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A PROPOSED GAMIFICATION FRAMEWORK USING SENTIMENT ANALYSIS AND FUZZY LOGIC IN HIGHER EDUCATION

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ABSTRACT

The traditional methods used to analyze and collect student feedback are not scalable, so determining levels of student satisfaction is difficult and entails various challenges. This paper aims to understand students' sentiments about the use of gamification in higher education. First, we measured student satisfaction with sentiment class. We observed that there is a direct relationship between the sentiment scores of the Senti WordNet lexicon (SWN) and student satisfaction level. If the sentiment score of the SWN lexicon increases, then student satisfaction also increases. The student satisfaction level was 81% for the SSAGS dataset. Furthermore, when using SVM, NB, and DT classifiers, we found that some aspects yield high results because students' opinions are positive, and their satisfaction levels are higher. For example, the accuracy of the motivation aspect is equivalent to 100% with the SVM and DT classifiers. Additionally, the accuracy of the clarity aspect and the improvement aspect is equivalent to 92.5% with the NB classifier. Second, the SSAGS dataset was evaluated, and this dataset comprises two different experiments, one using the SWN lexicon and the other using SVM, NB, and DT classifiers. Finally, the results showed high accuracy and high recall in the process of analyzing student opinions to determine the level of student satisfaction.

Keywords: *Sentiment Analysis, Gamification, Fuzzy Logic, Higher Education*

1. INTRODUCTION

The traditional methods used by teachers to motivate and encourage students in the educational system are not scalable, so determining levels of student satisfaction is difficult and entails various challenges [1]. Conventional methods also do not create a spirit of competition among students, although motivating students is the basis of a learning strategy [2]. Gamification is a vital method of motivating and encouraging students in universities. Gamification tests motivate students and facilitate a spirit of competition, encouraging students to achieve. Thus, gamification is a supportive way for learners to enjoy education [3].

Sentiment analysis (SA) analyzes students' opinions and sentiments, determining whether opinions are positive, negative, or neutral and whether the choice of an opinion is objective or subjective [4]. When analyzing students' sentiments, we can determine the level of student satisfaction through fuzzy logic (FL) and thus find whether it reflects the perceived genuine sentiment of the students' opinions [5]. There is a connection between SA and FL: their sentiment analysis system was developed by combining inputs of multiple forms (e.g., emojis), and they used FL to determine the exact level of a user's emotions through the following emotional labels: very positive, positive, negative, very negative. The results showed that tweets related to user satisfaction with Google, Amazon, and Microsoft cloud services achieved accuracy of 83%, recall of 89%, and F-score of 83% [6]. They proposed obtaining word scores based on word sentiment scores through Senti WordNet and AFINN lexicographers, with which they conducted their experiments on three datasets: the Film Polarity Dataset by IMDB, Pang-Lee, and the Hotel Ratings Dataset. Words' polarity, when comparing their ambiguous approach with modern, non-ambiguous methods revealed the superiority of the ambiguous approach [7]. They

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classified opinions into strong positive, positive, negative, and strong negative to summarize sentiment based on aspect using FL. They combined unusual sentences to calculate missing sentiment and achieve accurate results, which showed the applicability of extracting opinions in an effective way [8]. They introduced a new PSD approach to calculating emotions based on FL and SA. In contrast to traditional methods, PSD is based on a logical premise that emotions are related to each other, and experiments have shown that the proposed approach achieves similar accuracy when compared to well-known, traditional learning methods [9]. They focused on the fact that many consumers evaluate everything on the Internet, especially food in restaurants, to show their point of view, and these opinions are important in the decision-making process, especially in the group of uncertain comments, as manual evaluation and extracting real opinions is very difficult. To solve this problem, they used an automated methodology To extract opinions and obtain feedback, whether positive, negative, or neutral in these opinions, as this is done using sentiment analysis through a smart method called Neuro - Fuzzy Sentiment Classification, which is an automated method for estimating and predicting feelings, where they used Senti WordNet and POS to extract information and opinions, and they achieved accuracy High and knowing the products that consumers like, as well as quickly identifying their opinions, and thus making the decision and development accordingly [10]. They used many machine learning algorithms to evaluate the comments on the various topics on the online educational platforms, where they dealt with 6,000 reviews that they collected manually from 6 applications related to education and classified them through sentiment analysis, and they used logistic regression, which achieved the highest accuracy (88%) among five algorithms to rate reviews comments [11]. They analyzed feelings about the field of Business Information Systems (BIS) studies in order to reveal their perceptions about the field to explore their cultural background and may affect the professional competencies of students in the field of information technology in the field of (BIS). The analysis of the results provided a behavioral pattern for a successful student in the field of study (BIS) [12].

The key idea of this research is to show high accuracy and high recall in the process of analyzing student opinions to determine levels of student satisfaction in learning using gamification quizzes. This research recommends applying formative assessment in an innovative way, enriching the activities accompanying the educational process in higher education, and applying fuzzy logic to obtain a more accurate analysis.

2. MATERIALS AND METHODS

2.1 Sentiment Analysis

SA is one of the most continuous research areas in the field of text mining due to the presence of extensive web content that carries the opinions of people on social networking sites [13]. In addition, it is a field that integrates natural language processing and machine learning techniques to analyze people's opinions and sentiments. People's sentiments can be expressed via different measures, determining whether they are positive, negative, or neutral and determining whether a text is objective or subjective [14].

2.2 Fuzzy Logic (FL)

FL is a powerful tool that was designed to solve problems because it emulates human thinking, including all intermediate possibilities between the numeric values 0 and 1 [15]. In addition, FL gives flexibility in thinking as it considers all the information available to it and gives the best possible decision according to this information [16].

3. PROPOSED FRAMEWORK

The proposed gamification framework based on SA and FL (GFSAFL) is divided into four main phases as shown in Fig. 1.

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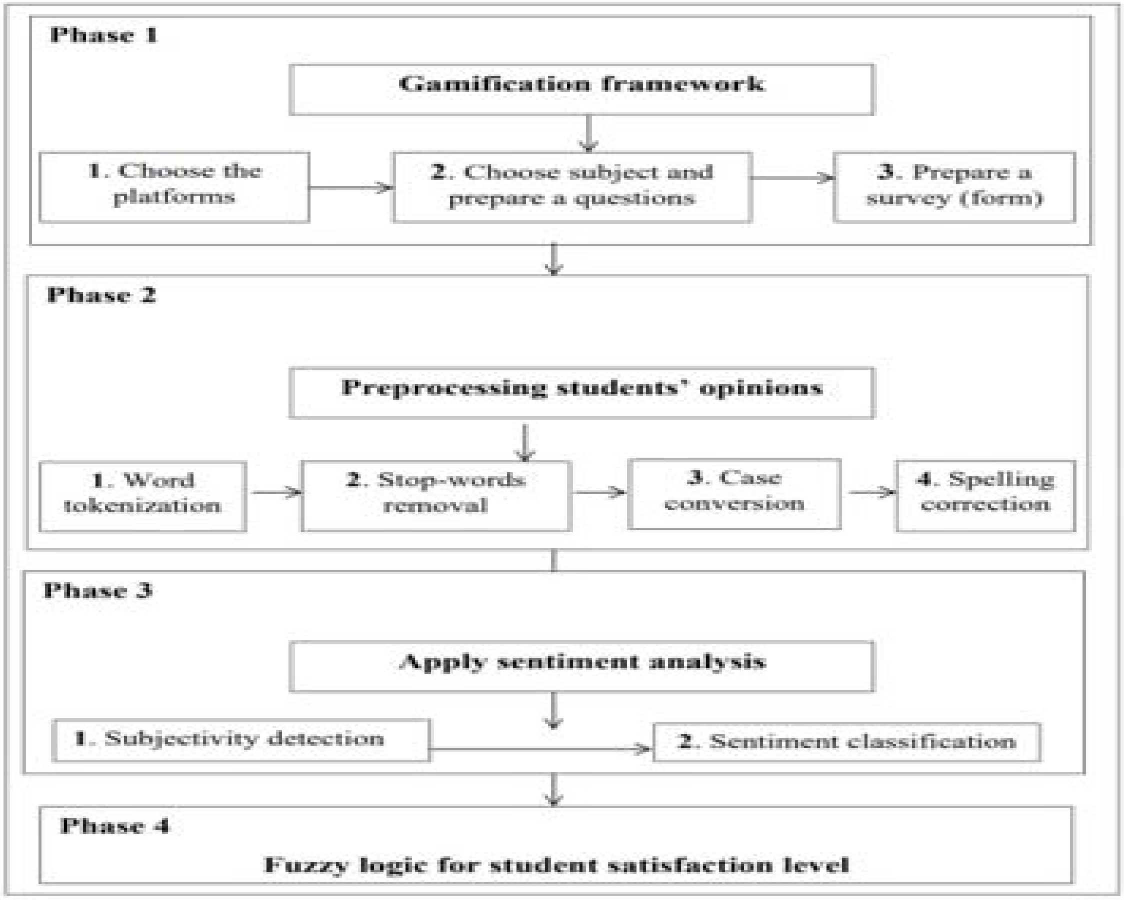
Figure 1: GFSAFL architecture



4. EXPERIMENTS AND RESULTS

4.1 Dataset Description (SSAGS Dataset)

The SSAGS (Student Sentiment Analysis on Gamification Style) dataset is used to analyze students' opinions on gamification in teaching process assessment on data security material for third-year students in the Computer Teacher Preparation Department. A set of different questions was made to evaluate four chapters of the data security material. After the third-year students answered each set of questions, they evaluated the gamification style used in each chapter of the data security material through five aspects: ease (Is the gamification style easy or not?), clarity (Is the gamification style clear or not?), organization (Is the gamification style organized in its evaluation of the content or not?), motivating and encouraging students (Is the gamification style motivating and encouraging for students or not?), and improving and developing students' achievement (Does the gamification style help improve and develop students' achievement with the material or not?). Each aspect consisted of 200 rows and had three labels: 0 (neutral), 1 (positive), and -1 (negative). Table 1 shows the number of positive, negative, and neutral opinions on the gamification style for each of the aspects.

Table 1: SSAGS Dataset Description

Aspect	Positive	Negative	Neutral
Ease of the gamification style	179	16	4
Clarity of the gamification style	168	21	11
Organize in its evaluation of the content	185	12	2
Improving the students 'achievement level	187	8	3
Motivating students	189	9	1

4.2 The Performance Measures

To evaluate the performance of the GFSAFL framework, accuracy (A), precision (P),

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recall (R), and F-score (F) measures were used. Equation (1) shows accuracy, which is a measure of the overall correctness of the GFSAFL framework; it is the number of students' opinions that are correctly classified divided by the sum of the total students' opinions. Equation (2) shows precision, which is defined as the number of relevant students' opinions retrieved by SA divided by the total number of students' opinions retrieved by that SA. Equation (3) shows recall, which is defined as the number of relevant students' opinions retrieved by an SA divided by the total number of existing relevant students' opinions [17]. Equation (4) shows the F-score, also called the F1-score, a measure of the GFSAFL framework's accuracy on a dataset. It is the average of precision and recall [18].

$$Accuracy = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \quad (1)$$

$$Precision = \frac{T_p}{T_p + F_p} \quad (2)$$

$$Recall = \frac{T_p}{T_p + F_n} \quad (3)$$

$$F1 - score = \frac{2 \ x \ Precision \ x \ Recall}{Precision + Recall} \quad (4)$$

where T_p (true positive) is the proportion of positive states that were correctly classified, T_n (true negative) is the proportion of negative states that were correctly classified, F_p (false positive) is the proportion of positive states that were incorrectly classified, and F_n (false negative) is the proportion of negative states that were incorrectly classified [19].

4.3 RESULTS AND DISCUSSION

Experiment 1: Senti WordNet lexicon (SWN)

The SSAGS dataset was used to analyze students' opinions on using gamification in teaching process assessments on data security material for the third-year students in the Computer Teacher Preparation Department. The SWN lexicon has been applied to every aspect of the dataset as the lexicon's way of working is based on polarity shifters and is compared with the training results to get feedback for students, whether positive, neutral, or negative.

4.3.1 Applying the sentiment analysis

- **Clarity in SSAGS**

Clarity is the first aspect of SSAGS to receive student feedback to analyze students' opinions on using gamification in teaching process assessments on data security material. Table 2 shows the calculated values of A, P, R, and F for the students' opinions using the SWN lexicon for clarity.

Table 2: A, P, R, and F for students' opinions using the SWN lexicon for clarity

clarity Aspect	Accuracy	Precision	Recall	F1-Score
1 (positive)	64.5%	95.81%	98.77%	97.26%
0 (neutral)	82.5%	76.92%	45.45%	57.14%
-1 (negative)	82%	70%	87.5%	77.78%

- **Ease in SSAGS**

Ease is the second aspect of SSAGS. Table 3 shows the calculated values of A, P, R, and F for the students' opinions using the SWN lexicon for ease.

Table 3: A, P, R, and F for students' opinions using the SWN lexicon for ease

Easy Aspect	Accuracy	Precision	Recall	F1-Score
1 (positive)	89.95%	90.5%	98.18%	94.19%
0 (neutral)	91.96%	50%	12.5%	20%
-1 (negative)	95.98%	81.25%	72.22%	76.47%

- **Organizing in SSAGS**

Organizing is the third aspect of SSAGS. Table 4 shows the calculated values of A, P, R, and F for the student's opinions using the SWN lexicon for organizing.

Table 4: A, P, R, and F for students' opinions using the SWN lexicon for organizing

ImprovementAspect	Accuracy	Precision	Recall	F1-Score
1 (positive)	87.37%	96.26%	97.83%	97.04%
0 (neutral)	95.45%	33.33%	16.66%	22.22%
-1 (negative)	91.92%	75%	75%	75%

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- **Improvement in SSAGS**

Improvement is the fourth aspect of SSAGS. Table 5 shows the calculated values of A, P, R, and F for the students' opinions using the SWN lexicon for improvement.

Table 5: A, P, R, and F for students' opinions using the SWN lexicon for improvement

Organizing Aspect	Accuracy	Precision	Recall	F1-Score
1 (positive)	87.43%	88.64%	97.61%	92.92%
0 (neutral)	90.45%	50%	5.26%	9.52%
-1 (negative)	96.98%	75%	75%	75%

- **Motivation in SSAGS**

Motivation is the fifth aspect of SSAGS. Table 6 shows the calculated values of A, P, R, and F for the students' opinions using the SWN lexicon for motivation.

Table 6: A, P, R, and F for students' opinions using the SWN lexicon for motivation

Motivation Aspect	Accuracy	Precision	Recall	F1-Score
1 (positive)	86.43%	96.29%	100%	98.11%
0 (neutral)	98.99%	100%	100%	100%
-1 (negative)	87.44%	100%	56.25%	72%

From the above, we find that some aspects have high results due to the SWN lexicon's ability to identify them according to the polarity shifters. It can thus classify the opinions, whether positive, neutral, or negative. Some aspects yielded low results due to the lack of certain polarity shifters in the SWN lexicon. Therefore, it is difficult to classify the opinions as positive, negative, or neutral.

4.3.2 Fuzzy logic for student satisfaction level

First, we defined the input and output variables. Our input variable was sentiment class, as shown in Fig. 2, and our output variable was student satisfaction, as seen in Fig. 3.

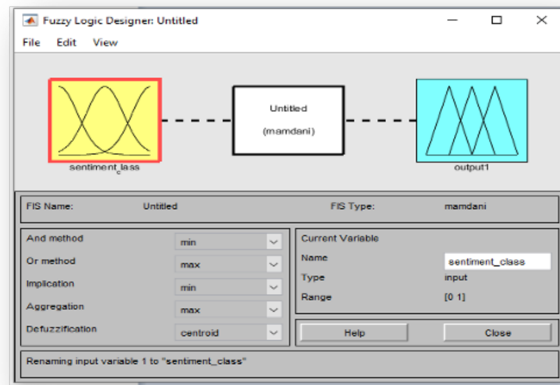

Figure 2: Fuzzy sets (input variable)

Second, we assigned three terms to students' opinions corresponding to input variables (negative, neutral, positive), as seen in Fig. 4, and output variables (not satisfied, moderate, satisfied), as shown in Fig. 5.

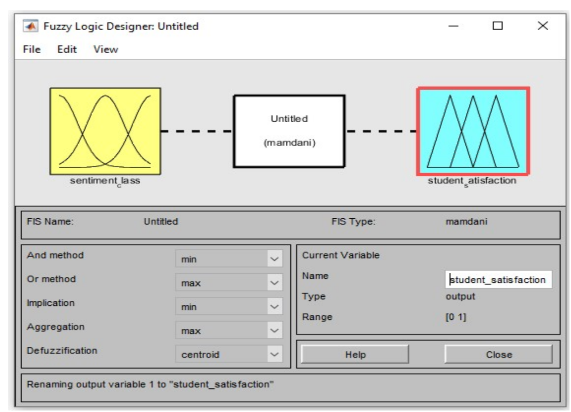

Figure 3: Fuzzy sets (output variable)

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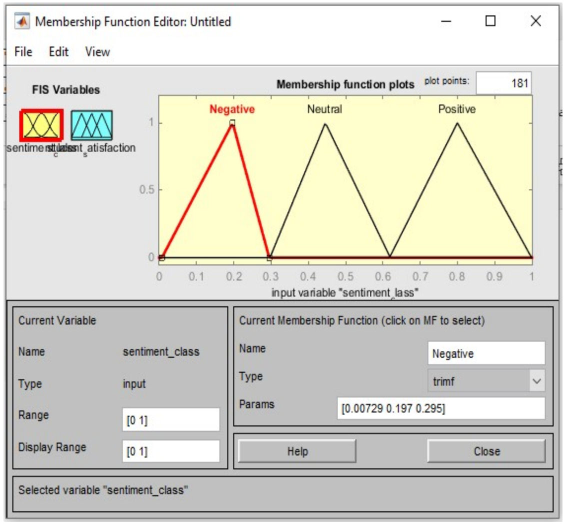

Figure 4: Fuzzification (secnd step in fuzzy logic)

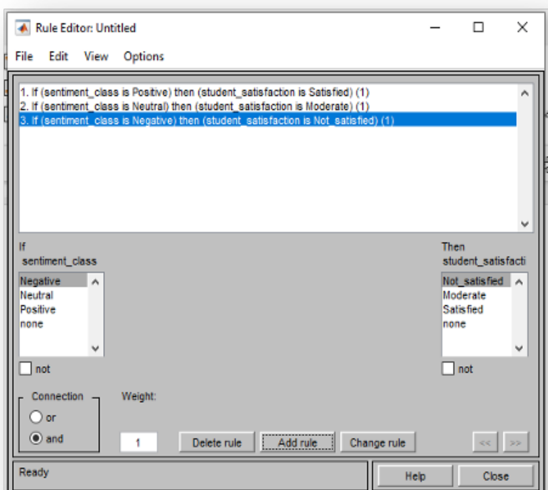

Figure 5: Fuzzification (second step in fuzzy logic: assign three terms to output variables (not satisfied, moderate, satisfied))

Third, the fuzzy rules are entered to produce a suitable result as shown in Fig. 6.

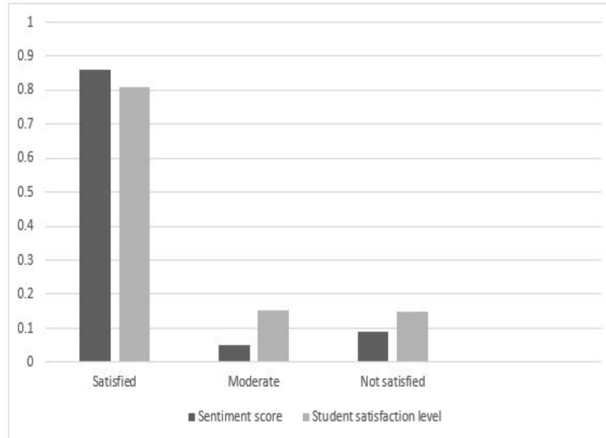

Figure 6: Fuzzy if/then rules (third step in fuzzy logic)

Fourth, we measured student satisfaction. We observed that there was a direct connection between the sentiment scores from the SWN lexicon and student satisfaction levels, as shown in Table7.

Table 7: Student satisfaction level averages with sentiment scores of the SWN lexicon in all aspects

	SWN lexicon	Student satisfaction level
1 (positive)	0.86	0.81
0 (neutral)	0.05	0.152
-1 (negative)	0.070	0.151

Fig. 7 shows a direct connection between the sentiment scores of the SWN lexicon and student satisfaction levels.

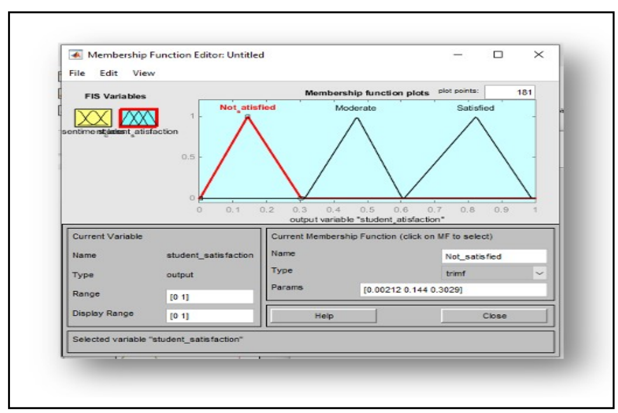

Figure 7: Evaluating student satisfaction level with sentiment scores

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Experiment 2: Using SVM, NB, and Decision Tree Classifiers

The SSAGS dataset was divided into 80% training data and 20% test data. Support vector machine (SVM), naïve Bayes (NB), and decision tree (DT) classifiers were selected and applied to the SSAGS dataset; they are the most popular machine learning classifiers and were used to analyze students' opinions on using gamification in teaching process assessments on data security material. The accuracy of the SVM, NB, and DT classifiers on each aspect of the SSAGS Dataset was tested. Several studies have used these classifiers with SA. [20], [21], [22], and [23] used SVM with SA; [24], [25], [26], and [27] used NB with SA; and [28], [29], and [30] used DT with SA.

- **Clarity in SSAGS**

Table 8 shows the average calculated values of A, P, R, and F for students' opinions (positive, neutral, and negative) using SVM, NB, and DT classifiers for clarity.

Table 8: A, P, R, and F for students' opinions using SVM, NB, and DT classifiers for clarity

Clarity Aspect	Accuracy	Precision	Recall	F1-Score
SVM	92.5%	93%	100%	96%
NB	92.5%	93%	100%	96%
DT	95%	95%	100%	97%

- **Ease in SSAGS**

Table 9 shows the average calculated values of A, P, R, and F for students' opinions (positive, neutral, and negative) using SVM, NB, and DT classifiers for ease.

Table 9: A, P, R, and F for students' opinions using SVM, NB, and DT classifiers for ease

Easy Aspect	Accuracy	Precision	Recall	F1-Score
SVM	95%	94%	100%	97%
NB	85%	85%	100%	92%
DT	92.5%	94%	97%	96%

- **Organizing in SSAGS**

Table 10 shows the average calculated values of A, P, R, and F for students' opinions (positive, neutral, and negative) using SVM, NB, and DT classifiers for organizing.

Table 10: A, P, R, and F for students' opinions using SVM, NB, and DT classifiers for organizing

Organizing Aspect	Accuracy	Precision	Recall	F1-Score
SVM	95%	95%	100%	97%
NB	90%	90%	100%	95%
DT	97.5%	97%	100%	99%

- **Improvement in SSAGS**

Table 11 shows the average calculated values of A, P, R, and F for students' opinions (positive, neutral, and negative) using SVM, NB, and DT classifiers for improvement.

Table 11: A, P, R, and F for students' opinions using SVM, NB, and DT classifiers for improvement

Improvement Aspect	Accuracy	Precision	Recall	F1-Score
SVM	95%	95%	100%	97%
NB	92.5%	93%	100%	96%
DT	100%	100%	100%	100%

- **Motivation in SSAGS**

Table 12 shows the average calculated values of A, P, R, and F for students' opinions (positive, neutral, and negative) using SVM, NB, and DT classifiers for motivation.

Table 12: A, P, R, and F for students' opinions using SVM, NB, and DT classifiers for motivation

Motivation Aspect	Accuracy	Precision	Recall	F1-Score
SVM	100%	100%	100%	100%
NB	90%	90%	100%	95%
DT	100%	100%	100%	100%

From the above, we find that some aspects yielded high results because students' opinions were positive, and their satisfaction levels were higher. For example, the accuracy of the motivation aspect is equivalent to 100% with the SVM and DT classifiers. Additionally, the accuracy of the clarity aspect and the improvement aspect is equivalent to 92.5% with the NB classifier.

5. CONCLUSION

This paper aims to understand students' sentiments about the use of gamification in higher education. The GFSAFL framework was divided into four phases: gamification framework, pre-processing students' opinions, applying SA, and FL classifiers for student satisfaction levels. We measured student satisfaction with sentiment class. We observed that there is a direct relationship between the sentiment scores of the SWN lexicon and student satisfaction levels. If the sentiment score of the SWN lexicon increases, then student satisfaction also increases. The student satisfaction level was 81% in the SSAGS dataset. Furthermore, when using SVM, NB, and DT classifiers, we found that some aspects yielded high results because students' opinions were positive, and their satisfaction levels were higher. For example, the accuracy of the motivation aspect was equivalent to 100% in the SVM and DT classifiers. Additionally, the accuracy of the clarity aspect and the improvement aspect was equivalent to 92.5% in the NB classifier. The results show high accuracy and high recall. In future work, we want to extend the scope of the applied gamification framework to more educational materials in higher education, expand our dataset to obtain more accurate results, apply a GFSAFL framework to a dataset in Arabic, improve the GFSAFL framework using deep learning, and use other classifiers for machine learning.

On one hand, three studies: [9], [31], [32] depended on getting opinions in general for their own dataset and using sentiment analysis with fuzzy logic. In this research, the GFSAFL framework was implemented on more than one aspect. Also, we have used the gamification framework to analyze the students' opinions based on sentiment and fuzzy logic.

On the other hand, [33], [9] used fuzzy logic to determine the level of student satisfaction. In this research, we used fuzzy logic and ML classifiers (SVM, NB, DT) to determine the student's level of satisfaction with the student's feedback about the questions placed in the gamification framework.

For future work, this work can be improved in multiple directions:

- Extending the scope of the applied of the gamification framework to more educational materials in higher education.
- Increasing our dataset to get more accurate results.
- Applying a GFSAFL framework to a dataset in Arabic.
- Improving GFSAFL framework using deep learning.
- Using other classifiers for machine learning.
- Recording students' opinions to be more accurate using another sentiment dictionary such as Senti Full.

In the future, we intend to improve the proposed framework to help people of determination and special abilities by using a dynamic application that they can interact with as it helps them in their understanding of the materials through the development of the gamification framework.

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