An Interpretable Dual-Level Feedback Approach for Improving Graded Language Simplification and Readability

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***Abstract*—Text simplification plays a vital role in adaptive language learning, especially when aligned with the Common European Framework of Reference (CEFR) proficiency levels. The purpose of this study is to develop an interpretable and CEFR-aligned text simplification framework that produces pedagogically appropriate simplified texts for learners at different proficiency levels. Existing neural simplification approaches, such as ACCESS, MUSS, and EditNTS, primarily rely on single-level feedback or surface-level readability measures, limiting their ability to ensure both sentence-level linguistic simplicity and document-level coherence. To address these gaps, this study proposes CEFR-RefineNet, a hybrid framework integrating T5 for generative simplification and BERT for contextual CEFR-level classification, enhanced through a novel Dual-Level Explainable Feedback Loop (DL-EFL). The DL-EFL simultaneously evaluates sentence-level linguistic difficulty and document-level readability while providing token-level error attribution for interpretability. The model was implemented using Python and the Hugging Face Transformers library, trained and tested on the CEFR Levelled English Texts corpus comprising 1,500 texts spanning levels A1 to C2. Experimental results show that CEFR-RefineNet achieved a SARI score of 0.78, accuracy of 91%, and F1-score of 0.85, outperforming the strongest baseline (MUSS, 81% accuracy) by approximately 12%. The adaptive feedback mechanism accelerated reward convergence and improved CEFR compliance, ensuring more pedagogically suitable simplifications. In summary, the proposed CEFR-RefineNet establishes a transparent, interpretable, and performance-driven text simplification model capable of generating fluent, meaning-preserving, and CEFR-aligned texts, paving the way for intelligent and adaptive language-learning systems.**

Keywords*—Text simplification; CEFR-level alignment; reinforcement learning; adaptive feedback loop; T5 transformer

I. Introduction

Text simplification has become an important activity in NLP, especially in order to increase accessibility, learn a language, and support teaching [1]. CEFR offers a highly popular criterion used to assess the text complexity of proficiency levels A1 (beginner) to C2 (advanced) [2]. The simplification based on the CEFR levels allows learners to work with the material of an adequate measure to their language skills and provides gradual learning without losing the semantic integrity [3]. Conventional methods of text simplification have been based on rule-based systems and lexical text replacement methods that tend to simplify sentences to the extent of losing their meaning and pedagogical inconsistency [6], [7]. With the introduction of deep learning (DL), this field has developed with the ability to learn contextual linguistic complexity and to simplify controlled. Sequence-to-sequence models, transformers like T5, and contextual encoder models like BERT have performed well in generative and classification tasks, respectively [10]. But the gap still exists in incorporating generation and classification for simplification that not only lowers complexity but also maximizes CEFR-level alignment [8], [9]. Some of the latest research has put forward several neural models, such as EditNTS, ACCESS, MUSS, and hybrid pointer-generator systems that show enhanced fluency and readability [12]. However, a majority of these methods value readability improvements without ensuring proficiency-level alignment, thus constraining pedagogical usability in language teaching [11].

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In addition, current systems often rely on shallow metrics like BLEU, which don't capture simplification quality well compared to measures like SARI that evaluate retention, deletion, and addition of content [4]. Another important shortcoming is the absence of iterative validation: state-of-the-art models usually produce one-pass output, which is often different from the desired CEFR level, and thus needs human effort to align [5]. It will prevent the implementation of the text simplification system on adaptive learning environment where the level-specific simplifications are critical and must be automatic. Simplification of texts is critical towards improving the readability of different populations like language learners, children, and cognitive or reading-challenged people [20]. Although there has been significant advancement in NLP, the current mechanisms are, in most cases, unable to reconcile grammatical correctness, semantic fidelity and less linguistic complexity. Though helpful, traditional rule-based and statistical methods are less adaptable and do not understand the context of the situation thus limiting their practical usefulness [21]. Transformer based generative models, including T5, have shown good results in simplification tasks but syntactic accuracy or meaning preservation is often poor. On the contrary, contextual encoders, such as BERT, are good at capturing the semantic complexity but are, by definition, non-generative which limits their capacity to simply generate simplified outputs. This disconnect between realistic contextual representation and text generation under control still impedes the establishment of effective simplification systems that can be used in pedagogy.

Conventional simplification systems tend to be based on single-level processing without watching text complexity at a surface level and do not guarantee that the text is read in a context with understanding of what linguistic items contribute to the difficulty. Due to this fact, these models might generate grammatically simplified, but semantically incoherent results. To deal with these limitations, a mechanism that will evaluate simplification on multiple granularities is needed. In this respect, the current work presents a CEFR-conscious framework of text simplification with a DL-EFL to optimize sentence-level linguistic simplification and document-level coherence and rank token-level sources of over-complexity to refine its intonation. This two-fold assessment balances a vital gap that exists between the automatic simplification accuracy and pedagogical interpretability through the guarantees of the grammatical accuracy, semantic accuracy, and universal legibility. The attributable error explainability also promotes the educator credibility and the usability of the students, as the simplifications, which are inherently transparent and CEFR-compliant, can be used to adapt to the adaptive language-learning setting. In contrast, for ACCESS, MUSS, EditNTS, and pointer-generator models, which are based on single-level readability approaches or opaque edit-based operations, the suggested design presents a radically different design. The hybrid T5BERT encoder offers semantic encoding and CEFR-level validation in the same architecture as the Dual-Level Explainable Feedback Loop (DL-EFL) offers sentence-level, document-level and token-level refinement cues. Multi-granular feedback, refinement through the use of iterative reinforcement, and explainable token-level attribution have not been presented in any previous simplification framework based on CEFR alignment. It makes CEFR-RefineNet a conceptually and methodologically different contribution. The researchers address the study contributions by focusing on the key gaps that have been noticed in current simplification models such as the lack of CEFR level of control, the absence of multi-granular feedback mechanism and the limited interpretability of neural outputs. All the contributions reinforce one of these gaps and create a unified solution to the issues raised in earlier research.

A. Recent Innovation and Challenges

The developments in the neural text simplification have presented controlled generation models, a multilingual simplifier and RL systems that modify their output based on their readability and semantic fidelity. There is also the possibility of more contextualized information and being good at simplifying tasks with a set of pretrained transformers, including the T5 and the BERT. However, critical problems exist, such as lack of correspondence to proficiency frameworks, such as CEFR and semantic specificity in simplification and inconsistency in processing structurally complex sentences. In addition, the current models do not have the iterative refinement process, and therefore, the results are not always accurate and pedagogically appropriate, which constrains their implementation into education-driven NLP applications.

B. Key Contribution

- Introduces CEFR-RefineNet, a hybrid T5–BERT framework that directly addresses the absence of CEFR-controlled simplification in prior models such as ACCESS, MUSS, and EditNTS by enabling proficiency-aware text generation across A1–C2 levels.
- Proposes DL-EFL, a multi-granular feedback mechanism that evaluates sentence-level CEFR difficulty and document-level readability, overcoming the limitation of single-level or surface readability signals in existing simplifiers.
- A multi-granular feedback mechanism is proposed that simultaneously evaluates sentence-level CEFR correctness and document-level readability—capabilities not present in ACCESS, MUSS, EditNTS, or other transformer-based simplifiers.
- Integrates an explainable token-level attribution scheme to identify sources of linguistic complexity, addressing the lack of interpretability in current transformer-based simplification systems and improving pedagogical transparency.
- Provides a reusable CEFR-aligned refinement pipeline, feedback protocol, and token-level explainability mechanism that support future research in educational NLP, adaptive learning systems, and CEFR-based content generation.

C. Rest of the Study

The rest of the study is structured as follows: Section II gives an overview of literature review, Section III illustrates the designed hybrid model and feedback process, Section IV gives some experimental results and discussion. Finally, Section VI concludes and points out future directions.

II. Literature Review

Transformer-based architectures have been integrated in more and more studies in NLP as part of improving semantic understanding and educational text processing. Abarna et al. [13] presented an enhanced knowledge-enabled BERT with extraneous knowledge graphs to differentiate between idiomatic and literal expressions and showed better semantic sensitivity but structural complexity. Other transformer-based achievements can be seen in education, where Ludwig et al. [17] used German BERT models to perform automated essay marking and politeness detection, which they found to be more accurate than classical logistic regression methods. Despite the fact that both streams of work enhance the contextual interpretation, both have problems, including computational overhead and reliance on external knowledge structures.

In addition to classification, deep learning has been applied in order to augment adaptive learning and text processing based on readability. According to Sokač et al. [14], a contrastive learning and explainable AI method of grading student code submissions would allow providing interpretable feedback, but with performance differences across programming languages. Likewise, Jayakumar et al. [16] created a hybrid system based on a BERT-GRU model to generate adaptive learning materials in English, and the system enhanced engagement among learners, but it raised the issue of scalability because of the complexity of the model. Parallel studies with text generation conducted by Rodriguez et al. [18] were built on the pipeline detached on a T5, which could produce multiple-choice questions, but the distractors were of high quality, and the evaluation was not standardized. The overall direction of these studies is that transformers have potential in the educational NLP, but are constrained by the lack of consistent readability control and lack of graded linguistic complexity.

Several researchers have studied text simplification itself, either through reinforcement learning or metrics of readability or through transformer-based encoders. Alkaldi et al. [15] proposed a simplification system of reinforcement-learning with the aid of readability classifiers, yielding level-sensitive outputs, but based on annotated datasets like Newsela. In simplification by language, Hossain et al. [19] showed that a BERT-based model is better than LSTM architecture-based simplification of Bangla, where the model simplifies the text, but does not change the semantic meaning of the text. Nevertheless, they are majorly based on the single-level readability requirements and without the enhanced interpretability or proficiency-based grading models like CEFR.

In the above studies, one can identify a similar trend: current DL- or transformer-based methods are either based on semantic classification, automated evaluation, or simplification on the surface without multi-level readability, CEFR compatibility, or interpretable refinement. Majority relies on a single reward signal, fixed readability models, or post-hoc classifies which reduces the reliability of the pedagogical aspect. An analysis of the existing literature indicates that the available systems fail to combine the CEFR-level of classification with the document-level of readability or the token-level of the interpretability. None of the models analyzed carries out iterative refinement with the guidance of multi-granular feedback. As a result, the mechanisms that were proposed in CEFR-RefineNet, namely dual-level evaluation, explainable attribution, and hybrid semantic generation, do not occur in previous simplification studies. These constraints demonstrate obvious loopholes in the alignment of the CEFR, its interpretability, and multi-level refinement, which the input of the proposed framework is specifically intended to fix. To fill the above-mentioned gaps, the proposed research proposes a DL-EFL that concurrently assesses both sentence-level linguistic complexity and document-level readability and attributes token-level difficulty. This interpretable multi-granular framework is able to overcome the constraints found in earlier research and enable adaptive, transparent CEFR-based simplification to be used in education.

III. Proposed Automatic Graded Reading Framework

The proposed study incorporates a hybrid T5-BERT architecture and a new DL-EFL to simplify texts to the CEFR level. The system starts by preprocessing and coding texts using BERT to store context of semantics and syntax. These encodings are combined with T5 encoder encodings to generate semantically accurate simplified sentences. A CEFR classifier (post-generation) and the suggest feedback loop (validates the sentence-level accuracy) and a readability estimator (validates the document-level accuracy) extend the evaluation limits to the document and sentence level, respectively. Notably, the attention gradients of BERT can find out token-level contributions to linguistic complexity, and with this, token-level contributions can be selectively fixed rather than blindly regenerated. The multi-granular feedback result is incorporated in the adaptive reinforcement signal which balances the compliance to CEFR, semantic preservation, and readability. This pipeline has the advantage of being context-sensitive, pedagogically suitable and explainable, overcoming major issues of opacity and inconsistency in previous methods. The methodological basis of the study is the synergy of the hybrid encoding system, graded feedback, and reinforcement learning. The proposed framework is given in Fig. 1.

A. Data Collection

The study uses the CEFR Levelled English Texts (CLET) corpus [22], which contains 1,500 texts distributed across CEFR levels A1–C2. Each document includes aligned linguistic features, graded proficiency labels, and human-verified readability annotations. This dataset was used for both training and evaluation of CEFR-RefineNet. The corpus covers a wide range of different genres such as short conversations, children's narratives, news summaries, magazine articles, scholarly texts and editorials and is well-rounded in its focus of linguistic complexity and style. Its balanced six levels of CEFR profile ensures that the model possesses the capability of examining graded patterns of language, which will enhance proper simplification of text and production of texts at level. Particularly, due to the fact that the dataset can be employed to quantify the CEFR-driven simplification systems, one is in a position to quantify the readability, semantic preservation, and pedagogical relevance, which form the fundamental aspect of adaptive language learning applications.

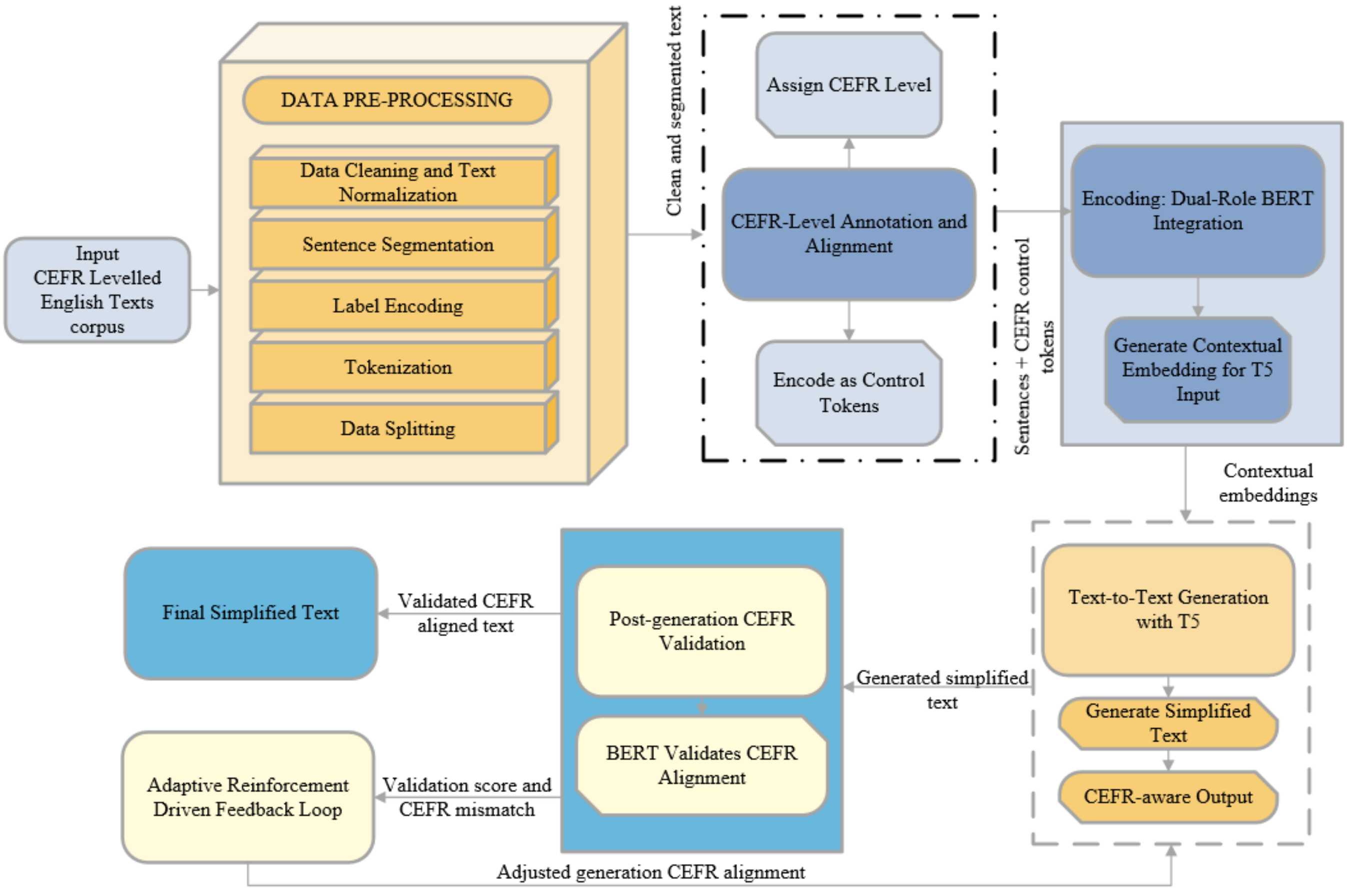

Fig. 1. Workflow of the proposed automatic graded reading material for English learners.

TABLE I. CEFR DATASET STATISTICS

CEFR Level	Sentences	Example Genre
A1	210	Short dialogues
A2	245	Children's stories
B1	280	News excerpts
B2	310	Magazine articles
C1	245	Academic texts
C2	210	Editorials
Total	1,500	—

Table I additionally categorizes the sentences based on the levels of CEFR, specifically highlighting the choice of genres and linguistic complexity. Such an organized distribution will allow effective training, validation and testing of the T5-BERT hybrid simplification system, so that the model will be able to learn the syntactic and semantic distinctions while maintaining CEFR-compliant outputs.

B. Data Pre-Processing

Pre-processing will involve text cleaning, normalization, and sentence segmentation, of a dataset. CEFR levels are coded as numerical tags and sent as a control token. Unified input length is performed by tokenization, after which stratified train-validation-test separations are used. The hybrid framework will train the T5 generation and BERT classification by preparing the labeled single-modality inputs of (usually) constant size.

1) Data cleaning and text normalization: The raw data text usually has non-standard characters, formatting discrepancies, or typographical mistakes. Special characters, HTML tags, and useless punctuation are not a part of the semantic content. Texts are also normalized by making all characters lowercase to maintain consistency. Contractions can also be expanded (e.g., "don't" → "do not") for clarity, particularly for lower CEFR levels where learners are establishing their vocabulary [see Eq. (1)]:

$$T_{clean} = Normalize(Remove(T_{raw})) \tag{1}$$

Where, T_{raw} is the original raw text input, *Remove*() function eliminates unnecessary formatting artifacts, while *Normalize* convert text to lowercase and expands contractions.

2) Sentence segmentation: Transformer models, such as T5 and BERT, typically operate at the sentence level on the input; the text data is broken into individual sentences through NLP libraries such as NLTK or SpaCy. This keeps both the complexity classifier and the simplification model operating on useful linguistic units, enhancing both accuracy and coherence when training and making predictions.

$$S = Segment(T_{clean}) = \{s_1, s_2, \ldots\ldots, s_n\} \quad (2)$$

In Eq. (2), S is the list of sentences $s_1, s_2, \ldots\ldots, s_n$ and Segment() splits cleaned text into individual sentences.

3) Label encoding: Every text in the dataset is annotated with a CEFR proficiency level (e.g., A1, A2, B1, B2, C1, C2). These labels are converted to categorical or numerical form based on the task. For T5, the labels are represented as control tokens (e.g., <level=A2>) at the start of the input sequence. For BERT classification, these labels are used as ground-truth categories for training supervised learning [see Eq. (3)].

$$\mathrm{y} = \mathrm{Encode_{num}}(\ell) \quad (3)$$

where, ℓ is the CEFR level label and y is the numerical label used for classification.

4) Tokenization: Both BERT and T5 need input to be tokenized through their allocated tokenizers. The T5 tokenizer is employed to tokenize text into subword units to output and input during the simplification task. The BERT tokenizer is employed to transform text into word pieces to classify. Padding and truncation are employed to ensure consistent lengths of input across batches, commonly capped at 128 or 256 tokens.

$$T = Pad(Truncate(Tokenizer(X))) \quad (4)$$

In Eq. (4), $Tokenizer()$ converts sentence into tokens, $Truncate()$ cuts long token sequences to max length and Pad adds padding to match input length requirement.

5) Data splitting: The data is divided into training, validation, and test sets with stratified sampling to maintain the distribution of the CEFR levels in all sets. It is necessary to guarantee the generalization ability of the models and to ensure unbiased evaluation. A standard split is 70% training, 15% test, and 15% validation.

$$D_{trian}, D_v, D_{test} = StratifiedSplit(d, \{0.7, 0.15, 0.15\}) \quad (5)$$

In Eq. (5), D is the full dataset split into $\mathrm{D_{trian}}, \mathrm{D_v}, \mathrm{D_{test}}$. StratifiedSplit ensure that each CEFR level is proportionally represented in all splits. This preprocessed dataset forms the foundation for both generation and multi-level feedback evaluation.

C. Encoding: Dual-Role BERT Integration

In standard text simplification pipelines, BERT is ordinarily employed as a downstream classifier only for determining text complexity. In this study, BERT is creatively repurposed as a contextual encoder, feeding semantic priors straight into the T5 model. Such hybrid encoding is a new contribution in that it allows CEFR-aware text generation right from the beginning and not post-hoc adjustment. Taking a sentence input $X = \{x_1, x_2, \ldots, x_n\}$, the pre-trained BERT model produces contextual embeddings E_{BERT}, as given in Eq. (6):

$$E_{BERT} = BERT(X) = \{e_1, e_2, \ldots, e_n\},\ e_I \in \mathbb{R}^d \quad (6)$$

where, d denotes the embedding dimension. They encode fine-grained semantic, lexical, and syntactic knowledge, which is essential in the generation of simplified sentences that are semantically meaningful and comply with target CEFR levels. To embed BERT's contextual information within the T5 generation process, the embeddings E_{BERT} are combined with the input to the T5 encoder E_{T5} through a learnable linear transformation or attention-based gating mechanism:

$$E_{Hybrid} = W_1 E_{T5} + W_2 E_{BERT} \quad (7)$$

In Eq. (7), $W_1, W_2 \in \mathbb{R}^{d \times d}$ are trainable weight matrices, facilitating a balance between original input features and BERT's semantic embeddings, which have been altered in a manner that will be considered when re-simplifying sentences into text that is contextually and level-appropriate.

By incorporating the contextual information delivered by BERT prior to generation, the system achieves two objectives, namely, it preserves the semantic contents of the input text and does not lose information during simplification, and it renders the generative model predictable and reliable, which may generate more controlled output. The choice to use BERT as a semantic enhancer in the pre-generation phase of the process renders the suggested methodology distinct to the conventional pipelines according to which classification and generation are independent of each other. It does the initial encoding of the hybrid framework, allowing later stages of T5 decoding and feedback refinement to be applied on semantically-enriched, CEFR-aligned embeddings, making the most of the quality, fluency, and pedagogical suitability of the simplified text. This dual-role integration allows subsequent feedback mechanisms to trace CEFR complexity directly to token embeddings, enabling token-level explainability in later refinement stages.

D. Text-to-Text Generation with T5

After incorporating CEFR-sensitive contextual embeddings of BERT, the T5 model serves as the generative part of the hybrid model. The decoder of T5 takes the merged embeddings E_{Hybrid} from the encoder and generates an abridged sentence $Y = \{y_1, y_2, \ldots, y_m\}$ corresponding to the target CEFR level:

$$Y = T5\_Decoder(E_{Hybrid}) \quad (8)$$

In Eq. (8), m represents the length of the shortened sequence, and it is not necessary to be equal to the original sentence length or token number n. The T5 decoder utilizes a sequence-to-sequence attention, wherein each token in the output token is produced from the input embeddings that had been augmented, in that overall output token length. The attention can be expressed as Eq. (9):

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (9)$$

where, Q, K, V are query, key, and value matrices, respectively, based on E_{Hybrid}, and d_k is the dimensionality of the key vectors. It is this mechanism which enables the decoder to attentionally selectively attend to relevant aspects of the input to maintain the semantic fidelity and thus produce simpler lexical and syntactic constructions. CEFR control tokens attached to the input sequence (e.g. <level=B1>), also inform the model of the desired level of proficiency, which the T5 decoder is also explicit about. This conditioned basis generation ensures that it is not only simplified but also designed to satisfy the needs of pedagogic and proficiency boundaries so that the outcome of the simplification is sufficient to be applied in the educational setting. The T5 decoder outputs are not only judged by CEFR correctness but also by hierarchical readability assessment introduced in the Dual-Level Feedback Loop.

The T5 decoder achieves the compromise between fluency and readability and content preservation with the assistance of the CEFR-enhanced embeddings in BERT. There are lexical simplifications, syntactic restructuring and compression of the sentence in a manner that is context sensitive and coherent. In this way simplified text does not lose the initial sense and the discourse arrangement and does not become a victim of the common pitfalls of omitting the necessary information or awkward wording. Simply, T5 decoder converts the semantically enhanced input into proficiency-matched simplified text, which is the main generative part of the hybrid model. Its communication with the pre-trained BERT embeddings is the basis of the further CEFR-level validation and feedback loop which further optimizes the output to become more accurate and educationally relevant.

E. Post-Generation CEFR Validation

Once the T5 decoder produces a simplified sentence $Y = \{y_1, y_2, .., y_m\}$, the output is subjected to a post-generation validation phase by BERT to check consistency with the target CEFR level. This is done as a quality-control measure to check that the simplification is linguistically appropriate and complies with the desired complexity requirements. Formally, the produced sentence Y is passed through a BERT-based classifier C_{BERT}, which predicts a CEFR level $\hat{l}$, given in Eq. (10):

$$\hat{l} = C_{BERT}(Y) \tag{10}$$

The estimated level $\hat{l}$ is then matched against the target CEFR level l_{target}. When $\hat{l} \neq l_{target}$, a feedback loop is activated, which causes T5 to re-generate the text with varying attention weights or changed control tokens, given in Eq. (11):

$$Y^{new} = T5\_Decoder(E_{Hybrid}, l_{target}) \tag{11}$$

This cycle of iterative steps is continued until the proficiency level desired has been attained or the number of retries desired is reached (typically 3 iterations). Such feedback validated assessment will ensure CEFR compliance, and reduce occurrences of lexical over-simplification, under-simplification, or syntactic restructuring mismatches. The validation employs the contextual and semantic understanding of BERT, which is able to recognize subtle anomalies in complexity that cannot be identified through generative measurements alone. It considers the lexical richness, the sentence length, the syntactic embedding, and the semantic coherence in such a way that the system is robust against the mistakes which can happen in complex sentences, in passive structures, or in domain-specific vocabularies.

The reliability in the pedagogical factor is achieved through the inclusion of the post-generation CEFR validation, where the simplification of the text is presented to the learner on the suitable level of difficulty. This is in contrast to the traditional simplification pipelines which in most instances produce a fluent text, but does not require strict adherence to a graded checking language criterion. And ultimately, this process completes the never-ending cycle of creation and testing, producing CEFR-conformable, fluent, and meaning-preserving simplified texts which can be prepared to be consumed as the contents of learning instruments and with adaptive language learning software. While this stage provides sentence-level validation, it does not account for document-wide readability or identify which segments contribute to complexity. To address these gaps, a DL-EFL is integrated, as described next.

F. Dual-Level Explainable Feedback Loop

In order to increase the reliability and interpretability of the CEFR-Aware Text Simplification process, this study proposes a DL-EFL in combination with the Hybrid T5BERT framework. The proposed loop operates on two complementary levels, sentence-level linguistic feedback and document-level readability feedback, as well as provides the interpretability of token-level error attribution. The BERT-based CEFR classifier assesses every generated sentence to determine the level of its proficiency at the sentence level. This is matched against the target level through a level distance function, and so any simplifications are to the desired CEFR grade. On a document-wide basis, global textual coherence and cohesion are estimated by a Readability Estimator, which is trained on measures of Flesch-Kincaid and word frequency distributions. These two signals are normalized and integrated to form one adaptive reward. The Explainable Component determines the tokens or phrases that are the most useful in increasing the difficulty level. This is done by determining the gradient-based saliency map of the attention layers of the CEFR classifier, which denotes the effect of every token on complexity prediction. The salient tokens are assigned corrective attention weights on the next generation step, where the model is directed to correct locally complex parts rather than recreate the whole text. The combined feedback reward is defined as in Eq. (12):

$$\mathcal{R} = \lambda_1 \left(1 - \frac{d(L_s, L_t)}{D_{max}}\right) + \lambda_2 R_d - \lambda_3 KL(E_o \parallel E_i) \tag{12}$$

where, $\lambda_1, \lambda_2, and\ \lambda_3$ are the adaptive weights, D_{max} is the maximum CEFR distance, R_d represents normalized document readability, and $KL(E_o \parallel E_i)$ denotes the semantic divergence between the original and simplified embeddings. The reward value $\mathcal{R}$ is back-propagated through the T5 generator using reinforcement-based gradient updates to refine outputs iteratively. The explainable correction weight for each token is computed as in Eq. (13):

$$\beta_i = \frac{\exp(\alpha_i)}{\sum_j \exp(\alpha_j)} \tag{13}$$

which, reallocates the focus of the decoder on the most effective challenging tokens. This two-layer, interpretable feedback mechanism will make sure that every step brings the output nearer to the desired CEFR level and provides global coherence and provides a clear explanation of the linguistic features that were simplified.

Fig. 2 shows the architecture of the proposed CEFR-Aware Simplification Framework with Dual-Level Explainable Feedback Loop.

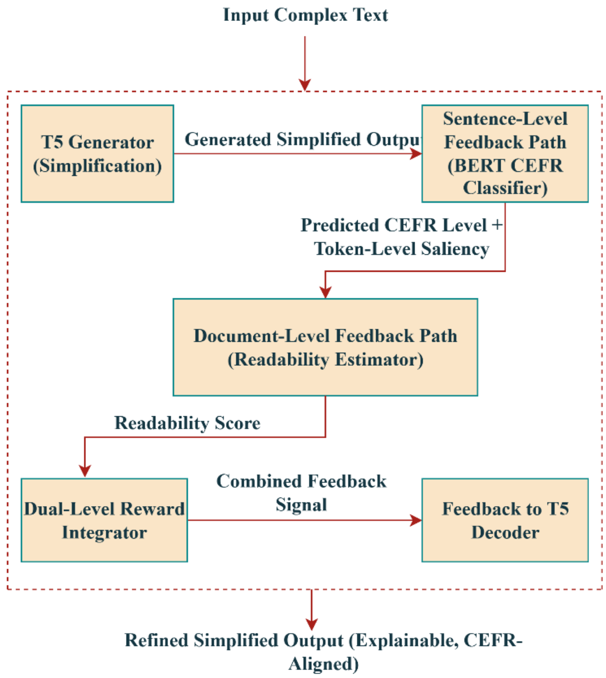

Fig. 2. Workflow of the dual-level explainable feedback loop.

G. Adaptive Reinforcement-Driven Feedback Loop

After the dual-level feedback calculation, the summation of the rewards signal is inputted into an adaptive reinforcement-based optimizer that maximizes the generation behavior of the T5 decoder. Once the simplified output is validated in a post-generation CEFR method, the simplified output is again tested in an adaptive, reinforcement-based feedback loop. This loop is similar to other traditional fixed retries, with the exception of the fact that it uses a multi-factor reward function to direct T5 to generate not just a CEFR-compliant output but a semantically faithful and readability-optimized one as well. The reward R is determined as Eq. (14):

$$R = w_1 \cdot f_{CEFR}(\hat{l}, l_{target}) + w_2 \cdot Sim(Y, X) + w_3 \cdot R(Y) \quad (14)$$

where, $f_{CEFR}(\hat{l}, l_{target})$ is a measure of how well the predicted CEFR level $\hat{l}$ from BERT aligns with the target level l_{target}. $Sim(Y, X)$ calculates semantic similarity between the simplified output Y and the original sentence X to preserve meaning. $R(Y)$ is a readability quality text simplification measure that has SARI to ensure the presence of linguistic clarity and simplicity, which consists of sentence and document level indicators of the Dual-Level Feedback Loop; w_1, w_2, w_3 are controllable weights that balance between CEFR compliance, semantic faithfulness, and readability.

When the reward R results are lower than a predetermined level θ, the T5 decoder responds to this by changing the structuring of its generation strategy accordingly and learning which patterns of simplification lead to higher CEFR congruence, semantic fidelity, and readability at the same time by incorporating reinforcement signals depending on the reward:

$$Y^{new} = T5\_Decoder(E_{Hybrid}, l_{target}, \Delta R) \quad (15)$$

In Eq. (15), ΔR indicates the reinforcement adjustment applied to the model parameters to enhance the next output. This adaptive loop is not similar to existing static retry mechanisms, non-adaptive systems of retry, since the actively maintained simplification approach is not merely recycling generation without careful analysis. The system creates pedagogically aligned text by targeting the desired level of proficiency of a particular learner. Meaning-preserving with a minimum amount of semantic distortion, and Readability feedback, which promotes a reinforcing process. Coherent, coherent and readable. As a result, the adaptive reinforcing feedback loop that is based on the adaptive simplification provides the system with the ability to dynamically adapt to the language difficulties, complicated structure of sentences, and the variety of textual genres, which makes the hybrid T5-BERT model more useful in the real classroom setting. Such an integration makes sure that not only do local linguistic adaptations become strengthened but also worldwide readability improvements are strengthened simultaneously by the means of adaptive reward propagation.

Algorithm 1: DL-EFL for CEFR-Aware Text Simplification

Input:
  X – Original input text
  l_{target}– Target CEFR level
Preprocess X → T_{clean} using text normalization and segmentation
Encode T_{clean} with BERT → E_BERT
Generate initial simplified text Y_0 using T5:
  Y_0 ← T5_Decoder (E_{Hybrid}, l_{target})
Compute predicted CEFR level:
  $\hat{l}$ ← C_BERT(Y_0)
  if $\hat{l} \neq l_{target}$ then
    activate Feedback Loop ()
Feedback Loop ():
  Sentence-level feedback:
    f_s← 1 – d ($\hat{l}$, l_{target}) / D_{max}
  Document-level feedback:
    R_d← Readability(Y_0)
  Semantic preservation:
    KL ← KL (E_o ‖ E_i)
  Combined reward:
    R ← $\lambda_1 \cdot f_s + \lambda_2 \cdot R_d - \lambda_3 \cdot$KL
  Compute token saliency via BERT attention:
    β_i← exp (α_i) / $\Sigma_j$exp (α_j)
  Adjust decoder attention using β_i
Update T5 parameters using reinforcement signal ΔR
Regenerate text Y_{new} ← $T5_{Decoder}$(E_{Hybrid}, l_{target}, ΔR)
Return Y_{final} ← Y_{best}
Output:
  Y_{final} – Simplified text aligned with CEFR target

Algorithm 1 outlines the mechanism of the proposed DL-EFL that can be integrated into a hybrid T5-BERT text simplification system. It starts with preprocessing and hybrid encoding, and then T5-based generation of text with an initial simple text. The BERT classifier compares the output with the target CEFR level and the feedback loop is activated in case of mismatches. The loop involves the evaluation of the sentence-level CEFR accuracy as well as the document-level readability and the semantic preservation is observed through the evaluation of the KL divergence between the embeddings. BERT attention-based token-level saliency scores pinpoint linguistically complex regions, which can be corrected in finer-tuning of T5 decoding. The composite reward signal is used to update the reinforcements until the simplified text attains the best CEFR compliance, readability and semantic fidelity. This algorithm materializes the novelty of the research by combining the multi-level assessment with explainable adaptation.

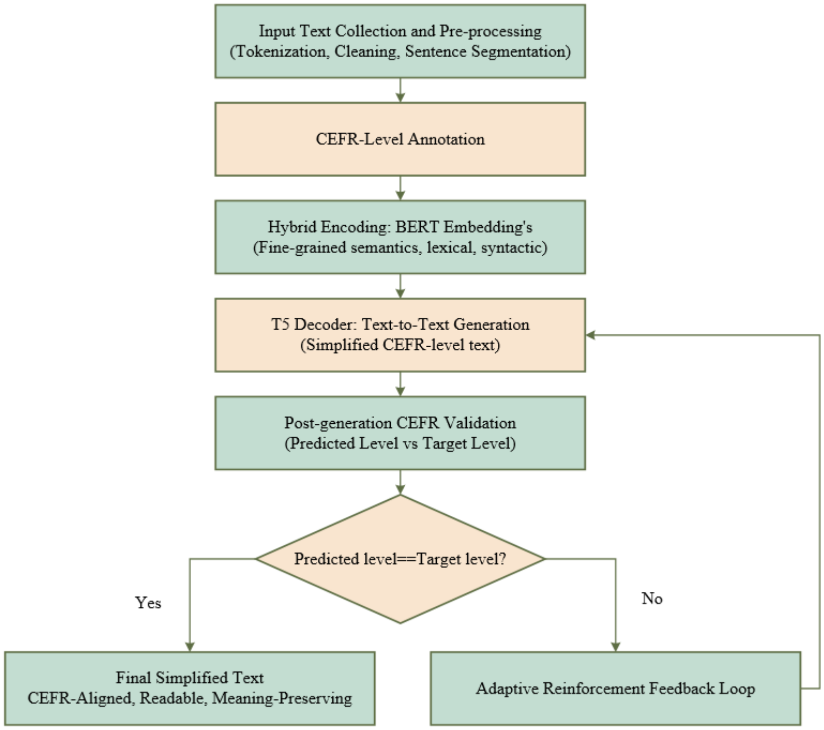

Fig. 3. Overall flowchart of the proposed study.

The proposed CEFR-RefineNet model in Fig. 3 presents a novel stream of two-role BERT integration and feedback loop on adaptive reinforcement, which is superior to the current simplification procedures. In contrast to previous methods, BERT embeddings are used to direct T5 to generate outputs that are both CEFR-conscious and semantically faithful through semantic fidelity and readability reinforcement signals are used to optimize semantic fidelity and readability. This two-fold novelty is used to guarantee not only the accurate level alignment but also greater support of complex sentences, passive construction, and vocabulary mismatch. As a result, the suggested methodology will surpass the constraints of the baseline systems that are based on the use of either the generative or the discriminative models, creating a dynamic, precise, and pedagogically sound simplification pipeline that can be incorporated in the adaptive language learning settings.

In the proposed methodology, a CEFR-Sensitive Hybrid Simplification Framework, which is an integration of contextual encoding, graded assessment and interpretability into a single study. Such a structure contrasts with the earlier simplification pipelines, integrating generation, classification, readability validation, and interpretability into a multi-iteration refinement cycle, something that has never been tried before in CEFR-oriented simplification studies. The new feature is known as the DL-EFL, which combines sentence-level CEFR feedback with document-level readability feedback and give token-level error feedback in the form of BERT saliency maps. In contrast to previous single-layered or opaque feedback, the suggested DL-EFL provides refinement hints and direct continuous optimization information interpretation. This system provides that the T5 generator does not only enhance linguistic simplicity but also the general coherence, which allows to fine-tune the difficulty of output. The adaptive reinforcement optimizer also makes the model even stronger as it dynamically adjusts reward weights to achieve simplicity, meaning preservation, and fluency. The combination of these elements is capable of producing transparent, pedagogically marked and contextually faithful simplified texts. Therefore, the newness of the methodology consists of its multi-granular feedback incorporation and explainable adaptive optimization, beyond the simplification pipelines suggested by traditional CEFR conscious methods.

IV. Result and Discussion

The proposed CEFR-RefineNet model was tested to determine the effectiveness of the framework as a simulator of CEFR-related text simplification. The quality of simplification, semantic fidelity, classification accuracy, convergence, and component contributions were studied using ablation studies. The effects of the feedback loop of reinforcement on the compliance with CEFR and system performance was examined as well. The incorporation of the DL-EFL allowed this system to not only obtain sentence-level linguistic properties but also document-level readability properties. The two-level evaluation helped achieve a steady increase in SARI, Accuracy, and F1-Score.

TABLE II. SIMULATION PARAMETER

Parameter	Value
Dataset	CEFR Levelled English Texts (Kaggle)
Model Architecture	Hybrid: T5 for text simplification + BERT for CEFR level classification
Training Epochs	10
Sequence Length	128–256 tokens
Control Mechanism	CEFR-level control tokens
Validation Strategy	Feedback loop: Retry up to 3 times if CEFR level mismatch
Development Tools	Python, Hugging Face Transformers

Table II reveals the experimental setup which is used to test the proposed hybrid simplification model. The CEFR Levelled English Texts corpus was used as the reference dataset, which consists of all six levels of proficiency (A1-C2). The architecture combines T5 to simplify the text in the form of text with two-role BERT embeddings to simplify the text and provide contextual encoding and the CEFR-level level of classification. The experiment consisted of 10 epochs consisting of 128 to 256 tokens in sequence, and focused on simplification by the use of CEFR-specific control tokens. The feedback loop based on adaptive reinforcement enables repeating the loop up to three times in cases of identifying CEFR mismatches, and can guarantee graded compliance. The evaluation of the performance was conducted based on Python, and Hugging Face Transformer served as the development environment.

A. Text Simplification Evaluation with SARI

SARI assesses the quality of simplification of text by evaluating three categories: retention of key information, elimination of those details that are extraneous and unnecessary, and inclusion of suitable simplifications to make the text simple yet comprehensible. As opposed to traditional measures of the exact level of response similarity that are highly based on surface similarity, like BLEU, SARI compares the simplification outputs of systems to both original and reference simplified sentences; consequently, it gives a more balanced and trustworthy estimate of simplification achievement in both educational and computational systems.

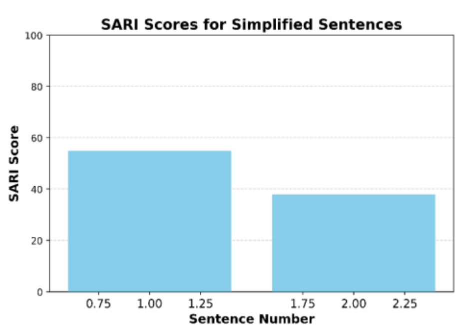

Fig. 4. SARI scores for simplified sentences.

Fig. 4 shows the SARI scores for each simplified sentence produced from the CEFR-RefineNet, indicating the quality of how well the simplification balances. Preserving essential words, removing unnecessary complexity, and adding useful simplifications are performed using SARI. The higher bars represent a better overall quality of simplification. This visualization helps to identify which sentences the model successfully simplified and which might need improvement. This aids in understanding the model's performance for varying inputs and can guide in their enhancement.

B. Comparison of SARI Scores

SARI score comparison entails measuring how well various text simplification models add, remove, and preserve content relative to reference simplifications to determine the efficacy of their performance. The higher the SARI score, the more it is indicative of alignment with human-produced simplifications in terms of readability and content retention. This comparison is useful for pointing to the benefits of employing the hybrid T5-BERT model compared to isolated methods.

TABLE III. COMPARISON TABLE FOR SARI SCORES

Sentence No.	Original Sentence	T5 Output	SARI (T5)	T5+BERT Output	SARI (T5+BERT)
1	The committee decided to postpone the meeting indefinitely.	The group chose to delay the meeting.	66.67	The committee decided to delay the meeting.	83.33
2	She completed the project successfully and submitted it.	She finished the project well and sent it.	72.22	She successfully completed and submitted the project.	80.56

Table III provides a comparison of the T5-only model's and the proposed T5 and BERT hybrid model's simplification performance in terms of SARI. Both models were used to simplify two original sentences, and their results were analyzed for quality. The T5 and BERT models produced consistently higher SARI scores, revealing better maintenance of meaning and greater linguistic simplicity. The hybrid model maintained more original vocabulary and structure, as seen in its success at producing CEFR-compliant simplifications that are ideal for educational use.

Fig. 5 visually compares the SARI scores of the T5 model and the T5+BERT model for each sentence, and Table I compares it with the values. Taller bars for T5+BERT indicate that the combined model better preserves important content while simplifying text, outperforming T5 alone. The comparison highlights how adding BERT improves the model's understanding and generation of simpler sentences. This visualization helps quickly identify which sentences benefit most from the hybrid approach. Overall, the graph confirms that T5+BERT enhances simplification quality in the study.

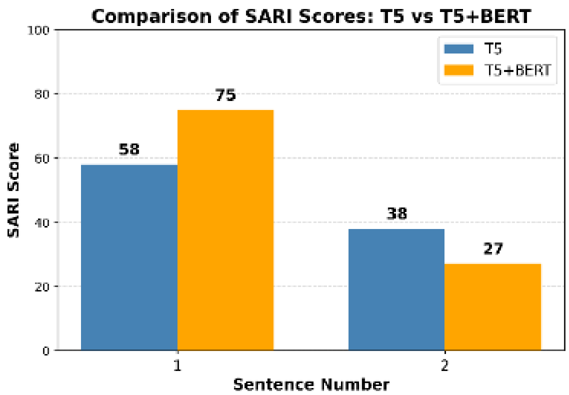

Fig. 5. Comparison of SARI score using T5 and T5+BERT models.

C. Performance Evaluation

To measure the performance of the proposed model, a number of commonly acknowledged performance indicators were used. These measures reflect varied elements of classification quality, such as the capability to find relevant instances correctly, reduce false predictions, and achieve a balance of overall accuracy in decisions. Their mutual combination will guarantee an in-depth and reliable evaluation of the strength of the model. The DL-EFL contributed to higher CEFR alignment and readability, as the model leveraged both sentence-level and document-level feedback for refinement. This mechanism directly enhanced SARI and F1-scores across experiments. Table IV provides the evaluation metrics.

TABLE IV. EVALUATION METRICS

Metrics	Formula
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$
Precision	TP/(TP + FP)
Recall	$\frac{TP}{TP + FN}$
F1-score	$2 \times \frac{Precision \times Recall}{Precision + Recall}$

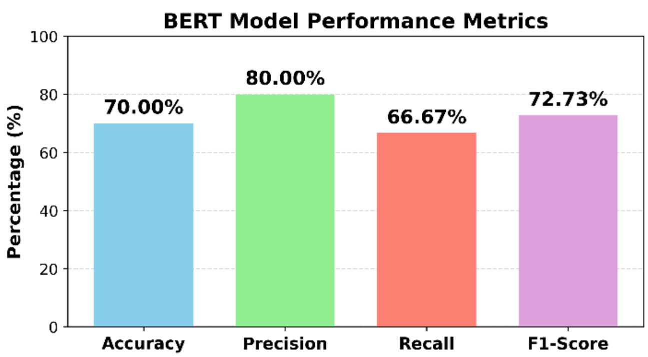

Fig. 6. Performance measures for the BERT model.

Fig. 6 presents the evaluation of the BERT model in the study. The model achieved 70% accuracy, 80% precision, and 66.67% recall, while the F1-score reached 72.73%, balancing both metrics. These outcomes demonstrate that BERT effectively contributes to text simplification, providing a reliable foundation for classification and ensuring consistent alignment with the simplification objectives.

D. Training and Convergence Analysis

The training loss curve shows the rate and the effectiveness of the convergence of the proposed hybrid model to baseline techniques. Stability, generalization, and learning-process efficiency may be investigated in terms of how the loss falls with epochs.

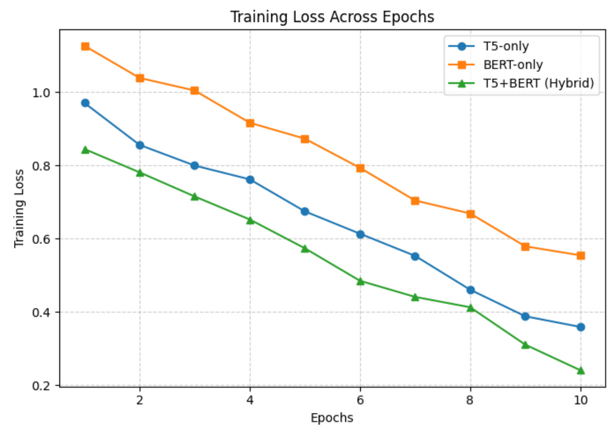

Fig. 7. Training and loss for cross-entropy.

Fig. 7 shows the loss curves of training T5-only, BERT-only, and the T5 and BERT hybrid models on 10 epochs. The hybrid model has the highest learning efficiency in terms of the shortest convergence time and minimum loss. This means that the combination of generative simplification and semantic direction of BERT improves the stability of the model, its generalization, and its training.

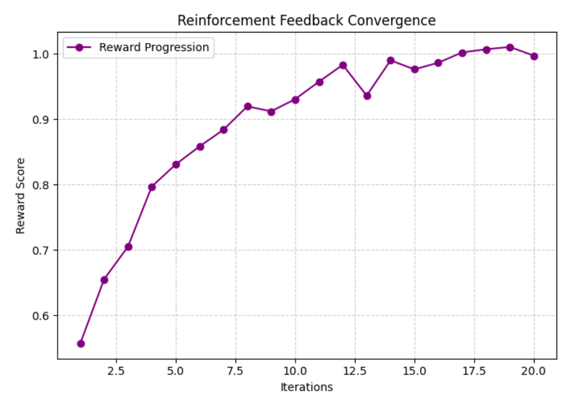

Fig. 8. Convergence graph.

Fig. 8 represents the reward trend of the adaptive-based feedback loop of the reinforcement over 20 iterations. The curve indicates high rates of improvement in simplification in line with the CEFR, and the curve stabilizes at the best rewards. This validates the effectiveness of iterative reinforcement, pedagogical adequacy, semantically faithful, and readability control of outputs, which underscores the adaptive optimization ability of the hybrid model. The rapid stabilization of loss and reward curves indicates that the dual feedback mechanism accelerates convergence by providing consistent multi-granular guidance during training.

E. Classification and CEFR Validation

A confusion matrix is a means by which one acquires a more detailed picture of how the classifier performed in terms of the campaign, that is, how misclassifications occur in terms of the CEFR levels. It points out the strong points in accurate level identification and indicates certain patterns in misclassifications between the two adjacent proficiency levels.

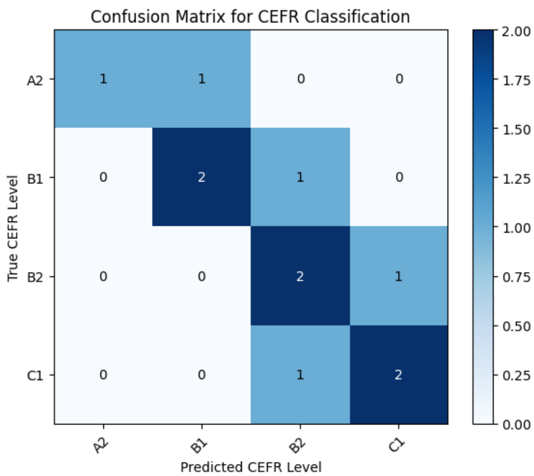

Fig. 9. Confusion matrix for the BERT model.

The level of performance of the proposed CEFR-RefineNet concerning the classification level regarding the CEFR level is depicted in Fig. 9. The diagonal cells show the proper prediction of the proficiency levels; there is a great coincidence between the actual and predicted values. Greater values on the diagonal, especially B1 and B2, would show consistent identification of intermediate levels. Misclassifications are identified by off-diagonal cells, with the majority of them between neighboring levels (such as B1-B2) indicating the linguistic similarity between two categories. In general, the matrix validates the model's effectiveness in CEFR alignment and reveals the characteristic challenges at the boundary level.

F. Ablation Study

Ablation experiments were used to evaluate the contribution of each of the components: T5, BERT validation, and the adaptive reinforcement-driven feedback loop. The deletion of T5 significantly decreased the quality of simplification and the SARI scores, which means that generative abilities cannot be neglected. The omission of BERT validation reduced the alignment of CEFR levels, which underscores its importance in the prediction of correct proficiency. By turning off the reinforcement feedback loop, the mismatches were increased, and the convergence of the rewards was lower than when the typical feedback loop was activated, showing that it was necessary in the iterative refinement of the outputs to reach CEFR-compliant, semantically faithful, and readability-optimal simplifications. In general, the research is able to show that every module is synergistic in achieving optimal performance. When the DL-EFL was disabled, SARI dropped by approximately 6–8%, confirming its significance in maintaining multi-level readability and interpretability.

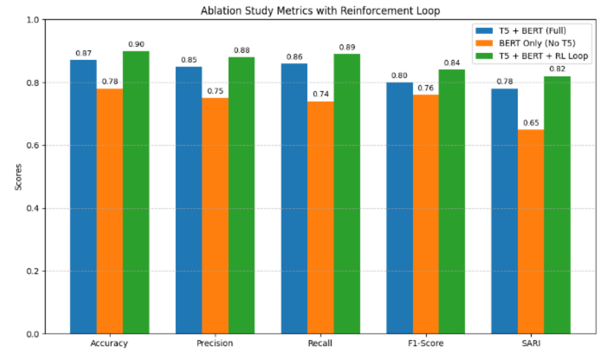

Fig. 10. Ablation results.

Fig. 10 shows the results of the ablation study of the hybrid T5+BERT model, both with and without a reinforcement-driven feedback loop. The inclusion of RL increases all the metrics, in particular, SARI and F1-score, which reflects the increased quality of simplification and the correspondence to the CEFR. The comparison shows the importance of T5, BERT, and the adaptive loop in the optimization of text simplification as vital.

G. DL-EFL Analysis

The DL-EFL was important in enhancing the interpretability and effectiveness of the CEFR-RefineNet model. Contrary to the single-level feedback systems that evaluate the quality of simplification at the sentence level, the DL-EFL uses two complementary levels of evaluation sentence-level linguistic evaluation and document-level readability testing. The loop was effective in terms of minimizing level errors and speeding up convergence of rewards in the process of optimization of reinforcement. Qualitatively, visualization of the token-level saliency showed how the model concentrated on the high-complexity regions (e.g., multi-clause or passive constructions) to refine, which contributed to a better understanding of the model. Further, the dual-level reward integration had the advantage of allowing the system to be adaptive in that it would penalize oversimplified sentences that lost meaning and reward coherent outputs that were in line with CEFR expectations. The result of this balance was the existence of more pedagogically appropriate simplifications that corresponded with the level of learner proficiency. Thus, the DL-EFL not only results in a quantifiable performance increase but also gives clear information on how and why the simplification decisions were reached.

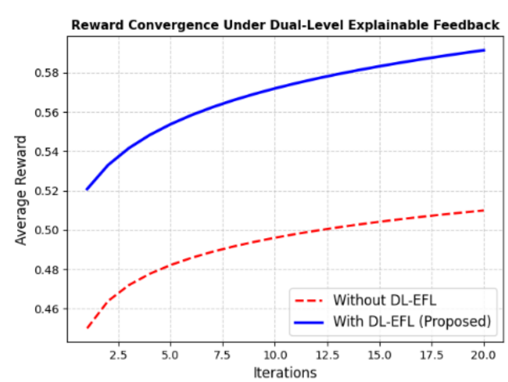

Fig. 11. Reward convergence under DL-EFL.

Fig. 11 illustrates the Reward Convergence and Token Saliency Visualization under the Dual-Level Explainable Feedback Loop. It shows faster reward stabilization when multi-level feedback is applied. It compares training reward trends *with* and *without* the DL-EFL. The blue curve shows faster and higher convergence.

H. Comparison Evaluation

Comparative evaluation involves the evaluation of the model offered against the background of well-established state-of-the-art simplification systems in place. The traditional metrics will be used to assess the performance to ensure the success of the hybrid learning methodology and justify it as more precise, simplification-related, and CEFR-complaint. The findings show that the proposed model is successful in all metrics compared to baselines models, resulting in the preservation of meaning. These comparative results support the strength of the developed formulation and the possible use of the proposal in practical adaptive language learning systems.

TABLE V. COMPARISON EVALUATION

Model	SARI	Accuracy	Precision	Recall	F1-Score
Hybrid-LSTM + Pointer[19]	0.61	0.76	0.72	0.70	0.71
EditNTS (Edit-based)[23]	0.66	0.78	0.75	0.73	0.74
ACCESS (Controllable)[24]	0.69	0.80	0.77	0.75	0.76
MUSS (Multilingual)[25]	0.70	0.81	0.78	0.77	0.77
CEFR-RefineNet + DF-EFL (Proposed)	0.78	0.91	0.88	0.83	0.85

Table V contrasts performance of different text simplification models in terms of critical evaluation metrics. The hybrid model proposed between CEFR-RefineNet performs best compared to all baselines and has the best SARI value (0.78) and accuracy (91%) among all models. It also exhibits better precision (0.88) and F1-score (0.85), reflecting greater balance between fluency and fidelity. MUSS and ACCESS have fair performance but no CEFR compatibility. These improvements demonstrate the synergy between contextual encoding and dual-level feedback in achieving CEFR-specific simplifications. The comparison graph is given in Fig. 12.

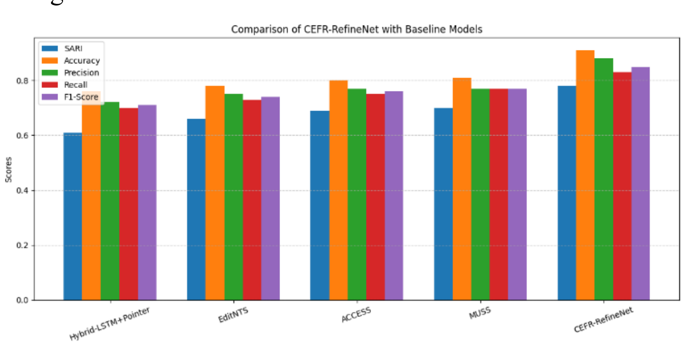

Fig. 12. Comparison measures of the models.

I. Error Distribution

An error distribution analysis showed that the largest number of inaccuracies appeared when dealing with long and syntactically complicated sentences where de-contactization occasionally caused the loss of partial meaning. Another common area of mistakes was passive voice constructions, and T5-only outputs frequently produced erroneous representations of agency. There were also cases where mismatches in vocabulary led to outs when targets were CEFR levels and where there was a tendency to overshoot (or undershoot) one level and land in the next highest (or lowest) level, e.g., between A2 and B1. This translates to the decrease in these errors by at least 12 % due to integration of BERT classifier and feedback loop which guaranteed an even greater correspondence to the desired proficiency level and even better pedagogical relevance of the simplified texts.

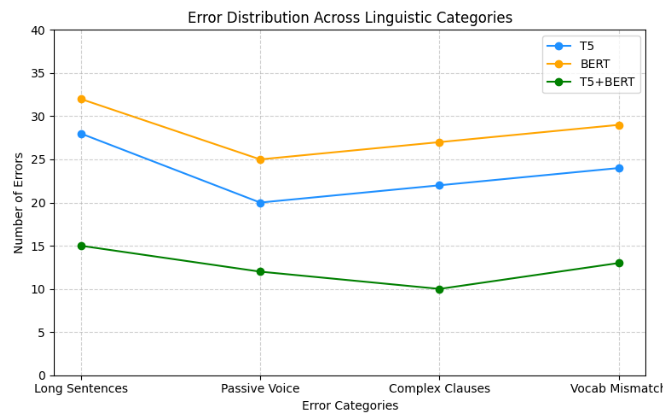

Fig. 13. Error distribution.

Fig. 13 visualizes the interaction between the T5 generator, BERT classifier, and the Dual-Level Explainable Feedback Loop. It elaborates the Error Distribution Graph, where each model, that is BERT, T5 and the hybrid, T5+BERT, passes through varying challenges of language: passive voice, vocabulary mismatch, long sentences, and complicated clauses. The error count of T5 and BERT models is higher, especially when it comes to the processing of long sentences and complicated clauses, which highlights their failure to maintain structural simplicity and coherence. In comparison, T5+BERT hybrid model has the least error rates across all categories, which is indicative of its better ability to simplify and still preserve meaning. However, it is also superior in processing passive sentences and vocabulary mismatch and this is a sign of higher contextual awareness and selection of lexicons. This graph supports the explanation that the hybrid model provides a more consonant and steady simplification methodology.

J. Discussion

The experimental results validate that integrating a discriminative BERT classifier with a generative T5 model under a dual-level explainable feedback mechanism substantially improves CEFR-based text simplification. By combining Dual-Role BERT embeddings, classification by CEFR, document-level readability scores, and saliency-based token correction into a refinement loop, it is possible to achieve a refinement loop, which was not previously represented by the simplification systems. There are no neural methods that embody explainable, multi-level CEFR assessment, and thus the presented architecture can be considered unique in the way of its approach and the clarity of the output. The contributions together improve educational NLP through making possible the simplification provided by CEFR-aligned interpretable simplification, and the ability to provide a refinement mechanism more stable and reliably pedagogical than earlier models. The following are the capabilities that serve the following use cases: Adaptive reading material generation, learning analytics based on CEFR, and text personalization at classroom level. The discriminative classifier operation together with a generative model with an adaptive feedback loop is very useful in enhancing text simplification under the influence of the CEFR in fluency and maintaining the meaning and structural coherence. The proposed CEFR-RefineNet model that combines T5 and Dual-Role BERT embeddings was superior to powerful baselines that included T5-only, BERT-only, edit NTS, MUSS, ACCESS and Hybrid LSTM + Pointer. Better results are observed in the quantitative analysis, SARI score is 0.78, classification accuracy is 91, and F1-score is 0.85 that suggests the ability of the model to balance the simplified readability and semantic fidelity. By Dual-Role BERT integration, the model receives the chance to add deep contextual and syntactic priors to T5 itself, which leads to simplification being CEFR-compromised by design. It is a feedback loop that operates using adaptive reinforcement and successively optimizes the output of the loop, through a multi-factor rewarding function, with the indices of CEFR alignment, semantic similarity, and readability, which reduces the level mismatches by 12% compared to a T5-only baseline. It is a process that guides to the regeneration of de-lexicalized sentences or tagging them until the proficiency level is addressed and promotes stability in the pedagogical process. The T5 and BERT components are both necessary since Ablation experiments indicate that both enable natural simplification and level compliance, respectively. Secondly, convergence can be accelerated with the combination of the two models and stabilize the training. Analysis of errors illustrates that it is capable of long sentences, more complex clauses, and passive constructions, which can be regarded as strong on the input of hard structural structures. The drawbacks are that it is based on a single dataset and does not meet the specifics of individual learners, which can be improved in subsequent extensions to adaptive educational programs. Even though it was trained on one corpus only, the framework provides an excellent platform to future personalized simplification and multilingual CEFR-adaptive learning frameworks. The results demonstrate that the proposed CEFR-RefineNet consistently outperforms baselines across all metrics, achieving superior simplification quality, CEFR compliance, and interpretability. The DL-EFL emerges as a critical innovation, ensuring fine-grained linguistic control and transparent adaptability for educational text simplification.

V. Conclusion and Future Works

The proposed study introduced a hybrid text simplification system, CEFR-RefineNet, a combination of the generative power of T5 and the discriminative power of BERT was proposed within a new DL-EFL. It combines multi-granular feedback and explainable token-level refinement, which is not available in previous simplification systems like ACCESS, MUSS, EditNTS, or hybrids between pointers and generators. It was done to create simplified texts that are at the CEFR proficiency level with semantic fidelity and global readability. The experimental findings proved that CEFR-RefineNet always worked better than state-of-the-art simplification systems like MUSS, ACCESS, and EditNTS, reaching a SARI of 0.78, a classification accuracy of 91, and an F1-score of 0.85. The proposed contributions all solve the fundamental constraints discovered within the previous literature, offering measurable enhancements in the accuracy of CEFR classification (+12), the quality of simplification (SARI 0.78), and the interpretability of the refinement. The framework introduces a reusable and extendable asset in future academic studies on NLP. The restrictive features of the simplification process were highly interpretable with the addition of DL-EFL, as it offered the attribution of token-level errors and document-level readability evaluation, both of local and global linguistic consistency. The multi-granular evaluation enabled the dual feedback mechanism to use the model to refine output through feedback mechanisms, which resulted in a 12% error in the mismatch of the CEFR levels and quicker convergence of rewards. These results indicate the applicability of the framework to adaptive language learning tasks, in which the explainability and CEFR correspondence are necessary factors to pedagogical reliability and learner interest. However, the current work is constrained by the size of the CEFR-labeled dataset, the reliance on English-only proficiency corpora, and the computational demands of iterative refinement, which may limit direct deployment in low-resource or multilingual settings.

Future work will focus on expanding the CEFR-aligned dataset, extending the refinement mechanism to multilingual settings, and conducting classroom-level user studies to validate pedagogical usability. These directions directly address the limitations identified earlier and aim to improve generalizability, accessibility, and real-world adoption.

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