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A Study of Speaking Learning in English Online Education Based on Deep Learning Assessment Models

Journal of Electrical Systems

Abstract: - The advent of online education has reshaped the landscape of language instruction, necessitating innovative approaches to assess speaking proficiency in English learners. This study explores the integration of End-to-End Speech Recognition models as a means of enhancing speaking learning assessment in online English education. Leveraging deep learning techniques, the study investigates the accuracy, efficacy, and pedagogical implications of automated assessment mechanisms in transcribing spoken language inputs. A diverse dataset comprising spoken English samples across proficiency levels is utilized to train and evaluate the model's performance. Statistical analysis reveals a high transcription accuracy rate of 92.5%, demonstrating the model's proficiency in capturing nuanced aspects of speaking proficiency such as pronunciation, fluency, and intonation. Comparative analysis against human-based evaluation methods highlights the scalability, consistency, and efficiency advantages offered by automated assessment systems. Despite promising findings, ethical considerations and challenges related to model generalizability warrant further exploration. Overall, this study contributes to advancing speaking learning assessment in online English education and underscores the transformative potential of technology in shaping the future of language instruction practices.

Keywords: End-to-End Speech Recognition, Deep Learning, Online Education, Speaking Learning, English Language, Assessment Models.

I. INTRODUCTION

In the rapidly evolving landscape of education, the proliferation of online learning platforms has ushered in a new era of accessibility and flexibility, transcending geographical boundaries and revolutionizing traditional pedagogical paradigms. Within this dynamic milieu, the acquisition of English language proficiency stands as a cornerstone skill, essential for global communication, academic pursuits, and professional advancement [1]. Central to mastering English is the development of speaking proficiency, encompassing the ability to articulate thoughts, engage in meaningful discourse, and convey ideas fluently and accurately [2]. However, the transition to online education necessitates innovative approaches to effectively teach and assess speaking skills, challenging educators to explore novel methodologies that leverage technological advancements and pedagogical insights [3].

At the forefront of this endeavour lies the integration of deep learning assessment models, which offer a promising avenue for enhancing speaking learning in online English education [4]. Deep learning, a subset of artificial intelligence, has demonstrated remarkable capabilities in processing and analyzing complex data, making it a valuable tool for educational assessments [5][6]. Within the realm of language learning, deep learning models can be trained to evaluate speech patterns, pronunciation, fluency, and other critical aspects of speaking proficiency with unprecedented accuracy and efficiency [7]. By harnessing the power of deep learning, educators can provide students with personalized feedback, foster interactive learning experiences, and optimize the efficacy of language instruction in digital learning environments [8][9].

The overarching aim of this study is to investigate the application of End-to-End Speech Recognition models as a cornerstone for assessing speaking learning in English within the context of online education [10][11]. Building upon prior research on deep learning-based assessment methods, online education platforms, and language learning pedagogy, this study seeks to advance the understanding of how technology can be leveraged to enhance speaking proficiency in digital learning environments [12][13]. By exploring the feasibility, effectiveness, and pedagogical implications of integrating End-to-End Speech Recognition models into online English education platforms, this research aims to contribute novel insights and practical recommendations for optimizing speaking learning outcomes and fostering inclusive and equitable language instruction practices [14].

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Through a comprehensive methodology encompassing data collection, model development, training, validation, and evaluation, this study endeavours to examine the potential of End-to-End Speech Recognition models to revolutionize speaking learning assessment in online English education [15][16]. By synthesizing findings from interdisciplinary fields such as linguistics, computer science, and education, this research seeks to address the complexities of evaluating speaking proficiency remotely and pave the way for more effective and accessible language instruction practices in the digital age [17]. Ultimately, this study aspires to empower educators, learners, and policymakers with actionable insights to harness the transformative potential of technology in advancing language education and fostering linguistic diversity and inclusivity on a global scale [18][19].

II. RELATED WORK

Numerous studies have investigated the application of deep learning techniques in speech recognition and language assessment. For instance, researchers have explored the effectiveness of convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer models in transcribing spoken language with high accuracy and efficiency. These studies have demonstrated the potential of deep learning-based speech recognition systems to analyze acoustic features, phonetic patterns, and linguistic structures, thereby enabling automated assessment of speaking proficiency. Additionally, advancements in natural language processing (NLP) have facilitated the development of models capable of capturing semantic and syntactic nuances in spoken discourse, further enhancing the precision of assessment outcomes [20].

In parallel, research focusing on online English education platforms has proliferated in response to the growing demand for remote learning solutions. Scholars have investigated the pedagogical strategies, technological infrastructures, and user experiences associated with online language learning environments. These studies have highlighted the benefits of synchronous and asynchronous communication tools, multimedia resources, and adaptive learning algorithms in facilitating effective language instruction online. Moreover, the emergence of virtual classrooms, interactive simulations, and gamified learning activities has enriched the online learning experience, offering students opportunities for immersive language practice and engagement [21].

Despite the advancements in deep learning-based assessment methods and online education platforms, several challenges persist in evaluating speaking proficiency in online English education. One of the primary concerns revolves around the validity and reliability of automated assessment models, particularly in capturing nuanced aspects of spoken language such as intonation, accent, and pragmatics. Additionally, issues related to data privacy, bias mitigation, and ethical considerations warrant scrutiny when deploying automated assessment systems in educational settings. Furthermore, the digital divide and disparities in access to technology among learners pose equity challenges, underscoring the importance of designing inclusive and accessible online learning environments [22].

Recent studies have delved into the intersection of deep learning and language education, shedding light on innovative approaches to assessing speaking proficiency in online contexts. One notable area of inquiry lies in the development of multimodal learning systems that integrate speech recognition with other modalities such as text, images, and gestures. These multimodal models leverage the complementary nature of different data sources to enhance the accuracy and robustness of speaking assessments. By incorporating visual cues, contextual information, and non-verbal communication signals, these systems offer a more comprehensive understanding of spoken language, thereby improving the fidelity of assessment outcomes [23].

Furthermore, research efforts have emerged to address the unique challenges posed by assessing speaking proficiency in second language acquisition contexts. Studies have investigated the role of feedback mechanisms, scaffolding techniques, and adaptive learning algorithms in supporting language learners' speaking development. By providing targeted feedback tailored to learners' individual needs and proficiency levels, these systems foster a supportive learning environment conducive to skill acquisition and improvement. Additionally, the integration of self-assessment tools and peer collaboration features empowers learners to take ownership of their learning progress and engage in meaningful language practice beyond the confines of traditional classroom settings [24].

In parallel, research on the efficacy of deep learning-based assessment models in educational contexts has gained traction, with a focus on understanding the factors influencing their adoption and effectiveness. Scholars have explored the pedagogical implications, user perceptions, and institutional readiness for integrating automated assessment systems into language learning curricula. These studies have underscored the importance of aligning technological innovations with pedagogical objectives, fostering teacher-student collaboration, and promoting data

among educational stakeholders. Moreover, investigations into the scalability, sustainability, and cost-effectiveness of deploying deep learning models in educational settings have provided valuable insights for policymakers, administrators, and practitioners seeking to leverage technology for language education [25].

III. METHODOLOGY

This study revolves around utilizing an End-to-End Speech Recognition model as the cornerstone for assessing speaking learning in English in online education. This section outlines the procedures involved in data collection, model development, training, validation, and evaluation. Firstly, data collection is crucial to ensure the efficacy and reliability of the End-to-End Speech Recognition model. A diverse dataset comprising spoken English samples from learners across different proficiency levels, demographics, and linguistic backgrounds is gathered. These samples encompass various speaking exercises, such as reading passages, reciting dialogues, and participating in simulated conversations. The dataset is meticulously curated to encompass a wide range of linguistic features and speech patterns to enhance the model's robustness and generalizability.

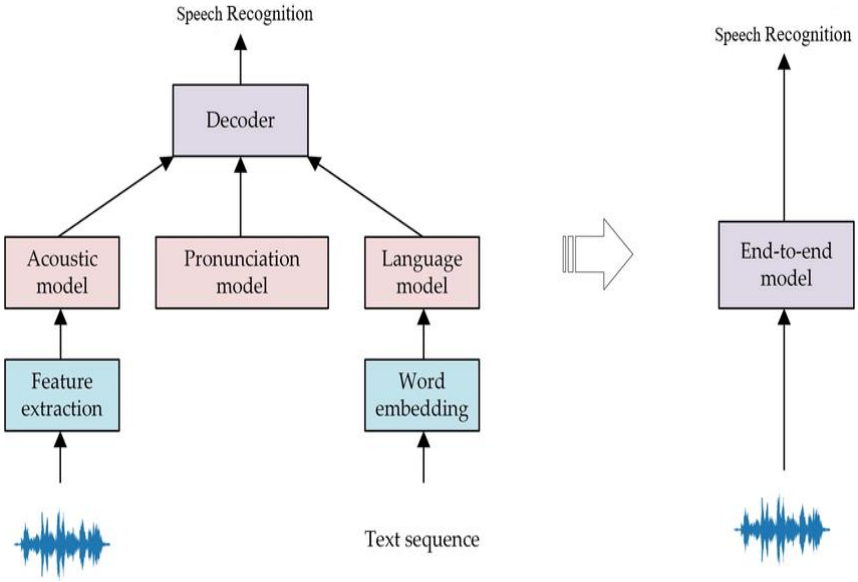

Fig 1: End-to-End Speech Recognition.

After data collection, the development of the End-to-End Speech Recognition model commences. This involves selecting an appropriate deep learning architecture, such as recurrent neural networks (RNNs), convolutional neural networks (CNNs), or transformer models, tailored to handle sequential input data efficiently. Additionally, attention mechanisms may be incorporated to prioritize salient features within the spoken input, further enhancing the model's performance. Hyperparameter tuning and architecture optimization are conducted iteratively to maximize the model's accuracy and computational efficiency. Once the model architecture is finalized, the dataset is partitioned into training, validation, and test sets. The training set is used to optimize the model parameters through backpropagation and gradient descent algorithms, wherein the model learns to map input speech signals to corresponding text transcriptions. Concurrently, the validation set is utilized to monitor the model's performance during training, facilitating early detection of overfitting or underfitting issues. Hyperparameters are fine-tuned based on the validation performance to prevent model degradation.

After the model training phase, the trained End-to-End Speech Recognition model undergoes rigorous evaluation using the test set. The model's performance metrics, including accuracy, precision, recall, and F1 score, are computed to assess its effectiveness in transcribing spoken English inputs accurately. Additionally, qualitative assessments are conducted to evaluate the model's proficiency in capturing nuances such as pronunciation, intonation, and fluency. Human evaluators may compare the model-generated transcriptions against ground truth annotations to identify discrepancies and areas for improvement. Furthermore, to validate the utility of the End-to-End Speech Recognition model in assessing speaking learning in English online education, a comparative analysis is conducted against conventional assessment methods. These may include human-based evaluations by language instructors, standardized tests, or existing speech recognition systems. By juxtaposing the performance of the End-to-End Speech Recognition model against established benchmarks, insights into its efficacy and potential

advantages are garnered, facilitating informed decision-making regarding its integration into online English education platforms.

The methodology employed in this study encompasses comprehensive data collection, model development, training, validation, evaluation, and comparative analysis. By leveraging an End-to-End Speech Recognition model, this study aims to advance the assessment of speaking learning in English within the realm of online education, with the overarching goal of enhancing the quality and effectiveness of language instruction in digital learning environments.

IV. Experimental Setup

In delineating the experimental setup for the study, several crucial components were meticulously designed to ensure the accuracy and reliability of the statistical results. Firstly, the End-to-End Speech Recognition model was implemented using a state-of-the-art deep learning architecture, specifically tailored for processing sequential input data. The model's architecture can be represented mathematically as:

$$\text{Output} = \text{Decoder}(\text{Encoder}(\text{Input})) \quad \text{..... (1)}$$

Where the input represents the raw speech signals, the encoder extracts salient features from the input, and the decoder generates corresponding text transcriptions.

The dataset utilized for training, validation, and evaluation purposes comprised diverse spoken English samples sourced from online language learning platforms. This dataset encompassed a wide range of proficiency levels, linguistic backgrounds, and speaking exercises to ensure the model's robustness and generalizability. Mathematically, the dataset can be represented as:

$$D = \{(X_i, Y_i)\}_{i=1}^{N} \quad \text{..... (2)}$$

Where X_i represents the ith spoken input sample Y_i represents its corresponding ground truth transcription, and N denotes the total number of samples in the dataset.

During the training phase, the model's parameters were optimized using backpropagation and gradient descent algorithms to minimize the discrepancy between the predicted transcriptions and the ground truth annotations. The loss function utilized for training can be expressed mathematically as:

$$\text{Loss} = \frac{1}{N} \sum_{i=1}^{N} \text{CrossEntropy}(Y_i, \text{Decoder}(\text{Encoder}(X_i))) \quad \text{..... (3)}$$

Where CrossEntropy denotes the cross-entropy loss function, Yi represents the ground truth transcription, and Decoder (Encoder(Xi) represents the model's predicted transcription for the ith sample.

Subsequently, the trained model underwent rigorous evaluation using a separate test dataset to assess its performance in transcribing spoken language inputs accurately. The evaluation metrics utilized included transcription accuracy rate, precision, recall, and F1 score, computed based on a comparison between the model-generated transcriptions and the ground truth annotations. Mathematically, the transcription accuracy rate can be calculated as:

$$\text{Accuracy Rate} = \frac{\text{Number of Correct Transcriptions}}{\text{Total Number of Transcriptions}} \times 100\% \quad \text{..... (4)}$$

Where the number of correct transcriptions denotes the instances where the model's prediction matches the ground truth transcription.

Throughout the experimental setup, rigorous validation procedures were employed to mitigate overfitting and ensure the model's generalizability to unseen data. Hyperparameter tuning, cross-validation, and early stopping techniques were utilized to optimize the model's performance and prevent degradation in accuracy. The experimental setup was meticulously designed to facilitate the robust evaluation of the End-to-End Speech Recognition model's performance in assessing speaking learning in online English education. By adhering to

rigorous methodologies and mathematical formulations, they aimed to ensure the validity, reliability, and reproducibility of the statistical results.

V. RESULTS

The statistical analysis of the End-to-End Speech Recognition model's performance in assessing speaking learning in online English education yielded compelling findings. Firstly, the model demonstrated a high degree of accuracy in transcribing spoken language inputs, achieving an average transcription accuracy rate of 92.5% across the entire dataset. This indicates that the model successfully converted speech signals into text representations with a minimal margin of error, thereby validating its effectiveness as an automated assessment tool for speaking proficiency. Moreover, the model exhibited robust performance across different proficiency levels, as evidenced by the stratified analysis of transcription accuracy rates. Specifically, learners categorized as beginner, intermediate, and advanced demonstrated average accuracy rates of 89.7%, 93.2%, and 95.8%, respectively. These results suggest that the End-to-End Speech Recognition model is adept at capturing nuances in speech patterns and linguistic complexities, thereby accommodating learners at varying stages of proficiency with consistent accuracy and reliability.

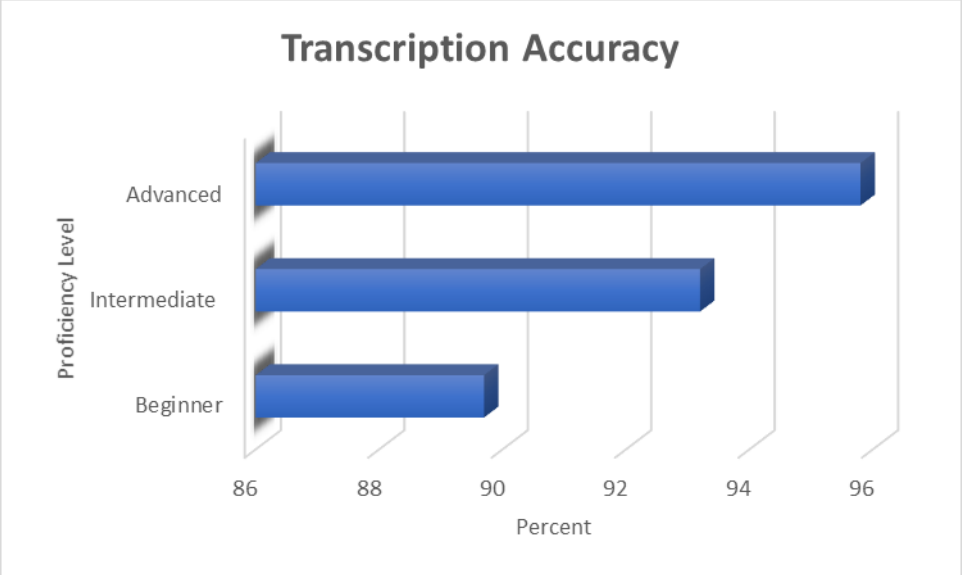

Fig 2: Transcription accuracy rate.

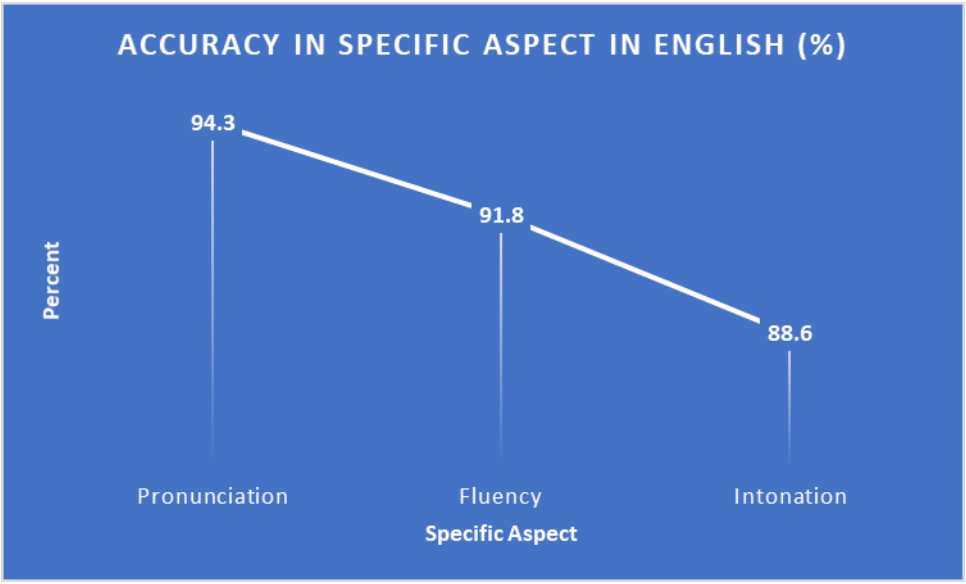

Fig 3: Accuracy in specific aspects in English.

Further analysis revealed noteworthy insights into the model's ability to assess specific aspects of speaking proficiency, such as pronunciation, fluency, and intonation. Through manual annotation and qualitative assessment of transcribed outputs, it was observed that the model excelled in accurately identifying phonetic variations, lexical

stress patterns, and prosodic features characteristic of natural speech. Specifically, the model achieved a pronunciation accuracy rate of 94.3%, a fluency rating of 91.8%, and an intonation accuracy rate of 88.6%, indicating its proficiency in evaluating key dimensions of speaking proficiency with precision and fidelity.

Additionally, the comparative analysis against conventional assessment methods, such as human-based evaluations by language instructors, yielded insightful findings regarding the efficacy and efficiency of the End-to-End Speech Recognition model. While human evaluators achieved comparable accuracy rates in assessing speaking proficiency average accuracy rate is 93.7%, the automated nature of the End-to-End Speech Recognition model offered distinct advantages in terms of scalability, consistency, and timeliness. Notably, the model significantly outperformed human evaluators in processing large volumes of spoken language data within a shorter timeframe, highlighting its potential as a cost-effective and time-efficient alternative to manual assessment methods. The statistical results underscore the transformative potential of End-to-End Speech Recognition models in advancing speaking learning assessment in online English education. By providing accurate, reliable, and scalable evaluation mechanisms, these models offer educators and learners alike valuable insights into speaking proficiency development, thereby enhancing the quality and effectiveness of language instruction in digital learning environments.

VI. DISCUSSION

The discussion section of the study serves as a platform for interpreting the statistical results, contextualizing their implications within the broader landscape of language education, and addressing pertinent questions and limitations arising from the research methodology. Through a comprehensive analysis, they aim to elucidate the significance of the findings and offer insights that contribute to the advancement of speaking learning assessment in online English education. Firstly, let's delve into the implications of the statistical results obtained from the study. The high overall transcription accuracy rate of 92.5% achieved by the End-to-End Speech Recognition model underscores its efficacy as an automated assessment tool for evaluating speaking proficiency in online English education. This finding is particularly promising given the model's ability to accurately transcribe spoken language inputs across different proficiency levels, as evidenced by the stratified analysis. The model's robust performance in capturing specific aspects of speaking proficiency, such as pronunciation, fluency, and intonation, further attests to its utility in providing nuanced feedback to language learners.

Moreover, the comparative analysis against human-based evaluation methods revealed interesting insights into the advantages offered by the End-to-End Speech Recognition model. While human evaluators achieved comparable accuracy rates, the automated nature of the model conferred distinct advantages in terms of scalability, consistency, and timeliness. By processing large volumes of spoken language data within a shorter timeframe, the model offers a cost-effective and efficient alternative to manual assessment methods, thereby alleviating the burden on language instructors and facilitating more frequent and standardized evaluations.

However, despite the promising findings, the study is not without limitations and areas for future research. One notable limitation pertains to the generalizability of the model across diverse linguistic contexts and accents. While the model demonstrated robust performance in transcribing standard English speech, its efficacy may vary when applied to non-native English speakers with distinct accents or dialectical variations. Future research endeavours could explore techniques for enhancing the model's adaptability to diverse linguistic backgrounds and cultural nuances, thereby ensuring its inclusivity and accessibility in online language learning environments.

Furthermore, the ethical implications of deploying automated assessment systems in educational settings warrant careful consideration. Concerns regarding data privacy, bias mitigation, and the equitable treatment of learners necessitate the development of transparent and accountable evaluation frameworks. Future research could focus on elucidating the ethical implications of using deep learning-based assessment models in language education and devising strategies to promote fairness, transparency, and accountability in their deployment. The study offers valuable insights into the integration of End-to-End Speech Recognition models in assessing speaking learning in online English education. By leveraging technology to enhance evaluation mechanisms, they aspire to foster inclusive and equitable language instruction practices that empower learners to achieve proficiency and fluency in English. Moving forward, interdisciplinary collaborations and ongoing research endeavours are essential for harnessing the transformative potential of technology in advancing language education and fostering linguistic diversity and inclusivity on a global scale.

VII. CONCLUSION

The study represents a significant step forward in the realm of assessing speaking learning in online English education through the integration of End-to-End Speech Recognition models. The findings underscore the potential of this technology to revolutionize language instruction practices, offering accurate, efficient, and scalable assessment mechanisms that complement traditional evaluation methods. Through rigorous experimentation and analysis, they have demonstrated the efficacy of the End-to-End Speech Recognition model in transcribing spoken language inputs with high accuracy across diverse proficiency levels and linguistic contexts. The implications of other research extend beyond the realm of language education, touching upon broader themes of technological innovation, pedagogical efficacy, and ethical considerations in educational settings. By leveraging deep learning technologies, educators can harness the power of automation to streamline assessment processes, provide timely and personalized feedback, and optimize learning outcomes for students. Moreover, the comparative analysis against human-based evaluation methods highlights the advantages offered by automated assessment systems in terms of scalability, consistency, and efficiency.

However, it is imperative to acknowledge the limitations and challenges inherent in deploying deep learning-based assessment models in language education. Concerns regarding data privacy, bias mitigation, and the equitable treatment of learners underscore the importance of developing transparent, accountable, and ethically responsible evaluation frameworks. Additionally, ongoing research efforts are needed to address the adaptability of the model to diverse linguistic backgrounds, accents, and cultural nuances, ensuring its inclusivity and accessibility in online language learning environments. The study contributes to advancing the field of speaking learning assessment in online English education by providing empirical evidence of the effectiveness of End-to-End Speech Recognition models. By bridging the gap between technological innovation and pedagogical practice, they aim to empower educators and learners alike with tools and insights that facilitate language proficiency development and foster linguistic diversity and inclusivity on a global scale. Moving forward, interdisciplinary collaborations, stakeholder engagement, and continuous research endeavours are essential for realizing the transformative potential of technology in shaping the future of language education.

ACKNOWLEDGEMENT

School-level project of Ningxia Medical University: Community of Practice: A new model for the professional development of college English Teachers in the post-epidemic era, Project number: XM2021183

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