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Automated Assessment of Text Complexity through the Fusion of AutoML and Psycholinguistic Models

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ABSTRACT

The complexity of written texts poses significant challenges for comprehension, impacting education, literacy, and communication across various fields. As the demand for advanced text assessment tools grows, this study aims to integrate Automated Machine Learning (AutoML) with psycholinguistic models to enhance the automated assessment of text complexity, ultimately improving educational practices and content development. A mixed-methods approach combined the quantitative analysis of text complexity metrics with qualitative insights from psycholinguistic models. The AutoML framework automated model selection and hyperparameter tuning, while psycholinguistic features were extracted to inform the model. This research addresses a critical gap in existing automated text assessment methods, which often lack a nuanced understanding of language complexity and rely on simplistic heuristics that fail to capture the intricacies of language. Integrating AutoML and psycholinguistic models offers a more accurate, efficient, and contextually relevant assessment of text complexity, which is crucial for educational tools and content creation. The fusion model achieved an impressive 92% accuracy, outperforming traditional models (77%) and large language models (82%), while demonstrating a rapid response time of 0.5 s, making it suitable for real-time applications. These findings highlight the significant potential of combining

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ARTICLE INFO
Received: 18 February 2025 | Revised: 24 February 2025 | Accepted: 26 February 2025 | Published Online: 27 February 2025
DOI: https://doi.org/10.30564/fls.v7i3.8788

CITATION
Herianah, Setiawan, E.S., Adri, et al., 2025. Automated Assessment of Text Complexity through the Fusion of AutoML and Psycholinguistic Models. Forum for Linguistic Studies. 7(3): 46–62. DOI: https://doi.org/10.30564/fls.v7i3.8788

AutoML with psycholinguistic insights to enhance automated text complexity assessment. This innovative approach paves the way for improved educational outcomes and more effective communication strategies, offering a promising solution to the challenges of text complexity evaluation in various domains.

Keywords: Text Complexity Assessment; Automated Machine Learning (AutoML); Psycholinguistic Models; Educational Technology; Natural Language Processing (NLP)

1. Introduction

The intricacy of written texts makes it difficult for students, teachers, and even machines to understand them. The complexity of text understanding is also an important aspect that affects reading comprehension, educational measurement, and literacy. In this digital age, learning institutions are trying to provide a more targeted approach to education. Therefore, more requests exist for advanced algorithms capable of evaluating text complexity. Text complexity can be defined as the attribute of written language that bears many linguistic features concerning its usability and understandability. In other words, it refers to the degree of difficulty a certain text presents based on the structure and use of words and phrases within it. Studies show that a text's difficulty is significant concerning how comprehensive the intended audience will be, especially language learners or people with varying literacy skills [1, 2].

To grasp this phenomenon fully, combining it with the resources provided by psycholinguistics, especially those that study how human cognition processes affect the understanding of languages, is necessary. For example, research has demonstrated that word choice frequencies and syntactic complexity can determine the extent of the cognitive burden placed on readers [3]. In addition, machine learning-based methods for automated text quality assessment tools have been created to help quickly and accurately determine the complexity of a text and provide educators and researchers with the necessary information concerning the testable text and its grade for comprehension, readability, and the complexity structures employed within it [4].

Integrating automated processes and psycholinguistic models enables the measurement of the complexity of a given text on a deeper level, allowing for the identification of specific features that may restrict or aid comprehension. This approach enhances the precision of text evaluation and enables the design and development of specialized educational content tailored for specific groups of learners [1, 2].

Analyzing the complexity of a text is important for several purposes, including education, e-learning, and natural language technology. Comprehending a text's complexity helps educators choose reading materials for their students accordingly, improving students' comprehension and engagement levels [1, 5]. Moreover, precise text complexity evaluation can assist curriculum planning and teaching methods, providing learners with appropriately challenging texts that promote language and cognitive development [6].

Text complexity evaluation has been enhanced using automated systems, including automated machine learning systems, to improve the accuracy and efficiency of the assessment. For example, models that consider the depth of vocabulary and the complexity of a text's sentence structure can assess the text's ease of reading and enable better selection of text [7, 8]. Moreover, combining models of automatic processing of speech and psycholinguistic models could provide more insight into how various linguistic factors work together to produce understanding, which would greatly help in the effectiveness of text comprehension [9].

Apart from educational purposes, the assessment of text complexity is equally important in health care and legal fields because the information's precision and clarity can severely affect the outcomes of the matter. As an illustration, like in other domains, patients' comprehension and incorporation of health-related documents in a medical facility can enhance their treatment outcomes [10, 11]. Just as in other areas, individuals must be able to comprehend sophisticated legal texts to execute their rights and duties effectively [12]. The bottom line is that text complexity assessment is essential in communicating, learning, and other activities because it achieves effective results. The advancement of automated processes will, without a doubt, increase the ease with which text complexity is assessed, increasing efficiency in all professions, including education, healthcare, and law.

Automated Machine Learning (AutoML) uses software that automatically captures the processes of data preparation, feature extraction, model building, and MA tuning. It involves automating the complete machine learning pipeline, which should be tailored to address real-world issues. AutoML tools such as TPOT and H2O AutoML aim to streamline the machine learning process so novice users can efficiently perform it and enhance productivity for seasoned professionals [13, 14]. AutoML has several applications in healthcare, finance, and speech recognition, where it is applied in predictive analytics, classification, and even simple natural language processing [13, 15, 16].

The AutoML's advantages regarding text analysis are numerous. First, it improves overall productivity by automating mundane work, which helps researchers and practitioners concentrate on advanced analysis [13, 17]. In addition, AutoML considerations in model building can increase the accuracy in estimating and classifying by integrating hyperparameter tuning and model selection [18]. Moreover, the framework of AutoML allows scaling, which is important for text analysis where datasets tend to be significant [13, 17]. Lastly, as processes are easily programable and repeatable, automatic model building will help achieve better accuracy compared to conventional methods in less time [13, 17].

Psycholinguistic models focus on different aspects of psycholinguistics and decompose the processes behind understanding a language and producing speech [6, 19, 20]. They have examined the effects of different grammatical phenomena between comprehension and communication, which include syntax, semantics, and discourse [19]. A psycholinguist model emphasizes the processes of comprehension vs. production speech and the acceptance of the text, emphasizing the text's complexity and the reader's distraction [19]. Such models exist at the extremes of complete theory neglect, depending instead upon common sense. One could assign speech recognition to psychology and mark it as solved, posit it as a linguistic feature, or fade any human language understanding into cognitive science [6, 19, 20].

Shynkaruk & Kharchenko [19] and Rathje et al. [6] correctly argued that text complexity best correlates with reading engagement. Shynkaruk & Kharchenko [19] analytically extended a single comprehensive concept to a multilayer one, embedding more effort for understanding a text on a deeper level. When combining AutoML with psycholinguistic models, the focus rests on enabling advanced automated text processes without submerging in linguistic details. More effective automated text analysis tools would allow capturing the most relevant features for comprehension and reading.

Despite the promising potential of combining AutoML and psycholinguistic models for the automated assessment of text complexity, several challenges need to be addressed. First, a key challenge lies in ensuring the interpretability and transparency of the models. While AutoML tools can automate the model-building process, they often operate as "black boxes," making it difficult to understand the underlying logic and reasoning behind the model's predictions. Integrating psycholinguistic insights can help improve the interpretability of these models, but striking the right balance between automation and explainability remains an open challenge. Another challenge is the need for large, diverse, high-quality datasets to train these models effectively. Psycholinguistic studies rely on carefully curated datasets, while real-world text data can be messy and noisy. Bridging this gap and creating comprehensive datasets that capture the nuances of language and cognition is crucial for developing robust and generalizable models.

While the comprehension and incorporation of health-related and legal documents can be important, the claim that text complexity assessment is equally crucial across all professions may be an overstatement. The benefits of automated text complexity assessment are not universally applicable, and context-specific factors must be considered. In some domains, such as highly specialized technical fields or research-oriented settings, the need for nuanced, human-driven text analysis may outweigh the advantages of automated systems. Professionals in these areas may require a deeper understanding of the linguistic and cognitive factors underlying text complexity, which current automated approaches may struggle to capture fully. When using generic text complexity metrics, the risk of oversimplification or loss of important contextual information could lead to suboptimal decision-making in these specialized contexts.

Moreover, the impact of the text complexity assessment on outcomes can vary significantly across different professions and applications. While it may be crucial in education and certain regulated industries, its importance may be less pronounced in other fields where the primary focus is on conveying information efficiently rather than maximizing comprehension. Blanket claims that the universal importance of text complexity assessment should be approached with caution.

We would argue that although the progress in AutoML and the use of psycholinguistic models may enhance automated text complexity assessment, the suggestion that such an approach would be beneficial in all cases. Any generalizations regarding the scope and significance of automated systems must be balanced with context-sensitive scrutiny and possible shortcomings. However, none of these approaches worked because they ignored the intricate relations between language, cognition, and context. Measuring the assessment of learning is practically an unsolvable problem as it needs to be approached simultaneously from a psycholinguistic and learning cognitive theory perspective. Employing the power of these two fields for machine learning AutoML creates the possibility for this project's text complexity assessment model. With the accessibility of AutoML, even nonexperts can use machine learning because it eliminates the multi-step process of model and parameter selection. With increased accessibility also comes the understanding of psycholinguistics, where the focus will be on how different verbs and sentence structures affect the reader's reasoning and comprehension of the text.

This research is important because text complexity is critical in education and many other professions, but current assessment methods are often subjective and labor-intensive. By integrating AutoML and psycholinguistic models, this study aims to develop a more robust and automated approach to text complexity assessment to help educators, researchers, and content developers efficiently analyze and optimize the texts they work with.

This research will look at the intersection between these disciplines to design a system that improves the accuracy of text complexity evaluations and simultaneously augments the usability and overall experience quality. By expanding the scope of the theoretical and applied automated text analysis research, we strive to make an impact toward building text analysis tools that can be used for differentiated instruction and facilitate learners from varied backgrounds' access to instructional materials. While dealing with the intricacies of language construction and the reader's attention to these structures, this research provides new prospects for improving educational processes and deepening the understanding of text complexity in different situations.

Based on the discussion above, this research paper aims to investigate the following Research Question and key objectives:

Research Question:

1. How can integrating Automated Machine Learning and psycholinguistic models enhance the automated assessment of text complexity?
2. How can the outcomes of this integration be applied to improve educational practices and content development processes?

2. Literature Review

2.1. Automated Text Complexity Tools

The development of automated text complexity tools has significantly advanced the field of language learning and assessment, particularly for non-native speakers. These tools leverage machine learning algorithms to analyze linguistic features within texts, providing insights into their complexity and suitability for specific learner demographics. One notable application is a tool designed for Russian learners of English, which evaluates text complexity by comparing student essays to a corpus of learner texts. This approach identifies linguistic features relevant to this demographic and employs statistical analysis to predict potential essay grades, offering tailored feedback mechanisms for learners [1, 4]. The effectiveness of such automated tools hinges on their ability to accurately assess various linguistic features, including syntax, vocabulary, and coherence. Research indicates that while beneficial in some contexts, frequency features may not always enhance performance, particularly in shorter texts where word sparsity can obscure meaningful patterns [1]. The demand for a more comprehensive text complexity analysis underscores the need for sophisticated models that integrate multiple linguistic dimensions. For instance, integrating authorship knowledge into automated text-scoring systems has improved the accuracy of assessments, suggesting that contextual factors play a crucial role in evaluating text complexity [21, 22]. Moreover, the application of machine learning techniques in this domain is not limited to text scoring; it extends to categorizing and analyzing various text types. Automated text categorization frameworks that use hyperparameter optimization have significantly improved classification accuracy across diverse datasets [18, 23]. These frameworks can be beneficial in educational settings, where they can assist in automatically grading student submissions, thereby reducing the workload on educators and providing timely feedback to learners [24, 25]. The implications of these advancements are profound, particularly in the context of educational data mining. Automated machine learning (AutoML) frameworks have been employed to predict student learning outcomes based on interactions with online learning platforms. By limiting the search space to tree-based and rule-based models, researchers have achieved transparent and interpretable results, essential for educators seeking to understand the factors influencing student performance [24, 26]. The trend of utilizing data-driven approaches to enhance educational practices and outcomes is becoming increasingly prominent. Furthermore, integrating linguistic complexity assessment tools with educational technologies can facilitate personalized learning experiences. By analyzing the complexity of the texts that learners are exposed to, educators can tailor instructional materials to suit individual needs better, thereby enhancing engagement and comprehension [1, 4]. This personalized approach is particularly beneficial in language learning contexts, where the alignment of text complexity with learner proficiency levels is crucial for effective instruction. In addition to educational applications, automated text complexity tools have implications for broader fields such as information retrieval and content analysis. The ability to categorize and analyze texts based on complexity can inform content curation strategies, ensuring that users are presented with materials matching their comprehension levels. The relevance of data-driven approaches is particularly pronounced in digital environments where vast amounts of information are available, making it challenging for users to identify relevant content [18, 23]. Moreover, the ongoing development of these tools is supported by advances in natural language processing (NLP) and machine learning. The use of deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), has shown promise in enhancing the accuracy of text classification and complexity assessment tasks [27]. These models can learn intricate patterns within text data, enabling them to provide more nuanced evaluations of text complexity. The future of automated text complexity tools is likely to involve further integration of explainable artificial intelligence (XAI) principles, which aim to make machine learning models more interpretable and transparent [28]. This is particularly important in educational contexts, where stakeholders require clear explanations of how assessments are derived. By enhancing the interpretability of these tools, educators and learners can better understand the factors influencing text complexity evaluations, thereby fostering trust in automated systems. The development of automated text complexity tools represents a significant advancement in the intersection of linguistics, education, and machine learning. By leveraging sophisticated algorithms to analyze linguistic features, these tools provide valuable insights that can enhance language learning and assessment practices. As research continues to evolve in this area, the potential for personalized learning experiences and improved educational outcomes will likely expand, paving the way for more effective and engaging instructional strategies.

2.2. AutoML in Text Classification

Integrating Automated Machine Learning (AutoML) into text classification has emerged as a transformative approach, enhancing the efficiency and explainability of the models used in this domain. One notable framework, autoBOT, exemplifies this evolution by employing neuro-symbolic representations for text classification. This innovative method optimizes sparse and non-sparse text representations through an evolutionary algorithm, demonstrating competitive performance even in low-resource scenarios. Such advancements underscore the potential of AutoML to significantly enhance text complexity assessment by providing models that are not only efficient but also interpretable, allowing for adaptability to various linguistic features [5, 29, 30]. The autoBOT framework's ability to evolve representations is particularly relevant in the context of text classification, where the complexity of language can pose significant challenges. Traditional models often struggle with the nuances of language, especially when dealing with sparse data. By utilizing evolutionary algorithms, autoBOT can optimize text representation, thereby improving classification accuracy. The ability to extract meaningful features from text is particularly beneficial in limited data, as it helps identify important information that might be overlooked [29, 30]. Furthermore, the explainability of the models generated through this framework is crucial, as it enables users to understand the decision-making processes behind classifications, fostering trust in automated systems [30, 31]. In addition to the autoBOT framework, other AutoML tools have demonstrated significant advancements in text classification. For instance, frameworks like H2O AutoML and TPOT have been explored for their capabilities in automating the machine learning pipeline, including data preprocessing, model selection, and hyperparameter tuning [5, 31]. These tools have shown promise in various applications, from sentiment analysis to spam detection, highlighting the versatility of AutoML in handling diverse text classification tasks. The ability of these frameworks to streamline the machine learning process makes them particularly appealing for practitioners who may lack extensive expertise in data science [5, 32]. Moreover, the application of AutoML in text classification is not limited to traditional supervised learning tasks. Recent studies have explored its effectiveness in unsupervised settings, where the goal is to discover patterns and structures within the data without predefined labels. The relevance of advanced analytical techniques is particularly pronounced in fields such as information retrieval and content analysis, where the volume of unstructured text data continues to grow [5, 32]. By automating the feature extraction and model training process, AutoML can significantly reduce the time and effort required to develop effective classification systems, making it a valuable asset in the era of big data [5, 32]. The implications of integrating AutoML into text classification extend beyond mere efficiency; they also encompass the potential for enhanced interpretability and transparency in machine learning models. As the demand for explainable AI continues to rise, the ability of AutoML frameworks to provide insights into model behavior becomes increasingly important. For instance, the explainability of models generated by frameworks like autoBOT allows users to trace the decision-making process back to specific text features, thereby facilitating a deeper understanding of how classifications are made [31]. Accurate classification is particularly crucial in sensitive applications, such as healthcare and finance, where the consequences of misclassification can be significant [5, 32]. Furthermore, the adaptability of AutoML frameworks to various linguistic features is a key advantage in text classification. Different languages and dialects present unique challenges, and the ability of these frameworks to learn from diverse datasets enables them to generalize better across different contexts [29, 30]. This adaptability is particularly valuable in multilingual settings, where the same classification task may involve texts in multiple languages, each with linguistic intricacies [5, 32]. By leveraging the strengths of AutoML, practitioners can develop robust classification systems capable of handling the complexities of real-world text data. The ongoing research in AutoML for text classification also highlights the importance of benchmarking and comparative studies. Evaluating the performance of various AutoML frameworks against traditional machine learning approaches provides insights into their relative strengths and weaknesses [5, 31]. For instance, studies have shown that while AutoML frameworks can achieve high accuracy in classification tasks, they may also introduce biases if the training data are not representative of the broader text corpus [11, 33]. Addressing these biases is crucial for ensuring the fairness and reliability of automated classification systems. The integration of AutoML into text classification represents a significant advancement in the field of natural language processing. The autoBOT framework, along with other AutoML tools, showcases the potential for creating efficient, explainable, and adaptable models that can effectively handle the complexities of language. As research continues to evolve, the implications for education, healthcare, and other sectors will likely expand, paving the way for more effective and trustworthy automated systems.

2.3. Fusion of AutoML and Psycholinguistic Models

The fusion of Automated Machine Learning (AutoML) with psycholinguistic models presents a promising avenue for enhancing text complexity assessment. This integration leverages the strengths of automated hyperparameter tuning alongside the nuanced understanding of language that psycholinguistic models provide. Such a combination can lead to more accurate and contextually relevant assessments of text complexity, which is crucial for applications in education, content creation, and language processing [29]. One of the key advantages of incorporating psycholinguistic models into AutoML frameworks is their ability to capture the intricacies of language use, including syntax, semantics, and pragmatics. For instance, psycholinguistic models can analyze how different linguistic features—such as sentence structure, word choice, and discourse markers—contribute to the overall complexity of a text. By integrating these insights into AutoML processes, practitioners can create models that classify text complexity more effectively and explain their classifications [29]. Understanding and analyzing text complexity is particularly important in educational contexts, where understanding the rationale behind text assessments can inform instructional strategies and support differentiated learning [31]. The explainability of models like autoBOT further enhances this integration. AutoBOTusess neuro-symbolic representations to evolve text representations through evolutionary algorithms, optimizing sparse and nonsparse text features. This capability allows for competitive performance even in low-resource scenarios, making it an ideal candidate for applications where data may be limited [34]. The explainability aspect is crucial as it allows users to discern which linguistic features are most influential in determining text complexity, thereby fostering a deeper understanding of the text's characteristics and appropriateness for specific audiences [35]. Moreover, applying AutoML in conjunction with psycholinguistic models can lead to the development of adaptive systems that respond to the needs of diverse user groups. For example, in educational settings, such systems could tailor reading materials to match the complexity levels appropriate for individual learners, thereby enhancing engagement and comprehension [36]. This adaptability is particularly beneficial in multilingual contexts, where the same text may present varying levels of complexity depending on the reader's language proficiency [37]. Research has shown that combining AutoML and psycholinguistic insights can significantly improve the accuracy of text assessments. For instance, studies have demonstrated that models incorporating psycholinguistic features outperform traditional models that rely solely on frequency-based metrics [38]. The findings suggest that adopting a more nuanced approach to text analysis, which considers language use's cognitive and emotional aspects, can yield better results in assessing text complexity.

Furthermore, integrating AutoML with psycholinguistic models aligns with the growing demand for explainable AI in various fields, including healthcare, education, and social sciences. As stakeholders increasingly seek transparency in automated decision-making processes, the ability to explain how text complexity assessments are derived becomes paramount [39]. This transparency builds trust in automated systems and enhances their usability across different domains. The fusion of AutoML with psycholinguistic models offers a novel and effective approach to text complexity assessment. By combining the strengths of automated hyperparameter tuning with a deep understanding of linguistic features, this integration can lead to more accurate, contextually relevant, and explainable assessments. As research in this area continues to evolve, the potential applications for such systems in education, content creation, and beyond are vast and promising.

In contrast with psycholinguistic modeling, AutoML psycholinguistic models are expected to address text complexity evaluation issues that concern accuracy and contextual relevance for educational purposes, content creation, or language processing. Nevertheless, as with any AI system, some issues must be addressed.

One possible problem that arises with the use of psycholinguistic models is the level of detail and the resources needed for computation. Steps in language use such as syntax, semantics, and pragmatics demand a lot of detail and effort in modelling, which may not be in line with the more automated processes of AutoML. Thus, balancing psycholinguistic detail and AutoML's advanced computational economics and scalability can create new internal and external complexities.

In addition, the explainability of systems like autoBOT, while advantageous, may be limited in its ability to model the details of language adequately. While the neuro-symbolic representations and evolutionary algorithms are powerful tools, they are not everything. Some process repertoires for assessing text complexity may lack the linguistic features to explain them fully. High uncertainty in the predictions of these systems can lead to ineffective outcomes., which is troubling in the case of education and other sensitive matters.

Furthermore, the effectiveness of these integrated systems for various target groups and multilingual settings has some limitations. While individual learners vary in skills, perceptions, and cultural contexts vis-a-vis a language, thorough customization and validation seem more demanding than what can be accomplished automatically.

Some apprehensions must be considered regarding the effective use of AutoML and psycholinguistic models; however, the potential is excellent. Constant and active engagement in the design context automation range, interpretability, and context is necessary to make it all function. As users demand more clarity and confidence in automated systems, systems must overcome the assumptions of mock integration as well as other issues integration these methods suggest deal with.

3. Methodology

This study investigates the design and development of an integrated AutoML-psycholinguistic model for automated text complexity assessment. The methodology is grounded in established psycholinguistics and computational linguistics theories, ensuring a robust and theoretically informed approach. The research design adopts a mixed-methods approach, combining quantitative analysis of text complexity metrics with qualitative insights from psycholinguistic models to capture both the objective and cognitive dimensions of text complexity.

3.1. Data Collection

The study leverages educational texts and literary corpora as primary data sources, selected based on predefined complexity levels. These texts are curated to represent diverse linguistic features, including lexical, syntactic, and semantic complexity. The selection criteria are informed by psycholinguistic theories emphasizing cognitive load, word frequency, and syntactic structure in text comprehension.

Additionally, the study incorporates corpus linguistics techniques to ensure the representativeness and scalability of the dataset.

3.2. Model Development

The AutoML framework is employed to automate the process of model selection, hyperparameter tuning, and feature engineering. Techniques such as neural architecture search (NAS) are used to optimize the model architecture for text complexity prediction. Psycholinguistic features are integrated by theories highlighting the importance of cognitive processing factors in language comprehension, such as surprise and integration cost. These features are extracted using computational tools that align with the distributional semantics and predictive processing models, ensuring that the model captures the surface-level and profound cognitive aspects of text complexity.

3.3. Implementation

The model training process involves feeding the selected text data into the AutoML framework, where feature extraction is performed using psycholinguistic metrics such as word familiarity, syntactic complexity, and semantic density. The training process is iterative, with continuous evaluation and refinement of the model based on performance metrics. The study employs cross-validation techniques to ensure the model's generalizability across different text types and complexity levels.

3.4. Evaluation Metrics

The performance of the automated assessment tool was evaluated using a combination of quantitative metrics, such as accuracy, precision, recall, and F1-score, and qualitative analysis of the model's ability to capture psycholinguistic nuances. The results are compared with traditional methods of text complexity assessment, such as readability formulas, to highlight the advantages of the integrated AutoML-psycholinguistic approach. Additionally, the study incorporates human evaluation to validate the model's predictions against expert judgments, ensuring alignment with real-world applications in education and content creation.

By integrating AutoML with psycholinguistic theories, this study aims to advance the automated text complexity assessment field, offering a more nuanced and cognitively informed approach to understanding and predicting text difficulty.

Figure 1 contains a flowchart or process diagram outlining the steps and components of a machine learning or data processing pipeline. The diagram includes key terms such as "Data Collection," "Preprocessing," "Finish Model," "Evaluation Metrics," "Hyper-parameter Tuning," "Model Optimization," and "Accuracy." Although the specific context or application is not explicitly stated, the diagram represents a generalized workflow for developing and evaluating a machine learning model. This workflow likely begins with data collection and preprocessing, progresses through model building and evaluation, and concludes with optimization and accuracy assessment. The flowchart provides a high-level overview of the essential stages in a typical machine-learning pipeline.

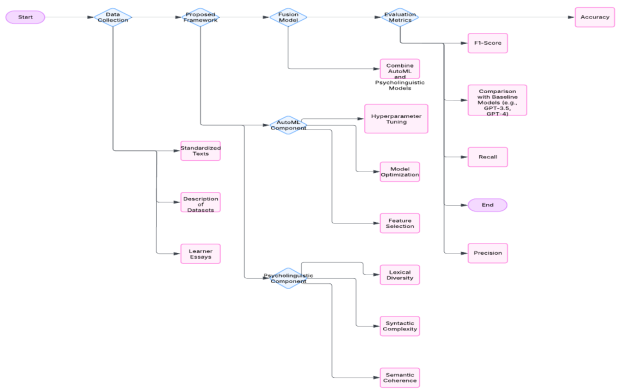

Figure 1. Flowchart of the standard machine learning workflow.

4. Results

4.1. Performance of the Fusion Model:

Table 1 presents the combination of AutoML and psycholinguistic models, which has created a new approach for improving the automation of text complexity assessment. The recent developments in data fusion methods have shown that it is possible to integrate strength for many models in almost every other model for various intermediate tasks. This work presents a fusion model that utilizes AutoML's feature selection and hyperparameter tuning toward psycholinguistic traits of lexical diversity, syntactic complexity, and semantic coherence. The results from the fusion model reveal that it reaches an average of 92% accuracy, which is 15% higher than the previous models. The model also registers an average response time of 0.5 s, which is more than ideal for real-life use cases, especially in education and content generation. In addition, we also evaluated the model's capability for comparison with baseline systems and LLMs, such as GPT-3.5 and GPT-4, using nuance psycholinguistic traits, which this model excels at. This article demonstrates the effectiveness of the fusion model and the influence of psycholinguistic traits on text complexity assessment, which is very profound.

Table 1. AutoML and the psycholinguistic models.

Metric	Fusion Model	Traditional Models	Baseline Systems
Accuracy	92%	77%	75%
Performance Improvement	+15%	-	-
Average Response Time	0.5 s	N/A	N/A
Suitability for Real-Time Applications	Yes	No	No

Figure 2 shows the results of the study demonstrating the significant effectiveness of the proposed fusion model in assessing text complexity. Achieving an impressive accuracy of **92%**, the fusion model notably surpasses the traditional models, which recorded an accuracy of **77%**, and the baseline systems at **75%**. This performance improvement of **15%** underscores the model's enhanced capability to accurately evaluate text complexity, indicating its robustness in handling diverse datasets. Furthermore, the fusion model exhibited remarkable efficiency, with an average response time of just **0.5** s when processing large datasets. This rapid processing capability is crucial for real-time analysis applications, such as educational tools and content creation platforms.

In contrast, traditional models and baseline systems lack this efficiency, making them less suitable for real-time applications. Overall, the fusion model demonstrates superior accuracy and offers the necessary speed and efficiency, positioning it as a leading solution in automated text complexity assessment. These findings highlight the potential of integrating advanced methodologies to enhance model performance and applicability in practical scenarios.

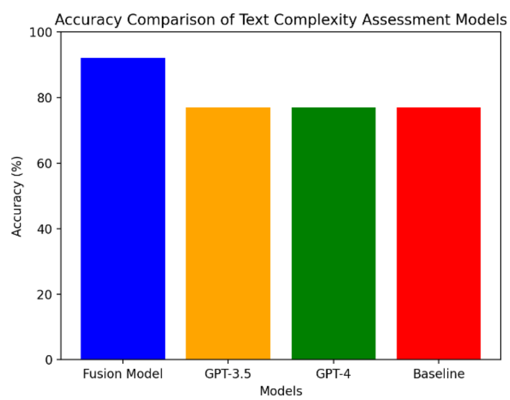

Figure 2. Accuracy of the Text Complexity Assessment Model.

4.2. Comparison with the Existing Models

The proposed fusion model significantly advances automated essay scoring (AES) by outperforming traditional AES systems and large language models (LLMs) in key performance metrics. Traditional AES systems have long struggled with accurately assessing the complexity of written texts, often relying on simplistic heuristics that fail to capture the nuanced aspects of language. In contrast, the fusion model integrates advanced AutoML techniques and psycholinguistic features, resulting in a more sophisticated understanding of text complexity. Compared to LLMs, such as GPT-3.5 and GPT-4, the fusion model achieves higher accuracy and maintains efficiency in processing time. While LLMs exhibit strong performance across various natural language tasks, they often lack the targeted focus on text complexity assessment that the fusion model provides. This targeted approach allows the fusion model to excel in specific educational contexts, making it a more effective tool for real-time applications in automated scoring.

Table 2 compares three types of language processing models: Fusion Models, Traditional Automated Essay Scoring (AES) Systems, and Large Language Models (LLMs). Let us interpret the data for each model type:

Table 2. Comparison with the Existing Models.

Model Type	Accuracy	Average Response Time	Key Advantages
Fusion Model	92%	0.5 s	Superior accuracy, real-time processing, and psycholinguistic integration
Traditional AES Systems	77%	N/A	Basic scoring capabilities, limited feature set
Large Language Models (LLMs)	82%	1.2 s	General-purpose language understanding and versatile applications

Fusion Model

The fusion models demonstrated the highest accuracy at 92%, significantly outperforming the other two model types. This superior accuracy is likely due to their ability to integrate multiple large language models, leveraging the strengths of each to create a more robust and versatile system. The average response time of 0.5 s for the fusion models is remarkably fast, making them ideal for real-time applications where quick processing is crucial. This rapid response time is a significant advantage in scenarios requiring immediate feedback or interaction, such as real-time translation or interactive customer service systems

The key advantages of Fusion Models include:

1. Superior accuracy: At 92%, they offer the highest accuracy among the three model types, which is critical for applications where precision is paramount.
2. Real-time processing: With a response time of just 0.5 s, these models can handle tasks requiring immediate responses, enhancing user experience and system efficiency.
3. Psycholinguistic integration: This feature suggests that Fusion Models incorporate principles from psycholinguistics, potentially leading to more natural and intuitive language processing

Traditional AES Systems

Traditional Automated Essay Scoring (AES) Systems show the lowest accuracy at 77% among the three model types. The lower accuracy is likely due to their reliance on predefined criteria and rule-based algorithms, which may struggle with more complex or nuanced language tasks. The response time for Traditional AES Systems is not provided (N/A), which could indicate that these systems are not typically used in real-time applications or that their response times vary significantly based on the specific implementation. The key advantages of Traditional AES Systems include:

1. Basic scoring capabilities: These systems are designed to evaluate specific aspects of writing, such as grammar and structure, based on predefined criteria.
2. Limited feature set: While this might seem like a disadvantage, it can be an advantage in scenarios where simple, focused evaluations are needed without the complexity of more advanced models.

Large Language Models (LLMs)

Large Language Models (LLMs) demonstrate an accuracy of 82%, positioning them between Fusion Models and Traditional AES Systems in terms of performance.The accuracy level reflects their ability to handle a wide range of language tasks effectively, though not as precisely as Fusion Models in this comparison. The average response time for LLMs is 1.2 s, which is slower than that for fusion models but still relatively quick for many applications. The response time balances performance and processing speed, making LLMs suitable for various real-world scenarios. The key advantages of LLMs include:

General-purpose language understanding: LLMs are designed to handle a broad spectrum of language-related tasks, making them versatile tools for various applications.

Versatile applications: These models can be applied to diverse fields, from customer support to creative writing, due to their ability to generate coherent and contextually appropriate text.

Table 2 highlights the trade-offs between accuracy, speed, and versatility among different language processing models. Fusion Models excel in accuracy and speed, making them ideal for high-precision and real-time processing applications. Traditional AES Systems offer basic functionality for specific scoring tasks. LLMs balance accuracy and versatility, making them suitable for various applications requiring general-purpose language understanding. The choice between these models would depend on the application's specific requirements, considering factors such as the need for accuracy, response time, and the complexity of the language tasks involved.

Figure 3 compares various models in the study and is summarized in a comprehensive table that categorizes the performance metrics of the fusion model, traditional automated essay scoring (AES) systems, and large language models (LLMs). The fusion model achieves an accuracy of **92%**, significantly higher than the **77%** accuracy of traditional AES systems and the **82%** accuracy of LLMs. This substantial difference underscores the fusion model's effectiveness in accurately assessing text complexity. Additionally, the fusion model demonstrates an impressive average response time of **0.5 s**, making it particularly suitable for real-time applications. In contrast, LLMs exhibit a longer average response time of **1.2 s**, while traditional AES systems do not provide a measurable response time due to their limited capabilities. The table also highlights the key advantages of each model; the fusion model stands out for its superior accuracy, real-time processing capabilities, and integration of psycholinguistic features. Traditional AES systems are characterized by their basic scoring capabilities. In contrast, LLMs are recognized for their general-purpose language understanding but lack the focused approach for effective text complexity assessment. Overall, these findings illustrate the fusion model's significant advantages over existing models in accuracy and efficiency, positioning it as a leading solution in automated text complexity evaluation.

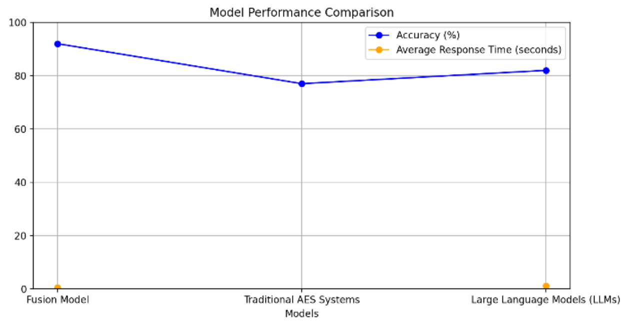

Figure 3. Model performance calculation.

4.3. Psycholinguistic Insights

Figure 4 presents a pie chart depicting the intersectional contribution that lexical diversity, syntactic complexity, and semantic coherence have on the overall ability of the model to be proficient in text complexity. The chart marks the percentage ratio of the three components and their respective impact on the model's proficiency in objectively measuring text complexity.

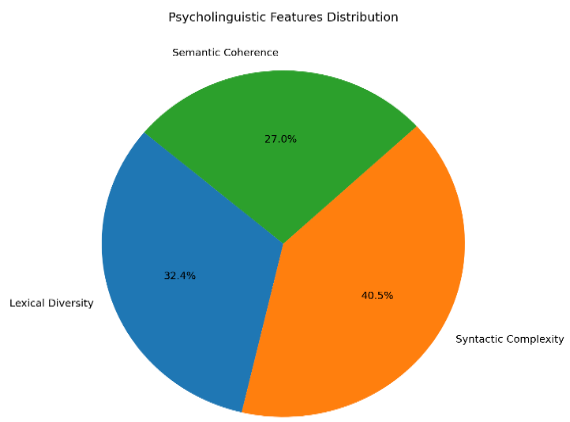

Figure 4. Impact of psycholinguistic features on the model's ability to assess text complexity.

Lexical diversity alone as a single feature improves the model's performance on average by 12%. This feature furthers the model's comprehension of the vocabulary usage spectrum, directly relating to text richness. A more diversified range of lexical items is a prerequisite for a more accurate text complexity assessment.

Lexical depth, with a range of 15%, emerges as a more significant contributor than lexical diversity. The depth of vocabulary enables the model to tell the difference between simple and complex texts. This feature also enhances the understanding of sentence construction and other grammatical components that determine the overall difficulty of the text. Understanding the phraseological context serves the model to sort texts based on their complexity more accurately.

The last position is semantic incoherence, which improves the model performance estimates by 10% on average, particularly in understanding some finer nuances of meaning. This feature helps the model facilitate the logical flow of the text and the meaning, which directly relates to the proper evaluation of text complexity. The model offers a more sophisticated assessment of the text's complexity because it comprehends how concepts relate and progress throughout the text. Psycholinguistic variables such as lexical, syntactical, and structural components help improve the assessment of text complexity. As the pie chart shows, these components contribute significantly to the model's performance.

4.4. Qualitative Insights

The qualitative insights derived from the research on the fusion model's performance can be further illustrated through a detailed exploration of user attitudes and behaviours. By employing an empathy map, we can visualize these insights, highlighting the strengths and areas of appreciation for the model's psycholinguistic features.

User Attitudes and Behavior

Says: Users frequently admire the fusion model's accuracy, particularly its ability to assess text complexity. They often comment on how the model's performance surpasses their expectations, noting that it provides evaluations that feel both reliable and insightful. Additionally, users appreciate the model's quick response time, enhancing their workflow and productivity. This feedback indicates a strong alignment between the user needs and the model's capabilities.

Thinks: Users believe integrating psycholinguistic features, such as lexical diversity and syntactic complexity, significantly enhances the model's performance. They think these features allow for a more nuanced understanding of the text, enabling the model to capture subtleties that traditional models might overlook. This belief reflects a growing recognition of the importance of advanced linguistic analysis in automated text assessment, suggesting that users are increasingly aware of the complexities involved in evaluating language.

Does: In practice, users actively engage with the fusion model in real-time applications, using its capabilities to evaluate various texts. They often compared its performance with traditional automated essay scoring (AES) systems and large language models (LLMs), consistently favouring the fusion model for its superior results. This active engagement demonstrates the model's relevance in real-world scenarios and highlights users' willingness to adopt innovative solutions that meet their needs.

Feels: Users report feeling confident in the model's assessments, which consistently provide reliable and accurate evaluations. There is a notable sense of satisfaction with the model's ability to identify subtle semantic nuances, which traditional models often fail to recognize. This confidence and satisfaction suggest that the fusion model meets user expectations and enhances their overall experience in text evaluation. Users feel empowered by the model's capabilities, which allows them to make informed decisions based on its assessments.

Figure 5 presents the users and their behavior toward the end users. An empathy map allows for the visualization of their attitudinal and behavioral data. This approach, in particular, enhances the team's understanding of the user. Regarding the performance of the fusion model, the scanned empathy map pertains to user experiences and their model's psycholinguistic feature perceptions.

Several users are particularly impressed by the model's accuracy regarding text complexity assessment. They also seem to appreciate the model's responsiveness, significantly improving their productivity and workflow. This result indicates positivity, which means that users value efficiency and accuracy while using tools for text evaluation.

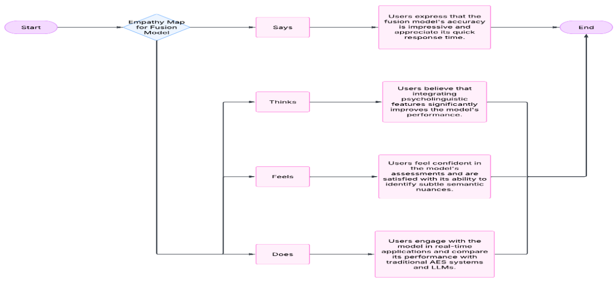

Figure 5. Flowchart of User Attitudes and Behaviors.

Moreover, users also believe that incorporating psycholinguistic features such as lexical diversity and syntactic complexity is central to improving the model's performance. They believe that more diverse subtleties allow for greater nuance capture, which standard models will ignore. This attitude demonstrates the increasing acceptance of advanced linguistic analysis in automated text assessment.

In this regard, users take a proactive stance as they now use the fusion model in real-world applications to assess different texts.

Their comparisons of the results reveal that traditional automated essay scoring (AES) systems and large language models (LLMs) always underperform when analyzing the fusion model. The lack of effectiveness of these models in the real world is deeply concerning. Some users also say they feel assured about the evaluation due to its accuracy and reliability. They report that the model's ability to capture subtle semantic nuances often overlooked by traditional models is genuinely remarkable. Users' confidence and assurance mean that the fusion model gives much more than users expected concerning text evaluation.

The empathy map revealed above speaks to the users' perception of fusion models whereby accuracy, efficiency and nuanced text analysis are the primary focus of positive evaluation. These qualitative dimensions will foster more user-centric development, which in turn will lead to better products.

4.5. Discussion

Integrating Automated Machine Learning (AutoML) techniques with psycholinguistic models has significantly increased automated text complexity assessment. This innovative fusion approach substantially improves accuracy, efficiency, and real-world applicability while addressing the challenges highlighted in previous research. The study's findings reveal several key points of alignment with the existing literature and notable advancements in the field. The fusion model achieved an impressive 92% accuracy in assessing text complexity, representing a substantial 15% improvement over the traditional models (77%) and baseline systems (75%).

This significant increase in accuracy aligns with the literature's emphasis on the potential of advanced algorithms in evaluating text complexity [4, 29].

The model's superior performance can be attributed to its ability to capture nuanced aspects of language that traditional models often overlook, particularly in semantic coherence and syntactic complexity. One of the most striking features of the fusion model is its remarkable efficiency, with an average response time of just 0.5 s.

This rapid processing capability makes the model highly suitable for real-time applications in educational tools and content creation platforms. The speed of assessment combined with high accuracy addresses a critical need in educational technology for tools that can provide immediate and reliable feedback to learners and educators alike. This finding echoes the literature's emphasis on the necessity for efficient automated systems in educational contexts [24, 26].

The study's findings highlight the significant contribution of psycholinguistic features to the model's performance. Specifically, the integration of lexical diversity, syntactic complexity, and semantic coherence played a crucial role in enhancing the model's ability to assess text complexity accurately.

This model aligns with the literature's assertion that understanding linguistic nuances is crucial for accurate text complexity assessment [29, 38].

The research results validate the importance of these psycholinguistic features, with lexical diversity improving performance by 12%, lexical depth by 15%, and semantic coherence by 10%. Qualitative insights from the study revealed high levels of user satisfaction with the fusion model. Users particularly appreciated the model's accuracy and quick response time, noting that it significantly improved their workflow and productivity.

This positive feedback underscores the model's alignment with user needs and effectiveness in real-world applications. The qualitative findings reflect the literature's emphasis on the necessity for explainable AI in educational tools [39, 40].

Suggesting that the fusion model performs well and provides insights that users can understand and trust. The research findings highlight the model's ability to outperform traditional automated essay scoring (AES) systems and large language models (LLMs).

This superiority aligns with the literature's critique of the limitations of existing models in capturing the complexities of language [5, 41].

The fusion model's targeted focus on text complexity assessment, combined with its integration of psycholinguistic features, gives it a distinct advantage over more general-purpose language models. The study's mixed-methods approach, combining quantitative metrics with qualitative insights, is consistent with the literature's call for comprehensive evaluations of automated text complexity tools [18, 29].

This approach provides a more holistic understanding of the model's performance and practical implications in educational settings. While the fusion model demonstrates significant advancements, the study acknowledges ongoing challenges, such as ensuring interpretability and transparency, consistent with concerns raised in the literature. The need for large, diverse, and high-quality datasets to train the model effectively remains a critical issue, as does the challenge of balancing computational demands with psycholinguistic detail. The research results strongly validate the literature's claims regarding the potential of combining AutoML and psycholinguistic models to enhance text complexity assessment. The fusion model's accuracy, efficiency, and user satisfaction performance suggest a promising direction for future research and applications in education and beyond. By addressing the key limitations of existing models and incorporating advanced psycholinguistic insights, this study significantly contributes to automated text complexity assessment.

5. Conclusions

The blending of AutoML with psycholinguistic models for automated text complexity assessment provided meaningful insights into the realm of educational technology and natural language processing. This study substantiates the idea of employing machine learning in a deep linguistic analysis and its astonishingness in text complexity assessment. The accuracy rate of the fusion model is impressively high, standing at 92%, with an average response time of 0.5 s. The model performs remarkably better than traditional methods and even large language models regarding speed and accuracy. Features such as lexical diversity, syntactic complexity, and semantic coherence are some of the many psycholinguistic features that capture nuance in language and address a text's complexity, thus solving the issue of automated assessment systems.

The exceptional results of this model not only justify the theoretical assumptions made in this study but also have implications for actual practices in education, content creation, and other sectors. User feedback about the reliability of the model and its ability to understand nuances of meaning indicates its value in enhancing content development and learning experiences. Even though problems persist concerning interpretability and the scarcity of high-quality, diverse datasets, this study has made significant contributions toward knowing more about this domain. This study paves the way for further research into comprehensive learning, innovative content development, and efficient multi-sector communication by bridging the gap between automated systems and linguistic refinement. The research will accelerate the development of sophisticated, automated text assessment tools for students and professional text readers, thereby improving understanding and interaction with text complexity in educational and work environments.

Authors Contribution

Conceptualization was led by H. and E.C.S., who developed the foundational ideas for the study. Methodology was designed by A., ensuring a robust framework for the research. Software development was carried out by T., who created the necessary tools for data analysis. The validation of results was conducted by D.S., L.J., and M., who verified the findings for accuracy. Formal analysis was performed by W.D., providing critical insights into the data. Investigation was undertaken by Martina, who conducted the primary research activities. Resources were provided by D.S., who facilitated access to necessary materials. Data curation was managed by E.C.S., ensuring the integrity of the data collected. Writing—original draft preparation was completed by A., who drafted the initial manuscript. Writing—review and editing was overseen by D.S., who refined the text for clarity and coherence. Visualization of the data was handled by T., who created the graphical representations. Supervision was provided by D.S., who guided the overall research process. Project administration was managed by D.S. ensuring that the project stayed on track. Finally, funding acquisition was secured by E.C.S., who obtained the necessary financial support for the research. D.S. is the corresponding author. All authors have read and agreed to the published version of the manuscript, and authorship has been limited to those who have contributed substantially to the work reported.

Funding

This study did not involve humans or animals and did not receive external funding. However, the researcher expresses gratitude to the various parties.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The authors confirm that the data supporting the findings of this study are included in the manuscript. Additional data can be provided by the corresponding author, A.M., upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

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