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Emotion Recognition of E-Learners from Text: A Review

[1]Lokesh Kumar Singh, [2]Ananya Verma, [3]Nidhi Raj, Satyam Jaiswal, Arindam Ghosh

[1]Student, [2]Student, [3]Student
[1]Department of Information Technology,
[1]Techno International New Town, Kolkata, Indai

Abstract : E-learning is making a firm progress towards personalized learning to shift the paradigm of teaching learning process entirely from conventional classroom teaching to online learning platforms. This shift is based on the idea of recognizing student emotion accurately in e-learning platforms to customize the learning process according student's preferences. E-learners sentiment is expressed in three modes audio, image, and text. We have conducted a survey in this paper for analyzing different architectures of recognizing emotions from textual contents. Our objective is to motivate more research work for creating frameworks of personalized learning-based platforms primarily to improve learning drive of a e-learner.

***IndexTerms* - E-learning, sentiment analysis, emotion recognition, personalized learning**

I. INTRODUCTION

In the dynamic realm of education, knowing students' emotions is as important as knowing what they understand. What if our education system could identify students' emotions based on the words they use? This survey dives deeper into the relationship between emotions and learning by exploring the field of determining students' emotions through texts. In this digital age, students' text becomes a valuable source of emotional information. With the help of smart computer programs, we can tap into this digital treasure trove, potentially revolutionizing education. By identifying patterns in students' expressions, teachers can adapt their teaching methods and create a more supportive learning environment. In the field of e-learning, it's essential to comprehend and address the emotions of students as they significantly affect their engagement, motivation, and learning results. With this in mind, we have developed a survey that focuses on emotion detection systems from text within an e-learning platform and make this survey available to the research community by providing a comprehensive overview of existing literature on emotion recognition of learners through text. We reviewed previous Works on this topic and selected the best ones that used either a lexical approach or a machine learning approach in their emotion detection systems. We examined approximately 30 studies that investigate emotion recognition from text, using various approaches such as lexicon-based methods, surveys, and machine learning techniques, including natural language processing (NLP), support vector machines (SVM), convolutional neural networks (CNN), latent Dirichlet allocation (LDA), and long short-term memory (LSTM) models. We have explored the different approaches and methodologies used for emotion recognition, the challenges and limitations that come with these methods, and the potential future directions in this field. This survey describes recent works in the field of detecting emotions from text.

Our objective of this survey is to motivate more research works on how to improve the learning will in online learning platforms which can provide recommendation to the learners. As will is directly related to a person's sentiment we included an extended survey on the topic of recognizing emotion of the e-learners from text mode. So that development of new frameworks of Intelligent Tutoring systems to improve the learning drive of a learner could be encouraged to attract more learners towards personalized e-learning as a sufficient alternative for physical classroom teaching. We justify the novelty of this work through the above exposition.

Our paper is organized as the following. We have described the literature review in Section III. Section IV contains comparative analysis of previous works and Section V focuses on Discussion and Future work.

II. Literature Review

We have conducted a brief survey of a few previous works where authors have proposed some model to recognition the emotion of the learners from their comments, feedback, emojis or any kind of textual content. We have categorized our survey in three parts fundamentally. In section A all the lexicon-based approaches are discussed. In section B all machine learning based approaches are reviewed. Which are further divided into different machine learning algorithms. Section C contents some previous survey works which are in intense proximity with our topic.

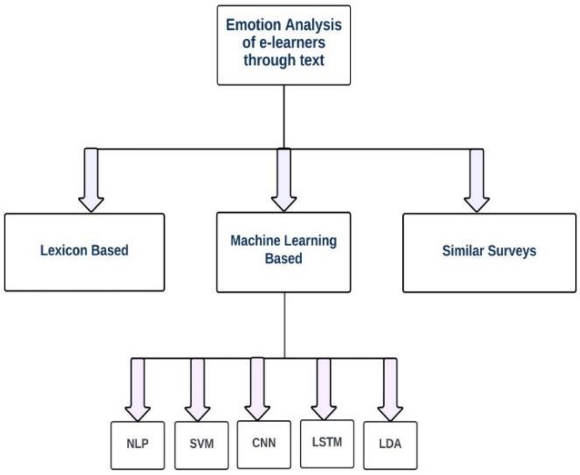

Fig.1. Block diagram of the survey

A. Lexicon Based Approach

The researchers have explored how to detect emotions in written text by proposing unique methods like Keyword Spotting Technique, Lexical Affinity, Emotion Ontology and Detector Algorithm [1]]used in spotting specific words, looking at word connections, and using different learning approaches. Despite some general problems like words having multiple meanings and difficulties in spotting emotions without certain words, the proposed method aims to improve detection by understanding meaning. Whereas, in future these methods can be refined results in more accuracy.

In this research paper [2] the author has suggested, adding a new way to recognize emotions in Moodle by using keyword- based method which finds emotions i.e. the way students write in Moodle chat and forum in accordance to how they feel. This proposal will prepare an emotion extraction and regulation of the learners to improve their performances. However, just looking at keywords might miss some emotions, and typing might not always show the right emotions. The paper suggests adding an enhanced tool to Moodle for handling the variety of emotions in future.

This research [3] looks at how students feel about their courses using feedback, focusing on active learning methods like Light Weight Teams and Flipped Classroom. It uses tools such as the NRC Emotion Lexicon, jsoup, Python NLTK, and Tableau for analysis and visualization. However, sometimes these tools might not get students' feelings correctly which causes the unclear understanding of emotions. To make it better, the study recommends looking at more ways of learning, like other active methods, and focusing on groups such as women and minorities, which will lead to a successful outcome.

Author in [4] discusses the importance of interaction between students and teachers in e-learning environments. It explores emotion detection methods in social media using technologies like Sentiment Analysis, Social Network Analysis, Natural Language Processing (NLP), and Parallel Computing. In the realm of emotion detection from text, a notable challenge arises when conflicting emotions coexist within the same textual content. This contradiction can pose a significant obstacle, introducing complexities in the same sentence.

The author proposed an improvement over the previous work in emotion recognition from text. They did this by making the system sensitive by performing deep semantic and syntactic analysis using various NLP tools. Author used WordNet, ConceptNet for this purpose. This model might fail to detect emotions from short texts, emojis, and grammatical errors[5].

In [6] author talks about the assessment of a methodology to analyse student comments within course evaluations, with a specific emphasis on opinion mining. It utilizes Natural Language Processing (NLP) and a Lexicon-based approach. The study explores the dual nature of course evaluations, emphasizing the significance of both quantitative feedback using Likert-type scales for measurable outcomes and qualitative feedback, allowing students to express feelings and suggestions. Impact of Active learning methods, such as Light Weight Teams and the Flipped Classroom Approach reveals a positive association between their implementation and heightened student positivity.
The author proposed a deep learning model for sentiment analysis in social media, focusing on the challenges of processing short and informal language with special terms and emoticons [7]. They used python for web crawling, and deep learning models such as LSTM, BiLSTM, and GRU, along with Word2Vec and GloVe for word embeddings in sentiment analysis on social media data. However, it's important to note potential limitations. Firstly, the framework may not fit all social media platforms well. Secondly, it doesn't cover all languages and expressions, mostly talks about positives without considering potential issues. To

enhance its applicability, we can apply to the framework to more social media platforms and can try to improve the framework to work well with different languages and cultures globally.

Authors in [8] introduces a new approach called 'multilevel sentiment network' to analyse the emotions expressed in movie reviews. This technique analyses key sentiment words and arranges movies based on their emotional characteristics. This research aims to enhance user understanding and potentially offer better movie recommendations. However, this approach has some limitations, including the fact that it was tested on a small dataset and did not compare its method to other existing methods used to analyse sentiment in text. The study can be improved by using larger datasets, conducting comparative studies, incorporating richer emotions, and developing interactive visualizations. These improvements can help overcome the limitations and unlock broader applications of the multilevel sentiment network approach.

Smith et al. discussed SKETCHMINER, a tool designed to assist teachers in gaining a better understanding of their students' drawings. SKETCHMINER uses technology to translate and analyse student sketches to identify common errors and to improve teaching methods. It utilizes graph theory to represent the topological structure of student sketches, data mining to analyse these structures for patterns and misconceptions, visualization technologies to display and interact with the results, and educational technologies to integrate the framework into an intelligent science notebook. The paper is limited to simple domains such as circuits and predefined symbolic elements, but the authors suggest expanding it to complex domains and incorporating machine learning. This could improve its generative nature and impact on educational practices in the future [9].

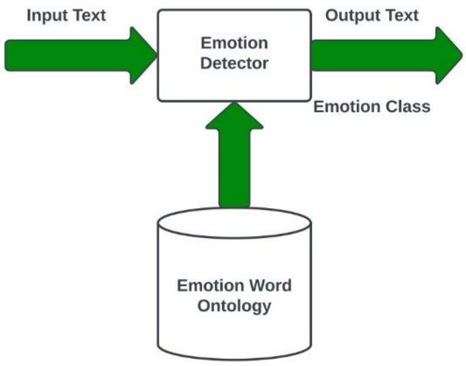

Fig.2. Working model of Lexicon based emotion detection from text documents.

B. Machine Learning Based Approach

i. Natural Language Processing (NLP)

The paper focuses on Sentiment Analysis, which is a way to understand if text like blogs or reviews is positive or negative. The researchers use natural language processing tools to break down the reviews into smaller parts, like words and phrases. They use a process that involves finding important features, ranking them, and training a computer program to correctly label the text[10].

In [11] authors tried to improve the existing technique to get overall emotion from comment text towards a certain image uploaded to the social network. They used LSA(Latent Semantic Analysis) as it is consider a more lightweight approach. They claim that this method has more efficiency than any of the previous methods. But the proposed method may not be able to accurately identify the overall emotion of an image if the comment text is very short or noisy and also the paper does not address the problem of sarcasm or irony in comment text, which can be difficult for LSA to detect. It can further be improved by expanding the emotion lexicon, addressing the problem of sarcasm and irony, and developing a web application for real-time emotion detection on social networks.

In this paper, the authors conducted a study on emotion mining from student comments in STEM education using sentiment analysis techniques, lexicon-based approaches, and natural language processing (NLP). It employed SVM, Naive Bayes, and jsoup for data extraction. They also used jsoup for HTML parsing, NLTK for text analysis, and Python/Tableau for visualization to understand student emotions over time. They found that students who were in classes that used active learning methods felt more positive than students in classes that used traditional teaching methods. The study's focus on computer science comments and reliance on self-reported emotions restrict its generalizability and causal conclusions. Exploring advanced emotion detection across diverse subjects and age groups can reveal deeper insights into student experiences in learning [12].

Leeman-Munk et al. proposes a new multimodal assessment framework for student learning that combines writing and drawing analysis. Previous research shows writing and drawing assessments capture different aspects of student knowledge. However, these studies only focus on one modality at a time, but this paper proposes a framework that integrates both approaches. The authors use convolutional neural networks for writing analysis and topology-based analysis for drawing. The combined framework offers even better accuracy compared to using only one modality. However, the study is limited to elementary students and specific science learning contexts. Future research can explore the application of this framework to other subjects and age groups, using different technology combinations based on the assessment requirements [13].

ii. Support Vector Machine (SVM)

The Author has proposed the development of a hybrid-based architecture for emotion detection in web blog data [14], which combines the study aims to blend meaning and structure details. Using these the researchers achieved an accuracy of 96.43% by employing a hybrid architecture with SVM. However, needing human-label examples could make it harder to use the model in different areas. Future research could concentrate on improving the model's ability to understand and enhance emotions from blog data.

The author proposes an emotion-embedding model to analyse emotion in a story text in [15]. According to the paper they collected 144,701 tweets and labelled each tweet with an emotional hashtag. Using this they built a CNN model for emotion classification and extracted the word embedding model and used this as a sample for classifying stories' emotions. Authors used a sample of the stories from ROC stories which is relatively a small dataset, apart from that the method does not consider the context of text stories which could potentially lead to an error in complex stories. These limitations can be improved by using story text for training the model and using a bigger dataset.

In [16] author explored the use of sentiment analysis to enhance e-learning systems. The authors propose a hybrid approach that incorporates feature selection with a Hidden Markov Model (HMM) and Support Vector Machine (SVM) classifier. This approach is found to outperform other sentiment analysis methods on a dataset of e-learning blog reviews. This study utilizes machine learning algorithms such as Naïve Bayes, SVM, and character-based N-gram models to classify sentiment in online reviews of e-learning systems. However, the study is limited to a specific domain of e-learning reviews and does not explore sentiment analysis in other educational contexts. Future research could expand the scope to include a broader range of educational platforms and advanced sentiment analysis techniques.

iii. Convolutional Neural Network (CNN)

In [17] author provided a comprehensive overview of the latest advances in textual emotion recognition (TER), with a focus on approaches that use deep learning. The paper also discusses the challenges of TER and the potential impact of this field on our lives. The paper talked about the techniques such as word2Vec , GloVe, and Deep neural network architectures such as CNNs and RNNs.

In [18] authors experimented to find the most efficient way to classify emotion in youtube comments. They compared the performance of different word embedding vectors like average word vector, average word vector with TF-IDF, paragraph vector, and Convolutional Neural Network (CNN) algorithm, and found out that CNN methods have the highest level of accuracy. which was found to be an improvement over the previous best result. This helps to improve customer service and enhance social media experiences. The paper still has limitations like it may not capture all the aspects of emotion, such as the context in which the comment is written and the speaker’s intent.

The work in [19] talks about the increase in different types of data with a special focus on the rise of text data in the big data era it highlights the importance of sorting and categorizing text, especially figuring out the feelings expressed in it for things like social network services like Facebook and websites where people discuss movies while traditional machine learning has been doing well. The author suggests deep learning specifically convolutional neural networks (CNN) to make it more effective. Its limitations lie in solely focusing on this platform and lacking analysis of factors influencing performance and robustness to noisy data.

In [20], the author explores the understanding of human emotions expressed in text on social media platforms. Methods like lexicon-based, machine learning-based, and deep learning-based approaches help in sentiment analysis to determine whether text is positive, negative, or neutral. but sometimes it fails due to the vast and unstructured nature of data generated every minute, which can be overcome by enhancing the current techniques and developing multi-lingual models for the future.

[21] proposes a novel model named AEC-LSTM for text sentiment detection, which aims to improve the LSTM network by integrating emotional intelligence (EI) and attention mechanism. AEC-LSTM is a model consisting of an emotion-enhanced LSTM (ELSTM), a topic-level attention mechanism, and a convolutional neural network (CNN). ELSTM captures emotional content, attention mechanism focuses on important topics, and CNN classifies sentiment. The AEC-LSTM model depends on pre-defined emotional lexicons, which limits its ability to capture complex emotions effectively. Future research could focus on developing more adaptive emotion recognition methods and integrating diverse data sources to enhance sentiment analysis in text.

Smith et al. proposes a new method for evaluating the understanding of elementary science students in [22]. This method combines written explanations and drawings to assess their level of comprehension. The proposed approach uses computer-based grading, which is more accurate in predicting post-test performance than human grading. It employs advanced technologies such as convolutional neural networks (CNN) for automated scoring of student writing and topology-based approaches for drawing analysis. The study recognizes that the system cannot handle new questions and subtle differences in student writing. To tackle this, the paper recommends improving how writing and drawing are combined, making scoring rules broader, and including common student misunderstandings.

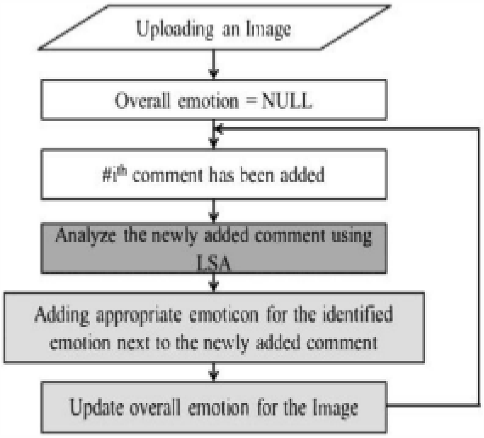

Fig.3. Process of getting overall emotion through NLP

iv. Long Short-Term Memory (LSTM)

The author proposes a method for identifying multiple emotions in social media text, going beyond single-emotion classification in [23]. They combined manual and semi-supervised methods to create a dataset where tweets are labelled with six emotions. They used word2vec to train social media text and to capture semantic, KNN, and Neural networks on labelled datasets to identify the emotions. There are limitations in handling sarcasm and emojis effectively, But these can be improved using sophisticated semi-supervised annotation approaches and using deep learning models.

The objective of the paper [24] is to investigate the effectiveness of a deep learning-based Long Short-Term Memory (LSTM) mechanism for identifying textual emotions. The study was conducted on a dataset of emotional classifications with six emotional groups. The authors found that LSTM-based text emotion classification achieved higher accuracy compared to existing learning methods. The limitations of the study include the use of a relatively small dataset and the fact that the experiment was only conducted on one language. This paper can further be improved by exploring the use of LSTMs with larger datasets and multiple languages.

v. Linear Discriminant Analysis (LDA)

In [25] author proposes an intelligent comment-mining system for MOOC platforms to analyse course comments and extract valuable insights. The basic idea behind analysing comments was to predict course popularity, provide students with emotional feedback to teachers for content improvement, and gather feedback for enhancing user experience. They used Latent Dirichlet Allocation (LDA) and Deterministic Emotional Information based Topic Model(DEI-TM) for this purpose. On the other hand, the paper poses a limitation in that it might not sufficiently address how well the method applies to various MOOCs.

The research in [26] focuses on developing a sentiment analysis framework for e-learning that can be used to detect the emotions of students in an e-learning environment. The author used Latent Dirichlet Allocation (LDA) and Mixed Graph of Terms (MGOT). This work possesses some limitations likes it relies on a single LDA model and the framework may not be able to accurately detect the emotions of students who are using slang or informal language. This paper can be improved by including extra emotions like boredom, frustration, and confusion etc. understanding complex emotions and require a large amount of data for training, which can be improved by introducing better deep-learning technologies.

C. Similar Surveys

In this paper [27] the author explores how computers can understand emotions in blog posts using natural language processing and machine learning techniques. The author utilizes sentiment analysis algorithms to analyse the emotional tone of the text and keyword-based methods to detect emotions to identify specific emotion-related words. Whereas these methods may struggle with understanding complex emotions and require a large amount of data for training, which can be improved by introducing better deep-learning technologies.

The author looks at how we can figure out emotions from text, using methods such as, Lexical and Machine learning models, which implies having good word resources is important for machine learning to work well [28]. However, methods that focus on keywords make it hard to decide which word represents which emotion, which can make things unclear. Also, making lists of emotions in an organized format takes a lot of time. The paper suggests that we should create groups of labelled examples, find ways to measure how good systems are, and analyse text more deeply to get better at detecting emotions in the future.

This paper [29] talks about how knowing emotions can affect decisions. It also uses fancy computer methods like recurrent neural networks (RNNs) and convolutional neural networks (CNNs) to understand emotions better in text. Meanwhile, it's tough to understand emotions in text because words can mean different things to different people & current methods struggle with classifying emotions accurately. It also suggests that we need better AI tools to understand emotions and make better decisions based on them.

In [30] authors explored various emotion detection models from text in social media. The paper reviews various emotion models like Ekman's model (Happy, Anger, Sad, Disgust, Fear , Surprise), and Plutchik's model (anger-fear, surprise-anticipation, joy-sadness, joy-sadness).It includes SENN (Semantic- Emotion Neural Network), BiLSTM-LM, Textual, and Emojis Classifications by Fuzzy Logic, HNN (Hybrid Neural Networks), Semantic-based model and VSM, Neural Networks, Naive Bayes Classifier, Python, Scikit-Learn, NLTK. Future research can focus on combining text, images, and audio data to create more comprehensive models for emotion detection.

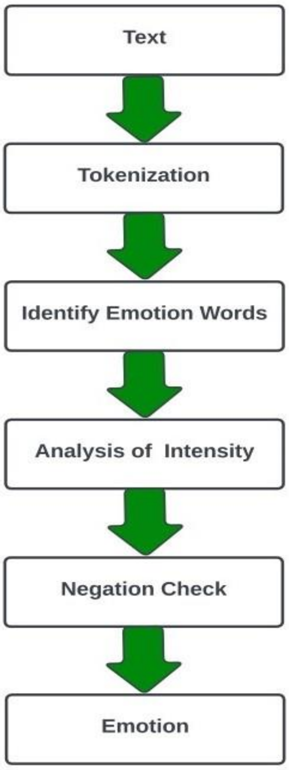

Fig.4. Working model of keyword spotting technique

III. Comparative analysis of previous works

In this section, we have elaborated our findings on some previous works on the topic similar to this study through Table 1. It is tabular representation of the literature review of section II in brief. Table 1 consists of four columns. The first column briefly summarizes the objective of the work. The second column indicates which algo or method is used. The third column indicates the limitations of the work. Lastly, the fourth column is a brief of future directions of works. We could conclude the novelty of this survey work through the observation of this table. As we are unable to find out any previous survey work on text-based sentiment analysis is used in e-learning.

Ref id	Objective	Technology/Algo	Limitation	Future scope
1	To automatically detect and classify eight basic emotions in text,	Natural Language Processing (NLP) and machine learning	Limited exploration of semantic context and linguistic nuances in emotion detection	Explore advanced techniques for improved detection considering semantic context and cultural variations.
2	Develop a hybrid-based architecture for emotion detection using semantic and syntactic information.	hybrid architecture with SVM,	Relies on human-annotated examples for training the model, potentially limiting portability across diverse domains.	Explore heuristics to reduce classification bias and enhance emotion detection across different contexts and domains.
3	Conducting a knowledge-based survey on textual emotion detection.	- Keyword Spotting Technique. - Lexical Affinity Method.	General limitations include ambiguity in keyword definitions	Future research can refine ontology,
4	To survey recent works in the field of Emotion Detection from text.	The paper explores emotion models, lexical and machine learning approaches.	Keyword-based approaches face challenges in determining emotion lexicon content, leading to subjectivity and potential ambiguity.	Emphasis on establishing annotated corpora, metrics for system evaluation, and deeper text analysis in emotion detection systems.
5	To review the state of emotion detection in textual data	NLP	multi-class classification nature of emotion detection,	improve decision-making processes, and enhance entity/organization assessments.
6	Propose emotion extraction in Moodle using text and integrate it into the e-learning platform to enhance learner performance.	Utilize keyword-based emotion extraction from learner text in Moodle chat, forums, and explore emotional intelligence models.	Reliance on keyword analysis may overlook nuanced emotions. Keystroke dynamics may have accuracy limitations.	develop intelligent regulation of negative emotions.
7	Analyse student feedback sentiments and emotions in course evaluations,	Use NRC Emotion Lexicon, jsoup, Python NLTK	General-purpose lexicon may not perfectly fit the educational domain;	Extend analysis to include more Active Learning methods, explore demographics.
8	Detecting emotions from textual data in social media platforms in the context of e learning	SENN BiLSTM-LM,Textual and Emojis Classifications by Fuzzy Logic,HNN model and VSM,Neural Network,Naive Bayes Classifier,Python, Scikit-Learn, NLTK	Ekman's and Plutchik's models have limitations in capturing the full range of human emotions	combining text, images, and audio data to create more comprehensive models for emotion detection.
9	Provide a comprehensive overview of the state-of-the-art methods for emotion detection from text in social media platforms.	1.Sentiment analysis 2. Social network analysis 3.NLP 4.Parallel Computing	Contrast in emotion	Develop models that can be used to understand the underlying causes of emotions.
10	Develop a recommender system for adaptive learning.	1. Semantic Representation: Ontologies (e.g., RDF, OWL) 2. Adaptation Strategy: Feedback loop	1.Inaccuracies or inconsistencies in the ontologies could negatively impact recommendation accuracy.	Utilize techniques like deep learning to analyze textual and behavioral data for even more personalized recommendations and adaptivity to individual learning styles.
11	Develop a framework for automatically generating rules for emotion recognition from text.	1. Ontologies such as Word Net and Concept Net 2. NLP	1. Disregard for semantic information in texts and the failure to regard the role of context in sentences.	1. Improved customer service. 2. Enhanced social media experiences.
12	To develop an automatic emotion recognition system to detect emotions in user's daily text	Word2vec, autoencoder, LSTM	Dependency on pre-trained word vectors, Limited ability to capture contextual information	1. Improved customer service. 2. Enhanced social media experiences.
13	Emotion classification from youtube comments	NLP,CNN	may not be able to capture all aspects of emotion, such as the context	1. Improved customer service. 2. Enhanced social media experiences.
14	Develop and evaluate a method for analysing student comments from course evaluations to assess the effectiveness of teaching innovations.	1. NLP 2. Lexicon-based method	method relies on predefined dictionaries, Misinterpretations can occur due to word ambiguity,.	1.Integrating information from audio, video, or facial expressions alongside text

15	To develop deep learning models for sentiment analysis in social media	Python for web crawling, and deep learning models such as LSTM, BiLSTM, and GRU,	1.The framework may not fit all social media platforms well. 2.It doesn't cover all languages and expressions,	1. Apply the framework to more social media platforms. 2. Improve to work well with different languages and cultures globally.
16	To target the sentiment analysis that classifies the given text into one of sentiment categories.	1. Convolutional neural networks (CNNs)	lacking analysis of factors influencing performance and robustness to noisy data.	CNNs have the potential to improve the accuracy of sentiment classification
17	To propose a method for emotion recognition in text stories using an emotion embedding model.	1.Emotion embedding model. 2. Support vector machine (SVM) classifier.	1 a relatively small dataset. 2. does not consider the context of the text stories.	using a larger dataset, considering context
18	The objective is to use emotion recognition and topic mining to analyze MOOC course comments	Latent Dirichlet Allocation (LDA), Deterministic Emotional Information based Topic Model (DEI-TM)	2. Lack of specific dataset	The paper's future scope includes enhancing personalized learning experiences in MOOCs
19	To propose a semi-supervised approach for data annotation and multi-emotion classification for social media text.	1. Word mover's distance (WMD). 2. Long short-term memory (LSTM) networks.	It's limitations include a small dataset, potential noise in labels, and inability to handle sarcasm or emojis effectively.	Future scope includes developing more sophisticated semi-supervised annotation approaches
19	To propose a semi-supervised approach for data annotation and multi-emotion classification for social media text.	1. Word mover's distance (WMD). 2. Long short-term memory (LSTM) networks.	It's limitations include a small dataset, potential noise in labels, and inability to handle sarcasm or emojis effectively.	Future scope includes developing more sophisticated semi-supervised annotation approaches
20	a stand-alone system that can detect alertness and emotion states in e-learning	1. Kalman filter:	1.The system is still under development and the accuracy needs to be improved.	improving the accuracy of the system and developing more sophisticated feedback mechanisms.
21	To get overall emotion from comment text	Latent Semantic Analysis (LSA)	may not be able to accurately identify the overall emotion of an image if the comment text is very short or noisy.	The future scope of this research includes expanding the emotion lexicon,
22	To review existing research on e-learning based recommender systems	1.Convolutio-nal neural networks (CNNs). 2.Recurrent neural networks (RNNs)	1. Difficulty of handling sarcasm and other forms of figurative language.	Addressing the challenges of heterogeneous data.
23	to develop a sentiment analysis framework for e-learning that can be used to detect the emotions of students in an e-learning environment	1. Latent Dirichlet Allocation (LDA). 2. Mixed Graph of Terms (MGOT):	may not be able to accurately detect the emotions of slang or informal language.	susing it to detect other emotions of students, such as boredom, frustration, and confusion. Additionally,
24	To propose a multilevel semantic network visualization approach for analysing sentiment words of movie review data.	Hierarchical clustering, Force-directed graph drawing	Difficulty of interpreting the visualization, Subjectivity of the sentiment lexicon	Developing interactive visualization tools that allow users to explore and manipulate the visualization in real time.
25	aims to evaluate the impact of the Light-Weight Team teaching model in computer science courses	NLP) Support Vector Machine (SVM) and Naive Bayes. .	Focus on a specific active learning approach (Light-Weight Teams	extending the method for assessing the Light-Weight Team teaching
26	To utilize sentiment analysis of user feedback to identify areas for improvement,	supervised machine learning algorithms, Maximum Entropy and Support Vector Machine algorithms, Hidden Markov model (HMM).	Inability to handle sarcasm and other forms of figurative language,Need for a large and labelled dataset.	1. Developing methods for handling sarcasm and other forms of figurative language in sentiment analysis.
27	To develop a novel deep learning model for sentiment analysis that integrates emotional intelligence and attention mechanism.	(CNN) Emotion-enhanced LSTM (ELSTM). AEC-LSTM model.	limited number of datasets, not consider the context of the text.	Explore the use of unlabelled data for training the AEC-LSTM model.
28.	a multimodal assessment framework for integrating student writing and drawing in elementary science learning.	CNN for writing assessment, topology-based model for drawing assessment	Trained on elementary science data only, not generalized to other domains.	Expand modalities, refine algorithms, real-world testing
29.	Introduce a comprehensive framework for assessing student	Natural language processing (NLP)	Trained on limited data, may not generalize to all domains	This framework could expand beyond science, tackling other subjects and grades.
30.	an innovative framework called SKETCHMINER for automatically analysing student-generated science drawings	Blend of computer vision, graph theory, data mining, visualization technologies	Requires semantically-grounded symbols, domain-specific, not free-hand drawings.	Adapting to new concepts, limited explanation power, and overlooking visual details are some snags.

Table 1. Brief tabular presentation of the survey

IV. Discussion and future work

Discussion and future work We have conducted this review based on emotion analysis of e-learners. We have analyzed previous works where authors used some machine learning algorithms or lexiconbased methods to capture emotion from the text of the e-learners. Different comments, feedback or discussion of e-learners are considered for analyzing their emotional state. Their emotional state is essential for recognizing the effectiveness of the e-learning courses to which they have been admitted. Sentiment analysis is gaining immense importance for e-learning recommendations and personalized learning. So in the future, we would like to conduct reviews on audio, image, and video-based or multi-modal emotion analysis of e-learners to enhance the quality of the online learning platforms and experience of e-learning.

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