RESEARCH ARTICLE

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Sentiment Analysis of user reviews in an Online Learning Environment: Analyzing the Methods and Future Prospects

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ABSTRACT

The pandemic compelled most of us to switch to remote & hybrid work culture from the traditional and eLearning from the traditional classroom-based learning. Although eLearning has opened boundless opportunities for students at minimal cost, it has also brought a major challenge for the educators. Some of these are- lack of one-to-one interaction between teachers and students, the inability of teachers to assess the quality of their teaching, and more. To make eLearning more effective, it is important for administrators to fill such gaps. This is where sentiment analysis can play a vital role. It can help educators analyze student feedback and optimize their teaching methods for the best results.

This paper is a systematic review of the learning-based methods available for sentiment analysis in an online learning environment- through online comments/reviews, web discussions or online forums, learning content, and student feedback. We also discussed some of the combined approaches used for Sentiment Analysis in online learning. Most importantly, the paper ends with a discussion of the limitations and challenges faced by researchers and the further scope for work in this field.

Concluding from the research available, Sentiment Analysis has proved to be effective for both educators and students through various channels such as reviews, comments, learning content, web discussions and forums, and more. It has helped teachers improve their teaching methodology and revise course content to better suit students. For students, this has led to better understanding of the course material and has provided them with access to quality learning.

Keywords: artificial intelligence, deep learning, online courses, sentiment analysis, student reviews.

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I. Introduction

Online learning, often known as e-learning, is the process of disseminating information through a variety of media, including CDs, webinars, e-books, and much more. The traditional approach of teaching kids using chalk and board has undergone a drastic transformation as learning shifted online, especially during the pandemic. Eighty-two percent of decision makers intend to increase digital learning resources because of the COVID-19 pandemic (Fosway Group, n.a.).

However, the online learning trend is recent and under development and holds massive potential for improvement. One of the best ways to assess gaps in the system is through the method of sentiment analysis through students' feedback, notes, remarks, comments, and other such data exchanged on student learning platforms. This not only helps teachers refine their methods of teaching, but also hints curriculum designers to introduce more relevant and useful content for users (Gottipati *et al*., 2017).

Sentiment analysis, also referred to as opinion mining, is a field of study that deals with opinions and feedback. It is a component of natural language processing, a branch of computer science and artificial intelligence that deals primarily with communication between people and computers through language Devika *et al*. (2016) and Liu (2012) describe sentiment analysis specifically as a science that examines opinions, sentiments, assessments, judgments, attitudes, and emotions concerning a good or service, an organization, a person, a topic, a problem, an event, and its characteristics. Subjectivity and Polarity are the two components of sentiment analysis. Polarity is a sentence that represents emotions, which can have a positive or negative value, whereas subjectivity is a sentence that expresses feelings, views, or beliefs. Expressing feelings can be considered an opinion, which can be classified as either positive, negative, or neutral (Altrabsheh *et al*., 2013).

Sentiment Analysis is a widely used technique in the business world to improve upon products and services based on customer reviews and feedback. However, its use is expanding from just product reviews to social media, election, stock market, disasters, medicine, cyberbullying, and more. (Mika *et al*., 2018).

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A. Machine Learning Methods for Sentiment Analysis

Machine learning methods for Sentiment Analysis are a collection of statistical methods used for classifying entities, sentiments, and other textual components. It enhances and automates SA's reliance on low-level text analysis, including Part of Speech (POS) tagging (Pand & Lee, 2008).

It further includes supervised, unsupervised, and semi-supervised learning, and is used to categorize and forecast an opinion, whether positive or negative (Ahmad *at al*., 2017) Samal and Panda (2017) mention transduction, learning to learn, and reinforcement learning as machine learning techniques. Several supervised learning algorithms, including Naive Bayes, Support Vector Machine (SVM), Random Forest, and Neural Networks, have demonstrated good performance in sentiment analysis. However, the quality of the training dataset has a significant impact on how well this supervised learning strategy performs. On the other hand, training datasets are not necessary for the unsupervised learning strategy.

1) Support vector machine (SVM)

Supervised learning models employing learning algorithms that evaluate data for regression and classification issues are known as support vector machines. Both linear and nonlinear data are used in it. If the data can be linearly separated, the SVM looks for the best separating hyperplane, a decision boundary that divides data into different classes. In the case of linearly inseparable data, the SVM uses nonlinear mapping to transform the data into a higher dimension. To successfully divide the given data into two halves, it attempts to minimize the dataset's dimensionality. The main benefit of SVM is its effectiveness in high dimensional spaces. Because support vectors employ a subset of the training points for their decision functions, the model is memory efficient.

2) K nearest neighbors' classifier

Neighbors-based classification is a form of instance-based learning that maintains examples of the training data. In this approach, classification is accomplished through straightforward voting of majority neighbors with regard to the test point. It uses similarity metrics to classify the training data points. This method also finds use in pattern recognition and estimation.

3) Random forest

Random forest is a machine-learning algorithm that can be used for both regression and classification. In this, a decision tree is built using a sample of data, the predictions are then obtained from each one, and the best option is then chosen by voting. Because it is an ensemble tree and thus less overfitting occurs, it performs better than a single decision tree. The bootstrap samples from the training set are used to construct each tree in the ensemble.

4) Naïve bayes

Naïve Bayes is a classification algorithm that assumes that pairs of features are independent of each other.

The Naive Bayes classifier works as follows: Let's say there exists a set of training data, D, in which each tuple is represented by an n-dimensional feature vector, X=x1, x2,…, xm, denoting m measurements made on the tuple from m features. Assume that there are m classes, C1, C2 ,..so on till CM. Given that a tuple Y the classifier will predict that Y belongs to CI if and only if:

$$P(Ci|Y) > P(Cj|Y),$$

where:
i,j[1,m] and IJ. P(C I|Y) – computed as:

In case of the feature space being limited, Naïve Bayes performs better than SVM. However, the vice versa is true for a bigger feature space.

5) Maximum entropy classifier

The Maximum entropy classifier does not consider any assumptions regarding the relationship amongst features. The model estimates conditional distribution of class labels by maximizing entropy of the system. Here's what a mathematical representation of conditional distribution looks like:

X – Feature vector
Y – Class label
Z(X) – Normalization factor
I –Weight coefficient

II. Sentiment Analysis in an Online Learning environment: A survey of available methods

A. Sentiment Analysis through Reviews and Comments

A term may have both positive and negative connotations depending on the context of use. The most crucial factor in making a decision is ascertaining the opinion or review of a product. Analyzing student reviews and comments helps researchers gain insights into students' sentiments with respect to online learning.

One such research (Kechaou *et al*., 2011) focused on finding optimal methods for opinion mining in the e-learning scenario, with the aim of helping developers improvise and promote the quality of relevant services. Research was done by experimenting on three feature selection methods advanced with HMM & SVM-based hybrid learning methods. The experimented selection methods were CHI statistics (CHI), IG (Information Gain) and MI (Mutual Information), out of which IG performed the best for sentimental terms selection and exhibited the best performance for sentiment classification as per the results.

Reference (Kanika & Aron, 2021) presents an effective approach towards sentiment analysis through opinions and messages exchanged over social media platforms. Using textual information from social media, this model identified agreement and disagreement statements that expressed positive or negative emotions through reviews and comments. The study examined the use of a probabilistic strategy based on the Latent Dirichlet Allocation (LDA) as a sentiment extractor in the domain of online learning. This method allowed for the automatic extraction of a graph called the Mixed Graph of Terms for a set of documents that are all members of the same knowledge domain. The study indicates how this graph comprises a set of weighted word pairs that can be used to classify sentiments. In this way, the system can gauge how pupils are feeling about particular subjects, and the instructor can adjust their style of teaching more effectively.

In another study (Noriko, 2000) researchers investigated a small graduate-level web-based distance education course at a prestigious US institution as the subject of a qualitative case study. They evaluated the upsetting experiences that students have when there are communication breakdowns and technological issues. Many of the books on remote learning that are created for administrators, teachers, and potential students skirt over this subject. Improving web-based distance education courses is today's necessity and this study highlights the difficulties related to instructional design, teacher and student preparation, and communication techniques.

The user's opinions and their assessments are crucial for the development of e-learning systems. As demonstrated in (Song *et al*., 2007) affective computing can be applied to e-learning. By analyzing facial expression, verbal speech, and text comments, researchers could understand the user/student sentiments. For opinion mining, it used automatic text analysis to extract opinions from websites where users discuss or explain their own ideas and evaluations of the services, as well as automatic sentiment analysis to determine the sentiment of those opinions. The views were located and extracted using conditional random fields. Sentiment analysis gave specific consideration to negative statements and degree adverbs. The strength calculation for opinion sentiment orientation was then presented. The experiment showed that sentiment analysis and opinion extraction have high levels of analytical precision and are beneficial to e-learning systems.

Xie *et. al*. (2019) proposed an improved algorithm based on the maximum entropy-PLSA model for sentiment analysis, and experiments done within the research prove that the classification method proposed by this paper has an ideal classification effect. In the proposed model, they have used the probabilistic latent semantic analysis (PLSA) to extract the seed emotion words from Wikipedia and the training corpus. Features are then extracted from these seed emotion words, which are the input of the maximum entropy model for its training. The test set is processed similarly into the model for emotional classification. Meanwhile, the training set and the test set are divided by the K-fold method. The model uses important emotional classification features to classify words, such as the relevance of words and context from the speech, relevance with degree adverbs, similarity with the benchmark emotional words, and so on.

Another model has been utilized in (Ortigosa *et al*., 2014), which employs machine learning and a lexical-based approach for sentiment analysis. Through an app created under the name Sentbuk, they used Facebook user comment data for the testing. Each 1,000 comments were randomly categorized as good, neutral, or negative. Through sentiment analysis, the suggested approach is able to identify students changing emotional states at any moment. The statistics are shown graphically every week.

In Esparza *et al*. (2017) Support Vector Machine and Random Forest are used to analyze the sentiments. 1040 comments were collected from SED and Twitter for the data set utilized in this investigation. Evaluating how well SVM and Random Forest work in terms of classifying the performance of teachers.

Reference (Ulah, 2016) focuses on sentiment analysis using multiple algorithms which are Support Vector Machine, Maximum Entropy, Naive Bayes & Complement Naive Bayes. The dataset used in the experiment was gathered from Facebook with a total of 1036 data consisting of 641 positive data, 292 negative data and the rest were neutral; these datasets were used in the feedback analysis using several techniques. Support Vector Machine and Maximum Entries are the best models for feedback analysis out of all the studied algorithms.

B. Sentiment Analysis through Web Discussions/Forums/Online Communities

In Yang *et al*. (2013) researchers implemented the Topic evolution for Topic Detection and Tracking (TDT) in the online learning web forums where Topics were interactive (new emerges and old decays), and their numbers were also dynamic. The model used by them was an adaptive topic evolution model based on Latent Dirichlet Allocation (LDA). The proposed model was able to detect the topic changes in terms of numbers as well the topic content evolution with time, helping in identifying hot spots over time. (This model uses the posterior of topics and word distribution in historical time windows to adjust the prior of current by linear weighted, which can find new topics and the vanished ones in text streams and automatically update the topic number).

Another study, with the aim of increasing effectiveness of online discussion forums, organized messages based on the topics detected in a hierarchical manner. The proposed semi-automatic method used Topic modeling and formal concept analysis (FCA), two Information Retrieval (IR) approaches, to identify discussion topics and present a hierarchical topic-centered view of messages. The model was tested by four forums of Italian distance learning universities which were actively followed by over 5000 students, thus yielding impressive results. (Cerulo *et al*., 2013).

Reference [20] is a research study focused on detecting the health-related hot topics in online communities/ disease discussion boards. With an aim to explore and understand people's needs and interests in health-related information, the proposed model replaces the old statistical topic analysis used in earlier studies. The proposed model used an Automatic topic detection method based on document clustering for extracting health-related hot topics, incorporating medical domain-specific features to represent communications in online health groups in addition to keyword-based features utilized in conventional text clustering. According to the study's findings done on three disease discussion boards, the most popular health-related topics include symptoms, tests, medications, treatments, and complications. The prominent subjects addressed in various sorts of disease discussion forums also differ significantly, as per investigation.

The article in (Li *et al*., 2013) aims to identify the opinion leader in the online learning communities, as they have the ability to influence the attitude and behavior of others in the community. The proposed method was an improved mix framework for opinion leader identification, which was validated by the experiments performed. This model ranked opinion leaders based on four distinctive characteristics:

expertise, novelty, influence, and activity, by analyzing textual content, user behavior, and time. Results from the model satisfactorily identified opinion leaders within learning communities.

In one study (Wang *et al*., 2020) researchers aim to provide a support system for online learning platforms so that they can assess the situation of the students' learning by using a novel model- Topic-sentiment analysis model, for opinion mining and sentiment analysis. Using this model, online learning platforms can not only get direction for following revision of the teaching plan but also get some clarity on hierarchical dependencies between different topics with the help of the topic-sentiment visualization framework. This lays the foundation for improving the accuracy of teaching content recommendation and optimizing the knowledge coherence of related courses.

C. Sentiment Analysis through Online Learning Content

In reference Nagori *et al*. (2011) researchers tried to optimize an effective learning environment for users in e-learning systems by identifying and recommending the relevant objects/ information. This not only helps users save time, but also adds to the net positive experience as well. The linguistic character of the texts/ documents in the corpus allowed for the integration of content information into the existing recommendation systems. The proposed personalized integrated model operates in two steps: a) Making topic analysis on a corpus using the Latent Dirichlet Allocation topic modeling technique; b) Adding a similarity metric to the content-based recommendation strategy. The proposed model brought good, recommended information for the users in the given experiments/ tests.

Another research (Ammar *et al*., 2010) in the same domain represents a study of the application of affective computing in intelligent tutoring. The major objective was to analyze learner facial expressions and demonstrate how affective computing, which is a component of comprehensive student tracking (traceability) to track student behavior throughout learning sessions, might contribute to this domain.

The article, reference (Obeleagu *et al*., 2019) describes a tool used for sentiment analysis. The tool makes a combined use of machine learning and algorithm approach. This project tries to advance existing methodologies by building on them. Combining academic and social characteristics in the attribute set proved effective in this regard. The data processing methods used in the tool's construction were given special consideration since they will have the most impact on the project's effectiveness and efficiency. By exploiting the cutting-edge capabilities of machine learning, this tool has the ability to offer pertinent projections for stakeholders (instructors, parents) in the educational system at all levels. The tool had considerable potential, and the outcomes were highly encouraging for machine learning applications, which are still in the early stages of development.

Clarizia *et al*. (2018) focuses on using the Latent Dirichlet Allocation (LDA) as a sentiment grabber in a probabilistic methodology while taking care of preserving the confidentiality of students' personal information. With the suggested method, a teacher can more effectively adjust their teaching style based on how the students are feeling about particular subjects/ topics. The recommended methods have been tried out in actual situations with successful and positive outcomes.

D. Sentiment Analysis-A Mixed Approach

Researchers in Dodero *et al.* (2013) take into account multiple points of view that emerged regarding the conception, development and maintenance of e-Learning solutions during the panel discussion of Software Development for e-Learning of the third workshop on software engineering for e-Learning (ISELEAR'12). This article presented six different ways to address the development of applications for E-Learning. Although the proposals differ in approaches and in the underlying details, all of them share a common goal, which is to facilitate the development of applications in this complex application domain. It therefore summarized and challenged the following viewpoints: Domain-specific development approaches, model-driven/language-driven development, system integration approaches, and grammar-oriented development are among the first six. Other approaches include automated approaches, the combination of different methodologies, emphasis on human and social aspects, and domain-specific development approaches. Even though these viewpoints support various engineering methodologies, they all aim to make it easier for interdisciplinary teams of software engineers, instructors, domain experts, students, and end-users to create complex e-Learning systems and solutions.

Shin *et al*. (2017) proposed several approaches that effectively integrate lexicon embeddings and an attention mechanism to a well-explored deep learning framework, Convolutional Neural Networks, for sentiment analysis. Experiments show that lexicon integration can improve the accuracy, stability, and efficiency of the traditional CNN model. The models proposed are based on a convolutional architecture and use naive concatenation, multichannel, separate convolution, and embedding attention for the integration of lexicon embeddings to CNN. Lexicon embeddings are derived by taking scores from multiple sources of lexicon datasets (SemEval-2016 Task 4 and Stanford Sentiment Treebank).

In the proposed approach, blending of the lexicon embedding into its corresponding word embedding is achieved by appending it to the end of the word embedding. Six types of sentiment lexicons are used to build lexicon embeddings and the proposed attention models are applied to every single word. And the derived attention heatmap analysis confirms that embedding attention vectors endow CNN models with explanatory features.

However, it is also important to notice that focusing on multiple words could give more promising information. Application of the attention mechanism to multiple words at the same time is a possible direction, and also to maximize the score, an ensemble of multi-layer CNN models could be applied.

E. Sentiment Analysis through Student Feedback

According to Shankararaman and others (Gottipati *et al*., 2017) using feedback to improve teaching and curriculum can enhance student learning outcomes and learning experiences. giving feedback to students in a way that will actually enhance their learning outcomes.

There are multiple pieces of research to improvise on students' learning experience and teacher's teaching methodology, which includes uses of various existing methods by improvising on them, new methods, and in some cases combination of multiple methods. Here are a few works worth mentioning.

Beginning with a study done by Colace, the model used in this research paper uses the algorithm that is a probabilistic approach based on the Latent Dirichlet Allocation (LDA) for sentiment analysis. For the testing 75 students used Moodle for sharing comments. The proposed model detects students' emotions about several topics, which helps the teachers to modify the learning methodology. (Colace *et al*. 2014)

Another study (Gottipati *et al*., 2017) employed text analytics and natural language processing to study sentiment analysis. Singapore Management University used its own "FACETS" technology to administer the student feedback survey online. putting forward a conceptual framework for studying student feedback.

In Kousalya and Subhashini (2008) online surveys of students were employed to gather the study's feedback data. Several sentiment analysis techniques were used to categorize student feedback based on polarity, and the random forest classification technique ended up having the highest accuracy.

Further Comparisons of the algorithms were done to find the best performing in this use case. Like in a study Dsouza *et al*. (2019) done which compares the Support Vector Machine, Multinomial Naive Bayes Classifier, and Maximum Entropy methods to improve the sentiment analysis from student's feedback. Data from the students' input was gathered online utilizing a google form for this study. As compared to the SVM and Maximum Entropy, the multinomial naive Bayes classifier method performs better when used to analyze the feedback of the students.

Another study Kandhro *et al*. (2019) in statistical analysis was done in this research paper which focuses on analyzing the sentiments of students using the Statistical Analysis: Long Short-Term Memory Model (LSTM). The study employed a total of 3000 student feedback data that were submitted at the end of 30 courses held in 2017 and 2018, respectively. Using the Long Short Term Memory Model to assess teachers' performance based on student's feedback offers the potential to address a number of issues with conventional approaches.

In another research by Lin *et al*. (2019) Naive Bayes, Support Vector Machine, Logistics Regression, and Gradient Boosted Decision Tree are used to analyze the sentiments of the students. 3,926 datasets recorded from the Beijing Institute of Technology's (BIT) postgraduate assessment system were utilized in the study. Assessing a teacher's performance based on a brief assessment from the students. The emotions of student reviews were examined using the conventional knowledge-based methodology.

Deep learning methods are one of the most common approaches used for sentiment analysis (Dang *et al*., 2020; Alantari *et al*., 2021) Deep learning is a technique that learns through a few different layers with state-of-the-art statistics and prediction results (Iqbal *et al*., 2022).

In a study (Dang *et al*., 2020), the authors have used deep learning-based LSTM models with different layers and parameters to classify data into classes and identify their exact sentiment. These deep learning models depicted better results in terms of accuracy, specificity, precision, and F1 measures. As compared to the other approaches mentioned in the work, these models performed better. Deep learning models have also been used by marketing researchers to analyze the text review. The customer reviews on online websites have data emerged as a great source for analyzing the experience. The authors in (Alantari *et al*., 2021) performed the analysis on the empirical trade-off between diagnostic and predictive skills and the results concluded that machine learning techniques based on neural networks provide the most precise predictions.

F. Summary: A Survey of Methods Available for SA in Online Learning

This table presents a summary of all the studies reviewed in this paper. It presents the findings and implications of each research against the respective topic names to give a clearer idea of the learning-based methods available for Sentiment Analysis in an online learning setup.

TABLE I: SUMMARY: A SURVEY OF METHODS AVAILABLE FOR SENTIMENT ANALYSIS

Year	Focus	Findings	Implications
2000	Student distress in a web-based distance education course (Noriko, 2000)	In this article, a small graduate-level web-based distance education course at a prestigious US institution is the subject of a qualitative case study. This essay investigates the upsetting experiences that students have when there are communication breakdowns and technological issues.	It is hoped that this study will deepen awareness of the difficulties related to instructional design, teacher and student preparation, and communication techniques.
2007	Opinion mining in e-learning system (Song *et al*., 2007)	The paper focuses on the application of affective computing in e-learning, by analyzing facial expression, verbal speech, and text comments to understand the user/student's sentiments.	The experiment demonstrates that sentiment analysis and opinion extraction have high levels of analytical precision and are beneficial to e-learning systems.
2008	Sentimental Analysis for Students' Feedback using Machine Learning Approach (Kousalya & Subhashini, 2008)	Collected student feedback through google forms and analyzed the data using multiple techniques.	According to the experimental findings, Multinomial Naive Bayes Classifier is more accurate Than other approaches.

TABLE I: CONTINUATION

2010	The Affective tutoring system (Ammar *et al*., 2010	This paper represents a study of the application of affective computing in intelligent tutoring.	The major objective is to analyze learner facial expressions and demonstrate how affective computing might contribute to this domain.
2011	LDA-based document recommendation model for e-learning systems (Nagori *et al*., 2011)	Puts forward a recommender system that recommends content that might be relevant to them so that instead of looking for information, they have it in their respective recommendations.	The personalized recommendation model is used to collect concepts that are useful for the learner.
2011	Improving e-learning with sentiment analysis of users' opinions (Kechaou *et al*., 2011)	Research was done on experimenting on three feature selection methods advanced with HMM & SVM-based hybrid learning methods.	This research focuses on finding optimal methods for opinion mining in the e-learning scenario, with the aim of helping the developers to improvise and promote the quality of relevant services.
2013	E-learning and sentiment analysis | Proceedings of the 6th International Conference on Information and Education Technology (acm.org) (Altrabsheh *et al*., 2013)	Investigates the Latent Dirichlet Allocation (LDA) which is a probabilistic approach for grabbing sentiments, during the online classroom learning process.	Effective and satisfactory results for the teachers to improve their teaching approach based on the detected mood/ sentiments of students on various topics.
2013	An improved mix framework for opinion leader identification in online learning communities (Li *at al*., 2013).	The aim of this research is to identify the opinion leader in the online learning communities. The proposed method is an improved mix framework for opinion leader identification, which was validated by the experiments performed.	This model ranked opinion leaders based on four distinctive characteristics: expertise, novelty, influence, and activity, by analyzing textual content, user behavior, and time.
2013	Online adaptive topic evolution model in web discussions (*Yang et al*., 2013).	Focuses on implementing the Topic evolution for Topic Detection and Tracking (TDT) in the online learning web forums where Topics are interactive (new emergencies and old decays) and their numbers are also dynamic. The model used is an adaptive topic evolution model based on Latent Dirichlet Allocation (LDA).	The proposed model was able to detect the topic changes in terms of numbers as well the topic content evolution with time, helping in identifying the hot spots over time.
2013	Topic-driven semi-automatic reorganization of online discussion forums- A case study in an e-learning context (Cerulo *at al*., 2013)	The proposed semi-automatic method uses Topic modeling and formal concept analysis (FCA), two Information Retrieval (IR) approaches to identify discussion topics and present a hierarchical topic-centered view of messages.	The model was tested in four forums of Italian distance learning university which were actively followed by over 5000 students, obtaining impressive results.
2013	Health-related hot topic detection in Online Communities using text clustering (Li *et al*., 2013).	The proposed model replaces the old statistical topic analysis used in earlier studies, which seems to be quite impractical for handling the online data that is being generated at an exponential rate.	According to the study's findings done on three disease discussion boards, the most popular health-related topics include symptoms, tests, medications, treatments, and complications.
2013	Development of E-Learning Solutions- Different Approaches, a Common Mission (Dodero *et al*., 2013)	This paper considers multiple points of view that emerged regarding the conception, development and maintenance of e-Learning solutions during the panel discussion of Software Development for e-Learning of the third workshop on software engineering for e-Learning (ISELEAR'12).	Even though these viewpoints support various engineering methodologies, they all aim to make it easier for interdisciplinary teams of software engineers, instructors, domain experts, students, and end-users to create complex e-Learning systems and solutions.
2013	An improved mix framework for opinion leader identification in online learning communities (Li *et al*., 2013).	The aim of this research is to identify the opinion leader in the online learning communities. The proposed method is an improved mix framework for opinion leader identification, which was validated by the experiments performed.	This model ranked opinion leaders based on four distinctive characteristics: expertise, novelty, influence, and activity, by analyzing textual content, user behavior, and time.
2014	SAFE- A Sentiment Analysis Framework for E-learning (Colace *et al*., 2014)	In this study, we examine the use of a probabilistic strategy based on the Latent Dirichlet Allocation (LDA) as a sentiment extractor in the domain of online learning.	Using textual information from social media, this model aims to identify agreement and disagreement statements that express positive or negative emotions through reviews and comments.
2014	Sentiment analysis in Facebook and its application to e-learning (Orgitgosa *et al*., 2014)	The study used lexical-based and machine learning methods to analyze user comment data and classify them as positive, negative, or neutral.	The system can display weekly data graphically and perceive students' emotional changes using Sentiment Analysis.
2016	Sentiment Analysis of students' feedback: A study towards optimal tools (Ulah, 2017)	Used Support Vector Machine, Maximum Entropy, Naïve Bayes, Complement Naïve Bayes to analyze student feedback.	The Support Vector Machine & Maximum Entropy came out to be the best among all of them.

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2017	Lexicon Integrated CNN Models with Attention for Sentiment Analysis (Shin *et al*., 2017)	Proposes several approaches that effectively integrate lexicon embeddings and an attention mechanism to a well-explored deep learning framework, Convolutional Neural Networks, for sentiment analysis.	Lexicon-integration can improve the accuracy, stability, and efficiency of the traditional CNN model.
2017	A sentiment analysis model to analyze students reviews of teacher performance using support vector machines (Esparza, *et al*., 2017)	With the help of a corpus of actual Spanish comments regarding teacher performance assessment, researchers introduce a model dubbed Social Mining in this work. To forecast whether comments would be classified as favorable, negative, or neutral, they used the Support Vector Machines technique with three kernels: linear, radial, and polynomial. As evaluation metrics, they evaluated sensitivity, specificity, and predictive values.	The findings of this study could inform future research on how to better classify comments and recommend trainings for teachers.
2017	Lexicon Integrated CNN Models with Attention for Sentiment Analysis (Shin *et al*., 2017)	Proposes several approaches that effectively integrate lexicon embeddings and an attention mechanism to a well-explored deep learning framework, Convolutional Neural Networks, for sentiment analysis.	Lexicon-integration can improve the accuracy, stability, and efficiency of the traditional CNN model.
2018	The evolution of sentiment analysis—A review of research topics, venues, and top cited papers (Mika *et al*., 2018)	This review paper focuses on the evolution of sentiment analysis with time, though they have majorly discussed from the top 20 cited papers from Google scholar and Scopus and a taxonomy of research topics.	Depicting the use of sentiment analysis expanding from the product reviews to social media, election, stock market, disasters, medicine, cyberbullying, etc.
2018	E-learning and sentiment analysis: a case study (Clarizia *et al*., 2018)	Focuses on using the Latent Dirichlet Allocation (LDA) as a sentiment grabber in a probabilistic methodology while taking care of preserving the confidentiality of students' personal information.	With the suggested method, a teacher can more effectively adjust their teaching style based on how the students are feeling about particular subjects/ topics. The recommended methods have been tried out in actual situations with successful and positive outcomes.
2019	An improved algorithm for Sentiment Analysis based on maximum entropy (Xie *et al*., 2019)	The model uses important emotional classification features to classify words, such as the relevance of words and context from the speech, relevance with degree adverbs, similarity with the benchmark emotional words.	The trials demonstrate the optimal classification effect of the proposed classification approach in this research.
2019	An improved algorithm for Sentiment Analysis based on maximum entropy (Xie *et al*., 2019)	The model uses important emotional classification features to classify words, such as the relevance of words and context from the speech, relevance with degree adverbs, similarity with the benchmark emotional words.	The trials demonstrate the optimal classification effect of the proposed classification approach in this research.
2019	Sentiment Analysis in Student Learning Experience (Obeleagu *et al*., 2019)	This paper explains a tool used for sentiment analysis. The tool makes a combined use of machine learning and algorithm approach. This project tries to advance existing methodologies by building on them.	By exploiting the cutting-edge capabilities of machine learning, this tool has the ability to offer pertinent projections for stakeholders (instructors, parents) in the educational system at all levels.
2019	Sentimental analysis of student feedback using machine learning techniques (Dsouza *et al*., 2019)	This study compares the Support Vector Machine, Multinomial Naive Bayes Classifier, and Maximum Entropy methods to improve the sentiment analysis from student's feedback. Data from the students' input was gathered online utilizing a google form for this study.	As compared to the SVM and Maximum Entropy, the multinomial naive Bayes classifier method performs better when used to analyze the feedback of the students.

TABLE I: CONTINUATION

2019	Sentiment Analysis of Students' Comments by using Long-Short Term Model (Kandhro *et al*., 2019)	The Long Short-Term Memory Model (LSTM) is used to evaluate how pupils felt about the textual feedback they received. The dataset has been created for this purpose based on student comments and divided into 70 and 30 percent for training and testing. The suggested model was trained using drop out values of 0.1 and 0.2, along with SoftMax and Adam. It was found that the model offers 90% and 99% accuracy during training and validation with 0.2 and 0.5 losses, respectively.	Using the Long Short-Term Memory model to evaluate teacher effectiveness based on student input offers the potential to address a number of issues with conventional approaches.
2020	Topic Sentiment Analysis in Online Learning Community from College Students (Wang *et al*., 2020)	The model is designed for topic wise sentiment analysis using topic-terminology hybrid matrix and document-topic hybrid matrix.	Refining further on the existing methods, the paper focuses on the negative comments in student reviews which can be used to improve the quality of teaching in the online learning environment.
2021	A systematic study of sentiment analysis for social media data (Kanika & Rajni, 2021)	An effective approach towards sentiment analysis through opinions and messages exchanged over social media platforms. Using textual information from social media, this model identified agreement and disagreement statements that expressed positive or negative emotions through reviews and comments.	In this way, the system can gauge how pupils are feeling about particular subjects, and the instructors can adjust their style of teaching more effectively.
2022	Sentiment Analysis of Consumer Reviews Using Deep Learning (Cobos *et al*., 2019)	The classification of the Since the text in the reviews might be of varying sizes, the feature encoding is used for converting each review into a fixed-length vector. The paper also investigated the impact of different preprocessing activities such as data cleaning, normalization, punctuation removal, text tokenization, stop word removal, superfluous space removal, POS tagging, and emotion conversion into meaningful text.	This study implemented deep learning-inspired long short-term memory and recurrent neural network-based models with different layers and parameters to classify data into classes and identify their exact sentiment. Three models were proposed and experimented on the well-known datasets: IMDB, Yelp, Cell Phones and Accessories, Amazon-Products, and Amazon-Fine-Food Reviews datasets. Performance measures such as accuracy, precision, recall, and F1-score proved to be better when compared to previous approaches.

III. CONCLUSION

Sentiment analysis can play a vital role in optimizing eLearning experience and empowering future generations to equip themselves with accessible resources. In fact, Clarizia *et al*. (2018) researchers used real datasets from a popular online learning platform called Moodle across three courses- Web Software Technologies, Computer Networks, and Introduction to Computer Science. Each of these courses were supported by a Twitter group and a Facebook group wherein students exchanged study material, comments, reviews and more. The researchers deployed a SA Module for sensing the mood of each of the students to build a Mixed Graph of Terms. This created a thermometer profile of the classroom's mood with respect to each topic. This allowed teachers to monitor the whole class and personalize learning content for each class.

FUTURE SCOPE OF WORK

Currently, sentiment analysis is being majorly used to describe the polarity of text- as positive, negative, or neutral. Analyzing conventional data such as feedback forms or review documents is much easier than short-length texts on social media or community forums discussions - such as comments, reviews, suggestions, and more. Even though acceptable and usable models are already in place which will definitely mature with time and efforts that are being put, a major domain of sentiment analysis has evolved with time which is analyzing the sentiments of the students based on facial expressions/ movements and speech, which is covered by very few. A more advanced SA mechanism for such instances needs to be built and more models need to be trained on these lines in order to fully unleash the potential of SA aided by machine learning and other learning-based models.

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