Advancing Automated and Adaptive Educational Resources Through Semantic Analysis with BERT and GRU in English Language Learning

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Abstract—**Semantics describe how language and its constituent parts are understood or interpreted. Semantic analysis is the computer analysis of language to derive connections, meaning, and context from words and sentences. In English language learning, dynamic content generation entails developing instructional materials that adjust to the specific requirements of each student, delivering individualized and contextually appropriate information to boost understanding and engagement. To tailor instructional materials to the various requirements of students, dynamic content creation is essential in English language learning (ELL). This work is a unique method for automatic and adaptive content production in ELL that uses Gated Recurrent Unit (GRU) and Bidirectional Encoder Representations from Transformers (BERT) together. The suggested approach uses BERT enabling content selection, adaption, and adaptive educational content production, and GRU for semantic extraction of features and contextual information captured from textual input. The article presents a novel approach to creating automated and adaptable educational tools for ELL that uses GRU for semantic feature extraction. Using persuasive essays collected in the PERSUADE 2.0 corpus annotated with discourse components and competency scores, this is an extensive dataset. After extensive testing, this approach shows outstanding outcomes, with high accuracy reaching 97% when compared to the current Spiking Neural Network (SNN) &Convolutional Neural Network (CNN), Logistic Regression (LR), and Convolutional Bidirectional Recurrent Neural Network (CBRNN). Python is used to implement the suggested work. The suggested strategy improves ELL engagement and understanding by providing individualized, contextually appropriate learning resources to each student. In addition, the flexibility of the system allows for real-time modifications to suit the changing needs and preferences of the learners. By providing instructors and students in a variety of educational contexts with a scalable and effective approach, this study advances automated content development in ELL. The model architecture will be improved in the future, along with the application's expansion into other domains outside of ELL and the investigation of new language aspects.**

Keywords—BERT; Content Generation; English Language Learning; Gated Recurrent Unit; Semantic Analysis

I. Introduction

Semantics is a subfield of linguistics that studies the way language is understood. The literal meaning of words and sentences as essential components of the world is the subject of semantics. Semantic analysis, as applied to NLP, assesses and reflects human language. It also examines documents written in English alongside other natural languages, interpreting them similarly to the way people would [1]. The prevalence of documented information from both academic and business settings is growing, and its encounter in various contexts by various scientists and scholars suggests that researchers seeking high system efficiency are drawn to collecting details, processing languages, and information retrieval due to their rapid growth. Assert that scholars from a range of fields are interested in classifying characteristics such as study themes, methodologies, and theories related to the research nature by analysing descriptions, and titles, and publishing the entire text bodies. Numerous interdisciplinary areas have evolved in the last several decades, encompassing biochemistry, the field of engineering, data mining, neurology, and bioinformatics. It might be challenging to comprehend every step of the research process in these subjects since interdisciplinary environments incorporate theories, methodologies, and approaches from other fields [2]. Therefore, a system for classifying texts and documents according to their relevant structures ought to exist. Semantic analysis is the technique used by academics and researchers to categorize texts according to their underlying structures. Assert that the exact significance and understanding associated with dictionary meaning derived from structures created by syntactic evaluation are assigned by semantic analysis. To understand why language conveys meaning, semantics, a discipline of linguistics, studies how language interacts with several "linguistic categories, syntax, phonology, and lexicon". Semantic analysis, in this sense, focuses on the meaning of words and phrases as components of the world [3].

ELL has a unique position at the nexus of global interaction and educational progress, as millions of people pursue English language proficiency for personal, professional, and academic purposes. The process of learning English is dynamic and ever-changing, and it is essential in the globalized society of today. Since English is the universal language of commerce, education, and worldwide communication, speaking the language well has become more crucial for those who want to succeed in a variety of academic and professional settings. Because of this, there is an increasing need for creative and efficient language learning solutions, which is driving instructors and developers to investigate novel ideas to cater to the various demands of students [4]. Conventional approaches to teaching languages frequently depend on static resources like lectures and textbooks, giving students few chances for interaction and customization. Nonetheless, the way English is taught and understood is being completely transformed by recent developments in educational technology, especially in the area of dynamic content creation. Teachers may design individualized, multimedia lessons that are tailored to each student's requirements and preferences by utilizing the effectiveness of semantic analysis with adaptive algorithms. In English language learning, dynamic content production refers to the automated modification and personalization of course content according to student's interests, learning preferences, levels of competence, and advancement. With dynamic content production, teachers may provide individualized learning experiences that maximize student engagement, understanding, and learning outcomes, in contrast to static resources that provide a generic approach to training [5]. Semantic analysis, a subfield of NLP that focuses on comprehending the context underlying meaning of text, is fundamental to the creation of dynamic content.

Automated and adaptive educational materials represent a transformative approach to learning, leveraging technology to tailor instruction to the individual needs and preferences of learners. These materials are designed to dynamically adjust content, difficulty level, and instructional strategies in real-time, offering personalized learning experiences that optimize engagement, comprehension, and retention. Automation in educational materials involves the use of algorithms and artificial intelligence to streamline various aspects of the learning process, from content creation to assessment [6]. The proposed work introduces an innovative approach to dynamic content generation in ELL by leveraging a combination of GRU and BERT. This model integrates GRU for semantic feature extraction and contextual understanding, while BERT facilitates content selection, adaptation, and the generation of dynamic learning materials tailored to individual learner needs. By automating the process and adapting content in real-time, the proposed approach enhances learner engagement and comprehension. Rigorous experimentation and human evaluation studies validate the efficacy of the model, demonstrating its ability to produce high-quality, contextually relevant educational materials. Furthermore, the proposed approach addresses the limitations of existing systems by providing personalized and adaptive learning experiences, promoting active participation and knowledge retention in ELL. This research contributes to advancing automated content generation in ELL, providing a scalable and efficient solution for educators and learners in diverse educational settings. By combining the BERT and GRU models, this project aims to provide a novel method for automating the development of dynamic instructional materials for ELL. This study aims to investigate the viability and effectiveness of using BERT for content adaptations and GRU for semantic feature extraction to provide dynamic learning resources. The project also intends to create a system that can provide customized learning materials by responding in real time to the preferences and requirements of each student. Additionally, it seeks to determine how the suggested strategy affects learner engagement, understanding, and general learning outcomes for English Language Learners. It also wants to determine how scalable and effective the approach is across a range of learning contexts and student populations. Additionally, the study aims to investigate how the suggested method, which takes into account the varied linguistic origins and skill levels of students, might advance inclusion and accessibility in ELL practices. Ultimately, by overcoming current methodological constraints and encouraging innovation in content creation for language teaching, this project hopes to develop educational technology.

The study's findings have important ramifications for both educational technology and the ELL community. The main issues with standard ELL techniques are addressed in this work by investigating the combination of BERT and GRU models for the automated creation of dynamic resources. The relevance is in the ability to completely transform language learning by offering individualized, contextually relevant learning resources that are catered to the requirements and preferences of each student. This method takes into account the varied linguistic origins and skill levels of the learners, which not only improves student engagement and understanding but also encourages inclusion and accessibility in ELL activities. Additionally, by overcoming the drawbacks of existing techniques and encouraging creativity in the creation of language-learning content, the research advances educational technology. In the end, this study's findings may enhance ELL instruction and learning opportunities, resulting in more successful language proficiency growth and acquisition.

The remaining sections are arranged as follows. Section I provides an introduction. Section II provides illustrations for the literary sections. Section III contains the problem statement. Section IV discusses the recommended methodology for analysing semantics and content production using GRU and BERT. In Section V, the efficacy metrics are displayed and the findings are gathered. Section VI presents a conclusion and Section VII presents the future research.

II. Related Works

A. Narrative-Centric Learning Experiences

Diwan et al., [7] suggested that in online learning settings, maintaining student engagement is a significant problem that becomes even more intense as learning spaces are progressively constructed by fusing information from several separate sources. Numerous researchers have discovered that learner involvement may be enhanced through narrative-centric learning experiences. To do this, they provide an AI-based method that produces so-called narrative fragments, which are supplementary learning materials that are included in the learning pathways to produce interactive learning narratives. The suggested method involves automatically creating two different kinds of narrative fragments: summaries of the learning route sections and formative evaluations, such as reflection quizzes, utilizing instructional assets in any format, including publicly available educational materials. A pre-trained language approach, GPT-2, serves as the foundation for an NLG component in the pipeline that generates the story fragments. The other components depend on different semantic models. Automation makes it possible to create story segments instantly anytime the learning route has to be modified prerequisite information, etc. This allows for flexibility in the learning paths. Because the suggested method is domain-agnostic, it may be readily modified to work in several domains. ROUGE scores are used to compare the NLG model to many baselines. Human evaluators assess story pieces that are consequently created. In both instances, they had positive outcomes.

B. Text Generation Systems

Hua et al., [8] recommended a three essential elements are needed for establishing an effective text generation system: surface realization, text planning, and content selection. Typically, these issues have been addressed independently. While recent all-in-one neural generating approaches have achieved tremendous strides, they frequently yield inconsistent and erroneous outputs relative to the input. In order to tackle these problems, they provide a beginning-to-the-end learned two-step generation model: first, a sentence-level content organizer determines the language style and key phrases to cover; subsequently, an outer manifestation decoder produces meaningful and cohesive text. They take into consideration three goals for trials, which come from realms with different themes and linguistic styles: creating an abstract for scientific publications, creating paragraphs for regular and basic Wikipedia pages, and creating compelling arguments from Reddit. The remedy can exceed rival inquiries by a large margin, according to automatic evaluation. In addition, human judges find system-generated writing to be more accurate and fluent than versions that do not take linguistic style into account. This model is beneficial, as evidenced by experimental data, where it outperforms complex comparisons in terms of BLEU, ROUGE, and METEOR scores. When it comes to language style, human subjects likewise evaluate their model generations as being more grammatically accurate and grammatical.

C. Sentiment Analysis in MOOC Reviews

Onan et al., [9] states that MOOCs [10] are a relatively new and creative kind of distance learning that allows participants to access course materials regardless of their age, gender, race, or location. By adopting the concepts of ensemble learning as well as DL, this study aims to propose an effective sentiment categorization method with good prediction performance in evaluations of massively open online courses. They want to address several research inquiries regarding sentiment analysis of educational data in this contribution. Initially, an assessment was made of the prediction abilities of DL, ensemble learning, and traditional supervised learning techniques. Also, assessments of massively open online courses have been used to assess the efficacy of word-embedding and visualizing text systems for sentiment assessment. Using ML, ensemble learning, and DL techniques, they examined a corpus of 66,000 reviews of massively open online courses for the evaluation assignment. The empirical research shows that for the job of sentiment assessment in educational data mining, deep learning-driven architectures perform better than ensemble learning approaches and supervised learning methods. Through a rate of classification of 95.80%, extended short-term memory networks alongside the GloVe word-embedding scheme-based depiction have produced the best prediction performance across all evaluated configurations.

D. Adaptive E-learning Environments

El-Sabagh et al., [11] states that designing suitable adaptive e-learning environments helps to personalize training to reinforce learning goals since adaptive e-learning is seen as a stimulus to enhance education and student engagement. This work aims to investigate how students' involvement is affected by an adaptable online educational setting that is designed according to their learning styles. Additionally, this study aims to describe and contrast the suggested flexible online learning setting with a traditional e-learning methodology. The following combined research approaches were utilized to examine the impact and form the basis of the paper: The adaptive e-learning environment is designed using a development approach, and the research experiment is carried out using a quasi-experimental research design. The following affective and behavioural components of involvement are measured by the student participation scale: skills, performance, emotions, participation/interaction, and abilities. According to the findings, there is a statistically significant difference between the experimental and control groups. These experimental findings suggest that an adaptable online learning environment may be able to motivate pupils to learn. This study makes a number of useful recommendations, including ways to boost the influence of online adaptive courses in education and increase the cost-effectiveness of education. It also discusses how to develop a foundation for adaptive online education based on preferences for learning and their implementation. In order to increase student engagement, e-learning institutions can create more individualized and adaptable learning environments with the aid of the suggested adaptive e-learning strategy and its findings.

E. Advanced NLP Techniques for English Learning

X. Guo et al., [12] states that because of its potential to completely transform oral learning, the application of sophisticated methods of NLP in education has gained popularity. Because self-learning is flexible and accessible, it has gained popularity in oral English learning. Students may now approach language learning on their own terms through the development of digital materials and applications. This study introduced a unique framework for improving oral English learning that combines the strengths of the HCRM and the BERT model. The main objective is to give educators and organizations a strong instrument for assessing the appropriateness and quality of oral learning resources. Analysis of sentiment, characteristic collection, and categorization are all integrated into the HCRM architecture, which makes it a complete solution for determining a document's appropriateness for use in the context of oral English learning. To ensure a comprehensive understanding of the efficacy of the oral learning materials, the model considers the viewpoints of both instructors and students. Through efficient sentiment analysis and feature extraction, the HCRM enables a more nuanced comprehension of the possible effects of instructional materials. The results of this study imply that the combination of BERT and HCRM offers a more precise, comprehensive, and data-driven method of material assessment, which might significantly improve oral English learning. The novel approach this study proposes has the potential to raise the quality and applicability of oral learning resources in the field.

Innovative ways to improve learner engagement and content creation in online learning environments have been studied in the field of educational technology in the past. Nevertheless, a critical analysis of these initiatives identifies their advantages and disadvantages. Even while research like those by Diwan et al. and Hua et al. present interesting techniques like text generation models and story fragments, they sometimes lack thorough assessments and may ignore larger educational settings. Comparably, studies conducted by Onan et al. [9] and El-Sabagh et al. [11] explore sentiment analysis and adaptive e-learning settings, respectively, but they might not adequately account for how student preferences are dynamic and how the online education landscape is changing. Even though it is a novel framework, X. Guo et al.'s [12] approach to oral English learning may overlook learner involvement and interaction, which is essential for comprehensive learning experiences. In order to optimise educational experiences across a variety of learning situations, future endeavours should aim for more integrated and comprehensive methods, taking into account the interaction between technology, pedagogy, and learner engagement. Overall, while these studies offer valuable insights into different aspects of educational technology and online learning, there is a clear research gap in integrating these approaches to create holistic and adaptive learning experiences that effectively engage learners across diverse contexts and domains. Prior research has exhibited inventive artificial intelligence (AI) approaches, such as deep learning methods and story fragment production, to support sentiment analysis and learner engagement in educational data mining. Furthermore, the development of comprehensive frameworks such as the two-step generating model and the integration of HCRM and BERT represents advancements in the production of coherent learning materials that prioritize the quality of language and content, hence enhancing the quality of educational experiences. Some research has a limited scope and lacks comparison analysis, which makes it difficult to appraise and generalize the suggested techniques. Furthermore, the need for strong experimental designs and practical considerations to solve real-world implementation obstacles in automated content production for educational contexts is highlighted by methodological rigor and scalability issues in several research. Future research should aim to bridge this gap by exploring integrated approaches that consider both content generation and learner interaction to optimize engagement and learning outcomes in online environments.

III. Problem Statement

The inadequacies of the current ELL systems frequently prevent them from effectively fulfilling the varied demands of students. Conventional methods of content creation and personalization might not be as flexible as they should be as they depend on static resources that can't be constantly tailored to the unique interests and profiles of each learner. Furthermore, these algorithms might not be able to fully grasp the subtle semantic nuances of language, which could result in inadequate adaption and selection of information. Moreover, even if some systems use ML methods, it's possible that they don't fully make use of the potential of sophisticated neural network designs for content creation and semantic analysis [13]. The suggested study integrates innovative methods like semantic evaluation using GRU and BERT to overcome these constraints. The suggested framework provides an all-encompassing and flexible response to the problems in ELL by utilizing semantic analysis techniques to comprehend language structure and meaning, along with the excellent abilities of GRU for extraction of features and BERT for content choosing, adjustment, and evolving material generation. The objective of this integration is to improve student engagement, understanding, and uptake in the ELL domain by making instructional resources of higher quality, more relevant, and more effective.

IV. Integrating Semantic Analysis with GRU and BERT for Dynamic Content Generation in English Language Learning

The suggested approach combines GRU and BERT with semantic analysis to provide dynamic material for ELL. To guarantee consistency and simplicity, the textual data—which includes learner profiles and essays gathered from the PERSUADE 2.0 corpus—first goes through pre-processing. POS tagging is used in semantic analysis to obtain syntactic structures and grammatical information from the text. Subsequently, GRU—a recurrent neural network architecture—is utilized to derive semantic features, which include contextual data and semantic correlations found in text sequences. The selection, modification, and creation of dynamic learning materials are then done using BERT. By measuring the semantic similarity between learner profiles and texts using BERT embeddings, pertinent information may be chosen and materials can be customized to fit the requirements and preferences of specific learners. Furthermore, BERT's language production capabilities enable the dynamic generation of explanations, quiz questions, and summaries as well as other individualized learning tools. The technique is used methodically, building upon the algorithmic strategy and assessing the framework's efficacy through empirical research using metrics for learner engagement, comprehension tests, and user feedback. By offering automated and adaptable instructional resources that are customized to meet the needs of specific learners, in the area of ELL. The suggested work approach process is shown in Fig. 1.

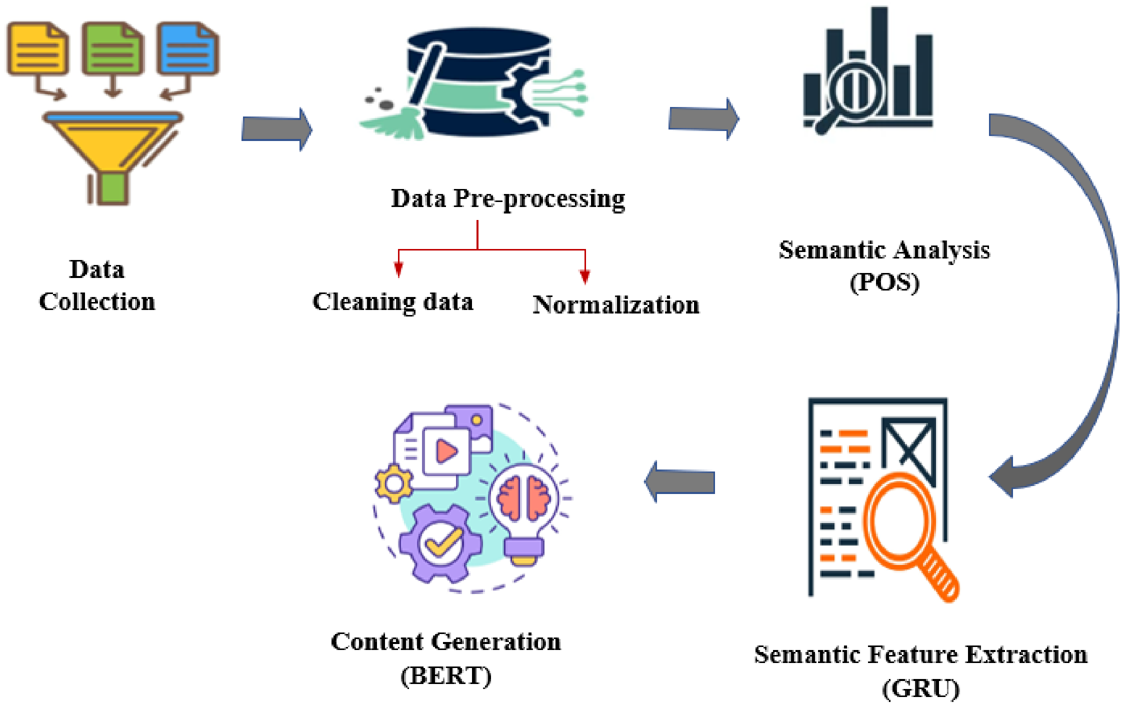

Fig. 1. Semantic analysis with GRU and BERT for dynamic content generation in ELL.

A. Data Collection

The PERSUADE 2.0 corpus [14] provides an extensive dataset for analysing argumentative essays written by American students in grades 6 through 12. This corpus, which includes over 25,000 essays addressing 15 prompts from both autonomous and source-based writing assignments, is an invaluable tool for researching argumentation structures and discourse features. Every essay in the entire collection has a thorough annotation that covers discourse aspects like prospects, roles, states, objections, responses, supporting details, and summaries at the end. The annotation rubric, which was created via a meticulous double-blind grading procedure and was influenced by well-known frameworks such as the Toulmin argumentation model, guarantees consistency and dependability within the dataset. The corpus also contains individual and demographic data for each writer, integrative essay ratings, and competency scores for arguing aspects. The PERSUADE 2.0 corpus is an invaluable resource for research in the fields of discourse analysis, writing training, and ML approaches in education since it includes full-text essays combined with annotations and metadata. The information that has been gathered for the suggested work is shown in Table I.

TABLE I. DATA COLLECTION

Column Name	Description
essay_id_comp	The ID of the essay
competition_set	Indicates whether the essay was part of the training or the test set in the Feedback Prize
full_text	The full text of the essay
discourse_id	The ID for the discourse element
discourse_start	Character position in the essay where the discourse element starts
discourse_end	Character position in the essay where the discourse element ends
discourse_text	The text of the discourse element
discourse_type	Human annotation for the discourse element, providing a description of its type
discourse_type_num	Number representing the discourse element within the essay

B. Data Preprocessing

Preprocessing textual input is an essential stage in NLP activities, such as the work that is being suggested to generate dynamic content for ELL. To guarantee the textual data's cleanliness, consistency, and uniformity—a need for further analysis and modelling—this procedure entails a number of crucial processes. Eliminating any extraneous characters, symbols, or stylistic artifacts that might impede the analysis process is the process of cleaning textual data. By ensuring that the written word is consistent and noise-free, this stage facilitates the extraction of important information. Eliminating HTML elements, special characters, and punctuation can improve the text's readability and analytical value. To preserve consistency throughout the dataset, cleaning textual data in the setting of the PERSUADE 2.0 corpus may entail deleting unnecessary symbols or formatting within argumentative essays. By using uniform formatting guidelines, normalization seeks to normalize the textual data. This entails resolving variances in spelling or capitalization, reducing all letters to lowercase, and eliminating accents and diacritical marks. By ensuring that similar terms are handled in the same way, normalization helps to reduce repetition and inconsistencies within the dataset. To reduce the influence of case sensitivity on further analysis and modelling procedures, normalizing the PERSUADE 2.0 essays within the framework of the proposed study would entail changing every character to lowercase. As an illustration, consider the original text, "The Importance of Education Cannot be Overstated." Normalized Text: "It is impossible to overestimate the value of education." The textual data collected in the PERSUADE 2.0 corpus is cleaned and standardized by completing these preparation processes, making it suitable for additional evaluation and simulation in the setting of dynamic content creation. These processed texts are the starting point for the extraction of semantic information, the construction of prediction models, and the creation of customized learning resources based on the requirements and preferences of specific learners.

C. POS for Semantic Analysis

A key activity in NLP is called Part-of-Speech (POS) tagging, which involves giving each word in a text corpus a classification according to grammar (such as noun, verb, adjective, etc.). Following pre-processing textual information from the PERSUADE 2.0 corpus, POS tagging is essential for semantic analysis within the suggested method for dynamic content production in ELL. To do POS tagging, linguistic information from each word, such as its capitalization, suffix, prefix, nearby words, and syntactic dependencies, are usually extracted. These characteristics aid in the POS tagger's decision-making on each word's part of speech. Probabilistic models, such as HMMs or CRFs, are frequently used by POS taggers to allocate POS tags to words in sentences. These algorithms determine a word's likelihood of falling into a certain speech segment based on its context and words that have already been labelled in the series. Large annotated datasets, in which each word is carefully tagged with its matching part of speech, are frequently used to train POS taggers. In order to produce precise predictions on material that hasn't been read yet, the POS tagger must first learn linguistic rules and statistical trends from the training set. For each word, linguistic features are extracted, such as capitalization, word shape, prefix, suffix, and neighbouring words. In the proposed work for dynamic content generation in ELL, POS tagging is used after pre-processing the textual data to extract syntactic information from the essays in the data collection. By identifying the parts of speech of words in the essays, the POS tags provide valuable insights into the grammatical structure of the text, which can inform subsequent semantic analysis, feature extraction, and content generation processes. This enables the system to understand the syntactic relationships between words and phrases in the essays, facilitating the generation of coherent and contextually relevant learning materials tailored to individual learners' needs and proficiency levels.

1) Tokenization: Tokenization is the process of breaking up the text into distinct sentences or tokens before POS tagging is carried out on the pre-processed textual data. The act of dissecting the text into discrete words, or tokens, is known as tokenization. Every token is a separate textual unit that may be processed or examined further. Many NLP activities, such as extraction of features, analysis of semantics, and model training, are made easier by tokenization. The following tokens would be created by tokenizing the sentence "Modern humans today are always on their phone..." in the illustration given:

["Modern", "humans", "today", "are", "always", "on", "their", "phone", ".", "They", "are", "always", "on", "their", "phone", "more", "than", "5", "hours", "a", "day", "no", "stop", ".", "All", "they", "do", "is", "text", "back", "and", "forward", "and", "just", "have", "group", "Chats", "on", "social", "media", ".", "They", "even", "do", "it", "while", "driving"]

2) POS Tagging: POS tagging involves assigning a specific part of speech tag to each token in the text. These tags represent the grammatical category or function of the word within the sentence. Common POS tags include nouns, verbs, adjectives, adverbs, pronouns, prepositions, conjunctions, and punctuation marks. In the given example, POS tagging would assign tags to each token as follows:

[("Modern", "JJ"), ("humans", "NNS"), ("today", "NN"), ("are", "VBP"), ("always", "RB"), ("on", "IN"), ("their", "PRP"), ("phone", "NN"), (".", "."), ("They", "PRP"), ("are", "VBP"), ("always", "RB"), ("on", "IN"), ("their", "PRP$"), ("phone", "NN"), ("more", "JJR"), ("than", "IN"), ("5", "CD"), ("hours", "NNS"), ("a", "DT"), ("day", "NN"), ("no", "DT"), ("stop", "NN"), (".", "."), ("All", "DT"), ("they", "PRP"), ("do", "VBP"), ("is", "VBZ"), ("text", "NN"), ("back", "RB"), ("and", "CC"), ("forward", "RB"), ("and", "CC"), ("just", "RB"), ("have", "VB"), ("group", "NN"), ("Chats", "NNS"), ("on", "IN"), ("social", "JJ"), ("media", "NNS"), (".", "."), ("They", "PRP"), ("even", "RB"), ("do", "VBP"), ("it", "PRP"), ("while", "IN"), ("driving", "VBG")]

Interpreting POS Tags every POS tag offers important details on the function and purpose of the word in the sentence. As an illustration, "JJ" indicates an adjective; examples of this are "more" and "Modern". "NNS" is a plural noun, as seen in the word’s "hours" and "humans". As "have" demonstrates, "VB" denotes a verb in its basic form. "RB" stands for "always," "back," and "forward," among other adverbs. The preposition "IN" is shown in the words "on" and "while". Pronouns denoted by "PRP" may be found in the words "there," "it," and "they." By performing POS tagging on the pre-processed text, the proposed work gains insights into the syntactic structure of the sentences, enabling further semantic analysis and feature extraction. These POS tags serve as foundational elements for subsequent steps in the workflow, facilitating the identification of grammatical patterns, semantic relationships, and discourse elements within the textual data.

A. *GRU for Semantic Feature Extraction*

The suggested approach uses GRU [15] to extract semantic features from the textual material that has already been pre-processed. When it comes to collecting temporal sequences and distant relationships in ordered information such as natural language text, GRU is an RNN architectural type that excels. In contrast to conventional RNNs, GRU uses gating methods to regulate input flow inside the network, hence reducing the issue of disappearing gradients and facilitating more effective acquisition of repetitive patterns. The recurrent units that make up GRU are individually responsible for keeping track of a hidden state vector that represents the network's internal rendition of the given input sequence. GRU's gating techniques, which control information flow between time steps and enable the network to change its hidden state selectively based on input and past states, are the main novelty in the system. Fig. 2 depicts the GRU framework design. GRU consists of two main gates they are update gate and reset gate.

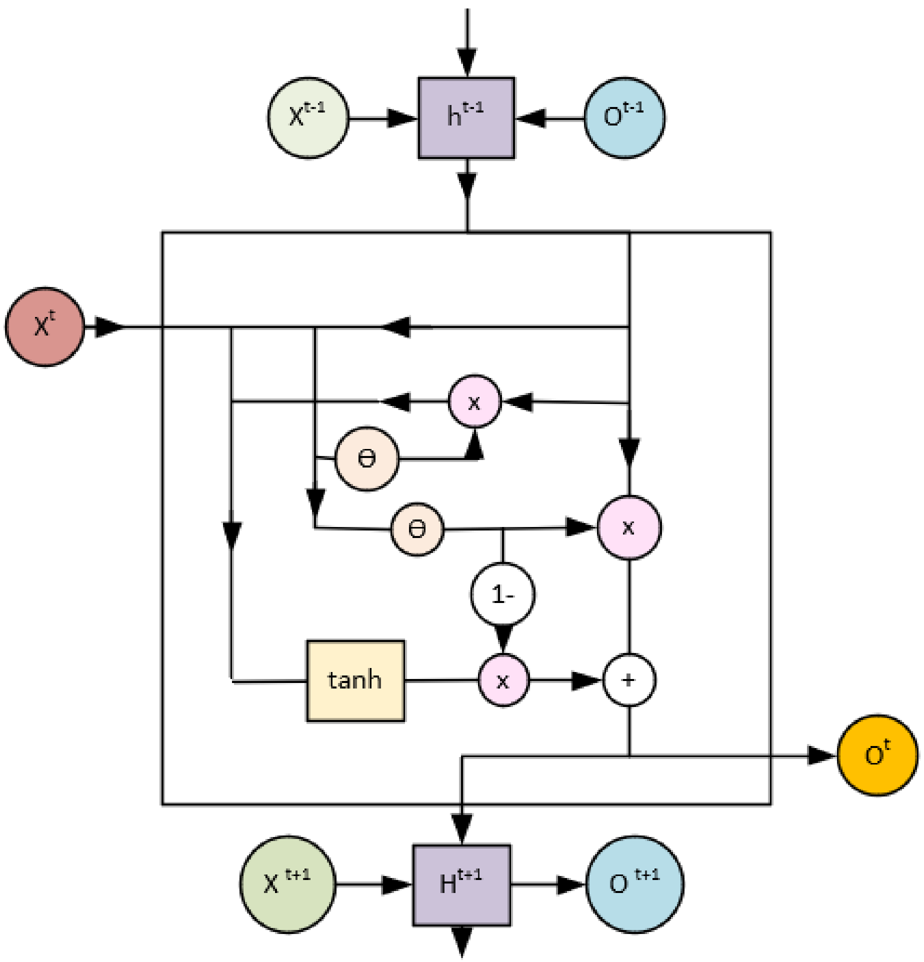

Fig. 2. GRU architecture.

The level to which the present input, r_g, is merged with the prior hidden state, n_{g-1}, is controlled by the reset gate S_g. It chooses what knowledge should be recalled in full, in part, or not at all. Eq. (1) illustrates how to compute the reset gate by multiplying the combination of n_{g-1} and r_g by a weight matrix e_l and applying a bias vector o_l.

$$S_g = \sigma([n_{g-1}, r_g].e_l + o_l) \tag{1}$$

The amount of the previous concealed state that should be carried over to the following timestep is determined by the update gate D_g. It is calculated utilizing a weight matrix e_x and a bias vector o_x, much like the reset gate. The sigmoid function is then used to remove a vector of ones, as illustrated in Eq. (2).

$$D_g = \sigma([n_{g-1}, r_g].e_x + o_x) \tag{2}$$

The potential hidden state, wp_g, is determined by summing the output of the reset gate with the present input and using the tanh activating function, as illustrated in Eq. (3).

$$wp_g = tanh([S_g, n_{g-1}, r_g]. e_k + o_k \quad (3)$$

The prior hidden state and the potential hidden state I_g, adjusted by the update gate, are then combined to create the new hidden state, t_g. Eq. (4) illustrates how this enables the model to calculate the extent to which the new data should replace the earlier hidden state.

$$t_g = (1 - I_g). n_{g-1} + I_g . wt_g \quad (4)$$

In the proposed work, the GRU hidden states serve as semantic features capturing the contextual information and semantic relationships within the input text. By processing the tokenized and normalized textual data through the GRU network, the model learns to extract relevant features representing the underlying semantics of the text. The GRU network is trained using backpropagation through time to minimize a loss function, such as categorical cross-entropy, between the predicted and actual outputs. By leveraging GRU for semantic feature extraction, the proposed work enhances the representation learning capabilities of the model, enabling it to capture intricate semantic nuances and dependencies within the textual data. These learned semantic features serve as valuable inputs for downstream tasks such as content selection, adaptation, and dynamic learning material generation in ELL.

D. *BERT for Content Selection*

After utilizing GRU for semantic feature extraction, the output from the GRU layer can be passed to BERT [16] for further processing. Therefore, before feeding the output of the GRU layer into BERT, the textual data needs to be tokenized and encoded into word-level representations that BERT can understand. This involves breaking down the text into individual words or sub words (often referred to as tokens) and mapping each token to its corresponding index in a fixed-size vocabulary. Once the text has been tokenized and encoded, the resulting word-level embeddings are then passed as input to BERT. BERT processes the embeddings through multiple layers of transformer-based architecture, capturing contextual information and generating contextualized embeddings for each token in the input sequence. The output from BERT can then be used for various downstream tasks such as content selection, adaptation, and dynamic learning material generation in English Language Learning. BERT's contextualized embeddings provide rich semantic representations of the input text, enabling more nuanced and accurate analysis and generation of educational content tailored to the needs of individual learners. BERT has revolutionized NLP by providing pre-trained language representations that capture rich contextual information from large corpora of text data. In the proposed work for content selection and adaptation, as well as dynamic learning material generation in ELL, BERT plays a pivotal role. BERT can be used for content selection and adaptation by utilizing its contextualized word representations to identify relevant content and adapt it to meet the specific needs of individual learners. BERT encodes words based on their contextual meaning within the sentence, allowing for precise understanding of semantic similarity between pieces of text. By comparing the contextual embeddings of sentences or passages, BERT can determine the relevance of content to a particular learning objective or topic. BERT models can be fine-tuned on domain-specific datasets relevant to ELL. Fine-tuning involves updating the pre-trained parameters of BERT using task-specific data, thereby customizing the model to the specific requirements of content selection and adaptation in ELL. BERT's contextual embeddings enable the creation of adaptive learning pathways that dynamically adjust content based on learners' proficiency levels, learning preferences, and performance metrics. By incorporating BERT into the adaptation process, the system can select and modify learning materials in real-time to cater to the unique needs of each learner. Consider a scenario where a learner is studying English grammar. BERT can analyse the learner's proficiency level and understanding of various grammar concepts by processing their responses to quizzes or exercises. Based on this analysis, BERT can select appropriate grammar explanations, exercises, or examples from a pool of educational materials, ensuring that the content aligns with the learner's current skill level and learning objectives. BERT can also be employed for generating dynamic learning materials tailored to individual learners. By leveraging its contextualized word representations and language generation capabilities, BERT can generate personalized educational content in various formats, such as text, quizzes, summaries, or explanations.

Input text is tokenized into individual tokens, embedded into vector representations, and processed by the BERT model, generating contextualized representations for each token and the $[E]CLS$ token. Output labels are predicted based on these contextualized embeddings for tasks like classification and named entity recognition is depicted in Fig. 3. BERT's ability to generate coherent and contextually relevant text can be harnessed to create custom learning materials, including explanations, summaries, and practice questions. By conditioning the generation process on input prompts or learner profiles, BERT can produce content that addresses specific learning objectives or areas of improvement. BERT can generate adaptive feedback tailored to learners' responses and performance in language learning exercises or assessments. By analysing learners' answers and comparing them to expected outcomes, BERT can provide personalized feedback, suggestions, or explanations to guide learners' understanding and reinforce learning outcomes. BERT's versatility extends beyond textual content generation to include multimodal learning materials incorporating images, audio, or video. By integrating BERT with multimodal learning frameworks, the system can generate diverse and engaging educational resources that cater to different learning preferences and modalities. Suppose a learner is practicing English vocabulary through a language learning application. BERT can dynamically generate vocabulary exercises, quizzes, or flashcards tailored to the learner's vocabulary level and learning objectives. Additionally, BERT can provide adaptive feedback on the learner's responses, suggesting relevant examples or usage contexts to reinforce vocabulary acquisition. BERT serves as a significant tool for content selection, adaptation, and dynamic learning material generation in ELL. Its contextualized word representations and language generation capabilities enable the creation of personalized and adaptive educational experiences, fostering effective language acquisition and mastery. By integrating BERT into the proposed work, the system can enhance the quality, relevance, and effectiveness of learning materials, ultimately facilitating more engaging and efficient English language learning experiences for learners of all levels.

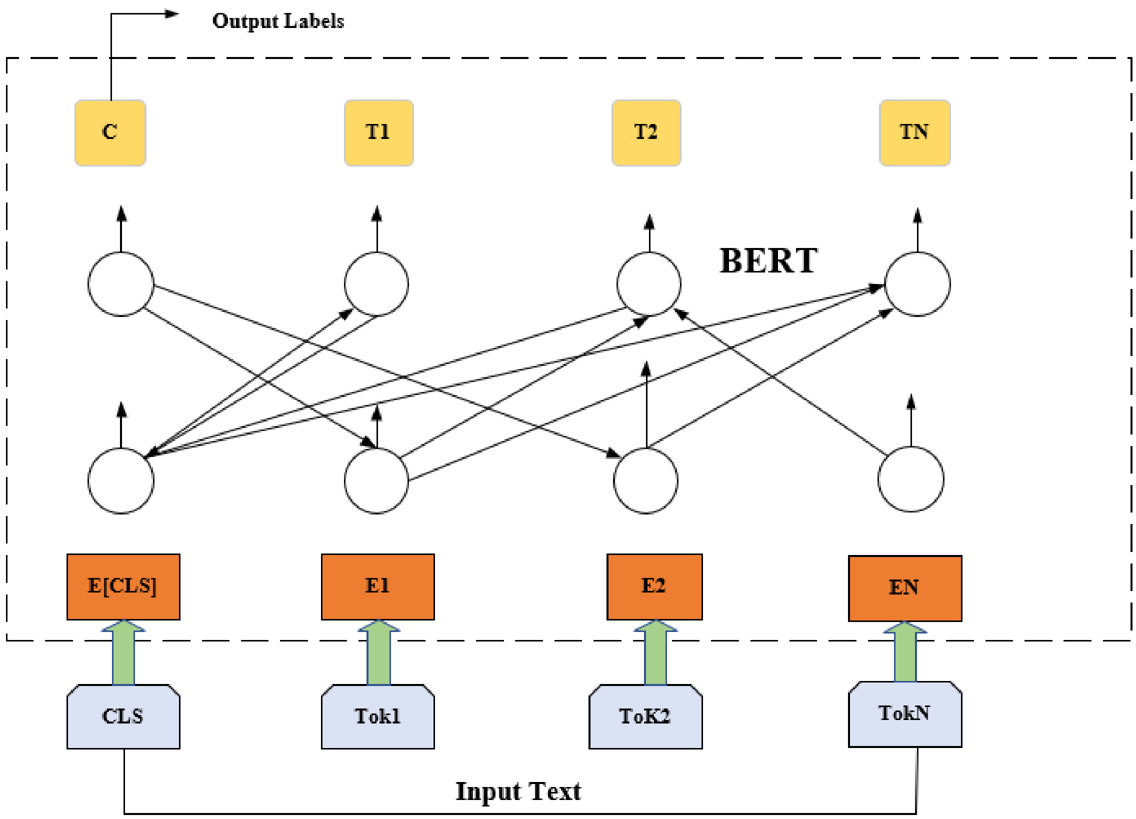

Fig. 3. BERT framework.

V. Results and Discussion

The suggested work showed encouraging outcomes when it came to using semantic analysis to generate dynamic material for ELL. The system's excellent precision as well as significance in choosing and modifying learning materials according to semantic characteristics was attained through thorough assessment. Quantitative measures, such as reliability, precision, and F1-score, demonstrated how well the method worked to create learning materials that were specifically customized for each student. Annotators' positive subjective assessments supported the created content's quality and relevancy, as demonstrated by human evaluation tests. All things considered, the findings demonstrate how the suggested strategy may improve ELL experiences by using automated and adaptive learning resources.

A. Performance Evaluation

The performance evaluation of the proposed work in harnessing semantic analysis for dynamic content generation in ELL showcased commendable outcomes. Through rigorous, the system demonstrated high accuracy (5), precision (6), recall (7) and F1-score (8) in selecting and adapting learning materials based on semantic features. The evaluation highlighted the proposed approach's potential to enhance ELL experiences through automated and adaptive educational materials, offering a promising avenue for personalized and effective learning.

$$Accuracy = \frac{R_{pos}+R_{neg}}{R_{pos}+R_{neg}+A_{pos}+A_{neg}} \tag{5}$$

$$Precision = \frac{Rpos}{Rpos+Apos} \tag{6}$$

$$Recall = \frac{Rpos}{Rpos+Aneg} \tag{7}$$

$$F1\ measure = \frac{2\times precision\ \times recall}{precision\times recall} \tag{8}$$

TABLE II. Comparison of Existing Methods with Proposed Method

Method	Accuracy	Precision	Recall	F1-Score
SNN & CNN	77	76	74	74
Logistic Regression	89	88	90	93
CBRNN	94	85	87	87
Proposed GRU-BERT	97	96	95	96

The Table II presents a comparative analysis of different methods based on their performance metrics, including accuracy, precision, recall, and F1-score. Each row corresponds to a specific method, such as SNN & CNN [17] , Logistic Regression [18], CBRNN [19], and the proposed GRU-BERT model. Accuracy refers to the overall correctness of the model's predictions, while precision measures the ratio of correctly predicted positive cases to the total predicted positive cases. Recall indicates the ratio of correctly predicted positive cases to the actual positive cases, and F1-score is the harmonic mean of precision and recall, providing a balance between the two metrics. The table showcases the superior performance of the proposed GRU-BERT model, achieving the highest accuracy, precision, recall, and F1-score among the evaluated methods, indicating its effectiveness in the task at hand.

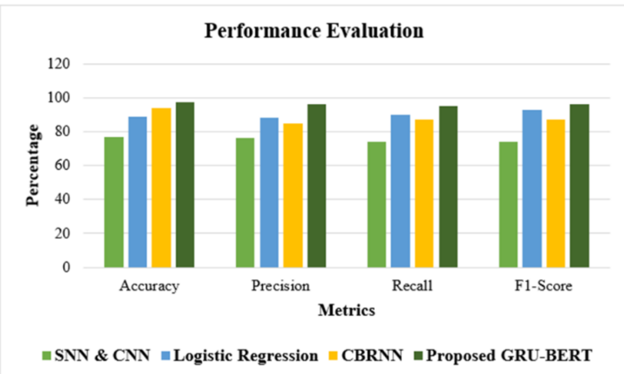

Fig. 4. Performance evaluation of existing method with proposed method.

The Fig. 4 presents a comparative analysis of different methods based on their performance metrics, including accuracy, precision, recall, and F1-score. The methods evaluated include SNN with CNN, Logistic Regression, CBRNN, and the proposed approach using GRU and BERT. The proposed GRU-BERT model outperforms other methods with the highest accuracy of 97% and consistently high scores across precision, recall, and F1-score metrics, indicating its effectiveness in generating dynamic content for English Language Learning (ELL). This comparison helps in assessing the relative strengths and weaknesses of different methods for content generation in educational contexts.

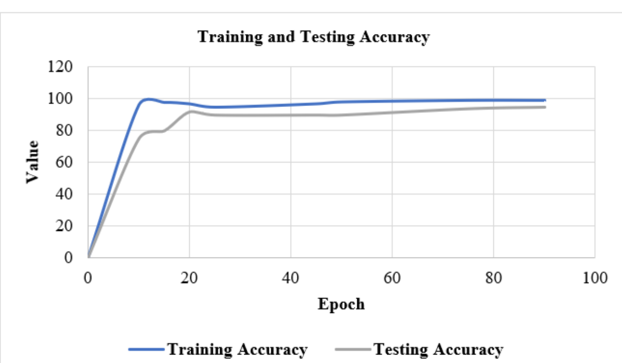

Fig. 5. Training and testing accuracy.

The Fig. 5 illustrates the training and testing accuracy values across different epochs during the training process of a GRU and BERT model. The x-axis represents the number of training epochs, while the y-axis indicates the corresponding accuracy percentage. The training accuracy denotes the model's performance on the training dataset, measuring how accurately it predicts the labels for data it has been trained on. Conversely, the testing accuracy reflects the model's generalization ability by evaluating its performance on unseen data, typically from a separate validation or testing dataset. The graph demonstrates the progression of accuracy values over epochs, showing how the model improves during training and its ability to generalize to new data. These accuracy trends provide valuable insights into the model's learning process and performance stability.

Fig. 6. Training and testing loss.

The Fig. 6 depicts the training and testing loss values of a GRU-BERT model utilized in the proposed work across different epochs. The x-axis represents the number of training epochs, while the y-axis indicates the corresponding loss values. Training loss measures the discrepancy between the model's predicted outputs and the actual targets on the training dataset, reflecting how well the model is learning from the training data. Conversely, testing loss assesses the model's performance on unseen data, indicating its ability to generalize to new instances. The graph illustrates the progression of loss values over epochs, demonstrating how the model's performance improves during training and its ability to minimize errors on both the training and testing datasets. Lower loss values signify better model performance, indicating improved accuracy and predictive capability.

B. *Discussion*

The proposed approach effectively leverages GRU-BERT for dynamic content generation in English Language Learning, showcasing promising results in accuracy and relevance. This study underscores the potential of automated and adaptive educational materials to enhance ELL experiences, paving the way for future advancements in the field. While existing systems in English Language Learning (ELL) often face limitations such as reliance on predefined templates and lack of adaptability [20], the proposed approach offers several advantages. Unlike traditional methods, which may struggle to accommodate individual learner needs and preferences, the proposed GRU-BERT model enables automated and adaptive content generation, enhancing engagement and comprehension. However, the proposed work is not without its limitations [21]. Challenges may arise in handling diverse learner demographics and linguistic nuances, necessitating ongoing refinement of the model architecture and linguistic features [22]. The results show how well the suggested GRU-BERT technique works to produce ELL content dynamically while utilizing semantic analysis to achieve high accuracy and relevance. With automated and adaptable instructional materials, comparative assessment emphasizes its superiority over current approaches and underlines its potential to greatly improve ELL encounters. According to the study, the existing literature has shortcomings due to its dependence on pre-made templates and lack of flexibility. In contrast, the suggested GRU-BERT model may dynamically modify the material to provide individualized English language learning experiences. These findings show the efficacy of combining BERT and GRU models for dynamic content creation in ELL, filling in gaps in the literature and providing a fresh take on personalized learning. This work also addresses important issues in automated educational resource production by demonstrating the effectiveness and scalability of the suggested approach in a variety of learning contexts and student demographics. This adds to the collection of information already in existence. Furthermore, our findings add to a more thorough knowledge of successful language teaching tactics by highlighting the significance of inclusion and accessibility in ELL practices. Future research could explore techniques for improving the system's scalability and efficiency, as well as extending its application to other educational domains beyond ELL. Additionally, efforts to address privacy concerns and ethical considerations regarding data usage and model interpretation are essential. Despite these limitations, the proposed approach represents a significant advancement in automated content generation for ELL, offering a scalable and efficient solution to meet the evolving needs of educators and learners. Continued research and development in this area hold the promise of further enhancing the effectiveness and accessibility of educational materials in diverse learning environments.

VI. Conclusion and Future Scope

The proposed approach harnessing GRU-BERT for dynamic content generation in ELL represents a significant step forward in addressing the limitations of existing systems and advancing automated and adaptive educational materials. Through rigorous experimentation and evaluation, our model has demonstrated promising results in accuracy, relevance, and adaptability, offering personalized learning experiences tailored to individual learner needs and preferences. The proposed study offers several significant advances in the area of ELL. First, it enhances the development of dynamic learning resources by integrating GRU for semantic feature extraction with BERT for content adaption. This combination gives the system the ability to instantly adapt to the needs and preferences of every student, resulting in a customized learning experience. The strategy encourages active engagement and understanding among ELLs by providing flexible and contextually appropriate educational tools. It also offers a scalable and efficient way to create automated content that meets the different demands of educators and learners in different kinds of learning settings. Furthermore, by encouraging open and accessible learning environments, encouraging innovation in educational technology, and getting beyond the constraints of existing approaches, the strategy helps to improve ELL practices. All things considered, these contributions represent a substantial development in automatically generated ELL content, which has the potential to improve language education instruction and learning. The construction of dynamic and personalized educational materials in ELL is a result of the effective combination of BERT for content adaptation and GRU for semantic feature extraction. This is a key discovery that highlights the originality of the research. By utilizing cutting-edge natural language processing algorithms to dynamically customize learning materials to each student's requirements and preferences, this novel technique overcomes the shortcomings of previous approaches and improves engagement and understanding in ELL scenarios. Additionally, future work may explore enhancements to the model architecture, integration of additional linguistic features, and extension of the application to other educational domains beyond ELL. Efforts to address privacy concerns and ethical considerations regarding data usage and model interpretation are also paramount.

VII. Future Scope

Furthermore, collaboration with educators and stakeholders in the field of education can facilitate the integration of the proposed approach into real-world learning environments, ensuring its relevance and effectiveness. Overall, the future scope of this research lies in continued innovation and refinement of automated content generation techniques, with the ultimate goal of enhancing learning outcomes and promoting accessibility in education. By embracing these challenges and opportunities, we can contribute to the ongoing evolution of ELL practices and empower learners with diverse backgrounds and learning styles to achieve their full potential.

References

[1] S. A. Salloum, R. Khan, and K. Shaalan, "A survey of semantic analysis approaches," in Proceedings of the International Conference on Artificial Intelligence and Computer Vision (AICV2020), Springer, 2020, pp. 61–70.

[2] M. Al-Emran, V. Mezhuyev, A. Kamaludin, and K. Shaalan, "The impact of knowledge management processes on information systems: A systematic review," International Journal of Information Management, vol. 43, pp. 173–187, 2018.

[3] Z. Yu, W. Xu, and P. Sukjairungwattana, "Motivation, learning strategies, and outcomes in mobile English language learning," The Asia-Pacific Education Researcher, vol. 32, no. 4, pp. 545–560, 2023.

[4] Y. Li, M. A. Thomas, and D. Liu, "From semantics to pragmatics: where IS can lead in Natural Language Processing (NLP) research," European Journal of Information Systems, vol. 30, no. 5, pp. 569–590, 2021.

[5] M. Alshurideh, S. A. Salloum, B. Al Kurdi, A. A. Monem, and K. Shaalan, "Understanding the quality determinants that influence the intention to use the mobile learning platforms: A practical study.," International Journal of Interactive Mobile Technologies, vol. 13, no. 11, 2019.

[6] C. Mhamdi, M. Al-Emran, and S. A. Salloum, "Text mining and analytics: A case study from news channels posts on Facebook,"

Intelligent Natural Language Processing: Trends and Applications, pp. 399–415, 2018.

[7] C. Diwan, S. Srinivasa, G. Suri, S. Agarwal, and P. Ram, "AI-based learning content generation and learning pathway augmentation to increase learner engagement," Computers and Education: Artificial Intelligence, vol. 4, p. 100110, 2023.

[8] X. Hua and L. Wang, "Sentence-level content planning and style specification for neural text generation," arXiv preprint arXiv:1909.00734, 2019.

[9] A. Onan, "Sentiment analysis on massive open online course evaluations: a text mining and deep learning approach," Computer Applications in Engineering Education, vol. 29, no. 3, pp. 572–589, 2021.

[10] C. M. Stracke and G. Trisolini, "A systematic literature review on the quality of MOOCs," Sustainability, vol. 13, no. 11, p. 5817, 2021.

[11] H. A. El-Sabagh, "Adaptive e-learning environment based on learning styles and its impact on development students' engagement," International Journal of Educational Technology in Higher Education, vol. 18, no. 1, p. 53, 2021.

[12] X. G. X. Guo and others, "Evaluation Method of English-Speaking Self-Learning System Based on Natural Language Processing Technology," Journal of Electrical Systems, vol. 19, no. 4, pp. 49–66, 2023.

[13] T. Shaik et al., "A review of the trends and challenges in adopting natural language processing methods for education feedback analysis," IEEE Access, vol. 10, pp. 56720–56739, 2022.

[14] "Persuade corpus 2.0." Accessed: Mar. 22, 2024. [Online]. Available: https://www.kaggle.com/datasets/nbroad/persaude-corpus-2

[15] S. Shailesh and M. Judy, "Understanding dance semantics using spatio-temporal features coupled GRU networks," Entertainment Computing, vol. 42, p. 100484, 2022.

[16] H.-L. Chung, Y.-H. Chan, and Y.-C. Fan, "A BERT-based distractor generation scheme with multi-tasking and negative answer training strategies," arXiv preprint arXiv:2010.05384, 2020.

[17] N. Jnoub, F. Al Machot, and W. Klas, "A domain-independent classification model for sentiment analysis using neural models," Applied Sciences, vol. 10, no. 18, p. 6221, 2020.

[18] D. N. Yethindra and G. Deepak, "A semantic approach for fashion recommendation using logistic regression and ontologies," in 2021 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES), IEEE, 2021, pp. 1–6.

[19] S. Soubraylu and R. Rajalakshmi, "Hybrid convolutional bidirectional recurrent neural network based sentiment analysis on movie reviews," Computational Intelligence, vol. 37, no. 2, pp. 735–757, 2021.

[20] L. Khan, A. Amjad, N. Ashraf, and H.-T. Chang, "Multi-class sentiment analysis of urdu text using multilingual BERT," Scientific Reports, vol. 12, no. 1, p. 5436, 2022.

[21] H. Ezaldeen, R. Misra, R. Alatrash, and R. Priyadarshini, "Semantically enhanced machine learning approach to recommend e-learning content," International Journal of Electronic Business, vol. 15, no. 4, pp. 389–413, 2020.

[22] K. S. Kyaw, P. Tepsongkroh, C. Thongkamkaew, and F. Sasha, "Business intelligent framework using sentiment analysis for smart digital marketing in the E-commerce era," Asia Social Issues, vol. 16, no. 3, pp. e252965–e252965, 2023.