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An Efficient Sentiment Analysis Technique for Virtual Learning Environments using Deep Learning model and Fine-Tuned EdBERT

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Abstract: In the present age of advancement in computing through the application of artificial intelligence, a host of programming and modules are designed to facilitate a virtual learning environment, each claiming its own efficacies and usefulness in virtual learning during the pandemic. The present paper endeavors to design a unique model, named for the first time as EdBERT, for sentiment analyses of virtual learners with most accuracy of their review classification. The model focuses on an improved version of sentiment analyses with Google BERT while facilitating educational feedback corpus. The methodology used is a comparative study using the tool 'fine-tuned Google BERT', which is trained at three different stages for understanding the language, context, sentiments and thus, performs classification of learners' feedback accurately. The model and its functioning are given in the discussion with valid proofs of accuracy testing and analyses. EdBERT stands as a state-of-the-art model in AIEd sentiment analyses with the best evaluation matrix so far with 87.89% accuracy, 88 % F1- score, 89 % Precision, 88 % Recall values. These values are of evaluation matrix is better than any other recent models discussed in the article. AIEd is comparatively new domain which is getting explored by academic researchers and scientists to im-prove the productivity of the learners, instructors and the learning environment. This work is a deep learning and natural language processing models can be used to provide reliable sentiment analysis with three basic sentiments class. Further this work can be extended with Plutchik's wheel of emotion that will help in capturing the emotions with help of AI and Deep Learning more correctly.

Keywords: *Virtual Learning Environment, Sentiment Analysis, Google BERT, Fine-Tuning, AIEd.*

1. Introduction

In recent years, research in artificial intelligence in education (AIEd) has increased considerably. It is noticeable that a large number of artificial intelligence (ai) and deep learning-based applications have also come up for the purpose, and researchers are at-tempting to apply ai at different levels of education, such as classroom teaching, assessments, grading, etc. It provides better accuracy and reliable outcome [1-2]. Automating the educational practices shows the potential of AIEd towards compliance with the readiness of industry 4.0. One of the key challenges in the learning environment is to provide personalized assistance to an individual learner. Personalization helps in improving the learning status. It also identifies the preferences and characteristics of the learners. Personalization attempts to engage learners in achieving learning goals [3]. Both physical and virtual learning environments (VLE) have their limits in terms of technological resources for completing routine activities. Learners achieve these learning activities and the outcomes of the activities measure the learner's performance. A learner's sentiment analysis helps in better prediction and reading into the idea of the course, instructors involved, contents and other concerns, which can im-prove the learners' performance [4]. The outcomes of the perception analysis can help the instructors in decision-making about a learner [5]. The major difference between the physical and virtual learning environment is that the physical mode allows face-to-face inter-action of the learners and instructors, while on VLE, they interact through reviews and discussion forums.

The juxtaposition of review and discussion is an important part of the students' training and the success index of the course. Learners' feedback and discussion forums are the sources of knowledge about the learners' perceptions. These reflect the feelings, opinions, understandings, participation, difficulties, doubts and expectations of a given course [6]. The instructor's use of pedagogical strategies can help achieve the learning goals. It also helps identify and integrate dissatisfied or discouraged learners and then puts them into groups [7]. An instructor perceives the issues related to a group learner and then changes the pedagogical strategies it is made to suit appropriately. In the case of VLE, the scenario is different as there is no face-to-face interaction in the mode. Instead, an instructor guides a learner through dialogues mediated by the texts or via some software to process cues as a teaching aid [8].

In the learning environment, a learner expects an instructor to be warm, welcoming, attentive and motivating during the teaching-learning process. The affective and cognitive relation between an instructor and a learner makes both parties feel confident and secure [9]. Researchers emphasize analyzing a learner's

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interactions, like feedback and discussion forums course [6]. Sentiment analysis is one of the emerging challenges in AIEd. With ai techniques, sentiments like anger, frustration, joy, trust, surprise, fear, motivation, etc. Can easily be identified. Discouragement during the course causes wrong decision making, resulting in course dropout [10]. Discouragement is caused when one is unable to match up with the course or fails to meet the deadlines or is unable to acclimatize with VLE software or learning management systems (LMS). Although VLE and e-learning are emerged as the most popular training and learning approach, both by industry and educational institutions. Drop-out from a course, as a matter of fact, is one of the issues of concern from all quarters. This can be improved considerably by using sentiment analysis. AI enabled techniques with the help of natural language processing (NLP) pre-trained models like bi-directional encoder representation of transformer (BERT) can help develop and analyze text data with optimum precession. These techniques can develop the computational model, which can identify a learner's agreement and disagreement with a given statement. Agreement to the statement is affirmation and conveys the positive feeling, while disagreement communicates the negative feeling.

This paper proposes a solution strategy that performs sentiment analysis of the learners' text reviews. The model designed is on the basis of the sample reviews of the course in which they are enrolled. The proposed model aims to retrieve important information about the learners. This framework identifies the positive and negative sentiments. Also, it can focus on specific learners and their emotional states during the course. In Section 2, we have presented Data sources and Literature Reviews. We have explained the framework and various analysis in Section 3. Results are shown in section 4. Section 5 presents discussion and conclusion of the work.

2. Literature Review

This section presents the required theoretical background for framework development. These theoretical foundations resulted from a bibliographical and systematic literature review on data visualization, sentiment analysis, and NLP with BERT. Data preprocessing transforms the data before passing it to the machine learning model. It transforms the raw input data into a complete, consistent, correct and clean dataset. Real-world data contains a lot of noise. That is not suitable for machine learning algorithms. So, data preprocessing is an integral part of machine learning practices [11]. Data preprocessing performs imputation of missing values, data transformation using any of these techniques label encoders, one-hot encoders, dummy value. It scales the numerical data. For this model, text preprocessing is very crucial. This comes under NLP preprocessing pipeline. For the development of this novel framework 'English' texts are used. Tokenization is the first stage of NLP preprocessing. It transforms the text data into a sequence of words. Before tokenization of the text data, lemmatization of text, removal of stop words, parts of speech tagging, and named entity recognition are performed [12]. Word embedding is an important stage in the NLP pipe-line that helps in the generalization capabilities of the neural networks [13-14]. Word embeddings are trained with multiword-grouped corpus and perform well with simple tokenized datasets. Word2Vec word embedding technique is an example of successful training with multiword-grouped corpus. This is very important to carefully preprocess the text data. Outcomes of the text preprocessing present meaning, context, and sentiment attached to it. Data visualization helps in visualizing and analyzing the data. It clearly represents the results through various graphical tools, e.g., graphs, heat maps, trees, etc. For this framework, the word cloud is an effective visualization tool that helps find the difference between the target classes [15]. Visualization of the data and results enhances cognition. It allows us to precisely understand and interpret the data [16]. These tools help highlight the learner's behavior, interactions, achievements, and sentiments.

2.1 Sentiment Analysis in VLE

This technique deals with feelings, perceptions, and emotions. It is a prominent field of research in the text mining domain. In AIEd, it is emerging research do-main. It helps in improving the quality of decision-making in VLE. This is getting equal attention in industry and research and generating high profit [17]. It analyzes the statement as positive, negative, or neutral [18]. This can also be measured as the class of emotions. These classes are identified as joy, trust, anger, disgust, fear, sad-ness, anticipation, and surprise [19]. Sentiment analysis can be incorporated with LMS. It can help in sentiment analyzing in real-time [20-21]. Sentiment analysis aid-ed in the design of the user interface and improved immersion in the learning process. Sentiment analysis can potentially improve learning outcomes, teaching effectiveness, and policy-making [22]. This can be used to generate early warnings before reaching to completion of the course [23].

This helps instructors to intervene early with the learners based on the in-tensity and duration of the emotion [24]. A literature review on sentiment analysis in a learning environment strongly indicates that data must be properly preprocessed. Poorly processed data leads to poor results [25]. The other challenge with sentiment analysis for VLE is that most of the datasets are unlabeled, and labeled data is less. Without pre-trained models, the models for sentiment analysis are slow, complex and costly. With the use of tools like transformers and BERT training times, effective models can be generated. The results generated using the sentiment analysis models must be verified using logical reasoning or psychological, motivational surveys [26]. The results of the sentiment analysis model correspond to the learning behavior and performance of the learners. Behavior triggers the emotions in VLE. It is noticeable in the literature that the distinct and in-depth analysis of emotions of learning can be done by allocating them to group tasks [27]. The learners' positive emotions about the curriculum lead them to achieve learning objectives. Studies noticed that emotional awareness and feedback positively impact the learners' performance [28]. Incorporating feedback and sentiment analysis can improve academic failures [29] and dropout rates. Identification of temporal sentiment features allows the instructors to immediately intervene with the learner with whom risk is involved. Combining temporal features is advised before performing the dynamic sentiment analysis [30]. Learners' sentiments change during the duration of the course. This change is the result of the learners' experience from the beginning till the end of the course [31]. It's recommended to conduct feedback multiple times to track the direction of the change of emotions. These continuous feedbacks will help narrow down the temporal features of the learners' sentiment and improve their learning. Literature indicates that sentiment analysis in VLE improves the teaching-learning process. It changes the overall impression of course assessment and evaluation. Studies have shown that learner's satisfaction can be predicted directly using sentiment analysis [32]. Various constituents in the VLE like course, instructors, deadlines, evaluations and timings have predictive relations with learner's satisfaction [33]. It also notices that learners appreciate the course contents and depreciate the video productions. However, its shown that course contents cause confusion and gradually produce negative emotions [29]. LMS's integrated with sentiment analysis also help understand the learners' behavior and attitude.

2.2 Bi-Directional Encoder Representation of Transformer (BERT)

Universal representation of text data is one of the major challenges faced in natural language processing. BERT is a major breakthrough in handling the challenge. It is a text attachment model that can perform various tasks related to NLP with very high precision. NLP has a wide range of applications. Chatbots, text summarization, voice assistants, and language translation are a few examples of NLP. The core idea of the development of such an application is to have an accurate text representation technique. It converts natural language to machine-understandable instructions. Transformers are used to represent encoded text to machines [34]. Transformers are a type of neural network and their use increased in different disciplines of machine learning (ML) and applied on sequence to sequence learning i.e., both input and output sequences will be a sequence. These models are used together with recurrent neural networks (RNN) and convolutional neural networks (CNN). Long short-term memory's (LSTMs) are used in together with the attention mechanism to enhance the learning efficiency. LSTM is one of the very popular techniques that can be used to predict the parameters of use [35]. Apart from this, hierarchical attention network (HAN) is also identified as one of the techniques for recognizing the contextual semantics for increasing the accuracy of the sentiment classification model [35]. Devlin proposed a linguistic model called BERT in 2018 at the Google AI lab [36].
This model is developed for deep learning of bidirectional text representation for subsequent use in ML models. NLP tasks can be either holistic or tokenized. Holistic natural language processing operates at the sentence level. Tokenized approach for natural language processing operates at individual text elements. Both holistic and tokenized method performs well in the pre-trained models. BERT is a pre-trained language model which reduces the design, training and testing time with accurate results. Pretrained models can be used for deep text representation. These representations are i) feature extraction approach ii) fine-tuned approach. BERT training is done in two stages i) pre-training on unlabeled data and then ii) training over the application-specific labeled data. It is based on multilayer bi-directional transformers. BERT has two variants i) BERT base with 12 encoder layers and 768 coordinates (110 mil-lion parameters) ii) BERT large with 24 encoder layers and 1024 coordinates (340 million parameters). BERT uses the word embedding technique to represent the in-put sequence. An arbitrary group of continuous text tokens is referred to as a sequence. BERT requires retraining with the data to understand and represent the text. For specific tasks, it's required to perform further pre-training, finetune retraining strategies BERT, multitask learning. BERT has shown 4.5% to 7% superior results for general language understanding evaluation (glue) test. BERT surpasses the accuracy of existing models on the Stanford question answering dataset (squad) benchmark test and scores 83.1. On the situations with adversarial generations (swag) bench-mark, it scores 86.3, which surpassed the capability of humans (score is 85.0) to understand the language [37- 39]. BERT is receiving an extremely positive response from the scientific community. This pre-trained model is capable of solving almost every language representation-related task. With transformers and attention BERT has shown the advantage of bidirectional contextual models for NLP. The result of this work is insured by the use of a random forest classifier. It is an ensemble technique introduced by Leo Breiman [40-41]. It has proved its efficiency in multiple classification tasks. Stacked ensemble classifiers are also one of the approaches that can also be used for enhanced prediction [42-43]. It uses a bagging and boosting approach to verify the class label before prediction.

3. Methodology

Since sentiment analysis is a naïve research domain in AIEd that's

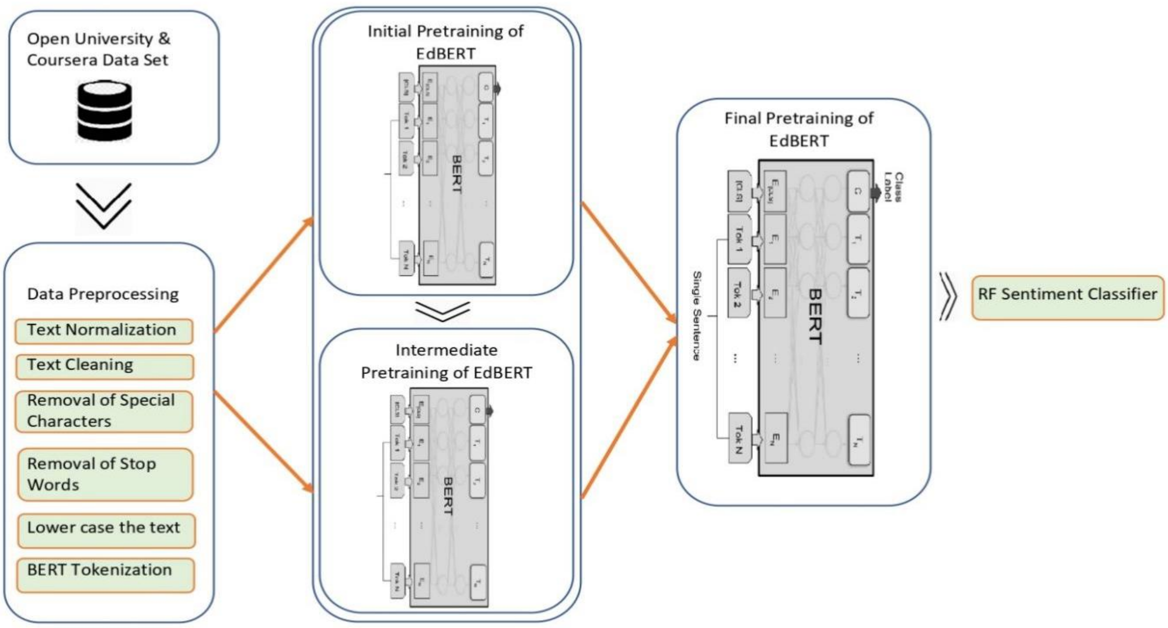

Fig 1. The proposed EdBERT model

why proper research is not available for this problem statement. However, various suggestions and solutions are proposed in different research articles.

This research work has been carried out using the learner's feedback and the sentiment is identified and classified from that. Apart from VLE, there are a number of research available for sentiment analysis on different social media platforms, e-commerce websites and applications, banking management systems, customer support systems, brand monitoring and competitive market research, etc. In this scenario learner's sentiment classification has been done. Sentiments are classified as i) positive sentiment ii) negative sentiment and iii) neutral sentiment. We have proposed a methodology that would work with Google BERT's Pytorch implementation for facilitating sentiment classification through educational data set, and it's henceforth to be known as "EdBERT". The proposed architecture is shown in Fig. 1.

Dataset is collected from Kaggle ([https://www.kaggle.com/septa97/100k-courseras-course-reviews-dataset). EdBERT is a supervised machine learning model. EdBERT is a monolingual version of BERT trained on the educational dataset. This model is trained over a down-sampled 100k review dataset, and 4823 text reviews are used. These reviews are of a minimum of 40 words and a maximum of 412 words. This is a balanced data set with all three categories in almost equal proportion. The input text is passed through several stages in the EdBERT model, and the model produces the sentiment classification after processing the reviews. These stages are discussed in the following subsections.

3.1 Review Preprocessing

This is an important stage in order to remove less important information and redundant features from the dataset. Fig 1 shows the pipeline of text preprocessing. These pipeline stages process the data one after another. Text normalization is the first step in transforming text data into a canonical form. It reduces the noise generated by a single word in multiple forms. Stemming and lemmatization are important tasks in text normalization. The text cleaning step removes punctuations, stops words, URLs, html tags, and numbers from the text, and makes it presentable.

Tokenization is used to splitting strings into words. It is well known that a neural network can operate only with numerical values. Indices should represent all words. Each word will have a unique index, and it will also have an embedding vector. BERT uses the feature of transformers and it provides a sinusoidal positional word embedding. This helps in removing the duplicate embedding values.

3.2 Fine-Tuning of EdBERT

It is used as a pre-trained model and is fine-tuned on the student's review dataset. Preprocessed input text data is tokenized by EdBERT tokenizer. This tokenized data is used for intermediate pretraining of EdBERT. This data is fed to the main model. The maximum input length of tokens is taken as 250, shown in Fig. 2.

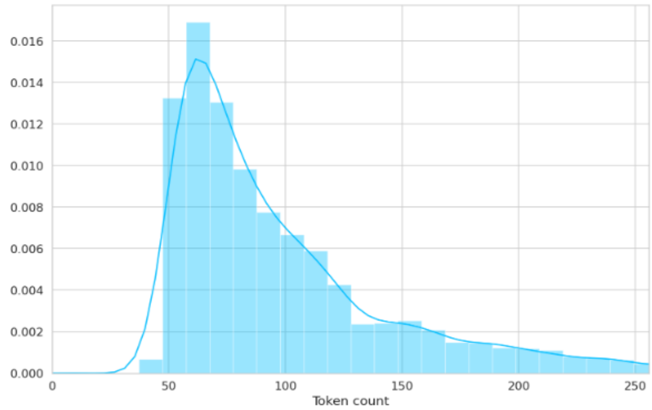

Fig 2. Distribution of tokens in EdBERT

In addition, Fig. 3 depicts the counts of the review samples. Pad tokens [pad] are used with short reviews to match the length of the largest one.

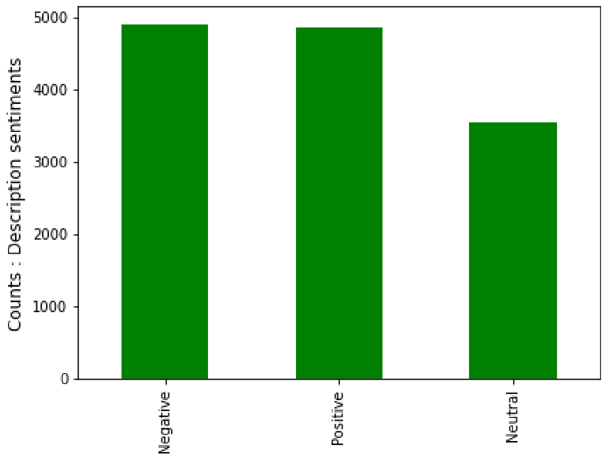

Fig 3. Review samples count for EdBERT

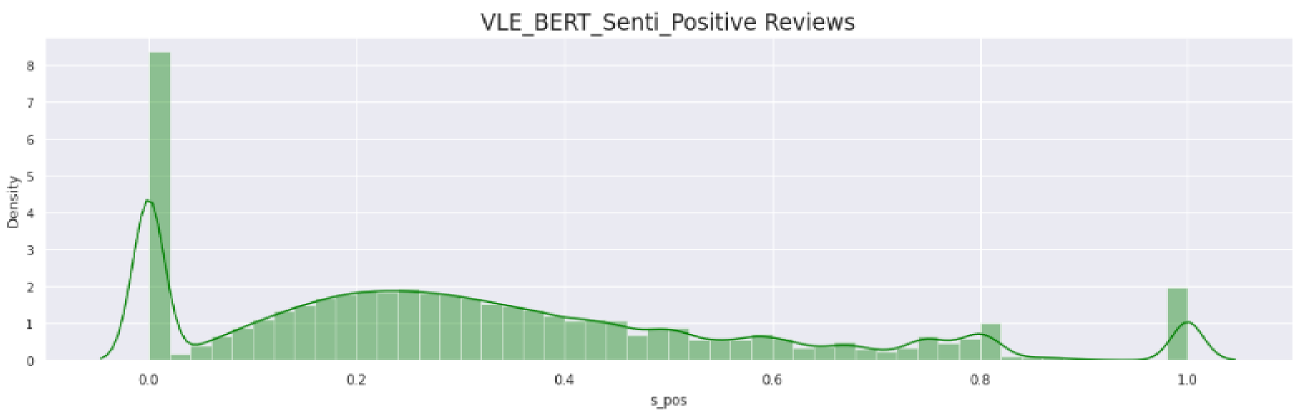

Fig 4. Distribution of positive reviews

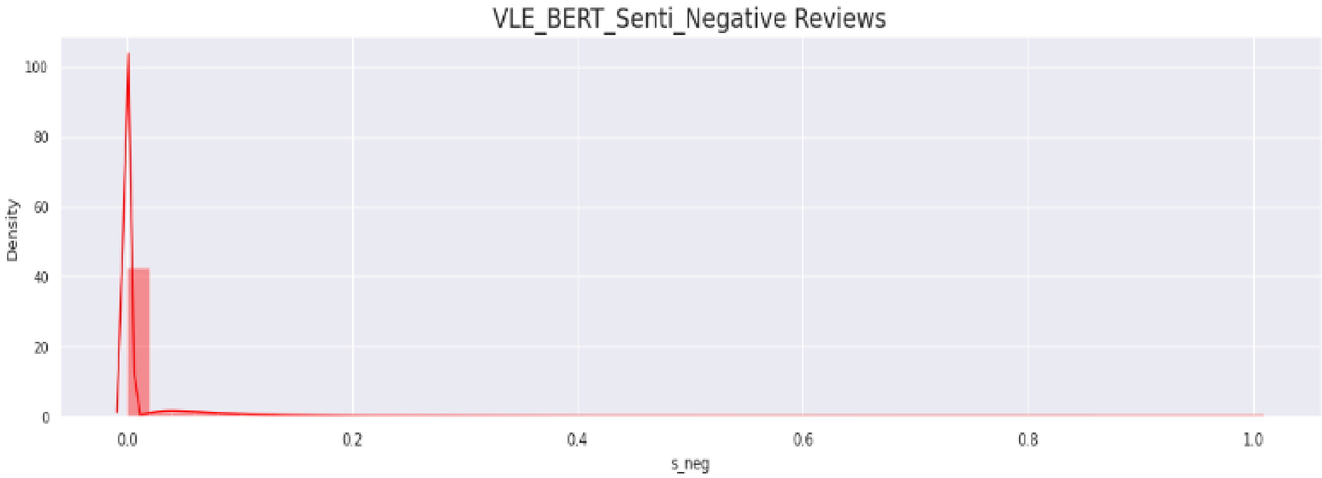

Fig 5. Distribution of negative reviews

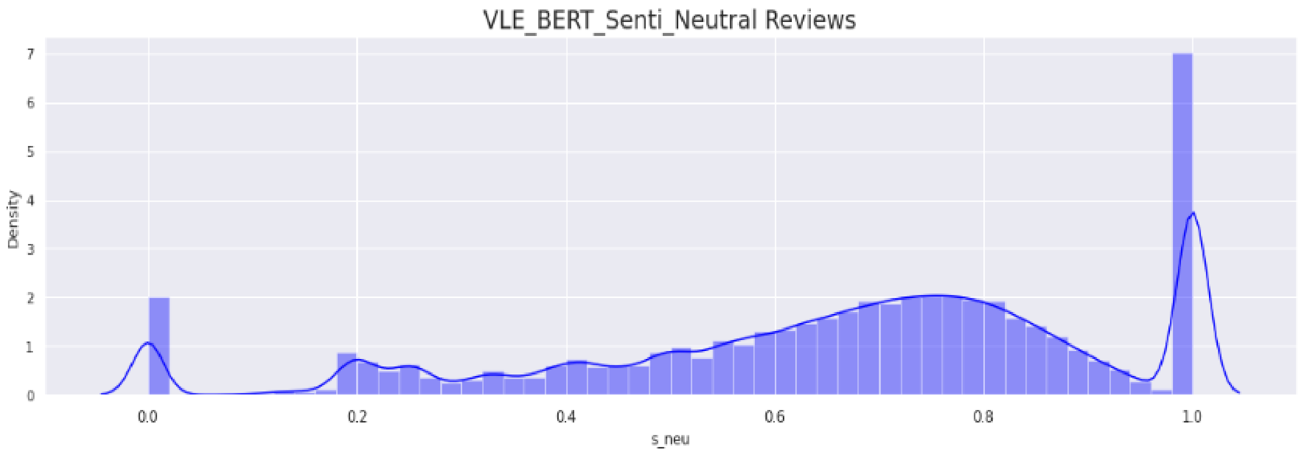

Fig 6. Distribution of Neutral reviews

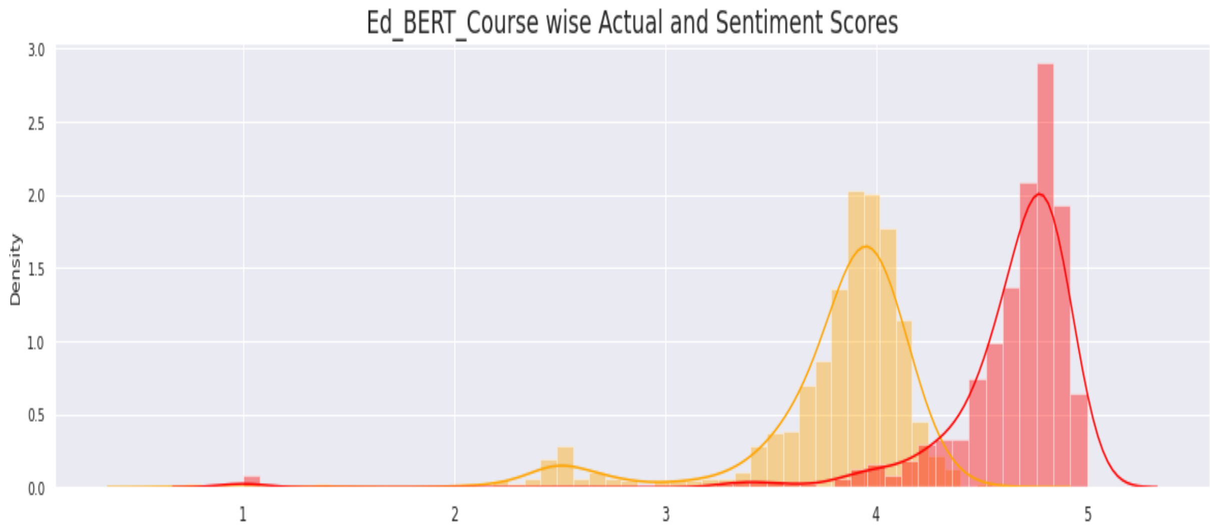

Fig 7. EdBERT Course wise actual and sentiment scores

The first token in BERT is termed as [CLS]. Each input sequence starts with [CLS] token. This [CLS] token influences the outcome at the final layer of the EdBERT model. The final pre-training of the EdBERT is done to comply with the task of sentiment analysis in educational environments. For sentiment analysis dropout layer and dense layer (fully connected layer) are added to the model. Three sentiments are to be analyzed hence. The Softmax activation function is used for multiclass classification. Adam optimizer with a learning rate of 2e-5, for 10 epochs, also with an error rate of 0.01%. The cross-entropy loss function computes the loss. Reviews are classified by the value of the first token, i.e. [CLS]. BERT model is trained and tested over the open university student review data set. This data set consists of three classes of sentiments. These classes are positive, negative and neutral sentiments. Fig. 4 shows the distribution of the positive sentiment against the polarity score. Fig. 5 shows the distribution of the negative sentiment against the polarity score. Fig. 6 shows the distribution of the neutral sentiment against the polarity score. Each student's feedback is passed through the EdBERT model, and its positivity and negativity scores are computed. This model works on the confidence gained from comparing each re-view's positivity and negativity scores. With given ratings and sentiment values course wise compound sentiment score is calculated. This compound sentiment score of actual rating and sentiment rating is shown in Fig. 7. Compared to the lowest and highest values, the average course rating is much greater. As a result, the course's quality is being upheld. The grade of advanced courses fluctuates, maybe as a result of their rarity. Given that a sizable amount of the data comes from them and that there are many introductory level courses, the distribution of beginner courses is pretty comparable to that of the overall rating chart. The grade for an intermediate course is not as high as it could be because participants are more qualified to judge and be critical because they have more background information on the subject. Courses have a higher mean value than specializations, but token. Cross entropy loss is required to be minimized for the data of the batch size of 16.

3.3 Random Forest for sentiment classifier

This is an added step to verify the accuracy of the model. Random forest is an ensemble machine learning technique that uses a number of decision trees for prediction and then uses the voting algorithm to make the final prediction [44]. The EdBERT model works in com-bination with the random forest technique to make accurate and precise predictions. Random Forest is a type of ensemble learning method for classification and regression that operates by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. In the case of sentiment analysis, Random Forest can be used to classify text data into positive, negative or neutral sentiment classes. The algorithm takes as input a set of features extracted from the text data, and the decision trees in the forest use these features to make predictions about the sentiment of the text.

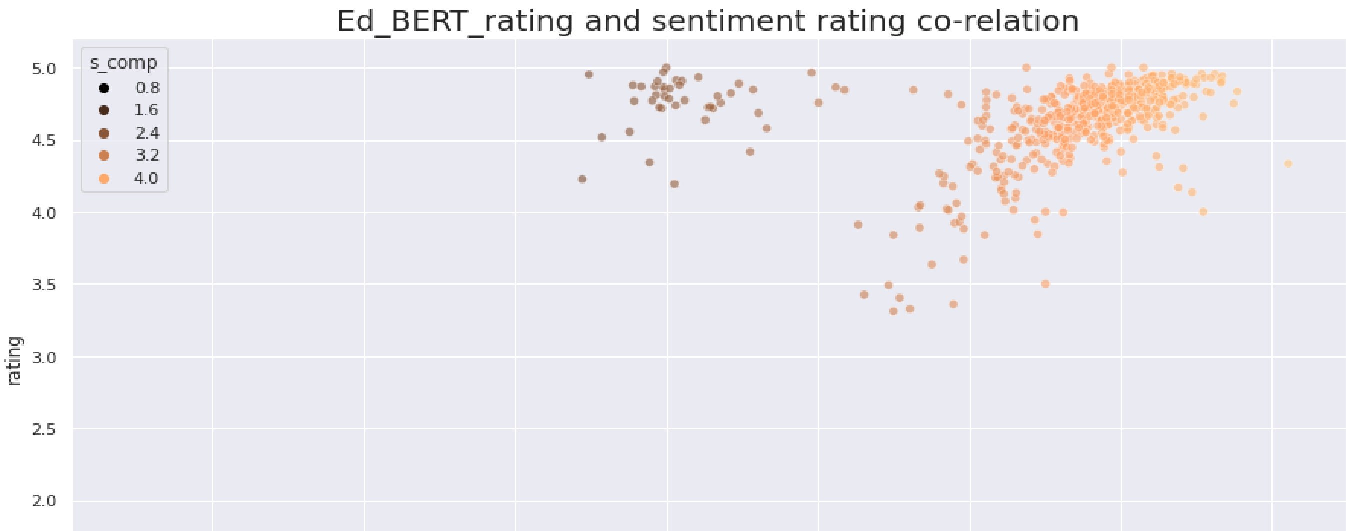

Fig 8. EdBERT rating and sentiment rating co-relation

BERT (Bidirectional Encoder Representations from Transformers) is a pre-trained language model that can be fine-tuned for specific NLP tasks such as sentiment analysis. To use BERT for sentiment analysis, you can extract features from the pre-trained model and use them as input to a Random Forest classifier. This approach leverages the knowledge captured by the pre-trained BERT model and fine-tunes it on the sentiment analysis task. The extracted features from BERT can capture important semantic information from the text data that can be useful in classifying the sentiment. The Random Forest classifier can then use these features to make the final prediction by combining the decisions made by multiple decision trees in the forest.

4. Results

EdBERT model is trained and tested over the open university student review data set. This data set consists of three classes of sentiments. These classes are positive, negative and neutral sentiments. Fig. 4 shows the distribution of the positive sentiment against the polarity score. Fig. 5 shows the distribution of the negative sentiment against the polarity score. Fig. 6 shows the distribution of the neutral sentiment against the polarity score. Each student's feedback is passed through the EdBERT model, and its positivity and negativity scores are computed. This model works on the confidence gained from comparing each review's positivity and negativity scores. With given ratings and sentiment values course wise compound sentiment score is calculated. This compound sentiment score of actual rating and sentiment rating is shown in Fig. 7. Compared to the lowest and highest values, the average course rating is much greater. As a result, the course's quality is being upheld.

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correlation between the number of students taking a course and the course rating for each university. The average number of students enrolled at each university is positively correlated with the number of courses the university offers. The average number of students enrolled increases as more courses are offered. Rating and sentiment co-relation is shown in Fig. 8.

The model is evaluated using the confusion matrix, the same matrix is used for a comparative study of the already established results [45-46]. EdBERT achieves accuracy (87.89%), precision (89%), recall (88%) and f-measure (88%). Table 1 presents the comparative performance study of the EdBERT. This model successfully classifies positive re-views with 95% precision, recall, and f1-scores. Negative reviews are classified with 73%, 61%, and 66% precision, recall and f1-score values. For neutral statements, the model performs classification with 39%, 47%, and 43% precision, recall and f1-score values. Ed-BERT is compared with multi-agent system (mas) for sentiment analysis (Márcio et al. 2021), multinomial naïve bays [47], sentiment mining using big data frame work [25], and ParsBERT [48]. This proposed model surpasses already established results on evaluation parameters. EdBERT, with three-stage fine-tuning can represent the words in positional encoded tokens, then it is trained over an educational corpus. The third fine-tuning makes the model capable of accurate classification. As mentioned earlier that this accurate outcome is supported by using an ensemble technique. Random forest assures that the results are convincing [49]. This model combines state-of-the-art deep learning technology with classical machine learning technique, which provides outstanding results discussed in Table 1.

Table 1. Comparative Analysis Sentiment Analysis Techniques (In %)

Sentiment Analysis Techniques	**Recall**	**Precision**	**F1-score**	**Accuracy**
Multi-Agent System [50]	87.32	81.04	42.03	73.88
Multinomial Naïve Bays [47]	84	87	87	83
Sentiment Mining using Big Data Frame Work [25]	16.15	28.87	18.87	86.62
ParsBERT [48]	82.6	82.04	81.3	81.69 (overall)
EdBERT (proposed model)	88	89	88	87.89

5. Conclusions

Sentiment analysis in a learning environment provides a representation of emotions, feelings, ideas, and perceptions. The model is an aid and decisive tool for an institute or an individual instructor to take immediate measures to improve learning outcomes. Feed-backs are abundant, but researchers face the challenge of scarcity of structured feedback dataset. Sentiment analysis will be the key feature in the success of the institute's endeavor of disseminating knowledge while reducing the rate of dropouts. This model would enable the learners to perform better. EdBERT is designed, trained, and tested against the four state-of-the-art models with an accuracy of 87.89% and it is to support the success of VLE. It is not limited to VLE. Instead, it can be used in any learning environment. This model's outcomes show that EdBERT can capture the complex sentiments present in the learners' feedback. This model has also outperformed various competitive models. These deep learning and natural language processing models can be used to provide reliable sentiment analysis for institutions, learners, and instructors.

Conflicts of interest

The authors declare no conflicts of interest.

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