators to review and override automated decisions when necessary.

#### \*\*2.8 Debates and Controversies\*\*

1. \*\*Accuracy and Bias\*\*: Critics argue that AGS systems may reinforce existing biases in training data, leading to unfair evaluations.

2. \*\*Ethical Concerns\*\*: The use of plagiarism detection tools raises privacy issues, as submissions are often stored in external databases.

3. \*\*Reliance on Automation\*\*: Some educators believe that overdependence on AGS undermines the importance of personalized feedback.

4. \*\*False Positives in Plagiarism Detection\*\*: Common phrases or shared knowledge often trigger plagiarism alerts, leading to unnecessary disputes.

#### \*\*2.9 Practical Implication\*\*

The integration of AGS with plagiarism detection has far-reaching implications for education:

- \*\*Efficiency\*\*: Institutions can manage large-scale assessments with minimal human intervention.

- \*\*Scalability\*\*: Automated systems are ideal for online learning platforms and MOOCs.

- \*\*Standardization\*\*: AGS ensures consistent grading across diverse student groups.

- \*\*Integrity Assurance\*\*: Built-in plagiarism detection fosters a culture of originality and ethical conduct among students.

#### \*\*References\*\*

- Shermis, M. D., & Burstein, J. (2013). \*Handbook of automated essay evaluation: Current applications and new directions\*.

- Maurer, H. A., Kappe, F., & Zaka, B. (2006). Plagiarism—a survey. \*Journal of Universal Computer Science\*, 12(8), 1050-1084.

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