TEXT READABILTY DETECTION FOR AI INTERVIEW VOICE BOT

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Abstract— The integration of artificial intelligence in the form of interview bots is revolutionizing the fields of recruitment, education, and customer service. A critical feature that enhances the effectiveness of these bots is text readability prediction, which assesses the complexity of user input and adjusts the bot's responses accordingly. This paper examines the significance of text readability prediction in interview bots, highlighting its role in improving user engagement, ensuring accessibility for individuals with diverse literacy levels, and providing personalized interactions. By tailoring responses to match the user's comprehension abilities, readability prediction not only enhances communication but also contributes to a more satisfying and efficient user experience. The implications of this technology are far-reaching, offering insights into how AI can be leveraged to create more adaptive and user-centric digital assistants.

Keywords— Text Readability, Interview Bot, User Engagement, Artificial Intelligence.

I. INTRODUCTION

In the age of artificial intelligence, interview bots are emerging as powerful tools in various domains, including recruitment, education, and customer service. These bots streamline processes, provide instant responses, and enhance user interactions. However, one of the primary challenges in developing effective interview bots is ensuring that they communicate clearly and appropriately with users of diverse backgrounds and literacy levels. This is where text readability prediction becomes crucial.

Text readability prediction involves analysing the complexity of written text to match it with the user's comprehension abilities. By integrating this feature, interview bots can adjust their language and tone, making responses more accessible and engaging for users. This adaptability not only improves communication but also enhances user satisfaction and experience. Effective readability prediction ensures that the bot can cater to a wide audience, including those with lower literacy levels or non-native speakers, thereby promoting inclusivity.

This paper delves into the significance of text readability prediction in the development of interview bots. It explores how this technology improves user engagement, accessibility, and personalization, ultimately leading to more effective and satisfying interactions. By leveraging readability prediction, interview bots can transcend mere functional roles to become sophisticated, user-centric digital assistants.

Another important section in the paper is Altenative Approaches on Data Sarcasm Detection, including the specific treatments for data sparsity, domain appropriability, and culture variances. Sarcasm detection systems have been useful in solving some problems but to excel further, we also assess the indicators employed to measure the systems' performance and note areas that need thorough investigation.

II. LITERATURE REVIEW

Sumegh Anglekar Et al [1] discusses a self-assessment tool for personality traits and interview preparation based on deep learning has been developed. Particularly in the context of different kinds of interviews, the tool seeks to assist people in analyzing their personality traits and suitability for distinct job profiles. In particular, sentiment analysis and natural language processing (NLP) algorithms are used in the paper to highlight the application of machine learning and artificial intelligence to personality trait analysis in interview scenarios like group discussions, scenario-based questions, video, and audio interviews.

Pasindu Senarathne Et al [2] has disscussed The creation and use of a Smart Interviewing System (SIS) that uses deep learning apps and Natural Language Processing (NLP) techniques to automate the conventional interviewing procedure. Interviewers and HR management staff conducting technology-related interviews stand to gain from the system's ability to translate human language into text-based inputs and evaluate candidate responses through deep learning. With the help of the SIS, interviewers should be able to pick qualified candidates with less effort and receive more accurate evaluations at each level of the interview process. The system was created with Python programming and the ReactJS Framework with the goal of reducing human error and locating the top candidates faster than with conventional interviewing techniques.

Ishita Chakraborty Et al [3] conducted a study, and this study uses conversational video interviews with many modalities to propose an AI and AI-human based model for salesforce hiring. With little measurement error, the AI model captures elements like two-way conversational engagement, real-time adaptation, and human body language to derive objective measurements of interviewees' sales effectiveness. The study forecasts the outcome variables of the AI model and isolates a candidate's "latent sales ability" based on sales experts' scores on a rubric. While the AI model can predict outcomes with a respectable degree of accuracy, adding human input to a hybrid AI-Human model improves performance by 67%. The study comes to the conclusion that the best way to improve performance at the lowest cost is to use human input based on the early phases of interviews, and that including one human professional evaluation in the hiring loop is ideal.

Rohan Patil, Et al [4] helps children develop their social skills for job interviews by simulating an employment interview using signal processing techniques and a social virtual character acting as a recruiter. The system consists of a 3D rendering environment, dialog/scenario manager, behavior manager, and real-time social cue identification system. Users can evaluate their performance with the aid of feedback such as speech rate, loudness, reaction time, facial preference, and head nodding. Grammar is checked by a speech-to-text system, and the findings are shown graphically. The method is comparable to tracking a candidate's development over several interviews.

Hung-Yue Suen Et al [5] aimed to predict each person's personality traits and interpersonal communication skills. 114 people were invited to participate in order to gather accurate information on their personality traits and communication skills. There were 57 interviewers and 57 interviewees. AVI-AI, an artificial intelligence (AI) decision agent built on a TensorFlow convolutional neural network (CNN), was used to create an asynchronous video interview platform. According to the experimental findings, AVI-AI can forecast a candidate's neuroticism, openness, agreeableness, and interpersonal communication abilities as judged by seasoned HR specialists. But it was unable to forecast extraversion and conscientiousness as judged by actual human raters.

B C Lee Et al. [6] This paper describes an AI-based interviewing system that was created with deep learning technology and used by five significant Korean public organizations. It has been demonstrated that the method, which makes use of more than 100,000 assessment data sets from 400,000 interview picture data sets, is effective and equitable in the market for job interviews. The system has attained high satisfaction levels of 85% in areas including work fitness, organizational fitness, and assessment procedures. Its dependability is 0.88 Pearson scores. The deep-learning-based job interview solution suggested in this study should be extended to written exams as well as personality and aptitude testing as AI-based solutions grow to encompass people management.

Sumegh Anglekar Et al [1] discusses a self-assessment tool for personality traits and interview preparation based on deep learning has been developed. Particularly in the context of different kinds of interviews, the tool seeks to assist people in analyzing their personality traits and suitability for distinct job profiles. In particular, sentiment analysis and natural language processing (NLP).

III. METHODOLOGY

DistilBERT:

Input Text Data:

The process begins with collecting raw text data that requires readability analysis. This data can be in the form of individual text snippets, paragraphs, articles, or any other text format. The primary objective at this stage is to ensure that the text data is appropriately formatted and ready for preprocessing.

Preprocess Text Data:

Preprocessing is a critical step that prepares the raw text data for model inference. This involves several sub-steps:

Tokenization: The text is split into tokens (words or sub words) using a tokenizer. For Distil BERT, a pre-trained tokenizer specific to the model is used. This step converts the text into a sequence of tokens that the model can process.

Lowercasing: In some cases, converting all text to lowercase can help in reducing variability in the text data.

Removing Punctuation: Stripping out punctuation may be beneficial, depending on the specific requirements of the readability analysis task. However, for DistilBERT, the tokenizer often handles punctuation effectively as part of the tokenization process.

Load DistilBERT Model:

The next step is to initialize a pre-trained DistilBERT model and its associated tokenizer. DistilBERT, being a smaller and faster version of BERT, is well-suited for tasks requiring efficient processing. The pre-trained model can be loaded from libraries such as Hugging Face's Transformers, which provide easy access to various pre-trained models.

Encode Text Data:

Using the DistilBERT tokenizer, the preprocessed text is converted into a numerical format. This typically involves generating input IDs, attention masks, and token type IDs. These numerical representations are necessary for the DistilBERT model to process the text.

Model Inference:

The encoded text is passed through the DistilBERT model to obtain embeddings or predictions. DistilBERT processes the input data and generates contextualized embeddings that capture the semantic meaning of the text.

Postprocess Model Output:

The raw output from the model is then postprocessed to derive meaningful insights. For readability prediction, this might involve aggregating the embeddings, applying a classification head, or using additional layers to interpret the model's output as readability scores or categories.

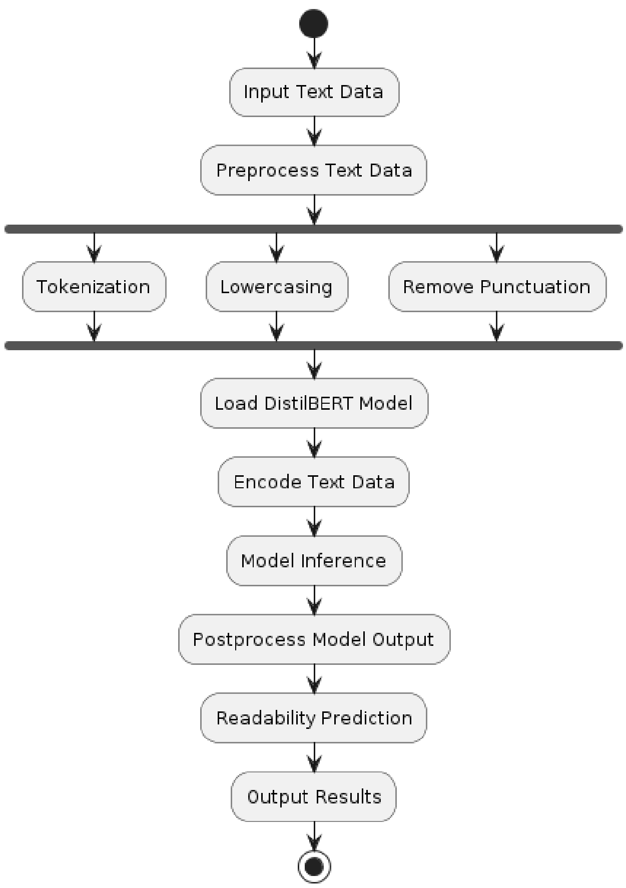


Fig-1 Flowchart of Distil Bert Model

This flowchart outlines the process for predicting text readability using DistilBERT, from inputting and preprocessing text data through to model inference and outputting readability results.

Key preprocessing steps like tokenization, lowercasing, and punctuation removal are highlighted, leading to model loading, encoding, inference, and final prediction.

Readability Prediction:

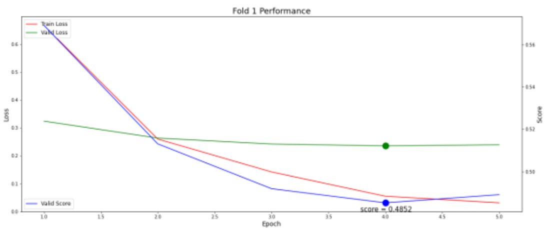
Based on the postprocessed model output, the readability of the text is predicted. This can be in the form of a numerical readability score (e.g., Flesch-Kincaid Grade Level) or a categorical classification (e.g., Easy, Medium, Hard). The exact nature of the prediction depends on the trained model and the specific readability criteria used.

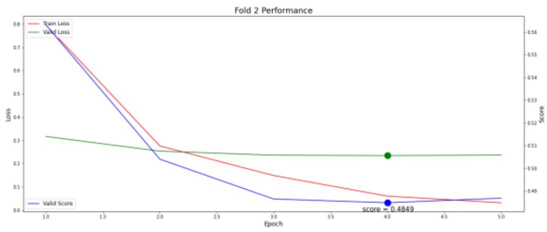
Output Results:

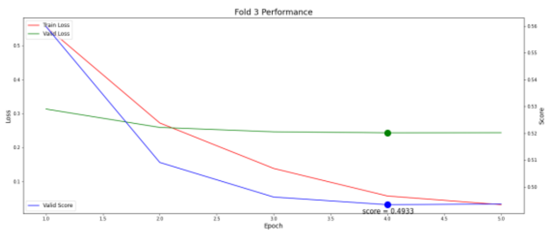
The final step is to output the readability prediction. This can be presented in various formats, such as a printed score, a graphical representation, or integration into a larger application or service. The results provide users with an understanding of how readable the given text is, based on the model's analysis.

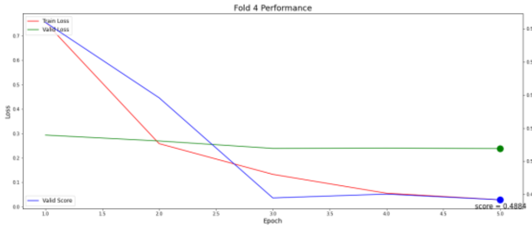
IV. RESULTS

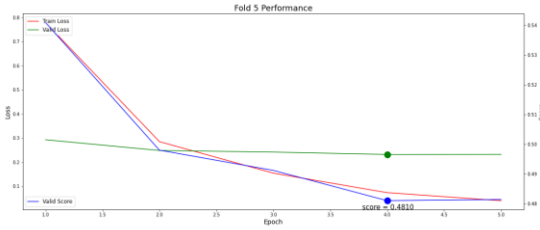
Trained for Different Folds:

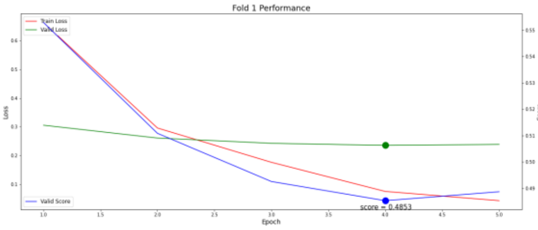


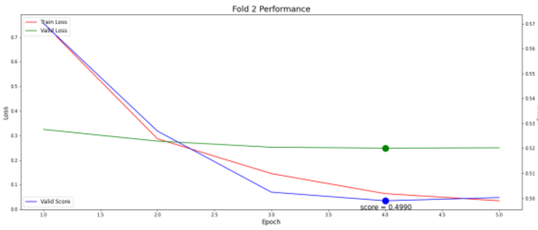


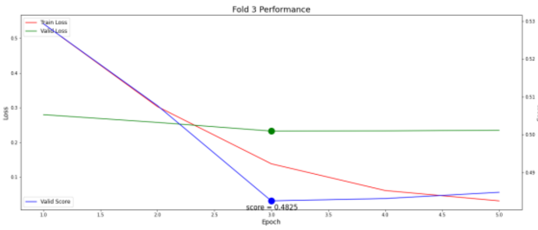


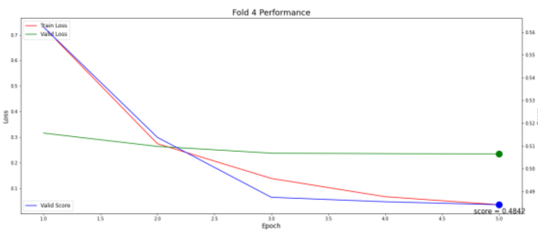


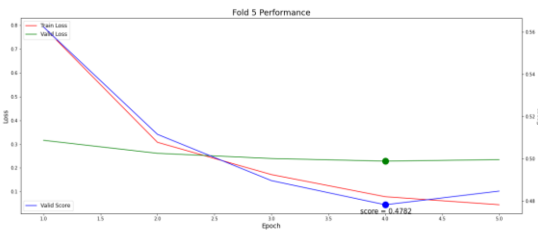


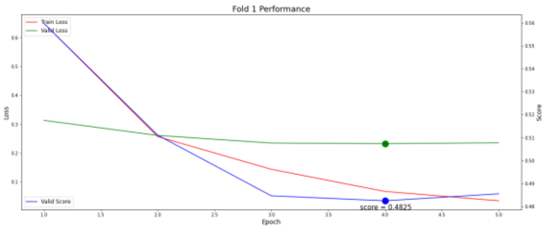


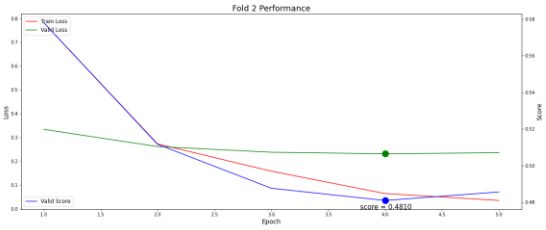


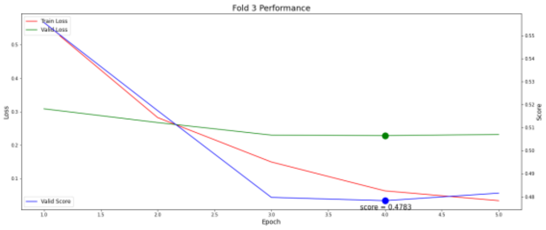




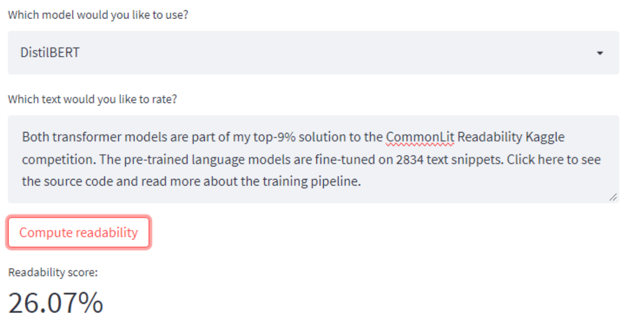








We have given some text and it given the readability percentage of the given text.



V. Conclusion

In conclusion, the methodology for text readability prediction using DistilBERT involves a structured sequence of steps, from preprocessing text data to leveraging the efficiency and performance of the DistilBERT model for inference. By systematically tokenizing, optionally lowercasing, and removing punctuation, and then encoding the text for model processing, we can effectively utilize DistilBERT's capabilities to generate accurate readability predictions. This approach not only enhances the efficiency of readability analysis but also ensures that the predictions are robust and practical for various applications in content creation, education, and user experience design.

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