Sentiment Dynamics Detection of Online Learning Impact using Hybrid Approach

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Abstract:

With the growth of technology, the concept of online learning has grown in popularity. The worldwide epidemic situation (Covid 19) has increased the use of online learning not just in Higher Education Institutions (HEIs), but also at all levels of education (ISED levels). In these hard times, technical advancements have played a greater role in creating awareness of the existence of online learning which has evolved as an alternate avenue for gaining and disseminating knowledge in a systematic way.

In this paper we investigate to detect the sentiment dynamics (SD) of tweets related to online education available on twitter platform and deduce conclusions about its impact on student's emotions. Over one lakh subjective tweets about the world's emerging online education system have been gathered via Twitter. Sentiment analysis was performed on the gathered dataset using the combination of dictionary-based and statistical-based approaches. Based on the findings of this analysis, we can infer the impact of online education and how people's attitudes have changed as a result of changes in the educational system. As a result, we would like to present a better comprehension of the sentiment dynamics of online education adoption.

Keywords: Sentiment Analysis (SA), NLP, Lexicon approach, Machine Learning, Polarity, Online Learning

1. Introduction:

Technological advancement and development of internet have had a significant impact on many sectors, including the online education. In the recent years, there has been a noteworthy increase in the number of online learners [1]. Online education, often known as e-learning, is a rapidly growing technology which aims to facilitate good education anytime and anywhere as long as you have access to the internet. The online learning technology has seen a remarkable metamorphosis in the last two decades since it was originally offered to the public.

Monitoring Learner Opinions (MLO) is a critical step in gathering relevant data and designing effective online interactive learning (OIL) sessions. Students' understandings of online courses, as measured by responses to teaching surveys, allow the detection of flaws and issues in learning techniques [2].

The goal of this work is to investigate sentiment analysis utilizing Natural Language Processing (NLP) and Machine Learning (ML) approaches [3][4].

Sentiment analysis or Opinion mining [5][11] seeks to detect the orientation of textual contents in terms of positivity/negativity indicated by the author in forum posts (e.g., Reviews, Tweets, blogs etc.) toward a target entity. The fundamental objective of sentiment analysis is to detect the polarity of sentiment represented in textual information. Emotions such as joyful, sad, furious, or positive, negative, or neutral, for example, can be used to identify a user's sentiment toward a specific subject or item [6]. This may be used to assess online learners' satisfaction, as well as their proclivity for online learning, and to enhance their services.

There are two types of sentiment analysis methods: lexicon-based [7] and machine learning-based. In lexicon-based approaches, the sentiment polarity is identified by using a dictionary. Machine learning approaches are used to model the learning model is constructed by training the supervised learning algorithm with a labelled collection of text documents. In machine learning-based sentiment analysis, traditional supervised learning methods such as the Naive Bayes algorithm (NBA), Support Vector Machines (SVM), and the K-Nearest Neighbour (KNN) algorithm implemented successfully [10]. In our approach we are employing the combined method of lexicon and ML based approach to detect the sentiment dynamics of online learning opinion.

Morphing unstructured text data connected to online education to structured data is a way of assessing people's views and feelings concerning online education. Text cleaning, text transformation, and dimension reduction are some pre-processing methods to generate organized textual data for the selection of meaningful and relevant text. As a result, examining this data is crucial in identifying the influence of the domain of ongoing/ emerging online education and offering improved feedback to educational institutions in order to enhance the quality of their services.

In view of the foregoing, previous research has a number of limitations, which did not lead us to propose a novel method for extracting knowledge that may be used from large social network textual data.

2. Related work:

Sentiment Analysis in online education is mostly focused on identifying a review's overall polarity (i.e., positive or negative) or sentiment rating (e.g., one-five stars). Balachandran and Kirupananda in their research laid the groundwork for combining opinion mining and sentiment analysis into the evaluation of higher education institutions. In their study the Standford NLP library was used for sentiment analysis which provides the method for processing the sentiment analysis and calculating the positive and negative percentages of the reviews [8].

Wang and Zhang illustrated the benefits of using LDA in opinion mining. They computed sentiment score using a sentiment scores matrix (SSM). This study proposes a methodology for online sentiment analysis of diverse Online learning community. The model generates the topic-terminology hybrid matrix and the document topic hybrid matrix by using LDA topi to pick genuine user comment information [9].

To examine public perception about online learning, Bhagat et al. used the dictionary-based technique of the lexicon-based method. The authors applied Sentiment Analysis, as well as web scraping, to learn about popular perceptions about online education and by using the TextBlob library, they computed the polarity and subjectivity scores of the extracted article [10].

Onan evaluated a corpus of 66,000 MOOC evaluations using a fusion model that included machine learning, ensemble learning, and deep learning techniques. In his research, supervised learning methods such as Nave Bayes, support vector machines, logistic regression, K-nearest neighbour, and random forest, as well as ensemble learning methods such as AdaBoost, Bagging, Random Subspace, voting, and Stacking, were used to evaluate the representation schemes, whereas in the deep learning-based approach, the author used word2vec, fastText, and GloVe, as well as deep learning architectures CNN, RNN, and BRNN with attention [11].

Neumann and Linzmayer examined the disadvantages of star ratings and looked into whether sentiment analysis using the vader model can accurately and efficiently evaluate student sentiments. They also investigated the feasibility of analyzing student emotions in big computer couraes [12].

Sangeetha and Prabha presented a technique that combining several layers with Long Short-Term Memory which enhances the output over a standard NLP approach [13]. Kastrati et al. suggested a paradigm for sentiment analysis of student data based on features and the polarity of a statement is determined by its content and feature [14]. Lundqvist et al. in their research discovered a link between the general attitude of postings and the comments provided regarding the MOOC online learning [15].

Dess et al. introduced a Deep Learning approach that analyses the sentiment polarity of textual reviews offered by learners after finishing online courses, starting with Word Embedding representations. They observed that when compared to other embedding types, context-trained Word2Vec embeddings had the lowest MAE values [16].

Moreno-Marcos et al. discussed the use of two lexical (unsupervised) methods on learners' emotions in online based learning, which were based on the usage of dictionaries of words and SentiWordNet. In addition, five supervised machine learning algorithms were utilized, with Random Forest emerging as the best [17].

Zhang et al. create a component called the confidence divider and build a confidence function to differentiate the classification quality of CNN. NB-SVM is then used to reclassify the predictions with low confidence. The experimental findings demonstrate that 3W-CNN performs well on four benchmark datasets [18].

3. Proposed Architecture and Methodology:

Our aim is to analyze the sentiment dynamics (SD) of students regarding online learning. Public domain dataset has been taken for collecting the online learning tweeter data. In this section, our proposed hybrid approach for analyzing Twitter sentiment dynamics (SD) is described. The proposed framework is shown below in Fig. 1)

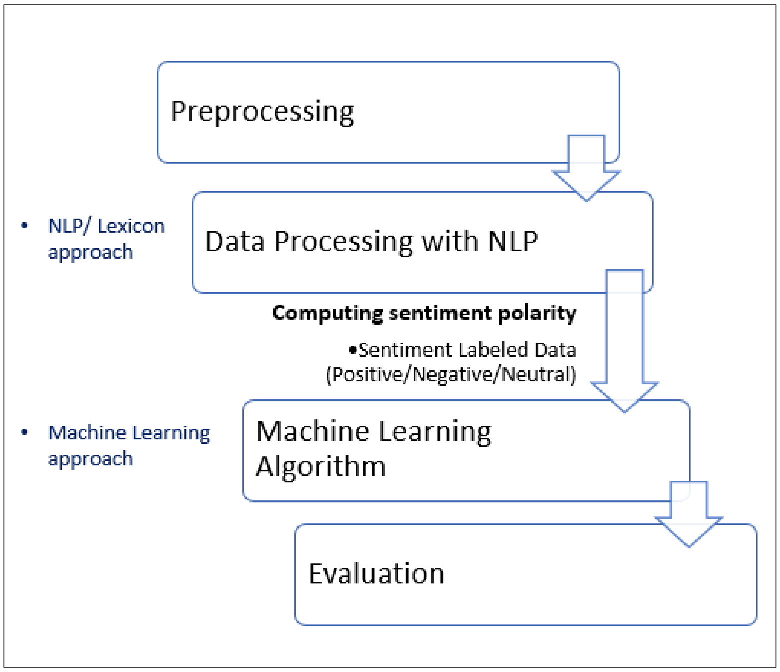


Fig.1 The semantic structure of the proposed methodology.

There are two major approaches to sentiment analysis.

- Unsupervised Lexicon-based approaches
- Supervised Machine Learning or deep learning approaches

3.1 Lexicon Based Classification Approach:

A lexicon is a collection of words that includes a dictionary, a vocabulary, and a book of words. In our situation, lexicons are specialised dictionaries or vocabularies which are designed specifically for sentiment analysis. These lexicons basically consist of a list of positive, negative and neutral polar words. The polarity scores assigned to positive, negative and neutral polar words in a document are calculated using various rule-based and dictionary-based techniques. After aggregating these scores, we get the final sentiment. Lexicon-based Sentiment Analysis techniques can be broadly classified into Dictionary-based and Corpus-based.

In Natural language processors (NLP), words(text) are converted into numbers and these numbers are then used to train the models to make predictions.

3.2 Preprocessing:

Data preprocessing comprises data cleaning, data integration, data transformation, and rata reduction. Classification, tokenization, stemming, and lemmatization are four of the most fundamental natural language processing methods used for pre-processing raw tweets into refined data.

- Stop words removal, removes words that appear often but don't help to understand the meaning or topics of a text. "is", "that", "you", "there", "at" etc. are some examples of stop words.
- Stemming is a technique which is used to reduce words to their root form. For example, the words "writes", "writing" or "write" can be grouped as their root form i.e., "write". It follows a rule-based approach.
- Lemmatization is a method for merging several inflected forms of words into a single root form with the same meaning. These words are called lemma. It follows a dictionary-based approach.
- Tf-idf (Term Frequency — Inverse Term Frequency) is a prominent feature extraction method and statistical concept for determining the frequency of terms in a corpus. The vectorizer will return a TF-idf matrix with the weights of each word in the corpus. The equation of calculating Tf-idf is given below.

$$TF\text{-}IDF\ (t) = TF\ (t) * IDF\ (t) \tag{1}$$

$$Tf\text{-}idf\ (t,d) * \log\ (N/df\ (t)) \tag{2}$$

where
TF (t)= (Number of times term t appears in a document)/ (Total number of terms in the document)
IDF(t)= Inverse Document Frequency, which measures how important a term is.
df = Document frequency
N = Number of documents

3.3 Sentiment Analysis:

We can finally focus on our major goal of this work after preprocessing and EDA. We compute the emotive aspects of the tweets, such as polarity and subjectivity using VADER. VADER (Valence Aware Dictionary and Sentiment Reasoner) is a lexicon and rule-based sentiment analysis tool. It is included in the Python NLTK library and can be used on unlabeled text data directly. VADER is capable of detecting emotional polarity and subjectivity. It calculates these figures based on predetermined word scores. Polarity is defined as a shift in value from -1 to 1. It indicates if the statement is favourable or negative. Subjectivity is a number that ranges from 0 to 1, indicating whether the statement is about a fact or an opinion (objective or subjective).

Here our focus is on the following two standard aspects at the sentence level:

- Subjectivity determination
- Opinion polarity (graduality)

The table 1 shows the polarity score obtained after classification of the tweeter texts. From the sign of the polarity score, the overall sentiment dynamic is portrayed as positive, negative, or neutral. Similarly in Fig.2, it is visible that positive tweets on online education are significantly more than negative ones. Fig.3 represents the visualization of polarity and subjectivity scores of the tweeter data.

Table 1: Polarity Scores of text after classification

	id	text	Positive	Negative	Neutral	Compound
0	0	innovate an innovative approach #quoteoftheday...	0.466	0.0	0.534	0.7269
1	1	The pandemic is raising concerns about how tee...	0.000	0.0	1.000	0.0000
2	2	STI: Staying Education-ready in the New Normal...	0.000	0.0	1.000	0.0000
3	3	Digital Learning Through Digital RCRT\n.\n.\nR...	0.000	0.0	1.000	0.0000
4	4	Upswing Classroom: Out and Out Virtual School,	0.000	0.0	1.000	0.0000

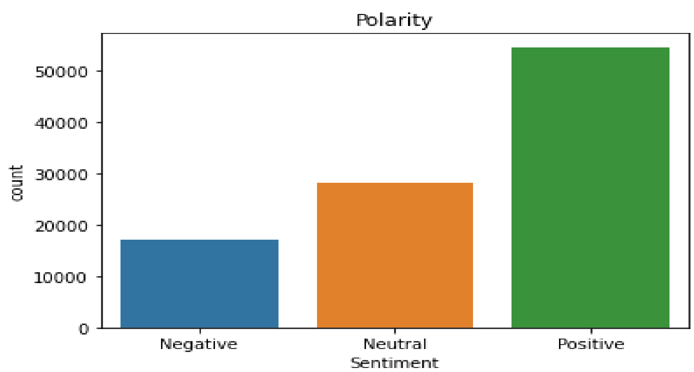


Fig.2 Polarity distribution of the dataset

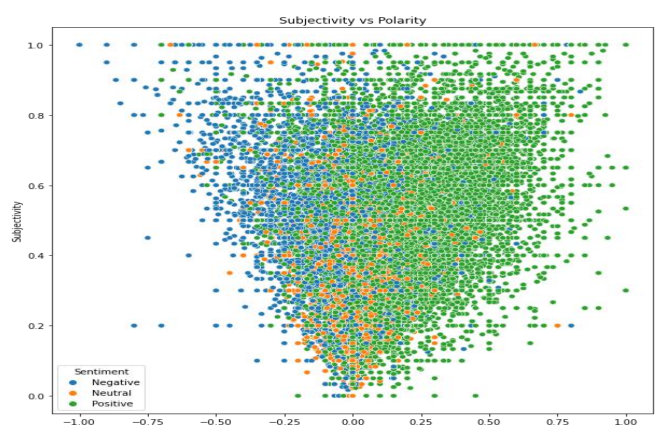


Fig.3 Subjectivity and Polarity Score of the Sentiments

Fig. 4 respectively shows the frequency distribution graph of top 50 most commonly used positive words in the dataset. In the similar manner Fig. 5 shows the frequency distribution graph of top 50 most commonly used.

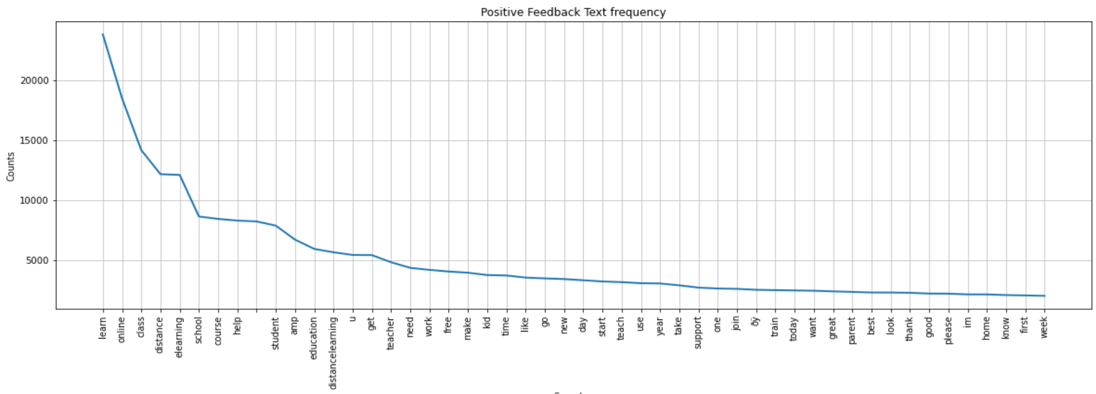


Fig.4 Frequency of Words with Positive Polarity of Sentiments

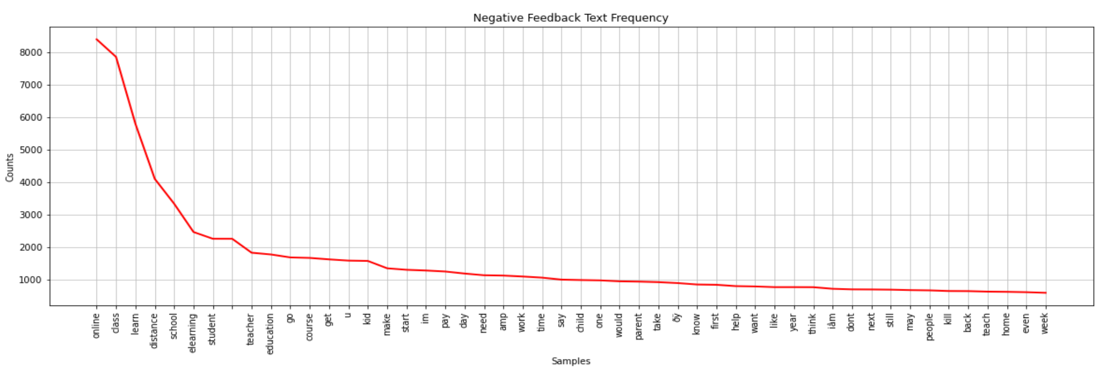


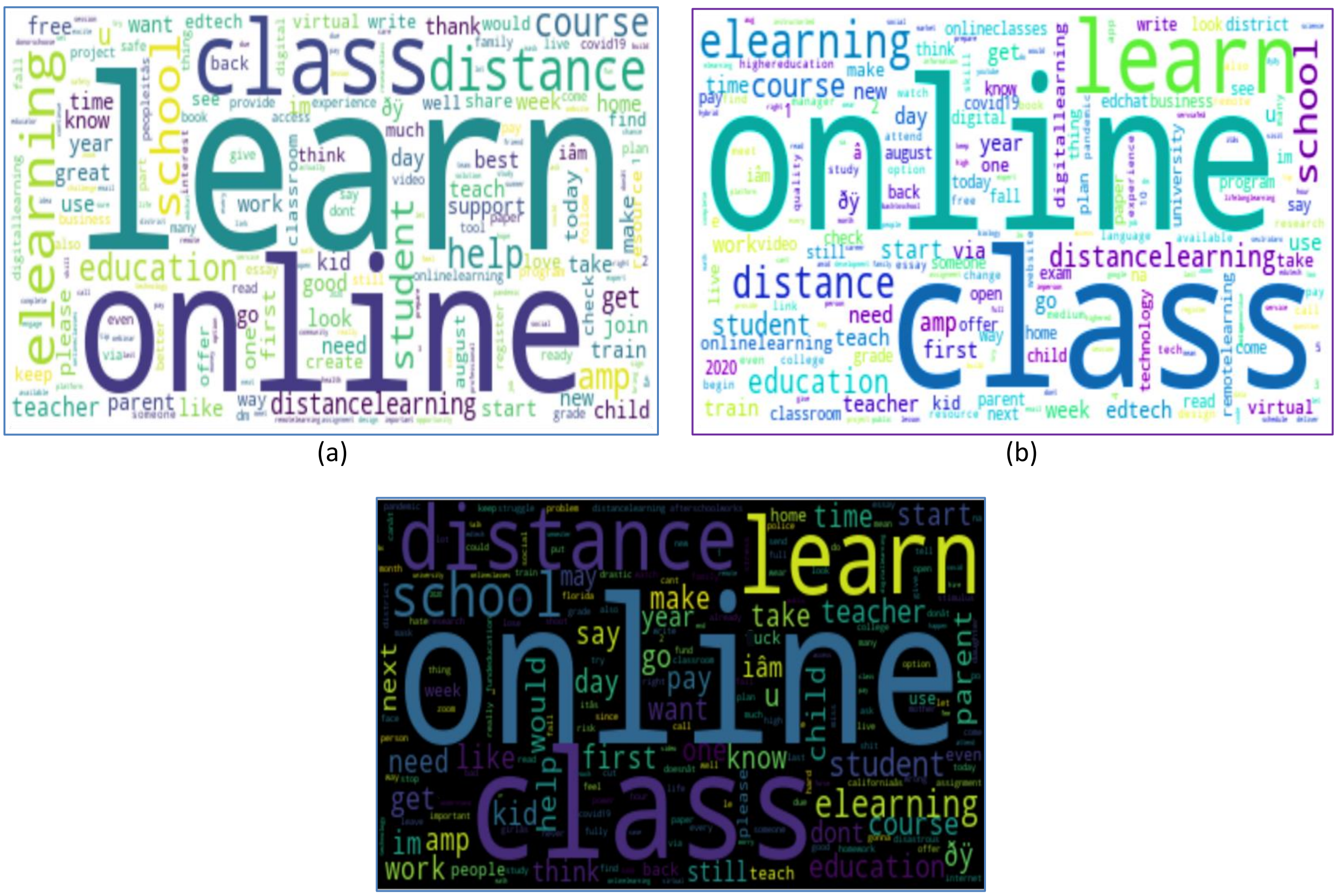
Fig.5 Frequency of Words with Negative Polarity of Sentiments

It is also essential to understand the most prevalent word occurrences in tweets. This will provide us with information on the structure and categorization of tweets. To depict this, a word cloud is used. The word cloud is created using the "WordCloud" application. The larger the term in the word cloud, the more frequently it appears in the corpus. Figures 6(a), 6(b), and 6(c) show word clouds of positive, neutral, and negative terms, respectively

Seemingly, people whose tweets are negative find online learning is boring, horrible, and terrible. On the other hand, some people like options for distance learning.

3.4 Building the Machine Learning Model:

We proceed with the next step to use Machine Learning Models (MLM), to analyze our dataset and determine which model best suits our dataset and then the model is used to predict test data outcome. In the earlier approach, the tweets have been labeled according to their polarity scores. Now the Machine Learning models are employed with the test and train data by using Multinomial Naive Bayes, LSTM, Support Vector Machine and Decision Tree Classifier. Following that, the outcomes of all models are compared, and the best model with the most successful feature extraction approach is chosen. In our case we use



(a) (b) (c)

Fig.6 (a) Word Cloud of Positive feedback Tweets (b) Word Cloud of Neutral feedback Tweets. (c) Word Cloud of Negative feedback Tweets

TF-IDF vectors as the features and the labels as the target. The suggested problem falls under the heading of Supervised Machine Learning (SML).

In Supervised Learning, the data consists of input and corresponding output variables. The machine learning system aims to predict outputs, Y based on the inputs, X. SML approach adopts the following formulation:

$$Y = f. (X) + e \qquad (3)$$

where

X=input variables
Y= output variable
e=error (which is unrelated to the input data X).

4. Model Evaluation:

The confusion matrix is used to measure the algorithm's accuracy. It demonstrates the efficiency of each classifier method when applied to a set of test data with known true values. By performing this we placed the model into its performance evaluation state. The confusion matrix has four values: TP (True positive), FP (False positive), FN (False Negative), and TN (True Negative) (True Negative). The total number of values in the matrix (TP+TN+FP+FN) indicates the total amount of data in the test data. The creation of a confusion matrix is seen in Figure 7. The efficacy of a model is evaluated using these four

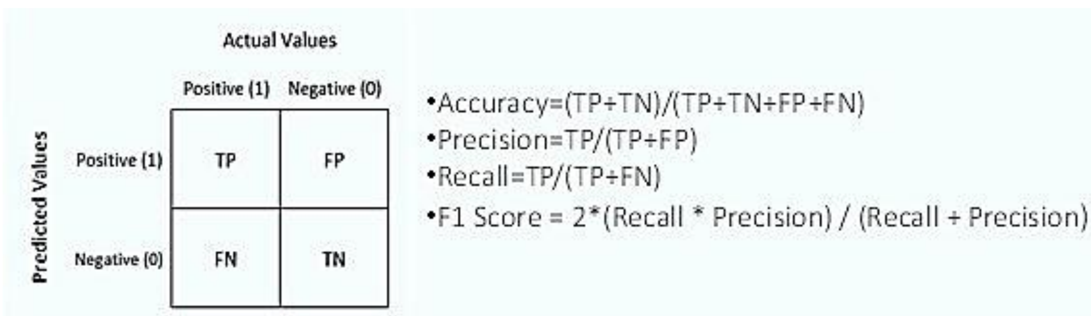


Fig.7 Standard Confusion Matrix

performance assessment parameters: accuracy, precision, recall, and F1 score.

The matrix is split into two dimensions, one is the predicted values and the other is the actual values along with the total number of predictions. The values predicted by the models are the Predicted values, whereas, actual values are the true values for the given

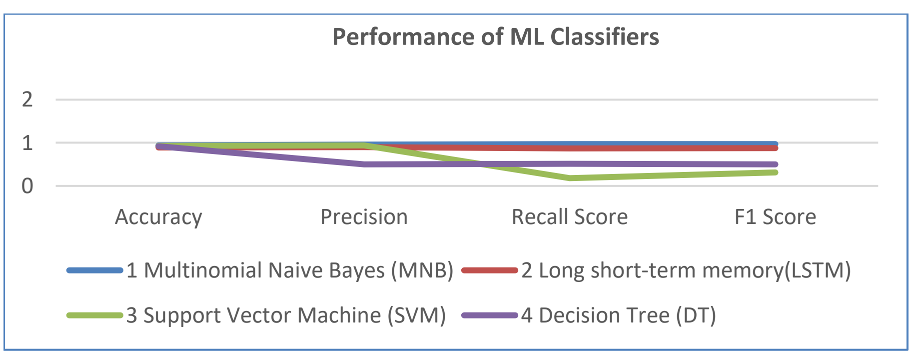


Fig. 8 Performance Evaluation of the ML Classifier models

observations

5. Result and discussion:

In this section, we present and analyze the results of the tests in order to assess the efficiency of the proposed technique utilizing a variety of evaluation metrics, including (i) accuracy (ii) precision, (ii) recall, and (iii) F1-score, to evaluate the suggested method's performance.

We investigated the data with summary statistics and visualization tools. We utilized VADER to determine the polarity of the tweets and then analyzed the results. As a result, we discovered that the majority of tweets in our sample are positive regarding distance learning. In terms of positive polarity of Sentiment dynamics, Multinomial Naive Bayes classifier achieved 94% accuracy. Fig. 8 summarizes the various performance evaluation parameters employed for the analysis of the machine learning classifiers in the current study.

6. Conclusion:

In this paper, we have described a hybrid method to detect the sentiment dynamics of opinion data from the dataset on online learning. A hybrid approach is generally referred to as a method that combines lexicon (corpus) based approaches and machine learning algorithms. The lexicon-analysis technique is utilized for sentiment analysis, followed by machine learning approaches. The dataset is first tokenized, and then the data is classified according to its polarity. Machine learning classifiers such as Multinomial Naive Bayes, Support Vector Machine (SVM), LSTM, and Decision Tree have been employed for classification. The suggested approach is quite successful, with an overall performance of 89-94 percent for positive polarity sentiments across all classifiers. This research also suggests a future scope in which sentiment dynamics of online learners may be analyzed on datasets consisting online learning opinions using deep learning techniques to improve accuracy.

Reference:

1. S. Das, P. P. Acharjya, H. Mondal, and M. Nandan, "Machine Learning Approach to Augment Performance of ISED Level-1 Students through their Online Learning Behaviour," International Journal of Mechanical Engineering, vol. 7 No. 1, pp. 5191–5204, Jan. 2022.

2. J. L. Rastrollo-Guerrero, J. A. Gómez-Pulido, and A. Durán-Domínguez, "Analyzing and Predicting Students' Performance by Means of Machine Learning: A Review," *Applied Sciences*, vol. 10, no. 3, p. 1042, Feb. 2020, doi: 10.3390/app10031042.

3. M. Khanbhai, P. Anyadi, J. Symons, K. Flott, A. Darzi, and E. Mayer, "Applying natural language processing and machine learning techniques to patient experience feedback: a systematic review," *BMJ Health Care Inform*, vol. 28, no. 1, p. e100262, Mar. 2021, doi: 10.1136/bmjhci-2020-100262.

4. I. Awasthi, K. Gupta, P. S. Bhogal, S. S. Anand, and P. K. Soni, "Natural Language Processing (NLP) based Text Summarization - A Survey," in *2021 6th International Conference on Inventive Computation Technologies (ICICT)*, Coimbatore, India, Jan. 2021, pp. 1310–1317. doi: 10.1109/ICICT50816.2021.9358703.

5. S. A. Waheeb, N. A. Khan, and X. Shang, "Topic Modeling and Sentiment Analysis of Online Education in the COVID-19 Era Using Social Networks Based Datasets," *Electronics*, vol. 11, no. 5, p. 715, Feb. 2022, doi: 10.3390/electronics11050715.

6. Z. Drus and H. Khalid, "Sentiment Analysis in Social Media and Its Application: Systematic Literature Review," *Procedia Computer Science*, vol. 161, pp. 707–714, 2019, doi: 10.1016/j.procs.2019.11.174.

7. M. Boukabous and M. Azizi, "Crime prediction using a hybrid sentiment analysis approach based on the bidirectional encoder representations from transformers," *IJEECS*, vol. 25, no. 2, p. 1131, Feb. 2022, doi: 10.11591/ijeecs.v25.i2.pp1131-1139.

8. L. Balachandran and A. Kirupananda, "Online reviews evaluation system for higher education institution: An aspect based sentiment analysis tool," in *2017 11th International Conference on Software, Knowledge, Information Management and Applications (SKIMA)*, Malabe, Dec. 2017, pp. 1–7. doi: 10.1109/SKIMA.2017.8294118.

9. K. Wang and Y. Zhang, "Topic Sentiment Analysis in Online Learning Community from College Students," *Journal of Data and Information Science*, vol. 5, no. 2, pp. 33–61, Apr. 2020, doi: 10.2478/jdis-2020-0009.

10. K. K. Bhagat, S. Mishra, A. Dixit, and C.-Y. Chang, "Public Opinions about Online Learning during COVID-19: A Sentiment Analysis Approach," *Sustainability*, vol. 13, no. 6, p. 3346, Mar. 2021, doi: 10.3390/su13063346.

11. A. Onan, "Sentiment analysis on massive open online course evaluations: A text mining and deep learning approach," *Comput Appl Eng Educ*, vol. 29, no. 3, pp. 572–589, May 2021, doi: 10.1002/cae.22253.

12. M. Neumann and R. Linzmayer, "Capturing Student Feedback and Emotions in Large Computing Courses: A Sentiment Analysis Approach," in *Proceedings of the 52nd ACM Technical Symposium on Computer Science Education*, Virtual Event USA, Mar. 2021, pp. 541–547. doi: 10.1145/3408877.3432403

13. K. Sangeetha and D. Prabha, "Sentiment analysis of student feedback using multi-head attention fusion model of word and context embedding for LSTM," *J Ambient Intell Human Comput*, vol. 12, no. 3, pp. 4117–4126, Mar. 2021, doi: 10.1007/s12652-020-01791-9.

14. Z. Kastrati, A. S. Imran, and A. Kurti, "Weakly Supervised Framework for Aspect-Based Sentiment Analysis on Students' Reviews of MOOCs," *IEEE Access*, vol. 8, pp. 106799–106810, 2020, doi: 10.1109/ACCESS.2020.3000739.

15. K. Lundqvist, T. Liyanagunawardena, and L. Starkey, "Evaluation of Student Feedback Within a MOOC Using Sentiment Analysis and Target Groups," *IRRODL*, vol. 21, no. 3, May 2020, doi: 10.19173/irrodl.v21i3.4783.

16. D. Dessí, M. Dragoni, G. Fenu, M. Marras, and D. Reforgiato Recupero, "Deep Learning Adaptation with Word Embeddings for Sentiment Analysis on Online Course Reviews," in *Deep Learning-Based Approaches for Sentiment Analysis*, B. Agarwal, R. Nayak, N. Mittal, and S. Patnaik, Eds. Singapore: Springer Singapore, 2020, pp. 57–83. doi: 10.1007/978-981-15-1216-2_3.

17. P. M. Moreno-Marcos, C. Alario-Hoyos, P. J. Munoz-Merino, I. Estevez-Ayres, and C. D. Kloos, "Sentiment analysis in MOOCs: A case study," in *2018 IEEE Global Engineering Education Conference (EDUCON)*, Tenerife, Apr. 2018, pp. 1489–1496. doi: 10.1109/EDUCON.2018.8363409.

18. Y. Zhang, Z. Zhang, D. Miao, and J. Wang, "Three-way enhanced convolutional neural networks for sentence-level sentiment classification," *Information Sciences*, vol. 477, pp. 55–64, Mar. 2019, doi: 10.1016/j.ins.2018.10.030.

19. O. Appel, F. Chiclana, J. Carter, and H. Fujita, "A hybrid approach to sentiment analysis," in *2016 IEEE Congress on Evolutionary Computation (CEC)*, Vancouver, BC, Canada, Jul. 2016, pp. 4950–4957. doi: 10.1109/CEC.2016.7744425.

20. I. El Alaoui, Y. Gahi, R. Messoussi, Y. Chaabi, A. Todoskoff, and A. Kobi, "A novel adaptable approach for sentiment analysis on big social data," *J Big Data*, vol. 5, no. 1, p. 12, Dec. 2018, doi: 10.1186/s40537-018-0120-0.