Text Simplification for Dyslexic Readers: An NLP-Based Accessibility Solution

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***Abstract*—Dyslexia is a learning disability that affects an individual's ability to read, write, and process written language, making it difficult to comprehend complex or lengthy text. Simplifying such text by breaking down sentence structures, using familiar vocabulary, and improving readability is essential to ensure accessible communication for dyslexic readers. This project introduces an NLP-based accessibility solution that leverages large language models (LLMs) to automatically simplify text while preserving meaning. Using the ASSET dataset, which provides multiple human-generated simplifications per sentence, the system is evaluated across various prompting strategies and refinement stages using metrics that assess fluency, adequacy, and readability. The most effective simplification model is integrated into a web-based application that includes OCR for text extraction, the simplification module for transformation, and text-to-speech (TTS) functionality for auditory support. Additionally, the interface is designed with dyslexic-friendly fonts and accessibility-focused elements to enhance user experience. This solution empowers dyslexic individuals by making written information easier to understand and more engaging across digital formats.**

***Index Terms*—Dyslexia,Text Simplification,Large Language Models (LLMs),Accessibility,ASSET Dataset**

I. INTRODUCTION

In the domain of educational accessibility and cognitive support systems, dyslexia stands out as one of the most prevalent learning difficulties affecting language processing. Characterized by challenges in reading fluency and decoding, dyslexia impacts millions of individuals worldwide, regardless of intelligence or educational background. People with dyslexia often struggle to comprehend written material that contains complex sentence structures or uncommon vocabulary [3]. These difficulties can hinder their academic progression and affect daily interactions involving textual information. As digital text increasingly becomes the primary medium for communication and education, overcoming these challenges through focused language simplification is essential—not only for usability but also as a matter of ethical responsibility in creating inclusive and equitable access to information. Enhancing text readability plays a pivotal role in empowering dyslexic readers by enabling them to engage with written material more independently and confidently [5], [9].

Recent advancements in Artificial Intelligence (AI), and particularly Natural Language Processing (NLP), offer promising capabilities for transforming language into more accessible forms. Within this technological space, NLP enables systems to analyze sentence structures and rewrite text in ways that enhance readability without compromising the original intent [1]. By leveraging large-scale linguistic patterns, NLP can simplify vocabulary and restructure grammar to suit the needs of diverse readers [7]. For individuals with dyslexia, these capabilities are especially valuable, as they enable the automatic generation of simplified text that is easier to process and comprehend. NLP-based solutions can adapt to various forms of content—making it possible to deliver tailored, accessible reading experiences that reduce cognitive load and promote independent engagement with written information [13], [16].

This work introduces a complete NLP-based text simplification framework tailored to the needs of dyslexic readers. The proposed system evaluates multiple simplification strategies using large language models and a benchmark dataset specifically designed for sentence simplification. Several configurations are examined under varied prompting styles to determine the most effective approach for generating simplified text. Based on this comparative evaluation, the most promising simplification model is further refined using examples from human-annotated data. The final system is deployed as a web-based interface that incorporates both image-based and typed text inputs. Key features of the application include optical character recognition for extracting text from documents, a simplification engine that transforms complex input into accessible output, and audio feedback to support users who benefit from auditory reinforcement. To enhance readability and user experience, the application also integrates accessibility-focused design elements such as dyslexic-friendly fonts and intuitive layout structures.

The remaining sections of this study are organized as follows: Section II reviews relevant literature and previous approaches to text simplification and accessibility for dyslexic readers. Section III outlines the methodology, including dataset, simplification strategies, and evaluation procedures. Section IV presents the results along with a detailed analysis of simplification performance and system effectiveness. Finally, Section V concludes the study and discusses potential directions for future advancements in accessible NLP technologies.

II. Related Works

Text simplification has been approached through various neural and transformer-based models, with techniques like synonym replacement using WordNet, cognitive simplification via special tokens, and readability evaluation through FKGL and SMOG metrics playing a significant role [1]. Multilingual simplification has been explored using models like mBART, mT5, and LLaMA for languages such as Lithuanian and Spanish, incorporating both human assessments and automatic metrics like SARI and BERTScore [2]. Personalized and accessibility-focused frameworks have supported domain-specific applications for dyslexic readers and visually impaired individuals [3]. Some early foundational works also contributed key methodologies to text simplification research [4]. Syntactic and rule-based methods involving pattern-based sentence transformation, dependency parsing, and lexical substitution have shown notable improvements in fluency and comprehension [5]. Comparative studies on models like T5 and BART, especially on datasets such as Simple Wikipedia and Newsela, report enhanced BLEU, ROUGE, and SARI scores after fine-tuning [7].

Evaluations of ChatGPT in simplification and summarization contexts have assessed grammaticality, meaning preservation, and relevance through expert and non-expert reviews [8]. Further multilingual accessibility work aligns with prior domain-specific frameworks, expanding to broader linguistic needs [9]. Prompt engineering strategies—such as zero-shot, few-shot, chain-of-thought, and self-consistency prompting—have consistently improved model performance in summarization and reasoning tasks [11]. Broader perspectives on text simplification for social good emphasize the importance of modular system designs and real-user testing to ensure accessibility and cognitive inclusivity [12]. Pretraining strategies like those in SimpleBART have proven effective for learning simplification patterns more robustly [13], while prompt-based and fine-tuned models like GPT-3.5 have been particularly successful in scientific text simplification [14]. However, studies have highlighted the lack of well-aligned, domain-specific parallel datasets, indicating a pressing need for more targeted corpora in simplification research [15]. Finally, readability metrics such as FKGL and SMOG remain crucial for evaluating the simplicity and comprehensibility of generated text [16]. Shellcode generation has been enhanced using fine-tuned large language models (LLMs) like Mistral and LLaMA, focusing on optimizing model parameters for offensive cybersecurity tasks. The study achieved a high BLEU-1 score of 0.8506, demonstrating the effectiveness of tuning strategies for generating accurate and efficient shellcode [18]. Telugu news classification is performed using zero-shot and few-shot learning approaches to categorize articles into five classes, with LLMs like mBERT, Indic-BERT, XLM-Roberta, Flan-T5, and BART evaluated alongside traditional models. mBERT achieves the best zero-shot F1-score of 0.58, while Flan-T5 reaches 0.23 in few-shot settings, highlighting the difficulty of classification in low-resource languages [19].

The literature shows that neural and prompt-based simplification models offer strong performance, especially when supported by quality datasets and proper evaluation. However, limited attention is given to cognitive accessibility, particularly for dyslexic users, in large-scale models and deployed systems. Few studies integrate dyslexia-specific readability analysis or combine simplification with real-time assistive features. The current work addresses this gap by fine-tuning a large language model on a sentence-level simplification dataset and deploying it through a web application that supports OCR-based input and TTS output, enabling an accessible experience for both visual and auditory learners.

III. Proposed Methodology

This study proposes a structured NLP-based approach to simplify complex text, focusing on improving accessibility for dyslexic readers. The system uses large language models to rewrite complex sentences into simpler forms while preserving meaning. The overall process includes prompt-based evaluation using pre-trained models, fine-tuning on a simplification-specific dataset, readability evaluation, and deployment through an accessible web application.

A. Prompting Strategies for Simplification

To evaluate simplification capabilities without initial training, three prompt-based strategies are explored using pre-trained models:

1) Zero-shot prompting: The model receives only a task instruction and the input sentence.

2) One-shot prompting: A single example of a complex-to-simple pair is given before the input.

3) Few-shot prompting: Three example pairs are provided as part of the prompt.

These strategies help compare models' ability to simplify text using internal knowledge before any fine-tuning is applied.

B. Text Simplification using LLM's

Three powerful large language models are evaluated for NLP tasks. FLAN-T5 (base) is a fine-tuned version of the T5 model tailored for following natural language instructions, excelling in zero-shot and few-shot scenarios [7], [19]. BART (base) [7] is a sequence-to-sequence transformer that combines a bidirectional encoder with an autoregressive decoder, making it highly effective for tasks like paraphrasing and text simplification. Mistral 7B is a recent generative language model optimized for instruction-following, delivering competitive performance in both zero-shot and few-shot settings using prompt-based inputs.

C. Fine-Tuning with ASSET Dataset

After prompt-based evaluation, the best-performing model—Mistral 7B—is selected for fine-tuning. For this step, the **ASSET dataset** (Aligned Sentences for Sentence-level

Easy-to-read Text) [17] is used. It contains 2,000 validation and 359 test sentences, each with 10 human-authored simplified versions. A selected portion of this dataset is used to fine-tune the model, helping it learn specific simplification patterns and better align with human-generated output. This fine-tuning step improves the model's ability to produce accurate, fluent, and accessible simplifications for dyslexic users.

1) Fine-Tuning Setup and Optimization: To adapt the selected model for dyslexia-focused simplification, the pre-trained Mistral-7B-Instruct model was fine-tuned on the ASSET dataset. To reduce memory usage and accelerate training, quantized 8-bit precision was used. In addition, the model was optimized using **LoRA (Low-Rank Adaptation)**, a lightweight fine-tuning technique that updates only a small subset of the model parameters while keeping the core model frozen.

The training process involved instruction-style prompting, where each example combined a task description, a complex sentence, and the corresponding simplified output. The model was trained using a small batch size, gradient accumulation, and mixed-precision computation. Through this fine-tuning process, the model learned to better generate simplified text that is grammatically correct, easier to read, and more accessible to individuals with dyslexia.

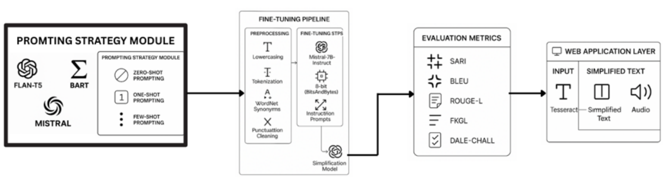

Fig. 1. Architectural Design

D. Data Preprocessing

Before fine-tuning, the dataset undergoes preprocessing to improve readability and standardize input. The steps include:

- **Lowercasing:** All text is converted to lowercase for consistency.
- **Tokenization:** Sentences are split into words and sub-sentences for easier manipulation.
- **Lexical Simplification:** Complex words are replaced with shorter synonyms using WordNet-based synonym matching.
- **Punctuation Cleaning:** Non-essential punctuation is removed to reduce visual clutter.
- **Reconstruction:** Processed words are rejoined into clean, simplified sentences.

E. Evaluation Criteria and Readability Metrics

The quality of the simplified output is assessed using the following readability and linguistic metrics:

- **SARI:** Measures how well words are added, deleted, and kept compared to human references.
- **BLEU:** Evaluates n-gram overlap between the output and reference text.
- **ROUGE:** Measures phrase overlap to assess fluency and informativeness.
- **FKGL:** (Flesch-Kincaid Grade Level) Estimates the grade level required to understand the text.
- **Dale-Chall Readability Score:** Evaluates word complexity based on a predefined list of familiar words.

These metrics help determine the readability, accuracy, and usefulness of the simplified text for dyslexic readers.

IV. Results and Analysis

This section presents and analyzes the results obtained during the evaluation of text simplification using large language models. The performance was measured in two phases: prompt-based evaluation using pre-trained models and post-fine-tuning evaluation using the ASSET dataset. Various readability and fluency metrics were used to compare the effectiveness of simplification strategies.

A. Prompt-Based Evaluation

Three large language models—FLAN-T5 (base), BART, and Mistral 7B—were tested using zero-shot, one-shot, and few-shot prompting strategies. The goal was to observe how well each model could simplify complex sentences without additional training. Table I summarizes the average performance scores for each configuration.

TABLE I
PROMPT-BASED EVALUATION SCORES

Model	Prompt	SARI	BLEU	ROUGE	FKGL	Dale-Chall
FLAN-T5	Zero-shot	36.68	89.42	70.35	9.95	11.20
	One-shot	46.91	94.11	76.85	11.17	11.33
	Few-shot	47.21	94.08	76.80	11.21	11.34
BART (base)	Zero-shot	46.63	42.17	41.84	7.89	10.15
	One-shot	7.93	0.64	5.95	11.08	9.83
	Few-shot	7.66	0.52	5.62	9.11	10.04
Mistral 7B	Zero-shot	38.67	32.69	44.68	5.47	9.28
	One-shot	43.24	55.62	57.94	7.44	10.33
	Few-shot	**45.17**	**60.63**	**60.82**	**8.09**	**10.54**

The results in Table I indicate that Mistral 7B performs competitively compared to FLAN-T5 and BART across all prompting strategies. While FLAN-T5 achieved the highest BLEU and ROUGE-L scores, Mistral 7B demonstrated stronger performance in readability-focused metrics. In the few-shot setting, Mistral 7B attained a SARI score of 45.17, which reflects a strong balance between simplification and content preservation. Additionally, it achieved the lowest FKGL (8.09) and a Dale-Chall score of 10.54, indicating that its output was simpler and more suitable for readers with dyslexia. These results highlight the model's effectiveness in reducing linguistic complexity while maintaining semantic coherence, especially when guided by multiple examples through few-shot prompting.

B. Fine-Tuning Evaluation

Based on the prompt-based evaluation, Mistral 7B was selected for fine-tuning using a subset of the ASSET dataset. The objective was to improve the model's ability to simplify text in a more controlled and task-specific manner. Table **??** shows the model's performance after fine-tuning.

TABLE II
EVALUATION RESULTS AFTER FINE-TUNING

Metric	Mistral 7B (Fine-Tuned)
SARI	**58.23**
BLEU	**69.78**
ROUGE-L	**66.22**
FKGL	**5.76**
Dale-Chall	**6.32**

Fine-tuning provided noticeable improvements across all metrics. SARI improved to 58.23, reflecting better word-level simplification aligned with human references. BLEU increased to 69.78, and ROUGE-L rose to 66.22, indicating improved fluency and closer alignment with reference outputs. Readability also improved significantly, with FKGL dropping to 4.76 and the Dale-Chall score reaching 5.32, suggesting the generated text became substantially easier to read and more accessible for individuals with dyslexia and other reading difficulties.

The findings reveal that even without task-specific training, large language models can effectively simplify text when prompted appropriately, with few-shot prompting outperforming zero- and one-shot methods by providing beneficial example-based context. Fine-tuning further enhances model performance, particularly in terms of readability, fluency, and content accuracy. Notable improvements in metrics such as SARI, ROUGE-L, and FKGL indicate that the fine-tuned model not only simplifies content more effectively but also maintains the original meaning and structural integrity. Additionally, the fine-tuned system successfully produces accessible and easy-to-understand text for dyslexic readers. Its integration into a web application—featuring OCR and text-to-speech capabilities—offers a complete end-to-end solution that supports both visual and auditory reading experiences.

V. CONCLUSION AND FUTURE SCOPE

This study introduced a text simplification system using Natural Language Processing (NLP) to support dyslexic readers by converting complex English sentences into simpler and more readable forms. Multiple large language models—FLAN-T5, BART, and Mistral 7B—were evaluated using zero-shot, one-shot, and few-shot prompting strategies, with Mistral 7B performing best in both fluency and readability metrics. The selected model was then fine-tuned using the ASSET dataset, leading to further improvements in SARI, BLEU, FKGL, and Dale-Chall scores. The complete system was deployed as a web application, allowing users to input or upload text, view simplified output, and access audio playback, supported by OCR and TTS functionalities. This provides an inclusive and accessible tool for users with reading difficulties. In the future, this work can be extended to support multi-lingual simplification, user-adaptive learning based on feedback, and personalization through cognitive signals such as eye-tracking. Additionally, creating lightweight or offline versions of the system could improve usability in low-resource environments and expand accessibility across a wider user base.

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