Aspect-based sentiment analysis: natural language understanding for implicit review

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Article Info

Article history:

Received May 5, 2024
Revised Aug 2, 2024
Accepted Aug 6, 2024

Keywords:

Aspect-based sentiment analysis
Bidirectional encoder representations from transformers
Machine learning
Natural language understanding
Semantic similarity

ABSTRACT

The different types of implicit reviews should be well understood so that the developed extraction technique can solve all problems in implicit reviews and produce precise terms of aspects and opinions. We propose an aspect-based sentiment analysis (ABSA) method with natural language understanding for implicit reviews based on sentence and word structure. We built a text extraction method using a machine learning algorithm rule with a deep understanding of different types of sentences and words. Furthermore, the aspect category of each review is determined by measuring the word similarity between the aspect terms contained in each review and aspect keywords extracted from Wikipedia. Bidirectional encoder representations from transformers (BERT) embedding and semantic similarity are used to measure the word similarity value. Moreover, the proposed ABSA method uses BERT, a hybrid lexicon, and manual weighting of opinion terms. The purpose of the hybrid lexicon and the manual weighting of opinion terms is to update the existing lexicon and solve the problem of weighting words and phrases of opinion terms. The evaluation results were very good, with average F1-scores of 93.84% for aspect categorization and 92.42% for ABSA.

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1. INTRODUCTION

Aspect-based sentiment analysis (ABSA) research on explicit sentence cases [1] has led to many developments in applying different methods for ABSA, which work on explicit sentence cases and implicit sentence cases. The development of ABSA research related to implicit cases has reached extraction work where aspects and opinions cannot be identified in a sentence. Several researchers have carried out research related to implicit opinion extraction. However, little work has been done related to extracting implicit opinions.

The implicit opinion extraction [2] can identify words that contain expressions of opinion that cannot be recognized as opinion terms for explicit aspect features. A study using a bag of words [3] worked on cases of implicit sentences that cannot be identified as aspect features or recognized by opinion features. Research on implicit opinion extraction by identifying explicit aspects [4] has also been conducted using the co-occurrence term approach to identify implicit aspects through implicit opinions. Another implicit opinion extraction [5] can categorize verbs and adverbs of nouns as implicit opinions. The implicit opinion extraction based on co-occurrence aspect terms in a corpus [6] has been carried out for the case of compound sentences. Then, implicit opinion extraction in compound and complex sentences [7] was also carried out. However, none of the above-mentioned studies looked at the extraction of different types of implicit opinion sentences in detail.

Implicit sentences, both aspect and opinion cases, can also occur in several different types of sentences. Sentences can be divided into four types based on their structure: simple, compound, complex, and compound-complex sentences. The type of sentence will certainly influence the extraction of aspect and opinion words. This is because of the issues we explained at the beginning of this section. Therefore, it is necessary to build a method to extract aspect and opinion words that are explicit and implicit in disambiguous and ambiguous sentences based on the type of sentence structure.

Ambiguous sentence factors have motivated studies related to sentiment analysis in the case of implicit opinion sentences. Ambiguous sentences have many sub-factors that affect the accuracy value in extracting aspect and opinion terms from a sentence [8]. These sub-factors include negation (conjunction analysis and punctuation marks), contrast transition, and intensifiers. However, the explicit and implicit extraction of aspects and opinions in disambiguous and ambiguous sentences based on the type of sentence structure has not been studied in depth.

Based on these issues, this paper proposes a method based on a comprehensive understanding of previous studies on implicit sentence cases, especially implicit opinions. For example, in a restaurant review case, "*This place is the most Japanese it can ever get*." The word *Japanese* can be either an adjective or a noun. Meanwhile, suppose the sentence is extracted using part of speech (POS) tagging [9]; the result is that *Japanese* is labeled JJ, representing an adjective. The tag labels are: This (DT) place (NN) is (VBZ) the (DT) most (RBS) Japanese (JJ) it (PRP) can (MD) ever (RB) get (VB) .(.). In previous studies, the results obtained from the extraction of aspect and opinion terms were *place* and *Japanese*, respectively, with "RESTAURANT" as the aspect category obtained, because they were not able to extract *Japanese* with "FOOD" as the aspect category. This research aims to accurately extract pairs of aspects and opinions, which are explicit and implicit, based on the four sentence structures simple, compound, complex, and compound-complex. Moreover, the results of these pairs will be processed to determine the aspect category and sentiment polarity of a review.

We use a restaurant review dataset that is well-annotated because it contains reviews with various types of sentences. The dataset was processed in the pre-processing stage. As input, we also used aspect category keywords taken from articles on Wikipedia. From the pre-processing results, we carried out the text extraction process. We built a set of rules based on sentence-word relations as a proposed text extraction method to get aspects and opinion terms that are explicit and implicit. In the text extraction, our method extracts sentences based on their structure: simple, compound, complex, and compound-complex sentences. These sentences are also classified into explicit aspect and explicit opinion (EAEO); implicit aspect and explicit opinion (IAEO); explicit aspect and implicit opinion (EAIO); and implicit aspect and implicit opinion (IAIO). Then, in the aspect categorization stage, the aspect terms successfully obtained using bidirectional encoder representations from transformers (BERT) embedding and semantic similarity are processed to obtain aspect categories based on four classes: ambiance, food, service, and price.

Furthermore, in the ABSA stage, the value of sentiment polarity is measured using the BERT sentiment analysis method by improving the lexicon based on the opinion lexicon and the implicit aspect lexicon. We manually added additional opinion term weighting to categorize sentiment polarity based on four classes: very positive, positive, negative, and very negative. Finally, we conducted an evaluation stage to measure the success of the proposed method for aspect categorization and ABSA by measuring accuracy, precision, recall, and F1-score.

2. RELATED WORK

2.1. Pre-processing

The pre-processing stage aims to process raw data into data that is ready to be processed. In this stage, tokenization is carried out, breaking down the tokens in a document to be taken as terms. Then, the stopword removal process is carried out by removing unnecessary terms contained in the tokenized results. Finally, the data processed by stopword removal is further processed by stemming, where each word is reduced to its root.

2.2. Keywords for aspect categories

The restaurant aspect categories were taken from the definitions and variables of aspect categories described in previous studies [10], [11]. This research used four restaurant aspect categories: atmosphere, food, price, and service. Meanwhile, the aspect keywords were taken from Wikipedia pages related to the definition and variables of aspect categories.

2.3. Text extraction

In sentiment analysis, text extraction aims to get aspect and opinion words. Text extraction research has produced many works [12]. The present research discusses problems that previous studies have not worked out in depth. We discuss text extraction based on two main tasks: sentence extraction and word extraction.

2.3.1. Sentence extraction

English sentence extraction is very closely related to the sentence type in a review. Based on their structure, English sentences consist of four classes: simple, compound, complex, and compound-complex sentences [13]. An in-depth approach is needed to extract the text in review cases along with possible sentence structures. An algorithm may work well on simple sentence cases because they only contain an aspect and an opinion word. It is different for cases with other sentence structures that may have more than one aspect and opinion word. Moreover, if the aspect and opinion words are not located close together in a sentence, then errors in choosing the aspect and opinion words will most likely occur when using a simple algorithm. The following are some illustrations of sentence extraction from review cases.

- A simple sentence is a sentence that only consists of one subject and one predicate. For example, *The perfect spot.*
- A compound sentence consists of two or more subjects and predicates connected by a conjunction. This conjunction consists of *and, or, but, either,* and *neither*. For example, *The food was well prepared and the service was impeccable.*
- A complex sentence consists of two or more subjects and predicates with a main and a subordinate clause connected by a subordination. This subordination extends the reach of the main clause by adding a statement of time, place, person, thing, or reason. For example, *My friend got the mushroom pizza, which tasted better.*
- A compound-complex sentence consists of three or more subjects and predicates. This type of sentence consists of a conjunction and a subordination in the sentence. For example, *The ambience is pretty and nice for conversation, so a casual lunch here would probably be best.*

2.3.2. Word extraction

In English, word extraction is very closely related to the task of retrieving the target words for further processing. Our method extracts words as aspect and opinion terms based on POS tagging with 36 labels. Then, it divides the reviews into four classes, namely: EAEO, IAEO, EAIO, and IAIO. Extracting explicit aspect and opinion terms can be easily done when there is NN as the aspect term label and JJ as the opinion term label in the sentence. However, if a sentence is implicit without NN or JJ, it will pose a specific problem in the text extraction. This division of word classes aims to identify and correctly extract the aspect and opinion terms that are explicit and implicit. Table 1 illustrates text extraction for sentence and word extraction cases. The word extraction concept implemented is based on the following four cases:

- In the EAEO case, aspect and opinion words are extracted by identifying sentences containing NN as the aspect term and JJ as the opinion term.
- In the IAEO case, aspect and opinion words are extracted by identifying sentences that do not contain NN as the aspect term but contain JJ as the opinion term.
- In the EAIO case, aspect and opinion words are extracted by identifying sentences containing NN as the aspect term but not JJ as the opinion term.
- In the IAIO case, aspect and opinion words are extracted by identifying sentences that do not contain NN as the aspect term and do not contain JJ as the opinion term.

Table 1. The proposed dataset representation

ID Reviews	ID Sentences	Reviews
1001	0	the wait time here for the food even more makes my stomach very rumbling
1002	0	the portion here for the food still makes my stomach very rumbling

2.4. Synonym-based term expansion

Synonym-based term expansion expands nouns and adjectives denoting the aspect and opinion words. This expansion process is carried out using WordNet [14]. Then, the expansion result will be extracted from word synonyms with the highest similarity value through the aspect category variables.

2.5. Definition-based term expansion

Definition-based term expansion is used to obtain higher accuracy of aspect and opinion word pairs. If synonym-based expansion is used to expand explicit nouns and adjectives, then we assume that explicit nouns and adjectives can also have implicit meanings. For example, *the waiting time here for the food makes my stomach feel hungry even more*, where the results of the noun and adjective pairs *stomach* and *hungry* have an implicit meaning related to the aspect category variable. Therefore, first, from the results of previous studies [15], we compiled a list of explicit opinion terms from explicit aspects and each category. Furthermore, suppose the opinion terms in the review are not present in the list of every aspect category that has been compiled; in that case, we will mark the opinion term as implicit. For example, the word *hungry* is not listed in the pair of explicit aspect terms *waiting time* and *food*, so the word *hungry* is labeled as an implicit opinion term.

Definition-based expansion is based on nouns and verbs with a noun-subject relationship with opinion terms labeled as implicit. Then, simple English Wiktionary expands nouns and verbs that denote terms of implicit aspect and implicit opinion. Moreover, BERT embedding is used to get the terms of each sentence in the related Wiktionary link. Finally, the expanding terms with the highest similarity value to the aspect terms in the review are taken as hidden terms.

2.6. Natural language understanding

Most natural language understanding (NLU) use neural network models that start by breaking down a sequence of strings into individual words, phrases, or entire sentences, a process known as tokenization. The tokenizer builds vocabulary and converts word sequences into integer sequences. Each integer is mapped to a value in the dictionary that encodes the entire corpus, with the keys in the dictionary being the vocabulary term itself. Similarly, the BERT model processes input tokens in three steps, where each token is the sum of three embeddings: Token embedding, Segment embedding, and Position embedding.

2.7. Term frequency-inverse corpus frequency

Term frequency-inverse corpus frequency (TF-ICF) [16] weights terms based on information from document *d* in cluster *c*. First, the frequency of term *t* in cluster *c* is denoted by TF_{ct}. Then, the number of clusters that exist *c* and the number of clusters containing the term *t*, cf_t, are used to calculate the inverse cluster frequency *t* denoted by ICF_t using the equation $log\frac{c}{cf_t}$. Finally, the TF-ICF weighting is calculated using (1).

$$TF - ICF_t = TF_{ct}\ x\ ICF_t \tag{1}$$

2.8. Semantic similarity

Semantic similarity [17] uses cosine similarity [18] to measure the similarity between aspect term w_x and aspect variable w_y. The cosine similarity equation is shown in (2). w_{xi} is a vector member from w_x and w_{yi} is a vector member from w_y.

$$similarity\ (w_x\ , w_y) = \frac{\sum_{i=1}^{n} w_{xi} w_{yi}}{\sqrt{\sum_{i=1}^{n}(w_{xi})^2}\sqrt{\sum_{i=1}^{n}(w_{yi})^2}} \tag{2}$$

2.9. BERT

BERT [19] is used to derive word context based on the semantic concept of a sentence. We divide the coordinates of the Cartesian diagram into four groups: very positive, positive, negative, and very negative. The x-axis indicates the strength of the sentiment value, whether it is strong or normal, and the y-axis indicates the polarity value of the sentiment, whether it is positive or negative.

2.10. Hybrid lexicon

A hybrid lexicon is the combination of an opinion lexicon [11] and an implicit opinion lexicon [20]. First, the opinion lexicon is used to get the opinion terms contained in the review. Then, if no opinion terms are obtained, candidate opinion terms are detected using the implicit opinion lexicon. The expansion of candidate opinion terms is based on the adverb degree relationship.

2.11. Opinion term degree weighting

Opinion term degree weighting aims to update the existing sentiment polarity y_i and sentiment strength x_i. Previous research [21] obtained sentiment polarity and strength from opinion terms. However, the opinion terms cannot be paired with existing aspect terms.

2. METHOD

The proposed method diagram is shown in Figure 1. Figure 1 shows that this research has several stages, including pre-processing, POS tagging, enhanced++ dependency parsing, text extraction, aspect categorization, and aspect-based sentiment analysis. This research uses aspect category keywords and a hybrid lexicon as the corpus to extract aspect and opinion terms.

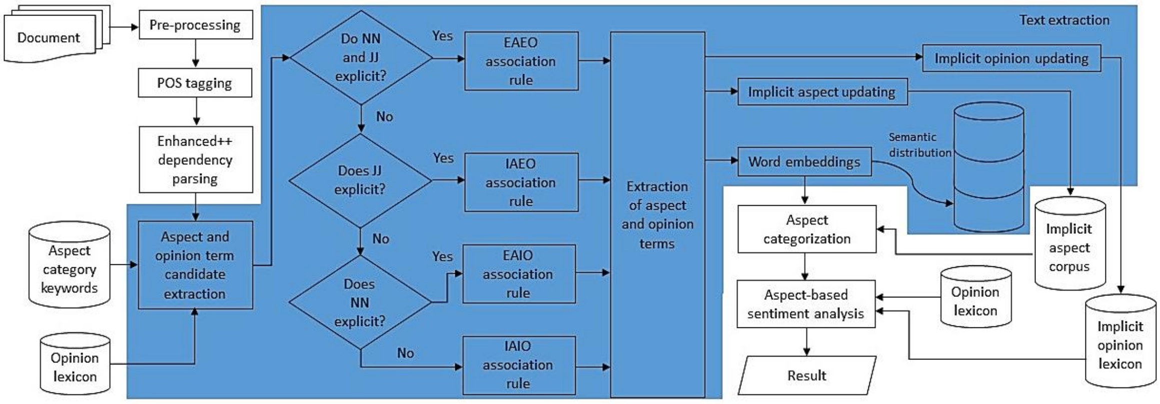

Figure 1. The proposed method diagram

3.1. Dataset

The dataset representation used in this study was taken from the Pontiki dataset [22] with 1,654 training data and 845 testing data. We also manually added some implicit sentences for the dataset to improve the accuracy of the measurement. The implicit sentence dataset consists of 800 training data and 200 testing data. The total proposed dataset is 3,499 sentences. The proposed dataset representation is shown in Table 1.

3.2. Pre-processing

We built the proposed pre-processing method consists convert into lowercase, stop word removal, and punctuation removal. Some symbols in the punctuation removal process are not removed because they are part of writing in sentence types based on their structure. These symbols consist of commas (,), semicolons (;), colons (:), single quotes (‘), double quotes (”), exclamation mark (!), question mark (?), and connect (-). Table 2 shows the illustration of pre-processing results.

Table 2. Pre-processing results

ID Reviews	ID Sentences	Sentence	Results
1001	0	The wait time here for the food even more makes my stomach very rumbling.	the wait time here for the food even more makes my stomach very rumbling
1002	0	The portion here for the food still makes my stomach very rumbling.	the portion here for the food still makes my stomach very rumbling

3.3. Keyword extraction

This research uses sources from Wikipedia [13] for aspect category keyword extraction. The keywords are used as the input variable for four aspect categories: ambiance, food, service, and price. The obtained keyword variables are extracted based on the number of term clusters generated from Wikipedia for the four aspect categories.

3.4. POS tagging and enhanced++ dependency

This stage proposes preparing the data for each word tag and each word relation as input to determine the candidate terms. The POS tagging is carried out using the tool from Stanford Core NLP [9] to extract the word type of each term. Then, the enhanced++ dependency parse [9] is carried out to extract term relations in the review. Table 3 shows the results of POS tagging and enhanced++ dependency for Review [1001].

Table 3. Results of POS tagging and enhanced++ dependency

ID Review	Reviews	POS tagging	Enhanced++ dependency
1001	The wait time here for the food even more makes my stomach very rumbling	*the <DT> wait <NN> time <NN> here <RB> for <IN> the <DT> food <NN> even <RB> more <RBR> makes <VBZ> my <PRP$> stomach <NN> very <RB> rumbling <VBG>*	*det(time, the), compound(time, wait), advmod(time, here), nmod:for(time, food), nsubj(makes, time), case(food, for), det(food, the), advmod(more, even), dep(makes, rumbling), nmod:pass(stomach, my), nsubj(rumbling, stomach), advmod(rumbling, very)*

3.5. Text extraction

The proposed text extraction is compiled based on four definitions: EAEO, IAEO, EAIO, and IAIO. Terms labeled as NN that exist in the aspect keyword variable are identified as explicit aspect terms. Then, terms labeled as JJ that exist in the opinion lexicon are identified as explicit opinion terms. Moreover, we also added a phrase extraction.

3.5.1. EAEO extraction

First, the candidate results of aspect and opinion terms are processed to obtain the words that indicate opinion terms in the opinion term extraction. The aspect term extraction aims to get the words that indicate aspect terms. The aspect term extraction also produces an entity corpus that will be used as input in the extraction process for cases of explicit aspect and implicit opinion. Open IE from Stanford NLP are used to identify the entities in each review, and they are stored in the entity corpus. Lastly, aspect and opinion candidate words are extracted. The EAEO extraction consists of several conditions, including:

a. There are a single NN and a single JJ.
b. There are a single NN and multiple JJs.
c. There are multiple NNs and a single JJ.
d. There are multiple NNs and JJs.

3.5.2. IAEO extraction

First, the candidate results of aspect and opinion terms are processed to obtain words that indicate opinion terms in the opinion term extraction. In the aspect term extraction, we use the implicit aspect corpus [6] as input to identify words that are implicit aspect terms. If the implicit aspect term cannot be identified, we search using an explicit co-occurrence context opinion term with the four aspect categories. Then, from the results of this process, an expansion process is carried out based on word synonyms to get the highest word similarity value from the co-occurrence context term results for the four aspect categories. The highest word similarity value is then extracted as the implicit aspect term. Furthermore, the resulting implicit aspect term is stored in the implicit aspect corpus. This implicit aspect corpus is updated automatically when a new implicit aspect term is obtained. Lastly, aspect and opinion candidate words are extracted. The IAEO extraction consists of the following conditions:

a. There is no NN, but there is one single JJ.
b. There is no NN, but there are multiple JJs.
c. NN or JJ are marked as implicit aspect terms based on the implicit aspect corpus list. For example, the review *the food is expensive*, where *expensive* is an opinion term marked as an implicit aspect of the term *prices*. Thus, the review contains an explicit aspect of the term *food* and an implicit aspect of the term *prices*. We added a new aspect and opinion term target based on the review ID number in this case. This case consists of the following conditions:
   - There are a single NN and a single JJ.
   - There are a single NN and multiple JJs.
   - There are multiple NNs and a single JJ.
   - There are multiple NNs and JJs.

3.5.3. EAIO extraction

First, the candidate results of aspect and opinion terms are processed to obtain intent words, which indicate implicit opinion terms in the intent extraction. Then, the entity corpus we collected is used to get words denoting aspect terms in the entity extraction. The two extraction results are paired based on the word relation that connects the intent words. We use the results of these intent-entity word pairs as input to get word definitions from Wikipedia. The entity-intent definition from the linked Wikipedia page is used to obtain the opinion term based on the explicit opinion term list that resulted from the EAEO extraction. Suppose we cannot produce an opinion term corresponding to an explicit opinion list. In that case, we expand based on the definition of all opinion terms identified from the target-linked Wikipedia page. Moreover, a co-occurrence context term is performed on the entity-intent pairs to get the word similarity with the highest value. The term with the highest value is marked as the implicit opinion term and saved in the corpus. This implicit opinion corpus is updated automatically when new implicit opinion terms are obtained. Lastly, the candidates of aspect and opinion terms are extracted. The EAIO extraction consists of the following conditions:

a. There is a single NN and no JJ.
b. There are multiple NNs and no JJ.
c. There are an NN and a JJ, but the pairing term of NN and JJ cannot be extracted using the relation rules NN and JJ in the EAEO extraction process. This case consists of the following conditions:
   – There are a single NN and a single JJ.
   – There are a single NN and multiple JJs.
   – There are multiple NNs and a single JJ.
   – There are multiple NNs and JJs.

We mark certain VERBs as implicit opinion terms based on the obj relation for review cases with an NN and no JJ. Then, the VERB is marked as the intent. To get the opinion term VERB relationship with the target aspect term NN, an association rule was built by taking the entities in the sentence based on the entity corpus resulting from the EAEO extraction. Then, the entity-intent is expanded based on the definition of the word taken from Wikipedia to get the actual word meaning in the sentence.

For instance, the review [1001] of *the wait time here for the food even more makes my stomach very rumbling* has: the aspect terms of *wait time*, *food*, and *stomach*; and there is no extracted opinion term. The terms of *wait time* and *stomach* are extracted as the entities. We pair the entities with their intent for definition-based expansion to extract the target opinion term based on the explicit opinion corpus. The extracted pairing terms of $entity{:}\,intent$ are *wait time:makes* and *stomach:rumble*. The pairing terms are used as the input for definition-based expansion results. Based on the definition expansion result, *wait time:makes* does not have a definition can be identified, and *stomach:rumble* has three definitions. We extract the explicit opinion term labeled as JJ in the extracted definition and the result is *hungry*. Finally, we extract the synonyms of *hungry* based on the definition as the result. The results are: *feeling*, *wanting eat*; *not eaten*, *few hours*, and *little eat*.

3.5.4. IAIO extraction

First, the candidate results of aspect and opinion terms are processed to obtain words that are labeled as implicit opinion terms. This step uses input from the implicit opinion corpus generated from the EAIO extraction. Meanwhile, in aspect term extraction, we use the implicit aspect corpus that was updated in IAEO extraction to get words denoting implicit aspect terms. Lastly, we extract candidate terms of aspect and opinion. The IAIO extraction consists of the conditions with no NN and JJ as explicit terms of aspect and opinion.

3.6. Aspect categorization

The proposed aspect categorization (AC) aims to measure and determine the aspect categories of the terms generated from the text extraction stage. In the AC stage, the NLU framework retrieves the extracted target aspect terms indicated by nouns and noun phrases. Explicit and implicit reviews can have one or more criteria based on the target aspect terms mentioned in each review. The target aspect terms are detected based on mentioning the explicit aspect term but not the actual target of the implicit opinion term. In addition, the expansion of aspect terms based on word synonyms and word definitions is also carried out to obtain more accurate aspect categories. We use BERT embedding [19] and Semantic similarity [18] to measure the similarity between the aspect terms and the four aspect categories: ambiance, food, price, and service.

For illustration, Table 4 shows the results of semantic similarity calculations in the aspect categorization stage of ID Review [1001]. The results of the three terms with the highest scores obtained in the text extraction stage replace terms were marked as implicit in the existing review. Then, the terms update measured the similarity value of the keyword variables from each aspect category. After updating the implicit terms, the highest average total similarity value was 0.8311 for Service aspect category. So, the aspect categorization results for ID reviews [1001] is “SERVICE”.

Table 4. Semantic similarity calculation results

Term list	Aspect 1	Aspect 2	Aspect 3	Aspect 4
wait time, food, makes, feeling, wanting eat	0.7984	0.8203	0.8378	0.7065
wait time, food, makes, not eaten, few hours	0.7876	0.8207	0.8399	0.7209
wait time, food, makes, little eat	0.7814	0.7983	0.8157	0.7037
Total Avg.	0.7891	0.8131	**0.8311**	0.7104

NB: Aspect 1 is ambiance; Aspect 2 is food; Aspect 3 is service, and Aspect 4 is price.

3.7. ABSA

The proposed research system is shown in Figure 1. Based on Figure 1, the proposed ABSA stage uses the input aspect category from the results of the aspect categorization stage. Then, the results of the opinion terms from the text extraction stage are used as input for determining the sentiment polarity. We use BERT sentiment analysis, a hybrid lexicon, and opinion degree weighting for ABSA methods.

3.7.1. BERT sentiment analysis

BERT sentiment analysis [23] is used to extract opinion words into four classes: positive, very positive, negative, and very negative. However, there is no explicit weighting of the opinion words, which causes some words to be classified incorrectly. For example, the word *expensive* is classified in the positive class. Moreover, complementary phrases that have not been captured also cause the same assessment between single and complementary opinion words. For example, *expensive* and *very expensive*. Therefore, we combined BERT with a hybrid lexicon and opinion degree weighting to overcome these problems.

3.7.2. Hybrid lexicon

We used a hybrid lexicon [15], combined the opinion lexicon and the implicit opinion lexicon, to handle problems in the existing lexicon and group each word based on the actual class. The opinion lexicon consisted of 6,800 words from two classes of positive and negative sentiments. Then, the implicit opinion lexicon was generated manually using the proposed text extraction method.

3.7.3. Opinion degree weighting

We manually added weighting degrees of opinion terms to handle problems in determining the sentiment and group complementary phrases based on the actual opinion term class. We updated the polarity and strength of sentiment using the Vader opinion lexicon [21]. The updated sentiments consist of very positive, positive, negative, and very negative.

To get the sentiment polarity value of all opinion terms y_i^j, we determined the range of values from +4 to -4 for the positive and negative classes. Then, to synchronize the sentiment polarity value of an opinion term y_i, we transformed the polarity sentiment value from +1 to -1 using the normalization function $y_i = \frac{y}{\sqrt{y^2+a}}$, where y is the opinion weight value of existing terms. After obtaining the normalized value of polarity sentiment, we calculated the total value of sentiment polarity based on adverb pairs using the equation $y_i{}' = u \times y_i$, where u is the adverb degree variable for sentiment polarity paired with the opinion term. For this reason, we compiled a list of adverb degree variable values that can affect the polarity of sentiment, as shown in Table 5.

Table 5. Value list of the adverb degree variable for sentiment polarity

Adverb degree variable for sentiment polarity			
Level	Variable	Aspect term target	Value
Level 1	*too*	Item of food taste type	-1
Level 2	*barely; scarcely*	All aspect terms	-0.5
Level 3	*almost; quite; somewhat; enough; little; less; least; a bit*	All aspect terms	+0.5
Level 4	other adverbs that do not exist at levels 1, 2, and 3; no intensifier	All aspect terms	+1

Furthermore, to obtain the sentiment strength value from the term x_i^j, we determined the value of the opinion term degree through pairs of intensifiers with a range of values. +1 to -1 for very positive, positive, negative, and very negative. The total value of the sentiment value for the strength of an opinion term was obtained by the equation $x_i{}' = v \times |y_i{}'|$, where v is the intensifier variable for the strength of the sentiment paired with the opinion term. Table 6 shows a list of adverb degree variable values used to determine the sentiment polarity of the opinion terms. Here, especially for the adverb *too*, we added to the strength of the judgment sentiment if the adverb was paired with an opinion term item, which is a type of food taste (i.e., sweet and salt). Table 7 shows the list of adverb degree variable values used to determine the sentiment strength of opinion terms.

Table 8 shows the result of sentiment polarity determination for review [1001]. Based on the proposed rule algorithm, the term *very rumbling* is extracted as the opinion term. Then, the sentiment score measurement result is -0.625. Finally, a score of -0.625 is classified as a very negative sentiment.

Table 6. Value list of the adverb degree variable for sentiment strength

Level	Variable	Value
Level 1	*too; very; a lot, lots, extremely; horribly; unusually; wonderfully; deeply; absolutely; fully; hardly; terribly; pretty; really; insanely; remarkably; greatly; highly; most; much; intensely; strongly; utterly; so; amazingly*	-1
Level 2	A variable mixture of levels 1 and 3	-0.5
Level 3	*almost; completely; barely; quite; somewhat; fairly; incredibly; enough; largely; scarcely; badly; little; less; least; just; purely; thoroughly*	+0.5
Level 4	No intensifier variable	+1

Table 7. F1-score results for AC and ABSA

Sentence type	Cases of aspect and opinion terms							
	Explicit		Implicit					
	EAEO		IAEO		EAIO		IAIO	
	AC	ABSA	AC	ABSA	AC	ABSA	AC	ABSA
Simple	0.9826	0.9891	0.9651	0.9506	0.9587	0.9272	0.8756	0.8498
Compound	0.9835	0.9831	0.9502	0.9558	0.9412	0.9070	0.9180	0.8689
Complex	0.9851	0.9733	0.9505	0.9552	0.9318	0.9143	0.8750	0.8539
Compound-complex	0.9780	0.9725	0.9485	0.9538	0.9176	0.9032	0.8493	0.8293
Average	0.9823	0.9795	0.9536	0.9539	0.9373	0.9129	0.8795	0.8505

Table 8. Result of sentiment polarity determination

ID Rev.	ID Sent.	Review	Extracted opinion term	Sentiment score	Sentiment result
1001	0	the wait time here for the food even more makes my stomach very rumbling	very rumbling	-0.625	very negative

4. RESULTS AND DISCUSSION

In this section, the performance of our study is described. First, the text extraction method for explicit and implicit reviews is explained. Then, the aspect categorization and the aspect-based sentiment analysis are also explained. Lastly, the results are also compared with other methods.

4.1. Text extraction result

The text extraction can properly extract the aspect and opinion terms, which are explicit and implicit, in four sentence types. The average F1-scores for explicit review cases of EAEO are 96.33% for explicit aspect extraction and 96.83% for explicit opinion extraction. The average F1-scores for implicit review cases of IAEO are 89.23% for implicit aspect extraction and 95.89% for explicit opinion extraction. The average F1-scores for implicit review cases of EAIO are 95.06% for explicit aspect extraction and 82.07% for implicit opinion extraction. The average F1-scores for implicit review cases of IAIO are 82.16% for implicit aspect extraction and 78.72% for implicit opinion extraction.

4.2. AC and ABSA results

The AC and ABSA results for four sentence types are shown in Table 8. Table 8 shows that the AC and ABSA methods can work properly in explicit and implicit sentences. The average F1-scores of AC for four sentence types are 98.23% for EAEO, 95.36% for IAEO, 93.73% for EAIO, and 87.95% for IAIO. Then, the average F1-scores of ABSA for four sentence types are 97.95% for EAEO, 95.39% for IAEO, 91.29% for EAIO, and 85.04% for IAIO. These results show that text extraction can help the AC method properly classify each review's aspect category. Moreover, the text extraction can help the ABSA method properly classify each review's sentiment polarity.

The comparison of ABSA cases worked on from several ABSA researches is shown in Table 9. Table 9 shows that the proposed method can work better than previous research. The proposed method can work on sentence cases of EAEO, IAEO, EAIO, and IAIO with four positive, positive, negative, and very negative sentiment classes. Meanwhile, many previous researches still worked on sentence cases of EAEO and IAEO with positive and negative sentiment classes. Previous research also worked on the sentence case of EAIO but not the sentence case of IAIO. However, the proposed method still works on restaurant domain reviews and does not try other domain reviews. The results still have false positives and negatives because the proposed method cannot expand the synonym of some implicit terms of aspect and opinion through Wikipedia source pages. For instance, the review *told us to sit anywhere, and when we sat, he said that it was reserved and told us to move*, which the implicit aspect term should be *he* as the variable of service aspect category, and the implicit opinion should be *told us to sit anywhere, he said it was reserved, told us to move* but the proposed method still cannot extract it accurately.

The proposed method can well take the aspect and opinion terms for the explicit and implicit reviews in simple, compound, complex, and compound-complex sentences. The results of the aspect and opinion terms carried out by the proposed method were processed to determine the aspect category and sentiment polarity accurately. The proposed method successfully classified the opinion terms into four sentiment strength classes: very positive, positive, negative, and very negative. Identifying pairs of aspects and opinion terms that are explicit and implicit is important because an implicit opinion term may have a target aspect category that is different from the existing explicit aspect term and has a sequence distance that is closer than the actual target aspect term distance. Classifying four sentiment classes into four aspect categories can also provide more convincing input for users in determining the desired restaurant choice. However, further research still needs to be carried out to resolve the problem of implicit opinion extraction, which cannot be resolved in this research. In addition, we hope the proposed method and research results can be developed and used for various domains, not just restaurants.

Table 9. Comparison of ABSA cases worked on

Researches	Review cases							
	Explicit		Implicit					
	EAEO		IAEO		EAIO		IAIO	
	Aspect	Opinion	Aspect	Opinion	Aspect	Opinion	Aspect	Opinion
Cadilhac [2]	✓	✓	✓	✓	✓	✓	✕	✕
Schouten [24]	✓	✓	✓	✓	✓	✓	✕	✕
Poria [25]	✓	✓	✓	✓	✓	✓	✕	✕
Chen [3]	✓	✓	✓	✓	✓	✓	✕	✕
Tubishat [26]	✓	✓	✓	✓	✕	✕	✕	✕
Proposed method	✓	✓	✓	✓	✓	✓	✓	✓

4.3. Evaluation result

In previous ABSA studies for restaurant review [22], the best F1-score is 0.7940, and the best accuracy is 0.7994. We compared our results with previous studies that used the same dataset [22]. Table 10 shows the comparison of the ABSA evaluation results in restaurant review [22]. The proposed ABSA method was proven to work better and more accurately than the previous studies [2], [3], [22], [24], [25] with obtained average F1-score total of 0.9242 and average accuracy total of 0.9233.

Table 10. Comparison of ABSA evaluation result in restaurant review [22]

Researches	Results			
	P	R	F	A
Pontiki [22]	N/A	N/A	0.6268	N/A
Cadilhac [2]	0.7692	0.7733	0.7712	N/A
Schouten [24]	N/A	N/A	0.7940	N/A
Poria [25]	0.8521	0.8815	N/A	N/A
Chen [3]	N/A	N/A	N/A	0.7994
Proposed method	0.9272	0.9214	0.9242	0.9233

5. CONCLUSION

This paper proposed an ABSA method: natural language understanding for implicit reviews. We built a set of rules as the NLU system that can solve the problem of extracting implicit reviews using text extraction that pays attention to different types of sentences and words. The text extraction can accurately retrieve pairing terms of aspect and opinion, which are explicit and implicit. The text extraction can also significantly increase the performances of the AC method with an average F1-score of 0.9382 and the ABSA method with an average F1-score of 0.9242. We compared the results of the obtained ABSA evaluation in restaurant reviews with those of previous studies. The obtained F1-score result of 0.9242 shows that the proposed method can work better than previous methods.

Understanding the implicit reviews is important to increase AC and ABSA performances. We hope this proposed method can be implemented on other review datasets in future work. The development of datasets for sentence types containing various characteristics of implicit opinions is still needed. Apart from that, we also hope that this proposed method can be further improved to get even better results, especially in the case of other sentences that we have not been able to do well.

ACKNOWLEDGEMENTS

This research was funded by Institut Teknologi Sepuluh Nopember (ITS) under *Penelitian Dana Departemen Program, Penelitian Keilmuan, Penelitian Flagship, Penelitian Kolaborasi Pusat* and under the Project Scheme of the Publication Writing and Intellectual Property Rights (IPR) Incentive (*Penulisan Publikasi dan Hak Kekayaan Intelektual/PPHKI*) Program 2024.

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