Using data mining techniques to extract students' attitudes toward e-learning

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ABSTRACT

The rapid expansion of e-learning platforms, where students can share their opinions and express their thoughts, has become a rich source of data for opinion mining and sentiment analysis. This study aims to develop an effective model for predicting students' attitudes about e-learning, with a focus on mining opinions that indicate positive or negative sentiments. The study was implemented in two stages. The first stage aimed to discover the most popular platform used in e-learning at the University of Mosul to collect the largest amount of data through comments posted within the platforms, also to identify trends in students' opinions towards e-learning. The results show that the focus of both lecturers and students revolved around well-known platforms such as Google Classroom and Google Meet, both of which had relative importance (45.33% and 42.29%, respectively). The second stage uses a machine-learning algorithm on the data collected to determine the impact of e-learning on students. Also, two feature selection approaches, information gain (IG) and CHI statistics, were explored and enhanced in addition to hidden Model Markov (HMM) and support vector machine (SVM)-based hybrid learning strategy. As a result, an opinion mining method was used to assist developers in improving and promoting the quality of relevant services.

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1. INTRODUCTION

Tan *et al*. [1] define learning management system (LMS) as a platform that provides lecturers and students with educational materials online. LMS helps instructors follow their students' progress and minimize the use of in-person teaching. LMS assists the educational process by constituting a central location for accessing material online. E-learning supports the educational process and enhances creativity. It provides guidance, counseling, examination organization, and management and evaluation of resources and strategies, known as e-Learning [2].

The e-learning review aims to support Iraqi faculty in successfully integrating e-learning broadly across Iraqi campuses. Faculty will understand e-learning concepts and methods, e-content, effective online pedagogy, and course design. Faculty will understand e-learning within the Iraqi higher education context and explore technologies relevant to online learning. Balogun and Ahlan [3] clarified that the need for e-learning has grown due to the change that occurred in the expectancies of training procedures and consequences. For example, many institutions have realized that education is no more the memorization of expertise; however, alternatively, the capability to solve the problem with novelty and verbal exchange competencies. Ameen *et al.* [4] identified the benefits that e-learning, from students' viewpoint in Iraqi universities, will bring to higher education in Iraq. Furthermore, they focus on the challenge students can face using e-learning systems in Iraqi universities.

Abdulrazak and Ali [5] attempted to target the problems that have been experienced with e-learning in Iraq and offering some suggestions that might contribute to reducing this delay to support the reality of education. Hundreds of professors, students, and teachers were involved in this research, and they are entirely aware of the basic implementation of electronic learning and the reasons for its delays. Several empirical studies have focused on challenges and Barriers, and opportunities of e-Learning Implementation in Iraq. Al-Azawei *et al*. [6] focus on the level of staff members and students' adoption, application, familiarity, and technology acceptance, confirming that social media is less complicated to use than e-learning platforms like Moodle. At the same time, Qureshi *et al.* [7] discovered that Electricity loss and English proficiency had been shown as the essential Barriers to efficient e-learning integration.

Karkar *et al*. [8] tried to compare teachers (trained and untrained) on their learning management system. They found that teachers who joined LMS training sessions had a higher degree of LMS operation. Educated teachers appeared to make relatively more lavish use of 'grade core' and 'evaluation tool' but comparatively used less 'content' in their teaching compared to other teachers who did not join any training workshop. There is an opportunity for social interactions in an online classroom, and the problem is that the communication is done through a written text. Therefore, there is a missing factor: body language and gestures, and instant feedback from the student "listener" [9] discuss the difficulties faced by online instructors in viding clear and visible guidance in an online environment. The asynchronous classroom looks a lot different than a traditional lecture because there is a focus on active learning, for instance, using a video mix, assignments, discussion, chat, and peer review. It is possible to divide lessons into smaller parts to manage time and communication with students [10].

Paula [11] suggests that the role and responsibilities of the instructor are critical factors for a successful lesson. Knowledge and skills are needed for effective teaching. The instructor needs to engage students in online teaching and learning [11]. Due to the rapid expansion of e-learning platforms, and the need for extracting the attitudes, opinions, and expectations of both lecturers and students, therefore it became vital to create an accurate and valid tool to predict such feedback. This study aims to develop an effective model for predicting students' attitudes about e-learning, with a focus on mining opinions that indicate positive or negative sentiments. Opinion mining also referred to as sentiment analysis or sentiment classification, is computer technology for understanding and interpreting opinion and sentiment by processing vast volumes of data in a way that allows humans to make decisions [12].

In the context of e-learning, sentiment analysis refers to the use of an automatic text analysis process to extract opinions and identify a wide range of comments made in e-learning forums and websites where learners discuss or describe their thoughts, opinions, and evaluations of the services provided. Early detection of customer complaints and service issues does, in fact, aid in reducing the risk of broadly spreading defective items and improving advertising methods [13].

Sentiment analysis is a classification problem. The aim is to estimate the sentiment polarity and then categorize it into positive and negative feelings to discover attitudes and viewpoints expressed in any form or language [14]. Sentiment analysis of e-learning platforms provides platform developers with a good perspective and a quick and effective tool to track public perceptions of these platforms, among other things. Corporations, educational institutions, and individuals alike have shown a strong interest in e-learning. E-learning systems are becoming increasingly prominent as an educational trend. It is a term used to describe teaching methods involving computers to convey knowledge in a nontraditional classroom setting. In e-learning, it is vital to be aware of users' perspectives and design an evaluation based on them [15].

Message boards or blogs are essential for e-learning system makers to employ as a mechanism for users to communicate, discuss, or share their ideas and comments on the services. Conducting systematic surveys of users' views and opinions is one of the essential roles of e-learning management to meet their wants and requirements as effectively as possible. This method allows people in charge of e-learning to immediately detect and address any potential issues during the program's execution. This research aims to create a training sentiment classification algorithm that will categorize student opinions on e-learning system services into positive and negative categories. As previously stated, many online reviews on e-learning blogs and forums are currently beyond the reach and visual capabilities. As a result, there is a pressing need for innovative systems that can automatically analyze and interpret the attitudes expressed in reviews by users (learners or instructors). As a result, improved sentiment classification algorithms that can automatically analyze whether the overall reviews of a specific e-learning system are positive or negative based on the examined e-learning blogs would be highly beneficial to developers. Due to the domain specificity of e-learning review mining, the performance of sentiment classification algorithms on e-learning system reviews should be examined. To alter and improve teaching methods and procedures by developing a conceptual framework that can extract, analyze, and forecast user sentiment (i.e., learners and tutors). As a result, the research's main contribution can be applied to various situations.

This platform has quickly become a gold mine for firms trying to monitor their reputation and brands by gathering and analyzing public opinion about them, their markets, and competitors, with millions of users and millions of messages posted every day. This study uses sentiment analysis to determine students' and teachers' attitudes regarding distance learning. Evaluation of the word bag features of text using supervised machine learning techniques [16] is a systematic way to classify emotions. All words can be filtered from a word bag vector using this method. Each text's appearance of words in such vectors is displayed as a textual feature. The phrase syntax tree [16] is another way to design an emotion classifier. The sentence is parsed to create a syntax tree representing the word relationships. Can then use the relationship between word polarity, POS properties, and syntax to build a model or pattern for an emotion classifier. Bag and words feature vectors are two distinct techniques to generate words. Dave *et al*. [17] also used machine learning approaches to investigate sentiment classification. Instead of employing all the words, they choose the top based on their generated scores.

Mullen and Collier [18] employ support vector machine (SVM) algorithm to examine word sentiment polarity, as well as subject and artist-oriented data. Anjaria and Guddeti [19] study presents a new way to predict the election outcome by leveraging influential user factors. It also provides a hybrid method of extracting opinions from Twitter data using direct and indirect characteristics using a SVM, naive bays, maximum entropy, and a supervised classifier based on artificial neural networks. Increase, Principal component analysis (PCA) has been integrated with SVM to reduce dimensions. da Silva *et al*. [20] used classifier ensembles and lexicons; the research provides a strategy for automatically classifying the sentiment of tweets. About a query term, tweets are categorized as positive or negative. Multiple learners are taught to tackle the same problem by using ensemble approaches. As shown in Figure 1.

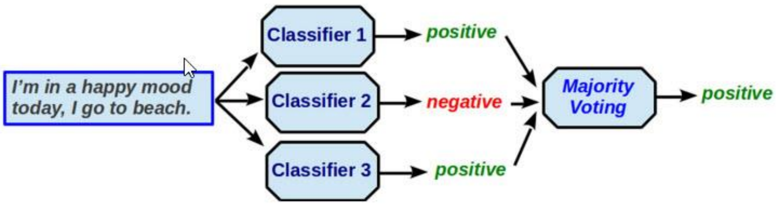

Figure 1. The combination rule is an example of majority voting, the majority of classifiers agree that the class is positive

Jain and Katkar [21] propose a mechanism for predicting Indian people's overall attitudes and predisposition toward political situations and issues. The suggested system flow is depicted in Figure 2. Twitter API v 1.1 is used to obtain raw training tweets. Following the collection of raw tweets, various preprocessing methods are used to sanitize the data. The same methods are used to gather and sanitize raw tweets to prepare the testing dataset. Various classifiers are used to examine the performance of classifiers after the training and testing datasets have been prepared. Saleh *et al*. [22], determine how the speaker or writer feels about many facets of a situation. In Figure 3, they have built the opinion mining process, in which each part has the following responsibilities: data collection, opinion identification, aspect extraction, opinion classification, production summary, and evaluation. This paper proposes data mining method, which has recently been researched in the business and computer realms, as a technical issue to be applied in the e-learning process, thereby introducing a new area of study. We must apply appropriate sentiment classification algorithms to mining evaluations collected from e-learning blogs and forums to study the data generated by this method.

The motivation behind this work is the e-learning platform has evolved into a comprehensive and diverse information resource. Due to the nature of documents, which enable users to post real-time remarks about their ideas on various issues, discuss current events, complain, and show a positive feeling for goods they use daily. Companies that create comparable gadgets have started polling these messages to see how people feel about them. Customers' reactions are often analyzed and responded to on these platforms by these firms.

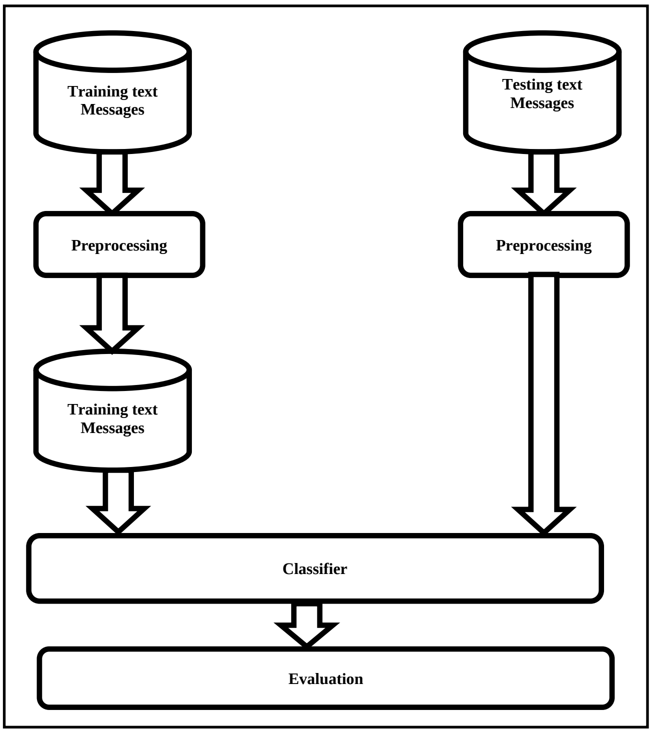

Figure 2. The figure shows a mechanism for predicting Indian people's overall attitudes and predisposition toward political situations

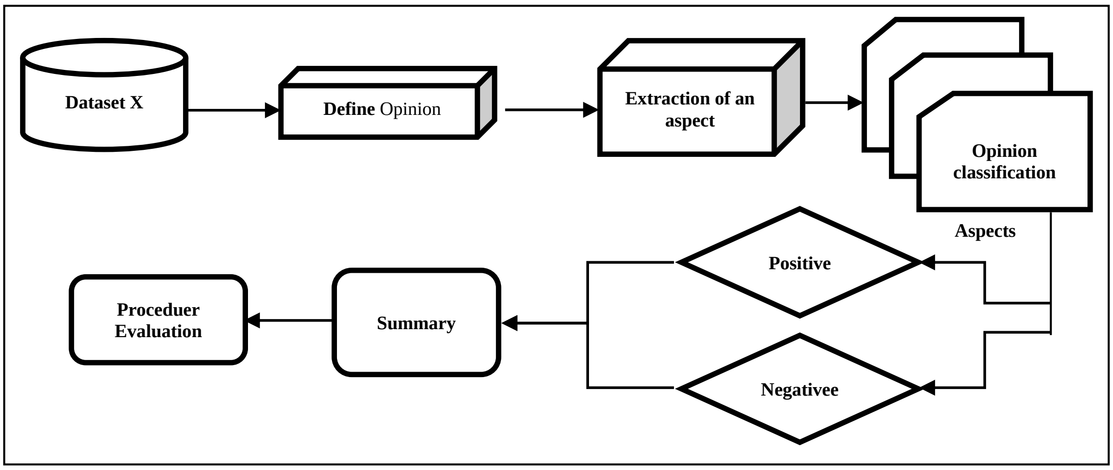

Figure. 3. Opinon mining process

2. METHOD

This study has two stages: first is to identify the most popular e-learning platform among students and tutors to extract many reviews. The second stage (explaind in Results and discussion) is to analyze the collected reviews from these platforms and other resources to predict students' and tutors' attitudes toward e-learning, which can be extremely useful to businesses looking to improve their products. First Stage included the following sections to identify the most popular e-learning platform.

2.1. Materials and methods

The first stage of the search determines how difficult educational platforms and e-learning technologies are to utilize. For example, it tries to identify the most popular video platforms and their characteristics from both the professor's and the student's perspectives. It also investigates the relationship between using these tools and the development of recommendations to improve the e-learning environment in Iraqi universities, namely the University of Mosul. It is worth noting that the majority of those who answered the questionnaire are professors and students at the University of Mosul, as the survey encompassed all 22 of the university's colleges and centers with various specializations.

2.2. The questionnaire

Due to COVID 19 restrictions, study restrictions were concentrated mainly at the University of Mosul and other Iraqi universities. The current research examines the difficulties in implementing e-learning tools and approaches from both the professor's and students' perspectives. A survey was created to gather thoughts and experiences from professors and students on LMS. Nearly 500 teachers and students took part in a discussion on their recent LMS experience, including what platform, applications, and tools they prefer to utilize.

2.3. Analytical hierarchical process AHP

The data was analyzed using the analytic hierarchy process (AHP) approach. AHP was established by Saaty in 1980. According to Ahmed and Al-Moula [23], AHP uses pair-wise comparison to extract relative weights from the factors in question. This method consists of three steps: first, organize parameters and assign importance degrees to them, then adopt a matrix of relative weights. The consistency ratio (CR) determines the degree of importance in the third phase. If CR is less than 0.1, the values do not need to be reweighted. The scale of relative importance is arranged (from 1 to 9), with 1 denoting the least important and 9 denoting the most important.

3. RESULTS AND DISCUSSION

3.1. Data tabling

The results show that the focus of both lecturers and students revolved around well-known platforms, as in google classroom with relative importance (45.33%) and google meet with relative importance (42.29%), as in Tables 1, 2, and 3. Most lecturers preferred not to use other explanation board applications due to a lack of knowledge of such applications and their benefits. Also, the results show most academic staff must maintain their knowledge and teaching abilities as well as engage in positive professional behavior with key e-learning apps that can benefit both the instructor and the student for the curriculum to be effectively delivered.

3.2. Data analysis

Individuals, things, or people who make up the subject of the research problem are referred to as the research community. Members of the teaching staff and students (undergraduate and graduate) at the University of Mosul and other Iraqi universities are the subjects of this study. A Case Study was curried out as a questionnaire survey was set to examine the essential platforms used in digital education and other educational aspects of the E-learning process. The questionnaire was provided to a group of specialist experts to obtain their feedback on the questionnaire's clarity and coherence and its applicability for assessing the research variables. Most of the feedback was good. This survey was sent to a variety of colleges and universities. This questionnaire had numerous components that covered faculty members and students who took part in the survey. It is critical to consider the roles, responsibilities, knowledge, and abilities required for a successful online education. A questionnaire is a tool for gathering introductory instructor comments. Figure 4 shows the most used platform in Iraqi universities especially, within Mosul university. The results of using the AHP approach to evaluate the data suggest that both professors and students focused on well-known platforms such as Google Classroom.

Table 1. Used tools by lecturers and students

		MEET	ZOOM	FCC	webix	WhatsApp	Facebook Messanger	Row Total	Relative Importance
1	MEET	1	7	8	9	9	9	43.00	47.98%
2	ZOOM	1/7	1	2	8	6	4	21.14	23.59%
3	FCC	1/8	1/2	1	7	3	2	13.63	15.20%
4	webix	1/9	1/8	1/7	1	1	0.5	2.88	3.21%
5	WhatsApp	1/9	1/6	1/3	1	1	0.5	3.11	3.47%
6	Facebook Messanger	1/9	1/4	1/2	2	2	1	5.86	6.54%
	Consisty Ratio = 0.0692								

Table 2. Used explanation board application

		no	Janboared	Powerpoint	Drawchat	White-board	Sketch board	Educreations	Cisco Webex Board	Powtoon	Row Total	Relative Importance
1	No	1	9	9	9	9	9	9	9	9	73.00	39.90%
2	Janboared	1/9	1	3	3	6	6	7	8	9	43.11	23.57%
3	powerpoint	1/9	1/3	1	1	2	3	3	4	4	18.44	10.08%
4	Drawchat	1/9	1/3	1	1	2	2	3	3	3	15.44	8.44%
5	White-board	1/9	1/6	1/2	1/2	1	1	2	2	2	9.28	5.07%
6	Sketch board	1/9	1/6	1/3	1/2	1	1	2	2	2	9.11	4.98%
7	Educreations	1/9	1/7	1/3	1/3	1/2	1/2	1	1	1	4.92	2.69%
8	Cisco Webex Board	1/9	1/8	1/4	1/3	1/2	1/2	1	1	1	4.82	2.63%
9	Powtoon	1/9	1/9	1/4	1/3	1/2	1/2	1	1	1	4.81	2.63%
	Consisty Ratio = 0.0480											

Table 3. Total platforms by lecturers and students

		Google Classroom	Edmodo	moodle	canvas	easyclass	sakai	Row Total	Relative Importance
1	Google Classroom	1	6	7	9	9	9	41.00	42.29%
2	Edmodo	1/6	1	4	8	8	9	30.17	31.11%
3	moodle	1/7	1/4	1	4	4	5	14.39	14.85%
4	canvas	1/9	1/8	1/4	1	1	2	4.49	4.63%
5	easyclass	1/9	1/8	1/4	1	1	2	4.49	4.63%
6	sakai	1/9	1/9	1/5	1/2	1/2	1	2.42	2.50%
	Consisty Ratio = 0.0888								

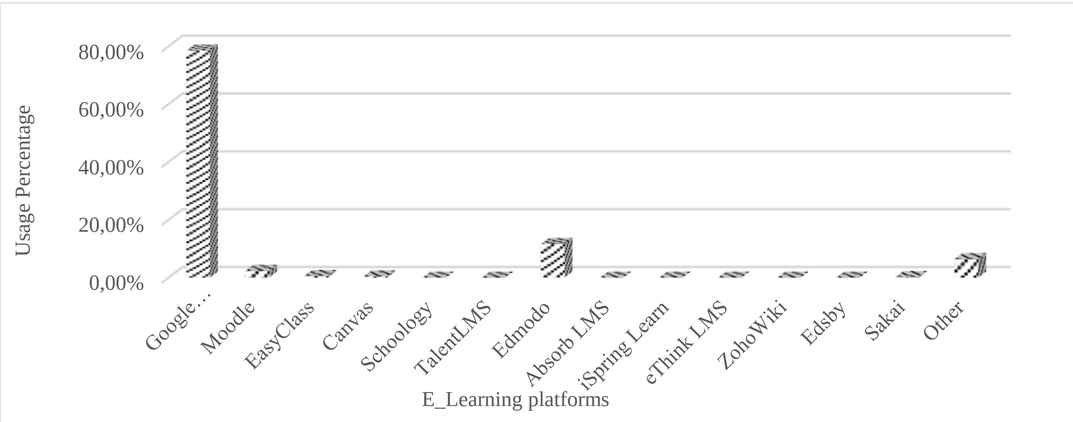

Figure 4. This figure depicts the most platform used in iraqi universities spicially within the university of Mosul

3.3. Sentiment analysis (Stage 2)

A trained statistical classifier is used for sentiment classification in supervised machine learning. The machine learning techniques are implemented using traditional bag-of-features architecture. This research proposes a method for predicting student tutors, especially Mosul University's overall attitudes on e-learning issues and scenarios. The planned gadget flow is depicted in Figure 5.

The raw training text messages are gathered with the use of API tools. After gathering raw data, various preprocessing methods are used to clean up the data. It might not be accessible when dealing with large amounts of data manually. However, using AI techniques such as sentiment analysis, we can detect the emotional tone in a text message in real-time, at scale, and with high accuracy.

3.3.1. Data preprocessing

Sometimes, text messages are not in a usable format. Various preprocessing methods for cleaning documents are used to acquire a document in a readable format. Stop words, and special characters are removed, spelling is corrected with a dictionary, abbreviations and slangs are replaced with expansions, and lemmatization is performed. The comments are stripped of any special characters and hyperlinks. In addition, duplicate messages are deleted from the training dataset.

3.3.2. Preprocessing of text

The goal of the sentiment analysis is to classify documents as either positive or negative attitudes by analyzing the data that has been posted. Text preprocessing and text categorization is done to accomplish this. Several preprocessing processes are carried out, as follows:

- Stop word removal: Words that aren't extremely significant in emotion classification are referred to as noise words. We've compiled a list of terms, such as prepositions, pronouns, and adverbs, that mostly comprise English pronouns, particles, special characters, and numbers.
- Tokenization: Each text post is divided into tokens, which are significant words.
- Data standardization: All words in a document are converted to lower case using data standardization techniques to ensure data uniformity.
- Stemming: Porter stemmer is applied to data to return each word to its stem and remove suffixes such as (-Ed, -ing, -ion, etc.) to reduce the document's complexity and processing time, thereby improving the model's performance.

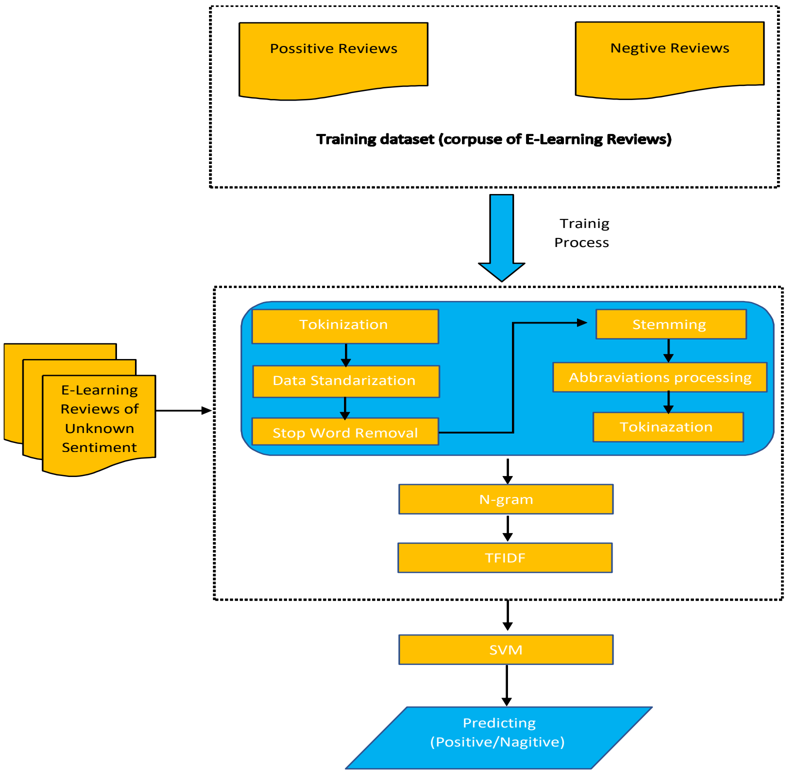

Figure 5. The proposed methodology

3.3.3. Feature selection

With the help of feature selection techniques, the number of input variables can be reduced to those that are thought to help a model predict the target variable the most effectively. A further advantage of feature selection is model interpretation. The output model is simpler and easy to understand with fewer characteristics. Feature selection methods are used to pick out discriminating terms for training and classification.

a. TFIDF

Sentiment analysis is used to solve a classification problem, typically a binary problem with positive and negative goal values. The machine learning model must first learn the sentiment score of each unique word in the document and how many times each word appears to make sentiment predictions on each text using sentiment analysis. We must specify features and target values to train the model when dealing with a supervised machine learning challenge. The model's features are vectorized text data that has been modified. TFIDF is one of the vectorizers that construct the features differently.

It's important to note that the techniques term frequency and inverse document frequency (TFIDF) vectorizer were utilized as input characteristics. The following formula can be used to compute the TF/IDF:

$$X_{i,wj} = \frac{1+\log(t_{i,wj})}{1+\log(\sum_i^N t_{i,wj})} \times \log(\frac{N}{\sum_{wj} t_{i,wj}}) \quad (1)$$

where $t_{i,wj}$ is the number of times the term wj appears in document i. As illustrated in the equation, the first term calculates the term frequency, whereas the second term calculates the inverse document frequency. The first term evaluates the number of times the word wj appears in document I normalized by the document's length.

b. N-Gram

An n-gram is a sequence of tokens or words of length n utilized in numerous text mining and natural language processing activities. The proposed technique constructs an n-gram for post pieces to extract keyword characteristics from a post. N-Gram features are extracted after the data has been preprocessed.

When n=2 is used, a two-word sequence is generated for each document. This step improves the classifier's accuracy because of the obtained information or features from two sequences of word pairings. Due to many factors, N-gram based extraction has been shown to have a reliable performance in extracting features from text:

- The most common roots in text data are automatically captured.
- N-good gram's representation does not necessitate the use of a specific vocabulary.
- It has a high tolerance for distortion and misspellings.

Feature selection can be considered as a search issue, with each state in the search space defining a subset of the features that are available. If a data set comprises three features A1, A2, and A3, and the existence of a feature is coded with 1 and its absence with 0, then there should be a total of 23 reduced-feature subsets coded with {0, 0, 0}, {1, 0, 0}, {0, 1, 0}, {0, 0, 1}, {1, 1, 0}, {1, 0, 1}, {0, 1, 1}, and {1, 1, 1}. When the search space is limited, the problem of feature selection is relatively simple because we can investigate all subsets in any order and the search will be completed quickly. The search space, on the other hand, is frequently quite large. In typical data-mining applications, the number of dimensions N is 2N. It is required to extract specific clues from the text to do machine learning. These hints may lead to effective proper classification. Feature vectors, (f1; f2; : : fn). A feature vector's coordinates reflect one clue, also known as a feature, "fi," from the original text.

This section will discuss a few different methods for selecting characteristics. The word-goodness criterion threshold is used in both of the procedures in this study to accomplish a targeted degree of term deletion from a corpus document's full vocabulary register. The two prerequisites are information gain (IG) and CHI statistics. Each of these methods generates a score for each feature. To pick features appropriate for each technique, we can utilize a heuristics-based strategy, which we define as follows. The average score is derived for all features.

The average score for each feature should be compared to the feature's score; if the feature's score is higher than the average, it should be picked. Additionally, by employing these feature selection procedures, the goal is to improve classification accuracy and get insight into the data.

c. Information gain (IG)

Information gain is also known as the goodness criteria in data mining [24]. Detecting the existence or absence of a specific/relevant word in a text estimates the quantity of data bits required for class prediction.

$$IG(t) = -\sum_{i=1}^{|c|} p(c_i) logp(ci) + p(t) \sum_{i=1}^{|c|} p(c_i|t) logp(c_i|t) + (\bar{t}) \sum_{i=1}^{|c|} p(c_i|\bar{t}) logp(c_i|\bar{t}) \quad (2)$$

where $p\ (c_i)$ signifies a class's probability of occurrence class c_i; The probability of a word t appearing is denoted by $p(t)$. The likelihood of a word t not occurring is denoted by $p(\bar{t})$.

d. Statistics from CHI

The CHI metrics can be used to evaluate a term's association to a category [16]. It's described as:

$$CHI(\boldsymbol{t}, \boldsymbol{c_i}) = \frac{\boldsymbol{N}\ X\ (AD-BE)^2}{(\boldsymbol{A}+\boldsymbol{E})\boldsymbol{X}(\boldsymbol{B}+\boldsymbol{D})\boldsymbol{X}(\boldsymbol{A}+\boldsymbol{B})\boldsymbol{X}(\boldsymbol{E}+\boldsymbol{D})} \quad (3)$$

$$CHI_{max}(t) = max_i\big(CHI(t, c_i)\big) \quad (4)$$

where A represents the number of times t and c_i occur together, and B represents the number of times t occurs without c_i; E represents the number of times $c_i$occurs without t; N is the total number of documents, and D represents the number of times neither c_i nor t occurs.

3.4. The proposed classifier

There is a secret gem, which is worth noticing. Probabilistic automata and the Markov Model HMM are tightly intertwined. A probabilistic automaton is a structure made up of states and transitions and a set of transition probability distributions. The hidden Markov model (HMM) was employed to deal with sentiment text classification in this research. We intend to develop a HMM based on a collection of text reviews from a particular class Cj. We will compare our integrated supervised data mining technique based on Hidden Model Markov HMM and SVM to the previously hand-classified training data to see if the reviews are more likely to have a "positive" or "negative" orientation at this time [25].

Its purpose is to determine how to determine all of the Markov model parameters that govern this area. A hidden Markov model is defined as q and v symbols within vector visible symbols. Indeed, we have utilized the HMM's [25] statement model, which accepts all compound terms (bigrams and/or trigrams) as well as symbols representing all relevant terms (unigrams) for a given class. The best approach to change the parameters of an HMM classifier is to build Markov models. A (SVM) is used for sentiment classification to find a viable approach for data categorization. Texts are divided into two categories: positive and negative. According to the structural risk minimization principle of computational learning theory, SVM seeks a solid background for dividing training data points into two classes (positive and negative). Furthermore, make decisions based on the selected support vectors being the only elements in the training set that are exclusively effective. The SVM classifier's findings are acquired using ten-fold cross-validation. Training reviews account for 80% of the evaluations performed on each fold, with testing reviews accounting for 20%. As a result, we have written to support vectormachine (SVMlight) [20].

Our combination classifier is completely disclosed in the next section. As previously stated, several different combining rules can link various classifiers. In a nutshell, the framework for combining classifiers can be described as; Assume that the classifier-selection stage selects N individual classifiers Ck (k = 1,....,N). Each classifier assigns a label LK (Lk = f1,...,fm) to one of the input samples (represented as Xk). Assume that the classifier Ck produces a measurement in the form of a posterior probability vector for each output.

$$p_k = [p(f1|X_k), \ldots\ldots, (f_m|X_k)]^t$$

where $(f_i|X_k)$ indicates the likelihood that the classifier would consider $\boldsymbol{X}$ to be labeled with $\boldsymbol{f_i}$.
Major voting rule:

$$assign\ z \rightarrow f_i$$
$$j = arg\ max \textstyle\sum_{i=1}^{N} \Delta_i \ (5)$$

where $\Delta_i = \begin{cases} 1\ L_k = f_i \\ 0\ \ L_k \neq f_i \end{cases}$
sum rule:

$$assign\ z \rightarrow f_i$$

$$j = arg\ max \textstyle\sum_{i=1}^{N} p(f_i|X_k)$$

max rule:

$$assign\ z \rightarrow f_i$$

$$j = arg\ max \left\{ max \begin{matrix} N \\ p \\ k=1 \end{matrix} (f_i|X_k) \right\} \tag{7}$$

mean rule.

$$assign\ z \rightarrow f_i$$
$$j = arg\ max \left\{ mean \begin{matrix} N \\ p \\ k=1 \end{matrix} (f_i|X_k) \right\} \tag{8}$$

Joachims [25], we can show that under various combining conditions, the combined HMM+SVM approach outperforms the individual HMM and SVM classifiers. As a result, the best combination classifier using the Sum rule appears to outperform the others (Major, Max, and Mean). Furthermore, for our combined classifier, the Unigrams, Bigrams, and Trigram's classifier obtains the best overall performance. This illustrates that increased n-grams order can help polaritycategorization, which explains its extensive use in our research.

3.5. Experimental results
3.5.1. Dataset

We created a data collection for the current study by extracting a set of e-learning reviews from a range of e-learning blogs, such as http://elearningtyro.wordpress.com and (http://elearningtech.blogspot.com/). Text reviews were also acquired using Moodle forums (http://docs.moodle.org/en/Forums) and other platforms like Google Classroom, as well as the survey questionary shared with students and instructors via Google Forum. (The forum module involves students (learners) and teachers working together.) (Tutors can provide feedback in the form of comments.) It's vital to notice that we have 1000 positive and 1000 negative texts in our data set. People have a pessimistic attitude; in addition, 80 percent of the materials used are related to training, with the remaining 20% being about testing.

3.5.2. Evaluation

The confusion matrix, which puts the classifier's given class (column) against the samples, is the most used instrument for evaluating classification performance—their genuine, authentic class (row). A matrix was used to describe the confusion for the validation step, as shown in Table 4.

Table 4. A confusion matrix

Class	Actual Positive	Actual Negative
Actual positive	True positive (TP)	False negative (FN)
Actual negative	False Positive (FP)	True negative (TN)

The efficacy of sentiment categorization is measured in terms of standard precision (P), recall (R), and F-measure (F), which are defined as:

$$Precision(POSITIVE) = \frac{TP}{TP+FP} \tag{9}$$

$$Precision(Negative) = \frac{TN}{TN+FN} \tag{10}$$

Precision: the ratio of accurate cases through the system outputs is known as precision.

$$Recall = \frac{TP}{TP+FN} \tag{11}$$

Recall (also called sensitive): The ratio of accurately predicted positive observations to all observations in the actual class is known as recall.To combine these two metrics into a single value, the F-measure is usually utilized. In terms of importance, the F-measure compares the relevance of recall to precision. The F-measure is obtained by giving precision the same weight as recall:

$$F1 - Score = \frac{2*Precesion*Recall}{Recall+Precesion} \tag{12}$$

$$F1 - score = \frac{TP}{TP+\frac{1}{2}(FP+FN)} \tag{13}$$

TP=number of true positives
FP=number of false positives
FN=number of false negatives

In terms of precision, recall, and F-measure, IG is the best at identifying sentimental phrases and conducting sentiment classification in most situations, as evidenced by the trial findings Table 5.The accuracy of our blog-collected e-learning corpus does not appear to be particularly good. This emphasizes how challenging it is to maintain a blog. This is mostly due to the obnoxious content that suffocates learning on these blogs. The fact that the bloggers are not professional writers adds to the problem. They hail from a variety of eras, cultures, locations, and faiths. As a result, when writing blogs or blog comments, people may not follow grammatical rules. Because they are accustomed to using Netspeak, even those who are fluent in English do not always write in a journalistic manner. Words are being shortened, and letters are being replaced with different letters and/or symbols. Known as NetSpeak, it is a method of reducing typing time. It's often difficult to decipher the true meaning of such characters or symbols. We discovered the frequent use of emoticons in e-learning blogs after examining them.

Table 5. Two feature selection methods' performance on our proposed learning model

	Positive			Negative		
	Precesion	Recall	F1-Score	Precesion	Recall	F1-Score
CHI	0.735	0.746	0.741	0.742	0.735	0.739
IG	0.794	0.843	0.831	0.817	0.793	0.798

4. CONCLUSION

In terms of precision, recall, and F-measure, IG is the best at identifying sentimental phrases and conducting sentiment classification in most situations, as evidenced by the trial findings.The accuracy of our blog-collected e-learning corpus does not appear to. It turns out that using sentiment analysis to investigate the character and structure of web forums and e-learning blogs is a good idea. A significant undertaking, yet the present accuracy prospects for effective forum conversation analysis sentiments. This type of analysis can aid in the development of a better product. Gaining a grasp of users' perspectives on e-learning systems to make them better. Our research has shown that combining sentiment classification into e-learning is a viable option. We found that when two selected features (IG and CHI) were applied to the sentiment classification of e-learning blogs and forums, our based hybrid classifier HMM and SVM with the rule Sum outperformed CHI and delivered better results.Another significant occurrence is the unique issues connected with mining e-learning reviews and analyzing e-learning blogs, which makes the process more difficult and complex, and it is this component that is at the root of our loss of accuracy.

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