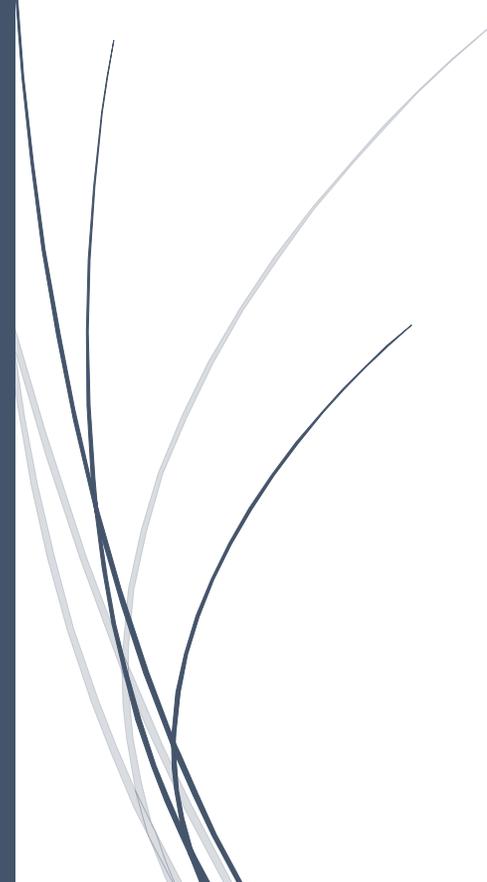


The logo for RADemics, featuring the text "RADemics" in white on a blue arrow-shaped background pointing to the right.

RADemics

Machine Learning Approaches for English Writing Skill Evaluation

A decorative graphic consisting of several thin, curved lines in shades of blue and grey, extending from the bottom left towards the center of the page.

R.Vignesh, Gopala Krishna Murthy

SATHYABAMA INSTITUTE OF SCIENCE AND
TECHNOLOGY, GOVERNMENT FIRST GRADE COLLEGE

Machine Learning Approaches for English Writing Skill Evaluation

¹R. Vignesh, Assistant Professor, Department of Computer Science and Engineering, Sathyabama Institute of Science and Technology, Chennai, Tamil Nadu, India. vignesh.star975@gmail.com

²Gopala Krishna Murthy, HR, Associate Professor, Government First Grade College, Nanjangud, Karnataka, India. gkmurthy123@gmail.com

Abstract

The assessment of English writing skills has undergone a transformative evolution with the integration of machine learning and automated evaluation systems. This chapter presents a comprehensive exploration of computational approaches for evaluating writing proficiency, emphasizing the extraction of lexical, syntactic, semantic, discourse-level, and stylistic features. Hybrid machine learning models that combine feature engineering with deep learning architectures are highlighted, demonstrating enhanced predictive accuracy and interpretability in scoring complex writing constructs. The chapter further investigates the evaluation of higher-order writing skills, including argumentation, persuasive writing, creativity, and stylistic sophistication, alongside the integration of semantic similarity and discourse analysis for holistic assessment. Adaptive and personalized feedback mechanisms are discussed, focusing on real-time error detection, skill-specific guidance, learner profiling, and adaptive difficulty levels that optimize learning outcomes. Opportunities for continuous improvement through integration with learning management systems are examined, emphasizing the potential of data-driven, individualized instruction. The insights presented establish a roadmap for future research and implementation of intelligent writing evaluation systems, bridging computational techniques with pedagogical objectives to advance English language education.

Keywords: Automated Writing Evaluation, Machine Learning, Hybrid Models, Higher-Order Writing Skills, Adaptive Feedback, Semantic Analysis.

Introduction

The evaluation of English writing proficiency has increasingly leveraged computational techniques to enhance objectivity, efficiency, and pedagogical effectiveness [1]. Traditional assessment methods, relying primarily on manual grading, are often subjective, time-consuming, and constrained by limited scalability [2]. Automated Writing Evaluation (AWE) systems have emerged as transformative tools in this context, employing algorithmic analysis to assess grammatical accuracy, syntactic structure, lexical richness, and overall essay quality. These systems provide consistent and reproducible scoring while enabling educators to focus on higher-order instructional strategies [3]. The integration of machine learning techniques into writing assessment further extends the capability of AWE systems, allowing for predictive modeling, nuanced feedback, and adaptive learning pathways. By harnessing large datasets of written text, machine learning models identify patterns and correlations that are difficult to detect through

manual evaluation alone, providing evidence-based insights into learner performance [4]. The advancement of natural language processing (NLP) and deep learning architectures has facilitated the development of models that move beyond surface-level error detection to capture semantic meaning, coherence, and discourse-level structures, supporting a more holistic evaluation of writing skills. These innovations have significant implications for English as a Foreign Language (EFL) instruction, standardized testing, and large-scale educational assessments [5].

Feature extraction constitutes a foundational element of computational writing assessment, encompassing the identification and quantification of measurable linguistic attributes. Lexical features, including vocabulary diversity, word frequency, and complexity, provide insight into a learner's lexical sophistication and expressive range [6]. Syntactic features, such as sentence structure, clause density, and part-of-speech patterns, inform evaluators about structural proficiency and grammatical control [7]. Semantic features capture contextual meaning, cohesion, and conceptual relationships within text, facilitating assessment of content relevance and argument strength. Discourse-level features address coherence, logical progression, and paragraph organization, supporting the evaluation of higher-order thinking and reasoning skills [8]. Stylistic features, including readability, sentence rhythm, and individual writing style, complement other linguistic measures by reflecting fluency, narrative engagement, and textual uniqueness [9]. The integration of these multidimensional features enables automated systems to replicate human evaluative processes more accurately, producing holistic scores that balance surface-level correctness with higher-order writing quality. Such comprehensive feature representation forms the basis for hybrid modeling approaches that combine engineered features with deep learning embeddings, creating robust predictive frameworks [10].

Hybrid machine learning models have emerged as a key innovation in automated writing evaluation, combining the interpretability of feature engineering with the representational power of deep learning architectures [11]. These models leverage structured linguistic features alongside contextual embeddings derived from recurrent neural networks, long short-term memory networks, or transformer-based architectures [12]. The result is a system capable of detecting latent patterns in text, identifying complex relationships among words, sentences, and paragraphs, and generating reliable predictions of writing quality [13]. Hybrid models address limitations of purely rule-based or neural approaches, providing both high accuracy and interpretability for educators and learners. By integrating these complementary techniques, scoring systems can account for both surface-level proficiency, such as grammar and syntax, and higher-order skills, including argumentation, creativity, and stylistic sophistication [14]. This dual approach facilitates personalized feedback, adaptive learning pathways, and scalable assessment, enabling the deployment of automated systems in diverse educational settings. Hybrid frameworks also support the analysis of longitudinal writing data, allowing models to track learner growth, detect emerging patterns, and provide targeted interventions aligned with individual developmental trajectories [15].