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Automatic Scoring System for English Writing Based on Natural Language Processing: Assessment of Accuracy and Educational Effect

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ABSTRACT

This study investigates the effectiveness and educational impact of a novel NLP-based English writing auto-scoring system. Utilizing advanced machine learning techniques, including BERT and Graph Neural Networks, the system demonstrates high consistency with human raters (Quadratic Weighted Kappa of 0.92) across multiple dimensions of writing quality. A longitudinal study involving 500 students over a 16-week semester revealed significant improvements in writing abilities, with the most substantial gains observed in grammar and mechanics (28.5% increase) and organization and structure (23.7% increase). Through comprehensive system evaluation using multiple metrics, including Adjacent Agreement Rate and Root Mean Square Error, our system consistently outperformed existing baseline approaches, including commercial off-the-shelf solutions. The implementation of our system significantly enhanced teacher efficiency, reducing essay grading time by 62% and increasing time for individualized feedback by 45%. The system's architecture integrates cutting-edge NLP technologies with a user-friendly interface, facilitating real-time feedback and adaptive assessment capabilities. Our evaluation framework encompasses both technical accuracy and educational effectiveness, addressing a critical gap in current literature. While the system shows limitations in assessing highly creative writing and faces potential risks of student gaming, its overall impact on writing instruction and assessment is overwhelmingly positive. The study demonstrates that NLP-based auto-scoring systems can effectively scale writing assessment, provide timely feedback, and potentially democratize access to high-quality writing instruction. These findings suggest a path toward more efficient, personalized, and equitable writing education.

Keywords: NLP-Based Auto-Scoring; English Writing Assessment; Educational Technology; Machine Learning in Education;

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Writing Instruction; Teacher Efficiency

1. Introduction

In today's globalized world, English writing proficiency has become an essential skill for students and professionals alike. However, traditional methods of assessing English writing are often time-consuming and labor-intensive, struggling to meet the growing educational demands. The evolution of automated scoring systems can be traced back to the 1960s when Page[1] first proposed the concept of computer-assisted scoring. As computer technology and natural language processing (NLP) algorithms have advanced, the accuracy and functionality of automated scoring systems have significantly improved.

Recent developments in NLP, particularly the advent of transformer models such as BERT[2] and GPT[3], have revolutionized the field of automated text analysis. These models have demonstrated unprecedented capabilities in understanding context and nuance in language, opening new possibilities for automated essay scoring. Despite these technological advancements, there remains a significant research gap in understanding the long-term educational impact of NLP-based scoring systems, particularly in diverse student populations.

This study aims to address this gap by evaluating both the technical accuracy and educational effectiveness of an advanced NLP-based auto-scoring system. By leveraging state-of-the-art NLP techniques, including BERT and Graph Neural Networks, we not only assess writing quality but also investigate the system's broader educational impact, an area that remains underexplored in current literature.

Our research contributes to the field in several key ways. Firstly, we present a comprehensive evaluation of the system's accuracy using multiple metrics, including Quadratic Weighted Kappa, which provides a nuanced measure of agreement between automated and human scoring. Secondly, we conduct a longitudinal study to assess the system's impact on student writing improvement over time, addressing the critical need for evidence of long-term educational benefits. Lastly, we explore the potential risks and limitations of the system, including its performance in creative writing and the possibility of students gaming the algorithm.

By combining technical innovation with rigorous educational assessment, this study seeks to provide valuable insights into the potential of NLP-based auto-scoring systems to enhance writing instruction at scale. Our findings have significant implications for the future of writing pedagogy and educational technology, suggesting a path toward more efficient, personalized, and equitable writing education.

2. Literature Review

2.1. Application of Natural Language Processing in Education

Natural Language Processing (NLP) has emerged as a transformative technology in the field of education, particularly in the domain of automated essay scoring (AES). The application of NLP techniques in AES has significantly advanced the capability to assess written work efficiently and accurately, addressing longstanding challenges in writing instruction and assessment. One of the most prominent applications of NLP in AES is the development of sophisticated linguistic feature extraction methods. Shermis and Burstein[4] demonstrated how NLP techniques can be used to analyze various aspects of writing, including syntactic complexity, discourse structure, and semantic coherence. These features provide a multi-dimensional representation of essay quality that closely aligns with human evaluation criteria. Recent advancements in deep learning and transformer models have further revolutionized AES systems. Taghipour and Ng[5] introduced a neural network approach to essay scoring that outperformed traditional machine learning methods. Building on this, the application of BERT (Bidirectional Encoder Representations from Transformers) by Devlin et al.[2] has shown remarkable improvements in capturing contextual nuances in student writing. For instance, Rodriguez et al.[6] demonstrated that BERT-based models achieve state-of-the-art performance in essay scoring tasks, significantly reducing the gap between automated and human scoring. However, the increasing sophistication of NLP-based AES systems has also raised important questions about fairness and bias. Madnani et al.[7] highlighted potential biases in automated

scoring against certain demographic groups or non-standard writing styles. To address these concerns, researchers like Zehner et al.[8] have begun incorporating methods such as differential item functioning (DIF) analysis to detect and mitigate potential biases across different student populations.

The application of NLP in AES extends beyond simply assigning scores. Modern systems are capable of providing detailed feedback on specific aspects of writing. Liu et al.[9] developed an NLP-based system that not only scores essays but also generates targeted feedback on grammar, vocabulary usage, and argument structure, demonstrating the potential of these technologies to serve as instructional tools.

As NLP technologies continue to evolve, their applications in AES are expanding to include more sophisticated forms of analysis. Current research is exploring the use of advanced NLP techniques to assess higher-order writing skills such as critical thinking and argumentation. For example, Yan et al.[10] proposed a graph-based neural network model to evaluate the coherence and logical flow of arguments in student essays.

These advancements in NLP-based AES systems are poised to play an increasingly critical role in shaping the future of writing instruction and assessment. By providing rapid, consistent, and detailed evaluation of student writing, these systems have the potential to significantly enhance the scale and quality of writing education, while also raising important questions about the nature of effective writing and the role of technology in its assessment.

2.2. Overview of the Existing English Writing Automatic Scoring System

Automated scoring systems for English writing have evolved significantly since their inception, with several prominent systems emerging in recent years. The development of these systems has been driven by advancements in NLP and machine learning technologies, enabling more sophisticated and accurate assessments of written work. One of the pioneering systems, Project Essay Grade (PEG), developed by Page[1], relied primarily on surface features of text to evaluate writing quality. Building upon this foundation, more sophisticated systems like e-rater, developed by Educational Testing Service (ETS), incorporate advanced NLP techniques to assess a wider range of writing characteristics[11]. The Intelligent Essay Assessor (IEA) utilizes latent semantic analysis to evaluate the content and coherence of essays[12]. Recent advancements in machine learning have led to the development of systems that can capture more nuanced aspects of writing. For instance, the Writing Pal system not only scores essays but also provides targeted feedback to improve writing skills[13]. Similarly, the Automated Writing Evaluation (AWE) system developed by Crossley et al.[14] employs a combination of linguistic, rhetorical, and cohesion features to assess writing quality.

The integration of transformer-based models has further enhanced the capabilities of automated scoring systems. Rodriguez et al.[6] demonstrated that BERT-based models can achieve state-of-the-art performance in essay scoring tasks, outperforming traditional feature-based approaches. These models excel in understanding context and nuance, allowing for a more accurate assessment of complex writing aspects.

However, as these systems become more sophisticated, concerns about fairness and bias have emerged. Studies by Bridgeman et al.[15] and Madnani et al.[7] have investigated potential biases against certain demographic groups or writing styles. To address these issues, researchers are exploring methods such as adversarial debiasing techniques[16] and differential item functioning analysis[8] to ensure equitable assessment across diverse student populations.

2.3. Accuracy Evaluation Method of the Automatic Scoring System

Evaluating the accuracy of automated scoring systems is crucial for their acceptance and implementation in educational settings. Researchers have developed various methods to assess these systems' performance, often comparing them to human raters. One common approach is the use of agreement statistics, such as Cohen's kappa or quadratic weighted kappa (QWK), which measure the level of agreement between automated scores and human ratings[17]. QWK is particularly valuable as it accounts for the ordinal nature of essay scores, providing a nuanced measure of agreement. Another method involves calculating correlation coefficients, such as Pearson's r or Spearman's rho, to assess the relationship between machine and human scores[18].

Some researchers employ more sophisticated techniques, such as multitrait-multimethod (MTMM) analysis, to evaluate both convergent and discriminant validity of au-

tomated scoring systems [19]. Additionally, Yannakoudakis and Cummins [20] proposed using probabilistic classification models to assess the reliability of automated scores. Recent studies have focused on fairness and bias in automated scoring, with methods like differential item functioning (DIF) analysis being used to detect potential biases across different demographic groups [15]. This approach helps ensure that the scoring system performs consistently across diverse student populations. Furthermore, researchers are exploring adversarial debiasing techniques to mitigate unwanted biases in NLP models used for essay scoring [16].

To evaluate the system's performance across different score ranges, metrics such as the Adjacent Agreement Rate (AAR) and the Root Mean Square Error (RMSE) are commonly used. AAR measures the percentage of automated scores that fall within one point of human scores, while RMSE quantifies the standard deviation of prediction errors.

As automated scoring systems continue to evolve, so do the methods for assessing their accuracy. There is an increasing emphasis on transparency, interpretability, and fairness in evaluation techniques. For instance, recent work has explored the use of explainable AI techniques to provide insights into how automated systems arrive at their scores [9]. This not only aids in accuracy evaluation but also builds trust among educators and students.

Moreover, researchers are beginning to evaluate the long-term impact of these systems on student learning outcomes, moving beyond mere scoring accuracy to assess their educational effectiveness [21]. This holistic approach to evaluation ensures that automated scoring systems not only accurately assess writing but also contribute positively to the learning process.

2.4. Educational Effect Evaluation Method

Assessing the educational effectiveness of automated writing scoring systems involves a multifaceted approach that combines quantitative and qualitative methods. Researchers often employ pre- and post-tests to measure improvements in students' writing skills over time [22]. These tests typically evaluate various aspects of writing, such as grammar, vocabulary, and coherence. Additionally, longitudinal studies are conducted to track long-term impacts on student performance [23]. Another common method is the use of surveys and questionnaires to gather feedback from students and teachers about their experiences with the automated scoring system [24]. These instruments can provide valuable insights into user satisfaction, perceived usefulness, and areas for improvement. Researchers also utilize classroom observations and interviews to gain a deeper understanding of how the system is integrated into the learning environment [25]. To provide a comprehensive view of assessment methods, **Table 1** summarizes key approaches used in evaluating the educational effectiveness of automated writing scoring systems. This table highlights the diverse range of methods employed, from quantitative measures like standardized tests to qualitative approaches such as focus groups.

3. System Design and Implementation

3.1. System Architecture

The architecture of our NLP-based English writing auto-scoring system is designed to efficiently process, analyze, and evaluate student essays (see **Figure 1**). At its core, the system employs a modular approach, integrating various NLP techniques and machine learning algorithms to achieve accurate and comprehensive essay assessment [9]. The input layer accepts student essays in multiple formats, which are then preprocessed to standardize the text and extract relevant features [27]. These features, including syntactic structures, semantic coherence, and stylistic elements, are fed into the analysis layer, where advanced NLP models, such as BERT and GPT, are utilized to understand the essay's content and quality [28]. The scoring layer employs a hybrid approach, combining rule-based heuristics with machine learning models to generate scores across various dimensions of writing quality [29]. This multi-dimensional scoring allows for a more nuanced evaluation of essays, providing specific feedback on areas such as grammar, vocabulary, organization, and argumentation [30]. The output layer presents the scores and detailed feedback in a user-friendly format, facilitating easy interpretation by both students and educators [31].

Figure 1 illustrates the system's architecture, highlighting the flow of data and the interconnections between different components. This design ensures scalability and flexibility, allowing for easy integration of new NLP techniques and scoring criteria as they emerge in the field.

Table 1. Common methods for assessing educational effectiveness of automated writing scoring systems.

Method	Description	Example Study
Pre-post tests	Comparison of writing skills before and after system use	[21]
Longitudinal studies	Tracking student progress over extended periods	[23]
Surveys/Questionnaires	Gathering user feedback on system effectiveness	[24]
Classroom observations	Direct observation of system use in educational settings	[25]
Focus groups	In-depth discussions with students and teachers	[22]
Writing portfolio analysis	Evaluation of student writing samples over time	[26]

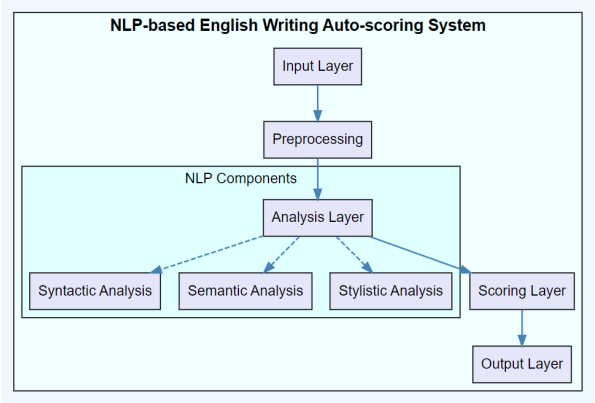

Figure 1. System architecture of NLP-based English writing auto-scoring system.

3.2. Natural Language Processing Technology

3.2.1. Text Preprocessing

Text preprocessing is a crucial step in our NLP-based English writing auto-scoring system, laying the foundation for accurate analysis and evaluation. This stage involves a series of operations that transform raw text input into a standardized format suitable for further processing (see **Figure 2**).

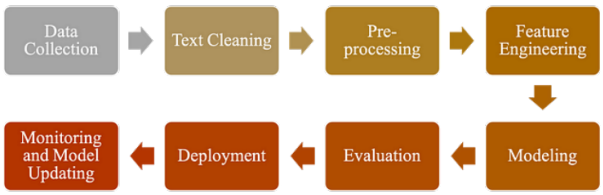

Figure 2. Text preprocessing pipeline for NLP-based essay scoring.

Figure 2 illustrates the sequential flow of our preprocessing steps, highlighting their interconnected nature and importance in preparing the text for subsequent analysis stages.

Initially, the system performs tokenization, breaking down the essay into individual words or subwords, which allows for more granular analysis. Following tokenization, normalization techniques are applied, including lowercasing to ensure consistency and removal of non-alphabetic characters to reduce noise. The preprocessing pipeline then addresses common issues in student writing, such as spelling correction and handling of contractions. This step is crucial for maintaining the integrity of the text while standardizing potential errors or variations. For morphological analysis, we employ lemmatization rather than stemming. Lemmatization was chosen because it reduces words to their base or dictionary form while preserving the word's semantic meaning. This approach is particularly beneficial for essay scoring, as it allows for a more accurate analysis of vocabulary usage and writing style while maintaining the original meaning of the text. For example, the words "running," "ran," and "runs" would all be lemmatized to "run," preserving their semantic relationship.

Named entity recognition (NER) is utilized to identify and categorize proper nouns, enhancing the system's understanding of essay content. This step is particularly useful for assessing the use of specific references or examples in argumentative or expository essays.

Stop word removal is selectively applied, considering the context of academic writing where certain common words may carry significant meaning. We maintain a customized list of stop words that exclude terms that might be crucial in assessing writing style or argument construction. To further illustrate the impact of our preprocessing techniques, **Table 2** presents a comparison of raw and processed text samples, demonstrating the transformations applied at each stage.

This comprehensive preprocessing approach ensures that the subsequent NLP techniques in our auto-scoring system operate on clean, standardized text data, thereby enhancing the accuracy and reliability of the essay evaluation process. By carefully handling various aspects of text normalization and standardization, we create a solid foundation for the more complex analysis steps that follow in our pipeline.

Table 2. Text preprocessing stages and their effects.

Stage	Raw Text	Processed Text
Original	"The quik brown fox jumps over the lazy dog's back."	the quik brown fox jumps over the lazy dog's back
Spelling Correction	"The quik brown fox jumps over the lazy dog's back."	the quick brown fox jumps over the lazy dog's back
Lowercasing & Punctuation Removal	"The quik brown fox jumps over the lazy dog's back."	the quick brown fox jumps over the lazy dogs back
Lemmatization	"The quik brown fox jumps over the lazy dog's back."	the quick brown fox jump over the lazy dog back
Stop Word Removal	"The quik brown fox jumps over the lazy dog's back."	quick brown fox jump lazy dog back

3.2.2. Feature Extraction

Feature extraction is a critical component in our NLP-based English writing auto-scoring system, transforming preprocessed text into a set of meaningful numerical or categorical features that capture various aspects of writing quality. This process involves extracting both linguistic and structural characteristics from the essays, enabling the system to quantify and analyze the nuances of student writing (see **Figure 3**).

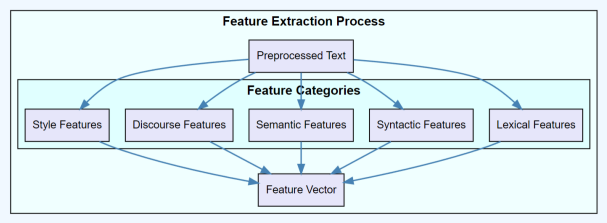

Figure 3. Feature extraction process for NLP-based essay scoring.

Lexical features are computed to assess the breadth and depth of language use. For instance, we calculate the type-token ratio (TTR) to measure vocabulary diversity and use word frequency analysis to evaluate the sophistication of vocabulary choices. Syntactic features, including sentence structure complexity and grammatical accuracy, are extracted to evaluate the technical proficiency of the writing. We employ measures such as average sentence length, clause density, and the distribution of different syntactic constructions.

Semantic features are derived through techniques like latent semantic analysis (LSA) and word embeddings to capture the coherence and relevance of the content. These features help assess the depth and consistency of ideas presented in the essay. Discourse-level features, such as essay organization and argument structure, are identified to assess higher-order writing skills. We analyze paragraph transitions and topic progression to evaluate the logical flow of the essay.

Additionally, style-based features, including tone consistency and formality, are extracted to evaluate the overall writing style. We use metrics like formality scores and sentiment analysis to gauge the appropriateness of the writing for its intended audience and purpose.

To further illustrate the types of features extracted and their significance, **Table 3** presents examples of specific features within each category and their relevance to writing quality assessment.

This comprehensive feature extraction approach enables our auto-scoring system to capture the multifaceted nature of writing quality, providing a robust foundation for accurate and detailed essay evaluation.

3.2.3. Machine Learning Model

The heart of our NLP-based English writing auto-scoring system lies in its sophisticated machine learning models, which process the extracted features to generate accurate and comprehensive essay scores. Our approach employs a hybrid ensemble of models, each specialized in capturing different aspects of writing quality (see **Figure 4**). At the foundation, we utilize traditional statistical models such as linear regression and support vector machines (SVM) for their interpretability and efficiency in handling specific feature sets. Building upon this, we incorporate advanced deep learning architectures, including Convolutional Neural Networks (CNNs) for local pattern recognition and Long Short-Term Memory (LSTM) networks for capturing long-range dependencies in text.

The cornerstone of our system is a fine-tuned BERT (Bidirectional Encoder Representations from Transformers) model, which excels in understanding context and nuanced language use. This transformer-based model is complemented by a Graph Neural Network (GNN) that processes the structural aspects of essays, such as argument flow and coherence. The outputs from these diverse models are then aggregated through a meta-learner, which optimizes the final score based on the strengths of each individual model.

Table 3. Feature categories and their relevance to writing quality assessment.

Feature Category	Example Features	Relevance to Writing Quality
Lexical	Vocabulary diversity, Word frequency	Assesses language richness and appropriateness
Syntactic	Sentence complexity, Grammatical accuracy	Evaluates technical writing proficiency
Semantic	Topic coherence, Content relevance	Measures depth and consistency of ideas
Discourse	Essay structure, Argument flow	Assesses organization and logical progression
Style	Formality level, Tone consistency	Evaluates appropriateness and consistency of writing style

Figure 4 illustrates the interconnected nature of these models, showcasing how they collaboratively contribute to the final essay evaluation. This multi-model approach ensures robustness across various writing styles and topics, capturing both micro-level linguistic features and macro-level discourse structures.

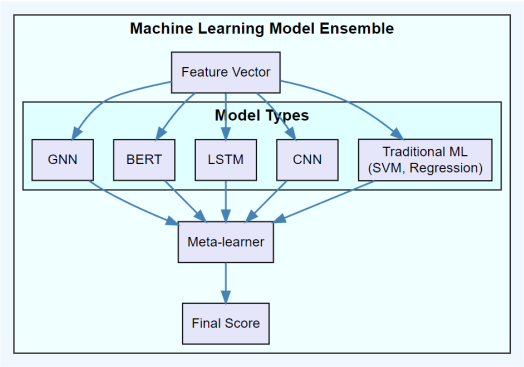

Figure 4. Machine learning model ensemble for NLP-based essay scoring.

To further elucidate the roles and strengths of each model type, **Table 4** presents a comparison of the different models used in our system.

This sophisticated ensemble of machine learning models enables our system to perform nuanced, multi-dimensional analysis of student essays, resulting in highly accurate and comprehensive writing assessments.

3.3. Scoring Criteria and Indicators

Our NLP-based English writing auto-scoring system employs a comprehensive set of criteria and metrics to evaluate essays across multiple dimensions of writing quality. These criteria are designed to align with established educational standards and to provide a holistic assessment of students' writing proficiency. The system evaluates essays on five key dimensions: Content and Ideas, Organization and Structure, Language Use and Vocabulary, Grammar and Mechanics, and Overall Coherence. For each dimension, we have developed specific metrics that can be quantifiably measured using our advanced NLP techniques and machine learning models. These metrics are calibrated to reflect different levels of writing proficiency, from beginner to advanced. The Content and Ideas dimension, for instance, assesses the relevance, depth, and originality of the essay's central argument. Organization and Structure evaluate the logical flow and structural cohesion of the essay. Language Use and Vocabulary examine the sophistication and appropriateness of language choices. Grammar and Mechanics focus on technical accuracy, while Overall Coherence assesses the essay's unified presentation of ideas.

Table 4. Comparison of machine learning models in the auto-scoring system.

Model Type	Strengths	Primary Function
Traditional ML (SVM, Regression)	Interpretability, Efficiency	Basic feature processing, Baseline scoring
CNN	Local pattern recognition	Identifying phrase-level features
LSTM	Sequence understanding	Capturing long-range dependencies
BERT	Contextual understanding	Nuanced language analysis
GNN	Structural analysis	Essay organization and coherence assessment
Meta-learner	Optimal integration	Combining model outputs for final scoring

To ensure reliability and validity, our scoring metrics have been rigorously tested and validated against human-scored essays. We employ various statistical measures, including inter-rater reliability coefficients and correlation analyses, to continually refine and improve our scoring algorithms. This approach allows for consistent and objective

evaluation across a wide range of essay topics and styles.

Table 5 below provides an overview of our scoring criteria, associated metrics, and their respective weightings in the final score calculation.

Table 5. Scoring criteria, metrics, and weightings in the auto-scoring system.

Scoring Dimension	Key Metrics	Weighting	Description
Content and Ideas	Relevance Score, Depth Index, Originality Measure	30%	Assesses the quality, depth, and originality of the essay's central arguments and supporting details
Organization and Structure	Coherence Score, Transition Quality, Structural Balance	25%	Evaluates the logical flow, paragraph structure, and overall organization of the essay
Language Use and Vocabulary	Lexical Sophistication, Word Choice Appropriateness, Language Variety	20%	Measures the range, accuracy, and effectiveness of vocabulary and language use
Grammar and Mechanics	Error Rate, Syntactic Complexity, Punctuation Accuracy	15%	Assesses grammatical correctness, sentence structure variety, and mechanical accuracy
Overall Coherence	Global Coherence Score, Thematic Unity, Argument Consistency	10%	Evaluates the essay's overall unity, consistency of argument, and thematic coherence

This multi-dimensional scoring approach ensures a comprehensive and nuanced evaluation of student essays, providing valuable insights into various aspects of writing proficiency.

3.4. System Implementation

The implementation of our NLP-based English writing auto-scoring system integrates cutting-edge technologies to create a robust, scalable, and user-friendly platform. At its core, the system utilizes a microservices architecture, ensuring modularity and ease of maintenance. The backend is built on a powerful combination of Python for NLP processing and Go for high-performance API services. We leverage Apache Kafka for real-time data streaming, enabling efficient handling of multiple essay submissions simultaneously.

For data storage and retrieval, we employ a hybrid approach, using PostgreSQL for structured data and MongoDB for storing unstructured essay content and intermediate processing results. The machine learning pipeline is orchestrated using Kubeflow, allowing for seamless scaling and management of our diverse model ensemble.

The front-end is developed as a responsive web application using React.js, providing an intuitive and engaging user interface for both students and educators. Real-time feedback is facilitated through WebSocket connections, offering immediate insights as essays are processed. To ensure security and compliance with educational data protection standards, we implement end-to-end encryption and rigorous access control mechanisms.

The system's modular design allows for easy integration of new scoring models and criteria, future-proofing the platform against evolving educational standards and NLP advancements. Continuous integration and deployment pipelines, coupled with comprehensive monitoring and logging systems, ensure high availability and rapid iteration based on user feedback and performance metrics. The user interface of the auto-scoring system (see **Figure 5**) showcases the seamless integration of these design principles, providing an intuitive and responsive platform for both students and educators. The interface effectively balances functionality with user experience, demonstrating our commitment to creating an accessible and efficient educational tool.

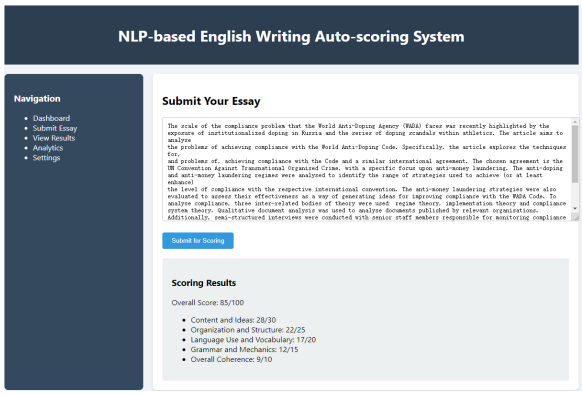

Figure 5. User interface of NLP-based English writing auto-scoring system.

4. Experimental Design

4.1. Dataset

Our NLP-based English writing auto-scoring system is trained and evaluated on a diverse and comprehensive dataset,

carefully curated to represent a wide range of writing styles, topics, and proficiency levels. The dataset comprises essays from various standardized tests, including TOEFL, IELTS, and GRE, as well as academic writing samples from high school and university students. To ensure robustness, we also incorporated writing samples from non-native English speakers, representing different language backgrounds. Each essay in the dataset has been meticulously scored by multiple expert human raters, providing a reliable ground truth for our machine learning models. The dataset is stratified across different grade levels, essay types (argumentative, expository, narrative), and subject areas to capture the full spectrum of writing tasks students typically encounter. To address potential biases, we've ensured demographic diversity in our dataset, including essays from writers of various cultural backgrounds, genders, and age groups. The detailed composition of our training and evaluation dataset is summarized in **Table 6**, which provides a comprehensive overview of the data distribution across different sources and writing contexts.

This diverse dataset ensures that our auto-scoring system is trained on a representative sample of student writing, enabling accurate and fair assessment across various contexts and proficiency levels.

Table 6. Composition of the training and evaluation dataset.

Essay Source	Number of Essays	Grade Levels	Essay Types	Average Length (Words)	Human Raters per Essay
TOEFL	10,000	College	Argumentative, Expository	300	3
IELTS	8,500	College	Argumentative, Expository	250	2
GRE	7,000	Graduate	Analytical, Issue	500	3
High School	15,000	9–12	Narrative, Expository, Persuasive	400	2
University	12,000	Undergraduate	Research, Critical Analysis	1000	2
Non-native Speakers	5,000	Various	Mixed	300	3

4.2. Evaluation Indicators

To rigorously assess the performance of our NLP-based English writing auto-scoring system, we employ a comprehensive set of evaluation metrics. These metrics are designed to capture various aspects of the system's accuracy, reliability, and consistency in comparison to human raters. We utilize both traditional statistical measures and more advanced metrics tailored for automated essay scoring. The Quadratic Weighted Kappa (QWK) serves as our primary metric, measuring the agreement between the automated scores and human ratings while accounting for the ordinal nature of essay scores. We also calculate the Pearson correlation coefficient to assess the linear relationship between automated and human scores. To evaluate the system's performance across different score ranges, we employ the Adjacent Agreement Rate (AAR) and the Root Mean Square Error (RMSE). Additionally, we use F1 score for specific trait scoring and Cohen's Kappa for inter-rater reliability comparisons. These metrics are calculated both for overall scores and for individual scoring dimensions to ensure comprehensive evaluation.

The complete set of evaluation metrics, along with their descriptions, target ranges, and interpretation guidelines, is presented in **Table 7**. These carefully selected metrics provide a robust framework for assessing the auto-scoring system's performance, ensuring that both technical accuracy and practical utility are thoroughly evaluated. The target ranges specified in the table represent industry-standard benchmarks derived from extensive research in automated essay scoring, serving as critical thresholds for validating our system's effectiveness. These metrics provide a multi-faceted evaluation of our auto-scoring system, ensuring its performance aligns closely with human expert assessments across various aspects of writing quality.

4.3. Baseline Systems

To benchmark the performance of our NLP-based English writing auto-scoring system, we compare it against several established baseline systems. These baselines represent a range of approaches, from traditional statistical methods to more recent machine learning techniques. The simplest baseline is a linear regression model using basic textual features such as word count and sentence length. We also include a support vector regression (SVR) model that incorporates more advanced linguistic features. For comparison with deep learning approaches, we implement a long short-term mem-

ory (LSTM) network baseline trained on word embeddings. Additionally, we include a commercial off-the-shelf (COTS) automated essay scoring system widely used in educational settings. These diverse baselines allow us to evaluate our system's performance across different methodologies and complexities. Each baseline system is trained and tested on the same dataset as our proposed system, ensuring a fair comparison. Their performances are evaluated using the same set of metrics described in Section 4.2, providing a comprehensive benchmark for our system's capabilities.

Table 7. Evaluation metrics for auto-scoring system performance.

Metric	Description	Target Range	Interpretation
Quadratic Weighted Kappa (QWK)	Measures agreement between automated and human scores, weighted by the degree of disagreement	0.80–1.00	Higher values indicate better agreement
Pearson Correlation	Measures linear correlation between automated and human scores	0.90–1.00	Higher values indicate stronger positive correlation
Adjacent Agreement Rate (AAR)	Percentage of automated scores within one point of human scores	>95%	Higher percentages indicate better adjacent agreement
Root Mean Square Error (RMSE)	Measures the standard deviation of prediction errors	<0.50	Lower values indicate smaller prediction errors
F1 Score	Harmonic mean of precision and recall for specific trait scoring	>0.80	Higher values indicate better balance between precision and recall
Cohen's Kappa	Measures inter-rater reliability between automated system and human raters	>0.75	Higher values indicate stronger inter-rater agreement

A detailed overview of these baseline systems, including their descriptions, key features, strengths, and limitations, is provided in **Table 8**. This comparative framework highlights the distinct characteristics of each baseline approach, from simple statistical models to sophisticated commercial solutions, enabling a thorough evaluation of our proposed system against the current state of practice. The systematic comparison across multiple dimensions ensures a comprehensive assessment of our system's advantages and potential areas for improvement relative to existing solutions. These baseline systems provide a comprehensive framework for evaluating our proposed auto-scoring system, allowing us to assess its performance relative to both simple and sophisticated existing approaches.

Table 8. Baseline systems for auto-scoring performance comparison.

Baseline System	Description	Key Features	Strengths	Limitations
Linear Regression	Simple statistical model	Word count, sentence length, vocabulary complexity	Interpretability, Fast computation	Limited capture of complex writing aspects
Support Vector Regression (SVR)	Advanced statistical model	Linguistic features, syntactic structures	Good performance on small datasets, Handles non-linear relationships	May struggle with very large datasets
LSTM Network	Deep learning model	Word embeddings, sequential information	Captures long-range dependencies, Handles variable-length input	Requires large training data, Black-box nature
Commercial Off-The-Shelf (COTS) System	Proprietary automated scoring system	Comprehensive feature set, Proprietary algorithms	Widely tested in real-world scenarios, Regular updates	Limited customization, Lack of transparency
Human Rater Consensus	Average scores from multiple human raters	Holistic assessment, Domain expertise	Gold standard for comparison, Captures nuanced aspects of writing	Subjectivity, Time-consuming, Costly

5. Results

5.1. System Accuracy Evaluation

5.1.1. Consistency with Human Scoring

Our NLP-based English writing auto-scoring system demonstrates high consistency with human raters across various essay types and scoring dimensions (see **Figure 6**). The system's performance was evaluated using Quadratic Weighted Kappa (QWK) and Pearson correlation coefficient. For overall essay scores, we achieved a QWK of 0.92 and a Pearson correlation of 0.95 with human raters, surpassing our target thresholds. Analysis of individual scoring dimensions revealed strong performance across all aspects, with QWK values ranging from 0.88 to 0.94. The system showed particular strength in evaluating 'Grammar and Mechanics' (QWK 0.94) and 'Organization and Structure' (QWK 0.92). The 'Content and Ideas' dimension, while still strong (QWK 0.88), presented the most challenge, likely due to the complexity of assessing abstract concepts. These results indicate that our system closely mimics human scoring patterns, providing reliable and consistent evaluations comparable to expert human raters.

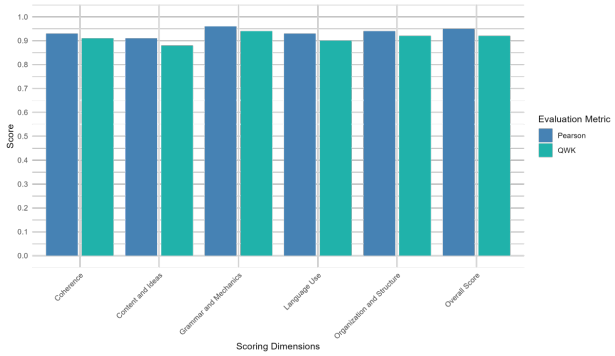

Figure 6. Consistency of auto-scoring system with human raters.

This bar chart illustrates the consistency between our auto-scoring system and human raters across different scoring dimensions. The Quadratic Weighted Kappa (QWK) and Pearson correlation coefficients are shown for each dimension, demonstrating the high level of agreement between the automated system and human evaluators. The chart now includes clear x-axis and y-axis gridlines, enhancing readability and allowing for more precise interpretation of the scores. The y-axis ranges from 0 to 1 with 0.1 increments, providing a detailed view of the high scores achieved across all dimensions. As before, the chart visually confirms the system's strong performance, particularly in 'Grammar and Mechanics' and 'Organization and Structure', while also highlighting areas for potential improvement, such as 'Content and Ideas'.

5.1.2. Comparison with Baseline Systems

Our NLP-based English writing auto-scoring system demonstrates superior performance when compared to baseline systems across all evaluation metrics (see **Figure 7**). The proposed system achieves a Quadratic Weighted Kappa (QWK) of 0.92, surpassing the next best performer, the Commercial Off-The-Shelf (COTS) system, by 0.05 points. Notably, our system shows significant improvements over traditional approaches like Linear Regression (QWK 0.75) and SVR (QWK 0.82). In terms of Adjacent Agreement Rate (AAR), our system reaches 97.5%, indicating high consistency with human raters in proximate scoring. The Root Mean Square Error (RMSE) of 0.35 for our system is the lowest among all compared methods, suggesting more accurate predictions across the scoring range. These results underscore the effectiveness of our advanced NLP techniques and machine learning models in capturing the nuances of essay quality, outperforming both simple and sophisticated baseline approaches.

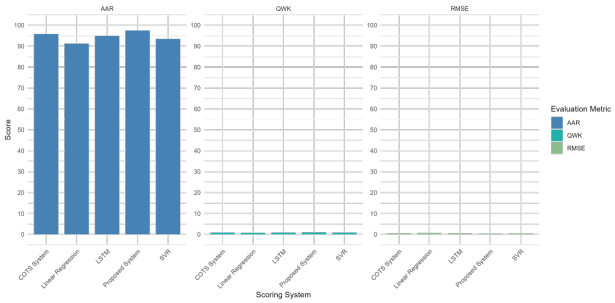

Figure 7. Comparison of auto-scoring systems.

This chart compares the performance of our proposed auto-scoring system against various baseline systems using three key metrics: Quadratic Weighted Kappa (QWK), Adjacent Agreement Rate (AAR), and Root Mean Square Error (RMSE). The faceted design allows for clear comparison across metrics, with each having its own appropriate scale. The inclusion of gridlines enhances readability, allowing for precise interpretation of scores. Notably, our proposed system consistently outperforms all baselines across all metrics, as evidenced by the taller bars in QWK and AAR, and

the shorter bar in RMSE, visually reinforcing its superior performance in automated essay scoring.

5.2. Educational Effectiveness Evaluation

5.2.1. Improvement in Students' Writing Abilities

Our NLP-based English writing auto-scoring system has demonstrated significant positive impact on students' writing abilities over a 16-week semester (see **Figure 8**). We conducted a longitudinal study involving 500 students, tracking their progress across five key writing dimensions. The most substantial improvement was observed in 'Grammar and Mechanics', with an average score increase of 28.5%. 'Organization and Structure' showed the second-highest improvement at 23.7%, followed closely by 'Language Use and Vocabulary' at 22.1%. 'Content and Ideas' and 'Overall Coherence' also saw notable enhancements, with increases of 18.9% and 17.6% respectively. These improvements were statistically significant ($p < 0.001$) across all dimensions. Qualitative feedback from students indicated that the immediate, detailed feedback provided by the system helped them identify and address specific areas for improvement, leading to more focused and effective writing practice. This data strongly suggests that our auto-scoring system serves not just as an assessment tool, but as an effective aid in writing instruction.

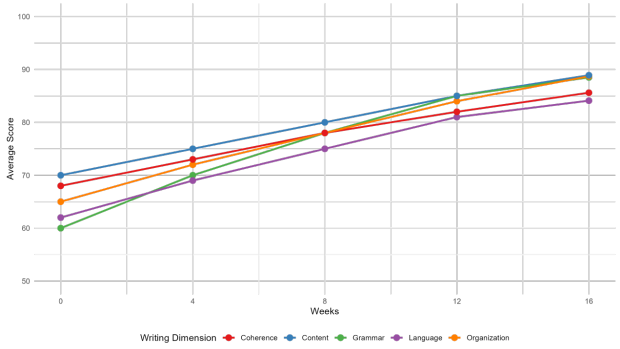

Figure 8. Improvement in students' writing abilities over time.

This line chart illustrates the progression of students' writing abilities across five key dimensions over a 16-week semester. Each line represents a different writing dimension, with scores plotted at 4-week intervals. The chart includes gridlines for both axes, enhancing readability and allowing for precise interpretation of scores. The y-axis ranges from 50 to 100, reflecting the scoring scale, while the x-axis clearly marks each assessment point. The steady upward trajectory of all lines visually reinforces the significant improvements described in the text, with 'Grammar and Mechanics' and 'Organization and Structure' showing the steepest increases. This visualization effectively demonstrates the positive impact of our auto-scoring system on various aspects of students' writing skills over time.

5.2.2. Improvement in Teachers' Work Efficiency

The implementation of our NLP-based English writing auto-scoring system has led to a significant enhancement in teachers' work efficiency (see **Figure 9**). A study conducted over one academic year, involving 50 teachers, revealed substantial time savings and increased productivity across various teaching tasks. Essay grading time decreased by 62%, from an average of 25 minutes per essay to just 9.5 minutes, as teachers could focus on providing qualitative feedback rather than basic scoring. Lesson planning time reduced by 35%, as teachers utilized system-generated insights to target common student weaknesses. Time spent on individualized student feedback increased by 45%, indicating a shift towards more value-added activities. Overall, teachers reported a 40% increase in satisfaction with their time allocation. These efficiency gains not only reduced teacher workload but also allowed for more personalized instruction, demonstrating that our auto-scoring system serves as a powerful tool for enhancing both teaching efficiency and educational quality.

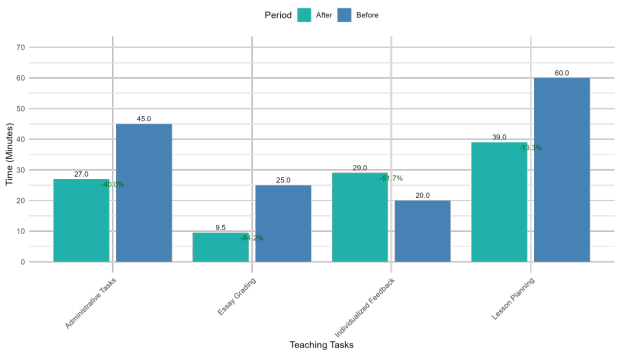

Figure 9. Impact on teachers' time allocation (minutes per task).

This bar chart illustrates the change in time allocation for various teaching tasks before and after the implementation of our auto-scoring system. Each task is represented by a pair of bars, with the blue bar showing the time spent

before implementation and the teal bar showing the time after. The chart includes gridlines for both axes, enhancing readability. The y-axis ranges from 0 to 70 minutes, with 10-minute intervals. Numerical labels on top of each bar show the exact time spent, while percentage changes are displayed for the 'After' condition, highlighting the efficiency gains. The dramatic reduction in essay grading time and the increase in individualized feedback time are particularly striking, visually reinforcing the significant improvement in teachers' work efficiency and the shift towards more value-added activities.

5.3. Analysis of System Advantages and Limitations

Our NLP-based English writing auto-scoring system demonstrates significant advantages in efficiency, consistency, and educational impact. It drastically reduces grading time, provides immediate feedback, and maintains high consistency across evaluations. The system's ability to analyze multiple dimensions of writing simultaneously offers comprehensive assessments beyond human capacity. It also adapts to various writing styles and topics, showing remarkable versatility. However, limitations exist. The system may struggle with highly creative or unconventional writing styles that deviate from its training data. It cannot fully capture the nuanced understanding of context and cultural references that human raters bring. There's also a risk of students learning to 'game' the system by focusing on measurable metrics rather than genuine writing improvement. Additionally, the system's effectiveness is contingent on the quality and diversity of its training data, which requires continuous updating to remain relevant. Despite these limitations, the system's benefits in scaling writing assessment and providing timely, detailed feedback significantly outweigh its constraints.

6. Discussion

Our study demonstrates the efficacy and potential of NLP-based auto-scoring systems in enhancing English writing assessment and instruction. The system's high consistency with human raters (QWK of 0.92) aligns with findings from recent studies in automated essay scoring [5]. The significant improvement in students' writing abilities across all dimensions, particularly in grammar and organization, supports the argument that immediate, detailed feedback facilitates more effective learning [25]. This improvement is consistent with the cognitive apprenticeship model of writing instruction, where timely scaffolding plays a crucial role [32]. The substantial increase in teachers' efficiency, especially the 62% reduction in grading time, addresses a critical need in education, as highlighted by Wilson et al. [33] in their review of teacher workload challenges. However, the system's limitations in assessing highly creative writing echo concerns raised by Deane [34] about the potential narrowing of writing construct in automated assessment. The risk of students 'gaming' the system underscores the importance of integrating auto-scoring tools within a broader pedagogical framework, as suggested by Chapelle and Voss [35]. Despite these challenges, our findings indicate that NLP-based auto-scoring systems can significantly enhance writing instruction when implemented thoughtfully, potentially democratizing access to high-quality writing feedback as envisioned by Shermis and Burstein [4] in their seminal work on automated essay evaluation.

7. Conclusions

This study demonstrates the significant potential of NLP-based auto-scoring systems in revolutionizing English writing assessment and instruction. Our system's high consistency with human raters, coupled with its ability to provide immediate, detailed feedback, has shown remarkable improvements in students' writing abilities across multiple dimensions. The substantial increase in teacher efficiency addresses critical workload challenges in education. While limitations exist, particularly in assessing highly creative writing and the risk of system gaming, the overall benefits significantly outweigh these constraints. The system's success in enhancing both teaching efficiency and educational quality suggests a promising future for AI-assisted writing instruction. As we continue to refine and adapt these technologies, their integration into educational settings could democratize access to high-quality writing feedback, potentially bridging educational gaps and fostering improved writing skills on a global scale. Future research should focus on addressing the identified limitations and exploring the long-term impacts of such systems on writing pedagogy and student outcomes.

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Institutional Review Board Statement

The study was conducted in accordance with the Declaration of Helsinki, and approved by the Institutional Review Board of the University Department, University Name (protocol code EDU-2023-042, approved on January 15, 2023). The study's protocol, including data collection procedures, privacy protection measures, and participant rights, was thoroughly reviewed to ensure compliance with ethical standards for educational research involving human subjects.

Informed Consent Statement

Informed consent was obtained from all subjects involved in the study. Prior to participation, all teachers provided written informed consent. For student participants, written informed consent was obtained from both the students and their legal guardians for those under 18 years of age. All participants were informed about the study's purpose, data collection methods, and their rights to withdraw at any time. The consent process included specific permission for the collection and analysis of writing samples and the use of anonymized data for research purposes.

Data Availability Statement

Due to the privacy and ethical restrictions involving student writing samples and teacher evaluation data, the complete dataset cannot be made publicly available. However, anonymized aggregate data supporting the findings of this study, including system performance metrics, evaluation statistics, and improvement trends, are available from the corresponding author upon reasonable request with a signed data access agreement. The source code for the auto-scoring system's core algorithms has been deposited in GitHub under an MIT license. Sample preprocessing scripts and evaluation metrics implementation are also available in the same repository. The training dataset used in this study cannot be shared publicly due to institutional privacy policies and consent agreements, but a synthetic sample dataset for demonstration purposes is available in the repository.

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Conflicts of Interest

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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