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Exploring Sentiments: An In-Depth Analysis of Opinions in Education-Focused Tweets

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ABSTRACT
Investigating students' views on online learning is important for reinforcing the best educational offerings. Analyzing reviews serves as a sensible device to assess the numerous emotional polarities expressed by college students, losing mild at the acceptance or rejection of unique academic policies. Leveraging social media discussions proves valuable in delving into students' critiques even though the unstructured nature of these facts poses demanding situations and hinders prediction model performance. This research endeavours to address those demanding situations using Natural Language Processing (NLP) strategies for analyzing unstructured textual content. They look at specializing in amassing social media information from the Twitter database. To ensure the reliability of the findings, a robust method is applied to eliminate noisy, besides-the-point, and redundant information. An essential element influencing type accuracy is function selection. This study introduces a fuzzy C-means Algorithm choice-making model to streamline huge capabilities extracted from the text feature units. The overall performance of the polarity category for social media information is evaluated using accuracy, precision, consideration, and f-rating measures. The evaluation outcomes spotlight the prevalence of the fuzzy c means-based SVM (FIT2S-SVM) classifier, reaching a maximum accuracy rate of zero.97 and outperforming current methodologies.

***Keywords:** Bag-of-words, Ensemble model, Feature reduction, Natural language processing, Principal component analysis, Sentiment analysis, Tweepy, Opinion mining*

1. INTRODUCTION

Opinion mining (OM), also known as sentiment evaluation, leverages Natural Language Processing (NLP) techniques [1] to investigate textual records on social media structures, mainly Twitter. NLP aids in figuring out the polarity of the given textual content, categorizing it as wonderful, terrible, or neutral [2]. OM performs a vital function in various fields, such as education and business, aiming to apprehend purchaser needs by analyzing comments. This emphasizes text statistics' polarity and extends to detecting feelings, urgency, and innovation [3].

The utility of OM includes using NLP capabilities and gadgets to gain knowledge of (ML) techniques [4, 5] to unveil the feelings behind social media conversations. This analysis spans company and non-business sectors, training, social media activities, and commercial enterprise-associated facts [6-10]. Recently, a hobby has been developing in applying sentiment evaluation to academic statistics. This involves reading online conversations among college students and academic professionals to realize student necessities and beautify the excellent education provided [11-13].

Educational Data Mining (EDM) is a method that aids organizations in discovering essential records impacting the instructional region. With the increasing integration of technology in instructional establishments, EDM has become pivotal in improving learning and teaching strategies. Notably, there has been a surge in tweets associated with faculties, mainly during the COVID-19 pandemic [14]. These tweets encompass many subjects, including the advertising of online instructions and updates from the Ministry of Education onboard tests and NEET tests. Analyzing such tweets affords treasured insights into the instructional landscape and enables the shaping of an extra superior mastering experience for college kids.

This amalgamation of sentiment evaluation, the mixing of software program era in training, and the prevalence of discussions related to schooling on social media structures underscore the effects of opinion mining across various domain names. This research endeavours to become aware of tweets associated with training, categorizing them based on whether or not they contain poor sentiments, are considered hate speech, or have high-quality sentiments. The discernment between tweets expressing negativity and positivity, along with racist remarks or compliments, is a critical issue of this exploration.

There is a developing need for computerized opinion-mining obligations, especially concerning scholar tweets, similarly emphasizing the importance of this research. Extracting critiques from social media systems, as highlighted by preceding research [15], poses a sizeable challenge. The computerized prediction of education-associated conversations, particularly in the aftermath of the COVID-19 pandemic [16, 17], has become a distinguished research region. Consequently, this has a look at targets to broaden an automatic model for predicting student opinions [18] by way of studying Twitter conversations, spotting the reviews of students as a valuable facts supply.

Understanding and comparing college students' evaluations of open and distance training is especially hard due to the casual nature of this academic machine. The consciousness of this investigation is to apply opinion mining to the contemporary training device using Twitter facts. The first objective is to gain insights into students' dissatisfaction, appreciation, and issues regarding their instructional reviews. Additionally, this research aims to help universities swiftly comprehend and devise techniques to enhance the satisfaction of education and related services. The article is composed as section 2 summarises the related studies on different student OM approaches and investigates the performance of different ML approaches. Section 3 presents the methodologies used for the mining task, and section 4 discusses results obtained by the different OM approaches. Finally, section 5 gives the decision obtained from the results of the research findings.

2. Related Studies

The reviewed literature presents diverse studies investigating education-based opinion mining from Twitter data, employing various methodologies and machine-learning approaches. Notable contributions include the hybrid feature selection method proposed by M. Alassaf et al. (2020) [19], which combines ANOVA f-score and SVM for enhanced accuracy in analyzing Arabic education-related tweets. Munish Saini et al. (2020) [20] explore behavioural responses to the national education policy through dynamic analysis and clustering of tweets, providing valuable insights. Giannakoulopoulos et al. (2019) [21] employ PCA and LDA to identify emerging topics in e-learning using Twitter data. Aljabri M et al. (2021) [22] focus on public opinions regarding distance learning policy changes in Saudi Arabia, achieving high accuracy but emphasizing the need for feature importance-based classification. Mujahid et al. (2021) [23] conducted sentiment analysis during the Covid-19 pandemic, evaluating ML and deep learning models. Manar Alassaf et al. (2022) [24] developed an opinion mining model utilizing ANOVA, with Naive Bayes and SVM classifiers proving effective.

The ensemble model proposed by Dimple Tiwari et al. (2019) [25] boosts social media data analysis accuracy. Ji Lixia et al. (2020) [26] provide a comprehensive review of methodologies in education-based big data, emphasizing the importance of reliable accuracy and noise-free data. Z. Kastrati et al. (2020) [27] introduce a CNN-Fast Text model for student opinion analysis in MOOCs, achieving high accuracy. Aydin et al. (2021) [28] investigated student sentiments on open and distance education, emphasizing the importance of appropriate NLP methods. Thomas Runkler et al. (2017) [29] developed a decision-making system focusing on risk consideration and uncertainty.

This literature synthesis underscores the challenges and advancements in education-based opinion mining. It sets the stage for the proposed study to address identified gaps and contribute novel solutions.

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3. OPINION ANALYSIS ON EDUCATIONAL TWEETS

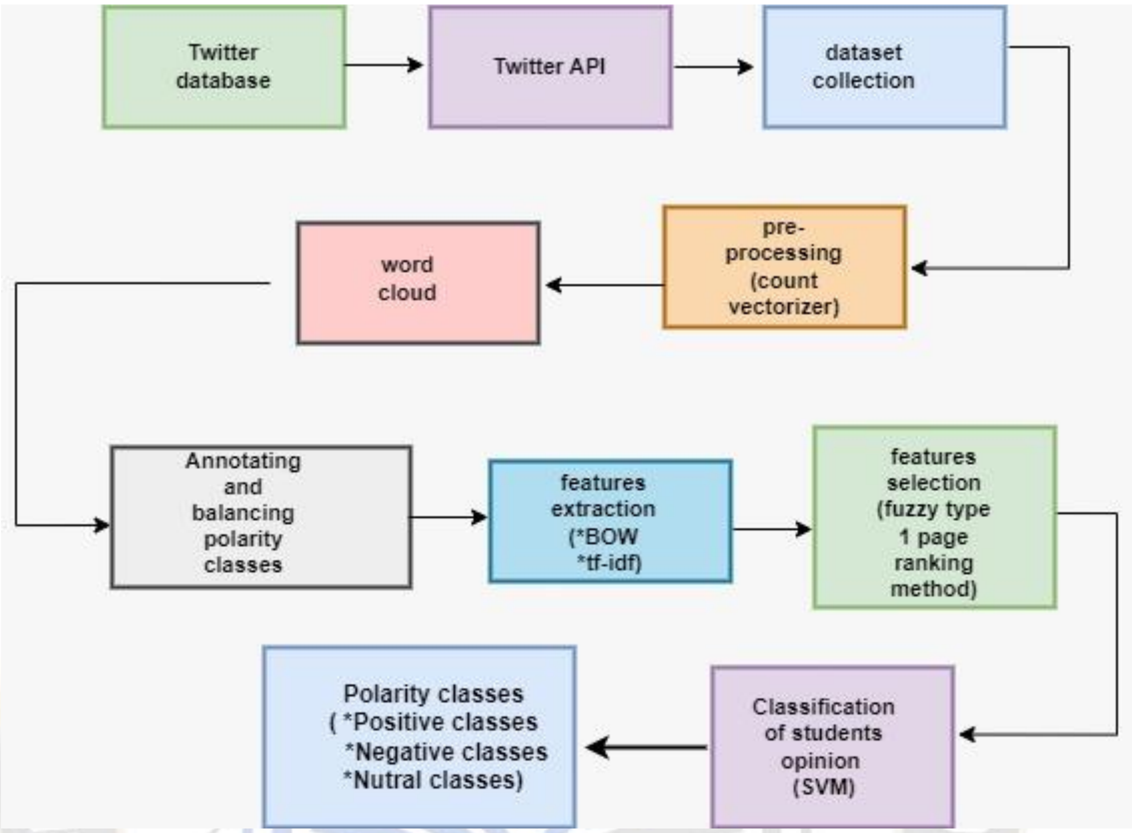

Figure 1: Architecture of Opinion Analysis On Educational Tweets

Figure 1 illustrates the overall opinion-mining process from educational tweets with ML techniques. Initially, this study uses Twitter text data to search for numerical features. Then, the preprocessing step eliminates unwanted texts from the Twitter data. So, this phase is critical for getting the most out of the raw text. This step makes the ML algorithms perform well. In the next stage of opinion, mining is adding all the special terms in the dataset to create a feature space. Then, it examines the text in the cleaned-up tweets. In this study, the Bag-of-Words(BOW) and TF-IDF methods are utilized for hunting for traits. It extracts feature information from the preprocessed text. The most relevant features are elected, and irrelevant features have been removed by applying the Interval type 2 fuzzy decision-making(IT2FDM) method. The SVM classifier utilizes the fuzzy-selected relevant features to classify the student's emotions-based polarity classes. Finally, the SVM model classifies the student's opinions as positive, negative, or neutral.

2.1. Data collection

In contrast to other social media networks, virtual users' tweets are visible to anybody using a Twitter account, and this content can be searched from anywhere.

Searching for other Twitter users' data like their location data, hashtags, content, username, retweets count, favourites count, and created date can be retrieved using Twitter API. It can retrieve all tweets on a specific topic in the last twenty minutes or a particular user's non-retweeted tweets. The performance of the FIT2S-SVM is evaluated using the publicly available Twitter dataset[30]. It contains 202645 tweets about distance learning. This dataset contains various hashtags and keywords related to online education and distance learning. The overall samples are separated as testing and training samples. This analysis utilized 30% of datasets for testing and 70% for model training.

2.2. Preprocessing

Twitter dataset contents are processed to reduce noise in human-readable text and increase the accuracy of the classifier's prediction results.

A vectorization technique in NLP turns a single token into a "vector," or a set of numbers. The vector is unique to the token under investigation and expresses several properties in this scenario. Vectors are also used to search for word similarity, classify text, and perform other NLP activities.

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Algorithm1: Preprocessing of Twitter Datasets
Step 1: Input raw_twitter_data = load_raw_twitter_data() **Step 2: Tokenization using CountVectorizer** vectorizer = initialize_count_vectorizer() tokenized_data = vectorizer.fit_transform(raw_twitter_data) **Step 3: Custom Preprocessing** processed_data = custom_preprocessing(raw_twitter_data) **Step 4: Encoding Vector** encoding_vector = vectorizer.transform(processed_data) **Step 5: Visualizing Word Frequency and Length** visualize_word_frequency_length(encoding_vector, vectorizer) **Step 6: Additional Count Vectorizer Parameters** vectorizer = initialize_count_vectorizer(max_features=15, min_df=2, max_df=0.8, stop words='English') tokenized_data = vectorizer.fit_transform(raw_twitter_data)

This study utilizes the Countvectorizer to perform tokenization; it breaks sentences into words using various preprocessing, such as converting words into lowercase, Additional parameters used by the Count vector functions are,

- The custom method helps to reduce the noise from the text data; some of the functions performed using the custom processing are converting text into the lowercase form, removing special characters, and using stems of the word using poster stemmer.
- The maximum vocabulary size set by the function is 15.
- Stop words are considered useless in sentences like 'A', 'The', etc.

removing the unique character, etc. The encoding vector returns the length of words and the number of occurrences of each word in a sentence.

- Min_df indicates the importance of the less frequent words; in this study, initialize the Cv3 with min_df set as 2.
- Max_df is opposite to min_df. It indicates the presence of words in a sentence a maximum number of times. It helps to identify stop words.

Table 1: Sample Twitter data before and after preprocessing

Twitter Content Before Preprocessing	**Twitter Content After Preprocessing**
Innovate an innovative approach #quoteoftheday #DigitalMarketing #DigitalLearning #blogger https://t...	innovate innovative approach quote day digital market digital learning blogger
A lakh rupees for online education that doesn't even support a stable network!?!?!? Sports Fee for what?? Is it even Logical??? We IITians need your support 🙏 @narendramodi @DrRPNishank @HRDMinistry @IITISM_DHANBAD#ReduceIITtuitionfee	lakh rupees online education does not even support a stable network sports fee, even logical need support Narendra Modi rpnishank ministry sites dhanbad reduceiittuitionfee
On a fair note, running an online semester costs less than an offline semester. Please reduce/defer/cancel the fees for this semester. @narendramodi @DrRPNishank @HRDMinistry#ReduceIITtuitionfee	fair note that running an online semester costs less than an offline semester. Please reduce defer cancel fees semester Narendra Modi drrpnishank ministry reduceiittuitionfee

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Twitter Content Before Preprocessing	Twitter Content After Preprocessing
The semester will be conducted online, but will NITians pay the FULL TUITION FEE amount? 62500 Is this justified?	The semester is conducted online, and the total tuition fee amount is justified.

Table 1 contains the Twitter contents on online and distance learning dataset samples. This study performs stop words, min df, max df, custom preprocessing, and limiting vocabulary size in the preprocessing stages. Algorithm1 represents the preprocessing of Twitter datasets.

2.3. Word clouds

More people have discovered in recent years that the word clouds can help them discern patterns and anticipate the future. As a result, they are increasing in popularity. For example, it can be used to see how customers react to new items or how word clouds depict the political agendas of potential election candidates in a given country. A visual representation tool like this might be helpful when figuring out the political objectives of persons who might run for office in a specific country. Tag clouds, or word clouds, display the tags or phrases on various websites and documents. For example, "context" describes how the word cloud was created. The majority of these entries are one-word keywords. A Word Cloud of all the words in this list may be seen below. Each word in this cloud of words has its font size and colour tone. As a result, this representation can help determine what powerful words signify in a circumstance. If the font size of a word is larger than the font size of other words in the cluster, it is more important in the collection. Word clouds can be constructed in various shapes and sizes depending on how the authors envision their objects. It works like this: Considering how many words are used while creating a Word Cloud is essential. More words in a Word Cloud make it challenging to read. A Word Cloud with many words becomes clogged and difficult to read. Good Word Cloud must always be clear and precise to work; this is the reason it is being utilized in this study.

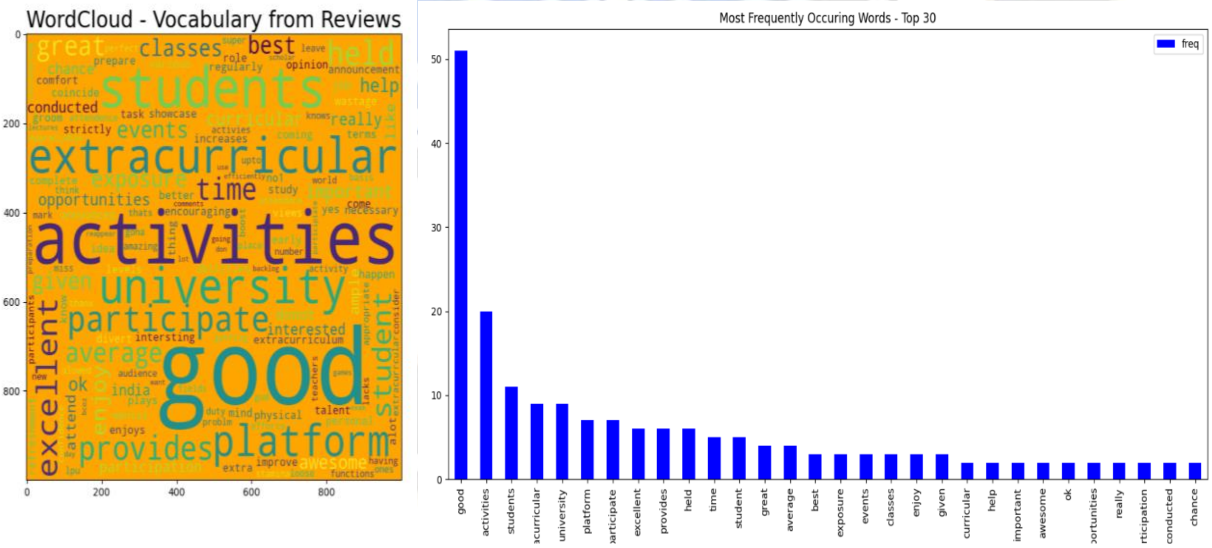

Figure 3: a)Vocabulary From Reviews and b) Most Frequently Occurring Words

This study uses Word Cloud to visually represent the most representative terms (i.e., the most frequent words) in a collection of student reviews. First, the experiment determines the terms that can be deleted from the word cloud in this task using the existing list of phrases and some different keywords. Then, using the 100 most often occurring words with at least five letters, the work creates an image and plots the Word Cloud structure for all students' thoughts and measurements to end the experiment. However, distinguish between rows with the same initial emotion and rows with a compound emotion. Figures 3(a) and (b) show the word's lexicon and its frequency of occurrence.

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2.4 Annotating Sentiment or polarity classes

Emotions expressed in a sentence are known as polarity. It is related to the sentiment of a word. Sentence evaluation is performed in two ways: rational and emotional. Example sentence for rational evaluation: "The study materials provided by the institutions are good". Similarly, emotional evaluations are expressed as "We enjoyed the communication classes". These two methods are helpful while annotating the polarity classes for each sentence.

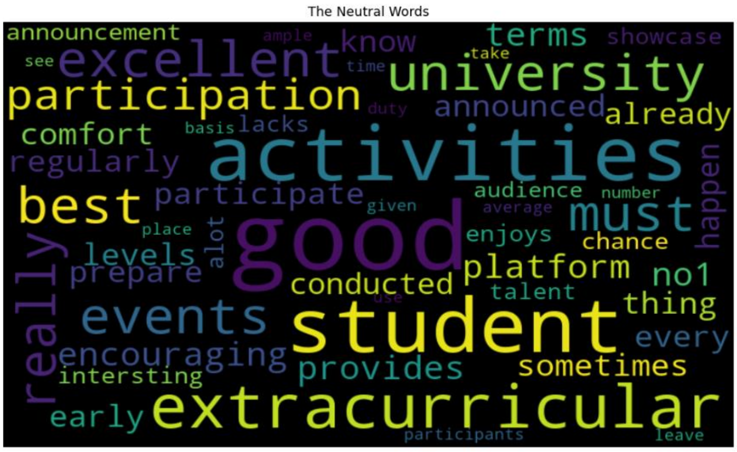

Figure 4: Neutral Words

Figure 4 depicts the optimistic viewpoint of neutral words. The dataset utilized in this study is annotated using five sentiment ratings: emotional negative (-2), rational negative (-1), neutral (0), rational optimistic (+1), and emotional positive (+2). If the user gives no opinion, then it is considered neutral. The dataset contains imbalanced samples for each class. This may lead to model fit issues; this has been avoided by generating artificial sample data for imbalanced classes. This study creates neutral class samples to balance the Twitter dataset. In addition, the core positive, negative, and neutral categories are fine-grained in this sentiment analysis. It can be performed utilizing a larger scale of categories. The neutral class is utilized to obtain an accurate opinion on the students' review.

2.4. Feature extraction

Extracting features from the students' comments from the Twitter database is quite tricky because the opinions given in the Twitter database may also contain sensitive content. So, using appropriate feature extraction techniques is crucial to accurately get students' opinions by analyzing their Twitter comments. BOW and TF-IDF are the two powerful methods utilized in this study to extract opinion features from the preprocessed data.

Bag-of-Word: The method is simple and flexible and may be used to extract characteristics from several text types. Regarding text representation, a BOW indicates how particular keywords appear in a given text. BOW is used to count the occurrence of a word in a sentence and forms a feature vector(FV). The FV contains information about the number of occurrences of each unique word. Commonly, BOW is utilized whenever a transform needs to be performed to construct a vocabulary of all matchless words. It helps the classifier to train the model by its frequencies.

Sample sentences (after preprocessing):

1) Online classes are becoming very popular today.
2) online class time should never be a stoppage.

Table 2: Sample tweets after feature extraction using BOW

S.No	Online	class	become	Popular	today	time	Should	never	stop
1	1	1	1	1	1	1			
2	1	1	0	0	0	0	1	1	1

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Table 2 contains the sample features of two sentences after applying the BOW. The resultant word frequency vector is combined with TF-IDF features to classify students' opinions.

Term Frequency-Inverse Document Frequency (TF-IDF): TF-IDF includes the frequency of terms in a document as one of its components. The term frequency in the current document and the inverse document frequency in the preceding document are measures of the word's frequency in the recent document. Inverse Document Frequency(IDF) determines the frequency of an expression in a document. It is used to extract weighted features from text data. It provides the weight of each term in the corpus to improve the classifier's performance. This method computes the product of TF and IDF.

$$TF(t,d) = \frac{n_t}{N_{(T,d)}} \tag{1}$$

The $TF(t,d)$ in eq(1) calculates the term frequency. The NT indicates the number of occurrences of a term in document d, and the $N_{(T,d)}$ represents the total term T in a document.

$$IDF = \log\frac{D}{n_d} \tag{2}$$

The IDF in eq(2) is used to compute the Inverse Document Frequency. It helps to estimate how important the whole corpus is. The term D represents the entire document in a corpus, and the n_d indicates the number of documents where the term t appears.

$$TF - IDF = TF * IDF \tag{3}$$

The $TF - IDF$ is used to compute the term frequency-inverse Document Frequency. The product value of TF and IDF is known as TF-IDF.

The extracted feature sets of each student's opinions on online and distance learning are utilized for the feature selection phase.

2.5 Feature selection

Extracted features might contain useless feature information as well. It can affect the classifier performance and require more resource utilization while handling big data (Eg, social media data). This is one of the significant issues in the Twitter dataset. This study resolves these issues by utilizing an interval type 2 fuzzy decision-making system. The FIT2S is expressed in this section. Membership values of the goal and constrained quantify the degrees of unity of the different decision options. The unity is subject to uncertainty in IT2FDM. Each option's lower and upper membership values quantify the corresponding utility's upper bound (best case) and lower bound (worst case). Per the type 1 interval decision system, the goal is constrained as computed and used to estimate optimal decisions.

$$\{u_{g_1}(x), \ldots, \quad (\quad) gums\ \} \tag{4}$$

The goals specified by the membership functions are expressed in eq(4).

$$\{u_{c_1}(x), \ldots, u_{c_n}(x)\ \} \tag{5}$$

The constraints the membership function specifies are expressed in eq(5).

$$x^* = \underset{x \in X}{\operatorname{argmax}}(u_{g_1}(x) \wedge \ldots \wedge u_{g_m}(x) \wedge u_{c_1}(x) \wedge . . . \wedge u_{c_n}(x)) \tag{6}$$

Single optimal decision x^* is defined in eq(6).

$$x^{\underline{*}} = \underset{x \in X}{\operatorname{argmax}}(\underline{u}_{\bar{g}_1}(x) \wedge \ldots \wedge \underline{u}_{\bar{g}_m}(x) \wedge \underline{u}_{\bar{c}_1}(x) \wedge . . . \wedge \underline{u}_{\bar{c}_n}(x)) \tag{7}$$

Defining the worst case(WC), IT2FDM made using eq(7) is straightforward.

$$x^{\bar{*}} = \underset{x \in X}{\operatorname{argmax}}(\underline{u}_{\bar{g}_1}(x) \wedge \ldots \wedge \underline{u}_{\bar{g}_m}(x) \wedge \underline{u}_{\bar{c}_1}(x) \wedge . . . \wedge \underline{u}_{\bar{c}_n}(x)) \tag{8}$$

The best case(BC) IT2FDM is calculated using eq(8). Instead of restricting the interval type 2 fuzzy decision to the WC and best case, allowing the specific level of risk $\beta \in [0,1]$. If the $\beta = 0$ or $\beta = 1$, the risk factor corresponds to the WC($x^{\underline{*}}$) and BC($x^{\bar{*}}$). So, it is necessary to define the risk level β to decide.

$$\begin{aligned} x^*_\beta = \underset{x \in X}{\operatorname{argmax}}(& ((1-\beta).\underline{u}_{\bar{g}_1}(x) + \beta.\ \bar{u}_{\bar{g}_1}(x)) \\ & \wedge \ldots \wedge ((1-\beta).\underline{u}_{\bar{g}_m}(x) + \beta.\ \bar{u}_{\bar{g}_m}(x)) \\ & \wedge . . . \wedge ((1-\beta).\underline{u}_{\bar{c}_1}(x) + \beta.\ \bar{u}_{\bar{c}_1}(x)) \\ & \wedge \ldots \wedge ((1-\beta).\underline{u}_{\bar{c}_m}(x) + \beta.\ \bar{u}_{\bar{c}_m}(x))) \end{aligned} \tag{9}$$

The operator $\wedge$ in eq(7), eq(8), and eq(9) indicates the intersection operation, which is used when the same t-norm. The best case and WC decisions in eq(7) and eq(8) compute the maximum value across the domain X from the minimum of all the membership functions at domain point x. It is equally gained by finding the highest membership grade across the domain of the fuzzy set, which is the intersection of all goals and constraints. Moreover, the alternative way to calculate the risk value and the properties of the IT2FDM is used as defined in [29]. The optimal decision built by the IT2FDM is identifying the significant feature sets from the feature vector. The elected significant feature sets of students' opinions on online and distance education are utilized to improve the performance of the classification model.

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2.6 Classifying polarity classes

The crucial stage in OM is predicting the polarity class of students' opinions on online and distance education. The classifier utilizes the feature sets constructed by the IT2FDM. The main objective of combining this fuzzy logic with the SVM classifier is to improve the classifier's performance. This study utilizes an SVM classifier to predict the student's opinions. SVM is one of the most widely used classification models for sentiment analysis. It performs the classification by locating the hyper-plane that is the best match for differentiating the classes. SVM linear model SVM is used with kernel sigmoid parameter c =3.0. each output is separated by estimating the posterior probability.

$$\hat{P}\left(\omega_j|f_i(x)\right) = \frac{1}{1+\exp\left(A_j f_j(x)+B_j\right.} \quad (10)$$

The sigmoidal function in eq(10) estimates the probability between actual and predicted class objects. The notation ω_j and $f_i(x)$ indicate a feature's actual and predicted class, respectively. The parameters A_j and B_j in eq(10) are estimated by decreasing the likelihood.

$$A_j|B_j = -\sum_{k=1}^{n} t_k \log(p_k) + (1+t_k)log(1-p_k) \quad (11)$$

The likelihood is calculated using eq(11). The p_k denotes the sigmoid function, and the target possibility assigned is represented as t_k.

$$\hat{P}\left(\omega_j|(x)\right) = \frac{\exp\left(A_j f_j(x)+B_j\right)}{\sum_{j=1}^{c}\exp\left(A_j f_j(x)+B_j\right)} \quad (12)$$

The student's polarity classes in the Twitter datasets are annotated with three classes. So, the soft-max function expressed in eq(12) is used to predict the sentiment analysis classes considered in this study. The crucial step of the FIT2S-SVM model is creating a significant feature set (feature vector) and fixing the parameters for the soft-max and sigmoidal functions. The Twitter dataset utilized in this study contains multiple classes. So, it is crucial to drive an unbiased dataset while training the SVM model. This study utilizes an IT2FDM approach to handle the unbiased dataset.

4. EVALUATION AND ANALYSIS

This section evaluates the enactment of the FIT2S-SVM model. This model is implemented in Python. The tensor flow is used, and it contains many DL and ML methods. The hyperparameters set for the SVM classifier are kernel =" linear" and C=3.0. The efficiency of the FIT2S-SVM model-based students' opinion prediction is compared with four performance-wise best opinion mining approaches such as LDA[21], PCA[21], CNN with FastTest[27], and ANOVA-SVM[24]. This comparison is made with recent reliable accuracy obtaining ML and DL model-based approaches. In this, the LDA, PCA, and ANOVA method-based approaches perform the opinion analysis with the help of the feature selection phase and the CNN with Fast Text approach is taken because it provides reliable accuracy in predicting different polarity classes. The Correctly classified Polarity class(CCPC), Wrongly classified polarity classes(WCPC), Wrongly classified negative polarity class(WCNPC), and Correctly classified antagonistic polarity classes(CCNPC).

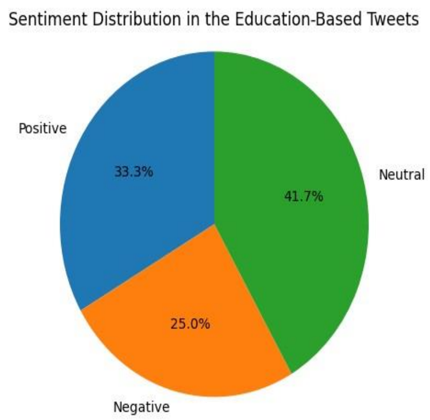

Figure 5: Sentiment Distribution

NLP and text mining are broad areas encompassing virtually all issues involving computer interaction with human speech or text. These two methods are subfields of Artificial intelligence. Given the subject's breadth and several fascinating challenges, word frequency models are commonly utilized as a starting point or as part of the solution to several various challenging problems. It is important to note that, while they are easy to execute, they are only sometimes the most effective solution. When using word frequency models to do sentiment analysis on student opinion datasets.

Table 3: Overall performance analysis of the Opinion analysis using Twitter data on online and distance learning

Measures	LDA	PCA	CNN with FastTest	ANOVA-SVM	FIT2S-SVM
Accuracy	0.82	0.89	0.93	0.95	0.97

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Precision	0.84	0.86	0.94	0.93	0.98
Recall	0.83	0.85	0.92	0.94	0.96
F1 score	0.82	0.84	0.91	0.92	0.99

Table 3 contains the overall performance

analysis of the Opinion analysis using Twitter data on online and distance learning. The overall results show that the FIT2S-SVM model obtained maximum values than comparison approaches for all the accuracy metrics.

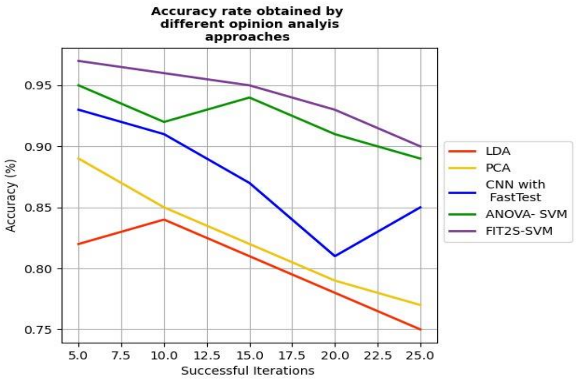

Figure 6: Accuracy rate analysis

Figure 6 demonstrates the accuracy rate obtained by different ML and DL models for predicting the opinion analysis classes (polarity classes). The results show that the FIT2S-SVM model obtained a maximum accuracy rate (0.97). It shows that the count vectorizer reduces the noisy information from the Twitter datasets to enhance the accuracy rate. So, the accuracy rate obtained by the FIT2S-SVM model increased up to 0.02.

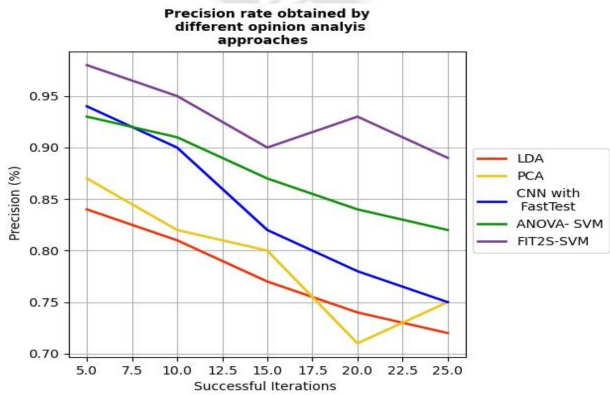

Figure 7: Precision rate analysis

Figure 7 demonstrates the precision rate obtained by different ML and DL models for predicting the polarity classes. The results show that the FIT2S-SVM model obtained a maximum precision rate (0.98). It shows that the BOW and TF-IDF methods extract all the possible features from the Twitter datasets to enhance the precision rate. So, the precision rate obtained by the FIT2S-SVM model increased up to 0.04.

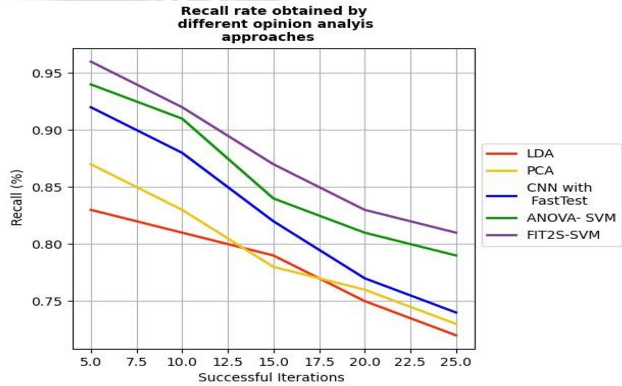

Figure 8: Recall rate analysis

Figure 8 demonstrates the recall rate obtained by different ML and DL models for predicting the student's opinion. The results show that the FIT2S-SVM model obtained a maximum recall rate (0.96). It shows that the Interval type 2 decision system used in this study to improve the recall rate from the Twitter datasets to improve the recall rate. So, the recall rate obtained by the FIT2S-SVM model increased up to 0.02.

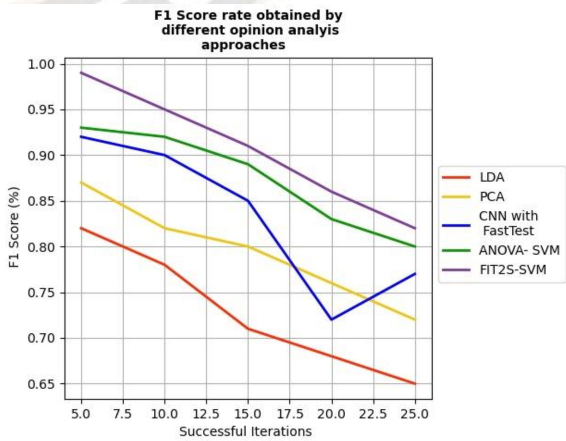

Figure 9: F1 score rate analysis

Figure 9 demonstrates the F score rate obtained by different ML and DL models for predicting the student's opinion. The results show that the FIT2S-SVM model obtained a maximum F score rate (0.96). It shows that the Interval type 2 decision system used in this study to improve the F score rate from the Twitter datasets to improve the F1 score rate. So, the f1 score obtained by the FIT2S-SVM model increased to 0.06.

5. CONCLUSION

The FIT2S-SVM model uses an ML approach for the sentiment classification of opinion-bearing words based on educational data over Twitter. Seed words bearing positive, negative, and neutral sentiments are compiled. Various accuracy measures evaluate the association between opinion's opinion-bearing words and polarity for seed word determination. The study's main objective is to accurately identify students' opinions on online and distance learning by analyzing social media content. This study contributes a FIT2S-SVM model to classify the polarity classes of students' emotions. The Interval type 2 fuzzy decision-making approach identifies the feature's importance in improving the SVM classifier's efficiency.

Moreover, the performance analysis in the resultant section proves that the FIT2S-SVM model obtained a maximum of 0.97 accuracy rate, and compared to other present studies, this model provides better accuracy. So, this study concluded that it achieved the research objective with maximum accuracy for classifying student emotional classes. Furthermore, the study is extended to utilize bio-inspired optimizers to reduce the functionalities and improve the classifier's performance.

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