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Research Article

Emotion Prediction from Online Course Reviews by Using Deep Learning

Muhammad Ahtesham Noor[1], Mustajeeb ur Rehman[2,*] and Muhammad Saddique[1]

[1]Department of Computer Science Bahria University Islamabad, 44790, Pakistan
[2]Department of Computing, National University of Modern Languages, Islamabad, 44790, Pakistan
[*]Corresponding Author: Mustajeeb ur Rehman Email: mustajib.rehman@numl.edu.pk
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Abstract: Massive open online courses (MOOCs) emerged as a pivotal solution for distance learning during the COVID-19 pandemic, effectively breaking down barriers related to age, gender, and geography. This study focuses on developing a robust and precise emotion classification model using advanced deep learning techniques, specifically targeting the reviews on Coursera's online learning platform. Our research dives into key questions surrounding the performance of different deep learning models, particularly comparing the Long Short-Term Memory (LSTM) network with a hybrid model that combines Convolutional Neural Networks (CNN) and LSTM. We hypothesize that this hybrid approach not only enhances the predictive accuracy of emotion analysis but also outperforms traditional supervised learning methods. By analyzing a comprehensive dataset of 140K course reviews, we demonstrate that the hybrid CNN-LSTM model, when coupled with sophisticated word embedding techniques, achieves superior results, reaching a peak accuracy of 93.80%. This work underscores the potential of hybrid models in capturing the complexities of human emotions in educational content, offering valuable insights for improving online learning experiences.

Keywords: COVID-19; Emotion Classification; Deep Learning; LSTM; CNN-LSTM Hybrid Model; Coursera Reviews

1. Introduction

The world sees standards shift their daily activities in the ongoing coronavirus (COVID-19) pandemic the way we meet people, relate, operate businesses, shopping, and learn online. Such world disasters directly affect our lifestyle, however. Corona outbreaks keeping schools, restaurants, and borders open.

Emotions add an influential role in human communication. Emotions are more valuable than successful communication. A lot of necessary points are balanced learning in humans is based on emotions. Emotion analysis and Affected computing are essential for AI and other research fields in many situations and businesses, both large and small. Emotion Analysis is used to create automated analysis reviews and opinions from Texts and documents. Online learning platforms played a massive role during the pandemic. Many students use many online learning platform channels for learning. This research will emphasize discovering collective reactions to student reviews' expressed emotions and opinions to online learning platforms. It will highlight to be given analyzing students' responses towards the performance of online courses. Emotion Analysis is the study of analyzing people's opinions, appraisals, assessments, behaviors, and feelings toward objects of different kinds write in a text. Like, services, organizations, individuals' issues, events, topics, and features. Emotion analysis operates on every possible domain, like consumer products, telecommunications, health care, e-commerce, education, ser- vice, financial, political campaigns, elections. When an Online Course Platform or institution wanted a community Emotions, it organized surveys and polls using online web platforms. It got reviews from these platforms, like forum discussions and blogs. From all this, they will get a lot of information about student opinions about the courses. Still, it is not easy to find valuable knowledge from that many student reviews.

Every site contains a massive amount of text that is not very easily translated reviewed. The reader will have to struggle to identify, refine the appropriate information. People are excited to know other people's Emotions for their profits, so they will ask friends and family when they need a view as per human psychology. Emotion analysis is applicable in organizations for effective decision-making. We need automated Emotion analysis. In 1999, the high-demanding Natural language processing studies (NLP). In previous years, web mining and opinion mining were useful. Emotion analysis grows up in every possible domain and industry that contains the text. Through sentimental analysis, convert the division of the text into groups determines the polarity of feelings.

Polarity characterizes a state as possessing opposing emotions. Polarity is positive, negative, neutral. Retrieves people's thoughts about the object known as Opinion Mining and describes the view expressed in a text extracted and analysis known as Emotion Analysis. Both methods are used to solve multi-step classification problems. There are three significant classification types of Aspect Level, Document Level, and Sentence Level. The document's polarity is based on a sentence or aspect; either is positive, neutral, or negative. The review data is considered the primary information unit in the Document-level analysis to classify the document's positive or negative opinion. Sentence level analysis is used to determine whether a sentence represents a standard positive or negative viewpoint. In many classifying applications, the texts are on sentence level, or the document level provides necessary detail. It does not mean that the positive view the reviewer writes the review is always opinionated positive. Likewise, a negatively reviewed document does not describe that the reviewer does not like all the entity's features. In a typical opinionated, the reviewer writes both negative, neutral, and positive opinions. However, most current approaches define the overall polarity, sentence, paragraph, or leaves not in detail. To get these hidden patterns, we need Aspect Based Sentiment Analysis. It identifies the aspects of entities. In mining and summarizing Analysis Aspect Based Sentiment is more complex. Aspect Based Sentiment Analysis systems have been made for various entities like Computers, Travel, Services, and Restaurants or Movie reviews in the past few years. Aspect Based Emotion Analysis systems use texts like (forum discussions and messages, product reviews, and comments) discussing Aspects like Phone selling reviews. The system retrieves the frequently discussed features. Aspects feature like Screen, Size, and Price of the entity and predict the sentiment that de- fines each aspect.

Table 1: Summary of the Previous Models used

Studies	SVM	NB	KNN	RF	DT	ANN	CNN	LSTM	Lexicon
[1]	-	-	-	-	-	-	-	-	T
[2]	-	-	-	-	-	-	-	-	T
[3]	-	-	-	-	-	-	-	T	-
[4]	T	-	-	-	-	-	-	-	-
[5]	-	T	-	-	-	-	-	-	-
[6]	T	-	-	-	-	-	-	-	-
[7]	-	-	-	-	-	-	-	-	T
[8]	-	T	-	-	-	-	-	-	-
[9]	T	-	-	-	-	-	-	-	-
[10]	T	-	-	-	-	-	-	-	-
[11]	T	-	-	-	-	-	-	-	-

[12]	T	-	-	-	-	-	-	-	-
[13]	T	T	-	T	-	-	-	-	-
[14]	T	-	-	-	-	-	-	-	-
[15]	T	-	-	-	-	-	-	-	-
[16]	T	T	-	T	-	-	-	-	-
[17]	-	-	-	-	-	-	-	-	T
[18]	-	-	-	-	-	-	-	-	T
[19]	-	-	-	-	-	-	-	-	T
[20]	-	T	-	-	-	-	-	-	-

[SVM] → Support Vector Machine [NB] → naive bayes

This section provides a synopsis of previous research in this area. The subject of inquiry. Adamopoulos [21] investigated user-generated content. online MOOC reviews to assess the effect of factors Course platforms and universities, for example, significantly impact student retention. Valakunde and Patwardhan conducted another report [15]. Students' performance summary comments were subjected to sentiment classification.

Nave Bayes used the frequency-inverse text frequency (TFIDF) approach, and support vector machines were used as machine learning algorithms. Wen et al [19]. Discussion boards for MOOCs. Students' dropout characteristics were identified using forum posts from three MOOCs in this scheme. In this model, the author collects posts from three MOOCs to classify student dropouts. The study reveals a strong relationship between the mood expressed in course forum feedback and MOOC completion rates. Altrabsheh et al [22] conducted another analysis. introduced a sentiment analysis focused on machine learning Methods for obtaining students' learning-related emotions from feedback reviews. In this approach, Student feedback is used to measure feelings about various courses, including leadership skills, database management, engineering, and Twitter information. Three traditional Ngram versions (namely unigram, bigram, and trigram). The Naive Bayes algorithm, as well as help vector machines in the classification process, the maximum entropy classifier, as well as the random forest algorithm, were used. Adinolfi and colleagues [23] The sentiment analysis system investigates student satisfaction on various online course sites, such as online course learning diaries and Twitter. Students and teachers' behavior has also been documented. Similarly, Bogdan [24] Sentiment research enhances course material and recognizes MOOC Courses' views. In another review, opinion analysis was an effective method for extracting views from students' comments on instructors' results [25]. For slant examination, the creator utilized assistance In the investigation, vector machines and an irregular woods calculation are talked about Moreno-Marcos et al [26] To reveal patterns in under- study action, characterize noticed results for vocabulary-based and AI put together conclusion classification calculations with respect to MOOC criticisms. Strategic relapse, support vector machines, choice trees, irregular timberland, and the Naive Bayes calculation are a portion of the regulated learning procedures utilized in this strategy. A random forest strategy was proposed by the study's findings. Data regarding the online success of higher education institutions drivers can also be extracted using text mining and sentiment analysis [11]. In the presented paradigm, research on topic modeling and profiling has extended to higher educational institutions Abdi et al [27]. Describe a multi-document, query-based, opinion-oriented summarizing method. To obtain sentiment orientation and personal knowledge, the suggested approach employs sentiment analysis. The summarizing module found related sentences from the user's questionnaire. Belbachir and Boughanem [28] To represent the questionnaire and text for sentiment analysis, language models from information retrieval were utilized. In addition, Al-Smadi et al. [29] Morphological, syntactic, and semantic characteristics were employed in the sentiment analysis process. Until recently, Bustillos et al [3] gave an intensive audit of AI and profound learning approaches for assessment mining in a shrewd learning climate. A few AI calculations (like Bernoulli Nave Bayes, multinomial Nave Bayes, support vector machines, straight help vector machines, stochastic inclination plunge, and K-closest neighbor calculation) and profound learning models, (for example, convolutional neural organization and long transient memory) were utilized in this work, just as a few profound learning structures, (for example, convolutional neural organization and long momentary memory). With a classification accuracy of 88.26 percent, the highest prediction efficiency was attained using a profound learning-based engineering. Likewise, Cabada et al [30] On educational reviews, two deep learning architectures (convolutional neural network and long short-term memory) were used, yielding an arrangement precision of 84.32 percent. Nguyen and Nguyen [31] For emotion analysis in video comments, a bidirectional neural Ngam bidirectional LSTM word embedding architecture was presented. A word with semantic and social data in short and significant distance cycles has been communicated in the given framework. Lin et al [32] On student evaluations of education, researchers looked at the prediction yield of information-based and AI-based slant examination systems. The Study, Lo´pez et al [33], On educational resource networks, a system focused on opinion mining and semantic profiling was presented. As of late, Onan [34] scientists took a gander at the prescient accomplishment of conventional characterization calculations, outfit models, and profound learning calculations on understudy appraisals of instructing. Another examination discovered, Wang et al [18] introduced a half-breed profound learning-based plot for slant investigation dependent on convolutional neural organizations and long.

2. Research Methodology

Deep learning and machine learning are two types of learning. Models for sentiment analysis methods have been defined. To accumulate a book corpus on the MOOC stage, we scraped the reviews from Coursera. We got the review data from a well-known online course platform. We collect course reviews from many Courses and Fields. We get almost 1835 Course review data, such as algebra, accounting, aerospace engineering, computer science, agriculture, data science, and education. We have collected around 140k reviews from different courses. Course feedback can be managed and stored from an online learning platform when students review their enrolled courses. We are using a point scale, and the overall average score describes the standard that has been processed in preparation for a course assessment. Using the content scores assigned by the students, we produced a labeled corpus. The reviews classified 1 or 2 as negative, while scores of 4 or 5 were positive. We receive both positive and negative feedback following the marking procedure.

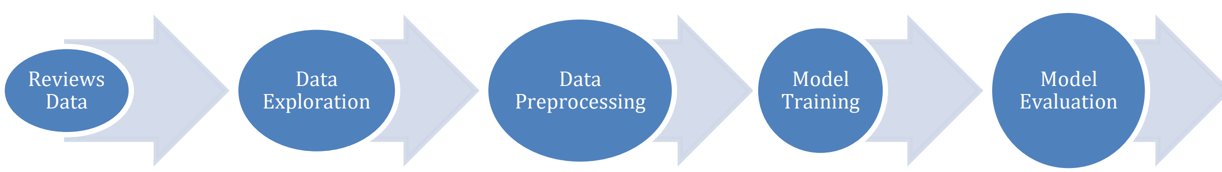

Figure 1: Workflow of study

2.1. Libraries

We are using TextBlob, nltk, plotty, Tensor-Flow. Keras genism, matplotlib, pandas to analyze Emotion In the second step, we import the dataset by using the panda's library.

We have a dataset that contains

- CourseId — Coursera course identifier
- Review — Customer Review Text
- Label — Customer Rating between 0 and 5

2.2. Data Exploration and Preprocessing

Adding sentiment score for review

- So, we will be doing the sentimental analysis for each review using TextBlob.
- TextBlob will assign a sentiment score to each review, ranging from -1 (negative sentiment) to 1 (positive sen- timent), with 0 being neutral.

Courses with the maximum number of reviews

Convert five classes into two classes

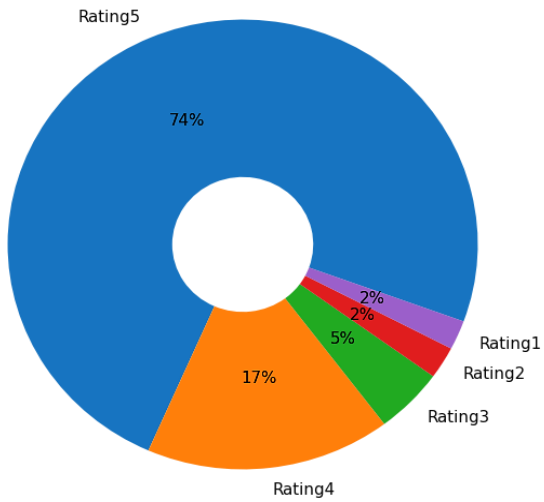

Figure 2: Percentage of Ratings

The following table 2 describes the emotions-oriented classes used to review the courses.

Table 2: Dataset converted with Emotion Orientation

Emotions Orientation	Course Review
Happy	Great, clear, concise explanations on everything. A collaborative effort with teams and specialists worldwide sharing their contributions to this body of knowledge. Particularly congratulate the effort to make this a well-rounded conversation both on the biological effects and economic, political, and communications side of this problem.
Sad	This course does not say anything about digitization which is the core subject of the digital wave.
Happy	Wonderful! Simple and clear language, good instructors, great stuff! Highly recommend!
Sad	This course contains no new material. It does not tell you anything, but rather displays well recognized information in an exciting manner. There are more productive ways to spend your time.

Because the main goal is to distinguish good and negative feedback, we divided the five-star rating system into two categories: (Happy = 1 and Sad = 0)

Figure 3: Common Words Used in Positive Reviews

2.3 Training Modal

2.3.1. Tokenize text data

We use the top 20000 unique terms due to computational costs. Tokenize the comments first, then turn them into sequences. I maintain 50 words to keep the number of words in each remark to a minimum.

2.3.2. Build neural network with LSTM

An embedding layer is the first layer in the network. The layer allows the system to extend each token into a larger vector, allowing the network to represent a word meaningfully. The layer accepts a first argument of 20000, which is the size of our vocabulary, and a second input parameter of 100, which is the dimension of the embeddings. The third argument is input length, which is set to 50 and represents the length of each comment sequence.

2.3.3. Train the network

There are about 1.6 million comments, and it takes a while to train the model in a MacBook Pro. To save time I have used only three epochs. GPU machines can be used to accelerate the training with more time steps. I split the whole datasets as 60per for training and 40per for validation.

2.3.4. Build Hybrid Neural Network Model with LSTM and CNN

The LSTM model performed admirably. However, training three epochs takes an eternity. Improving the network by adding a Convolutional layer is one technique to reduce training time. Image processing gives rise to Convolutional Neural Networks (CNN). They apply a filter to the data and generate a higher-level representation. They have been proven to perform very well for text, while lacking the sequence processing capacity of LSTMs.

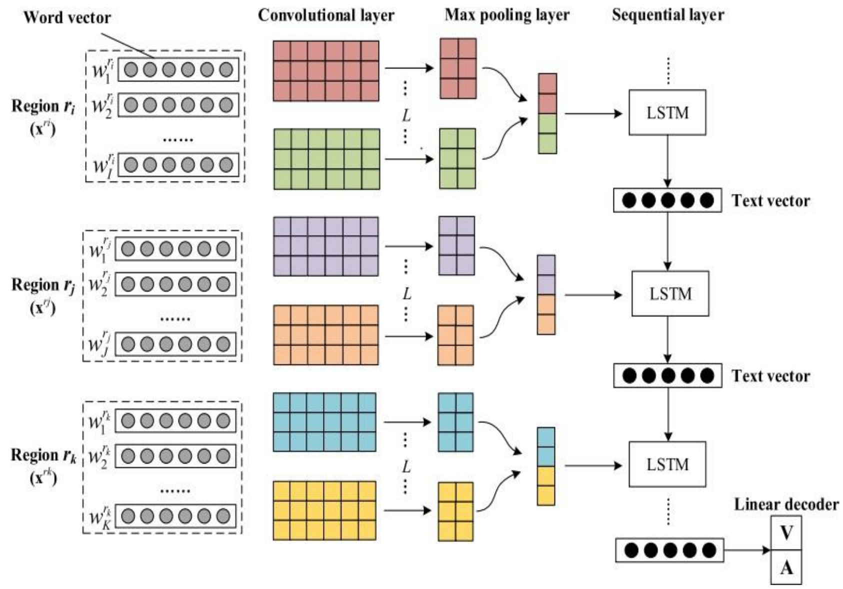

Figure 4: CNN-LSTM Model Working

3. Results

In both deep networks, we trained our data set on LSTM and CNN-LSTM Hybrid Modal. We used a supervised approach using labels on the below bar chart. Based on emotion classification, Result-LSTM and Result-CNN outperformed the baseline strategy on student reviews. LSTM obtains the best performance getting a score of 93.38% and the baseline is 93.30% Using CNN-LSTM Hybrid Model, Achieving the performance result, 93.80 % and the baseline is 91.05% performed better and improved the efficiency of Model. On our data set, CNN-LSTM Hybrid Approach performed better. CNN, which focuses only on partial information, and LSTM, which focuses only on global information in the context, both performed best among the contrast models we tested BiLSTM. On the other side, the focus was reversed on capturing the context's global information. However, it also ignored the comments' incomplete information. The CNN- LSTM model outperformed the baseline model by roughly 2per, since CNN was able to capture the properties of the incomplete data. and LSTM was used to complement the characteristics of the global information in the context, considerably improving the accuracy rate. Due to the present rapid creation of linguistic literature, common words have tended to be given new meanings, popular phrases have continued to be generated, and semantics might be read differently in various phrases, particularly in comment texts.

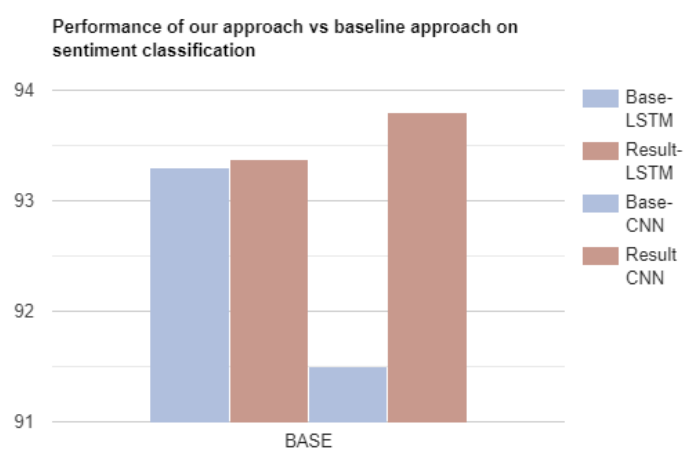

Figure 5: F1 Score percentage

4. Conclusions

Massive open online courses (MOOCs) are the cutting-edge alternatives to distance learning in the covid-(19) epidemic on these learning platforms, participants have not faced any problems like geography-related, race, age, gender barriers. Emotion analysis is applied to Data from an online learning site to collect feedback on a course, encouraging teachers to develop their teaching methods and students to have ac- cess to high-quality instructional materials. In this paper, we examined a corpus that included 140k MOOC evaluations using machine learning, deep learning techniques. In the first neural network modal, we used LSTM and a single embedding layer. In the second modal, an additional 1D convolutions layer was built to reduce training time on top of the LSTM layer. The network architecture is the same as in Model-2, but I use pre-trained glove 100-dimension word embedding. We consolidated two profound learning structures with two- word inserting plans (word2vec and GloVe) (i.e., Convolutions neural organization and long momentary memory by having these two models using a half breed design) in the deep learning-based method. This research aims to improve the accuracy and efficiency of Emotion classification with high predictive quality in the educational domain, MOOC feedback. The algorithms for predictive performance and deep learning have been written. This study has functional applications. According to the empirical research findings, deep learning architectures outperform conventionally supervised learning approaches. Long Short-term Memory Networks (LSTM) and CNN We accomplished the best prescient outcomes for deep learning architectures. The scientific research shows that the GloVe word embedding system produces better predictions. Choosing a suitable representation scheme is a key step in designing AI based estimation order plans. In this regard, the trial review provides detailed analytical evidence for various text representation systems, both supervised and unsupervised. Learning methods, Deep learning architectures for educational data processing, which could act as the field's benchmark methodological findings. We present the first large free online course review corpus, which could be helpful for future research.

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