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Improve the Accuracy of the System SENTIMENT ANALYSIS FOR Students about Teaching Using (GWO-CNN)

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Abstract

Sentiment analysis has become a vital area of research in artificial intelligence, particularly within natural language processing. With the widespread sharing of opinions and sentiments online, organizations, businesses, and governments can leverage automated tools to analyze feedback and evaluations. In the context of education, the increasing focus on student engagement and attendance has highlighted the importance of understanding feedback in institutional settings. This study employs a lexical sentiment analysis approach to determine the polarity of student responses, using the Vietnamese Student Feedback Corpus (UIT-VSFC), which contains 16,175 sentences of student feedback. The dataset was translated into English for analysis. The proposed method achieved an impressive accuracy of 98%. Additionally, machine learning techniques, including Naïve Bayes (NB), K-Nearest Neighbors (KNN), and Support Vector Machines (SVM), were applied, resulting in accuracies of 94%, 88%, and 92%, respectively.

Keywords: GWO , CNN, Machine learning, SENTIMENT ANALYSIS, NLP.

تحسين دقة نظام تحليل المشاعر للطلاب حول التدريس باستخدام الشبكة العصبية التلافيفية وخوارزمية الذئب الرمادي

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الخلاصة

لقد أصبح تحليل المشاعر مجالًا حيويًا للبحث في مجال الذكاء الاصطناعي، وخاصة في معالجة اللغة الطبيعية. ومع انتشار تبادل الآراء والمشاعر عبر الإنترنت، يمكن للمؤسسات والشركات والحكومات الاستفادة من الأدوات الآلية لتحليل الملاحظات والتقييمات. وفي سياق التعليم، سلط التركيز المتزايد على مشاركة الطلاب وحضورهم الضوء على أهمية فهم الملاحظات في البيئات المؤسسية.

تستخدم هذه الدراسة نهج تحليل المشاعر المعجمية لتحديد قطبية استجابات الطلاب، باستخدام مجموعة ملاحظات الطلاب الفيتنامية (UIT-VSFC)، والتي تحتوي على 16175 جملة من ملاحظات الطلاب. تمت ترجمة مجموعة البيانات إلى اللغة الإنجليزية للتحليل. حققت الطريقة المقترحة دقة مذهلة بنسبة 98٪. بالإضافة إلى ذلك، تم تطبيق تقنيات التعلم الآلي، بما في ذلك خوارزميات (NB)، و K (KNN)، و (SVM)، مما أدى إلى دقة 94٪ و88٪ و92٪ على التوالي.

الكلمات المفتاحية : خوارزمية الذئب الرمادي , الشبكة العصبية التلافيفة , التعلم العميق , تحليل المشاعر , معالجة اللغة الطبيعية .

1. Introduction

Sentiment analysis has been a popular tool in a variety of industries during the last ten years, including social networks, business, and education. Because of the huge volume of information and the nature of the language employed, digesting student perspectives can be challenging, especially in the sector of education[1] . Sentiment analysis is being used more and more in this discipline, although it is still difficult. Numerous reviews in the academic literature have looked at the state of sentiment analysis applications from different angles in this discipline. Nevertheless, there isn't a thorough study of the literature that systematically classifies the studies and findings of machine learning (ML), deep learning (DL), and natural language processing (NLP) solutions for sentiment analysis in education. The existing educational system generates enormous amounts of data every day in a variety of formats, much of which contains important but hidden information. Sentiment analysis and opinion mining approaches can offer major benefits, one of which is the ability to find and extract hidden pearls from the vast ocean of educational data. Students' thoughts and opinions are an important source of data for examining how they behave in relation to a course and subject as well as for examining teacher feedback to improve performance in institutions and policies. While "sentiment analysis" and "opinion mining" may sound similar, they differ slightly in that the former deals with identifying and evaluating people's ideas on a certain topic, while the latter refers to extracting and analyzing emotive words and phrases[2].

We consider both methods to be equally applicable to this investigation. Positive, negative, or neutral sentiment/opinion polarity reveals a person's attitude toward a particular entity. In contrast, emotions are the sentiments that a person displays in relation to a certain topic. For the identification and categorization of emotions, numerous hypotheses have been put out since the 1960s. Emotions are divided into eight categories according to a study by Plutchik: surprise, anger, fear, joy, sadness, disgust, and trust. Words, sentences, or documents can all be subjected to sentiment analysis. Still, addressing feelings manually is not possible given the volume of documents[3]. Data processing must therefore be automated. NLP is used to do sentiment analysis on text-based, sentence-based, or document-based language corpora. Pure NLP techniques, such as dictionary- and lexicon-based methods, are employed for sentiment analysis in the majority of research articles in this topic. This paper's usage of traditional machine learning classifiers is quite low. The subject of sentiment detection and classification has seen a transition in recent years from purely natural language processing (NLP)-based methods to deep learning-based modeling. This transition has been reflected in a high volume of recent publications. If we look at the previous literature, we find that a study [4] on sentiment analysis in the educational field focused on identifying the methods and resources used in sentiment analysis and identifying the main benefits of using sentiment analysis on educational data. Further information is provided from different dimensions, including bibliographic sources, research trends and patterns, and the latest tools used in statistical analysis. Rather than listing data sources, we present four categories of education-based data sources used in statistical analysis. Also, to provide more service to the researcher in the field of sentiment analysis, we will present more than one set of studies based on learning methods, techniques used, and the most commonly used vocabulary related to education for sentiment analysis. Han, Z. et al. (2020) [5] A summary of sentiment analysis in the context of education is provided. A framework for multimodal sentiment detection and analysis (SDA) is presented by the study's authors. Our review seeks to cover all aspects of sentiment analysis for educational content, with a systematic focus on textual information, as opposed to concentration on textual, audio, and visual cues.. offered a methodical mapping of deep learning and natural language processing for sentiment analysis on student comments. Of the 612 articles located in learning platform environments, this study looked at 92 of them. The search was conducted using the PRISMA framework, yielding only publications published in the period of 2015 to 2020. This study showed that the field of sentiment analysis on student feedback using NLP and deep learning is expanding quickly. However, structured datasets, standardized solutions, and work aimed at expressing sentiments are necessary for the field to reach full maturity in research and development [6].

Nguyen et al. (2018) [7] analyzed the sentiment analysis of instructional material using four machine learning and natural language processing techniques: Naive Bayes, Maximum Entropy, Long Short-Term Memory, and Bi-directional Long Short-Term Memory.

Edalati, M., et al.(2020) . [8]These models, however, relies only on the basic NLP techniques to process data for finding sentiments. To better capture domain specific sentiments for educational feedback, there is a need to incorporate both semantic and contextual information form users input.

Sangeetha, K.(2021). [9] experimented on 16,175 Vietnamese students' feedback to classify their sentiments (positive, negative, and neutral). They converted the dataset to the English language for polarity classification.

Arai, K . (2022).[10] proposed a system for categorising students' feedback using opinion mining from students' feedback data collected from a University in Vietnam over a two (2) year period in 2017 and 2018. The data was organised into three (3) classes: positive, negative and neutral, and a sentiment dataset of 5000 classified sentences was built from the dataset. The sentiment analysis system is widely applied in many scientific fields, including business, social networks, and education. This research will talk about the process of sentiment analysis for lecturers using artificial intelligence algorithms Using hybrid Gray W lf Optimizer and Convolutional Neural Network (GWO-CNN).

1.1 Problem Statement

Universities face significant challenges in collecting student feedback on teacher performance due to the increasing number of students and the complexity of languages and terminology used. Traditional methods such as paper-based questionnaires require a lot of time and effort, making it difficult to obtain a comprehensive and reliable evaluation. This paper proposes an automated system based on sentiment analysis using CNNs and performance optimization using GWO algorithm, to provide an advanced solution that efficiently addresses these challenges, and enables faster and more accurate collection of student feedback, while reducing the cost and time required.

1.2 Sentiment Analysis Levels

Many levels of sentiment analysis have been explored, including the document, sentence, phrase, and aspect levels. Figure illustrates sentiment analysis at many levels, including document, sentence, phrase, and aspect levels[11].

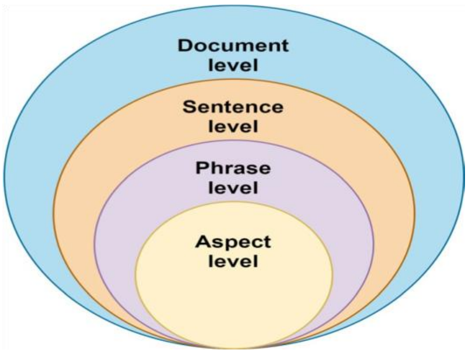

Figure -1 Sentiment analysis stages [12]

3 The proposed method Model

In the field of sentiment analysis, polarity identification is one of the most important applications of natural language processing. In this research, we will focus on students' opinions about these two teachers in the field of education.. In this research, the lexical method of sentiment analysis is confirmed. After completing the opinion pre-processing process, a file of words is created. Opinions are prepared for the analytical processing of sentiments or opinions. Word Polarity The proposed algorithms were implemented after converting the words into a vector. Each note stored in the data set of this vector has the polarity of each word from the overall feedback. Next, the overall polarity of the feedback is counted. After converting the words into vectors, they are entered into the proposed GWO and CNN algorithms to determine and evaluate the opinions and the polarity of the opinions. Figure (1-3) A view of the proposed method system framework. Teacher feedback is an important and vital resource for interdisciplinary research that includes a combination of two different types of research fields, namely, sentiment analysis and education. In our research, we will use data from a Vietnamese university after converting it into English.

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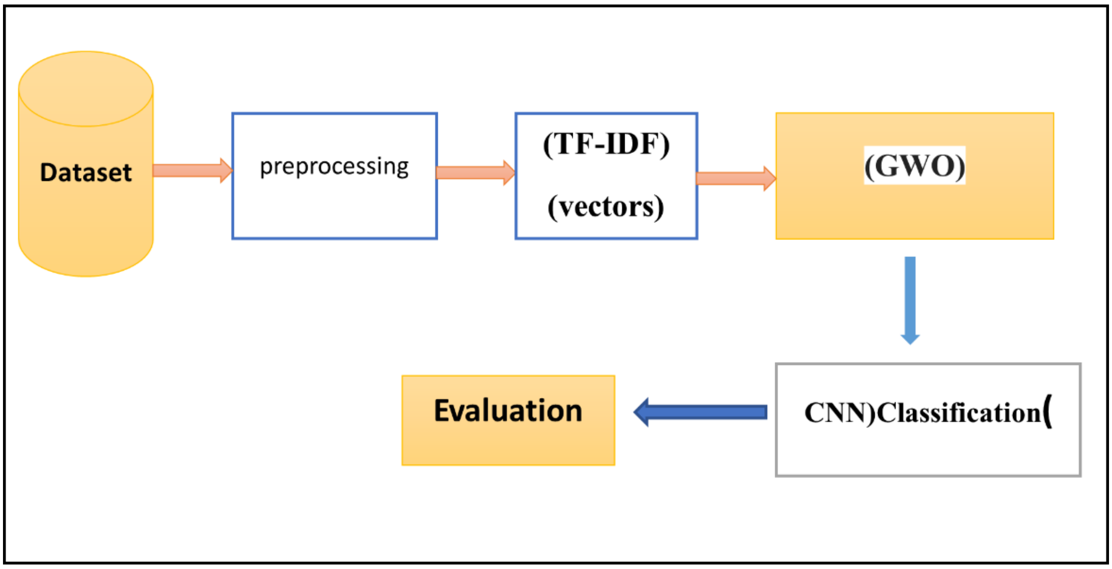

Figure -2 Flowchart of the proposed method

3.1 pre-processing stage

Before using notes for students, there are procedures and interventions that should be considered in the text of students' notes to improve sentiment analysis's accuracy, for many reasons such as, removing any non-textual elements: before processing the text Student Feedback Any non-text elements such as images or formatting should be removed. Removing stop words can help reduce noise in the text and make the text more efficient for analysis. Convert to lowercase Reducing the number of unique words in the text can be achieved by changing all of the text to lowercase. Removing stop words: Words like "a" and "an," which have no meaning, are frequently used as stop words in English. These actions can assist in getting ready for student feedback.. Figure (3) explains the pre-processing steps.

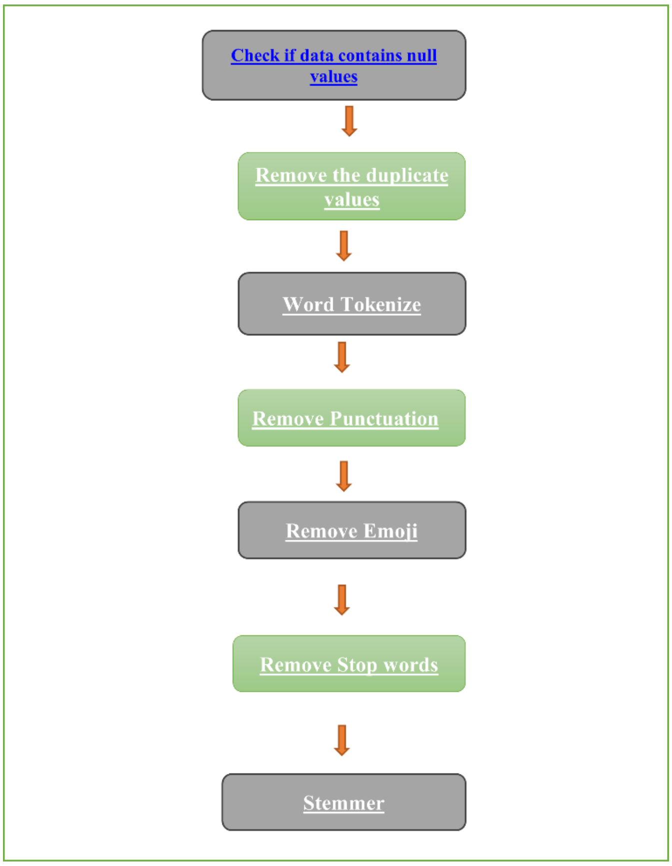

Figure -3 Pre-processing steps

3.2 Feature selection

Used the GWO technique in 2015 to mimic the management structure and hunting behavior of gray wolves in the wild. The ability to calculate gray wolves is essential to their social structure and hunting order. We may say that there are four groups based on the hierarchy of gray wolves in this mod. Alpha wolf, beta wolf, delta wolf and omega wolf are three wolves[13].

The alpha is the leader or dominant wolf and the alpha wolves follow the alpha wolves. There are other wolves. When it comes to gathering authority, the alpha wolf is the most grounded. The second member of the wolf pack social pecking order is the beta wolf. Many times, the beta helps the alpha, the leader, the wolf. Although they are separated into Omega Wolves, Delta Wolves must be exposed to Alpha and Beta Wolves[14].

3.3 GWO

Algorithm used in 2015 to mimic the behavior and structure of gray wolves in the wild. The hunting method is collective. They first identify the prey and its location and begin tracking it, then approach it to surround it under the leadership of the alpha wolf.

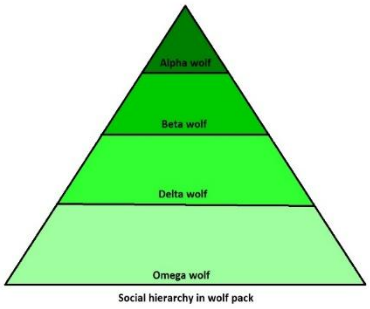

Figure- 4 Structure of gray wolves in hunting

$$\vec{D}\alpha = \left|\vec{C}_{1}.\vec{X}\alpha(t) - \vec{X}(t)\right| \quad (3\text{-}1)$$

$$\vec{D}\beta = \left|\vec{C}_{2}.\vec{X}\beta(t) - \vec{X}(t)\right| \quad (3\text{-}2)$$

$$\vec{D}\delta = \left|\vec{C}_{3}.\vec{X}\delta(t) - \vec{X}(t)\right| \quad (3\text{-}3)$$

Where :

$\vec{D}\alpha$, $\vec{D}\beta$, $\vec{D}\delta$ It expresses the longitudinal vectors between the prey and the wolves (alpha, beta, delta).

$$\vec{X}_1 = \vec{X}\alpha(t) - \vec{A}_1.(\vec{D}\alpha) \quad (3\text{-}4)$$

$$\vec{X}_2 = \vec{X}_{\beta}(t) - \vec{A}_2.(\vec{D}\beta) \quad (3\text{-}5)$$

$$\vec{X}_3 = \vec{X}_{\delta}(t) - \vec{A}_3(\vec{D}\delta) \quad (3\text{-}6)$$

$$\vec{X}(t+1) = \frac{\vec{X}^1 + \vec{X}_2 + \vec{X}_3}{3} \quad (3\text{-}7)$$

Where :

$\vec{X}_1$, $\vec{X}_2$, $\vec{X}_3$ Experimental vector abbreviation for alpha, beta, delta wolves.

3.4 - Structures of convolutional neural networks (CNN)

(CNN) is a type of feedforward artificial neural network in which individual neurons are grouped together in such a way that they feed back to overlapping regions of the visual field. CNN is likely to be an organic change[9].

During Hoebel's first study with Wiesel on the visual cortex of cats in 1968, it was found that the visual cortex consists of a complex pattern of neurons. Such neurons are sensitive to small subregions of the visual field called responsive regions.

Subareas are tiled to cover the entire visible area. These neurons act as close filters along the information domain and are also suitable for exploiting the local neighborhood relationships shown in typical images[6].

Early work by Fukushima [evaluates schemes that rely on these close networks among neurons and on progressively coordinated image transformations. In this study, it has been observed that whenever the neurons are deployed on the last layer splashes at different positions against the exact parameters, a kind of transient invariance is achieved[15].

3.5 Types of basic layers in CNN algorithm.

In CNN algorithm, there are two types of basic layers: convolutional layers with pooling layers. Also, in contrast to the progress made by dynamic CNN, the decrease in demand is summarized in the inclusion of CNN.

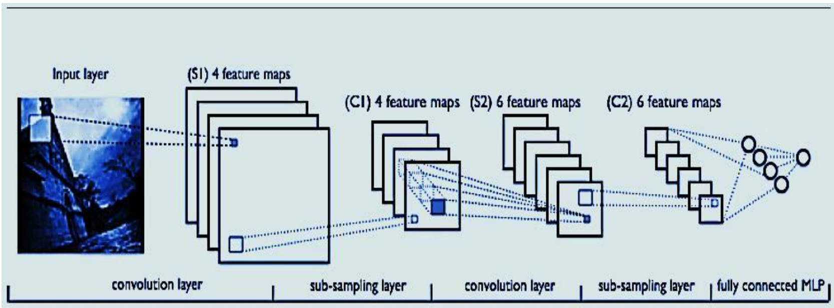

Figure-5. Simple CNN flowchart [15].

1-**Convolutional layer :** The convolution layer is the central building block of CNN, which changes CNN compared to conventional artificial neural networks.

2-Composite Layer : The merge layer is neatly embedded in a CNN structure between the convolution layers alternately. The capacity of the merge layer is to reduce the purpose of feature maps, thus not changing spatially as well as reducing the problem of overfitting [11].

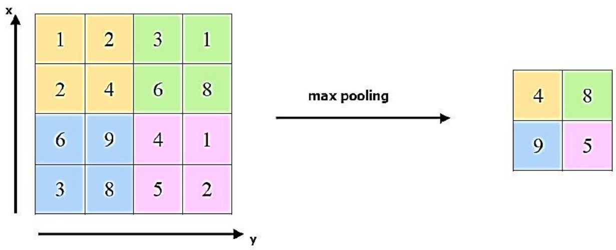

Figure- 6. Demonstration of the maximum merge technique used in the CNN merge layer[7].

3.6 GWO-CN

The proposed structure process mechanism is to enter the data and pre-process it so that the data is ready and free of repetition, numbers and commas, and then convert words to numbers. The provided text features will be extracted using Gray Wolf Optimization (GWO) technique. Finally, the convolutional neural network will be applied.

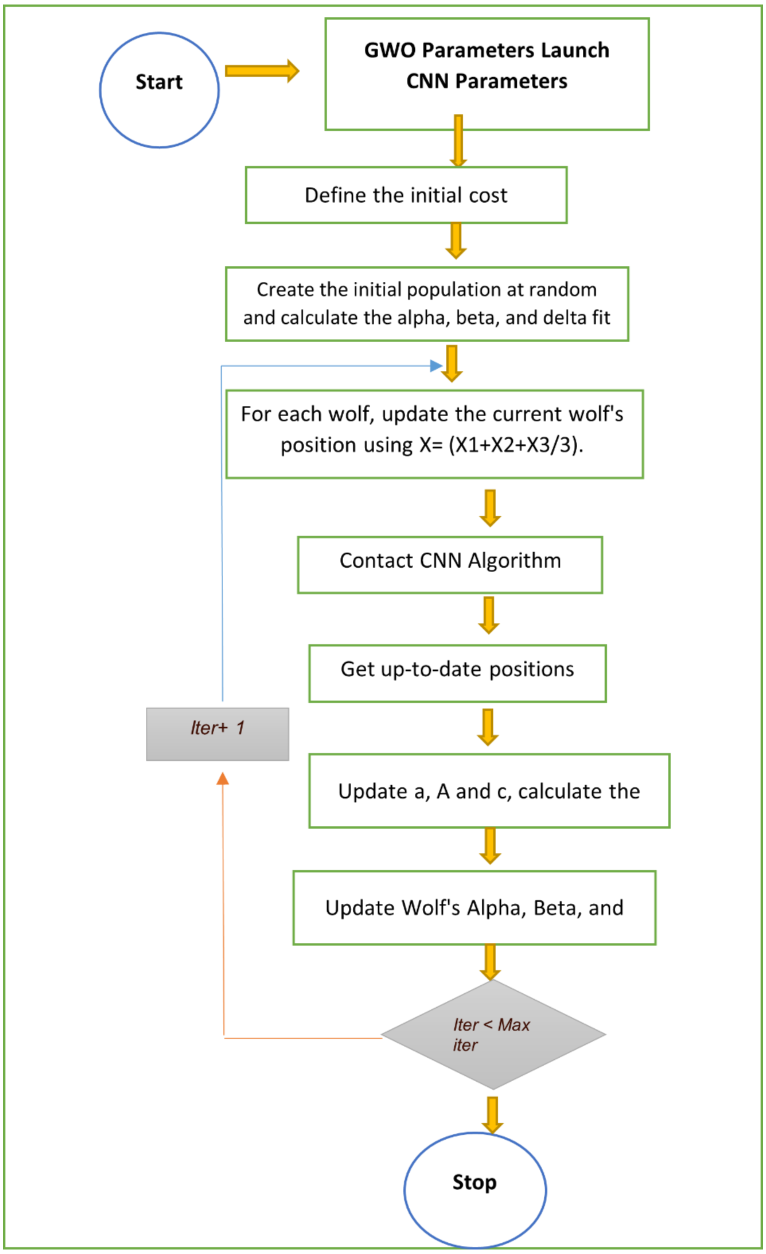

Figure -7 Flowchart of the combination of GWO-CNN algorithms

4. Experiment Results

4.1 Dataset

In this research, we use the Vietnamese Student Feedback Corpus (UIT-VSFC), this dataset consists of 16175 student feedback sentences [16]. This dataset includes sentiment-based classification and topic-based classification, in which the focus is on sentiment-based classification. The dataset is in Vietnamese, and we have converted it into English. The dataset includes positive, negative and neutral polar sentiments as shown in Table (1).

Table 1- Shows students' comments and opinions about teachers

num	emotions	Sentences
1	positive	The lecture was well presented and easy to understand for the student.
2	Negative	I didn't enjoy the lecture.
3	Neutral	I have no comment.

Translating data from Vietnamese to English affected the model's performance and evaluation through several factors There are many positive factors that have an impact on data translation, the most prominent of which are: Accuracy in translation Some words in Vietnamese have different meanings. Translating the Vietnamese dataset into English affected the model's performance through some potential biases, such as:

Difference in meaning: Some Vietnamese words have more than one meaning.

Inconsistency in translation: Different translation styles may lead to data discrepancies.

Grammatical differences: Different grammar rules between the two languages may cause some information to be lost.

To reduce bias, we have followed scientific steps and have experts review the translation in both languages to ensure accuracy of meaning and preservation of cultural context.

4.2 Evaluation criteria

After introducing the comparison method, the data set as well as the evaluation criteria, Now we show the results. But before that, let's explain the structure of GWO. The parameters of GWO are shown in Table (2).

Table 2- GWO parameters for feature extraction

parameters	GWO
Number of search agents	30
Maximum repetitions	10
Dimensions	800
Top_score	Alpha_score
Top _pos	1. 27
D_alpha	1.022
D_beta	0.478
D_delta	0.088

Table 3- Evaluation of emotion classification task in UIT-VSFC

Algorithm	Property	Dataset	Precision	Recall	F1-score	accuracy
GOW-CNN	Uni-gram	UIT-VSFC	0.82	0.84	0.83	0.88
GOW-CNN	Bi-gram	UIT-VSFC	0.65	0.66	0.62	0.71
GOW-CNN	BOW	UIT-VSFC	0.89	0.90	0.89	0.93
GOW-CNN	TF-IDF	UIT-VSFC	0.97	0.95	0.96	0.98

Table (3) word embedding method (TF-IDF) was applied with other methods ((Uni-gram - Bi-gram - BOW)) and the accuracy result was (0.98).

4.3 Comparison with machine learning algorithms

We will use machine learning algorithms commonly used in classification (SVM, NB, and KNN) on the dataset used in our research.

Table 4- Comparison of the results of machine learning algorithms

classifier		Dataset	Precision	Recall	F1-score	Accuracy
	NB	UIT-VSFC	0.91	0.92	0.93	0.97
	SVM	UIT-VSFC	0.95	0.93	0.93	0.97
	KNN	UIT-VSFC	095	0.94	0.95	0.96
Proposed	GWO-CNN	UIT-VSFC	0.97	0.95	0.96	0.98

The proposed method (which combines Neural network and Grey wolf algorithm) outperforms traditional classifiers such as Naive Bayes, SVM, and KNN due to several factors. First, the GWO algorithm helps to optimize the neural network parameters more accurately, which enhances the classification ability more effectively. Moreover, the neural network has a greater ability to handle complex data and extract nonlinear patterns, which is not possible for traditional classifiers. The proposed method also has a greater ability to adapt to changes in data thanks to the GWO algorithm, which helps to improve the accuracy of the model in different environments. Finally, the combination of intelligent optimization using GWO and deep learning using neural network leads to an overall improvement in performance, which explains the superiority in classification accuracy of 98% compared to other methods whose accuracy did not exceed 0.97.

4.4 Evaluation of professors' performance

In table (5), we will present the results of students' opinions about professors' performance in course subjects.

Table 5- shows the evaluation.

Teaching	Course content	Examination	Laboratory work	Library facilities	Extracurricular activities
1	-1	0	1	-1	0
1	0	1	1	-1	1
0	1	-1	0	1	1
1	1	0	-1	1	0
1	0	-1	1	0	-1

Table 6- Presents students' opinions about professors' teaching performance

Teaching	Course content	Examination	Laboratory work	Library facilities	Extracurricular activities
Polarity that is positive	Polarity that is Negative	Neutral polarity	Polarity that is positive	Polarity that is Negative	Neutral polarity
Polarity that is positive	Neutral polarity	Polarity that is positive	Polarity that is positive	Polarity that is Negative	Polarity that is positive
Neutral polarity	Polarity that is positive	Polarity that is Negative	Neutral polarity	Polarity that is positive	Polarity that is positive
Polarity that is positive	Polarity that is positive	Neutral polarity	Polarity that is Negative	Polarity that is positive	Neutral polarity
Polarity that is positive	Neutral polarity	Polarity that is Negative	Polarity that is positive	Neutral polarity	Polarity that is Negative

4.5 Comparison of studies

To complete the analysis of this research in an integrated and scientific and systematic way, the model presented for this study has been compared with other methods and techniques presented by a number of researchers in recent scientific articles.

Sangeetha, K., and D. Prabha. [9] The study dealt with the analysis of students' comments using the LSTM model to predict whether their opinions were positive, negative or neutral. In this study, the LSTM model was relied on only, and there was a weakness in the ability to process large texts and temporal disparity that occurs in the data.

Nguyen, Phu XV, et al.[16] In this study, they compared traditional classifiers and deep learning models to analyze Vietnamese students' comments. using the LSTM model to predict whether their opinions were positive, negative or neutral. This study focused on the Vietnamese language and was not generalized to other languages.

In the two studies that compared the proposed system, the focus was on LSTM, which often causes problems when dealing with long texts and large data.

proposed methods In our study we introduced a new approach by integrating the GWO algorithm with the CNN algorithm to improve the stability of the model and reach the best data processing. The training process is faster for the model and thus outperformed the study on previous studies of flexibility and improvement.

Table (7) shows the comparison of the proposed methods and techniques on the problem of identifying a group of students from recent researches and articles in terms of efficiency. According to the results of the proposed technology in this study, it has the highest rate. This system has recorded 98% efficiency.

Table 7- Comparison between Proposed method and different methods

Method	Accuracy	Algorithm used
Method [9]	83.03%	
Method [16]	92%	(Maximum Entropy, LSTM, BiDirectional LSTM)
Proposed method	98. %	GWO - CNN

5. Conclusion

Sentiment analysis systems are one of the systems whose demand has increased with the increase of textual information transmitted through the Internet. For this reason, the main purpose used in our study is to elicit opinions about lecturers' performance and use that feedback to evaluate lecturers' performance. In this research, we used the Vietnamese Student Feedback Corpus (UIT - VSFC), which contains 16,175 student feedback sentences. This dataset includes both sentiment-based classification and topic-based classification, we focused on sentiment-based data classification. The dataset is in Vietnamese, which is converted to English in our work. The dataset includes positive, negative and neutral emotions. The time evaluation scale applied to our proposed system was 98%. The accuracy of our system applied Machine Learning (ML) techniques under Supervised Vector Machine (SVM), K-Nearest Neighbor (K-NN), and Simple Bayes (NOTE) which Commonly used in our classification polarity classification dataset was created. which resulted in accuracies of 97%, 96% and 97%, respectively. In the second part, we applied the proposed sentiment analysis system to extract students' opinions. We found the proposed method to provide an excellent demonstration of the management of the educational institution on the performance of teachers in six dimensions (teaching, knowledge, evaluation, experience, behavior and in general) allowing them to improve the performance of teachers in this aspect. I see.

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