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Cooking Recipe Rating Based on Sentiment Analysis

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Abstract--- *Sentiment analysis of feedback on food recipe is to classify user responses to the positive or negative feedback on the food recipes. The suggested approach is appropriate by counting the polarity words on the food domain for evaluating feedback or opinions about food recipes. The aim of this research is to help users select the preferred recipes on online food commution from various food recipes. The program will rate the recipe, based on visitor feedback. So, it made finding the correct recipe simpler for people. With several people searching with online recipes this program would be helpful.Recipes you read obviously won't be the same as what you find after training. There are a number of inaccurate recipes you'll find online. Recipes must be rated by the user in order to cause the correct peoples. Here we propose a program that allows users to pick categories and post the recipes. Recipes are scored by the guests and commented on. So user will finish by finding a correct recipe.*

Keywords--- *Food recipes, Sentiment analysis, Text analytics, Comment analysis*

I INTRODUCTION

There are several food groups with recipes on how to cook recently because users with the same interests shape the community to support each other in sharing, searching, advertising and making decisions. Furthermore, participants of food communities will be able to comment on food recipes and share their cooking experiences through each recipe. Some comments accept that dishes made using those recipes taste good while some comments disagree and offer the details to improve the dishes recipe. Hence, these user feedback about other people's food recipes are useful tools to help members make a choice and select the recipe they'll choose from various food recipes. Additionally, the recipe authors can improve their own recipes after feedback from other peoples.

While on popular food websites there is a star rating for food recipes, the rating may not be accurate as community members can vote on the food recipes by providing scores without the accuracy of the realistic preferences. In addition, the preferred score summarizing from the reviews of all the individual recipes would be more accurate than the star rating ones. Therefore, if there is the program that can automatically analyze details about food recipes from all user reviews, the score rating description and comment community classification are the useful information. An research method also demonstrates the value of observing consumer behavior after research.

Analysis of sentiment, or so- opinion mining, requires the analysis of natural language, text analytics and computational linguistics to recognise polarities of sentiments. One basic aim of opinion mining is to collect valuable knowledge from the thoughts, behaviors, views and emotions of people on goods, events or topics. The

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aim of sentiment analysis is to classify the polarity of a given text into documents, in sentences or phrases, based on opinions or attitudes expressed in summaries. Analysis of sentiments may also be the fundamental component of text- monitoring and general view towards real- individuals, such as items and users.

Other people's opinions or feedback are key factors in consuming behavior and actions as most people regularly seek out others 'views before they make the decision to do the right.Furthermore, customers or users often post service reviews or comment on items that express their opinions and exchange online personal experiences with them, such as reviews, comments, and online.Additionally, businesses also try to gain feedback on their goods and services from the public or customers.

Finding and reading viewpoints or comments on the Internet, however, and extracting the correct information remain difficult tasks due to a large number of texts and a variety of interesting information.It will be difficult for the human reader to recognise appropriate texts and precisely summarize the details and opinions found in them.Human text knowledge research often has prejudices and weaknesses because people often pay attention to views which are compatible with their own favourites.

In addition, users can enter a sentiment target as a parameter (e.g. subjects, subjects, or products) and look for positive or negative feelings about the target. It is also widely accepted, therefore, that extracting feelings from text is a serious semantic problem, even for human beings. In addition, sentiment analysis is also unique to the area, since the polarity of certain words depends on the sense in which they are used. For example, in mobile devices the word "small" is the positive feature, while this word is the negative polarity in 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 information in this paper are defined in the sections below.Section 2 discusses the associated functions of an examination and description of sentiments.Next, section 4 displays experiments and the effects.

II RELATED WORKS

Opinion or sensation classification approaches can be categorized into two major categories: 1) classification based on supervised learning using machine learning; 2) classification based on unsupervised learning based on semantic orientation. Sentiment classification with supervised learning uses the training data to learn how to classify the test data into three classes: neutral, positive, or negative. Any established supervised learning methods, such as decision tree classifier, naive Bayesian classification, and support vector machines (SVMs), can be applied to sentiment classification.On the other hand, the technique of sentiment analysis by the semantic orientation method does not require prior training data because the positive or negative class identification can be measured directly by positive and negative feeling scores, such as lexicon-based sentiment analysis. The key objectives of the sentiment analysis with the semantine-oriented approach are to quantify and identify the subjectivity and opinion in text by generally capturing evaluative factors and power or intensity against topics or ideas. Additionally, the aggregation of sentiment with sentiment words for each person and other lexicons are very descriptive and reliable.

There are several experiments on Twitter analyzing tweets, feedback and comments about social networks using the combined semantine-oriented technique with machine learning. The outcome of these researches expresses that the efficiency of the automatic classification of feelings is appropriate to users, and the knowledge obtained is very useful.

The approach for analyzing subjectivity applies semantic word knowledge and the decision tree classifier to analyze airline service communications. The application's outcome will help both the customer and the airline service provider pick only opinions or comments from other Twitter materials. Customers may also opt to pick from various airline brands the service they want. The next related work on subjectivity analysis is the methodology of opinion mining in. Subjective messages are categorized into two classes: optimistic or negative messages about airline services.It analyzes the syntactic and semántic word information in the post, and produces the post features of the Na ıve Bayes classification for learning opinions classes. The result will show that the automated sentiment analysis of Twitter data enables both clients and providers of airline service to benefit.

The classification of sentiment established a lexicon-enhanced method for producing a collection of words of sentiment using the word knowledge from a lexicon of feeling. Such sets of feelings are the sets of feeling features to learn from five classes of online product feedback and to test the emotion classification model.

An in-depth study of user feedback was given in the article on two major social networks, Yahoo and Yahoo! news. The goal is to better understand the input of the audience on the social network. To obtain a better understanding of the community's commenting behaviour, the textual data, the thread structure of the comments and related content are analyzed.

The paper discusses the notion of usefulness in the content of comments on social media and compares it from the point of view of end-users and experts. Machine learning is applied to identify comments using syntactic and semantine tools, including the content of the user. Furthermore, comments can be categorized using the fairly straightforward apps.

The findings have shown that these analytical methods are very useful to users, customers and product suppliers in various contexts, according to all the related works. Therefore, a food domain comment analysis using sentiment analysis can generate new knowledge and summarize valuable information about food recipes for users and recipe authors.

For this study, the proposed sentiment analysis of user comments on food recipes is the improved methods from which to obtain higher analytical results. These studies have the same goal of classifying commentary on food recipe into three groups: neutral, positive, or negative. There were several changes to the analytical methodology mentioned in section 3. For example, the word "not" that is used in abbreviated forms is identified and marked accordingly with the helping verbs in text messages. Some widely used online word abbreviations and spoken words are often marked as "positive" or "bad," such as the words "omg, OMG-Oh My God" and "yum" expressing the positive attitude. In addition, the different uses of other derogatory terms to characterize food are applied to the polarity lexicon, e.g. weirdly and oddly. The better result is also seen in section 4.

The features of these comments are similar to those of short, informal textual messages which, unlike product reviews or article documents, do not focus on sentence-level sentiment classification processes. Although the sentiment of most thematic reviews is analyzed in the classification of sentence-level and document-level sentiment, the tasks of sentiment analysis of short informal messages are divided into term-level and message-level. The feeling of a word or a phrase inside a message is identified (term-level) like the phrase-level sentiment analysis in before the sensation of a short informal text message (message-level) is classified.

Moreover, the sensation of each sentence in short informal text messages may be understood by the polarity or subjectivity of words that appear in the sentences (like the sentence-). The words in each domain are therefore essential for defining terms as positive or negative sentiments. For example, it is not possible to decide the positivity or the negativity of the adjective word "moist," because the polarity score (PosScore and NegScore) in the SentiWordNet is the zero value, but this word is the positive meaning of the food.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 . Additionally, Negation cues, e.g. the words “never” or “not” from are examined for the sentiment analysis.

Consequently, the article and this study reviewed a lot of commentary messages with phrases and words about food recipes to better define the positivity or negativity of the food domain for words or expressions. Therefore, the suggested food recipe statement sentiment analysis using the semantine orientation approach is an extensive study of terms and their context regarding food. Furthermore, the software's description details of the feelings or views applying this sentiment analysis is sufficient to satisfy the food group members. In addition, training data do not need to examine the feeling of text comments.

Another related work on feedback on food recettes is the study of suggestions to develop food recipes. The user's feedback on food recipes are defined into two categories with suggestions or without suggestions.The suggestion or advice will help members of the food community modify or adapt the food recettes.WordNet semantine word knowledge is used in the cycle of analysis to classify nouns as the ingredients of the food.Evaluation of suggestions is added to be another element of analysis on the program analyzing food recipe.

III SENTIMENT ANALYSIS OF FOOD RECIPECOMMENTS

This analysis proposes the technique of sentiment analysis for comments on food recipes, and also develops certain processes of analysis from the study of comment in. The purpose of this sentiment analysis is to classify the comments from community members on food recipes into favorable, positive and negative categories. The proposed sentiment analysis is based on syntactic and semantic word or phrase details in the commentary messages, e.g. the abbreviated forms of negative supporting verbs, the positivity or the negativity of words in a generated polarity lexicon. The analytical processes are composed of pre-processing, identification of word polarity, estimation of sentence and comment polarity ratings.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.

III.I. Pre-processing

All comments on food recipes area unit gathered as texts from the web food community. There area unit four steps within the reprocessing method to arrange the input word information for the polarity word detection method.

The first step is that every one special characters area unit detected to delete messages from user comments thanks to those characters, i.e. "#" and "@," that don't relate to feelings. First, the second stage converts all the capital letters to minuscular characters. Instead, within the third step, some sentence punctuations, such as." "and, "divide all sentences of recipes 'comments into individual sentences! ".

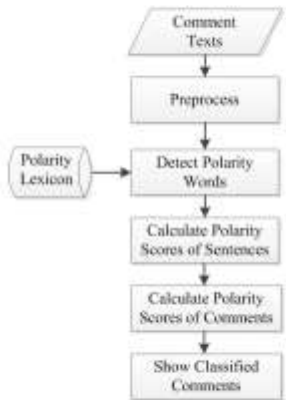

Fig.1: The Sentiment Analysis of Food Recipe Comment.

In the final step of the pre-processing process, all words in all sentences of the user's comment are divided into individual words, using space between two words and some punctuations, such as," "and-."

After the pre-processing process, the word sequences of all the words in the user's comments are collected and some words are handled by syntax to provide knowledge for the next process. For example, some words that are usually used in abbreviated forms in text messages and the meaning is "not" are marked as words that have the opposite meaning of sentiment. Some of the 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):

It's delicious! I used fresh, skinless chicken breasts and olive oil instead of melted butter. Chicken has been moist and tasty! Thank you for the great recipe!"

For the comment, the output of the pre-processing method is outlined as follows: All letters area unit reborn into small letter letters and this comment consists of 4 sentences separated by the exclamation point!") ("and the total stop.").

"Delicious"

"I used new skinless, deboned chicken breasts and oil in situ of liquid butter" "humid and attractive chicken" "thanks for the amazing recipe".

Then, all words are separated by the sapce and the (“,”). The word sequences of all sentences are ordered.

Another recipe’s comment input (Comment 2):

"I was thus excited to undertake this instruction however i used to be thus unsuccessful with the result. It hasn't been as superb as all the comments did".

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

(“.”).

“i was very excited to try this recipe, but I was so unscuessfull at the outcome”

“it **didn’t** taste as good as all the comments made it out to be”.

Then, all individual words are divided by the space and the comma (“,”). The word with opposite meanings (“didn’t”) in the abbreviated form is marked. .

III.II. Detecting Polarity Words

To detect polarity words, this research creates a new polarity lexicon for the SentiWordNet-based domain. Many words from many comments about food recipes are collected to filter the words of subjectivity. All words are analyzed by a freeware text analysis to count the frequency of words. Words found in SentiWordNet are considered polarity words in the lexicon. The user interface of the freeware text analysis[21] is shown in Fig. 3 Examples of words and their details, including sentiment scores in the SentiWordNet, are provided inFig. 4.

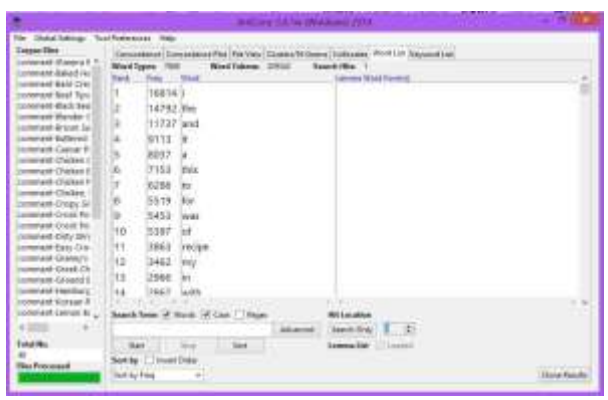

Fig.3: The User Interface of the Text Analysis Freeware.

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 SentiWordNetSentiWordNet-based domain

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-based domain[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 analysis in the food domain because of focuses 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.

best	better	
flavorful	flavourful	
favorite	favourite	
like	liking	
worry	worried	worries

Fig7 : The words with different forms

However in the proposed sentiment study, there is no method for word stemming. Stemming is to reduce words to their basic shapes or stems. For example, 'agree' is the stem or the base form of the words 'agree,' 'agree,' and 'agreeable.' Thus, the generated polarity lexicon contains words in all forms, as shown in Fig.7.

In addition, words with the opposite meaning are marked as words reflecting the reverse sense of emotions when translating with other words, i.e. "no" and "never."

In addition, in our polarity lexicon, the individual words of all sentences in the comments of the recipes are compared to the polarity terms. The terms used in the lexicon for polarity are identified and marked with the polarity. The sentence series of words is often used to describe the context of the sentiments. After this step, the polarity scores are detected and marked with the subjectivity words or polarity words in the sentence.

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 itout 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"

III.III. 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.

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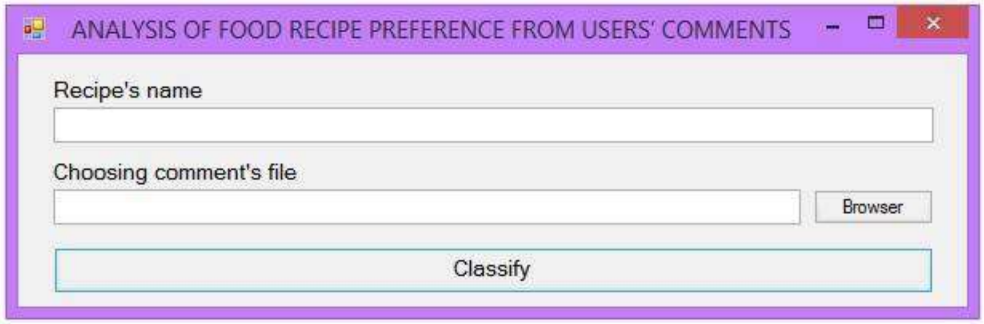

Fig.8: The User Interface of the Software for Recipe's Comment Analysis (Input).

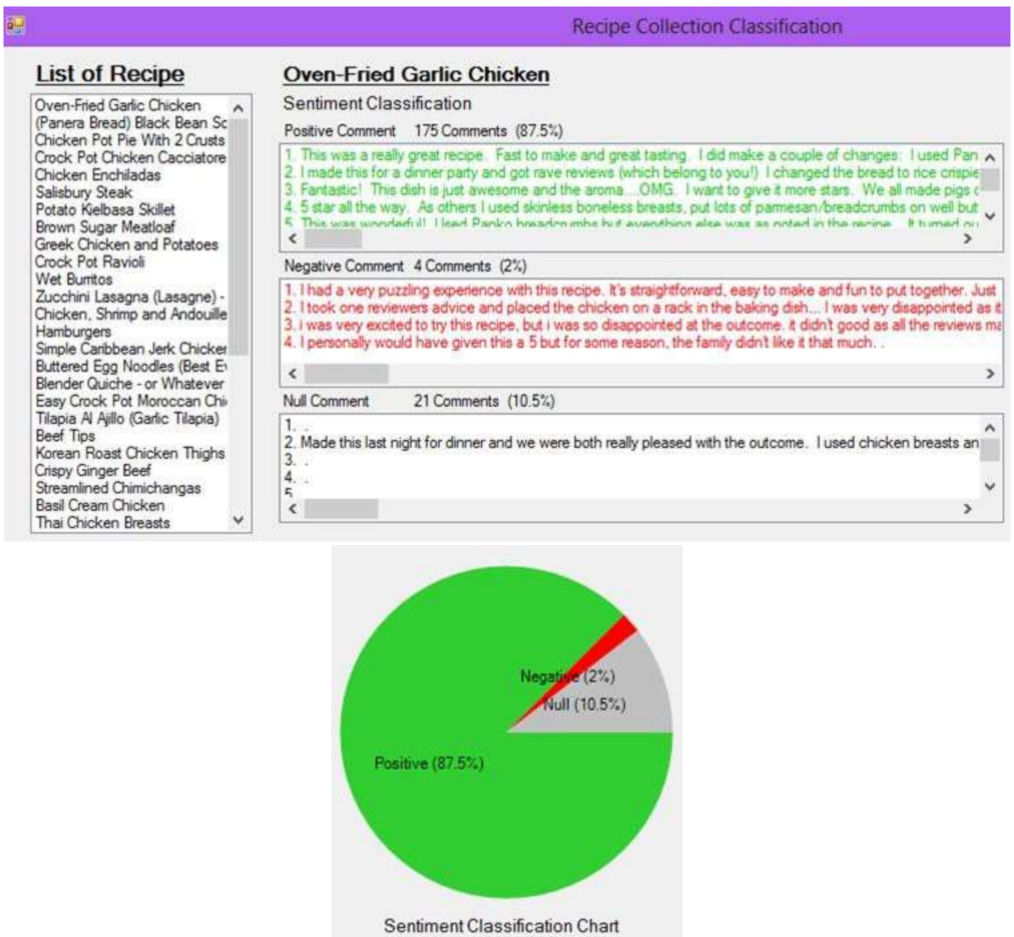

Fig.9: The User Interface of the Software for Recipe's Comment Analysis (Output for the First Recipe).

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

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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.

"*delicious* (+)" "+"

"i used fresh skinless, boneless chicken breasts and olive oil instead of melted butter" "0"

"chicken was *moist* (+) and *tasty* (+)" "+"

"thanks for the *great* (+) recipe" "+"

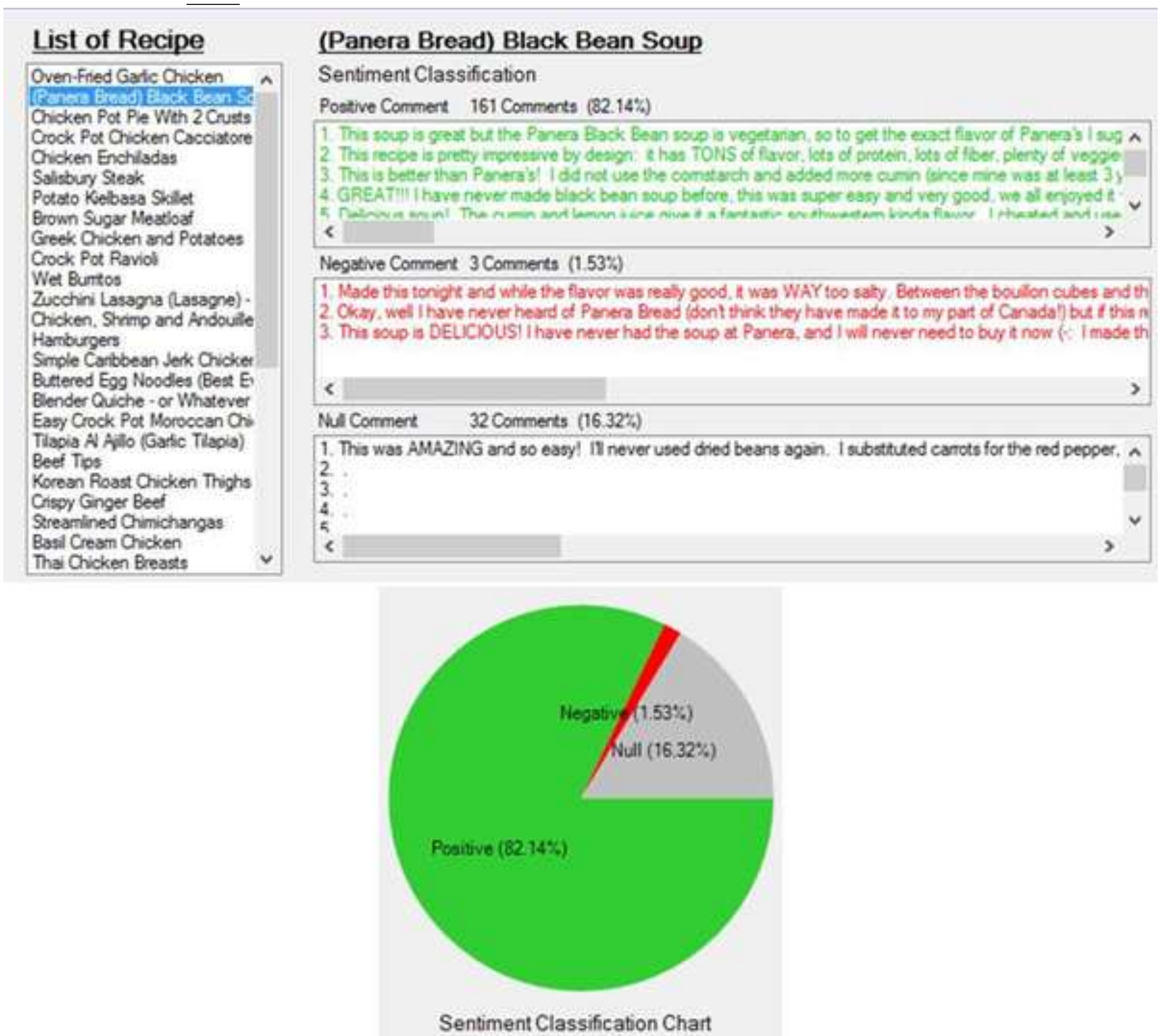

Fig.10: The User Interface of the Software for Recipe's Comment Analysis (Output for the Second Recipe).

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.

IV 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.

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

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

% Neg Accuracy

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

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

% Neu Precision

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

% Pos Precision

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

% Neg Precision

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

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.

IV.I. 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

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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 Semantic 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 Semantic 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 Semantic [22] and this Research.

Comments	Actual Comments	Predicted Comments by Semantic [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.

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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%

IV.II. Experiment 2

Experiment 2 was performed on the set of commentary messages from recipes composed of the keyword "pizza" consisting of 22 comments in the neutral class and 322 in the positive class, including 10 comments in the negative class.

Table 10 displays the results of the comment review of the recettes for neutral feedback on comment messages from the food group website, such as Table 1. Top. Values in the second column in Table 1 are the number of real statement classes to be compared with the number of the correct classes predicted and the number of the incorrect classes predicted.

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 comments made by 22 neutral comments are properly listed as the neutral class, and there is no expected erroneous comment. In the other classes, 313 comments of 332 non-neutral messages are accurately predicted as the other classes, while 19 non-neutral comments are wrongly listed as the neutral voice.

For constructive feedback, Table 11 summarizes the findings of the comment review of the recipes. In the second column you can see the number of actual positive comments and the number of actual no positive comments.

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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

There are 302 positive comments that are correctly categorized as the positive class according to the result in Table 11, while 20 positive comments are incorrectly categorized as non-positive. Also no good reviews about the recipe are equally graded as the other grades, however.

Table 12 demonstrates the results of the comment review of the recipes for negative feedback from the website of the food group, 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, in Table 6 all 10 negative comments are correctly marked as negative class in the same way as neutral class. Whereas in non-negative comment class, there is only one statement incorrectly categorized as the negative comment.

Report on the accuracy rate and the precision rate, which reflects the efficiency of the proposed sentiment analysis, Table 13 and Table 14, similarly

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%

The overall accuracy of the proposed sentiment analysis is more than 90%, referring to the accuracy level in Table 13. The outcomes of all classification of the comments are high precision levels.

According to the accuracy ratings in Table 14, both positive and negative comments are high values that surpass 90%. Even the neutral class has a precision rate of over 50%. This result can indicate that comments on food recipe can be analyzed using the proposed sentiment analysis method to successfully identify the feeling. Table 14: Result of Recipes' Comment Analysis on the Precision Rate.

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 good accurately and acceptably precise. Consequently, a lots of reviews 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.

V CONCLUSION

Currently there is an immense potential for knowledge over social networks. Opinions or observations, including facts or experience, may be found in different materials. Additionally, views or suggestions from other peoples are very helpful in making our own decisions. The automated methodology for evaluating views or feedback would also be the useful method for assisting users, clients, consumers and providers.

For previous reasons, this research proposed an analysis of the sentiment of food recipe comments on the food domain using syntactic and semantine word and text analysis information. The words of subjectivity about the food are also collected, and the lexicon of polarity is created. The consequence of the proposed study is the program that can evaluate sentiments on comment messages about food recipes from several contents. Additionally, this proposed approach will help the food group members make decisions about preferred food recipes from different recipes. In addition, the writers of the recipe may obtain knowledge about how many people like the recipes or hate them. The guy, in future work Profiles of people posting on recipes, such as nationality and age, will be compiled by groups of people to evaluate recipes comments.

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