Sentiment Analysis of Food Recipe Comments

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ABSTRACT

Sentiment analysis of food recipe comments is to identify user comments about the food recipes to the positive or the negative comments. The proposed method is suitable for analysing comments or opinions about food recipes by counting the polarity words on the food domain. The benefit of this research is to help users to choose the preferred recipes from different food recipes on online food communities. To analyse food recipes, the comments of each recipe from members of the community will be collected and classified to neutral, positive or negative comments. All recipes' comment messages are processed using text analytics and the generated polarity lexicon. Therefore, the user can gain the information to make a smart decision. The evaluation of the comment analysis shows that the accuracy of neutral and positive comment classification is about 90%. In addition, the accuracy of negative comment identification is more than 70%.

Keywords: Food recipes, Sentiment analysis, Text analytics, Comment analysis

1. INTRODUCTION

There are many food communities with recipes on how to cook recently because of users with the same interests forming the community to help each other in sharing, searching, advertising, and decision making [1]. In addition, members in food communities can comment on food recipes and exchange their experiences about cooking by each recipe. Some comments agree that dishes made using those recipes taste good while some comments disagree and give the information to improve the recipe of dishes. Therefore, these user comments about food recipes from other persons are valuable resources to help members make a decision and choose the recipe that they will prefer from various food recipes. Furthermore, the recipe authors can improve their own recipes following comments from other persons.

Although there is a star rating for food recipes on popular food websites, the rating may not be reliable because members of the community can vote the food recipes by giving scores without the practical preference consistency. Moreover, the preference rating summarizing from all actual recipes' comments will be more trustworthy than those of star rating. Therefore, if there is the system which can automatically analyse information from all user comments about food recipes, the summary of score rating and the classification of comment groups are the valuable information. The benefit of an analysis system is also shown on studying consumer behaviour following sentiment analysis [2] [3].

Sentiment analysis, or so called opinion mining involves natural language processing, text analytics, and computational linguistics to identify sentiment polarities. One basic objective of opinion mining is to extract useful information about products, events or topics from people's opinions, attitudes, views and emotions [4]. Another objective of sentiment analysis is to classify the polarity of a given text on documents, in sentences or phrases depending on summaries expressed opinions or attitudes [5]. Sentiment analysis can also be the fundamental component in the text-driven monitoring and the general sentiment towards real-world entities, such as products and consumers [6]. Opinions or comments from other people are core factors of the consuming manner and actions because most people often seek out the opinions of others before they make the decision to choose the right things that they want [7]. In addition, consumers or users always post reviews of services or give comments about products which express their opinions and exchange personal experiences about them on the internet, such as reviews, blogs, and forum discussion in the online communities. Furthermore, businesses always want to find public or consumer opinions about their products and services.

However, finding and reading opinions or comments on the internet and filtering the suitable information remain challenging tasks because of a huge volume of texts and a variety of interesting things. The human reader will have difficulty identifying relevant texts and accurately summarizing the information and opinions contained in them. Sometimes human analysis of text information has biases and limitations because people often pay attention to opinions that are consistent with their own favourites [4]. Additionally, users can input a sentiment target as a query (e.g. topics, subjects or products), and search for positive or negative sentiments towards the target [8]. Therefore, it is also widely accepted that extracting sentiments from text is a hard semantic problem even for human beings. Moreover, sentiment anal-

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ysis is still domain specifi c because the polarity of some terms depends on the context in which they are used [9]. For example, the word "small" in the mobile devices is the positive feature, while this word is the negative polarity in the agricultural products, such as fruits. There is the relationship between the context of text and the sentiments of text, thus the subject-dependent sentiment analysis is more informative and more useful than the subject-independent analysis.

For all previous reasons, this research proposed the automated sentiment analysis of food recipes' comments using text analytics. The aim of comment analysis is to classify food recipes' comments into three groups that are neutral, positive and negative groups by detecting and counting positive and negative words in the food domain.

The detail in this paper will be described in the following sections. The related works of sentiment analysis and classification are explained in section 2. The proposed method described in section 3. Next, experiments and the results are demonstrated in section 4. Finally, the conclusion of this research is summarized and presented in section 5.

2. RELATED WORKS

Opinion or sentiment classification techniques can be classified into two main categories that are 1) the classification based on supervised learning using the machine learning; 2) the classification based on unsupervised learning with the semantic orientation approach. Sentiment classification with a supervised learning uses the training data to learn the classification model for determining the testing data into three classes: neutral, positive or negative. Any existing supervised learning methods can be applied to sentiment classification, such as decision tree classifier, naive Bayesian classification, and support vector machines (SVMs) [4]. On the other hand, sentiment analysis technique by the semantic orientation approach does not require prior training data because the positive or negative class identification can be calculated directly by positive and negative sentiment scores, such as lexicon-based sentiment analysis [10]. The main objectives of the sentiment analysis with the semantic oriented method are to measure and to classify the subjectivity and opinion in text by generally capturing evaluative factors and potency or strength towards subject topics, or ideas. In addition, the aggregation of sentiment for each entity and certain lexicons with sentiment words are very informative and efficient [6].

There are some studies analysing messages on Twitter, reviews and comments on social communities using the semantic oriented technique combined with the machine learning. The result of these researches expresses that the performance of the automatic sentiment classification is acceptable for users and the gained information are very useful.

The subjectivity analysis method [2] applies the semantic information about words and the decision tree classifier to analyze messages about airline services. The outcome of the application can help both the customer and the provider of airline services to select only opinions or comments from many contents on Twitter. Furthermore, customers can make a decision to choose the airline services that they want from different airline brands. The next related work of subjectivity analysis in [2] is the opinion mining technique in [5]. The subjective messages about airline services are classified into two groups that are positive or negative messages. This technique analysis the syntactic and semantic information about words in the message and generates message features for learning opinion groups by Naïve Bayes classifier. The result can show that both customers and providers of airline services can take advantages from automated sentiment analysis of Twitter data.

The sentiment classification [11] developed a lexicon-enhanced method to generate a set of sentiment words using the word information from a sentiment lexicon. The sets of sentiment words are the sets of sentiment features to learn and evaluate the sentiment classification model using five sets of online product reviews.

The article [12] provided an in-depth analysis of user comments in two prominent social Web sites, namely YouTube and Yahoo! News. The aim is to achieve a better understanding of community feedback on the social Web. The textual contents, the thread structure of comments, and associated content are analysed to obtain a comprehensive understanding of the community commenting behavior.

The paper [13] discusses the notion of usefulness in the content of social media comments and compares it from end-users as well as expert perspectives. The machine learning is applied to classify comments using syntactic and semantic features, including the user content. In addition, the relatively straightforward features can be used to classify comments.

According to all related works, the results showed that these analysis techniques are very beneficial for users, consumers and product providers in different domains. Therefore, the comment analysis of food domain using the sentiment analysis can generate the new knowledge and summarize the valuable information about food recipes for users and recipe authors.

The proposed sentiment analysis of user comments about food recipes in this research is the improved methods for obtaining the higher performance of analysis from [14]. Both studies have the same objective, which is to classify food recipe comments into three groups: neutral, positive or negative messages. Several improvements have been made to the analysis technique described in section 3. For example, the word "not" which are used in abbreviated forms with the helping verbs in text messages are detected and labelled accordingly. A few word abbreviations and spoken words commonly used online are also identified as "positive" or "negative", such as the words "omg, OMG - Oh My God" and "yum" expressing the positive attitude. Moreover, the different forms of some negative words to describe food, e.g. weird and weirdly, are added to the polarity lexicon. Furthermore, the better result is shown in section 4.

The characteristics of these comments are similar to those of short informal textual messages which analysis processes do not focus on sentence-level sentiment classification unlike product reviews or article documents. While the sentiment of most topic reviews is analysed in sentence-level and document-level sentiment classification, the sentiment analysis tasks of short informal messages are separated into term-level and messages-level [15]. The sentiment of a word or a phrase within a message is detected (term-level) like the phrase-level sentiment analysis in [16] before the sentiment of a short informal textual message is classified (message-level). However, the sentiment of each sentence in short informal textual messages can be recognized by the polarity or the subjectivity of terms occurring in the sentences (like sentence-level). Thus, the words in each domain are important to identify terms as positive or negative sentiments. For example, the adjective word "moist" cannot be determined the positivity or the negativity, including the polarity score (PosScore and NegScore) in the SentiWordNet [17] is the zero value, but this word is the positive meaning in the food domain. Moreover, some words, e.g. tasting, which clearly is positive for the food, may be the positive or negative feature in different contents because there are more than one synset terms with different polarity scores in the SentiWordNet [17]. Additionally, Negation cues, e.g. the words "never" or "not" from [18] are examined for the sentiment analysis.

Consequently, the article [14] and this research studied many comment messages with phrases and words about food recipes to appropriately identify the positivity or the negativity for words or terms in the food domain. Therefore, the proposed sentiment analysis of food recipe comments using the semantic orientation approach is the intensive analysis of words and their meaning about foods. In addition, the summary information of the sentiments or opinions of the software implementing this sentiment analysis is adequate to satisfy the members of the food community. Furthermore, there is no need for the training data to analyse the sentiment of text comments.

Another related research about food recipe comments is the suggestion analysis for improving food recipes [19]. The user comments about food recipes are classified into two groups that are comments with suggestions or without suggestions. The suggestion or the guidance can help food community members to modify or adapt the food recipes. The semantic information of words from WordNet [20] is included in the analysis process to identify nouns being the food ingredients. The suggestion analysis is applied to be another feature of the software analyzing food recipe comments.

3. SENTIMENT ANALYSIS OF FOOD RECIPE COMMENTS

This research proposes the sentiment analysis technique for food recipes' comments and also improves some analysis processes from the comment analysis in [14]. The objective of this sentiment analysis is to classify food recipes' comments from community members into neutral, positive and negative groups. The proposed sentiment analysis is based on syntactic and semantic information of words or phrases in the comment messages, e.g. the abbreviated forms of negative helping verbs, the positivity or the negativity of words in a created polarity lexicon. The analysis processes are composed of pre-processing, detecting polarity words, calculating polarity scores of sentences and comments. This technique analyses recipe comment messages by words' information from the polarity lexicon to detect polarity words for the sentiment classification. The sentiment analysis of food recipe comments is shown in Fig. 1.

3.1 Preprocessing

All comments of food recipes are collected as texts from the food online community. In the preprocessing process, there are four steps to prepare the input word data for the detection process of polarity words.

The first step is that all special characters are detected to delete from user comment messages because of these characters, i.e. "#" and "@", do not relate to the sentiments. Next, all capital letters are changed to lowercase characters in the second step. Then, in the third step, all sentences of recipes' comments are divided into individual sentences by some sentence punctuations, such as "." and "!".

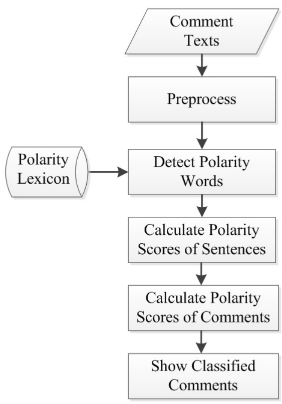

Fig.1: *The Sentiment Analysis of Food Recipe Comments.*

Finally, all words in all sentences of the user comment are separated into individual words in the final step of pre-processing, using space between two words and some punctuations, for example "," and "-".

After the pre-processing process, the word sequences of all sentences in the user comment are collected and some words are handled by syntax to provide knowledge for the next process. For example, some words which are usually used in abbreviated forms in text messages and the meaning is "not" are labelled as words presenting the opposite meaning of sentiments. Some words with their common abbreviated forms are shown in Fig. 2.

don't (do not)	didn't (did not)
isn't (is not)	aren't (are not)
wasn't (was not)	wouldn't (would not)

Fig. 2: *The Words in Abbreviated Forms.*

A recipe's comment input (Comment 1):

"Delicious! I used fresh skinless, boneless chicken breasts and olive oil instead of melted butter. Chicken was moist and tasty! Thanks for the great recipe!"

The output of the pre-processing process for the comment is described as follows: All letters are transformed into lowercase letters and this comment consists of four sentences which are divided by the exclamation point ("!") and the full stop (".").

"delicious"
"i used fresh skinless, boneless chicken breasts and olive oil instead of melted butter"
"chicken was moist and tasty"
"thanks for the great recipe"

Then, all individual words are separated by the space and the comma (","). The word sequences of all sentences are ordered.

Another recipe's comment input (Comment 2):

"I was very excited to try this recipe, but I was so disappointed at the outcome. It didn't taste as good as all the reviews made it out to be."

The output of the pre-processing process for the comment is explained as follows: All letters are converted into letters in lowercase and this comment consists of two sentences which are divided by a full stop (".").

"i was very excited to try this recipe, but I was so disappointed at the outcome"

"it **didn't** taste as good as all the reviews made it out to be"

Then, all individual words are separated by the space and the comma (","). The word with opposite meanings ("didn't") in the abbreviated form is labelled.

3.2 Detecting Polarity Words

To detect polarity words, this research creates the new polarity lexicon for the good domain based on the SentiWordNet [17]. Many words from many comments about food recipes are collected to filter subjectivity words. All words are analysed by the text analysis freeware [21] to count the frequency of words. Words found in the SentiWordNet [17] are considered to be polarity words in the lexicon. The user interface of the text analysis freeware [21] is displayed in Fig. 3 and examples of words and their information, including sentiment scores in the SentiWordNet [17] are presented in Fig. 4.

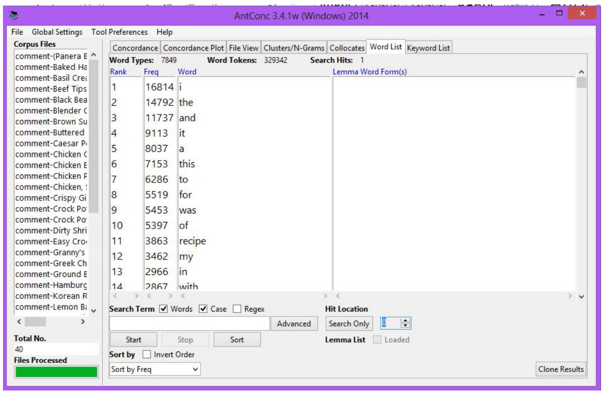

Fig. 3: *The User Interface of the Text Analysis Freeware.*

Pos = v	PosScore = 0.625	NegScore = 0
SynsetTerms = love		
Pos = a	PosScore = 0	NegScore = 0.75
SynsetTerms = disappoint		
Pos = a	PosScore = 0.875	NegScore = 0
SynsetTerms = fabulous		
Pos = a	PosScore = 0	NegScore = 0.5
SynsetTerms = sorry		
Pos = v	PosScore = 0.5	NegScore = 0
SynsetTerms = enjoy		

Fig. 4: *The Information of Words in SentiWordNet.*

The subjectivity words in the created polarity lexicon are assigned the polarity to be positive or negative using PosScore and NegScore of words from the SentiWordNet [17]. In addition, some subjectivity words are inserted into the polarity lexicon, while some existing words are reassigned the positivity or the negativity manually after considering many comment messages about food recipes. However, polarity words in the lexicon are reviewed by the expert to identify polarity scores (positive or negative). Therefore, our created polarity lexicon is suitable for text analytics in the food domain because of focusing on words from this domain. Fig. 5 and Fig. 6 show the example of positive words and negative words in the lexicon, respectively.

amazing	awesome	beautiful
best	better	delicious
nice	perfect	tasty

Fig.5: *The Words with Positive Scores.*

awful	bad	disappoint
hate	mess	problem
salty	terrible	

Fig.6: *The Words with Negative Scores.*

However, there is no process for word stemming in the proposed sentiment analysis. Stemming is to reduce words to their base forms or stems. For example, 'agree' is the stem or the base form of the words 'agrees', 'agreed', and 'agreeable'. Therefore, the generated polarity lexicon contains words in all different forms as shown in Fig.7.

best	better	
flavorful	flavourful	
favorite	favourite	
like	liking	
worry	worried	worries

Fig.7: *The Words with different forms.*

Furthermore, words with the opposite meaning when interpreting with other words, i.e. "not" and "never", are marked as words representing the reverse meaning of sentiments.

In conclusion, the individual words of all sentences in recipes' comments are compared to polarity words in our polarity lexicon. The words found in the polarity lexicon are detected and are labelled with the polarity. The sequence of words in the sentence is also used to interpret the meaning of sentiments. After this process, the subjectivity words or polarity words in the sentence are detected and tagged the polarity scores.

According to the previous comment examples in section 3.1, Comment 1 consists of four detected polarity words that are shown in italic and underline font style as follows:

"*delicious*"
"i used fresh skinless, boneless chicken breasts and olive oil instead of melted butter"
"chicken was *moist* and *tasty*"
"thanks for the *great* recipe"

All these polarity words ("delicious", "moist", "tasty", and "great") also have sentiment scores more than zero.

"*delicious (+)*"
"i used fresh skinless, boneless chicken breasts and olive oil instead of melted butter"
"chicken was *moist* (+) and *tasty* (+)"
"thanks for the *great* (+) recipe"

Comment 2 contains two detected polarity words that are "disappointed" and "good".

"i was very excited to try this recipe, but I was so *disappointed* at the outcome"

"it **didn't** taste as *good* as all the reviews made it out to be"

The first sentiment word "disappointed" has the negative polarity score (less than zero), while the second word "good" has the sentiment score more than zero and also the negative verb "didn't" is marked as follows.

"i was very excited to try this recipe, but I was so *disappointed* (-) at the outcome"

"it **didn't** taste as *good* (+) as all the reviews made it out to be"

3.3 Calculating Polarity Scores

The calculating polarity score process is composed of two steps that are calculating polarity scores of the sentence and calculating polarity scores of the comment.

In calculating polarity scores of the sentence, the summation of all polarity word scores in each sentence is calculated. Then, the polarity scores of the sentence are defined by the result of the summation. Unfortunately, some words, presenting opposite meaning or representing reverse meaning when are interpreted with other words expressing sentiments, occur in the sentence. Therefore, the polarity word scores of these sentiment words may change into opposite values that are positive to negative (more than zero changed to less than zero) or negative to positive (less than zero changed to more than zero). The previous situations depend on the sequence of words that occur in the sentence.

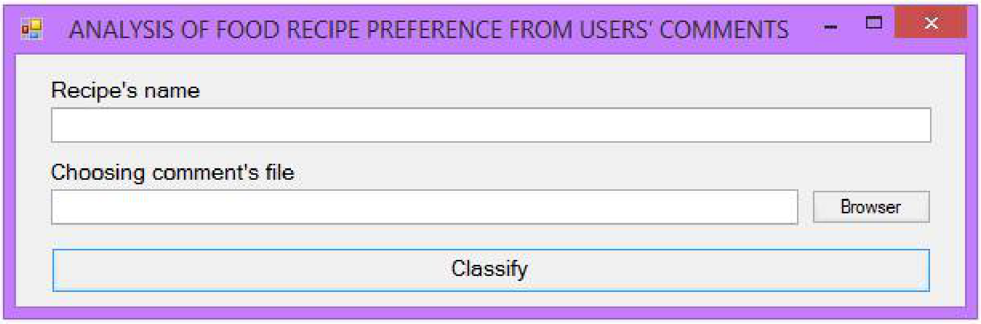

Fig.8: *The User Interface of the Software for Recipe's Comment Analysis (Input).*

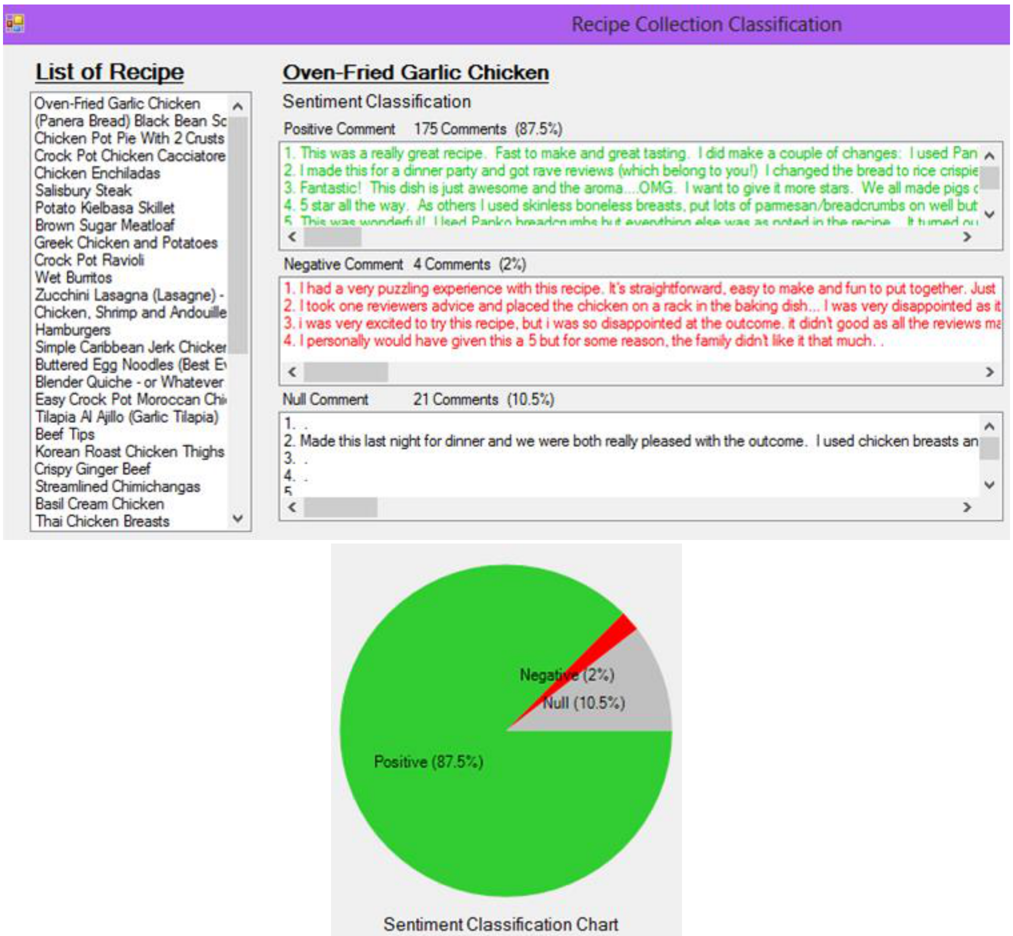

Fig.9: *The User Interface of the Software for Recipe's Comment Analysis (Output for the First Recipe).*

To calculate polarity scores of the comment, the summation of polarity scores of all sentences in the comment are calculated. If the polarity scores of the comment are more than zero, these comments are classified to positive comments. On the other hand, comments are classified into negative groups, when the summation of sentences' polarity scores less than zero. If the summation of the scores is equal zero, comments are identified as neutral comments.

According to the comment examples in section 3.1, all individual sentences contain at most one polarity word, so the polarity scores of each sentence equal the polarity score of the word found in the sentence. Consequently, the polarity scores of the first, the third and the fourth sentence of Comment 1 are more than zero, while the second sentence has zero polarity score. The details are displayed as follows.

"<u>delicious</u> (+)" "+"
"i used fresh skinless, boneless chicken breasts and olive oil instead of melted butter" "0"
"chicken was <u>moist</u> (+) and <u>tasty</u> (+)" "+"
"thanks for the <u>great</u> (+) recipe" "+"

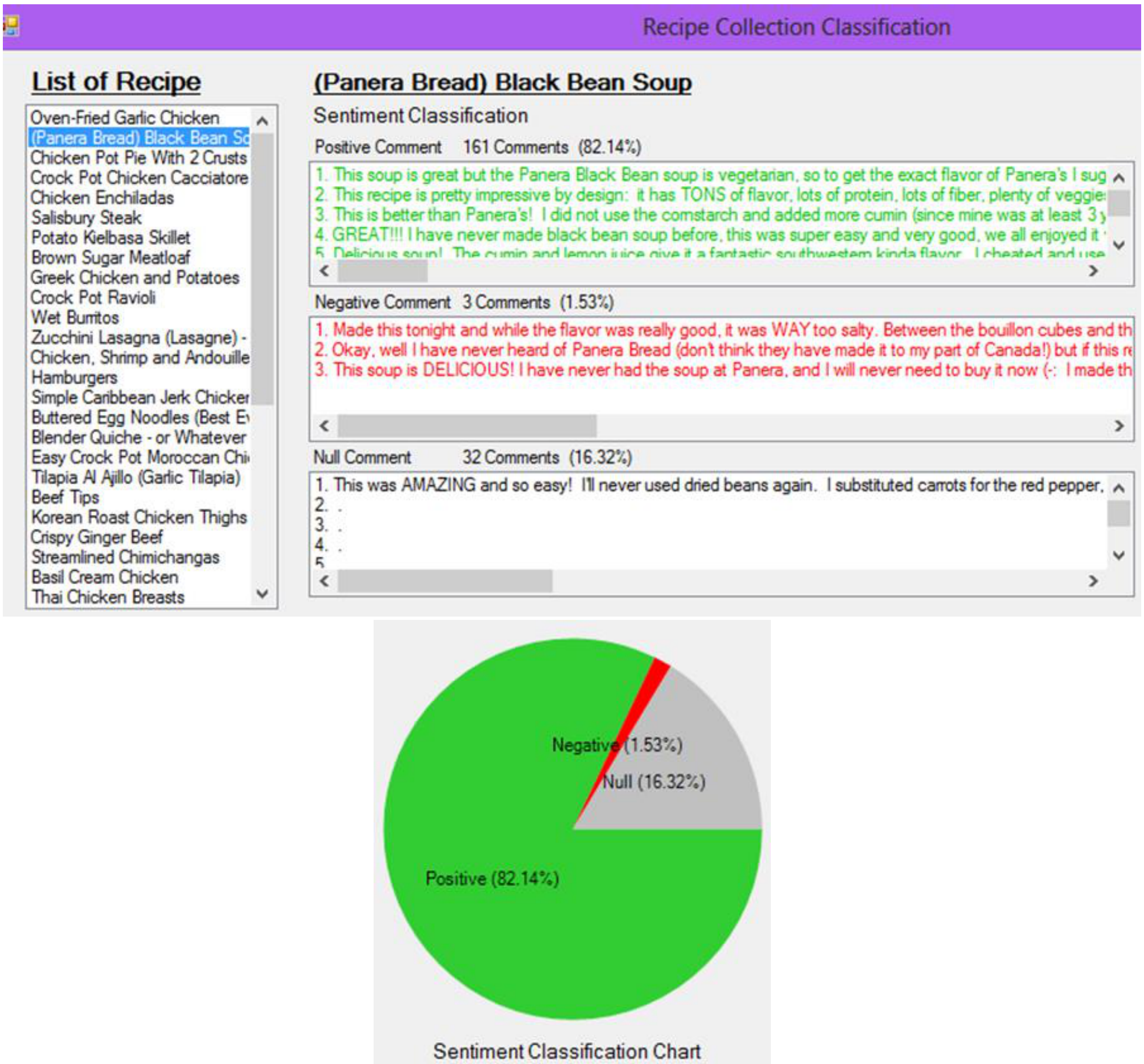

Fig.10: *The User Interface of the Software for Recipe's Comment Analysis (Output for the Second Recipe).*

So, the polarity score of the comment is more than zero because the summation of all sentence polarity scores is more than zero. The comment example (Comment 1) is classified as the positive comment. For another comment example (Comment 2), the polarity scores of both sentences are less than zero. The detail is displayed as follows.

"i was very excited to try this recipe, but I was so *disappointed* (-) at the outcome" "-"

"it **didn't** taste as *good* (+) as all the reviews made it out to be" "-"

The second sentence of Comment 2 contains the word with opposite meaning and the positive polarity word, so the polarity score of this sentence is less than zero. Consequently, the summation of all sentence polarity scores is less than zero and Comment 2 is identified as the negative comment.

In this final process, all comments about the recipe from users identified by the previous steps are shown for expressing the food recipe preference. Comments of each recipe are separated into three groups: positive, negative and neutral (null comment). The user interfaces of the software implementing the proposed sentiment analysis of comments about food recipes are shown in Fig. 8, Fig. 9, and Fig. 10. The outputs from the software are the overview of all comments about each food recipe and the summary of how many comments are in the positive, negative or neutral group. The positive comment can mean that the person who writes the comment message prefers the food recipe. On the other hand, the negative comment can represent that the person who comments on the recipe does not like it. In conclusion, the users can gain knowledge about the proportion of food recipe comments classified by the sentiment analysis.

4. EXPERIMENT AND RESULT

The experimental research was conducted on collecting comment messages of food recipes from the famous food community website "http://www.food.com". The experiment was designed to analyse the user comments about food recipes automatically using the proposed sentiment analysis. The result of sentiment analysis for recipes' comments is three groups of comment messages that are neutral, positive or negative comments.

To classify comments, the summation of polarity scores of all sentences in the comment are calculated and compared to zero value. The polarity score of the comment equals zero that means this comment is classified to the neutral comment group. If the summation of the polarity score of the comment more than zero, the comment is identified as the positive comment class. While the comments with the negative summation of polarity scores are categorized as the negative comment class.

Therefore, the results of the proposed sentiment analysis are figured by the accuracy value comparing the actual classes with correct predicted classes. Moreover, the precision value is calculated by the result of predicted classes with correct predicted classes.

The analysis performance is evaluated by the accuracy rate and the precision rate. The accuracy rate of neutral, positive and negative classification is calculated by (1), (2), and (3), respectively.

% Neu Accuracy

$$= \frac{\text{the number of correct neutral comments } \times 100}{\text{the number of actual neutral comments}} \quad (1)$$

% Pos Accuracy

$$= \frac{\text{the number of correct positive comments } \times 100}{\text{the number of actual positive comments}} \quad (2)$$

% Neg Accuracy

$$= \frac{\text{the number of correct negative comments } \times 100}{\text{the number of actual negative comments}} \quad (3)$$

In the same way, the precision rate of neutral, positive and negative classification is calculated by (4), (5), and (6), respectively.

% Neu Precision

$$= \frac{\text{the number of correct neutral comments } \times 100}{\text{the number of predicted neutral comments}} \quad (4)$$

% Pos Precision

$$= \frac{\text{the number of correct positive comments } \times 100}{\text{the number of predicted positive comments}} \quad (5)$$

% Neg Precision

$$= \frac{\text{the number of correct negative comments } \times 100}{\text{the number of predicted negative comments}} \quad (6)$$

There are two input data sets which are explained in this section. The first experiment describes the detail of the first input data set and result in the following section. In addition, the second input data set and result are explained in the next following section.

4.1 Experiment 1

The experiment 1 was conducted on collecting recipes' comment messages of 40 different food recipes which are 7,222 comments.

These comments are identified into neutral, positive and negative groups by the expert views manually. These comment messages are the same dataset from the comment analysis of food recipe preferences [14], but the identified classes of comments are reviewed and revised carefully by more than one expert person. All comments messages are composed of 548 comments in the neutral class and 6,620 comments in the positive class, including 54 comments in the negative class.

Table 1 indicates the results of recipes' comment analysis for neutral comments on comment messages from the food community website. Values in the second column in Table 1 are the number of the actual comment classes which will be compared with the number of the correct predicted classes and the number of the incorrect predicted classes.

According to the result in Table 1, 540 comment messages of 548 neutral comments are correctly classified as the neutral class, while 8 neutral comment messages are incorrectly classified.

Table 1: *Result of Recipes' Comment Analysis for Neutral Comments.*

	Actual Comments	Neutral (Predicted)	Others (Predicted)
Neutral	548	540	8
Others	6,674	443	6,231
Summary	7,222	983	6,239

On the other hand, 6,231 comment messages of 6,674 which are not in neutral class are correctly classified as the other classes, while the rest (443 comments) is incorrectly classified as the neutral comment.

Table 2 indicates the results of recipes' comment analysis for positive comments. The number of actual positive comments and the number of actual non-positive comments are shown in the second column of Table 2.

Table 2: *Result of Recipes' Comment Analysis for Positive Comments.*

	Actual Comments	Positive (Predicted)	Others (Predicted)
Positive	6,620	6,141	479
Others	602	11	591
Summary	7,222	6,152	1,070

According to the result in Table 2, there are 6,141 comment messages of 6,620 positive comments correctly classified as the positive class, while there are 479 positive comments is incorrectly classified by sentiment analysis of recipes' comments. On the other classes, 591 comment messages of 602 non-positive messages are correctly classified as the other classes, while 11 are incorrectly classified as the positive comment.

Similarly, Table 3 shows the results of recipes' comment analysis for negative comments from the food community website.

Table 3: *Result of Recipes' Comment Analysis for Negative Comments.*

	Actual Comments	Negative (Predicted)	Others (Predicted)
Negative	54	41	13
Others	7,168	46	7,122
Summary	7,222	87	7,135

Referring to the result in Table 3, values in the second column are the number of the actual negative comment classes and the other classes. For sentiment analysis of recipes' comments, 41 comment messages of 54 negative comments are correctly classified as the negative class, whereas the other group of comment messages (13 comments) is incorrectly classified. On the other hand, 7,122 comment messages of 7,168 non- positive messages are correctly classified as the other classes, whereas 46 non-negative comments are incorrectly classified as the negative comment.

To evaluate the performance of proposed sentiment analysis, the accuracy rate and the precision rate are calculated and revealed in Table 4 and Table 5, respectively.

Table 4 is pointed to the results of recipes' comment analysis on the accuracy rate comparing the actual classes of comments with the correct predicted class.

Table 4: *Result of Recipes' Comment Analysis on the Accuracy Rate.*

Comments	Actual Comments	Correct Prediction	Percent of Accuracy
Neutral	548	540	98.54%
Positive	6,620	6,141	92.76%
Negative	54	41	75.93%
Summary	7,222	6,722	93.08%

Referring to evaluated accuracy rate in Table 4, the overall accuracy of this sentiment analysis is more than 90%. The results of both neutral and positive classifications are high accuracy rate (more than 90%) and the accuracy of negative classification is more than 75%. This can be interpreted that this proposed method can determine all classes of comments effectively for accurateness.

To discuss the result of the negative classification, the accuracy is lower than other classes because there are too few negative comments messages. The automate comment analysis cannot identify the comment successfully on the small data size.

Table 5 discloses the results of recipes' comment analysis on the precision rate calculating by the number of predicted comments in predicted class and the number of the correct predicted comments.

Table 5: *Result of Recipes' Comment Analysis on the Precision Rate.*

Comments	Predicted Comments	Correct Prediction	Percent of Accuracy
Neutral	983	540	54.93%
Positive	6,152	6,141	99.82%
Negative	87	41	47.13%

According to the precision rates in Table 5, only the positive class of comment messages is high value which is more than 90%. The results of both neutral and negative classifications are low precision rate. These can understand that the proposed sentiment analysis should be improved on neutral and negative comment detection for lack of completeness. Nevertheless, this sentiment analysis system can work effectively in practice because most comments about recipes on the online food community are positive comments.

One reason of this situation is that there are various writing styles, so the automatic system cannot detect some words or some writing styles of the positive or negative sentiment correctly. For example, few positive comments were classified to negative or neutral comments shown in Fig. 10 because there is only one positive word in upper case contained within each comment, while there is at least one negative word in these comments. Consequently, the calculated polarity scores of the comments are zero or less than zero and the automatic sentiment classification cannot identify these comments accordingly.

However, the performance of the proposed sentiment analysis is higher than that of sentiment analysis by Semantria [22]. Semantria is a commercial sentiment analysis tool developed by Lexalytics, Inc. which applies sentiment analysis to tweets, facebook posts, surveys, reviews or enterprise content [22]. One output of this tool is the number of text messages in three categories (neutral, positive, negative). The result of classifying the sentiment of this experimental data using Semantria is shown in Table 6 and is compared with the actual comment classes and the result of the proposed sentiment analysis. The proportion of food recipe comments classified by the sentiment analysis in this research is more similar than the result of Semantria to the proportion of actual comment classes. Therefore, the sentiment classification of this research is more suitable than sentiment classification by the general sentiment analysis tool for the food domain.

Table 6: *Result of Recipes' Comment Analysis by Sentiment Analysis of Semantria [22] and this Research.*

Comments	Actual Comments	Predicted Comments by Semantria [22]	Predicted Comments
Neutral	548 (7.59%)	3,012 (41.71%)	983 (13.61%)
Positive	6,620 (91.66%)	4,092 (56.66%)	6,152 (85.18%)
Negative	54 (0.75%)	181 (1.63%)	87 (1.20%)
Summary	7,222 (100%)	7,222 (100%)	7,222 (100%)

Moreover, the performance of proposed sentiment analysis is compared to that of comment analysis in the article [14]. The comparisons between the accuracy results of sentiment classification from the article [14] and those from this research are presented in Table 7 and Table 8. The number of correctly classified comments on the sentiment classes from both studies has been compared with the number of actual comments in each class.

Table 7: *Result of Recipes' Comment Analysis from the Article [14] and this Research.*

Comments	Actual Comments	Correct Prediction from [14]	Correct Prediction
Neutral	548	514	540
Positive	6,620	6,075	6,141
Negative	54	13	41
Summary	7,222	6,602	6,722

Table 8: *Result of Recipes' Comment Analysis on the Accuracy Rate from the Article [14] and this Research.*

Comments	Percent of Accuracy from [14]	Percent of Accuracy
Neutral	93.80%	98.54%
Positive	91.77%	92.76%
Negative	24.07%	75.93%
Summary	91.42%	93.08%

According to the correct comment classification and the accuracy rates in Table 7 and Table 8, all classes of comment messages classified by the proposed sentiment analysis have higher accuracy than those identified by the article [14]. Thus, the performance on accuracy for the sentiment classification in the research is obviously improved upon and is especially enhanced for the negative comments. Two reasons for increasing accuracy on the negative class of comments are that the different forms of negative words are discovered properly and the abbreviated forms of "not" contained in words, e.g. "didn't" and "don't" are detected correctly. In the same way, the abbreviated forms of some words and their positive or negative meaning are appropriately identified, so the overall accuracy of sentiment analysis can be increased.

Furthermore, the performance of sentiment classification on the precision in this research is compared to that of comment classification in the article [14]. The comparison results are displayed in Table 9. There are higher values of the precision rate for all sentiment classes like compared results of the performance on accuracy. These can indicate that the sentiment analysis about foods can be enriched by the proposed analysis processes in this research which are improved from the comment analysis [14].

Table 9: *Result of Recipes' Comment Analysis on the Precision Rate from the Article [14] and this Research.*

Comments	Predicted Comments from [14]	Correct Prediction from [14]	Percent of Precision from [14]	Percent of Precision
Neutral	1,025	514	50.14%	54.93%
Positive	6,119	6,075	99.28%	99.82%
Negative	78	13	16.67%	47.13%

4.2 Experiment 2

The experiment 2 was conducted on collecting recipes' comment messages composed of the keyword "pizza" which are 22 comments in the neutral class and 322 comments in the positive class, including 10 comments in the negative class.

Table 10 indicates the results of recipes' comment analysis for neutral comments on comment messages from the food community website like Table 1. Values in the second column in Table 1 are the number of the actual comment classes which will be compared with the number of the correct predicted classes and the number of the incorrect predicted classes.

Table 10: *Result of Recipes' Comment Analysis for Neutral Comments.*

Comments	Actual Comments	Neutral (Predicted)	Others (Predicted)
Neutral	22	22	0
Others	332	19	313
Summary	354	41	313

According to the result in Table 10, all comment messages of 22 neutral comments are correctly classified as the neutral class, and there is no incorrect predicted comment. On the other classes, 313 comment messages of 332 non-neutral messages are correctly predicted as the other classes, while there are 19 non-neutral comments incorrectly classified as the neutral comment.

Table 11 indicates the results of recipes' comment analysis for positive comments. The number of actual positive comments and the number of actual non-positive comments are shown in the second column.

Table 11: *Result of Recipes' Comment Analysis for Positive Comments.*

Comments	Actual Comments	Positive (Predicted)	Others (Predicted)
Positive	322	302	20
Others	32	0	32
Summary	354	302	52

According to the result in Table 11, there are 302 positive comments are correctly classified as the positive class, while 20 positive comments are incorrectly classified as non-positive class. However, all non-positive recipe comments are correctly classified as the other classes.

Table 12 shows the results of recipes' comment analysis for negative comments from the food community website like Table 3.

Table 12: *Result of Recipes' Comment Analysis for Negative Comments.*

Comments	Actual Comments	Negative (Predicted)	Others (Predicted)
Negative	10	10	0
Others	344	1	343
Summary	354	11	343

According to the result in Table 12, all 10 negative comments are correctly classifies as the negative class in the same way of neutral class in Table 6. Whereas there is only one comment in non-negative comment class incorrectly classified as the negative comment.

Table 13 and Table 14 figure on the accuracy rate and the precision rate, which represents the performance of proposed sentiment analysis, similarly Table 4 and Table 5.

Table 13: *Result of Recipes' Comment Analysis on the Accuracy Rate.*

Comments	Actual Comments	Correct Prediction	Percent of Accuracy
Neutral	22	22	100.00%
Positive	322	302	93.73%
Negative	10	10	100.00%
Summary	354	334	94.35%

Referring to accuracy rates in Table 13, the overall accuracy of the proposed sentiment analysis is more than 90%. The results of all comment classification are high accuracy rate.

According to the precision rates in Table 14, both of positive and negative comment messages are high values which are more than 90%. There is only neutral class having the precision rate more than 50%. This result can confirm that food recipe comments can be analysed to classify the sentiment successfully using the proposed sentiment analysis system.

Table 14: *Result of Recipes' Comment Analysis on the Precision Rate.*

Comments	Predicted Comments	Correct Prediction	Percent of Precision
Neutral	41	22	53.66%
Positive	302	302	100.00%
Negative	11	10	90.91%

As a result, the proposed sentiment analysis of food recipe comments is high accurately and acceptably precise. Consequently, a lot of comment messages about food recipes on the food community can be analysed for summarizing the sentiments automatically. Furthermore, the software with this comment analysis is an advantage in the decision making for users and recipes' authors.

5. CONCLUSION

At the present time, a huge capacity of information is available over social communities. Opinions or Comments may be contained in various contents, including the information or knowledge. Moreover, opinions or comments from other peoples are very useful in our own decision making. Therefore, the automated technique which can analyse opinions or comments will be the valuable tool to assist users, customers, consumers and providers.

For the previous reasons, this research proposed sentiment analysis of food recipe comments on the food domain using the syntactic and semantic information of words and text analysis. The subjectivity words about the food are also collected and the polarity lexicon is generated. The outcome of the proposed analysis is the software that can analyse sentiments from many contents on comment messages about food recipes. In addition, this proposed method can help the members in the food community to make decisions about preferred food recipes from various recipes. Furthermore, the recipe authors can gain information that how many peoples like or dislike the recipes. In the future work, the personal profiles of people who comment the recipes, e.g. nationality and age, will be collected to analyse recipe comments by the groups of people.

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