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BUILDING A CHATBOT SYSTEM TO ANALYZE OPINIONS OF ENGLISH COMMENTS

Nguyen H.V., Tan N., Quan N.H., Huong T.T., Phat N.H. **Building a Chatbot System to Analyze Opinions of English Comments.**

Abstract. Chatbot research has advanced significantly over the years. Enterprises have been investigating how to improve these tools' performance, adoption, and implementation to communicate with customers or internal teams through social media. Besides, businesses also want to pay attention to quality reviews from customers via social networks about products available in the market. From there, please select a new method to improve the service quality of their products and then send it to publishing agencies to publish based on the needs and evaluation of society. Although there have been numerous recent studies, not all of them address the issue of opinion evaluation on the chatbot system. The primary goal of this paper's research is to evaluate human comments in English via the chatbot system. The system's documents are preprocessed and opinion-matched to provide opinion judgments based on English comments. Based on practical needs and social conditions, this methodology aims to evolve chatbot content based on user interactions, allowing for a cyclic and human-supervised process with the following steps to evaluate comments in English. First, we preprocess the input data by collecting social media comments, and then our system parses those comments according to the rating views for each topic covered. Finally, our system will give a rating and comment result for each comment entered into the system. Experiments show that our method can improve accuracy better than the referenced methods by 78.53%.

Keywords: chatbot, offensive comments, behavioral culture, online, ontology, opinion mining, sentiment analysis.

1. Introduction. Many people use the Internet these days to communicate information. Information disseminates often, and many people's thoughts and comments are expressed. Therefore, taking into account and comprehending these remarks are beneficial. Therefore, there are numerous researches on user opinions in online journals [1] and numerous programs to study people's psychology and ideas can use with social networks like Twitter and Facebook [2]. For instance, keeping an eye on a particular brand's reputation on social media might give candidates an insight into the ambitions of voters, allowing them to adapt their speeches and actions. Financial market analysis can also use the comment analysis system, so similar to the stock market.

Nowadays, a ChatBot is a computer program that conducts an instant messaging conversation [3]. It can automatically answer questions and handle situations. In a ChatBot, the creators' algorithm determines the scope and complexity of the chatbot. It uses in various applications such as e-commerce, customer service, healthcare, banking and finance, and entertainment.

From another perspective, artificial intelligence and Natural Language Processing (NLP) integrated with machine learning algorithms play a significant role in today's technology. The survey on artificial intelligence in chatbots is based on a computer program that uses artificial intelligence to mimic human decision-making while providing various services [4]. In [4], the paper provides a survey based on multiple platforms used to build a chatbot to deliver various services to various users. The designed techniques used to create the chatbot are determined by the services that will be provided to the users. The chatbot will gain experience by learning from previous experiences and employing various algorithms. The data can be trained to the chatbot, allowing it to check with the knowledge base and to provide accurate answers to the user's query via client-side applications.

The research [5] on the structure of a chatbot using artificial intelligence (AI) aims to assess, diagnose, and recommend immediate safety and prevention measures for patients who have been exposed to nCOV-19 and acts as a virtual assistant to assist in measuring the severity of the infection through symptom analysis and connecting with competent medical facilities as it moves into the severe stage . In addition, some researches use Natural Language Processing (NLP) and Deep Learning (DL) techniques to develop a chatbot that can engage in interactive conversations with visitors during the MPU opening day [6], or AI-based chatbots to engage customers [7]. The authors 0recommend Restaurant Chatbots [8], Chatbot Using AI in the Healthcare Service Market [9], and Conversational AI [1] in the restaurant, medical, or communication industries. Furthermore, in the art exhibition, a group of authors presented an NLP-based solution for conversational agents [11]. In general, the authors have mentioned a lot of words, all of which have produced significant results, but using NLP to analyze and evaluate opinions has yet to be mentioned, and the evaluation analysis still needs to be improved in terms of comment evaluation.

With its clear benefits, Chatbot has become more and more popular. With the advent of technology 4.0, people have integrated more into the virtual and real world. Because of the rapidly increasing needs of society, it requires a large amount of manipulation, but choosing a large number of valuable comments for ourselves is essential. In this article, we propose a chatbot system that performs the following tasks:

– First: Collect and identify positive comments and remove negative ones;

– Second: Use many comments to evaluate the quality of the words;

– Third: Utilize an evaluation method to choose valuable comments for businesses.

The remaining paper is as follows. Section 2 gives an overview of the related work. The theory background is described in Section 3, followed by criteria for evaluating comments in Section 4. Next, the proposed model is presented in Section 5. Section 6 provides an evaluation. Finally, the paper is concluded in Section 7.

2. Related Work. According to the findings, chatbots are being expanded into almost every field, such as [12], an educational chatbot for the Facebook Messenger platform. Similarly, in a study [13], the software would also ask questions based on the candidate's previous responses, using a Natural Language Processing (NLP) model, which is very useful in this process. Following the interview, the software would analyze the data gathered to determine the best candidate for the offered position. As a result, the project JARO chatbot aims to simplify the hiring process. On the other hand [14], conversationally built with technology in mind, automated medical chatbots have the potential to reduce healthcare costs while improving access to medical services and knowledge. The method created a diagnosis bot that converses with patients about their medical questions and problems to provide an individualized diagnosis based on their diagnosed manifestation and profile. A practical method for determining discoverability and features such as language, subject matter, and developer platform [12]. Or for the patients, a framework that acts as a virtual assistant is created using ML algorithms. It can predict symptoms, recommend doctors, and investigate patient treatments by interacting with them – efficient patient health care with encouraging results [15].

On the one hand, the system creates a chatbot for academic purposes using NLP and ML that various educational institutions can use. There are two modes available: audio and text. Instead of being placed on the inquiry disk's waiting list, users can interact with the bot. The same question is asked in various forms to test accuracy [16]. As a result, the plan is to combine intent classification and natural language processing to create an interactive user interface and a chatbot. The model is intended to recognize user's queries and generate SPARQL queries [17]. Deep learning techniques were used to develop an online video lecture assistantm that improves Q&A data quality by incorporating multiple chatbots from various perspectives for a single video [18].

On the other hand, another approach is building a Chatbot model for Vietnamese comment management [19]; the author has also mentioned some changes to the algorithm proposal and significant improvements. However, this method is limited to this study's scope – Vietnamese language research. In this work, our approach is more extensive, and we develop an assessment based on the views of all the social network members. In addition, our method is based on the analysis of reviews and personal opinions about one or more products that are extended on social networks.

Furthermore, one report indicated that the chatbot design is primarily based on the device learning the rule. There are three steps to enforcing this chatbot. Raw records are pre-processed at the start. As a result, a data set is created. The splitting process occurs during the second step [20]. Some other techniques are used, such as [21]. The authors use an academic website, for example, how the system quickly calculates the bully word or no longer. In [21], various techniques are used here, including device mastery, fuzzy judgment, sample matching, and sentiment evaluation.

Recently, according to a survey by [22], there are 74 articles suggested chatbots. The studies mainly focused on application, methodology (methods used, sample size, sample type, and countries studies), and bibliometrics (publishing, citation, and spotlight agency). The main objective is to conduct a systematic review of high-quality journal research articles to summarize the current state of research on chatbots to identify their role in digital business transformation. On the contrary, we conducted a deep dive to assess the views of the English commentaries, from which to evaluate and give helpful information for businesses when promoting products on social networks.

As described in [23], a Chatbot application is a direct communication channel between the company and the end user in various fields, such as e-commerce or customer service. The authors used Xatkit in this paper. Xatkit solves these issues by providing a set of platform-independent Domain-specific Languages for defining chatbots. Xatkit also includes a runtime engine that deploys the chatbot application and manages the defined conversation logic on selected platforms. However, evaluating our opinion with this application is difficult because Xatkit depends on the accompanying tool, whereas our method is independent and has strong analytical and adaptive capabilities. The same experience-based research using Evatalk[24] is still limited when it only focuses on measuring people's satisfaction, not analyzing the human point of view carefully.

In addition to the articles on application development, there are a few articles on the exploratory potential of chatbots in providing online emotional support to people based on stress triggers. That is quite exciting; the authors have developed a social interaction agent based on empirical research to converse with stressed people seeking mental support. The author also addressed chatbot questions in helping users deal with stressful situations in [25]. In a similar study [26] the authors used queries developed on QA forums by Software Engineering practitioners. Both of the primary research methods are very intriguing. Nonetheless, both investigate the Software Engineering practitioner's feelings or processing.

Chatbot communication research [27], in which robots communicate with humans in natural language in an open domain, has made significant progress. However, it still has several unsolved issues, such as a need for more diversity and contextual relevance. Based on the retrieved prototype, the author proposed a retrieval polishing model (RP) to generate feedback polishing. The method relies on the response receiver and is focused on selecting the prototype for contextual retrieval. However, while this method improves improve fluency, contextual relevance, and response diversity significantly based on the number of prototypes, it results in a too complex system when dealing with a large sample flow. However, the authors wanted to know how/if the usability of the significantly improved method [28], based on the SOCIO chatbot prototype model, had changed. The author also attempts an empirical evidence-based evaluation of the usability of SOCIO V1 to the updated version, which necessitates comprehensive verification of test results to change performance, efficiency, satisfaction, and quality. That is feasible when evaluating with a small margin for error for experimentation, but there are still many risks when measuring only one parameter without measuring another.

In general, with the parsing technique of English sentences and words, with a recommendation system, we have improved the accuracy up to 78.53%.

3. Theory background. Natural Language Processing (NLP) literature with a variety of language analysis techniques, which only a small subset has been observed with regularity in sentiment mining. The most common is part of speech tagging [29], but there are also papers detailing classifiers using resolution [30] and even using a full syntactic parse tree [31], or Nasukawa et al [31] proposes a method to apply parsing to sentiment analysis.

In this part, we conduct Natural Language Processing (NLP) as follows:

– First: We analyze sentences and divide the comment sentences into words;

– Second: We use The Penn Treebank POS tags are divided into three categories: adjectives, nouns, and verbs;

– Third: Using SentiWordNet can be tweaked by using these tags to look at the meaning of words that match their POS tags.

Finally, to evaluate a comment, we also do a grammatical analysis to assess the statement. From there, we analyze and, based on the collected words, consider other people's comments online in society to conclude. We analyze and rewrite the sentence based on the conditions listed in Table 1.

Table 1. Meaning of the symbols

Type	Meaningful	Type	Meaningful
S	Sentence	***RP***	Particle
NP	Noun Phrase	***LST***	List marker
PP	Prepositional Phrase	***PRT***	Particle
VP	Verb Phrase	***UCP***	Unlike Coordinated Phrase
CC	Coordinating conjunction	***SYM***	Symbol
CD	Cardinal number	***TO***	to
DT	Determiner	***UH***	Interjection
EX	Existential there	***VB***	Verb, base form
FW	Foreign word	***VBD***	Verb, past tense
IN	Preposition/subordinate conjunction	***VBG***	Verb, gerund/present participle
JJ	Adjective	***VBN***	Verb, past participle
JJR	Adjective, comparative	***VBP***	Verb, non-3rd ps. sing. present
JJS	Adjective, superlative	***VBZ***	Verb, 3rd ps. sing. present
LS	List item marker	***WDT***	wh-determiner
MD	Modal	***WP***	wh-pronoun
NN	Noun, singular or mass	***WP$***	Possessive wh-pronoun
NNP	Proper noun, singular	***WRB***	wh-adverb
NNPS	Proper noun, plural	***PRP***	Personal pronoun
NNS	Noun, plural	***PRP$***	Possessive pronoun
PDT	Predeterminer	***RB***	Adverb
POS	Possessive ending	***RBR***	Adverb, comparative
RBS	Adverb, superlative		

Our system is designed to use many comments to evaluate the quality of comments for better analysis and evaluation using the comments entered into the system. Furthermore, our system provides an evaluation method to select valuable opinions for businesses, thereby bringing quality products to users. For example, we can see that we will rewrite the sentence in a parsed form in Figure 1, and the sentence above is rewritten in the form of TreeBank in Figure 2.

$$
\begin{array}{lll|lll}
S & \to & NP\ VP & DT & \to & \text{the} \\
NP & \to & \left\{\begin{array}{l} DT\ NNS \\ DT\ NN \\ NP\ PP \end{array}\right. & NNS & \to & \left\{\begin{array}{l} \textit{children} \\ \textit{students} \\ \textit{mountains} \end{array}\right\} \\
VP & \to & \left\{\begin{array}{l} VP\ PP \\ VBD \\ VBD\ NP \end{array}\right. & VBD & \to & \left\{\begin{array}{l} \textit{slept} \\ \textit{ate} \\ \textit{saw} \end{array}\right\} \\
P & \to & IN\ NP & IN & \to & \left\{\begin{array}{l} \textit{in} \\ \textit{of} \end{array}\right\} \\
 & & & NN & \to & \textbf{cake}
\end{array}
$$

Fig. 1. Parsing by sentence

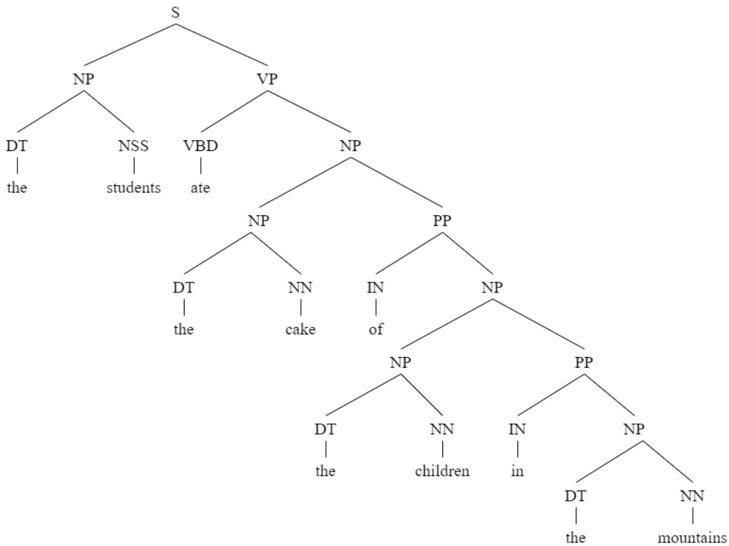

Fig. 2. Treebank

4. Design of Criteria for Evaluating Comments. The evaluation of emotions is quite essential to work, based on the general assessment of a specific topic is very reasonable when the opinions are more and more popular on social networking sites. The evaluation is always essential in the analysis for practical applications later. Based on this, we build a plan (Figure 3) to evaluate comments on social networks to find reasonable solutions for suitable products that society wants in the future.

Assessing the comments is a big challenge for Chatbots. Within the research scope of this paper, our system evaluates based on the parsing of the sentence and then evaluates the content and, finally, the commenter's evaluation conclusion. However, the problem encountered is that many comments need to be corrected; for example, short comments, acronyms, or grammatically incorrect, etc. Based on this content, we evaluate the comments to conclude whether they are negative or positive through previously trained vocabulary.

4.1. Negation. Negation is used to indicate that the comment is negative. In general, negative reviews will bring benefits to businesses.

In this paper, our Chatbot system will analyze comments based on the content and language processing analysis. The comments that our system evaluates can benefit businesses when the system can be a yardstick to assess products on social networking sites. We use categorical phrases to show negative comments through negative words. Such as "bad," "terrible," etc., in a sentence. For example, "This computer is terrible", the word "terrible" here indicates that the comment is negative. Here, we do not analyze whether the sentence is negative [32].

In natural terms, the evaluation is based on the proposed algorithm to determine the positive or the negative. The algorithm is based on a training dataset to make comment conclusions.

4.2. Positivity. Positivity is used to indicate that the comment is positive. We use categorical phrases to show positive comments through positive words. Such as "good," "excellent," etc., in a sentence. For example, "This computer is excellent," the word excellent here indicates that the comment is positive. Again, keep in mind that we do not analyze whether the sentence is positive [32].

Recently, many businesses often ignore responding to positive reviews because they think it is unnecessary, but in reality, you need to respond to all user experience reviews. That shows the brand's professionalism and effectively builds customer trust and loyalty. Using the following article [33] to learn how to respond to positive comments with Chatbot is to improve your business's customer service.

Moreover, through customer reviews, the enterprise can expect to increase or expand its production scale. On the other hand, mass-creating products without regarding to customers will directly impact the business and the company's interests.

5. Our proposed model. In this section, we propose a system structure in which the system is divided into several main parts, including Ontology and Preprocessing as described in Figure 3.

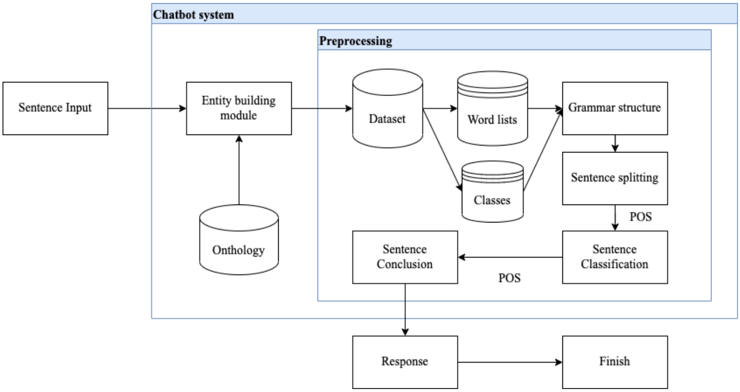

Fig. 3. Proposed System Structure

5.1. Ontology. In this part, we create a module (called: Entities building module) to take the product type as input. This module is in charge of retrieving the knowledge base from Ontology and extracting all entities from the corresponding branch of the product.

The entity is a critical component in the spam detection system, serving as the foundation for the search process and matching Ontology. A sentence can contain a single entity, multiple entities, or none. Preprocessing modules will perform and recognize this entity and save the entity identified in data preprocessing to assist the algorithm in identifying spam reviews. The entity here is not just the named entities but all entities in a sense defined by the researchers. We describe an entity as the word meaning, which brings specific knowledge in the reviews, to use these entities to find the product knowledge contained in the reviews. This definition states that adjectives and nouns are two types of words we have chosen to filter into the desired entity.

An ontology cannot cover all meaningful aspects of a field, so specific objectives are used for identifying spam reviews. Extracted entities are focused on product components or properties. As a result, the entity will be collected and distributed to the class groups based on their common characteristics following the statistics.

First, the system's input is a sentence, which is responsible for receiving a sentence to process and analyze whether that sentence is positive or negative. Next, the input data will pass through an Ontology used to create an entity (Entity building module), assisting the system in evaluating the words that the system has previously processed. This is the foundation for the search process. Ontologies search and match.

Furthermore, a sentence may contain one or more entities, or none, which can be understood as critical keywords to support faster and more accurate processing and assessment of sentence properties. The preprocessing modules will recognize these entities, calculate and save the probability results determining the positive or negative of the entity to support the matching of entities in the sentence.

5.2. Preprocessing. The preprocessing module analyzes the content and title of the review and produces the data required by the classification model. Figure 3 depicts the division of preprocessing work.

The essential input to the model is the content of the review. As a result, normalizing must be completed before proceeding with the other processing steps to create standard data sources and avoid error analysis.

There are numerous methods for extracting words from a text. We chose the way n-gram models of unigram, combined with the POS tagging model, for this study. Stanford University's POS tagging tools (Stanford POS Tagger) have a relatively large database and have been widely used in the study of language processing. We chose this tool for the word-splitting module because of its high accuracy and processing performance. To do this, we did the following simulation:

First, the dataset here includes Comments collected from sources on the Internet such as forums, social networks, websites, etc. Then, through Grammar Structure, label POS for each element of the sentence through the POS labeling model (Stanford University's POS tagger has a sizeable available database and has been applied extensively in natural language processing research courses). We chose this tool in processing word decomposition in sentences and structural analysis of components in sentences because it has relatively high accuracy and has been applied in many places in analyzing nature processing language.

Second, the processing of sentences after they have been separated into words will match with WordLists and Classes used to classify what type of sentence the sentence belongs. Our system divides into five sentence types: simple, conditional, comparative, compound, and special sentence. Depending on the type of sentence, the system has different ways of processing words in the sentence to get accurate results. Specifically, after being decomposed into words and labeled through the POS model, the sentence will be sorted into an array to browse each word in the sentence, from which the system will evaluate whether each word is in it. How likely it is that the word has such a character depends on whether the word is positive or negative. After evaluating each word in the sentence, the system will classify positive or negative comments.

A specific generative grammar aims to provide a set of rules that generate (or, more abstractly, license, predict, etc.) all phrase structure trees that correspond to English grammatical sentences. This means that only the word sequences standardized by a linguist and a syntactic structure description (phrase structure) would be considered correct and complete sentences. The rules also include claims about the constituent structure of English.

5.3. Database design. Many languages are used to write social networks. As a result, it must apply to all languages and libraries. It must be constantly updated and expanded to ensure the chatbot's effectiveness. There are two factors required to ensure:

– The number of English words must be large enough to avoid confusion.

– The program can handle frequent updates without requiring cumbersome manipulations.

For example, English is challenging to evaluate due to its large area of vocabulary and grammar. Specifically, it contains 12 tenses [34] and complex structures. Moreover, with the number of comments increasing, we focus on assessing the opinions of the comments. Thus, a dictionary can break sentences into meaningful words and phrases. We calculate and draw opinion conclusions based on evaluation and analysis based on meaningful words or phrases.

5.4. System model. The opinion analysis system consists of 3 main components in Figure 3:

– Data set: Includes comments collected from sources on the Internet such as forums, social networks, websites, etc.

– Sentence classification in Figure 4: it is the function of classifying sentences commenting on their sentence types, such as simple sentences, compound sentences, negative sentences, comparative sentences, etc.

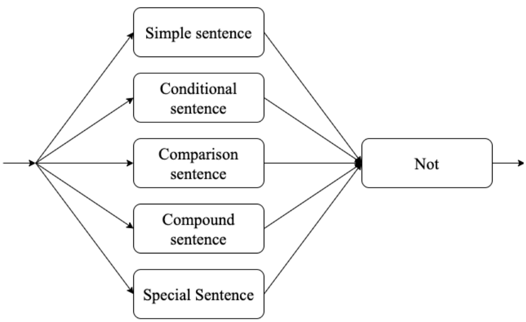

Fig. 4. Sentence classification model

– Result: The final feature will decide which group the comments belong to, positive, negative, or neutral.

The classification model has five classification features of basic sentence types, including simple sentences, conditional sentences, comparative sentences, compound sentences, and special sentences. In addition, for each of the above categories, there is a negative test in the sentence.

On the one hand, in the chatbot system, there is an equally important part of machine learning training.

Read data. The system reads data from the existing data file and adds data to lists. Word is a list containing POS-tagging for each word in a sentence, and classes is a list containing the classification type of the sentence here is positive. And the negative document is a list that includes both words and classes. In addition, there are ignore-words, a list of elements that can ignore in a sentence, and it does not affect the evaluation of sentence classification.

Word tokenization. In this step, we will look at each token (i.e., word by word of a sentence) and try to predict the phrase type of this token. It can be a noun, a verb, an adjective, and so on. Knowing each word's role in a sentence can help determine the meaning. The original part-of-speech model is trained by feeding millions of English sentences with each word of speech tagged, reproducing those behaviors. Note that, this model is purely based on statistics - it needs to understand what these words mean, as humans do. It only knows how to guess a part (i.e., a comment) of speech based on similar sentences and observations it has seen before.

Text lemmatization. Lowercase each word and remove duplicate comments. Lemmatization is to bring words to their original format by using a lookup table of the actual vocabulary of the words in the sentence. There may be rules for dealing with comments we can have never seen before.

Create training model. The prepared dataset is forwarded to the sequential build model to the respective weight of the process. Then the system will save the trained model of the system for deployment. Below is a detailed description of the proposed algorithm.

– Step 01: Layer 1, 128 neurons, dropout(0.01). Layer 2, 64 neurons, dropout(0.01).

– Step 02: Compile the network with parameters to train the network to evaluate the optimization.

– Step 03: Learning Rate = 0.001.

On the other hand, we define classify sentences in the Chatbot system as follows:

5.4.1. Simple sentences. Simple sentences express a straight point of view, in which the sentence can contain at most one verb (or possibly none, e.g., good or bad). Example sentences are as follows: Samsung is good.

After going through the POS tagging system, this sentence will give the following results: Samsung_NN is_VBZ good_JJ. The sentence contains one subject (Samsung), one verb (is), and one adjective (good).

The sentence above is positive because we see that there is the adjective good, which is a positive word.

Therefore, to determine the point of view on a single sentence, we need to identify the adjectives (or adverbs) in the sentence that indicate positive or negative. Currently, we use two dictionaries with more than 6,800 adjectives expressing opinions (1 set of positive adjectives and 1 set of negative adjectives).

For this type of sentence, we build a Chatbot system that handles the following steps in turn:

– Step 01: Label sentences (POS tagging).

– Step 02: Find adjectives.

– Step 03: Find out which order the adjective belongs to (positive/negative).

– Step 04: Conclude.

Negative on a simple sentence. Let’s consider the example "The Dell’s sound quality is not pretty good" in a sentence containing the adjective good. This is a positive word, so with the steps above, we would conclude that this is a positive opinion sentence, but it is clear that the above sentence has the exact opposite opinion. As we have seen in the above sentence containing the negative word (not), this is the key word to determine the point of view of the above sentence. Without it, the above sentence is entirely positive, so we need to check if it contains a negative word. We have to reverse the point of the sentence.

5.4.2. Conditional sentences. Conditional sentences are sentences that describe hypothetical effects or situations and their consequences. In English, various conditional joins can be used to form sentences. A conditional sentence consists of two clauses: A conditional clause and a consequential clause, which depend on each other. This relationship has important implications for describing the opinions of sentences. For the sake of simplicity, comment words (also known as opinion words) (e.g., great, beautiful, bad) alone cannot determine the opinion in a sentence. A conditional sentence can contain many comment words or phrases but may not express an opinion [35].

About here, we will describe a few examples to parse this sentence form:

Example 1: "If someone makes a beautiful and reliable car, I will buy it" expresses the opinion that there is no sympathy for any car, even though "beautiful" and "reliable" are two words that mean positive comments. However, this does not mean that a conditional cannot express opinions/comments.

Example 2: "If you are looking for a phone with good voice quality, don't buy this Nokia phone." It has a negative connotation with the "voice quality" of "Nokia phone," although here there is a positive comment "good" in the conditional on complementing "voice quality." However, according to the above sentence, the point of view is the opposite.

Furthermore, we noticed that most conditional sentences contain the word If. However, there are also many other dependent join words such as: even if, unless, in case, assumption/supposing, as long as, etc. Corresponding to each word (phrase) also gives different evaluation conditions.

For this type of sentence, we analyze some assessment skills as follows:

Firstly: Find the position of the commented words/phrases.

Secondly: POS tags comment words; comment words can use in some of the following cases, not all sentences containing an opinion, for example, I trust Motorola, and He has a trust fund both contain the word trust. But only the previous sentence has an idea.

Thirdly: Find words that do not indicate an opinion; similar to how to find comment words related to an idea, here are some words that imply the opposite. Words like wondering, thinking, and debating of the user ask questions or expresses doubt.

Fourthly: Tense patterns and basic tenses use to create a set of features. We identify the first word in both conditional and consequential clauses by searching for related words using POS tags. Fifthly: In sentences with or without the characters '?' and '!'.

Sixthly: Conditional associations used in sentences (if, even if, unless, only if, etc.) are considered a feature.

Seventhly: Conditional clause length and consequences. Using simple punctuation rules in the language, we automatically segment sentences into conditional and consequential clauses. Usually, the conditional is very short and does not affect the statements of opinion.

Eighthly: The use of negative words like not, don't, and never, etc., often change the opinion of a sentence; for example, adding negative words before comment words can change the idea of a sentence from positive to negative.

In addition, to handle more complex sentences, we propose to analyze and perform the following in Table 2:

If the condition contains VB/VBP/VBZ $\rightarrow$ 0 conditional;

If consequent contains VB/VBP/VBS → 0 conditional;
If the condition contains VBG → 1^{st} *conditional*;
If the condition contains VBD → 2^{nd} *conditional*;
If the condition contains VBN → 3^{rd} *conditional*.

Table 2. Tenses to identify comparative sentence types

Type	Linguistic	Condition POS tags	Consequent POS tags
0	If + simple present → simple present	VB/VBP/VBZ	VB/VBP/VBZ
1	If + sim present → will + bare infinitive	VB/VBP/VBZ/VBG	MD+VB
2	If + past tense → would + infinitive	VBD	MD+VB
3	If + past perfect → present perfect	VBD/VBN	MD+VBD

5.4.3. Comparative sentences. A helpful note about comparative sentences is that in each such sentence, there is usually a comparative (e.g., “better,” “worse,” and –er) or superlative (e.g., “best,” “worst,” and the word –est). The objects to compare often appear on either side of the word comparison. An excellent sentence can have only one entity, e.g., “Camera X is the best.” For simplicity, the author uses comparative words (sentences) and superlative words (sentences).

The comparative words mainly identify the preferred entities in a comparative sentence in the sentence. Some comparative words explicitly indicate user preferences, for example, “better,” “worse,” and “best.” We call such words opinionated comparative words. For example, given the following sentence: “the picture quality of Camera X is better than that of Camera Y,” Camera X is a popular product due to its comparative point of view word “better.”

However, many comparators do not have a specific point of view, or their opinion (positive or negative) depends on the context or the application domain. For example, the word "longer" does not hold the conventional wisdom to show that the length of some feature of one entity is greater than that of another. However, it can represent a desired (positive) or undesirable (negative) state in a particular context. For example, given the following sentence: "the battery life of Camera X is longer than Camera Y," "longer" clearly wants to represent the desired state of "battery life" (although the object in the sentence does not support a clear opinion). "Camera X" is also the favorite with "battery life" among the compared cameras. The opinions in the above sentence are called implicit opinions.

Sentences with opinion words (for example, "better" and "worse") are usually easy to deal with. The key to solving our's problem is to identify the opinions (positive or negative) of the context-dependent comparative words. To conclude, two questions arise: (1) what is context, and (2) how can context be used to help determine the opinion of a comparative word?

The simple answer to question (1) is the whole thing. However, the entire sentence and the context could be more straightforward because much irrelevant information, which can confuse the system. Intuitively, we want to use the most accurate context that can confirm the point of view of the word comparison. So, the context must have entity features to compare and find the comparison word. To answer the second question (2), we need more information or knowledge because there is no way a computer program can solve the problem by analyzing the sentences themselves. In this article, we propose to use customer evaluation information on the Chatbot system to help solve the problem.

5.4.4. Compound sentences. A compound sentence is a sentence that contains the following words: but, although, however, and nevertheless. For this type of sentence, the meaning will often be the opposite of the user's original desire.

Example: This is great. However, I hate it; although this is good, I won't buy it, etc.

For this type of sentence, we propose to evaluate according to the following steps:

– Step 01: Identify sentences containing but, although, however, and nevertheless, not.
– Step 02: Split the above sentence into simple sentences.
– Step 03: Processing simple sentences.
– Step 04: Conclusion.

5.4.5. Special sentences. Special sentences are sentences that contain special words or contain dichotomous words. For example:

– Dell has a fast processor.
– Dell has a fast battery.

We can see that fast here is fast, which is fine if you have a fast processor, but it is terrible for battery life. As for how to deal with this, we have established a dictionary of associated words and their views. Here, we can understand that "processor+fast->Positive", "Battery+fast->Negative".

6. Evaluation

6.1. Experimental Settings. In this section, we proceed to install and test. The experiment was written in Python and tested on a 64-bit Windows 11 Pro computer with the following configuration: 16384MB of RAM and an 11th Gen Intel(R) Core(TM) i5-11400H 2.70GHz, 2688 Mhz, 6 Core(s), 12 Logical Processor(s). Besides, we use negative and positive words with 6800 words [32]. The data we collect are products, including computers (531 sentences), routers (879 sentences), and Speakers (689 sentences) [36] to test.

When working with text data, we must perform various preprocessing steps on the data before building a machine learning or deep learning model. We must apply various operations to preprocess the data based on the requirements. Tokenization is the most fundamental and first thing you can do with text data. Tokenizing is dividing a large text into small parts, such as words. We iterate through the patterns, tokenizing the sentence with the nltk.word tokenize() function and appending each word in the words list. We also make a class list for our tags. We will now lemmatize each word and remove any duplicates from the list. Lemmatizing converts a word to its lemma form and creates a pickle file to store the Python objects used during prediction.

Furthermore, in Table 3, we also test with ten comments that we give manually and evaluate and compare our system prices.

Table 3. Result of evaluation between the system Chatbot and Human

N.	**Some English comments on social networks**	**Evaluates**		**Conclusion**
		Our ChatBot	**Human**	
1	Hardware with very stable performance.	Positive	Positive	**True**
2	This program contains suspicious, malicious code.	Negative	Negative	**True**
3	More memory will run smoother.	Positive	Positive	**True**
4	If I leave this computer here for a month, it will malfunction.	Negative	Negative	**True**
5	In terms of performance, this year's gaming computer is better.	Positive	Positive	**True**
6	This program performed worse than expected compared to the previous run.	Negative	Negative	**True**
7	It's been a long time since he used his calculator, but it still works fine with minor repairs.	Positive	Positive	**True**
8	He tried to remove malicious programs from his computer, but it failed and even crashed his computer.	Negative	Negative	**True**
9	Fantastic, it works without problems!	Positive	Positive	**True**
10	Dammit, the laptop is so old!	Negative	Negative	**True**

The results show that the system we evaluated correctly with our manual evaluation reached 100%. To calculate the above result, we use the following formula [19]:

$$Correct detection rate = \frac{The correct number of comments}{Total number of comments}. \quad (1)$$

– **Correct detection rate**: Accuracy of comments on the system.

– **The correct number of comments**: The correctly evaluated sentences that the input already knows.

– **Total number of comments**: The total number of whole sentences tested.

In this part, the proposed is compared with two reference methods, A Chatbot for Changing Lifestyle in the Education method (called **ACCLE**) and Interactive Transport Enquiry with AI Chatbot (called **ITEAI**). A summary of those reference methods is described as follows.

– ACCLE [37]: The author proposes a Chatbot system to serve to learn between teachers and students. The system is implemented by having students ask questions in the Chatbot in the form of text. Then the system processes it through natural language processing and deep learning technology. Finally, the system processes to answer the student. However, this system only serves schools and has yet to analyze the respondents' emotions.

– ITEAI [38]: Similar to the **ACCLE** method, this method also builds a Chatbot system that confirms the user's current location and final destination by asking some questions. The design of this method checks the user's query and extracts the appropriate entries from the database. This approach aims at the receiver to get all the information about the bus name and number. Them so that the person can safely move to the desired location.

Although the methods used have their strengths, our approach has been evaluated based on training, information extraction, and evaluation based on human emotions to assess the overall and give good results for the desired user.

Based on the dataset used and having the correct sentence classification, we conducted a test with 230 (Negative: 67, Positive: 163) sentences with the data file Computer.txt, with Router.txt with 222 (Negative: 81, Positive: 141) sentences, and Speaker.txt with 284 (Negative: 63, Positive: 221) sentences rated as standard negative and positive (Figure 5).

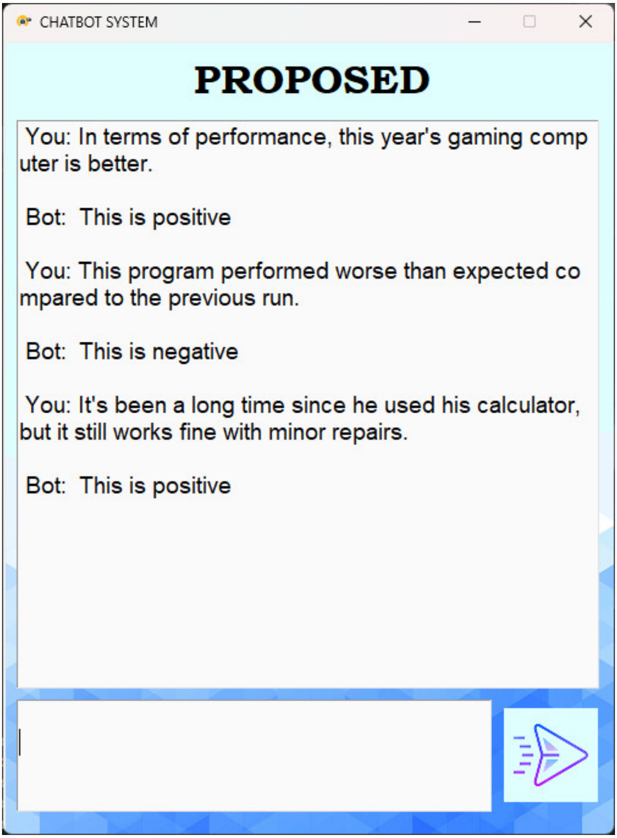

Fig. 5. GUI - The proposed

In this paper, we have referenced two related works. Unfortunately, our system gives better results than the two referenced methods in Table 4.

Table 4. Performance of the proposed and reference methods

Type	**ACCLE**	**ITEAI**	**The proposed**
The number of negative sentences	368	271	290
The number of positive sentences	2	290	288
Total number of comments	736	736	736
Rate of the positive sentence	**50.27%**	**76.22%**	**78.53%**
Build finished in 1 minute	10s	55s	46s
Build finished in	70.0679s	55.1462s	46.2025s

The results in Table 4 show that the proposed method always accounts for a higher percentage than the remaining methods when considering 736 sentences. The ACCLE approach shows low results when it comes to the average at 50.27%, while the ITEAI method gives results of 76.22% or more. The proposed method reached the lowest level at 78.53%.

7. Conclusion. We have built a Chatbot model to deal with some simple sentences, such as simple sentences, and comparison sentences with conditional and compound sentences, which are reliable, but for memorable sentences because there needs to be more time to solve the problem.

The paper has built an automatic evaluation model of opinion mining over a Chatbot system. This concept developed in response to the current issues that businesses face as social networks grow, but quality values remain limited. A series of document reviews to ensure consistency in all work, and the chatbot was determined to be the best model to meet the requirements. Chatbot research draws connections to learn more about emerging transient technologies and compatible algorithms such as Artificial Intelligence, Machine Learning, Python, and Natural Language Processing (NLP). The results show that our proposed method is up to 78.53%.

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СОЗДАНИЕ СИСТЕМЫ ЧАТ-БОТОВ ДЛЯ АНАЛИЗА МНЕНИЙ АНГЛОЯЗЫЧНЫХ КОММЕНТАРИЕВ

Нгуен Х.В., Тан Н., Куан Н.Х., Хыонг Ч.Т., Пхат Н.Х. **Создание системы чат-ботов для анализа мнений англоязычных комментариев.**

Аннотация. Исследования чат-ботов значительно продвинулись за эти годы. Предприятия изучают, как улучшить производительность, принятие и внедрение этих инструментов, чтобы общаться с клиентами или внутренними командами через социальные сети. Кроме того, предприятия также хотят обращать внимание на качественные отзывы клиентов в социальных сетях о продуктах, доступных на рынке. Оттуда, пожалуйста, выберите новый метод для улучшения качества обслуживания своих продуктов, а затем отправьте его в издательские агентства для публикации на основе потребностей и оценки общества. Несмотря на то, что в последнее время было проведено множество исследований, не все из них затрагивают вопрос оценки мнений о системе чат-ботов. Основная цель исследования в этой статье — оценить человеческие комментарии на английском языке с помощью системы чат-ботов. Документы системы предварительно обрабатываются и сопоставляются мнения, чтобы предоставить заключения на основе комментариев на английском языке. Основанная на практических потребностях и социальных условиях, эта методология направлена на развитие контента чат-бота на основе взаимодействия с пользователем, что позволяет осуществлять циклический и контролируемый человеком процесс со следующими этапами оценки комментариев на английском языке. Сначала мы предварительно обрабатываем входные данные, собирая комментарии в социальных сетях, а затем наша система анализирует эти комментарии в соответствии с рейтингом просмотров по каждой затронутой теме. Наконец, данная система будет давать рейтинг и результат комментариев для каждого комментария, введенного в систему. Эксперименты показывают, что данный метод может повысить точность на 78,53% лучше, чем упомянутые методы.

Ключевые слова: чат-бот, оскорбительные комментарии, культура поведения, онлайн, онтология, анализ мнений, анализ настроений.

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