A course review analysis using bidirectional long short-term memory model

Murthy Venkata Surya Narayana Tatavarthy, Naga Lakshmi Vadlamani
Department of Computer Science, GITAM (Deemed to be University) Visakhapatnam, Andhra Pradesh, India

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ABSTRACT

In recent years, sentiment analysis and online review analysis have gained popularity as critical components in the growth and development of educational courses. An innovative method has been created to increase the quality of learning experiences by rapidly collecting relevant data from course comments. This technique leverages bidirectional encoder representation from transformers (BERT) for word vector training. When combined with a learning mechanism, the recommended BERT accurately predicts the sentiment of online course reviews. Additionally, a dual-channel model based on Bi-directional long short-term memory (Bi-LSTM) is employed to improve sentiment data and semantics. Following data collection from the Coursera dataset, preprocessing approaches such as tokenization, stop words removal and sentence metric creation are applied to convert input data into word vectors and identify fundamental text units using text segmentation. The results demonstrate the proposed approach's superiority over existing methods, offering an accuracy of 81.45%, recall of 94.9%, precision of 93.7%, and F-score of 93.7%.

Corresponding Author:

Murthy Venkata Surya Narayana Tatavarthy
Department of Computer Science, GITAM (Deemed to be University) Visakhapatnam
Gandhi Nagar, Rushikonda, Visakhapatnam-530045, Andhra Pradesh, India
Email: tvsnmurthy@gmail.com

1. INTRODUCTION

In the past few decades, technological advancements in education and the growing demand for online teaching in colleges and schools have increased significantly. Online learning has proven beneficial for various educational purposes and research [1]. Sentimental analysis in e-learning focuses on contextually mining unstructured text to extract attitudes, emotions, and evaluations, aiming to identify and collect opinions and sentiments from a given source. This approach serves as a means to locate and gather opinions and sentiments from a designated data source [2]. Massive open online courses (MOOCs) are a prominent technique in distance education, offering learning content to users without gender, and age barriers. However, analyzing reviews for MOOCs presents various challenges due to their unstructured nature, brevity, and varying lengths, which complicate accurate sentiment analysis [3], [4]. Sentiment analysis, in this context, aims to construct a system that strives to understand user opinions on various products or events [5]. This study examines the efficacy of e-learning by analyzing user attitudes towards e-learning. In the field of sentiment analysis for text, there is significant potential to extract and analyze sentiments [6]. E-learning platforms that incorporate artificial intelligence (AI), leverage network, and computer technologies to optimize time management and enhance learning efficiency [7]. Sentiment analysis in e-learning platforms is a challenging and complicated subject, as extracting significant features and producing correct results is demanding due to the unstructured, high-dimensional, and imbalanced nature of the data. The accuracy and efficiency of current approaches are constrained as a result of their limitations in addressing these issues. Therefore, there is a need for more effective methods to manage complex data, improve accuracy, and enhance the sentiment analysis process.

Although sentiment analysis has advanced in recent years, several challenges remain, particularly in the context of e-learning platforms. Key areas requiring substantial progress include managing irony and sarcasm, addressing the complexity of educational data, and providing immediate responses. Successful sentiment analysis models must also address issues such as class imbalance, integrating existing knowledge, and ensuring scalability and efficiency. E-learning is widely used in prediction and evaluation techniques, where sentiment analysis helps organize and make sense of the data. This structured data can then be leveraged for predictive and evaluative purposes, ultimately enhancing the e-learning experience. Evaluating large volumes of unstructured data with emotional and contextual relevance remains a significant challenge [8]. One of the most difficult tasks in e-learning involves designing and implementing online assessments; however, the online test environment is highly conducive to cheating due to the availability of numerous unregulated datasets [9]. This research employs dictionary-based techniques within a lexicon-based strategy to collect data by scraping information from the web. With technological advancements, the volume and subjectivity of social web data have increased, presenting challenges in handling this heterogeneity [10], [11]. Sentiment analysis in online learning is an analytical method that combines statistics and machine learning (ML) to assess customer feedback and evaluate communication systems [12]. This approach integrates both ML and deep learning (DL) techniques, which have various applications in understanding public opinion, customer feedback, and more [13]. These models are trained on feature vectors that can be classified as positive or negative [14]. However, data sparsity is a major challenge in recommended systems, where consumers provide ratings on a limited number of items, making it difficult to develop effective recommendation approaches [15].

Mrhar *et al*. [16] introduced a novel technique for sentiment analysis by exploiting the strengths of the deep learning architectures namely, CNN and long short-term memory (LSTM). It employed a Bayesian neural network (BNN) model to measure uncertainty in sentiment analysis tasks to improve prediction reliability and manage any uncertainties. This model outperformed other models in sentiment analysis tasks on MOOC platforms. However, the suggested strategy could be improved further by expanding the number of deep learning classifiers and analyzing their performance in terms of various evaluation measures. Kumar and Jayagopal [17] suggested an LSTM model for sentiment classification. The results demonstrated that this method produced greater results at educational levels with fewer categories in comparison to other models. Chen *et al*. [18] designed MOOCs to understand the factors of learner satisfaction. MOOCs learners had both positive and negative sentiments, aimed at achieving satisfaction. However, the suggested method was required to consider revising its classes for segregation for enhanced classification performance and accuracy. Kastrati *et al*. [19] developed MOOCs for automatic analysis of opinions and reviews. These MOOCs were designed on multidimensional concepts for effective learning. The proposed MOOCs included a supervision approach that offered improved effectiveness of manual clarifications. However, the suggested method needed to focus on generalizability, particularly with standard databases, as benchmark datasets helped enhance both generalizability and robustness.

Jatain *et al*. [20] developed a co-training, semi-supervised deep learning model for sentiment categorization, efficiently utilizing a small quantity of labeled data with a significant amount of unlabeled data. This method produced efficient outcomes, equivalent to algorithms trained on large labeled datasets, rendering it useful to determine the elements that influenced course analysis. The suggested approach increased model robustness with data augmentation techniques such as Mixup. According to the overall analysis, course review analysis is a complex task due to the intricate data, high dimensionality, dataset diversity, and limited accuracy. The sentiment analysis process is further complicated by the unstructured and imbalanced nature of the data, along with the need for context-specific analysis. These challenges make it difficult to accurately evaluate student satisfaction, opinions, and sentiments, ultimately affecting the quality of the e-learning process. As a result, the current approach struggles to effectively explore, identify features, and navigate high-dimensional spaces to address these issues. To efficiently explore and exploit the solution space in course review analysis, we recommend using bidirectional encoder representation from transformers (BERT) combined with Bi-LSTM. The major contributions of this paper are outlined as follows; Tokenization, stop word removal, and sentence metric creation were applied to pre-train the process on the dataset, transforming the input string into word vectors and identifying fundamental units through text segmentation. Then, the BERT model integrates multiple learning algorithms and an attention mechanism to accurately determine the sentiment of online course reviews. Further, the attention mechanism of Bi-LSTM was utilized to create a dual-channel system, extracting sentiment data and enhancing semantic understanding. The structure of this study is as follows: section 2 outlines the proposed technique. Section 3 explains the BERT word embedding combined with Bi-LSTM. Section 4 presents a comparative and quantitative analysis of the proposed method against existing approaches. Finally, section 5 provides the conclusion.

2. PROPOSED METHOD

In this study, BERT word embedding combined with Bi-LSTM is proposed to accurately determine the emotional orientation of online course reviews. The overall process includes the input dataset, pre-training, sentence salience score prediction, and output summary generation. A block diagram illustrating the BERT word embedding-based Bi-LSTM technique is presented in Figure 1.

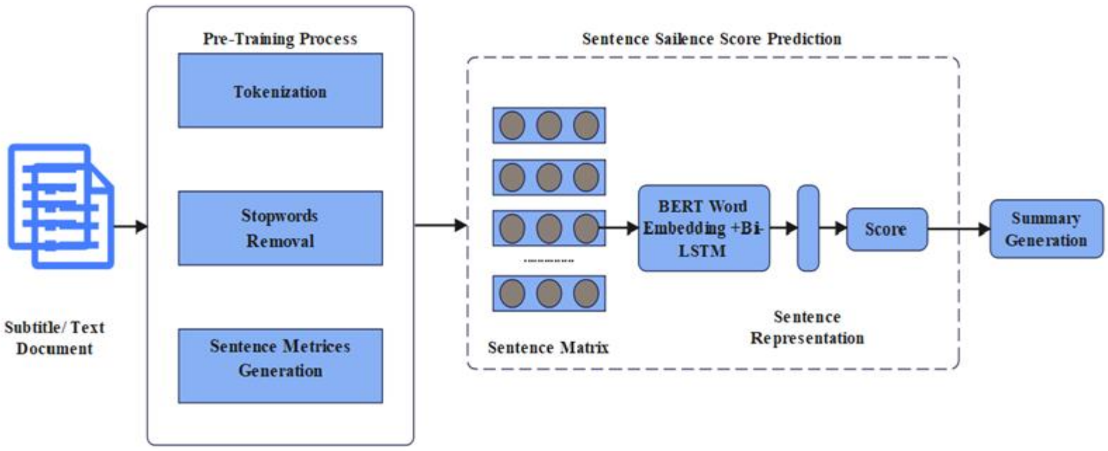

Figure 1. Overall process for online course review

2.1. Dataset collection

This study acknowledges the limitations of existing methods, such as manual or interactive surveys, which may be biased as some learners are reluctant to freely express their opinions. To overcome this, the research adopts a different approach by analyzing comments written by learners on discussion boards within online course platforms, such as the Coursera dataset. This method offers a more unfiltered and spontaneous insight into learners' true thoughts and feelings, potentially providing a more authentic representation of their opinions. The authors aim to enhance the quality of this research by leveraging this collection of data [17].

2.2. Tokenization

After data collection, normalization, and punctuation removal are applied to preprocess the output data. In the initial step, the input text document undergoes tokenization, which pre-trains the dataset for text processing. This text segmentation process involves transforming the input string into word vectors while identifying its essential components. Tokenization, a key step in natural language processing (NLP), breaks down text into individual units. It is the process of dividing a phrase, sentence, paragraph, or entire document into smaller components, referred to as tokens. This method helps replace sensitive data with uniquely identified symbols, ensuring that all critical information is retained while maintaining data security [21].

2.3. Stop words removal

After tokenization, stop word removal is employed to eliminate frequently occurring words that carry little orientation or information. The average word frequency in positively labeled documents is similar to that in negatively labeled documents. Sentiment analysis is then conducted after removing stop words from the unprocessed text samples. Stop word removal is one of the most commonly used procedures in several NLP applications, with the goal of eliminating terms that appear frequently across all texts, as they contribute little to the meaning.

2.4. Sentence metrics generation

After stopping word removal, the keywords are processed by the sentence metrics subfield of NLP, which employs statistical language models and artificial intelligence to generate natural language writings that meet specific communication requirements. A sentence-generating module receives an input description, which is used to connect and produce a coherent expression for natural language output. This module is utilized by organizations to develop long-form content, providing tailored reports and unique content for web or mobile apps.

2.5. Sentence salience score prediction

The initial pre-training process involves tokenization, stop word handling, and sentence metrics, which are then used to predict sentence salience scores. The salience score for an object indicates the entity's relevance or importance within the entire document. It represents the significance of a linguistic feature in the context of a larger text [22]. A distinctive characteristic is likely to be noticed by the human reader.

2.6. Sentence matrix

The word is fed into the sentence matrix for feature extraction, where it forms pairs of phrases connected by a transformation that preserves their structure and grammatical status. The sentence matrix consists of sentences that are both syntactically and semantically structured. Each sentence contains five words, carefully crafted by selecting unique combinations of words. Additionally, these phrases are synthesized using 400 audio fragments, which maintain and offer realistic inflections for the synthetic speech. A critical step involves converting this type of matrix text into spoken words for the first time in an aural-visual mode, utilizing recorded segments of high-definition video.

3. BERT WORD EMBEDDING-BASED BI-LSTM

The input word features given to BERT are processed using a free and open-source framework for ML in NLP. The BERT is designed to assist computers in understanding the meaning of complex terms. The goal of NLP approaches is to comprehend human language as it is used in everyday conversation. Typically, BERT is employed for tasks like predicting missing words in a sentence, which differs from the traditional approach known as word embedding [23]. Although both methods can handle various NLP tasks, word embedding typically requires substantial amounts of labeled data to perform effectively.

This methodology is chosen because BERT can capture contextual relationships between words, which is especially important in educational contexts where contextual awareness and sophisticated language are crucial. Furthermore, Bi-LSTM's ability to represent long-range relationships and sequential dependencies in text data enhances BERT's capabilities [24], making it possible to capture nuanced language shifts and complex sentiment patterns. The combination of BERT and Bi-LSTM has also shown advanced results in various NLP tasks, such as sentiment analysis. This suggests that the proposed method for sentiment analysis in e-learning settings achieves high accuracy and efficacy [25].

3.1. Bidirectional long short-term memory

Furthermore, the Bi-LSTM layer is utilized to capture bi-directional time dependencies and relevant features to increase prediction accuracy over unidirectional LSTM. The Bi-LSTM layer performs both forward and backward operations on the data to analyze online course reviews [26]. A memory cell (C_t) and three gates: input gate (i_t), an output gate (o_t), and a forget gate (f_t) are required to make up a unidirectional LSTM network. The network's information flow is controlled by these gates. While f_t manages the retention of prior information stored in the internal memory unit, i_t regulates the entry of fresh information at each time step. Additionally, the output that the internal memory unit evaluates is controlled by o_t. After processing input data (x), the LSTM network keeps a hidden state (h) that symbolizes its memory capacity. In (1), (2), and (3) determine the input gate value (i_t), input cell candidate state value ($\tilde{C}_t$), and forget gate activation value (f_t), respectively, and control network's dynamics.

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i \quad (1)$$

$$\tilde{C}_t = \tanh\,(W_c.[h_{t-1}, x_t] + b_c \quad (2)$$

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f \quad (3)$$

LSTM algorithm plays a significant part in efficiently managing system functions. This is accomplished by capturing and preserving important information over extended periods, including data from before the current output time. Furthermore, the input gate regulates the flow of initial information and updates the cell state at time t, as computed by (4). Subsequently, the output gate value is determined by (5), utilizing the updated memory cells. Finally, the hidden state is calculated using (6), which measures the output of the LSTM cell.

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (4)$$

$$O_t = \sigma(W_o.[h_{t-1}, x_t] + b_o \quad (5)$$

$$h_t = O_t * \tanh(C_{t)} \quad (6)$$

Where the W_i, W_c, W_f, and W_o are weights, σ denotes the sigmoid function, $*$ denotes the product of outer vectors, while the offsets are demarcated as b_i, b_c, b_f, and b_o. The forward and the backward law of time series information is fully considered for the prediction of time series to effectively improve prediction accuracy using the Bi-directional LSTM. This unique architecture allows it to update information before and after data transmission, enabling it to make comprehensive decisions by considering both past and future data context. The forward and backward calculations are visually depicted in Figure 2. The horizontal arrow signifies temporal dependencies in time series data, flowing in both directions of the model. However, information processing within the model occurs unidirectionally, progressing sequentially from the input layer to the hidden layer, and ultimately to the output layer.

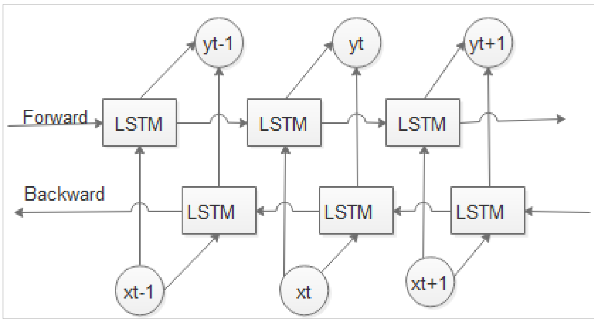

Figure 2. Structure of Bi-LSTM

3.2. Feature extraction

BERT primarily modifies the attention mechanism of the higher layers to adjust the behavior of the intermediate and final layers. At the same time, BERT is capable of preserving knowledge across two layers, enabling it to assess the consistency of the fine-tuning process across different datasets. Since the attention score reflects the underlying relationships between various words, the model extracts the output representation of each layer for feature extraction. Bi-LSTM is used to measure the changes in output representation during fine-tuning, indicating the adjustment in BERT's feature extraction process. It derives the task representation vector through the powerful feature extraction capability of BERT, which is easier to optimize compared to more complex representations [27]. As a result, the word embedding process assigns significant features to weights, and these important features are then passed to LSTM for vector classification. Table 1 presents the constraints of the proposed BERT with the Bi-LSTM model.

Table 1. Parameter settings of BERT with Bi-LSTM

Parameters	Values
Dropout rate	90.35
Hidden size	0.25
Batch size	32
Length	128
Learning rate	0.0001
Regularization coefficient	0.6
Optimizer	Adam

3.3. Required outcomes

The input sentence salience scores are used to classify outputs as positive or negative. The objective is to calculate both negative and positive scores for specific words and phrases within a text review. SentiWordNet assigns two emotion scores to each WordNet entry: one for positivity and one for negativity, with each score ranging from 0 to 1.

4. RESULTS AND DISCUSSION

This passage presents the output obtained from the BERT with the Bi-LSTM model, which is then compared to the results of previous methods assessed using the same datasets. The variety of student perspectives, emotions, and experiences further complicates sentiment analysis in e-learning. As a result, there exists a significant research gap in developing accurate and reliable sentiment analysis models that can effectively classify and analyze student sentiments in e-learning environments. The results of the proposed educational content classification model employing BERT with Bi-LSTM are provided. The validation of the proposed BERT word embedding-based Bi-LSTM model is compared to existing algorithms using the collected Coursera dataset. The proposed image recovery algorithms are executed on a workstation running Python 3.7.3 environment with 8 GB RAM, and a 2.2 GHz processor. In addition to the accessible methodologies, the metrics and performance analysis used for educational content classification are described in the following sections.

4.1. Performance metrics

The proposed categorization process is achieved by integrating BERT with the Bi-LSTM model for word embedding classification. The BERT-based Bi-LSTM model is assessed by comparing it with previous approaches and is evaluated using various constraints to validate the proposed techniques. The performance parameters considered for the BERT-based Bi-LSTM model are described as follows; Accuracy is the ratio of successfully predicted outcomes to the total number of predictions, and it is used to evaluate model classification, as defined in (7). Precision is defined as the ratio of correctly predicted positive outcomes to the total number of predictions classified as positive, as given in (8). Recall is defined as the percentage of correctly predicted positive outcomes to the total number of actual positive outcomes, and it can be expressed mathematically in (9). The F-score evaluates the model's accuracy by calculating the harmonic mean of precision and recall, as described in (10).

$$Accuracy = \frac{Number\ of\ corrected\ predictions}{Overall\ predictions} \tag{7}$$

$$Precision = \frac{TP}{TP+FP} \tag{8}$$

$$Recall = \frac{TP}{TP+FP} \tag{9}$$

$$F-Score = \frac{TP}{TP+\frac{1}{2}(FP=FN)} \tag{10}$$

4.2. Quantitative analysis

This section explains the proposed quantitative evaluation of the methodologies utilizing BERT. Table 2 presents the results obtained from the suggested classification approach employing BERT with Bi-LSTM for course review analysis. It provides information on the estimated outcomes for course review categorization in terms of F-measure, accuracy, precision, and recall. Table 2 shows the quantitative analysis of Bi-LSTM using the BERT approach to assess course evaluations. Performance is evaluated using F-score, precision, accuracy, and recall metrics. Accuracy is the ratio of correct predictions to total predictions used in the classification method. The F-score, a measure of the model's overall performance, achieves a high value of 93.791% for both the Bi-LSTM and BERT techniques. The recall rate, which indicates how well the model identifies relevant information, achieves 94.909%. Precision, reflecting the accuracy of positive predictions, obtains 93.744%. Finally, the overall accuracy achieved by the model representing the correctness of the model's predictions, is 94.125%. BERT, a straightforward technique, creates subsets of examples to accurately classify the unique data. The Bi-LSTM, an enhancement of LSTM, improves the model's processing of sequential data. Thus, the suggested method performs efficient classification, as demonstrated in the quantitative analysis in Figure 3.

Table 2. The BERT-based Bi-LSTM quantitative analysis

Methods	Accuracy (%)	Precision (%)	Recall (%)	F-Score (%)
CNN with Bi-LSTM	79.786	74.073	77.249	75.786
Proposed	81.459	93.744	94.909	93.791

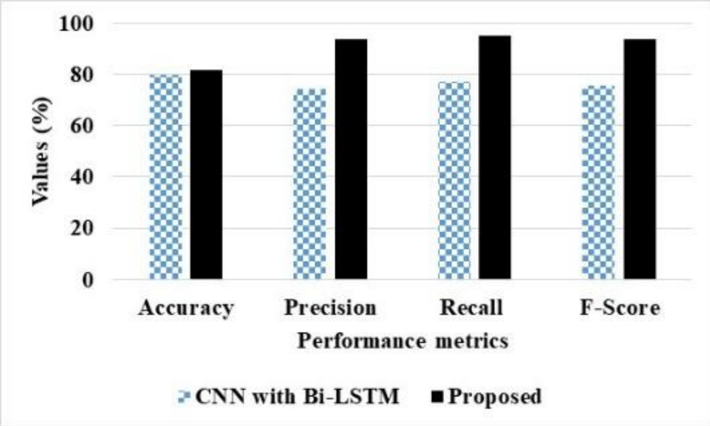

Figure 3. Quantitative analysis of the suggested techniques

4.3. Comparative analysis

This section presents an evaluation of the proposed BERT-based Bi-LSTM model in comparison with existing methods, including CNN-LSTM [16], MOOCs [19], and a semi-supervised deep learning model [20] to assess the performance of the BERT with Bi-LSTM. Generally, BERT is a straightforward procedure that constructs subsets of data to accurately classify unique data. Bi-LSTM is an enhancement of LSTM that improves system performance in sequential classification tasks. Table 3 demonstrates that the proposed model is evaluated against conventional models based on precision, recall, and F-score.

Table 3. BERT with Bi-LSTM techniques for comparative analysis

Methods	Precision (%)	Recall (%)	F-Score (%)
CNN-LSTM [16]	90.35	85.32	91.27
MOOCs [19]	81.37	81.28	81.16
Semi-supervised DL methods [20]	82.52	81.92	82.89
BERT-Bi-LSTM	93.72	94.9	93.7

During implementation, the existing techniques [16] achieve 90.35% precision, 85.32% recall, and 91.27% F-score. The method from [19] achieves 81.37% precision, 81.28% recall, and 81.16% F-score, while [20] achieves 82.52% precision, 81.92% recall, and 82.89% F-score. In comparison, the proposed BERT with Bi-LSTM model achieves superior results, with 93.07% precision, 94.9% recall, and 93.07% F-score. A graphical comparison of the BERT with the Bi-LSTM approach is shown in Figure 4.

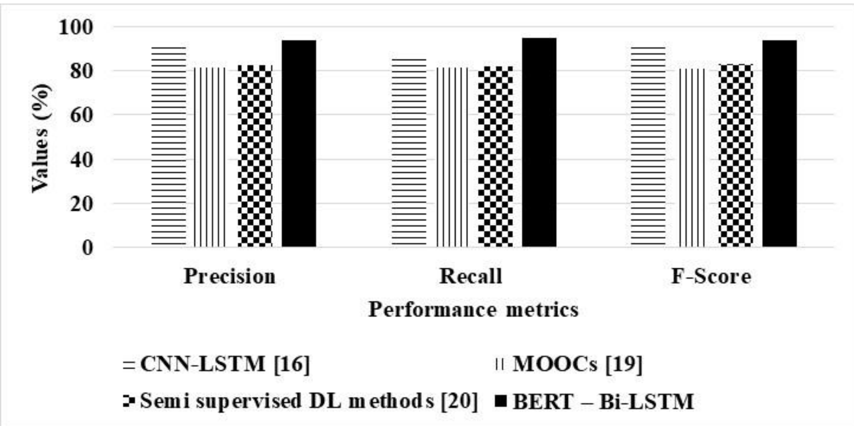

Figure 4. Comparative analysis of the proposed method

4.4. Discussion

The existing research analysis has concentrated mainly on analyzing sentiment at the document level which neglects the significance of aspect-level sentiment analysis in understanding complex student emotions. Therefore, this research addresses these gaps by investigating the effectiveness of a BERT with a Bi-LSTM model in aspect-level sentiment analysis of online course reviews. The texts from various courses, across different levels, exhibit significant differences in both the keywords used and the sentence structures. Consequently, the model struggles to accurately classify these recordings into specific classes or categories, as the variations make it challenging to determine the classification. The results of the proposed BERT with Bi-LSTM outperformed the conventional models based on accuracy, recall, precision, and F-score metrics. The comparison, clearly shows that the existing MOOCs [19] achieved 81.37% precision, 81.28 recall, and 81.16% F-score, and semi-supervised DL [20] also achieved 82.52% precision, 81.92% recall, and 82.89% F-score; similarly, the comparison clearly demonstrates that the existing CNN-LSTM [16] achieved 90.35% precision, 85.32% recall, and 91.27% F-score. The proposed BERT-Bi-LSTM approach outperformed these existing techniques by accomplishing 93.07% precision, 94.9% recall, and 93.07% F-Score, respectively. However, when applying the BERT with Bi-LSTM models into new domains or datasets, it requires significant fine-tuning or retraining, since it is a time-consuming and resource-intensive process. In the future, this limitation will be tackled by using transfer learning models. From the overall discussion, it evidently proves that BERT with Bi-LSTM shows more effective performances than the existing methods such as CNN-LSTM [16], MOOCs [19], and semi-supervised DL [20].

5. CONCLUSION

In this study, course review analysis is categorized by the BERT with Bi-LSTM algorithm. NLP techniques such as tokenization, stop word removal, and sentence matrix construction are used in data pre-processing. During course review, the collected features are given to the suggested classifier model through BERT with Bi-LSTM. The BERT classifier is a simple algorithm that creates subsets to correctly classify the unique data. This study uses BERT with Bi-LSTM for sentiment analysis in e-learning. The output demonstrates that BERT with Bi-LSTM outperforms conventional models based on accuracy, recall, precision, and F-score metrics while analyzing course reviews. The study shows how well deep learning methods work for sentiment analysis in online learning environments. The potential applications for the suggested sentiment analysis include online course building, course evaluation, and personalized learning. Further, the potential extension of this research includes multimodal sentiment analysis, cross-cultural sentiment analysis, and real-time sentiment analysis. Overall, the suggested techniques achieve better results with an accuracy of 81.45%, recall of 94.9%, precision of 93.7%, and F-score of 93.7% compared to existing approaches. For the research field, these results support the creation of sentiment analysis algorithms for e-learning environments that are precise and reliable. Similarly, for the community, these results have real-world applications for educators, instructional designers, and creators of online courses. In future progress, this research will be further extended by analyzing various user evaluations to efficiently enhance the quality of online courses.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Murthy Venkata Surya Narayana Tatavarthy	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	✓
Naga Lakshmi Vadlamani		✓				✓	✓	✓	✓	✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research related to human use has been complied with all the relevant national regulations and institutional policies in accordance with the tenets of the Helsinki Declaration and has been approved by the authors' institutional review board or equivalent committee.

DATA AVAILABILITY

The data that support the findings of this study are openly available in [Coursera Forums] at https://github.com/elleros/courseraforums.

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BIOGRAPHIES OF AUTHORS

Murthy Venkata Surya Narayana Tatavarthy presently working as Associate Professor at the National Institute of Fashion Technology and Research Scholar in the Department of Computer Science, GITAM Institute of Science, GITAM (Deemed to be University) Visakhapatnam, Andhra Pradesh. His research areas of interest are cloud computing, artificial intelligence, and data analytics. He can be contacted at email: tvsnmurthy@gmail.com.

Naga Lakshmi Vadlamani presently working as a Professor at the Department of Computer Science GITAM Institute of Science, GITAM (Deemed to be University) Visakhapatnam, Andhra Pradesh. Her areas of interest include cloud computing, big data, blockchain technologies, and machine learning. She has presented papers in various national and international journals and conferences. She can be contacted at email: nvadlama@gitam.edu.