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Optimization of College English Writing Teaching Strategies based on Sentiment Analysis

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Abstract

The variety of comments has grown so quickly since emotions analysis became more popular. This study explores the optimization of college English writing teaching strategies through the application of sentiment analysis. By systematically collecting and analysis the students feedback, teachers comments and the performance data. However, it is hard to figure out how people feel from the huge number of comments. Sentiment analysis (SA) is a quick, easy, and automatic way to find out what users think and feel. This paper focus on the purpose of sentiment analysis, which compares different techniques, looks into the areas where sentiment analysis can be used, which highlights the problems and restrictions that students have faced, suggests ways to fix these problems. The study proposed Sentiment based Gradient Function Optimization (SGFO) algorithm for analyzing strategies of college English writing teaching strategies using sentiment analysis. The results show that with the help of the proposed system, the participants made a significant progress in how they used emotion words. In particular, people who were proficient showed bigger gains with the SGFO algorithm. The participants were also positive about the tool support because it helps them use emotion words more effectively in their work. The study results stated that the proposed model has provided an accuracy of 98.7%.

Keywords: Sentiment Analysis, college English writing, teaching strategies, emotions

1. Introduction:

Today, English is regarded as the language of science, technology, diplomacy. Learning the English language gives us access to a wealth of knowledge and scientific resources. The English language is used in multinational corporations and institutions. Today, English is the most prevalent language on the web, with more than 60% of the top 10 million websites being displayed in English [1]. Strategy is part of the teacher's method for carrying out teaching tasks. It seeks to implement ideas, plans, and goals over a set length of time. In the field of education, strategy can be defined as a plan, approach, or a set of activities aimed to attain certain educational goals [2]. Classroom interaction is the process by which various components interact in a certain teaching and learning setting to achieve a specific teaching objective and teaching goal. For educators, in order to effectively involve students in the teaching and learning process, they must apply interactive, communication, and feedback skills on both sides of the interaction [3]. The teacher's approach to teaching writing is crucial because it must be engaging and successful in order to help students grasp writing and become engaged in the process of learning. Thus, in order to improve students' writing abilities, English teachers should make the effort to look for and develop new models for presenting materials. Fun teaching materials are necessary to provide an efficient and directed teaching and learning process, as per the teacher's instructions. These materials can pique students' interest in the subject matter and increase their motivation to study writing.

As Chinese college become more aware of the need to improve the English language, there have been many changes to how English is taught, how textbooks are made, how students are tested, and how they are taught.

* Place the footnote text for the author (if applicable) here.

The problems with teaching English in colleges right now don't help students communicate better with English, which makes it hard to teach well [4]. The point of this paper is that colleges and universities should set up tracking and evaluation systems to make sure that teaching is effective and take specific steps to follow through on them. Opinion mining is another name for sentiment analysis. It looks at how people's thoughts, feelings, opinions, assessments, attitudes, and emotions about things and their qualities are expressed in written text [5]. Things like products, services, organizations, people, events, problems, and topics can be entities. Sentiment analysis is the process of using a special program to look at information and figure out whether it shows a positive, neutral, or negative mood. Different kinds of software tools use different kinds of emotions analysis. A "lexicon sentiment model" uses a list of words and the emotion scores that go with them to do sentiment analysis [6]. A significant method uses emotions orientation dictionaries and judgment rules that have already been set. However, this method has trouble getting around set emotional word limits, which makes it less useful for data analysis. Machine learning algorithms like Naive Bayes (NB), Deep learning like RNN, BP neural Network used in the second way to make text analysis more flexible and accurate. Even though it works, this approach only looks at the general polarity of emotions in a sentence and does not look at things like teaching methods, attitudes, or communication styles.

2. Literature Review:

The study's proposed random matrix theory has several advantages over conventional approaches, and it may be used to help students learn and speak English more fluently [7]. The experimental results demonstrate that the detection probability approaches 80% when the number of sample points is 82 and the noise ratio signal is 16 database. This substantially enhances the effectiveness of strategy optimization and classroom random detection performance in English instruction. Their study also emphasized the extraction of opinions from texts and reviews found on different websites [8]. It was limited to allusions to the specific item under examination, rather than concentrating on the sentiment from a lengthy text like the entire document. Natural language processing (NLP) was used as a technique, and it worked pretty well, consistently providing results with over 86% accuracy across all tests. This demonstrated that sentiment analysis of interactive less texts and personalized exercise some suggestions were better suitable for the study's suggested technique [9]. Furthermore, the research institute's interactive text sentiment analysis model is innovative because it is a part of the emotional features is based short-text extension algorithm, which aids in resolving the issue of feature brought on by short missing features in brief texts. This study reviewed the issue in a case-by-case basis using in-depth analytical approaches [10]. The outcome demonstrates that the teacher's method charts was effective. Charts are an excellent teaching tool for writing because they are an eye-catching, easy-to-use, and efficient way to get students engaged in the content that is being covered in class [11]. Charts can be utilized to teach writing skills since they offer a concise overview of the subject in writing. This study focus on optimized neural network set of weights and limits to create a model that may be used to assess the caliber of instruction [12]. Enhancing the BP algorithm's performance, cutting down on running time, and raising prediction accuracy and efficiency are the goals. The model's efficacy and dependability will be confirmed by using the trained network model to evaluate the caliber of instruction at institutions. This study to prevent potential issues in university-applied teaching, future classroom teaching design and adjustment must perform well in the related preparation [13]. The next stage is to create a corpus for a mobile Internet and cross-media college English teaching platform so that instructors can travel and students can select their own learning styles [14].

3. Methodology

Data collection: The first data corpus is made up of data from a university and a course on student feedback. Approximately 2,000 student comments from the July 2022–July 2023 course, as well as 1,700 comments from students after the course ended, are included in the dataset. About 400 student evaluations and comments for lectures and laboratory sessions following middle term and final semester exams for a course with a single instructor are included in the dataset. Along with direct evaluation of performance on student, we employed the survey on students and comments for 20 courses teach by various university instructors to examine the system dependability.

Preprocessing of Data: In this stage, the Sentiment Analysis approach gets the gathered information ready for additional process. There are six steps in this process.

1. *The tokenization process*. The R tokenizes function divides student comments into words, or tokens.
2. *Lowering the case*. To make it easier to match words in student comments with words in the NRC Emotion Lexicon, characters are changed to lower case.5. The tm_map function from the R tm package is used for this phase.
3. *Standardization*. Content that has been shortened is normalized by mapping it to commonly used Internet slang terms using a glossary. For instance, the terms "gud" and "awsm" correspond to "good" and "awesome," respectively.
4. *Stemming*. The tm_ map function in R's SnowballC package is used to translate terms in student comments to their root word in order to aid word matching even further. For instance, "move" replaces "moving,""moved," and "movement."
5. Content that is no longer relevant is removed. To increase the efficiency and response time of the system, stop words and punctuation are eliminated since they are not significant to SA.
6. *Translation into another language*. The Google Transliterate API is utilized to transliterate the text in order to tackle the problem of mixed language usage in student comments.

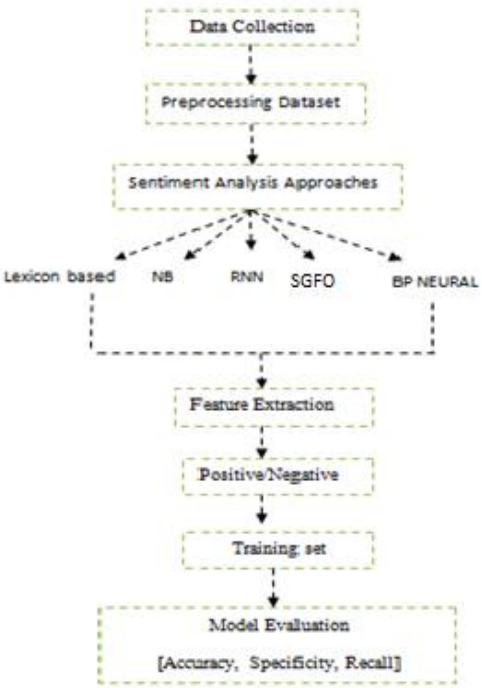

Figure1: Proposed Method

Sentiment analysis techniques

In general, there are four types of SA approaches: deep learning, hybrid, lexicon-based, and standard machine learning. Figure 2 shows ways to sentiment analysis. Researchers have also been looking for more effective ways to finish the task faster and with less computer usage.

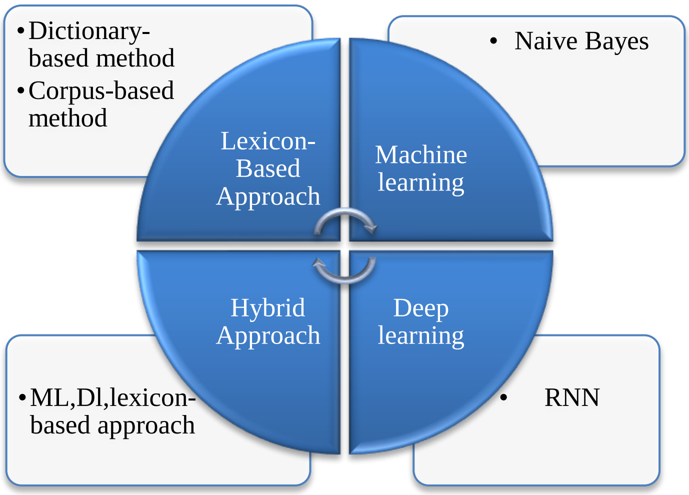

Figure 2: Sentiment Analysis methods

3.1 Lexicon-based approach

This approach requires the use of a sentiment lexicon to score the tokens that have been gathered. Due to the possibility of disparate attitudes for the same word in different sectors, this method is domain reliant and is unsupervised [15].Dictionary-based and corpus-based methods are the two general categories of lexicon-based methodologies. The drawbacks and advantages of lexicon-based methods are listed in Table 1.

Table1: The categories of lexicon-based methods

Technique	Advantage	Disadvantage
Dictionary-based approach	Quickly access word definition in the vocabulary	Unable to recognize opinion terms with specific content areas that are not yet included in the dictionary
Corpus-based approach	The ability to recognize distinct content-oriented opinion expressions. The result are better when domains are different.	Performance varies because of the lexicons wide range.

The different ways to use a lexicon-based method are:

- Method based on dictionaries: In this method, a dictionary is made by starting with a few words. After that, we can use an online dictionary, thesaurus, or WordNet to add more words that are similar or opposite to those you already have. The dictionary is getting bigger until no more words can be added. The dictionary can be improved by looking it over by hand.
- A method based on corpora: This finds the sentiment orientation of words that are unique to the context. This method has two ways to do things, which are:
- Method based on statistics: Positively charged words that are not always consistent. If they appear more than once in negative words, they have negative polarity. If the frequency is the same in both positive and negative writing, the word is said to be neutral.
- Semantic method: This method gives words that are semantically related to them emotional values. This can be done by finding synonyms and antonyms for that word.

$$Stsc = \frac{number\_of\_positive\_words - number\_of\_negative\_words}{Total\_number\_of\_words}$$

3.2Naive Bayes Using Machine Learning Approach

Naive Bayes is a classifier based on probabilities, which means that given a document d, it gives $c \in C$, the class $\hat{c}$that has the highest posterior probability. We use the symbol ^ to mean "our closest estimate of the correct class" in equation (1).

$$\hat{c} = avg \max_{c \in C} p(c|d) \qquad (1)$$

Bayesian reasoning is an idea that has been around since Bayes's work. It was first used to classify text. The idea behind Bayesian classification is used by the Baye formula to change equation 1 into other probably events that are used. The Bayes rule comes in equation (2);. It lets us divide any conditional probability $P(x|y)$ into three other probabilities.

$$P(x|y) = \frac{P(y|x)P(x)}{P(y)} \qquad (2)$$

Then, we can put equation (2) into equation (1) to get equation (3):

$$\hat{c} = avg \max p(c|d) = \text{argmax} \frac{P(d|c)P(c)}{P(d)} \qquad (3)$$

We can make equation (3) easier to understand by taking out the term $P(d)$. We can do this because we will figure out$\frac{P(d|c)P(c)}{P(d)}$) for each possible class. But $P(d)$ stays the same for every class because We're always looking for the best possible class for document d, so it share the same $P(d)$. So, we can pick the class that makes this basic formula work best:

$$\hat{c} = avg \max p(c|d) = \text{argmax} P(d|c)P(c) \qquad (4)$$

The Naive Bayes model is a model that is generative because equation.(4) seems to make a claim about a document is made: first, chosen by a class from $P(c)$, and then chosen by the words from $P(d|c)$. This process could even be used to make fake papers, or at least documents with fake word counts.
In order to find the most likely class ˆc for a given document d, we pick the class that has the greatest product of two probably event: the prior likely outcome of the class $P(c)$ and the likely hood of the document $P(d|c)$ as illustranked in equation (5)

$$\hat{c} = avg \max p(d|\text{c})\ P(c) \qquad (5)$$

P(d|c) is Likelihood probability: There is a chance that the information given that a theory is true.

P(c) is Prior likely outcome: Chance of a before the hypothesis looking at the facts.

It's possible to think of a file d as a collection of traits f1, f2,..., fn:

$$\hat{c} = \underset{c \in C}{\text{argmax}}\ P(f1,f2 \ldots f_n|c)P(c) \qquad (6)$$

However, Equation 6 is still difficult to directly solve. Without making a few predictions that make things easier, figuring out the chance of every possible combination. So, Naive Bayes models make two presumptions that make things easier [16].

	Advantage	Disadvantage
Naive Bayes	To predict a group of datasets, Naive Bayes is a quick and simple machine learning method.It can sort things into both two or more groups, or "binaries."Compared to the other algorithms, it does a good job of making multi-class estimates.	Naive Bayes thinks that all features are separate and have nothing to do with each other, so it can't figure out how features are connected.

Table 2:Advantage and disadvantage of Naive Bayes

3.3 RNN using deep learning Approach

A recurrent neural network (RNN) is a different kind of neural network that is perfect for working with time series data or data that has sequences. Simple deep learning approach of neural networks with feedforward function can only handle data points that don't depend on each other [16]. But if we have data that is ordered in a way that one point relies on the point before it, we need to change the neural network to take into account how these points are connected. RNNs have "data" that lets them keep track of the states or data of previous inputs so they can make the next output in the process. we can expand the network for k steps to get the result at time step $k + 1$. The feedforward neural network and the expanded network are a lot alike. The rectangle in the stretched network shows that something is being done. For instance, we have an activation function f in equation (7)

$$h_{t+1}=(x_t,h_t,w_x,w_h, b_h)=f(w_x x_t+w_h h_t+b_h) \quad (7)$$

- The output y at time t is computed as:
- $y_t=f(h_t,w_y)=f(w_y. h_t+b_y)$ (8)
- Here, · is the dot product.

In this way, an RNN's feedback pass is when it figures out the secret unit values and the output after k time steps. The weights that are connected to the network are shared over time. There are two sets of weights for each recurrent layer: one for the enter the value and one for the hidden unit. This last feedback layer figures out the final result for the mth time step. It works the same way as any other layer in a normal feedback network [17].

RNN algorithm

- Repeat till the stopping criterion is met:
    - Set all a to zero.
    - Repeat for $t = 0\ to\ n - m$
        - Forward propagate the network over the unfolded network for k time steps to compute all a and b
        - Compute the error as: $x = bt + m - pt + m$
        - the error across the unfolded network and update the weights

3.4 Hybrid approach

These two methods—lexicon-based standard DL and ML—are combined in the hybrid approach. In this common way, sentiment analysis combines the study of language and the meanings of words in their environment. In this study, we used a combination method that mixed the SVM and Relief algorithms.

Data preprocessing using steerable filters (SF)

Since SF relies on the calculation of the sentiment analysis derivative of Gaussians, local orientation maps of a feedback can be created using these filters. In essence, SF is a linear combination of the second derivatives of

Gaussian distributions. The following formula (9) computes a 2-dimensional Gaussian at a specific pixel for an image i (a, b). Equation (10) describes the SF formulations with a direction of θ. While the variable R, which is the deviation of the Gaussian function, is fixed, the outcome map of an image is created by integrating the outputs of individual SFs with varied θ values. The values of θ in this study vary between $0°\ to\ 360°$ at intervals of $30°$. Equation (11) is also used to compute the final answer map that SFs produce for an image i.

$$g(R, a, b) = \frac{1}{\sqrt{2\pi R}} exp \frac{-(b^2+a^2)}{2R^2} \quad (9)$$

$$f(\theta, R, a, b) = g_{aa}cos^2(\theta) + 2g_{ab}cos(\theta)sin(\theta) + g_{bb}sin^2(\theta) \quad (10)$$

$$R(a, b) = f(\sigma, a, b, \theta) * i\ (a, b) \quad (11)$$

Where the variances of the Gaussian function is represented by its independent parameter$R$. Gaussian 2nd derivatives are indicated by g_{aa}, $g_{ab,}$ andg_{bb}. $*$Indicates the convolutional operators sign.

3.5 BP Neural Network's teaching Strategies

1) BP model:

Choosing the input methods and steps: The neurons in the enter value process is set to n = 6 because there are 7 things that affect performance. These add up to:

x_1 means to teach, answer questions, and check schoolwork;

$x_2$means to find important points and problems that need to be solved;

x_3 means to pay attention to what was taken from the information,

$x_4$means language, description, and work that was written properly on board. Using tools at the college English level

$x_6$shows that students are interested, the content is positive, and

$x_7$shows that students did well on tests and the network results were positive.

This means that $m = 1$ is the number of neural in the output layer. The estimated score of the training test is shown by Y.

Figuring out the method of encryption: A BP neural network of three-layer with a basic layout is picked out. This means that there is a 1st layer, and the encryption process gets a Sigmoid transform function. At the moment, there isn't a perfect diagnostic model that can show how many neurons are involved in the hidden process [18]. However, the images below can helps to make the best choice. Ranking of hidden objects. The model says that the input node is 7, so:

$$n = \log_2^2 n \quad (12)$$

In equation (12), n is the number of values cells, and equation (13) is achieved.

$$n_1 = \sqrt{n + m^+}a \quad (13)$$

In equation (26), m is the number of neural output, n is the number of units in input, and a is the constant of f [1, 10].

Processing in BP network design:

- The BP neural network's filtering process usually uses the Sigmoid transform function to prepare data inputs. This works to improve speed of training and sensibility and lower the the Sigmoid function of saturation, so the file format value should between 1 and 0. That is why it needs to be done. age [1,0] to make sure that the info we enter is right for that time. Normalization comes in different forms, and this one uses the following method [14]:

$$X = \frac{x - x_{max}}{\mathrm{x}_{\mathrm{max}} - x_{min}} \qquad (14)$$

- Processing raw data with an inverse transform. The output variables must also be preprocessed in the right way if the node with output layer also uses the sigmoid function transformation. There are different ways to do preprocessing, and each piece of writing uses a different set of formulas. It is to note, though, that once the preprocessed data training is done, the network's final result needs to be turned around to get the real value.
- Execution of a teaching quality neural network model for rating in MATLAB simulation: In this BP network, the middle layer neuron move using a sigmoid theta function. Because urine happened at a certain point in time [0,1], the urinary layer in the change in neural activity was named a sigmoidal function logarithmic. By following these steps, we can use MATLAB to make a BP network that meets the above conditions.

$$threshold \;=\; [01; 01; 01; 01; 01; 01; 01] \qquad (15)$$

$$net \;=\; newf(threshold, [19,1]('tansig, logsig\}, 'traingdx) \qquad (16)$$

In both Formula (15) and Formula (16), the network's input vector starts out with a value of [0,1]. The network's training function is train dx. The fees for the course can be changed, which is a good change to the BP formula.

3.6 Writing teaching strategies using SGFO

The SGFO (Sentiment based Gradient Function optimization) technique for optimizing writing strategies combines the Gradient function algorithm's optimization (GFO) capacity with the discriminatory capability of support vector machine. This technology, which combines the GFO's extraordinary foraging behavior with the power of machine learning, presents a unique technique to figuring out fractures on teaching strategies in an efficient and precise manner. SGFO enhances each the characteristic proficiency technique and the type version, ensuing in progressed overall performance and adaptability to numerous teaching and writing situations, making it a promising opportunity for students to improve their fluency.

Feature selection using the SGFO approach could lead to lots-improved classification results. SGFO is a revolutionary optimization approach inspired via the uncommon "Gradient Boosting" action of the support vector machine that entails learning strategies with machine learning. An algorithm is developed using the movement as an analogy, classifying the students and selecting the best one from each group. Some of the particles are given the capacity to reorganize the group based on how fit their group leader is. The following specified stages are how the SGFO approach works:

- **Stage 1: Initialization (I):** The process starts with certain initial values put up. This includes figuring out how many students there are, where they start, and how fast they move. Every group's variable, including the number of leaders and admirers, is also specified. A wide foundation for investigation is provided by the beginning, which guarantees that the algorithm begins with a varied collection of particles dispersed throughout the searching space.

- **Stage 2: Random Cohort (RC):** The preset parameters are gene-ranked at random by the matrix. Because of this randomness, the initial group of students is guaranteed to be diverse, avoiding an early convergence to less-than-ideal solutions. Keeping the algorithm's exploratory nature requires random initialization.
- **Stage 3: Fitness Calculation (FC):** Using the system's goals as a guide, a fitness computation is what comes next. Fitness in this sense describes how effectively a particle satisfies the required parameters or how near the ideal solution it is. After assessing every particle, the Gradients function provides a fitness value that represents how well it performed. The total amount of particles in Equation (17) is represented.

$$f_j = \min(d) \tag{17}$$

- **Stage 4: Group Formation (GF):** There are multiple groups of particles, and every group has a leader. All group's residual particles are followers.. Every group's leader directs the quest for the best answer, with followers supporting and learning from the leader.
- **Stage 5: Leader Evaluation (LE):** Every group leader's level of performance is evaluated. A ranking of the best and weakest leaders is created by comparing them using performance values. This comparison makes it easier to see which leaders are best at directing their teams toward the best answers.

Stage 6: Group Reorganization (GR): The capacity to reshuffle the group is bestowed upon some followers depending on the leaders' level of performance. This continual restructuring keeps the population from becoming stagnant and preserves diversity. In Equation (18)), m, the quantity of described followers byM_f, and the count of leaders byM_l.

$$M_f = m - M_l/M_l \tag{18}$$

- **Stage 7: Update of Positions and Velocities (UP&V):** Here, the count of students in the search area is referred to as its present condition. It is ensured that performance is always moving toward greater outcomes by changing these settings (see equation (19-20).

$$M_f = int\ (\propto * \, rand) \tag{19}$$

$$n_{j,i} = Max\ (n_{j\ i-1} - \ + M_f, 0) \tag{20}$$

Here $n_{j,i}$ is the leader. The optimal favorite is different as follows equation (18-19).

$$M_1 = \sum_2^m M_j \tag{21}$$

$$n_{1i} = n_{1c-1} \mp M_1 \tag{22}$$

- **Stage 8: Convergence Check (CC):** The method analyzes the written scores of the top students to determine whether it has convergence. The method ends if the increase in the value of performance is less than a predetermined threshold. This avoids needless calculations by guaranteeing that the optimizing procedure ends when an ideal or nearly perfect solution is identified (Equation (23-24).

$$U_j(1+S) = \omega U_j(S) + d_1 r_1 \left(P_j(S) - y_j(S)\right) + d_1 r_1 \left(G_j(S) - y_j(S)\right) \tag{23}$$

$$y_j(1+S) = y_j(S) + U_j(1+S) \tag{24}$$

Using this hybrid technique, SGFO effectively addresses the issues of fracture detection on emotions. Its adaptive nature and capacity to handle complicated datasets make it a promising tool for improving highway safety by efficiently identifying problem areas and making timely maintenance decisions. Algorithm 1 displays the proposed method.

Algorithm 1: SGFO

Step 1: *Import necessary libraries*

$$and\ import\ numpy\ as\ np$$
$$from\ sklearn.svm\ import\ SVC$$
$$from\ sklearn.model\_selection\ import\ train\_test\_split$$
$$from\ sklearn.metrics\ import\ accuracy\_score$$

Step 2: *Define the SGFO class*

class SGFO:

$$def\ \_\_init\_\_\ (self, C = 1.0, kernel = 'rbf', gamma = 'scale'):$$
$$self.C\ =\ C$$
$$self.kernel\ =\ kernel$$
$$self.gamma\ =\ gamma$$
$$self.model\ =\ None$$
$$def\ train\ (self, X\_train, y\_train):$$
$$self.model\ =\ SVC(C = self.C, kernel = self.kernel, gamma = self.gamma)$$
$$self.model.performance(X\_train, y\_train)$$
$$def\ predict(self, X\_test):$$
$$return\ self.model.predict(X\_test)$$

Step 3: *Load and preprocess the datavalue*

Step 4: *Split the datavalue into training and testing sets*

$$X\_train, X\_test, y\_train, y\_test\ =\ train\_test\_split(X, y, test\_size, random\_state)$$

Step 5: *Initialize and train the SGFO model*

$$sgfo\ =\ SGFO\ ()$$
$$sgfo.train(X\_train, y\_train)$$

Step 6: *Make predictions on the testing set*

$$y\_pred\ =\ sgfo.predict(X\_test)$$

Step 7: *Evaluate the model*

$$accuracy =\ accuracy\_score(y\_test, y\_pred)$$

Print ("Accuracy:", accuracy)

4. RESULT AND DISCUSSION

Methods Impact on Students Use of Emotional Words

The study looked at whether student benefited from the suggested tools support by comparing how well they used mood words in their prewriting and post-writings. To reduce analytical bias, we also gave students Error Reduction Ratios (ERRs) along with the gain numbers. Figure 3 shows the error reduction ratio (ERR), which is a number that shows how many mistakes the student made between the full-mark and the pretest.

$$ERR\ =\ Post - Pre/Max - Pre \qquad (30)$$

As we use a six-point scale, Max is the highest score possible, and pretest and posttest are the scores from the pretest and posttest. Take note that mistakes in this research show that emotion-based words were used in the wrong way. One student's score went from 4 to 5, and the other's went from 5 to 6. This study is an example of how two students' scores went up by one point (out of 6). There were 20.0% improvements ((5−4)/5) and 16.7% improvements ((6−5)/6) for them. At first glance, it looked like the learner who got a better score did not make as much progress as the learner who got a lower score. The truth is that it can be hard for students who did better at the start to make big changes. However, the ERR shows something different. The learner who started with lower scores has improved by 50.0% ((5−4)/(6−4)), while the learner who started with better scores has improved by 100.0% ((6−5)/(6−5)). We used ERR to look at participants' results because it gives us a different view of how learners are improving. Figure 3 shows how each judge's score was given separately, which helped us understand how they felt about the students' use of mood words. We began by looking at the avg scores of the learner on the pretest and posttests.

Table 3: performance of pretest and posttest

Judges 1				Judges 2			
	no	Pretest	Score increased	Avg ERRs	pretest	Score increased	Avg ERRs
student	34	3.20	1.80	0.62	3.57	1.92	0.91
High proficiency	16	4.35	0.29	0.35	4.45	1.43	0.88
Low proficiency	19	2.25	2.91	0.68	3.24	2.34	0.94

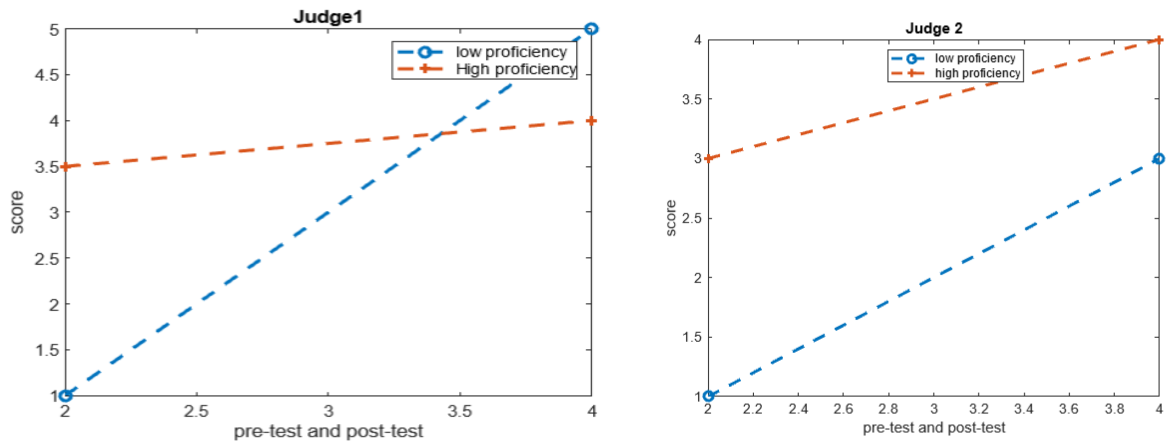

Figure 3: Different proficiency level

Lexicon-Based Approach

Based on lexicon-based predictions, a sentiment score above 0 means a positive emotion, a sentiment score of 0 suggest a neural sentiment, and a sentiment score below 0 suggest a negatives sentiment analysis [20]. We can think of these three groups as classes, which makes our prediction job easy to set up. It looks like the lexicon-based method isn't very good at what it does; only 43% of were correctly classified. This method didn't work well at all for neural words, most likely because the formula for emotion scores and the dictionary we used don't directly deal with neural words. However, were marked as either negative or positive, and the lexicon-based classifier did a little better for emotions (F1-scores of 53% and 42%, respectively), as shown in figure 4.

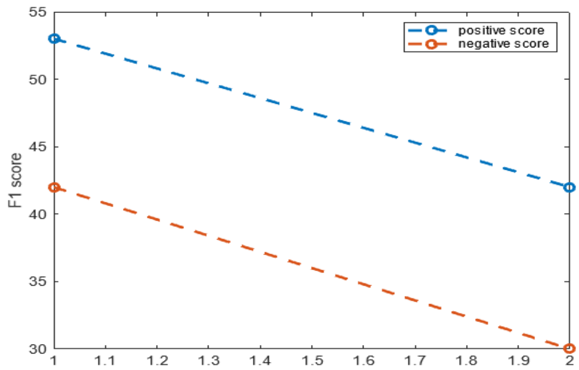

Figure 4: Emotions in Lexicon-based approach

Naive Bayes Algorithm using Machine Learning

In general, some easy binary detection jobs helps to identify the ways to test text classification. In spam identification, for instance, the aim is to mark each writing as either being junk ("positive") or not being junk ("negative"). This means we need to know for each item (email) our system marked it as junk or not [19]. These are the labels for each file that we are trying to match. These labels for people will be called "standard labels," as shown in Figure 5. The accuracy equation is in the bottom right corner of the table. Precision might seem like a measure, Since the classes aren't fair, accuracy doesn't work well.

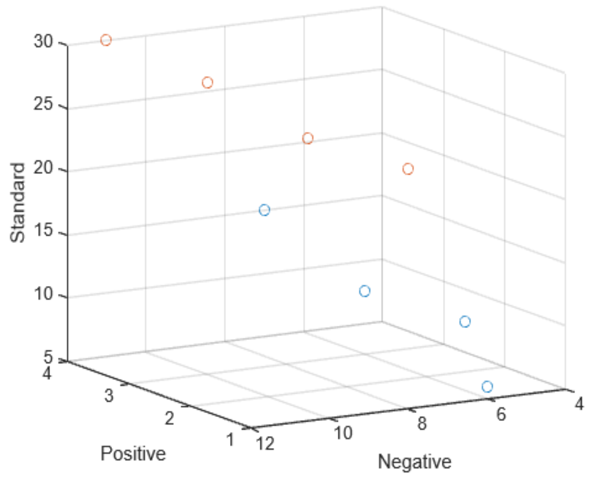

Figure 5: Standard labels value

RNN using Deep Learning

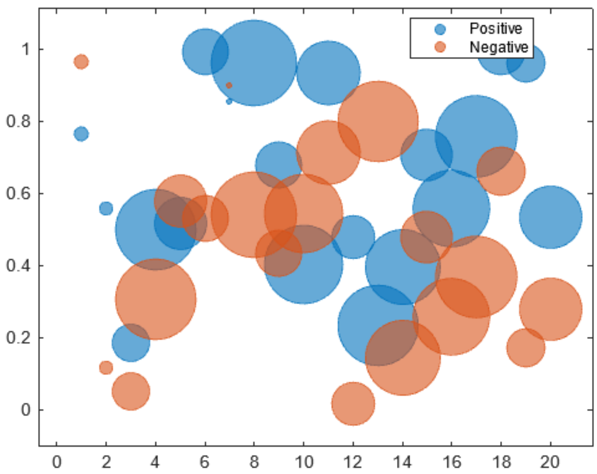

Figure 6: RNN feedforward result

The weights of the network are shared over time, as shown in Figure 6. Every recurrent layer has two sets of weights: one for the data input and one for the hidden unit. The last feedforward layer figures out the final output, which can be either positive or negative, as shown in the picture. It should be no more than 57%.

SGFO

When it came to teaching strategies and methods, 78% of teacher evaluations were marked as excellent, 15% as average, and 10% as poor. When it came to student evaluations of feelings, 73% were marked as excellent, 19% as average, and 12% as poor. In teacher evaluations, 82% of teachers said they were excellent, 10% said they were average, and 8% said they were poor. In student ratings, 75% said they were excellent, 15% said they were average, and 10% said they were poor. Findings from the experiment show that using SGFO to judge the quality of English teaching change in colleges leads to good results, helping both students and teachers understand.

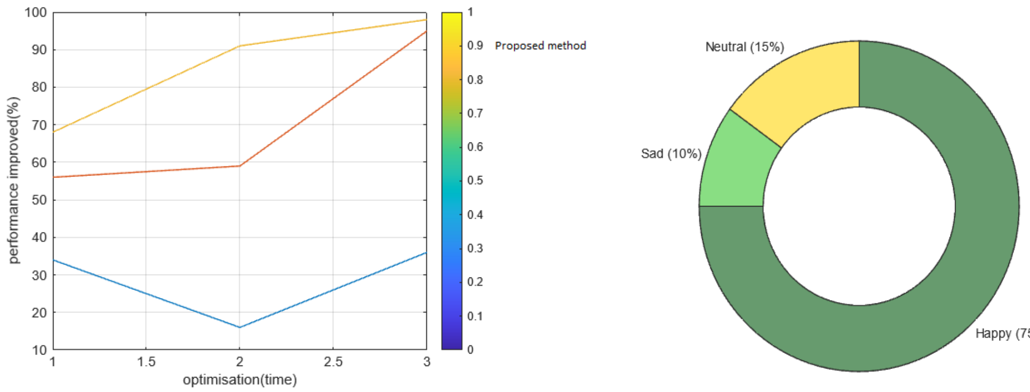

Figure 7: Analysis of students and teachers English writing, teaching improved range of strategy and their emotions

Analyzing the experimental results in Figure 7 reveals various variations in the enhancement of student's performance following the use of the proposed technique and this proposed method SGFO to optimize college English writing and teaching strategies. The improvement range of the method used in this study is the biggest one among them when compared to the initial performance improvement range, and the final improvement range is very constant.

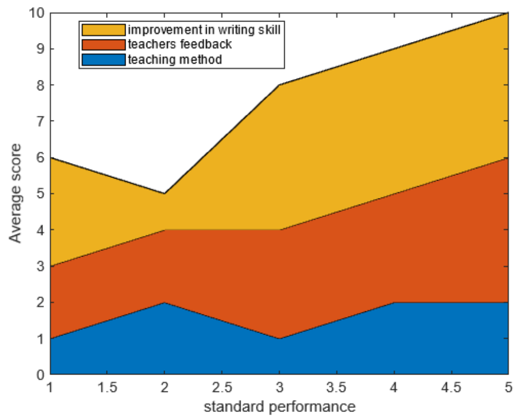

Figure 8: observing the students activities in universities

Item	Average score	Standard performance
Improvement in writing skill	6.2	9.8
Teachers feedback	3.5	5
Teaching method	2.1	3.5

Through the observation of their performance in class, the students' response to the new teaching methodology was evaluated using SGFO technology. The following are the specific observation indicators: 1) Classroom participation, which is measured by both the number and quality of student speeches during class discussions, as well as by the students' responses to other students' speeches; 2) Commitment to writing tasks, which is measured by the amount of time students spend writing assignments during and after class, as well as by their level of concentration while writing; 3) Acceptance of teacher feedback, which is measured by the circumstances in which students receive feedback from teachers, including their comprehension of the comments and how they apply them in subsequent writing. It is evident from the observation notes, which are displayed in Figure 8, that students were happy with the teacher's feedback, actively cooperated with the new teaching strategy, and dedicated more time and effort to writing assignments than they had previously.

BP neural Network

The data show that 90% of teachers were ranked as excellent, 11% as good, 2% as good, and 1% as poor in their attitude toward teaching. When students rate teachers' attitudes, 80% say they are great, 14% say they are good, 6% say they are average, and 0% say they are poor. In the same way, 82% of teachers were ranked as Excellent, 16% as good, 7% as good, and 1% as poor in their teaching material ratings. The same is true for students: 82% of students were ranked as excellent, 17% as good, 3% as average, and 1% as poor. When it comes to teaching techniques and methods, 96% of teacher evaluations are good, 4% are average, and 0% are poor. On the other hand, 94% of student evaluations are Excellent, 7% are good, 5% are average, and 1% are poor. As shown in Figure 8, 98% of students gave teachers excellent ratings, 2% gave them good ratings, 2% gave them average ratings, and 0% gave them bad ratings. This means that 89% of teachers thought the teachers were effective.

Overall rating	Grading
$x>=9$	Excellent
$8.0<=x<9$	Very Good
$7\leq x<8$	Good
$x<6$	Poor

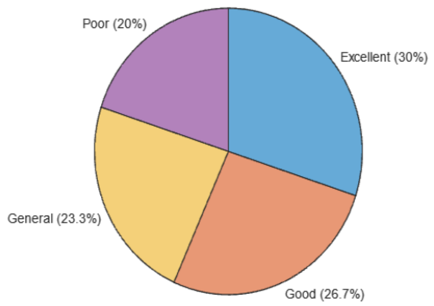

Figure 9: BP neural teaching strategy rating

Performance of proposed model:

By using the SGFO method, students' English results can also show how the way they are taught has changed, which can lead to real-world changes for the students. The average English score for students in the same class went up from 68.8 to 70.8, the number of students who met the requirements went up from 72 to 128, and the number of students with more than 85 points went up from 24 to 35. These changes were seen in the systems used for academic administration. By checking the attendance records of English class students, it was seen that the rate of attendance went up from 80% at the start of the term to 96% by the end, as shown in Figure 10.

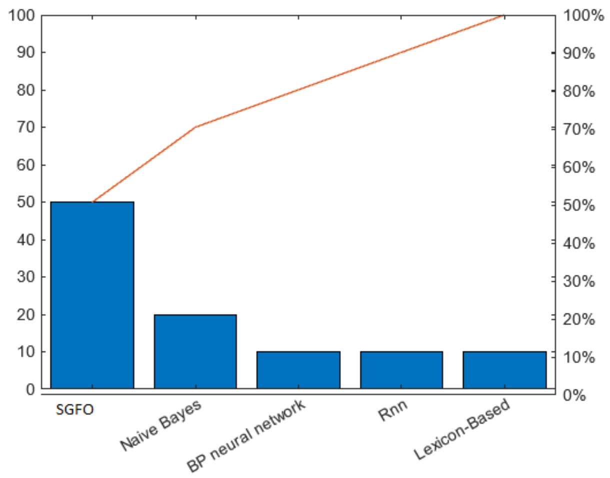

Figure 10: Performance comparison of all methods

Accuracy, Specificity, Recall:

The number of features was reduce by 97.9%, and 95 features were chosen from the original accuracy, specificity, and memory features. These data show that the SGFO algorithm works well as a feature selection algorithm and does a good job of classifying sentiment. The SGFO method does not need any specific parameter changes to work at its best, which is what makes this high quality function possible. With an accuracy of 98%, a precision of 83.6%, and a recall rate of 95.2%, this graph also shows that the SGFO algorithm can now do feature selection for classification sentiment as well as or better than the other feature selection algorithms with accuracy and Specificity. Specificity shows what number of the things that the system found (i.e., the things that the system marked as positive) are actually positive (Refers to the number of things were correctly identified by the system based by input values on recall in figure 11.

Recall =no. of true positive / no of true positive + no of false negatives (31)

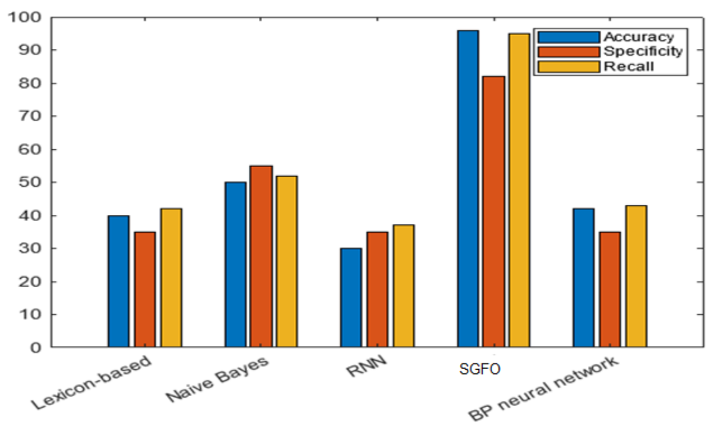

Figure 11: Accuracy, Specificity, Recall

5. Conclusion

This study also shows that the approach has a big impact on sentiment analysis since emotions play a major role in filtering out distracting and irrelevant information from the data, which can lead to somewhat accurate classification findings. The feature selection procedure will be challenging because it consumes a lot of processing power, and indirectly hurting the sentiment classification accuracy if this excessive and unnecessary data is not removed. Thus, based on the findings of sentiment analysis in English writing and teaching methodologies, the feature selection algorithm SGFO helps in raising the accuracy of sentiment classification to higher levels.

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