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PAPER

Hybrid Deep Learning Model to Predict Students' Sentiments in Higher Educational Institutions

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ABSTRACT

Sentiment analysis has been widely used in various fields of social media, education, and business. Specifically, in the education domain, the usage of sentiment analysis is difficult due to the huge amount of information, the nature of language, and processing the diverse perceptions of students. Deep learning emerges as an advanced concept in the realm of machine learning that learns features automatically from raw text data, making them well-suited for sentiment analysis tasks. In recent years, deep learning has been used in analyzing the sentiments. Deep learning architectures have surpassed other machine learning paradigms for performing sentiment analysis. The ability to analyze automatically the students' sentiments enables HEI to process huge amounts of unstructured data quickly, efficiently, and cost-effectively. The paper aims to predict the sentiments of students' reviews posted in VLE regarding online learning that enables the educators to optimize their teaching methods for the best results. This study paper explores the usage of CNN, LSTM, and hybrid CNN-LSTM for the prediction of sentiments. The proposed hybrid CNN-LSTM architecture achieves superior performance compared to other baseline algorithms with respect to accuracy, precision, recall, and F1 score. According to outcomes, the recommended technique achieves remarkable accuracy of 97%. The findings facilitate the progress of a more efficient deep learning sentiment prediction system that gives valuable insights from a huge volume of students' textual data.

KEYWORDS

deep learning, online learning, sentiment analysis, opinion mining, sentiment prediction

1 INTRODUCTION

Sentiment analysis, referred to as opinion mining, is a prevalent task in NLP for extracting sentiments from textual data. With the subsequent growth of social media, online communities, and virtual learning platforms, enormous data is available on the web. Sentiment analysis involves analyzing the textual content of students' reviews, emotions, comments, feedback, attitudes, and opinions. This harnesses the

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power of automated sentiment analysis methods that transform the unstructured reviews into useful information. Deep learning models emerge as a dominating approach that learns features from multiple layers and provides accurate predictions. They extract complex features and patterns from unstructured textual data that makes them a vital tool for sentiment analysis. This approach offers potential to accurately identify intricate features in data, surpassing the capabilities of traditional methodologies. They can understand the text beyond simple definitions, read the context, sarcasm, etc., and can recognize the real feelings of the writer. The process of students' sentiment prediction using deep learning techniques encompasses various stages, namely, data collection, data pre-processing, implementing deep learning models, and evaluating the model performance in sentiment prediction tasks. These collective procedures empower HEI to extract valuable information from textual content, facilitating efficient decision-making strategies.

Analysis of sentiments employing deep learning algorithms provides valuable insights to extract large amounts of unstructured textual data and can be applied in various fields, namely customer feedback analysis, marketing analysis, social media marketing, and brand reputation management [1]. Sentiment analysis has received significant attention in analyzing the unstructured data forms from social media and is referred to as text organization, which classifies the opinions in different ways, namely positive, negative, neutral, etc. In the field of NLP, the challenge is the lack of labeled data. For solving this issue, deep learning techniques are used as they are effective owing to their automatic learning capability [2].

Humans and technology are becoming intertwined, which enables the collection of enormous amounts of unstructured, opinionated data. Sentiment analysis, a topic of ongoing NLP study, is the task of accurately analyzing subjective information from this data. Deep learning has become the preferred way for performing sentiment analysis tasks over other machine learning algorithms, offering a wide range of architectures to analyze the sentiments [3]. The fusion of ChatGPT with multi-model CNN has shown remarkable performance and advancements in a variety of applications. By integrating ChatGPT, the model reveals deep insights into decision-making processes, fostering researchers with confident results and thereby enhancing interpretability, user experience, and improved outcomes [4]. This study explores predicting the students' sentiments in enhancing the educational procedures using deep learning algorithms. The rapid growth of deep learning is reshaping the NLP and sentiment analysis domain, and there is a need to develop a hybrid deep learning architecture for students' sentiment prediction in HEI. The key contributions of this study are as follows:

1. A real-time dataset is built based on the comments posted by the higher education students in VLE about online learning.
2. Deep learning techniques, namely CNN and LSTM, are used to predict learners' sentiments.
3. An efficient hybrid deep learning technique that integrates CNN-LSTM is developed that shows enhanced accuracy.
4. The performance of the hybrid approach is measured with various evaluation metrics.

The remaining sections of this paper are designed as shown. Section 2 discusses background works on analyzing the sentiments. Section 3 demonstrates materials and methods. Section 4 explains various deep learning architectures for analyzing the sentiments. Section 5 focuses on implementation and experimental outcomes. Section 6 describes conclusions and future research enhancements.

2 BACKGROUND WORKS

Sentiment analysis has been extensive across various fields of education, social networks, and business over the past ten years. The application of opinion mining is evolving but is still challenging, especially in the educational sector, where handling and processing learners' ideas are crucial, owing to the vast amount of data and the nature of language that learners use. Reading all the reviews is a time-consuming process; therefore, more efficient methods have to be developed, as opinion mining can overcome the shortcomings they are facing currently [5]. The most widespread NLP technique for determining human intents from their reviews is opinion mining, otherwise referred to as sentiment analysis. This is applied in the education sector to get feedback from students and improve the pedagogy of their teaching-learning practices. With the development of AI methodology and sentiment annotation techniques, student responses may be labeled according to their sentiment orientations without much human interference [6].

The importance and popularity of students' feedback have increased currently, when most of the educational institutions have migrated to online mode. In the past few years, analyzing the sentiments has been employed increasingly for examining students' opinions towards educator assessment. Sentiment analysis techniques provide identifying and retrieving hidden patterns from the ocean of education data. Recently, NLP applications, machine learning, and deep learning solutions for opinion mining in the educational field indicate a growing interest [7]. Nowadays, deep learning approaches are anticipated for diverse analysis of sentiments and have attained state-of-the-art outcomes. The study delivers the performance analysis of various deep learning architectures on real-world datasets at the sentence level, document level, aspect-based level, aspect-term extraction, emotion detection, multi-lingual, multi-model sentiment classification task, opinion summarization, and opinion spam detection tasks [8].

M-learning has increased student participation and engagement, improved collaboration between instructors and students, and facilitated real-time feedback, permitting authentic learning and assessment for supporting education communities in HEI. Easy-to-follow lesson plans, convenient communication, and mobile device coaching will be beneficial to students. To increase students' fluency in speaking English, the study suggests implementing a learning-based CNN technique. The CNN algorithm achieves 98.67% accuracy for mobile English training compared with various other approaches [9]. A web crawler is used to collect MOOC course review comments, and the gathered data is preprocessed using various subsequent stages, and then deep learning techniques are used to train the sentiment analysis models to obtain sentence-based and aspect-based sentiment analysis outcomes. Outcomes demonstrate that the training model achieves over 90% accuracy [10].

The latest hotspot for predicting the sentiments is employing deep learning techniques. Numerous study works are carried out in NLP with deep learning approaches using CNN, RNN, and LSTM [11]. Sentiment analysis is becoming a more significant way for analyzing opinions, emotions, and views articulated in social media content. A huge volume of user-generated data, which provides valuable statistics on trends, customer behaviors, and public opinions, is easily accessible owing to the exponential growth of social media platforms. Intrinsic characteristics of the Twitter language, in addition to the messages' brevity and lack of context, make sentiment analysis on social networks difficult. A hybrid deep learning model merging convolutional and LSTM layers is proposed that detects polarity in Twitter postings with 91% accuracy [12].

Individual person's tweets are analyzed using hybrid deep learning approaches, and the study applies sentiment analysis using 5-point scale classification. ANN classifies users' opinions, and the Modified Salp Swarm algorithm is used to optimize the weights. The work proposed results in better accuracy when compared to various machine learning algorithms with reduced time consumption. ANN achieves 92% accuracy and 91.3% precision compared to other classifiers [13]. Sentiment analysis in the educational field plays a crucial role in investigating students' feedback for both traditional and online learning settings. This is an efficient way to get effective suggestions for both educators and platforms to know where improvements are necessary for a better teaching experience. Both machine learning and deep learning algorithms are applied recently to automate the process of learners' sentiments [14].

Analysis of sentiments on social media platforms, namely Twitter and Facebook, has emerged as a powerful tool for recognizing users' opinions. However, accuracy and efficiency of sentiment analysis are hindered by challenges encountered in NLP. Nowadays, deep learning architectures are promising solutions to solve sentiment analysis problems such as sentiment polarity. In this context, the authors perform sentiment analysis experiments using three deep learning approaches, namely DNN, CNN, and RNN. The CNN model offers better performance with accuracy and processing time. They stated that future research should emphasize improving accuracy and processing outcomes [15].

Deep learning algorithms excel in sentiment analysis. The proposed CNN+LSTM and CNN+GRU, compared to other deep learning algorithms, show quantitatively high performance across various datasets. Using TF-IDF features, CNN+LSTM exhibits its higher accuracy scores of 81.36, 95.55, 74.80, and 93.45 consistently [16]. In the arena of NLP, text classification is a classic task. A hybrid model of LSTM-CNN is proposed that efficiently improves the text classification accuracy. The proposed model combines the benefits of LSTM and CNN to make up for the deficiencies of CNN. The classification accuracy was 87.31% on the validation set and 91.17% on the test set [17].

Analyzing the sentiments based on BERT was implemented for exploring deep semantic text information. The fusion model of BiGRU and TextCNN applied in the study exhibits high accuracy of 87.68% in analyzing the sentiments of college students' teaching assessment texts. This encourages practical applications of flexible management concepts in university education and offers more useful reference material for teaching management at universities [18]. Dimensional sentiment analysis recognizes continuous numerical values in multiple scopes, namely valence-arousal space. Compared to categorical approaches that emphasize binary classification of sentiments, the dimensional approach provides more fine-grained analysis of sentiments. The study suggests combining CNN and LSTM for the prediction; process and experimental outcomes show that the CNN-LSTM architecture outperforms lexicon, regression, and NN-based methods with an RMSE of 0.874 [19].

The proliferation of blogs on the cloud enables the generation of enormous amounts of information in a variety of formats, including reviews, attitudes, and opinions. Finding a way to extract useful information from big data, categorize this into various classes, and forecast end users' sentiments or emotions is therefore desperately needed. LSTM and CNN can be implemented for various NLP tasks for significant and efficient outcomes. The hybrid proposed CNN-LSTM architecture achieves 91% accuracy and outperforms baseline deep learning and machine learning algorithms [20]. Hybrid deep learning sentiment analysis approaches that integrate LSTM, CNN, and SVM are constructed and tested on 8 textual tweets and review datasets of diverse fields. Hybrid models are compared with three baseline algorithms, namely, SVM, LSTM, and CNN. For the evaluation of each technique, reliability and computational time were considered. Hybrid models improved the sentiment analysis accuracy when compared to single models [21].

Twitter sentiment analysis uses various methods where deep learning techniques have gained surprising outcomes in recognition of emotions. The study focuses on classifying users' emotions in Twitter messages using deep learning algorithms, namely LSTM and RNN. The experiment illustrates LSTM has better competence in predicting sentiments. The system gains 88.47% accuracy for positive/negative classification on the LSTM model [22]. Analysis of sentiments is an NLP process that encompasses identifying and classifying text emotions. This is quite a complicated process of recognizing emotions and offensive terminologies in comments as noise occurs in code-mixed data. Different pre-trained models, namely LR, CNN, Bi-LSTM, BERT, RoBERTa, and Adapter-BERT, are implemented. Outcomes show that Adapter BERT executes better compared to other algorithms with 65% accuracy for analyzing the sentiments and 79% for detection of offensive language [23].

Students' feedback analysis is laborious work and time-consuming if handled manually. The study explores deep-learning-based architectures that have fascinated a lot of attention in the educational field. A deep learning teaching process is proposed for classifying learners' comments as positive and negative. This takes the benefit of CNN, BiLSTM, and attention layer with an accuracy of 88.78% [24]. In order to understand the current status of education, it is important to examine perspectives on the substantial transformation of educational systems globally due to the extensive adoption of e-learning. In this study, a model for analyzing the sentiments of learners' textual feedback on e-learning is proposed that blends BiLSTM with fuzzy logic. The proposed system outperforms compared algorithms with an accuracy and F1 score of 86% and 85% [25].

To improve the performance of faculties, students' opinions are helpful. Deep learning models are accomplishing superior study results when compared to machine learning approaches. In the proposed system, students' feedback is analyzed using word2vec and CNN. This results in feedback classification of strength, weakness, and recommendations to faculties [26]. A huge number of start-up organizations aims at providing sentiment analysis services owing to their diversified functional uses. The aim of the study is to create a fusion model for analyzing the sentiments exactly from the perception of customer review summarization. LSTM applies HFV for classifying the input reviews. Proposed hybrid feature extraction applying LSTM (HFV+LSTM) reveals greater performance for all evaluation parameters that are considered. The model achieved the average precision, recall, and F1-score of 94.46%, 91.63%, and 92.81% [27]. For capturing both local and contextual information from, a multi-channel CNN with Bidirectional LSTM is proposed in the study. The attention layer significantly increases classification accuracies. The proposed model achieves 94.13% accuracy, which shows superiority among other models, which brings innovative change in text analysis [28].

Analysis of sentiments is a complex process due to the deficiency of significant information in brief texts. In recent years, deep neural networks such as CNN and RNN have been employed extensively for extracting information from data sentiments with good results. Standalone CNN and RNN would not improve the performance of the system. The combination of CNN BILSTM and CNN BiGRU shows improved results. CNN BiGRU shows better performance with 95.42% [29]. BERT-LSTM-CNN deep learning techniques are proposed for extracting students' emotions from their reviews scraped from the Coursera education platform. Pre-trained BERT, a word embedding method, extracts the textual features. LSTM retrieves semantic relations among words, and CNN extracts complex local features. Based on the outcomes, the suggested model performs better with 79.75% accuracy [30].

Adaptive Learning Analytics (ALA) models enhance student learning outcomes and satisfaction. The ALA model comprises various key functions, namely evaluation, acquisition, and analysis. The model provides a comprehensive approach for HEIs aiming for excellence. The theoretical framework integrates decision modeling and big data analytics for analyzing different datasets, thereby increasing decision quality within the educational context [31]. The Educational Data Mining (EDM) approach is used for predicting the students at risk for improving the efficiency of academic tasks. Multiple prediction models, including RF, LR, DT, NB, SVM, KNN, XGBoost, and ensemble voting classifiers, were implemented. Notably, the ensemble voting methods achieved the highest overall accuracy of 86% and assist educators in making proactive decisions through timely alerts [32].

Handling reviews posted by learners is an arduous, time-consuming task if handled manually and unrealistic to deal with huge-scale unstructured feedback from the virtual learning environment. For overcoming the shortcomings of these problems, the current study sheds light on deep learning models that automatically predict the learners' opinionated text. Deep learning has emerged as an extremely exclusive solution for addressing these challenges owing to automatic and hierarchical learning capabilities. However, the prevailing methods of textual classification and prediction can be enhanced as of the multifaceted concept of textual semantic information and strong context relevance. A hybrid model is proposed that combines CNN and LSTM on pre-trained word2vec. CNN effectively extracts the high-level features with convolutional and max-pooling layers. LSTM captures long-term dependencies between sequences of words. For the experiment, the real-time dataset is used that is divided into a training and test set. The study outcomes achieve increased performance accuracy when compared with the contribution of other researchers.

3 MATERIALS AND METHODS

The study aims to predict the students' sentiments based on their comments posted in VLE. The methodology comprises the subsequent steps. First, the real-world data is gathered from the students, and data pre-processing methods are applied with NLP techniques to eliminate special characteristics, symbols, and stop words from the feature space. Pre-processed text is then fed into word2vec to convert it into a features matrix. CNN extracts the complex local features. Outcomes of CNN are forwarded into the LSTM model to extract long-term dependencies between words. Finally, a fully connected hybrid model predicts the students' sentiments.

3.1 Description

The first phase is the data collection phase. Real-world data was collected from students of various higher education institutions throughout India. The well-structured e-questionnaire was distributed to the target respondents belonging to diverse academic divisions and levels. This was broadly classified into various factors, namely, demographic features, device usage characteristics, self-efficacy, familiarity with cloud platform usage, readiness, and effectiveness of online learning. Students have posted their opinions, reviews, feedback, and comments regarding online learning. The dataset used in this study contains 2650 reviews posted by the learners in VLE, which comprised 1415 positive, 1010 neutral, and 225 negative samples. The dataset was split into two subsets, 80% for training the model and 20% for testing to evaluate the classification performance.

3.2 Data pre-processing

Text cleaning and pre-processing are necessary to get accurate predictions of sentiment analysis. This is the crucial step in NLP that involves cleaning and transforming raw text data into machine-readable format. The reviews presented in the dataset were cleaned and pre-processed using various pre-processing tasks, including text cleaning, removing stop-words, stemming, tokenization, part-of-speech, normalization, etc. The primary step in data cleaning is to eliminate punctuation marks, special characters, digits, unwanted symbols, and stop words. This is done by using Regex (regular expression), as they are the powerful tool in text pre-processing for NLP. Then the words are transformed into lower case. After lowercasing the data, stop words, namely I, am, with, that, it, my, and, to, etc., are eliminated from the dataset using NLTK's (Natural Language Toolkit) stop words. They should be removed to improve the model performance. Lemmatization is performed, which considers the context first, then converts the words to their meaningful root form called lemma and returns valid words for easy interpretation. For instance, the terms problems, accomplishments, and solutions may have the roots problem, accomplishment, and solution, respectively. PoS tagging is applied wherein each word is given a particular part of speech, such as adjective, verb, noun, or adverb.

The tokenization process breaks down a piece of text, like a sentence or a paragraph, into individual words called tokens. The token occurrences in a document can be directly used as a vector representing that document. This process immediately converts unstructured text reviews into numerical vectors suitable for deep learning. Text in each learner's review is vectorized, and the dataset is split according to training data and test data. The hyperparameter used is max_words, which denotes the maximum number of words to be kept based on the word frequency. Learners' reviews are of different lengths; hence, sequence padding is implemented as the deep learning models require input data with the same length; padding is used to ensure all sequences have the same length. The pad_sequence() function converts a list of sequences into NumPy arrays. After pre-processing the text, word2vec embedding are used. These allow words to be represented as vectors better for deep learning models.

4 DEEP LEARNING-BASED FRAMEWORKS FOR ANALYZING THE SENTIMENTS

Deep learning architectures have revealed important advancements and excellent outcomes in analyzing the sentiments. Deep learning methods are popularly used to predict sentiments and are superior to other methods with regard to accuracy, data size, feature handling, context, and syntactic aspects [33]. Deep learning is a powerful machine learning paradigm that utilizes multi-layered neural networks for learning complex patterns of data, powering breakthroughs in areas of NLP and computer vision. They evolve as potent computational techniques that discover intricate semantic text representations automatically from data. Sentiment analysis tasks can be performed robustly by implementing different deep learning models. The study proposes a fusion model that integrates CNN and LSTM for predicting learners' sentiments.

4.1 CNN

This is a type of deep learning technique that has gained a lot of attention in the study domain for performing NLP related tasks. CNN comprises multiple layers, namely convolutional, pooling, and fully connected layers. CNN models are inspired by the visual processing of the human brain and are well-suited for extracting hierarchical patterns. The study implements Conv1D to predict the students' sentiments. Text as a sequence is passed to CNN that extracts appropriate features from local input patches permitting for representation modularity fostering data efficiency. The embedding matrix is passed to the embedding layer. CNNs are several layers of convolutions with activation functions like Relu (Rectified Linear Activation Unit) that make it possible to model non-linear relationships and easier to train the model for getting better results by producing much larger gradients. A 3-layered 1D ConvNet is implemented and flattened at the end using the GlobalMaxPooling1D layer, then fed to a dense layer. The predictions are made by feeding the vector to the dense layer of 5 units. The softmax activation function is applied particularly for multi-class classification tasks, which transforms the values into a vector of probabilities. The optimizer used in the study is Adam (Adaptive Moment Estimation), which is an iterative optimization algorithm used to minimize the loss function during the training of neural networks. The loss function sparse_categorical_crossentropy is applied as the classification involves three class labels, namely, positive, negative, and neutral. The model is trained on preprocessed reviews and sentiments, using a batch size of 100 and running for five epochs. The number of epochs is the amount to which the model can loop around and learn. Figure 1 represents the block diagram of the CNN model.

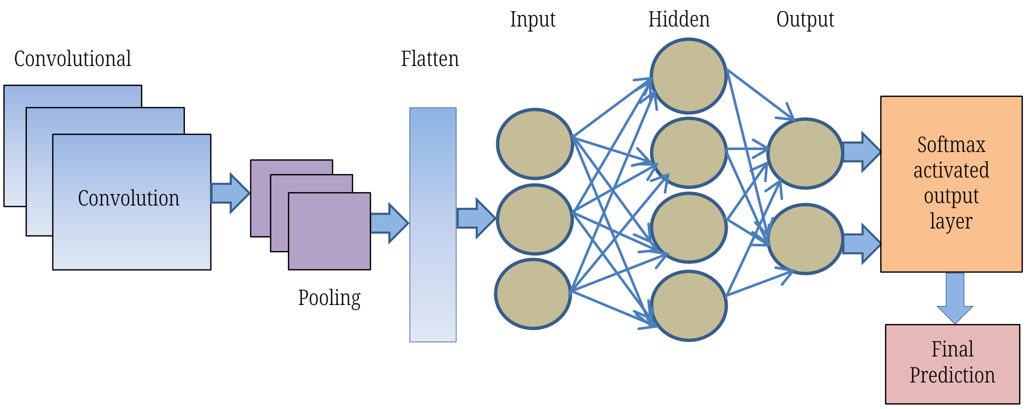


Fig. 1. Block diagram of CNN model

4.2 LSTM

LSTM networks are RNN extensions designed to learn sequential data and their long-term dependencies more precisely than standard RNNs. They are commonly used in deep learning applications, namely speech recognition, natural language processing, and stock forecasting. They involve a memory cell at the top that helps with carrying the information from a specific time instance to the next time instance in an effective way. This enables remembering a lot of information from preceding states when compared to RNNs, thus overcoming the vanishing gradient problem. LSTM comprises three main gates; 1) forget gate, 2) input gate, and 3) output gate. Information that is no longer valuable in cell state is discarded with the forget gate. Two inputs, h_{t-1} (information from previous hidden cell) and x_t (information from the current cell), are passed to the gate and multiplied with weight matrices, followed by the addition of bias. Outcomes are fed over an activation method that provides a binary output. The input gate updates the cell state and decides which information is significant and stores certain relevant data in the memory. The process of retrieving relevant information from the current cell state to be represented as an outcome is done by the output gate. The equations of LSTM gates are:

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

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \quad (2)$$

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \quad (3)$$

In the above equations, f_t, i_t, *and* o_t represent forget, input, and output gates; W represents the weight matrix; h_{t-1} and x_t indicate the concatenation of the current input and previous hidden state; b is the bias, σ is sigmoid activation function. The LSTM model is built using keras' sequential API, indicating that the model is built layer by layer in a sequential manner. This includes model initialization, adding essential LSTM layers, and model compilation. The LSTM layer is added with 256 memory units. After the LSTM layers, a dense layer with 3 units is included, corresponding to three sentiment classes. The Adam optimizer is used. The loss function sparse_categorical_crossentropy is applied as the classification involves multi-class. The model is trained on the preprocessed reviews and sentiments, using a batch size of 100 and executed for 5 epochs. Figure 2 depicts a block diagram of the LSTM model.

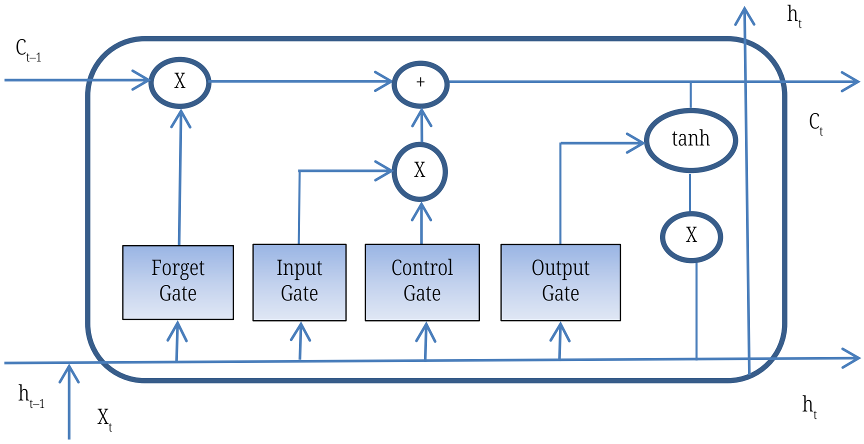


Fig. 2. Architecture of LSTM network

4.3 Proposed hybrid CNN-LSTM model

The framework of the proposed hybrid CNN-LSTM architecture is presented in Figure 3. The text analysis method established on CNN can obtain appropriate features through pooling, yet it is difficult to obtain contextual information that can be leveraged using LSTM. The LSTM framework receives the extracted features from the encoder (CNN) as input. Training data, in addition to various LSTM gates, are continually adjusted so that the LSTM model can determine connections within input and output sequences. CNN-LSTM fusion comprises an initial convolutional layer that receives word embedding as input. The output will then be pooled to a smaller dimension that is then passed into the LSTM layer. The idea of this model is that CNN extracts local features and LSTM layers use the ordering of features for learning about inputs and text ordering. The embedding layer transforms the integer sequences representing words into dense vectors of fixed size. This is crucial for handling categorical data, particularly textual data. SpatialDropout1D of 0.2 is used to perform variational dropout in NLP models. Next, an LSTM layer is added with 256 memory units. The LSTM layers are effective in processing text sequences, as they can capture the temporal dependencies between the elements in the sequence. Dropout and recurrent dropout layers are added, which are regularization methods where input and recurrent connections to LSTM units are excluded from activation and weights are updated while training a network. This minimizes overfitting and increases model performance. After the LSTM layers, the dense layer with 3 units is included, corresponding to three sentiment classes. The optimizer used is the Adam optimizer. The loss function sparse_categorical_crossentropy is applied as the classification involves multi-class. The model is trained on the preprocessed reviews, using a batch size of 100 and executed for 5 epochs. The softmax activation function is applied in the output layer to get probabilities for each class. The combination of CNN with LSTM gives us results with improved accuracy. The input shape, batch size, and epochs are the same for all three models. To optimize the performance of the proposed model, various hyperparameters are used. The summary of hyperparameters and their values is depicted in Table 1.

Table 1. Details of hyperparameters

Hyperparameter	Values
SpatialDropout1D	0.2
Dropout	0.2
Recurrent Dropout	0.2
Batch size	100
Epochs	5
Activation Functions	Relu, softmax
Optimizer	Adam

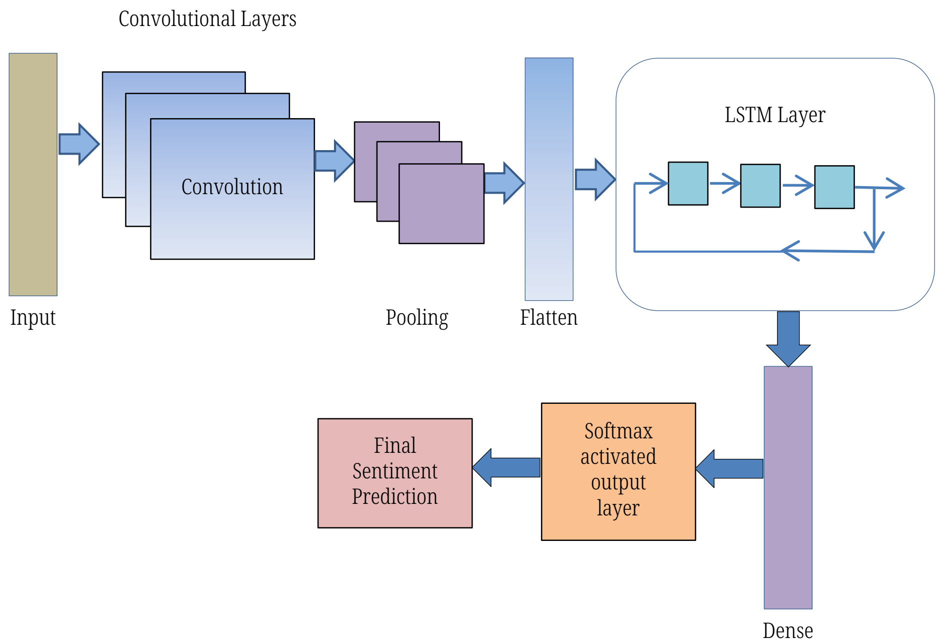


Fig. 3. Proposed system architecture of hybrid CNN-LSTM for sentiment prediction

5 IMPLEMENTATION AND EXPERIMENTAL RESULTS

Real-time data comprising 2560 reviews posted in VLE by the students towards online learning were used for the evaluation of the deep learning algorithms. The study proposes a hybrid deep learning CNN-LSTM approach that integrates the functionalities of CNN and LSTM that aims to predict the sentiments of learners' reviews with superior performance. Word2vec is used to represent the words as vector space, and this uses two techniques, 1) continuous bag of words (CBOW) and 2) skip-gram, to convert words into vectors. CBOW predicts a target word according to the context of the surrounding words in text or sentences. The skip-gram model is a method for learning word embedding and is trained using enormous amounts of unstructured data for capturing context and semantic similarity among words. Both the techniques learn weights that act as word vector representations. The proposed hybrid CNN-LSTM architecture shows better performance with accuracy, precision, recall, and F1 score compared to the other deep learning algorithms.

5.1 Performance evaluation

The model performance is measured using Scikit-Learn Libraries in Python. The best hyperparameters are gained after repetitively executing the model with various parameter values. The performance of a multi-class classification model is assessed by incorporating various evaluation metrics, namely accuracy, precision, recall, and F1 score, as presented in the following equations. Accuracy is a metric that describes how the model performs across all classes. This is the ratio between the number of correct predictions and the total number of predictions. Precision evaluates the correctness of positive predictions. Recall measures the model's ability to detect positive samples. The F1 score is the harmonic mean of the precision and recall.

$$Accuracy = \frac{TP + TN}{Total\ Number\ of\ Samples} \tag{4}$$

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

$$F1\,Score = \frac{2 * P * R}{P + R} \tag{7}$$

Where TP is true positive, TN is true negative, FP is false positive, and FN is false negative. The CNN model achieves an accuracy of 94%, the LSTM exhibits 96% accuracy, and the hybrid CNN-LSTM model shows 97% accuracy (refer to Table 2). Figure 4 shows enhanced prediction performance of the proposed hybrid CNN-LSTM model.

Table 2. Performance comparison of hybrid CNN-LSTM with CNN and LSTM

Deep Learning Models	CNN	LSTM	CNN-LSTM
Accuracy	94	96	97
Precision-macro avg	91	92	95
Precision-weighted avg	94	96	97
Recall-macro avg	82	92	91
Recall-weighted avg	94	96	97
F1 Score-macro avg	85	92	93
F1 Score-weighted avg	93	96	97

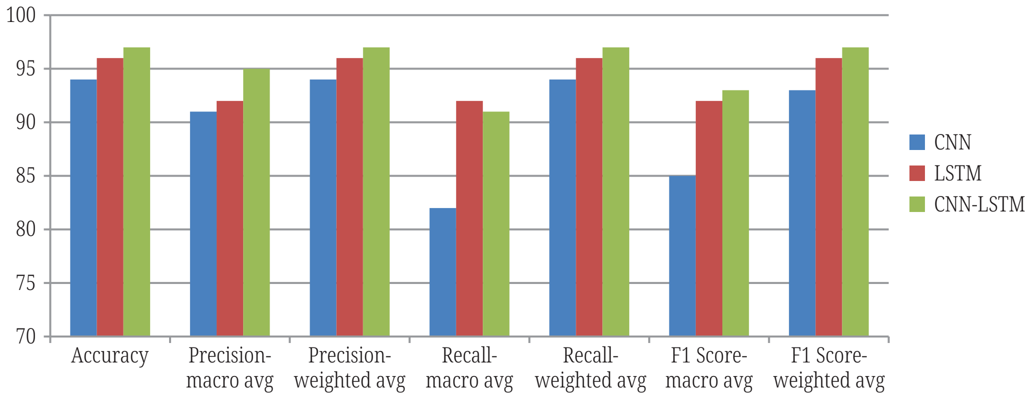


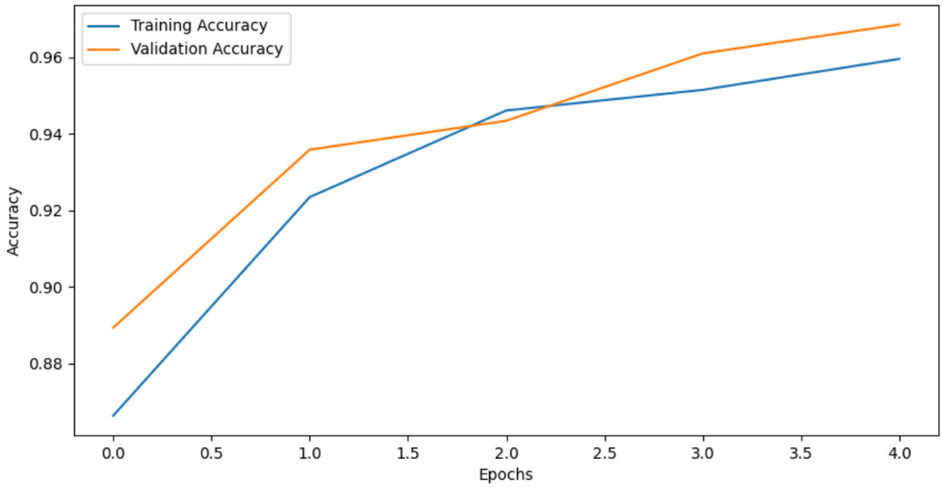
Fig. 4. Sentiment Prediction Results of CNN, LSTM, and Proposed Hybrid CNN-LSTM

5.2 Training and validation accuracy

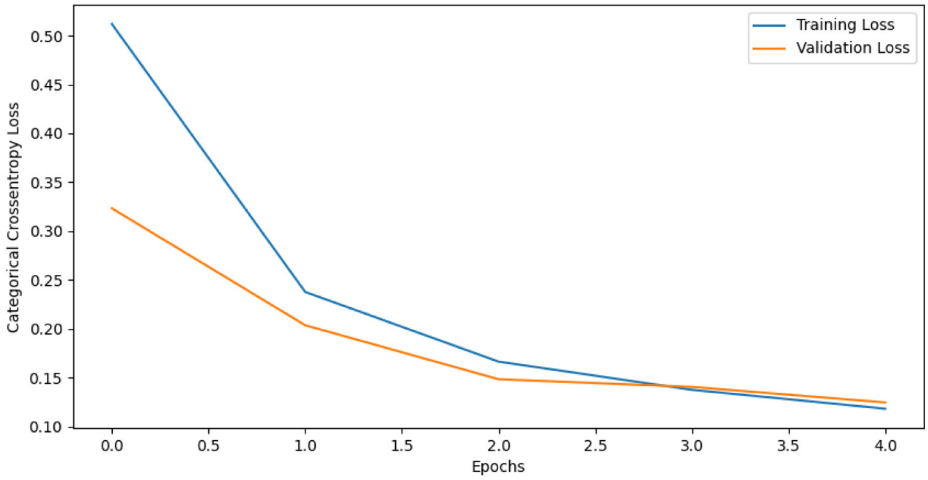
In deep learning, training and validation accuracies are essential metrics for evaluating model performance. During training, the model learns from training data by adjusting its weights and biases. Training accuracy measures the model's performance on the training data. This indicates how accurately the model predicts the correct labels for the training samples. The validation set monitors the performance of the model on unseen data. This subset of data is critical to maintain, as these samples are not used for training. After each training epoch, the model is evaluated on the validation set. Validation accuracy enables understanding of how the system generalizes to new data.

5.3 Training and validation loss

Loss is measured on training and validation sets. This implies how well the system works after each iteration of optimization. The main aim is to see both the training loss and validation loss are decreasing. Lower the training and validation loss; the model performs better. Both losses would be roughly the same value, as long as the validation loss stays close to the training loss, determining that the model is continuing to learn generalized things about the data. Training and validation performance of the proposed hybrid CNN-LSTM model is depicted in Figure 5.



a) CNN-LSTM Accuracy



b) CNN-LSTM Loss

Fig. 5. Training and validation performance accuracy, loss of CNN-LSTM model

6 CONCLUSION AND FUTURE WORK

Sentiments are a valuable information source for analyzing learners' behavior regarding a topic, course, or educators' performance. The higher educational institutions can reform the policies and procedures for their improvements based on the sentiments posted by learners. Sentiment analysis approaches have progressed from simple rules to advanced machine learning and deep learning solutions. Deep learning architectures have shown excellent outcomes in learning and predicting the students' sentiments significantly. This has proven to be superior in representing and analyzing complex language structures. The study implemented deep learning algorithms like CNN and LSTM and proposed a hybrid CNN-LSTM architecture, through which sentiment prediction can be accomplished in a more accurate and efficient way. The input student reviews can be transformed into feature vectors that allow employing an effective, robust, reliable sentiment prediction system that facilitates knowing the perceptions of the higher education students. The experimental outcomes of the study indicated that the proposed hybrid CNN-LSTM model functions magnificently compared to other approaches with an accuracy of 97% for sentiment prediction. A more accurate prediction of sentiments will be possible using hybrid deep learning approaches.

The limitation of this study is that the deep learning model is restricted to the educational field that involves students' reviews posted in a virtual learning environment. With the growth of the internet and social media networks, users can share their opinions, thoughts, and reviews on all kinds of topics in different languages. Further, research could implement models that can handle reviews in multiple languages. Moreover, the technique can be applied to other sentiment domains such as emotion detection, product reviews, and brand reputation management in order to gain deeper insights.

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