Fuzzy-Based Sentiment Analysis System for Analyzing Student Feedback and Satisfaction

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Abstract: The feedback collection and analysis has remained an important subject matter for long. The traditional techniques for student feedback analysis are based on questionnaire-based data collection and analysis. However, the student expresses their feedback opinions on online social media sites, which need to be analyzed. This study aims at the development of fuzzy-based sentiment analysis system for analyzing student feedback and satisfaction by assigning proper sentiment score to opinion words and polarity shifters present in the input reviews. Our technique computes the sentiment score of student feedback reviews and then applies a fuzzy-logic module to analyze and quantify student's satisfaction at the fine-grained level. The experimental results reveal that the proposed work has outperformed the baseline studies as well as state-of-the-art machine learning classifiers.

Keywords: Student feedback analysis, sentiments, opinion words, polarity shifters, lexicon-based.

1 Introduction

Sentiment Analysis (SA) also called opinion mining, is the field of study that analyzes people's opinions, sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, events, and topics. Due to the emergence of social media sites like Facebook, Twitter, and other web forums, online users express their sentiments which provide an important clue about their activities and feedback.

Like other online users, students also express their opinions on different sites, which provides an important clue in the form of feedback regarding their subjects, tutors and other facilities provided to them. Detection and classification of such feedback is important to be analyzed, as students express sentiments towards course, teaching faculty and other

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academic facilities, provided to them. It is also beneficial in terms of classifying student's feedback and quantifying their satisfaction, which can assist in improving the academic facilities provided to the students and preparation of annual confidential reports [Asghar, Kundi, Ahmad et al. (2018); Rajput, Haider and Ghani (2016)].

The traditional techniques of classifying student feedback are not scalable, motivating researchers to develop automated techniques. In this work, we focus on the problem of classifying a student's review as satisfied, moderate, or not-satisfied. The task faces different challenges, such as different kinds of extremism, various targets and multiple ways of representing the same semantics. The existing studies of student feedback analysis are based on lexicon-based techniques [Nasim, Rajput and Haider (2017)] or use classical feature representation schemes followed by a classical machine learning classifier. However, recently, fuzzy-based sentiment analysis techniques have yielded better results for complex problems in different domains such as business, healthcare, and others.

Fuzzy-based sentiment analysis is one of the feasible solutions for analyzing user feedback and satisfaction. In this technique scores of user sentiments are computed using different dictionaries of sentiment words annotated with their semantic orientation i.e., polarity and strength [Asghar, Kundi, Ahmad et al. (2018)], and in the next phase, the fuzzy logic module can be applied to compute user satisfaction at different levels of granularities [Ghani, Bajwa and Ashfaq (2018)]. In this work, we present a novel technique of utilizing the aggregated sentiment score of each student's feedback (review) and make it input to the fuzzy logic module for quantifying student feedback and satisfaction. For analyzing student feedback and satisfaction, we take the task of fuzzy-based sentiment analysis as a multi-label classification task. We define the reviews R={r1,r2,r3,….rn}, and a class tag (positive, negative and neutral) is assigned by using SentiWordNet lexicon. The aim is to design a fuzzy-based sentiment analysis model, which takes sentiment score as input and can measure the student satisfaction level as either satisfied, moderate, or not-satisfied. The response given by the students concerning their perceptions of the teacher, department, faculty, etc. and other issues about their institution, can be used for the improvement of the education, and teaching staff. We propose a technique to identify and classify such content.

In this work, we propose to compute sentiment scores of opinion words and modifiers, and then use the aggregated sentiment score as an input to the fuzzy-logic module for analyzing and measuring the student feedback and satisfaction. As baselines, we compare with student feedback evaluation systems proposed by Rajput et al. [Rajput, Haider and Ghani (2016); Nasim, Rajput and Haider (2017); Yousif and Shaout (2018)], based on the lexicon entries and supervised learning, which lacks in providing an evaluation of student feedback at a fine-grained level. In this work, we answer the following research questions: ***RQ1***. How can we perform efficient classification of opinion words expressed by a *student in their feedback by revising the sentiment scoring technique proposed in the baseline method?* ***RQ2***. *What is the efficiency of fuzzy-based student feedback sentiment classification system with and without considering polarity shifters?* ***RQ3.*** *What is the efficiency of fuzzy-based sentiment analysis of student feedback w.r.t to state-of-the-artwork and different supervised Machine Learning Algorithms?*

The contributions of this work are summarized as follows:

(i) Development of sentiment scoring technique for assigning proper polarity score to opinion words expressed by the students in their feedback.

(ii) Classification of polarity shifters with respect to opinion words in the student textual responses.

(iii) Development of fuzzy-based sentiment analysis system for analyzing student feedback and satisfaction.

(iv) Performance evaluation of the proposed system with respect to the baseline method.

The rest of the article is organized as follows: Section 2 presents a review of literature; proposed methodology is presented in Section 3; result and discussions are summarized in Section 4; and the final chapter presents the conclusion and future work.

2 Related work

In this section, we present an overview of the selected studies on student feed-back analysis systems.

A sentiment-based teacher evaluation system is developed by Haider et al. [Haider and Ghani (2016)], applying different text analysis techniques supported by the lexicon. Their model overcomes the limitation of traditional questionnaire-based student evaluation techniques by providing an insight into the teacher performance using the automated method. The sentiment at word-level are computed using word frequency and word polarity, to accumulate the sentiment score of the student's overall attitude. The system used Nymi software and improved results are obtained with respect to the baseline method.

The machine learning and lexicon-based approach for collecting and analyzing student feedback with respect to performance evaluation of teachers si proposed by Nasim et al. [Nasim, Rajput and Haider (2017)]. The proposed model was trained using lexicon-based and TF-IDF features for analyzing student sentiments expressed for teacher's performance evaluation. A dataset of 1230 students was acquired and an accuracy of 93% was achieved.

Yousif et al. [Yousif and Shaout (2018)] proposed a fuzzy-based computational model for measuring and classifying the performance of teaching staff on the basis of student feedback collected using questionnaires and surveys. Experimental results are encouraging showing performance improvement over similar methods.

Pavani et al. [Pavani, Gangadhar and Gulhare (2012)] proposed fuzzy driven performance evaluation system, based on different factors. Fuzzy inference system is formulated to map given input to a given output fuzzy logic. Two membership functions are applied and compared and the function having little role in determining the +ive or -ive direction is also reported.

Jyothi et al. [Jyothi, Parvathi, Srinivas et al. (2014)] proposed a fuzzy-based performance evaluation model for analyzing the performance of the teaching faculty in technical institutions. A set of rules and inference system is introduced. Fuzzification and defuzzification are applied to transform, analyze and interpret student feedback for performance evaluation. The model is helpful in preparing annual confidential reports.

The lexicon-based sentiment analysis system was proposed by Kaewyong et al. [Kaewyong, Sukprasert, Salim et al. (2015)] for automatic feedback analysis of students regarding teacher evaluation. Data is collected from 1148 student responses about 30 teachers, available publicly at www.ratemyprofessor.com. After applying different preprocessing steps, manually created lexicon is used to assign sentiment scores to opinion words. Different statistical techniques, such as Pearson's correlation and Spearman's rank, were applied to show the effectiveness of the proposed system.

A supervised machine learning-based sentiment analysis system for analyzing student reviews about teacher's performance is proposed [Esparza, de-Luna, Zezzatti et al. (2017)]. Support Vector Machine (SVM) is used for classifying reviews into positive, negative or neutral. The results show the satisfactory performance of the proposed system with respect to comparing methods.

Different categories of emotions are detected and classified from textual responses regarding student feedback [Mac and Calvo (2010)]. For this purpose, latent sentiment analysis and non-negative matrix factorization (NMF) are implemented, and it is reported that NMF model performed better. However, better results can be achieved by extending-student feedback corpora.

Instead of using traditional questionnaire-based feedback evaluation, an automatic sentiment-based performance evaluation system is proposed by Kumar et al. [Kumar and Jain (2015)]. The supervised and semi-supervised machine learning approaches are used, supported by the feature identification and computation module. The results show that the Naïve Bayes algorithm performed better by achieving an accuracy of 90%. However, using a machine learning algorithm like SVM and Neural Network, along with specific knowledge can produce better performance.

A student feedback system is proposed [Nitin, Swapna and Shankararaman (2015)] using different text analysis techniques, such as topic extinction through clustering, sentiment classification via link pipe, and summarization using J Free Charts. It is reported that clustering along with cosine similarities is efficient for topic extraction and logistic regression performed better for sentiment classification.

A faculty rating system based on student feedback is proposed by Nitin et al. [Nitin, Swapna and Shankararaman (2015)]. For this purpose, the Naïve Bayes classification algorithm was implemented, and faculty were classified into different classes based on five-star rating. Further improvement can be made by increasing the size of the data set and applying other classifiers.

A conceptual framework for gathering and analyzing student sentiment using text analysis techniques such as preprocessing, sentiment abstraction and feedback summarization is proposed by Gottipati et al. [Gottipati, Shankararaman and Gan (2017)]. To evaluate of effectiveness of the proposed framework, a case study was conducted by selecting courses from the school of information system.

To analyze student feedback in real-time mode, [Altrabsheh, Cocea and Fallahkhair (2014)] proposed an automatic sentiment-base feedback analysis system using different machine learning techniques, supported by a different combination of features and preprocessing steps. The results obtained show that the Support Vector Machine (SVM) has achieved the highest accuracy of 95%.

A voting and symbol method based on machine learning is proposed by Pong-Inwong et al. [Pong-Inwong and Kaewmak (2016)] for evaluating the performance of teaching faculty. For this purpose, different machine learning algorithm, such as Naïve Bayes, Decision tree, J48, and ID3 were used. The results depict that voting and symbol method combined with Chi-Square has given improved performance than the other methods.

The work proposed by Koufakou et al. [Koufakou, Gosselin and Guo (2016)] used different machine learning algorithms, such as K-Nearest Neighbor and Naïve Bayes with a bag of words and TF-IDF computation for classifying student feedback comments regarding the undergraduate courses. A small data set of student feedback about course evaluation was used, which was one of the major limitations of their work.

A sentiment classification for analyzing student feedback collected from Facebook and Twitter regarding their teachers is proposed by Altrabsheh et al. [Altrabsheh, Gaber and Cocea (2013)]. For this purpose, two machine learning algorithms, namely Naïve Bayes and Support Vector Machine were used. Results show that both classifications provided satisfactory results.

A lexicon-based approach is used to analyze student textual feedback for predicting the performance of teaching faculty [Aung and Myo (2017)]. The method is based on a manually created lexicon containing sentiment words and intensifiers. The result was presented in a way showing sentiments of a student at different levels of granularities.

An emotion detection system in E-learning domain is proposed by Binali et al. [Binali, Wu and Potdar (2009)]. The system was capable of classifying student opinions regarding learning progress. Gate software was used to implement the framework.

3 Equations and mathematical expressions

Firstly, we present a few baseline techniques and then present the proposed technique. In all such techniques, either lexicon is used or a feature vector is created for a given tweet, which is applied as its feature set with the classifiers.

Baseline methods: We perform experiments with three baseline methods, namely: (i) lexicon-based SA for student feedback analysis [Rajput, Haider and Ghani (2016)], (ii) fuzzy-based student feedback analysis [Yousif and Shaout (2018)], and (iii) Supervised machine learning approach for teacher’s performance evaluation [Nasim, Rajput and Haider (2017)]. The first study Rajput et al. [Rajput, Haider and Ghani (2016)] has used lexicon for sentiment scoring of opinion words only, whereas, we have proposed improved sentiment scoring technique for both opinion words and modifiers used in student feedback. The 2nd baseline study [Yousif and Shaout (2018)] has used traditional questionnaire-based data collection and analysis, whereas our proposed work uses the sentiment-based approach in which aggregated sentiment score is made input to the fuzzy logic module for analyzing student feedback and satisfaction. Finally, machine learning techniques are applied by Nasim et al. [Nasim, Rajput and Haider (2017)] for student feedback analysis based on classical feature sets.

Proposed method: We investigate Fuzzy-based sentiment analysis for analyzing student feedback and satisfaction inspired by Ghani et al. [Ghani, Bajwa and Ashfaq (2018)] work on applying fuzzy-based SA for measuring customer loyalty, we leverage fuzzy-based SA for analyzing student feedback and satisfaction.

The proposed system (Fig. 1) employs a fuzzy-based SA approach for analyzing student feedback in terms of classifying opinion and emotion words expressed in the feedback comments. The proposed system is beneficial for the education sector with respect to automated analysis of student comments/feedback about the teaching faculty for improving the quality of faculty.

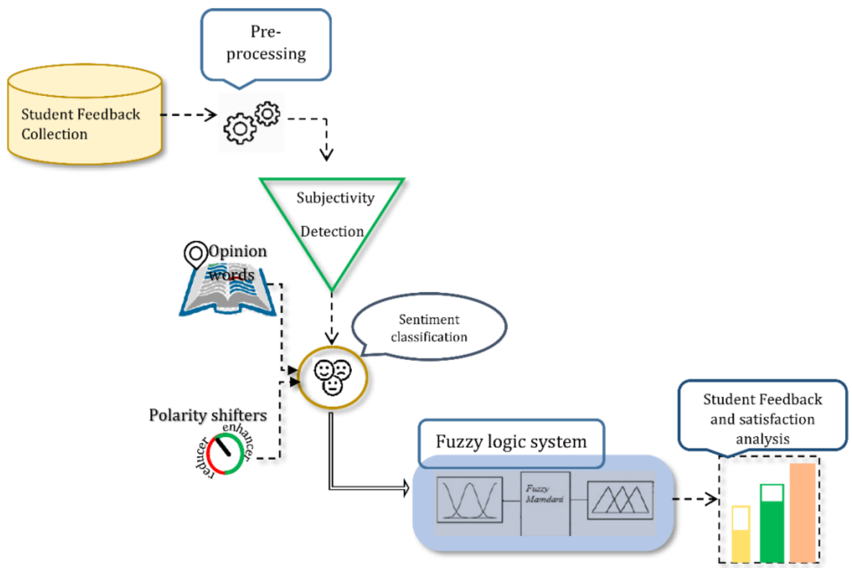

Figure 1: Proposed system

3.1 Lexical resources used

We used the following lexical resources in the proposed work.

3.1.1 Opinion lexicon

The opinion lexicon [Lu Bing (2004)], contains more than six thousand +ive and -ive opinion words. A sample list of positive and negative opinion words is presented in Tab. 1 and Tab. 2.

Table 1: A partial list of positive opinion words

Affection	Satisfactory	Marvelous	Affordable
Courage	Favourite	Peaceful	Believable
Progress	Fearless	Effective	Gorgeous
Regard	Efficient	Favor	Feasible

Table 2: A partial list of negative opinion words

Injustice	Insensitivity	Sadness	Wrong
Loud	Conflict	Shameful	Lack
Foolish	Aggression	Violent	Lose
Mysterious	Forbidden	Disagree	Unfaithful

3.1.2 Sentiword net

The SentiWordNet (SWN) lexicon contains more than sixty thousand entries, used for assigning sentiment scores to opinion words appearing in the student feedback text. For example, in the text "I am very impressed by his teaching method", the word "very" depicts polarity shifter and the word "impressed" is an opinion word. Each word in SWN has three sentiment scores: +ive, -ive and neutral, having values between 0 and 1. In Tab. 3, a sample word from SWN is presented, having POS tag, sense-id, synsets and gloss terms.

Table 3: SentiWordNet sample entry of word "comfortable"

Term	POS_ Tag	Sense ID	Pos_ Score	Neg_ Score	Neu_ Score	Synset	Gloss
Comfort able	A	479330	0.625	0	0.375	comfortable#1 comfortable#2 comfortable#3 comfortable#4 comfortable#5	free from stress or conducive to mental ease; "was settled in a comfortable job, one for which he was well prepared"

3.2 Student feedback collection

The student feedback data is collected from different feedback sites such as [Nagle (2001); Swapceinski (1999)]. These public datasets contain teacher evaluation conducted in different universities. Tab. 4 shows the detail of the acquired dataset.

Table 4: Detail of dataset

Dataset	Description	Total No. of reviews	No of positive reviews	No. of negative reviews
D1	Student feedback	1415	955	249

3.3 Preprocessing

This module is applied to remove noise from the acquired dataset by applying different preprocessing steps, such as sentence and word tokenization, stop word removal, stemming, lemmatization and spell correction [Asghar, Khan, Ahmad et al. (2013)].

Tokenization: Python-based NLTK tokenizer is used for segmenting the text into small parts, called tokens.

Stop word removal: NLTK has stop-word corpus which comprises of the stop-word list for many languages. So, in the next step, the tokenized text is further processed by removing stop-words by using Python NLTK.

Case conversion: In case of conversion, the uppercase words in the feedback are changed into lower case. For example, the word "WOW", is change to "wow".

Spelling correction: This module is used to correct spelling mistakes committed by the user while typing review sentences. The python-based library, namely A spell is used for this.

3.4 Sentiment classification

This module performs two basic operations: (i) subjectivity detection, and (ii) sentiment classification. An overview of each module is presented as follows.

3.4.1 Subjectivity detection

In this phase, input text from student feedback is classified as subjective or objective using different opinion lexicons. The objective text contains no opinion words, whereas the subjective text includes opinionated terms [Asghar, Khan, Zahra et al. (2017)].

The subjectivity detection classification module aims at identifying and retaining subjective words, phrases, and tweets by checking their existence in a number of opinion lexicons. For a given review, each sentence is scanned for checking the existence of opinion terms with the help of different opinion lexicons.

A sentence having one/more opinion words is labeled as subjective, otherwise, it is declared as an objective tweet. For example, in a tweet: "The teaching style is amazing", the word "beautiful" is an opinion term, and therefore, we mark this tweet as subjective using Eq. (1).

$$\mathrm{Tweet}_{\mathrm{sub\_obj}} = \begin{cases} \text{subjective}, & \text{if } ((w_x \in OL)) \\ \text{objective}, & \text{if } (w_x \notin OL)\vee \end{cases} \tag{1}$$

where Wx is a word in a given tweet, OL is an opinion lexicon,

The proposed subjectivity detection module (Fig. 2) eliminates non-opinion terms while retaining the opinion terms, and resultantly, time and effort required for calculating scores of words in subsequent sub-modules also reduce.

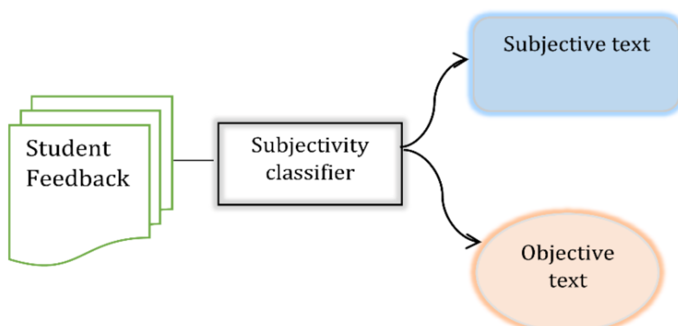

Figure 2: Subjectivity classification

Tab. 5 shows a sample list of tweets labeled as subjective or objective by the subjectivity detector module. The tweet is tagged as subjective if it carries one/more opinion words. For example, tweet#1 is labeled as subjective due to the presence of opinion words: *"love"* and *"enjoy"*.

Table 5: Example tweets with subjectivity detection

Tweet#	Review Tweet	Opinion Word(s)	Subjective/Objective
1	The teaching style is excellent	"excellent"	Subjective
2	My teacher encourages me	"encourage",	Subjective
3	Abdullah is performing classroom tasks	---------	Objective
4	Aziz cooperates consistently with the other colleague and other students	"cooperates", "consistently"	Subjective
5	My teacher is confident, and a great role model for us	"confident", "positive","great"," role model"	Subjective

3.4.2 Sentiment classification

In this step, a lexicon-based sentiment classification technique is applied by computing sentiment scores of opinion words and polarity shifters. This module is an extension of the work proposed by Rajput et al. [Rajput, Haider and Ghani (2016)] by revising the sentiment scoring technique for opinion words, and polarity shifters to efficiently classify the student's feedback. They used word frequency and word polarity, whereas, we propose to assign sentiment scores to both opinion words and modifiers using the lexicon-based technique, which resulted in improved performance.

Sentiment classification of opinion words in student feedback

The sentiment classification of opinion words is performed using Sent WordNet scoring technique [Asghar, Khan, Ahmad et al. (2017b)] as follows:

According to the SWN structure, each word has more than one sense. So, we consider three sentiment scores: +ive, -ive and neutral for multiple senses in SWN [Asghar, Khan, Ahmad et al. (2013)] to decide accurate sense for a sentiment word. Using Eq. (2), Eq. (3), and Eq. (4), we take an aggregate of sentiment score for each of +ive, -ive and neutral words.

$$Agr\_pos(w_j) = \sum_{j=0}^{n} pos\_w(j) \tag{2}$$

$$Agr\_neg(w_j) = \sum_{j=0}^{n} neg\_w(j) \tag{3}$$

$$Agr\_neu(w_j) = \sum_{j=0}^{n} neu\_w(j) \tag{4}$$

In the next step, Eq. (5)-(7) are used to calculate the positive, negative and neutral words average sentiment scores that are given as follows;

$$P_{avg}(w_j) = {Agr\_pos(w_j)}/{totalsyn(w_j)} \quad j = 1 \dots n \tag{5}$$

$$N_{avg}(w_j) = {Agr\_neg(w_j)}/{totalsyn(w_j)} \quad j = 1 \dots n \tag{6}$$

$$Neu_{avg}(w_j) = {Agr\_neu(w_j)}/{totalsyn(w_j)} \quad j = 1 \dots n \tag{7}$$

where, the aggregate sentiment scores of the jth +ive, -ive and neutral synset of a word w_j is denoted by $Agr\_pos(w_j)$,$Agr\_neg(w_j)$, $Agr\_neu(w\text{j})$ $totalsyn$ is the total number of synsets for the word w_j.

Consider the example text shown in Tab. 6.

Table 6: Example Text with part-of-speech tagging and sentiment word

Example text	*Long vacations.*
POS tagged text	*Long/JJ vacations/NN*
Sentiment word	*Long*

In Tab. 6 the part of speech tag for sentiment term ("long") is adjective (JJ), whereas, in SWN, there are 12 senses for the word "long", 1 for the verb, 2 for adverb and 9 senses for an adjective. Applying Eq. (5)-(7), the average +ive, -ive and neutral scores for 9 senses of an adjective, are calculated as follows:

$$Ps_{Score}(long) = \frac{(0.125 + 0 + 0 + 0 + 0 + 0.250 + 0.375 + 0.00 + 0.250)}{9} = 0.111$$

$$Ng_{Score}(long) = \frac{(0.375 + 0 + 0 + 0 + 0 + 0 + 0.5 + 0.5 + 0.12)}{9} = 0.167$$

$$Neu_{Score}(long) = \frac{(0.5 + 1 + 1 + 1 + 1 + 0.75 + 0.875 + 0.5 + 0.63)}{9} = 0.722$$

It is obvious from above computations, that 0.111, 0.167 and 0.722 are the average +ive, -ive and neutral sentiment scores of all senses of word "long" respectively.

The final sentiment score is computed by choosing the dominant sentiment score of an opinion word "opw", as follows:

$$sen\_score(opw) = \begin{cases} Ps_{Score} & if \max(Ps_{Score}, Ng_{Score}, Neu_{Score}) = Ps_{Score} \\ Ng_{Score} & if \max(Ps_{Score}, Ng_{Score}, Neu_{Score}) = Ng_{Score} \\ & else \\ Neu_{Score} & \end{cases} \quad (8)$$

The sen_score(opw) is +ive, if the mean +ive score (Ps_{Score}) is larger than the mean -ive $(Ng_{Score}), and\ neutral\ neu_{Score})$ score, else -ive. The sentiment score is neutral $neutral(neu_{Score})$ if the mean +ive and -ive sentiment scores are identical or the neutral sentiment score is larger than the +ive and -ive. In the aforementioned case, the sentiment scores $(Ps_{Score}, Ng_{Score}, Neu_{Score})$ for the word "long" are {0.111, 0.167, 0.722}. The dominant polarity score is: sen_score("long")="0.722".

In Tab. 7 a sample list of opinion words is shown.

Table 7: A sample list of opinion words with sentiment scores

Opinion Word	**Sentiment Score**	**Remarks**
Faithfully	(+0.25)	Score assigned SWN-based scoring scheme (Eq. (3.1))
Focused	(+0.125)	Score assigned SWN-based scoring scheme (Eq. (3.1))
Independently	(-0.375)	Score assigned SWN-based scoring scheme (Eq. (3.1))
Organized	(-0.125)	Score assigned SWN-based scoring scheme (Eq. (3.1))
Hesitate	(+0.25)	Score assigned SWN-based scoring scheme (Eq. (3.1))
Unsatisfied	(-0.875)	Score assigned SWN-based scoring scheme (Eq. (3.1))

Sentiment scoring of polarity shifters

Intensifiers are the terms, which increase or decrease the intensity of opinion words in a sentence. For example, "very", "somewhat", "slightly", "too", "really", "extremely" etc., increase or decrease the semantic orientation of opinion word.

In this work, we used 50 English intensifiers. We assigned a polarity score to each intensifier by using the numeric values (e.g., 1, -1, 0.5, -0.5), proposed by [Asghar, Khan, Ahmad et al. (2017b)] to compile a list of +ive and –ive intensifiers (Tab. 8).

Let $list\_pol\_shft$ is a list of positive and negative intensifiers represented as:

$list\_pol\_shft$ = {list of positive and negative intensifiers}

If a term is present in a list of +ive or -ive intensifiers, then the sentiment score of the neighboring opinion word is calculated as follows:

$$sentiment_{score\_pol\_shifter}(opw) = \begin{cases} \left(sen\_score(opw) + \left(sen\_score(opw) * sen\_score\left(pol_{shft}\right)\right)\right), \\ \qquad if\ (pol\_shft \in\ list\_pol\_shft) \end{cases} \quad (9)$$

where the word *pol_shft* represents a word belonging to a list of polarity shifters, *opw* is an opinion word, *sen_score(pol_shft*) is a sentiment score of the polarity shifter obtained from polarity shifter list *list_pol_shft*. The polarity score of nearest sentiment word is calculated by multiplying the sentiment score of polarity shifter by the sentiment score of an opinion word (using Eq. (9)).

Table 8: Polarity shifters

Intensifier	**Score**	**Intensifier**	**Score**	**Intensifier**	**Score**
Too	+45%	Totally	+70%	Extremely	+80%
Pretty	+20%	Less	-50%	Very	+50%
Quite	-20%	Hardly	-70%	Slight	-40%
Completely	+100%	Really	+15%		

3.5 Applying an example student feedback review on proposed model

An example of student feedback is as given as follows: <feedback> *"the lecture was quite bad. i am really unsatisfied with it."*.

Taking the first sentence: To perform the sentiment classification on given feedback, we first use the sentiment classification of opinion words (Section 3.3) in the first sentence. The sentiment score of the opinion word "bad" is computed as "-0.625 ", which is negative. Similarly, the sentiment score of the polarity shifter "quite" is -20%. Using the polarity score of modifier and its associated opinion term is computed using Eq. (9) as follows:

$$sentiment_{score\_pol\_shifter}("quite\ bad") = \begin{cases} \left(sen\_score("bad") + \left(sen\_score("bad") * sen\_score("quite")\right)\right) \end{cases}$$

0.625+[-0.625*(-20%)]=0.45 Here, the opinion word "helpful" is available in the SWN, its score is 0.25, and the enhancer modifier "extremely" has weightage of -0.2. Therefore, we received a revised score of -0.5.

Taking the second sentence: We take the 2nd sentence of feedback as: "i am really unsatisfied with it." In this sentence, the sentiment score of opinion word "unsatisfied" is computed as "-0.875 ", which is negative. Similarly, the sentiment score of the polarity shifter "really" is "15%". Using the polarity score of modifier and its associated opinion term is computed using Eq. (9) as follows:

$sentiment_{score\_pol\_shifter}("really\ unsatisfied")$
$= \left\{ (sen\_score("unsatisfied") + (sen\_score("unsatisfied") * sen\_score("really"))) \right.$

= -0.875+ [-0.875*15%] = -1. Here, the opinion word "unsatisfied" is available in the SWN, its score is 0.875, and the enhancer modifier "really" has weightage of 0.15. Therefore, we received a revised score of -1.

Tab. 9 shows sample sentences and their associated opinion words and enhancer.

Table 9: Review text and its associated opinion words and modifier

Sentence id	Input sentence	Opinion words			
		positive	Negative	Enhancer Modifier	Reducer Modifier
1	*the lecture was quite bad.*	-	Bad (-0.625)	-	quite (sentiment score: 0.2)
2	*i am really unsatisfied with it.*	-	unsatisfied (-0.875)	really (sentiment score: -0.15)	--

3.5.1 Computing sentence-level sentiment score

To compute the sentiment score of the entire feedback, the average score of all sentences is computed as follows:

$$avg_{score} = \frac{1}{n} \times \sum_{i=1}^{n} opw_{r_{score}}(P_{shifter})_i \tag{10}$$

where "$opw_{r_{score}}(P_{shifter})_i$" is the revised sentiment score of an ith sentence (Eq. (10)) and "n" is the total no. of sentences in given feedback. Taking the example review and putting the values in Eq. (10), we get:

$$avg_{score} = \frac{-0.5 + (-1)}{2} = -0.75$$

The value of "avg_{score}" calculated lies in the range [-1, 1]. As it is necessary that the value of "avg_{score}" should be in between the [0, 1], so we normalize its value using min-max normalization; upon applying min-max normalization to "avg_{score}", we get the normalized value as follows:

$$avg_N = \frac{avg_{score} + 1}{2} \tag{11}$$

$$avg_N = \frac{-0.75 + 1}{2} = 0.12$$

Using the aforementioned computations, we classify the student feedback as follows:

$$Student\_feedback\_sentiment\_class = \begin{cases} Negative(N), & if\ (avg_N > 0\ and\ \ avg_N \leq 0.3) \\ Neutral(Nu), & else\ if\ (avg_N > 0.3\ and\ avg_N \leq 0.6) \\ Positive(P), & else\ if\ (avg_N > 0.6\ and\ avg_N \leq 1) \end{cases} \quad (12)$$

3.6 Output of sentiment analysis system

The output of SA is the sentiment class assigned on the basis of Eq. (12). Putting the aforementioned value of avg_N computed using Eq. (11) ("avg_N =0.12)", where sentiment score is evaluated using Eq. (4), then we get the sentiment class as:

$Student\_feedback\_sentiment\_class(c) = "Negative$"

The aforementioned sentiment class, i.e., "Negative" is the output of our proposed sentiment analysis system. In the next phase, we measure student satisfaction by applying different steps of the fuzzy logic system as follows.

3.7 Fuzzy-based system for student satisfaction level

In this step, to quantify the student satisfaction level from a given student feedback a fuzzy logic system is used (Fig. 3). The used fuzzy logic system contains the following steps.

(i) Fuzzy sets: Determine the input and output linguistic variables and their associated terms.

(ii) Fuzzification: The crisp input is converted to the fuzzy values using a membership function.

(iii) Construct the membership functions for the fuzzy sets

(iv) Fuzzy if/then rules are constructed

(v) Defuzzification: The fuzzy values are converted into crisp values (non-fuzzy values).

Mathematically, the fuzzy logic system is described in Eq. (13) as follows [Ghani, Bajwa and Ashfaq (2018)].

$$A = \{x, uA(x))| \ x \ \epsilon \ X) \quad (13)$$

where μA (x) represents the membership function or degree of membership function, of x in A and X, is the Universal set.

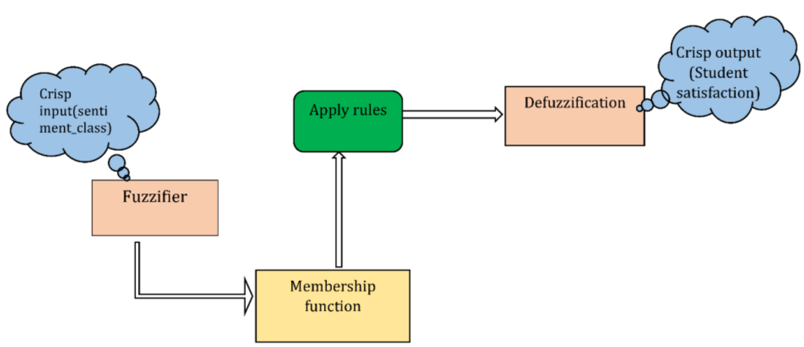

Figure 3: Fuzzy logic based system

3.7.1 Input and output linguistic variables

In our work, we take sentiment class as an input linguistic variable and student satisfaction as an output variable as shown in Tab. 10.

Table 10: Input and output linguistic variable

Type	Linguistic variable
Input variable	Sentiment class
Output variable	Student satisfaction

3.7.2 Fuzzification

In a fuzzy logic system, we first identify the input and output variables. In this step, to obtain the fuzzified values, the transformation of crisp input values into the fuzzy set is performed and this process of conversion is known as fuzzification [Wang, Zhang and Xu (2016)].

Based on the input-output linguistic variable, we determine their associated linguistic terms. We assigned three linguistic terms for the input variable and similarly, three linguistic terms have been taken for the output variable as shown in Tab. 11.

Table 11: Linguistic variable and linguistic terms

Input	
Linguistic variable	**Linguistic terms**
Sentiment class	Negative(N)
	Neutral(Nu)
	Positive(P)
Output	
Linguistic variable	**Linguistic terms**
Student satisfaction	Not satisfied
	Moderate
	Satisfied

3.7.3 Membership function

The fuzzy logic system used a membership function to plot the fuzzy sets. Different types of membership functions are available like Bell membership, triangular membership function, and Gaussian membership [Alam and Pandey (2017)]. In our proposed work, we take triangular membership function which is described in Fig. 4.

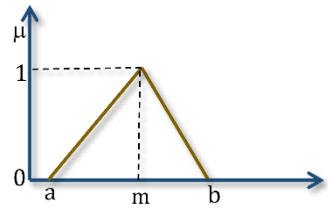

Figure 4: Graphical representation of trimf

The triangular membership function is defined by three parameters [a, b, c], where a denotes lower boundary, b is an upper boundary, 0 is the membership degree and m represents the center, where membership degree is 1 (Eq. (14)).

$$trimf(x:a,b,m)=\begin{cases}0 & x\le a\\ \frac{x-a}{m-a} & a\le x\le m\\ \frac{b-x}{b-m} & m\le x\ \le b\\ 0 & c\le x\end{cases} \tag{14}$$

The membership functions for the linguistic terms of the sent_class variable is plotted as shown in Fig. 5.

Fuzzy sets	*Membership function*
Negative	Triangular
Neutral	Triangular
Positive	Triangular

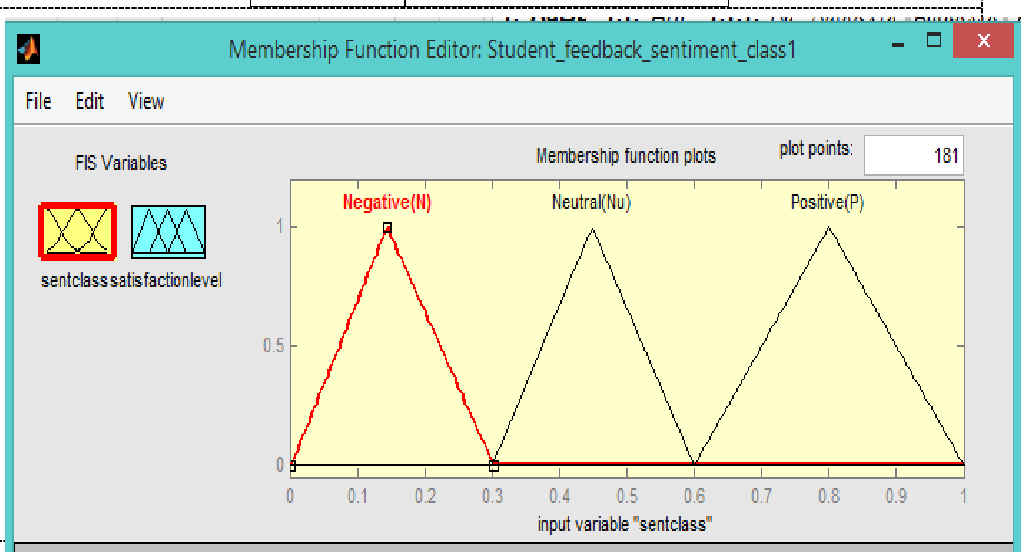

Figure 5: Membership functions for sentiment class

3.7.4 Design if/then rules

In this step, the fuzzy rules are designed to take the conclusion. These rules are simple and expressed as follow [Darestani and Jahromi (2009)]:

IF (antecedent) THEN (consequence)

where, If part is known as antecedent and then part is known consequent. Tab. 9 shows different fuzzy rules:

Table 12: Fuzzy Rules for student satisfaction

If/then Rules:-
1. If(sentclass is **negative**) then (studentsatisfaction is **Notsatisfied**)
2. If(sentclass is **neutral**) then (customersatisfaction is **moderate**)
3. If(sentclass is **positive**) then (customersatisfaction is **satisfied**)

3.7.5 Defuzzification

Finally, to determine student satisfaction, the defuzzification function is used in which fuzzy values are transformed into the crisp values. In the proposed work, the Mamdani inference system is used, which computes the center of gravity using Eq. (15) as follows [Ghani, Bajwa and Ashfaq (2018)];

$$Y = \int_{min}^{max} \mu(y) y dy \Big/ \int_{min}^{max} \mu(y) dy \tag{15}$$

where Y is the result of defuzzification, μ(y) is the membership function, y is the output variable, min is the lower limit, and max is the maximum limit for defuzzification.

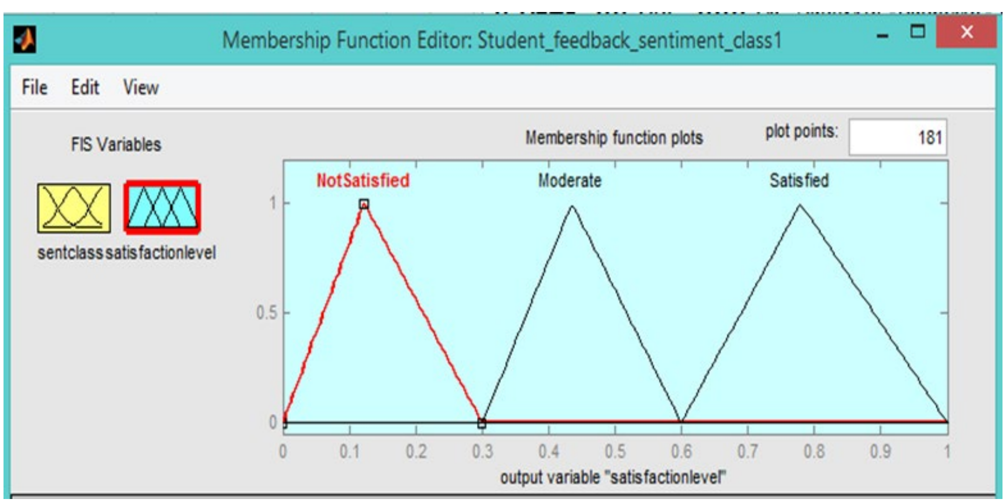

Figure 6: Membership functions for output variable student satisfaction

To measure student satisfaction with the sentiment class, we simulate the rules in MATLAB. For instance, in Fig. 7, if the sentiment score is 0.12, which is considered as negative, then the student satisfaction is 0.141, considered as not-satisfied and very close to the sentiment score.

In Fig. 6, the membership function for the output variable student satisfaction, is plotted.

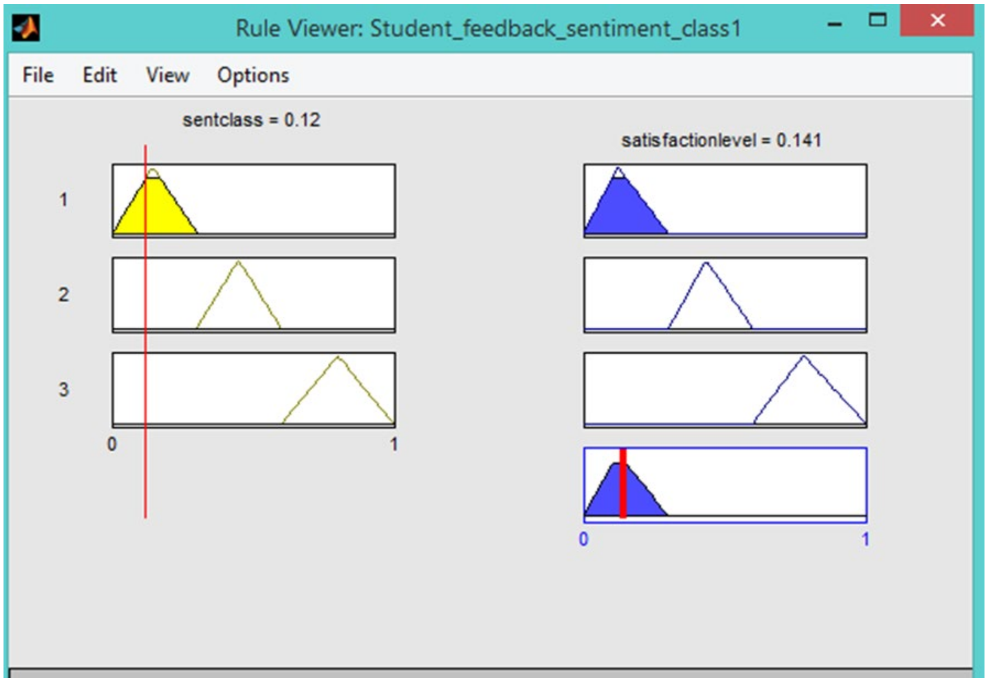

Figure 7: Matlab rule viewer

For the given input student review "*the lecture was quite bad. i am really unsatisfied with it*", we have reached to the conclusion that student satisfaction level is *"not-satisfied"*, which means the student is not satisfied on the basis of example feedback, presented in Section 3.3.2.

The pseudo-code steps for the development of the proposed system is presented in Algorithm 1.

Algorithm 1: Algorithm for efficient classification of sentiment and measuring student satisfaction level.

Input: Student feedback

Output: Student satisfaction level

#Retrieve "dataset" feedback

1. **Student Feedback collection**
2. **Preprocessing**
3. **Subjectivity detection(S) (Eq. (1))**
4. **for (Opw *in* S AND polarity_shifter *in* S)**
5. **if(Opw $\in$ SWN) then**
6. **Obtain Opw score from SWN (Eq. (5)-(7))**

```
7.              if (polarity_shifter ∈ list_pol_shft) then
8.                  Obtain polarity_shifter score (Tab. 8)
9.              end if
10.         end for
11. Calculate final sentiment scoring (Eq. (12))
12. Assign sentiment as positive, neutral, and negative.
#Use the fuzzy logic system.
13. Perform Fuzzification on sentiment classes (Eq. (13))
14. Apply if/then rules (Tab. 9)
15. Defuzzification (Eq. (15))
16. Output the student satisfaction level as 'dissatisfied', 'neutral', and 'satisfied'.
```

4 Result and discussion

In this chapter, results are analyzed on account of conducting experiments and answers are given to the posed research questions.

4.1 Experiment #1

Answer to RQ1: To answer this research question, "How can we perform efficient classification of opinion words expressed by a student in their feedback by revising the sentiment scoring technique proposed in baseline method?", we applied a fuzzy-based technique for the sentiment classification of student feedback (the technique discussed in methodology). Additionally, we conducted an experiment on the state of art machine learning classifier namely Naïve Bayesian (NB), Random Forest (RF), Support Vector Machine (SVM).

Tab. 13 shows result on account of applying the aforementioned machine learning classifiers and it is evident the proposed model performed better. The basic reason behind the efficient classification of the proposed model with respect to Machine Learning (ML) classifiers is that both opinion word and polarity shifters are detected and assigned proper sentiment scores, and resultantly our proposed system efficiently classified the input text in the form of student feedback.

Table 13: Comparison with machine learning classifiers

ML classifiers	P	R	F	A
NB	0.82	0.79	0.72	0.78
RF	0.85	0.85	0.84	0.85
SVM	0.78	0.79	0.78	0.78
Proposed (Our work)	**0.87**	**0.97**	**0.90**	**0.89**

4.2 Experiment #2

Answer to RQ2: "What is the efficiency of fuzzy-based student feedback sentiment classification system with and without considering polarity shifters?"

In the second experiment, we evaluated the performance of the proposed system with and without considering polarity shifters. While considering polarity shifters, Tab. 14 shows that the proposed system performed slightly better in terms of Accuracy (A), Recall (R), F-measure (F). However, Precision (P) results are identical in both the cases, i.e., "with polarity shifters" and "without polarity shifters".

Table 14: Comparative results with and without polarity shifters

	A	P	R	F
With polarity shifters	0.85	0.87	0.97	0.94
Without polarity shifters	0.81	0.83	0.95	0.89

4.3 Experiment #3

Answer to RQ3: "What is the efficiency of fuzzy-based sentiment analysis of student feedback using opinion words and polarity shifters w.r.t to state-of-the-artwork and different supervised Machine Learning Algorithms?"

To answer RQ3, the performance of the proposed system is compared with that of baseline studies [Rajput, Haider and Ghani (2016); Nasim, Rajput and Haider (2017); Yousif and Shaout (2018)] using different performance evaluation metrics, namely precision, recall, f-measure, and accuracy. Result presented in the Tab. 15, show that the proposed model outperformed the baseline work [Rajput, Haider and Ghani (2016); Nasim, Rajput and Haider (2017); Yousif and Shaout (2018)] in terms of improved precision and f-measure. The recall of the two systems is the same. However, the precision, f-score and accuracy of the proposed system are higher than the baseline works.

Table 15: Comparison with baseline studies

Study	Method	P	R	F	A
Rajput, Haider and Ghani (2016)	Lexicon-based	0.40	0.97	0.57	0.79
Nasim, Rajput and Haider (2017)	supervised	0.79	0.82	0.80	0.82
Yousif and Shaout (2018)	Classical Fuzzy-based	0.81	0.83	0.81	0.84
Proposed	Sentiment Driven Fuzzy-based sentiment analysis	0.89	0.97	0.90	0.94

4.4 Evaluating student satisfaction level

We plot a chart for measuring the efficacy of the proposed fuzzy-based model shown in Fig. 8. The x-axis denotes the student satisfaction level and the y-axis denotes the sentiment score. Fig. 8 shows that if we have a sentiment score of 0.4 (Negative), then the customer satisfaction level is also 0.4(Not-satisfied). So it is observed that there is a direct relationship between sentiment score and student satisfaction level, i.e., if sentiment score is increasing, then customer satisfaction also increases.

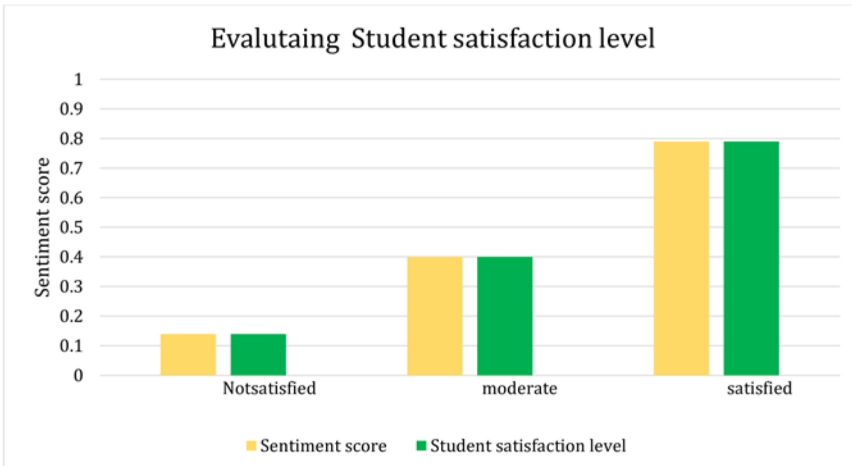

Figure 8: Evaluating student satisfaction level with a sentiment score

4.5 Statistical analysis

To investigate whether the proposed Fuzzy-based Sentiment Analysis for student satisfaction and feedback analysis with polarity shifters, is statistically significant than that of classical sentiment-based technique without polarity shifters and does not occur by chance, we conducted two experiments. From the dataset, we randomly choose 250 reviews in which each review is classified by both the proposed and classical sentiment-based techniques. The null and alternate hypothesis is formulated as follows" .

H0: Both the models have the same error rate, and **HA:** Both models error rate is significantly different.

McNemar's test is computed as follows:

$$\chi^2 = \frac{(|m_{01} - m_{10}| - 1)^2}{(m_{01} + m_{10})} \tag{16}$$

The significance results are presented in Tab. 16.

Table 16: Performance difference between the proposed model (with polarity shifters) and baseline (without polarity shifters) using significance test

		Baseline model [Rajput, Haider and Ghani (2016)] without polarity shifters	
		Correctly Classified	**Incorrectly Classified**
Proposed model (with Polarity shifters)	**Correctly Classified**	160	35
	Incorrectly Classified	17	38

The McNemar's Chi-squared statistic is 5.6 and the p-value is 0.018 with 1 degree of freedom, Hence, the null hypothesis is rejected (*p*-value<0.5).

The experiments are conducted to evaluate the performance of one of the baseline SA without using polarity shifters presented (Tab. 16). The baseline approach shows poor performance in terms of accuracy, precision, recall, and f-measure for student satisfaction analysis. However, the fuzzy-based approach with polarity shifters is significantly better than the baseline method [Rajput, Haider and Ghani (2016)] with an accuracy of 82%.

The statistical test validates that performance difference between that the proposed method (with polarity shifters) and the baseline method [Rajput, Haider and Ghani (2016)] (without polarity shifters) is statistically different. For 52 reviews, we can observe the discordant (Tab. 16) between the two models. i.e., the two models behave differently "with polarity shifters" and "without polarity shifters".

From the above discussion, it is evident that the inclusion of polarity shifters significantly improved the performance of the proposed system for the fuzzy-based SA od student satisfaction and feedback analysis.

5 Conclusion

The proposed system employs a fuzzy-based approach for the sentiment classification of student feedback by classifying opinion words and polarity shifters present in the student feedback comments. First of all, the student feedback data available as an open-source, is preprocessed using different preprocessing techniques, such as stop word removal, tokenization, case conversion and spell correction. In the next step, sentiment classification of sentiment words and polarity shifters is carried out. An overall sentiment score is computed. Finally, the fuzzy logic system is applied to analyze customer feedback and satisfaction.

The experimental results are encouraging, and it is observed that the proposed system performed better than the baseline works and other state-of-the-art machine learning classifiers, in terms of accuracy, precision, recall, and f-measure.

Limitations

The proposed approach has the following deficiencies:

1) Experimentation is performed on a data set with limited size, comprising of 1415 reviews collected as student feedback. This limited size of data set resulted in performance degradation of the system.

2) The sentiment scoring of opinion words is based on the SentiWordNet (SWN) lexicon. The basic limitation of Senti WordNet (SWN) is lack of sufficient word coverage and certain words are not assigned a correct Senti WordNet (SWN) score.

3) The proposed system cannot correctly classify certain opinion words and polarity shifters. For example, the input sentence: "*He hardly late from the class*" the modifier "*hardly*" treated as negative. The overall score and class became negative. However, the afore-mentioned sentence is actually giving positive sentiment. i.e., He is so punctual that he rarely comes late to class.

4) One of the major limitation is associated with the lexicon-based approach is that if a word or polarity shifter is not available in the given sentiment lexicon, then the system cannot correctly classify the student feedback.

5) As it is the era of social media like Facebook and Twitter, where students express their sentiments using emoticons and slang terms. However, the proposed system lacks the ability to classify such construct (emoticons and slang terms).

Future direction

1) The performance of the system can be improved by increasing the size of the dataset. Furthermore, experimentation on multiple datasets needs to be carried out with respect to student feedback.

2) To assign more accurate sentiment score to opinion words, another sentiment lexicon, such as SentiFull and SenticNet needs to be investigated.

3) To correctly classify opinion words and polarity shifters, corpus-based sentiment scoring technique needs to experiment.

4) It is required to conduct an experiment using machine learning and deep learning techniques for efficient classification of student feedback by overcoming the "out-of-word" issue of a sentiment lexicon.

5) To improve the performance of the proposed system, emoticon lexicon and slang lexicon with proper sentiment scoring needs to be investigated.

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Ethical Approval: This article does not contain any studies with human participants performed by any of the authors and does not contain any studies with animals performed by any of the authors.

Data Availability: The supplementary data used to support the findings of this study are available from the corresponding author upon request.

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